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Qualitative and Quantitative Approaches

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pair of emotions, circle the one that you think has more intensity." For the studies of 15 emotions, there would be n(n-1)/2 = 15(14)/2 = 105 pairs: anxious-bored, hatefear, disgust-excitement, tired-shame, etc., etc.

Each item in a set appears n-1 times in the set of all pairs, so in the case of the 15 emotions, informants would see hate, for example, paired with each of the other 14 emotions. This gives each emotion 14 chances to win—to be circled as having higher intensity, in this case. The number of times an item wins in this game is its rank order. Ranking data can be analyzed with various statistical methods, including the cultural consensus model (Further Reading: paired comparisons. Also see Further Reading, chapter 10).

CULTURAL CONSENSUS ANALYSIS

Historically, anthropologists described cultures in terms of norms—the Navajo are matrilocal, the Yakö practice double descent—but a landmark paper in 1975 by Pelto and Pelto made clear that intracultural variation—based on things like gender, age, economic status, occupational specialization, and so on—was the norm. Some cultural knowledge, like the names of the months, is widely shared but much cultural knowledge is distributed unevenly. We hear, for example, that women know more about fashion than men do in the United States and that men know more about cars than women do. We hear that young people in the Amazon village where we're working aren't learning the names and uses of medicinal plants as much as their elders did. How can we test if knowledge in particular cultural domains varies by gender or age? Cultural consensus analysis gives us a way to measure the extent to which people agree about the contents of a cultural domain—to measure domain-specific cultural competence.

CULTURAL COMPETENCE

Consensus analysis is based on a long and distinguished intellectual history on the power of collective wisdom, going back to a paper by the Marquis de Condorcet (1785) on the probability of a jury reaching a correct decision (Batchelder and Romney 1986) in legal cases as opposed to relying on the judgment of a single person. In 1907, Francis Galton attended a fair in Plymouth, England where 800 people guessed the weight of an ox. The ox weighed 1,198 pounds. The spread of guesses went from 1,074 to 1,293 pounds but the mean was 1,196 pounds (Galton 1907a, 1907b)—almost dead on.

And Robyn Dawes (1977) asked 25 male members of the faculty in psychology at the University of Oregon to rate the height of all other 24 colleagues using five scales, like those I discussed in chapter 11: semantic differential (from short to tall), Likert-like (extremely short to extremely tall), and so on. The first factor scores for the five scales—the score on the underlying variable with which all the scales were associated—correlated .98 with the actual height of the men. The title of Dawes's article was "Suppose We Measured Height with Rating Scales Instead of Rulers?" Well, the answer is: As long as you take the average of a bunch of people on those scales, you can lose the rulers and do pretty well. (For a review of collective wisdom, see Surowiecki 2004.)

James Boster (1985, 1986) walked 58 Aguaruna Jivaro women (in Peru) through a garden that had 61 varieties of manioc. He asked the women waji mama aita? ("What kind of manioc is this?") and calculated the likelihood that all possible pairs of women agreed on the name of a plant. Boster had planted the garden himself, so he knew the true identification of each plant. Sure enough, the more women agreed on the identification of a plant, the more likely they were to know what the plant actually was. In other words, people who know a lot about—are highly competent in—a cultural domain tend to agree

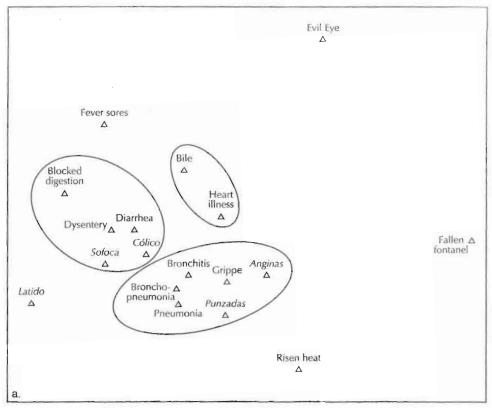


FIGURE 16.19a.

MDS of Pichátaro term-frame data.

SOURCE: J. C. Young and L. Y. Garro, "Variation in the Choice of Treatment in Two Mexican C Communities," Social Science and Medicine, Vol. 16, pp. 1453–63, figure 2, 1982.

with each other about the content of the domain and people who know little tend to disagree.

When Agreement Equals Knowledge: Equation 1

Romney et al. (1986) took all this a step further by showing exactly how, and under what conditions, agreement among a set of people equals knowledge. (For details of the proof, see the original article by Romney et al. [1986] and see Borgatti and Carboni [2007] and Weller [2007] for particularly clear explanations of the theory.) Weller (2007) is a key resource for instructions on how to run consensus analysis and how to interpret the results. In brief, there are two equations: one expressing the probability that a person answers a question correctly and one expressing the probability that two people agree on the answer to a question. The first equation comes from classical test theory—the kind that produces all those standardized tests you've taken all your life.

$$m_i = d_i + 1 - d/L$$
 Formula 16.1

Adjusting for Guessing

This equation says that the probability of getting the answer to a question right (m_i) is the probability that you know the answer (d_i) plus the probability $(1 - d_i/L)$ that you

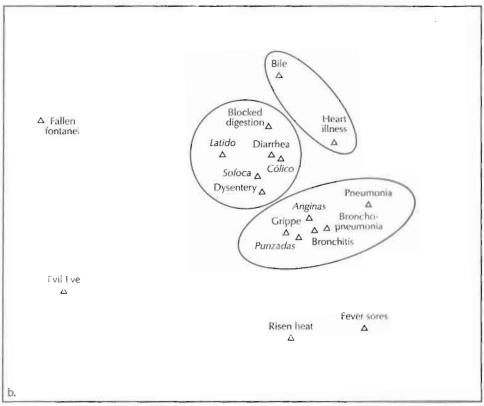


FIGURE 16.19b.

97 (011)

MDS of Uricho term-frame data.

SCURCE: J. C. Young and L. Y. Garro, "Variation in the Choice of Treatment in Two Mexican C Communities," Social Science and Medicine, Vol. 16, pp. 1453–63, figure 3, 1982.

guess right if you don't know the answer, and where L is the number of choices available for guessing. In a true-false question, for example, there is a .50 probability of guessing the right answer at random. In a question with three answers, the probability of guessing right is .33. In a test where each question has five answers, it's .20. The formula for adjusting a test score for guessing is

$$K = [S - 1/L]/[1 - 1/L]$$
 Formula 16.2

where K = actual knowledge, S is the original test score, and L is the number of choices available when a student has to guess the answer (see Borgatti 1997; Weller 2007).

Table 16.10 shows the answers by one student to 25 multiple choice questions on one of my Introduction to Anthropology exams. The questions on this exam each had five possible answers, so the student made 25 choices of a number between 1 and 5. To find out how well the student did on the whole exam, we count up the number of matches between the student's vector of numbers and the vector that represents the correct answers and we divide by the total number of questions. This student got 19 matches, or 19/25 = .76.

The student's adjusted knowledge score would be:

$$K = [.76 - .20]/[1 - .20] = .70$$

Please rate the following emotions in terms of their intensity, where "1" indicates the least amount of intensity, and where "5" indicates the greatest amount of intensity.

ANXIOUS	1	2	3	4	5
ENVY	1	2	3	4	5
LONELY	1	2	3	4	5
BORED	1	2	3	4	5
ANGUISH	1	2	3	4	5
HATE	1	2	3	4	5
DISGUST	1	2	3	4	5
FEAR	1	2	3	4	5
EXCITEMENT	1	2	3	4	5
SHAME	1	2	3	4	5
TIRED	1	2	3	4	5
LOVE	1	2	3	4	5
ANGER	1	2	3	4	5
SAD	1	2	3	4	5
HAPPY	1	2	3	4	5

FIGURE 16.20.

An example of a rating scale.

Table 16.10 Grading a Test with an Answer Key for 25 Multiple-Choice Questions

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
ınsı	we	rs																						
3	3	2	3	2	1	4	3	2	2	5	5	2	2.	5	5	1	3	1	4	2	1	5	4	1

In other words, d, for this student—the probability that she actually knows the answer to any question on the test—is .70.

When Agreement Equals Knowledge: Equation 2

The second equation in the consensus model is the probability that two people, i and j, agree on the answer to a question. There are four ways for this to happen: (1) i and j both know the answer with probability d; (2) i knows the answer and j guesses correctly; (3) j knows the answer and i guesses correctly; and (4) neither i nor j know the answer but they make the same guess, which may or may not be the correct one. The combined probability here is:

$$m_{ij} = d_i d_j + \frac{1 - d_i d_j}{L}$$
 Formula 16.3

which, as Borgatti and Carboni (2007:454) say, in a marvelous understatement, is "pleasingly analogous to" the first equation.

Assumptions of the Model

In other words, under certain conditions, "we can estimate the amount of knowledge of each person by knowing only the pattern of agreement among persons in the group" (Borgatti and Carboni 2007:455). Here are the conditions:

- Informants share a common culture and there is a culturally correct answer to any
 question you ask them. The culturally correct answer might be incorrect from an outsider's perspective (as often happens when we compare folk knowledge about illnesses
 or plants or climate to scientific knowledge). Any variation you find among informants
 is the result of individual differences in their knowledge, not the result of being members of subcultures.
- Informants give their answers to your test questions independently of one another. Consensus analysis is not for focus-group data.
- All the questions in your test come from the same cultural domain and are more-orless of equal difficulty. No fair asking about the uses of medicinal plants and the rules of kinship in the same test.

Running Consensus Analysis

If these assumptions are met, we can run a factor analysis of the corrected-for-guessing, people-by-question matrix. The results tell us if our informants share a single culture about the domain we're testing and, if they do, what their knowledge of that domain is and how knowledge varies among them.

Factor analysis, remember, is a set of statistical techniques for reducing a data matrix to a set of underlying variables. It is used in the development of attitude scales to look for packages of specific items (like how you feel about gun control or abortion or single-sex marriage) that measure different aspects of big, underlying variables (like rightish or leftish political orientation).

In consensus analysis, it is used to test whether there is a single, underlying component of shared knowledge or culture. If there is, then there will be one major factor—knowledge of the domain—and each person's score on that factor is their competence in the domain. One major factor—a single culture—is indicated when (1) the first factor is large relative to the second (you'll know this if the first eigenvalue in the factor analysis is at least three times the size of the second), and (2) no informant has a negative score on the first factor since (if there is a single culture, people shouldn't have negative knowledge of it).

If the ratio of the first to the second eigenvalue is less than 3-to-1 or if there are negative scores on the first factor, then there may be more than one culture in the group of informants who took the test. For example, men and women may represent different cultural subgroups for some domains, as might members of different ethnic or religious groups. You can test this by running a consensus analysis on the subgroups separately.

There are two other possibilities. First, one group of people may be competent in a domain while another group knows little about it. For example, Romney et al. (1987) asked 26 undergraduates (13 men and 13 women) about the effectiveness of 15 kinds of birth control. Seven of the men had negative scores on the first factor of the analysis, so Romney et al. ran the analysis separately on the men and the women. For the women, the

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ratio of the first to the second eigenvalue was more than 4-to-1, so there was one big underlying factor (knowledge about the effectiveness of birth control methods) and the women's factor scores were all positive. For the men, the ratio was about 1-to-1, and six of the 13 had negative scores on the first factor. In other words, for those 13 men, it wasn't just that they didn't share a culture about the domain, they had little or no knowledge of the domain at all.

Another possibility is that you've got a shaman, or the equivalent, in your sample. If you run a consensus analysis and find one or two negative first-factor (knowledge) scores out of a large sample, it may be that you've included people whose knowledge about the domain is so specialized it doesn't jibe with that of others in the mainstream. It is to the advantage of shamans everywhere, whether their knowledge is about curing illness or making money on the stock market, to protect that knowledge by keeping it maximally different from mainstream knowledge. Use consensus analysis to find highly knowledgeable informants but never pass up the chance to interview a shaman.

Retrieving the Answer Key to a Test

If there is a single culture—if there is one major factor representing knowledge of the domain and if there are no negative scores on that factor—then informant scores on the first factor represent their knowledge about—their competence in—the domain. And because of the relationship between formulas 16.1 and 16.3—that is, the relation between agreement and knowledge—we can retrieve the answer key to the set of questions on the test by looking at the most common answers—that wisdom-of-crowds thing again—and by giving more weight to the answers of the high scorers on the test when the crowd is split on the answers to a particular culture.

I tested this, using UCINET (Borgatti et al. 2002) on data from a 1995 intro class in anthropology. There were 168 students in the class and the exam had 60 questions. Recall that the ratio of the first eigenvalue to the second should be at least 3-to-1 to conclude that there is a consensus. In this case, the ratio was more than 20-to-1, so there was, indeed, one big underlying factor associated with the answers that students gave to the questions on the test. Because the purpose of the test was to gauge students' knowledge of the material, the factor can be interpreted as knowledge, and each student's score on that big factor can be interpreted as his or her score on the test.

Figure 16.21 shows the correlation between the first factor score for each student and the score that each student actually got on the test. The correlation is 0.96—almost perfect. It's so close, in fact, that had I lost the answer key, I could have given every student his or her factor score as the grade for the test with no impact on the final grade for the course. And this is no fluke: Borgatti and Carboni (2007:458) ran this analysis on a test of 91 students in an organizational behavior class and got a 0.95 correlation—again, almost perfect.

The answer key for my test that was derived from the analysis was also almost perfect. Taking the majority answers to the 60 questions and adjusting for guessing, the analysis got 58 right. Here are the two questions that it missed:

"Natural selection" selects for:

- (1) reproductive success.
- (2) survival of the fittest.
- (3) survival of the species.
- (4) adaptive radiation.
- (5) random mutations.

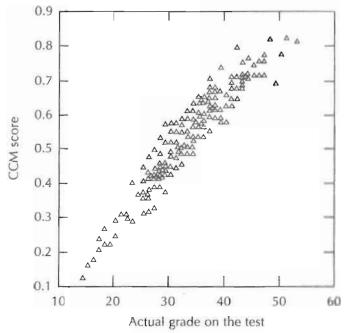


FIGURE 16.21.
Plot of raw grades and scores from a cultural consensus analysis on an Intro to Anthropology test. The correlation is 0.96.

The first hominid to live in regions with cold winters was:

- (1) Homo erectus.
- (2) Homo hablis.
- Homo sapiens neandertalensis.
- (4) archaic Homo sapiens.
- (5) Australopithecus afarensis.

For the first question, 70 students picked (1), reproductive success (the correct answer), but 79 students picked (2), survival of the fittest. For the second question, 49 students picked (1), Homo erectus (the correct answer) but 90 students picked (3), Homo sapiens neandertalensis. (In those days, Neanderthals were still classified as a subspecies of modern humans. Today, some anthropologists would classify them as a separate species.) Popular culture—about Neanderthal Man and about the phrase "survival of the fittest"—was just too powerful to be overcome fully by some anthropology lectures (box 16.6).

What this means is that if you can retrieve an etically correct answer key, you can apply the model (cautiously, always cautiously... see box 16.6) to tests of enic data—like people's ideas about who hangs out with whom in an organization or what people think are good ways to cure a cold, avoid getting AIDS, take care of a baby, etc. It still takes knowledge of the local culture to fully understand the distribution of knowledge about a cultural domain. But when we ask people during fieldwork to tell us the uses of various plants or to list the sacred sites in a village or to rate the social status of others in a community, we don't want to know only their opinions. We want to know the uses of the

BOX 16.6

CULTURAL CONSENSUS AND MULTIPLE ANSWER KEYS

Hruschka et al. (2008) used frame elicitation in interviews with women in Matlab, Bangladesh, about the causes and symptoms of postpartum hemorrhage. Of the 149 in their sample, 98 were lay women, 37 were traditional birth attendants (TBAs), and 14 were skilled birth attendants (SBAs)-that is, women who had been trained in modern medical techniques for midwifery. When Hruschka et al. ran the data through consensus analysis, the ratio of the first to the second eigenvalue was nearly 6-to-1 and there were no negative competencies. This indicated a single cultural model. But when they picked the data apart, none of the SBAs agreed with the statement "alga (evil spirits) is a cause of excessive, life-threatening bleeding," whereas 84% of TBAs and 78% of lay women agreed. This turned out to indicate a pattern: The SBAs agreed among themselves about many of the items in the cultural knowledge test; the lay women and the TBAs agreed among themselves; and the two groups disagreed. In other words, the two groups of women were drawing their answers to test questions from different answer keys. Hruschka et al. point out that "anthropologists have long observed this possibility in modern society," citing work by Margaret Mead (1940) and Fredrik Barth (2002).

plants and the location of the sacred sites and the social status of people. We never had an answer key to tell whether informants were reporting this information accurately. Now we do.

MAKING UP QUESTIONS FOR A FORMAL CONSENSUS TEST

A really important part of running a formal consensus analysis is building good test items. This takes work. Start with systematic and in-depth interviews with knowledgeable informants about the domain you're investigating and do a close analysis of those qualitative data so that you can create sensible questions—that is, questions that reflect the content of the domain. We expect professors who make up course exams to know the material cold, and you should expect no less of yourself when you make up questions for a formal consensus analysis. About half the questions should be positive (true, yes, agree) and about half should be negative (false, no, disagree).

Jeffrey Johnson and David Griffith (1996) studied what people in North Carolina know about the link between seafood safety and coastal pollution using the formal cultural consensus model. First, they asked some expert informants to free-list (1) the kinds of pollution along the Atlantic coast (examples included acid rain, chemical runoff as the result of coastal erosion, and so on); (2) the species (clams, crabs, tuna) that might be affected by the various types of pollution; and (3) problems that might arise, like diseases in fish. From these data, Johnson and Griffith identified 12 types of pollution, 11 causes of pollution, and 10 species. Next, they asked a convenience sample of commercial fishermen and local residents of various ethnic backgrounds to (1) pile sort the types of

pollution; (2) link each pollutant to the problems they cause; and (3) identify the species that each pollutant affected the most.

Johnson and Griffith asked the informants to explain why they made all these linkages and transcribed the results. Then, three coders went through the transcripts, tagging statements about the how seafood, pollutants and various risks to health and the environment were related. There were 53 statements identified by at least two of the three coders. The researchers turned these into a true-false knowledge test, with half the statements positive (true) and half being negative. For example, "heavy metals cause sores on both fish and people" is true (positive), but "heavy metals are necessary nutrients for both fish and people" is false (negative). Finally, they gave the test to 142 people in the area including: (1) a representative sample of 132 people, stratified by residence (rural-urban), income (high and low), and ethnicity (white and black); (2) 10 students from their university; and (3) 10 marine scientists. They analyzed the 142(people)-by-53(statement) matrix using the formal consensus model. The first eigenvalue in the analysis of the agreement matrix was over seven times bigger than the second. Those 142 people, despite coming from such different backgrounds, drew from a single culture in answering the 53 questions on the test about seafood and pollution.

Fine-grained analysis, though, turned up some interesting differences. The consensus was that the following statement was true: "Much of the pollution dumped into coastal and ocean waters has no effect on the flavor or seafood." The scientists, however, disagreed.

The Informal Model: Pile Sorts, Triad Tests, and Rank Ordered Data

When you have ordinal or ratio or rank-ordered data, including data from pile sorts and triad tests, use the informal model of consensus analysis (Weller 2007) (box 16.7).

BOX 16.7

LUMPERS AND SPLITTERS

Be careful, though: With free pile sorts, some people make just a few piles and others make many. Lumpers and splitters are technically not responding to the same cues when you ask them to sort items freely into piles. This means you can test whether there is a single culture—whether most people see the relations among a set of items in a pile sort similarly—and you can look for informants who are most representative of the culture, but you wouldn't put much stock in individual factor scores or use those scores as input into any other analysis.

In this model, you create a people-by-people similarity matrix from the original people-by-item test and factor the similarity matrix. You can do this in most statistical packages, but ANTHROPAC and UCINET will do it automatically. Here's an example.

Adam Kiš (2007) found that people in the village of Njolomole, Malawi had stopped going to every funeral because, with AIDS, there were just too many to go to. Kiš asked 23 people to: "Name all of the reasons you can think of for attending a funeral." He listed the 12 reasons cited most often on a piece of paper and asked 30 people. If there were

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too many funerals in your village so that you could not attend each one, which of the following reasons would be the most important in helping you decide which funerals to attend?" Then he asked people to mark the next most important reason, and the next, and so on down the list. Table 16.11 shows his data.

These are rank-ordered data, so the informal consensus model is appropriate. To do this, correlate all pairs of rows in table 16.11 and turn it into a 30-by-30, people-by-people similarity matrix (any statistical package will do). The result for the first 10 rows is shown in table 16.12.

Read table 16.12 as follows: Informants 4 and 9 are highly and positively correlated (0.741); informants 6 and 2 are hardly correlated at all (0.070); informants 2 and 3 are weakly and negatively correlated (-0.364); and so on. The negative correlation for informants 2 and 3 means that they tended to rank the reasons for going to a funeral in some opposite ways. For example, looking across rows 2 and 3 of table 16.11, informant 2 ranked HEL (helping the family of the deceased with funeral preparations) last on his list, and informant 3 ranked it third.

Next, factor analyze the 30-by-30 matrix of informant agreements using a variant of factor analysis called minimal residuals (or MINRES) or maximum likelihood (ML). I did this with SYSTAT, but you can use SPSS or any major statistical package. The results are in figure 16.22. The first factor is large, relative to the second (the ratio is 3.157), which means that there is a single culture at work, despite the differences in the way people ranked their reasons for going to a funeral. There is a nice range of scores—from 0.07 (for informant 2) to 0.92 (for informant 30)—and there are no negative scores, but some people (like informants 10, 11, 22, 25, and 30) are clearly more knowledgeable about the shared reasons for going to a funeral than others are.

Kiš interviewed these knowledgeable informants in depth and asked them why reciprocity (attending someone's funeral so that his or her family will attend your family's funerals) was the runaway most-important reason given and why carrying the coffin and partaking of the traditional funeral feast were ranked so low. It turned out that carrying coffins was only for young men and his sample of 30 informants did not have that many young men in it. If he'd had more young men in his sample, this might have resulted in a higher overall ranking of eating as a reason for attending a funeral, since coffin bearers get generous portions of food.

Selecting Domain-Specific Informants

This brings up a really interesting use of consensus analysis: selecting domain-specific informants. Table 16.13, from Weller and Romney (1988), shows the number of informants you need to produce valid and reliable data about particular cultural domains, given that the three conditions of the model are more-or-less met. (I say "more-or-less" because the model is very robust, which means that it produces very similar answers even when its conditions are more-or-less, not perfectly, met.) Just 10 informants, with an average competence of .7 have a 99% probability of answering each question on a true-false test correctly, with a confidence level of .95. Only 13 informants, with a relatively low average competence of .5 are needed if you want a 90% probability of answering each question on a test correctly, with a confidence level of .95.

And, as table 16.14 shows, when you have interval level data, if you interview 10 informants whose responses correlate .49, then the aggregate of their answers are likely to correlate .95 with the true answers. Consensus analysis, shows that: (1) Only a relatively small sample of informants are needed for studying particular cultural domains; and (2)

ز

						Re	Reason					
Informant -	REC	SOR	HEL	CUS	REL.	EAT	/ FRI	GIF	CON	000	CHU	COF
-	4	ę	2	7	9	12	11	80	ro.	10	e	o
2	е.	Ω	12	4	17	7	8	2	60	6	10	9
m	4	מ	8	6	2	12	11	8	9	2	10	7
4	рЭ	4	2	10	Ω	12	9	7	-	11	6	00
വ	2	11	ო	10	4	12	9	9	-	7	8	o
9	က	œ	6	2	7	12	10	9	2	÷	4	-
7	-	∞	10	9	Ω	12	_	4	2	6	က	11
8	က	7	2	æ	۲	0	2	11	4	10	9	12
6	က	2	4	11	-	12	8	S	7	10	6	9
10	-	Ω	e	2	0	12	-	00	4	7	9	o
	2	4	۲.	-	2	12	11	9	က	00	0	10
12	-	2	4	9	g)	12	80	D	7	n	10	11
13	က	44		വ	14	6	7	9	89	2	12	10
14	4	10	7	9	, -	12	7	6	ო	00	2	11
15	2	വ	n	-	11	12	20	6	4	9	80	1
16	2	ო	9	4	11	12	8	7	- -	2	6	10
17	7	4	80	9	Ø	12	01)	m	2	5	2	11
13	←	00	3	9	D	12	4	11	2	1	o.	10
19	2	4	-	∞	o	12	8	7	10		2	9
20	-	10	7	11	80	12	10	4	9	m	6	7
21	2	ഹ	\$0	7	9	12	,	11	4	6	ന	10
27	ሎን	ख	2	-	9	12	A	6	2	11	00	01
83	F	67)	2	11	7	12	10	2	4	9	80	6
24	12	10	D	∞	-	1	2	1	က	4	9	O
1400 1400	2	-	7	က	4	12	8	10	2	o	9	11
26	-	44	m	2	Ŋ	0	200	9	4	10	12	11
5.3	,-	4	2	6	IJ	12	00	က	11	7	9	10
28	5	7	4	2	c)	12	6	1	10	80	က	9
29	0	4	Ø	വ	-	12	4	89	9	10	7	11
30	-	2	4	9	വ	12	The state of the s	œ	က	7	6	10

The list of reasons give: REC = reciprocity fattending a specific person's funeral so that his or her family intendence will attend your family's funerals), SOR = sorrow, HEL = to her family or the deceased with funeral preparations, CUS = going out of custom, REL = going because ego is a relative of the deceased, EAT = to eat the requisite funeral family or the deceased, GIF = to bring gifts to the family of the deceased, CON = to console the family of the deceased, GOO = to say good byte to the deceased, CHU =: going because ego is a member of the seme church as the deceased, COF = to carry the coffin.

SOURCE A. Kis, NAPA Bulletin 27 pp. 129-140, 2007. Table 1, p. 134. Used by permission.

Table 16.12 Correlation Matrix for the First 10 Rows of Table 16.11

	1	2	co	4	ro	9	7	00	6	10
-	1.000	-0.231	0.399	0.650	0.273	0.245	0.406	0.336	0.601	0.699
2	-0.231	1.000	-0.364	-0.028	-0.098	0.070	0.273	-0.147	-0.007	0.105
3	0.399	-0.364	1.000	0.420	0.462	0.378	0.084	0.175	0.587	0.364
4	0.650	-0.028	0.420	1.000	0.748	-0.049	0.441	0.601	0.741	0,455
5	0.273	-0.098	0.462	0.748	1.000	0.245	0.587	0.622	0.448	0.336
9	0.245	0.070	0.378	-0.049	0.245	1.000	0.608	0.042	-0.112	0.622
7	0.406	0.273	0.084	0.441	0.587	0.608	1.000	0.483	0.280	0.469
80	0.336	-0.147	0.175	0.601	0.622	0.042	0.483	1.000	0.406	0.140
თ	0.601	-0.007	0.587	0.741	0.448	-0.112	0.280	0.406	1.000	0.196
10	0.699	0,105	0.364	0.455	0,336	0.622	0.469	0.140	0.196	1.000

FACTOR ANALYSIS

Method of extraction: Maximum likelihood

Method of rotation: NONE

Minimum eigenvalue to retain: 1.0

EIGENVALUES

FA	CTOR	VALUE	PERCENT	CUM %	RATIO		
1:		12.709	42.4	42.4	3.157		
2:		4.026	13.4	55.8	1.444		
3:		2.788	9.3	65.1	1.177		
4:		2.368	7.9	73.0	1.253		
5: 6:		1.889	6.3	79.3	1.038		
6:		1.820	6.1	85.3	1.295		
7:		1.405	4.7	90.0	1.181		
8:		1.190	4.0	94.0	1.254		
Ind 123456789	0.750 0.070 0.589 0.756 0.645 0.539 0.633 0.542 0.594	scores on th	e first factor: 11 12 13 14 15 16 17 18	0.774 0.514 0.707 0.722 0.633 0.380 0.803		21 22 23 24 25 26 27 28 29	0.506 0.826 0.712 0.090 0.824 0.739 0.666 0.577 0.606
10	0.820		20			30	0.922

FIGURE 16.22.

Factor analysis of the complete 30 × 30 matrix implied by table 16.12.

Table 16.13 Minimal Number of Informants Needed to Classify a Desired Proportion of Questions with a Specified Confidence Level for Different Levels of Cultural Competence

Proportion of		Average le	vel of cultural con	ipetence	
questions	.5	.8	.7	.8	.9
.95 confidence level					
0.80	9	7.	4	4	4
0.85	11	7	4	4	4
0.90	13	9	6	4	4
0.95	17	11	6	6	4
0.99	29	19	10	8	4
.99 confidence level					
0.80	15	10	5	4	4
0.85	15	70	7	5	4
0.90	21	12	7	5	4
0.95	23	14	9	7	4
0.99	>30	20	13	8	6

SOURCE: S. C. Weller and A. K. Rommey, Systematic Data Collection, p. 77. © 1988. Reprinted by permission of Sage Publications.

There will be variation in knowledge among informants who are competent in a cultural domain.

Consensus analysis is great for finding top people who can talk about well-defined areas of cultural knowledge. But if you are doing general descriptive ethnography and you're looking for all-around good informants, consensus analysis is not a substitute for

Table 16.14 Agreement among Individuals and Estimated Validity of Aggregating Their Responses for Different Samples

			Validity		
Agreement	0.80	0.85	0.90	0.95	0.99
0.16	10	14	22	49	257
0.25	5	8	13	28	148
0.36	3	5	8	17	87
0.36 0.49	2	3	4	10	51

SOURCE: S. C. Weller and A. K. Romney, Systematic Data Collection, p. 77. © 1988. Reprinted by permission of Sage Publications.

the time-honored way that ethnographers have always chosen key informants: luck, intuition, and hard work by both parties to achieve a working relationship based on trust (Further Reading: consensus analysis).

Cultural Consonance

An important development in the use of consensus analysis is the cultural consonance model by William Dressler and his colleagues (Dressler, Baliero et al. 2007; Dressler et al. 1996) and the application of the consonance model to the study of lifestyle and health. Here, lifestyle is defined as having things and doing things that one needs to have and do so as to have a good life as an X, where X is whatever people you're working with. Material things might be anything from a bicycle to a Ferrari, while behavioral things might be anything from visiting the district capital at least once a year to only flying first class, depending on where you're working.

To get a material-style-of-life scale, you need a list of, material goods and leisure activities. The list can come from inventorying homes, from open-ended interviews about leisure, from free lists, from the *Style* section of the local newspaper. . . . You can create a Guttman scale of the items, as Pollnac et al. (1975) and DeWalt (1979) did, or you can ask people, as Dressler does (1996) to rate each item from 1-to-3 for its importance to living a good life (1 = not at all important, 2 = somewhat important, and 3 = very important). If you have 20 or fewer items, you can ask people to rank order them in terms of importance. A trick here is to ask people to divide the items first into three piles (unimportant to very important) and then to rank the items within each pile. This is easier for people to do than to rank order a lot of items in one go.

The informants-by-lifestyle-items matrix can then be analyzed to see if the pattern of responses indicates a cultural consensus about what it takes to be living well. Dressler did this in Brazil and found that 22 of 39 material and behavioral items were considered somewhat important or very important for an ideal lifestyle. Then, in a later survey, Dressler asked what percentage of those 22 culturally important things people owned. He calls this measure "cultural consonance"—the fit between what people do and what the cultural consensus says they ought to do. It turns out that cultural consonance in lifestyle accounts for a significant amount of the variation in blood pressure and other health outcomes.

The consensus model is a major contribution to social science. Besides cultural consonance, it is being used in studies comparing of folk and scientific ecological and medical knowledge (Byron 2003; Chavez et al. 1995; Ross and Medin 2005; Torres 2005), acculturation (Ross et al. 2006), and many other areas (Further Reading: consensus analysis).

FURTHER READING

Measuring salience: J. J. Smith et al. (1995); Sutrop (2001); Thompson and Juan (2006).

Multidimensional scaling: Bolton and Vincke (1996); Kruskal and Wish (1978); Romney et al. (1972); Schweizer (1980); Shepard et al. (1972); Sturrock and Rocha (2000); Weisner (1973).

Cluster analysis: Aldenderfer and Blashfield (1984); Doreian (2004).

Sentence frames: Hruschka et al. (2008).

Consensus analysis: Caulkins (2001); de Munck et al. (2002); Furlow (2003); Garro (2000); Handwerker (2002); Harvey and Bird (2004); Jaskyte and Dressler (2004); M. L. Miller et al. (2004); Reyes-García, Byon et al. (2003); Reyes-García, Godoy et al. (2003); Swora (2003).

