Using SPSS to Analyse Repertory Grid Data

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Introduction: A little history.

Since 1983 people have been asking me for assistance in analysing their grid data. I have never been sure just what I had done to be cast in this role, but once pinned down (and this has not been easy; as many people can testify);I have sometimes been able to assist by referring them to articles I have published (e.g Bell, 1988, 1990a), papers I have presented, or the computer program I have written. However, somewhat to my chagrin, the most common request I have had since the mid-eighties, has been for an unpublished, unpresented, and otherwise rather tacky little working paper entitled "Analyzing Repertory Grid data using SPSSx 2.1".

Until recently, when the first version of the present document appeared (Bell, 1995b),I was still asked for copies of this, but like most things I had lost the original (as many people can testify); and the copy of a copy of a copy was faded and barely legible. Not only that, SPSSx2.1 was long gone, and some of the syntax may not have worked any more. In the intervening years SPSS has gone into many different versions, mainframe, Mac, PC Dos, and PC Windows, all of which have slightly different syntax and capabilities. Now however, SPSS is moving towards a single system, currently available in the mainframe and Windows versions.

This present version was initially presented as a paper in Wollongong and again as a poster in Barcelona (Bell, 1995b), although the work on multiple grids derives from a paper presented in Perth, Cambridge, and in a somewhat revised version, in St Andreasberg (Bell, 1994a). You can see I like to get good mileage out of a conference paper. This version also incorporates material on the use of OVERALS, presented in Barcelona (Bell, 1995a).

The syntax and output following has been devised and obtained (respectively) using the Windows version 6.1. Users should pay no attention to the file specification, since they are either peculiar to me (as in the data list statements) or generated automatically by SPSS

There are two distinct situations in which researchers may want to analyse grid data - where there is a single grid and where there are multiple grids. SPSS and other statistical packages are almost mandatory for multiple grid analysis, since almost all grid specific computer packages are design for single grid analysis, but the generic statistical packages can also be used in various ways to analyse single grids.

Single grid analysis

Setting up the grid

SPSS is most conveniently used by setting up two files, one with that data in it, and one with the file description. Figure 1 shows the SPSS command file, and Figure 2 shows the data file. This grid is taken from Bell & McGorry (1992). The file is organized so that each column corresponds to the ratings for a given element, and each row corresponds to the ratings for a given construct, at the end of each row is a label for the construct [note it is designated as an alphanumeric variable by the (A)]. Labels for the elements are defined in the command file (Figure 1), although elements are also given names corresponding to the element label. This complexity of labelling is necessary because different components of SPSS will label output differently. SPSS will treat this grid by recognizing elements as *variables* and constructs as *cases*.

```
data list file='c:\grids\grid.dat'
 / bipolar schiz psychiat criminal average aids diabetes cancer
   stress usualme menow me6mth staffme idealme 3-30
   conlab 33-43 (A).
var labels
 bipolar,'person with manic depressive illness'/
 schiz, 'person with schizophrenia'/
 psychiat,'psychiatric patient'/
 criminal,'convicted criminal'/
 average,'average person'/
 aids, 'AIDS patient'/
 diabetes,'person with diabetes'/
 cancer,'person with cancer'/
 stress,'person under stress'/
 usualme,'myself as I usually am'/
 menow,'myself as I am now'/
 me6mth,'myself as I will be in six months'/
 staffme,'myself as the staff see me'/
 idealme,'my ideal self'/
 conlab, 'Construct label'.
```

Figure 1. SPSS command file for a single grid.

```
   3 5 3 7 4 2 1 1 7 1 1 1 2 1  good
   4 5 4 7 3 3 1 2 7 2 1 1 3 1  dependable
   6 7 4 7 3 7 1 2 6 1 1 1 2 1  safe
   7 7 4 7 2 7 2 4 7 1 1 1 2 1  clearheaded
   7 7 5 7 2 7 1 4 7 2 2 1 3 1  stable
   7 7 5 7 6 5 4 4 7 7 7 3 7 7  predictable
   4 5 4 7 2 1 2 2 7 1 1 1 2 1  intelligent
   7 7 5 7 1 7 1 1 1 1 7 1 7 1  free
   6 7 4 7 1 7 7 7 7 1 4 1 4 1  healthy
   5 5 4 7 1 1 3 4 4 1 1 1 3 1  honest
   5 7 5 6 1 2 2 4 5 1 1 1 3 1  rational
   5 6 5 7 1 5 3 4 5 1 1 1 2 1  independent
   6 5 5 7 2 7 3 4 7 1 1 1 1 1  calm
   6 7 6 7 1 7 3 4 7 3 7 1 7 1  understood
```

Figure 2. Repertory Grid data file.

Analysing the Grid

Summary measures: By Elements or Constructs Individually

Distribution Statistics

Descriptive statistics can be readily used to tell us separate things about each element, using for example, the commands in Figure 3.

```
DESCRIPTIVES
  VARIABLES=bipolar schiz psychiat criminal average aids
diabetes cancer
  stress usualme menow me6mth staffme idealme
  /FORMAT=LABELS NOINDEX
  /STATISTICS=MEAN STDDEV MIN MAX .
```

Figure 3. SPSS commands for basic Element Statistics.

While these commands are over-elaborate, in that a number of defaults are spelled out, this is because they were produced by "pasting" from a dialogue box in SPSS Windows. Most of the commands shown in this document were produced in this fashion.

The results are shown in Figure 4. The grids were rated with a seven-point scale, so that the MIN and MAX numbers show that range used to describe elements across constructs.

```
Number of valid observations (listwise) =       14.00

                                                   Valid
Variable      Mean    Std Dev   Minimum   Maximum      N  Label

BIPOLAR       5.57       1.28         3         7     14  person with manic dep
SCHIZ         6.21        .97         5         7     14  person with schizophr
PSYCHIAT      4.50        .76         3         6     14  psychiatric patient
CRIMINAL      6.93        .27         6         7     14  convicted criminal
AVERAGE       2.14       1.46         1         6     14  average person
AIDS          4.86       2.51         1         7     14  AIDS patient
DIABETES      2.43       1.65         1         7     14  person with diabetes
CANCER        3.36       1.60         1         7     14  person with cancer
STRESS        6.00       1.75         1         7     14  person under stress
USUALME       1.71       1.64         1         7     14  myself as I usually a
MENOW         2.57       2.53         1         7     14  myself as I am now
ME6MTH        1.14        .53         1         3     14  myself as I will be i
STAFFME       3.43       2.06         1         7     14  myself as the staff s
IDEALME       1.43       1.60         1         7     14  my ideal self
```

Figure 4. Basic Element Statistics.

The Mean (average) statistic shows where each element is located on average across constructs. Thus CRIMINAL is located furthest from the positive poles, while ME6MTH is located closest to these. The Standard deviation shows how each element varies across the constructs, with low values indicating elements that are seen in a fixed fashion, evaluated positively, e.g., ME6MTH, in all ways; or negatively in all ways, e.g., CRIMINAL.
Finding similar statistics for constructs is more complex. There are two ways of doing this. one is to create new variables as functions across elements, and then list the cases for the new variables, as shown in Figure 5, or to "flip" the data matrix over, and use DESCRIPTIVES as in Figure 6. This latter procedure is simpler and more flexible, and the output for this is shown in Figure 7.

```
COMPUTE mean = MEAN(bipolar,schiz,psychiat,criminal,
```

```
                    average,aids,diabetes,cancer,usualme,
                    menow,me6mth,staffme,idealme) .
COMPUTE stddev = SD(bipolar,schiz,psychiat,criminal,
                    average,aids,diabetes,cancer,usualme,
                    menow,me6mth,staffme,idealme) .
LIST variables=mean,stddev,conlab.
EXECUTE .
```

Figure 5. Alternative commands for finding Construct Statistics.

One reason for including the construct name (left pole only here, but it doesn't really matter), is that in the FLIP command, the variable containing the construct labels, CONLAB, is used to create the variable names for the constructs.

```
FLIP
  VARIABLES=bipolar schiz psychiat criminal average aids
  diabetes cancer stress usualme menow me6mth staffme idealme
 /NEWNAME=conlab  .
DESCRIPTIVES
  VARIABLES=good dependab safe clearhea stable predicta intellig
  free healthy honest rational independ calm understo
  /FORMAT=LABELS NOINDEX
  /STATISTICS=MEAN STDDEV SKEWNESS
  /SORT=MEAN (A) .
```

Figure 6. Preferred commands for finding Construct Statistics.

Slightly different statistics are requested here. Minimum and Maximum tend to be less important when ratings are made across constructs, since respondents are more conscious of the range of ratings particularly with elicited constructs since in the defining of the poles, the extremities are usually implied. [One can also assume that variances or standard deviations will also be more homogeneous.] In order to examine relative lopsidedness of constructs, the skewness statistic has been requested, and constructs are presented in order of ascending means (i.e. less like the labelled (positive) pole).

```
FLIP performed on 14 cases and 17 variables, creating 14 cases
and 15 variables.  The working file has been replaced.



Variable CONLAB has been used to name the new variables.  It has
not been transformed into a case.

A new variable has been created called CASE_LBL.  Its
contents are the old variable names.


New variable names:

CASE_LBL GOOD     DEPENDAB SAFE     CLEARHEA STABLE   PREDICTA
INTELLIG FREE     HEALTHY  HONEST   RATIONAL INDEPEND CALM
UNDERSTO

(continued on next page)
```

```
(continued)

Number of valid observations (listwise) =       14.00

                                                      Valid
Variable      Mean    Std Dev Skewness S.E. Skew          N  Label

GOOD          2.79       2.19     1.09       .60     14
INTELLIG      2.86       2.18     1.05       .60     14
HONEST        2.93       1.98      .53       .60     14
DEPENDAB      3.14       2.07      .81       .60     14
RATIONAL      3.14       2.14      .44       .60     14
INDEPEND      3.36       2.17      .15       .60     14
SAFE          3.50       2.56      .40       .60     14
CALM          3.64       2.50      .20       .60     14
CLEARHEA      3.79       2.67      .30       .60     14
FREE          3.86       3.01      .08       .60     14
STABLE        4.00       2.57      .16       .60     14
HEALTHY       4.57       2.62     -.47       .60     14
UNDERSTO      4.79       2.52     -.60       .60     14
PREDICTA      5.93       1.44     -.94       .60     14
```

Figure 7. Construct Distribution Statistics.

Thus in this grid elements were labelled more towards GOOD and less towards PREDICTAble. Notice the standard deviations are much more similar than for the element statistics, and the Skewness statistics tend to mirror the means. The Skewness statistics however, are standardized and can be compared across grids.

Golden Section Statistics

Adams-Webber (1990) and others have produced some robust findings about the way respondents categorize themselves and others with respect to the positive and negative poles of constructs. Although these findings were derived for dichotomous data only, Bell & McGorry showed how this approach could be generalized to ordinary rated grids. Figure 8 shows the commands to recode the data, and Figure 9 shows the means in golden section proportion form.

```
DO REPEAT xelem=bipolar to idealme.
COMPUTE xelem = (8 - xelem)/7.
END REPEAT.
DESCRIPTIVES VARIABLES=bipolar to idealme/ STATISTICS=MEAN.
```

Figure 8. Rescaling Grid Data for Golden Section Measures.

```
Number of valid observations (listwise) =       14.00

                    Valid
Variable      Mean      N  Label

BIPOLAR        .35     14  person with manic depressive illness
SCHIZ          .26     14  person with schizophrenia
PSYCHIAT       .50     14  psychiatric patient
CRIMINAL       .15     14  convicted criminal
AVERAGE        .84     14  average person
AIDS           .45     14  AIDS patient
DIABETES       .80     14  person with diabetes
CANCER         .66     14  person with cancer
STRESS         .29     14  person under stress
USUALME        .90     14  myself as I usually am
MENOW          .78     14  myself as I am now
ME6MTH         .98     14  myself as I will be in six months
STAFFME        .65     14  myself as the staff see me
IDEALME        .94     14  my ideal self
```

Figure 9. Golden Section Measures for Elements.

Measures comparing Elements: Self-Other Discrepancies

Self-Other distances can be readily calculated in SPSS as shown in Figure 10. Output is shown in Figure 11.

```
DO REPEAT xelem= bipolar schiz psychiat criminal average aids
                 diabetes cancer stress usualme me6mth staffme
                 idealme.
COMPUTE xelem = xelem-menow.
END REPEAT.
DESCRIPTIVES VARIABLES= bipolar schiz psychiat criminal average
            aids diabetes cancer stress usualme me6mth staffme
            idealme
  / STATISTICS=MEAN
  / SORT=MEAN (A) .
```

Figure 10. Self- Other discrepancy calculation commands.

```
Number of valid observations (listwise) =       14.00

                    Valid
Variable      Mean      N  Label

ME6MTH       -1.43     14  myself as I will be in six months
IDEALME      -1.14     14  my ideal self
USUALME       -.86     14  myself as I usually am
AVERAGE       -.43     14  average person
DIABETES      -.14     14  person with diabetes
CANCER         .79     14  person with cancer
STAFFME        .86     14  myself as the staff see me
PSYCHIAT      1.93     14  psychiatric patient
AIDS          2.29     14  AIDS patient
BIPOLAR       3.00     14  person with manic depressive illness
STRESS        3.43     14  person under stress
SCHIZ         3.64     14  person with schizophrenia
CRIMINAL      4.36     14  convicted criminal
```

Figure 11. Sorted Self-Other Average Discrepancy across Constructs.

This shows a readily distinguished splitting of the element group by the figure MENOW.

Measures comparing Constructs: Intensity, Cognitive Complexity and other measures of Grid variation.

There have been many measures of the degree to which correlations between constructs in a grid are similar, and several studies comparing these (e.g. Epting, *et al.*, 1992; Feixas *et al.*, 1992). Some of these measures can be directly calculated through SPSS, and for other measures, surrogate statistics may be used.

For example, the intensity measure as defined by Fransella and Bannister (1977, p.60) is not a good measure as the sum of all correlations squared (since it ignores overlap between correlations). Better measures are those based on the squared multiple correlation.

Squared multiple correlation measures can be found in REGRESSION procedures, but also in FACTOR. Using REGRESSION is tedious, since a different equation must be specified for each construct. In theory the SPSS add-on module PRELIS can be used more simply with the instructions as in Figure 12, however in the version I have there is a bug and this will not run. Using FACTOR to give Kaiser's Measure - of - Sampling - Adequacy (MSA) can also be useful, since this index ranges between zero and 1.0, with 0.50 being a critical level, and is available both for each construct and as an overall statistic. The instructions for this are also shown in Figure 12. Unfortunately, the construct correlation matrix for this particular grid cannot be inverted and so these statistics cannot be calculated here. This problem can occur with reasonable frequency for grids, which, after all, are fairly small sets of data in statistical terms.

```
* Using PRELIS to regression all variables on each other
PRELIS VARIABLES= good TO understo
 / REGRESSION = good TO understo WITH good TO understo.

* Using FACTOR to find Measures of Sampling Adequacy -
* PRINT AIC KMO is the critical subcommand
FACTOR
  /VARIABLES good dependab safe clearhea stable predicta
   intellig free healthy honest rational independ calm understo
  /MISSING LISTWISE /ANALYSIS
  good dependab safe clearhea stable predicta intellig free
  healthy honest rational independ calm understo
  /PRINT AIC KMO
  /CRITERIA MINEIGEN(1) ITERATE(25)
  /EXTRACTION PC
  /ROTATION NOROTATE .
```

Figure 12. Squared-Multiple-Correlations as Intensity commands.

An alternative which can provide similar information, but is not subject to the same problems, is simply to carry out a principal components analysis of the construct correlations. The commands for this are shown in Figure 13 and the output in Figure 14.

```
FACTOR
  /VARIABLES good dependab safe clearhea stable predicta
   intellig free healthy honest rational independ calm understo
  /MISSING LISTWISE /ANALYSIS
  good dependab safe clearhea stable predicta intellig free
  healthy honest rational independ calm understo
  /PRINT INITIAL CORRELATION EXTRACTION
  /CRITERIA MINEIGEN(1) ITERATE(25)
  /EXTRACTION PC
  /ROTATION NOROTATE .
```

Figure 13. Principal Components as Intensity commands.

For the sake of completeness, we also print out the construct intercorrelations here, although these could be obtained, though not always so compactly, in other SPSS routines.

```
Correlation Matrix:


              GOOD  DEPENDAB      SAFE  CLEARHEA    STABLE  PREDICTA  INTELLIG

GOOD       1.00000
DEPENDAB    .95735   1.00000
SAFE        .77379    .84035   1.00000
CLEARHEA    .71627    .81453    .96216   1.00000
STABLE      .71009    .83791    .95627    .97619   1.00000
PREDICTA    .43403    .44258    .30219    .21628    .31170   1.00000
INTELLIG    .92805    .94284    .72963    .74932    .74123    .36445   1.00000
FREE        .24011    .34928    .55820    .48502    .57645    .40598    .25476
HEALTHY     .42469    .52216    .64042    .77810    .71838  -.00873    .56727
HONEST      .67051    .75361    .62890    .71134    .69507    .21410    .85364
RATIONAL    .71169    .80989    .75574    .81371    .82331    .25294    .86129
INDEPEND    .68095    .79257    .87774    .93192    .90964    .10732    .79257
CALM        .68755    .78366    .90604    .95753    .92135    .07790    .73854
UNDERSTO    .46547    .61160    .64948    .66913    .76047    .42014    .54103 (cont'd)

(continued)
              FREE   HEALTHY    HONEST  RATIONAL  INDEPEND      CALM  UNDERSTO

FREE       1.00000
HEALTHY     .42049   1.00000
HONEST      .39853    .69008   1.00000
RATIONAL    .45665    .69594    .92740   1.00000
```

INDEPEND	.49141	.82638	.84816	.89788	1.00000		
CALM	.37111	.78450	.67860	.74260	.93302	1.00000	
UNDERSTO	.79799	.70746	.55256	.64780	.67703	.61050	1.00000

Extraction 1 for analysis 1, Principal Components Analysis (PC)

Initial Statistics:

Variable	Communality	*	Factor	Eigenvalue	Pct of Var	Cum Pct
		*				
GOOD	1.00000	*	1	9.81222	70.1	70.1
DEPENDAB	1.00000	*	2	1.37255	9.8	79.9
SAFE	1.00000	*	3	1.31628	9.4	89.3
CLEARHEA	1.00000	*	4	.67326	4.8	94.1
STABLE	1.00000	*	5	.32818	2.3	96.4
PREDICTA	1.00000	*	6	.24263	1.7	98.2
INTELLIG	1.00000	*	7	.12226	.9	99.1
FREE	1.00000	*	8	.06983	.5	99.6
HEALTHY	1.00000	*	9	.03201	.2	99.8
HONEST	1.00000	*	10	.02266	.2	99.9
RATIONAL	1.00000	*	11	.00507	.0	100.0
INDEPEND	1.00000	*	12	.00260	.0	100.0
CALM	1.00000	*	13	.00044	.0	100.0
UNDERSTO	1.00000	*	14	.00000	.0	100.0

PC extracted 3 factors.

Factor Matrix:

	Factor 1	Factor 2	Factor 3
GOOD	.81816	.06233	-.50649
DEPENDAB	.90962	.07294	-.36341
SAFE	.92433	.01426	.03898
CLEARHEA	.94869	-.12732	.10130
STABLE	.95397	.01855	.12170
PREDICTA	.33868	.83124	-.30139
INTELLIG	.88005	-.04589	-.41411
FREE	.55547	.54462	.53926
HEALTHY	.77424	-.27112	.38788
HONEST	.84234	-.13087	-.10778
RATIONAL	.90977	-.07992	-.06083
INDEPEND	.95150	-.22192	.12740
CALM	.90707	-.27468	.09256
UNDERSTO	.76711	.36770	.39674

(continued on next page)

```
(continued)

Final Statistics:


Variable     Communality  *  Factor   Eigenvalue   Pct of Var   Cum Pct
                          *
GOOD             .92980   *     1       9.81222       70.1        70.1
DEPENDAB         .96479   *     2       1.37255        9.8        79.9
SAFE             .85611   *     3       1.31628        9.4        89.3
CLEARHEA         .92649   *
STABLE           .92520   *
PREDICTA         .89650   *
INTELLIG         .94808   *
FREE             .89596   *
HEALTHY          .82339   *
HONEST           .73828   *
RATIONAL         .83776   *
INDEPEND         .97083   *
CALM             .90680   *
UNDERSTO         .88106   *
```

Figure 14. Principal Components of Construct Correlations.

We can see from the end of the output, that 3 factors account for 89.3% of the variance. Thus these three factors pretty well represent the total grid. Therefore the communalities, which represent the proportion of variance in each construct that can be explained by the three factors, are more than useful operationalizations of Fransella and Bannister's Intensity measure. INDEPENDent (.97083) and DEPENDABle (.96479) are most closely aligned with the total grid while HONEST (.73828) is the most independent of the constructs. This part of the output (or earlier) also shows the percentage of variance explained by the first factor (70.1), indicating the degree to which a single super-construct can account for the correlations among constructs. Epting *et al.,* (1992) have shown this index to correlate highly with the average correlation used by Fransella and Bannister. The factor loadings shown here are largely meaningless and should be ignored.

It might seem useful to also factor the element correlations. However, there is a problem with this, and it is not to be generally recommended. Element correlations are affected by the alignment of the construct poles. If we were to reflect a construct (i.e. reverse its poles) nothing would be changed in the actual grid, however the inter-element correlations would change (Mackay, 1992) giving different principal component solutions. If the technique only specifies the emergent pole however, such analysis is valid.

The same caveats also apply to another approach to cognitive complexity, that proposed by Bell and Keen (1981) via the intra-class correlation, although it is shown here for completeness. The intra-class correlation is in fact closely related to coefficient alpha, the traditional test index of reliability (Bell, 1990). Thus the SPSS module RELIABILITY can be used to determine this kind of index, either for elements, or, by flipping the data, for constructs. The commands for this are as shown in Figure 15.

```
RELIABILITY
  /VARIABLES=bipolar schiz psychiat criminal average aids
   diabetes cancer stress usualme menow me6mth staffme idealme
```

```
  /FORMAT=NOLABELS
  /SCALE(ALPHA)=ALL/MODEL=ALPHA
  /STATISTICS=ANOVA .
FLIP
  VARIABLES=bipolar schiz psychiat criminal average aids
  diabetes cancer stress usualme menow me6mth staffme idealme
 /NEWNAME=conlab  .
RELIABILITY
  /VARIABLES=good dependab safe clearhea stable predicta
   intellig free healthy honest rational independ calm understo
  /FORMAT=NOLABELS
  /SCALE(ALPHA)=ALL/MODEL=ALPHA
  /STATISTICS=ANOVA .
```

Figure 15. Commands for calculating reliability as cognitive complexity.

Output for these analyses is shown in Figure 16. Coefficient Alpha provides the essential information; the intraclass correlation is .8163 for elements and .9625 for constructs, indicating a greater degree of similarity between constructs than between elements. The Analysis of Variance tables are not necessary, however they serve to show how the variation between elements and constructs is partitioned. In the first part of the output (the element-wise analysis) "measures" stand for elements, and "people" stand for constructs. In the second part of the output (after the flipping), the reverse is the case; "measures" stand for constructs and "people" stand for elements.

```
 ****** Method 1 (space saver) will be used for this analysis ******

  R E L I A B I L I T Y   A N A L Y S I S  -  S C A L E  (A L P H A)


                       Analysis of Variance

Source of Variation     Sum of Sq.       DF       Mean Square      F       Prob.

Between People            139.0612       13          10.6970
Within People            1013.1429      182           5.5667
  Between Measures        681.0612       13          52.3893   26.6615   .0000
  Residual                332.0816      169           1.9650
Total                    1152.2041      195           5.9087
     Grand Mean        3.7347


Reliability Coefficients

N of Cases =     14.0                   N of Items = 14

Alpha =    .8163

(Some FLIP output deleted)New variable names:

CASE_LBL GOOD     DEPENDAB SAFE     CLEARHEA STABLE   PREDICTA
INTELLIG FREE     HEALTHY  HONEST   RATIONAL INDEPEND CALM
UNDERSTO
                                                                (continued on next page)
(continued)
 ****** Method 1 (space saver) will be used for this analysis ******

  R E L I A B I L I T Y   A N A L Y S I S  -  S C A L E  (A L P H A)


                       Analysis of Variance

Source of Variation     Sum of Sq.       DF       Mean Square      F       Prob.
```

```
Between People           681.0612       13          52.3893
Within People            471.1429      182           2.5887
  Between Measures       139.0612       13          10.6970    5.4438  .0000
  Residual               332.0816      169           1.9650
Total                   1152.2041      195           5.9087
     Grand Mean        3.7347



Reliability Coefficients

N of Cases =     14.0                   N of Items = 14

Alpha =    .9625
```

Figure 16. Coefficient Alpha as an index of Cognitive Complexity for both Elements and Constructs.

Mapping relationships among constructs or elements.

There is firstly the simple business of representing a relationship between two constructs or two element and there is also the need to consider pattern among a series of such relationships. There are three traditional methods for mapping construct or element inter-relationships; factor analysis, clustering, and multidimensional scaling. In the previous section, commands were shown for setting up a principal components analysis, and only a rotation method needs to be added to make this appropriate for mapping relationships. In this section the focus will be on clustering and multi-dimensional scaling.

Bivariate relationships

From time to time, and perhaps more in counselling and case-study situations, there may be the need to consider relationships between a pair of constructs (or elements). Below are shown some commands for considering a pair of constructs, in this example DEPENDABle and RATIONAL. One advantage of standard statistical packages, is that a wide range of measures of association may be calculated. In this example, we ask for correlations and some asymmetric measures which will tell us if one construct predicts the other better than it is predicted by the other, i.e., the uncertainty coefficient (treating the data as nominal, and an ordinal coefficient, Somers' D. We suppress the table, and use SPSS's graphics to plot the elements in the joint construct space instead. Figure 17 shows these commands (note flipping the grid first to make the constructs the variables).

```
FLIP
  VARIABLES=bipolar schiz psychiat criminal average aids diabetes
  cancer stress usualme menow me6mth staffme idealme
  /NEWNAME=conlab  .
CROSSTABS
  /TABLES=dependab  BY predicta
  /FORMAT=NOTABLES
  /STATISTIC=UC CORR D .
GRAPH
  /SCATTERPLOT(BIVAR)=dependab WITH predicta BY case_lbl (NAME)
  /MISSING=LISTWISE .
```

Figure 17. Commands for comparing two constructs.

Figure 18 shows the printed output and Figure 19 the plot of elements.

```
{FLIP printout omitted)

DEPENDAB  by  PREDICTA

Number of valid observations = 14
                                                                   Approximate
     Statistic                    Value        ASE1      Val/ASE0   Significance
--------------------            ---------    --------    --------  ------------



Uncertainty Coefficient :
   symmetric                      .35248       .09135     3.09090     .79757 *3
   with DEPENDAB dependent        .30532       .09897     3.09090     .79757 *3
   with PREDICTA dependent        .41687       .08313     3.09090     .79757 *3


Somers' D :
   symmetric                      .35714       .21001     1.58933
   with DEPENDAB dependent        .40984       .23422     1.58933
   with PREDICTA dependent        .31646       .19689     1.58933


*3 Likelihood ratio chi-square probability

Number of Missing Observations:  0
```

Figure 18. Statistics relating two constructs.

Both asymmetric coefficients show that PREDICTAble predicts DEPENDABle better than the reverse (i.e. is more superordinate) although the difference is not large (particularly for Somers' D) and not significant in comparison with the standard errors (ASE1 = asymptotic standard error). The plot clearly shows the asymmetry however.

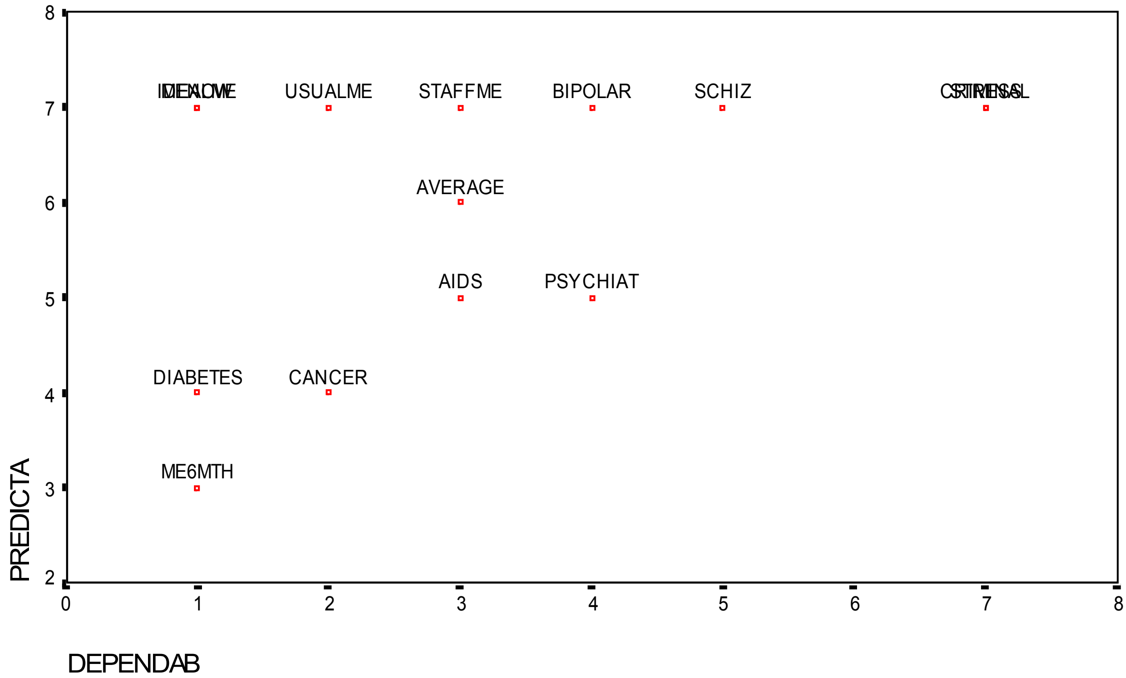

Figure 19. Element plot for constructs PREDICTAble and DEPENDABle.

Clustering

There are definite advantages in using SPSS (or other statistical packages) for clustering grid data as they tend to offer a larger range of coefficients of similarity and a larger range of clustering methods than do the specific grid analysis packages. The problem in correlating elements noted earlier can be overcome here by using Euclidean distances as a measure of association, since these are invariant over construct reflection and give consistent results. Figure 20 shows the commands for clustering elements and constructs. It can be seen that the data do not need to be "flipped" for interrelating constructs, since it is possible to relate cases (i.e. the rows or constructs) to one another via the VIEW = CASES command, and the constructs may be labelled by the CONLAB variable.

```
PROXIMITIES
  bipolar schiz psychiat criminal average aids diabetes cancer
  stress  usualme menow me6mth staffme idealme
  /MATRIX OUT ('C:\WINDOWS\TEMP\spssclus.tmp')
  /VIEW=VARIABLE
  /MEASURE=EUCLID
  /PRINT NONE
  /STANDARDIZE=NONE .
CLUSTER
  /MATRIX IN ('C:\WINDOWS\TEMP\spssclus.tmp')
  /METHOD WARD
  /PRINT NONE
  /PLOT DENDROGRAM .
ERASE FILE=
  'C:\WINDOWS\TEMP\spssclus.tmp'.
PROXIMITIES
  bipolar schiz psychiat criminal average aids diabetes cancer
  stress usualme menow me6mth staffme idealme
  /MATRIX OUT ('C:\WINDOWS\TEMP\spssclus.tmp')
  /VIEW=CASE
```

```
  /MEASURE=EUCLID                    /*(continued on next
page)

  /PRINT NONE
  /ID=conlab
  /STANDARDIZE=NONE .
CLUSTER
  /MATRIX IN ('C:\WINDOWS\TEMP\spssclus.tmp')
  /METHOD WARD
  /ID=conlab
  /PRINT NONE
  /PLOT DENDROGRAM .
ERASE FILE=
  'C:\WINDOWS\TEMP\spssclus.tmp'.
```

Figure 20. Clustering commands for Elements and Constructs.

Figure 21 (a & b) shows the cluster dendograms for constructs and elements, respectively.

```
Dendrogram using Ward Method

                           Rescaled Distance Cluster Combine

    C A S E      0         5        10        15        20        25
 Label      Num  +---------+---------+---------+---------+---------+

 clearheaded   4   -+-+
 stable        5   -+ +---+
 safe          3   ---+   +-------------------------+
 independent  12   ---+---+                         |
 calm         13   ---+                             +---------------+
 honest       10   -+-----------+                   |               |
 rational     11   -+           +-------------------+               |
 good          1   -+           |                                   |
 dependable    2   -+-----------+                                   |
 intelligent   7   -+                                               |
 healthy       9   -----------+-----+                               |
 understood   14   -----------+     +-----+                         |
 free          8   -----------------+     +-------------------------+
 predictable   6   -----------------------+
```

Figure 21a. Clustering of Constructs.

```
* * * * * H I E R A R C H I C A L   C L U S T E R   A N A L Y S I S * * * *


Dendrogram using Ward Method

                        Rescaled Distance Cluster Combine

   C A S E         0         5        10        15        20        25
  Label     Num  +---------+---------+---------+---------+---------+

  USUALME    10   -+-+
  IDEALME    14   -+ |
  ME6MTH     12   ---+-----------+
  AVERAGE     5   ---+           +---------------------------------+
  MENOW      11   -+---------+   |                                 |
  STAFFME    13   -+         +---+                                 |
  DIABETES    7   ---+-------+                                     |
  CANCER      8   ---+                                             |
  PSYCHIAT    3   -----+---+                                       |
  AIDS        6   -----+   |                                       |
  BIPOLAR     1   -+-+     +---------------------------------------+
  SCHIZ       2   -+ +---+ |
  CRIMINAL    4   ---+   +-+
  STRESS      9   -------+
```

Figure 21b. Clustering of Elements.

The clustering for elements shows distinctions between present and other self figures, some physical illness figures, but less clear distinctions involving psychiatric and other figures. The clustering of the constructs does not seem to show any clear groups on standard lexical grounds.

Multidimensional Scaling

Separate Representation of Constructs and Elements
Multidimensional scaling can be carried out for elements and constructs separately using ALSCAL in SPSS. The commands for this are shown in Figure 22. Construct scaling could be carried out without "flipping" the file, by simply replace VIEW=VARIABLE with VIEW=CASE in the PROXIMITIES command. However this would leave the output without construct labels, since variable names are used to label ALSCAL output.

```
PROXIMITIES bipolar schiz psychiat criminal average aids
  diabetes cancer stress usualme menow me6mth staffme idealme
  /PRINT NONE /MATRIX
  OUT('C:\WINDOWS\TEMP\spssalsc.tmp')
  /MEASURE=EUCLID /STANDARDIZE=NONE /VIEW=VARIABLE .
ALSCAL
  /MATRIX= IN('C:\WINDOWS\TEMP\spssalsc.tmp')
  /LEVEL=ORDINAL
  /CONDITION=MATRIX
  /MODEL=EUCLID
  /CRITERIA=CONVERGE(.001) STRESSMIN(.005) ITER(30) CUTOFF(0)
  DIMENS(2,2)
  /PLOT=DEFAULT .
ERASE FILE='C:\WINDOWS\TEMP\spssalsc.tmp'.
FLIP
  VARIABLES=bipolar schiz psychiat criminal average aids
  diabetes cancer stress usualme menow me6mth staffme idealme
  /NEWNAME=conlab  .
PROXIMITIES good dependab safe clearhea stable predicta intellig
  free healthy honest rational independ calm understo
  /PRINT NONE /MATRIX
  OUT('C:\WINDOWS\TEMP\spssalsc.tmp')
  /MEASURE=EUCLID /STANDARDIZE=NONE /VIEW=VARIABLE .
SPLIT FILE OFF.
ALSCAL
  /MATRIX= IN('C:\WINDOWS\TEMP\spssalsc.tmp')
  /LEVEL=ORDINAL
/CONDITION=MATRIX
  /MODEL=EUCLID
  /CRITERIA=CONVERGE(.001) STRESSMIN(.005) ITER(30) CUTOFF(0)
  DIMENS(2,2)
  /PLOT=DEFAULT .
ERASE FILE='C:\WINDOWS\TEMP\spssalsc.tmp'.
```
Figure 22. Multidimensional scaling commands for elements and constructs separately.

As in the cluster analysis, Euclidean distances were specified as the basis for scaling. Correlations could have been used for constructs, although some ALSCAL commands would have had to be changed; i.e. /LEVEL=ORDINAL(SIMILAR) and CUTOFF(-1.0).

The element output is shown in Figure 23, and the element configuration in Figure 24.

```
Iteration history for the 2 dimensional solution (in squared
distances)

                  Young's S-stress formula 1 is used.

                Iteration     S-stress      Improvement

                    1           .06547
                    2           .04853         .01694
                    3           .04589         .00264
                    4           .04490         .00100

                         Iterations stopped because
                 S-stress improvement is less than   .001000


            Stress and squared correlation (RSQ) in distances

RSQ values are the proportion of variance of the scaled data
(disparities) in the partition (row, matrix, or entire data)
which is accounted for by their corresponding distances.
             Stress values are Kruskal's stress formula 1.
For  matrix
    Stress  =   .05581      RSQ =  .98596


           Configuration derived in 2 dimensions



                   Stimulus Coordinates

                        Dimension

Stimulus   Stimulus     1        2
 Number      Name

    1      BIPOLAR    1.2643   -.1492
    2      SCHIZ      1.6945   -.0829
    3      PSYCHIAT    .5079    .0067
    4      CRIMINAL   2.2076    .2129
    5      AVERAGE   -1.1732    .5361
    6      AIDS       1.1008   -.7263
    7      DIABETES   -.9243    .3190
    8      CANCER     -.1515    .4429
    9      STRESS     1.6468    .8229
   10      USUALME   -1.4446   -.1303
   11      MENOW      -.9854   -.9365
   12      ME6MTH    -1.7289    .1979
   13      STAFFME    -.3255   -.6364
   14      IDEALME   -1.6885    .1230
```

Figure 23. Multidimensional scaling output for elements.

The measure of fit for this solution, STRESS, gives a value of 0.05581, which is satisfactory even by Kruskal's (1964) very conservative rule of thumb. A better guide to satisfactory levels of stress may be found in Spence & Ogilvie (1973). It can be seen that there is much greater variation in element locations on dimension 1 than on dimension 2, although what is usually regarded as the more important is the configuration of points, as shown in Figure 24.

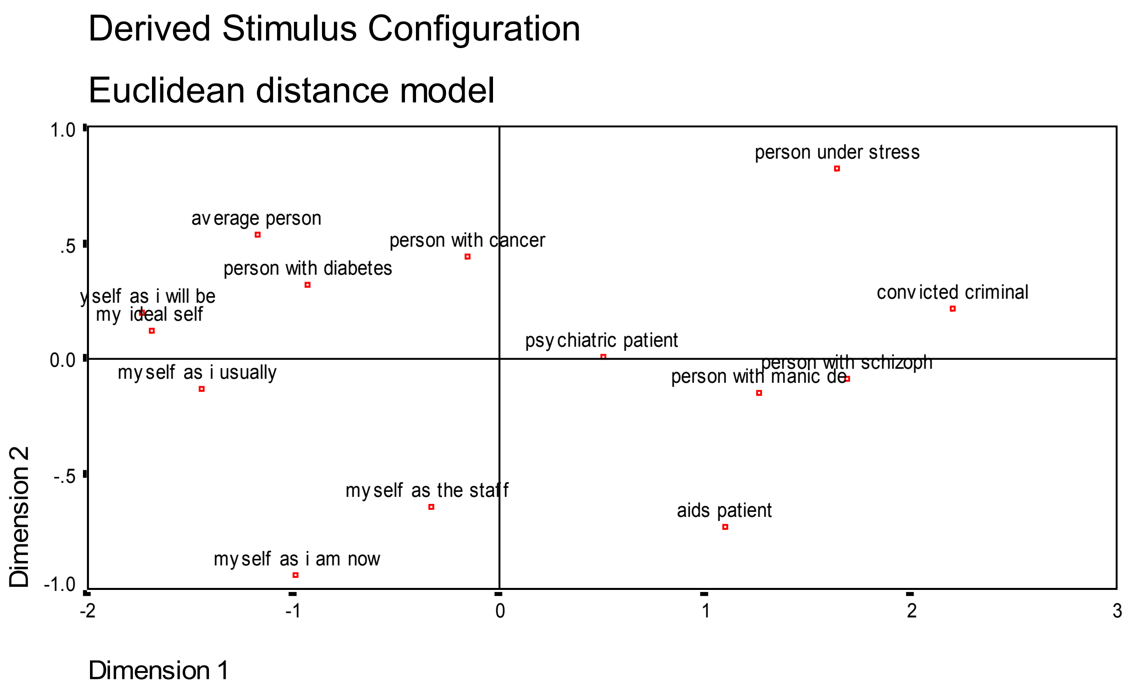

Figure 24. Multidimensional Representation of Elements.

Conclusions drawn from this configuration would be similar to those drawn from the cluster analysis. Rathod (1981) has argued that spatial representations are more stable, however this is an instance where the convergence of representations supports the notion that the structure found is inherent in the grid and is not an artifact of the method of analysis. This convergence does not appear for the constructs.

Figure 25 shows the configuration for constructs from the multidimensional scaling.

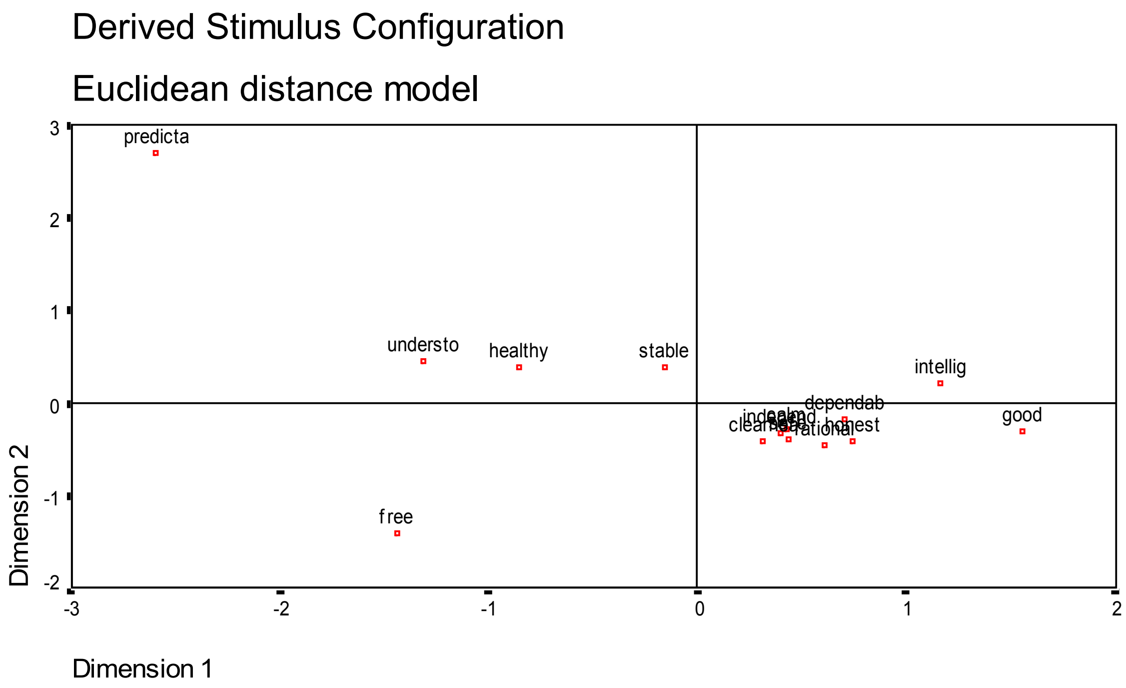

Figure 25. Multidimensional Representation of Constructs.

Here there is less congruence with the clustering shown in Figure 21. FREE and PREDICTAble are isolated (as in the cluster solution) but there is a clumping of constructs that is not evident in the cluster analysis.

Some reasons for this can be seen in the construct output shown in Figure 26. It can be seen that the solution took more iterations to converge than did the element solution. Furthermore, the stress value was appreciably worse.

```
Iteration history for the 2 dimensional solution (in squared
distances)
                  Young's S-stress formula 1 is used.

                Iteration     S-stress      Improvement
                    1          .20352
                    2          .13952          .06400
                    3          .12491          .01461
                    4          .11838          .00653
                    5          .11465          .00373
                    6          .11171          .00294
                    7          .10914          .00257
                    8          .10666          .00248

(Iterations omitted)

                   18          .08790          .00117
                   19          .08708          .00082

                         Iterations stopped because
                 S-stress improvement is less than   .001000
(continued next page)
```

```
(continued)
            Stress and squared correlation (RSQ) in distances

RSQ values are the proportion of variance of the scaled data
(disparities) in the partition (row, matrix, or entire data)
which is accounted for by their corresponding distances.
             Stress values are Kruskal's stress formula 1.

                For  matrix
    Stress  =   .14508      RSQ =  .94796

                Configuration derived in 2 dimensions

                   Stimulus Coordinates

                        Dimension

Stimulus   Stimulus     1        2
 Number      Name

    1      GOOD       1.5555   -.2985
    2      DEPENDAB    .7051   -.1791
    3      SAFE        .4344   -.3903
    4      CLEARHEA    .3141   -.4130
    5      STABLE     -.1589    .3858
    6      PREDICTA  -2.5899   2.7124
    7      INTELLIG   1.1662    .2260
    8      FREE      -1.4414  -1.4123
    9      HEALTHY    -.8534    .3842
   10      HONEST      .7475   -.4048
   11      RATIONAL    .6042   -.4610
   12      INDEPEND    .3942   -.3223
   13      CALM        .4304   -.2899
   14      UNDERSTO  -1.3080    .4628
```

Figure 26. Multidimensional scaling output for constructs.

Joint Representation of Constructs and Elements

1. The Unfolding Model.

ALSCAL in SPSS can be used to produce a joint configuration of elements and constructs using what is known as an unfolding model. The commands for this are shown in Figure 27. Here the data are directly scaled and the cases (constructs) of the data matrix are represented as ROWs. This has the drawback of leaving the constructs unlabelled, so that the user has to manually label the constructs on the output and/or plot.

```
ALSCAL
  VARIABLES= bipolar schiz psychiat criminal average aids
  diabetes cancer stress usualme menow me6mth staffme idealme
  /SHAPE=RECTANGULAR /INPUT ROWS(14)
  /LEVEL=ORDINAL
  /CONDITION=ROW
  /MODEL=EUCLID
  /CRITERIA=CONVERGE(.001) STRESSMIN(.005) ITER(50) CUTOFF(0)
  DIMENS(2,2)
  /PLOT=DEFAULT .
```

Figure 27. Commands for joint representation of constructs and elements.

Figure 28 shows an edited version of the fit part of the output.

```
Iteration history for the 2 dimensional solution (in squared
distances)
                  Young's S-stress formula 2 is used.

                Iteration     S-stress      Improvement

                    1           .51388
                    2           .44978         .06410
                    .
                    . (iterations omitted here)
                    .
                   47           .18467         .00175
                   50           .17949         .00171

 Iterations stopped because this is iteration    50

            Stress and squared correlation (RSQ) in distances

RSQ values are the proportion of variance of the scaled data
(disparities) in the partition (row, matrix, or entire data)
which is accounted for by their corresponding distances.
             Stress values are Kruskal's stress formula 2.

                         (Row Stimuli Only)
    Stimulus    Stress      RSQ   Stimulus    Stress      RSQ

        1         .187     .968       2         .170     .973
        3         .160     .975       4         .108     .989
        5         .114     .988       6         .323     .910
        7         .251     .942       8         .155     .976
        9         .281     .925      10         .282     .925
       11         .207     .960      12         .082     .994
       13         .093     .992      14         .242     .946

       Averaged (rms) over stimuli
    Stress  =   .204      RSQ =  .962
```

Figure 28. Fit for joint representation of constructs and elements.

It should be noticed first that this solution does not converge, indicating that the obtained configuration is not the best possible. Increasing the ITER(50) command in Figure 27 might improve things - although this has already been increased from the default 30. The second thing to notice is that this uses a different measure of fit, known as Stress Formula 2. This gives higher values, as can be seen in Levine (1978). But we also have a fit index for each row (construct). Hence we can see that row 6 (INDEPENDent) is a poor fit, while row 12

(HEALTHY) seems to be a better fit. Stimulus coordinates are listed in Figure 29.

Stimulus Coordinates

Stimulus Number	Stimulus Name	Dimension 1	2
Column			
1	BIPOLAR	1.8917	-.6402
2	SCHIZ	1.9135	-.6507
3	PSYCHIAT	1.4063	-1.3203
4	CRIMINAL	1.9638	-.5541
5	AVERAGE	-1.2745	1.2275
6	AIDS	1.7788	-.6505
7	DIABETES	.1423	1.2882
8	CANCER	.6921	1.3902
9	STRESS	.8488	1.7981
10	USUALME	-.5950	1.1962
11	MENOW	.0313	-1.7526
12	ME6MTH	-.1595	1.0282
13	STAFFME	.2018	-1.8232
14	IDEALME	-.4284	1.1190
Row			
1		.0964	-.1484
2		-.0085	-.1565
3		-.7813	-.2839
4		-1.3670	-.5480
5		-1.3508	-.5123
6		.3198	.0018
7		-.0872	-.2498
8		-.7116	1.9313
9		-1.1007	-.8124
10		-.4434	-.3083
11		-.6337	-.2472
12		-.8436	-.2830
13		-1.0719	-.4525
14		-.4296	.4133

Figure 29. Unfolding Coordinates for Elements and Constructs (rows).

It can be seen that constructs are not labelled. This is also true for the corresponding plot of elements and constructs shown in Figure 30.

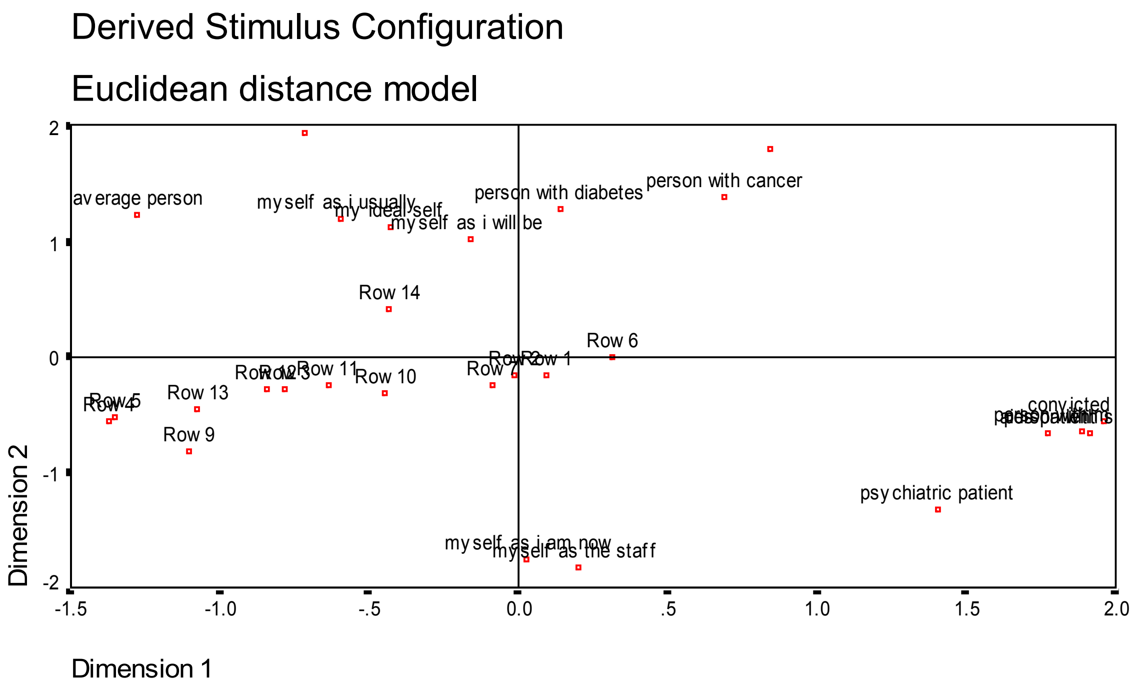

Figure 30. Plot of Unfolding representation of Elements and Constructs.

2. <u>The Correspondence Analysis Model.</u>

SPSS has recently (well, relatively recently) added a new group of modules for scaling categorical data. One of these modules is ANACOR, a method of scaling the rows and columns of a table. This technique is variously called correspondence analysis, optimal scaling, and dual scaling among other names. It was originally devised (over 50 years ago) for scaling of contingency tables, however it can actually be used with any data table. Consequently it can be used to scale the elements and constructs of a repertory grid. It has several advantages over the unfolding model shown above. Firstly it is a principal components solution and therefore does not have the minimization problems (e.g. failure to converge, as shown above); secondly it can cope with grids where ratings may be unvarying for an element; and thirdly it provides fit statistics for both elements and constructs. Like ALSCAL however, it does not label the constructs. Figure 31 shows the commands for analysing a grid.

```
GET FILE='c:\aa\onegrid.sav'
 / DROP = conlab.
ANACOR TABLE=ALL(14,14)/VARIANCES=SINGULAR ROWS COLUMNS
 /PRINT  SCORES /PLOT=JOINT(20).
```

Figure 31. Commands for a Correspondence Analysis of a grid.

To carry out a correspondence analysis in the simplest fashion with SPSS it is necessary for all variables to be included. Thus the above commands first eliminate the construct label variable, CONLAB, by dropping it as the stored data file is retrieved. ANACOR cannot be run from Windows dialogue boxes hence the syntax here is carefully crafted by hand.

The command VARIANCES=SINGULAR ROWS COLUMNS generates clumsy output for rows and columns but can be informative. PRINT SCORES is included to suppress other printing which is less relevant for a grid, and PLOT=JOINT(20) is included to lengthen the element labelling to 20 characters maximum.

Figure 32 shows an edited version of the output, with the larger output of correlations and variances for each element and construct cut to a few illustrative examples.

A N A C O R - VERSION 0.4
BY
DEPARTMENT OF DATA THEORY
UNIVERSITY OF LEIDEN, THE NETHERLANDS

Dimension	Singular Value	Inertia	Proportion Explained	Cumulative Proportion
1	.23852	.05689	.373	.373
2	.20321	.04129	.271	.644
3	.15752	.02481	.163	.807
4	.12137	.01473	.097	.903
5	.08388	.00704	.046	.949
6	.06620	.00438	.029	.978
7	.03942	.00155	.010	.988
8	.02846	.00081	.005	.994
9	.02573	.00066	.004	.998
10	.01507	.00023	.001	.999
11	.00854	.00007	.000	1.000
12	.00477	.00002	.000	1.000
13	.00004	.00000	.000	1.000
		---------	----------	----------
Total		.15249	1.000	1.000

Row Scores:

Row	Marginal Profile	Dim 1	2	*(labels added by hand)*
1	.053	.317	.778	good
2	.060	.190	.493	dependable
3	.067	.328	.063	safe
4	.072	.420	-.128	clearheaded
5	.077	.172	-.094	stable
6	.113	-.882	.738	predictable
7	.055	.384	.414	intelligent
8	.074	-.853	-.721	free
9	.087	.083	-.536	healthy
10	.056	.245	-.035	honest
11	.060	.285	-.060	rational
12	.064	.369	-.223	independent
13	.070	.486	-.114	calm
14	.092	-.520	-.408	understood

(continued on next page)

(continued)
Column Scores:

Column	Marginal Profile	Dim 1	2

```
   1 person w    .107     .108    -.191
   2 person w    .119     .172    -.095
   3 psychiat    .086     .154    -.109
   4 convicte    .133     .298     .063
   5 average     .041     .009    1.211
   6 AIDS pat    .093     .040    -.557
   7 person w    .046     .139    -.314
   8 person w    .064     .370    -.319
   9 person u    .115     .495     .358
  10 myself a    .033    -.864     .857
  11 myself a    .049   -1.407    -.529
  12 myself a    .022    -.194     .506
  13 myself a    .066    -.756    -.232
  14 my ideal    .027    -.895    1.131


Variances and Correlation Matrix of the singular values:

Dim Variances           Correlations between dimensions
  1      .001           1.000
  2      .001            .101    1.000


Variances and Correlation Matrix of scores of Row      1

Dim Variances           Correlations between dimensions
  1      .494           1.000
  2      .299           -.301    1.000


Variances and Correlation Matrix of scores of Column   3
  psychiatric patient

Dim Variances           Correlations between dimensions
  1      .076           1.000
  2      .092            .203    1.000

Variances and Correlation Matrix of scores of Column   9
 person under stress

Dim Variances           Correlations between dimensions
  1      .115           1.000
  2      .194           -.722    1.000
```

Figure 32. Correspondence Analysis (ANACOR) output for grid.

The first table is effectively the principal components of the grid rescaled by the row and column sums. The "Singular Value" (or Eigenvalue) can be interpreted as the correlation between the rows and columns given the scores (or weights) shown in the subsequent tables. The "Inertia" is this value squared and is thus the proportion of common variance. While two dimensions have been retained here as the default, this table suggests that it might be useful to examine a three-dimensional solution for this grid. The Row scores are the dimensions used to plot constructs. Labels here have been subsequently added to facilitate explanation. On the first dimension *predictable* and *free* are distinguished from other constructs, but on the second dimension these are contrasted.

The "Marginal Profile" reflects the lopsidedness of the constructs, higher values indicating higher ratings. Thus for the column scores, Ideal Self has a value of .027, which in looking at the last column of the grid (Figure 2) can be seen to be principally ratings of 1. This table does show one problem with the printed output for ANACOR, in that only the first 8 characters of the variable label are used to label the columns. For this grid, the labelling becomes quite ambiguous. [The problem does not occur for the plotting of elements and rows (constructs) as shown in Figure 33.] The variances and correlations between dimensions provide indications of the confidence with which we can regard the locations of the points. The variances indicate errors for the dimensional coordinates (though for grid data they cannot be treated exactly as errors). The correlations show the separability of the dimensions, thus for large values (e.g. for person under stress) there is little independence between dimensions.

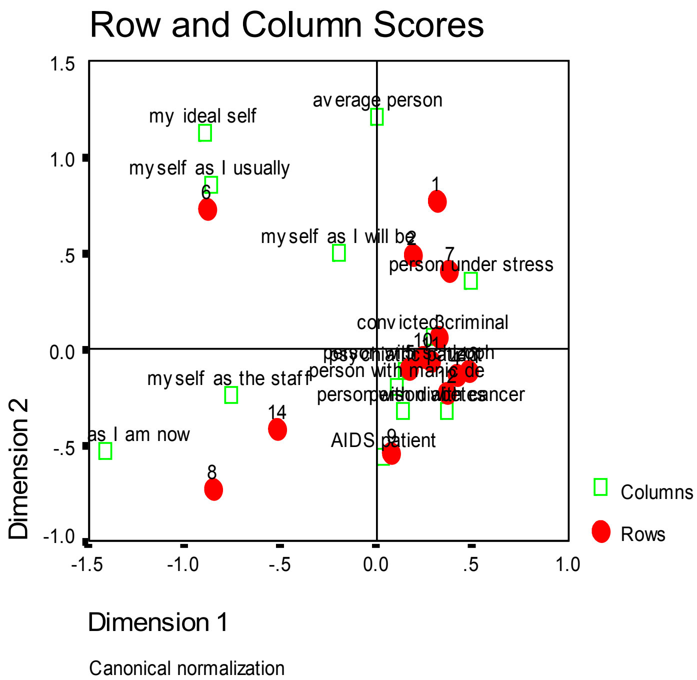

Figure 33. Correspondence Analysis (ANACOR) plot for grid.

This figure shows a more integrated picture than does the unfolding solution in Figure 30. While there is the similar splitting of the self now staff view of self from the other self figures, there is a clearer distinction between the other self figures and the other figures. The constructs (shown as rows in both figures) are also more differentiated in the correspondence analysis solution.

Multiple grid analysis

Data Structures

The analysis of multiple grids can take several grid structures. These are shown in Table 1, where they are arranged in increasing order of restriction.

Table 1. Possible Multiple Grid Data Structures handled by SPSS.

Structure	Type	Columns	Rows
1	I	Same numbers of different elements	Varying* numbers of different constructs
2	I	Same numbers of different constructs	Varying* numbers of different elements
3	II	Same numbers of different elements	Same constructs
4	II	Same numbers of different constructs	Same elements
5	II	Same elements	Varying* numbers of different constructs
6	II	Same constructs	Varying* numbers of different elements
7	III	Same elements	Same constructs
8	III	Same constructs	Same elements

* or Same

The eight structures have been grouped into three types. The analyses that can be carried out depend on the type of structure, therefore those grids structures with the same type can, as a rule, be analysed in the same way. In general, any type of structure can also be analysed as a structure with a lower type. It should be noted that the number of columns must always be the same, whether or not the columns refer to the same elements (or constructs) across grids.

Setting up the Data File

As with a single grid, SPSS is most conveniently used for multiple grids by setting up two files, one with that data in it, and one with the file description. Figure 34 shows the SPSS command file, and Figure 35 shows part of the data file. These grids are also taken from Bell & McGorry (1992), and is an example of Structure 7 in Table 1.

```
data list file='c:\aa\multi\multgrid.dat'
 / grid construc bipolar schiz psychiat criminal average aids
  diabetes cancer stress usualme menow me6mth mestaff idealme
  1-48.
variable labels
 grid, 'Grid Number'/
 construc, 'Construct'/
 bipolar,'person with manic depressive illness'/
 schiz, 'person with schizophrenia'/
 psychiat, 'psychiatric patient'/
 criminal, 'convicted criminal'/
 average,'average person '/
 aids, 'AIDS patient'/
 diabetes,'person with diabetes'/
 cancer, 'person with cancer'/
 stress,'person under stress'/
 usualme,'myself as I usually am'/
 menow, 'myself as I am now'/
 me6mth, 'myself as I will be in six months'/
 mestaff,'myself as the staff see me'/
 idealme,'my ideal self'.
value labels
  construc
 1 'good'                         8 'free'
 2 'dependable'                   9 'healthy'
 3 'safe'                         10 'honest'
 4 'clearheaded'                  11 'rational'
 5 'stable'                       12 'independent'
 6 'predictable'                  13 'calm'
 7 'intelligent'                  14 'understood'.
```

Figure 34. SPSS Command file for Multiple Grid Analysis.

The data file differs from that for a single grid, in that the file should contain a field that identifies each grid, that is the number will be repeated for each row of the grid. If there is other data, such as some kind of group indicator, then this should also be indicated in a column that is repeated for each row of the grid. Additionally, where the rows of a grid refer to the same constructs (or elements), it is useful to number the rows. Subsequently each column corresponds to the ratings for a given element, and each row corresponds to the ratings for a given construct, in the odd-numbered data structures in Table 1, while constructs and elements would be reversed in the even-numbered data structures. At the end of each row there may be a label for the row (construct or element). This labelling will depend on the energy of the person setting up the file. If this is you it may well be too much trouble (as it was for me). Labels for the columns may be defined in the command file. If these vary across grids (structures 1 thru 4) they must be generic names (e.g. for structures 1 & 3, element1 to element9), but if they are the same (structures 5 thru 8) they may be identifying labels, as in Figure 34.

```
  1  1  6  3  4  5  2  3  2  3  5  2  3  4  2  1
  1  2  5  4  5  6  1  3  2  2  4  2  3  3  2  1
  1  3  6  7  2  7  2  6  2  4  5  2  1  5  2  1
  1  4  4  6  2  2  1  2  1  2  5  2  1  5  2  1
  1  5  3  4  3  1  2  3  1  3  4  2  1  4  2  1
  1  6  7  5  4  7  1  4  1  2  4  2  1  7  2  1
  1  7  3  4  2  2  2  2  1  2  5  2  1  6  2  1
  1  8  5  4  4  7  1  7  3  7  5  2  1  7  2  1
  1  9  7  7  5  2  1  7  5  7  3  5  5  7  3  1
  1 10  4  4  4  7  2  2  3  2  3  3  2  5  2  1
  1 11  5  5  5  4  2  4  4  3  4  4  3  6  3  1
  1 12  2  6  4  4  2  7  2  3  5  6  5  4  3  1
  1 13  5  5  4  2  2  2  2  2  6  4  2  4  3  1
  1 14  6  6  5  4  2  2  2  2  6  3  2  5  4  3
  2  1  4  6  5  7  4  4  4  4  6  4  4  3  4  2
  2  2  6  7  5  7  3  3  4  4  7  3  3  1  2  1
  2  3  6  7  5  7  3  7  4  5  5  2  2  1  2  1
  2  4  7  7  6  7  2  4  3  5  7  2  2  1  6  1
  2  5  6  7  5  7  3  4  4  4  7  2  2  1  2  1
  2  6  7  7  6  7  4  4  4  4  7  7  7  7  7  5
  2  7  4  4  5  4  2  4  3  4  3  2  2  2  3  1
  2  8  6  5  6  7  1  7  1  5  4  1  2  1  3  1
  2  9  7  6  6  7  2  7  7  7  4  1  1  1  2  1
  2 10  4  6  4  7  3  4  4  4  4  2  2  2  1  1
  2 11  6  7  5  7  3  4  4  4  6  2  2  1  2  1
  2 12  6  7  6  4  1  7  4  6  4  1  2  1  3  1
  2 13  5  7  6  7  2  4  4  4  6  2  1  1  1  1
  2 14  6  7  6  7  2  7  4  6  7  4  1  1  1  1
  3  1  2  4  3  6  1  1  1  1  2  7  3  1  1  1
  3  2  5  5  5  7  2  1  3  1  7  1  1  1  2  1
  3  3  4  7  3  7  3  7  1  1  5  4  7  3  2  1
  3  4  7  7  5  4  2  7  3  2  7  1  1  1  3  1
  3  5  7  4  5  5  3  4  5  7  7  3  2  1  2  1
  3  6  7  7  7  7  3  5  2  3  7  6  2  4  5  1
  3  7  2  1  4  5  4  3  1  2  3  2  1  1  2  1
  3  8  6  7  7  7  1  5  1  7  7  5  7  3  7  1
```

Figure 35. Portion of multiple grid data showing 2 (and part of a 3rd) grids.

Type I Grids - Nothing in Common

Remember Type I have nothing in common except the number of columns. Consequently they must be treated as single grids. All that can be done in SPSS is therefore to repeat a kind of analysis on each grid. This is easy to achieve using the fact that each grid is numbered by "splitting" the data file. Figure 36 shows the commands for finding descriptive statistics for elements.

```
SORT CASES BY grid.
SPLIT FILE BY grid.
DESCRIPTIVES
  VARIABLES=bipolar schiz psychiat criminal average aids diabetes
  cancer stress usualme menow me6mth staffme idealme
  /FORMAT=LABELS NOINDEX
  /STATISTICS=MEAN STDDEV MIN MAX .
  /SORT=MEAN (A) .
```

Figure 36. Commands for Repeating Descriptive analysis by Grids.

Some of the output is shown in Figure 37, where the repeated analysis can be seen.

```
GRID:    1
```

```
Number of valid observations (listwise) =        14.00

                                                   Valid
Variable      Mean    Std Dev   Minimum   Maximum      N  Label

IDEALME       1.14        .53         1         3     14  my ideal self
AVERAGE       1.64        .50         1         2     14  average person
DIABETES      2.21       1.19         1         5     14  person with diabetes
MENOW         2.21       1.42         1         5     14  myself as I am now
MESTAFF       2.43        .65         2         4     14  myself as the staff s
USUALME       2.93       1.33         2         6     14  myself as I usually a
CANCER        3.14       1.75         2         7     14  person with cancer
PSYCHIAT      3.79       1.12         2         5     14  psychiatric patient
AIDS          3.86       2.03         2         7     14  AIDS patient
CRIMINAL      4.29       2.23         1         7     14  convicted criminal
STRESS        4.57        .94         3         6     14  person under stress
BIPOLAR       4.86       1.51         2         7     14  person with manic dep
SCHIZ         5.00       1.24         3         7     14  person with schizophr
ME6MTH        5.14       1.29         3         7     14  myself as I will be i

GRID:    2


Number of valid observations (listwise) =        14.00

                                                   Valid
Variable      Mean    Std Dev   Minimum   Maximum      N  Label

IDEALME       1.36       1.08         1         5     14  my ideal self
ME6MTH        1.71       1.64         1         7     14  myself as I will be i
MENOW         2.36       1.55         1         7     14  myself as I am now
USUALME       2.50       1.61         1         7     14  myself as I usually a
AVERAGE       2.50        .94         1         4     14  average person
MESTAFF       2.79       1.81         1         7     14  myself as the staff s
DIABETES      3.86       1.23         1         7     14  person with diabetes
CANCER        4.71        .99         4         7     14  person with cancer
AIDS          5.00       1.57         3         7     14  AIDS patient
PSYCHIAT      5.43        .65         4         6     14  psychiatric patient
STRESS        5.50       1.45         3         7     14  person under stress
BIPOLAR       5.71       1.07         4         7     14  person with manic dep
SCHIZ         6.43        .94         4         7     14  person with schizophr
CRIMINAL      6.57       1.09         4         7     14  convicted criminal
```

Figure 37. Repeated Element Statistics for Two Grids.

Note that although the grid data analysed here is Type IV not Type I, it must be remembered that grids with *more* commonality in their structure can usually be analysed as grids with *less* commonality. All the procedures shown for single grids may be run in this fashion - with two exceptions. Firstly, it is not possible to 'flip' the file and analyse rows (say, constructs) as if they were columns or variables. Secondly, it is not possible to run ANACOR for a correspondence analysis of the grid in this way. To do either of these things you must analyse each grid separately. However many other analyses remain possible.

Type II Grids - One Thing in Common - either Elements *or* Constructs

Having one thing in common (either elements or constructs) increases the options for analysis to include models that in some way 'tie' the separate grids together. Such a question might be posed as "Do the different grids show similar or different patterns of relationships among the common elements (or constructs)?". There are two ways this question can be addressed.

Discriminant Analysis
Discriminant analysis is a classical statistical technique rarely associated with repertory grid data. However, if the grid data conforms to either structure 5 or 6 (i.e. the columns in the data set are common), then discriminant function analysis can be used to show how these common aspects differentiate between the grids. Figure 38 shows discriminant function analysis commands for a step-wise analysis (since this enables pairwise testing between grids with an

F-ratio).

```
DISCRIMINANT
  /GROUPS=grid(1 4)
  /VARIABLES=bipolar schiz psychiat criminal average aids
  diabetes cancer stress usualme menow me6mth mestaff idealme
   /METHOD=RAO
  /PRIORS  EQUAL
   /HISTORY NOSTEP END
  /STATISTICS=FPAIR TABLE
  /CLASSIFY=NONMISSING POOLED .
```

Figure 38. Discriminant Analysis commands for Grids and Elements.

The output for this is shown in Figure 39.

```
- - - - - - - -   D I S C R I M I N A N T   A N A L Y S I S - - - - - - - -

On groups defined by GRID      Grid Number


            56 (Unweighted) cases were processed.
             0 of these were excluded from the analysis.
            56 (Unweighted) cases will be used in the analysis.



Number of cases by group

                Number of cases
  GRID      Unweighted     Weighted  Label
         1          14         14.0
         2          14         14.0
         3          14         14.0
         4          14         14.0

     Total          56         56.0



 - - - - - - - -   D I S C R I M I N A N T   A N A L Y S I S - - - - - - - -

On groups defined by GRID      Grid Number



(Some feedback output deleted)

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```

(Continued)

---------------- Variables in the Analysis after Step 4 ----------------

Variable	Tolerance	F to Remove	Rao's V
PSYCHIAT	.9316780	3.9695	140.0253564
AVERAGE	.8756172	6.8034	120.3737614
ME6MTH	.8133765	19.9543	60.0819358
IDEALME	.8593555	4.3011	153.4784269

---------------- Variables not in the Analysis after Step 4 ----------------

Variable	Tolerance	Minimum Tolerance	F to Enter	Rao's V
BIPOLAR	.6047639	.6034018	.8313236	185.8907517
SCHIZ	.8937412	.8090352	2.0268965	190.9979765
CRIMINAL	.9840751	.8117295	3.1714952	202.9168685
AIDS	.8433686	.7623390	1.4452391	198.5456297
DIABETES	.8254466	.7759805	1.4453233	188.2151923
CANCER	.8121753	.8006301	2.8286847	198.4309405
STRESS	.8360147	.7956154	.6235705	187.1286357
USUALME	.7472725	.6949041	2.3832397	194.0499868
MENOW	.7355245	.6536394	1.9560690	204.8643977
MESTAFF	.6935368	.6935368	.8932524	186.1924639

F statistics and significances between pairs of groups after step 4
Each F statistic has 4 and 49 degrees of freedom.

Group	1	2	3
2	28.3306 .0000		
3	19.7961 .0000	1.3871 .2522	
4	31.8697 .0000	1.3975 .2487	3.3302 .0172

F level or tolerance or VIN insufficient for further computation.

Summary Table

Step	Action Entered	Action Removed	Vars in	Wilks' Lambda	Sig.	Rao's V	Sig.	Change in V	Sig.
1	ME6MTH		1	.44048	.0000	66.05282	.0000	66.05282	.0000
2	AVERAGE		2	.30863	.0000	111.26697	.0000	45.21416	.0000
3	PSYCHIAT		3	.24227	.0000	153.47843	.0000	42.21145	.0000
4	IDEALME		4	.19177	.0000	182.76677	.0000	29.28834	.0000

(Continued)

(Continued)

Canonical Discriminant Functions

Fcn	Eigenvalue	Pct of Variance	Cum Pct	Canonical Corr	:	After Fcn	Wilks' Lambda	Chi-square	df	Sig
					:	0	.191767	84.225	12	.0000
1*	3.3118	94.23	94.23	.8764	:	1	.826870	9.695	6	.1381
2*	.1632	4.64	98.87	.3746	:	2	.961809	1.986	2	.3705
3*	.0397	1.13	100.00	.1954	:					

* Marks the 3 canonical discriminant functions remaining in the analysis.

Standardized canonical discriminant function coefficients

	Func 1	Func 2	Func 3
PSYCHIAT	.51398	-.07896	-.39881
AVERAGE	.63742	-.00443	.78853
ME6MTH	-.93504	.15502	.17451
IDEALME	.39304	.92994	-.25984

Structure matrix:

Pooled within-groups correlations between discriminating variables
and canonical discriminant functions
(Variables ordered by size of correlation within function)

	Func 1	Func 2	Func 3
ME6MTH	-.60880*	.49641	.25321
DIABETES	.25952*	-.04599	.09904
STRESS	.22440*	.10466	-.17889
AIDS	-.15056*	-.13404	-.14548
IDEALME	.13014	.98723*	-.08704
MENOW	-.23107	.27628*	.10626
USUALME	-.14353	.27408*	.22012
MESTAFF	.03653	.23551*	-.11550
CRIMINAL	-.02564	.10104*	.07098
AVERAGE	.33870	.17846	.89114*
PSYCHIAT	.31851	-.07316	-.57798*
BIPOLAR	.07940	.00020	-.35205*
CANCER	-.01432	-.16101	-.23545*
SCHIZ	.04205	.08805	-.18902*

* denotes largest absolute correlation between each variable and any discriminant function.

Canonical discriminant functions evaluated at group means (group centroids)

Group	Func 1	Func 2	Func 3
1	-2.97485	.11399	-.03672
2	1.14809	-.23154	-.28594
3	.43130	-.45728	.23980
4	1.39546	.57483	.08286

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```
(Continued)

Classification results -

                     No. of    Predicted Group Membership
   Actual Group       Cases         1          2          3          4
--------------------  ------   --------   --------   --------  --------

Group       1            14        14          0          0          0
                                 100.0%        .0%        .0%        .0%

Group       2            14         0         10          2          2
                                    .0%      71.4%      14.3%      14.3%

Group       3            14         1          5          7          1
                                   7.1%      35.7%      50.0%       7.1%

Group       4            14         0          3          3          8
                                    .0%      21.4%      21.4%      57.1%

Percent of "grouped" cases correctly classified:  69.64%

Classification processing summary

        56 (Unweighted) cases were processed.
         0 cases were excluded for missing or out-of-range group codes.
         0 cases had at least one missing discriminating variable.
        56 (Unweighted) cases were used for printed output.
```

Figure 39. Discriminant Function Analysis Output.

This is rather voluminous output. Features of interest are as follows. The first thing of interest is to note which elements differentiate between the grids and which do not (shown as Variables in the Analysis after Step 4 etc). Only four elements distinguish between these grids.

The next feature are the pair-wise F-tests between groups (i.e. grids). here it can be seen that the first grid differs from the other three, but there are no significant differences between the other three.

The summary table simply repeats earlier information. On the next page, the chi-square statistical test shows that after removing the first function, the value of 9.695 on 6 degrees of freedom, is not significant (p=.1381). Thus we need to bear on mind that only function 1 will subsequently be off importance.

Although four elements provide the best discrimination in terms of weighting coefficients, identification of the nature of this discriminating function can sometimes better be gauged by examining the correlation between the variables and the functions. ME6MTH (self in six months) is the key element discriminating the first grid from the other three by either result.

The classification results show how well constructs can be allocated to their correct grid. As might be expected the first grid can be identified perfectly, but the others have much poorer identification with their constructs.

Multidimensional Scaling

Replicated Multidimensional Scaling.
A straightforward extension of the single grid multidimensional scaling for elements or constructs separately (Figures 22 through 26) is through replicated multidimensional scaling where a representation is found for the common elements, the different grids being taken as replications. Commands for such an analysis are shown in Figure 40.

```
SORT CASES BY grid .
SPLIT FILE BY grid .
PROXIMITIES bipolar schiz psychiat criminal average aids
  diabetes cancer stress usualme menow me6mth mestaff idealme
  /PRINT NONE /MATRIX
  OUT('C:\WINDOWS\TEMP\spssalsc.tmp')
  /MEASURE=EUCLID /STANDARDIZE=NONE /VIEW=VARIABLE .
SPLIT FILE OFF.
ALSCAL
  /MATRIX= IN('C:\WINDOWS\TEMP\spssalsc.tmp')
  /LEVEL=ORDINAL
  /CONDITION=MATRIX
  /MODEL=EUCLID
  /CRITERIA=CONVERGE(.001) STRESSMIN(.005) ITER(30) CUTOFF(0)
   DIMENS(2,2)
  /PLOT=DEFAULT .
ERASE FILE='C:\WINDOWS\TEMP\spssalsc.tmp'.
```

Figure 40. Commands for Replicated Multidimensional Scaling of Common Elements across Grids.

Printed output is shown in Figure 41, and a plot of the elements shown in figure 42.

```
Iteration history for the 2 dimensional solution (in squared
distances)
                  Young's S-stress formula 1 is used.

                Iteration     S-stress      Improvement
                    1          .33589
                    2          .31797         .01792
                    3          .31503         .00293
                    4          .31419         .00084

                       Iterations stopped because
                 S-stress improvement is less than   .001000

            Stress and squared correlation (RSQ) in distances

RSQ values are the proportion of variance of the scaled data
(disparities) in the partition (row, matrix, or entire data)
which is accounted for by their corresponding distances.
             Stress values are Kruskal's stress formula 1.

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```

```
(Continued)

        Matrix     Stress      RSQ    Matrix     Stress      RSQ
           1         .311     .481       2         .169     .846
           3         .244     .680       4         .188     .809

        Averaged (rms) over  matrices
    Stress  =   .23463      RSQ =  .70399
Configuration derived in 2 dimensions

                   Stimulus Coordinates
                        Dimension

Stimulus   Stimulus     1        2
 Number      Name
    1      BIPOLAR    1.4942   -.0233
    2      SCHIZ      1.6010    .4834
    3      PSYCHIAT   1.0500   -.3897
    4      CRIMINAL   1.4085   1.1646
    5      AVERAGE   -1.1970   -.1605
    6      AIDS        .8681   -.8678
    7      DIABETES   -.5342  -1.0983
    8      CANCER      .3427  -1.0330
    9      STRESS     1.2155    .3572
   10      USUALME    -.9193    .6652
   11      MENOW     -1.2194    .2566
   12      ME6MTH     -.8693   1.2199
   13      MESTAFF   -1.1765    .0553
   14      IDEALME   -2.0642   -.6298
```

Figure 41. Printed Output for Element Multidimensional Scaling replicated across grids.

The stress values are not good for this solution, and can be seen to be worst for the first grid, confirming the distinction that was found in the discriminant analysis between this grid and the others. It may well be that a better solution overall would be found by re-running this analysis with the first grid removed.

Nevertheless, Figure 42 shows the 'average' configuration across all three data sets. This can be compared with the single grid plot shown in Figure 24. It can also be compared with the configuration obtained in the next analysis.

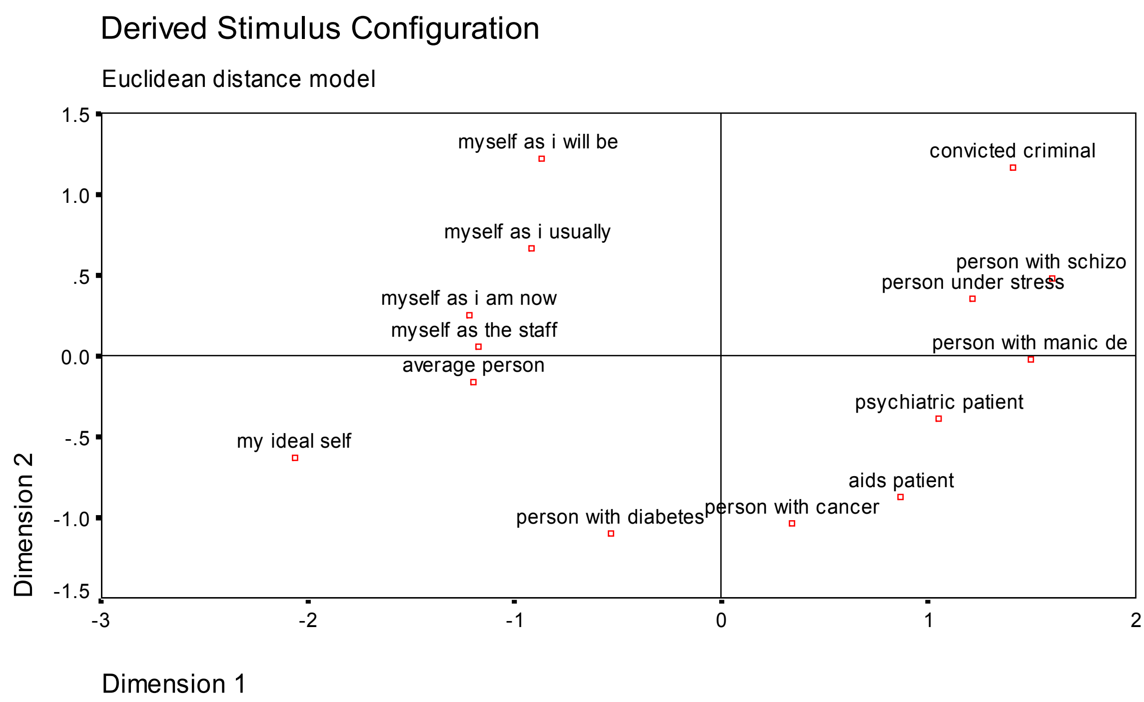

Figure 42. Plot of Element Multidimensional Scaling replicated across grids.

Individual Differences Multidimensional Scaling.

In the previous analysis no attempt was made to include the grids in the model, except to see how well they fitted the solution. A model which incorporates weights for the solutions, and thus allows for differences between grids, can be carried with ALSCAL. Accordingly a joint solution can be found and (in theory) by applying the weights to this, individual configurations for each grid created. Commands for this are shown in Figure 43.

```
SORT CASES BY grid .
SPLIT FILE BY grid .
PROXIMITIES bipolar schiz psychiat criminal average aids
 diabetes cancer stress usualme menow me6mth mestaff idealme
 /PRINT NONE /MATRIX
  OUT('C:\WINDOWS\TEMP\spssalsc.tmp')
  /MEASURE=EUCLID /STANDARDIZE=NONE /VIEW=VARIABLE .
SPLIT FILE OFF.
ALSCAL
  /MATRIX= IN('C:\WINDOWS\TEMP\spssalsc.tmp')
  /LEVEL=ORDINAL
  /CONDITION=MATRIX
  /MODEL=INDSCAL
  /CRITERIA=CONVERGE(.001) STRESSMIN(.005) ITER(30) CUTOFF(0)
  DIMENS(2,2)
  /PLOT=DEFAULT.
ERASE FILE='C:\WINDOWS\TEMP\spssalsc.tmp'.
```

Figure 43. Commands for Individual Differences (by Grid) Scaling of Common Elements.

Printed output is shown in Figure 44.

```
Iteration history for the 2 dimensional solution
(in squared distances)

                  Young's S-stress formula 1 is used.

                Iteration     S-stress      Improvement

                    0           .27103
                    1           .27021
                    2           .23577         .03444
                    3           .23392         .00185
                    4           .23322         .00070

                         Iterations stopped because
                 S-stress improvement is less than   .001000


            Stress and squared correlation (RSQ) in distances

RSQ values are the proportion of variance of the scaled data
(disparities) in the partition (row, matrix, or entire data)
which is accounted for by their corresponding distances.

             Stress values are Kruskal's stress formula 1.

        Matrix     Stress       RSQ    Matrix     Stress       RSQ
           1         .196      .860       2         .133      .944
           3         .304      .595       4         .134      .943

        Averaged (rms) over  matrices
    Stress  =   .20400      RSQ =  .83533

           Configuration derived in 2 dimensions

                   Stimulus Coordinates

                        Dimension

Stimulus   Stimulus     1        2
 Number      Name

    1      BIPOLAR     .9632   1.2951
    2      SCHIZ      1.2746   1.1524
    3      PSYCHIAT    .9336    .0707
    4      CRIMINAL   1.2080   1.4335
    5      AVERAGE    -.7458  -1.0736
    6      AIDS        .8333    .2762
    7      DIABETES   -.2384   -.9796

(Continued next page)
```

```
(continued)

    8      CANCER      .4738   -.4633
    9      STRESS      .9466    .7297
   10      USUALME    -.8738   -.2390
   11      MENOW      -.9167   -.9604
   12      ME6MTH    -1.2555   1.1419
   13      MESTAFF   -1.0559   -.5303
   14      IDEALME   -1.5471  -1.8532



Subject weights measure the importance of each dimension to each
subject. Squared weights sum to RSQ.
A subject with weights proportional to the average weights has
a weirdness of zero, the minimum value.
A subject with one large weight and many low weights has a
weirdness near one.
A subject with exactly one positive weight has a weirdness of
one, the maximum value for nonnegative weights.


                      Subject Weights

                                Dimension
   Subject  Weird-      1        2
   Number    ness

      1     .9553    .0577    .9254
      2     .9209    .9709    .0341
      3     .2187    .6022    .4819
      4     .9420    .9707    .0249
Overall importance of
each dimension:      .5627    .2726

                Flattened Subject Weights

                     Variable
Subject   Plot     1
 Number  Symbol
   1       1   -1.5455
   2       2     .8720
   3       3    -.2220
   4       4     .8955
```

Figure 44. Output for Individual Differences (by Grid) Scaling of Common Elements.

This solution can be seen to be reasonably similar (though not exactly so) to the replicated one, at least in terms of the configuration (shown in Figure 45). The stress values present a different picture however. By allowing grid weights, the first grid is able to be fitted better, and it is the third grid which does not fit as well in this scheme. The weights show the first grid to weight the second dimension most, i.e. "stretching" the distinction between 'myself as I will be' and 'my ideal self', while the second and fourth grids are almost identical in emphasizing the distinction between the self and psychotic figures (i.e. dimension 1).

Using the grid weights in other analyses is difficult, and there are two possibilities. One is to only use the flattened weights from ALSCAL. The other is to change the subcommand /CONDITION=MATRIX to /CONDITION=UNCONDITIONAL. This makes the assumption that ratings in one grid are comparable with ratings in another. When this assumption is made, the weights for the separate dimensions may be used in other analyses (such as ANOVA).

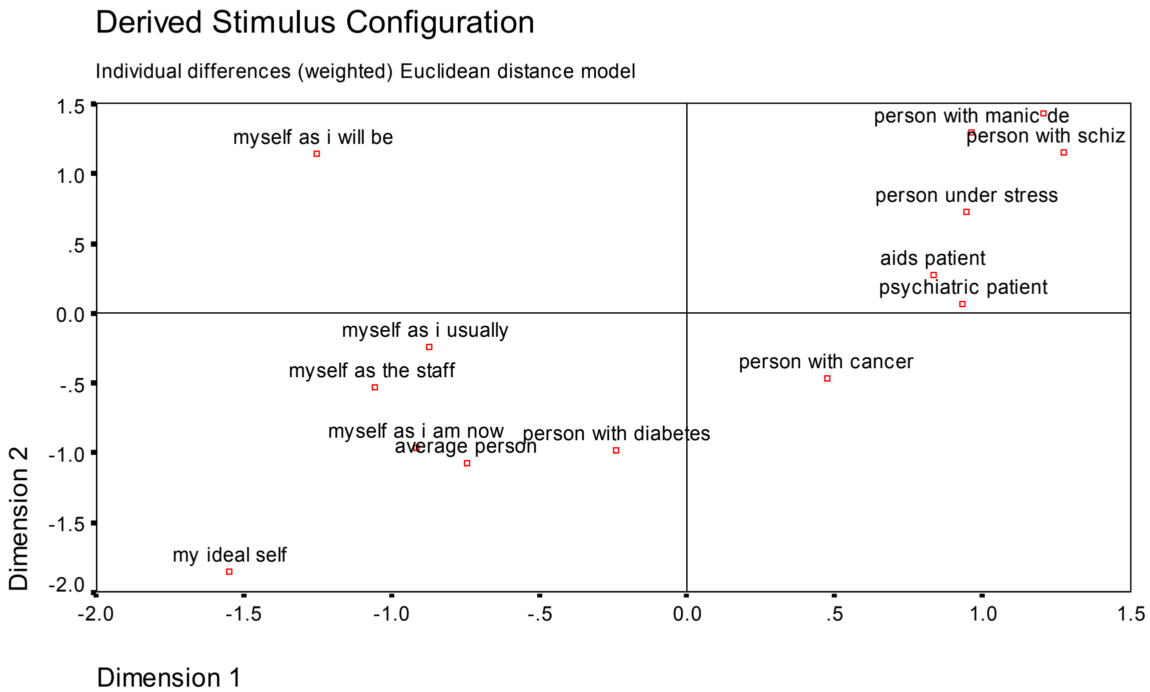

Figure 45. Plot of Individual Differences (by Grid) Scaling of Common Elements.

Common Construct Analyses

In the above scaling analyses the elements in each grid have been represented because they were in common. If they had not been, but simply represented the same number of different elements in each grid, while the constructs (which were treated here as though they were different) were in fact the common aspect of the grids (i.e. data structure 3 in Table 1), then the above scalings could have been carried out by changing /VIEW=VARIABLE to /VIEW=CASE in the PROXIMITIES instruction.

Different Construct Analysis

One of the earliest (if not the earliest) attempt to represent different constructs from different grids, where common elements provided the link; was in Slater's PREFAN programme, written up in Slater (1979).

This approach treats the constructs from different grids as though they were constructs from a single "supergrid". Such an approach can be used here, by adopting the unfolding commands for a single grid (Figure 27) setting the number of rows (/ROWS=) equal to the total number of constructs. Alternatively, the correspondence analysis approach (Figure 31) could similarly be used. The only problem with this approach is that it will confound between-grid variation and within-grid variation in constructs, and thus should be employed with caution.

Type III Grids - Both Elements and Constructs in Common.

Just as the multidimensional scaling of elements (or constructs) could be extended from the single grid in the Type II analyses above, the unfolding joint representation of elements and constructs in a grid can be extended to multiple grids.

Replicated Unfolding Solution

The commands for a replicated unfolding solution for multiple grids with both common elements and common constructs is shown in Figure 46.

```
ALSCAL
  VARIABLES= bipolar schiz psychiat criminal average aids
  diabetes cancer stress usualme menow me6mth mestaff idealme
  /SHAPE=RECTANGULAR /INPUT ROWS(14)
  /LEVEL=ORDINAL
  /CONDITION=ROW
  /MODEL=EUCLID
  /CRITERIA=CONVERGE(.001) STRESSMIN(.005) ITER(30) CUTOFF(0)
  DIMENS(2,2)
  /PLOT=DEFAULT .
```

Figure 46. Commands for Replicated Unfolding representation of Elements and Constructs.

Figure 47 shows the printed output. As in the single grid unfolding, convergence did not occur. The output shows detailed stress for each grid by construct (row) and overall (some detailed output for grids 3 and 4 has been omitted here). Grids 2 and 4 fitted best. As for the earlier unfolding solution (Figure 28) these are stress formula 2 values which Levine (1978) suggests will be 'approximately two and a half times the corresponding average stress values of formula one'. Thus these unfolding stress values are actually better (i.e. lower) than those for the scaling solutions in Figures 41 and 44, indicating a somewhat better fit.

```
                  Young's S-stress formula 2 is used.

                Iteration     S-stress      Improvement

                    1          .49653
                    2          .47930          .01723
                    3          .46929          .01001
                    .
(some iterations omitted)
                    .
                    .
                   27          .30304          .00882
                   28          .29424          .00880
                   29          .28543          .00881
                   30          .27660          .00883

                       Iterations stopped because
                         this is iteration    30


            Stress and squared correlation (RSQ) in distances

RSQ values are the proportion of variance of the scaled data
(disparities) in the partition (row, matrix, or entire data)
which is accounted for by their corresponding distances.
```

```
           Stress values are Kruskal's stress formula 2.



                              Matrix    1
                            (Row Stimuli Only)
      Stimulus    Stress       RSQ   Stimulus    Stress       RSQ

          1         .337     .892        2         .133     .983
          3         .261     .935        4         .321     .901
          5         .406     .840        6         .277     .928
          7         .555     .706        8         .240     .945
          9         .528     .745       10         .345     .885
         11         .403     .845       12         .573     .690
         13         .416     .835       14         .377     .862

      Averaged (rms) over stimuli
   Stress  =   .389      RSQ =  .856

                                Matrix    2
                            (Row Stimuli Only)
      Stimulus    Stress       RSQ   Stimulus    Stress       RSQ

          1         .248     .941        2         .166     .973
          3         .174     .971        4         .212     .957
          5         .178     .969        6         .379     .865
          7         .409     .843        8         .201     .961
          9         .315     .905       10         .269     .930
         11         .150     .978       12         .162     .974
         13         .150     .978       14         .172     .971

      Averaged (rms) over stimuli
   Stress  =   .242      RSQ =  .944


                              Matrix    3

(separate construct data omitted)

      Averaged (rms) over stimuli
   Stress  =   .348      RSQ =  .883


                              Matrix    4

(separate construct data omitted)

      Averaged (rms) over stimuli
   Stress  =   .248      RSQ =  .941
```

(Continued on next page)

(Continued)

Averaged (rms) over matrices

Stimulus Number	Stimulus Name	RSQ
1		.904
2		.975
3		.926
(Some RSQ values omitted)		
14		.933

Averaged (rms) over stimuli and matrices
Stress = .313 RSQ = .906

Configuration derived in 2 dimensions

Stimulus Coordinates

Stimulus Number	Stimulus Name	Dimension 1	Dimension 2
Column			
1	BIPOLAR	1.8700	-.7186
2	SCHIZ	2.0335	.0702
3	PSYCHIAT	1.4912	-1.3480
4	CRIMINAL	.3134	2.6232
5	AVERAGE	-2.2541	1.0421
6	AIDS	.4873	-1.9834
7	DIABETES	-.2428	-1.7714
8	CANCER	.0855	-2.0231
9	STRESS	1.7919	.4497
10	USUALME	1.0066	.8645
11	MENOW	.9603	.4569
12	ME6MTH	1.1557	.3703
13	MESTAFF	1.0448	.0955
14	IDEALME	.3190	.8373
Row			
1		-.7006	-.3840
2		-.8666	-.1947
3		-.6374	.0333
4		-.8488	.0510
5		-.5466	.3393
6		-1.3002	-.2550
7		-.2492	.0365
8		-.8737	.2670
9		-.9878	.7491
10		-.3695	-.3279
11		-.6435	-.0399
12		-.5884	.4759
13		-.6514	.0616
14		-.7987	.2227

Figure 47. Output for Replicated Unfolding representation of Elements and Constructs.

Figure 48 shows the plot of elements and constructs (labelled as rows). The plot shows something not evident in the stimulus coordinates above. All the constructs are located in a very similar position. This may represent a "degenerate" solution which has computational problems, or it may indicate that elements are similarly located on all constructs. This could be checked by computing construct correlations.

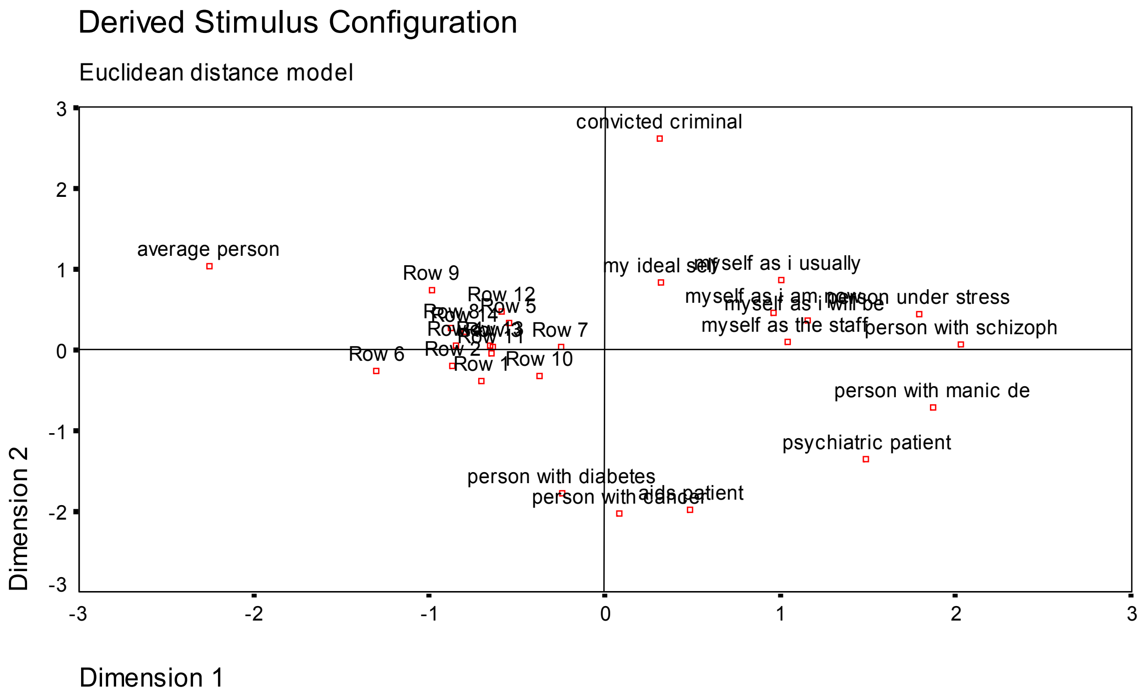

Figure 48. Plot for Replicated Unfolding representation of Elements and Constructs.

Individual Differences Unfolding Solution

Figure 49 shows the commands for carrying out the individual differences unfolding. The difference between this and the replicated solution lies only in the model command (/MODEL=INDSCAL instead of /MODEL=EUCLID).

```
ALSCAL
  VARIABLES= bipolar schiz psychiat criminal average aids
  diabetes cancer stress usualme menow me6mth mestaff idealme
  /SHAPE=RECTANGULAR /INPUT ROWS(14)
  /LEVEL=ORDINAL
  /CONDITION=ROW
  /MODEL=INDSCAL
  /CRITERIA=CONVERGE(.001) STRESSMIN(.005) ITER(30) CUTOFF(0)
    DIMENS(2,2)
  /PLOT=DEFAULT .
```

Figure 49. Commands for Weighted Unfolding representation of Elements and Constructs.

Output is shown in Figure 50.

```
Iteration history for the 2 dimensional solution (in squared distances)

                  Young's S-stress formula 2 is used.

                Iteration     S-stress      Improvement

                    1           .50191
                    2           .48424         .01767
                    3           .47171         .01253
                    .
```
(some iterations omitted)
```
                    .
                    .
                   26           .39906         .00197
                   27           .39709         .00197
                   28           .39511         .00198
                   29           .39308         .00203
                   30           .39094         .00214

                         Iterations stopped because
                           this is iteration    30


            Stress and squared correlation (RSQ) in distances

RSQ values are the proportion of variance of the scaled data
(disparities) in the partition (row, matrix, or entire data)
which is accounted for by their corresponding distances.
             Stress values are Kruskal's stress formula 2.

                              Matrix    1
                            (Row Stimuli Only)
       Stimulus    Stress      RSQ   Stimulus    Stress      RSQ

           1         .456     .798       2          .161     .975
           3         .574     .685       4          .533     .737
           5         .590     .655       6          .414     .840
           7         .625     .631       8          .361     .880
           9         .646     .626      10          .453     .800
          11         .635     .631      12          .693     .536
          13         .578     .674      14          .566     .681

       Averaged (rms) over stimuli
    Stress  =   .538      RSQ =  .725


                              Matrix    2
                            (Row Stimuli Only)
       Stimulus    Stress      RSQ   Stimulus    Stress      RSQ

           1         .439     .807       2          .263     .931
           3         .276     .924       4          .307     .907
           5         .273     .926       6          .428     .841
           7         .405     .851       8          .277     .923
           9         .240     .945      10          .471     .780
          11         .269     .928      12          .181     .967
          13         .278     .923      14          .234     .946
```
(Continued on next page)
(Continued)
```
       Averaged (rms) over stimuli
    Stress  =   .322      RSQ =  .900


                              Matrix    3
```
(separate construct data omitted)
```
       Averaged (rms) over stimuli
```

```
    Stress  =   .498      RSQ =  .760


                              Matrix    4
(separate construct data omitted)


       Averaged (rms) over stimuli
    Stress  =   .329      RSQ =  .896

Averaged (rms) over  matrices

     Stimulus Stimulus           RSQ
      Number    Name

         1                      .828
         2                      .948
         3                      .776
         4                      .862
         5                      .850
         6                      .853
         7                      .741
         8                      .833
         9                      .823
        10                      .792
        11                      .814
        12                      .730
        13                      .783
        14                      .853


Averaged (rms) over stimuli and  matrices
    Stress  =   .433      RSQ =  .820

(Continued on next page)
```

Configuration derived in 2 dimensions

Stimulus Coordinates

Stimulus Number	Stimulus Name	Dimension 1	Dimension 2
Column			
1	BIPOLAR	-1.6126	-1.0797
2	SCHIZ	-1.6415	-1.2651
3	PSYCHIAT	-1.6097	-.7463
4	CRIMINAL	-.8099	-2.1749
5	AVERAGE	.5410	.1247
6	AIDS	-1.4813	1.3080
7	DIABETES	-.7724	.9929
8	CANCER	-1.2688	1.3651
9	STRESS	-1.3970	-1.3500
10	USUALME	.0842	-1.0974
11	MENOW	.0642	-.8221
12	ME6MTH	-.0503	-1.0024
13	MESTAFF	-.1467	-.7507
14	IDEALME	.8028	-.4566
Row			
1		-.2335	.8464
2		.6061	1.2563
3		.9961	.4353
4		.8237	.8965
5		.8336	-.1460
6		.3833	1.8794
7		-.4398	-.0761
8		1.4070	.2179
9		1.7627	-.6128
10		-.3901	.4941
11		.3781	1.1130
12		1.1957	-.5080
13		.6381	.9025
14		1.3367	.2562

Subject weights measure the importance of each dimension to each subject. Squared weights sum to RSQ.
A subject with weights proportional to the average weights has a weirdness of zero, the minimum value.
A subject with one large weight and many low weights has a weirdness near one.
A subject with exactly one positive weight has a weirdness of one, the maximum value for nonnegative weights.

(Continued on next page)

```
(Continued)
                      Subject Weights

                               Dimension
   Subject  Weird-      1        2
   Number    ness

      1      .0257    .7342    .4311
      2      .1950    .7284    .6078
      3      .0918    .7121    .5031
      4      .3042    .8874    .3300
Overall importance of
each dimension:       .5911    .2293


                Flattened Subject Weights

                     Variable
Subject   Plot      1
 Number   Symbol
   1        1      .1102
   2        2    -1.1319
   3        3     -.5342
   4        4     1.5560
```

Figure 50. Printed output for Weighted Unfolding representation of Elements and Constructs.

This solution is not as good as the replicated one in terms of stress, although the configuration shown in Figure 51 is more differentiated in terms of the constructs.

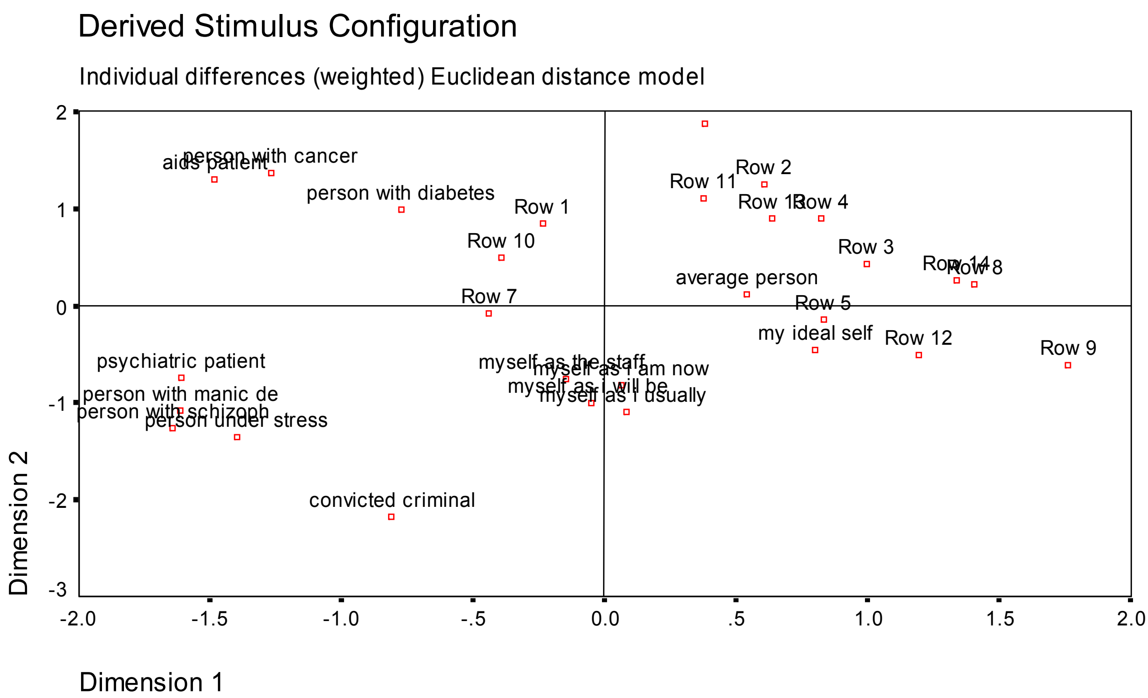

Figure 51. Plot for Weighted Unfolding representation of Elements and Constructs.

The grid weights are shown in Figure 52. Here the primary differentiation is for grid 4 which weights dimension 1 more heavily. This is not as great as appears in the plot, as recourse to the subject weights in Figure 50 show.

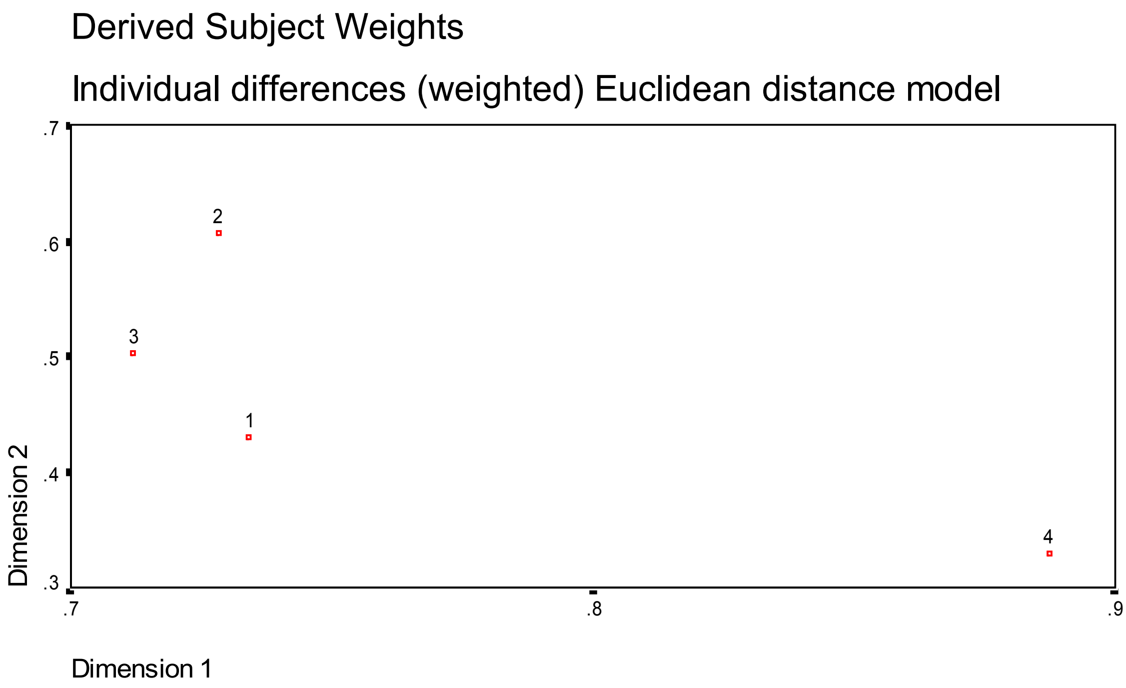

Figure 52. Plot for Grid Weights in Weighted Unfolding representation of Elements and Constructs.

Testing the Commonality of Construing.

In grids with common elements and common constructs, it is possible to test the commonality of construct usage. If we have reasonably large numbers of persons completing such grids, we can define a common construct as one that is responded to similarly by such people (Bell, 1996). In such a case, the correlations among the elements for that construct should be accounted for by a single factor. (Since we are dealing construct by construct here, the orientation of construct poles is irrelevant, and element correlations may be calculated.) In this case. While the present data file (only four grids) is too small to carry out such an exercise in any realist sense, Figure 53 shows the commands to carry out such an exercise.

```
SORT CASES BY construc .
SPLIT FILE
  BY construc .
FACTOR
  /VARIABLES bipolar schiz psychiat criminal average aids diabetes cancer
  stress usualme menow me6mth mestaff idealme  /MISSING LISTWISE /ANALYSIS
  bipolar schiz psychiat criminal average aids diabetes cancer stress
usualme
  menow me6mth mestaff idealme
  /PRINT INITIAL DET
  /CRITERIA FACTORS(1) ITERATE(25)
  /EXTRACTION ML
  /ROTATION NOROTATE.
```

Figure 53. Commands to assess commonality of construing.

Here maximum-likelihood factor analysis has been specified, since it is possible to assess each construct as a latent trait (Bell, 1990b). The determinant can be used to calculate a Tucker-Lewis reliability coefficient.

More Complex Grid Situations

In the single grid representation discussed earlier, it was shown that correspondence analysis provided an alternative representation. Correspondence analysis can be defined as finding weights for set of constructs, and weights for a set of elements, so that the correlation between the two weighted sets is maximized. This correlation (the correlation ratio, eta, in the correspondence analysis situation) is also the familiar *canonical correlation* of the general linear model, where the weights are linear. In both situations there can be more than one dimension, there being a correlation and sets of weights for each dimension. This approach has been generalized by van der Burg and de Leeuw (1988) to deal with multiple sets of variables, rather than the two. Their generalization also allows for the analysis of nominal, ordinal, and interval data. Thus this approach can also be used to find representations of the Type III multiple grids dealt with here. It can also be used for such grids in more complex situations. The sub-sections following have been adapted from a paper presented at the 11th International Congress on Personal Construct Psychology (Bell, 1995) where the facet of occasion was added to those of persons, constructs, and elements. This paper also illustrates how this approach can yield information not available in other analytic approaches. The approach, known as OVERALS, is included in SPSS (under Data Reduction → Optimal Scaling).

The Analysis of Multiple Repertory Grids over Multiple Occasions: An Application of the OVERALS algorithm.

Abstract:

If we think of repertory grids as being *two-set* data (*elements* and *constructs*), then multiple grids will be *three-set* data, and multiple-occasion multiple grids will be *four-set* data. OVERALS is a very general scaling procedure designed to handle data classified into multiple sets. In this paper we shall examine how the approach may be used with four-set data, grids completed by a group of recovering psychotic patients on four occasions.

Introduction.

Studies of multiple grids are rare and usually have been unable to integrate the analysis of such grids over time while retaining all facets of the data (see e.g. Bell & McGorry, 1992).

The problem is that traditional psychological data analysis seeks to produce a representation of one set of variables. In multiple-occasion multiple-grid terms this would be *one* of the sets of : elements or constructs or persons or occasions.

Since the pioneering work of Slater (1964) , researchers using single repertory grids have been accustomed to interpreting joint element-construct representations or representations of *two* sets of variables.

It has been suggested (Bell, 1990, p.40) that three sets of variables (elements, constructs, and persons (or occasions) may be represented through three-mode factor analysis (as in Bell & McGorry (1992) , or Kroonenberg, 1985) or through weighted multi-dimensional unfolding as earlier in this document.

Multiple-occasion multiple grid data contains four sets of variables: elements, constructs, persons (or grids) and occasions. There are few ways such data can be represented. Four-mode factor analysis has been proposed (Lastovicka,1981) but has not been applied in practice.

A possible model that deals with any numbers of sets of variables has been proposed by van der Burg & de Leeuw (1988). In this paper we consider this model (known as OVERALS) with reference to the data set previously analysed by Bell & McGorry (1992).

The OVERALS Model

The OVERALS model is defined by van der Burg & de Leeuw (1988) as a form of homogeneity analysis with restrictions. Homogeneity analysis (otherwise known as multiple correspondence analysis) determines transformations of the categories of variables to maximize homogeneity. The simplest form of homogeneity analysis is correspondence analysis which has been applied to repertory grids (Bell, 1994; Moliner *et al*., 1985) where transformations have been found for elements and for constructs, enabling a spatial representation of the element-construct space to be found. In this situation the elements are regarded as categories of a variable, likewise the constructs are categories of another variable. Weights are thus found that maximize the canonical correlation between these two super-variables, the element-set and the construct-set.

Homogeneity analysis generalizes this concept from a two set situation (i.e. elements and constructs) to multiple sets. Again weights are devised for the multiple sets to maximize the canonical correlation between these sets.

OVERALS extends this model in two ways. Firstly it allows for the imposition of rank-one restrictions (i.e., one-dimensional) on the transformations of the categories of a variable. This can be important where variables have ordered categories - such as for constructs on which elements are rated or ranked. The second important extension is to allow for the analysis of sets of variables. Thus variables can be grouped together as a set of constructs, rather than treated as categories of a single variable as in correspondence analysis. Here weights are found for the variables within sets, as well as for the categories within variables, in order to maximize the canonical correlation.

Ordinary principal component analysis can be seen as submodel of this, where there are a number of sets, each containing one variable (e.g. a construct) where weights are found for each set (variable) to maximize the eigenvalue (which is simply a transformation of the canonical correlation). Traditionally, categories of variables are ignored in that data are treated as interval data, however this is not essential. Caputi (1994) has shown how principal components may be found for grid data treated as ordinal rather than interval measurement.

The Data:

The Subjects:
These data were from a larger study of the recovery style of psychotics. Twenty patients were assessed in the recovery stage or and these with a further fifteen also assessed just prior to discharge with the repertory grid. Of these 35 patients, 28 were subsequently followed up after discharge. The average interval between the two testings was 17 weeks. Twenty nine subjects were followed up with a fourth testing, approximately one year later, . However only 14 patients were assessed on all four occasions, and these form the bases for the following analyses.

The Repertory Grid
The Repertory Grid was that used as an example elsewhere in this document.

Data Setup
The data were set up in a similar fashion to the multiple grid data in Figure 35, except that a variable was added to indicate occasion, and the grids were transposed, so that the columns became constructs and the rows, elements. This was done to take advantage of the OVERALS information about weights, as will be shown later.

The command file to carry out the OVERALS analysis is as shown in Figure 54.

```
data list file='c:\aa\multi\4grid\4grid.flp'
 / person grid element 1-9
    good     depend   safe     clear    stable   predict  intell
 free     health   honest   rational independ calm     understd 10-37.
variable labels
 grid, 'Occasion'/  person, 'Person'/  element, 'Element'/
 good,     'good'/  depend,   'dependable'/  safe,     'safe'/  clear,
'clearheaded'/
 stable,   'stable' /  predict,  'predictable'/  intell,   'intelligent'/
free,     'free'/
 health,   'healthy'/  honest,   'honest'/  rational, 'rational'/
independ, 'independent'/
 calm,     'calm'/  understd, 'understood'.
value labels
 element
 1 'person with manic depressive illness'   2 'person with schizophrenia'
 3 'psychiatric patient'   4 'convicted criminal'   5 'average person '
 6 'AIDS patient' 7 'person with diabetes'   8 'person with cancer'
 9 'person under stress' 10 'myself as I usually am'
11 'myself as I am now'  12 'myself as I will be in six months'
 13 'myself as the staff see me'  14 'my ideal self'/
 grid 1 'I' 2 'II' 3 'III' 4 'IV'.
OVERALS
  /VARIABLES=grid(4) person(14) element(14) good(7) depend(7) safe(7)
  clear(7) stable(7) predict(7) intell(7) free(7) health(7) honest(7)
  rational(7) independ(7) calm(7) understd(7)
  /ANALYSIS=grid(SNOM) person(MNOM) element(MNOM) good(ORDI) depend(ORDI)
  safe(ORDI) clear(ORDI) stable(ORDI) predict(ORDI) intell(ORDI) free(ORDI)
  health(ORDI) honest(ORDI) rational(ORDI) independ(ORDI) calm(ORDI)
  understd(ORDI)
  /SETS 4 (1, 1, 1, 14)
  /DIMENSION=2
  /PRINT WEIGHTS FIT QUANT
  /PLOT LOADINGS NDIM(ALL,MAX)
  /MAXITER = 100
  /CONVERGENCE = .00001
  /INITIAL=RANDOM .
```

Figure 54. Command file for OVERALS analysis.

Figure 55 shows the first portion of the data file, showing the four grids for the first person,.

```
  1  1  1 4 6 6 7 7 6 4 2 3 4 5 5 6 2
  1  1  2 2 2 2 2 2 3 2 1 1 2 3 2 2 3
  1  1  3 2 3 4 4 4 3 2 4 3 2 3 4 3 5
  1  1  4 6 6 7 6 5 6 2 5 4 5 5 2 2 5
  1  1  5 2 3 3 4 2 2 3 4 3 4 3 2 4 2
  1  1  6 2 5 6 2 3 4 2 3 3 2 4 2 3 2
  1  1  7 2 3 2 2 2 3 2 2 4 4 3 2 2 2
  1  1  8 4 4 6 4 4 3 2 4 4 2 3 2 2 2
  1  1  9 6 4 3 2 3 3 2 3 4 2 4 2 3 2
```

```
1  1 10 1 1 1 1 1 1 2 2 2 2 2 1 2 2
1  1 11 1 1 1 1 1 1 2 1 2 2 1 1 2 2
1  1 12 1 1 1 1 1 1 2 1 2 1 2 1 1 2
1  1 13 2 2 2 2 2 2 2 2 2 2 2 2 2 2
1  1 14 1 1 1 1 1 1 1 1 1 1 1 1 1 1
1  2  1 3 3 3 3 3 4 4 3 3 4 4 3 2 3
1  2  2 3 4 3 2 3 2 2 2 2 2 3 2 2 2
1  2  3 2 3 3 2 3 3 2 2 2 3 2 3 3 2
1  2  4 3 3 4 4 3 3 2 2 2 3 2 2 2 2
1  2  5 3 4 3 2 3 3 2 2 3 2 3 2 3 2
1  2  6 4 5 6 2 2 3 2 3 2 2 2 2 2 2
1  2  7 2 2 3 2 2 2 2 2 2 2 3 2 2 2
1  2  8 3 3 6 3 2 3 2 2 6 2 3 2 2 2
1  2  9 4 3 5 5 5 5 3 2 6 4 3 3 3 2
1  2 10 2 2 2 2 2 2 2 2 2 2 2 2 2 2
1  2 11 3 3 3 2 3 2 3 2 2 2 2 2 2 2
1  2 12 1 2 2 1 1 1 2 1 2 2 2 2 2 2
1  2 13 2 2 2 2 2 2 2 2 2 2 2 2 2 2
1  2 14 1 1 1 1 1 1 1 1 1 1 1 1 1 1
1  3  1 4 5 6 6 5 5 6 6 6 6 6 6 6 7
1  3  2 4 5 3 2 2 3 4 3 3 3 3 2 4 4
1  3  3 3 3 3 3 4 3 2 2 2 2 2 2 2 1
1  3  4 2 3 2 2 2 2 2 1 2 2 1 2 2 1
1  3  5 3 2 3 3 3 2 3 3 3 3 3 3 3 3
1  3  6 4 3 5 6 3 4 5 5 7 3 4 3 2 6
1  3  7 4 3 3 4 4 4 4 4 4 3 3 3 2 2
1  3  8 6 3 4 3 4 4 4 4 5 4 3 3 4 4
1  3  9 5 4 4 3 3 3 2 2 2 2 2 2 2 2
1  3 10 2 3 2 2 2 2 2 2 2 2 2 2 2 2
1  3 11 2 2 2 2 2 2 2 2 2 2 2 2 2 2
1  3 12 2 2 2 2 2 2 2 2 2 2 2 2 2 2
1  3 13 3 3 3 2 2 3 2 3 2 3 3 3 2 2
1  3 14 2 2 1 1 1 1 1 1 1 1 1 1 1 1
1  4  1 3 3 4 4 4 3 2 3 2 2 2 2 3 4
1  4  2 2 2 3 3 3 3 2 2 2 2 2 2 3 4
1  4  3 3 3 3 3 3 3 2 3 3 3 3 3 3 4
1  4  4 3 2 5 3 4 4 4 3 4 4 4 4 4 4
1  4  5 2 2 2 2 2 2 2 2 2 2 2 2 2 2
1  4  6 4 5 6 6 6 6 3 6 4 4 4 3 4 6
1  4  7 2 3 4 4 4 4 3 4 3 4 4 4 4 4
1  4  8 3 2 6 4 4 4 2 3 4 4 4 4 4 5
1  4  9 3 3 3 3 3 3 3 3 3 3 3 3 3 3
1  4 10 2 2 3 2 2 2 2 2 2 2 2 2 2 2
1  4 11 1 1 2 1 1 1 1 1 1 1 1 1 1 1
1  4 12 2 2 2 2 2 2 2 2 2 2 2 2 2 2
1  4 13 2 2 2 2 2 2 2 2 2 2 2 2 2 2
1  4 14 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

Figure 55. Portion of Grid data file for Persons by Occasions by Grids.

The variable list indicates how many categories each variable has (in parentheses). The analysis list shows what the nature of these categories are - snom & mnom are nominal variables, the s & m indicating whether the weights should be constrained to be equal for all dimensions (s = single) or should be allowed to vary (m=multiple). (This can be varied as the present example subsequently shows.)The sets subcommand indicates how many sets there are, and how many variables are in each set. The potential printout is enormous and even the default is large. Many kinds of plots can be produced, although many of these are poorly set up and are better re-plotted from the coordinates printed.

OVERALS Results.

Results pertaining to the Range of Convenience of the Constructs

Since each element was rated on each construct using a 1 to 7 scale and this scale being thus an ordinal one, the quantification determined by OVERALS could be used to assess the range of convenience of constructs. The quantification values represented those values which maximized the variance. Where ratings translated into similar quantifications, it could thus be assumed that the different ratings did not provide differential information. A construct with only two levels of quantification did not therefore have as great a range of convenience as did a construct with four levels of quantification. Furthermore the profile of the relationship between quantifications and ratings showed where the discrimination on the construct occurred.

For these data four profile patterns were obtained. Four parts of the printout have been selected here and is shown in Figure 56.

Variable: DEPEND dependable Set: 4

Type: ORDINAL Missing: 7

Category	Marginal Frequency	Quantification
1	98	-.79
2	142	-.79
3	152	-.74
4	223	.07
5	82	1.23
6	53	2.30
7	27	2.30

Variable: FREE free Set: 4

Type: ORDINAL Missing: 7

Category	Marginal Frequency	Quantification
1	106	-2.35
2	85	-.55
3	109	-.05
4	199	.60
5	103	.60
6	101	.60
7	74	.60

(Continued on next page)

(Continued)

Variable: INTELL intelligent Set: 4

Type: ORDINAL Missing: 7

Category	Marginal Frequency	Quantification
1	87	-2.41
2	154	-.54
3	194	.27
4	285	.59
5	33	.59

6	14	1.09
7	10	3.01

(continued)

Variable: UNDERSTD understood Set: 4

Type: ORDINAL Missing: 7

Category	Marginal Frequency	Quantification
1	92	-1.39
2	105	-1.39
3	114	-.27
4	201	.06
5	99	1.22
6	94	1.22
7	72	1.22

Figure 56. Quantification of Construct Categories from OVERALS.

The first pattern is exemplified by *dependable*, but also applied to *rational* and *stable* and was characterized by differentiation (different quantification values for different categories) in the middle of the scale but not at the extremes (where different categories has the same quantifications). The second pattern, shown as *free* also applied to *independent, predictable,* and *clear-headed*, where the differentiation occurred at the 'negative' end of the construct, *i.e. imprisoned, dependent, unpredictable,* and *confused.* The third pattern was exclusive to *understood*, where discrimination occurred at this pole, while the last pattern, exemplified by *intelligent* but also was true of *calm, honest, healthy,* and *safe*, showed a broader discrimination across the whole construct from these positive poles to *misunderstood, irritable, sick,* and *afraid*, respectively.

The one plot asked for in the OVERALS commands was for the component loadings (not used in the original paper). This produced a plot as shown in Figure 57. Elements (in general) were equidistant from all constructs, indicating no linking of a particular construct with every element. The same was true for Occasion. Dimension 2 showed the differentiation among the constructs with respect to Persons.

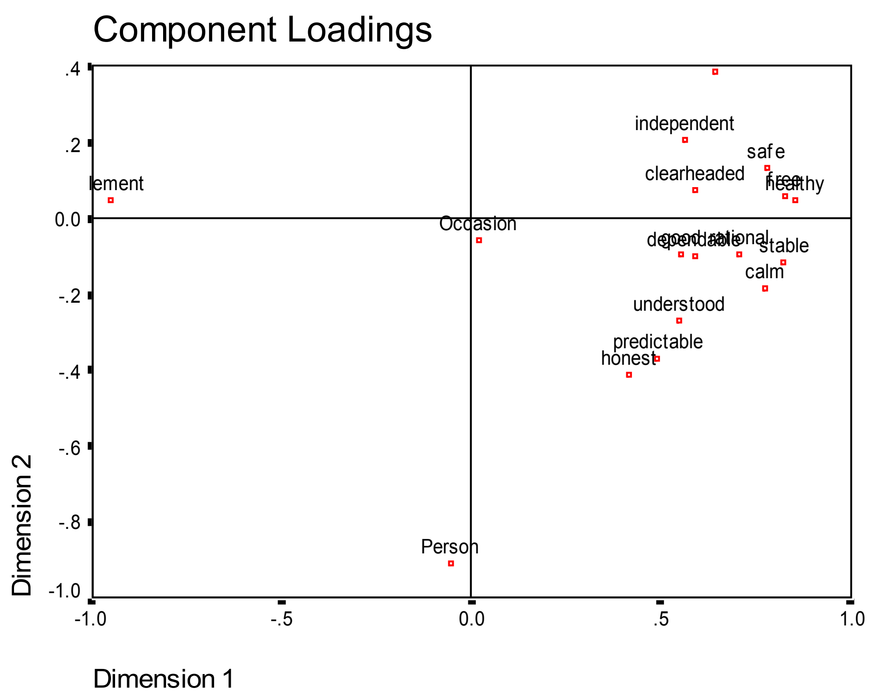

Figure 57. Component plot produced by OVERALS.

The data for constructs is derived from the output shown as Figure 58.

Component Loadings for Single Variables

Projections of the Single Quantified Variables in the Object Space

	Dimension 1	Dimension 2
GRID	.033	-.060
PERSON	-	-
ELEMENT	-	-
GOOD	.429	-.543
DEPEND	.611	-.461
SAFE	.783	-.076
CLEAR	.738	-.101
STABLE	.803	-.083
PREDICT	.449	-.403
INTELL	.621	.054
FREE	.807	.075
HEALTH	.800	.286
HONEST	.471	-.661
RATIONAL	.451	-.388
INDEPEND	.589	.118
CALM	.836	-.044
UNDERSTD	.757	-.042

Figure 58. Construct coordinate values.

The paper redrew these data, and those for the subsequent figures, by pasting these values and labels into another SPSS file, as shown in appendix to this document. The resulting configuration for constructs is as shown in Figure 59.

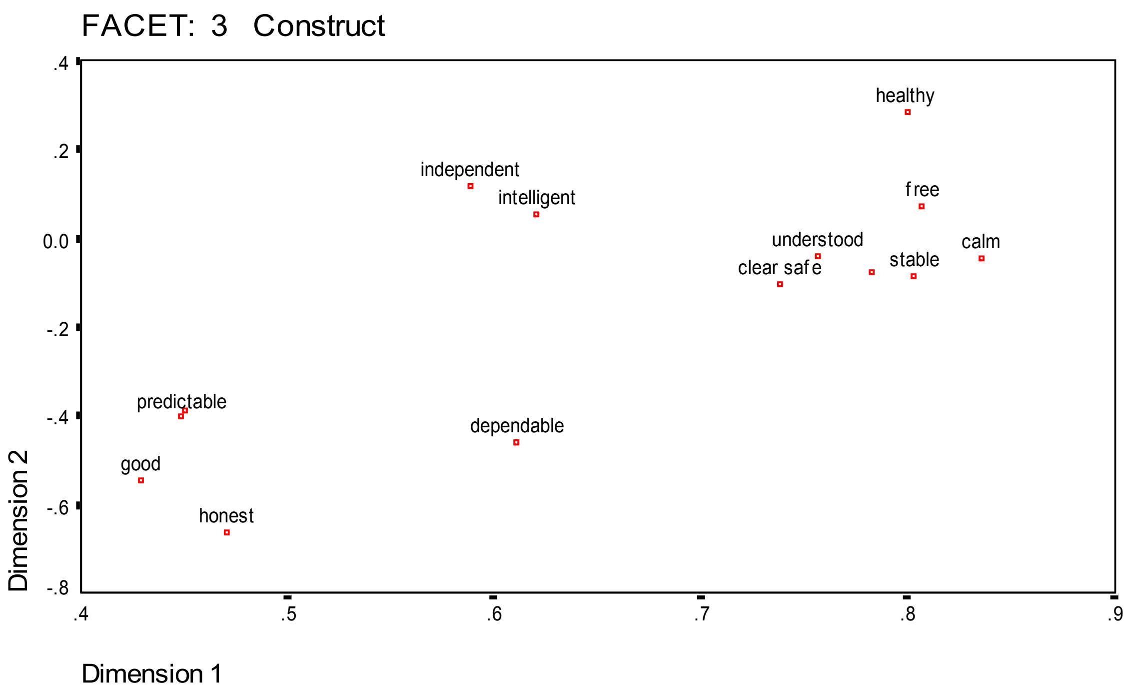

Figure 59. Configuration of Constructs from OVERALS analysis.

A loose group of constructs which could be construed as reflecting qualities important in interpersonal contact : *good, honest, predictable,* and *dependable* can be seen in the lower left hand corner. *Independent* and *intelligent* go together, although interestingly, *rational* which is not shown on the diagram is not obscured by these but by *predictable*. A tight group of personal qualities *clear, safe, stable, calm, free, understood*, and to a lesser extent, *healthy* can be seen in the upper right hand corner.

The Configuration of Elements

The configuration of elements is shown in Figure 60. Two axes can be seen, the vertical differentiation the illness figures *diabetic, cancer patient,* and *AIDS patient* from *convicted criminal*; while the horizontal axis differentiates *ideal self* from these, and, more specifically, the mental illness figures, *schizophrenic, manic depressive, person under stress,* and (obscured) *psychiatric patient*. The figure of *me now* is obscured by *staff view of me* and *usual me* although *me in six months* is closer to *ideal self*.

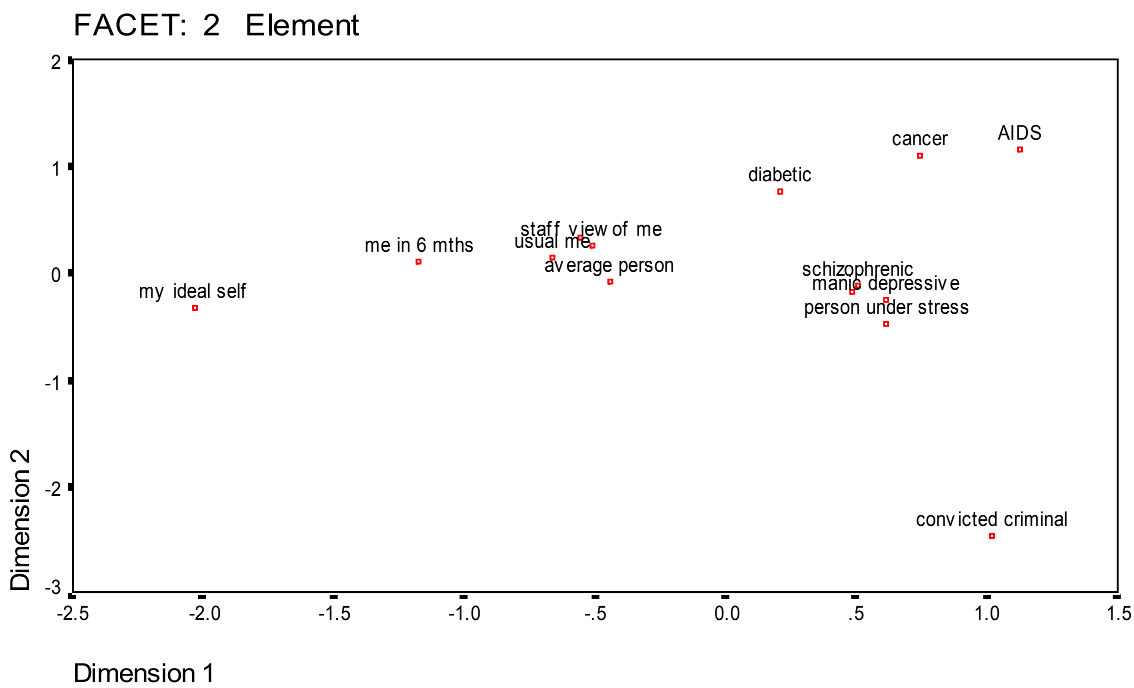

Figure 60. Configuration of Elements from OVERALS analysis.

Changes over Time

The configuration of points representing the four testing occasions is shown in Figure 61. Initially these data were constrained to be ordinal (since the occasions were clearly ordinal in time) however the fit was poor, and consequently the data were refitted with the occasions constrained to be 'single nominal' , i.e. where the same quantification would apply for each dimension.

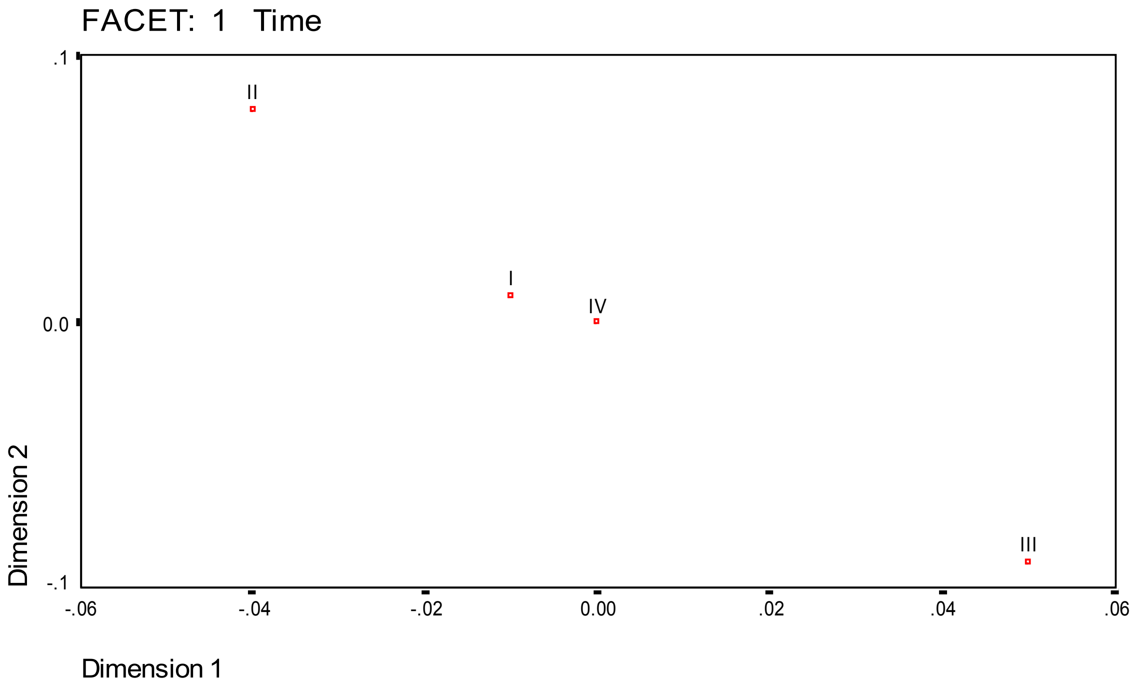

Figure 61. Configuration of Occasions from OVERALS analysis.

Even though the data were not constrained to be ordinal, it might be expected that the four occasions would form an ordered sequence. As Figure 6 shows this was not the case. The first and fourth occasions were similar, while the second and third occasions were most different. Thus no sense of development or orderly recovery was apparent.

Configuration of Persons

While the configuration of persons was not interpreted here, Figure 62 is useful for diagnostic purposes, since it shows a reasonable heterogeneity or spread of persons, without there being any notable outliers.

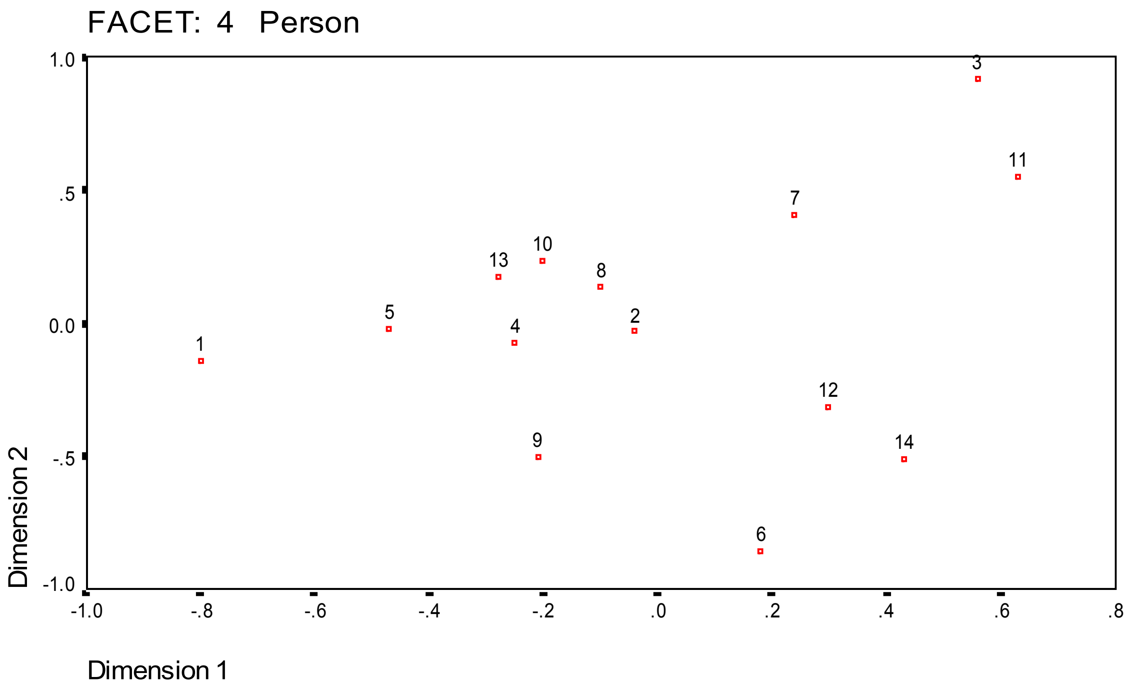

Figure 62. Configuration of Persons from OVERALS analysis.

Fit of the solution

Figure 63 shows the fit statistics for this solution. The fit of .918 was not particularly good, with 46% being accounted for, although ten random sets of data were generated and the mean fit for these was only .711 (36%) with a standard deviation of .009. Hence the fit for this solution was appreciably larger than for random data.

The fit can be seen to be best for constructs and elements but substantially poorer for persons and occasions The two dimensions were of reasonably similar importance as can be seen by the roughly equal canonical correlations.

Figure 62 also shows important diagnostic information about the solution in the multiple fit statistics which provide information about the level of discrimination provided by each variable. The highest level of multiple fit is clearly obtained by elements. No substantial amounts of fit are obtained by grids, occasions, or any of the constructs other than *Healthy* and *Honest*.

Loss per Set			
		Dimension	
	Sum	1	2
Set 1	1.998	1.000	.998
Set 2	1.649	.846	.803
Set 3	.521	.225	.296
Set 4	.160	.067	.092
Mean	1.082	.534	.547
Fit	.918		
Eigenvalue		.466	.453

Multiple Fit			
		Dimension	
	Sum	1	2
GRID	.005	.001	.004
PERSON	.354	.155	.199
ELEMENT	1.481	.776	.705
GOOD	.060	.001	.059
DEPEND	.053	.010	.043
SAFE	.066	.038	.028
CLEAR	.050	.024	.026
STABLE	.059	.030	.029
PREDICT	.031	.002	.029
INTELL	.053	.001	.052
FREE	.079	.048	.031
HEALTH	.379	.097	.282
HONEST	.268	.008	.260
RATIONAL	.026	.002	.024
INDEPEND	.022	.003	.019
CALM	.031	.029	.002
UNDERSTD	.038	.036	.001

Figure 62. OVERALS Fit statistics.

Discussion and Conclusions

This last result suggests that the dominant characteristic of this data is provided by the configuration of elements rather than the constructs used, or the points in the recovery, or differences between the patients. It may not have mattered what constructs were used, or at what points in time the data were collected, or who was completing the grid.

In fact the configuration is not unlike the configuration one might expect from a sample of normal persons. Views of *self, average person,* and others' views of *self* are central to this configuration, *ideal self* is to one side, and the undesirable figures are opposed to the ideal with another dimension of differentiation between the *ill, psychiatric patient,* and *criminal*.

This suggests that the way these people see the world of these figures, is a view that is split off (i.e., the fragmentation corollary) from the reality of their situation. Whether this is a true reflection of their mental processes, or whether it is an artifact imposed by either the supplied structure or the actual elements and constructs used, cannot be determined.

However, the dominance of the element configuration in the solution is interesting. Personal Construct Theory traditionally emphasizes the role of constructs, leaving elements as a way of eliciting constructs, or as a way of evaluating constructs (e.g., through the range corollary).

Yet here the empirical evidence obtained from OVERALS suggests that the constructs were of substantially lesser importance.

An implication for quantifiable research with supplied grids, is that researchers should pay more attention to the supplied elements than constructs. Providing the constructs supplied are not fragmented from the system of core constructs, these latter will drive the ratings of elements on the supplied constructs, and, by careful examination of the obtained configuration of elements, conjectures may be made as to the nature of these superordinate constructs.

An advantage of analysis using the OVERALS algorithm, is that such possibilities may be readily tested. OVERALS also clearly allows grid data collected in complex designs to also be represented.

Concluding Remarks.

There are points to be remembered in using SPSS to analyse grids.

First, the approaches outlined in this report are not always the only ways of carrying out these analyses. Other ways may be devised which are just as good if not better.

Second, this catalogue is not exhaustive - although I might add I have been exhausted by producing it. Some simple things, like how to use a compute statement to reflect a construct, I have not included either because it is trivial (or because I forgot).

Third, many of the results obtained are conflicting in some ways. This is not necessarily a problem with SPSS or with this grid data, rather it reflects a more general problem with grids being small data sets and susceptible to numeric or artefactual problems (Bell, 1997).

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Appendix.

Command and data files used to produce Figures 58 though 61. Note some labels have been omitted. This is to improve readability as the version of SPSS simply overwrites close labels.

```
data list
 / facet 1 dim1 13-18 (3) dim2 21-26 (3) label 29-48 (a).
var labels dim1 'Dimension 1' / dim2 'Dimension 2'.
value labels facet 1 'Time' 2 'Element' 3 'Construct' 4 'Person'.
begin data.
1            -.01     .01   I
1            -.04     .08   II
1             .05    -.09   III
1             .00     .00   IV
2             .62    -.24   manic depressive
2             .49    -.18
2             .51    -.11   schizophrenic
2            1.02   -2.46   convicted criminal
2            -.44    -.08   average person
2            1.13    1.16   AIDS
2             .21     .77   diabetic
2             .75    1.10   cancer
2             .62    -.48   person under stress
2            -.66     .15   usual me
2            -.55     .33
2           -1.17     .11   me in 6 mths
2            -.51     .26   staff view of me
2           -2.03    -.33   my ideal self
3             .429   -.543  good
3             .611   -.461  dependable
3             .783   -.076
3             .738   -.101  clear safe
3             .803   -.083  stable
3             .449   -.403  predictable
3             .621    .054  intelligent
3             .807    .075  free
3             .800    .286  healthy
3             .471   -.661  honest
3             .451   -.388
3             .589    .118  independent
3             .836   -.044  calm
3             .757   -.042  understood
4            -.80    -.14    1
4            -.04    -.03    2
4             .56     .92    3
4            -.25    -.07    4
4            -.47    -.02    5
4             .18    -.85    6
4             .24     .41    7
4            -.10     .14    8
4            -.21    -.50    9
4            -.20     .24   10
4             .63     .55   11
4             .30    -.31   12
4            -.28     .18   13
4             .43    -.51   14
end data.

*/(continued)

SPLIT FILE
  BY facet .
GRAPH
  /SCATTERPLOT(BIVAR)=dim1 WITH dim2 BY label (name)
 /MISSING=LISTWISE .
```