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ABSTRACT

This paper considers the use of commonality analysis as an effective tool for analyzing relationships between variables in multiple regression or canonical correlational analysis (CCA). The merits of commonality analysis are discussed and the procedure for running commonality analysis is summarized as a four-step process. A heuristic example is offered as a demonstration of the use of commonality analysis, and the potential limitations and advantages of commonality analysis are discussed. An appendix contains the Statistical Package for the Social Sciences syntax for the heuristic data set. (Contains 1 figure, 4 tables, and 19 references.) (Author/SLD)

Running head: COMMONALITY ANALYSIS

Commonality Analysis:

A Method of Analyzing Unique and Common Variance Proportions

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Paper presented at the annual meeting of the Southwest Educational Research Association, Austin, TX, February 15, 2002.

Abstract

The present paper considers the use of commonality analysis as an effective tool for analyzing relationships between variables in multiple regression or canonical correlational analysis (CCA). The merits of commonality analysis are discussed and the procedure for running commonality analysis is summarized in a four-step process. A heuristic example is offered as a demonstration of the use of commonality analysis, and the potential limitations and advantages of commonality analysis are discussed.

Commonality Analysis:

A Method of Analyzing Unique and Common Variance Proportions

The rise of regression and other GLM techniques as alternatives to "OVA" techniques (e.g. analysis of variance and covariance) is well documented (cf. Elmore & Woehike, 1988; Goodwin & Goodwin, 1985; Stone-Romero, Weaver, & Glenar, 1995; Willson, 1980). However, OVA techniques continue to be popular (Goodwin & Goodwin, 1985; Willson, 1980) and have been used in about 25% of the articles published in three educational journals between 1978 and 1987 (Elmore & Woehike, 1988). One potential reason for the continued use of OVA techniques is that they allow the division of the dependent variable variance into partitions including the main effects and interactions of the independent variables (Daniel, 1989). This should not be a valid reason, however, for choosing an OVA technique over regression. As explained by Kerlinger and Pedhazur (1973), multiple regression

> ...can be used equally well in experimental or non-experimental research. It can handle continuous and categorical variables. It can handle two, four, or more independent variables... Finally... multiple regression analysis can do <u>anything the analysis of variance does</u>- sum of squares, mean squares, F ratios- and more. (p. 3, emphasis added)

One of the techniques for analyzing the main effects and interactions of independent variables that can be used in multiple regression and other GLM techniques is commonality analysis. This technique can be used in both univariate and multivariate cases (Thompson, 1985). The purpose of this paper is to discuss the merits of

commonality analysis and to review the steps in implementing this technique in the cases of both multiple regression and canonical correlation analysis (CCA).

Researchers using multiple regression statistical techniques have several alternative results to consider as part of their data analysis. According to Seibold and McPhee (1979), the results commonly examined include the multiple correlation between the dependent variable and the independent variables together, the level of statistical significance of this relationship, and the standardized or unstandardized regression weights and their levels of statistical significance. Seibold and McPhee (1979) argued that one area rarely analyzed by researchers is the decomposing of R^2 to identify (a) the proportion of variance uniquely accounted for by each independent variable and (b) the proportion accounted for by combinations of the independent variables. Seibold and McPhee (1979) asserted:

> Advancement of theory and the useful application for research findings depend not only on establishing that a relationship exists among predictors and the criterion, but also upon determining the extent to which those independent variables, singly and in all possible combinations, share variance with the dependent variable. Only then can we fully know the relative importance of independent variables with regard to the dependent variable in question. (p. 355)

Commonality Analysis

Commonality analysis is a technique that analyzes both the unique and common variance that two or more independent variables explain in a dependent variable (Seibold & McPhee, 1979). Specifically, it considers the relationship, in this case a correlation coefficient, that a particular independent variable has with a specified dependent variable.

Furthermore, commonality analysis is considered in the context of multiple regression in which multiple independent variables that may be correlated are analyzed together. In this situation, independent variables may be correlated to both the dependent variable and to each other.

Figure 1 offers a visual representation of the relationships considered in commonality analysis. From this Venn diagram one can see that independent variables one and two (V1 and V2 respectively) account for unique variance (U1 and U2) and common variance (C12) of the total explained variance (U1 + U2 + C12) for the dependent variable (DV). Commonality analysis separates these three portions of variance explained (U1, U2, and C12) to allow a more complete explanation of how the independent variables are related to the dependent variable (Thompson, 1985).

Indeed, while commonality analysis is the term used to describe this technique, "comm-unique" analysis might serve as a more appropriate term as it emphasizes both the unique and common portions of the variance as important in the analysis. As pointed out by Thompson (1985):

> For each independent variable, commonality analysis indicates how much the variance of the dependent variable is "unique " to the predictor, and how much of the predictor's explanatory or predictive power is "common" to or also available from one or more of the other predictor variables. (p. 53)

Canonical Commonality Analysis

Canonical correlation analysis (CCA) subsumes regression as part of the general linear model (GLM) (Thompson, 1984). Indeed, regression can be considered a special case of CCA in which there are multiple independent variables but only one dependent

variable. CCA, on the other hand, includes multiple dependent variables and multiple independent variables. CCA analyzes the relationship among the dependent variables, among the independent variables, and between the optimal combination of the dependent variables and the optimal combination of the independent variables. The combination of dependent variables, and the combination of independent variables are called "variates" and represent the linear combinations of variables with the maximum possible Pearson correlation (Stevens, 1996).

As stated previously, commonality analysis considers the unique and common variance between multiple independent variables and one dependent variable. To run commonality analysis as part of CCA, therefore, one must first compute composite variate scores for the criterion side of the model. This new composite dependent variable can then be used as part of the commonality analysis.

Commonality analysis as part of CCA can be summarized in four steps (Leister, 1996):

1- Run canonical correlation analysis.
2- Calculate criterion composite scores.
3- Run multiple regression on each of the possible combinations of predictor variables.
4- Calculate the unique and common variance partitions.

Steps one and two above are specific to canonical commonality analysis. Steps three and four, however, are sufficient for commonality analysis in a case of multiple regression as there is only one dependent variable to consider. A heuristic example is presented here to demonstrate how these four steps are applied as a part of CCA.

Heuristic Example

This example considers the potential relationship between employment qualifications (education and previous experience) and salary (current salary and beginning salary). The scores for twenty-five participants on these four variables are offered in Table 1. This data fit the use of CCA as the question can be asked, "To what extent can one set of two or more variables be predicted or explained by another set of two or more variables?" (Thompson, 1984, p. 10). Furthermore, commonality analysis can be employed to see the amount of "unique" explanatory power of each predictor and the amount of "common" explanatory power shared between two or more predictors (Thompson & Miller, 1985).

Step 1- Run Canonical Correlation Analysis

The first step in conducting canonical commonality analysis is to run CCA. The SPSS syntax for this step, using the heuristic data set is offered in the Appendix under the section denoted as "step 1." The purpose here for running CCA is to derive the canonical functions and their respective standardized canonical function coefficients.

Standardized canonical function coefficients are standardized "weights" and, as part of the general linear model, are the equivalent of beta weights in multiple regression (Thompson, 1984). These coefficients can be found in the SPSS output and are reproduced in Table 2. Note that these coefficients are listed as part of one of two "functions." A function represents a weight system and is equivalent to the equation in multiple regression (Thompson, 1984). In CCA, the number of possible functions is equal to the number of variables in the smaller of the two variable sets (Stevens, 1996). Because both of the variable sets in our example have two variables, there can be only

two functions. From Table 2 one sees that function 1 consists of .415 for "salary" and .623 for "salbegin" as its standardized canonical coefficients. Function 2 consists of -.844 for "salary" and 1.784 for "salbegin" as its standardized canonical coefficients. It should be noted here that it is the coefficients of the dependent variable that are of interest in this case. They will be used to form the composite dependent variable in the next step of commonality analysis. Standardized canonical coefficients are also calculated for the independent variables as part of CCA but are not used as part of commonality analysis.

Insert Table 2 about here

Step 2- Calculate the Criterion Composite Scores

In discussing the process of canonical correlation analysis, Thompson (1984) explains:

> In effect, the analysis proceeds by initially collapsing each person's scores on the variables in each variable set into a single composite variable. The simple or bivariate correlation between the two composite scores (one for each of the two variable sets) is a canonical correlation. (p. 14)

For purposes of commonality analysis, however, one must only combine the multiple dependent variables to form one composite dependant variate. This variate score can then be used as the dependent variable in the multivariate commonality analysis. The multiple independent variables are retained as they will be analyzed for their unique and common power in explaining changes in the composite dependent

variable. In this case, education and previous experience are maintained to analyze their unique and common influence on a composite score comprised of beginning and current salary.

The composite variate score is obtained by first multiplying the standard canonical function coefficients from step 1 with the Z-scores on the individual criterion or dependant variables. Then, the products are summed to create the synthetic criterion composite variables, one for each function. The function coefficient values must be input into the SPSS syntax manually while the values for the Z-scores are obtained automatically as part of the SPSS command. This process is reproduced in the syntax of the Appendix, under the heading "step 2".

<u>Step 3- Run multiple regression on each of the possible combinations of predictor variables.</u>

The remaining steps for commonality analysis are the same in the case of canonical correlation analysis and multiple regression. In step 2 the multiple dependent variables from canonical correlation analysis were summed to create a composite dependent variable. The multiple independent variables were retained and what is left is essentially a case of multiple regression on the synthetic composite criterion variable.

Step 3 begins the process of determining the unique and common variability components of the independent variables. The unique contribution of an independent variable is found by first partialing out the other independent variables and looking at the "squared semipartial correlation" (R^2) between the dependent variable and the selected independent variable (Wisler, 1969). The common variability component is "the common element or commonality of [the independent variables] or the proportion of

variance in Y predictable using [any one of the variables]" (Murthy, 1994, p. 5). The sum of the unique components and the common component is equal to the squared multiple correlation. For a case including two predictors, such as our example, the relationship can be expressed as:

$$R^2_{y.12} = U_1 + U_2 + C_{12}$$

where $R^2y._{12}$ is the squared multiple correlation of Y with variables 1 and 2 in the model, U_1 is the unique contribution of variable 1 (educ), U_2 is the unique contribution of variable 2 (prevexp), and C_{12} is the common element or commonality of variables 1 and 2, or the proportion of variance in Y predicted using either variable 1 or variable 2.

Essentially, commonality analysis utilizes the R^2s from all possible combinations of the independent variables to determine the unique and common components of the overall explained variance. The number of possible combinations of the independent variables can be determined by the formula 2^p-1, where p represents the number of independent variables examined in the model (Rowell, 1996). In this example there are two independent variables (educ and prevexp). The number of possible combinations is therefore $(2^2-1) = 3$.

From this formula it is apparent that as the number of independent variables increases, the number of possible combinations increases exponentially. With five independent variables, for example, there are 31 possible combinations (2^5-1). An analysis of these many combinations becomes cumbersome and has prompted some to argue for alternative methods such as cluster analysis, factor analysis, or theory in cases

where there are more than five independent variables (Mood, 1969; Seibold & McPhee, 1979; Wisler, 1969). Alternatively, one could limit the number of independent variables to five to utilize the strength of commonality analysis, which is to consider all possible combinations and therefore provide an unbiased determination of intercorrelated variables (Rowell, 1996).

Once the number of possible combinations has been determined, a regression should be run for each one. In our example, three regressions will be run for each function. Recall that each function is the equivalent of an equation in multiple regression. Because there are two functions, a total of six regressions will be run. For each function, the first regression will include only variable one (educ) in the model, the second will include only variable 2 (prevexp), and the third will include both variable 1 and variable 2. SAS provides a useful program (PROC RSQUARE) to calculate and print out all R^2 values in ascending order for all possible combinations of the entered independent variables. Alternatively, SPSS requires that each regression is calculated individually. The SPSS syntax for the six regressions ran in this example is presented in the Appendix under the heading "step 3." By running this syntax, the R^2 for each regression is obtained for use in the next step of the commonality analysis.

Step 4- Calculate Unique and Common Variance Partitions

As mentioned previously, the number of possible combinations of independent variables is equal to 2^p-1 where p is equal to the number of independent variables in the model. This equation also represents the number of possible unique and common portions of variance. After all possible regressions have been run, the unique variance partition for each particular variable is then determined by subtracting the unique variance (R^2) for

each of the other independent variables from the variance (R^2) for all independent variables combined. Rowell (1991) developed a table that includes the formulas for two-predictor, three-predictor, and four-predictor models (see Table 3). In addition to assisting one in calculating the unique and common components, this table also provides a visual representation of how commonality analysis can become more complex with the addition of only one or two predictor variables. It becomes apparent that commonality analysis potentially becomes less valuable as the number of predictor variables increases beyond four or five variables.

Insert table 3 about here

In the example used in this paper, the formula for the variance unique to variable 1 would be:

$$U1 = R^2(12) - R^2(2)$$

where $R^2(12)$ represents the R^2 with both variables 1 and 2 in the model, and $R^2(2)$ represents the R^2 when only variable 2 is in the model. Similarly, the formula for the variance unique to variable 2 would be:

$$U2 = R^2(12) - R^2(1)$$

where $R^2(1)$ represents the R^2 when only variable 1 is in the model. Finally, the common element or commonality of variable 1 or 2, or the portion of variance that is predictable using either variable 1 or 2 is captured by the formula:

$$C12 = R^2(1) + R^2(2) - R^2(12)$$

Earlier it was determined that this case of CCA has two functions. It follows, therefore, that calculations for U1, U2, and C12 will be done for each function. Using the formulas listed above, variance for U1, U2, and C12 is calculated as follows:

Function 1

$U1 = -.022 + .215 = .193$

$U2 = -.211 + .215 = .004$

$C12 = .211 + .022 - .215 = .018$

Funtion 2

$U1 = -.121 + .135 = .014$

$U2 = -.002 + .135 = .133$

$C12 = .002 + .121 - .135 = -.012$

With the unique and common components determined, it becomes helpful to organize the results in table form. Table 4 represents the results calculated above.

Insert table 4 about here

Note that the table is divided into two sections, which represent the two canonical functions. The summation of each of the two columns represents the explanatory power

of each of the two variables included in this analysis, "educ" and "prevexp". In function one it is apparent that "educ" accounts for a majority of the variance (21.1%) in the composite dependent variable. Furthermore, a very small amount of variance (1.8%) is "common" or explained by either "educ" or "prevexp" being in the model. This small number, along with the small amount of variance explained by "prevexp" (2.2%) indicates that education is responsible for almost all of the variance explained in function one.

Function two is the inverse of function one with "prevexp" accounting for a majority of the explained variance (12.1%) relative to "educ" (.2%). Note in this case that the common variance explained by either "educ" or "prevexp" is negative (-1.2%). This is an indicator of a suppressor effect occurring in function two (Thompson & Miller, 1985). A negative commonality indicates that the explanatory power of one variable is greater when the other is used (Beaton, 1973).

Discussion

Two limitations of commonality analysis should be noted (Leister, 1996). First, there are no statistical significance tests conducted for commonality analysis. This limitation is not necessarily a hindrance, however, as statistical significance tests are conducted as part of CCA or multiple regression prior to running commonality analysis. The second limitation, as addressed previously, is the number of variables that can effectively be analyzed as part of commonality analysis. While the smaller number of variables recommended by commonality analysis may provide a more parsimonious explanation, it may prevent a complete explanation when more variables should be included.

Despite its limitations, commonality analysis does have important advantages (Daniel, 1989; Thompson & Miller, 1985). First, it does not rely on a scale conversion such as that sometimes used in ANOVA, therefore honoring the relationships between variables (Kroff, 2002). In addition, commonality analysis considers the overlap of variance, which can be important in the social sciences where variables are often correlated with one another.

In summary, commonality analysis can be an effective tool for analyzing the variance in a dependent variable that is unique and common to multiple independent variables. It provides information regarding the importance of each independent variable to the dependent variable in question. Without this information, researchers may misinterpret or even miss important relationships. As Seibold and McPhee (1976) concluded regarding their suggested use of commonality analysis, "to rely solely on standard multiple regression indicators (R, R^2, F, betas, and associated probabilities) may be risking underreporting these findings, obscuring more complex relationships, and misleading readers as to the theoretical and practical significance of the results" (p. 365).

References

Beaton, A.E. (1973). Commonality. Princeton, NJ: Educational Testing Service. (ERIC Document Reproduction No. ED 111 829)

Daniel, L.G. (1989, March). Commonality analysis with multivariate data sets. Paper presented at the annual meeting of the American Educational Research Association, San Francisco. (ERIC Document Reproduction No. ED 314 483)

Elmore, P., & Woehlke, P. (1988). Statistical methods employed.in American Educational Research Journal, Educational Researcher, and Review of Educational Research from 1978 to 1987. Educational Researcher, 17, 19-20.

Goodwin, L.D., & Goodwin, W.L. (1985). Statistical techniques in AERJ articles, 1979-1983: The preparation of graduate students to read the educational research literature. Educational Researcher, 14(2), 5-11.

Kerlinger, F.N., & Pedhazur, E. J. (1973). Multiple regression in behavioral research. New York: Holt, Rinehart & Winston.

Kroff, M. (2002). Mutilating data and discarding variance: The dangers of dichotomizing continuous variables. Paper presented at the annual meeting of the Southwest Educational Research Association, Austin, TX. (ERIC Document Reproduction Service number forthcoming).

Leister, K. D. (1996, January). Canonical commonality analysis. Paper presented at the annual meeting of the Southwest Educational Research Association, New Orleans, LA. (ERIC Document Reproduction Service No. ED 395 959)

Mood, A.M. (1969). Macro-analysis of the American educational system. Operations Research, 17, 770-784.

Murthy, K. (1994, April). Commonality analysis for the regression case. Paper presented at the annual meeting of the American Educational Research Association, New Orleans, LA. (ERIC Document Reproduction Service No. ED 367 694)

Rowell, K. (1991, January). Partitioning predicted variance components into constituent parts: How to conduct commonality analysis. Paper presented at the annual meeting of the Southwest Educational Research Association, San Antonio, TX (ERIC Document Reproduction Service No. ED 328 589)

Rowell, R.K. (1996). Partitioning predicted variance into constituent parts: How to conduct regression commonality analysis. In B. Thompson (Ed.), Advances in social science methodology (Vol. 4, pp. 33-43). Stamford, CT: JAI Press.

Seibold, D. R., & McPhee, R. D. (1979). Commonality analysis: A method for decomposing explained variance in multiple regression analyses. Human Communication Research, 5, 355-365.

Stevens, J. (1996). Applied multivariate statistics for the social sciences. Mahwah, NJ: Lawrence Erlbaum Associates.

Stone-Romero, E.F., Weaver, A.E., & Glenar, J.L. (1995). Trends in research design and data analytic strategies in organizational research. Journal of Management, 21, 141-157.

Thompson, B. (1984). Canonical correlation analysis: Uses and interpretation. Newbury Park, CA: Sage Publications.

Thompson, B. (1985). Alternate methods for analyzing data from education experiments. Journal of Experimental Education, 54, 50-55.

Thompson, B., & Miller, J.H. (1985, February). A multivariate method of commonality analysis. Paper presented at the annual meeting of the Southwest Educational Research Association, Austin, TX. (ERIC Document Reproduction Service No. ED 263 151)

Willson, V.L. (1980). Research techniques in AERJ articles: 1969 to 1978. Educational Researcher, 9(6), 5-10.

Wisler, C.E. (1969). Partitioning the variance explained in a regression analysis. In G.W. Mayeske, C.E. Wisler, A.E. Beaton, Jr., F.D. Weinfield, W.M. Cohen, T. Odada, J.M. Proshek, and K.A. Tabler (Eds.), A study of our nation's schools. Washington, D.C.: Office of Education, HEW.

Table 1

Heuristic Data Set

i.d.	educ	salary (000)	salbegin (000)	prevexp
1	15	57	27	144
2	16	40	19	36
3	12	21	12	381
4	8	22	13	190
5	15	45	21	138
6	15	32	14	67
7	15	36	19	114
8	12	22	10	0
9	15	28	13	115
10	12	24	14	244
11	16	30	17	143
12	8	28	12	26
13	15	28	14	34
14	15	35	17	137
15	12	27	14	66
16	12	41	15	24
17	15	46	14	48
18	16	104	28	70
19	12	42	14	103
20	12	26	12	48
21	16	39	15	17
22	12	22	13	315
23	15	24	11	75
24	12	17	9	124
25	15	21	9	171

Table 2

Standardized Correlation Coefficients for the Dependent Variables

	Function	
	1	2
Salary	.415	-1.844
Salbegin	.623	1.784

Table 3

Formulas for Unique and Commonality Components of Variance

Two Predictor Variable

$U1 = -R^2(2) + R^2(12)$
$U2 = -R^2(1) + R^2(12)$
$C12 = R^2(1) + R^2(2) - R^2(12)$

Three Predictor Variables

$U1 = -R^2(23) + R^2(123)$
$U2 = -R^2(13) + R^2(123)$
$U3 = -R^2(12) + R^2(123)$
$C12 = -R^2(3) + R^2(13) + R^2(23) - R^2(123)$
$C13 = -R^2(2) + R^2(12) + R^2(23) - R^2(123)$
$C123 = R^2(1) + R^2(2) + R^2(3) - R^2(12) - R^2(13) - R^2(23) + R^2(123)$

Four Predictor Variables

$U1 = -R^2(234) + R^2(1234)$
$U2 = -R^2(134) + R^2(1234)$
$U3 = -R^2(124) + R^2(1234)$
$U4 = -R^2(123) + R^2(1234)$
$C12 = -R^2(34) + R^2(134) + R^2(234) - R^2(1234)$
$C13 = -R^2(24) + R^2(124) + R^2(234) - R^2(1234)$
$C14 = -R^2(23) + R^2(123) + R^2(234) - R^2(1234)$
$C23 = -R^2(14) + R^2(124) + R^2(134) - R^2(1234)$
$C24 = -R^2(13) + R^2(123) + R^2(134) - R^2(1234)$
$C34 = -R^2(12) + R^2(123) + R^2(124) - R^2(1234)$
$C123 = -R^2(4) + R^2(14) + R^2(24) + R^2(34) - R^2(124) - R^2(134) - R^2(234) + R^2(1234)$
$C124 = -R^2(3) + R^2(13) + R^2(23) + R^2(34) - R^2(123) - R^2(134) - R^2(234) + R^2(1234)$
$C134 = -R^2(2) + R^2(12) + R^2(23) + R^2(24) - R^2(123) - R^2(124) - R^2(234) + R^2(1234)$
$C234 = -R^2(1) + R^2(12) + R^2(13) + R^2(14) - R^2(123) - R^2(124) - R^2(134) + R^2(1234)$
$C1234) = R^2(1) + R^2(2) + R^2(3) + R^2(4) - R^2(12) - R^2(13) - R^2(14) - R^2(23) - R^2(24)$
$\quad - R^2(34) + R^2(123) + R^2(124) + R^2(134) + R^2(234) - R^2(1234)$

Note. From "Partitioning Predicted Variance Components into Constituent Parts: How to Conduct Commonality Analysis," by R. K. Rowell, 1991, Advances in Social Science Methodology, 4, p. 36.

Table 4

Commonality Analysis Summary Table

Function 1

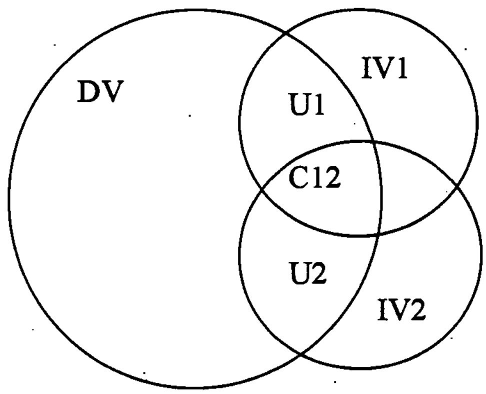
Component	educ (U1)	prevexp (U2)
Unique to educ	.193	
Unique to prevexp		.004
Common to educ/ prevexp	.018	.018
Sum of Components	21.1%	2.2%
R^2 of prediction with Canonical composite scores	.211	.022

Function 2

Component	educ (U1)	prevexp (U2)
Unique to educ	.014	
Unique to prevexp		.133
Common to educ/ prevexp	-.012	-.012
Sum of Components	.2%	12.1%
R^2 of prediction with Canonical composite scores	.002	.121

Figure Caption

Figure 1. Venn diagram representing unique variance (U1 and U2) and common variance (C12) of DV explained by IV1 and IV2.


DV
IV1
U1
C12
U2
IV2

Appendix

```
COMMENT ***************************************************
COMMENT  Step 1
COMMENT ***************************************************
set blanks=sysmis undefined=warn printback=list.
Title'Canonical Commonality Analysis'.
data list
 file='a:\commonsalary.txt'fixed records=1 table
/1 educ 1-3 salary 4-6 salbegin 7-9 prevexp 10-12.
list variables=all/cases=9999/format=numbered.
Manova
 salary salbegin with educ prevexp
 /print=signif (eigen dimenr)
 /discrim=stan corr alpha (.99)
 /design.
Descriptives variables=all/save.
list variables=all/cases=22/format=numbered.
COMMENT***************************************************
COMMENT  Step 2
COMMENT  Insert standardized canonical coefficients for dependent variables in
COMPUTE   compute formulas below.
COMMENT***************************************************
compute crit1=(.415*zsalary) + (.623*zsalbegi).
compute crit2=(-1.844*zsalary) + (1.784*zsalbegi).
descriptives variables=all.
COMMENT***************************************************
COMMENT Step 3
COMMENT***************************************************
subtitle'1a regression to pred canonical syn w/ 2 preds'.
regression variables=crit1 crit2 educ prevexp/dependent=crit1/
 enter educ prevexp.
subtitle'1b regression to pred canonical syn w/ 2 preds'.
regression variables=crit1 crit2 educ prevexp/dependent=crit2/
 enter  educ prevexp.
subtitle '2a regression to pred canonical syn w/ educ'.
regression variables=crit1 crit2 educ prevexp/dependent=crit1/
 enter educ.
subtitle '2b regression to pred canonical syn w/ educ'.
regression variables=crit1 crit2 educ prevexp/dependent=crit2/
 enter educ.
subtitle '3a regression to pred canoncial syn w/ prevexp'.
regression variables=crit1 crit2 educ prevexp/dependent=crit1/
 enter prevexp.
subtitle '3b regression to pred canonical syn w/ prevexp'.
regression variables=crit1 crit2 educ prevexp/dependent=crit2/
enter prevexp.
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