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Implementing ODA from Within Stata: Assessing Split-Half Reliability Using a Polychotomous Attribute

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This paper illustrates testing a directional (i.e., confirmatory) hypotheses for a split-half reliability study using a polychotomous attribute having four categories, via the Stata package for implementing ODA.

Recent papers[1-25] introduce the new Stata package called **oda**[26] for implementing ODA from within the Stata environment. This package is a wrapper for the MegaODA software system[27-29], so the MegaODA.exe file must be loaded on the computer for the **oda** package to work.[30] To download the **oda** package, at the Stata command line type: "ssc install oda" (without the quotation marks).

Using the split-half method to estimate reliability requires only one test administration. Items on the test are separated into two groups called "split-halves" and the agreement between the split-halves is corrected for attenuation and called the split-half reliability for the total test. Every person completing a pair of split-halves is hypothesized to receive identical scores on both split-halves.[31]

This paper demonstrates use of the **oda** package to evaluate a directional hypothesis for a design in which two split-halves are separately used to categorize a sample of undergraduates into one of four mutually exclusive categorical typologies: androgynous (dummy-coded as 1), instrumentally-typed (2), expressively-typed (3), or undifferentiated (4).[31-39]

Methods

Data

Yarnold obtained data assessing instrumentality and expressiveness (each using 20 items) for 68 undergraduates.[32] The 20 "I" items were randomly split into two halves (I_1 and I_2), as were the 20 "E" items (E_1 and E_2). Separately using each pair of split-halves (I_1, E_1) and (I_2, E_2), each undergraduate was classified into one of the four dummy-coded categorical typologies. Finally, separately for every undergraduate, the categorical typology (1-4) was determined for the first and second split-half.

Analytic Process

We test the directional ("confirmatory") alternative hypothesis that subjects classified as type *t*

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(t = 1, 2, 3, or 4) by split-half 1 (four-category class variable) are similarly classified by split-half 2 (four-category “polychotomous” attribute). The null hypothesis is this is not true.[30,40] Analysis was accomplished using the following **oda** syntax (see the help file for **oda** for a complete description of syntax options):

```
oda sh1 sh2, pathoda("C:\ODA\")
store("C:\ODA\") iter(25000)
direction(< 1 2 3 4) cat
```

This syntax is explained as follows. Here “sh1” is the polychotomous *class* variable and “sh2” is the polychotomous *attribute*; the directory path where MegaODA.exe and other files generated in analysis are stored is “C:\ODA\”; 25,000 iterations (repetitions) are used to obtain a permutation *p*-value; and the directional hypothesis is that polychotomous codes of the class variable and attribute are identical.[26] The **oda** package produces an extract of the total output produced by ODA software seen below (the complete output is stored in the specified directory with the extension “.out”).

```
ODA model:
----------
IF SH2 = 1 THEN SH1 = 1
IF SH2 = 2 THEN SH1 = 2
IF SH2 = 3 THEN SH1 = 3
IF SH2 = 4 THEN SH1 = 4

Summary for Class SH1  Attribute SH2
-----------------------------------

Performance Index           Train
-----------------          ------
Overall Accuracy            64.71%
PAC SH1=1                   73.33%
PAC SH1=2                   61.11%
PAC SH1=3                   68.42%
PAC SH1=4                   56.25%
Effect Strength PAC         53.04%
PV SH1=1                    64.71%
PV SH1=2                    61.11%
PV SH1=3                    81.25%
PV SH1=4                    52.94%
Effect Strength PV          53.34%
Effect Strength Total       53.19%

Monte Carlo summary (Fisher randomization):
------------------------------------------
Iterations:  25000
Estimated p: 0.000000
```

As seen, the classification performance of the ODA model corresponds to a statistically significant (conventionally reported as per-comparison $p<0.0001$) effect. Effect strength for sensitivity (ESS) is labelled in the output as “Effect Strength PAC” (Percentage Accurate Classification). For the confirmatory hypothesis ESS is 53.04%, which barely exceeds the minimum criterion (ESS≥50) for classification as a relatively strong effect.[31] But, an exact discrete confidence interval for this result would overlap the region reflecting a moderate effect.[41,42]

Classification performance of the ODA model is summarized in a cross-classification table, illustrated for this example below.

Actual Class	*Predicted* Class 1	2	3	4	PAC (%)
1	11	2	2	0	73.33
2	3	11	0	4	61.11
3	2	0	13	4	68.42
4	1	5	1	9	56.25

Here, PAC is “percentage accuracy in classification,” also called model sensitivity.[31] Since there are four class categories, sensitivity of 100%/4 = 25% is expected by chance for each of the four categories. Best performance was achieved for class 1 (androgynous), and worst performance was achieved for class 4 (undifferentiated). Exact discrete confidence intervals for sensitivity could be obtained for each class category.[41,42]

We believe ODA should be considered the preferred statistical approach *vs*. alternative methods since it avoids statistical assumptions required of conventional models, is insensitive to skewed data or outliers, and has the ability to handle any variable metric including categorical, Likert-type integer, and real number measurement scales.[31] Compared to other methods, only ODA can identify the optimal (maximum-accuracy) assignments (categorical attributes) or cutpoints (ordered attributes) which exist for the attribute, that in turn facilitates use of measures

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of predictive accuracy. ODA can evaluate model reproducibility using multiple methods, allowing assessment of potential cross-generalizability of the model when applied to classify independent random samples.[31] We therefore recommend that researchers employ the ODA framework to evaluate the statistical hypotheses which are explored in their laboratory and field research endeavors.[43-61]

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Author Notes

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