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Implementing ODA from Within Stata: Exploratory Hypothesis, Binary Class Variable, Categorical Ordinal Attribute

Paul R. Yarnold, Ph.D. and Ariel Linden, Dr.P.H.
Optimal Data Analysis, LLC Linden Consulting Group, LLC

This paper describes how an exploratory (post hoc, nondirectional, two-tailed) hypothesis involving a binary (dichotomous) class variable and a categorical ordinal (three-level) attribute is evaluated using MegaODA software using the new Stata package implementing ODA analysis.

Recent papers[1-13] introduce the new Stata package called **oda**[14] for implementing ODA from within the Stata environment. Because this package is a wrapper for the MegaODA software system[15-17], the MegaODA.exe file must be loaded on the computer for the **oda** package to work (MegaODA software is available at https://odajournal.com/resources/). To download the **oda** package, at the Stata command line type: "ssc install oda" (without the quotation marks). This paper demonstrates use of the **oda** package to evaluate a nondirectional hypothesis involving a binary class variable, and an ordinal (three-level) attribute.

Methods

Data

We consider data from Snyder, Wills, and Grady-Fletcher comparing outcomes of two types of marital therapy for unhappily married couples.[18] Arbitrary dummy-codes identified two types of *therapy*: insight=1, behavioral=2. Therapy *outcome* was rated on a three-category ordinal scale ranging from worst to best outcome: divorced=1, no change=2, improved=3. Data for every subject was entered in free format on a separate line as space-delimited text (ASCII) characters.[19]

Analytic Process

We repeat the ODA analysis previously conducted on these data (see example 5.6, *Optimal Data Analysis: A Guidebook with Software for Windows*[20]). The nondirectional or "two-tailed" alternative hypothesis is that the binary class ("dependent") variable *therapy* can be discriminated on the basis of *outcome* (ordinal attribute or "independent variable"). The null hypothesis is that this is not true. Weighting by prior odds (the default setting) is used to obtain a model which maximizes ESS (i.e., classification accuracy normed *vs*. chance), and a total of 25,000 Monte Carlo iterations are used to estimate Type I error (i.e., *p* value).[20]

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For these data, **oda** is implemented using the following syntax to test the *a priori* hypothesis for the attribute *outcome* (see the **oda** help file for a complete description of syntax options):

```
oda therapy outcome, pathoda("C:\ODA\")
store("C:\ ODA\output") iter(25000)
```

The above syntax is explained as follows: The variable "therapy" is the *class* variable; the variable "outcome" is the *attribute*; the directory path where the MegaODA.exe file is located on the computer is "C:\ODA\"; the directory path where the output and other files generated during the analysis are stored is "C:\ODA\output"; and 25,000 iterations (repetitions) are used to compute the permutation *p*-value.

The **oda** package produces an extract of the total output produced by the ODA software (the complete output is stored in the specified directory with the extension ".out").

As seen in the **oda** output, the ODA model is interpreted as follows: "if *outcome* $\leq$ 1.5 then predict *therapy* = 2; otherwise, predict *therapy* = 1." Couples in behavioral therapy were predicted to be divorced, whereas couples in insight therapy were predicted to show no change or improvement. As seen, this model correctly classified 89.66% of the couples in behavioral therapy, but only 46.15% of the couples in insight therapy.

Effect strength for sensitivity (ESS) is labelled in the output as "Effect Strength PAC" (Percentage Accurate Classification). The ESS is 35.81% which corresponds to an effect of moderate strength[20] with permutation $p<0.0055$. In summary, ODA identified a model which discriminated therapeutic methods with moderate strength, and this effect was statistically significant.

```
ODA model:
----------
IF OUTCOME <= 1.5 THEN THERAPY = 2
IF 1.5 < OUTCOME THEN THERAPY = 1


Summary for Class THERAPY  Attribute OUTCOME
-------------------------------------------

Performance Index           Train
-----------------          ------
Overall Accuracy            69.09%
PAC THERAPY=1               89.66%
PAC THERAPY=2               46.15%
Effect Strength PAC         35.81%
PV THERAPY=1                65.00%
PV THERAPY=2                80.00%
Effect Strength PV          45.00%
Effect Strength Total       40.40%


Monte Carlo summary (Fisher randomization):
-------------------------------------------
Iterations:  25000
Estimated p: 0.005480
```

Discussion

This paper shows how to use ODA to identify the model that maximally discriminates between any two categories of a class variable using a categorical ordinal attribute.

ODA should be considered the preferred approach over other methods because 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.[20] Moreover, in contrast to other methods, ODA also has the unique ability to ascertain optimal (maximum-accuracy) assignments (categorical attributes) or cutpoints (ordered attributes) on the attribute, which facilitates the use of measures of predictive accuracy. Furthermore, ODA can perform cross-validation using LOO (and many other methods[20]) which allows for assessment of potential cross-generalizability of the model to independent random samples.

For these reasons we recommend that researchers employ ODA and CTA frameworks to evaluate the statistical hypotheses which are explored in their laboratory and field research endeavors.[21-35]

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Author Notes

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