

Executing ODA from Within Stata: Combining Boosted Regression and ODA to Estimate Treatment Effects for Multi-Valued Treatments

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This paper demonstrates how boosted regression can be used in conjunction with ODA to estimate treatment effects for multivalued treatments using the new Stata package for implementing ODA.

Studies in which participants are randomized to treatment are considered the gold standard for assessing causal inference since randomization putatively ensures that the study groups do not differ systematically in their characteristics, and consequently, estimated treatment effects are assumed to be unbiased.¹ If randomization is infeasible, investigators rely on statistical techniques that model treatment assignment²⁻⁸ in order to control for threats to validity which may compromise causal interpretation of the results.⁹⁻¹¹

A common approach used to estimate treatment effects in studies in which there are multiple treatment arms is to first estimate propensity scores using multinomial logistic regression, then compute the inverse probability of treatment weights (IPTW), and finally to use those weights in a weighted regression to evaluate the outcomes.⁸

This paper demonstrates how this entire process can be performed using two machine learning algorithms (boosted regression to compute the probabilities of treatment, and ODA to evaluate the weighted outcomes), thus avoiding the many assumptions required by the conventional parametric procedures.

Both procedures are implemented in Stata. **boost** is a community-written package that performs boosted regression¹² and **oda** is a new Stata package¹³ for implementing ODA from within the Stata environment. This package is a wrapper for the MegaODA software system¹⁴⁻¹⁶, so the MegaODA.exe file must be loaded on the computer for the **oda** package to work.¹⁷ To download the **oda** package, at the Stata command line type: “ssc install oda” (without the quotation marks).

Methods

Data

The data for our empirical example come from a disease management program designed for patients with congestive heart failure and implemented in a large health plan located in the western USA.⁶ Individuals with the condition were contacted and invited to enroll in the program. Those agreeing to participate received one of the following interventions: (1) periodic telephone calls (CALL), from a nurse to discuss self-management behaviors (n=654), or (2) remote tele-monitoring (RTM), which entailed daily electronic transmission of the participant's disease-related symptoms to a database followed by a call from the nurse if symptoms appeared to indicate the onset of an acute exacerbation (n=705). Assignment to either intervention arm was conducted by the program nurse and based largely on subjective assessment of the patient's psycho-social needs,¹⁸⁻²⁰ past levels of health care utilization, and the patient's preferred level of contact. The primary goal of the intervention was to reduce avoidable hospitalizations.^{21,22} Patients with congestive heart failure, but not participating in the program, received their usual medical care and served as controls (n=6612) in this study (see [6], and [8] for a more comprehensive description).

Analytic process

The steps involved for analyzing multivalued treatments include: (1) estimating the generalized propensity score using multinomial boosted regression with the multiple-level treatment variable as the outcome. Using this approach every individual receives one propensity score corresponding to the probability of assignment to each treatment, conditional on baseline characteristics. Thus, in the current data, three propensity scores were estimated for each individual corresponding to their probability of assignment to non-participation, the CALL and RTM

interventions, respectively; (2) a single weight is computed based on an individual's inverse probability of receiving their actual treatment; and (3) treatment effects are computed using weighted ODA.

The **oda** syntax for performing the outcomes analysis is as follows:

```
oda multreat hosp, pathoda("C:\ODA\")  
store("C:\ODA\output") iter(10000)  
seed(1234) wt(iptboowt)
```

This syntax is explained as follows: the multi-treatment variable is the *class* variable; the count of hospitalizations (per person) is the *attribute*; the directory path where the MegaODA.exe file is located on my computer is "C:\ODA\"; the directory path where the output and other files generated during the analysis are stored is "C:\ODA\output"; the number of iterations (repetitions) for computing a permutation *P*-value is 10,000; the seed is set to 1234 to allow us to replicate permutation results (any integer value can be used as seed); and the inverse probability weight is specified as the *wt()*.

As shown in the **oda** output (Table 1), the ODA model is interpreted as follows: "if the number of hospitalizations ≤ 4.5 , then predict that the treatment group is 1 (CALL). If hospitalizations are > 4.5 and ≤ 7.5 , then predict that the treatment group is 2 (RTM), and if hospitalizations are > 7.5 , predict that the treatment group is 0 (controls)." The weighted effect strength for sensitivity (wESS) is labelled in the output as "Weighted PAC" for each of the three levels of treatment. Weighted ESS was very weak for the control group (wESS=0.15%) and for the RTM group (wESS=1.06), but was very strong for the CALL group (wESS=98.79).²³

This model was not statistically significant in training analysis ($P < 0.940$) indicating that the three treatment arms could not be discriminated on the basis of the number of hospitalizations per person. In other words,

there was no statistically reliable treatment effect.

Table 1: Stata **oda** Output

```
ODA model:
-----
IF HOSP <= 4.5 THEN MULTREAT = 1
IF 4.5 < HOSP <= 7.5 THEN MULTREAT = 2
IF 7.5 < HOSP THEN MULTREAT = 0

Summary for Class MULTREAT Attribute HOSP
-----

Performance Index          Train
-----
Overall Accuracy          8.37%
Overall wtd Accuracy     31.63%
PAC MULTREAT=0           0.15%
PAC MULTREAT=1           98.78%
PAC MULTREAT=2           1.56%
Effect Strength PAC       0.24%
wtd PAC MULTREAT=0       0.15%
wtd PAC MULTREAT=1       98.79%
wtd PAC MULTREAT=2       1.06%
Effect Strength wtd PAC   0.00%
PV MULTREAT=0            90.91%
PV MULTREAT=1            8.17%
PV MULTREAT=2            20.37%
Effect Strength PV        9.73%
wtd PV MULTREAT=0        30.28%
wtd PV MULTREAT=1        31.57%
wtd PV MULTREAT=2        39.89%
Effect Strength wtd PV    0.87%
Effect Strength Total     4.98%
Effect Strength wtd Total 0.43%

Monte Carlo summary (Fisher randomization):
-----
Iterations: 10000
Estimated p: 0.940400
```

The cross-classification table for the ODA model is presented in Table 2. As seen, the sample is highly skewed: 82.9% of the subjects were Controls, 8.2% were RTM, and 8.9% were CALL.

Discussion

This paper demonstrates how the new Stata package **oda** can be used to evaluate treatment effects in studies of multivalued treatments after boosted regression estimates the generalized propensity score. This methodology should be considered the preferred approach over commonly-used parametric models because ODA avoids the assumptions required of these 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.²⁴ In contrast to conventional statistical models, ODA has the ability to ascertain where optimal (maximum-accuracy) cutpoints are on the outcome variable, which in turn, facilitates the use of measures of predictive accuracy. Moreover, ODA can perform cross-validation using LOO to assess the cross-generalizability of a statistically significant training model to potentially new study participants or non-participants.²⁵ Finally, the findings continue to support our recommendation to employ the ODA and CTA frameworks to evaluate the efficacy of health-improvement interventions and policy initiatives.²⁶⁻⁴¹

Table 2: Cross-Classification Results for Training Analysis

	<u>Predicted Class</u>				
<u>Actual Class</u>	<u>Controls</u>	<u>RTM</u>	<u>CALL</u>	<u>PAC</u>	<u>wPAC</u>
Controls	10	6,566	36	0.15	0.15
RTM	1	646	7	98.78	98.79
CALL	0	694	12	1.56	1.06
PV	90.91	8.17	20.37		
wPV	83.33	8.16	4.44		

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Author Notes

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