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The use of model based recursive partitioning as an analytic tool in child welfare

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ABSTRACT

Child welfare agencies are tasked with investigating allegations of child maltreatment and intervening when necessary. Researchers are turning to the field of predictive analytics to optimize data analysis and data-driven decision making. To demonstrate the utility of statistical algorithms that preceded the current predictive analytics, we used Model Based (MOB) recursive partitioning, a variant of regression analysis known as decision trees, on a dataset of cases and controls with a binary outcome of serious maltreatment (defined as hospitalization or death). We ran two models, one which split a robust set of variables significantly correlated with the outcome on the partitioning of a proxy variable for environmental poverty, and one which ran the same variable set partitioned on a variable representing confirmed prior maltreatment. Both models found that what most differentiated children was spending greater than 2% of the timeframe of interest in foster care, and that for some children, lack of Medicaid eligibility almost doubled or tripled the odds of serious maltreatment. We find that decision trees such as MOB can augment risk assessment tools and other data analyses, informing data-driven program and policy decision making. We caution that decision trees, as with any other predictive tool, must be evaluated for inherent biases that may be contained in the proxy variables and the results interpreted carefully. Predictive analytics, as a class, should be used to augment, but not replace, critical thinking in child welfare decision making.

1. Introduction

1.1. Background

Children reported to child welfare for suspected maltreatment have been estimated to be at two to almost six times greater risk of death than those who are not (Jonson-Reid, Chance, & Drake, 2007; Putnam-Hornstein, 2011). Currently, many child welfare jurisdictions use actuarial tools to help determine which of these children—already at risk by virtue of child welfare involvement—are at the greatest risk of a subsequent report. These tools, such as the Structured Decision Making (SDM) risk assessment (Children's Research Center, 2009), used in many states across the U.S., rely on individual and family attributes (for example: age of the youngest child and caregiver substance abuse history) to calculate a cumulative risk score that broadly classifies families into low, moderate, high and very high risk of having subsequent maltreatment *report* (Freitag & Mordes-Noya, 2007). We know of no tool in use by child welfare that addresses risk of subsequent maltreatment *injury*.

Previous studies have found that families categorized by the SDM tool as “high” or “very high" risk have greater recurrence rates

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(i.e., were more likely to be subjects of a subsequent child welfare referral within a specified timeframe of an index child welfare referral) than families categorized as “low” or “moderate” risk (Johnson, 2011, Baird & Wagner, 2000; D’andrade, Austin, & Benton, 2008; Johnson, 2004; Loman & Siegel, 2004; Shlonsky & Wagner, 2005; Wiebush, Freitag, & Baird, 2001). However, risk assessment tools used in child welfare are generally plagued with reliability and validity problems (Camasso & Jagannathan, 2013; Knoke & Trocme, 2005). Studies of sensitivity and specificity of actuarial tools in child welfare are scarce; those that do exist found misclassification to be as high as one in three families (Johnson, 2011; Loman & Siegel, 2004).

Poor classification performance of child welfare risk tools may in part be a function of the absence of universally accepted factors that constitute risk of child maltreatment, leaving individual tools in jeopardy of excluding critical factors. Different jurisdictions adopt different compositions of risk factors. For example, in Minnesota, the SDM risk tool includes variables for primary parent parenting skills, age of the primary parent, and whether the offender was an unmarried partner of the primary parent (Minnesota Department of Human Services, 2015), while the California SDM risk tool has none of those items. California includes housing stability and family size (California Department of Social Services, 2015), risk factors that Minnesota does not include.

The effort to develop a better child welfare risk assessment tool has most recently delved into the developing field of “predictive analytics,” albeit with some debate (Russell, 2015). Predictive analytics, broadly defined, encompasses a combination of data mining and statistics-based algorithms used to attempt to predict future outcomes. Perhaps the best known example is International Business Machines Corporation (IBM) Watson Analytics (IBMWA), which combines several analytical tools in a relatively user-friendly package (Hoyt, Snider, Thompson, & Mantravadi, 2016). While products such as Watson are making predictive analytics more accessible, many of the underlying statistical tools have been in use for many years.

1.2. Decision trees

One such set of tools are the statistical methods known collectively and informally as *decision trees*. Popular in biostatistics to aid in diagnostic as well as prognostic activities (Bellazzi & Zupan, 2008; Dreiseitl & Ohno-Machado, 2002) and in economics for activities such as credit score modeling and fraud detection (Lee, Chiu, Chou, & Lu, 2006; Ngai, Hu, Wong, Chen, & Sun, 2011), decision trees partition independent variables into successive subsets, providing a visual of a tree-like structure that describe clusters of characteristics (independent variables) predictive of the outcome (dependent variable). Because each step in the successive partitioning is based on the previous step, decision trees are also referred to as *recursive partitioning* (Birke, 2015). Decision trees typically outperform traditional logistic regression models, and can provide misclassification rate (sensitivity and specificity) estimates as well as confidence intervals at each progressive variable split (Lemon, Roy, Clark, Friedmann, & Rakowski, 2003), an advantage over current risk assessment algorithms.

Perhaps the best-known version of decision trees is the classification and regression tree (CART) model, pioneered by Breiman, Friedman, Olshen, and Stone (1984) as a method to identify high risk (for death) heart attack patients, using data collected within the first 24 h of hospitalization. If the response variable is binary (death/survival), the CART algorithms partition the data into groups (classification) and if the response variable is continuous (survival *time*, for example), CART organizes the variables into predictive branches in a regression tree (Breiman et al., 1984). CART first identifies the variable that most differentiates the outcome, then moves to the next distinguishing variable and continues until no further variables split into distinct groups (Breiman et al., 1984).

1.3. Decision trees and risk assessments

In the past 15 years, a few researchers have begun to apply the use of CART methods to determine risk of violence. Specifically, Steadman et al. (2000) developed the Iterative Classification Tree (ICT) that correctly classified about 73% of a sample of exiting inpatient psychiatric patients into low and high-risk groups for likelihood of committing a subsequent violent offense (Monahan et al., 2000, 2005; Steadman et al., 2000).

Using child welfare data, Sledjeski, Dierker, Brigham, and Breslin (2008) conducted a CART analysis to model recurrence of child maltreatment—defined as families with a substantiated baseline investigation who experienced a subsequent substantiated investigation within 18 months (Sledjeski et al., 2008). Testing variables derived from the target child welfare population’s risk assessment tool, the resulting model had 87% sensitivity and 65% specificity, showing promise as a parsimonious and useful tool, though the researchers cautioned that small sample size (n = 244) and item scoring subjectivity (poor interrater reliability) limitations restricted the interpretation of the results to exploratory in nature.

Most recently, Schwartz, York, Nowakowski-Sims, and Ramos-Hernandez (2017) used C5 and CHAID algorithms with machine learning features to build decision trees on a dataset of over 78,000 child welfare involved children (Schwartz et al., 2017). The models created decision trees and calculated odds ratios for the outcomes of investigation decision (substantiated, not substantiated) and service referral intensity (low, moderate, or high). The initial model had predictive accuracy of 85%, improving to 95% when the names of caseworkers were included (Schwartz et al., 2017). The researchers conclude that the use of predictive analytics including machine learning could clearly improve the accuracy and utility to of risk assessment instruments.

The Sledjeski et al. (2008) and Schwartz et al. (2017) decision tree studies used the outcome of confirmed (substantiated) maltreatment events, rather than reports of suspicion of maltreatment—the focus of most, if not all, child welfare risk assessment tools. Substantiation as an outcome is less prone to bias, especially surveillance bias (over reporting of some populations compared with others), than relying on occurrence of a maltreatment allegation (Coulton, Crampton, Irwin, Spilsbury, & Korbin, 2007).