The Application of Classification Trees to Pharmacy School Admissions

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In recent years, the American Association of Colleges of Pharmacy (AACP) has encouraged the application of big data analytic techniques to pharmaceutical education. Indeed, the 2013-2014 Academic Affairs Committee Report included a “Learning Analytics in Pharmacy Education” section that reviewed the potential benefits of adopting big data techniques. Likewise, the 2014-2015 Argus Commission Report discussed uses for big data analytics in the classroom, practice, and admissions. While both of these reports were thorough, neither discussed specific analytic techniques. Consequently, this commentary will introduce classification trees, with a particular emphasis on their use in admission. With electronic applications, pharmacy schools and colleges now have access to detailed applicant records containing thousands of observations. With declining applications nationwide, admissions analytics may be more important than ever.

Keywords: predictive analytics, admissions, decision tree

INTRODUCTION

Classification trees attempt to separate data into maximally homogenous groups in terms of an outcome of interest. For example, the restaurateur depicted in Figure 1 wants to know when customers will wait to be seated at his restaurant, as opposed to leaving to go elsewhere. Accordingly, he/she recorded information about 12 customers. The restaurateur found that the number of patrons in the restaurant best differentiated customers in terms of waiting. When there were no patrons in the restaurant, no one waited; when there were some patrons, everyone waited; and when the restaurant was full, two customers out of six waited. Restaurant type, however, was not as informative as crowd size, because as many people waited as did not wait at each type of restaurant: at the French and Italian restaurants, one waited and the other did not, while at the Thai and burger restaurants, two waited, and two did not. In other words, no clear distinction between waiting and not waiting could be drawn. Figure 1 also introduces another attribute: whether or not the customers were hungry. None of the satiated customers in the “full” group waited, but half of the hungry ones did. The next step would be to determine which variable(s) split the hungry customers into homogenous groups of waiters and non-waiters.

Classification trees’ clearest advantage is their interpretability. By portraying the analysis as a series of binary classifications, they provide a straightforward graphic for non-statisticians, unlike logistic regression, which can be difficult to interpret when many variables are included. Classification trees, however, can capture complex relationships without the added interpretational difficulty. Furthermore, when the relationship between one’s predictors and the dependent variable is markedly non-linear, classification trees tend to yield much more accurate predictions than logistic regression.

Despite their advantages, classification trees are prone to overfitting. That is, classification trees are apt to model both the relationship between the variables of interest and that data’s idiosyncrasies. For example, if a researcher is trying to model the relationship between students’ demographic information and first-year PharmD grades, and the data contains four students from New York with high P1 GPAs, a categorization tree may indicate that living in New York is an important predictor of P1 GPA when it is just a quirk of that particular data. As a consequence, the tree algorithm will not make accurate predictions when it is applied to new data with new idiosyncrasies.

Because of this limitation, it is important to build one’s classification tree on an initial dataset (the training set) and then apply it to a new dataset (the test set) to determine how well it generalizes before deploying it. Traditionally, the analyst randomly splits the data 80-20, using 80% of the data for the training set and 20% for the test set. Analysts may also choose to use k-fold cross-validation...
to increase generalizability. To further improve a tree’s
generalizability, researchers can use random forests. To
generate a random forest, the algorithm randomly selects
a subset of variables from all variables and generates
a classification tree based on each subset. For example,
pharmacy programs may be interested in predicting
whether an applicant will progress normally. When using
common variables such as applicant age, pre-pharmacy
science GPA, biology PCAT, and applicant’s highest de-
gree, the algorithm may select PCAT and pre-pharmacy
science GPA, and generate a tree based on only those
variables. In addition to randomly selecting variables,
the algorithm also randomly selects cases, such that the
randomly selected variables are only used to build a tree
on a subset of the cases. The predictions of the randomly
generated trees are then combined to produce a more gen-
eralizable estimate. Randomly generating and combining
trees improves generalizability because each tree only
produces estimates based on part of the data; hence there
is a great deal of variance in the trees. Since the trees are
unlikely to be dependent on one another (because they are
generated from a different set of variables) some will
overestimate the outcome and others will underestimate
the outcome; thus, their aggregate estimate should be an
accurate representation of the outcome in the population.
Consequently, this tree should generalize well. Analysts,
however, should still use training and test datasets or
k-fold cross-validation with random forests, and regres-
sion for that matter.

Classification trees also suffer from non-statistical
limitations in that they require advanced statistical train-
ing and programming ability. Most assessment staff do
not have this skillset. Additionally, classification trees
require very large datasets for optimal performance –
ideally 3,000+ cases. Most pharmacy colleges do not
have that many student records. If a college is large,
well-established, and has the necessary expertise, how-
ever, classification trees can be valuable tools.

**Example**

The classification tree in Figure 2 displays the rela-
tionship between enrollment status and several variables
available in pharmacy school applications. The tree can be
interpreted as follows: The zeroes and ones at the top of
each box show the outcome for the majority of applicants
in the group – every group in which at least 50% of the
applicants enrolled is labeled with a one. In the first box,
which represents the data before any splitting, there is a zero
in the top position because most applicants who were ex-
tended an offer did not enroll. The proportion indicates the
percent of people in each group who enrolled. In the first
box, the 0.48 means that 48% of students who were ex-
tended an offer eventually enrolled. Finally, the percentage
indicates the percent of all applicants who are in that group.
This number is 100% in the first box because it represents
all of the data before it is split into groups.

The box in the lower left corner of the tree represents
the information in which a school would be most interested
(ie, the type of applicant most likely to enroll). As shown,
36% of applicants with at least one bachelor’s degree
holding parent (ParentEd >= .5 is “yes”), who attended a
four-year college (FourYear >= .05 is “yes”) and earned
a pre-pharmacy GPA above 2.6 (PrePharmGPA > 2.6 is
“yes”) enrolled. Collectively, this group represented 50% of
all applicants. It should be noted that if a variable is
coded as 1 and 0, like parent education (ParentEd), the
software that generated the tree denotes splits by less than
or greater than 0.5. Less than 0.5 is “the group coded as 0”
whereas greater than 0.5 is “the group coded as 1.” In the
case of the classification tree in Figure 2 FourYear >= 0.5
is “no” means that the applicant did not attend a four-year
institution because “four year institution” was coded as 1.
When applied to the test set, the example tree predicted 70.6% of the cases accurately. To further improve the tree’s accuracy, researchers could include additional attributes (e.g., whether a student has a competing offer) or use a random forest. Accordingly, the random forest on the training data predicted 77% of the cases in the test dataset correctly. If the leadership (deans, associate/assistant deans, etc.) is comfortable with 77%, then the tree will be ready for use in admission decisions.

**CONCLUSION**

Categorization trees can be used to facilitate a variety of decisions across the pharmacy education spectrum. One potential use is developing a predictive model to aid in admissions decision as described by Muratov and colleagues. In this project, the authors developed a pharmacy school performance predictive model to identify applicants for interviews based on their likelihood of academic success. While the Muratov and colleagues’ model relies primarily on cognitive factors, such admissions models also can include non-cognitive factors that may expand the utility of the model for an institution. For example, to aid in identifying applicants who fit the school’s mission or, as illustrated in this paper, to identify applicants most likely to enroll, which in turn can inform the recruiting process. A potentially innovative use of categorization trees is in support of a school’s assessment of student APPE readiness as addressed in Standard 24.3 of ACPE Standards 2016. Determining APPE readiness is challenging because readiness includes skills commonly referred to as soft skills; students’ proficiency in these areas (or lack thereof) often does not manifest until they have begun APPEs. Examining data from relevant courses and experiences during the didactic years may allow for earlier identification of students who may need additional preparation prior to entering the APPE portion of the curriculum. Indeed, classification trees, and techniques like them, may be useful in any situation where prediction is required.

Classification trees are also very useful for exploratory analyses. For example, if an institution wishes to identify the demographic characteristics of struggling students, a classification tree could be a valuable tool. To this end, the authors of this commentary built a classification tree to visualize the relationship between application information: PCAT scores, pre-pharmacy math/science GPA, whether the student attended a four year institution, whether the student was from our region, age, and gender, and whether the student failed at least one class during their first year. While the results were not entirely surprising in that students with low pre-pharmacy math/science GPAs and low biology PCAT scores were more likely to fail a course than those with higher scores, the tree also indicated that students outside of the traditional age range (less than 22 or greater than 32) were prone to struggle. While this solitary tree should not be used for prediction, it uncovered a potential issue that may have otherwise gone unnoticed.

It is increasingly important that Doctor of Pharmacy programs develop methods for analyzing programmatic data in ways that facilitate decision making. Big data and associated analytics have already shown promise at universities...
that are willing to invest in them. After using big data analytics to identify at-risk students (and assign them to appropriate interventions), Georgia State University saw a 6% increase in graduation rate over three years, a half-semester decrease in the amount of time required to graduate, and better performance in STEM courses by first-generation students. While it was the school’s intervention that ultimately increased student performance and retention, the statistical models showed them were to target their efforts. Similarly, pharmacy programs can use tools like classification tree analysis to gain insight into their applicant pools and student performance in ways that go beyond traditional analyses.

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