Using Machine Learning and Predictive Modeling to Assess Admission Policies and Standards

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Abstract - Tennessee has recently updated its interpretation of *higher education access* to encompass not only college participation but *college completion.* Following suit, Tennessee has moved away from a university and college funding formula primarily based on headcount to one based on retention, progression, and graduation. This change has further incentivized administrators at public universities and colleges to better understand and discover ways to improve student retention. Fortunately, there is a swath of data available to administrators that may be helpful in predicting a student's success – particularly as it relates to retention. In many instances, factors affecting retention rates can be traced back to the institution's admission standards and policies. Determining *admissions success* considers the relationship between these standards and policies and the institution's retention rates. In this paper, we present predictive models we have built on data that is available at the time a student applies for college. In our experiments, we demonstrate results on five years of student data from a mid-sized university with a yearly enrollment over 11,000 students. The ultimate goal of this research is to build models on data available at the time of application to *predict* whether or not a student will be an *admission success*.

Introduction

If today's college administrators in Tennessee weren't already clamoring to find new ways to increase the rate of academic success at their institution, the Complete College Tennessee Act of 2010 (CCT) forced them to start. Access to higher education has historically been thought of as providing students with the opportunity (or admission) to study at an institution of higher education. CCT, following in the footsteps of Complete College America, essentially redefines access to higher education as not only providing students *admission* to an institution of higher education but also providing the continued support that enables the student to *graduate* from that institution. When considering the admission standards of an institution, it is certainly hoped that there is a high degree of correlation between these standards and a student's potential for academic success at the institution. For the purposes of this paper, we define *admissions success* to be an instance where an institution's admissions standards predict a student's academic success with relatively high accuracy. To put it simply, when an admitted student succeeds academically he is considered an *admissions success* For traditional college applicants, many institutions primarily use a student's high school grade point average and recent standardized test scores to determine admissibility while some other institution-specific requirements may be considered to some degree.

While a student's high school GPA and standardized test scores have historically proven to be quite reliable in predicting academic success, an institution can explore the idea that *other* institutional-specific factors may affect the reliability and validity of these more traditional factors. If we can isolate factors available at the time of a student's application that historically correlate with *academic success* at an institution, this would enable an institution to predict the likelihood of academic success before offering an admissions decision. These factors can then be used to reevaluate current admission requirements, serve to aid evaluators during an appeal to an admissions decision, or even inform intervention counselors of current students that may need additional assistance. Admissions standards that more accurately reflect student characteristics that correlate with academic success can offer numerous advantages: institutional, federal, and state resources spent on students with little to no chance of success (even with intervention) can be targeted to students with a higher probability of success; students might be less likely to deplete personal resources at an institution where they have no to low probability of success and might then attend another *better fitting* institution; graduation rates will increase giving the institution better rankings; and funding will increase due to increases in "Degree Per 100 FTE" and "6-Year Graduation Rate" (www.tn.gov/thec/Divisions/Fiscal/fiscal_affairs.html).

The purpose of this work is to not only identify which factors could be potentially useful for determining whether or not a college applicant is going to be an *admission success*, but also to lay out a *process* that is repeatable. Ultimately, this will allow other institutions to *predict* whether or not their applicants will be successful *using their own data*.

Admission Policies and Standards

As much as institutions strive to increase retention rates through programs and services for currently enrolled students, a strategic retention effort must also encompass an evaluation of the admissions policies and standards that ultimately determine which students have the opportunity to enroll. At the very least, these policies and standards should be aligned to student characteristics that indicate a relatively high potential for academic success at the institution. While true *admissions success* could be viewed as graduation, there are several factors that may impede a student from graduating from an institution. The State of Tennessee has chosen four benchmarks to indicate academic success at four-year institutions: the completion of 24, 48, 72 hours, and the completion of a bachelor's degree. *Admission success* conceptually increases with each benchmark. For the purposes of this research, it is necessary to establish a binary definition of success as opposed to *degrees* of success. Admissions success is defined in this research to be an admitted student's completion of twenty-four semester hours with a 2.75 college grade point average (GPA) OR an admitted student's completion of seventy-two semester hours. The first component of this definition of success aligns with the eligibility requirements of the state's lottery scholarship program while the latter includes students that do not meet the previous criteria due to issues acclimating to a college curriculum. This definition catches well-performing students that transfer out before seventy-two hours as well as students who will likely continue to graduation but experience a "rough start". The graduation benchmark was not used due to the idea that many other factors apart from academic ability might prevent success before this final benchmark is reached. It is the aim of this paper to detail one institution's effort to determine which elements available at the time of a student's application predict a reasonable level of admission success for traditional freshmen. The institution's current admission standards to freshman standing are a 2.5 high school GPA with a 17 ACT composite score OR a 2.0 high school GPA with a 19 ACT composite score. In each case every ACT sub-score must be at least 15.

Machine Learning and Predictive Modeling

The process of *machine learning* (and data mining) is concerned with the discovery of patterns in data. Using the knowledge gained in the process allows one to adjust their actions accordingly. Tom Mitchell defines machine learning as a field of study that is "concerned with the question of how to construct computer programs that automatically improve with experience" (Mitchell 1997). Current real-world examples of this are numerous, including viewing recommendations on Netflix (www.netflix.com), shopping recommendations on Amazon (www.amazon.com), and Facebook's News Feed which is based upon the user's personal interactions with other users (www.facebook.com).

There are several different types of machine learning algorithms, primarily of which are the following: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. For the purposes of this work, we were only concerned with *supervised learning* – or more generally, the learning of a model from labeled data (Mohr et al. 2012). Specifically, we are interested in *predictive modeling* which in broad terms is the use of historical data to identify a targeted goal (Wikipedia). The field of predictive analytics is used in a wide variety of areas including (but certainly not exclusive to) marketing (Fletcher 2011), healthcare (Stevenson 2011), and financial services (Korn 2011). The objective is to extract information from data and use that knowledge to predict trends and behavior patterns.

In our work we are concerned with predicting admissions success at our university given certain student characteristics available at the time of the student's application. If accurate predictions are possible, then the rate of admissions success (see above definition) could be increased with targeted actions. In Section 2 we present previous work in predictive modeling as it pertains to college admissions. In Section 3 we present the data that we used along with the data mining processes that were used to prepare the data for analysis. Section 4 discusses the experiments that were conducted and Section 5 presents the results and our analysis of the data. We then conclude the paper with some final observations and our plans for future work.

Related Works in Admissions Predictive Modeling

Recently, the College Board performed a statistical analysis of SAT scores to determine the potential success of a college-bound student (Patterson et al. 2012). In this work, their goal was to predict the first-year GPA of students based solely upon the SAT scores taken during high school. What they discovered was that each of the test scores, whether they took them multiple times or not, had equal predictive weight for determining college GPA. This approach, however, was purely statistical in nature (predicting a GPA) and was not based upon our definition of admissions success.

Similarly, Fu examines the effectiveness of traditional admissions criteria at a large, public university (Fu 2012). Using regression techniques, she determines that high school GPA is the most predictive of first-year college GPA. While this study provides some correlation between more data points such as high school GPA, SAT, and TOEFL scores (for international students), the ability to address overall admissions success was not a goal.

Other works have dealt with a variety of specific attributes associated with determining the potential success of college-bound students. Some have put forth differing approaches to testing the students – everything from psychological tests (Bailey 2003) to behavioral ones like the Rainbow project that attempts to remove socio-economic and racial barriers (Sternberg 2012). Other ideas have included decision support systems to help students, who have already been admitted into college, predict their own academic success (Mellalieu 2011).

What we will present in the following sections is not only the steps for predicting college admissions success, but also a predictive approach that takes advantage of machine learning methodologies that have demonstrated success in a myriad of other domains.

Student Admissions Data

Our hypothesis is that machine learning algorithms can aid in the prediction of student admission success at an institution of higher learning, where the process is not specific to the institution. In other words, the same algorithms and steps that we took to predict the success of students admitted to our institution can be used elsewhere. In broad terms, the machine learning algorithms are part of an overall *data mining* process. Data mining is the process of collecting, filtering, storing, and processing data in support of some analytical objective (Han and Kamber 2006). Machine learning is the application of algorithms to a set (or subset) of data for the purposes of performing the analytical step (Mitchell 1997).

The following sections briefly discuss the data mining steps that we took to *pre-process* the data for eventual predictive capabilities.

Data Collection

We were provided with student data from the University's student information system (SIS) from the Fall 2008 to the Spring 2012 semesters. This information was provided in an Excel file, containing 52,717 records, with each record representing one student. Each record has 454 fields, representing data from areas within the SIS.

Data Filtering

The provided data file included data from both applicants and enrolled students at the University. Those that were not accepted or simply did not enroll were filtered out. Graduate and transfer students were also filtered out in order to be examined at a later time. Since traditional (under 21 years of age) freshman represent the largest population of student at the University, our initial efforts focused exclusively on these students. We also threw out a few other records (although not very many), where field values were anomalous - perhaps due to operator input error. For example, we examined the maximum, minimum, total, and average values of the fields like ACT score, SAT score, and GED score. This helped us identify outliers, such as a 60 grade point average for GED students. Finally, we focused on students who were only full-time (i.e., took at least 12 hours of course work each semester in which they enrolled). In the end, there are 1,585 records that meet our selection criteria from the Fall 2008 traditional freshmen cohort. The Fall 2008 cohort was chosen to allow these student ample time to reach 72 earned hours. Additional cohorts will eventually be added to build more robust models that can be applied more broadly. Any conclusions from this initial data should be limited to the Fall 2008 cohort until more cohorts can be added.

Classification

Over the course of this work, we experimented with several *success* metrics. These were based on state and university definitions of retention -- specifically the popularity of fall-to-fall retention metrics -- as well as collective decisions about what constituted *success*. After some fine-tuning and experimentation, the final definition of *admission success* is as follows: A student who has a college GPA of 2.75 or higher AND completes (earns) 24 hours at the university level; OR a student who completes (earns) 72 hours at the university level. A student who satisfies either of those requirements is considered an *admission success*. The first component of this definition of success aligns with the eligibility requirements of the state's lottery scholarship program while the latter includes students that do not meet the previous criteria due to issues acclimating to a college curriculum. This definition catches well-performing students that transfer out before seventy-two hours as well as students who will likely continue to graduation but experience a "rough start". The graduation benchmark was not used due to the idea that many other factors apart from academic ability might prevent success before graduation is reached. The data that was provided included attempted hours and earned hours with the semester GPA for each term the student was enrolled as well as cumulative quality hours and points with a calculated GPA at each semester. To classify successful students for the first definition of success, cumulative GPA was examined at each semester and recorded if the student's quality hours were 1 or greater but also 36 or less. The latter definition of success was tracked by summing a student's earned hours for each semester the student enrolled. Extracting quality hours for each semester the student is enrolled may increase the accuracy of classifying students into the first definition of success.

This placed each of our students in one of two groups: *admission success* students ("Y") and non-*admission success* students ("N"). This classification system allowed us to analyze the data for both groups of students to find patterns and trends for each group.

Experiments

As stated above, we had access to data from all students who applied to the University from Fall 2008 to Spring 2012. For a student who merely applied to the University, we had access to the student's application data (name, gender, address, application date, high school information - ACT scores and GPA, and more). For students who enrolled at the University, we had access to University information such as attempted and earned hours by semester, major, cumulative college GPA by semester, and more in addition to the aforementioned data.

With this data -- specifically cumulative college GPA and cumulative earned hours by semester -- we determined whether or not a student was an *admission success*, as defined above, and indicated it accordingly. After each student was classified as an *admission success* "Y" or "N", we began to run a series of tests using the WEKA software package. These tests consisted of pulling certain attributes we were interested in from our database, cleaning up that data, and feeding it to WEKA in order to generate certain rules for the selected attribute(s).

Data Cleaning

In order to get accurate and worthwhile results, we need to "clean" the data that has been collected and processed (see previous section). The raw data needs to be formatted, bounded in some cases, and resolved (e.g., make sure that all fields are accurate - in other words, remove the "garbage") before feeding it to WEKA. The most common issue is the lack of an attribute for a particular student. For example, some students do not have an ACT score for whatever reason (an international student, the student substituted an SAT score, etc.). In the cases where we are interested in ACT scores, those students would be excluded. Similar logic was followed for many of the others fields in our data set. For example, if we are interested in looking at students' composite ACT scores, high school GPAs, and application dates in relation to their *admission success* classification, all three of those fields would need to be populated (not null) in a student's record order for that particular student to be included in our analysis.

Other data cleaning steps include formatting changes and type conversions, such as when we need to compare different data types (a MM/DD/YY date compared to a MM/DD/YYYY date as simpler example) to each other. Bounding certain attributes is also necessary in some cases such as making sure GPAs higher than 5.0 are not included in our analysis.

Again, we decided to use traditional, full-time (i.e., taking no less than 12 hours per semester) freshmen ONLY when conducting our experiments and analysis because A) this is the largest and most critical subset of students at the University studied here; and B) it allows us to compare students of diverse backgrounds while still having a consistent baseline for comparison. In other words, we were able to compare "apples to apples" and "oranges to oranges". A student's status as a traditional freshman was indicated by a particular value in a *student type* attribute, and in conjunction with a *cohort term* attribute we were able to determine each student's first semester of study.

WEKA

Once we clean the data in which we are interested, accomplished almost exclusively using SQL commands against the data stored (see previous section), we export the table containing the data to a .csv file (i.e., comma-delimited text file). This file is then imported into the WEKA tool.

We chose to experiment with a variety of machine learning algorithms for classifying and predicting which students would be successful and which ones would not. However, in order to be intuitive (and practical) for admissions personnel, we decided to use WEKA algorithms that would produce understandable rules: Simple CART, J48, and JRip. The Simple CART algorithm is a version of the famous CART algorithm which uses a minimal, cost-complexity pruning strategy to improve classification (Breiman et al. 1984). The J48 algorithm is a version of the famous C4.5 algorithm (Quinlan 1993). In short, the C4.5 algorithm uses training data (in our case, student records) to build a decision tree capable of predicting the class to which a data element belongs (in our case, admissions success or not admissions success). C4.5 does this by analyzing the records at each node in the tree to determine which attribute splits those records in subsets that best improve the decision tree's ability to predict class membership. The JRip algorithm is based upon the RIPPER (Repeated Incremental Pruning to Produce Error Reduction) approach which is a propositional rule learner (Cohen 1995).

Results and Analysis

First, let's take a look at the rules generated from running the **Simple CART** algorithm on the data defined in the previous section:

1. IF (high school GPA < 2.545), student is likely **NOT** to succeed.
2. IF (high school GPA < 3.035 and >= 2.545) AND
   (applied days from first day of class < 276), student is likely **NOT** to succeed
3. IF (high school GPA >= 3.035) AND
   (applied days from first day of class < 276), student is likely to **SUCCEED**
4. IF (high school GPA >= 2.545) AND
   (applied days from first day of class >= 276), student is likely to **SUCCEED**
5. IF (high school GPA > 3.34), student is likely to **SUCCEED**

The advantage of these rules is that they are simple to understand. However, they do not provide as much detail or insight as one would like (as will be shown with the next set of experiments). From these rules, one would gather that low high school GPAs and late application dates do not contribute to academic success. With the Simple CART algorithm (using default settings), we are able to *correctly classify* students 70.8% of the time. In fact, our true-positive accuracy (i.e., how often we predict that a student will succeed and they do succeed) is 84.6%. However, our overall accuracy is diminished when we attempt to classify those students that we believe will not succeed, as we are only accurate 57.4% of the time.

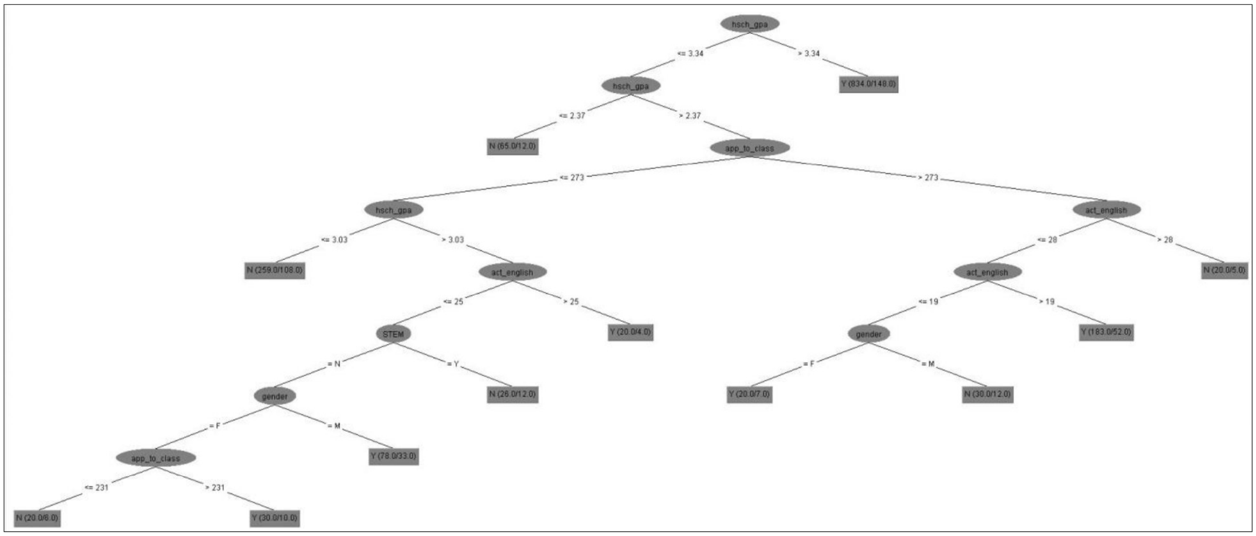

Figure 1: Decision tree from J48 experiment

Figure 1 shows the decision tree that resulted from running WEKA's **J48** algorithm on the data defined in the previous section. From this tree (and the corresponding textual output produced in WEKA), we are given the following rules and classifications (compiled for clarity):

1. IF (high school GPA <= 2.37), student is likely **NOT** to succeed
2. IF (high school GPA > 3.34), student is likely to **SUCCEED**
3. IF (high school GPA > 2.37 and <= 3.03) AND
   (applied days from first day of class <= 273), student is **NOT** likely to succeed
4. IF (high school GPA > 3.03) AND
   (applied days from first day of class <= 273 and > 231) AND
   (ACT English <= 25) AND (NOT a STEM major) AND
   (gender = Female), student is likely to **SUCCEED**
5. IF (high school GPA > 3.03) AND
   (applied days from first day of class <= 231) AND
   (ACT English <= 25) AND (NOT a STEM major) AND
   (gender = Female), student is likely **NOT** to succeed
6. IF (high school GPA > 3.03) AND
   (applied days from first day of class <= 273) AND
   (ACT English <= 25) AND (a STEM major), student is likely **NOT** to succeed
7. IF (high school GPA > 3.03) AND
   (applied days from first day of class <= 273) AND
   (ACT English <= 25) AND (NOT a STEM major) AND
   (gender = Male), student is likely to **SUCCEED**
8. IF (high school GPA > 3.03) AND
   (applied days from first day of class <= 273) AND
   (ACT English > 25), student is likely to **SUCCEED**
9. IF (high school GPA > 2.37) AND
   (applied days from first day of class > 273) AND
   (ACT English <= 19) AND (gender = Female), student is likely to **SUCCEED**
10. IF (high school GPA > 2.37) AND
    (applied days from first day of class > 273) AND
    (ACT English <= 19) AND (gender = Male), student is likely **NOT** to succeed

11. IF (high school GPA > 2.37) AND
    (applied days from first day of class > 273) AND
    (ACT English <= 28 and > 19), student is likely to **SUCCEED**
12. IF (high school GPA > 2.37) AND
    (applied days from first day of class > 273) AND
    (ACT English > 28), student is likely **NOT** to succeed
13. IF (high school GPA > 3.34), student is likely to **SUCCEED**

One may notice that rule 12 seems counter-intuitive. This is most-likely due to the small population sizes associated with this rule (20 students). Even though their high school GPA could be low, and they applied ~9 months out from the first day of classes, you would think an ACT English score greater than 28 would indicate a better than average student. This type of noise is to be expected with smaller populations such as this.

With the J48 algorithm, we are able to *correctly classify* students 69.7% of the time (slightly less than JRip). However, our true-positive accuracy is similar at 84.3%, and even this algorithm is slightly better at 62.2% when attempting to classify those students that we believe will not succeed.

While we used mostly default settings and parameters for the J48 algorithm, we did adjust the *minimum number of objects* value. This parameter defines the minimum number of instances per leaf. In other words, for a student to be classified as a success/non-success *for a specified rule*, there must be at least 20 students. We found that when we chose a lower value, the tree was not as manageable, as various small (and statistically insignificant) groups of students were "skewing" the rule generation. Conversely, a value higher than this results in the generation of a rule based solely on high school GPA.

Finally, let's take a look at the rules generated from running the **JRip** algorithm on the data defined in the previous section, which produces some other interesting rules:

1. IF (high school GPA <= 2.64) AND
   (ACT English >= 23), student is likely **NOT** to succeed
2. IF (applied days from first day of class <= 262) AND
   (high school GPA <= 2.96) AND
   (ACT Reading >= 21 and <= 23) student is likely **NOT** to succeed
3. IF (applied days from first day of class <= 284) AND
   (highest composite ACT <= 21) AND
   (high school GPA <= 2.54), student is likely **NOT** to succeed
4. IF (applied days from first day of class <= 298) AND
   (high school GPA >= 2.86 and <= 3.11), student is likely **NOT** to succeed
5. IF (high school GPA <= 3.6) AND
   (applied days from first day of class <= 272) AND
   (ACT English <= 20) AND
   (highest composite ACT >= 20), student is likely **NOT** to succeed
6. IF none of the rules above apply, student is likely to **SUCCEED**

It is apparent that this model did not do as well to filter out noise as the other models. The rules detailed in 1, 2, 4, and 5 each contain some rather counter-intuitive reasoning. For example, students that have a 2.64 or lower high school GPA will be successful unless they have a 23 or *higher* English ACT sub-score. Rule 3 is reasonable given past research, however, in that students that apply less than ~9 months before classes with a 21 or less ACT composite scores and a 2.54 or less high school GPA are likely not to succeed. Although these rules do reveal factors that are significant to admissions success they are not easily translated into practical action.

We also did some simple analysis outside of WEKA with a pair or particularly important attributes: *composite ACT* score and *high school GPA*. As stated above, it has been shown that high school GPA is the most important factor in determining first-year success at a university. With this in mind, we grouped students by high school GPA (after cleaning the data as described above) and plotted the GPAs against the percentage of students in each group classified as an *admission success* "Y", as shown in Figure 2.

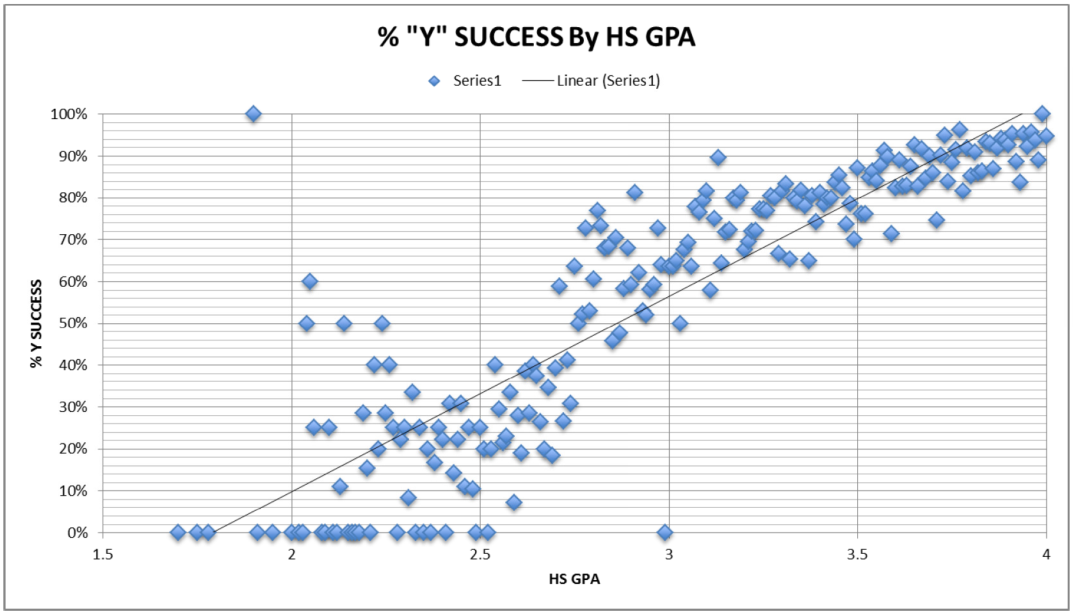

Figure 2: Success based upon High School GPA

From the figure, we can see that students with lower high school GPAs are far less likely to succeed (by our definition of success) than those with higher high school GPAs. The higher amount of fluctuation and "0% success" (as well as the lone "100% success") in the low-end GPAs are due to there being a much smaller number of students with GPAs in that range; there are only seven students with a high school GPA below 2.0, and only 330 with a high school GPA below 2.5.

We also decided to plot the same graph with composite ACT scores rather than high school GPA, which is shown in Figure 3. Again, it is shown that students with lower composite ACT scores are less likely to succeed than those with higher composite ACT scores.

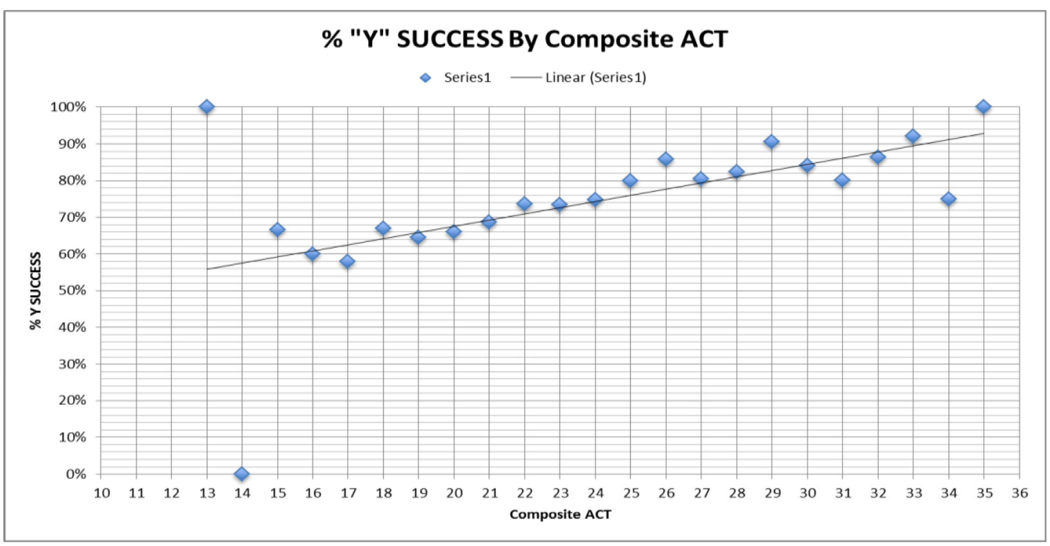

Figure 3: Success based upon composite ACT score

Conclusions

It has been shown that predicting *admissions success* for traditional freshmen via machine learning and predictive modeling is possible with a relatively high degree of accuracy. The established rules can be utilized in various ways when rerun with multiple cohorts including but not limited to: refining the current admission standards for incoming traditional freshmen, assisting committees and admissions personnel with appeals to admissions decisions, and assessing the level of intervention necessary for current students. It could also be reasonable to use machine learning results such as these to better utilize performance based funding models. The data presented here shows that some sort of action may be necessary to address the lack of success for students with less than a 2.55 high school GPA. Determining the specific actions that need to be taken will require coordination with the University's faculty and staff. These actions could include modifying the current admissions standards (after board approval) and increasing intervention efforts for currently enrolled students. It is also interesting that the students' English sub-scores on the ACT were often the next most significant factor to success after high school GPA and application date. Another element of this data that needs further exploration is that students with a 3.03 or less high school GPA are not successful if they apply over about 9 months from the first day of class regardless of other factors. Conclusions from this aspect of the data could lead to staggered admission standards during the application cycle (whether published or not). This data could also aid admissions personnel in determining the result of applications from students with marginal credentials. Future research will be performed on other populations of students (adult-learners and transfer students) in an attempt to draw similarly helpful conclusions for these populations. As data mining capabilities increase on campus, it is also foreseeable that other student attributes could be added in hope of increasing the accuracy of models, particularly to guard against false negative predictions.

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