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Novel Technique for Analyzing the Effects of Cognitive and Non-Cognitive Predictors of Student Course Withdrawal in College

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Abstract

In this study, the author applied a novel technique to a database of college students to identify the cognitive and non-cognitive factors that predict college students' course withdrawal behaviors. The author analyzed predictors such as high school grade point average (HSGPA), standardized test scores (ACT–American College Test or SAT-Scholastic Aptitude Test), number of credit hours enrolled in during the current semester, previous credit hours passed, college CGPA until current semester and number of hours withdrawn, gender, and age. Data mining software algorithms were used to study information about undergraduate students at a west-south-central state university in the US. The study results revealed that two factors, number of enrolled credit hours and a student's age, had the largest effect on collegiate course withdrawal behaviors, irrespective of HSGPA and standardized test scores. Other researchers have discovered similar results when they applied t-test, simple regression, multiple regression, and discriminant analysis tools. Lastly, the empirical analysis showed that the data mining technique outperformed alternatives. These techniques can be applied to similar studies on college student databases and can be a suitable instrument for administrators of the colleges.

Introduction

Each semester of an academic year, a substantial proportion of students withdraw partially or entirely from their courses. The major consequences of withdrawals include delaying graduation, lengthening the total time for education, and wasting university resources such as faculty underload, computing labs, library resources, and other support services. In this study, the author considered two scenarios: 1) it is in the students' best interest to complete a course if they have a higher chance of earning a final grade of 'D' or better, and 2) the student completed the course but earned an 'F', in which case withdrawal would have been a better decision. Some college administrators believe that course withdrawals are the result of the university failing to meet the needs of its students. Another view of this topic is the effect from students' financial or personal problems (Lucier, 2019). Overall, this is a complicated mix of cognitive and non-cognitive variables that cause students to drop courses within days of beginning them. Predicting student success is really a process of determining what group that individual feels is most appropriate. In general, a student's academic skill set and drive are the most important factors when avoiding withdrawal and doing well academically. The skill set may include self-belief, critical self-reflection, independent learning, self-management, social skills, dealing with stress, critical thinking, academic ability, and information literacy (McMurray, 2011; Moore, 2004; Morisano, Peterson, Shore, Hirsch, & Pihl, 2010; Muris, 2001; Schunk, 2003).

Cognitive traits such as persistence and motivation are also crucial. There are socioeconomic and health-related factors that can cause withdrawals, such as family crises, financial aid loss, personal or family illness, work schedule, inadequate internet access, and unanticipated job opportunities. In this study, the author assumed that such determinants could not be controlled by the students themselves and did not reflect on their academic prowess. The motivation of using data mining techniques to analyze information from a 10-year cohort of undergraduate students came from the inherent definition of the term. Data mining involves discovering new knowledge from databases. The findings may be unpredictable from the database. Also, there are no implicit assumptions that the underlying relationships between the predictors and the dependent variables are linear or non-linear link functions or monotonic.

Previous studies indicated that standardized tests such as the American College Test (ACT) or the Scholastic Aptitude Test (SAT) were poor predictors of student success (Mirchandani, Lynch, & Hamilton, 2001; Carter, Bryant-Lukosius, DiCenso, Blythe, & Neville, 2014; Markert & Monke, 1990; Ebmeir & Schmulbach, 1989). In this current study, the author used seven additional variables along with test scores, as the database contained complete information of these factors. Additionally, literature was available on these factors as well, which enabled valid comparisons with findings of this work. These variables included age, gender, high school grade point average (HSGPA), credit hours taken (HRTK) during the current semester, previous credit hours passed (HRPS), college CGPA up until current semester, and number of hours withdrawn. Usually, studies with data sets similar to the one used in this current study use statistical techniques such as linear regression, multiple regression, and discriminant function analysis. Unfortunately, research utilizing data mining techniques to predict student course withdrawal behaviors is scant. Accordingly, two algorithms of data mining—the decision tree and association rule—were applied to this study.

Gadzella, Stephens, and Baloglu (2002) used linear regression analysis to study the effects of non-cognitive predictors, such as age, and cognitive predictors, such as learning style, on the academic performance of 105 students at a southwestern state university. The authors saw significant differences among age groups on course grades and withdrawal patterns. The oldest age group (34 to 57 years) performed the best and had the highest level of compliance in the study. Wolfe and Johnson (1995) used multiple regression analyses to identify SAT, HSGPA, and 32 personality factors to predict the college performance of 201 students at the State University of New York in Geneseo. They concluded that the following factors had the greatest effect: HSGPA (accounting for 19% of the variance), self-control (9%), and SAT (5%). It is notable that self-control was a function of age and number of attempted credit hours. Similarly, another researcher used multiple regression in a study of 505 freshmen at Portland State University to predict college performance with HSGPA, SAT scores, and age (Swiatek, 2007). That study revealed that non-traditional students aged 20-33 had a better perception about their courses and workload than traditional-age students of 19 and younger, considering how the former cohort had significantly lower HSGPA than the latter.

Kyoshaba (2009) used a Pearson products moment correlation statistical tool on survey data from a random sample of 340 undergraduate students at Uganda Christian University. There was a significant relationship between student HSGPA and standardized test scores with their academic performance. However, there was no relationship between the students' age and academic performance. Ting and Bryant (2001) used discriminant analysis to predict student retention at a southeastern comprehensive public university. Their analysis was a stepwise procedure that showed how acquired knowledge in a field was the only predictor for fall semester retention, whereas family influences and successful leadership experience were significant predictors for spring semester retention. Miller, Ryceka, and Fritsona (2011) adopted descriptive statistics, such as mean and standard deviation, and comparative statistics, such as an independent t-test (SPSS), on a student database. They found that high levels of classroom attendance and attentiveness increased a student's odds of remaining in a class.

In academia, student success has been one of the primary conversations on campuses across the world. Educational consideration, such as academic performance, is one of the most important attributes for student success. The earlier faculty or academic advisors identify students who are struggling academically, the better they are able to help those students get back on track before they are forced to withdraw from courses. That begs the question, which students are most likely to withdraw from their courses? And, what are the appropriate attributes for predicting student course withdrawal? The author developed this study in order to answer these questions. Additionally, the author aimed to create a robust and easy-to-understand data mining model for predicting student course withdrawal behaviors.

Materials and Methods

Many colleges collect more data than they actually need for an analysis. Some examples of information gathered include age, gender, birth year, high school location, high school GPA, high school graduation status, ACT and SAT scores, parents' education level, major, college GPA in each semester, withdrawal from courses in each semester, household size, parents' annual gross income, student's marital status, admission date, attempted hours, and number of remedial courses. In this current study, the author used data from 8208 students, who were in a ten-year cohort at a west-south-central state university of the US, and examined a set of eight attributes of each student. The data had adequate statistical power to analyze and derive predictions about the students.

In this study, the data from these 8208 students were partitioned into three groups, based on their major field of studies: 2156 students were science or engineering majors, 1232 students were non-declared majors, and 4820 students were non-science or non-engineering majors. The Records and Registration Department of the west-south-central university employed Oracle database software to store and process information generated from student records. In addition, it holds student enrollment and progress data. Structured query language (SQL) was used to extract data from the eight attributes for the 8208 students and transferred them into Excel files. In relational database management systems, SQL is used to communicate with a database. Thereafter, the data mining software imports data from these *Excel* files, which can them be mined by decision tree and association rules.

The author utilized a novel data mining technique to analyze information. There are numerous commercial or non-profit data mining software programs to choose from. For this study, the author used Waikato Environment for Knowledge Analysis (WEKA) (2018), a well-evaluated, openly available data mining software package. This application was adopted in order to accomplish this data mining study. WEKA is an assortment of computation algorithms for data mining activities and can either be functional to a dataset or called from programmer's own Java code. WEKA inherently uses several interfaces for pre-processing, classification, regression, clustering, association rules, and visualization of data, and is also well-matched for creating new computational schemes.

Data Mining Techniques

The author used two data mining algorithms, the decision tree and association rule. The association rule is effective for finding patterns of highly associated attributes. The decision tree is most effective for characterizing patterns of difference classes. Generally, the results from the decision tree, which are called decision rules, are easier to interpret than those from the association rule. However, due to its technical limitation, the decision tree may not always produce valid results for a skewed distribution.

Classification by Decision Tree

Data classification, which can be done in a controlled learning application, includes outcome rules or decision trees that screen the given data into predefined classes. For any representative problem in the realm of classification-rule learning, the conventional decision tree is very large is difficult to search exhaustively. In fact, the computational complexity of finding an optimal classification decision tree is NP hard (non-deterministic polynomial time hard). Figure 1 shows the basic steps of the decision tree algorithm (Han, Kamber, & Pei, 2011).

Input: The training *samples* are represented by discrete-valued attributes; the set of candidate attributes is the *attribute list*.
Output: A decision tree.
Steps:
(1) create a node *N*;
(2) **if** *samples* are all of the same class, *C* **then**
(3) return *N* as a leaf node labeled with the class *C*;
(4) **if** *attribute-list* is empty **then**
(5) return N as a leaf node labeled with the most common in *samples*; // majority voting
(6) select *test-attribute*, the attribute among *attribute-list* with the highest information gain;
(7) label node *N* with *test-attribute*;
(8) **for each** known value a_i of *test-attribute* // partition the samples
(9) grow a branch from node N for the condition *test-attribute* = a_i;
(10) let s_i be the set of *samples* in samples for which *test-attribute* = a_i; // a partition
(11) **if** s_i is empty **then**
(12) attach a leaf labeled with the most common class in *samples*;
(13) **else** attach the node returned by Generate decision test (s_i, *attribute-list-test-attribute*);

Figure 1. Decision tree algorithm.

Classification by Association Rule

An association rule suggests firm connotation associations among a group of objects (such as "happen together" or "one infers the other") in a database. A set of certain transactions, where each transaction is a set of literals (items), the association rule will find a countenance of the form X→Y, where X and Y are sets of items. The spontaneous sense of such a rule is that transactions of the database that contain X are inclined to hold Y. An example of an association rule can be: "35% of transactions that contain steak also contain sauce; 3% of all transactions have both of these items". Here, 35% is called the confidence of the rule, and 3% is the support of the rule. The delicate part of this procedure is to find all association rules that placate user-specified, least support, and least confidence limits. Figure 2 shows the pseudo code of the Apriori algorithm (Tang, Chuang, Hsi, Lin, Yang, & Chang, 2013).

Function apriori-gen (L_{k-1})
set $C_k \leftarrow 0$
for (all $L_{k-1}.item_p$, $L_{k-1}.item_q$, $L_{k-1}.item_p[i] = L_{k-1}.item_q[i]$, $\forall i \in \{1,\ldots, k-2\}$)
$c = \{L_{k-1}.item_p[1],\ldots, L_{k-1}.item_p[k-2)], L_{k-1}.item_p[k-1], L_{k-1}.item_q[k-1]\}$
if ($\forall L_{k-1}.item \subset c$)
$C_k \leftarrow C_k \cup c$
end if
end for
end Function

Figure 2. Pseudo-code of the Apriori algorithm of association rules.

Results and Findings

The main goal of this study was to determine predictors for student course withdrawal behaviors. The author attempted to understand which groups of students were more likely to withdraw from one or multiple courses, because dropping classes was a potential indicator of academic performance. For example, the authors believed that a student withdrawing from multiple courses may indicate difficulty in keeping up with coursework. Students who have problems with class assignments and exams can get assistance from the university though services such as tutoring, counseling, advising, and mentoring. Generally, there are different withdrawal patterns from advanced courses based on a student's major. For instance, the degree of preparation in pre-college algebra or trigonometry can have a significant impact on an engineering student's withdrawal from differential calculus; however, this may not be the case for a liberal arts student. To identify the college performance patterns for different students, the author partitioned the students into three groups: students of science or engineering, non-declared majors, and non-science or non-engineering majors. There may be other ways to set student groups, but the author adopted this method for simplicity of handling the current database.

For each group of students, the experiment on withdrawal investigated the relationship between withdrawal and a set of selected cognitive and non-cognitive variables, including age, gender, major, HSGPA, SAT total score or ACT composite score, college CGPA, credit hours enrolled or taken

(HRTK), and withdrawn during any semester. The patterns obtained from this procedure can be used to predict freshman student performances. The university may also use these patterns to improve student recruitment and retention. For each experiment, if the decision tree algorithm had a valid result, the author only presented that result, as it was easy to understand; otherwise, the result from the association rule algorithm was presented. The thresholds for minimum support and confidence of the association rule algorithm were set to 0.05 and 0.7, respectively.

Students with Science or Engineering Majors

For this group of students, no valid result on withdrawal was generated from the decision tree algorithm. However, the association rule algorithm did generate a set of rules. Among them, two rules described patterns of withdrawal, while the rest described patterns of non-withdrawal. The following rules show the withdrawal pattern.

1. No students with 2 ≤ HSGPA< 3 and 12 ≤ HRTK<15 ever withdrew from a class.
2. No students with 18 <age ≤ 19, 12 ≤ HRTK<15, and 20≤ ACT score <20 ever withdrew from a class.

A specific observation in the data mining results showed that 66% of female students majoring in biology had at least one course withdrawal during the academic year. The overall finding of this group showed that only 17% of students majoring in science or engineering disciplines may have withdrawn in their entire college life.

Students with Non-Declared Majors

The contingency Table 1 shows that withdrawal is related to three categorical variables, HRTK, CGPA, and age, and reveals an interesting pattern. When taking between 9 and 15 credit hours, and with a CGPA greater than 3.0, a student is less likely to withdraw from enrolled classes (from 70% to 82% confidence).

Table 1. Withdrawal patterns of non-declared major students.

HRTK	CGPA	Age	Withdrawn	Confidence level
HRTK<=3	CGPA <2	age ≤ 19	No	84%
		20 ≤ age ≤ 39	Yes	70%
3< HRTK <=6	NS*	age ≥ 40	No	72%
6< HRTK <=9	CGPA ≥ 3	NS*	No	70%
9< HRTK <=12			No	77%
12< HRTK <=15			No	82%

* NS represents a statistically non-significant ($\alpha = 0.05$ and $p > 0.05$) value of the attribute found by data mining that had no influence on prediction.

The more credit hours taken by students with a high CGPA, irrespective of age, the more confidence they have in passing their classes. Moreover, non-declared students, who are older than 40 years and enrolled in one or two classes, usually do not withdraw (association rule's confidence level was 70%). Student registered for ≤ 3 credit hours with a CGPA ≤ 2.0 and between 20 and 39 years of age are 70% likely to withdraw from their courses. One way to explain this finding is that such students are unsure about their course of study or attending college in general.

Students with Non-Science and Non-Engineering Majors

Like Table 1, the contingency Table 2 demonstrates that course withdrawal is related to three categorical variables: HRTK, CGPA, and age. When taking 9-15 credit hours, and with a CGPA greater than 3.0, student are less likely to withdraw from classes (with 79% to 97% confidence). When enrolled in one or two classes, non-science and non-engineering majors with low CGPA ≤ 1.0 and ≤ 21 years of age are more likely to withdraw from course(s). It appears that this group is more vulnerable to dropping out of college and is in greater need of counseling and advising.

Evaluating Data Mining Results with ANOVA

The results shown in Tables 1 and 2 can be further evaluated using a statistical analysis of variance (ANOVA) technique. Association rule prediction showed that with withdrawal, the dependent variable was associated with three categorical independent variables: HRTK, CGPA and age. A three-way ANOVA determined a statistically significant relationship among HRTK, CGPA, age, and withdrawal $F(2, 8205) = 11.05$, $p < 0.001$, $\eta^2 = 0.50$. The strong point of this relationship, calculated by η^2, was solid for HRTK, which accounted for 50% of the variance in course withdrawal. From the results of the three student groups, the classifications by the decision tree can be summarized in a series of logical if-then conditions. The decision tree method of data mining does not require the implicit assumption that there are underlying relationships between the predictor variables and dependent variable, just like t-test, regression analysis, or descriptive statistics. In statistics, the generalized linear model generalizes linear regression by allowing the linear model to be related to the response (dependent) variable via a linear or non-linear link function and by allowing the magnitude of the variance of each measurement to be a function of its predicted value (Dalgaard, 2007). However, classification by the association rule method showed that all existing relationships in the database placate to a level of least support and least confidence constraints. The target of information finding is not pre-determined in association rule mining like it is with decision tree.

Table 2. Withdrawal patterns of non-science and non-engineering major students.

HRTK	CGPA	Age	Withdrawn	Confidence level
HRTK ≤ 3	CGPA<=1	18 ≤ age ≤ 21	Yes	72%
		22 ≤ age ≤ 24	No	67%
		25 ≤ age ≤ 29	No	81%
		age ≥ 35	No	83%
3< HRTK ≤ 6	CGPA ≥ 3	NS*	No	87%
6< HRTK ≤ 9			No	79%
9< HRTK ≤ 12			No	87%
12< HRTK ≤ 15			No	94%
HRTK>15			No	97%

* NS represents a statistically non-significant ($\alpha = 0.05$ and $p > 0.05$) value of the attribute found by data mining which had no influence on prediction.

Analysis of the study results showed that the most important attributes to academic performance are as follows: student academic factors (CGPA, HRTK) and cognitive attributes. Older (age>19) science or engineering majors with reasonable course loads (HRTK<15) had the lowest probability of course withdrawals. Course loads (HRTK), using number of credit hours as a metric, had a positive association with school withdrawal for both non-declared, non -science, and non-engineering major students. Academic advisors and counselors can apply the study's findings when planning course schedules that move students towards a simpler, easier route to graduation.

Student academic performance (CGPA) in the previous semester influenced whether they withdraw from courses in the current semester. For example, students with a high ratio of passed units to enrolled units in the previous semester were less likely to withdraw in the current semester. As expected, high numbers of failed or incomplete courses were associated with a higher risk of course withdrawal. Teaching evaluations and peer-to-peer faculty observations are the foremost tools for finding the root causes of these risky courses. Reorganizing the teaching pedagogy of these courses may overcome bottlenecks and save institutional resources.

Limitations of the Study

At this point, it is necessary to recognize certain limitations of this study. For example, there were other variables, such as parents' education, household size, wage earning, parents' annual gross income, marital status, dependency status, developmental courses required, that could have been studied. The authors perceived that analyzing the impact of these variables would have been useful, but faced limitations: 1) an extensive search showed virtually no studies that applied these additional variables; 2) the computation of the decision tree or association rule became NP (non-deterministic polynomial) hard in terms of required processing power by adding even a few extra variables. Inclusion of a mixed-method approach (data mining and statistical techniques) could be more interesting, which is the author's goal for future work.

Conclusions

In this paper, the author presented the application of a new technique for studying undergraduate student databases to identify course withdrawal behaviors. The students were divided into three groups, based on their major: science or engineering, non-declared majors, and non-science and non-engineering majors. Data mining often requires data preprocessing to ensure quality results. WEKA provided all of these functions. Findings of the study proved that the data mining algorithms of decision tree and association rule were well-matched for analyzing college student databases, because there is often little prior knowledge or a coherent set of theories or forecasts regarding which cognitive and non-cognitive variables (HSGPA, ACT/SAT, gender, or age, etc.) are related and how. It also demonstrated that the number of credit hours in which students were enrolled and age determined student course withdrawal features. Surprisingly, high school GPA and standardized test scores were not necessarily real signs. In general, then, researchers may conclude that the novel technique presented here can be a useful tool for college administrators to determine withdrawal patterns of the vast majority of their students, which eventually will save institutional resources. Additionally, administrators may be able to locate students vulnerable to withdrawal from classes, as so many students are on financial aid every year. Thereafter, faculty may put statements on their syllabi and be encouraged to talk with these students early on about the ramifications of withdrawing from their classes.

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Biography

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