Tutoring for Retention

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ABSTRACT

Peer tutoring is a simple, low-cost intervention that can be implemented in CS1/2 courses. It is hypothesized that peer tutoring helps students build a sense of community, succeed in course work, and build confidence to take further courses in the major. This paper examines the latter two hypotheses by examining the predicted and actual behavior of students in CS1/2. Course performance improvements were observed, which also strongly influence retention in computing-related courses. The measures also point to further research directions, such as social influences and the impact of peer tutoring relative to office hours or online forums.

Categories and Subject Descriptors
K.3.2 [Computer And Information Science Education]: Computer Science Education

General Terms
Measurement, Human Factors

Keywords
CS1/2, peer tutoring, recruitment, retention

1. INTRODUCTION

Five years ago, computer science education was in crisis. CS1 enrollments had plunged to a fifth of their previous levels. A variety of programs were quickly implemented at many institutions to try to increase enrollment, improve retention in the program and support student success. At Indiana University, a recruitment initiative, TryIT [15], targeted over one thousand first-year women and included a peer tutoring program to support new recruits. A year and a half later, the peer tutoring program was expanded to cover three courses: CS1, CS2 and a non-major programming course. However, the effectiveness of the peer tutoring program has never been formally examined. Informal observations indicate that concurrently with its expansion, retention rates have risen. Furthermore, student success has increased. This paper approaches these informal observations with more formal methods.

This paper proceeds with an explanation of the basis of our analysis. That is followed by a description of the peer tutoring program. We then examine the questions of “Does peer tutoring improve student performance?” and “Does peer tutoring improve retention?” We conclude with a description of a more detailed study covering more factors that can be used to enrich such recruitment and retention efforts.

2. RELATED WORK

As computer science emerged as a distinct field from mathematics and other engineering disciplines, much attention was paid to predicting success. A number of programming aptitude tests (PATs) were developed and targeted at retraining and certifying professionals in computing-related activities. These PAT batteries strongly correlated with mathematical ability. In the 1980s, the focus shifted from retraining, to predicting success in training, and then to predicting success in computing courses. Factors considered ranged from prior educational experience to psychological factors. The quantity of high school math courses passed (though not necessarily the exact GPA) consistently highly correlated with success in freshman computing courses [2, 7, 8]. This correlation in high school math also held with introductory level college math [1, 8, 10, 16]. Similar correlation to ACT and SAT scores composite score [2, 8] emphasize the importance of math education but also the co-importance of language-related skills [13]. College math placement tests at the University of Tennessee at Martin (variants of which exist at most universities) were found to predict the success of students in computing courses [8].

Interesting results from these early studies of prediction include: (1) success in introductory computer science courses is predicted on both logical and linguistic basis [2, 8], and (2) most simple predictors (e.g., SAT, ACT, GPA) can only account for 20-30% of the variability seen in actual course performance [7, 8].

An earlier examination of the peer tutoring program at Indiana University showed a positive trend in retention and overall success rate in CS1 after the introduction of peer tutoring [15]. The degree to which this uptick can be attributed to peer tutoring and external factors was not examined, although the trend has continued. The study presented here looks at the impact of peer tutoring in a more struc-
can observe and work with other students, thereby gaining through homework problems provides a place where students students [4]. Providing an informal environment for working with on difficult cases. These “programming in the large” approaches are modeled and debugging strategies are emphasized. Tutoring helps form a community of students. The space is cheerful and inviting, well-lit and appropriately decorated [3], with ten computers and empty tables for those with laptops. A large whiteboard, scrap paper, and comfortable chairs appoint the space. Free snacks (e.g., cookies, chips, muffins, fruit) and drinks are provided at each session. The peer-to-peer nature of the interactions and the important fact that the tutors have no grading responsibilities means the discourse is more balanced than between student and professor. The student and the tutor have a similar status and speak a similar language. The students are more comfortable expressing opinions, more honest about their level of understanding, and more willing to take risks in proposing problem solving strategies [11].

3. TUTORING PROGRAM OVERVIEW

For each of the tutored classes, we hire a graduate student supervisor, and three undergraduate students who took the course within the previous two semesters, earned an A or A+, and are currently enrolled in some CS major course. Each week, two of the three tutors for each course lead a session. These sessions run three hours, in the evening, usually one or two days before the week’s homework assignment is due. We typically schedule two sessions during exam weeks and towards the end of the semester.

We rely on professor recommendations to identify potential tutors from the students who took the class the previous semester. We choose students with excellent content knowledge, distinct communication skills, and role-model potential. To date, we have hired 53 tutors and 70% have been women. For the supervisor, we hire a graduate student who is familiar with the course but who is not directly involved with the course during the current semester. The supervisor’s responsibilities include setting the weekly schedule, training tutors, and approving time cards for the tutors.

A faculty member directs the program; responsibilities include appointing the tutors and supervisors, coordinating the initial training session, scheduling the facilities, setting up the payroll, and assessing the program. The cost of the program is about $1,200 per course per semester.

3.1 Goals

The principle goal of the peer tutoring program is the retention of able students in the class, through future classes, and in the major.

Increase programming self-efficacy: Many students suffer from incorrect estimates of their own absolute and relative ability in computing. This distorted view leads capable students to abandon their studies even when they are performing well. This is especially pronounced in female students [4]. Providing an informal environment for working through homework problems provides a place where students can observe and work with other students, thereby gaining a better understanding of their peers’ abilities as related to their own.

Develop community: By providing an environment where students can make friends with others in the major, peer tutoring helps form a community of students. The space is cheerful and inviting, well-lit and appropriately decorated [3], with ten computers and empty tables for those with laptops. A large whiteboard, scrap paper, and comfortable chairs appoint the space. Free snacks (e.g., cookies, chips, muffins, fruit) and drinks are provided at each session. The peer-to-peer nature of the interactions and the important fact that the tutors have no grading responsibilities means the discourse is more balanced than between student and professor. The student and the tutor have a similar status and speak a similar language. The students are more comfortable expressing opinions, more honest about their level of understanding, and more willing to take risks in proposing problem solving strategies [11].

Informal mentoring: The tutoring sessions provide an opportunity for tutors to mentor younger students regarding their next steps. This includes what courses to take, where to find jobs, and information about clubs and activities. Since the tutors are recruited from the pool of students who recently completed the CS course, they act as socially similar peers and role models of successful students.

Model soft skills: The peer tutoring sessions provide an environment where effective problem decomposition strategies are modeled and debugging strategies are emphasized. Tutors are trained in talk-out-loud and pair-programming protocols to model their own thought processes for students. Students are then encouraged to help each other through similar techniques. Critical analysis for debugging and corner case identification are modeled by tutors in these sessions. Students also benefit from working with others to approach programming problems. There are always two tutors in every session, so a tutor has another person to consult with on difficult cases. These “programming in the large” skills, often difficult to convey in lecture and lab formats, are essential to success in computing. Students who develop these skills are more self-sufficient, leading to greater confidence in their abilities and increased retention in the major.

Increase diversity: A desired side-effect of peer tutoring is increasing the participation of women in computing. To this end, we place excellent, qualified women students in the tutoring positions whenever possible. By creating the appearance that women are well represented, we hope to make it a future reality.

4. QUESTION 1: PERFORMANCE

As mentioned in Section 3, peer tutoring is provided to help students develop skills relevant to the course materials. How well the program achieves this goal is the focus of this analysis. Our principle question was, “At what level of tutoring participation, if ever, can performance changes be measured?” We used several measures to both predict and evaluate the performance of individuals in selected courses.

Data Set

Data concerning CS1 and CS2 courses at Indiana University, Bloomington, was collected starting in fall 2009. The data includes three basic components: (1) a priori predictors of success (used to identify peers); (2) tutoring logs; and (3) success measurements.
We use three measurements to predict success in computer science courses, identified from earlier literature (see Section 2). The first is an SAT equivalent score calculated by the university at matriculation. SAT equivalent is equal to the SAT score if an SAT score is provided. If an ACT score is provided instead, it is converted to a score in the same range as the SAT using the SAT-ACT Concordance Tables provided by CollegeBoard [5]. SAT-Equivalent will be referred to simply as SAT for the remainder of this document. This measure can be directly translated to other institutions, but loses predictive power as the time since the test was taken increases.

The second indicator is the cumulative GPA of the student at the time of enrollment in the course [17]. This value does not experience the time degradation that SAT scores do since the most recent GPA is always used. However, GPA values cannot be known for first semester freshman. This eliminates 43 people from analysis based on this measure. GPA calculation is fully described on IU Registrar’s website [9].

The third indicator is a math skills assessment (MSA) test administered to the majority of incoming students at Indiana University (foreign students do not always take the MSA). MSA is a 26 question, multiple-choice advising tool used, in conjunction with SAT score, to help students select an appropriate college math course. The MSA covers topics in algebra and pre-calculus. (There is a separate test to determine calculus placement that students can elect to take.) MSA scores are indicated by the number of questions answered correctly. Since math and CS skills are correlated [1], MSA has been used by the computer science program to direct new students to appropriate CS courses. The prerequisite for CS1 at Indiana University is “high school precalculus math” (an MSA score of at least 12) and CS2 requires only CS1 or equivalent. The MSA score is the most focused a priori indicator used. It suffers from time degradation, like the SAT, and is not as directly portable. However, an informal survey indicates that similar tests exist at many universities and thus a corresponding indicator probably exists. MSA is similar in purpose and construction to the instrument validated as a predictor for computing success at the University of Tennessee at Martin [8].

Tutoring logs indicate which tutoring session students attended. When a student attends a session, they are encouraged (but not required) to sign the log book. Tutoring sessions are typically available once a week during a semester. On average 6 students attend each session, but up to 26 have attended. Though the temporal information has been retained, this study uses only aggregate information. For the purposes of this analysis, a student is considered “tutored” if they attended two or more sessions during the semester. Tutoring data is summarized in Table 1.

Success in a course is determined by looking at three end-of-course values: the homework grade, the final exam grade, and the official course grade. In all three cases, the values were examined as the percentage of total points possible.

This allows comparison across semesters and course sections where small variations in the total points available occur. This three-part examination of success was conducted to improve the assessment of which skills peer tutoring impacts. The course grade is a composite of all of the skills learned, and often the only grade that students care about. However, the tutoring sessions focused on homework assignments, and thus we expect to see an impact on homework grade more than any other.

The three components of the data set came from separate sources. The a priori indicators originate from the registrar and were provided to us by the Associate Vice Provost for Undergraduate Education. Success indicators were collected with the cooperation of the course instructors. Only students who completed the course were considered in this study (though data concerning students who withdrew was also collected). Tutoring attendance was assessed with the help of dated logs. As described in Section 4, each student was encouraged to sign in when attending a tutoring session. These logs were retained and encoded for the purposes of this study. This data set is available upon request to other researchers.

### Analysis Performed

The analysis performed was a series of linear regressions with normally distributed errors. All analysis was performed using The R Project for Statistical Computing [12]. In all cases, an interact between tutoring and an a priori indicator was considered to predict a success indicator. This leads to a default model with one dependent variable and three independent variables. The default models were considered for simplification using ANOVA analysis with a model that did not include the interaction [6]. In all cases, the simpler model was retained (use of the more complex model will be explicitly noted in discussion), though further simplification to just the dependent variable and tutoring was only warranted for homework grades. A p-value < .01 was considered significant for model simplification, but a p-value < .05 was accepted for other analysis.

Determining what constituted a “tutored” individual was approached analytically. Exploratory analysis on preliminary data indicated that treating tutored count directly would be problematic. With the full data set, each integral value of tutored counts was considered as a division point for tutored vs. not tutored with respect to MSA. Two

### Table 1: Tutoring counts by session for all semesters (313 total students).

| Students | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9+ |
|----------|---|--|--|--|--|--|--|--|--|--|--|
|          | 186 | 38 | 23 | 20 | 9 | 8 | 7 | 7 | 4 | 11 |

### Table 2: Parameter estimates and significance values for each a priori indicator. Individuals were considered “tutored” if they attended two or more sessions.

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Predictor Estimate</th>
<th>Tutoring Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSA Course</td>
<td>1.370***</td>
<td>7.413**</td>
</tr>
<tr>
<td>MSA Final</td>
<td>1.964***</td>
<td>.920</td>
</tr>
<tr>
<td>MSA Homework</td>
<td>.778</td>
<td>12.957*</td>
</tr>
<tr>
<td>SAT Course</td>
<td>.056***</td>
<td>9.306**</td>
</tr>
<tr>
<td>SAT Final</td>
<td>0.085***</td>
<td>3.887</td>
</tr>
<tr>
<td>SAT Homework</td>
<td>-.001</td>
<td>9.600</td>
</tr>
<tr>
<td>GPA Course</td>
<td>5.460***</td>
<td>4.797</td>
</tr>
<tr>
<td>GPA Final</td>
<td>7.687***</td>
<td>-3.574</td>
</tr>
<tr>
<td>GPA Homework</td>
<td>2.710</td>
<td>16.836**</td>
</tr>
</tbody>
</table>
or more tutoring sessions attended was selected because this marked the start of a series of significantly impacting values.

Discussion

The analysis performed yielded several interesting results. Parameter estimates and p-value ranges are given in Table 2.

First, earlier work using MSA-like tests, SAT scores and GPA as predictors of success in computing courses is confirmed by our analysis. In all cases, the overall course grade and the final exam scores were significantly predicted by the a priori indicator. This analysis further indicates that the CollegeBoard ACT to SAT translations can be used along side of raw SAT scores for this purpose. Interestingly, none of these indicators significantly predicted homework performance. This lack of predictor for homework performance limits any analysis of peer tutoring’s impact on homework grades because we have no clear predictor. However, important lessons can still be learned.

Second, tutoring had an significant impact on the course grade in two of the three predictors (SAT and MSA). We consider this an indication that peer tutoring had a positive impact on course performance, however, this effect was secondary to that of the a priori predictor. Interpreting the parameter estimate, a 7-9% increase in overall course performance was experienced by tutored students.

Third, peer tutoring did not have a significant impact on final exam grades. The difference between final and course evaluation cannot be used to estimate the impact of tutoring on homework scores because in-class participation, lab assignments and the mid-term also influence the final grade.

Finally, no a priori indicator was found to be a significant predictor of homework grades. As an a posteriori test, the impact of tutoring count on homework grade was measured and found significant (estimate = 3.169; p-value = .001). This indicates a strong relationship between tutoring and homework grades, approximately 3% per additional session. However, the baseline of this measurement is not known because of the lack of an a priori indicator. Furthermore, there

Table 3: Tutoring counts vs. retention breakdown for the Fall 2009 semester (150 total students).

<table>
<thead>
<tr>
<th>Sessions</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>Totals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lost</td>
<td>29</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>3</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>49</td>
</tr>
<tr>
<td>Retained</td>
<td>66</td>
<td>16</td>
<td>5</td>
<td>4</td>
<td>0</td>
<td>5</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>101</td>
</tr>
</tbody>
</table>

Figure 2: MSA vs expected grade with tutoring highlighted.

is insufficient data at higher session counts to be confident in any analysis (see Table 1).

While pursuing model simplification, the ANOVA comparing the interaction-including model with the simpler models occasionally returned a p-value between .05 and .01. Though below the significance level we established, this warrants further investigation as more data is collected. It indicates that students with certain a priori indicator levels also tend to use (or avoid) peer tutoring. This explanation is plausible given that tutoring is one of many study tools and use of employing tools also tends to predict academic success. The lack of significant impact of tutoring when using GPA as a predictor may also be caused by this overlap of study tools and peer tutoring.

5. QUESTION 2: PROGRAM RETENTION

An informal observation of students who participated in peer tutoring indicated that they were more likely to take additional courses in computer science. This analysis investigates this observation more formally.

Data Set

The data sources employed to evaluate program retention are the same as those used in the prior question. A student was considered retained if they were enrolled in CS1 or CS2 and then took any additional majors focused computer science course in the subsequent three semesters. Due to the longitudinal nature of retention, only students enrolling during the fall 2009 semester can be fairly evaluated for retention at this time. This data is summarized in Table 3. A single instructor taught all classes except one section of CS2, which was taught by a professor who followed the same curriculum as the other CS2 section in this study. Information on subsequent course enrollment originated with the university registrar’s office, but was provided by the Associate Vice Provost for Undergraduate Education.

Performance in introductory courses is also a strong predictor of retention in a degree program. A minimum level of performance is often a pre-requisite to future courses. Therefore, final course grade was also considered in this analysis. Course performance data was collected from official records kept by course instructors. (Limitations are discussed for all questions in Section 6.)

Analysis

Regression analysis was performed comparing retention in the program to the final grade in the course and participation in tutoring. Final grade was included in the model because it is highly correlated with retention taking further courses in a degree program. Tutoring participation was treated as a continuous variable on the number of times tutoring was attended. Since course retention is a binary variable, a binomial error distribution was used in a generalized linear regression. The original regression used a mixture
model with respect to tutoring and final grade, but ANOVA analysis indicated that a simplified two-factor model was sufficient [6]. A p-value of < .05 was considered significant.

Discussion

The two-factor model of program retention indicated two informative findings. First, students are retained based on their course score (with p-value of < .001). This is a very strong effect, with an estimated impact coefficient of .04. Although not surprising, it does indicate that increases in course score translate into increased retention. Second, the fitted model indicated that tutoring did not significantly impact retention rates. This indicated that, beyond the increase in grade, there was no measurable difference in retention based on attendance at tutoring. Any effect of tutoring on retention independent of course success is expected to be small, and may not be discernible given the small sample size.

Due to small sample sizes over two tutoring sessions, analysis was repeated considering all individuals who had attended two or more tutoring sessions as “tutored.” However, this further treatment did not change the lack of significance impact of tutoring on retention.

6. LIMITATIONS

The principle limitation and source of error in this study is the division of tutored and untutored individuals. The tutored individuals are a self-selecting population, so our data represents a convenient sample. Though controls have been established for a priori indicators available through the academic setting, many other factors could influence participation in the available tutoring. This includes mundane matters such as scheduling conflicts with the tutoring sessions to more complex matters such as social disposition. This analysis assumes that conflicting factors are shared across the tutored and untutored populations in a comparable fashion.

The second source of error is undercounting of student attendance at tutoring sessions. This comes from two sources. First, students were not required to sign in at a tutoring session. They were originally encouraged with the justification that only attendance counts were desired. As such, approximately 20% of log entries are for “anonymous” or similar placeholders. It is certain that some students did not sign in at all. Second, under-reporting of tutoring is certain because four of the log sheets have been lost. We made no attempt to recover the information on these log sheets, nor to proxy its possible contents analytically. The analysis presented here represents the data as collected. Using an optional sign-in also hides a potentially significant data point: length of stay. Tutoring sessions last three hours, but a person attending for thirty minutes appears the same in the data as one staying the full duration. Total tutoring time likely varies between individuals.

A source of error that impacts the use of composite course grades and homework grades is the lack of controls on when, where and how much of the work is done for the course. As is common, students are expected to do much of the work outside of class, and environment impacts performance. During the second half of CS2 (eight weeks), students work in pairs on a long-term project. Although they must meet certain milestones along the way, they ultimately receive a single project grade for their efforts. The homework grade for CS2 is calculated as a weighted combination of the regular weekly assignments from the first half of the semester and the project grade. An additional confounding factor is that students in CS1 and CS2 are offered an appeal process on their weekly homework assignments. Students may submit a homework assignment for a replacement grade within two weeks of its due date. In the extreme case, an F on a homework can be upgraded to a B. Earning a B after appeal is indistinguishable from a B that was originally earned. The impact of the appeal process likely masks some of the effects of tutoring. For this reason, the final exam score is also considered independently, even though homework was the focus of the peer tutoring.

The fourth limitation of this study derives from inaccuracy of a priori indicators. The SAT and GPA scores are not specific to computer science, though they do generally predict academic success in a post-secondary setting. The SAT and MSA scores suffer a loss of predictive power as the time between their administration increases. The MSA has not been formally validated, but it has been in use at Indiana University for about 30 years. None of the indicators are specifically tailored to computer science. This limitation is unavoidable as no direct predictor of success in computer science is available for the population being studied.

7. FUTURE WORK

Future work divides into three large groups: (1) further analysis with the data set already acquired; (2) acquisition and analysis of more detailed data on CS1 and CS2 students; and (3) studying the impact of tutoring on the larger educational picture.

The existing data includes the dates during the semester students attended tutoring sessions. The presented analysis did not consider this temporal aspect. There are reasons to believe that tutoring is helpful at all stages of the semester. Early on, it may help establish effective study and work habits. Mid-semester is when many foundational concepts are encountered, and the small relative difference between peers might provide the most opportunities for peer teaching. Late in the semester, as homework becomes more challenging, the cooperative aspects of the peer tutoring environment may provide opportunities for students to collectively work through problems they would otherwise abandon. All of these are plausible arguments, but our work has not establish which (if any) effects actually occur. If a reason for difference in early/mid/late semester tutoring can be assessed, an effective difference in impact would help improve resource allocation.

The analysis presented is focused on immediate and objective measures of student performance. However, this does not indicate how the effects were achieved. Is it a sense of engagement in the material or the additional skills practice that raises the grade? Do the social aspects of peer tutoring matter to student performance or retention in the program? Understanding how peer tutoring benefits students can guide refinement of existing programs and implementation of new programs. To achieve this, more detailed information about participants in CS1 is required. A pre- and post-survey of educational attitudes, skills self-assessment and interests is being piloted in fall 2010. The survey design builds on the work of Spence [14], who found that mathematics self-efficacy is among the most significant predictors of mathematics achievement. Responses will be analyzed.
to illuminate (1) a profile of students who opt in to tutoring (independent of the success predictors) and (2) a more detailed examination of the impact of tutoring.

In addition to the short-term continuation rate, we hypothesize peer tutoring improves retention of students in the computer science major. This may be the result of increased success, or of building of a stronger sense of community. Assessing this requires tracking individuals beyond the first few classes. The survey being piloted poses questions about major/minor intentions. Tracking of actual retention can be accomplished through standard educational records, which can also address some questions of performance. Having an a priori predictor of success that can be used to estimate success in a course three to four years later would be required for a well-founded assessment of a performance impact of tutoring in CS1 in a later course.

These last two points align with research into the psychological factors of computing and computing education. Tools such as the Myers-Briggs Temperament Indicator and TTS personality measurements have been correlated prior with success in computing courses [1, 16]. Examining these predictors of success and the relative impact of peer tutoring could help indicate how psychological factors influence both participation in and benefits from peer tutoring. Confidence scales developed to assess self-efficacy in math can be adapted to create a confidence scale for programming and we can measure the change in confidence between the tutored and untutored groups.

Independent of the students being tutored, an interesting question is how the peer tutors themselves are impacted by the tutoring program. As mentioned in Section 4, tutors are recruited from those who recently completed the course successfully and have continued in the major. To establish if acting as a peer tutor has an impact on later class performance, CS1 and CS2 grades could be used as a baseline measure for performance and compared to performance while acting as a tutor.

Many of the proposed directions can be targeted to investigate questions surrounding under-represented groups. For example, women are more likely to leave the computer science major, independent of their actual abilities [4]. Assessing the particular impact of peer tutoring on women and other minorities is an important future work.

8. CONCLUSIONS

Informally, peer tutoring has been observed to improve both retention of individuals in the computer science program and student performance in individual classes. Our analysis has validated both of these claims. Given the relatively low cost and known positive impact, further study of the impacts of peer tutoring is warranted. Further study is required to measure and quantify the many perceived tangible benefits the peer tutoring program has on the students, the tutors, and the culture and climate of the computer science program. Beyond studying peer tutoring, we can recommend that peer tutoring programs be expanded, both at Indiana University and other schools.

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10. REFERENCES


