ASSOCIATION RULES MINING IN STUDENTS' GRADES IN DEGREE PROGRAM RELATED COURSES

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Abstract

A variety of analysis tools exist for information extraction and knowledge mining from the students' result database. This paper presents data mining approach applied to find association rules and discover interesting patterns from the students' performance in programming, English, and programming courses of engineering degree program. The patterns' analysis assures to offer some supportive and constructive direction to educational decision makers and administrators in higher education institutions for the enhancement and modification of teaching methodology, updating of curriculum, and modifying prerequisites of different courses.

Keywords: Educational Data Mining, Knowledge Discovery in Databases, Apriori Algorithm

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1. Introduction

The past several decades have witnessed a rapid growth in the use of data and knowledge mining as a means by which academic institutions extract useful hidden information in the student result repositories in order to improve students' learning processes, restructure curriculum and/or modify the prerequisites of the courses [a]. There are numerous data mining tools not limited to [1 – 3] available and are used for data analyse from many different aspects. Educational data mining is fast becoming an interesting research area which allows researcher to extract useful, previously unknown patterns from the educational databases for better understanding, improved educational performance and assessment of the student learning process [4]. One of the he purposes of educational data mining is to investigate hidden information from students' grades' database in academic institutions.

Generally an undergraduate engineering degree program curriculum comprises of a number of courses including English courses, mathematics courses, basic science courses, engineering core courses, and advanced courses. The courses may have certain prerequisite(s) that a student must pass to gain the knowledge in form of a skill or ability which is necessary for the successful completion of a course. It is a general perception that students whose performance was excellent in a prerequisite of a course or some related course(s) would also perform well in the course. The essential part of curriculum of a computer science and engineering degree program is programming. The programming is taught at introductory level, intermediate level and advanced levels. The programming often requires expertise in many different subjects, including knowledge of the application domain, analytical skills, and comprehension of the program requirement specification. One of the main objectives of the calculus courses is to develop analytical skills in the student whereas the English courses develop the comprehension of the problem statements in programming or any other area.

Data mining techniques have been employed to solve different problems in the educational environment. Some of these applications include students' classification based on their learning performance; detection of irregular learning behaviours; e-learning system navigation and interaction optimization; clustering according to e-learning system usage; systems' adaptability to students' requirements and capacities [5 – 9]. In studies [10, 11] data mining techniques have been used to discover the common factors affecting the learners' performance and students' behaviour patterns. Aforementioned literature review illustrates that different types of

investigations have been undertaken on students' assessment data to mine and discover a variety of essential knowledge. However, no KDD study has been carried out to investigate an association between the performance of students in programming, mathematics, and English courses. The knowledge discovered from such a study would potentially be quite valuable not only for carrying out the course and program revision activities but also for determining the overall effectiveness of teaching and learning process and course prerequisite requirements.

In this paper, we investigate this important topic of research and present an analysis of programming, mathematics, and English results using association rule mining technique. The rules meeting the predefined support and confidence are mined to expose the hidden knowledge from the available result data of courses in these three areas. These mined rules are analyzed to review the existing association among these courses and recommend constructive actions to academic planners. This analysis have uncovered a number of important facts that are extremely helpful for curriculum planners, developers and academic managers in carrying out a range of essential activities such as assessing and reviewing the course and program curricula and learning methodologies. All of these activities, if done properly, play a pivotal role for the enhancement of students' performance which undoubtedly can be characterized as an ultimate goal of any academic program and the institution.

In section 2, we present relevant information about knowledge discovery process along with the data mining and association rule that we have used for the discovery of hidden knowledge. The results of the analysis and the rules discovered from the present study are discussed in section 3. The conclusions of our work are given in section 4.

2. Preliminaries

Association rule mining finds interesting associations and/or correlation relationships among large set of data items. Association rules show attributes' value conditions that occur frequently together in a given dataset [13]. The preliminaries necessary to understand for performing data mining on any data are discussed below.

Let $I = \{I_1, I_2, I_3, ..., I_m\}$ be a set items. Let D, the task relevant data, be a set of database transactions where each transaction $T \subseteq I$. Each transaction is an association with an identifier, called transaction identification (TID). Let X and Y are set of items. A transaction T is said to contain X if and only if $X \subseteq T$. An association rule is an implication of the form $X \Rightarrow Y$,

where $X \subset I, Y \subset I$, and $X \cap Y = \phi$. The interestingness of the rule is measured by *support* (s) and *confidence* (c). They respectively reflect the usefulness and certainty of the discovered rule.

The *support* of an association rule is the ratio (in percent) of the transactions that contain $X \cup Y$ to the total number of transactions in the database. Therefore, if we say that the support of a rule is 5% then it means that 5% of the total transactions contain $X \cup Y$. The *support* is the statistical significance of an association rule.

The *confidence* is the ratio (in percent) of the number of transactions that contain $X \cup Y$ to the number of transactions that contain *X*. Thus, if we say that a rule has a confidence of 85%, it means that 85% of the transactions containing *X* also contain *Y*. The confidence of a rule indicates the degree of correlation in the dataset between *X* and *Y*. The *confidence* is a measure of a rule's strength. Often a large confidence is required for association rules.

A set of items is referred to as an itemset. An itemset that contains k items is a *k-itemset*. The occurrence frequency of an itemset is the number of transactions that contain the itemset. If the relative support of an itemset *I* satisfies a prescribed minimum support threshold, then *I* is a frequent itemset.

2.1. Apriori Algorithm

Apriori is a seminal algorithm proposed by R. Agarwal and R. Srikant [14] in 1994 for mining frequent itemsets for Boolean association rules. The following lines state the steps in generating frequent itemset in Apriori algorithm. Let C_k be a candidate itemset of size k and L_k as a frequent itemset of size k.

Join Step: C_k is generated by joining $L_{k-1}$with itself

Prune Step: Any (k-1)-itemset that is not frequent cannot be a subset of a frequent k-itemset

Pseudo-code:

C_k: Candidate itemset of size k

L_k : frequent itemset of size k

L_1 = {frequent items};

for (k = 1; L_k !=∅; k++) **do begin**

C_{k+1} = candidates generated from L_k;

for each transaction *t* in database do

increment the count of all candidates in C_{k+1} that are contained in *t*

L_{k+1} = candidates in C_{k+1} with min_support

end

return $\cup_k L_k$;

2.2. Task Relevant Data Collection

We analysed the students' results data of introductory programming course, calculus, English comprehension and technical writing courses. The results in latter two English courses were averaged for each student as one course. The grades of each student were transformed into transactions (TID, programming grade, mathematics grade, and English grade) where student ID will serve as TID, however, it is not included while applying data mining algorithm.

2.3. Data Preprocessing

The real-world databases are highly susceptible to noisy, missing, and inconsistent data due to their typically huge size and their likely origin from multiple, heterogeneous sources. Low-quality data will lead to low-quality mining results [15]. Therefore, data pre-processing is an important task in data mining. The data we used was in the scores and letter grades (A, B+, B, C+, C, D+, D, F, IC, W, and WF). We used five grades only i.e. A, B, C, D, and F. Therefore, the grade data was transformed from existing eleven (11) to five (05) grades. All other grades were discarded. A snapshot of the raw assessment data, pre-processed data and transformed data are shown in Table 1. Table 1(a) is the raw data of all the courses (P represents grades in programing course, M represents grades in calculus course, E-1 is used for English comprehension course, and E-2 is used for technical writing course) whereas Table 1(b) (A, B+, B, C+, C, D+, D, F converted to A, B, C, D, and F) is the pre-processed data (Stage-1). The transformed data is given in Table 1(c).

Table 1: (a) Raw assessment data, (b) Pre-processed Data, (c) Transformed result data

(a)

P	M	E	E
C+	C+	A	C+
C	B+	A	A
C+	B	B	B
C	C+	B+	A
A	A	A	A
C	C+	B+	B
D	D	B+	D+
D	C	C+	C+
C	C	A	D+
C+	D+	C	D+
F	D	C	F
C+	A	B+	B
B+	A	A	A
C	B	B+	A
B+	A	B+	B+
D+	B	B+	B+

(b)

P	M	E	E
C	C	C	A
C	C	B	A
C	C	B	B
C	C	C	B
A	A	A	A
C	C	C	B
D	D	C	B
D	C	C	C
C	C	C	A
C	D	C	D
F	D	C	F
C	C	A	B
B	B	A	A
C	C	B	B
B	B	A	B
D	C	B	B

(c)

Preprocessed				Transformed		
P	M	E	E	P	M	E
C	C	C	A	P_C	M_C	E_C
C	C	B	A	P_C	M_C	E_A
C	C	B	B	P_C	M_C	E_B
C	C	C	B	P_C	M_C	E_A
A	A	A	A	P_A	M_A	E_A
C	C	C	B	P_C	M_C	E_B
D	D	C	B	P_D	M_C	E_C
D	C	C	C	P_D	M_C	E_C
C	C	C	A	P_C	M_C	E_C
C	D	C	D	P_C	M_D	E_D
F	D	C	F	P_F	M_D	E_D
C	C	A	B	P_C	M_A	E_B
B	B	A	A	P_B	M_A	E_A
C	C	B	B	P_C	M_B	E_A
B	B	A	B	P_B	M_A	E_B

There are many algorithms available in the literature that are employed to mine association rules implementing the above stated two-step process. In this study we used Apriori algorithm to generate hidden patterns in the students' result data from the three courses; programming, mathematics, and English.

2.4. Data Cleaning

It is fundamental truth that incorrect or inconsistent data can lead to false conclusions and hence wrong inferences and decisions. Therefore, high quality data needs to pass a set of quality criteria; accuracy, integrity, completeness, validity, consistency, uniformity, density, and uniqueness. There are a number of data cleaning techniques [15] in the literature such as fill missing values, binning, regression, and clustering. We used the following criteria to clean our data:

- If a student's grade in any course is other than the grades A, B+, B, C+, C, D+, D, and F then remove all such tuples from the result data.
- If a student is transferred from other university and credits are transferred in any of the courses under investigation then remove all such tuples.
- We also merged the result of two English courses into one according to the criteria explained in section 2.3.

2.5. Data Transformation

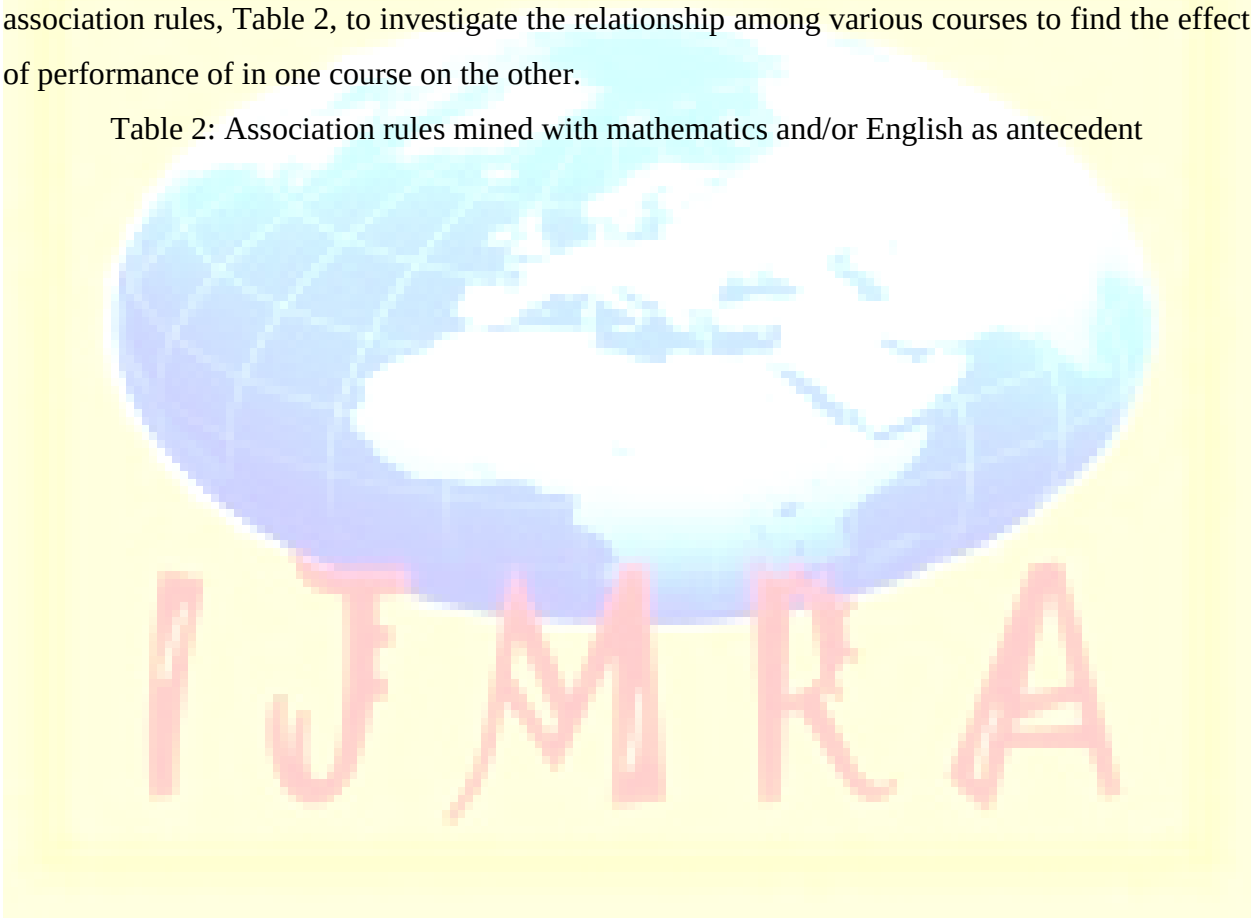
The result data in each course was pre-processed to grades (Stage-2) A(>= 90), B(>= 80), C(>=70), D(>= 60), and F(<60) as shown in Table 1(c). These grades were concatenated with the course name for example an P-A represents A grade in programming courses and M-B represents a B grade in mathematics course which is calculus in our study. The final processed form (Stage-

3) of grades data is shown in Table 1(c). The transaction shown in the highlighted rectangular box represents a transaction ready to be used in Apriori algorithm.

3. Results and Rules Analysis

In literature review, most of the authors emphasized on linking students' overall performance [10, 11, 16] to their knowledge mostly for prediction or finding the impact of students failing in one course or the other. This kind of work is not helpful to see the relationship between various courses taken by students within one program and to validate how the students' performance is affected in taking courses in differed orders. In this paper, we mined knowledge in the form of association rules, Table 2, to investigate the relationship among various courses to find the effect of performance of in one course on the other.

Table 2: Association rules mined with mathematics and/or English as antecedent



(a) minimum support 0.08 and confidence 0.80

Rule #	Antecedent	Consequent	Support	Confidence
1	P-A	M-A	0.09	1.00
2	E-A & P-A	M-A	0.09	1.00
3	P-A	M-A & E-A	0.09	1.00
4	P-B	M-B	0.12	1.00
5	P-C	M-C	0.38	0.88
6	E-A & P-C	M-C	0.10	1.00
7	E-B & P-C	M-C	0.17	1.00
8	E-C & P-C	M-C	0.10	0.86
9	M-A	E-A	0.09	1.00
10	P-A	E-A	0.09	1.00
11	M-A & P-A	E-A	0.09	1.00
12	M-A	E-A & P-A	0.09	1.00
13	M-A	P-A	0.09	1.00
14	M-A & E-A	P-A	0.09	1.00
15	M-B	P-B	0.12	1.00
16	M-C & E-A	P-C	0.10	0.86

(b) minimum support 0.07 and confidence 0.70

Rule #	Antecedent	Consequent	Support	Confidence
17	M-A	P-A	0.09	1.00
18	M-A & E-A	P-A	0.09	1.00
19	M-B	P-B	0.12	1.00
20	M-C & E-A	P-C	0.10	0.86
21	M-C & E-B	P-C	0.17	0.71

(c) minimum support 0.06 and confidence 0.70

Rule #	Antecedent	Consequent	Support	Confidence
22	M-A	P-A	0.09	1.00
23	M-A & E-A	P-A	0.09	1.00
24	M-B	P-B	0.12	1.00
25	M-B & E-B	P-B	0.07	1.00
26	M-C & E-A	P-C	0.10	0.86
27	M-C & E-B	P-C	0.17	0.71

(d) minimum support 0.05 and confidence 0.50

Rule #	Antecedent	Consequent	Support	Confidence
28	M-A	P-A	0.09	1.00
29	M-A & E-A	P-A	0.09	1.00
30	M-B	P-B	0.12	1.00
31	M-B & E-A	P-B	0.05	1.00
32	M-B & E-B	P-B	0.07	1.00
33	M-C	P-C	0.38	0.63
34	M-C & E-A	P-C	0.10	0.86
35	M-C & E-B	P-C	0.17	0.71
36	M-D	P-D	0.07	0.50

The analysis of our study of three engineering degree courses taught in different semesters is presented in Table 2. The association rules depicted in this table are mined using a data mining tool Sipina [2], freely available software for academicians and researchers. This tool allows mining the association rules by setting various supports and confidence thresholds. It is observed that by lowering the minimum support threshold there is a marked increase in the number of association rules generated by Sipina tool.

The analysis of the generated rules presented in Table 2 show that rule 13 (support = 0.09, confidence 1.00) and rule 15 (support = 0.12, confidence 1.00) indicates that students who performed excellent in mathematics course also performed well in programming course. A similar trend is observed in rules with lower supports and confidences; rules 17, 22, 24, 28, and 30. Furthermore, rule 14 (support = 0.09, confidence 1.00) shows that student who got A grade in English and mathematics also got A grade in programming course. There are rules (33 and 36) which reveal that students who got poor grades in mathematics also got poor grades in programming course. The rules 20, 21, 26, 27, 34, and 35 represent that even though students' grades are very good in English but poor grades in mathematics still produced poor grades in programming course. Some of the rules 14, 18, 23, 25, 29 and 31 discovered the knowledge that if students are good in mathematics and English then definitely they will perform better in programming courses. We could not find any rule that may prove that good grades in English is a base for good grade in programming courses.

A relationship between minimum support, minimum confidence, and rules generated by the tool are illustrated in Figure 1.

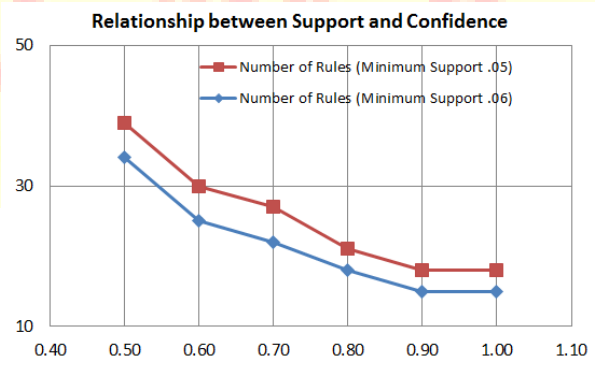


Fig. 1: Relationship between support, confidence, and rules

The discovered rules are evident that if a student's performance is excellent in mathematics or mathematics and English then he/she must perform better in the programming courses but

excellent performance in English alone does not guarantee same performance in programming course. This could be due to the reason that the students understand the problem by translating the problem statement in English to their native language. The rules discovered in this study do confirm many findings from previous studies using non KDD approaches [17, 18]. There is a positive correlation between the students' problem solving ability and their programming performance.

The discovered knowledge could prove beneficial for academic advisors to design their strategies to counsel students performing poorly in mathematics course during their first year of the university and assist them better in succeeding future programming courses. Several non KDD studies [19, 20] showed that success in Mathematics was a good predictor of success in computer science and support the mined rules in the present study. These findings can also be used to counsel or guide school graduates seeking admission into computer science undergraduate programs. The students possessing better mathematics grades at school can be advised to join undergraduate computer science programs whereas the students having poor grades can be cautioned about facing potential difficulties in programming courses if they choose to pursue computer science degrees at the university.

We believe that the generated association rules are of great help for the curriculum planners, academic advisors, and admission counsellors. The curriculum planners can certainly use the hidden knowledge and patterns discovered in the present study for redesigning the curriculum and/or changing teaching and assessment methodologies to ensure that the students are fully equipped or prepared to undertake programming courses. On the other hand the academic advisors and admission counsellors can devise better strategies for guiding and assisting perspective students.

4. Conclusion

The paper presented the potential use of one of the data mining approaches called association rule mining algorithm in enhancing the quality and experience of students' performances in higher education. The analysis reveals that there are students who got excellent grades in mathematics also performed very well in a programming course that could serve as an important feedback for instructors, curriculum planners, academic advisors, admission counsellors, and other stakeholders in making informed decisions for evaluating and restructuring curricula,

redefining the prerequisites of courses, and devising robust counselling strategies with a view to improve students' performance in computer science disciplines.

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6. References

[1] http://www.cs.waikato.ac.nz/ml/weka [accessed on 8 March 2012]

[2] http://eric.univ-lyon2.fr/~ricco/sipina.html [accessed on 8 March 2012]

[3] http://www.knime.org [accessed on 8 March 2012]

[4] A.Y.K. Chan, K.O. Chow, and K.S. Cheung. Online Course Refinement through Association Rule Mining, *Journal of Educational Technology Systems*, Volume 36, Number 4/2007 – 2008, pp 433 – 444.

[5] B. Dogan and A. Y. Camurcu. Association Rule Mining from an Intelligent Tutor, *Journal of Educational Technology Systems*, Volume 36, Number 4/2007 – 2008, pp 444 – 447.

[6] B. M. Bidgoli, B.A. Kashy, G. Kortemeyer, and W. F. Punch. Predicting Students Performance: An Application of Data Mining Methods with the Educational Web-based System LON-CAPA, *Proceedings of ASEE/IEEE Frontier in Education Conference*, Boulder, CO: IEEE, 2003.

[7] R. Damasevicius. Analysis of Academic Results for Informatics Course Improvement using Association Rule Mining. *Information Systems Development towards a Service Provision Society*. ISBN 978-0-387-84810-5 (print), published by Springer US, 2009. pp 357 – 363.

[8] L, Talavera, E. Gaudioso. Mining Students Data to Characterize Similar Behavior Groups in Unstructured Collaboration Spaces. *Proceedings of the Artificial Intelligence in Computer Supported Collaborative Learning Workshop at the ECAI* , Valencia, Spain, 2004.

[9] S. Z. Erdogan, M. Timor. A Data Mining Application in a Student Database. *Journal of Aeronautics and Space Technologies*, Vol. 2, Number 2., 2005. pp 53 – 57

[10] A. K. Domminguez, K. Yasef, and J. R. Curran. Data Mining for Individualized Hints in eLearning, *Proceedings of EDM Educational Data Mining Conference*, Pittsburg PA, USA,

2010.

[11] D. H. Shanabrook, D. G. Cooper, B. P. Woolf, and I. Arroyo. Identifying High-Level Student Behavior Using Sequence-based Motif Discovery, *Proceedings of EDM Educational Data Mining Conference*, Pittsburg PA, USA, 2010.

[12] U. Fayyad, G. Piatetsky-Shapiro, and P. Smyth. The KDD Process for Extracting Useful Knowledge from Volumes of Data, 1996. *CACM* 39 (11), pp. 27-34.

[13] J. Han and M. Kamber. Data Mining: Concepts and Techniques, *Morgan Kaufmann Series in Data Management Systems*, 2006.

[14] R. Agrawal and R. Srikant. Fast Algorithms for Mining Association Rules. *Proceedings of 20th International Conference on Very Large Database*, Santiago, Chile, 1994.

[15] J. Han, M. Kamber, J. Pei, Data Mining: Concepts and Techniques. *The Morgan Kaufmann Series in Data Management Systems*, 3rd Edition, 2011.

[16] L. Talavera and E. Gaudioso. Mining Student Data to Characterize Similar Behavior Groups in Unstructured Collaboration Spaces, *Workshop on Artificial Intelligence in CSCL*, 16th European Conference on Artificial Intelligence, ECAI, Valencia, Spain, 2004.

[17] N. Pillay and V. Jugoo, An Investigation into Student Characteristics Affecting Novice Programming Performance. ACM SIGCSE Bull., 2005. vol. 37, pp. 107-110.

[18] C. M. Ricardo. Identifying Student Entering Characteristics Desirable for a First Course in Computer Programming. *Dissertation Abstracts*, 1983. A44(1), 96.

[19] J. Konvalina, S. Wileman, L. J. Stephens. Math Proficiency: A Key to Success for Computer Science Students, *Communications of the ACM*, May 1983. Vol 26, No. 5, pp 377-382.

[20] P. F. Campbell, G. P. McCabe. Predicting the Success of Freshmen in a Computer Science Major, *Communications of the ACM*, November 1984. Vol.27, No. 11, pp 1108-1113.