

Gogus, A. & Ertek, G. (2012). "Statistical Scoring Algorithm for Study Skills and Kolb's Learning Styles". Presented at the International Conference of New Horizons in Education-2012 (INTE-2012), Prague, CZECH REPUBLIC, June 6, 2012.

Note: This is the final draft version of this paper. Please cite this paper (or this final draft) as above. You can download this final draft from <http://research.sabanciuniv.edu>.

INTE 2012

Statistical Scoring Algorithm for Learning and Study Skills

Aytac Gogus ^{a*}, Gurdal Ertek ^b

^aCenter for Individual and Academic Development, Sabancı University, Tuzla, Istanbul 34956 Turkey

^bFaculty of Engineering and Natural Sciences, Sabancı University, Tuzla, Istanbul 34956 Turkey

Abstract

This study examines the study skills and the learning styles of university students by using scoring method. The study investigates whether the study skills can be summarized in a single universal score that measures how hard a student works. The sample consists of 418 undergraduate students of an international university. The presented scoring was method adapted from the domain of risk management. The proposed method computes an overall score that represents the study skills, using a linear weighted summation

scheme. From among 50 questions regarding to learning and study skills, the 30 highest weighted questions are suggested to be used in the future studies as a learning and study skills inventor. The proposed scoring method and study yield results and insights that can guide educators regarding how they can improve their students' study skills. The main point drawn from this study is that the students greatly value opportunities for interaction with instructors and peers, cooperative learning and active engagement in lectures.

© 2012 Published by Elsevier Ltd.

Keywords: study skills, study habits, learning, university students, scoring algorithm

1. Introduction

There are several factors that affect the students' ability to complete a college degree successfully. While college admissions officers' consider mainly the predictors of academic success by looking high school GPA and standardized test scores, many researchers are interested in identifying variables that affect the college retention and dropout (Proctor et al., 2006). Examples of these variables include student motivation, self-concept, beliefs regarding success, learning styles, and study skills (Goldfinch & Hughes, 2007; Marriott and Marriott, 2003; Proctor et al., 2006).

Study skills characterize the students' capability in acquiring, recording, and using information and ideas (Harvey & Goudvis, 2000). Study skills include different types of activities, such as time management, students' information processing skills, setting appropriate goals, selecting an appropriate study environment, applying suitable note-taking strategies, concentrating, selecting main ideas, self-testing, organization, and

managing anxiety (Coughlan & Swift, 2011). Students do not bring class not only their general ability that can affect their academic success but also bring demographic variables such as gender, age, culture, and race; psychological variables such as academic self-efficacy; and motivation and behavioral variables such as time management skills (Nonis & Hudson, 2010). In addition to these, there is one more important asset: study skills or strategies that students use to learn, such as paying attention in class, taking good notes, and reading the study material before a lecture (Nonis & Hudson, 2010).

The strategies students adopt in their study are influenced by a number of social-cognitive factors and have an impact upon their academic performance (Prat-Sala & Redford, 2010). The study of Prat-Sala and Redford (2010) indicates that both intrinsic and extrinsic motivation orientations were correlated with approaches to studying. In addition, research on student learning in higher education has identified clear associations between variations in students' perceptions of their academic environment and variations in their study behavior (Richardson, 2006). Furthermore, both achievement goals and study processing strategies theories have been shown to contribute to the prediction of students' academic performance (Phan, 2011). There are several empirical evidences showing how study habits impact academic performance (e.g., Coughlan & Swift, 2011; Nonis & Hudson, 2010). Lack of study skills influences drop-outs from higher education (Byrne & Flood, 2005). In the first year, strategies to improve retention and preparation between the student and the institution are required (Tinto, 2006). For this purpose, study skill courses have come out as suitable interventions to bolster academic skill development and increase the liability of student retention and satisfaction and success in higher education (Coughlan & Swift, 2011; Enfait & Turley, 2009; Fergy et al. 2008). Various inventories have been identified in literature (e.g. Jones, 1992; Tomes, Wasylkiw, & Mockler, 2011; Weinstein & Palmer, 2002), yet a fundamental question that remains unanswered is whether the learning and study skills can be summarized in a single universal score that measures how hard a student works.

2. Scoring literature

A major novelty of this paper is the adoption of the scoring approach from the field of financial management into the field of education sciences. Scoring is a popular approach in the management of service industries, and especially in financial management (Ertek et al., 2011). Financial institutions such as banks, investment funds and insurance companies are known to use surveys to characterize their customers along a dimension of interest, such as the propensity to take financial risk. This enables them to integrate the survey results into their Customer Relations Management (CRM) systems, and to offer customized financial services to their customers. For example, the institution can emphasize safety and predictability of investments for customers who are categorized as risk-averse, while emphasizing potential gains to customers who are categorized as risk-seeking.

Ertek et al. (2011) offer a methodology to determine weights for the questions of a given survey, applying a regression-based algorithm. As applied to the domain of finance, their methodology enables the calculation of a risk score for each survey respondent, which can then be used for customizing the offerings made to each respondent. The problem of appropriately combining the values for different questions in a survey into an overall metric is also encountered in education sciences. To this end, this paper adopts the methodology developed by Ertek et al. (2011) for the scoring of study skills of university students.

3. Methodology

3.1. Participants and Data collection

Participants were the undergraduate students of an international university in Istanbul, Turkey. The sample size was 3500 students. From 512 voluntary participants,

418 students' responses were analyzed, as 94 students did not respond to all items in the survey. Forty-three per cent of the participants were ($n = 181$) female and 57% were male ($n = 237$). The survey was administrated to students from three different faculties: (1) Faculty of Engineering and Natural Sciences (FENS); (2) Faculty of Arts and Social Sciences (FASS), and (3) Faculty of Management (FMAN). Sixty two per cent of the students ($n = 260$) were participated from FENS and 37.8% ($n = 158$) were participated from FASS and FMAN. Students from FENS were overrepresented, since they form the majority of university population.

The survey instrument, the aim of the research and the consent form were mentioned to undergraduate students via e-mail and also by means of students who took the introductory project course PROJ 102 in the 2009-2010 Spring semester. There were 50 questions as learning and study skills. Each survey application lasted approximately half an hour. 50 items, called *perception attributes*, were developed and participants were instructed to indicate how frequently they used each study skill on a scale ranging from 1 (*never*) to 5 (*always*) (Gogus & Gunes, 2011).

3.2. Scoring algorithm

The scoring algorithm starts with the survey data, which consists of the answers given by I respondent students to J questions on study skills. The algorithm returns an overall study skill score for each respondent, as well as weights for questions. The survey data is fed into the risk scoring algorithm as a matrix, with I rows corresponding to the I respondents and J columns corresponding to the J attributes. The algorithm determines which attributes are to be used in scoring; the weights for each attribute, and based on these, the scores for each respondent. The detailed mathematical notation and the pseudo code of the scoring algorithm are given in Appendix B of Ertek et al. (2012). Here,

we will briefly describe how the algorithm operates. The initialization step in the algorithm transforms multiple choice data into numeric values between 0 and 3. In the collected survey data the numerical values corresponding to choices (a, b, c, d, e) would be (0.00, 0.75, 1.50, 2.25, 3.00). One important condition in here is that for all the questions, the choices should be ordered in the same order. In our case, this is choice “1” corresponding to the least level of a skill, and choice “5” corresponding to the highest level.

Following the initialization phase, the attribute values are fed into a regression based algorithm. The algorithm operates iteratively, until scores converge. The stopping criterion is satisfied when the average absolute change in scores in the final iterations is less than the threshold provided by the analyst. At each iteration of the algorithm, a linear regression model is constructed for each attribute, and the response in the incumbent score vector. Based on the regression, weights for the attributes are updated at the beginning of each iteration. One characteristic of the algorithm is that it allows for change in the direction of signs when the choices for an attribute should take decreasing -rather than increasing- values from choice “1” to the final choice “5”. Hence, the algorithm not only eliminates irrelevant attributes, but also suggests the real direction of study skills for the choices of a given attribute, given the presence of other attributes. The algorithm is a self-organizing algorithm (Ashby, 1962), since the scores it computes converge at a desired error threshold.

4. Results

The weights were obtained for each of the 50 questions. The study skills with the highest weights are (S27, S24, S26, S03), referring to the following study skills: (S27) answering questions of the instructor during the class, (S24) seeking help from the instructor outside the lecture hours, (S26) asking questions during class, and (S03) learning by listening during class. This is a fundamental insight into what really counts with regards to the overall study skills.

Six of the 50 questions (S09, S32, S08, S14, S19, S40) are assigned a weight of 0 by the algorithm. That is, the algorithm removes these six questions from the risk score computations, because they fail to impact the overall scores in a statistically significant way, given the presence of the other 44 attributes, observed in the range (0.29, 1.65). The hypothesized directions of choice ranks are found to be correct for all the questions, except S33, S15, S47. For these three questions, selecting choice “1” translates into a *higher* value of overall study skill compared to selecting choice “2”, and same for (2, 3), (3,4), (4, 5), *opposite* of all the other questions. The first 30 questions in the weight range (0.85, 1.65) can be selected to observe study skills and effective learning habits of university students. Figure 1 shows the distribution of overall (standardized) study skill scores.

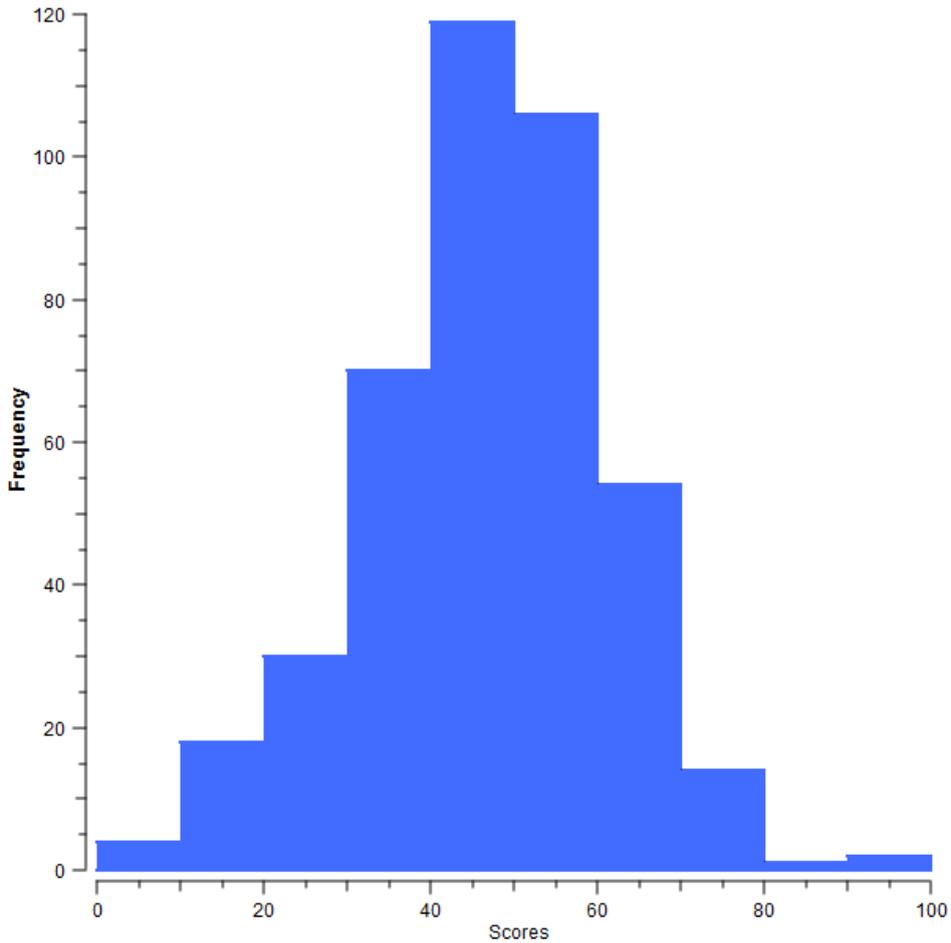


Figure 1. Distribution of overall (standardized) study skill scores.

5. Conclusions

This paper presents a scoring method adapted from the domain of risk management. The proposed method computes an overall score that represents the study skills, using a linear weighted summation scheme. The highest ranking questions in the weight range (0.85, 1.65) can be enough to observe study skills and effective learning habits of university students. Instead of using 50 questions, the researchers can use much fewer questions in the future studies. The proposed method and study yield results and insights that can guide educators regarding how they can improve their students' study habits.

The top four questions have the highest scoring indicate that variables related to students' interactions with their instructors and active participations have significant impact on the overall study skill levels. This data implies that students want to be active learners. Students appreciate if the instructors integrate active learning techniques into instruction (Gogus, 2012).

The contributions of this study are:

- 1) Using a scoring approach to represent the study skills of students in a single dimension.
- 2) Adopting a technical method developed in the domain of risk management to the field of educational sciences, and implementing it with real data.
- 3) Ranking the importance of study skills, with regards to how much they contribute to the overall study skills, and thus improving the understanding of the importance of study skills in the overall picture.

Contributions 1 and 2 are, to the best of our knowledge, unique in the educational sciences field. Instead of simple arithmetic calculations such as addition, subtraction, or multiplication, we introduced a technical method that automatically computes the weights for the involved factors. This method can identify study skills that do not contribute to the overall “study skills score” of students by assigning a weight of zero. The method can also identify whether a particular study skill, which is believed to be positively related to a student's overall skill, may in fact be negatively related.

Acknowledgements

The authors thank Murat Kaya for his contribution in the development of the scoring algorithm, and Murat Mustafa Tunç for his help in the editing of the paper and conduct of the statistical tests.

References

- Ashby, W.R. (1962). Principles of the self-organizing system. *Principles of Self-organization*, 255–278.
- Byrne, M., & B. Flood. (2005). A study of accounting students' motives, expectations and preparedness for higher education. *Journal of Further and Higher Education* 29(2), 111–24.
- Coughlan, J. & Swift, S. (2011). Student and tutor perceptions of learning and teaching on a first-year study skills module in a university computing department. *Educational Studies* , 37(5), 529- 539.
- Ertek, G., Kaya, M., Kefeli, C., Onur, Ö., & Uzer, K. (2012). Scoring and predicting risk-taking behavior. In *Behavior Computing: Modeling, Analysis, Mining and Decision*, Cao, Longbing; Yu, Philip S. (Eds.). Springer, Berlin.
- Fergy, S., Heatley, S., Morgan, G., & Hodgson, D. (2008). The impact of pre-entry study skills training programmes on students' first year experience in health and social care programmes. *Nurse Education in Practice* 8: 20–30.
- Gogus, A. & Gunes, H. (2011). Learning styles and effective learning habits of university students: A case from Turkey. *College Student Journal*, 45(3), 586-600.
- Gogus, A. (2012). Active learning. In Seel, N.M. (2012) (Eds.), *The Encyclopedia of the Sciences of Learning*. New York: Springer. ISBN 978-1-4419-1427-9.
- Goldfinch, J. & Hughes, M. (2007). Skills, learning styles and success of first-year undergraduates. *Active Learning in Higher Education*, 8; 259-273.
- Harvey, S., & Goudvis, A. (2000). *Strategies that work: Teaching comprehension to enhance understanding*. York, ME: Stenhouse.

- Jones, C. H. (1992). *Technical manual for the Study Habits Inventory*. Jonesboro: Arkansas State University.
- Marriott, N. & Marriott, P. (2003). Student learning style preferences and undergraduate academic performance at two UK universities. *International Journal of Management Education*, 3(1): 4–13.
- Nonis, S. G. & Hudson, G. I. (2010). Performance of college students: Impact of study time and study habits. *Journal of Education for Business*, 85, 229-238.
- Phan, H.P. (2011). Cognitive processes in university learning: A developmental framework using structural equation modeling. *British Journal of Educational Psychology*, 81(3), 509–530.
- Prat-Sala, M. & Redford, P. (2010). The interplay between motivation, self-efficacy and approaches to studying. *British Journal of Educational Psychology* 80(2), 283-305.
- Proctor, B., Prevatt, F., Adams, K., Hurst, A., & Petscher, Y. (2006). Study skill profiles of normal-achieving and academically struggling college students. *Journal of College Student Development* , 47(1), 37-51.
- Richardson, J. T. E. (2006). Investigating the relationship between variations in students' perceptions of their academic environment and variations in study behaviour in distance learning. *British Journal of Educational Psychology*, 76(4), 867–893.
- Tinto, V. (2006). Research and practice of student retention: What next? *Journal of College Student Retention*, 8 , 1-19.
- Tomes, J. W., Wasylikiw, L., & Mockler, B. (2011). Study for success: diaries of students' study behaviours. *Educational Research and Evaluation*, 17(1), 1-12.
- Weinstein, C. & Palmer, D. (2002). LASSI User's Manual for those administering the learning and study strategies inventory (2nd ed.). Clearwater, FL: H and H Publishing Co..