An Investigation of Psychometric Measures for Modelling Academic Performance in Tertiary Education

Geraldine Gray, Colm McGuinness, Philip Owende
Institute of Technology Blanchardstown
Blanchardstown Road North
Dublin 15, Ireland
geraldine.gray@itb.ie

ABSTRACT

Increasing college participation rates, and a more diverse student population, is posing a challenge for colleges in facilitating all learners achieve their potential. This paper reports on a study to investigate the usefulness of data mining techniques in the analysis of factors deemed to be significant to academic performance in first year of college. Measures used include data typically available to colleges at the start of first year such as age, gender and prior academic performance. The study also explores the usefulness of additional psychometric measures that can be assessed early in semester one, specifically, measures of personality, motivation and learning strategies. A variety of data mining models are compared to assess the relative accuracy of each.

Keywords

Educational data mining, academic performance, ability, personality, motivation, learning style, self-regulated learning.

1. INTRODUCTION

Factors impacting on academic performance have been the focus of research for many years and still remain an active research topic [5], indicating the inherent difficulty in defining robust deterministic models to predict academic performance, particularly in tertiary education [14]. Non progression of students from first year to second year of study continues to be a problem across most academic disciplines. This is particularly true of the Institute of Technology[1] sector in Ireland, where students have a weaker academic history than university students, and there is increasing numbers of non-standard students in the classroom [12]. This increase in participation poses a challenge to colleges to respond in a pro-active way to enable all leaners achieve their potential.

Educational Data Mining (EDM) is emerging as an evolving and growing research discipline in recent years, covering the application of data mining techniques to the analysis of data in educational settings [4, 17]. EDM has given much attention to date to datasets generated from students' behaviour on Virtual Learning Environments (VLE) and Intelligent Tutoring Systems (ITS), many of which come from school education [1]. Less focus has been given to college education, and in particular, to modelling datasets from outside virtual or online learning environments. This paper reports on the preliminary results of a study to analyse the significance of a range of measures in building deterministic models of student performance in college. The dataset includes data systematically gathered by colleges for student registration. The usefulness of additional psychometric measures gathered early in semester one is also assessed.

2. STUDY CRITERIA

In deciding on measures to include in the study, four key areas were reviewed: aptitude, personality, motivation and learning strategies. These were chosen firstly because research highlights these factors as being directly or indirectly related to academic performance [18], and secondly because these factors can be measured early in semester one. The following sections will report on correlations between individual factors and academic achievement, and also look at regression models of combinations of measures. All studies cited below are based on college education.

2.1 Influence of learner ability

There is broad agreement that ability is correlated to academic performance, although opinions differ on the range of sub factors that constitute ability [8]. For example, some studies have used specific cognitive ability tests to measure ability, for which there is extensive validity evidence. However such tests have been criticised with regarding to the objects of measurment. For example Sternberg 1999 [19] asserts that high correlation between cognitive intelligence scores and academic performance is because they measure the same skill set rather than it being a causal relationship. Therefore many studies use data already available to colleges to measure ability, i.e. grades from 2nd level education or SAT/ACT (Scholastic Aptitude Test / American College Testing) scores [18]. In a meta analysis of 109 studies by Robbins et al 2004 [16] prior academic achievement based on high school GPA or grades was found to have moderate correlation with academic performance (90% CI: 0.448 $\pm$ 0.4,). Average correlation between SAT scores and aca-

[1]The Institute of Technology sector is a major provider of third and fourth level education in Ireland, focusing on the skill needs of the community they serve (www.ioti.ie).

demic performance was lower (90% CI: 0.368± 0.035).

2.2 Influence of personality

Factor analysis by a number of researchers, working independently and using different approaches, has resulted in broad agreement of five main personality dimensions, namely openness, agreeableness, extraversion, conscientiousness and neuroticism, commonly referred to as the Big Five [9]. Of the five dimensions, conscientiousness is the best predictor of academic performance [20]. For example, Chamorro et al 2008 [6] reported a correlation of 0.37 with academic performance ($p<0.01$, $n=158$). Openness is the second most significant personality factor, but results are not as consistent. Chamorro et al 2008 [6] reported a correlation of 0.21 ($p<0.01$, $n=158$) between openness and academic performance. However the strength of the correlation is influenced by assessment type, with open personalities doing better where the assessment method is not restricted by rules and deadlines [10]. Studies on the predictive validity of other measures of personality are inconclusive [20].

2.3 Motivational factors

Motivation is explained by a range of complementary theories, which in turn encompass a number of factors, some of which have been shown to be relevant, directly or indirectly, to academic performance [16]. Factors relevant to academic performance in college include achievement motivation (drive to achieve goals), self-efficacy and self-determined motivation (intrinsic and extrinsic motivation). In Robbins et al 2004 meta analysis of 109 studies, self-efficacy and achievement motivation were found to be the best predictors of academic performance [16]. Correlations with self-efficacy averaged at 0.49 ±0.05 (CI: 90%), correlations with achievement motivation averaged at 0.303 ± 0.04 (CI: 90%). Self-determined motivation is not as strong a predictor of academic performance [11].

2.4 Influence of learning strategies

The relationship between academic performance and personality or motivation is mediated by a students approach to the learning task. Such learning strategies include both learning style (such as deep, strategic or shallow learning approach) [6] and learning effort or self-regulation [13].

Analysing the influence of learning style directly on academic performance, some studies show higher correlations with a deep learning approach [6], while others cite marginally higher correlations with a strategic learning approach [5]. The difference in these results can be explained, in part, by the type of knowledge being tested for in the assessment itself [21]. Many studies argue that there is a negative correlation between a shallow learning approach and academic performance [5].

Self-regulated learning is recognised as a complex concept to define, as it overlaps with a number of other concepts including personality, learning style and motivation, particularly self-efficacy and goal setting [2]. For example, while many students may set goals, being able to self-regulate learning can be the difference between achieving, or not achieving, goals set. Violet 1996 [21] argued that self-regulated learning is more significant in tertiary level than earlier levels of education because of the shift from a teacher-controlled environment to one where a student is expected to manage their own study. A longitudinal tertiary level study by Ning and Dowling 2010 [13] investigating the interrelationships between motivation and self-regulation found while both had a significant influence on academic performance, motivation was a stronger predictor of academic performance.

2.5 Combining psychometric measures

Individually the factors discussed above are correlated with academic performance. Also of relevance is how much of the variance in academic performance they account for. Cassidy 2011 [5] accounted for 53% of the variance in a regression model including prior academic performance, self-efficacy and age ($n=97$, mean age=23.5). Chamorro-Premuzic et al 2008 [6] accounted for 40% of the variance in a regression model including ability, personality factors and a deep learning strategy ($n=158$, mean age=19.2). A similar variance was reported by Dollinger et al 2008 [7] (44%) in a regression model including prior academic ability, personality factors, academic goals and study time ($n=338$, mean age=21.9). However not all studies concur with these results. In a study of non-traditional students, Kaufmann et al 2008 [11] accounted for 14% of the variance in a model with prior academic performance, personality factors and self-determined motivation ($n=315$, mean age=25.9). This suggests that models based on standard students may not be applicable to a more diverse student population.

There is clearly overlap, either correlation or causal, between the factors discussed above. A dataset that includes these measures will have a complex pattern of interdependencies. This raises questions on how best to model this type of data, what dimensions are useful to include, and how consistent are results across student groups.

3. THE STUDY DATASET

This study was based on first year students at an Institute of Technology in Ireland. 30% of first year students took part ($n=713$) based on their participation in online profiling during induction. Data was gathered over two years, September 2010 and September 2011. Students were from a variety of academic disciplines including computing, engineering, humanities, business and horticulture. The age range was [18,60] with an average age of 23.75. Average CAO Points[2] was 257.9 ± 75. 59% of the students were male.

The data was compiled from three sources:

1. Prior knowledge of the student: Table 1 lists attributes used from data available following student registration. This includes age, gender and ability measures based on prior academic performance. Access to full time college courses in Ireland is based on academic achievement in a set of state exams at the end of secondary school. Students have a grade for Maths, English, a foreign language, and four additional subjects chosen by the student. These subjects were categorised as science, humanities and creative / practical.

[2]CAO Points are a measure of prior academic performance in Ireland, range [0,600].

2. Psychometric data: Table 2 lists the additional measures used which were assessed using an online questionnaire developed for the study (www.howilearn.ie). The questionnaire was completed during first year induction. It covered measures of personality, motivation, learning style and self-regulated learning. Questions are taken from openly available, validated instruments.

3. Academic performance in year 1: A binary class label was used based on end of year GPA score, range [0-4]. GPA is an aggregated score based on results from between 10 and 12 modules delivered in first year. The two classes were poor academic achievers who failed overall (GPA<2, n=296), and strong academic achievers who achieved honours overall (GPA≥2.5, n=340). To focus on patterns that distinguish poor academic achievers from strong academic achievers, students with a GPA of between 2.0 and 2.5 were excluded, giving a final dataset of (n=636).

4. RESULTS

To date, six algorithms have been used to train models on the dataset, Support Vector Machine(SVM), Neural Network(NN), k-Nearest Neighbour (k-NN), Naïve Bayes, Decision tree and Logistic Regression, using RapidMiner V5.2 (rapid-i.com). Models were run on the full dataset, and also on two subgroups of the dataset split by age. An age boundary of 21 was chosen because the majority of under 21s had a poor academic performance (61%), whereas the majority of over 21s had a strong academic performance (70%). All datasets were balanced by over sampling the minority class, the attributes were scaled to the range [0,1], and model accuracy was assessed using cross validation (k=10). Model accuracy for data available at registration only (prior) was compared to model accuracy when psychometric data was included (all). Results and model parameters are detailed in Table 3.

When modelling all students using prior attributes only, pairwise comparison of the mean accuracies using least significant difference ($d_{lsd} = 5.07, p = 0.05$) indicates model performance was comparable across learners, with the only significant pairwise difference being between Naïve Bayes (75.74%) and SVM (69.41%). Model accuracies changed marginally when psychometric variables were included. The most notable change was the SVM model, where model accuracy increased from 69.41% to 75% ($t(18) = 2.05$, $p = 0.055$). The accuracy of most models improved when trained on younger students only. Again the most notable change was the SVM model. It increased from 69.41% to 82.62%, which was significant ($t(18) = 3.53, p = 0.0024$). Model accuracies changed marginally when psychometric variables were included for this group.

Models trained on older students were the least accurate with the exception of an SVM model using all attributes, which achieved the highest accuracy of all models at 93.45%. Accuracies for Decision Tree and Logistic Regression were particularly poor, with models performing no better than random guessing. In this student group, prior academic performance was not available for 38% of the students (n=108), explaining the improvement in accuracies when psychometric attributes were included in the models. When students with missing data were removed from this group, including psychometric measures did not improve model accuracies significantly for any of the models. SVM again had the highest accuracy at 91%, while Neural Networks achieved similar accuracies to the under 21 student group.

Table 1: Data available from the college

Learner Ability measures, mean and standard deviation:	
Aggregate Mark (CAO points) (258±76)	
English Result (45.5±18)	Maths Result (23.8±14)
Highest Result (64.7±14)	Humanities Average(39.7±13)
Science Average (31.8±16)	Creative Average (47.9±19)
Other factors:	
Age (23.75±7.6)	Gender (m=440, f=304)

Note: Range for age is [18,59], valid range for CAO points is [0,600], valid range for other values is [0,100]

Table 2: Additional measures*

Personality, Goldbergs IPIP scales (http://ipip.ori.org):	
Conscientousness (5.9±1.5)	Openness (6.35±1.3)
Motivation, MSLQ [15]:	
Intrinsic Goal Orientation(7.1±1.4)	Self Efficacy (6.8±1.5)
Extrinsic Goal Orientation (7.8±1.4)	
Learning style, based on R-SPQ-2F [3]:	
Shallow Learner (1.4±2)	Deep Learner (5.2±2.9)
Strategic Learner (3.5±2.5)	
Self-regulated Learning, MSLQ [15]:	
Self Regulation (5.8±1.3)	Study Effort (5.9±1.7)
Study Time (6.2±2.3)	

*The mean, standard deviation, and instrument from which questions were sourced are given for each measure. Valid range for all measures is [0,10]

5. CONCLUSION

Results from this study show that models of academic performance in tertiary education can achieve good predictive accuracy, particularly if younger students and mature students are modelled separately. This suggests that patterns are different for standard versus non-standard students. The preliminary analysis has demonstrated that good accuracy can be achieved based on data already available to colleges. Including additional psychometric measures improves predictive accuracy for mature students, but the evidence so far suggests this is due to missing data regarding prior academic performance rather than the additional added value of the psychometric measures themselves.

The most accurate models were SVMs trained on under 21s and over 21s separately. In general, models that can learn more complex patterns, and handle high dimensionality, are getting higher accuracies for both student groups. The difference in accuracy across models is most pronounced for mature students, suggesting the patterns in that subgroup are more complex. When training a single model for all students, including students for whom prior academic results are not available (i.e. the quality of the dataset is reduced), models give comparable accuracy (73.82%±1.8).

The results published here represent early results from the study. Further analysis of the psychometric measures is required to determine their predictive value, and also their usefulness in understanding how the profile of students who fail

Table 3: Model accuracies (% mean and st. dev)

Dataset	Attributes	SVM*	NN**	k-NN (k=16)	Naïve Bayes	Decision Tree	Log Reg
Full (n=636)	prior	69.41 $\pm$7.11	74.32 $\pm$4.72	73.97 $\pm$4.46	75.74 $\pm$5	72.94 $\pm$5.78	72.01 $\pm$6.41
	all	75 $\pm$4.88	75.33 $\pm$7.99	74.85 $\pm$3.63	72.35 $\pm$6	74.56 $\pm$5.54	70.84 $\pm$3.60
Under21 (n=350)	prior	82.62 $\pm$9.47	78.1 $\pm$8.7	76.9 $\pm$4.77	77.14 $\pm$5.55	70 $\pm$4.42	74.94 $\pm$6.22
	all	80.71 $\pm$10.4	78.1 $\pm$5.3	79.05 $\pm$5.41	79.29 $\pm$7.76	69.76 $\pm$4.89	76.45 $\pm$6.47
Over 21 (n=286)	prior	77.03 $\pm$9.56	72.29 $\pm$11.33	64.99 $\pm$7.33	57.16 $\pm$16.79	50.62 $\pm$1.41	48.96 $\pm$22.12
	all	93.45 $\pm$4.41	77.31 $\pm$9.3	71.7 $\pm$4.86	57.16 $\pm$16.79	50.62 $\pm$1.41	52.47 $\pm$18.08
Over 21 no missing data (n=178)	prior	91.03 $\pm$6.46	78.3 $\pm$11	71.54 $\pm$11.47	62 $\pm$11	51.5 $\pm$1.36	64.31 $\pm$10.71
	all	91.03 $\pm$6.46	79.6 $\pm$12.12	70.69 $\pm$6.1	69.26 $\pm$5.67	51.5 $\pm$1.36	66.26 $\pm$10.07

prior: attributes available from the college, all: all attributes
*Anova kernel, epsilon=0.7 and C=1.
*Learning rate=0.7, and momentum=0.4, 2 hidden layers (10,5).

differs from those who do well. To date, two subgroups have been examined, split by age. Other subgroups will be reviewed, including an analysis of differences across academic disciplines, and an analysis of students with GPA between 2.0 and 2.5 (not included in this study). Finally, model accuracies will be verified by testing the models against a third year of data, students registered in September 2012.

6. ACKNOWLEDGEMENTS

The authors would like to thank the Institute of Technology Blanchardstown (www.itb.ie) for their support in facilitating this research, and the staff at the National Learning Network Assessment Services (www.nln.ie) for their assistance in administering questionnaires during student induction.

7. REFERENCES

[1] R. S. J. D. Baker and K. Yacef. The state of educational data mining in 2009" a review and future visions. *Journal of Educational Data Mining*, pages 3–17, 2010.

[2] T. Bidjerano and D. Y. Dai. The relationship between the big-five model of personality and self-regulated learning strategies. *Learning and Individual Differences*, 17:69 – 81, 2007.

[3] J. Biggs, D. Kember, and D. Leung. The revised two-factor study process questionnaire: R-spq-2f. *British Journal of Education Psyhcology*, 71:133–149, 2001.

[4] T. Calders and M. Pechenizkiy. Introduction to the special section on educational data mining. *SIGKDD*, 13(2):3–3, 2011.

[5] S. Cassidy. Exploring individual differences as determining factors in student academic achievement in higher education. *Studies in Higher Education*, pages 1–18, 2011.

[6] T. Chamorro-Premuzic and A. Furnham. Personality, intelligence and approaches to learning as predictors of academic performance. *Personality and Individual Differences*, 44:1596–1603, 2008.

[7] S. J. Dollinger, A. M. Matyja, and J. L. Huber. Which factors best account for academic success: Those which college students can control or those they cannot? *Journal of Research in Personality*, 42:872–885, 2008.

[8] D. P. Flanagan and K. S. McGrew. Interpreting intelligence tests from contemporary gf-gc theory: Joint confirmatory factor analysis of the wj - r and kait in a non - white sample. *Journal of School Psychology*, Vol. 36, No. 2:151 – 182, 1998.

[9] L. R. Goldberg. The development of markers for the big-five factor structure. *Psychological Assessment*, 4 (1):26–42, 1992.

[10] R. Kappe and H. van der Flier. Using multiple and specific criteria to assess the predictive validity of the big five personality factors on academic performance. *Journal of Research in Personality*, 44:142–145, 2010.

[11] J. C. Kaufman, M. D. Agars, and M. C. Lopez-Wagner. The role of personality and motivation in predicting early college academic success in non-traditional students at a hispanic-serving institution. *Learning and Individual Differences*, 18:492 – 496, 2008.

[12] O. Mooney, V. Patterson, M. O'Connor, and A. Chantler. A study of progression in higher education: A report by the higher education authority. Technical report, Higher Education Authority, Ireland, October 2010.

[13] H. K. Ning and K. Downing. The reciprocal relationship between motivation and self-regulation: A longitudinal study on academic performance. *Learning and Individual Differences*, 20:682–686, 2010.

[14] Z. A. Pardos, R. S. J. D. Baker, S. M. Gowda, and N. T. Heffernan. The sum is greater than the parts: Ensembling models of student knowledge in educational software. *SIGKDD Explorations*, 13(2), 2011.

[15] P. Pintrich, D. Smith, T. Garcia, and W. McKeachie. A manual for the use of the motivated strategies for learning questionnaire. Technical Report 91-B-004, The Regents of the University of Michigan, 1991.

[16] S. B. Robbins, K. Lauver, H. Le, D. Davis, and R. Langley. Do psychosocial and study skill factors predict college outcomes? a meta analysis. *Psychological Bulletin*, 130 (2):261–288, 2004.

[17] C. Romero and S. Ventura. Educational data mining: A survey from 1995 to 2005. *Expert Systems with Applications*, 33:135–146, 2007.

[18] N. Schmitt, F. L. Oswald, T. Pleskac, R. Sinha, and M. Zorzie. Prediction of four-year college student performance using cognitive and noncognitive predictors and the impact on demographic status of admitted students. *Journal of Applied Psychology*, 2009.

[19] R. Sternberg. Intelligence as developing expertise. *Contemporary Educational Psychology*, 24:359 – 375, 1999.

[20] A. B. Swanberg and Ø. L. Martinsen. Personality, approaches to learning and achievement. *Educational Psychology*, 30(1):75–88, 2010.

[21] S. E. Volet. Cognitive and affective variables in academic learning: the significance or direction and effort in students' goals. *Learning and Instruction*, 7(3):235–254, 1996.