Introverts and Extroverts in eLearning systems: When Personality Matters

Peter Kratky, Jozef Tvarozek, Daniela Chuda

Abstract: *Students with different personality might behave in different ways while working in e-learning systems. E-learning systems could benefit from availability of personality models as it could provide personalized content to students and thus improve effectiveness of learning. This paper provides analysis of activity in online learning system used by university students described with several numerical indicators of activity. The indicators show significant correlations with overall academic results of students and particularly with personality traits. Those low in extroversion tend to work on more exercises in the system. In addition to this, models to predict activity based on personality profile are proposed in the article.*

Key words: *activity in e-learning system, student activity and personality, predicting activity, personality model.*

INTRODUCTION

E-learning systems are example of software which might suffer a lot from one-size-fits-all approach. The way the system is designed usually provides a good studying experience to a certain group of people, but on the other hand there are students who do not acquire it easily. Imagine a situation that an introvert person enjoys digging in a hard problem while an extrovert person prefers variety of short tasks. Our assumption is that personality matters in how users interact with such a learning system.

In our work we analysed activity of students in an online learning system [6] developed and used at our faculty. We defined several indicators of activity in the system expressing students' characteristics such as willingness to study, cleverness and determination. We examined relationship of activity and personality traits in order to better understand for which users is the system suitable the most and what could be improved to engage users of all personality types. The results show that less extroverted students tend to work on more tasks (programming exercises) in the system. We also used machine learning to predict activity of a student with decent success rate regarding total number of tasks and unsolved tasks.

RELATED WORK

In the field of behavioural psychology there is a great research about how to measure personality. One of the most popular models used by psychologist is Big Five personality taxonomy describing five personality traits – openness, conscientiousness, extroversion, agreeableness, neuroticism [5]. Description of particular dimensions of the model is in Table 1. To measure the personality characteristics, questionnaires are used. The most popular one is NEO FFI which consists of 60 questions about the subject and filling the form takes approximately 10 minutes [1]. This tool is often used in academic research when studied influence of personality.

Table 10. Overview of Big Five Dimensions [5]

Dimension	Properties of people with high score
Openness	Interest in searching new things and inexperienced stimuli, unconventional
Conscientiousness	Self-discipline, prudence, following rules, strong will, active planning, organizing and completing tasks
Extroversion	Socializing, cheerfulness, searching new options and experiences
Agreeableness	Obedience, cooperation, friendliness, helping others
Neuroticism	Emotional lability, shyness, sadness, embarrassment

Personality and information systems have been discussed mostly in connection to *personalization* of systems. Such systems are able to adapt to user characteristics and preferences. Benefits of knowing personality in educational system were highlighted by Lepri [4] as it might increase effectiveness of studying.

Several studies explain web usage according to personality of users. Tuten [7] found that trait openness was positively related to using the web for entertainment and product information seeking while the trait neuroticism was related to lower level of activity on the web in general. Study by Landers [3] shows that people high in conscientiousness are more likely spend time for academic purposes rather than leisure functions. Cullen [2] provides few findings about behaviour in online communities, such as people high in extroversion tend to seek sense of friendship, those high in neuroticism tend to seek sense of belonging.

ACTIVITY IN ONLINE LEARNING SYSTEM

We examined our online learning system [6] offering multiple tasks (programming exercises) each week of an academic term for students to solve. It integrates a simple development environment for programming in C/C++/Java programming language. This means that a student is able to write a program online with syntax highlighting, and to compile and run it online as well as to see if output of the program is correct.

Data Recorded

For each task started by a student we recorded whether it was successfully solved and how many attempts had been made until the output was correct. We analyzed data collected during a period of 2 years in 8 courses held at the university, totaling in 86 794 tasks records from 1260 students.

The first data insight shows that students tend to do less activity in the last weeks of a term. Figure 1 illustrates number of students (of introductory programming course) who started to solve a particular task as well as number of students who actively worked on it. In other words, some tasks were just shown to the students while those with advanced progress had at least one submitted solution. We refer to this characteristic of performing activity during the whole term as willingness to study.

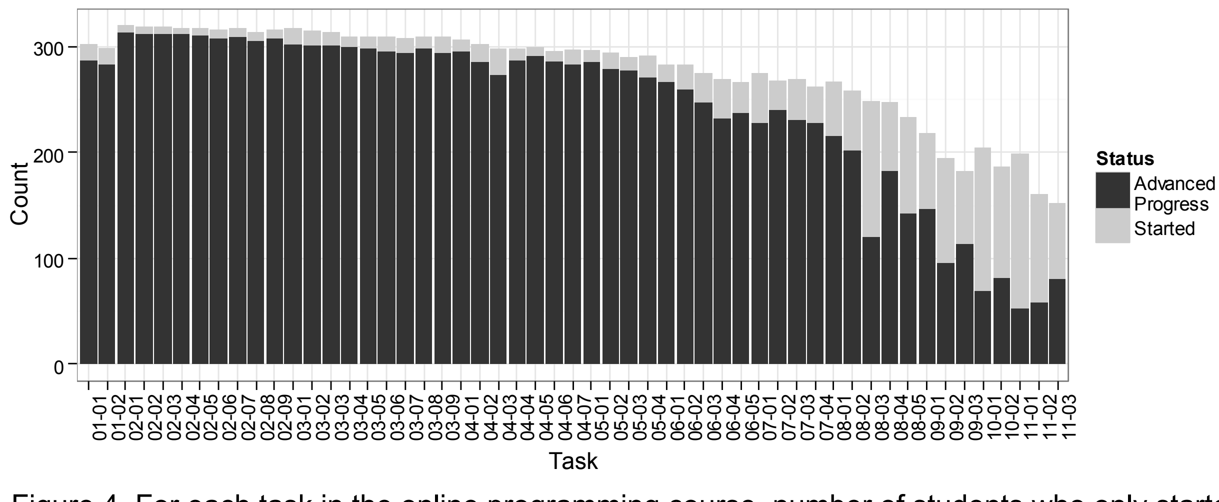

Figure 4. For each task in the online programming course, number of students who only started (light columns) a task, and students who actively worked (dark columns) on it. Id of a task is composed of two numbers – course week and task number within the week.
Course dataset: 321 users, 14 734 task answers

A common report which is interesting for teachers deals with cleverness or success of students. We provide histograms of successfully solved tasks per user as well as number of attempts to arrive at a correct solution in the Figure 2.

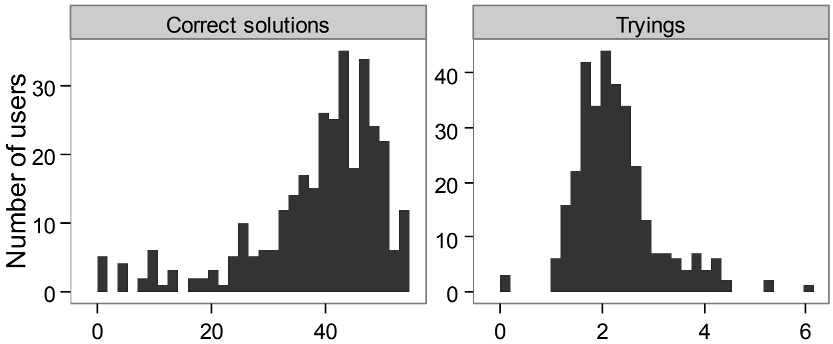

Figure 5. Number of correct solutions per student, average number of attempts (if successfully solved task) per student, in an online introductory programming course

The last insight deals with determination of students. There are students who do not give up and struggle until they deliver a correct solution and on the opposite site there are students who give up easily. Figure 3 shows ratio of accomplished and given up tasks per user.

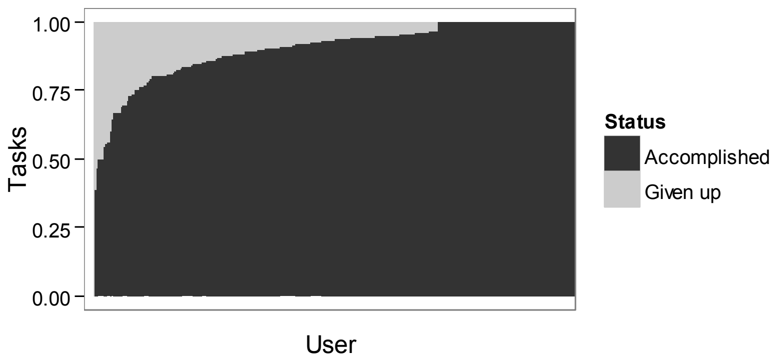

Figure 6. Ratio of accomplished tasks and given up tasks in an online programming course

Indicators of activity

We defined 8 features of activity summarized in Table 2. We characterized *willingness to work* with number of started tasks, tasks in advanced progress and ratio of tasks in first three weeks and last 3 weeks. Tasks in advanced progress are normalized according to started tasks.

As for *cleverness* characteristic we use number of successfully solved tasks (with respect to all tasks) and attempts average count per correctly solved task.

Determination of a student to complete tasks could be characterized with average number of attempts per task, number of attempts per unsolved task, unsolved tasks count and ratio of solved tasks count to unsolved tasks count. The ratio takes into account tasks which have at least two submissions.

Total number of attempts could be understood as both determination and cleverness. If it rises we could assume that the student struggles hard and also that the student has troubles. But on the other hand, we do not know nothing about determination of the student if she solves task within few attempts.

Relationship of indicators and academic results

Interestingly, but not surprisingly, indicators of activity in the online learning system are related to academic results. We examined correlations with weighted average results of students (1.0 is best) and the dataset used was the same as above. Significant negative ones are with tasks in advanced progress (-0.4), ratio of tasks in first and last 3 weeks (-

0.4), successfully solved tasks (-0.37). Positive correlation is with unsolved tasks (0.33).

Table 11. Summary of activity indicators mapped to 3 characteristics of a student

Indicator of activity	**Characteristics of a student**
Number of started tasks (NT)	Willingness to work
Ratio of tasks in advanced progress (RPT)	
Ratio of tasks in first and last 3 weeks (RWT)	
Ratio of successfully solved tasks (RST)	Cleverness
Attempts per solved task (AST)	
Ratio of unsolved tasks (RUT)	Determination
Attempts per unsolved task (AUT)	
Ratio of solved to unsolved tasks (RSUT)	

PREDICTING ACTIVITY FROM STUDENTS’ PERSONALITY

In order to better understand how personality could affect the activity in the learning system, correlations of activity indicators and personality traits were examined. We collected filled-in Big Five questionnaires from 105 students and the scores were converted to percentiles of Slovak population. Distributions of particular traits for students at our faculty are depicted in Figure 4. We have more students very low in extroversion and neuroticism than usual. On the other hand students high in agreeableness are rather missing.

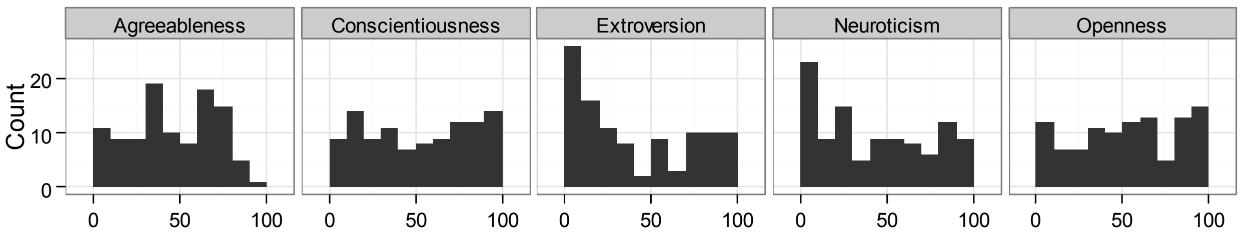

Figure 7. Distributions of Big Five traits of students in the learning system

Relationship of indicators and personality traits

We studied correlations on 3 datasets, each related to different course due to differences in tasks count and difficulty. First dataset includes 27 students who provided personality and activity data, second dataset 29 students and third one 26. We found several relatively significant correlations in each dataset (see Table 3), however there is one intersection across datasets only - a negative correlation of extroversion and number of tasks started. Some other relationships we found were between conscientiousness and solved tasks and unsolved as well, extroversion and unsolved tasks, conscientiousness and attempts to solve tasks successfully. It seems that introvert people work harder in the system. Also conscientious students seem to have better preparation what results in more successful work on tasks.

Predicting activity

Although the found correlations between variables are not very relevant, we also examined classification accuracy based on combination of personality traits. For each indicator of activity classification models were built (5 personality traits as inputs, single indicator as an output). As long as indicators are real numbers, we discretized it into three categories (*low*, *medium*, *high*) in the preprocessing phase. Values with percentiles below 33% were marked as *low*, further below 66% as *medium* and the rest as *high*. Models were trained and evaluated in WEKA tool. We used multilayered perceptron (neural network) and Naïve Bayes simple classificators which were evaluated with 5-fold cross validation using dataset consisting of 29 users. The results are summarized in Table 4. Number of started tasks as well as ratio of unsolved tasks is quite predictable with 76% and 79% success rate respectively.

Table 12. Significant ($p<0.05$) correlations between personality traits and activity indicators. There are three lines in the cells representing correlations found in each of three datasets

	NT	RPT	RWT	RST	AST	RUT	AUT	RSUT
Openness	- -0.33 -		0.31 - -			- -0.28 -		
Conscientiousness		- 0.41 -	- 0.35 -	- 0.49 -	-0.42 - -	- -0.50 -		
Extroversion	**-** **-0.31** **-0.28**	- - -0.30	- - -0.27			- -0.40 -		- 0.29 -
Agreeableness		- - -0.29	-0.30 - -		-0.29 - -		-0.28 - -	
Neuroticism								

Table 13. Success rates of models to predict indicators of activity (3 classes – low, medium, high) based on Big Five personality traits

	NT	RPT	RWT	RST	AST	RUT	AUT	RSUT
Multilayered Perceptron	**76%**	28%	41%	38%	34%	**72%**	21%	48%
Naïve Bayes Simple	**62%**	24%	41%	38%	38%	**79%**	24%	48%

CONCLUSIONS AND FUTURE WORK

This work described activity of students in an online learning system used at our faculty [6]. We defined several indicators of activity which correlates significantly to overall academic results of students. The indicators were also correlated with personality types. We tested these relationships on three datasets (up to 30 people each) however negative correlation between extroversion and total tasks was found only. Machine learning algorithms were used to predict total tasks and unsolved tasks based on personality profile with success rate of 76% and 79% respectively. The results show that providing personality profile in an e-learning system might be useful to predict behavior of a user in order to adapt to his/her character. Observations of such findings support existence centralized personality service at our faculty which has been developed in order to serve personality traits to multiple e-learning systems.

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The paper has been reviewed.