The relation of convergent thinking and trace data in an online course

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Abstract: Many prediction tasks can be done based on users' trace data. In this paper, we explored convergent thinking as a personality-related attribute and its relation to features gathered in interactive and non-interactive tasks of an online course. This is an under-utilized attribute that could be used for adapting online courses according to the creativity level to enhance the motivation of learners. Therefore, we used the logfile data of a 60 minutes Moodle course with N=128 learners, combined with the Remote Associates Test (RAT). We explored the trace data and found a weak correlation between interactive tasks and the RAT score, which was the highest considering the overall dataset. We trained a Random Forest Regressor to predict convergent thinking based on the trace data and analyzed the feature importance. The result has shown that the interactive tasks have the highest importance in prediction, but the accuracy is very low. We discuss the potential for personalizing online courses and address further steps to improve the applicability.

Keywords: Convergent thinking, creativity, online course, MOOC, prediction.

1 Introduction

Learners differ in their knowledge level, in their preferences on how to learn, and in their personality. Especially in the field of creativity training, a huge dispersion of effects found for individual methods, showing that there is no one-size-fits-all learning environment for all participants. However, in times of rapid technological, cultural, and societal changes, creativity becomes even more important and successful teaching settings are of utmost interest. Personalization of online learning formats can be one way to address such diverse needs of the individual learner [BES98]. Online course suppliers use some kind of learning management system (LMS) that can collect trace data of learners. Using data-driven approaches, individual learner behavior can be used to base predictions upon [AH11], like learner success [Vi16], the dropout rate [Kl14], or personality-related attributes [KSG13], [Rü19]. Before online courses can properly be personalized, the dimension of interest needs to be captured, to make it manageable. Traditionally, creative competencies are best captured by using either performance measures, reports of past performances, or self-reports about individual beliefs of their creative abilities [SLM04]. All of them have in

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common that they are time-consuming for the participant to fill out, and – especially in the case of actual performance measures – very time-consuming to evaluate [Si08]. To minimize the time required to assess the learner's creative abilities, and to maximize the positive learning experience in an online course by avoiding longer assessments, a more indirect way of collecting the information is required. Online courses provide the unique feature that data can be collected on how individuals interact with the learning material. Thus, the individual style, the time taken for each task, the effort put into the material are automatically assessed. It would thus be wise, to also use it for the purpose to adapt courses to better fit individual needs.

2 Related Work

Logfile data has already been used in online courses to predict personality-based attributes [Rü19]. The authors used a neural network for prediction, that shows high accuracy. In general, there is the problem that classical "black box" technology is used where the results show that the models perform well in cross-validation. However, to see an effect does not mean that we have an explanation for the cause [SGS93]. Thus, we can only see that these methodologies are working, but we do not get a deeper understanding of the underlying relations. Rüdian et al. [Rü20] have shown that a prediction of scores performs equal using a neural network or a decision tree, whereby the latter is explainable based on rules, which is important for learners and tutors to understand the reasons for a concrete prediction. In the case of creativity, we know that it can be enhanced and trained very effectively, using diverse training and enhancement methods [SLM04]. Although most methods reveal a positive impact on individuals' creative abilities, the positive effect varies hugely between study participants. For once, creatively gifted participants usually benefit less from training [SLM04], possibly as they already pushed their cognitive creative abilities to a limit. Most commonly, two different types of creative thinking are distinguished: associative/divergent thinking (DT), vs. convergent thinking (CT). DT leads to a great number of possible solutions to an open-ended problem, whereas CT leads to one fitting solution to a closed problem [Cr06]. This distinction can also be found in the testing of creative abilities. Whereas DT measures a person´s ability to associate widely and come up with as many and diverse ideas as possible, CT measures focus on intricate tasks, which demand the participant to find one uncommon solution to a closed problem. People tend to prefer and perform differently on these measures, just like people tend to improve their performances differently [SLM04]. To our best knowledge, no research examines relations of convergent thinking and trace/performance data of users in an online course. With this paper, we want to bridge that gap and test whether it is possible to assess one form of creative behavior – convergent thinking – using the click data collected in an online course. Based on the knowledge that an analysis of trace can predict aspects of personality [KSG13], we postulate the following research questions. RQ1: Does the score of interactive creative tasks correlate higher with convergent thinking than non-interactive tasks? RQ2: Do interactive tasks have a higher importance in predicting convergent thinking than non-interactive tasks?

3 Methodology & Results

A new creativity-related online course based on Moodle was developed to have full control and access to the trace data collected within the LMS. The online course consists of multiple modules, including content pages, and interactive tasks using H5P, namely multiple-choice questions about the prior presented content, and two gamified, interactive tasks: a "memory" game with pairs of terms and their definition, as well as a sequence game, where inventions have to be brought into the correct time-based sequence of their origin. We take these interactive tasks as an approximation of creative tasks. Convergent thinking was assessed using the most common measurement, the Remote Association Test (RAT) [La14]. The task is to provide a single term that fits as an associational bridge to unite three words. There is only one word that is the correct answer to a given problem. As an example, *soda* would be the correct response to the triad *fountain / baking / pop*. The score for this test is the sum of items correctly answered out of 20 total items. Each item was presented for 20 seconds. In two separate validation studies, the Spearman-Brown reliability for the Remote Association Test was .92 and .91, respectively, certifying a very high measuring precision [Me62].

The course was presented as a study on the online participant recruitment platform *Prolific*. As a precondition, participants had to be at least 18 years old, a minimum approval rate on Prolific of 95%, and fluent in the German language, as our online course is in German. Those who did not engaged with the interactive tasks were rejected. Participants gained 8€/h to complete the full course. Participation in the course lasted 61 minutes on average (SD = 20.3). They came from all over the globe, with the majority of 40% from Poland, and 11% from Germany. The mean age was 23 years (SD = 5), ranging from 18 to 50. 99% of the participants were students. 128 participants fully participated in the online course. We used the logfile table of the Moodle database (namely "logstore_standard_log") to get the trace data of all users, including the performance data that could be found in the H5P table "hvp_xapi_results". We extracted 59 features, consisting of 48 trace features and 11 items of interactive tasks. The trace features are 24 pages, where the time was measured that the learners spent on them plus the information whether they went back to the page multiple times (e.g. to search for correct answers), in sum 48. Each participant took part in the RAT test.

To address the research questions, we first examined Pearson Correlation Coefficient (PCC) between all data (trace and performance) and RAT scores and ordered them by absolute value. Then we compared the scores of interactive with non- interactive tasks to examine whether we detect a difference based on both types, that could be plausible according to [Ha20]. To address RQ2, we trained a Random Forest Regressor (RFR) [LW02] for predicting RAT scores. To avoid unbalancing problems, we balanced the data and defined three buckets (low-medium-high RAT score) in which we put our samples. As we focus on the personalization of online courses, it is sufficient to have rough classes that can be used to define target groups [Rü19]. Then we trained the Regressor using Sklearn in Python. Therefore, we used two methods: a) using all trace and performance data of our participants that we have, and b) only the two features that we identified in

RQ2. To evaluate the prediction accuracy, we used the 10 fold cross-validation (CV) to test for predictions that have not been used for training the model. Considering a), we used 59 features and emphasized the performance data of interactive tasks. For b) we used the features of the two gamified tasks only and compared the accuracy with a).

The time to solve the "memory" game (PCC=0.28) and the score of the ordering task in the sequence game (PCC=0.18) have the highest PCC related to the RAT scores. The absolute PCCs of the remaining features are much lower (for the non-gamified tasks as well as for the remaining trace data). The two correlations found are weak, but they are the highest in our dataset and limited to the two gamified tasks that we labeled to be tasks that require convergent thinking in the overall course. This result shows that there is a possible relation between gathered features in interactive gamified tasks and the convergent thinking score, determined by using the RAT.

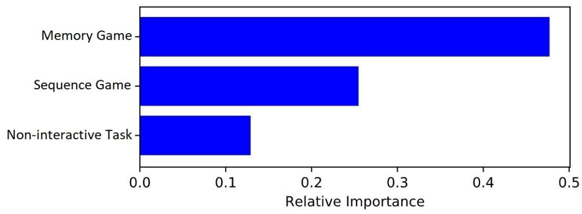

Fig. 1: Feature importance to predict convergent thinking in an online course.

Fig. 1 shows the importance of our features using the RFR, where the two interactive tasks have the highest importance that we also identified in RQ1, which answers RQ2. With the limitation to our dataset, we trained the RFR and optimized all parameters. The model achieved an accuracy of 42.4 in a 10-fold CV using all 59 features for training. Further, we used the two identified features of RQ1 and RQ2 only, namely the time that the learners needed to solve the memory game and the score that they achieved in finding the right sequence in the interactive task. Using these two features only, we achieved an accuracy of 41.2, which is comparable with the previous one. The interactive tasks of the online course have the highest importance on predicting RAT. Thus, we can conclude that this is a promising result as we only had two interactive tasks where the prediction is better than a random choice in this early stage of our research, but not ready to be useful in a practical setting. Having more interactive tasks to improve the result is the target of further studies.

4 Discussion

Using trace data from interactive tasks in an online course, we were able to predict convergent thinking in terms of low, medium, and high with higher accuracy than guessing. We found weak correlations between the interactive tasks and the cognitive thinking score. These absolute correlations are the highest ones from the set of all tasks in the course. Individual differences in intelligence might be an alternative way to explain these results. However widespread the acceptance of the RAT as a measurement for creativity, it shows a great closeness to the intelligence concept, with correlations between 0.34 and 0.42 with typical measures of intelligence [LHT14]. In contrast, related to our study, observing classical multiple-choice questions only (labeled as non-interactive tasks), we could not find significant correlations and besides, they have low importance in predicting RAT scores. Further, we can see that the difference in predicting the RAT score using the overall trace and performance data or only the two features of high importance result in an equal accuracy. This is an important finding regarding the principle of the data economy. Art. 5, 1c) of the GDPR [GD21] focuses on data minimization, which is an important topic if we want to use the method with data processed in the EU. Focusing on the gamified tasks only (which equals 3.3% of the features) still leads to a trade-off regarding the achievable accuracy. As we used two interactive tasks which are a proxy for creative tasks only, we assume that having more explicitly creative in an online course can be beneficial to increase the accuracy. This is part of ongoing research.

As creativity is a complex phenomenon, it contains several conceptual aspects. Thus, the interpretation of our results is strongly bound to the concept of CT, as one aspect of creativity, but - not to be misunderstood - as the whole creativity concept. Plus, we will perform further analysis to approximate the complexity of the concept of creativity that captures DT, as well as further measures of self-evaluation and intrinsic motivation. Prior research has shown, that creative performance is hugely influenced by the individual´s motivation to engage with creative problems and tasks [AP16]. This motivation is highly influenced by situational conditions, as well as the individual conviction of own creative competencies. Such self-evaluations can be best improved through individual, adequate, and in tendency positive feedback. This could all be done by a personalized and smart online system. When the prediction of creative abilities will accurately be possible in online courses, they could be used to increase the efficiency of learning outcomes. Finding the right fit between task difficulty and the subjective feeling of potential mastery of the task leads to the greatest engagement within the task. With ideal conditions, a state of flow could be achieved, in which the learner is completely immersed and in full enjoyment with the task [CAN90]. Such a stage, especially as positive emotions are in place, is ideal for learning and the feeling of competence and control. We can use the predicted CT score to generate interactive tasks adjusted according to the learner needs. Creators and instructors of courses should not just focus on gamification as a way to engage learners and to ease the learning process, but also from the economical data-assessment perspective on how to gain the most enriched learner profile that can be used efficiently for personalization.

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