

COGNITIVE SKILL MEASUREMENT OF STUDENT USING SUPPORT VECTOR MACHINE

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Abstract

Cognitive skills (CS) play an imperative role in performance of any individual. Knowing the level of cognitive skill of student, we can predict their performance. Latest methods are insufficient to address the challenges created by study characteristics of a student. We present a multilayer method to predict student's cognitive skills. The proposed method consists of three stages. First is the quantization, during this multilayer model is initiated by splitting study characteristics into six factors (study time, travel time, outing time, free time, family relationships and health), and range is assigned to the above mentioned factor. Second, the range of CS is divided into 21 periodic intervals (0 – 20). The component-wise division of study characteristics and CS is done to ensure prediction accuracy. Third, simulation between CS intervals and study characteristics layers. Finally, we analyzed the simulated data using machine learning algorithms. The machine learning algorithms support vector machines (SVMs) is used for our study. The proposed method is tested on the students' performance data sets in UCI repository. The results shows that SVMs achieve higher accuracy than other the traditional approach.

Keywords — Cognitive skills, Study related characteristics, quantization, Machine learning algorithms, Support vector machines.

I INTRODUCTION

Cognitive skills is referred to as human ability to process, learn new things, or perform something intelligently. Different factors like anger and stress can affect such skills while age and different diseases have long-lasting effect on these skills. Cognition is define as a process in which inputs collected by different input methods are processed, transformed, consumed, and stored. According to scientific definition, cognition is a mental process that uses working memory and inferring capabilities for speaking, reasoning, problem solving and other decision making activities. In psychology, the term cognition is referred as individual psychological function to process information. In social psychology cognition is termed as a branch to explain the group dynamics, behavior and attitude. In cognitive engineering, says that, it is a process of brain or mind used to process information that can be both natural and unnatural, doing consciously or unconsciously.

Cognitive abilities that are the combination of different brain processes [1] are analyzed differently in diverse fields. Cognitive ability is affected by the emotions such as happiness, sadness, anger, fear, disgust, surprise as well as stress. Intensity of emotions has a great impact on the behavior, attention and decision making of a human being [2]. The relationship between human and its environment is understood, then we can determine the intensity of emotion of that specific person. Emotions have a great impact on cognitive skills because performance of a person not only depends upon cognitive skills but also depends on different human emotions and motivations [3].

Cognitive Skills (CS) prediction is necessary to track the time-varying knowledge state of a student. This can be useful to identify the weaknesses of students in their performance and help them in recovering these deficiencies. The prediction of the student's CS depends on different factors, such as study schedule, family-related characteristics, and problems due to frustration [4]. Many surveys have conducted relating cognitive skill with students' characteristics [5]. There are several methods to predict students' CS using grades and study-related information of the students [6].

Recent methods provided significant contributions in predicting student's cognitive skill, however, they are insufficient for the measurement of CS in different circumstances. To accurately modulate student's CS, we use quantization, modulation, and simulation of study characteristics. It consists of study time, travel time, outing time, free time, family relationships and health. Our proposed work includes (1) quantization of study characteristics and cognitive skills of the student, (2) design a model and (3) simulation of the nonlinear relationship between CS and study characteristics. Finally, machine learning technique support vector machine is applied to the simulated data. Therefore, the method can predict CS of the students.

In our proposed method during quantization study characteristics is divided into six factors, and specific ranges are assigned to these factors, i.e., 1) travel timing schedule (1 to 5), 2) study schedule (1 to 4), 3) Outing schedule (1 to 5), 4) free timing (1 to 5), 5) parent's relationship (1 to 5) and 6) health (1 to 5). Six study characteristics constitute the model. The CS is split into 21 intervals. This method increases the accuracy and preciseness of the student's skills prediction. After simulation the value is trained and tested using machine learning technique i.e., support vector machine for more accurate prediction of CS.

Moreover, section II presents the related work. Methodology is explained in section III while the result and discussed in section IV. The paper is concluded in section V.

II RELATED WORK

Xu *et al.* [7] focused on multiple base predictors and matrix factorization approach to predict students' skills for the qualification of degree requirements. They have faced three challenges such as; (1) dissimilarity in student background, (2) the selected courses, (3) the progress information of the student. Method mainly focused on evolving states of student's performance and course relevance. The main drawback is that, the method fails to achieve accurate quantization. Different machine learning techniques as Naive Bayes, decision

tree, and the regression analysis were used, but this method is not able to predict student's performance on the basis of quantization and simulation. Student's characteristics were not split into different layers as well as modeling [8].

Iqbal *et al.* [9] collected data in information technology university Lahore. Compared the collaborative filtering matrix factorization and restricted Boltzmann machine to predict the skills of the students that based on their grades. Student's performance is dependent on their study-related schedules. So, this method has limitations for the prediction based on Study related characteristics. A method for the childhood development is proposed. It has limitations during evaluation of the study-related, and family-related characteristics [10].

Ohye *et al.* [11] focused on three generation family structure to address the challenges and problems in a family system. Health care model developed at the Veteran and Family Clinic of the Home Base Program, a partnership between the Red Sox Foundation and Massachusetts General Hospital designed to improve treatment engagement of veterans with posttraumatic stress disorder (PTSD) and related conditions, and to provide care to the entire military-connected family. Fosco *et al.* [12] also concentrated on the family-related issues that are addressed by family checkup. Therefore, the most significant attribute of SRC is the family relationship of a student. Thus, the primary need is to select the correct family and study related characteristics of the students and then correctly quantize it to modulate the relationship between CS and SRC This study was conducted with 2 overarching goals: (a) replicate previous work that has implicated the Family Check-Up (FCU), a multilevel, gated intervention model embedded in public middle schools, as an effective strategy for preventing growth in adolescent depressive symptoms and (b) test whether changes in family conflict may be an explanatory mechanism for the long-term, protective effects of the FCU with respect to adolescent depression.

Livieris *et al.* [13] implemented a user-friendly software tool in student's CS prediction. The tool uses a neural network classifier to predict the performance of a student in a mathematics course of the first year of Lyceum. In student's CS measurement circumstances (during cognitive tasks), focusing only on tools can compromise the novelty of the method because an accurate and precise prediction system need proper quantization and modulation of the problem. RNN, NN, and Bayesian Inference, etc. can be used in different node. The tool was tested by a small number of teachers who were enthusiastic with its predictions as they felt they were close to their own based on their extensive teaching experience.

In another experiment Dorner and Gerdes [14] developed a model about motivation, emotion and intelligence/ cognitive functions. The author tried to show that the efficiency or performance of someone is not only depending on cognitive function but it also dependent one emotion and motivation. The author showed through experiment that there is an interaction between emotion, motivation and cognitive function. As it is a known fact that lack of motivation brings the performance considerably down so, in this research relation among emotion, cognition and motivation is investigated through experiments. The result of the paper showed that cognitive processes can be affected by the environment and can be increased through

proper motivation. This paper gives us a good research direction and motivation to find association among emotions and cognitive skills.

In [15] the author states that emotions influence human Cognitive Skills by influencing human perception, his/her behavior, attention and decision making. The author gives reference to LRMB [1] in which it is claimed that emotion influence human Cognitive Skills. In this paper the author claimed and presented some core effects (Human Emotions) that human Cognitive functions can be affected by the alteration in these core effects. This paper gives us knowledge about relation among emotions and Cognitive Skills. It claims that Cognitive Skills can highly affected by different human emotions.

In [16] the impacts of age on spatial processing (Cognitive Skills) were analyzed through a proper experiment in which 37 adults (all ages, Children, Young, and Elder) were tested. The user was asked to play the Game with 2DOF Manipulandum. The Manipulandum was a robotic arm through which user can control the Game. The Game was containing some motors tasks through which he/she performance has been analyzed. The results showed that the thinking time interval for all the users was same but general angular error rate and average directional error rate was highly different between different aged users. Children and elderly users' error rate was same and high as compared to young adults. This shows that the performance in spatial and cognitive processing of elderly and children are relatively low as compared to young individual. This research was performed on 3 groups but the proposed research should be performed on young group of different ages and gender to identify the ratio between young users of different ages.

In [17] the author declared that the performance of male and female are different for cognitive tasks. The author conducted an experiment over 91 adults (53 female and 38 male) having ages from 18 to 25. The subjects were tested by giving two types of cognitive tasks (one was simple and other was complex) and background music (country music, jazz music, rock music, traffic and silent) was played. The result showed that the rock music has affected (increased) the reaction time of male in adults in simple and complex tasks. Noise affected the accuracy of male adults in both simple and complex tasks. Finally the author hypothesize that men are more quickly and easily influenced by a stimulus that is irrelevant. According to Plutchik there can be eight different emotions as: Fear, Trust, anger, sadness, joy, disgust, anticipation and surprise. He arranged these in a graphical shape that is known as Plutchik wheel of emotion as shown in Fig. 1. Such Categorization of emotions is not new; in past Aristotle also arrange human emotions as: anger, love, shame, fear, kindness, pity, envy, and indignation.

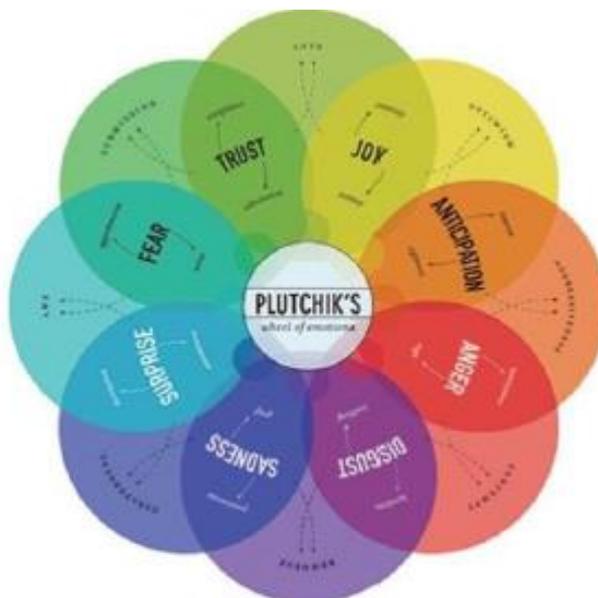


Fig. 1. Plutchik's wheel of emotions¹.

III METHODOLOGY

First the range of student's cognitive skill is split into 21 periodic intervals (with a period of 1). A component-wise quantization of student's skills that has ensured a significant prediction accuracy and precision. The CS is divided into four partitions. First partition P1 (Low CS) ranges from 0 to 5, second partition P2 (Average CS) from 6 to 10, third partition P3 (Good CS) from 11 to 15 and the fourth partition P4 (Excellent CS) from 16 to 20. Meanwhile the study characteristics are split into six layers as (1) travel schedule, (2) study schedule, (3) outing schedule, (4) free timing and (5) parent's relationships (6) health. The study time reveals that how many hours a student studies (irrespective of schooling time) while the outing time represents the refreshment schedule (in hours) of a student. Free time shows a student's timing schedule for other activities (except for sleeping and the above defined schedules), the family environment represents the relationship between the students' parents and health reveals current health. The assigned ranges (from 1 to 5) to five partitions (travel, outing, free timing family relationship, and health). On the other hand, a separate range (from 1 to 4) has assigned to the study schedule of a student. Characteristics is achieved. Then the value are Characteristics is achieved. The simulation of CS and study characteristic is achieved. Simulation output and feed it into a machine learning algorithm support vector machine.

SVM is a learning system developed by Vapnick (1995) based on the structural risk minimization (SRM) principle. Compared to the traditional empirical risk minimization (ERM) principle, which minimizes the errors in training data, SRM minimizes an upper bound on the expected risk. This feature enables SVM to be more accurate in generalization.

The SVM method was first used to handle classification problems (pattern recognition) by mapping nonlinear functions into linear functions “in a high dimensional feature space”. However, by introducing a loss function, an SVM model can also be applied to regression problems as well. For regression purposes, ϵ – insensitive loss function is often used. ϵ is a small number that makes the predictive error (difference

between the predicted value $f(x)$ and the actual value y) ignorable. In general, ϵ is set as a small positive number or zero, ϵ – insensitive loss function. Fig 2. Illustrate the SVM classifier architecture.

$$L_{\epsilon} = |y - f(x, w)| = \begin{cases} 0 & \text{for } |y - f(x, w)| \leq \epsilon \\ |y - f(x, w)| - \epsilon & \text{otherwise} \end{cases}$$

where u is the parameter to identify, and ϵ is a user-defined precision parameter.

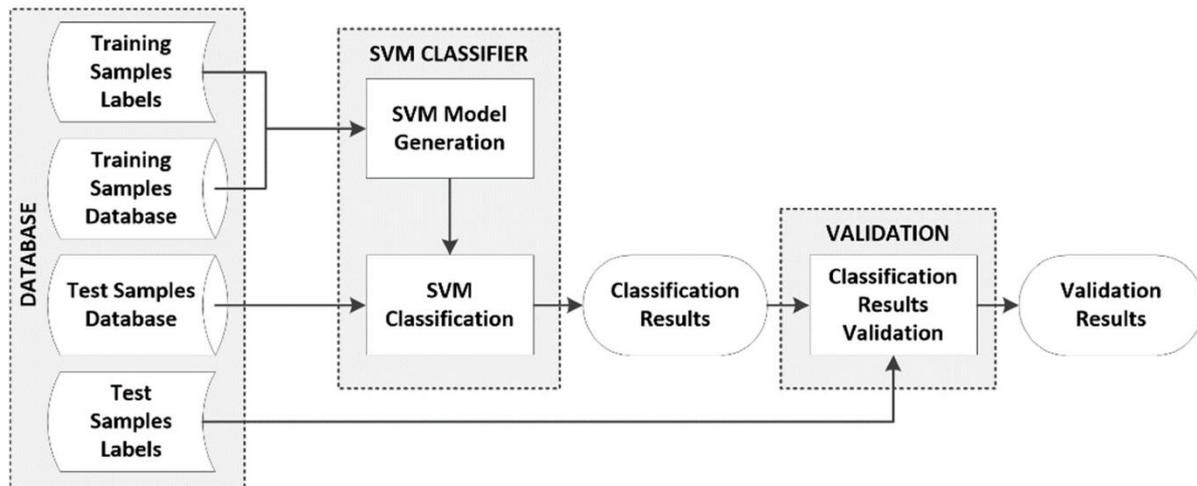


Fig 2. SVM Classifier Architecture.

VI. RESULTS

The performance of the classifiers is assessed using the standard measures of accuracy, recall, precision and F1.

Accuracy - Accuracy is simply a ratio of correctly predicted observation to the total observations. For our model, we have got 0.943 which means our model is approx. 94% accurate.

$$Accuracy = \frac{\sum_{i=1}^4 (TP_i)}{\sum_{i=1}^4 (TP_i + FP_i + TN_i + FN_i)}$$

Precision - Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. We have got 0.987 precision which is pretty good.

$$Precision = \frac{(TP_i)}{TP_i + \sum_{i=1}^3 (FP_i)}$$

Recall (Sensitivity) - Recall is the ratio of correctly predicted positive observations to the all observations in actual class. We have got recall of 0.931 which is good for this model.

$$Recall = \frac{(TP_i)}{TP_i + \sum_{i=1}^3 (FN_i)}$$

F1 score - F1 Score is the weighted average of Precision and Recall. In our case, F1 score is 0.945.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

V CONCLUSION AND FUTURE SCOPE

In the current study, we presented a cognitive Skills (CS) measurement method that depends on the quantization of student's study characteristics. The contributions of the proposed approach are threefold. First is the quantization, during this multilayer model is initiated by splitting study characteristics into six factors (study time, travel time, outing time, free time, family relationships and health), and range is assigned to the above mentioned factor. Second, the range of CS is divided into 21 periodic intervals (0 – 20). The component-wise division of study characteristics and CS is done to ensure prediction accuracy. Third, simulation between CS intervals and study characteristics layers. Finally, we analyzed the simulated data using machine learning algorithm. The results show that the proposed multilayer CS measurement method achieved significant precision, recall, F1 score and accuracy measures values. In Future, different machine leaning technique can be applied to find more accuracy.

REFERENCES

- [1] Y. Wang, Y. Wang, S. Patel, and D. Patel, "A Layered reference model of the brain (LRMB)," *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, pp. 124-133,2006.
- [2] L.-F. Rodriguez, F. Ramos, and Y. Wang, "Cognitive computational models of emotions," in *Proc. 2011 10th IEEE International Conference on the Cognitive Informatics & Cognitive Computing*, 2011.
- [3] O. AlZoubi, I. Koprinska, and R. A. Calvo, "Classification of braincomputer interface data," presented at the 7th Australasian Data Mining Conference, Glenelg, Australia, 2008. [4] E. A. Patall, R. R. Steingut, A. C. Vasquez, S. S. Trimble, K. A. Pituch, and J. L. Freeman, "Daily autonomy supporting or thwarting and students' motivation and engagement in the high school science classroom," *J. Educ. Psychol.*, vol. 110, no. 2, pp. 269_288, 2017.
- [5] J. Härkönen, F. Bernardi, and D. Boertien, "Family dynamics and child outcomes: An overview of research and open questions," *Eur. J. Population*, vol. 33, no. 2, pp. 163_184, 2017.

- [6] S. Ahmad, K. Li, H. A. I. Eddine, and M. I. Khan, "A biologically inspired cognitive skills measurement approach," *Biol. Inspired Cogn. Archit.*, vol. 24, pp. 35_46, Apr. 2018.
- [7] J. Xu, K. H. Moon, and M. van der Schaar, "A machine learning approach for tracking and predicting student performance in degree programs," *IEEE J. Sel. Topics Signal Process.* vol. 11, no. 5, pp. 742_753, Aug. 2017.
- [8] M. Pojon, "Using machine learning to predict student performance," M.S. thesis, Fac. Natural Sci. Softw. Develop. Univ. Tampere, Tampere, Finland, 2017.
- [9] Z. Iqbal, J. Qadir, A. N. Mian, and F. Kamiran. (2017). "Machine learning based student grade prediction: A case study." [Online]. Available: <https://arxiv.org/abs/1708.08744>
- [10] A. S. Lillard, M. D. Lerner, E. J. Hopkins, R. A. Dore, E. D. Smith, and C. M. Palmquist, "The impact of pretend play on children's development: A review of the evidence," *Psychol. Bull.*, vol. 139, no. 1, pp. 1_34, 2013.
- [11] B. Y. Ohye *et al.*, "Three-generation model: A family systems framework for the assessment and treatment of veterans with posttraumatic stress disorder and related conditions," *Prof. Psychol., Res. Pract.*, vol. 46, no. 2, pp. 97_106, 2015.
- [12] G. M. Fosco, M. J. Van Ryzin, A. M. Connell, and E. A. Stormshak, "Preventing adolescent depression with the family check-up: Examining family conflict as a mechanism of change," *J. Family Psychol.*, vol. 30, no. 1, pp. 82_92, 2016.
- [13] I. E. Livieris, K. Drakopoulou, and P. Pintelas, "Predicting students' performance using artificial neural networks," in *Proc. 8th PanHellenic Conf. Int. Participation Inf. Commun. Technol. Edu.*, 2012, pp. 321_328.
- [14] D. Dorner and J. Gerdes, "Motivation, emotion, intelligence," in *Proc. the International Conference on Systems and Informatics*, Yantai, 2012.
- [15] L.-F. Rodriguez, F. Ramos, and Y. Wang, "Cognitive computational models of emotions," in *Proc. 2011 10th IEEE International Conference on the Cognitive Informatics & Cognitive Computing*, 2011.
- [16] Y. Jing, S. Jing, C. Huajian, S. Chuangang, and L. Yan, "The gender difference in distraction of background music and noise on the cognitive task performance," in *Proc. the Eighth International Conference on Natural Computation*, Chongqing, 2012.
- [17] A. A. Samadani and Z. Moussavi, "The effect of aging on human brain spatial processing performance," in *Proc. the Annual International Conference of the IEEE on Engineering in Medicine and Biology Society*, San Diego, CA 2012.