Yang, J. C. et al. (Eds.) (2018). Proceedings of the 26th International Conference on Computers in Education. Philippines: Asia-Pacific Society for Computers in Education

Cluster-based Outlier Analysis of Carefulness Among Students using Physics Playground

Michelle BANAWAN [a*] & Ma. Mercedes RODRIGO[b]
[a]*Ateneo de Davao University, Philippines*
[b]*Ateneo de Manila University, Philippines*
*mpbanawan@addu.edu.ph

Abstract: We explore a student carefulness model using cluster-based outlier analysis. In a related work by the authors, a predictive model of student carefulness was created, built and empirically validated using Philippine samples. Carefulness was found to exist in the dataset and could be robustly predicted using features derived from Physics Playground's interaction logs. In this work, we found that clusters of outliers existed in the dataset and studied how these affect the model. In our prior work we found that carefulness did not have any linear relationship with post-test learning gains. Investigating the outliers, in this study, resulted to findings that post-test learning gains of the outlying (least careful) and non-outlying (more careful) groups are significantly different. Further, we also found that the degrees of carefulness between the clusters within the non-outlying groups were also significantly different. With this finding, educational pedagogies and interventions can be more effective when we consider that carefulness among students are varied and can be addressed distinctly and not in general to be able to achieve the desired learning gains.

Keywords: Carefulness, cluster-based outlier analysis, Physics Playground

1. Introduction

We study carefulness in the context of Physics Playground (PP), an educational game that supports learning Newtonian Physics. Carefulness has been modeled by PP developers as a facet of conscientiousness (Shute, et.al., 2013) and have identified in-game predictors. In our prior work, we have empirically validated these predictors using sample datasets from at least three different locations in the Philippines. Carefulness is a characteristic of a student's actions that can be described as mindfulness, alertness, attentiveness or being thorough (Banawan, Rodrigo, Andres, 2017). In this study, we investigated the phenomenon of outliers and discover its effect on the student carefulness model for Physics playground within Philippine sample sets. This study would like to answer the research questions: With outlier analysis, which factors differentiate the students in terms of carefulness predictors?

2. Methods

2.1 Student Carefulness in Physics Playground

Physics Playground (PP) is a two-dimensional educational game designed for learning qualitative Physics. The player is expected to apply Newton's three laws of motion by drawing objects and any of the different agents like ramp, pendulum, lever or springboard in the game's levels/problems. A non-verbal understanding of the physical world and how it operates is exhibited by the player as he/she comes up with solutions to the different game levels. PP has been the test bed of prior work in investigating student behavior, affect or learning in general (Moore & Shute, 2017), (Ventura, Shute & Small, 2014). PP developers modeled carefulness and identified candidate in-game indicators. Carefulness means giving close and cautious attention to the task at hand and being thorough/painstaking in its execution (Morris, 1969). When a student is careful, he/she is most likely to avoid trivial and/or careless errors and is less likely to commit mistakes improving overall student performance (Gong, Rai, Beck, & Heffernan, 2009). In the authors' previous work, a student carefulness model for PP has been empirically validated using the candidate predictors of the game developers and expanded these predictors to include in-game indicators of social science constructs that have been researched to be related to carefulness, i.e. reflectivity, mastery and novelty (Banawan, Rodrigo, & Andres, 2017).

2.2 Cluster-based Outlier Detection

Outliers are usually removed as they distort the resulting model. Not handling outliers skews the model such that the mean and covariance estimates of the observations do not reflect actual behavior of the data. There is, however, merit in outlier detection and analysis. Outlier detection has been used to find anomalies in datasets to better understand the deviation of observation points to the central tendencies or behavior exhibited by the entire sample. It involves finding patterns (anomalies, discordant observations, faults, defects, peculiarities, etc.) in data that do not conform to expected behavior (Chandola, et.al. 2009). A number of outlier detection work used clustering to detect outliers (Elahi, et.al., 2008) (Pamula, Deka, & Nandi, 2011) and resulted to an understanding of students' behavior and detect students with learning problems (Romero, & Ventura, 2007). For this paper, the dataset was normalized to rescale the attribute values using the statistical normalization, z-transformation or z score. Then, we used X-means clustering (Pelleg & Moore, 2000) to discover the optimal number of clusters (Jain, 2010). Further, we used the local outlier factors (LOF) in outlier detection (Breunig, Kriegel & Sander, 2000). We also computed the post-test learning gains from the test results of the students prior to and after their PP usage and performed independent t-tests to verify if there is a significant difference between the carefulness and post-test learning gains means between the clusters.

3. Results and Discussion

3.1 Outliers and Non-outliers

Three well-separated clusters (clusters 0, 1 & 2) were formed after the X-means clustering algorithm was used. LOF was used in the computation of outlier scores of each student, which resulted to outliers found in the three clusters. Cluster 1 had all points computed as outliers, making cluster 1 an outlying cluster. The non-outliers were found only from the two clusters, i.e. Cluster 0 & 2. The mean carefulness of the outlying (2.24) and non-outlying (2.46) groups show that the outliers tend to be less careful than the non-outliers. The non-outliers, clusters 0 & 2, can be described as those who have more mastery as evidenced by the resulting cluster centroids for the features: badges earned, time spent on the problems and the re-attempts and those who, while also careful, did not exhibit the same level of mastery respectively. For the outlier group (least or not careful students), we found three sub-groups: (1) those who spent the longest time solving problems yet solved the least number of problems; (2) those who were able to solve the problems but solved them too fast; and (3) those who solved the problems in a non-optimal way by drawing the most number of objects;

3.2 Comparison of Means of Carefulness and Post-test Learning Gain

The results of the one-tailed distribution t-test of the 2 clusters in the non-outliers reveal that there is a significant difference between their mean values ($p = 0.00016$). Hence, within the non-outliers, there are 2 significantly different clusters, i.e. one cluster being the more careful cluster than the other. The result of the t-test on the post-test learning gain showed that there is a significant difference between the learning gains of the non-outliers from those of the outliers ($p=0.02648$). The two clusters of non-outliers are not significantly differentiated in terms of post learning gains but the outliers and non-outliers has been found to be significantly differentiated, with the non-outliers having higher post-learning gains than the outliers.

4. Conclusion and Findings

We found that carefulness exists in both the outliers and the non-outliers and a statistically significant difference has been found between the means of the carefulness of the two clusters of students in the non-outlying (more careful) group, i.e. one cluster is more careful than the other. Interestingly, post-learning gains did present to be statistically differentiated between the outliers and non-outliers when in the authors' previous work post-test learning gains did not have any relationship to the predictors of carefulness. As a contribution to this field of study, carefulness can exist in varying levels or degrees among students regardless of their level of mastery and creativity. With the outliers identified in this study, a clearer model of student carefulness has resulted: (1) that non-outliers (those who can be considered as careful students) can have significantly varying degrees of carefulness; (2) that post-test learning gains are more significantly pronounced with non-outliers than the outliers; and (3) that carefulness can even exist within the outliers, which explains why the previous work of the authors was able to build the predictive model given the entire dataset even without any anomaly or outlier detection.

Acknowledgements

We would like to thank Physics Playground developers and researchers, Dr. Valerie Shute, Dr. Matthew Ventura, and their colleagues at the Florida State University for collaborating with the authors.

References

Banawan, M. P., Rodrigo, M. M. T., & Andres, J. M. L. (2017). Predicting Student Carefulness within an Educational Game for Physics using Support Vector Machines.

Breunig, M. M., Kriegel, H. P., Ng, R. T., & Sander, J. (2000, May). LOF: identifying density-based local outliers. In *ACM sigmod record* (Vol. 29, No. 2, pp. 93-104). ACM.

Chandola, V., Banerjee, A., & Kumar, V. (2009). Anomaly detection: A survey. *ACM computing surveys* (CSUR), 41(3), 15.

D. Q. Goldin and P. C. Kanellakis. On similarity queries for timeseries data: Constraint specification and implementation. In *CP*, pages 137–153, France, September 1995

Elahi, M., Li, K., Nisar, W., Lv, X., & Wang, H. (2008, October). Efficient clustering-based outlier detection algorithm for dynamic data stream. In *Fuzzy Systems and Knowledge Discovery*, 2008. FSKD'08. Fifth International Conference on(Vol. 5, pp. 298-304). IEEE.

Gong, Y., Rai, D., Beck, J. E., & Heffernan, N. T. (2009). Does Self-Discipline Impact Students' Knowledge and Learning?. *International Working Group on Educational Data Mining*.

Jain, A. K. (2010). Data clustering: 50 years beyond K-means. Pattern recognition letters, 31(8), 651-666.

Moore, G. R., & Shute, V. J. (2017). Improving Learning Through Stealth Assessment of Conscientiousness. In *Handbook on Digital Learning for K-12 Schools* (pp. 355-368). Springer, Cham.

Morris, W. (1969). *American heritage dictionary of the English language*. American *heritage.*

Pamula, R., Deka, J. K., & Nandi, S. (2011, February). An outlier detection method based on clustering. In *Emerging Applications of Information Technology (EAIT)*, 2011 Second International Conference on (pp. 253-256). IEEE

Pelleg, D., & Moore, A. W. (2000, June). X-means: Extending k-means with efficient estimation of the number of clusters. In *Icml* (Vol. 1, pp. 727-734).

Romero,C. and Ventura, S. ,"Educational data Mining: A Survey from 1995 to 2005".Expert Systems with Applications (33) 135-146. 2007.

Shute, V. J., Ventura, M., & Kim, Y. J. (2013). Assessment and learning of qualitative physics in newton's playground. *The Journal of Educational Research*, *106*(6), 423-430.

Ventura, M., Shute, V., & Small, M. (2014). Assessing persistence in educational games. *Design recommendations for adaptive intelligent tutoring systems: Learner modeling*, *2*, 93-101.

Whimbey, A. *(1980). Students can learn to be better problem solvers. Educational* Leadership, 37(7), 560-565.