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

Let's Take a Break: Analysis of the Incubation Effect Among Students Using a Learning Game for Physics

May Marie P. TALANDRON[a,b*], Ma. Mercedes T. RODRIGO[a*]
[a]*Ateneo de Manila University, Philippines*
[b]*Central Mindanao University, Philippines*
*mmptalandron@cmu.edu.ph, *mrodrigo@ateneo.edu.ph

Abstract: This study continues prior work of the investigation and modeling of Incubation Effect, a phenomenon in which a momentary break helps the generation of a solution to a problem, among students using in a computer-based learning environment called Physics Playground. This paper attempts to improve the detection of IE-False by identifying notable features among instances of unsuccessful incubation by using a combination of t-SNE dimensionality reduction and x-means clustering techniques. We found that there are overlaps on some characteristics of IE-True and IE-False incidences but discovered features that do not make a break beneficial which are low success rate prior to post-incubation, too many levels played during the incubation phase even if some of these are similar to the unsolved problem, a lengthy incubation duration, and too much attempts on the level which has been previously related to frustration.

Keywords: Incubation Effect, t-SNE, clustering, Physics Playground

1. Introduction

Taking a break from a series of failed attempts to solve a problem may facilitate the solution process (Fulgosi & Guilford, 1970; Gilhooly, Georgiou, & Devery, 2013; Penaloza & Calvillo, 2012; Sio & Ormerod, 2009). This momentary break is known by the name incubation (Sio & Ormerod, 2009). During some incubation periods, an internal mental process associates new information with past information to generate solution ideas (Medd & Houtz, 2002). In the context of education, students who get stuck in a problem-solving activity may temporarily engage in another task, after which, they return to the original problem and find a solution. When the student solves the problem after incubation, the phenomenon and its positive result is called the Incubation Effect (IE). This phenomenon is divided into 3 phases: (Gilhooly et al., 2013): (1) pre-incubation phase, (2) incubation phase, and (3) post-incubation phase. The pre-incubation phase is the period when the student tries to solve a problem and gets stuck. Incubation happens when the student decides to take a break from the unsolved problem to either rest or try other problems. The post-incubation phase occurs when the student returns to the unsolved problem and tries to solve it again.

This study continues prior work (Martinez, Obispo, Talandron, & Rodrigo, 2016; Talandron, Rodrigo, & Beck, 2017) where the model was able to predict IE but has the tendency to predict many incubation instances as beneficial even if they weren't. This time, we attempt to focus on detecting instances where breaks were not beneficial to the problem-solving tasks. In this research we ask: when is a break not beneficial in the context of the incubation effect?

2. Prior Work

Prior work on IE in the context of classroom tasks (Ellwood, Pallier, Snyder, & Gallate, 2009; Fulgosi & Guilford, 1970; Gilhooly et al., 2013; Penaloza & Calvillo, 2012; Sio & Ormerod, 2009) investigated which specific factors lead to successful incubation and suggested that engaging in a different activity may produce a better outcome. On the other hand, (Penney, Godsell, Scott, & Balsom, 2004) claimed that engaging in a task with similar nature would promote priming which allows students to realize the correct solution to the problem but (Segal, 2004) said that the task during incubation has no effect on its outcome.

The initial investigation of the incidence of incubation effect in the context of a computer-based learning environment was conducted by Martinez et al., (2016) and found evidence that majority of the students who took a break after being stuck in a particular level were able to solve the problem. Also, they found a relationship between incidence of incubation and frustration.

To further explore the IE phenomenon, (Talandron et al., 2017) attempted to model IE and examined possible factors that predict the successful outcome of incubation using logistic regression with feature selection and resulted to a model with four features: total badges earned prior to post-incubation, the problem's level of difficulty, total attempts made prior to post-incubation, and time interval of post-incubation. They noted that incubation was no longer helpful to relieve mental exhaustion in the later part of the 2-hour activity session.

3. Methodology

3.1 Physics Playground

Physics Playground (PP), formerly known as Newton's Playground, is a two-dimensional computer-based educational game designed to teach concepts of qualitative Physics for high school students. This same environment was used in the prior work on IE (Martinez et al., 2016; Talandron et al., 2017). The game environment simulates how physical objects work in relation to Newton's laws of motion (Shute & Ventura, 2013). The objective is to guide the green ball to the red balloon by drawing simple machines. A player gets a gold badge if the problem was solved using at or below a par number of objects determined by the game designers. Otherwise, a silver badge is given. Further gameplay details are discussed in prior studies (Banawan, Rodrigo, & Andres, J M, 2015; Martinez et al., 2016; Palaoag, Rodrigo, Andres, Andres, & Beck, 2016; Talandron et al., 2017) which also used PP as the learning environment.

3.2 Data Set

The data used in this study is the same dataset in prior work on IE (Martinez et al., 2016; Talandron et al., 2017). It was collected from 60 2nd year high school students with aged 13 to 18 years old (M=15.7). Twenty-nine were from a public junior high school; and 31 from a private university, both in Baguio City, Philippines. The students took a pre-test, after which they played PP for 2 hours. The interactions of each player were recorded and logged into a file. After playing, the students took a post-test.

3.3 Feature Variables

In prior attempt to model IE (Talandron et al., 2017), they used a total of 14 handcrafted features based on IE literature and mapped them with the features from the interaction logs of the students. Aside from the 14 features, this study added 3 more features in relation to how the students tried to solve the problem in each potential IE. As mentioned in the previous section, each level has 1 or 2 canonical solutions (i.e. the ideal solution for playground 1 level 2 is a ramp). Based on this information, we looked at the similarity of the problems encountered during the incubation period and added two features: 1) total levels played during incubation similar to level X and 2) similarity rate which was computed as total levels similar to X during incubation over all levels played during incubation. Also, the duration of their post-incubation phase was taken into consideration. In total, this study used 17 features.

3.4 Data Visualization and Clustering

According to literature (Bouveyron & Brunet-Saumard, 2014; Ding, He, Zha, & Simon, 2002; Marbac & McNicholas, 2016) clustering may not be as effective when used in high dimensional data and suggested that a dimensionality reduction technique is applied first. More so, it is helpful to get a preview of the structure of the data through visualization to see if there are indeed possible clusters. The t-Distributed Stochastic Neighbor Embedding (t-SNE) (Maaten & Hinton, 2008) is a technique well suited for the visualization of high-dimensional datasets. There are several ways to implement t-SNE and dimensionality can be lessened to as low as two dimensions. In this study, we chose to have the two resulting dimensions which was visualized through a scatter plot with each data point identified by its respective label. The value of perplexity was chosen based on which gave the highest t-SNE-nearest neighbor accuracy rate.

From the t-SNE visualization, we get an insight of the structure of the data which can then help decide if it is appropriate to do clustering. Thus, when possible clusters are present, we then use a clustering technique to group the cases. In this study, we used X-means clustering which is a variation of K-means clustering that treats cluster allocations by repetitively attempting partition and keeping the optimal resultant splits, until some criterion is reached (Pelleg & Moore, 2000). We then plot the result of each cluster model onto the t-SNE graph. Each cluster was then analyzed to extract notable features.

4. Results and Discussion

4.1 Data Visualization and Clustering

Thirty-seven (62%) out of 60 players exhibited potential IEs (PIE) resulting to a total of 180 PIE. Seventy-seven (43%) of these were IE-true while 103 (57%) were IE-false. Using t-SNE, the dataset of 180 potential IEs with 17 features was reduced and visualized in a two-dimensional plot to uncover data structure that may be helpful in the analysis of the incubation effect. Figure 1 shows the t-SNE graph where we can see possible groups of data points. The label S means "solved" for IE-True and NS means "not solved" for IE-False. Several runs of t-SNE were conducted with varying values for perplexity and in order to decide on the most appropriate value, the one with the highest t-SNE nearest neighbor accuracy was selected. In this result, the perplexity of 20 yield the highest t-SNE nearest neighbor accuracy of 81%.

From the t-SNE result in Figure 1, we can already observe possible groups of data points. Then, we applied x-means clustering which resulted to 4 clusters with a Davies–Bouldin index of 0.07, which were plotted into our t-SNE graph (Figure 2).

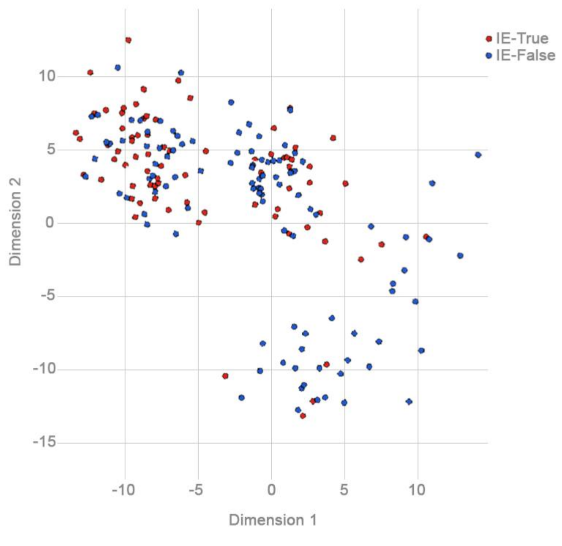

Fig. 1. t-SNE visualization of all Potential IEs

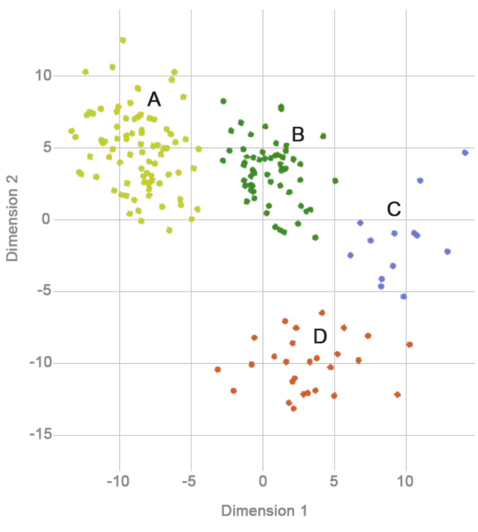

Fig. 2. X-means clusters from the t-SNE output

In Figure 3, the t-SNE plot with the identified clusters show that IE-True is very rare in clusters C and D and almost all potential IEs resulted to IE-False in these clusters. We focus our analysis in identifying distinct characteristics of clusters C and D.

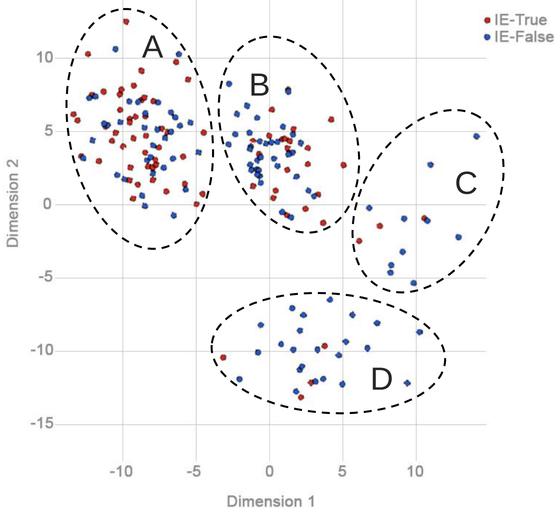

Fig. 3. t-SNE plot showing the clusters based on x-means clustering

For us to interpret the characteristics of these clusters based on the 17 features, we analyzed the features for each cluster. Significant differences in the data for each feature for each cluster were also validated using Scheffé's method and false discovery rate for multiple comparisons. Table 1 shows 7 notable features out of 17 for clusters C and D.

Table 1

Potential IE clusters table of means

Attributes	Clusters			
	A	B	C	D
(F3) Total attempts on level X	1.72	2.13	**2.31**	**3.59**
(F5) Incubation duration	8.74	7.44	**59.48**	**41.04**
(F7) Badges earned during incubation	1.45	1.38	**3.62**	**3.27**
(F8) Levels played during incubation	4.02	6.32	**42.31**	**28.18**
(F9) Levels played during incubation similar to level X	1.80	3.52	**15.08**	**14.95**
(F16) Total levels played prior to post-incubation	20.65	50.63	**88.23**	**55.95**
(F17) Success rate prior to post incubation	0.60	0.50	**0.19**	**0.25**

We found that notable features in clusters C and D are the following:

1. (F3) Total attempts on level X – Prior work (Martinez et al., 2016) showed a relationship between frustration and the incidence of potential IEs which means that frustrated students tend to re-attempt the levels more. However, results indicate that more attempts on the unsolved level were not helpful even after taking a break. There were also observations of multiple consecutive attempts on the unsolved problem during the pre and post incubation periods which might be indications of wheel-spinning (unproductive persistence) which was previously investigated and observed in the same data set (Palaoag et al., 2016).
2. (F5) Incubation duration – Based on the investigation of Martinez et al., (2016), for a 2-hour session, the average incubation duration of IE-True is at 11 minutes. There was no significant correlation between incubation duration and success rate, but results show that a lengthy break seems to be ineffective.

3. Productivity – these are (F7) badges earned during incubation, (F8) levels played during incubation, (F16) total levels played from the beginning of the session until the post-incubation phase, and (F17) success rate from the beginning of the session until the post-incubation phase for a particular potential IE, respectively. It can be seen from table 1 that for clusters C and D, the numbers of levels played during the incubation period are more than 5 times higher than those in clusters A and B. However, the badges earned are just around twice as much. This discrepancy contributed to the relatively low success rate in clusters C and D which means that taking a break is not as helpful if one was unproductive before and during the incubation period. Previous study (Ellwood et al., 2009; Fulgosi & Guilford, 1970; Gilhooly et al., 2013; Penaloza & Calvillo, 2012; Sio & Ormerod, 2009) said that incubation period with high cognitive demand tasks resulted to smaller incubation effect more so if the learner has not been productive with these tasks.
4. (F9) Total levels played during incubation that are similar to the unsolved problem in terms of the canonical solutions and total levels played during incubation – It might seem odd that playing more levels similar to level X during the break was not beneficial. However, if we take into consideration the total number of all levels played during the break (F8) as well the total number of levels played from start of the session until the post-incubation phase (F16) which were both relatively high, we can infer that the similarity might have been overshadowed by all the other levels that the player attempted to solve. Also, having played many levels can cause fatigue even during the break which prior work (Ellwood et al., 2009; Talandron et al., 2017) considered to be a hindrance to beneficial incubation.

5. Conclusion, Contribution, and Future Work

This study aims to further understand incubation effect by using visualization and clustering. Results showed that some features of IE-True and IE-False seem to overlap and warrants deeper analysis. On the other hand, on the clusters where the incidence of IE-True is rare and IE-False is prevalent, we are able to identify features which most likely lead to an ineffective break.

Some of these features were similar to the findings of (Talandron et al., 2017) in terms of playing too many levels before and during the break without reaching a certain rate of productivity which, according to previous researchers (Ellwood et al., 2009; Fulgosi & Guilford, 1970; Gilhooly et al., 2013; Penaloza & Calvillo, 2012; Sio & Ormerod, 2009), may not result to a positive incubation effect. There were also features that were not included in the previous IE model (Talandron et al., 2017) which are the length of incubation and similarity of levels encountered to the unsolved problem. IE authors (Fulgosi & Guilford, 1970; Sio & Ormerod, 2009; Smith & Blankenship, 1991) reported evidence that the length of incubation may improve performance during the post-incubation period but in the case of IE in PP, an incubation period which is greater than half of the total session duration was no longer helpful. In terms of the similarity to level X, (Penney et al., 2004) said that engaging in a task with similar nature would promote priming which allows students to realize the correct solution to the problem. However, this study showed that even if you engaged in similar problems but overwhelmed the supposedly priming process with a high number of other problems, then incubation may not be effective.

Incubation effect may not be a familiar term but its context is a common phenomenon and the benefits of incubation may be incorporated into computer-based learning environments to help students' performance. The prior and present work on IE in PP can only be considered preliminary. Experimental researches where a controlled environment can be designed can be conducted in order to test these results and discover more factors that may or may not make a break beneficial in the context of a computer-based learning environment.

Acknowledgements

The authors would like to thank Mr. Joshua Martinez and Mr. Jun Rangie Obispo for their valuable contribution in the initial investigation of incubation effect in Physics Playground which paved way for this study and Prof. Valerie Shute for her assistance on questions about Physics Playground specifically about the canonical solutions. We also would like to thank the Ateneo Laboratory for the Learning Sciences and the Ateneo de Manila University Department of Information Systems and Computer Science. This study was made possible through a grant from the Philippines' Department of Science and Technology Philippine Council for Industry, Energy and Emerging Technology Research and Development entitled "Stealth assessment of student conscientiousness, cognitive-affective states, and learning using an educational game for Physics."

References

Banawan, M. P., Rodrigo, M. M., & Andres, J M, J. (2015). An Investigation of Frustration Among Students Using Physics Playground. Presented at the 23rd International Conference on Computers in Education, China.

Bouveyron, C., & Brunet-Saumard, C. (2014). Model-based clustering of high-dimensional data: A review. *Computational Statistics & Data Analysis*, *71*, 52–78.

Ding, C., He, X., Zha, H., & Simon, H. D. (2002). Adaptive dimension reduction for clustering high dimensional data. In *Data Mining, 2002. ICDM 2003. Proceedings. 2002 IEEE International Conference on* (pp. 147–154). IEEE.

Ellwood, S., Pallier, G., Snyder, A., & Gallate, J. (2009). The incubation effect: Hatching a solution? *Creativity Research Journal*, *21*(1), 6–14.

Fulgosi, A., & Guilford, J. P. (1970). Short-Term Incubation in Divergent Production. *The Journal of Creative Behavior*, *4*(2), 131–132.

Gilhooly, K. J., Georgiou, G., & Devery, U. (2013). Incubation and creativity: Do something different. *Thinking & Reasoning*, *19*(2), 137–149.

Maaten, L. van der, & Hinton, G. (2008). Visualizing data using t-SNE. *Journal of Machine Learning Research*, *9*(Nov), 2579–2605.

Marbac, M., & McNicholas, P. D. (2016). Dimension Reduction in Clustering. *Wiley StatsRef: Statistics Reference Online*.

Martinez, J. C., Obispo, J. R. C., Talandron, M. M. P., & Rodrigo, M. M. T. (2016). Investigating the Incubation Effect among Students playing Physics Playground. Presented at the 24th International Conference on Computers in Education, Mumbai, India.

Medd, E., & Houtz, J. C. (2002). The effects of facilitated incubation on fourth graders' creative writing. *Educational Research Quarterly*, *26*(2), 13.

Palaoag, T. D., Rodrigo, M. M. T., Andres, J. M. L., Andres, J. M. A. L., & Beck, J. E. (2016). Wheel-Spinning in a Game-Based Learning Environment for Physics. In *International Conference on Intelligent Tutoring Systems* (pp. 234–239). Springer.

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

Penaloza, A. A., & Calvillo, D. P. (2012). Incubation provides relief from artificial fixation in problem solving. *Creativity Research Journal*, *24*(4), 338–344.

Penney, C., Godsell, A., Scott, A., & Balsom, R. (2004). Problem Variables that Promote Incubation Effects. *Journal of Creative Behavior*, *38*(1), 35–55.

Segal, E. (2004). Incubation in Insight Problem Solving. *Creativity Research Journal*, *16*(1), 141–148.

Shute, V., & Ventura, M. (2013). *Stealth assessment: Measuring and supporting learning in video games*. MIT Press.

Sio, U. N., & Ormerod, T. C. (2009). Does incubation enhance problem solving? A meta-analytic review. *Psychological Bulletin*, *135*(1), 94.

Smith, S. M., & Blankenship, S. E. (1991). Incubation and the persistence of fixation in problem solving. *The American Journal of Psychology*, 61–87.

Talandron, M. M. P., Rodrigo, M. M. T., & Beck, J. E. (2017). Modeling the Incubation Effect Among Students Playing an Educational Game for Physics. In *International Conference on Artificial Intelligence in Education* (pp. 371–380). Springer.