Proceedings of the 2020 Annual General Donald R. Keith Memorial Capstone Conference
West Point, New York, USA
April 30, 2020
A Regional Conference of the Society for Industrial and Systems Engineering

Modeling Learners: Identifying Learner Profiles in the Game of Snake

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Author Note: The authors listed above are currently seniors at the United States Military Academy at West Point and worked under the direction of their advisors, LTC Randal Hickman and COL Ricardo Morales. They are working with Lockheed Martin's Advanced Technology Laboratory (ATL), a key lab for the biggest defense contracting company in the United States. The authors would like to thank Lockheed Martin and their advisors for all their support.

Abstract: The U.S. Navy needs a training assistant that tracks, models, and enhances learning for sailors. Critical to improving the learning process is providing the right training at the right time, ensuring engaged and motivated learning, and a persistent learner record. This requires the ability to identify specific learner profiles that correspond to individual sailors. Lockheed Martin collected data of college students playing the game Snake as a basis for defining and identifying learner profiles. This West Point effort used the Lockheed data to develop three models to represent the varying learner types: a linear, exponential, and logarithmic learning model. The models are used to categorize learners, assisting educators in developing a tailored learning experience. Educators are capable of individualizing learning experiences through the implementation of motivational cues. Learning profiles can be traced over a lifetime of learning to provide career-long training.

Keywords: Learner Profiles, Linear Model, Exponential Model, Logarithmic Model

1. Introduction

1.1 Context

By Fiscal Year-2021, the U.S. Navy will spend over $930 million on computer-based, on-ship training modules (Werner, 2018). The goal of this training is to remotely deliver Ready, Relevant Learning (RRL) to sailors in the fleet. RRL is aimed at teaching Sailors tasks that they would have learned at Naval A-School or their Military Occupational Specialty (MOS) school. This program is based off an inefficiency during A-School where sailors spend weeks learning various skills that have minimal applicability once in the fleet. This new initiative will track sailor training strengths and deficiencies, while providing dynamic and goal-oriented training programs over the computer that target specific sailor skills.

The Navy has identified two major hurdles implementing computer-based trainings: motivation and engagement ("LIME Overview," 2017). Some Sailors skip through training events, un-motivated to complete the various modules. To combat this issue, the Office of Naval Research (ONR) has identified the need for a dynamic training program that provides motivational cues to keep Sailors engaged. To introduce this stimulus at exactly the correct moment, ONR hired Lockheed Martin to develop a responsive learning environment for Sailors that must identify when motivation is dwindling for each individual Sailor. This requires the development of learning profiles that model learning styles, motivation, and material retainment of knowledge over time – the start point for this research effort at West Point supporting Lockheed Martin's program.

1.2 Problem Definition

Learning with Intrinsic Motivation Enhancement (LIME) focuses on implementing rewards to achieve maximized learning without undermining a learner's inherent interest (Perez, 2018). Key components that drive a learner are motivation and engagement. These components are what LIME uses as a deciding factor to attribute an individual to a learner profile. However, without accepted models tailored to learning trajectories, it is impossible to determine when learner motivation and engagement begin to falter. These models can be built using the game "Snake" as a proxy for engagement during computer-based trainings. "Snake" is a feasible option as a proxy for computer-based Sailor training because of the continued focus on a screen and the level of focus required. Both “Snake” and Sailor training require significant focus over time. Based on the performance of individuals playing “Snake,” individual learning models predicting plateaus in motivation and engagement can be created.

1.3 Problem Statement

Today’s Sailors are typically trained on a “one-size-fits-all conveyor-belt-training-model” that does not account for individual learners’ motivation and engagement (“LIME Overview,” 2017). The U.S. Navy desires to create a training assistant that tracks and models Sailors’ learning profiles to introduce precise motivational cues. Using the game “Snake” as a proof of concept, different learning models will be produced to track the learning trajectories of individuals with the hope of predicting when plateaus in motivation and engagement occur.

2. Background

2.1 Learning Profiles

In order to identify a learning profile, it is important to understand how individuals learn and apply the material. Cognitive learning describes the progression of processing information, which moves from sensory input, passes through the cognitive system, and finds the response (Lynch, 2018). Without these steps, learning is not achieved. The brain processes information through many different forms, whether from actively searching for knowledge, watching others perform tasks, or simply memorizing information. This begs the question of how people learn better? With over 13 different types of cognitive learning, there is a need to recognize different learning styles to ensure all learners can reach their full potential (Lynch, 2018). It is also important to recognize the difference between expert and novice learners, for the difference between the two greatly impacts the learning curve. Expert learners use strategic knowledge, self-regulation, and reflection techniques to influence their learning curves, whereas novice learners focus on memorization and basic cause and effect (Ertmer and Newby, 1996). In return, expert learners minimize plateaus and see consistent exponential or linear increase, while a novice learner has inconsistent patterns that may plateau for extended periods of time or even decrease.

In addition, learners can also be categorized based on the shape of their learning curve. A learning curve is the graphical relationship between the amount of learning and the time it takes to learn (Center4Study, 2016). The most common are linear learners, exponential learners, and logarithmic learners. Linear learners experience the same output as they input. For every increase in “x” (effort or input) there is a proportional and constant increase in “y” (output or skill). In an exponential learner, large increases in effort are needed to see minimal progress; however, progress accelerates and could continue to do so without additional effort (Hendricks, 2014). In a logarithmic learner, for every small increase in “x” there is a disproportionately large increase in “y” early on. However, over time, the increase in “x” will produce a much smaller increase in “y” and the progress will slow (Hendricks). By identifying the shape of an individual’s learning curve, instructors can input additional instruction in places where plateaus, a decrease in slope, or a stagnant learning occur.

2.2 Life-Long Learning

After a learning profile is identified, the next challenge becomes sustaining this throughout a lifetime. Forward thinking provided the Personal Assistant for Life-Long Learning (PAL3). This is an automated system that is supported by the Office of Naval Research. The PAL3 allows an individual to choose a topic and then creates a list of courses to facilitate the training. This allows individuals to have custom profiles that provides a tailored learning experience (Swartout, 2016). In addition to the courses, the PAL3 also provides motivation in the sense that learning becomes more relevant. Individuals are more motivated to learn if they see schooling as a relevant part of their lives, have the skills to accomplish tasks, and feel responsible for their own learning. Allowing individuals to understand their learning profiles and providing them with the tools to continuously learn, increases the likelihood to achieve life-long learning.

3. Methodology

3.1 Data Format

Lockheed Martin chose thirty college students to play the classic video game "Snake" as a good learning proxy to develop learning profiles (Perez, 2018). Students play for ten minutes for four different intervals. At the end of every interval, the number of trials, length of the snake, and the time elapsed for each trial was recorded. Every time the snake hit the wall or ran into itself, a new trial would start within that ten-minute interval. An example of the Lockheed Martin data is shown in Figure 1.

Time	X (Head)	Y (Head)	X (Food)	Y (Food)	Length
0	14	20	7	13	5
0.1183	14	21	7	13	5
0.2353	14	22	7	13	5
0.3513	14	23	7	13	5
0.4683	14	24	7	13	5
0.5853	14	25	7	13	5
0.7023	14	26	7	13	5

Figure 1. Original Data for one Student

In Figure 1, the time column displays the time lapsed, X (Head) and Y (Head) are the coordinates of the snake, X (Food) and Y (Food) are the coordinates of the food the snake is trying to reach, and length is the length of the snake calculated by number of grid coordinates it occupies.

3.2 Data Cleaning

While the client's data precisely reported the movement of the snake during each trial, it did not provide any "score" value by which to measure the success of any learner's performance. In order to measure the successes of each learner with a common scoring measure, this research developed a new scoring metric by melding two provided variables into a combined measure of success. The two variables considered were survival time and length of the snake. The score variable enabled the group to clean the data, only retaining that which was relevant to creating an objective score for each learner's performance over time through their ten-minute trials. Survival time represents the time a snake survives within each game. Given the objective of the game is to increase the length of the snake as much as possible, it has a higher weight to the score. Length is the most important, so a weighted coefficient of .8 was determined. A second weighted coefficient was added for the survival time. The coefficients were multiplied to their respective data, yielding the score metric shown in (Equation 1).

$$Score = (.8)(length) + (.2)(survival\ time) \tag{1}$$

In order to determine if these coefficients were highly sensitive, the authors conducted an empirical sensitivity analysis. The model was insensitive to minor changes in weights, provided that the length attribute was more heavily weighted than the survival time attribute. An example of the cleaned and scored data from Figure 1 is found below in Figure 2. The "A" column is the weighted coefficient for length of the snake and "B" is the weighted coefficient for the survival time of the snake. The trial column shows the number of trials the individual had within the ten minutes. Survival time is the time elapsed for each game or trial. The score column includes both scoring components as shown in Figure 2.

A	B	Trial #	Survival Time	Score
0.8	0.2	1	12.961	8.99
0.8	0.2	2	186.05	80.41
0.8	0.2	3	299.96	89.59
0.8	0.2	4	315.91	71.18
0.8	0.2	5	355.00	88.60

Figure 2. Data Cleaning and Scoring

3.3 Creating Models

After cleaning the data, the next objective was to interpret it in a meaningful way for this research effort. Given the expertise of the advisors and researchers on this team paired with the stakeholder's input regarding areas of further study from previous research, creating and verifying learner profiles was the most salient information to learn from the data. While learner profiles had been theorized in previous literature, the body of knowledge lacked objective functions by which to classify learners as best fitting one or the other profile. The team's primary contribution to the body of knowledge concerning the client's research is creating the base objective functions by which to classify a learner's behavior during these trials into one of three descriptive learner profile models: Linear Model, Exponential Model and Logarithmic Model. These three models were developed from the research of Hendricks to classify a learner. Given these suggested forms, the research team defined new variables to develop the Linear model (Equation 2), the Exponential Model (Equation 3) and the Logarithmic Model (Equation 4).

$$y = ax + h \tag{2}$$

$$y = e^{(ax+h)} + v \tag{3}$$

$$y = v - e^{(-a(x+h))} \tag{4}$$

The variables are defined as follows: *y* is the score, *a* is how quickly the learner learns the skill of the game, *x* is the game/trial number, *v* is the isotonic achievement of learning, and *h* is the entry-level skill of an individual before beginning their first scored trial. These were determined by key components to define a certain learner profile. The analysis of the models generated a score for each trial. Once each score was generated, the models were fitted to a learner profile.

3.4 Fitting Learners to Models

In order to fit the models to a specific learner profile, the Sum of Squared Error (SSE) equation (Equation 5) was used, where *y*

$$SSE = \sum(y - \hat{y})^2 \tag{5}$$

is the actual score earned, and $\hat{y}$ is the output of the learner model. SSE determines the accuracy of the model by taking the sum of the squared errors for the "Snake" performance of each trial during the 10-minute duration. By minimizing the SSE, optimal parameter values for the three learning model for each experimental subject are determined. The model with the lowest SSE for that individual is selected as the learning style for that subject. Figure 3 contains the modeling results for the same data shown in Figures 1 and 2, with optimized coefficients for each learning model.

	v	a/Slope	h/Intercept	SSE
Linear Model		6.515	50.281	4518.815
Exponential Model	1.299	0.0513	4.182	5587.724
Logarithmic Model	124.787	0.299	-16.299	2741.868

Figure 3. Modeling Output for Learning Profiles

As seen in Figure 3, green designates the lowest SSE for this individual, yellow is the second lowest SSE, and red is the highest SSE. In this case, the best fit for a learner profile for this individual is the Logarithmic Model. In order to provide a better visual for the best fit of the models, the model was placed in a graph. The graph for Logarithmic follows (Figure 4):

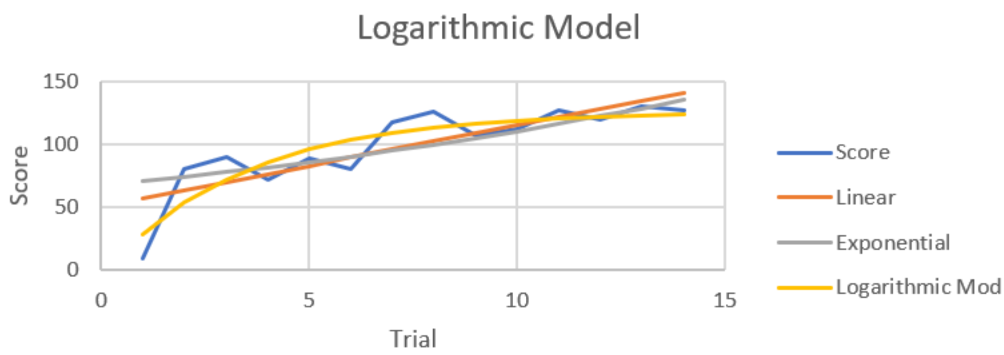

Figure 4. Logarithmic Model

Similarly, many learners also had best fits to linear or exponential learning models. For example, Figure 4 shows a learner who best supports the logarithmic profile while Figure 5 shows a learner who best fits the exponential.

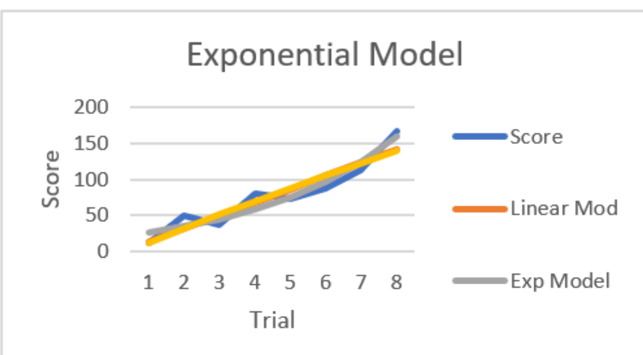

Figure 5. Exponential Model

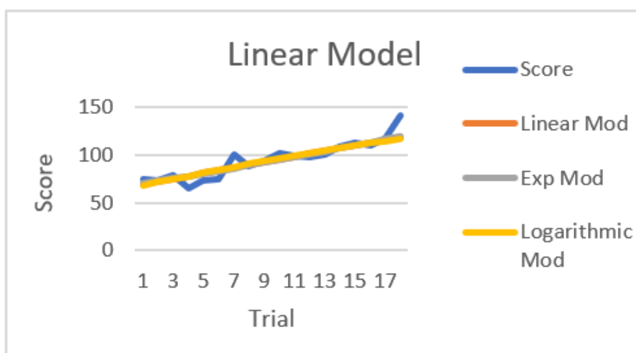

Figure 6. Linear Model

4. Findings

After fitting the 30 learners to models, we found that all three of the learning profiles served as the best learning style for some individuals. Linear learners tended to develop their skills at a constant rate. There may be instances where a linear learner shows dips or peaks, but they tend to see steady improvement. An exponential learner took longer to grasp the skills at first, but then saw scores increasingly higher over time. Logarithmic learners saw steady rates of improvement or even rapid rates of improvement at first, followed by a performance plateau. This represents an individual who understands the basic concepts but may lose interest or fail to apply the material consistently. We also found instances of non-learning and decrease in performances. Some individuals displayed an inability to improve their score overtime, while some started with a relatively high score and decreased every game after. These individuals require more attention throughout their training. It is important that stakeholders identify these individuals to ensure that they can stay focused and/or receive the help that they need in order to begin to see improvements and minimize the stakeholder's training cost.

5. Conclusion

5.2 Limitations

The Snake game serves as a proof of concept that learning profiles can be identified. Although possible to identify learning types through Snake, playing Snake may not be the best determinant of learning ability because it is a very simple game that does not require significant skill. Basing critically important learner models off individual's ability to play Snake, can be considered a dangerous form of extrapolation. Attempting to use a video game as a proxy for real learning can potentially be inaccurate and is thus a limitation. This means that it is difficult to apply the same learning profiles to different tasks. For example, the learning curve identified for an individual during the Snake game may not be the same profile while learning calculus. Moreover, the same profile may not be transferrable to different topics within the same subject. An individual may have a separate learning profile for algebra than calculus. The brain does not process all information the same. Rather than applying a singular learning curve to an individual, many learning curves need to be obtained to provide a tailored, subject specific, learning experience. Without more experiments involving the same learners under different learning circumstances, this investigation is limited in its ability to accurately gauge individuals' total learning profile. However, this research was an important first step developing learning profiles and methods to optimize parameters and select a best learning profile among candidate options for students.

5.3 Recommendations

The most appropriate way to analyze these learner profiles is within the context that they reside. This project should not be viewed as a final product for Lockheed Martin, but rather as a significant contribution of developing and selecting learner models that may be used as a critical aspect of future research. The data should be treated as a verification that different types of learners exist and how much individual learners vary even in a game as simple as Snake. Future researchers must realize the rudimental aspect of using Snake as a proxy for learning. This project should be used as a launch pad for future investigations that have the goal of fine tuning the mathematical models to get more accurate and wholistic learner identification. More complete learner identification will lead to further development of the PAL3 project and better identification when to introduce specified motivational cues.

5.4 Future Work

To mitigate the difficulties of applying multiple profiles to different learning situations, the PAL3 needs to be further developed to account for multiple simultaneous learner profiles. The PAL3 needs to be able to track learning profiles within different fields of knowledge. This means that the PAL3 should have specified learning profiles for Sailors' mathematics, reading, writing, problem solving, and technical skills. This will allow the PAL3 to accurately provide timely motivational cues in varying training situations and environments. The next step in the process is to create a program that can track current learner profiles, while identifying when and how to motivate Sailors within their training modules. These programs need to validate current models, while using untested populations to verify the accuracy of the models for future population.

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