A Skill Tracing Model for Player Character Control in STG

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Abstract: STGs, a longstanding video game subgenre, have grown more intricate over time, deterring new players. To address this, a training system is required to improve character control skills in STG games. Bayesian Knowledge Tracing (BKT) is a common approach researchers use to monitor and assess students' progress. While BKT is effective in evaluating intellectual knowledge, it falls short in assessing character control skills in STG, a form of motion knowledge. This study proposes a Skill Tracing (ST) model that combines BKT approaches to monitor both cognitive knowledge and character control abilities. Results indicate its superiority in skill-tracking tasks over traditional BKT, offering a more accurate prediction of players' skill levels.

Keywords: STGs, Bayesian Knowledge Tracing, skill modeling, character movement classification

1. Introduction

STG, a challenging video game subgenre, demands exceptional reaction speed and skill mastery. Despite a loyal fanbase, its complexity hampers novice skill acquisition, affecting their experience. Matching challenge to skill level is vital for enjoyment (Sweetser & Wyeth, 2005), making skill training crucial. Traditional methods like repetitive practice are time-consuming and unspecific. Designing a focused training system for STG novices is essential for rapid skill mastery, requiring skill learning tracing.

Skill tracing constitutes a vital component of the STG skill training system, allowing it to comprehend a player's learning progress and skill proficiency. The Bayesian knowledge tracing (BKT) method (Corbett & Anderson,1994) is commonly employed to model and monitor a student's mastery of knowledge. While in most concept-based learning scenarios, researchers merely assess whether a student has comprehended a concept or not, the situation differs when a player aims to master a gaming skill. In this context, it becomes important to not only gauge a player's familiarity with concepts such as game tips or tactics, but also to evaluate whether the player can effectively apply this information during gameplay, drawing upon their physical capabilities. This distinction implies that BKT might not be optimal for accurately modeling player skills.

This research aims to extend the BKT model to monitor player control skill learning in STG game. To achieve this, the following research questions will be addressed:

1. How can the BKT model be extended from knowledge learning tracing to encompass skill learning tracing?
2. Dose the proposed model outperform the BKT model in the context of STG skill tracing?

2. Proposed Method

2.1 Skill Tracing Model

In skill learning, applying acquired knowledge involves the body's physical ability to become adept at the technique, while knowledge learning involves purely intellectual engagement. Physical ability here refers to coordinating bodily functions for motor tasks, encompassing coordination, reflexes, balance, and spatial orientation.

Assuming skill mastery ('S' in Equation (1)) results from the overlap of conceptual understanding ('K' in equation (1)) and physical familiarity ('B' in Equation (1)), it can be represented as: $\mathbf{S = K \cap B}$ (1)

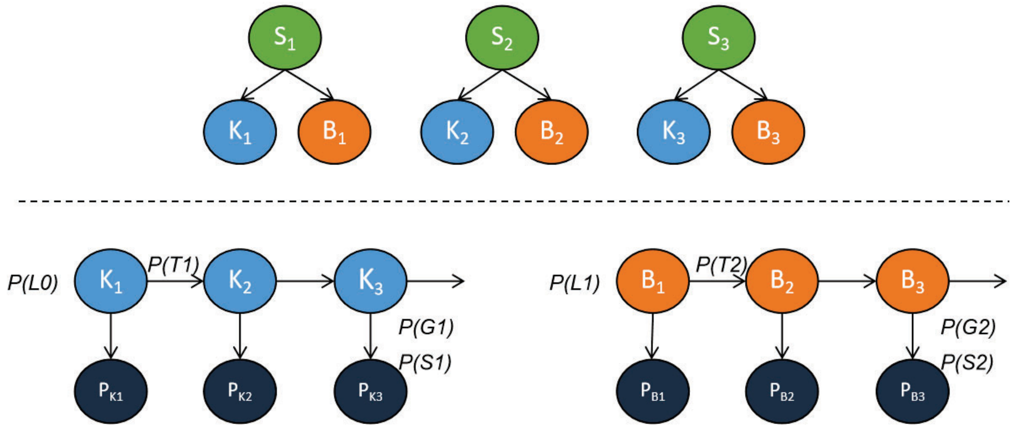

Figure 1. The structure of ST model

We proposed a Skill Tracing model (ST) based on the BKT model and Equation (1). Figure 1 is the structure of the ST model. The parameters comprise two sets of [P(L), P(T), P(G), P(S)], each belonging to a distinct BKT model. These four parameters represent the probabilities of prior knowledge, learning new material, guessing, and making errors during the learning process. We combine the predictions of the two BKTs and determine the player's skill mastery state S using Equation (1). Two sets of responses, P_K and P_B, are gathered from the observable layer. These responses are obtained from the same game stage at each step of the learning sequence. P_K denotes whether a player used a tactic in the game, helping predict the knowledge level (K) representing their understanding of that specific tactic in a stage. Tactic use is detected by analyzing keypresses and character movement. Treating a stage as a time series, the MrSQM time series classifier (Nguyen, T. L., & Ifrim, G., 2021) is employed to identify tactic application. P_B indicates whether a player completed a stage, and it's used to predict the body ability (B), indicating the player's capacity to finish a game stage at a specific difficulty level.

2.2 Game environment and skill setting

In this study, the gaming environment is the self-developed game "stgST," created using the open-source game engine LuaSTG (LuaSTG Wiki, n.d.). StgST comprises 18 stages with distinct bullet patterns outlined in Table 1. Our research centers on character control skills, vital for survival in the game. In this context, we define skills as employing specific tactics to dodge corresponding bullet patterns as shown in Table 1).

Table 1. *Abstract character control skill from bullet pattern and its tactic*

Pattern name	**Tactic**	**Skill**
Aimed Shot	Tiny Moving	Use tiny moving to avoid aim-shot
	Restream	Use restream movement to avoid aim-shot in screen edge
Round Shot	Circling	Use circling movement to avoid round shot
Bottom Bullet	Upper Avoiding	Move to upper screen to avoid bottom bullet
Revenge Bullet	Hold Fire	Stop shooting to avoid revenge bullet

3. Experiment and Result

We conducted an experiment to collect player data, recording a total of 957 game rounds from 21 players. The author manually recorded instances of player failures per round, while keypress information and character movement were automatically recorded. We assumed a stage to be cleared if a player failed in it fewer than four times. Player keypress and character movement were categorized into different patterns using a pre-trained MrSQM model, derived from author-generated play data.

The player data were modeled using the PyBKT Python library (Badrinath, A., Wang, F., & Pardos, Z., 2021). We compared the modeling outcomes of the ST and BKT models on player data, additionally assessing the impact of introducing the "forgets" parameter. The "forgets" parameter, introduced by Qiu, Y. et al. (2011), signifies the tendency for students to forget knowledge at a certain rate during the learning process.

Taking into account the imbalanced input data, we employed F1 score and balanced accuracy as metrics to assess the models. As indicated in Table 3, the results demonstrate that irrespective of the presence of the "forgets" parameter, the ST model surpasses the BKT model in F1 score by approximately 7% and in balanced accuracy by about 5.5%.

Table 2. *F1 score and balanced accuracy of four models.*

	F1 Score	Balanced Accuracy
BKT	0.500	0.684
BKT + forgets	0.511	0.695
ST	0.570	0.747
ST + forgets	**0.577**	**0.751**

4. Conclusion & Future Work

In this study, we proposed a new model called the ST model to track a player's progress on the task of character control skill. The ST model is an extension of the BKT model, differentiating between knowledge-learning and skill-learning tasks. We validated the model on the player character control skill-learning task and found that it outperforms BKT. In addition, we found that the parameter forgot had essentially no effect on the results of the experiment, probably because the duration of the experiment was so short that players were unlikely to forget.

In future research, we would like to complete a skill training system for novice STG players. Additionally, we plan to explore the potential application of the ST model to other types of skill-learning tasks beyond game-based scenarios.

References

Badrinath, A., Wang, F., & Pardos, Z. (2021). pyBKT: an accessible python library of Bayesian knowledge tracing models. arXiv preprint arXiv:2105.00385.

Corbett, A. T., & Anderson, J. R. (1994). Knowledge tracing: Modeling the acquisition of procedural knowledge. User modeling and user-adapted interaction, 4, 253-278.

LuaSTG Wiki. (n.d.). Main Page. Retrieved from http://en.luastg.shoutwiki.com/wiki/Main_Page.

Nguyen, T. L., & Ifrim, G. (2021). MrSQM: Fast time series classification with symbolic representations. arXiv preprint arXiv:2109.01036.

Qiu, Y., Qi, Y., Lu, H., Pardos, Z. A., & Heffernan, N. T. (2011, July). Does Time Matter? Modeling the Effect of Time with Bayesian Knowledge Tracing. In EDM (pp. 139-148).

Sweetser, P., & Wyeth, P. (2005). GameFlow: a model for evaluating player enjoyment in games. Computers in Entertainment (CIE), 3(3), 3-3. doi: 10.1145/1077246.1077253