# Research on Scaffolding: Using Algorithmic Modeling of Players' Knowledge Growth from Game Log Files

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## Abstract

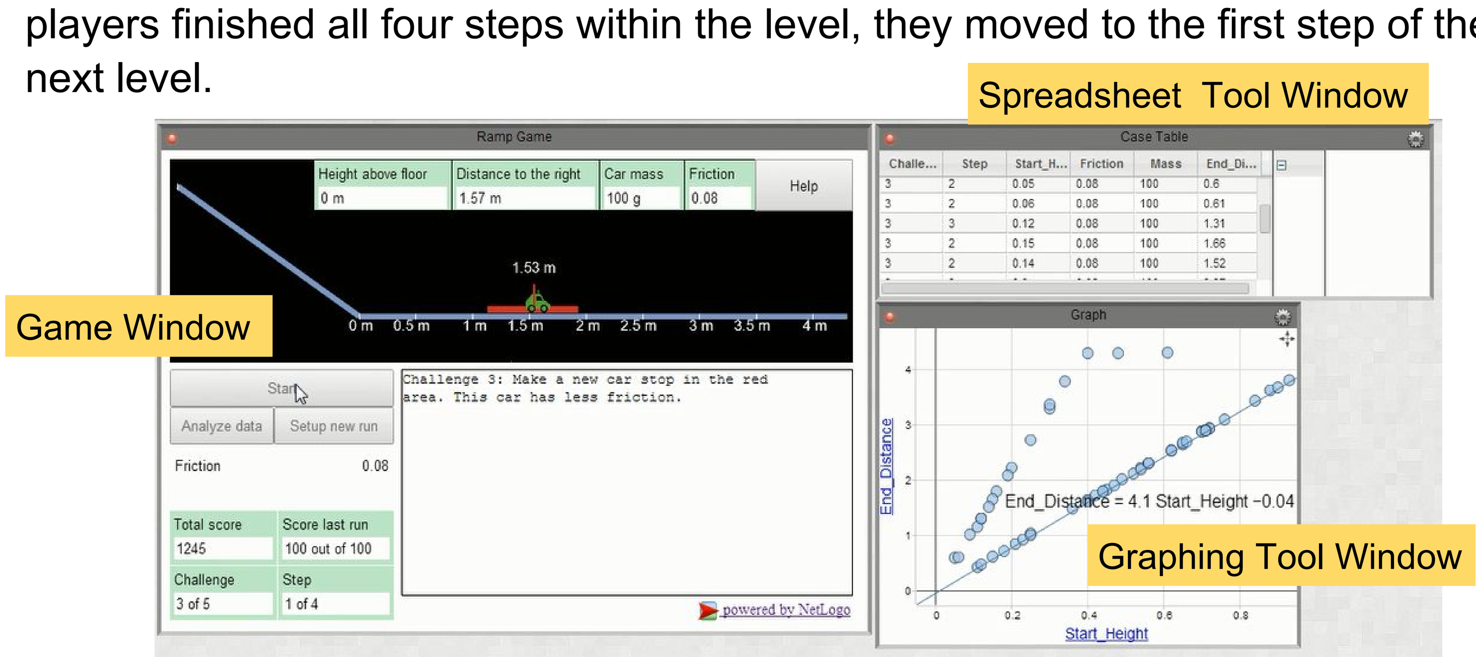
Digital games can provide an opportunity for players to learn new scientific knowledge (Honey & Hilton, 2011). Players' transactions with digital games and related game performances can be automatically collected in time-stamped log files (Martin & Sherin, 2013). Like human observations however, log files are unfiltered observations made by machines of which values can only be revealed by prudent applications of appropriate research methodology. In this study, we collected data from log files generated by high school students playing a serious game on a computer and analyzed game score patterns based on Monte-Carlo Bayesian Knowledge Tracing (MC-BKT). We found a significant scaffolding effect on knowledge gain when students used a graphing tool as compared to when they did not.

## Research Questions

1. How does MC-BKT capture players' knowledge growth during a game?
2. How do MC-BKT analysis results determine whether an embedded graphing tool worked to support players' knowledge growth?

## Research Context

Research was conducted with a game featuring a car sliding down on a ramp of which surface had some friction. (See below.) The ramp game consisted of five levels requiring players to apply more and more sophisticated knowledge about the relationships among the variables associated with the ramp system. Each level consisted of 3 or more steps. For each step, players needed one or more trials to be successful. Players' performance for each trial is scored on a 0 to 100 scale. If scored 65 points or higher, players moved to the next step within the level. If players finished all four steps within the level, they moved to the first step of the next level.




The screenshot above shows three windows. The game window (left), the spreadsheet tool window (upper right), and the graphing tool window (lower right). Using the graphing tool, players visualize the trend of the game data collected in previous trials and predict the winning move based on the pattern emerging from the game data. In this study, the graphing tool was not automatically available to players. Players needed to click from a menu button to call the graphing tool during the game.

## Data Sources and Analysis

42 groups of high school physics students played the ramp game where the spreadsheet tool was available for all groups but the graphing tool window had to be activated by them. We recorded all of the log files generated from the gameplay and applied MC-BKT to estimate four BKT parameters associated with each game level for each group of players. We applied mixed effects ANOVA on each BKT parameter with player group as a random effect and graph usage as a fixed effect.

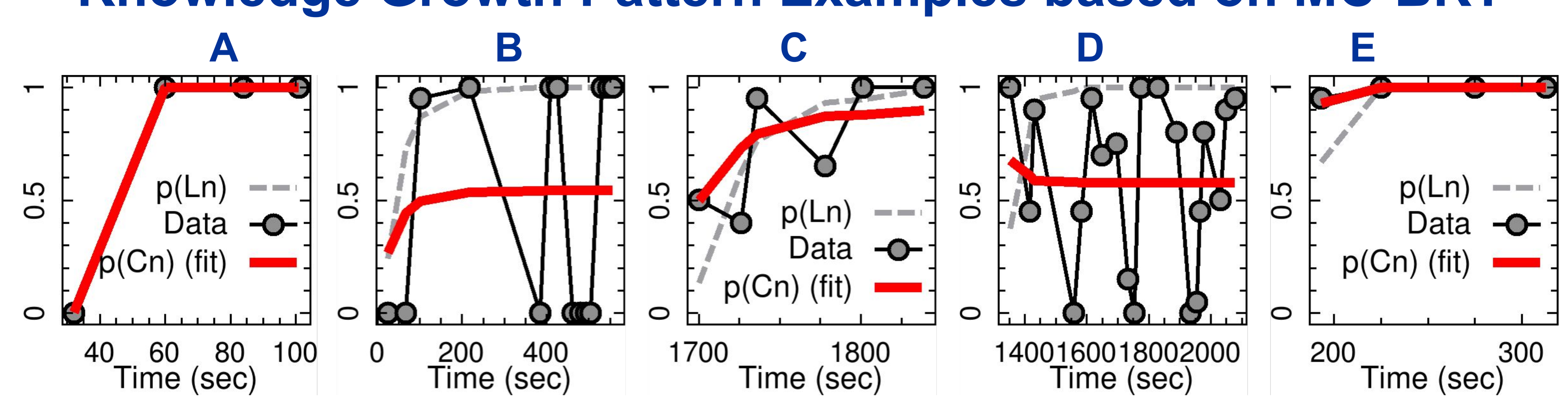
## MC-BKT

To track players' knowledge growth, we used the Bayesian Knowledge Tracing (BKT) model (Corbett & Anderson, 1995). BKT considers a knowledge variable as latent and estimates the knowledge growth curve from observed performances as a function of time. The BKT analysis produces four parameters: initial knowledge (L0), transition (T), guessing (G), and Slip (S). See Table below. Since conventional BKT analyses are originally developed to estimate BKT parameters for the entire sample of players (Lee & Brunskill, 2012), we developed the MC-BKT algorithm to make BKT parameter estimates for each player's knowledge growth (Gweon et al., 2015).

## Bayesian Knowledge Tracing (BKT) Parameters

| BKT parameter | Parameter description |
|---|---|
| $p(L_0)$ | Initial knowledge parameter associated with the probability that the student already knows the target knowledge prior to the task |
| p(T) | Transition parameter associated with the probability of becoming knowledgeable at a given level |
| p(G) | Guessing parameter associated with the probability of guessing correctly without the target knowledge (false positive) |
| p(S) | Slip parameter associated with the probability of making a mistake when in fact the student has the target knowledge (false negative) |

## Knowledge Growth Pattern Examples based on MC-BKT




**MC-BKT Parameter estimates related to five knowledge growth patterns**

| | A | B | C | D | E |
|---|---|---|---|---|---|
| p(L0) | 0.0 | 0.2 | 0.1 | 0.4 | 0.7 |
| p(T) | 1.0 | 0.7 | 0.6 | 0.7 | 1.0 |
| p(G) | 0.0 | 0.2 | 0.4 | 0.7 | 0.8 |
| p(S) | 0.0 | 0.5 | 0.1 | 0.4 | 0.0 |
| Interpretation | Fast growth from no to full knowledge | Slow growth from no to full knowledge | Fast growth from partial to full knowledge | Stalled knowledge growth | Knowledge existed from the beginning |

Note that (1) Slip parameter shows mistakes players make when in fact they are learning the knowledge. The higher the slip, the more the errors committed by players; (2) Guessing parameter shows the discrepancy between players' scores as compared their predicted knowledge growth at that moment. Therefore, low guessing parameter values show players do not score high initially when their knowledge is supposedly low. High guessing parameter values show players' score high initially which could indicate having knowledge before the play or successful random guessing.

## Mixed effects ANOVA results on BKT parameter estimates

Note: all parameters ranged from 0 to 1.

| BKT parameter estimates | Without graph | | With graph | | Graph effect |
|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | F, p |
| (a) P(Li): Probability of having knowledge before the level | .18 | .10 | .15 | .12 | F = .99, p = .32 |
| (b) P(T): Probability of becoming knowledgeable within the level | .56 | .18 | .52 | .18 | F = .43, p = .52 |
| (c) P(G): Probability of guessing correctly without knowledge | .37 | .29 | .26 | .23 | F = 6.4, p < .05 |
| (d) P(S): Probability of making mistakes with knowledge | .41 | .20 | .31 | .16 | F = 11.5, p < .01 |

## Results

After controlling for player group effects, Mixed Effects ANOVA results show that the probability of guessing and the probability of slipping were significantly reduced for those who used graphs to guide their game play as compared to those who did not. This indicates that the graphing tool reduced random errors and encouraged players to notice relationship patterns from the graph.

## Conclusions

1. The MC-BKT algorithm can be useful to track players' knowledge growth in game-like simulations without utilizing external tests.
2. The algorithm allows researchers to associate the effect of scaffolding tools embedded in an interactive learning environment with the knowledge growth.
3. It can be combined with other data to investigate how factors such as players' characteristics, behaviors, and task features impact the knowledge growth.

## References

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