Using Gameplay Data to Investigate Students' Problem-Solving Behaviors in Zoombinis

Research Background

Purpose

Game-based learning environments have been shown to increase students' engagement and achievement [3], in which the tasks are constructed with complex problems. It enables students to engage in a variety of problem-solving scenarios. Students' problem-solving in game-based learning environments is dynamic [2] and implicit [1], making it challenging to uncover their problem-solving stages and strategies.

- 1. Integrated data mining techniques.
- 2. Problem-solving processes in game-based learning environments.

Learning Context

Zoombinis is designed as a puzzle-based game situated in problems, allowing many scaffolded problem-solving processes for young students [4]. In this study, the learning context is a certain puzzle called Pizza Pass. This puzzle has different difficulty levels, wherein one or more trolls block the Zoombinis' paths. Each troll requires a pizza with specific topping set.



Figure 1. A screenshot of Pizza Pass gameplay.

Measures

- Trial and Error: There is no evidence of ordered or planned behaviors shown in students' gameplay. Actions are independent of the previous one and not testing any hypotheses.
- Systematic Testing: Evidence shows that students are trying to reveal the underlying rules with ordered and planned gameplay behaviors. Actions are dependent on the previous one.
- Implement Solution: Completing a pattern of solutions with one or whole dimension of the rules solved.
- Generalize Solution: Evidence shows that a sequence of strategic actions is repeated across multiple attempts to solve one or more puzzles.

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Methodology

Data was collected from 158 students in grades 3-8 (88 males, 70 females) who played with at least two puzzles of *Pizza Pass*. There were 11014 attempts generated from students' gameplay data in total. CHMM modeled students' each attempt as one specific problem-solving stages, while sequence mining identified frequent patterns among these attempts. All the data were processed with Python codes.

Event	Object-Attribute_Selected	Object_Attribute1	Solution_Attribute1	Extra_Info
SELECT-PIZZA_TOPPING	Pizza: Pepper	P_01000000	P_01100000	•
SELECT-PIZZA_TOPPING	Pizza: Cheese	P_01010000	P_01100000	•
SELECT-PIZZA_TOPPING	Pizza: Mushroom	P_01010001	P_01100000	•
DELIVER_PIZZA_ICE_CREAM	·	P_01010001	P_01100000	•
TROLL_DISLIKES_SOMETHING		P_01010001	P_01100000	Arno
TROLL_REJECTS_DELIVERY		P_01010001	P_01100000	Arno
	Event SELECT-PIZZA_TOPPING SELECT-PIZZA_TOPPING SELECT-PIZZA_TOPPING DELIVER_PIZZA_ICE_CREAM TROLL_DISLIKES_SOMETHING TROLL_REJECTS_DELIVERY	EventObject-Attribute_SelectedSELECT-PIZZA_TOPPINGPizza: PepperSELECT-PIZZA_TOPPINGPizza: CheeseSELECT-PIZZA_TOPPINGPizza: MushroomDELIVER_PIZZA_ICE_CREAMImage: CheeseTROLL_DISLIKES_SOMETHINGImage: CheeseTROLL_REJECTS_DELIVERYImage: Cheese	EventObject-Attribute_SelectedObject_Attribute1SELECT-PIZZA_TOPPINGPizza: PepperP_01000000SELECT-PIZZA_TOPPINGPizza: CheeseP_01010000SELECT-PIZZA_TOPPINGPizza: MushroomP_01010001DELIVER_PIZZA_ICE_CREAMP_01010001P_01010001TROLL_DISLIKES_SOMETHINGP_01010001P_01010001TROLL_REJECTS_DELIVERYP_01010001P_01010001	EventObject-Attribute_SelectedObject_Attribute1Solution_Attribute1SELECT-PIZZA_TOPPINGPizza: PepperP_010000000P_01100000SELECT-PIZZA_TOPPINGPizza: CheeseP_01010000P_01100000SELECT-PIZZA_TOPPINGPizza: MushroomP_01010001P_01100000DELIVER_PIZZA_ICE_CREAMP_01010001P_01100000TROLL_DISLIKES_SOMETHINGP_01010001P_01100000TROLL_REJECTS_DELIVERYP_01010001P_01100000

Figure 2. Examples of students' gameplay log data.

Results

Results from CHMM

Table 1 shows several examples illustrating how to identify students' problemsolving stages by CHMM. Each attempt was classified as the corresponding stage i where its log-likelihood was the largest (λ_T : Trial and Error; λ_S : Systematic Testing; λ_I : Implement Solution; λ_G : Generalize Solution). To validate the accuracy of the developed model, 10-fold cross-validation was applied. CHMM had 93.53% agreement with human labels, performed an ROC/AUC score of 0.76.

Table 1. Examples of the identification results.

Human Labels	СНИИ	Log-Likelihood			
		λ_T	λ_S	λ_I	λ_G
Trial and Error	Trial and Error	-3.34	-6.75	-5.34	-14.74
Systematic Testing	Implement solution	-3.57	-2.09	-2.05	-3.31
Implement solution	Implement solution	-3.40	-1.78	-1.74	-2.84
Generalize Solution	Generalize Solution	-4.72	-2.28	-2.77	-1.90

According to CHMM, students' gameplay attempts can be categorized as different problem-solving stages, which helps us better understand students' problemsolving processes and locate the struggling moments when students were stuck in a certain stage.

Besides, CHMM suggests that the transition between two stages is likely to occur when the log-likelihoods are close. In summary, CHMM not only efficiently labels students' problem-solving stages but also indicates the probabilities of transitions happening.

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Results

Results from sequence analysis

Five problem-solving strategies were found: test pizza toppings one by one (Test*ing one*); combine one untested and all other correctly tested pizza toppings (Additive); replace one pizza topping while keep others remained (Replacing); remove selected pizza toppings one by one (*Winnowing*); select the complement of previous pizza toppings (Subtracting).

Strategy	Frequent pattern	Number of students
Testing one	$S1 \rightarrow D \rightarrow S3 \xrightarrow{*} D$	158
Additive	$S1 \rightarrow D \rightarrow S1 \rightarrow S2 \rightarrow D^{**}$	127
Replacing	$S1 \rightarrow S5 \rightarrow D \rightarrow S1 \rightarrow S4 \rightarrow D$	93
Winnowing	$S1 \rightarrow S2 \rightarrow S3 \rightarrow D \rightarrow S1 \rightarrow S2 \rightarrow D$	65
Subtracting	$S1 \rightarrow S3 \rightarrow S5 \rightarrow D \rightarrow S2 \rightarrow S4 \rightarrow D$	52

Select topping 3.

^{**} Deliver the combination of topping 1 and 2.

According to Table 2, *Testing one* is the most commonly used strategy, which may efficiently help students get out of loops and facilitate their systematic problemsolving processes.

Conclusion

By applying CHMM and sequence analysis, we obtained a thorough depiction of students' problem-solving behaviors in *Zoombinis*. This integrated method can be utilized to analyze students' implicit problem-solving stages and discover effective problem-solving strategies in game-based learning environments.

References

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