

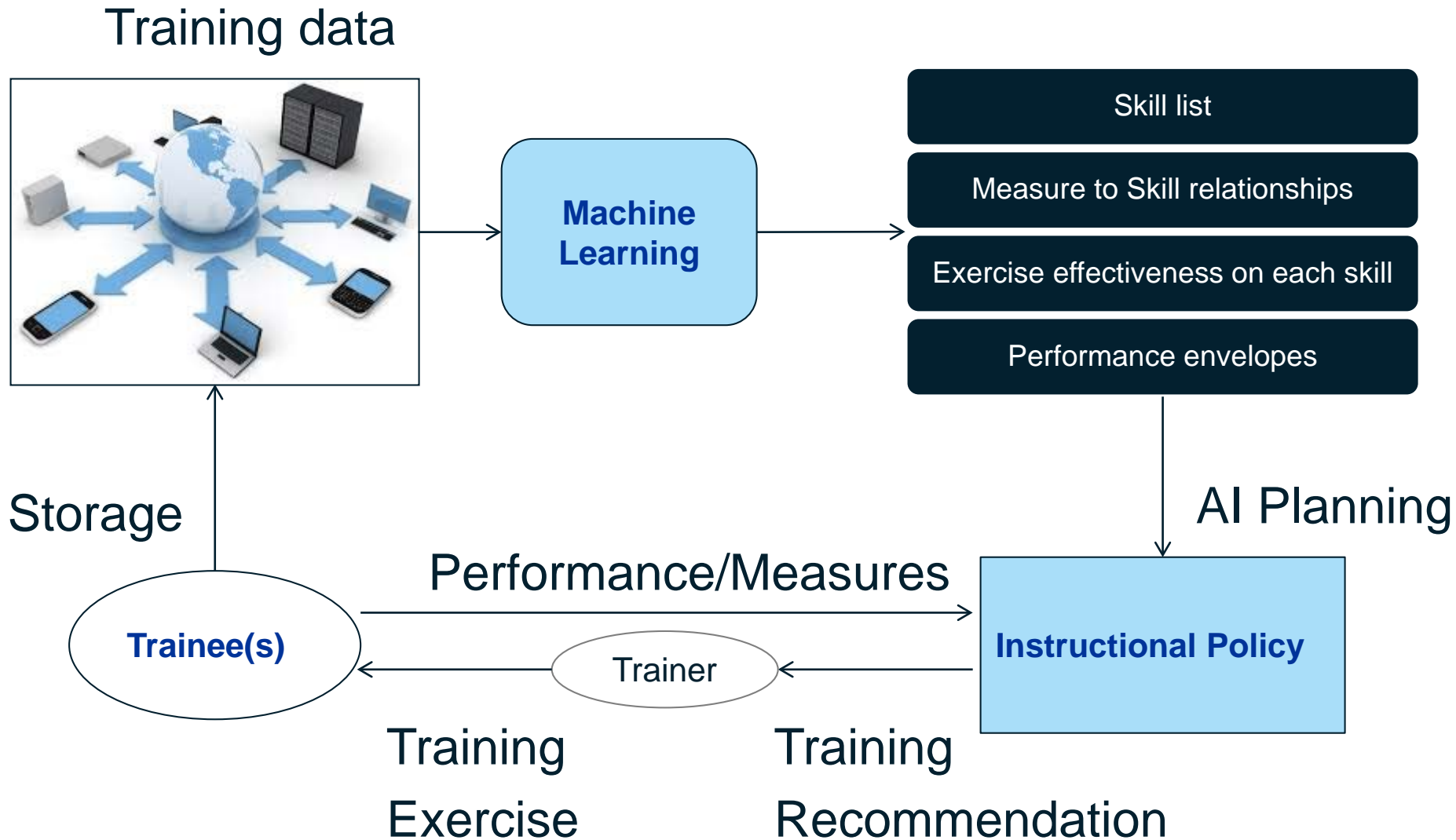


Educational Data Mining Using GIFT

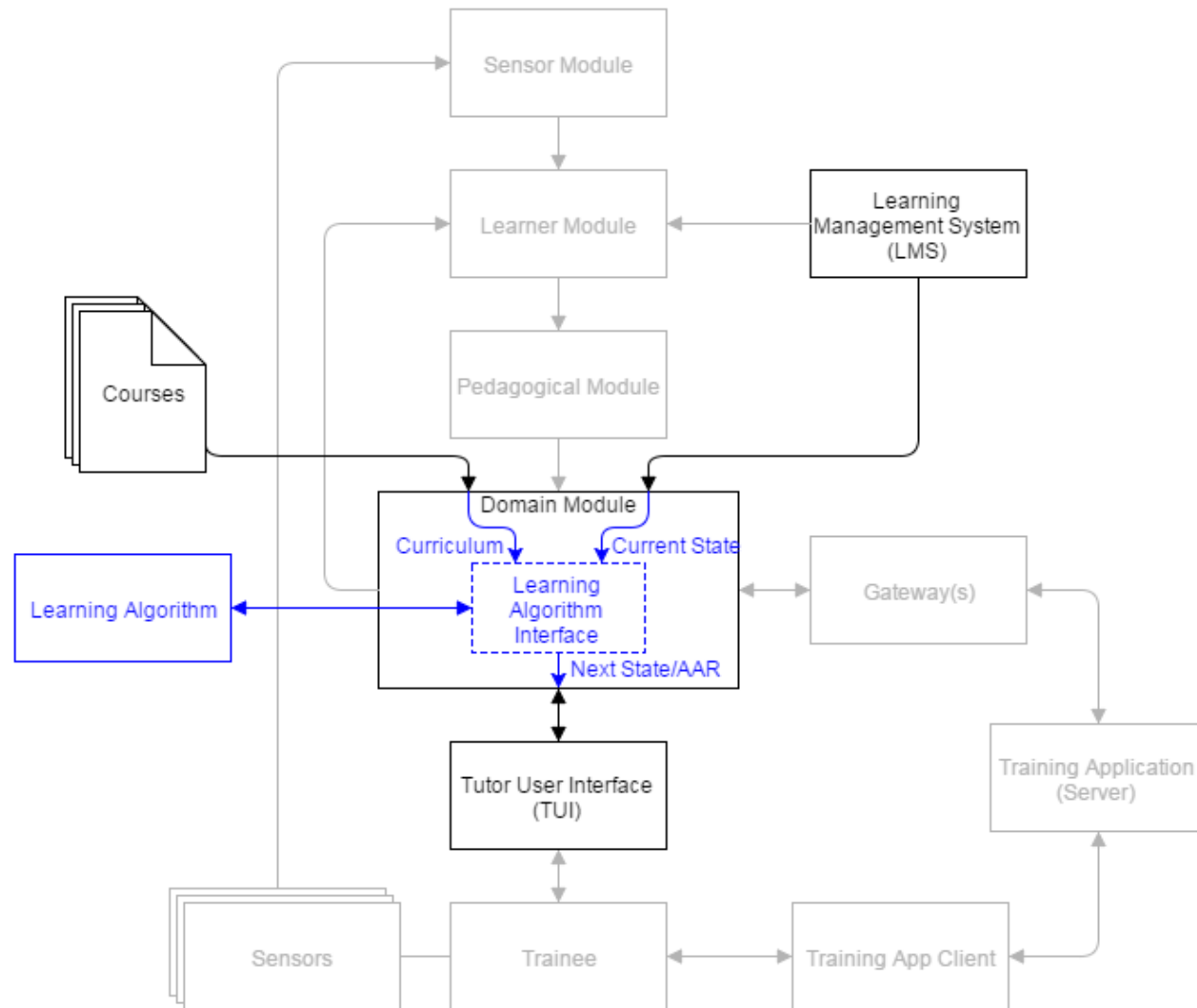
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After Action Review

- Several questions related to ITS's motivate this work
- What is the best content for a personalized After Action Review (AAR)?
 - Personalization implies:
 - Understanding learner Knowledges, Skills, and Abilities (KSA's)
 - Understanding KSA's in the training domain
 - Understanding how training measures relate to those KSA's
 - Implementation of a policy to select the AAR given the above



- Data mining software to extract results from the GIFT LMS
- After Action Review based on the data mining
- Implementation of training policy software that personalizes training based on the information in the AAR
- Improvements to GIFT-powered Newtonian Talk to implement the above
- Improvements to GIFT Cloud to enable a data collection study

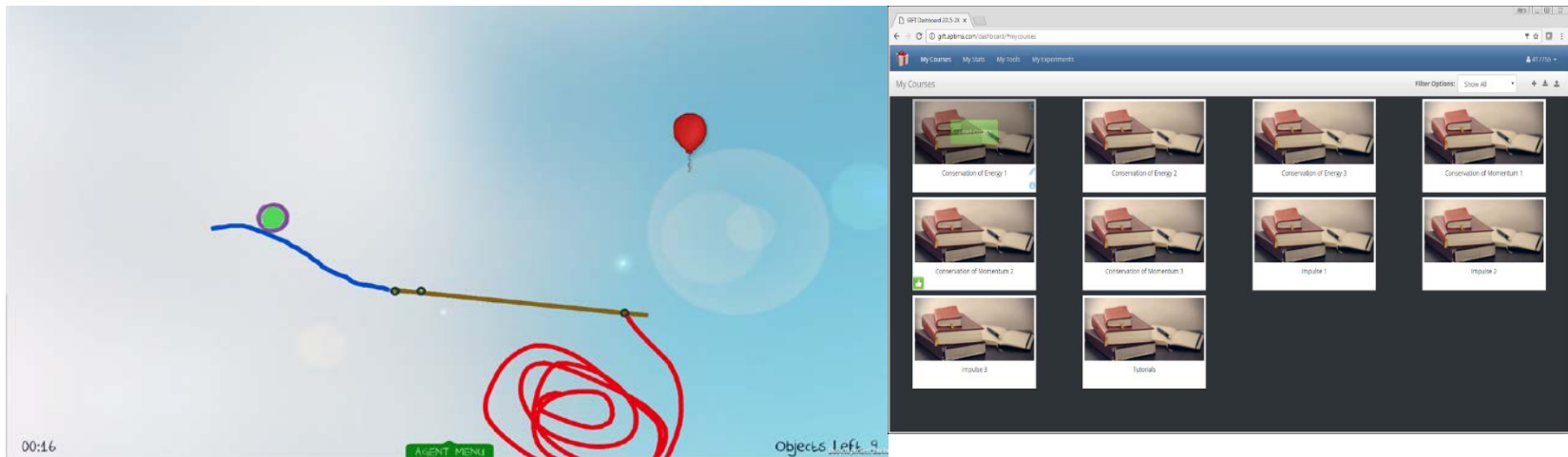


Sequence of events

1. The student takes a pre-test to assess physics knowledge.
 2. An adaptive learning algorithm (e.g., MDP) determines which course the student should take next.
 3. An AAR screen shows the results of the learning algorithm, including level of expertise in each skill.
 4. The learning algorithm also makes a recommendation for which course the student should take next.
 5. The student takes the next course.
 6. The process repeats (go to step 2 above) 9 times.
 7. After the 9th scenario, the learning loop ceases and the student takes a post-test.
- The **LMS** was modified to store a custom construct called student state
 - Messages were added to support transmission between GIFT modules
 - The **Domain Module** was enhanced to include classes that represent an adaptive AAR policy
 - The Domain Module was also used to get/set user state in the LMS.
 - **Tutor UI**: The tutor UI was tweaked to display AAR.

Newtonian Talk

- Use Case: GIFT-powered Newtonian Talk (Zhou et al., 2015)



Data mining model

- **State** is defined as a k-tuple of numbers, e.g., $\langle 3, 5, 5, 1 \rangle$
 - For this study, we automatically extracted these from the measures in the LMS
- **Actions** are the options available to the tutor
 - Selection of modules and AAR
- **Transition** is the modeled effect of each action
- **Observations** are the modeled probability of receiving a measure, given learner state
 - Taken from IRT: $p(\text{correct}) = \frac{1}{1 + e^{\sum_k w_i^k (d_i^k - \theta_j^k)}}$
- This corresponds to a Partially Observable Markov decision Process (POMDP) model

Student Data

Student ID	Seq Number	Scenario	Score	Time
111	1	Lesson A	10/10	5s
111	2	Lesson C	1/10	10s
111	3	Lesson B	7/10	1s
192	1	Lesson A	5/10	5s
192	2	Lesson D	1/10	10s

Lesson Data

Scenario	Feature 1
Lesson A	Video
Lesson B	Quiz
Lesson C	Speaking

Student Data

Inference via Machine Learning

Student ID	Seq Number	Scenario	Score	Time	Skill 1	Skill 2	Skill 3
111	1	Lesson A	10/10	5s	Untrained	Untrained	Untrained
111	2	Lesson C	1/10	10s	Beginner	Untrained	Untrained
111	3	Lesson B	7/10	1s	Beginner	Untrained	Untrained
192	1	Lesson A	5/10	5s	Untrained	Untrained	Untrained
192	2	Lesson D	1/10	10s	Untrained	Untrained	Untrained

Lesson Data

Inference via Machine Learning

Scenario	Feature 1	Skill 1 Applicability	Skill 1 Difficulty	Skill 2 Applicability
Lesson A	Video	Very	Easy	N/A
Lesson B	Quiz	N/A	N/A	Moderate
Lesson C	Speaking	N/A	N/A	N/A

Student Data

Inference via Machine Learning

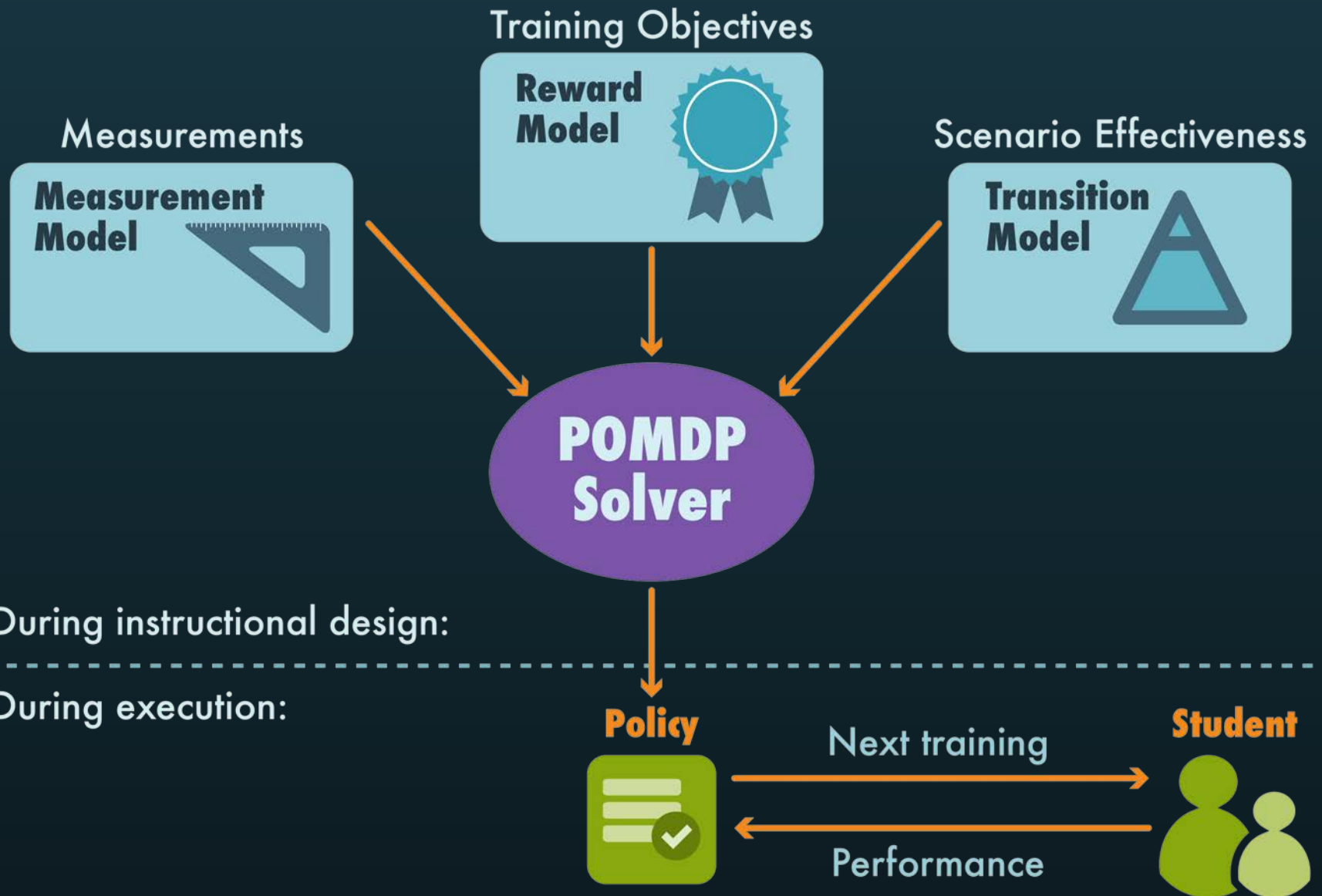
Student ID	Seq #	Scenario	Score	Time	Skill 1	Skill 2	Skill 3
111	1	Lesson A	10/10	5s	$\theta_1^{111}(1)$	$\theta_2^{111}(1)$	$\theta_3^{111}(1)$
111	2	Lesson C	1/10	10s	$\theta_1^{111}(2)$	$\theta_2^{111}(2)$	$\theta_3^{111}(2)$
111	3	Lesson B	7/10	1s	$\theta_1^{111}(3)$	$\theta_2^{111}(3)$	$\theta_3^{111}(3)$
192	1	Lesson A	5/10	5s	$\theta_1^{111}(1)$	$\theta_2^{111}(1)$	$\theta_3^{111}(1)$
192	2	Lesson D	1/10	10s	$\theta_1^{111}(2)$	$\theta_2^{111}(2)$	$\theta_3^{111}(2)$

Lesson Data

Inference via Machine Learning

Material	Feature 1	Skill 1 Applicability	Skill 1 Difficulty	Skill 2 Applicability
Material 1	Video	a_1^1	d_1^1	a_2^1
Material 2	Quiz	a_1^2	d_1^2	a_2^2
Material 3	Speaking	a_1^3	d_1^3	a_3^3

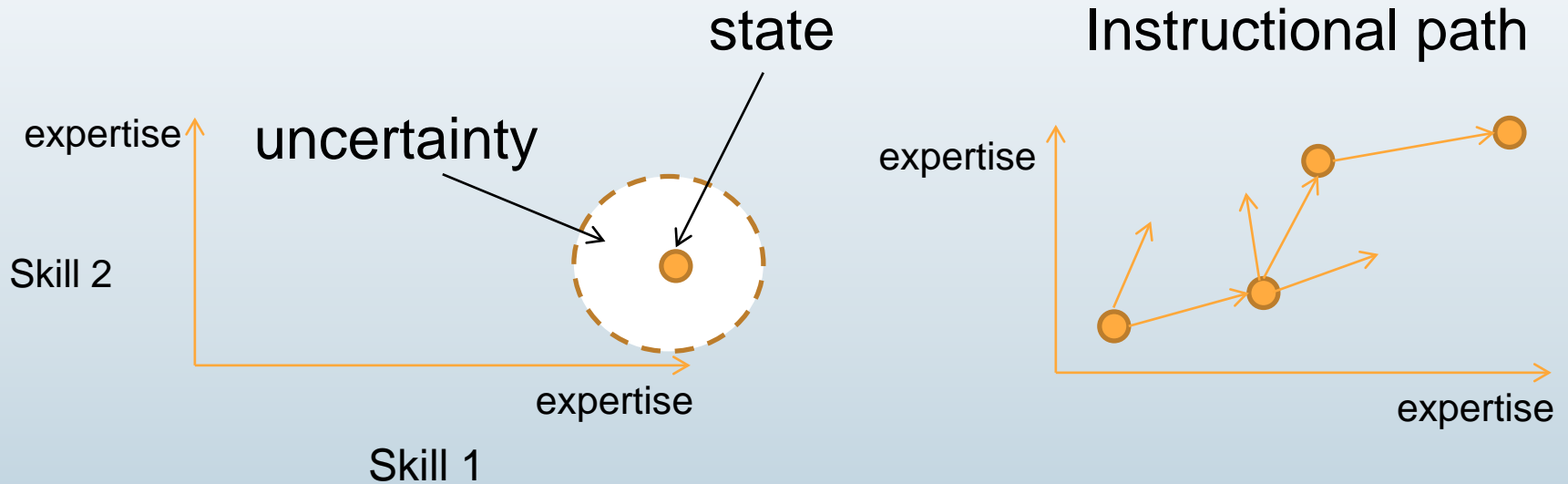
POMDP Overview



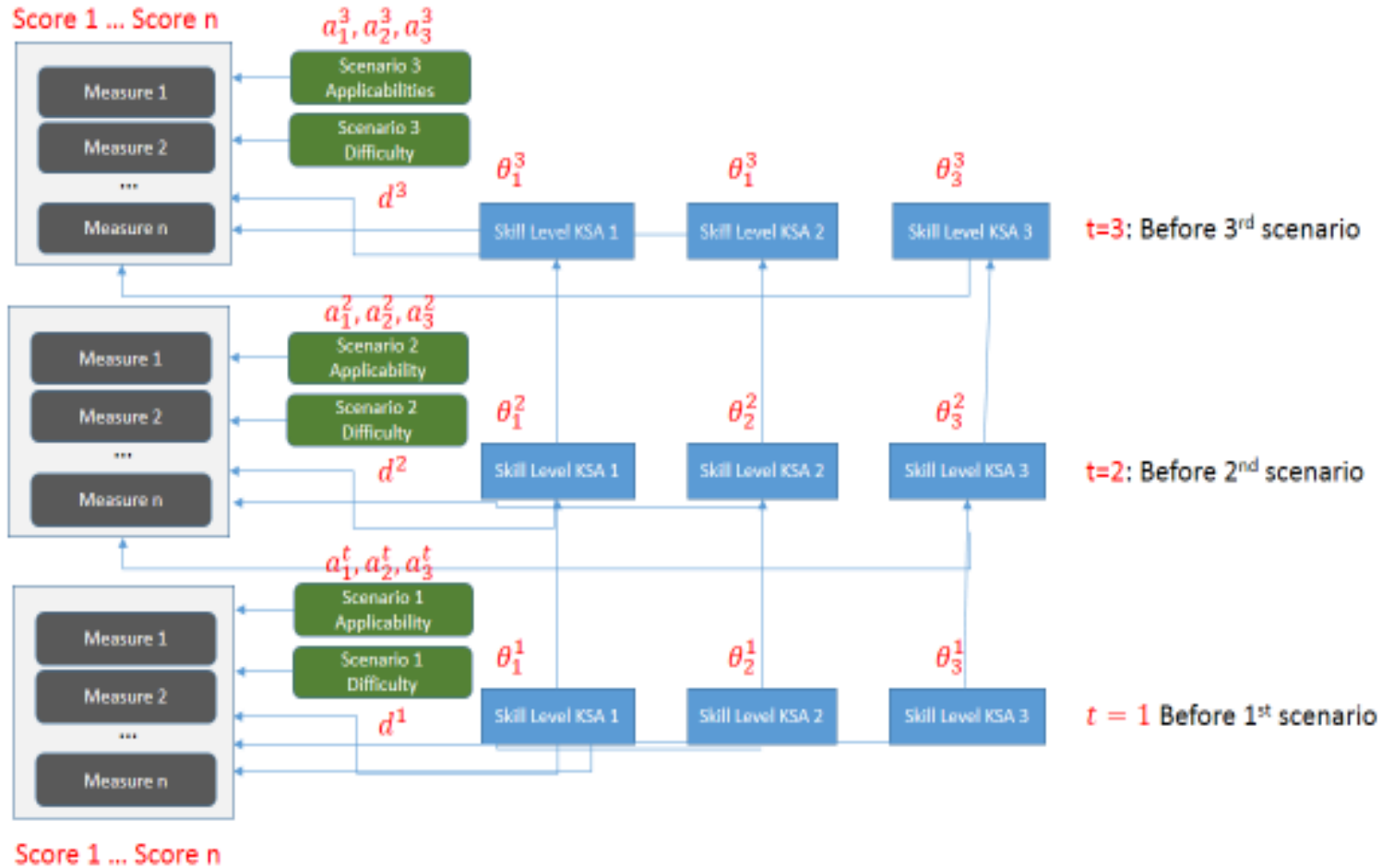
Sequential Optimization under Uncertainty

Intelligent mathematical modeling approach called POMDP (Partially Observable Markov Decision Process)

Reasoning under Uncertainty (left)
Sequential Optimization Model (right)



Model



Model for GIFT

Course	Name	draw pin	draw spring	draw anything	draw pinned	draw freeform	draw ramp
Playground 1, Puzzle 1	Tutorial 1						
Playground 1, Puzzle 2	Tutorial 2						
Playground 1, Puzzle 3	Tutorial 3						
Playground 1, Puzzle 4	Tutorial 4						
Playground 1, Puzzle 5	Tutorial 5						
Playground 2, Puzzle 1	Impulse 1	X	X				
Playground 2, Puzzle 2	Impulse 2	X	X				
Playground 2, Puzzle 3	Impulse 3	X	X				
Playground 3, Puzzle 1	Momentum 1			X	X		
Playground 3, Puzzle 2	Momentum 2			X	X		
Playground 3, Puzzle 3	Momentum 3			X	X		
Playground 4, Puzzle 1	Energy 1					X	X
Playground 4, Puzzle 2	Energy 2					X	X
Playground 4, Puzzle 3	Energy 3					X	X

Data mining results (1)

- We collected data for 42 students running through sequences.
 - We extracted this data, used it to learn a model

Course #	General	Draw Anything	Draw Freeform	Draw Pin	Draw Pinned	Draw Ramp	Draw Spring	User Ramp	User Spring
0	2	1	1	2	2	0	0	0	1
1	3	1	1	3	3	0	0	0	1
2	3	2	2	3	3	1	1	0	2
4	3	3	2	5	4	1	1	0	2
5	7	3	2	5	5	2	2	1	2
6	7	4	3	6	5	2	2	2	3
7	8	5	4	7	5	2	2	3	3

One student's progression

Data mining results (2)

Course ID	Sampled Difficulty
p2p1.course.xml	7
p2p2.course.xml	6
p2p3.course.xml	6
p3p1.course.xml	4
p3p2.course.xml	5
p3p3.course.xml	4
p4p1.course.xml	1
p4p2.course.xml	5
p4p3.course.xml	5
tutorials.course.xml	1

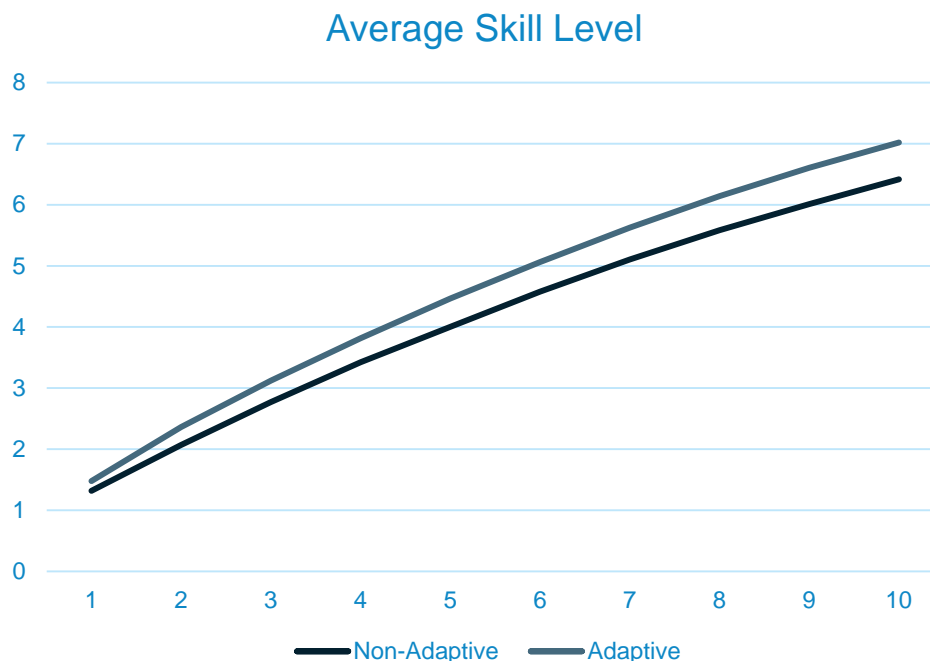
Course difficulties

Transition probability for one course, for trainees who are currently at Level 0

0	1	2	3	4	5	6	7	8	9
71.1%	28.3%	.6%	0	0	0	0	0	0	0

Simulated students

- We simulated 10000 students using the learned data model
 - We used the learned model to compare an adaptive to a random training strategy in Newton's Playground



Next steps (1)

- Use for AAR

The image displays two side-by-side screenshots of an 'After Action Review' (AAR) interface for a puzzle game, one for a Novice user and one for an Expert user.

Novice AAR:

- Individualized Puzzle Feedback:**
 - Place the pin at the very end of the springboard
 - Make the weight contain at least 10 loops
- Mastery Feedback:** In order to shoot the ball higher, release the weight and delete it in quick succession. This will increase impulse and therefore the acceleration of the ball.
- Expert Puzzle Demonstration:** A video titled 'Looping Expert Example Video' showing a red ball looping around a springboard.
- Personal Statistics:** Shows 'Time' (15) and 'Attempts' (53) with bar charts. Includes buttons for 'Replay Puzzle', 'Next Recommended Puzzle', and 'Exit'.

Expert AAR:

- General Success Parameters:**
 - Place the pin over halfway down the springboard
 - Make the weight contain at least 4 loops
 - Delete the weight when the ball is at least two-thirds of the way onto the springboard
- User Performance:** A video titled 'Looping User Video' showing the user's performance.
- Personal Statistics:** Shows 'Time' (9) in a circle.
- User Proficiency on Puzzle 7 Compared to Population:** A line graph showing 'Number of Users' (0-40) vs 'Puzzle Times (s)' (0-40). A red vertical line is at 10s, and a blue line shows performance times peaking around 20s.
- Recommended Action:** Includes buttons for 'Next Recommended Puzzle' and 'Replay Puzzle'.

- Use for adaptive training

Next steps (1)

- Use for AAR

The image displays two side-by-side screenshots of an 'After Action Review' (AAR) interface for a puzzle game. The left screenshot is for a 'Novice' user, and the right is for an 'Expert' user.

Novice AAR Interface:

- Individualized Puzzle Feedback:**
 - Place the pin at the very end of the springboard
 - Make the weight contain at least 10 loops
- Mastery Feedback:**

In order to shoot the ball higher, release the weight and delete it in quick succession. This will increase impulse and therefore the acceleration of the ball.
- Expert Puzzle Demonstration:** A video titled 'Looping Expert Example Video' showing a red ball looping around a springboard.
- Personal Statistics:**
 - Time: 15 (Puzzle)
 - Attempts: 53 (Playground)
 - Buttons: 'Replay Puzzle', 'Next Recommended Puzzle', 'Exit'

Expert AAR Interface:

- General Success Parameters:**
 - Place the pin over halfway down the springboard
 - Make the weight contain at least 4 loops
 - Delete the weight when the ball is at least two-thirds of the way onto the springboard
- User Performance:** A video titled 'Looping User Video' showing the user's performance.
- Personal Statistics:**
 - Time: 9
 - Buttons: 'Next Recommended Puzzle', 'Replay Puzzle'
- User Proficiency on Puzzle 7 Compared to Population:** A line graph showing the number of users (0 to 40) versus puzzle times (0 to 40 seconds). The graph shows a peak in user count around 20-30 seconds. A vertical red line is drawn at approximately 10 seconds, indicating the user's performance time.

- Use for adaptive training

Conclusions

- We produced techniques for machine learning information saved to an LMS in GIFT
 - The technique populates a model of the domain
- We ran a data collection study, to learn the model parameters
 - Based on this study, we can simulate students
- The work involved several enhancements so that we could run the study on GIFT Cloud and recommend next content
- Next step, run an adaptive training study
 - Populate with AAR



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