Evidence-based Method for Iterative Online Course Engineering with Students' Performance Profile

Noboru Matsuda and Machi Shimmei

Department of Computer Science

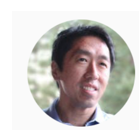
North Carolina State University

Key Learning Technologies

- **M**assive **O**pen **O**nline **C**ourse

- **I**ntelligent **T**utoring **S**ystems

Massive Open Online Course (MOOC)

- Self-contained, streamlined instruction
  - Evidence-based design (Clark & Mayer, 2003)
- Active learning
  - Multi-media, multi-modal, multi-activity (Collins, 2013)
- Potentially scalable
  - Machine Learning @ Stanford (Ng, 2011) **1.1M** 
  - Learning how to learn @ UCSD (Sejnowski & Oakley, 2014) **1.2M**

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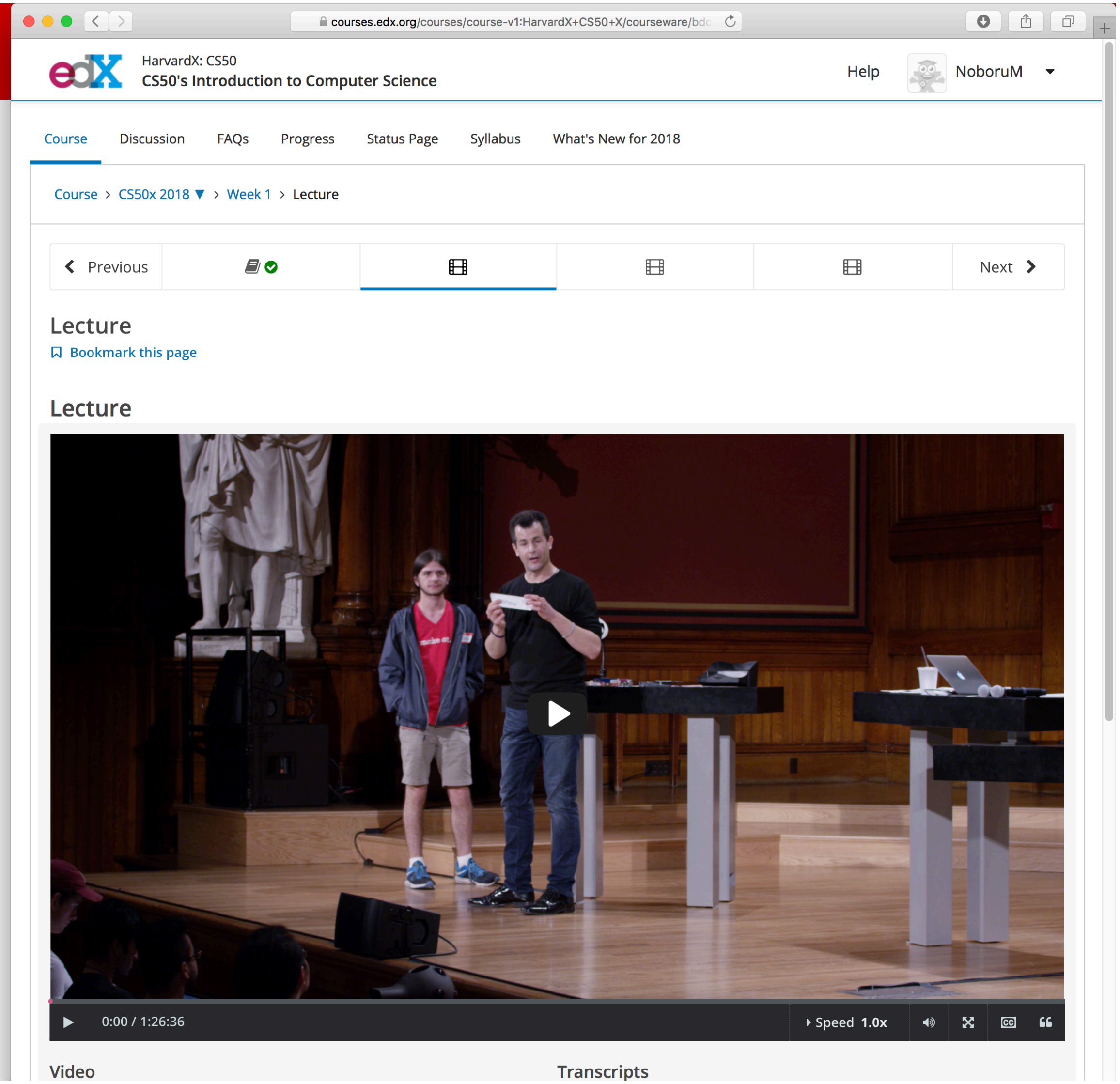
Traditional MOOC

- Mostly, collection of videos



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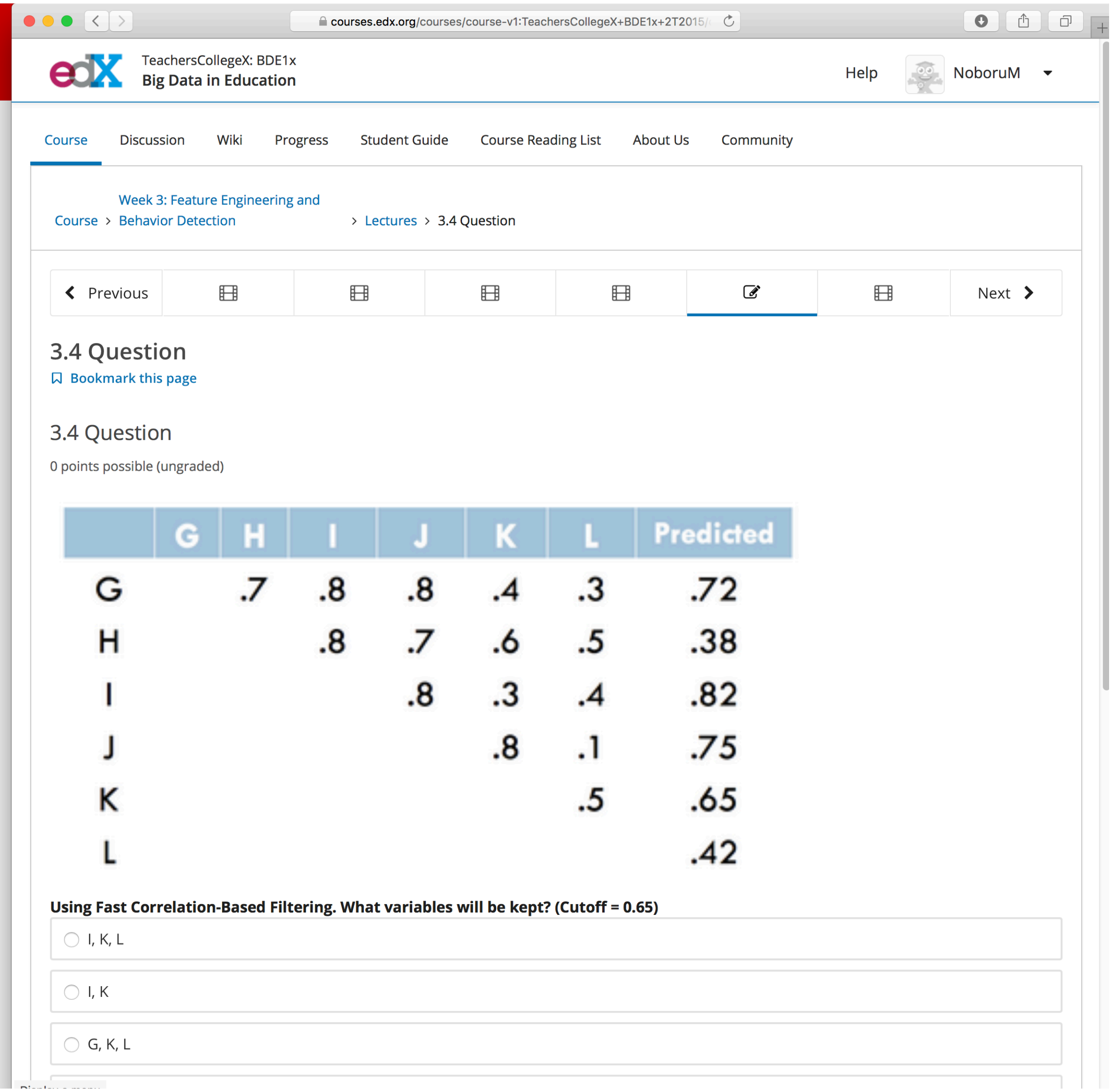
Traditional MOOC

- … and some assessments.



courses.edx.org/courses/course-v1:TeachersCollegeX+BDE1x+2T2015/

TeachersCollegeX: BDE1x
Big Data in Education

Help NoboruM

Course Discussion Wiki Progress Student Guide Course Reading List About Us Community

Course › Week 3: Feature Engineering and Behavior Detection › Lectures › 3.4 Question

Previous Next

3.4 Question

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3.4 Question

0 points possible (ungraded)

	G	H	I	J	K	L	Predicted
G		.7	.8	.8	.4	.3	.72
H			.8	.7	.6	.5	.38
I				.8	.3	.4	.82
J					.8	.1	.75
K						.5	.65
L							.42

Using Fast Correlation-Based Filtering. What variables will be kept? (Cutoff = 0.65)

- I, K, L
- I, K
- G, K, L

MOOC: Challenges

- Lack of individualization
  - Ineffective learning (no learning!)
  - Disengagement / drop-out

- Lack of systematic content creation & validation
  - Where should we start from?
  - How can we iteratively make it better?

Intelligent Tutoring Systems (Cognitive Tutors)

- Aimed mastery learning (Anderson et al. 1995)
  - Focus on a particular type of problem
- Macro- and micro-level adaptations (VanLehn 2006)
  - Adaptive problem sequence
    - Knowledge Tracing (Corbett & Anderson 1995a)
  - Immediate feedback and just-in-time hint
    - Model Tracing (Corbett & Anderson 1995b)

ITS: Challenges

- Scalability / Generality
  - Too expensive to build
  - Mostly good for procedural skill acquisition
    - What about conceptual learning?

- Robustness of Learning
  - Luck of learning to solve with justifications

Summary of Challenges

- To overcome the issues of MOOC and ITS, there is a critical need to innovate a technology that
  - provides adaptive instruction while promoting synergetic learning
- An evidence-based curriculum development is essential
  - to build a large scale online course

Our Solution

- Evidence-based learning engineering methods
  - **PASTEL** (**P**ragmatic methods to develop **A**daptive and **S**calable **T**echnologies for next generation **E-L**earning)
- Adaptive Online Courseware
  - **CyberBook**
    = MOOC + Intelligent Tutoring Systems + Adaptive Control

CyberBook

- "Adaptive" online courseware
  - Problem sequencing
  - Just-in-time scaffolding
  - Mastery practice (aka cognitive tutoring)
  - Proactive detection of unproductive failure

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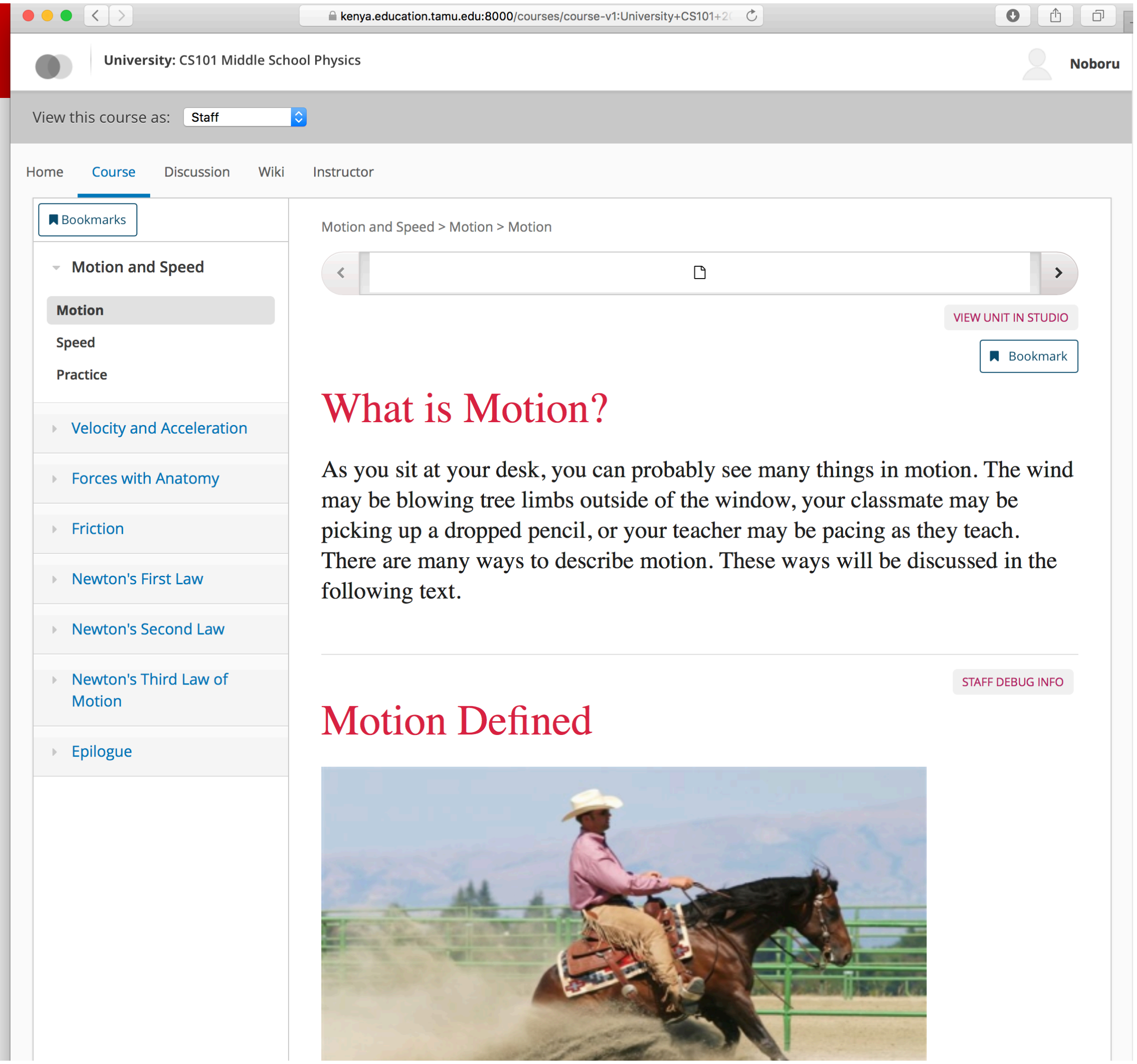
CyberBook: Example



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CyberBook: Adaptive Scaffolding

Reading Checkpoint

According to Newton's Second Law: increasing force (1) ______ acceleration and increasing mass (2) ______acceleration.

Answer for (1):

Answer: makes ✖ *Incorrect, please try it again.*

Click this link to review the course content and examples on solving this question.

Check Hints

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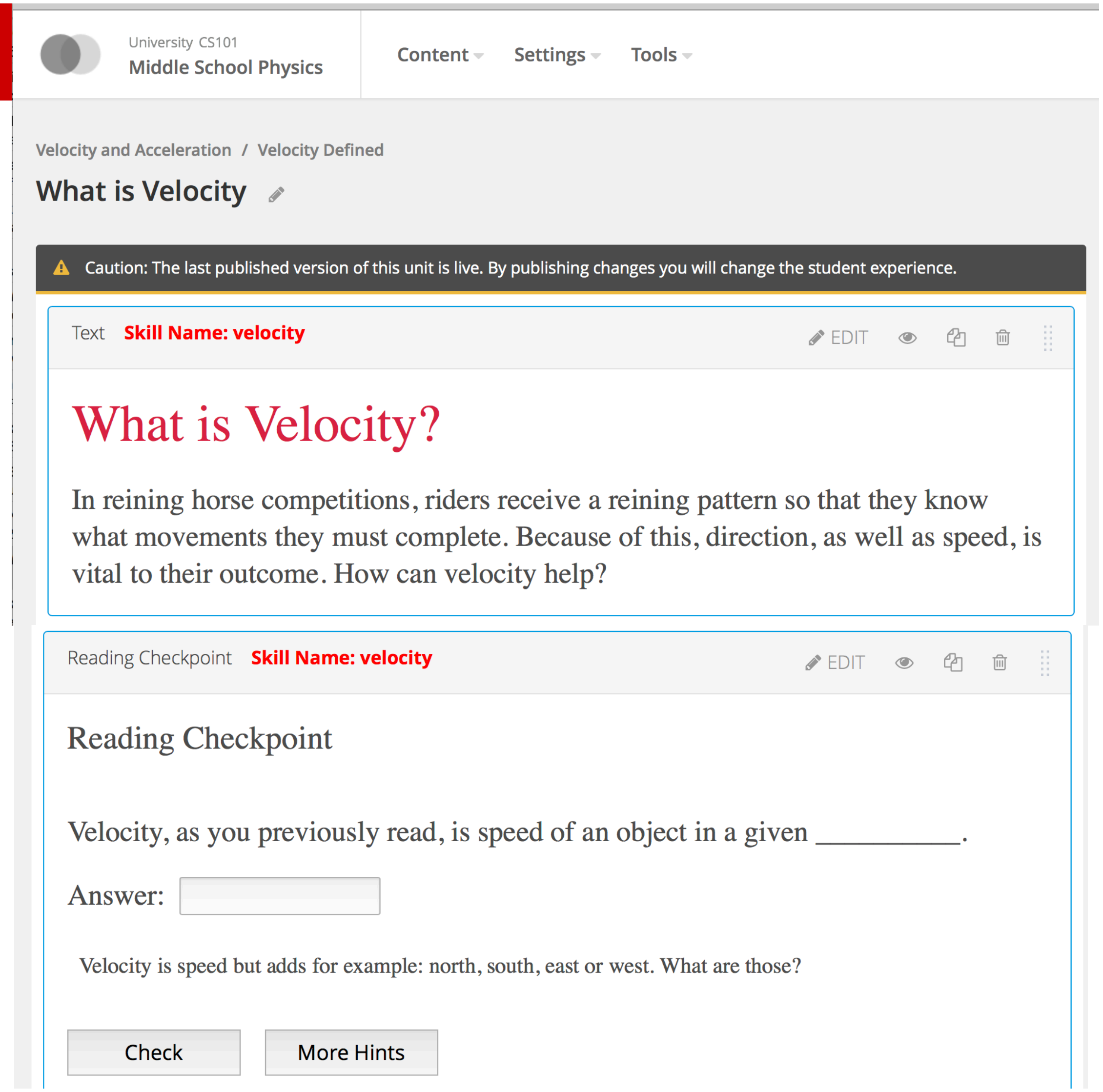
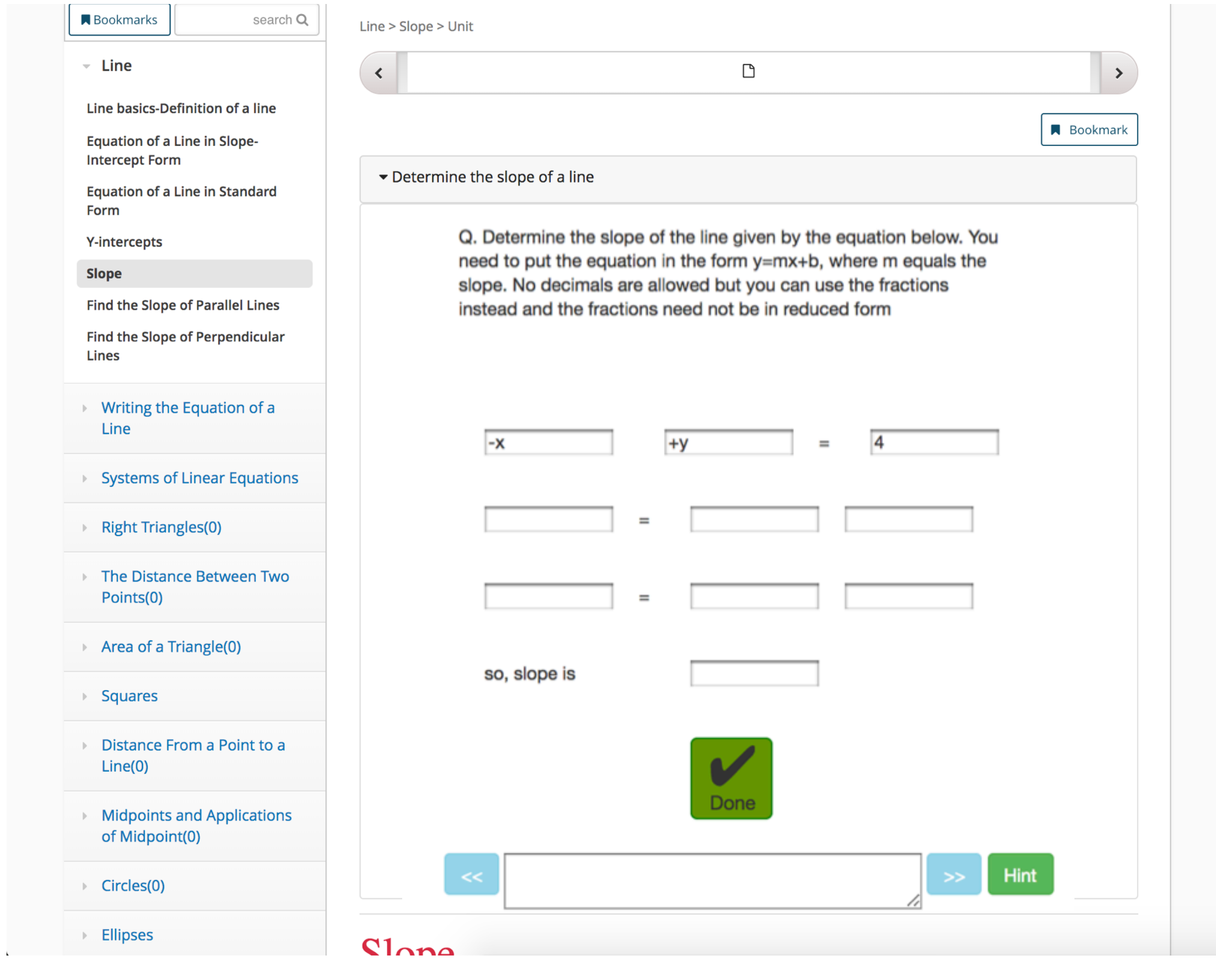
Skill Name Association



CyberBook: Cognitive Tutor Integration

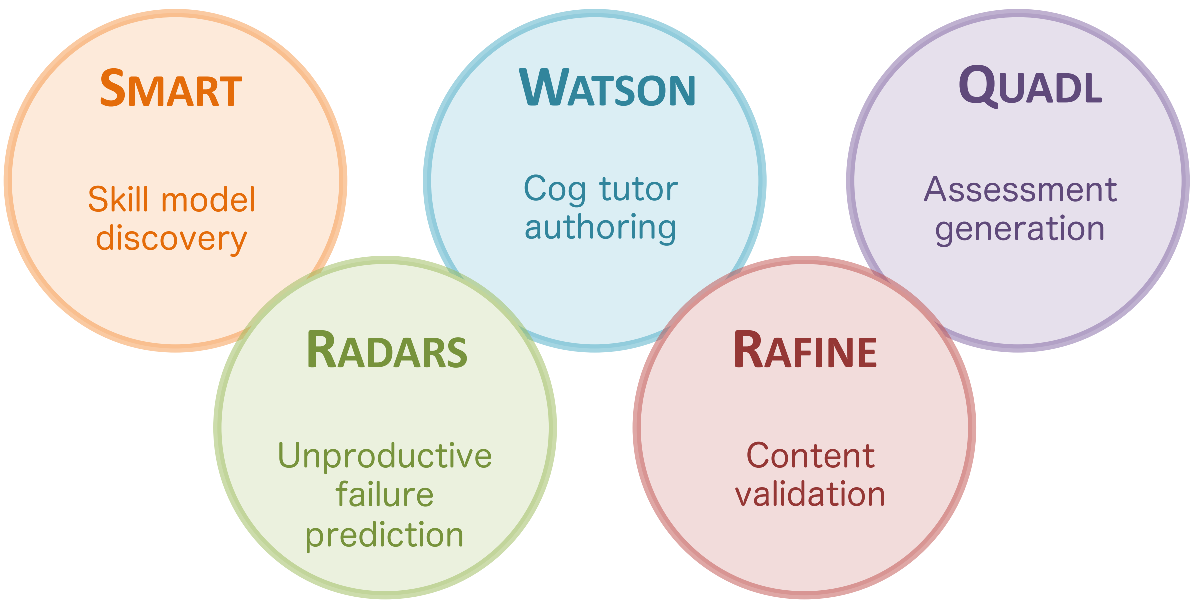


Technological Challenges

- Automatic validation of courseware content
- Rapid creation of a valid skill model
- Affordable authoring of cognitive tutors
- Automatic creation of formative assessments
- Reliable prediction of unproductive failure

Technology Innovations

- PASTEL: Evidence-based, iterative learning engineering methods



The PASTEL methods

Technological Challenges

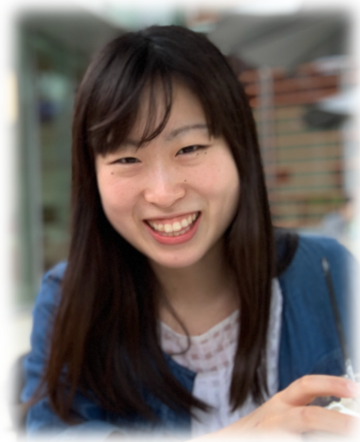
- Automatic validation of courseware content
- Rapid creation of high-quality skill-models
- Affordable creation of cognitive tutors
- Automatic creation of formative assessments
- Reliable prediction of unproductive failure

WATSON
Cog tutor authoring

QUADL
Assessment generation

RADARS
Unproductive failure detection

RAFINE
Content validation



Problem: RAFINE

- Creating effective large-scale online course is very hard [Slavich & Zimbardo, 2012] [Clark & Mayer, 2003]
- Existing design theories still require iterative engineering [Fishman *et al.*, 2004]
  - Identifying issues with the courseware is one of the challenge.

SOLUTION: RAFINE

- RAFINE (**R**einforcement learning **A**pplication **F**or **IN**cremental courseware **E**ngineering)
  - Automatically identifies relatively less effective instructional components on existing online courseware based on actual students' learning data

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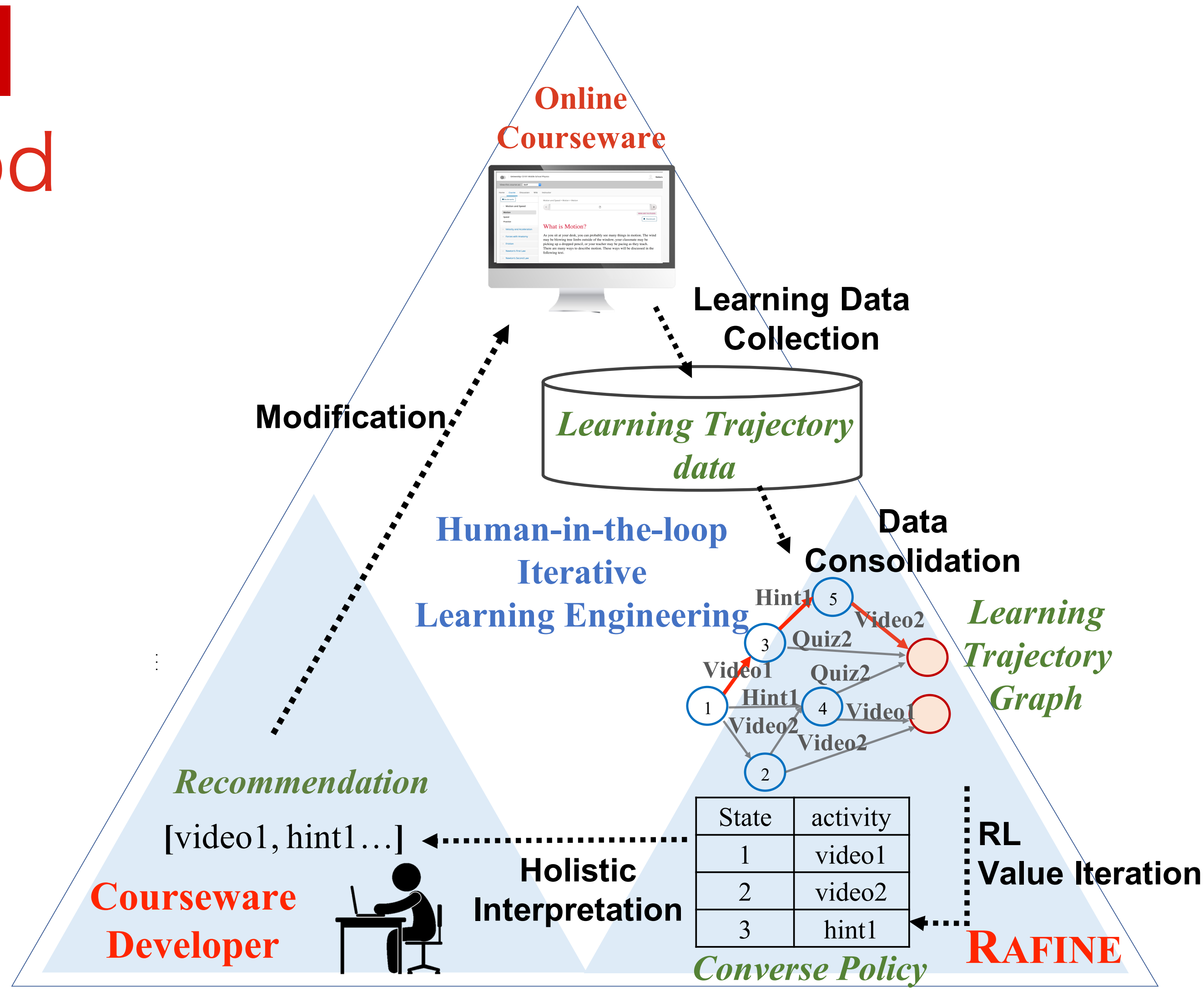
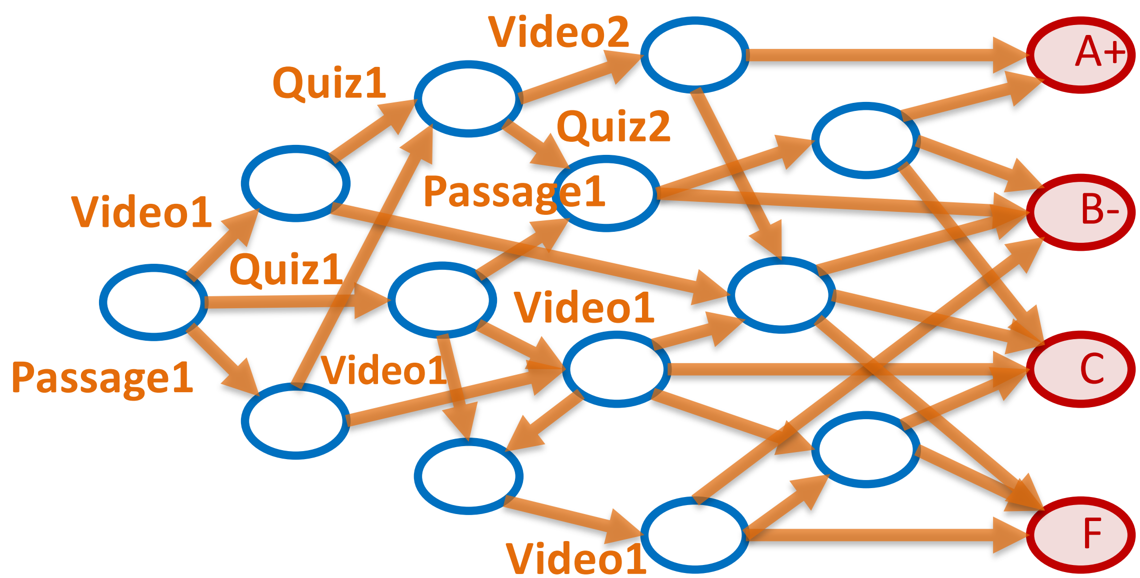
RAFINE Method



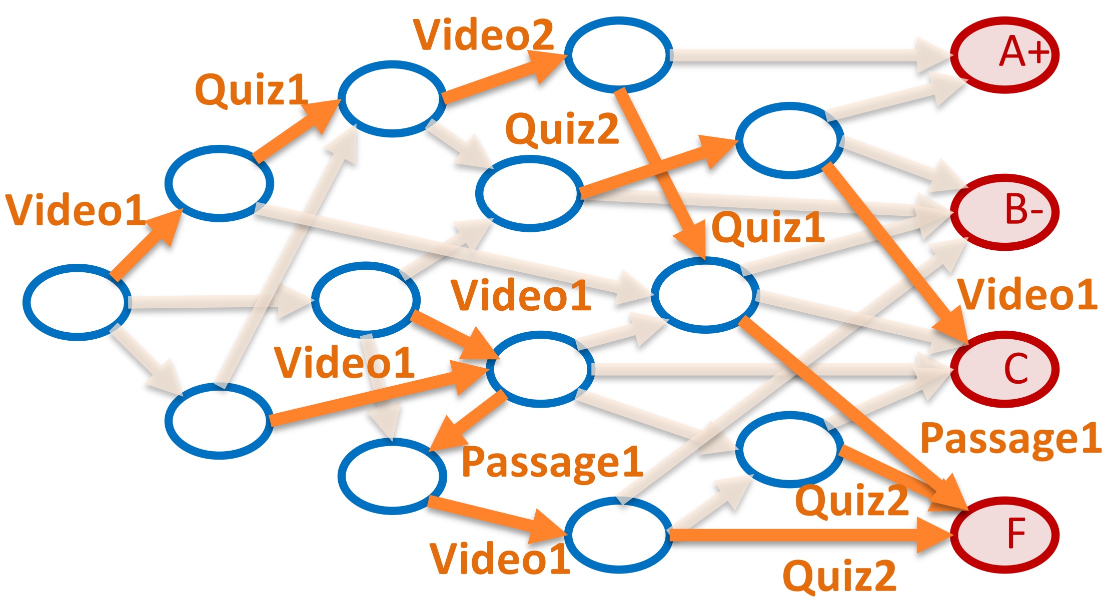
Reinforcement Learning

- Given a state transition graph (MDP) with goals and a reward for each state,
- Compute a policy which shows optimal actions to be taken at a particular state
  - to maximize a likelihood of reaching to desired goals [Sutton *et al.*,2018]

Learning Trajectory Graph



Converse Policy



Atomic vs. Holistic Policy Interpretation

- Atomic interpretation of a policy
  - An optimal action at **each** state is predicted.
  - Tells which action should (or should not) be taken.
- Holistic interpretation of a policy
  - A collection of actions suggested as a policy over **all** states is analyzed.
  - Tells which actions are useful (or useless).

Atomic vs. Holistic Interpretation

- Hypothesis:
  - By holistically analyzing a policy action set, relatively ineffective actions can be identified.
- In the current application…
  - A holistic interpretation of a policy action set induced from learning trajectory data will suggest the effectiveness of instructional components

Converse Policy

- The action that minimizes the value function

$$\pi(s) = \underset{a \in A(s)}{\operatorname{argmin}} \underbrace{\sum_{s' \in S} T(s, a, s')\big(R(s, a, s') + \gamma V^{\pi}(s')\big)}_{\text{Value function } V(s)}$$

- The action that yields the least successful learning

Reward

- $R(s, a, s') = \begin{cases} -0.14\ (ml(s) = ml(s') < 0.85) \\ -0.05\ (ml(s) < ml(s') < 0.85) \\ 0.95\ \ (0.85 \leq ml(s')) \end{cases}$
- $ml(s)$: *masterly Level at state s*
- A reward at state s become the greatest when the successor state s' is a terminal state $(ml(s') \geq 0.85)$

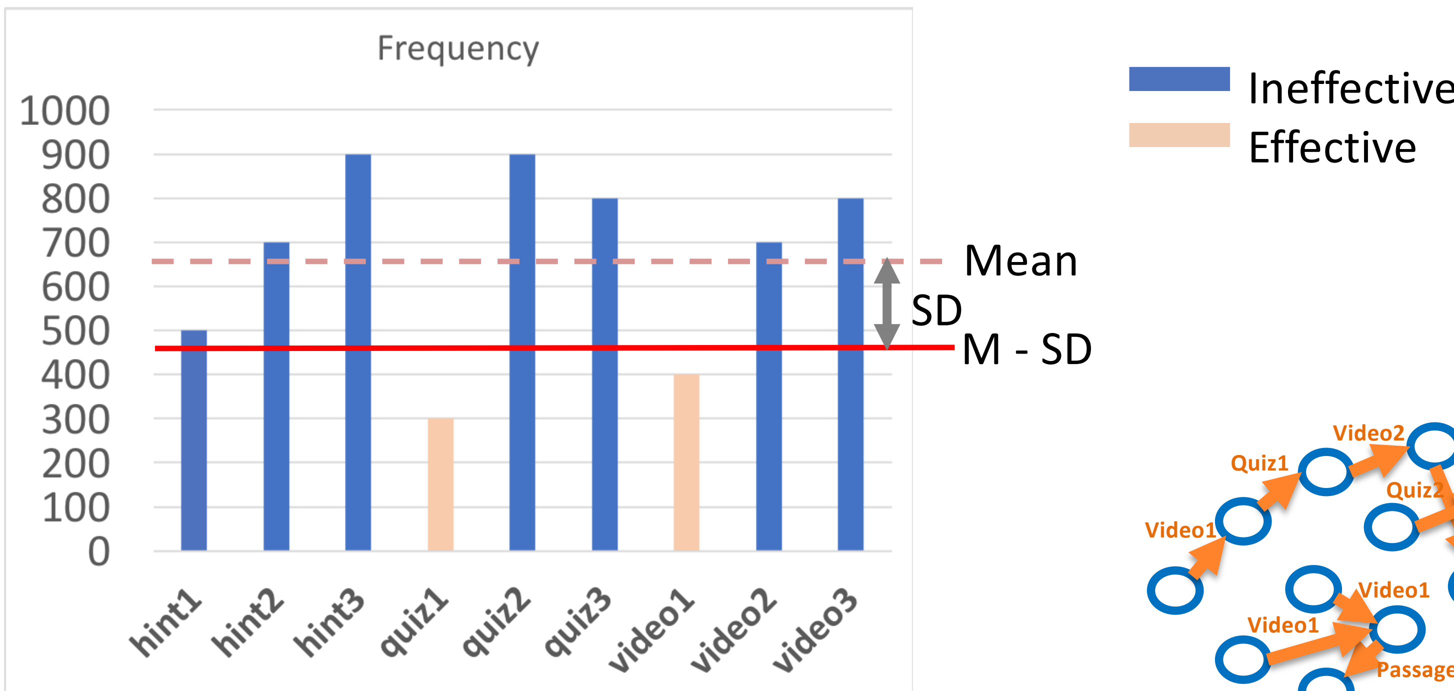
Frequency Heuristic

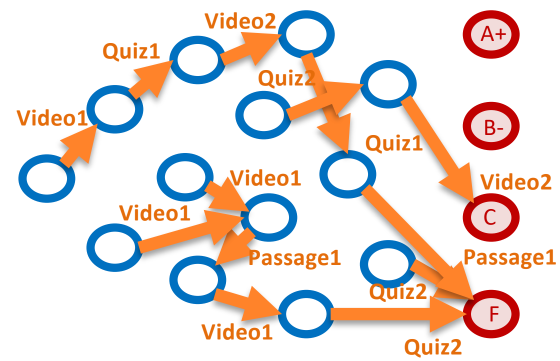
- Relatively ineffective instructional components tend to appear in a converse policy action set more frequently than effective ones
- Instructional components that appear in a converse policy more than a pre-defined cut-off are included in a recommendation for refinement

Frequency Heuristic (Cont.)

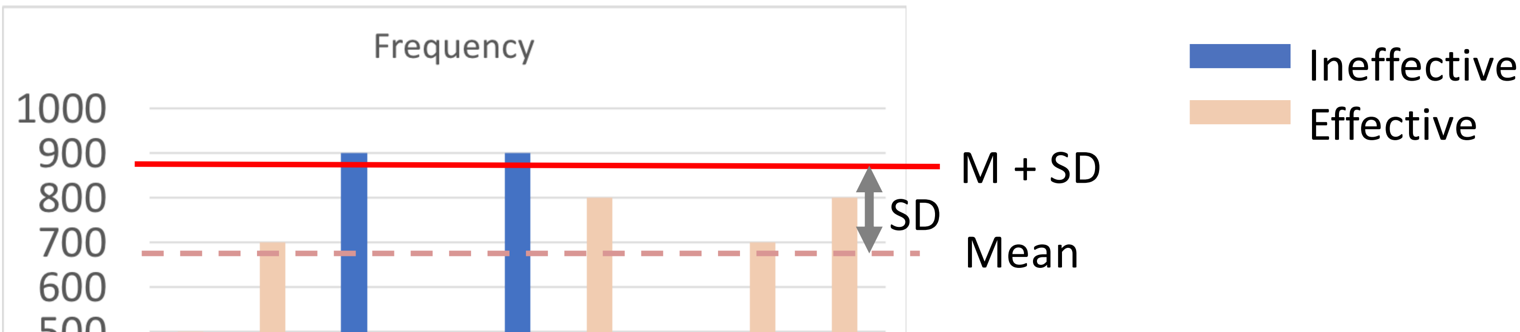
- How frequent is "frequent"?
  - Mean freq. (M) ± Standard deviation of freq. (SD)

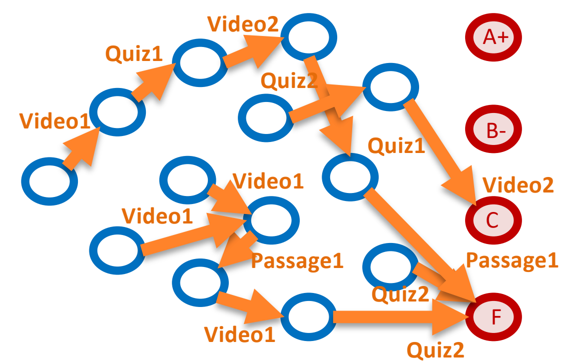
Example: Frequency Heuristic (M–SD)





Example: Frequency Heuristic (M+SD)





Research Questions

1. Can a converse policy correctly differentiate ineffective instructional components from effective ones?
2. How robust is the converse policy to detect relatively ineffective instructional components against different conditions of learning data?
3. How accurately does the frequency heuristic compose a recommendation?

Simulation Study: Method

- To apply RAFINE, each instructional component is needed to be tagged with a skill
  - No such online courseware is currently available
- As a proof of concept, hypothetical students' learning trajectories on mock online courseware were used
  - Justifies future efforts

Simulation Study: Method

- Mock online courseware
  - 9 videos, 9 quizzes with 9 hints in total
    - coded as either effective or ineffective
  - Masterly level (ML) increased at each commitment to an instructional component
    - Effective instructional compo. increases ML more than ineffective ones

Simulation Study: Data

- Quality of courseware (effective : ineffective)
  - High (8:1), Med (4:5), Low (1:8)
- Contrast in the impact of taking an effective vs. ineffective instructional compo. on mastery level
  - Large, Moderate, Small
- In total 9 learning scenarios
  - Quality (High, Med, Low) $\times$ Contrast (L,M,S)

Simulation Study: Data (Cont.)

- For each scenarios, 100 instances of course offerings were simulated each with 1,000 simulated students
  - 1 Learning trajectory Graph (LTG) consists of 1,000 students data.
- Converse policy was computed for each LTG from each 9 learning scenarios
  - 100 converse policies for each scenarios
  - Total 900 converse policies == 900 recommendations

Converse policy as a quality indicator

- Compare the frequency of individual component in policy action set
- Normalized Frequency (NF) of instructional compo. for skill θ

$$-\frac{|S^{\pi}(\theta)|}{|S^{A}(\theta)|} = \frac{\text{Num. of states in the LTG where } \theta \text{ is the policy action}}{\text{Num of states where } \theta \text{ was taken.}}$$

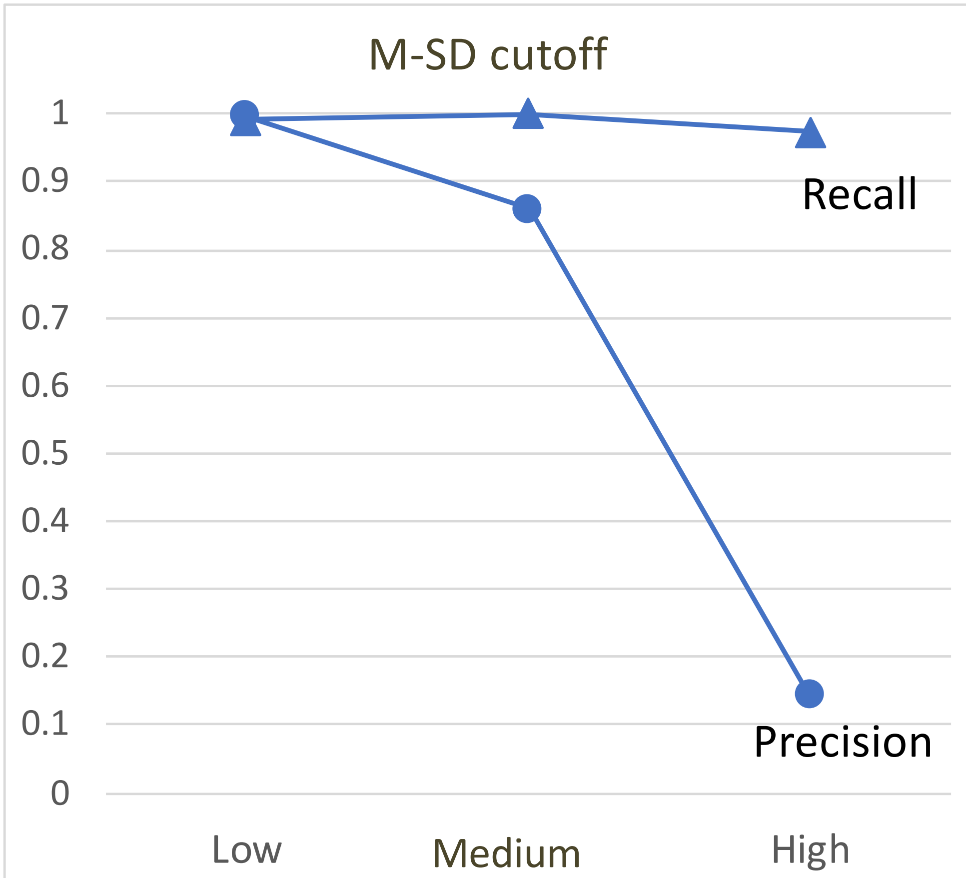
Comparison of the mean NF (inef. vs. ef.)

	Contrast					
	Large		Moderate		Small	
Quality	Inef.	Ef.	Inef.	Ef.	Inef.	Ef.
High	0.7±0.2	0.2±0.1	0.7+0.1	0.1±0.1	0.5±0.1	0.2±0.1
	(effect size=4.0)		(5.7)		(3.1)	
Med.	0.4±0.1	0.1±0.05	0.4±0.1	0.1±0.04	0.4±0.1	0.2±0.1
	(7.9)		(8.5)		(3.6)	
Low	0.4±0.1	0.04±0.04	0.4±0.1	0.04±0.03	0.4±0.1	0.1±0.1
	(9.2)		(10.0)		(4.5)	

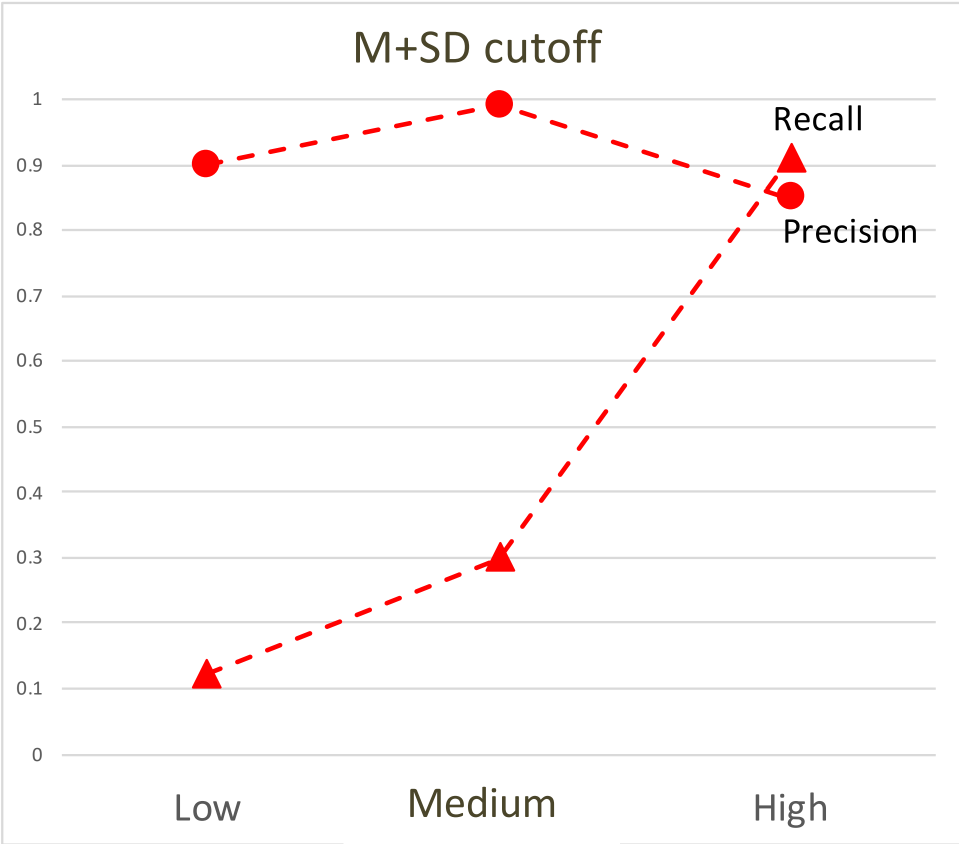
Converse Policy as a Quality Indicator

- Frequency heuristic hypothesis was supported
  - **Ineffective** instructional components were selected more than **effective** as a converse policy
- Converse policy was robust enough to discriminate the effectiveness of the instructional component regardless of quality and contrast of online courseware

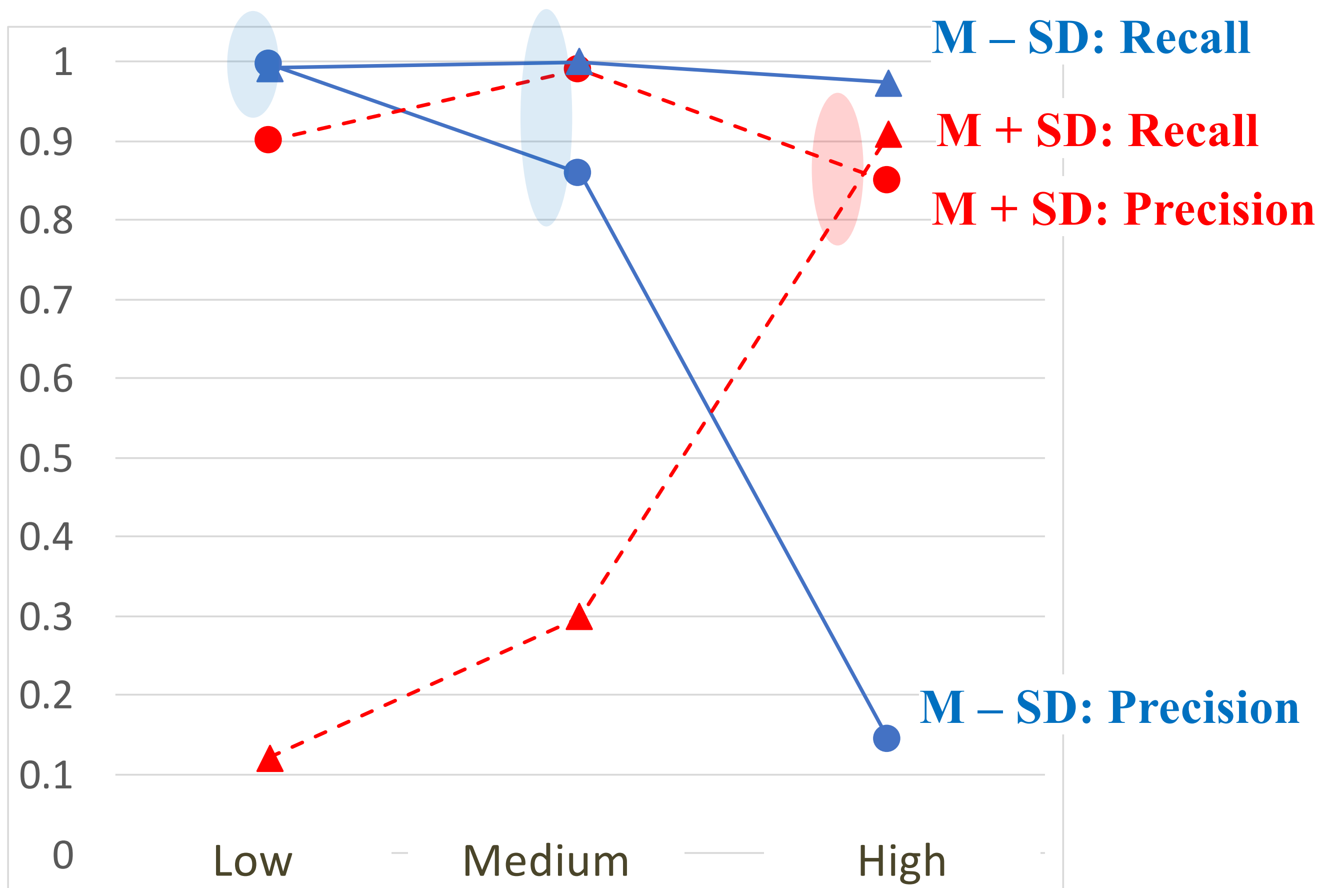
Frequency Heuristic for recommendation



Frequency Heuristic for recommendation



Frequency Heuristic for Recommendation



Frequency Heuristic for Recommendation

- Over 90% of ineffective instructional components were correctly taken as a recommendation when an appropriate cut-off was used based on the maturity of the courseware

Conclusion (RAFINE)

- Holistic interpretation over a converse policy is a powerful analytic tool for the quality control
- Converse policy computed based on actual learning data will provide an insight into the usefulness of instructional component of online courseware

Limitations and Future study

- How much students' individual differences affect the "effectiveness" of each instructional component
  - Assume that the majority vote applies
- Evaluate RAFINE method in authentic learning settings

Conclusion (Self-Improving System)

- With RAFINE, we have half-built self-improving adaptive online courseware
- The remaining half is to let the machine automatically generate the content
  - Semi-automated creation of ITS
  - Question generation

Thank you!