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

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Key Learning Technologies

• Massive Open Online Course

• Intelligent Tutoring Systems
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
Traditional MOOC

- Mostly, collection of videos
Traditional MOOC

• ... and some assessments.
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
  – Focus on a particular type of problem (Anderson et al. 1995)

• 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** (Pragmatic methods to develop Adaptive and Scalable Technologies for next generation E-Learning)

• 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
What is Motion?

As you sit at your desk, you can probably see many things in motion. The wind may be blowing tree limbs outside of the window, your classmate may be picking up a dropped pencil, or your teacher may be pacing as they teach. There are many ways to describe motion. These ways will be discussed in the following text.

Motion Defined
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.
Skill Name Association

What is Velocity?

In reining horse competitions, riders receive a reining pattern so that they know what movements they must complete. Because of this, direction, as well as speed, is vital to their outcome. How can velocity help?

Reading Checkpoint

Velocity, as you previously read, is speed of an object in a given __________.

Answer: __________

Velocity is speed but adds for example: north, south, east or west. What are those?
CyberBook: Cognitive Tutor Integration

Line basics - Definition of a line
Equation of a Line in Slope-Intercept Form
Equation of a Line in Standard Form
Y-intercepts
Slope
- Find the Slope of Parallel Lines
- Find the Slope of Perpendicular Lines
- Writing the Equation of a Line
- Systems of Linear Equations
- Right Triangles(0)
- The Distance Between Two Points(0)
- Area of a Triangle(0)
- Squares
- Distance From a Point to a Line(0)
- Midpoints and Applications of Midpoint(0)
- Circles(0)
- Ellipses

Q. Determine the slope of the line given by the equation below. You need to put the equation in the form $y = mx + b$, where $m$ equals the slope. No decimals are allowed but you can use the fractions instead and the fractions need not be in reduced form.

$-x + y = 4$

$2x + 3y = 6$

So, slope is
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

**SMART**
Skill model discovery

**WATSON**
Cog tutor authoring

**QUADL**
Assessment generation

**RADARS**
Unproductive failure prediction

**RAFINE**
Content validation
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
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 (Reinforcement learning Application For INcremental courseware Engineering)
  - Automatically identifies relatively less effective instructional components on existing online courseware based on actual students’ learning data
RAFINE Method

Online Courseware

Learning Data Collection

Data Consolidation

Learning Trajectory Graph

RL Value Iteration

Courseware Developer

Holistic Interpretation

Converse Policy

Modification

Human-in-the-loop Iterative Learning Engineering

Recommendation

[video1, hint1…]

Courseware Developer

Learning Trajectory data

Value Iteration

Modification

Learning Trajectory Graph

RL Value Iteration

Courseware Developer

Holistic Interpretation

Converse Policy
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

[Diagram showing nodes connected with arrows labeled Video1, Quiz1, Video2, Quiz2, Passage1, and Quiz2. Nodes are labeled A+, B-, C, and F.]
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

\[ \pi(s) = \arg\min_{a \in A(s)} \sum_{s' \in S} T(s, a, s')(R(s, a, s') + \gamma V^{\pi}(s')) \]

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)

![Frequency Chart]

Mean

SD

M - SD

Ineffective

Effective

Matsuda & Shimmei

Rafine @ MARC 2019
Example: Frequency Heuristic (M+SD)

[Graph showing frequency distribution with categories such as hint1, hint2, hint3, quiz1, quiz2, quiz3, video1, video2, video3. The graph compares ineffective and effective categories using M+SD and SD measures.]
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) × Contrast (L,M,S)
Simulation Study: Data (Cont.)

- For each scenario, 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 scenario
  - 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 $\theta$

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

<table>
<thead>
<tr>
<th>Quality</th>
<th>Large</th>
<th>Moderate</th>
<th>Small</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inef.</td>
<td>0.7±0.2</td>
<td>0.7±0.1</td>
<td>0.5±0.1</td>
</tr>
<tr>
<td>Ef.</td>
<td>0.2±0.1</td>
<td>0.1±0.1</td>
<td>0.2±0.1</td>
</tr>
<tr>
<td>High</td>
<td>(effect size=4.0)</td>
<td>(5.7)</td>
<td>(3.1)</td>
</tr>
<tr>
<td>Med.</td>
<td>0.4±0.1</td>
<td>0.4±0.1</td>
<td>0.4±0.1</td>
</tr>
<tr>
<td></td>
<td>0.1±0.05</td>
<td>0.1±0.04</td>
<td>0.2±0.1</td>
</tr>
<tr>
<td></td>
<td>(7.9)</td>
<td>(8.5)</td>
<td>(3.6)</td>
</tr>
<tr>
<td>Low</td>
<td>0.4±0.1</td>
<td>0.4±0.1</td>
<td>0.4±0.1</td>
</tr>
<tr>
<td></td>
<td>0.04±0.04</td>
<td>0.04±0.03</td>
<td>0.1±0.1</td>
</tr>
<tr>
<td></td>
<td>(9.2)</td>
<td>(10.0)</td>
<td>(4.5)</td>
</tr>
</tbody>
</table>
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

- **M-SD cutoff**
  - Recall
  - Precision

- **Axes**:
  - X-axis: Low, Medium, High
  - Y-axis: Precision and Recall

- **Graph** shows the relationship between the M-SD cutoff and Precision and Recall across different levels of frequency (Low, Medium, High).
Frequency Heuristic for recommendation

![Graph showing M+SD cutoff, Precision, and Recall]

- M+SD cutoff
- Precision
- Recall

- Low
- Medium
- High
Frequency Heuristic for Recommendation

- **M – SD: Recall**
- **M + SD: Recall**
- **M + SD: Precision**

Legend:
- **Low**
- **Medium**
- **High**

Graph showing recall and precision across different frequency levels.
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!