Simulation Model of Learning Recommendation in Guided Learning Pathways

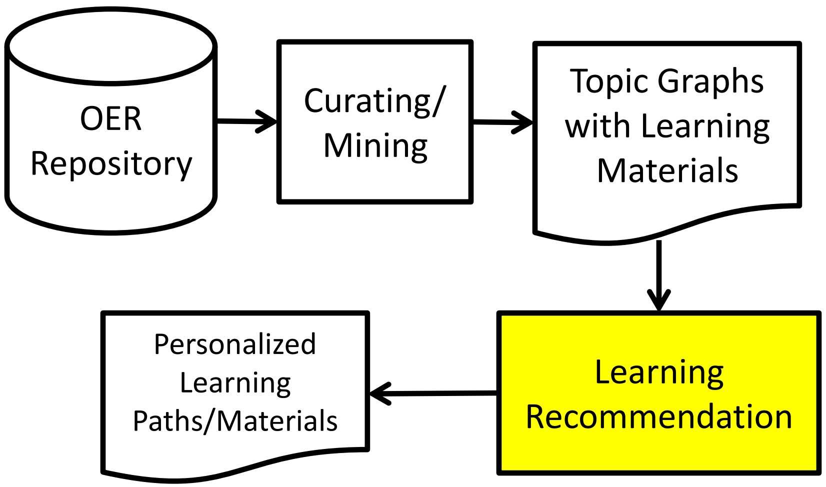
Jun Wang
Cole Shaw
Kanji Uchino
Richard Larson

FUJITSU

Massachusetts Institute of Technology

Background

- MIT and Fujitsu initiate a project for creating an advanced online learning environment, Guided Learning Pathways (GLP)
  - provide **uniquely personalized guidance** to learners
  - and in turn can help them maximize their individual rate of learning.
- Efficient and effective pedagogy-oriented **recommendation mechanisms** are critical for delivering optimized guidance on learning pathways and materials in GLP.



Problems

- The ideal and obvious way to evaluate and make use of recommender systems is to collect and analyze real data generated by real learners in real-world field experiments
- But real-world field experiments
  - Costly
  - Cannot be easily repeated and adjusted with specific time frame
- Simulation can be a possible solution
  - Rigorous experimental design
  - Fine-grained control over many possible kind of potential learners with a wide range of learning abilities and styles
  - No ethical and practical constraints of field experiments

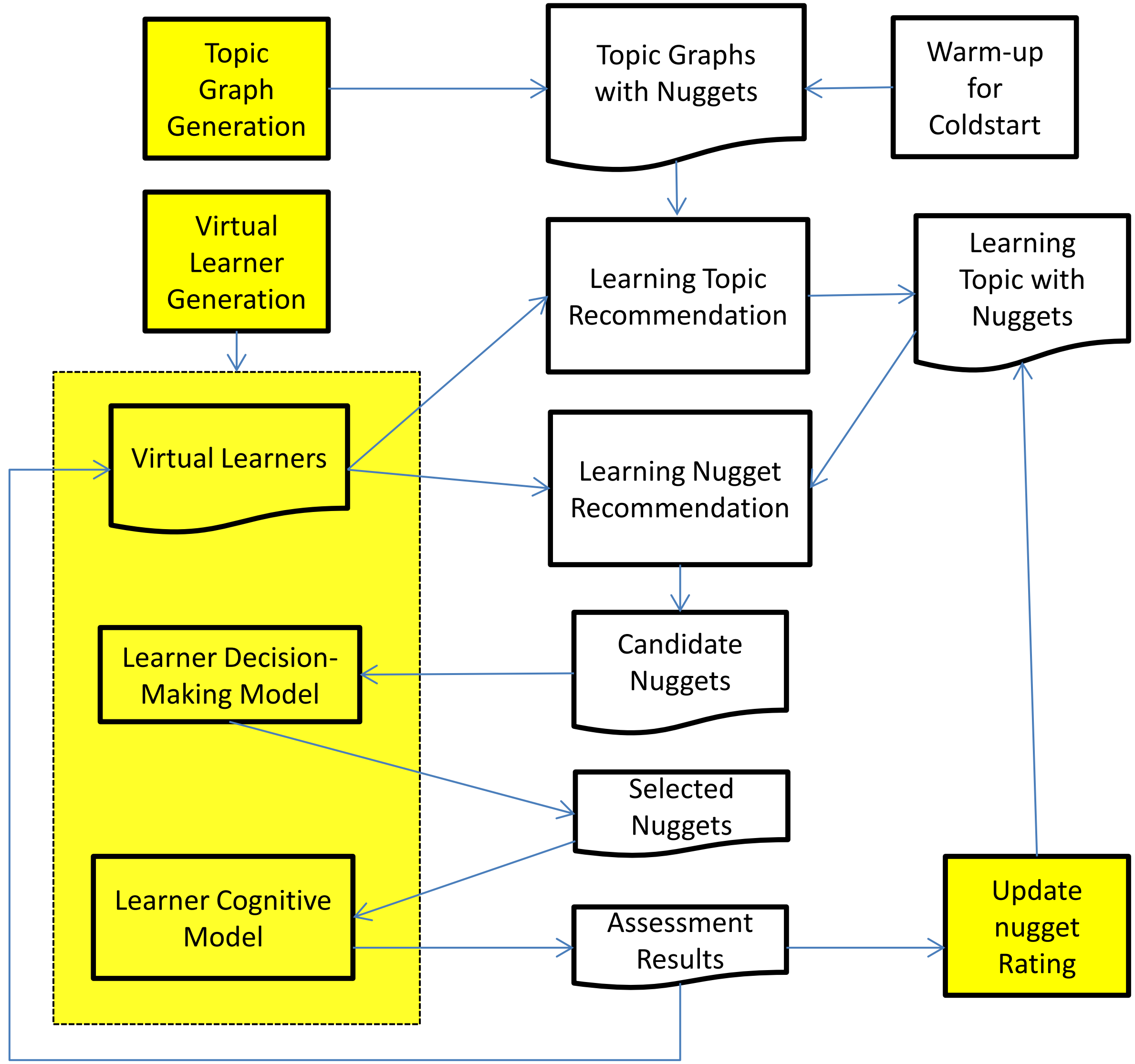
Contributions

- We present a novel simulation model for exploring various recommendation mechanisms used for guided learning pathways, based on
  - Automated topic-graph generation
    - Real-world random graph generator
  - Virtual learner generation
    - Integration of advanced learner cognitive models and decision making models
- Our experimental results show that simulation studies can efficiently and effectively support the analysis and optimization of learning recommender systems.
  - implicit ratings and warm-up processes lead towards more effective and faster learning goal achievement.

Related work

- Adaptive learning platform from Knewton
  – seems to imply that a virtual student's learning of a subject depends on a predefined learning curve, and is a deterministic process. This is different than our stochastic methodology based on dynamic Bayesian network.
- Simulations to evaluate the effects of recommender systems for learners in informal learning networks by the Open University in Netherlands
  – involve some meta-data including competence or difficulty levels, which are very hard to be acquired from real learning materials in OERs online
  – a relatively simple method based on calculating the number of successfully completed learning activities for a specific competence level

Simulation Model

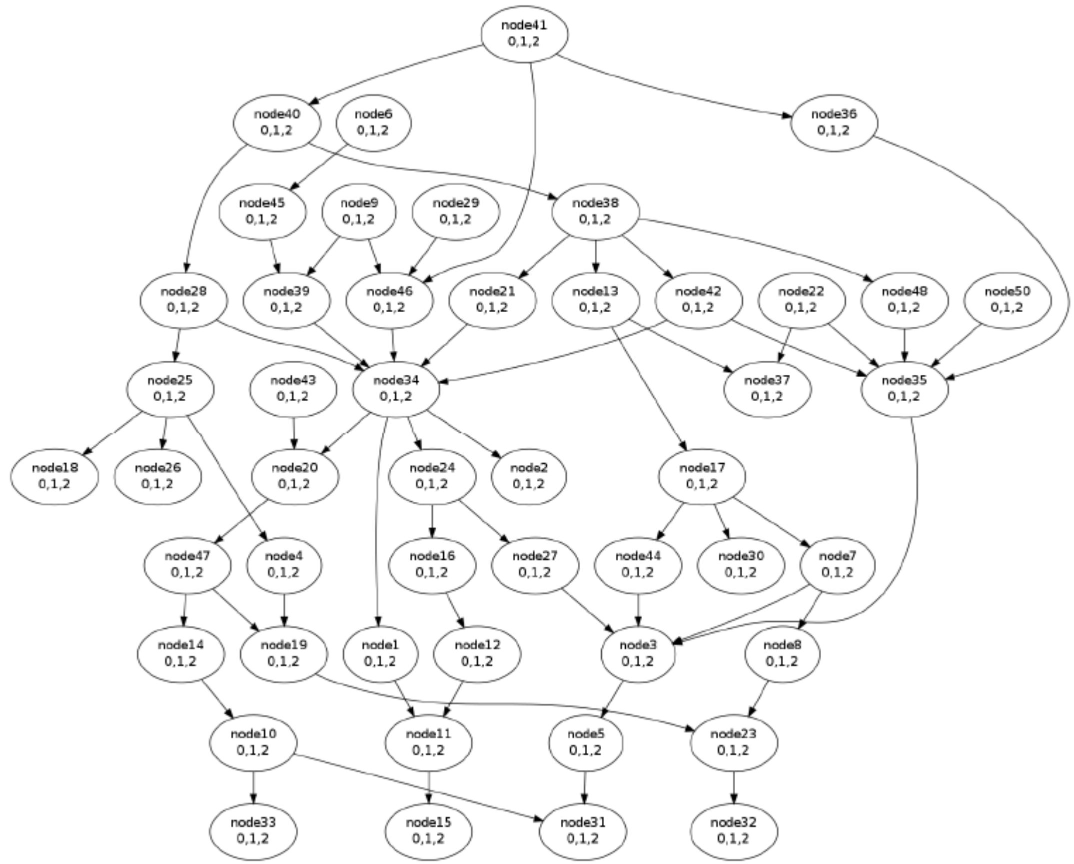


Topic Graph Generation (1)

- Learning topic
  - an individual basic concept or objective within a subject or domain, and is usually part of a course syllabus in traditional education systems.
  - For instance, within Calculus, topics could include Functions, Limits, Derivative and Integral, etc.
- Learning nuggets
  - learning materials that pertain to a specific topic
  - contain some basic meta-data including learning styles, such as visual (videos), auditory (podcasts), textual (lecture notes) and kinesthetic (exercises and other activities), and related majors.
  - Sometimes, nuggets may contain quality information, which is rated based on feedback of learners' outcomes over time

Topic Graph Generation (2)

- Topic graphs
  - a directed acyclic graph (DAG), in which each node represents a learning topic within a specific knowledge domain.
  - Directed links represent prerequisite relations between learning topics in a domain



Topic Graph Generation (3)

- Real-world topic graphs are limited, and costly to be created and maintained by human
- We hope the simulation system can be applied to evaluation of various recommendation algorithms in future applications involving topic graphs with different sizes from different domains.
- We designed a automated synthetic (random-graph) generator for learning topic graphs as benchmarks
  - which is trying to reproduce specific topological properties like (in/out)-degree distributions discovered in real-world graphs, and can easily scale up/down the generated topic graphs.
  - A specific number of learning nuggets are also generated and associated with each learning topic node, and they are given MAJOR and LEARNING STYLE attributes using a specific random model.

Topic Graph Generation (4)

confirm the topology properties specified by users or extracted from existing real-world graph

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Specify the topic graph size and number of nuggets

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Generate a directed acyclic graph with random-graph generator reproducing topology properties and size

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Generate a specific number of nuggets associated with each graph node

↓

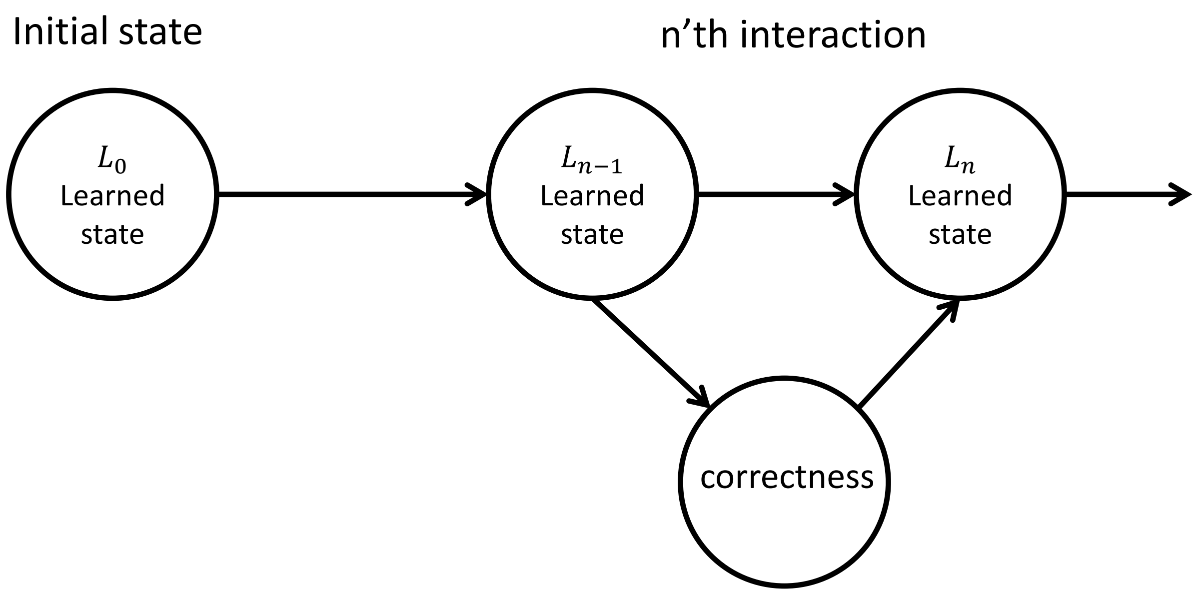
Assign MAJOR and LEARNING STYLE attributes to nuggets using a specific random model

Virtual Learner Generation

- Virtual Learner
  - could study learning nuggets and traverse the topic graph generated
  - has a specific learning goal for a specific MAJOR in mind
  - and has a preferred LEARNING STYLE and some amount of previous knowledge
- Virtual Learner Model
  - COGNITIVE MODEL to simulate human learning process
  - DECISION-MAKING MODEL to simulate selection from the GLP nugget recommendations

COGNITIVE MODEL

- To adapt to individual differences in learner knowledge, engagement, and motivation
- In order to select the learning materials and methods of presentation best suited for a specific learner is dependent on **accurate assessment of the learner's knowledge**, termed learner cognitive model
- Apply the **Bayesian Knowledge Tracing** (BKT) in a novel fashion to simulate virtual learners within the GLP simulation.
  - The model is assigned unique cognitive attributes and used to predict the probability that a specific learner can answer the next assessment involving the current topic correctly
  - The learner cognitive model is updated after each assessment to reflect mastery of the current topic.
  - Mastery is determined as with BKT and defined as when the learner model estimates a specific threshold probability of topic mastery.
  - The BKT model can be represented as a Dynamic Bayesian Network



The BKT model can be represented as a Dynamic Bayesian Network

Parameters in Bayesian Knowledge Tracing

- P(L): prior probability a learner had learned a topic before assessment
- $P(L_{n-1}/C_n)$,$P(L_{n-1}/E_n)$: posterior probability of learner had learned a topic after assessment
- P(G): a learner who does not know a topic can either guess and give a correct answer with probability P(G) or give an error answer with probability 1-P(G).
- P(S): A learner who knows a learning topic can either slip and give an error answer with probability P(S) or give a correct answer with probability 1-P(S)
- P(T): at each assessment, regardless of correctness, the learner may make the transition from the unlearned to the learned state with learning probability P(T)

Customize learning ability of virtual learners

- Along with these four parameters ($p(L_n)$, $p(G)$, $p(S)$, and $p(T)$), each virtual learner has four weights that “customize” their learning ability (wL, wG, wS, and wT) and are re-calculated for each content topic on the theory that each student has a different ability / tendency to understand each topic. These are calculated as a random factor around the four parameters, and they vary per student, per topic. To calculate the adjusted parameters, we use the process outlined in Corbett et al. (2000) for parameter pX and weight wX:
  - $odds_{form} = \frac{pX}{1-pX}$
  - $weighted = odds_{form} * wX$
  - $pX_{new} = \frac{weighted}{1+weighted}$

- Thus each topic is calculated with its own probabilities for each student, on the assumption that students find different topics are harder or easier to learn than other topics. The mastery level is then calculated with pX_{new} for each parameter.

DECISION-MAKING MODEL

- Learners select their own learning nuggets from a list of recommendations, and generally learners don't follow the recommendations 100% of the time.
- This has to be reflected in the virtual learners' decision-making model
- we also used a simple random model to select learning nuggets from candidates recommended by learning nugget recommendation algorithms.
  - For example, 81% of the time learners will follow a recommendation, and the other 19% of the time they will select from the remaining nuggets of not recommended.

Virtual Learner Generation

Specify the number virtual Learners

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Generate virtual learners with styles and major randomly

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Assign cognitive model to each virtual learner with specified common parameters (P(L),P(S),P(G),P(T))

↓

Learning ability of each student is customized and re-calculated for each topic

↓

Assign decision-making model to each virtual learner

Learning Topic recommendation

- Learners must master each content topic in the topic graph that falls within their major field of study, and learners need to follow prerequisite relations between topics to achieve the learning goals.
- A learner can also select a specific topic as the target learning goal, and topic recommender performs a breadth-first search of the topic graph to determine which learning topics are required for the learner to achieve the target goal.
- eliminates the topics where the learner already shows sufficient mastery

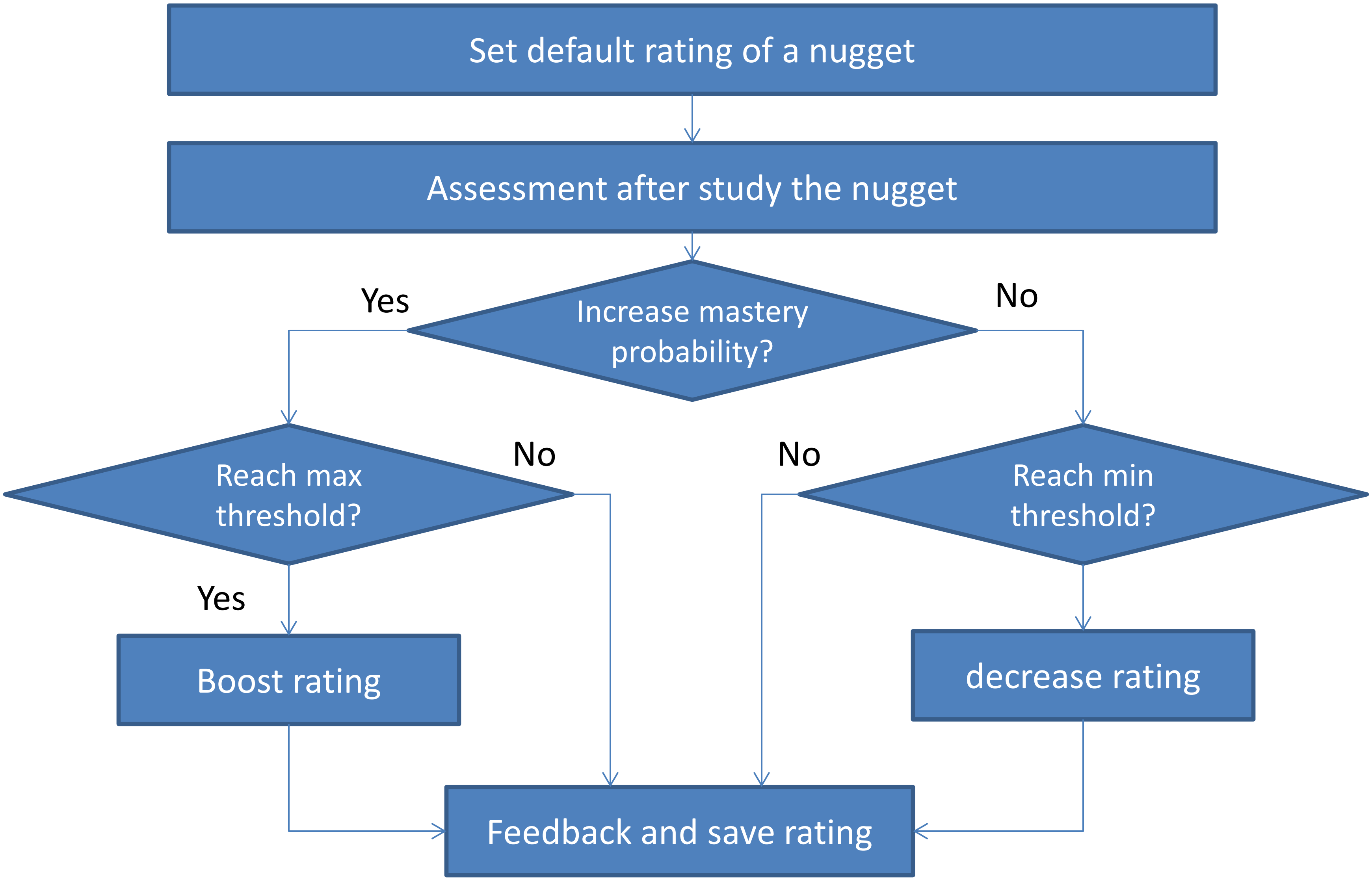
Learning Nugget Recommendation

- Different learning nugget recommendation algorithms have been tested with the simulation model.
  - Random
  - Match on style and major
  - Weighted ranking
    - **w1***matchmajor*+**w2***matchstyle*+**w3***rating*

Update nugget rating

- Quality of a nugget is a latent attribute that affects how much each learner can learn from the nugget. Instead of relying on explicit and direct feedback from learners, ratings of nuggets are calculated based on learning outcomes of learners and over time should reflect nugget quality.
- Rating of a nugget goes up if a learner passes an assessment after using the nugget, and rating goes down if a learner fails an assessment after using the nugget. The rating of each nugget will be updated over time and improve in accuracy with the number of learners.
  - For example, initial default rating of each nugget is 3, and the rating changes after a learner studies the nugget and has a corresponding assessment (increase by 0.5 with success, decrease by 0.5 with failure). The Maximum is 5 and minimum is 0

Update nugget rating



Warm-up

- The "cold-start" problem happens when no behavioral data is saved in the recommender system in the beginning, but simulations can enable us to use a "warm-up period" where the simulation computes the emerging behavior of learners over a specific period of time as a synthetic data set for the recommender system.
- After this warm up period, we can start the measurement of the experimental data for the applied recommender system.
- In our case, the "warm-up" can help us to solve the "cold-start" problem of rating data.
- For example, the simulation runs a set of virtual learners through the entire topic graph to generate ratings for each of the nuggets. 5 virtual warm-up learners are created for each major and each learning style (i.e. with 3 majors and 3 learning styles, a total of 45 warm-up learners).

Simulation Experiments (1)

- 12 iterations = 12 different content maps
  - 50 nodes, 30 nuggets per node
  - 3 learning styles, 3 college majors
- Each iteration, tested 15 virtual learners, each with different Bayesian Knowledge Tracing coefficients (varied per topic), learning styles, and majors
- 3 algorithms as outlined above
- "reset" the virtual learners and learning history for each algorithm (kept them on the same map, but wiped out their knowledge)—same learners on the same map, testing different recommendation algorithms
- Warm-up, did the exact same as above, but with 45 "warm-up" virtual learners per iteration in addition to the 15 "test" learners

Simulation Experiments (2)

Algorithms and configuration	Average Cycles	Std Dev.
Random	356.82	88.91
Match on Style and Major	348.81	95.24
Weighted Ranking (cold-start)	281.15	49.04
Weighted Ranking (warm-up)	245.91	26.07

- Measurement
  - learners’ study time to master learning topics
  - we looked at the number of nuggets/assessments required for learners to master all of the learning topics in the topic graph-conceptually, and this could be like a timemeasure
- Results
  - The simulation results showed that our implicit rating-based recommendation algorithm can dramatically improve the time efficiency with around 20%,
  - and adding warm-up process for handling cold- start can further improve another 13% and significantly benefit the recommendation algorithm.

Summary

- Our study showed that the simulation model and data can support the analysis of learning recommendation mechanisms prior to starting the costly process of practical implementation during real-world field experiments
- Especially, the simulation results showed that our implicit rating-based recommendation algorithm can an dramatically improve the time efficiency
- Adding warm-up process for handling coldstart can further improve and significantly benefit the recommendation algorithm.