Overview of machine learning and statistical techniques used to implement the Adaptive eXplanation Improvement System: multi-armed bandits algorithms and Thompson sampling. They will be compared to methods used for another crowdsourcing implementation: ConceptScape.

I. Summary of the technology

The axis algorithm is actualized in two different stages.

The reinforcement-learning, Bayesian inference method utilized is the Multi age bandit problem. This multi bandit problem is implemented through Thompson sampling, which exercises the tradeoff between exploration and effectiveness, similar to the idea of .

By listing how

Future possibilities is immense, as this means huge costs can be cut. The scaling of this technology shouldn't be costly, from the learning stage of the algorithm as well as the massive implementation stage.

II. Describe the theories applied from course:

Describe the type of explicit feedback mechanism used

Ethically, the separation between X and Y is not only cost effective in optimizing the effectiveness of sample sizes, it also allows the program to make clear to the user that some of these explanations are displayed for evaluation reasons. The explicit public benefit might even lead the user to evaluate with more effort.

CIII. Compare to other technology recently available, and the effectiveness of each (if available)

a. In other words, compare it to other ways of solving the multi armed bandit problem.

IV. Concerns:

1. Sample size and whether they're equivalent to who these online systems seek to target. (They used some target characteristics, but the fact that Turk pays $3.50 is very constricting) Both regionally and in terms of math proficiency rates
2. Why weren't instructors used more as users
3. Sample size of four questions and comparative quality is also relatively small
    a. It prevents one from seeing what type of problems or what subject of problems might these axis generated answers not work as well
4. Was wondering why no adjustment to the average score of the user is used.
    a. I guess it doesn't matter if 4 problems are shown to all anyways
5. As described, using future scoring as a second optimizing outcome is certainly a diversifying enhancement
6. As described, personalizing for a learner's tendencies for confusion can lead to the usage of contextual multi-armed bandits

Comparison to Concept Map method:

Similarities:

1. Mturk
2. Crowdsourced

3. Both tested the key assumptions that A. crowdsourced were as helpful as instructors, that the filtered/selected were more effective than the non-filtered. B. Concept maps are helpful to learning
    a. However, the second used a qualitative approach to concept maps are helpful through open-ended questions.
    b. However, by going with a qualitative approach, it was able to discover unintentionally sought nuance such as seeing concept maps before watching videos (before domain knowledge is obtained) is not helpful to their understanding.
4. Interesting that concept map is pursued b/c NLP techniques that automate tech is currently insufficient to generalize to lectures with diverse visual representations.
    a. However, the latter relies on automatic document clustering API provided by MeaningCloud [1] to group the concepts by their meaning and use DBSCAN (Density-Based Spatial Clustering of Applications with Noise
5. In both ways, the process itself of generation and evaluation of explanations/maps is a learning process in itself, and it's something both studies can further determine the exact effects of.
6. Similar con: the former only has 4-question sample size and the latter a 3-lecture sample size.
7. Expert ~= Concept Scape > Novice

Differences:

1. List concepts, link concepts, explain relationships
    a. Workers can do either one of the three, whereas in above they have to do all 3

What technologies were used for Concept Map?

Prior crowdsourcing works:
For example, to provide real-time captions for deaf
and hard of hearing users, Lasecki et al. ask learners in a classroom to collaboratively caption what they hear using Scribe
[16]. Recent work in Massive Open Online Courses (MOOCs)
mines traces of MOOC learners' interactions with video to
adaptively alter the video interface to highlight sections other
students have paid attention to [12]. More active learnersourcing is observed in Crowdy, which embeds prompts for learners
to summarize subgoals in sections of an instructional video
While giving learners a useful learning exercise, the system
converts the learnersourced summary labels into a browsable
text outline for the video