This review seeks to overview of reinforcement learning technique used to implement the Adaptive eXplanation Improvement System (AXIS): Thompson sampling. This Bayesian-inference crowdsourcing technique will be compared to those used for ConceptScape, another crowdsourcing implementation in mass-online education.

I. Summary of the technologies

In brief, the AXIS program intends to crowdsource the production and filtering of user-generated explanations of online problems. In the study, it is separated into a deployment and evaluation stage, where the former involved the production of explanations as well as dynamic evaluation and filtering of just-produced explanations, while the latter involved the evaluation of the post-filtered user-generated explanations relative to the discarded user-generated explanations and to the instructor-generated explanations. However, in a real-world, the deployment stage will be core technology, while the evaluation stage is only necessary for academic studies confirming the findings of this study to other situations. The deployment relies on a method for the multi-armed bandit problem: Thompson sampling. The sampling method helps the program select whether to ask the user to further evaluate a highly rated explanation, or whether to explore an explanation without many ratings.[1]

In brief, the ConceptScape program intends to crowdsource the production and filtering of user-generated concept maps for online video lectures. In the study, it is separated into three parallel stages: Concept and Timestamp Generation, Concept Linking, and Link Labeling. Each of those three stages are further divided into substages, for a total of eight substages. Unlike AXIS, the stages implemented in the study will be very similar to those of the initial real-world implementation. The deployment is based on two core technologies: automatic document clustering for grouping similar user-generated concepts and Density-Based Spatial Clustering of Applications with Noise for generating timestamps through clustering. The deployment is also powered by the iterative setting of agreement thresholds for various pruning substages. [2]

II. Relation to techniques covered in Text Infosystems

The dilemma that multi-armed bandit algorithms aim to balance is between the exploitation of already-gained information and the further exploration of uncertain estimates. This is a very similar dilemma to the one Beta-Gamma Threshold Learning seeks to balance with content-based filtering recommender systems.[3] Both techniques encourage exploration in the beginning when one isn't certain about the low-sample size information already gathered, and less so when the sample sizes are rather robust. [1, 3] Such design also incentivizes the identification of potentially higher-rated explanations.

ConceptScape and AXIS are both feedback-based systems utilizing relevance feedback.[4] In future implementations, perhaps implicit feedback can be utilized to lessen the effort of users. For instance, after a pool of highly-rated explanations are identified, the rating of the

[1] Williams, Joseph Jay, et al. "Axis." *Proceedings of the Third (2016) ACM Conference on Learning @ Scale*, 2016, https://doi.org/10.1145/2876034.2876042.
[2] Liu, Ching, et al. "Conceptscape." Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, 2018, https://doi.org/10.1145/3173574.3173961.
[3] "Lesson 6.6: Recommender Systems: Content-Based Filtering - Part 2." Performance by ChengXiang Zhai, *Coursera*, University of Illinois, Urbana-Champaign, https://www.coursera.org/learn/cs-410/lecture/7M0GD/lesson-6-6-recommender-systems-content-based-filtering-part-2. Accessed 7 Nov. 2021.
[4] "Lesson 5.1: Feedback in Text Retrieval." Performance by ChengXiang Zhai, Coursera, University of Illinois, Urbana-Champaign, https://www.coursera.org/learn/cs-410/lecture/gw3fo/lesson-5-1-feedback-in-text-retrieval. Accessed 7 Nov. 2021.

evaluation can be augmented by how often the explanation is revisited by the student to aid him in future problems.

III. Key similarities between the two techniques

The core assumptions of the two crowdsourcing techniques are similar. Their mutual assumptions were that crowdsourced explanations and maps are as helpful as those from an instructor, that the filtered and selected explanations and maps are more effective than the filtered.

The studies on the two techniques are also similar. The greatest similarity is the fact both used Mechanical Turk participants, which have the benefit of being more representative than convenient laboratory participants, but aren't as representative of targeted population as an implemented study on a Massive Open Online Course would have been.

Both studies found that the explanations and maps generated by users are almost as good as those designed by the expert, while both are significantly better than those of the novice. However, given the sample-size concern mentioned below, this similarity can't be taken as certain.

IV. Key differences between the two techniques

Although they're both crowdsourced, ConceptScape's evaluation used a more qualitative approach than AXIS's by asking open-ended questions to the user, whereas AXIS limited its evaluation stage to quantitative ratings of explanations. 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.

While ConceptScape relies on a text categorization technology in automatic document clustering[5] and another mining technology in DBSCAN, the evaluation of text in AXIS was not automatable. The evaluation of the effectiveness of an explanation in respect to a certain problem is too complex to be reliably implemented by a current NLP technique.

V. Reservations about the two techniques

My greatest concern with both methods is that AXIS only tested on a sample of four math questions and ConceptScape on a sample of three computer science lecture videos. While understandable as this study is only to gauge if further studies on these technologies should be carried out, it's nevertheless uncertain to extrapolate the implementation of these technologies to areas not related to math and computer science, respectively. For instance, a student evaluator might struggle to identify the most effective explanation for an English literature grammatical question in ways that might apply less to math. If the student evaluator was an English learner who does not yet understand the jargons of English grammar, an otherwise effective explanation might appear to be a set of demotivating jargon. However, the system

[5] "Lesson 10.8 Text Categorization: Methods." Performance by ChengXiang Zhai, *Coursera*, University of Illinois, Urbana-Champaign, https://www.coursera.org/learn/cs-410/lecture/KKDXC/10-8-text-categorization-methods. Accessed 7 Nov. 2021.

does not catch the nuance if the explanation is effective for the vast majority of non-English learners.

The small number of problems tested is a compounding concern, as one cannot be reasonably sure that only that subset of questions within the two fields would garner this effective of explanations and videos. The overall effect can be more or less effective. A large enough number of problems can turn this reservation into a strength, as the software can diversify its problems to study how explanations for different sub-topics of a single subject vary in effectiveness.

VI. Future Studies

For both, the process itself of generation and evaluation of explanations and maps is a learning process in itself. Identifying its exact learning reward as a proportion of the total learning gained is worthwhile for future studies.

The authors also noted two key areas to further study that I concur with.[1,2] First, using scoring on future problems attempted as a second optimizing outcome certainly helps validate the effectiveness of the user-generated explanations and maps. Second, personalizing for a learner's tendencies for confusion can lead to the usage of contextual workflow implementations for both programs.

VII. Conclusion

Mass-online education platforms have opened the possibilities of implementing cost-effective, widely accessible education resources. AXIS through Thompson sampling and ConceptScape through automatic document clustering and DBSCAN have shown to be potential candidates to cost-effectively generate effective problem explanations and concept maps. Further studies with larger sample sizes of problems and a more representative sample of students would help validate these candidates.

The future possibilities of these technologies can be immense, as this means huge personnel costs for generating explanations and maps can be conserved. The scaling of this technology shouldn't be costly, from the learning stage of the algorithm as well as the massive implementation stage.