Exploration Maps, Beyond Top Scores: Designing Formative Feedback for Open-Ended Problems

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ABSTRACT
Learners are being exposed to abstract skills like innovation, creativity and reasoning through collaborative open-ended problems. Most of these problems, like their real-world counterparts, have no definite starting or ending point, and have no fixed strategies to solve them. To help the learners explore the multiple perspectives of the problem solutions there is an urgent need for designing formative feedback in these environments. Unfortunately, there are barriers to using existing EDM approaches to provide formative feedback to learners in these environments: (1) due to the vast solution space, and the lack of verifiability of the solutions it is impossible to create task and expert models, thus making the detection of the learners progress impractical; (2) formative feedback based on individual learner models does not scale well when many learners are collaborating to solve the same problem. In this work, we redefine formative feedback as reshaping the learning environment and learners' exploration paths by exposing/enlisting "fugues" as defined by Reitman [28]. Through a case study approach we, (1) validate methods to extract learners' "fugues" from a collaborative open-ended museum exhibit, (2) design formative feedback for learners and educators using these extracted fugues in real-time, (3) evaluate the impact of exposing fugues to group of learners interacting with the exhibit.

Keywords
Data-driven, Formative feedback, Open-ended learning environments, Ill-defined problems, collaborative learning

1. INTRODUCTION
With the recent advances in storage and retrieval methods of data and increased computing power the way we look into learning processes has changed [2]. We are now able to collect data to the most minute detail which was not possible in the absence of tracking devices and computer-based interactive learning environments. These improvements in instrumentation make rich interactive "classrooms of the future" [32] amenable to computer-driven monitoring and support, but it's not a matter of just applying existing analytic approaches. The vast majority of learning analytic techniques are predicated on assumptions about learning environments that may not hold. While there have been many examples of using data mining to track students' progress through interactive learning environments using log files (e.g.,[12, 1, 23, 10, 27, 3, 5, 14, 6, 24]) most of these learning experiences have been developed with reference to expert envisioned solutions which act as a strong model that the learners need to follow [9]. For example, learners are given a well-defined, fixed goal with known, optimal number of steps to reach this goal, and known, fixed number of choices that can be made by the learner at each step. In such circumstances any user action can easily be judged as taking them closer to or farther away from the goal [20]. This clarity often underpins the structure of model based Intelligent Tutoring Systems (ITS), which typically combine exhaustive, a priori "strong" models of the content domain and prior learner performances with models of the student's current progress to generate guidance [35]. These well-constrained problem spaces have successfully been used by data miners, who rely on a priori models and on post hoc analysis to provide formative feedback to the students [10, 3] or to their teachers [23], to provide formative feedback to the environment designers [12, 23], or to provide evaluative feedback on the nature and scope of mistakes made by learners in the environment [1, 27].

However, these constrained problem spaces often do not reflect problems found in the real world. Real-world problems often possess multiple solutions, where each can be attempted with multiple alternative theories, or sometimes lack the theories to verify solutions; or possess multiple task structures leading to overlapping sub-problems which thus demand novelty rather than replication from the learner [19, 9]. Additionally, these problems are often solved by groups of people who each bring in a new perspective, perspectives which are critical to preserve in order to develop workable solutions for real-world problems like climate change, social change and many others. Due to the varying dimensions wherein open-endedness can exist, the notion of open-endedness is quite vague, and oftentimes it is difficult to differentiate open-ended problems from well-defined problems; in actuality these problems seem to exist on a continuum. Simon [31], defined open-ended problems as having three features: (1) indefinite starting points, (2) indefinite ending points, which constitute goals - either are not clearly de-

Aditi Mallavarapu and Leilah Lyons "Exploration Maps, Beyond Top Scores: Designing Formative Feedback for Open-Ended Problems" In: *Proceedings of The 13th International Conference on Educational Data Mining (EDM 2020)*, Anna N. Rafferty, Jacob Whitehill, Violetta Cavalli-Sforza, and Cristobal Romero (eds.) 2020, pp. 790 - 795

fined or are complex and imprecise, and (3) with no clear strategies to solve the problem. While presenting learners with simplified and constrained problems can be a good way to help them come to understand the core properties of a domain, exposing learners to less constrained, more open-ended problems can help them get experience with disciplinary processes and dispositions [20]. Owing to the recommendations of many educational standards both formal and informal educational settings are giving the learners opportunities to practice these disciplinary processes and develop disciplinary dispositions by exposing the learners to open-ended, project-based student centered approaches [29]. Since these problems expose the learners to a rather large solution space, some researchers have argued that open-ended learning environments, and the exploratory learning styles often promoted to go along with them, are simply not workable in educational settings [17]. While other educational researchers have argued that rather than giving up on exposing learners to open-ended problems, educators and researchers should instead seek to support learners in their explorations via proper supports [13], like scaffolds and formative feedback. We argue that data mining offers great potential for supporting open-ended learning via data-driven formative feedback.

1.1 Formative Feedback

Formative feedback has been defined as "information communicated to the learner that is intended to modify the learner's thinking or behavior for the purpose of improving learning" [30]. Formative feedback has been used extensively to support learners while solving well-defined problems, as when a learner is given a hint based on his "distance" from the goal, or a suggestion based on the expert model to get him "closer" to this model. These forms of formative feedback are inherently tied to an assumption of one fixed goal, making them unsuitable for open-ended problems which can have a dynamically evolving state space thus demanding that the learners' goals evolve with them. Moreover, it can be challenging to fit a fixed goal perspective to collaborative learning environments, both pragmatically (instrumentation is a challenge) and conceptually (how one can go about ascribing "credit" to multiple learners when they jointly create a solution - is a theoretically undefined proposition - we don't yet have theories of learning, and thus metrics, that fully account for and embrace the multifaceted ways groups of learners support one another and their joint endeavors).

Summarizing, there are two main barriers to adapting existing formative feedback approaches for use in open-ended collaborative learning environments: (1) due to the vast solution space, and the frequent lack of solution verifiability, it is difficult to create an exhaustive task or expert models, thus making the detection of the learners' progress challenging [25]; (2) Most of the formative feedback in well-constrained problems is based on individual learner models, which does not scale well when many learners are collaborating to solve the same problem, a known problem in the field. To supply formative feedback for open-ended collaborative learning environments, a fundamental re-conceptualization of how formative feedback is structured, and the techniques used to distill it from collected data, are needed.

2. PROPOSED CONTRIBUTION

This research proposes to re-conceptualize formative feedback (and how it is derived from logged data) so as to support learners in open-ended, collaborative learning environments. First, we make the deliberate decision to step away from measuring or modeling individual learner "progress" - rather than placing the learner, and his or her actions, at the center of our analytics, we instead place the *solution space* at the heart of our analysis. We conceptually relate formative feedback for open-ended problems to what Lynch et al. [19] called *Discovery Support Systems*. We redefine it to be about modeling/capturing the aspects of the problem space explored by the learner(s) so far - and how the course of that exploration has unfolded so as to have exposed aspects of the problem space to the learner.

There has been considerable research on design and impact of feedback in both ill-defined tasks and problems (E.g [4, 8, 11, 26, 9]) with methods like partial task models and in well-defined ([16, 7]) tasks and problems with model-based, constraint-based and expert solution-based approaches (See Lynch et al. [19], Fournier-Viger et al. [9] for extensive review). However, these studies have designed feedback by constraining some aspects of the open-ended problem making it less open-ended [9] and have reported findings and issues related to feedback design as very complex and often mixed [19]).

The purpose of our proposed data-driven formative feedback methods is to empower the learners themselves to reshape their exploratory path through the problem space such that it can be made more amenable for exposing learners to critical events, insights, and contrasts. These can range from simple evaluative feedback suggesting "correct" or "incorrect" where verifiable solutions are available, to complex elaborate maps illuminating the trajectory of exploration, or even tying the highlights of the exploration path with external concepts and theories. As an analogy - if prior methods of formative feedback are akin to giving a tourist step-by-step directions to reach a destination, we are attempting to produce an annotated map. We thus re-situate the problem-solving decision-making with the learners themselves, and see our mission as providing them with relevant, situationally-salient information to make those decisions.

We desire to give learners a sense of how their explorations map to the larger space of possibilities within the learning environment. In a truly open-ended learning environment, the space of possible action may be infinite, but there are often nonetheless common repeating patterns in action-response pairings. The more data we collect on how learners make use of a given learning environment, the better our map of the problem space - much like a travel guide that has been annotated by multiple tourists. To conceptualize what it means to provide a data-derived "annotated map" to learners in open-ended environments, we thus lean on the "fugue" construct developed by Reitman [28]. In music, a "fugue" is a short melody or phrase which is taken up by other instruments. We argue that data mining can be used to detect "fugues" developed by prior learners in response to certain situations within the problem space, "fugues" that could be presented to new learners as potential directions to pursue. Additionally, the "fugue" concept can be used to help learners reflect on their own exploration paths: are they relying on very similar "melodies", or branching out and trying new compositions? The value of the "fugue" concept is that it is not in contradiction with a multi-learner environment - the piece of music, as produced by the whole orchestra, is the subject of analysis.

2.1 Research Questions

We follow Reitman [28] recommendation of conceptualizing the problem solving in open-ended learning environments as "fugues" (like in music) where the learners could adopt a component solution and successively develop interweaving parts to that component of the solution. This leads us to:

RQ 1: What kinds of methods can be used to design domain-independent formative feedback to enable exploration and conceptualization of such "fugues"?

The idea of adopting problem solving in this manner implicitly includes metacognitive support (by providing learners with an exploration map of known "fugues"), and implicitly invites collaboration where the developmental work of one group can be picked up and further developed by others. We explore what features of the problem-solving would best motivate this kind of learning and how we could exploit these features through data-driven methods to design formative feedback.

RQ 2: How do these "fugues" of solutions repositories evolve as we expose more solutions? What limitations and advantages evolve as we expose more solutions?

As more and more groups attempt the problems the repository of known "fugues" expands, thus surfacing new possibilities for formative feedback and teaching methods in the existing domain like (1) a view into how learning, collaboration, innovation takes place in such ill-defined domain, (2) provide guidance for intervention by any humans-in-the-loop (e.g., educators), (3) use the repository to design context-specific (for learners directly) feedback for known actions/tasks, and motivate the design for similar domains by laying down foundations for (4) for the design of Intelligent Tutoring Systems which might not have a expert model readily available, and (5) for designing adaptive learning environments for ill-defined problems, where the problem can change difficulty level by tracking learners to have explored certain paths or length of paths. For my dissertation, I will explore the utility of formative feedback for the in-domain applications ((1)-(3)). However, the expansion of the "fugues" also references potential limitations of the methods, for example (1)the running time constraints for processing the data- a real-time formative feedback poses certain limitations on the time spent in processing the result which makes effectiveness rather than efficiency of the feedback a priority, (2) detecting and referencing the most commonly occurring "fugue" from/to the learners might potentially indicate tunnel vision, so helping the learners diversify "fugues" while preventing recursion problem must take precedence. Maintaining an effective balance to resolve these limitations would also be the scope of my dissertation.

RQ 3:What impact does the use of these "fugues" based formative feedback have on the learning opportunities in an open-ended learning environment? We would like to measure the impact of the redefined formative feedback for open-ended learning environments designed in RQ 2 (with visitors and the educational staff) to validate our conceptualization and usefulness of formative "fugues" in aiding exploration and the effects of scaling on the formative feedback.

2.2 Case: Collaborative Open-Ended Simulation Based Museum Exhibit

We propose to design formative feedback for a mixed reality, simulation-based museum exhibit. Connected Worlds is an open-ended complex systems exhibit that can support up to 50 simultaneous users to explore and manipulate the ecosystem. Visitors interact with the simulation by diverting the flow of simulated water on the gallery floor, and by planting seeds in the biomes simulated on the wall projections. They are tasked with maintaining the diversity of four different biomes via planting and managing water resources. It serves as a good testing ground because the exhibit does not provide the learners with fixed goals or constraints for strategies encapsulating the two characteristics of open-ended learning environments: no verifiable solutions or end goals and no clear strategies to solve/ maintain the diversity. The visitors have to constantly work together to maintain the diversity and manage resources in the ecosystem, and there can be a varied different ways of doing the same, with interaction of the actions varying substantially across contexts nominally of the same type, producing different results across-context, a recognized quality of an open-ended task [33].

2.3 Preliminary Work and Future Directions

We have designed and built a system for unobtrusively collecting the "collective" interaction data while the visitors groups interact with the system and with each other, which is undergoing iterations to capture more facets of data. In prior work, Mallavarapu et al. [21] the data capturing system was validated by the use of a mobile interface to visualize the data for visitors, and the study showed that formative feedback influenced the problem-solving strategies the visitors were using. This study helped us establish the impact of formative feedback in an open-ended learning environment like our test site. In addition to the experimental and control contrasts in the above study we have collected interaction log-data from 32 school sessions which can be used for post-hoc processing, identification, validation of methods to design formative feedback. We propose a taxonomy of methods that can be used on the well-defined to ill-defined continuum to design formative feedback (See Table 1). Another work has recently used the school groups data to study and decipher the temporal cause-effect relationships between the learners' collective interactions and the systemic responses [22]. This provided a conceptualization to the design of *Prediction based Feedback* (See Table 1). Our immediate future efforts will focus on applying and validating these methods with the current data in extracting and designing formative feedback for this environment. These methods will then be used through the mobile device to evaluate the impact on the exploration taking place in the exhibit.

3. ADVICE SOUGHT

1. What validation methods can be used to evaluate the methods that can extract the "fugues"? We acknowl-

Type of formative feedback	Information needed by recipient	Information needed by Analytics	Applicable analytic approaches	Applicable to ”fugues”
Model based Feedback	Next steps to take, demonstration of a certain step, evaluation of skills and actions, Progress towards goals	“Goal” decomposition tree, Correct example(s), metric of correctness, task to action and skill mapping	Knowledge tracing map from goals to skills and tasks, expert models.	
Violation based Feedback	“Favourable” actions and ”distance” from goals due to the action	Set of constraints on the “correct” behavior, Rules for task	Detecting when certain rule is violated.	
Sequence based Feedback (showing only ongoing interaction)	Solution paths, actions on the path	Definition of what constitutes a solution path, temporal order of *current* actions	Sequence mining where consequences of frequent previously seen sequences can be used as feedback.	X
Prediction based Feedback (showing only ongoing interaction)	Predicted Consequence of actions	Causal model of the learner interactions	Causal Inference, Regression.	X
Contrast based Feedback	examples that contrast on one or more dimensions of goals	Definition of dimension(s) of contrast and highlights for goals	Sequence mining, Ability to extract “Highlights”, goals from interactions, clustering using defined dimensions of contrasts.	X
Trajectory based Feedback	A exploration map of path travelled placing them on continuum of paths	definition of dimension(s) of path characterizations, differentiating metrics	Sequence mining, Ability to extract/ differentiate trajectories, clustering.	X
Task/Events based Feedback	attempted tasks/ uncovered events on the trajectory	definitions of tasks and/ or events and their temporal order, definitions of trajectory	Ability to extract “tasks” from the actions, constituting them as trajectories, clustering depending on the definitions of tasks.	X
Comparison based Feedback	collection of trajectories attempted (till now)	definitions of trajectories, differentiating metrics	Ability to extract/ differentiate trajectories, clustering.	X

Table 1: Types of Formative feedback, information conveyed by them and details of the methods for the continuum of Learning Environments

edge that we are using the existing EDM methods to validate their applicability to our problem-space. We would want to evaluate each method for the same.

2. What other external factors need consideration when designing formative feedback for open-ended learning environments. For example, when designing formative feedback for problems tackled by individual learners researchers have explored the effect of individual differences [15, 34] on the impact of formative feedback through individual learner models; While evaluating the impact of formative feedback in collaborative open-ended learning environments - what factors do we need to consider?

3. Should we consider to establish a generalizability to this redefinition of formative feedback and its impact by validating our approach through another equivalent environment?

4. CONCLUSIONS

As we move from individually tackled well-defined problems to open-ended real-world problems to allow the 21st century learners to explore with their peers, we also need to make a move from “solution” based formative feedback to a more *Socratic* method [18] of providing feedback to enable explorations, thus giving the learners an opportunity to contemplate the implications of their decisions. Working synergistically with the learning environment the feedback should expose to the learners the opportunities to learn and practice abstract skills like reasoning, creativity, innovation, and encouraging the same in a collaborative environment. We identify the feedback for collaborative open-ended learning environments to have characteristics like meta-cognitive support, support for “collective” learner efforts, and be predicated on the characteristics of the problem space rather than the learner actions.

5. ACKNOWLEDGMENTS

This material is based upon work supported by the National Science Foundation under Grant Nos. 1623094 and 1822864,

and would not have been possible without the aid given by museum staff.

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