Formative Fugues: Reconceptualizing Formative Feedback for Complex Systems Learning Environments

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Abstract

The Next Generation Science Standards and the National Research Council recognize systems thinking as an essential skill to address the global challenges of the 21st century. But the habits of mind needed to understand complex systems are not readily learned through traditional approaches. Recently large-scale interactive multi-user immersive simulations are being used to expose the learners to diverse topics that emulate real-world complex systems phenomena. These modern-day mixed reality simulations are unique in that the learners are an integral part of the evolving dynamics. The decisions they make and the actions that follow, collectively impact the simulated complex system, much like any real-world complex system. But the learners have difficulty understanding these coupled complex systems processes, and often get "lost" or "stuck," and need help navigating the problem space. Formative feedback is the traditional way educators support learners during problem solving. Traditional goal-based and learner-centered approaches don't scale well to environments that allow learners to explore multiple goals or solutions, and multiple solution paths (Mallavarapu & Lyons, 2020). In this work, we reconceptualize formative feedback for complex systems-based learning environments, formative fugues, (a term derived from music by Reitman, 1964) to allow learners to make informed decisions about their own exploration paths. We discuss a novel computational approach that employs causal inference and pattern matching to characterize the exploration paths of prior learners and generate situationally relevant formative feedback. We extract formative fugues from the data collected from an ecological complex systems simulation installed at a museum. The extracted feedback does not presume the goals of the learners, but helps the learners understand what choices and events led to the current state of the problem space, and what paths forward are possible. We conclude with a discussion of implications of using formative fugues for complex systems education.

Keywords: complex systems education, computational formative feedback, interactive digital exhibits, participatory exhibits, causal modelling complex systems.

INTRODUCTION

To prepare learners for the future workforce, educational researchers and policymakers have been drawing increasing attention to exposing learners to the skills, disciplinary processes and dispositions required to solve the 21st century problems (National Research Council, 2010). One of these essential skills is systems thinking (NGSS, 2013; National Research Council, 2012), which can help learners understand and address many of the social and global problems that we face today. Since the behavior in many of these systems is intrinsically difficult to understand (due to the uncertainties in the dependencies and the dynamic interactions among the various components at different levels of organization), they have been termed complex systems. The disciplinary skills, practices, and habits of mind needed to comprehend such systems, are not readily understood or adopted (Hmelo-Silver & Azevedo, 2006; Yoon et al, 2018; Jacobson & Wilensky, 2006). For example, one of the properties that complex systems can exhibit is emergence - meaning that a given outcome arises from the interactions of many smaller factors, without any centralized control (Yoon, 2008; Jacobson, 2001). Coming to understand a complex system thus requires learners to master not just the content, but to also adopt an epistemological stance that rejects a deterministic, “clockwork” understanding of how systems function (Yoon, 2008; Jacobson, 2001; Chi et al., 2012). To understand emergence, learners need to recognize that their every action contributes to the emergent outcome emulating the decentralized operation. It can have effects that are separated spatially and temporally across the different system components. To introduce learners to concepts like these, researchers have been exploring a host of new digitally supported learning environments that expose learners to complex open ended, real-world problems. These environments allow learners to work collaboratively to both experience and comprehend the complex real-world problems in which they are immersed (Yoon et al., 2018).

Importantly, the immersiveness in these environments demands that the learners play a part in the evolving complex system, much like the real-world complex systems that are a product of interacting human and natural systems. The nature of these problems requires learners to engage in exploration-based learning (Moradi et al., 2020) and apply disciplinary skills and practices to solve problems, imposing learning goals that prioritize the process of solving the problem over the quality of the solution. However, in addition to the complex systems phenomena with which the learners engage, the skills and practices the learners deploy for exploration-based learning (like keeping track of the explorations, regulating the problem-solving activities by constantly engaging in planning, monitoring, or evaluating) are notoriously hard to measure (Mallavarapu et al., 2015). These challenges have held back the support and scaffolds that can be provided to the learners to help them understand the disciplinary processes, in turn hampering the very goal of effectively implementing these digital learning environments (Goh et al., 2012; Slattery et al., 2012; Mallavarapu et al., 2015).

Formative feedback is the traditional way educators support learners during problem solving, by giving learners information based on their distance or deviation from the goal. But open-endedness in these new digital environments imparts loosely bound goals or reward functions, thus affording a very large solution space - with multiple possible solutions, multiple strategies for reaching the solutions, and multiple actions that make up the strategies (Mallavarapu & Lyons, 2020). Additionally, complex systems properties encapsulate nonlinear and dynamic state changes that require the learners to evolve their goals, redefine the sub-problems and the associated solutions they will tackle as they discover previously unknown or emergent parts of the problem. This makes their experience non-deterministic and unrepeatable, which in-turn renders the traditional goal-based methods unfit for tracking their progress in these environments. For example, certain phenomena likely to happen within a complex system may not emerge in exactly the same way, or at the same time, each time a system is enacted or simulated. This means that any feedback given to the learners to help them internalize the concepts and epistemologies needs to be relevant to the learners' current context. Thus, to aid learners understand and acquire the complex systems disciplinary processes we need to develop methods that can make visible the complex systems processes that the learners experience, monitor the skills and practices the learners exhibit while solving these problems as a process and provide them as formative feedback. Indeed, even in more traditional educational scenarios, contextual feedback has been shown to be useful as a driving force for motivation, effectiveness and efficiency in learning (Fancsali, 2015; Verbert et al., 2013).

Our motivation for this work is to provide contextually relevant formative feedback for learners who are engaged with an ecology-based, complex systems, open-ended learning environment called Connected Worlds, installed at a science museum. The exhibit has won multiple design awards and engages groups of visitors to cooperate or interfere with one another, encouraging them to disrupt or improve the state of an ecological simulation (Mallavarapu et al., 2019). The exhibit was designed to evidence the critical phenomena hard to comprehend when just viewing the simulation, as a third party. It instead makes a large group of learners part of the emergent complex system, allowing them to trigger and interrupt the complex systems phenomena. However, the coupled nature of the human and natural systems simulation makes it difficult for the learners to identify the processes they trigger and interrupt collectively, and they often express confusion about "what was really going on." To be fair, when a human-based complex system couples with a natural complex system, they together form a completely new complex, dynamic, interconnected system which has its own unique feedbacks, behaviors and functions that can be triggered by events in either constituent system (Ferraro, Sanchirico, & Smith, 2019). Understanding these behaviors and functions is crucial to make an informed decision about what actions to take next.

We present this work to address the need to provide learners of Connected Worlds situationally relevant formative feedback that can help them understand the current situations, make decisions, and take actions in order to guide their explorations in the open-ended solution space. Through this work we provide two contributions: conceptual contribution of newly conceived formative feedback, called formative fugues, and methodological contribution of a data-driven computational method for extracting formative fugues from prior learners' data.

After a review of existing work in the area, we first discuss the conceptual contributions, in which we reconceptualize the traditional definition and functions of formative feedback as *formative fugues*, modifying it to meet the demands of these modern-day complex systems open-ended learning environments. We then address the methodological contributions and discuss a computational approach that can expose the learners' exploration paths to generate *formative fugues* for Connected Worlds. The *formative fugues* generated through this process highlight the different cause-effect chains that connect the actions by different visitors at different times and at spatially different locations, exposing the complex systems processes under play in a meaningful manner. Our approach uses collective visitor interaction logs that record the changes in the simulated system state due to the different visitor actions and decisions to model the complex system. Our decision to collect data at the system level, instead of tracking individual learners in the space, was set to maximize the possibility of surfacing the effects of the decentralized actions on the system. The causal relationships are then used as embeddings to extract contextual formative feedback as salient patterns from the interaction data. We further elaborate on the implications of using *formative fugues*, for three stakeholders: the learners, educators and educational researchers, and its delivery mechanisms.

RELATED WORK

Digital learning environments have made way for "living labs" (Salgado, 2004) that expose learners to real-world problems and provide the instrumentation to observe learning. In this section we describe with examples the features of such complex open-ended learning environments that allow learners to experience the real-world problems. The very complex nature of these problems presents a need for contextually relevant formative feedback to guide and motivate the learners to explore the concepts. We survey the implications of analytically monitoring learning in these environments and the correlation between the nature of the analytical techniques used by researchers to extract formative feedback and the learning goals defined by the environment.

Complex Open-ended Learning Environments (COpELE)

Ideally, the open-endedness of digital learning environments that enable multiple solutions, multiple strategies to solve each solution and multiple paths to each of those strategies (Le et al., 2013) arises from the absence of, or loosely defined goals or reward functions. The learners are expected to evolve their goals, strategies and actions according to the context of their interaction. Additionally, complex systems exhibit special qualities like: 1. Hysteresis, or path dependence (meaning that the actions that are possible to undertake are dependent on events early on in the unfolding of the system, preventing backtracking); 2. A near-infinite number of system states that include both stable states (where the system can resist changes to this state for a longer period of time) and nonlinear rapid regime shifts (tipping points which cause abrupt changes in the system states); and 3. Emergence of unique phenomena at the global level, which are not visible at the local level but arise due to the interactions among system elements present at the local levels. All these dimensions together portray a sense of randomness in the behavior of the complex system.

So, with each goal and strategy implementation that the learners explore - hysteresis imposes restrictions on which alternatives are propagated forward, thus constraining learner choices (Lynch et al., 2012), while nonlinearities and emergence makes learner progress non-monotonic and dynamic. The learners need to adopt a non-reductive systems-thinking approach to understand the order and structure of multiple causes and consequences that coexist at many different scales of time, space, and organization (Jacobson, 2001). This perspective requires constantly shifting focus between local and global thinking - understanding how the action at a local level impacts the behavior of the local entities and the processes at both the local and the global levels, to unravel emergence. This can be a difficult perspective to attain while enmeshed in the problem-solving process. Researchers have suggested that learners can begin to comprehend emergence by performing mental exercises that juxtapose local-level perspectives with global-level perspectives (Jacobson & Wilensky, 2006; Goldstone & Wilensky, 2008) and have stressed the importance of learners coming to understand the causal connections present in the complex system (Grotzer, 2012) to help them transition from an event-based way of experiencing systems phenomena to a process-based understanding (Grotzer et al., 2013). Learners need opportunities to experience complex systems phenomena firsthand, motivating challenges to encourage them to explore the phenomena, and they need assistance to orient them to these new forms of decentralized thinking. While this kind of learning can be accomplished via technology-free activities, like the classic 1960s "Beer Game" participatory simulation, the affordances of simulation technologies for enacting complex systems and permitting learner engagement with them are undeniable.

Simulation Based COpELE

The need to expose learners to complex systems has led to a range of simulation-based learning environments which engage learners in different ways. There are a number of single-user simulation environments, some which engage learners in programming the behavior of local-level agents, like NetLogo (Wilensky, 1999), StarLogo (Klopfer, 2003; Klopfer et al., 2005), and AgentSheets (Repenning et al., 2000). Others, like STELLA (Richmond & Paterson, 2001) and Model-It (Jackson et al., 1996), ask learners to model the system itself. Asking learners to model agents and systems can be very effective for supporting their understanding of systems but is very challenging for learners - it requires a lot of teacher support, and is not an inherently motivating task.

As a consequence, a number of researchers have looked towards more participatory and collaborative methods for exposing learners to complex systems, from in-person participatory simulations where learners enact a complex system while digitally supported in their role-play by mobile devices (Colella, 2000; Ioannidou et al., 2010; Danesh et al., 2001; Soloway et al., 2001) to purely online Multi-User Virtual Environments (MUVEs), which help learners explore systems by practicing scientific inquiry and reasoning skills by virtually interacting with their peers through discussions and chat windows [e.g., EcoMUVE (Grotzer et al., 2011), EcoXPT (Thompson et al., 2016; Dede et al., 2017)], to more involved co-located full body participatory simulations [e.g. RoomQuake (Moher, 2008), WallCology (Malcolm et al., 2008), BeeSim (Peppler et al., 2010)], and more recently collaborative mixed reality and virtual reality based immersive simulations [e.g. MEteor (Tscholl et al., 2013), Evoroom (Slotta et al., 2013), Learning Physics through Play (LPP) project (Enyedy et al., 2015), ELASTIC^{3}S (Planey & Lindgren, 2018), and Connected Worlds (Mallavarapu et al., 2019)]. The immersive mixed reality simulations have evolved from affording the learner a passive role (like in the programming-based environments and the MUVEs) to an active role, where the learners (their actions and interactions with each other and with the system) influence the complex-systems phenomena.

The learning environments expose the learners to diverse complex system topics that extend into the real world, spanning digital and real-world artifacts (Mallavarapu & Lyons, 2021). These experiences emulate real-world complex systems and problems, which couple a human-based system (that the participants bring through their interactions with each other) and a natural system (the simulation) - each affecting the other. The goal of these environments is to make the learners aware of both the global and local perspectives for the complexities present in the problems, with the ecological validity and educational rationale of letting learners face challenges they would face in the real world. Presenting open-ended problems that are less constrained, permits learners to set their own goals and coordinate actions to explore these problems in service of those goals. This exploration acts as motivation for engaging learners to investigate such phenomena. Many real-world complex systems problems, like climate change, require deep understanding and skills for managing the phenomena. It especially requires an understanding of how the human-based complex system, where people, and their individual decisions, co-constitute the natural complex system triggering complex phenomena. The system requires people to continuously coordinate their actions as they strive to explore the system, devise goals, and attain or maintain desirable system states. Illustrating how each simple action impacts the current state and/or future actions while the learners are engaged in maintaining the system, can help the learners adopt and understand the new perspective of systems thinking.

Implications of Complex Open-ended Solution Space

The learning environments reviewed above succeed at exposing learners to complex open-ended problem solving. While the more collaborative and immersive versions are highly successful at motivating learners' engagement, these elements also make it much harder for educators to offer guidance and support to learners. The vague (or emergent) goals and few (or no) constraints that allow the learners the opportunity to explore more of the complex problem domain (Bauer et al., 2017), limit the ability of the researchers and educators to easily monitor and track learning processes. The exploration-based learning that goes along with these open-ended problems presents unique opportunities often missing in traditional learning experiences. Traditionally, learning experiences have been known to pose "simple" problems, with well-defined goals that impose restrictions on the actions, and the order of the actions the learners can take to implement strategies to reach the unique solution. The greater the constraints, the more precise is the learner's goal, which can hamper a learner's exposure to the full problem space - as the learner is incentivized to exploit the problem domain rather than explore it. This is true for open-ended problems that also are complex systems based, where constraining the learners' goals and actions through well-defined functions can lead to systematically ignoring or oversimplifying the processes that account for the "complex" nature of these problems (Jacobson & Wilensky, 2006), hiding the very properties that these problems and learning environments were designed to expose the learners to.

Some problems embedded within the complex systems are even described as having no correct or incorrect answers, but only answers that are better or worse when compared to each other in terms of some domain dependent heuristics (e.g., the problems in Bauer et al., 2017 and Mallavarapu et al., 2015). Such problems with non-verifiable solution states ensure that the learning goal is not to achieve a certain "terminal" state but rather the learners are required to actively manage the system. However, this requires that the learners have considerable prior knowledge that they search, update and filter during the exploration process while keeping track of the historical events that elicit these changes. While, this has educational benefits, as it places learners in a position to make evaluative judgements, engaging exploratively with complex systems demands additional support to understand, search, filter and update the exploration paths.

Challenge of Adapting Traditional Formative Feedback to Complex Open-ended Problems

Traditionally, 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" (Shute, 2008, p.2). This definition portrays formative feedback as being provided in response to the learner's actions in the form of a verification of the accuracy of the action, a hint for the next action, or a content-based explanation guiding the learners towards the correct action. These kinds of formative feedback work well with individual learners. They have been used extensively to support them while solving simple well-defined problems, and they are inherently tied to an assumption of one fixed goal, making them unsuitable for solving complex open-ended problems, which can have a dynamically evolving solution space. 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). The theories of learning that could conceptually fully account for and embrace the multifaceted ways groups of learners support one another and their joint endeavors are currently very fragmented and underdeveloped (Mallavarapu & Lyons, 2020).

To supply formative feedback for these newly conceived COpELE, a fundamental re-conceptualization of how formative feedback is structured, and the techniques used to distill it from collected data, are needed. Black and Wiliam (1998) identified two main functions of formative feedback to manage the cognitive aspects of the learning process: 1. The *directive aspect*, which communicates the gap between the current level of performance and the desired level of performance, and 2. The *facilitative aspect* that explains the concepts to the learner and guides them towards the revision or conceptualization. For these functions to hold for collaborative, open-ended learning environments, we need to relax the assumptions on what the desired level of performance is, and help the learners visualize the many different possibilities of goals, strategies, and actions.

Because of the immense amount of detail and multiple parallel processes interacting to shape the complex system, extracting feedback that is specific to the learners' experience and that can serve either the facilitative or directive aspects is non-trivial. The feedback generation mechanism should first be able to extract the details of individual processes and then clearly relate the processes to the larger complex systems phenomena. In complex systems there may actually be a near-infinite number of states a system can assume, thanks to systemic nonlinearity, and a near-infinite number of paths that learners take through that state space. It is thus impossible to map out the state space, or the learners' action space, a priori. We argue that data-mining the learners' interaction data offers a great potential to extract specific nuances highlighting the complex systems processes and deliver them as formative feedback in these novel learning environments. If applied correctly, data mining can build a picture of the space of possible states and actions, experienced by learners, and generalize them in usefully bounded ways. It has the ability to capture the fundamental functions and elements of formative feedback highlighted in the literature, while complementing the features of complex systems processes with which learners are engaged.

Computational Methods for Extracting and Delivering Formative Feedback

Computational methods have been successfully used to monitor learner progress with a wide range of simple problems (e.g., Harpstead et al., 2013; Andersen et al., 2010; Martinez-Maldonado et al,, 2013; Gobert et al., 2013; Rafferty et al., 2013; Biswas et al., 2013; Desmarais & Lemieux, 2013; Jarušek et al., 2013; DiCerbo & Kidwai, 2013; Müller et al., 2013), largely due to the simplifying assumptions researchers can make when representing learners' engagement with such problems. But computationally monitoring learners' engagement with COpELE entails accounting for all possible actions, strategies, and goals, which can be difficult to map especially when open-ended learning environments present complex systems problems, because - 1. there may be many unexplored and unknown exploration paths that need to be mapped to provide the full picture, and 2. there are multiple strands of processes in play simultaneously. Surfacing the process most relevant to the learner requires knowledge of their goals, intentions, and the cause-effect relationships at varying scales of time, space, and organization. Computational methods used to document the problem spaces of open-ended complex systems learning environments should expose the details of the complex systems properties like randomness, nonlinear dynamics, and emergence that arises due to the learners' explorations, but do so without constraining the sprawl of learners' idiosyncratic exploration activity.

Although limiting the learners' ability to explore, the predictable order and consequences of actions in traditional "simple" problems lend the advantage of allowing the use of learner-centric computational methods to provide the learners with feedback that is fit to their own progress. These approaches build "expert" models that map the possible actions and strategies for each well-defined goal. At each step these techniques compare the learners' actions to the "expert" model, providing them feedback based on distance or deviation from the goal or next permissible action. However, these learner-centric methods are not practical in collaborative settings, and do not scale well for open-ended experiences with a large and evolving solution space where the learners' goals and understanding of the problem space evolve with it.

Due to the presence of this 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 (Kirschner & Clark, 2006). While other educational researchers have argued that rather than giving up on exposing learners to complex open-ended problems, educators and researchers should instead seek to support learners in their explorations via proper supports (Hmelo-Silver, Duncan, & Chinn, 2007), like scaffolds and formative feedback. Should such support be viable and feasible to produce, the argument against complex, open-ended learning environments would no longer carry weight. Given the potential benefits of open-ended learning, then, there is a compelling argument for devising efficient and effective formative feedback.

We argue that the need to support learner explorations by exposing the underpinning complex systems processes to help the learners internalize the concepts, goes beyond the traditional supports that monitor the "quality" or "completeness" of the *solutions*. Thus, the rethinking and remodeling of complex systems education that has been initiated through the virtual and participatory simulations must be followed by reconceptualizing formative feedback. Exploration support could provide the contextual feedback that not only highlights learners' own experiences but also provides them a mechanism for "informed discovery" by surfacing alternatives for how complex systems could evolve. To this end, we present a reconceptualization of the formative feedback that complements COpELE, and devise a novel computational technique that can extract contextual formative feedback to surface the different complex systems process at play during learners' explorations.

FORMATIVE FUGUES: RECONCEPTUALIZATION OF FORMATIVE FEEDBACK FOR COpELE

We have reconceptualized the nature of formative feedback for COpELE by shifting the focus of the analysis that generates learner-centric feedback to problem-space-centric feedback. As an analogy - if traditional formative feedback was akin to giving a tourist step-by-step direction to reach a destination, the COpELE formative feedback attempts to produce an "annotated map", highlighting the crucial decision points, while paring away unnecessary details. Embracing the exploration-based learning supported by these environments, we resituate the decision-making power with the learners themselves, and see our mission as providing them with relevant, situationally salient information to make those decisions. The annotated map to this problem space is drawn from the explorations of prior learners, which necessitates finding commonalities across these learner experiences. While it may be the case that a given end-to-end use of a complex system simulation is completely unique, there will be a number of self-similar chains of events, even if they may occur at different times and places from one simulation session to another. We have dubbed these self-similar chains *formative fugues*, drawing on the notion of "fugue" as described by Reitman (1964), which in music is a short motif, melody or phrase that can be taken up by other instruments, or musicians and developed further. Each fugue has an initial state. However, the terminal state and the series of intentional actions leading up to the terminal state, dubbed the transformation path, are objects of the learners' evolving goals and interactions. In other words: fugues may not be identical, but they "rhyme." The flexibility and multiplicity in the choice of transformation paths from the starting state leading up to the same or different terminal state is what makes the fugues suitable for the reconceptualized formative feedback for COpELE. Thus, the annotated map is more like a crowd-sourced travel guide annotated by multiple travelers, where the annotations are binned and summarized to represent certain *kinds* of engagement with the city (e.g., a number of them sought out a fancy dining experience, whereas others sought to peruse a museum).

We define the formative fugues as *information that is communicated to support explorations and exposes the different possibilities in the problem space*. To specifically support the complex systems facet of the problems, this definition captures the context of the actions. This answers three very important questions that learners exploring a complex systems-based learning environment often ponder: 1. *Which action(s) can produce the desired effects?*, an important yet difficult to predict property in complex systems due to emergence which we dub as "extrapolative feedback", 2. *How did the system arrive at the current state?*, which can be hard for a casual observer to infer given the nonlinear dynamics of state evolution and the multiplicity of possible causal chains at play, we call "explanatory feedback" and 3. *What other possibilities exist that have been explored by the prior learners?*, exposing the different exploration paths in the exploration map that can expose learners to complex systems processes that have not been explored by them yet, which we call "exemplary feedback". We call these three types the "3Es" of formative fugues and together they help the learners relate their actions and outcomes to larger causal chains to answer these questions.

The 3Es draw strong parallels with the functional aspects of formative feedback as defined by Black and Williams (1998) discussed earlier but parsing it into three distinct functions that can support explorations in COpELE. *Extrapolative* feedback is similar to the directive definition in Black and Wiliam (1998), but with the assumptions of fixed goals or standards relaxed to accommodate multiple solutions and strategies. This function provides actionable insights that could suggest the possible options for steps the learners could take but without making restrictive assumptions about the learners' goals. It specifically provides the learners with a "contextualizing function" that can help learners understand the causal interconnections and other complex semantics between the actions they can take and the consequences of those actions on the system state. We further divide the *facilitative* function as defined by Black and Wiliam (1998) into *explanatory* feedback that makes relevant the causal chains available for the learners' reflection of their experiences. These expose the various interconnections that were triggered by the learners' decisions explaining the sequence of events that has brought them to the current state or phenomenon. *Exemplary* feedback shows the learners the scope of possibilities within the learning environment and allows them to make their own choices about what to do next, thus guiding the "informed inquiry". In the next section, we discuss the novel computational method that extracts formative feedback that complements the reconceptualised functions for a simulated complex systems learning environment.

CONNECTED WORLDS: ECOLOGICAL COMPLEX SYSTEMS MUSEUM EXHIBIT

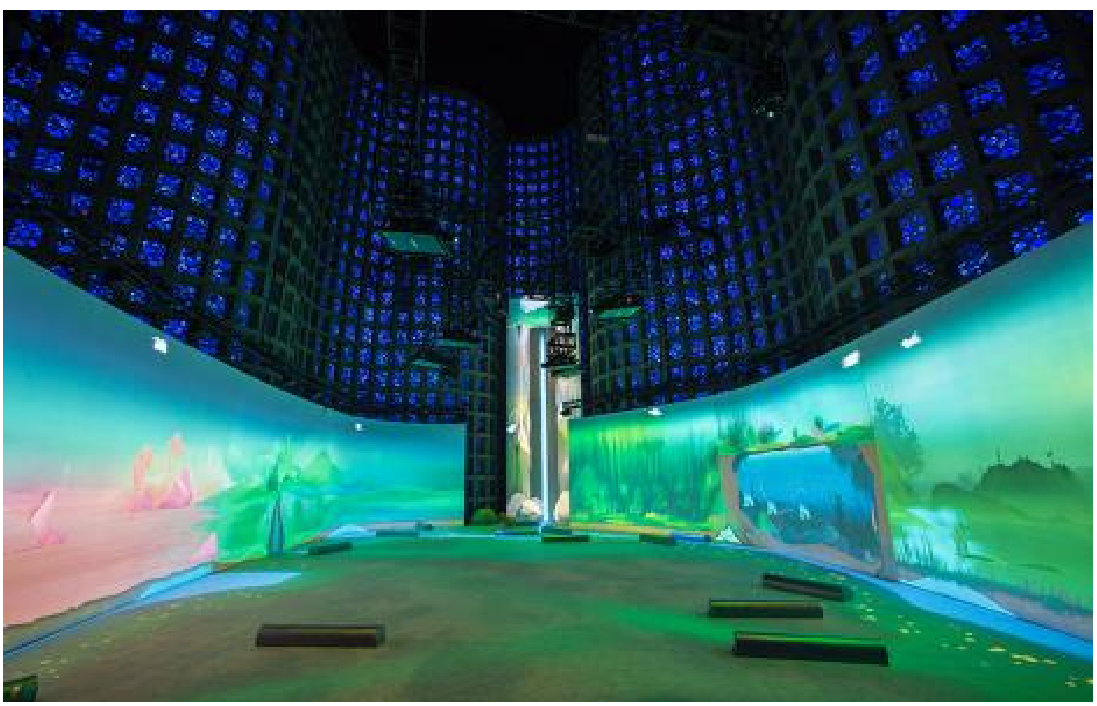

Figure 1. Connected Worlds exhibit showing the biomes and water sources (clockwise): desert, mountain valley, plains, waterfall, jungle, reservoir, and wetlands.

We highlight the potential of the computational method as we design formative feedback to be used in the context of a mixed reality, simulation-based participatory museum exhibit, Connected Worlds, that is currently installed at the New York Hall of Science. The exhibit allows learners to explore the concepts of ecological complexity and systems thinking. Connected Worlds is an immersive open-ended complex system exhibit that can support up to 50 simultaneous users to explore and manipulate the ecosystem. The exhibit is composed of four plantable biomes and three sources of water (see Figure 1). Visitors interact with the simulation by diverting the flow of water projected on the gallery floor from the water sources (see Figure 2), and by planting seeds in the biomes on the wall projections. They can plant seeds by holding their hand up in front of the screens and dropping their hand when the seed they want to plant appears on-screen (visitor gestures detected by Kinect cameras). If sufficient water is present, the seed will sprout. Different plants attract and support different animals as sources of food or shelter. The simulation includes a simplified model of "ecological succession", meaning that initially visitors can only plant small plants like grasses, but when sufficient grasses are present, the "soil" can support larger, more elaborate plants. Visitors supply water to the biomes by dragging large stuffed "logs" around the floor of the exhibit (detected by infra-red cameras), diverting the flow of water from the 6-story Waterfall and the Mountain Valley and Reservoir screens (water sources). When water is supplied to a biome it gets collected as "groundwater." The plants in the biomes cause water from the biomes to evaporate and form clouds, which return water to the ecosystem through rain, emulating a real-world water cycle.

Figure 2. A top-down view of the exhibit with visitors interacting with the exhibit. The tangible logs are being used to direct water towards the biomes.

The visitors are tasked with maintaining the diversity within and among four different biomes via planting and managing water resources. It serves as a perfect testing ground for observing the evolution and interaction of the coupled natural and human systems because the exhibit, like any real-world complex system, does not provide the learners with fixed goals or constraints for strategies and actions encapsulating the three characteristics of open-ended learning environments. There are no verifiable solutions or explicit end goals, no clear strategies, and no fixed paths to solve/maintain the diversity. The visitors must constantly work together to maintain diversity and manage resources across the ecosystem, and there can be a variety of different ways of doing so, with interactions varying substantially across contexts nominally of the same type, producing different results across-context, a recognized quality of complex open-ended environments (Mallavarapu et al., 2019). The entire experience is a dynamic system in which many complex interactions result in emergent phenomena, which can be local, teleconnected, or global that visitors must cogitate about and seek solutions that demand causal reasoning, cooperation, and experimentation. However, the open-endedness of the experience and the complex properties that present themselves at varying scales of time, space and organization often makes it difficult for the learners to identify and hence engage in informed inquiry. Thus, formative feedback becomes very important for the learners engaged with Connected Worlds to transform their experience from a mere playful experience to that of "informed inquiry" where they uncover new properties and understand the ecological phenomena within Connected Worlds.

METHOD

Data Collection

Connected Worlds is equipped with an automatic data logging system which unobtrusively records the simulation settings and its state every second, producing rows of time-stamped information that is saved as a CSV file at the end of the session (which we consider "raw" data). At each second, the log records state information as 93 variables, including: types and number of plants (both alive and dead), types and number of animals, water and clouds present in biomes and water sources, and number of users in front of each screen.

The exhibit is frequented by visitors between the age groups 3-60 years (up to 50 persons at a time), with about 3000 visitors a day. The large footprint makes it pragmatically impossible to instrument each visitor with tracking devices. Moreover, tracking visitors through sensors or camera-based equipment requires the devices be calibrated to the space and the visitors, while maintaining identity records of the visitors, which has serious ethical implications. Our museum serves populations for whom identifiable information can become politically weaponized (e.g., undocumented residents). Collecting and storing sensitive data has implications (perhaps against the intentions of the researchers) that could negatively impact the learners (Mallavarapu & Lyons, 2021). We thus avoid using these methods. Additionally, video recording school groups or young visitors in general requires special considerations about parental consent. So, in keeping with the ethical data logging parameters, the data includes no identifiable information about the visitors. This ensures that we do not record data on who performed which actions, and the way the log files are structured there is no clear indication of any individual goals, strategies, or even causal chains of events to help explain how the system state evolved due to a single visitor's action. The data, however, indicates how the group's decisions in the space collectively impacts the complex system.

To shortlist groups and select log files for analysis, we used school group reservations data from the museum's Visitor Services department (collected under IRB-approved protocol), to guarantee that the same facilitation script and simulation parameter settings were used for the Connected Worlds simulation, and to obtain the size of each school group and their grade levels. Similar to the interaction log data, these visitor logs did not include any identifiable visitor information. No other demographic information was collected by our Visitor Services department. The data was analyzed retrospectively years after it was collected, we obtained implied consent at the time of data collection by posting a sign at the entrance indicating that research is in progress (because our data does not include any identifiable visitor information our IRB only requires that we obtain implied consent).

Participants

This work uses the raw exhibit interaction data collected during the visits of 67 school groups over the period of October 2017- October 2019. In these planned visits, each school group had exclusive access to the Connected Worlds environment for a 12-minute open interaction session, that followed a 3-minute orientation to Connected Worlds (an introduction on how to interact with it, how to plant and how to divert water) and an orientation to the learning goal of promoting and sustaining diversity. The selected school group sessions averaged 28.5 participants in size, of an average age of 11 years, ranging from grade 2 (typically 7-8 years old) to grade 9 (typically 14-15 years). We opted to include multiple age cohorts in our sample because of our interest in identifying and listing the nuances in the response of the system to the visitors' Connected Worlds interactions and their multiplicity, embracing both the diversity of the learners' approaches and the age-groups of learners interacting with the system.

Procedure: Computationally Extracting Formative Fugues

Researchers have exploited the absence of concrete descriptions of behavior or action patterns in open ended learning environments through unsupervised methods like sequence mining (e.g., Segedy et al., 2015; Paaßen et al., 2017; Price et al., 2017; Wallner, 2015; Saadat & Sukthankar, 2020; Martinez et al., 2011). The advantage of these techniques is that they bootstrap the definition of a "pattern", sequences of learners' actions or behaviors, from the data, which evolves as more and more data becomes available. This representational strategy is useful because, unlike close-ended learning environments where the outcomes of interest are end states (e.g., learner's answer to a problem), in open ended learning environments the "outcomes" of interest are actually the processes by which learners engage with the different aspects of the problem domain (e.g., the step-by-step process).

This technique works for open-ended learning environments, where at any given moment the changes to the system state can be readily mapped to a single action-event triggered by the learner (e.g., click of a button). However, in environments which portray complex system behaviors, characteristic of Connected Worlds, there often exist multiple action-events occurring simultaneously. Additionally, each event influences the system at varying scales of time, adding a temporal dimension to the definition of the event. We wanted to capture how the state of a dynamic open-ended simulation changes as a result of the co-evolutionary process between learners' actions and system responses to provide formative feedback. But without the knowledge of the correct causal and the temporal order for a specific system, extracting sequences that reveal the behavior of the system is non-trivial. Applying sequence mining would produce a large number of patterns with spurious, causally invalid sequences. Identifying the causal order of events, both sequentially and temporally is necessary to automatically prune out sequences that are spurious. We devise a novel computational method that allows us to identify the specific causal relationships and specific temporal latencies between the actions, and we use those details to provide formative feedback to the educators for them to use to help the learners.

Computational Pipeline to Extract Causally Valid Patterns

Researchers have used causal modelling to uncover the rules followed by the local entities in complex systems automatically from observed data. They are also able to assess the sensitivity and validity (Chen et al., 2012) of the extracted rules. However, crucial to this is first representing the components that constitute the dynamic interactions while also capturing the relationships between these components to make the underlying complex systems processes observable. In the case of Connected Worlds, we have a human-based complex system (formed by the group of visitors interacting among themselves) interacting with the simulated complex (natural) system. To represent the combined complex system resulting from this interaction, the behavior and/or functions of both the constituent systems need to be correctly represented. Although a virtually designed environment might have a predictable response to each individual action, the collective learners' interactions constitute a complex system whose dynamics are not completely known or predictable. Additionally, when the two systems interact it makes the effects of collective actions for these systems difficult to comprehend let alone provide useful feedback to the participant.

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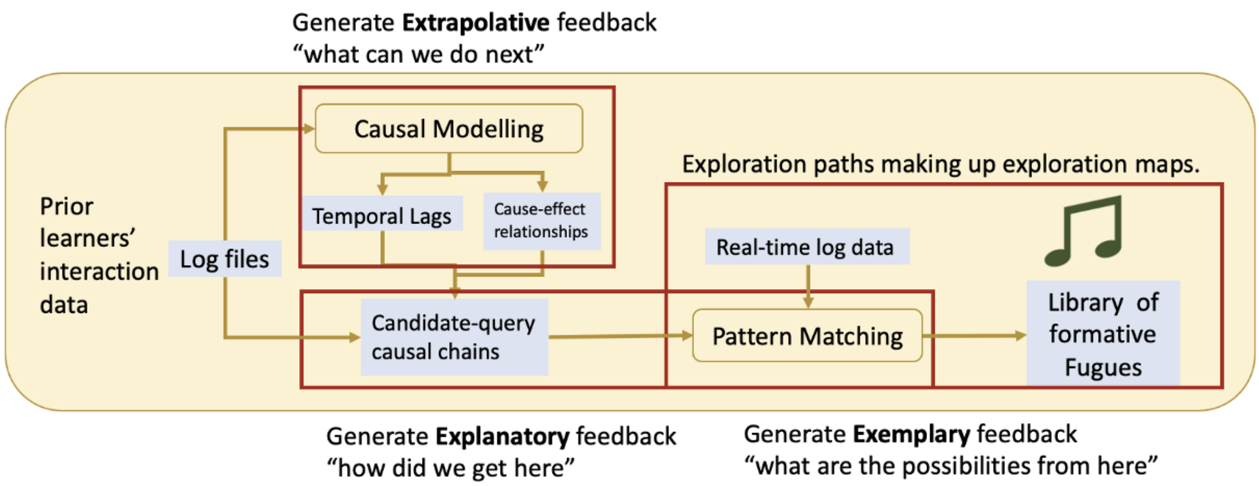

Figure 3. Novel computational pipeline for generating formative fugues with the sub-processes generating the 3Es. The processes are highlighted in the boxes with red borders and labeled outside of the figure margins. The *Extrapolative* feedback is extracted from the causal details (temporal lags and cause-effect relationships) learnt from the prior learners' interactions by the causal model. Causal chains are generated using these causal details, which are used as query sequences with the pattern matching algorithm to generate contextual *Explanatory* feedback from the real-time log data. The entire corpus of matched query sequences combines to produce a library of formative fugues, which provides *Exemplary* feedback, and contributes exploration paths for the exploration map.

To provide formative feedback that is useful, the Connected Worlds model should capture the different component relationships between the two complex systems, while also capturing relationships within the individual systems. Additionally, because there are apparent temporal delays between the time at which changes take place at the cause and the time at which its effect actually becomes apparent, we also needed to model the temporal delays between the different components. Since, in our case, we did not have the knowledge of all the semantics of the coupled system to model it effectively, we adopted an unsupervised machine learning method called causal modelling.

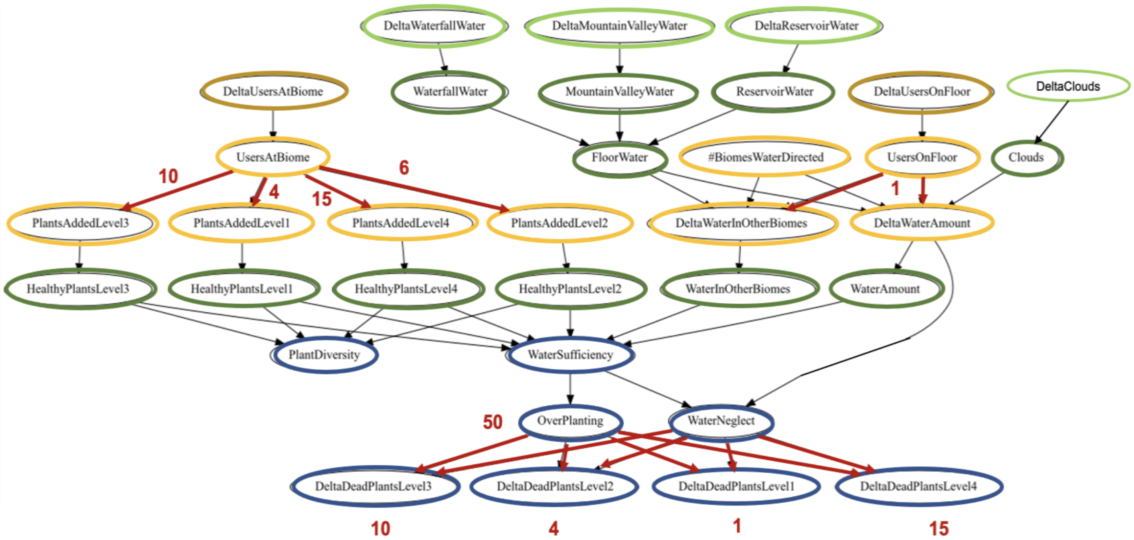

Figure 4. Connected Worlds causal model. The biome "health" metrics (blue nodes), human controlled (yellow nodes) components, system (green nodes) components. Red arrows represent nonzero time lag between the change in the cause and the occurrence of the effect.

The causal model (see Figure 4) characterizes the valid causal order and identifies the temporal lags between each causal pair, in turn revealing the complex system processes. We used that information to mine patterns that preserve causal context, we dub these patterns *causal chains*. We use a custom-tailored subsequence pattern matching algorithm to find these causal chains in the learners' interaction data. The sequences obtained from this novel computational pipeline (shown in Figure 3) with causal model followed by the pattern matching technique are included as a part of the fugue library and conform with three different functions of the reconceptualized formative feedback. In the next section, we discuss each component of this pipeline in detail and describe with examples the 3Es we were able to extract for Connected Worlds. Extrapolative feedback is extracted from the causal modelling approach. Explanatory feedback is derived from the sequences extracted after pattern matching the causal chains, indicating explanations for "how did we get here". Exemplary feedback is distilled from the complete set of mined sequences exposing the different exploration paths in the learning environment as experienced by previous learners. The 3Es of the fugues allow us to characterize the processes that are an interplay between the action-events (those triggered by learners) and system-events (events arising due to intra-system interactions). Bringing these processes to the surface allows us to tell stories of how an event evolved, how learners responded to that event, and for providing the learners choices by showing them what is possible in the space.

Modelling Connected Worlds

Causal modelling and the computational methods that go along with it can represent the complexity of the system generated by the data. An advantage of causal models is that they can capture the details of what changes could lead to what effects, without human intervention. Causal modelling is an unsupervised machine learning approach that characterizes observed data as pseudo randomized trials and quantifies the effects of one variable on the other by learning the semantics directly from the data – without an extensive labelling process (as is followed in supervised machine learning approaches). The Directed Acyclic Graph (DAG) representing a causal model, has nodes that represent variables, and edges that represent the relationships between those variables. The model supports the computational quantification of the effect of manipulation of one variable on another.

Drawing from the knowledge of how learners interact with the exhibit, how the exhibit responds and the kinds of challenges that the educators on the exhibit floor experience responding to questions from the visitors, we constructed the causal model for Connected Worlds (see Figure 4), generalized at the biome level. The model exploits the fact that each biome in Connected Worlds is designed to have analogous behavior - representing the self-similarity property of complex systems. The model includes the different systemic causes that capture how the system behaves indicated by the green nodes, *DeltaWaterfallWater*, *DeltaMoutainValleyWater*, *DeltaReservoirWater*, *DeltaFloorWater* represent the changes in the water levels at each of the sources and the nodes *WaterfallWater*, *MoutainValleyWater*, *ReservoirWater*, *FloorWater* represent the water levels in the water sources, Waterfall, Mountain Valley, Reservoir and the floor respectively; the water levels in the biomes represented by the nodes *WaterAmount* and *WaterInOther Biomes*; number of plants in the biome are represented by the *HealthyPlantLevel* nodes; the change in number of clouds in the biome are represented by the *DeltaClouds* and the number of clouds represented by Clouds. The learner actions and learner controlled causes are indicated in yellow nodes, with the changes in the number of users on floor and at the biomes represented by the *UsersOnFloor* and *UsersAtBiome* nodes respectively, the planting actions for different levels of plants is represented by *PlantsAddedLevel* nodes and water diversion decision, #BiomeWaterDiverted, indicating the number of biomes water was simultaneously diverted to, the water diversion actions represented by *DeltaWaterAmount* and *DeltaWaterInOtherBiomes* nodes indicate the amount of water diverted towards the biomes.

Table 1
Causal Model Identified Time Lags Between Crucial Cause-Effect Pairs

Cause variable	Effect variable	Identified time lag (in seconds)
UsersAtBiome	PlantsAddedLevel1	4
UsersAtBiome	PlantsAddedLevel2	6
UsersAtBiome	PlantsAddedLevel3	10
UsersAtBiome	PlantsAddedLevel4	15
UsersOnFloor	DeltaWaterInOtherBiomes	1
UsersOnFloor	DeltaWaterAmount	1
OverPlanting	DeltaDeadPlantsLevel1	50
OverPlanting	DeltaDeadPlantsLevel2	50
OverPlanting	DeltaDeadPlantsLevel3	50
OverPlanting	DeltaDeadPlantsLevel4	50
WaterNeglect	DeltaDeadPlantsLevel1	1
WaterNeglect	DeltaDeadPlantsLevel2	4
WaterNeglect	DeltaDeadPlantsLevel3	10
WaterNeglect	DeltaDeadPlantsLevel4	15

The different touch points between the two complex systems (human and natural) and within the individual system define the edges between the nodes. To qualitatively understand the effect of these human systemic interactions on the simulated ecological system, we defined a few outcome metrics that reflect the health of the system represented as a function of the various systemic and human-action nodes, indicated in blue in the model. Specifically, we have two metrics: 1. The *PlantDiversity* metric (adopted from the domain of ecology) to reflect on the diversity of the plant life in the biomes and 2. The *WaterSufficiency* metric which is indicative of the ability of the biome to support plant life. Additionally, to explain the death of plants - we defined two nodes *OverPlanting* and *WaterNeglect* reflecting the situation leading to plant death in the biome. The red arrows indicate relationships with a non-zero temporal latency (i.e., the influence on the system is not instantaneous, but becomes apparent after a certain unknown temporal lag), black arrows indicate relationships that influence the system instantly.

Identifying Causal Temporal Lags

Analytically, given a set of observations of the variables represented by the nodes and the set of all conditional independence claims as seen in a causal diagram, a causal model can be used to inform statistical tests that can quantify the effect of one variable on another. We use this quantified effect to identify the causally valid unknown temporal lags between the pairs of nodes connected by red arrows in the causal model (see Figure 4). We use the causal model to perform sensitivity analysis, by systematically varying the latency between observed cause and effect pair values and identify the time lag which yields maximum effect for the particular pair of variables. Additional details about model construction, choice for nodes and edges, effect estimation methods and time-lag identification computation methods can be found in (Mallavarapu, Lyons, Zheleva, & Uzzo, in prep.).

Table 1 shows the different cause-effect pairs and the identified temporal lag for that pair. Surprisingly, the temporal lags between the *UsersAtBiome* and the *PlantsAddedLevel* variables is clearly indicative of ecological succession programmed into the Connected Worlds "soil", where the increase in the temporal lag with the increase in the plant levels - indicates that the visitors first plant smaller grass-like plants (Level1 plants) to be able to make the "soil" fit for larger shrubs and trees (represented by Level2, Level3 and Level4 plants). Another important detail to notice is that out of the two causes for plant death in Connected Worlds, *WaterNeglect* ought to kill the plants faster than *OverPlanting*. An important semantic captured in the identified temporal lags, is that the plants in Connected Worlds "store" small amounts of water as they absorb groundwater. When the biome has been neglected of water, smaller plants - which have smaller capacities to store water are seen to perish first followed by larger shrubs and trees - which survive a little longer due to the stored water. However, when the biome experiences an overplanting situation, the lack of ground water gradually withers away all plants irrespective of their size in 50 seconds. The effect of *UsersOnFloor* on the water levels in the biomes (indicated by the nodes *DeltaWaterInOtherBiomes* and *DeltaWaterAmount*, as they adjust the logs on the floor to divert water towards one or more biomes, is almost immediate, indicated by the one- second lag.

Generating Causal Chains

The causal order of the events as represented in the model and the temporal lags as learnt from the data by the model, were used to generate event sequences that we call as causal chains. To generate an exhaustive set of causal rules of behavior defining Connected Worlds complex system, we generated causal chains of varying length to capture all possible interactions. We manually constructed 261, 2-event causal chains tallying each cause-effect pair from the causal model and the causally valid temporal lags between them for each of the four biomes in Connected Worlds. Because complex systems can exhibit nonlinear dynamics, it was necessary to consider the direction of the change in the variable (whether the value increased or decreased). We modified the definition of the event to include the direction of change generating an exhaustive set of rules as per the causal model. So, each event captured four attributes: the change direction, the name of the variable, the biome (spatial location) in which the variable value changed and the temporal lag at which its consequent event would follow (refer to figure 5).

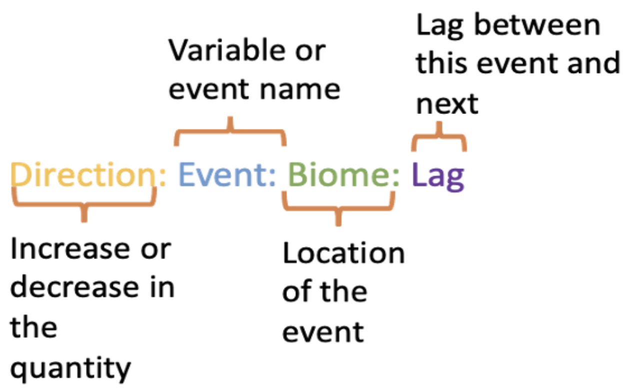

Figure 5. Multivariate definition of the event considered for causal chain generation. Direction defines whether the value of the variable increased or decreased; Event represents the name of the variable. Biome indicates the location at which the event took place and Lag represents the temporal lag at which the next causally valid event should follow.

For example, a 2-event causal chain for the variable pair *MountainValleyWater* and *FloorWater* is: A decrease in Mountain Valley water leads to an increase in floor water within zero seconds. Here, the order of the variables is captured from the causal model - where the cause variable, the *MountainValleyWater* should precede the effect variable, i.e., the *FloorWater,* and the temporal lag is zero seconds (the effect is instantaneous). Another example would be, detection of over planting in Desert is followed by the death of level 3 plants in the Desert after 50 seconds, here the temporal lag identified in Table 1 is used to construct the 2-event causal chain. Similar sequences will exist for other three biomes as well.

To automate the process of creating causal chains, we used a custom feed-forward sub-sequence algorithm (see Appendix A). The algorithm seeds the longer causal chains from the manually created list of short 2-event causal chains incrementally. For example, the 2-event causal chains would be used to generate 3-event causal chains, which are then used to generate 4-event causal chains, and so on. For example, for the set of 2-event causal chains: {a,b} and {b,c}, the 3-event causal chain formed from these constituent sequences: {a,b,c} strictly follows the causal model as three nodes chained in that order. Figure 6 shows the examples of causal connections between three hypothetical nodes a, b, and c. This sub-sequence generator only allows causally valid sequences to propagate into longer event sequences, while pruning out other non-causal event sequences.

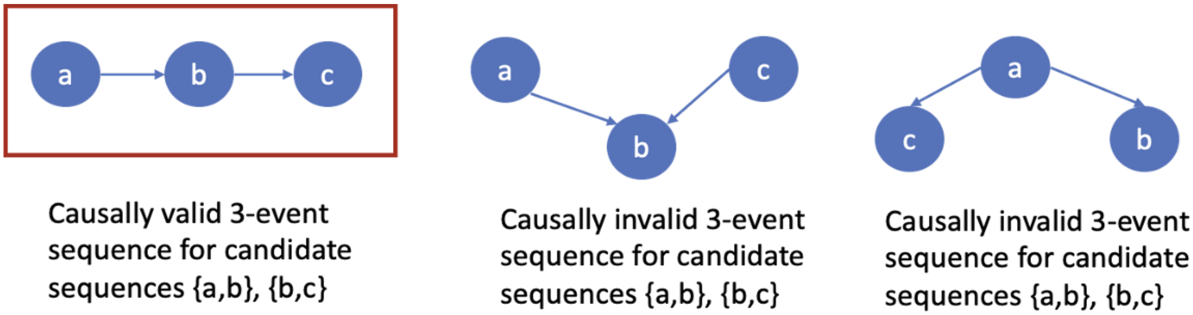

Figure 6. Selection of causally valid chains during the feed-forward sub-sequence generation. This process generates only causally valid chains. {a, b, c} represents three events, where a connects to b and precedes b, and b connects to c and precedes c. For the 2-event causal chains {a,b} and {b,c} the only valid 3-event causal chain is {a,b,c} which follows the causal model: a is connected to b and precedes b, and b is connected to c and precedes c.

The algorithm stops when shorter chains cannot be causally combined further. Figure 7 shows an example of 3-event and 4-event Connected Worlds causal chain generation from the seed of three 2-event causal chains, considering the multi-variate description of the events. This exhaustive set of causal chains represents the query set for the next process in the computational pipeline: the pattern matching algorithm.

Pattern Matching Causal Chains

Computationally, pattern matching is the problem of identifying a pattern of sequence from the database of large numbers of sequences that match the query sequence. It has been traditionally used for retrieving information of interest from large repositories, in applications like keyword-based search in handwritten and digital documents, DNA and protein matching, etc. (Papapetrou et al., 2011). Pattern matching becomes computationally expensive when 1. The number of sequences that can be formed using different event combinations is exceptionally large (the search space) and 2. The number of sequences to be searched is large (the query space). In our case, the search space was limited by generating it in real-time, using the real-time log data. The data being collected from the learners' interactions (representing the changes in state of the system), is converted to represent events (in real-time), where an event is a non-zero change in the value of the variable. The Method section above has more details. These events are used to construct causal chains, which we call samples. Like the causal chains that represent the query space, these are also generated by the feed-forward generation technique and follow the causal model. The pattern matching algorithm then performs a look-up of each query causal chain in the set of sample causal chains to select the ones that were found. This process is done in a recursive fashion, such that for comparing the longer causal chains the filtered sample set should contain all the shorter components of the longer causal chain. This allows us to limit both the query space and the search space further by only looking for causal chains that match the current context.

2-event candidate-query sequences:
Increase: Users: Wetlands (4) → Increase: Plant Level 4: Wetlands
Increase: Plant Level 4: Wetlands (0) → Increase: Water Neglect: Wetlands
Increase: Water Neglect: Wetlands (0) → Increase: Plant death Level 2: Wetlands

3-event candidate-query sequences:
Increase: Users: Wetlands (4) → Increase: Plant Level 4: Wetlands (0) → Increase: Water Neglect: Wetlands
Increase: Plant Level 4: Wetlands (0) → Increase: Water Neglect: Wetlands (0) → Increase: Plant death Level 2: Wetlands

4-event candidate-query sequences:
Increase: Users: Wetlands (4) → Increase: Plant Level 4: Wetlands (0) → Increase: Water Neglect: Wetlands (0) → Increase: Plant death Level 2: Wetlands

Figure 7. The feed-forward sub-sequence generation process. Seeding from three 2-event causal chains for the Wetlands biomes, the algorithm forms two 3-event causal chains and one 4-event causal chains. Each event is defined with four attributes: the change direction, the name of the variable, the biome (spatial location) in which the variable value changed and the temporal lag at which its consequent event would follow. The longer the causal chain, the more detailed it is. The algorithm stops at 4-event causal chains, as there is no other 4-event causal chain to extend it to a 5-event causal chain.

RESULTS

To understand the kinds of causal chains and formative feedback that this method yields for Connected Worlds, we performed the pattern matching on the entire corpus of 67 files of prior learners' interaction data (see section 5 for more details on the data). Considering the 26 nodes represented in the causal model with respect to each biome in Connected Worlds, we recognized 10037 total causal chains (the query space) that range from 2-events to 8-events in length. These were matched to the causal chains in the data (see Table 2). Most of the short causal chains were found in the data while the longer causal chains were rare.

Figure 8 shows the distribution of the match counts of causal chains across the biomes. The fugues have similar distributions across the biomes, with Desert having the most fugues, followed by Wetlands, Jungle and Plains (without any significant differences). This distribution of fugues echoes how visitors interact with Connected Worlds, e.g., the Desert

Table 2
Descriptive Fugue Counts per Sequence Length: The query space is the total number of possible fugues, and sample space is the number of fugues detected in the data corpus.

Sequence length	# possible fugues (query space)	# causal chains matched (sample space)
2-event	261	257
3-event	400	387
4-event	672	558
5-event	1344	1052
6-event	1984	1459
7-event	3072	1608
8-event	2304	11
Total	10037	5332

and Wetlands permit the richest engagement because their spatial arrangement allows visitors to easily divert water. We next discuss the examples of 3E formative fugues that were extracted from the computational pipeline, drilling deeper into the nature of the information the fugues could deliver as formative feedback.

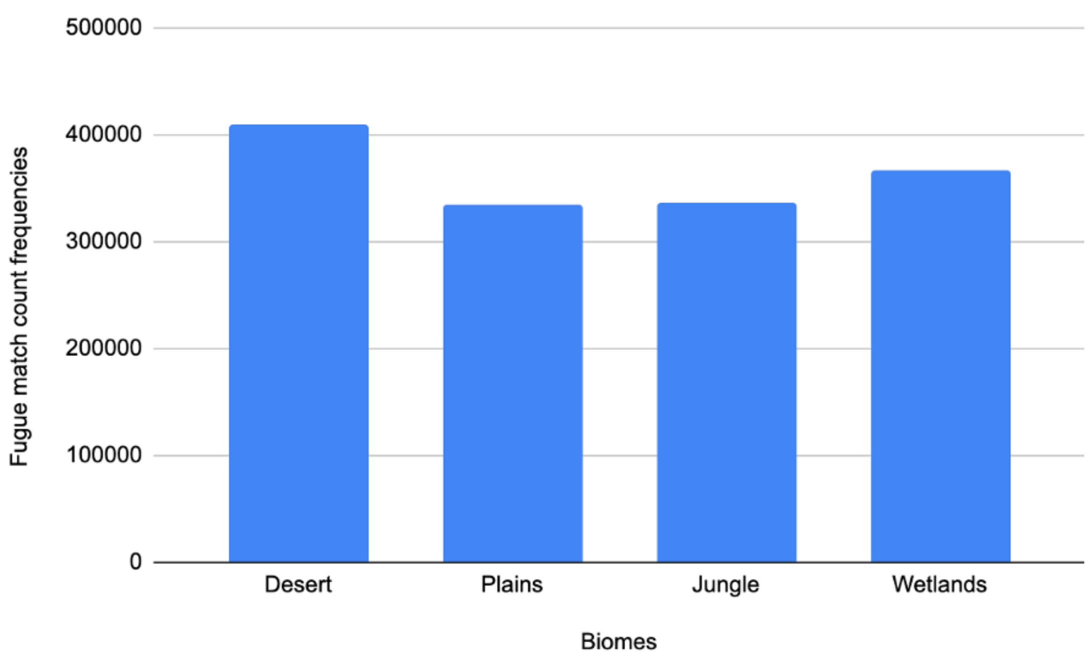

Figure 8. Distribution of the match frequencies of the causal chains across the biomes.

Extracted Fugues

Moving away from traditional directive and facilitative feedback (Black & Wiliam, 1998), common in the closed-ended and simple learning environments that use learner-centric methods, we conceptualized the 3Es of COpELE formative fugues: *extrapolative*, *exploratory* and *exemplary* feedback.

1. *Extrapolative* feedback supports the multiple actions dimension of open-ended learning and elicits the "contextualizing function" that can help the learners make a knowledgeable choice about their next actions. The contextualizing function is provided in the form of exposing the nuances between the various causes and their corresponding effects. This function of the feedback is mostly extracted from the semantics learnt by the causal model.
2. *Explanatory* feedback supports the multiple strategies dimension and often reflects back in exposing the causal chain that can help answer "how did we get here?" This function of feedback is extracted post-pattern matching in the computational pipeline.
3. *Exemplary* feedback supports the multiple goals dimension of the open-ended learning and exposes the possibilities in the space showing the different complex systems phenomena that the learners can expose. The different causal chains in the fugue library provide the exemplary candidates.

In this section we provide one example for each type of formative fugue for the Connected Worlds exhibit data.

Extrapolative Formative Feedback

We used the causal model to "extrapolate" the possibilities of what *can* happen given the situation. This gives the learners an opportunity to make informed decisions about their explorations. What we call *extrapolative* feedback is similar in some aspects to a hint or a recommendation that is provided to the learner in "simple" learning environments (e.g., intelligent tutoring systems), but also differs from them as it does not give learners a "closed" option of what they have to do next, instead it makes them aware of the range of possibilities of what could happen.

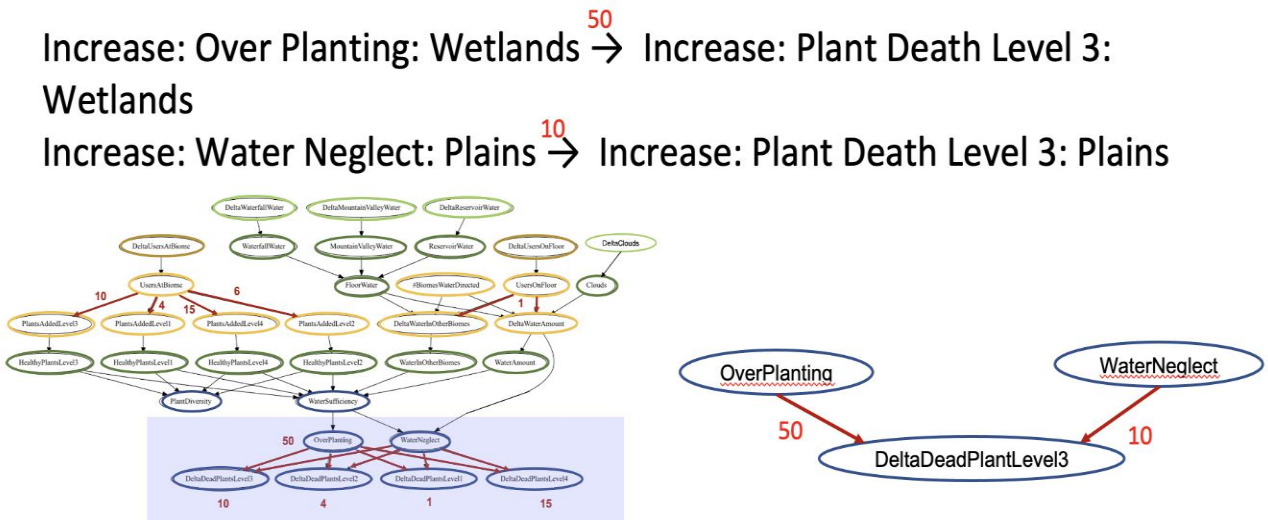

Figure 9. Example of *Extrapolative* formative fugues (top), showing over planting situation in Wetlands resulting in level 3 plant death in 50 seconds, and water neglect situation in Plains resulting in level 3 plant death in 10 seconds. (The numbers shown above the arrows indicate temporal lag in seconds). These fugues are drawn from the shaded region of the causal model (bottom left). The partial causal tree (bottom right) shows the causal events in the fugues.

An important component of the design of formative feedback is the timing of its delivery (Shute, 2008). This is especially true when learners are interacting in an immersive learning environment, where they may only have a certain amount of time to act before events transpire. The time lag between causes and effects is an important piece of information and the causal model allows us to extrapolate this information. For example, one important question that emerges is how long plants can survive in biomes without tending. Plants in a biome can die due to two causes: 1. Because they haven't been watered recently (represented in the model as *WaterNeglect* node) or 2. The visitors planted more plants than the biome's groundwater can support (represented as *Overplanting* node in the causal model). Both of these actions take place sometime before plant death (see Figure 9). Figure 9 shows two fugues that matched the learners experience with the exhibit, one with *OverPlanting* leading to plant death after 50 seconds and other with *WaterNeglect* leading to plant death in 10 seconds after the event. We can use the information in real time when neglect or over planting begins, to notify visitors that they have a 10-second window or a 50-second window respectively, in which to act to prevent level 3 plant deaths in the respective biomes. The extrapolative formative feedback can thus provide the learners a triage list that can help them prioritize and plan their actions and decisions in the exhibit.

Explanatory Formative Feedback

We used the feed-forward sub-sequence generation and the pattern matching algorithms discussed above to mine the *Explanatory* fugues. The fugues identify the specific causal chains that lead to the particular state of interest, explaining the evolution of a phenomenon that they have experienced. Each causal chain of interest represents a very short episode, explaining the evolution and interactions between various components of the complex system that led to the current state. Learners in Connected Worlds often express confusion about "what was really going on" in the simulation and often comment - "I was doing well with plants and then suddenly all my plants died, I don't know why!". The explanatory feedback is able to address such questions by revealing causal chains that match the learners' concerns. The explanatory feedback presents the longest available causal chain from the data. For example, one of the causal chains that was most frequent in the prior learners' data is shown in Figure 10.

Figure 10. *Explanatory* formative fugue example (left), showing a causal chain starting with users at the Wetlands planting large trees which pushes the Wetlands into a state of water neglect leading to death of smaller plants in Wetlands. The partial causal tree shows the variables contributing to the fugue color coded to match the fugue sample (right). The lags are annotated in red by the arrows. Some zero lag nodes have been omitted from the fugue for clarity indicated by a dotted arrow in the partial tree.

Figure 10 shows the number of users at the Wetlands, who then plant large trees at the Wetlands. The planting pushes the Wetlands in a water neglect condition, ultimately leading to the death of the smaller plants in Wetlands. Such explanatory feedback can be used in reflection to highlight the complex systems dynamics at play (e.g., in this case small actions large effects, where the action of planting leads to the death of plants already planted in the biome).

Exemplary Formative Feedback

The set of matched causal chains extracted from the computational process contributes to building exploration maps that can be used by the educators as examples and to understand visitors' exploration patterns. Each exploration path exemplifies the multiplicity of the possibilities in the complex system. For example, learners often question if they *can* divert water to more than one biome at a time and what its influence will be on the biome's or other biome's health. Consider the two candidate fugues, F1 and F2 shown in Figure 11.

F1:
Decrease: Water: Floor $\xrightarrow{1}$ Water Diverted to two biomes (Desert and Wetlands) $\xrightarrow{0}$ Increase: Water: Desert $\xrightarrow{0}$ Increase: Water Shortage: Wetlands $\xrightarrow{0}$ Increase: Water Neglect: Wetlands $\xrightarrow{4}$ Increase: Plant Death Level2: Wetlands

F2:
Increase: Users: Floor $\xrightarrow{1}$ Water Diverted to one biome (Plains) $\xrightarrow{0}$ Increase: Water: Plains $\xrightarrow{0}$ Increase: Water Shortage : Jungle $\xrightarrow{0}$ Increase: Over Planting: Jungle $\xrightarrow{50}$ Increase: Plant Death Level1: Jungle

Figure 11. *Exemplary* formative fugue examples F1 and F2. The fugue sequences start with different events (decrease of water levels on the floor and increase in the number of users on the floor), followed by water diversion events ultimately leading to death of plants in some other biome.

F1, shows a fugue that is an attempt to share water between the desert and the Wetlands, because they were dealing with scarcity in the Wetlands, which intensified into a neglect situation. The shared water did not reach the Wetlands fast enough to save the plants. On the other hand, F2 shows how diverting water selfishly to the Plains killed the plants in the Jungle. In this case they ignored the water scarcity in the Jungle and diverted their water resources to the Plains, so the situation that could have been salvaged was ignored. Although both examples lead to death of plants, they show two different decisions can lead to similar outcomes indicating the non-linear dynamics at play in the complex system. The exemplary feedback could therefore be useful in surfacing the different strategies that are being used in a particular context (plant death for F1 and F2 in the above example). We can use such examples to provide pointers for educators to engage the learners in a discussion about their intentions and their consequences as reflected from these fugues.

DISCUSSION

This work distinguishes three kinds of formative feedback for COpELE, (*extrapolative* feedback, *explanatory* feedback and *exemplary* feedback which highlights the big picture for the learners - showing the learners the scope of possibilities within the learning environment and allowing them to make their own choices about what to do next in the learning process. We envision a formative fugues library built with this method that grows as learners interact with the learning environment, documenting and exposing larger "exploration maps", augmenting it with their own exploration paths together with alternative exploration paths for a particular "context". For each component of the fugue, the causal semantics and the exploration paths used to build exploration maps. They are extracted from the various methods in the computational data driven pipeline. Since the emphasis of the formative fugues, and the library constructed from this method is on the problem space rather than an individual learner's cognition, this method readily supports collaborative problem solving. Overcoming the issues that made traditional formative feedback and the computational methods used to extract them unsuitable for COpELE, the 3Es of formative fugues embrace exploration-based learning inherent in COpELE. The generalizability of this approach lies in its suitability for both complex open-ended experiences such as Connected Worlds, as well as traditional "simple," open-ended learning environments, providing formative feedback to learners across a range of learning settings.

The computational method devised to support the reconceptualized formative feedback provides three advantages. Because it bootstraps on the explorations of prior learners, it has the ability to expose the crucial decision points and the complex systems dynamics that arise due to the different decisions. moreover, the extraction process makes the fugue library easily extendable, adding previously missing exploration paths as they become evident in learners' interactions. Most importantly, it exposes the learners to the possibilities in the space without levying any presumptions about their goals.

These advantages bring to the surface new possibilities for formative feedback and teaching methods for complex systems, such as: 1. A view into how exploration based learning takes place, useful for educational researchers for understanding learning processes; 2. Revealing activity patterns for designers to improve the design of the learning environments; 3. Provide guidance for intervention by humans-in-the-loop (e.g., educators); 4. Use the fugue library to design context-specific (for learners directly) feedback; and 5. As a foundation for designing adaptive learning environments for complex problems, where the problems can change difficulty level by tracking the kinds of complex systems phenomena the learners have explored.

LIMITATIONS

Currently, the causal model constructed for Connected Worlds considers limited cross-biome interactions (the *DeltaWaterInOtherBiome* node), by modelling the causality as a function of the subsystem or local level processes. The current model is unable to bring other important complex systems properties to the surface, like emergence, which could explain how the cumulative and distributed changes at spatially distant local levels influence the behaviors at the global level. Modelling global effects requires a major effort to resituate causality as the function of the processes across the individual biomes and devising new health metrics that indicate effects at both local and global scales. Such a new model would need to consider the heterogeneity among the biomes, (e.g. the biomes could differ in the attention or the extent and types of interactions from the visitor groups due to the visual effects or the physical location of the biome), which might have an impact on the dynamics of the global system health. Since the current goal of feedback is to motivate the learners to "act" or "understand the effects of their actions," the causal model was scoped at the local-subsystem level, which is internally homogenous.

Technically, as the causal model becomes more complex, the fugue library will expand, and pragmatic issues in searching and time of the search will need to be resolved to make it efficient and effective for feedback. For example, when using the fugue library to provide real-time feedback, the running time constraints for processing the data (e.g., constructing samples and matching it with query fugues of interest) may make effectiveness rather than efficiency of the feedback a priority. Another important consideration is detecting and referencing the most commonly occurring "fugue" from the learners' interactions, which might potentially indicate confusion or misunderstanding, so helping the learners diversify "fugues" by annotating the fugues with more high-level complex systems properties while preventing recursion problem must take precedence. Maintaining an effective balance to resolve these limitations would be a major part of design tools for formative fugue delivery systems. Additionally, the current model prevents us from studying complex system properties like nonlinear state dynamics, which involve studying and understanding state evolution trajectories of a single variable through a series of different stable and unstable states due to external variables.

FUTURE WORK

The conceptualization of formative fugues and the innovation of the methods that are compatible with it are at its very inception, in this work we highlighted a novel computational method that is able to bring the reconceptualized formative fugue functions (the 3Es) to the surface. The next step is to fully validate the formative fugues with respect to the learning environment and identify the complex systems properties that are missing and those that are evidently present in these fugues. The evaluation would include looking into the nature of the missing properties and correlating the ability of the computational methods to capture them. Once we enlist the properties that can be readily captured by the method, we need to identify the hurdles for learners in adopting/enacting them during their interactions, which could be due to system capabilities or pragmatic difficulties (e.g., very short response times).

Further, in thinking about usage of the formative fugues, consideration of the presentation medium (e.g., mobile tablets), representation forms of the fugues (e.g., textual, visual, through notifications, etc.) and interpretability of the representation within the pragmatic constraints of its use are needed. To this effect, we are in the process of incorporating the insights we gained via formative fugues into a data-driven mobile tablet tool that is being used by educators on the exhibit floor, similar to (Mallavarapu et al., 2019). We are in the midst of building a "Human-in-the-Loop" socio-technical system that can allow educators to help visitors engage with the exhibit in real time, providing formative guidance at critical, "just-in-time" moments through these extracted fugues. Future work will examine if these educator interventions distilled from formative fugues shift learner engagement with the complex system in more productive directions, and what lessons visitors learn about the system as a consequence.

CONCLUSIONS

Complex open-ended interactive simulations permit educators to create ever more engaging learning environments, and to showcase learning problems and scientific phenomena that are not well-suited for traditional media like textbooks (Barab & Dede, 2007). A number of classroom-based simulated learning environments have proliferated out-of-pace with our ability to effectively support learners as they engage with and learn from these simulations. (Grotzer & Solis, 2015; Wilensky, 1999), web-based (Amplify, 2000; Concord Consortium, 2020; Azevedo et al., 2004), and museum-based (Ma et al., 2015; Lyons et al., 2015; Mallavarapu et al., 2019; D'Angelo et al., 2015). Data-driven computational approaches offer potential for scaffolding the learning that takes place within these learning environments, but this promise can be realized only if the analytic techniques chosen suit the problem domain and the explorative learning goals that these environments afford. Methods that look past the "solutions" to the "processes" enmeshed with learning are needed for providing feedback. The vision for these methods is to support the learners with insights and opportunities to contemplate the implications of their decisions and understand the complex processes leading to the consequences through a *Socratic* method (Lynch et al.,2010) of providing feedback to enable explorations. Complex-system problems have an emergent and dynamic nature, where the learners' actions co-constitute the situations and the future actions. The need to surface these semantics makes using traditional educational data mining techniques challenging to glean insights for formative feedback intended to improve learner engagement with the system.

The "fugue"-based approach to characterizing formative feedback for complex systems learning offers the following potentials: 1. Through the extrapolative, explanatory and exemplary functions of formative feedback, the formative fugues library encourages the learners to explore. By providing actionable insights the extrapolative feedback engages the learners to engage in "informed inquiry". The exemplary feedback contextualizes the learners to see "how else did people get themselves into this state?" and "where else can we go from here?" without constraining their choices or making assumptions about their goals; The explanatory feedback can help learners build a robust understanding of the complex systems processes by connecting the abstract simulation patterns (observed in the "fugues") with their real-world learning experiences, learners can create the strong mental models needed to comprehend complex systems (Grotzer & Solis, 2015); 2. Fugues support research into the process of open-ended learning, as they expose learning trajectories (mapping the breadth and depth of explorations) to allow educators and researchers to characterize and track learners' understandings and explorations; and 3. The fugues could be used as conceptual seeds provided to the educator (human-in-the-loop), so that they can help learners better engage with complex systems beliefs.

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Appendix A

The Feed-forward Causal Chain Generation Algorithm

Given:

CQ = Empty set of causal chains

L = Set of manually constructed 2-event causal chain

n= 2

Function Feed-forward (n, L):

1. L = Set of constructed n-event causal chain (n ¿=2)
2. M = Empty set of (n+1)-event causal chain
3. For every pair (S1, S2) of n-event causal chains in L

   // For e.g. for 2-event causal chains S1 and S2

   // // S1: candidate-query with events a,b

   // S2: candidate-query with events b,c

   (a) If S1- first event is equal to S2 - last event:

      i. Construct S' which is a (n+1)-event sequence by appending last event of S2 to S1 ii. Add S' to the set to M
4. L = M
5. Append L to CQ
6. If L = null: Return CQ
7. else: Call Feed-Forward (n+1, L)

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