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Data Collection in Open Ended Learning Environment for Learning Analytics

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Abstract: As the development and use of Open-Ended Learning Environments (OELEs) continues to increase, supporting students' learning in these environments with Intelligent Tutoring is rapidly becoming an important area of research. Many existing learning environments guide students in step-by-step processes to reach their learning goal; consequently, data preprocessing is well defined. In OELEs, in contrast, students may achieve task goals through multiple pathways, and there exist multiple ways to assess performance. We present a simulation OELE designed to teach students decision-making in a complex problem solving task. To provide Intelligent Tutoring Support, we are required to track performance along several dimensions. We present our approach to extract data for performance assessments that can be leveraged to provide Intelligent Tutoring Support. We generalize our approach and present guidelines applicable for similar OELEs.

Keywords: Learning Analytics, Open Ended Learning Environment, Data Processing, Data collection.

1. Introduction

Adaptive learning environments or Intelligent Tutoring Systems (ITS) tune learning content to learners' needs and preferences, which are identified from their interactions with the system recorded in log files. To help learners to achieve their learning goals, data from log files are analyzed, for the purpose of modeling the learner and provide support targeted as specific student needs..

Most adaptive learning system help students by supporting their problem solving step-by-step. Such forms of scaffolding are possible in domain with well-defined learning goals geometry or addition. Examples of popular adaptive learning systems are Cognitive Tutor[1], or Wayang outpost[2]. Recent work, however, has begun to develop adaptive learning systems to support learners through metacognitive tutoring in complex problem solving, learning processes that many education researchers consider an essential element for education (ISTE 2007; UKEd 2013). Metacognitive skills are critical processes involving the structuring of the solution process, searching for information, interpreting it, exploring alternate solution paths, and constructing and testing potential solutions (Brophy 2013 & Winne 2010). A recent development in supporting learning of metacognitive skills are open-ended learning environments (OELE) (e.g. Biswas et al. 2016). In general, OELEs provide students with a complex problem to solve, and with tools and resources that support the problem-solving task (Jonassen et al. 2002). Examples of OELE are MetaTutor (Azevedo et al., 2012), Betty's Brain (Leelawong and Biswas, 2008), and Crystal Island (Jonathan et al., 2011). OELEs are distinct from adaptive learning systems in that students benefit in terms of the development of metacognitive skills that go beyond the acquisition of domain-specific cognitive skills (Hannafin et al., 1994).

[1] http://www.carnegielearning.com/learning-solutions/software/cognitive-tutor/
[2] http://wayangoutpost.com/

Developing automated support for learning metacognitive skills represents a novel challenge to developers of adaptive learning systems. In many adaptive learning systems the task goals and the paths through which the goals can be achieved are well defined. In OELEs, in contrast, students can achieve task goals through multiple pathways. Students may, for example, chose paths that involve sacrificing short-term advantages for long-term benefits. Hence, the students' interaction generates huge log data compared to traditional adaptive learning systems, and opens the question of which data to extract from log records to be used directly as performance measures, or as the basis for making inferences on performance.

In this paper we present the approach we developed to track performance in an OELE called *UrbanSim*, a turn-based simulation environment, where a counterinsurgency scenario evolves in an urban environment. In *UrbanSim,* students make moves to achieve the goals of the mission that is primarily defined with regard as reducing insurgent activities and creating a viable economic, social, and political environment for the local population. At each turn, students select a set of operations to conduct in different regions of the operating theater, and then observe and analyze their effects. *UrbanSim* simulates a complex social and political environment where operations can have multiple short-and long-term effects. Effective problem solving in this complex domain requires several skills, such as conducting operations in line with prescribed generic strategies, matching operations to the conditions of individual regions, selecting operations in line with general operational guidelines, and advancing the key goal of counterinsurgency operations: to gain the support of the local population. We take on the challenge of tracking student performance by analyzing the actions students take in the environment and the effects generated by these actions. We follow the sequence of turns that students make, compare how they adjust their turns to analyze the situations that occur as the game progresses, and how well they align their actions to achieve pre-defined goals.

UrbanSim includes logging processes that create records of the players' action as well as almost all of the data generated in the simulation, i.e., the game state. Our work evolved as our understanding of the simulation and the domain improved. With this understanding we were able to develop performance indicators that allow us to assess students. A critical task of this evolving work was to identify those log data that are the basis for automated performance assessment. This paper describes in detail the process through which the understanding of a domain and of a simulation can be the basis to select records of student activities in OELEs for performance assessment.

2. Approach

Tracking performance in UrbanSim is a non-trivial task because the key goal of counterinsurgency – to increase the percentage of the population supporting a legitimate government – can be achieved along several paths and requires several competencies. As in many other instances of complex problem solving, UrbanSim requires competencies that in their own right are insufficient to advance towards the goal state, but need to be combined to achieve an overall goal. Key to our approach is to specify several sub-components of what is meant by performance in *UrbanSim*. Students may excel in one skill but may show sub-optimal performance in another; thus, by defining performance along several dimensions, a basis to provide targeted support for students' learning is available.

Specifying sub-components of performance tells us which data to extract from log records, as well as how to pre-process log data so that inferences can be made. Some measures require the aggregation of log data, while others function as the basis for inferences toward more general performance measures. We exemplify our approach now by describing in detail how performance is measured in counterinsurgency/UrbanSim.

3. Counterinsurgency and the UrbanSim Open-Ended Learning Environment

Counterinsurgency is the comprehensive civilian and military effort designed to simultaneously defeat and contain insurgencies and addresses their root causes. Legitimacy – fostering effective governance by a legitimate government – is its main objective. Counterinsurgency operations, therefore, aim to defeat insurgents while also working with local political and religious leaders to increase population support, separate (to protect) the population from insurgents, and ultimately install Host Nation (HN) governance that promotes self-sufficiency and economic growth.

In *UrbanSim* (McAlinden et al., 2008), shown in the Figure 1, users assume command of a counterinsurgency operation in a fictional Middle-Eastern country. Users have access to information about the area of operation, including intelligence reports on individuals and groups; variables representing the operational environment; indicators of how well they are doing in relation to the Superior's commands (Lines of Effort); and the Population Support meter. When students select counterinsurgency operations to conduct, they must take into consideration the following constraints: the state of the urban area, the values of the Lines of Effort (i.e. how well they are progressing with respect to the Superiors' directives), the state of the operational environments in individual regions where the operations are conducted (PMESII) and the values of the Population Support meter.

Further, students need to follow a counterinsurgency approach called **C**lear, **H**old, **B**uild (CHB). CHB is a broad strategy with three distinct phases. First, military forces *clear* an area of insurgents. Second, they focus on *holding* the cleared area and preventing further insurgent infiltration. Third, they focus on building up the area's government, police forces, and infrastructure such that the local population is able to safeguard the area independently, develop local governance, and focus on economic improvement.

Students conduct their operations by assigning operations as Operation Orders to available units in the Synch Matrix (the Figure 1, lower left). Once committed, the simulation executes the orders and models its effect on and the key values. During this phase, *additional* events caused by other agents (e.g., the insurgents, the local population) can occur (e.g., the detonation of an IED) that are displayed at the beginning of a new turn. The combination of all activities may result in net changes to the local population support and LOE scores.

At each turn, students are informed about the effect of operations committed in the previous turn. Operations typically affect LOE, PMESII and Population Support values, both of which can be inspected on the map or by activating information pages.

Figure 2. *UrbanSim*: city map; Synch Matrix (lower left), LOE values (lower right); SITREPs, SIGACTs (left border), Intel Officers S2, S3 (right border)

4. Tracking Performance in UrbanSim

To track performance and make inferences on students' strategies, we distinguish between 1) performance values (e.g. scores on the Lines of Effort, the percentages of Population Support) and game state variables (e.g. number of turns completed), which we leverage to infer 2) more general structures directing behavior. These structures represent domain-specific strategies, such as implementations of aspects of the Clear-Hold-Build doctrine.

An example of an instantiation of a strategy is detecting whether students conduct operations in line with the CHB strategy: by analyzing values of all regions over a few turns, we obtain the number of regions in the Clear, Hold or Build phase, thus measuring students' ability to conduct operations aligned with CHB: if the CHB strategy is conducted appropriately, the number of regions in the Clear phase will decrease, while the number of regions in the Hold and Build phase will increase When CHB is detected as a strategy, inferences on students' analysis and interpretation of region values can be made.

At each turn, we leverage log data to detect students' performance and strategies by computing the values of the metrics presented now.

<u>CHB Count:</u> Once students have obtained and analyzed information, they are expected to conduct operations in line with the CHB strategy. PMESII analyses, and especially the M value (representing the degree of military control over a region), play a particularly important role in executing the strategy. We detect whether students' follow the CHB strategy by counting the number of regions in the Clear, Hold or Build phase at each turn.

<u>Lines of Effort:</u> the trend of the LOEs at each turn is tracked to obtain a measure of students' adherence to the Superior's command.

<u>Population Support:</u> Population Support is logged as *for*, *against*, and *neutral* percentages, adding up to 100%. It is the key measure to assess student performance. *UrbanSim* scores performance at the end of the game with the formula: (*For* * 2) + *Neutral* – *Against*.

<u>PMESII Match:</u> the measure represents students' ability to select the most effective operations, given the PMESII values of a region. The measure is the sum of Match values for all operations in a turn. Match of an individual operation is calculated by summing its effect on 3 PMESII values (Military, Information, and Social) and identifying the most effective operation. Match is the difference between the sum of effects of the conducted operation, and the sum of effects of the most effective operation. The calculation of the effect is weighted by the magnitude of PMESII values.

<u>Mission Goals:</u> The Mission Description of the scenario explicitly requires the achievement of three specific mission goals: 1) increase the support of the town's Mayor; 2) prevent the influx of insurgents from the Mountains in the North, hence secure the Northern area and 3) repair the airport to facilitate the movement of personnel and goods. The measure is the sum of the number of operations at each turn conducted to further the specific mission goals.

5. Discussion and Conclusion

In this paper, we have described the development of performance measures in a complex simulation environment. Our approach consists in developing detailed definitions of what is meant by performance in solving a complex problem. This necessarily to develop an understanding of the domain and the multiple ways in which problems in the domain may be solved. Defining performance and identifying approaches to solving the problem gives directions in identifying which log data to analyze. We have shown examples of performance measures that 1) require the aggregation of log data (e.g. 'PMESII Match'), or 2) require including general game state data (e.g. number of turns completed) or 3) can be computed with reference to specified problem solving goals ('Mission Goals'). We believe that our approach is generalizable to other environments where students learn by solving complex problem; and that the approach will be a useful basis for other researchers to guide the analysis of log data in OELEs.

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