Modeling Narrative-Centered Tutorial Decision Making in Guided Discovery Learning

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Abstract. Interactive narrative-centered learning environments offer significant potential for scaffolding guided discovery learning in rich virtual storyworlds while creating engaging and pedagogically effective experiences. Within these environments students actively participate in problem-solving activities. A significant challenge posed by narrative-centered learning environments is devising accurate models of narrative-centered tutorial decision making to craft customized story-based learning experiences for students. A promising approach is developing empirically driven models of narrative-centered tutorial decision-making. In this work, a dynamic Bayesian network has been designed to make narrative-centered tutorial decisions. The network parameters were learned from a corpus collected in a Wizard-of-Oz study in which narrative and tutorial planning activities were performed by humans. The performance of the resulting model was evaluated with respect to predictive accuracy and yields encouraging results.

Keywords: Narrative-centered learning environments, Game-based learning environments, Guided discovery learning, Dynamic Bayesian Networks.

1 Introduction

Recent years have seen significant growth in research on interactive narrative-centered learning environments for creating story-based learning experiences that are both engaging and pedagogically effective [1, 2]. These environments encourage students to learn by actively participating in story-based problem-solving activities. Narrative-centered learning environments can form the basis for discovery learning [3] that supports students' active exploration of a subject matter. Discovery learning encourages students to learn by trial-and-error. Utilizing the scientific method, students pose questions, design and perform experiments, collect data, and evaluate hypotheses [4]. Despite the potential benefit of discovery learning, studies have indicated that it can be ineffective when students receive no guidance in the form of coaching and hints from a teacher or learning environment [5]. These studies suggest that discovery learning that is accompanied by guidance can be more effective than pure discovery learning [4, 6].

Narrative-centered learning environments actively monitor students interacting with the unfolding storyworld to make decisions regarding the next action to perform in service of guiding students' learning experiences. Through this process, the system attempts to make effective narrative-centered tutorial decisions while managing the story structure and scaffolding student interaction. A key challenge for these environments is devising accurate models of narrative-centered tutorial decision-making, i.e., determining the next narrative-centered tutoring action to perform.

A promising approach to building effective interactive narrative-centered environments is devising empirically informed models of narrative-centered tutorial decision making. By utilizing a corpus of human interactions within a narrative environment, models of tutorial decision-making can be learned from data.

This paper presents a dynamic Bayesian network (DBN) approach to modeling narrative-centered tutorial decision-making. The approach supports learning models from a corpus and integrating different sources of evidence affecting decisions. A corpus collection study was conducted using a Wizard-of-Oz methodology with students interacting with a customized version of the CRYSTAL ISLAND interactive narrative-centered learning environment [2] in which wizards provide the narrative planning, tutorial planning, and natural language dialogue functionalities of the system. Students exhibited positive learning outcomes while interacting with the learning environment. Analyses of the DBN models learned from the corpus reveal that empirically informed dynamic Bayesian networks offer a promising approach for narrative-centered tutorial decision making. To our knowledge, this is the first model of narrative-centered tutorial decision making that has been learned from a corpus of human-human tutorial interactions.

2 Background

Narrative-centered learning environments provide students with the ability to actively participate in problem-solving activities by leveraging narrative to create engaging experiences in rich virtual interactive storyworlds. A broad range of techniques has been proposed to create interactive story-based learning environments that are both engaging and pedagogically effective. TEATRIX is designed to help students in the process of collaborative fairy-tale-based story creation [7]. Carmen's Bright IDEAS implements an agent-based interactive pedagogical drama. It is an interactive health intervention system designed to teach social problem-solving skills to mothers of pediatric cancer patients [8]. FEARNOT! is a storytelling application for social education against bullying [9]. By suggesting coping behaviors for virtual agents involved in bullying incidents, students develop empathetic relationships with the agents. STABILITY and SUPPORT OPERATIONS is a multi-agent system that features socially intelligent virtual humans to assist trainees for developing leadership and negotiation skills [10]. The TACTICAL LANGUAGE AND CULTURE TRAINING SYSTEM is designed to help students learning knowledge of foreign language and culture [1]. Plan-based representations have been explored for driving tailored scaffolding during narrative interaction with students [11]. Although prior work has investigated approaches for narrative and tutorial action selection, little work has explored the

creation of empirically informed computational model of narrative-centered tutorial decision-making, which is the focus of the work reported here.

3 Narrative-Centered Tutorial Decision-Making Model

Interactive narrative is a time-based phenomenon. To be able to select the most appropriate tutorial decisions in narrative-centered learning environments, a model of narrative-centered tutorial decision making has to utilize numerous observations that change over time. Because Dynamic Bayesian networks (DBNs) can explicitly characterize models' belief state over time, DBNs provide a natural representation for describing worlds that change dynamically over time [12], and DBNs have demonstrated significant promise for use in intelligent tutoring systems [13, 14].

The high-level structure of the dynamic Bayesian network model created for narrative-centered tutorial decision-making is shown in Figure 1. The figure illustrates three time slices and their corresponding tutorial decisions: *tutorial decision*$_{t-2}$, *tutorial decision*$_{t-1}$, and *tutorial decision*$_t$. The three time slices include representations of the narrative observation including information on the physical state of the storyworld and progression of the narrative. Each time slice encodes a probabilistic representation of the belief about the overall state of the narrative.

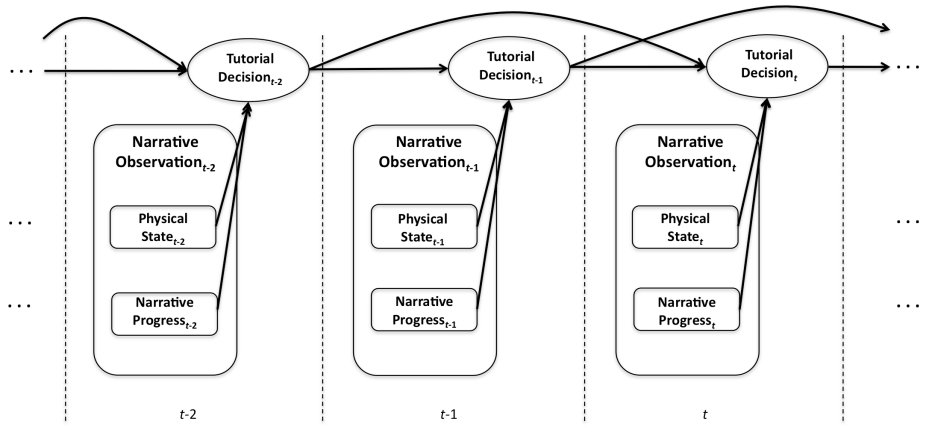

Fig. 1. Dynamic Bayesian network model for narrative-centered tutorial decision-making

The *tutorial decision* nodes model the knowledge of prior decisions. The *physical state* nodes model the location of characters in the storyworld (i.e., student, wizard) which are represented as quantized virtual world locations. The *narrative progress* nodes model the storyworld's narrative structure. To characterize the progress of the narrative, we analyzed the story structure utilizing a narrative arc framework. Utilizing the current phase of the narrative arc as an observation provides the model with evidence about the high level structure of the unfolding narrative [15]. The model considers the current beliefs about the physical state and narrative progress

represented in *narrative observation*$_t$. It also considers prior history of *tutorial decision*$_{t-1}$ and *tutorial decision*$_{t-2}$. Using the links from *tutorial decision*$_{t-1}$, *tutorial decision*$_{t-2}$, *physical state*$_t$, and *narrative progress*$_t$ the model captures how each of these influences *tutorial decision*$_t$.

Given the DBN structure, the values in the conditional probability tables (CPTs) for each observation node in the network can be learned using a corpus. Setting observed evidence on the learned model and updating the network allows the likelihood of decisions to be computed at each time slice.

4 Corpus Collection Environment

A customized WOZ-enabled version of the CRYSTAL ISLAND narrative-centered learning environment with Wizard-of-Oz functionalities was created (Figure 2) to act as a corpus collection tool to investigate narrative-centered tutorial decision-making. CRYSTAL ISLAND is a virtual learning environment designed for the domain of microbiology for eighth grade science education featuring a science mystery situated on a remote tropical island. Within the story, the student plays the role of a science detective attempting to discover the identity of an infectious disease plaguing the island inhabitants. CRYSTAL ISLAND is built with Valve Corporation's Source™ Engine, the game engine utilized for Half Life®2.

Fig. 2. WOZ-enabled CRYSTAL ISLAND

The WOZ-enabled CRYSTAL ISLAND [15] extends the learning environment, using the networked multiplayer features of the Source™ Engine, to include a character driven by a wizard, who assists the student in solving the mystery. Wizards provide the tutorial planning and narrative planning functionalities as well as spoken dialogue for their character. Playing the role of the camp nurse, the wizard works collaboratively with the student to solve the science mystery. Together in the virtual environment they carry on rich conversations using voice chat and observe one another's actions while engaging in problem-solving activities.

In addition to directing the navigation, spoken communication, and manipulation behaviors of the nurse character in the virtual environment, the wizard controls the progression of the story and scaffolds student interactions by utilizing the *narrative dashboard*. The narrative dashboard enables the wizard to initiate key narrative-centered tutorial decisions in the environment (e.g., introducing new patient symptoms) analogous to narrative-centered tutorial planners [16]. Table 1 describes the decisions that can be enacted by the wizard using the narrative dashboard.

Table 1. Narrative-centered tutorial decisions

Decisions	Tutorial Type	Descriptions	Freq
START-SESSION	*Define Problem*	Wizard gives a brief explanation of the student's objectives and goals.	6.2%
INTRODUCE-SCIENTIFIC-METHOD	*Background Information*	Wizard explains to the student and suggests they use the scientific method while diagnosing the mysterious illness.	6.2%
INTRODUCE-WORKSHEET	*Background Information*	Wizard explains usage of the diagnosis worksheet to help the student formulate and refine their hypothesis.	6.2%
EXAMINE-PATIENT-SYMPTOMS	*Hint*	Wizard and student work together to examine symptoms of each of the patients.	8.1%
UPDATE-WORKSHEET	*Confirm Understanding*	Wizard reminds the student to update the diagnosis worksheet with new knowledge and hypothesis.	13.7%
READ-DISEASE-BOOKS	*Hint/Advice*	Wizard guides the student to read relevant disease information in the library, which helps them refine their hypothesis.	13.9%
INTRODUCE-HEADACHE	*Hint*	Wizard triggers an action resulting in a patient moaning and complaining about having a headache.	6.2%
TEST-CAMP-ITEMS	*Advice*	Student and wizard test food items the expedition team took with them from camp.	5.4%
TEST-OUTSIDE-CAMP-ITEMS	*Advice*	Student and wizard test food items the team found during their expedition.	3.4%
TEST-CONTAMINATED-BANANAS	*Advice*	Student and wizard test the bananas, which end up being contaminated.	3.4%
INTRODUCE-DIRTY-WATER	*Hint*	Wizard triggers an event causing a door to open and a water bottle to appear in the infirmary room.	5.2%
INTRODUCE-LEG-CRAMPS	*Hint*	Wizard triggers an event causing one of the patients to complain about leg cramps.	3.6%
COMPLETE-WORKSHEET	*Confirm Understanding*	Wizard asks student to update all remaining information that has not been entered and formulate their final hypothesis.	6.4%
REPORT-RESOLUTION	*Confirm Understanding*	Wizard asks student to explain their final hypothesis and how they arrived at their conclusion using the scientific method.	6.2%
END-SESSION	*Confirm Understanding*	Wizard thanks student and tells her that the patients will be treated based on her finding.	6.2%

There are fifteen narrative-centered tutorial decisions that wizards enact in the environment. Table 1 also summarizes the relative frequency of each decision, i.e., the ratio of the number of occurrences of specific decisions to the total number of decisions in all sessions. The frequencies range from 3.4% to 13.9% (M = 6.7%, SD = 3.2%). The corpus collection environment records detailed logs of actions performed by the student and wizard within the virtual environment, including decisions made by the wizards using the narrative dashboard. These logs provide a rich source of data to build empirically driven models of narrative-centered tutorial decision making.

5 Corpus Collection Study Method

A corpus collection study was conducted with thirty-three eighth-grade students (15 males and 18 females) from a public school ranging in age from 13 to 15 (M = 13.79, SD = 0.65). Two wizards participated in the study, one male and one female. Each session involved a single wizard and a single student. The student and wizard were physically located in separate rooms throughout the session. The students' sessions lasted no more than sixty minutes (M = 38, SD = 5.15). After completing the session, student trace data, pre-test, and post-test were collected to analyze the wizards' narrative-centered tutorial decision-making and measure learning outcomes while interacting with the WOZ-enabled CRYSTAL ISLAND. During model evaluation one of the participants was eliminated as an outlier—the data were more than three standard deviations from the mean—leaving thirty-two usable trace data logs.

6 Results and Discussion

For the DBN model, there are a total of 22 time slices, 88 nodes, and more than 830 conditional probabilities present in the narrative-centered tutorial decision-making network. The model was implemented with the GeNIe/SMILE Bayesian modeling and inference library developed at the University of Pittsburgh's Decision System Laboratory [17]. Given the network structure of the DBN, we learned the probabilities of each node in the network by performing parameter learning for the conditional probability tables (CPTs). The Expectation-Maximization algorithm from the SMILearn library was used to learn the CPT parameters. After CPT parameters were learned, the resulting network was used to make inferences about the narrative-centered tutorial decision nodes in the model.

An analysis was conducted to investigate the use of dynamic Bayesian networks for modeling narrative-centered tutorial decision-making. To compare the effectiveness of the DBN model against a baseline, a bi-gram model was developed in which only the previous tutorial decision was used to predict the next tutorial decision. The bi-gram model achieved a tutorial decision predictive accuracy of 71%. A leave-one-out cross validation method was employed. To analyze the effectiveness of the DBN structure for narrative-centered tutorial decision-making prediction, an aggregated confusion matrix was built for the model to compute the overall accuracy. In the prediction evaluation, the DBN model achieves tutorial decision prediction

accuracy of 93.7%. The DBN model exhibited a 23% accuracy improvement over the bi-gram model. It appears that providing evidence regarding narrative structure, physical locations, and tutorial decision history can significantly improve narrative-centered tutorial decision prediction.

It is important to note that students interacting with the WOZ-enabled version of CRYSTAL ISLAND achieved significant learning outcomes. They exhibited learning gains ($M = 2.20$, $SD = 1.58$) as measured by the difference of their post-test ($M = 8.05$, $SD = 1.57$) and pre-test scores ($M = 5.85$, $SD = 1.27$). A matched pairs t-test between post-test and pre-test scores shows that the learning gains were significant, $t(19) = 6.24$, $p < 0.0001$. For the learning outcome analysis, thirteen of the participants were excluded due to incomplete data on either the pre-test or post-test.

7 Conclusion

Narrative-centered learning environments offer significant promise for guided discovery learning. Making narrative-centered tutorial decisions is critically important for achieving pedagogically effective story-based learning experiences. In this paper, we have presented an empirically driven narrative-centered tutorial decision-making model for interactive narrative centered learning environments. A corpus collection study was conducted using a Wizard-of-Oz methodology with students interacting with a WOZ-enabled version of the CRYSTAL ISLAND learning environment. Using machine learning, we automatically acquired a narrative decision-making model based on observations of the narrative-centered tutorial decision history, location, and narrative arc. The study reveals that students exhibited significant learning outcomes while interacting with the WOZ-enabled CRYSTAL ISLAND, and using dynamic Bayesian networks for narrative decision-making appears to be a promising approach to devising accurate models.

Two directions for future work are particularly important. First, it will be important to develop models that not only indicate the best narrative-centered tutorial decision to make but also the appropriate time to intervene. A follow-on investigation should be conducted to learn models of the proper timing of narrative-based tutorial decision-making behaviors that contribute to the most effective and engaging learning experiences. Second, during the study, wizards used natural language dialogue to guide students' activities and control the progression of the story, in addition to the utilizing the narrative dashboard. Devising adaptive models of dialogue for narrative-centered learning environments is a promising line of investigation.

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