Recognizing Opportunities for Mixed-Initiative Interactions based on the principles of Self-Regulated Learning

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Abstract

Mixed-Initiative Interaction is a naturally-occurring feature of human interactions. Mixed-initiative systems exhibit various degrees of involvement in regards to the initiatives taken by the user or the system. One of the key elements for successful mixed-initiation is the ability of the system to recognize opportunities for mixed-initiative interactions. In this paper, we propose a mechanism based on the principles of Self-Regulated Learning (SRL) to formally recognize opportunities for mixed-initiative interaction in the domain of Education in Online Learning Environments. Our approach targets educational domains where online learning systems guide learners to gradually modify their learning process to incorporate effective use of SRL strategies. We achieve this by encoding SRL-specific knowledge in an OWL-based formal ontology and by using JESS as the inference engine to recognize strategies and tactics used by learners in specific reading and problem-solving activities. Eventually, we hope to be able to automatically recognize patterns of usage of strategies and tactics by learners over a period of time. Using such patterns we demonstrate how the system recognizes opportunities for mixed-initiative interactions to guide learners who veer away from optimal SRL strategies.

Introduction

Mixed-Initiative Interaction (MII) is a naturally-occurring feature of human interactions. The motivation behind our research is to capture the process of this natural phenomenon and deduce reasons for interactions initiated by the system. Mixed-initiative systems exhibit various degrees of involvement in regards to the initiatives taken by the user or the system. One of the key elements for successful mixed-initiation is the ability of the system to recognize opportunities for mixed-initiative interactions. In this paper, we propose a mechanism based on the principles of Self-Regulated Learning (SRL) [Winne1997, Zimmerman2002] to formally recognize opportunities for mixed-initiative interaction in the domain of Education in Online Learning Environments.

We developed a mixed-initiative interaction (MII) framework based on the model of pair-programming[1] [Williams2003] where the system plays the role of a more experienced partner and initiates interaction with the learner as dictated by the model. In a similar approach, our system initiates interactions that are based on the principles of Self-Regulated Learning (SRL) in online learning depending on the learners' progress in the domain. SRL is a theory that concerns how learners develop learning skills and how they develop expertise in using learning skills effectively. SRL comprises a set of strategies and tactics employed by learners to regulate their own learning processes. It arises from two key observations. First, learners' goals for learning take precedence over goals set by teachers, authors of curricula, and developers of learning objects. Second, learners are in charge of how they learn. They choose which study tactics and learning/problem-solving strategies to use as they strive to achieve their goals. Research shows learners often set unsuitable goals, have a limited repertoire of learning skills, often do not use learning skills they have, and frequently need extensive help to manage learning and collaborative tasks. These provide the opportunities for system-initiated interaction. In our work, opportunities for mixed-initiative interactions are recognized based on the sequences of strategies and tactics used by the learners. The system observes the fine-grained interactions of the user with the online material, translates such interactions into coarse-grained strategies and tactics, recognizes patterns of usage of strategies and tactics, matches these patterns against the optimal strategies and tactics prescribed by SRL, and triggers system-initiated interactions to prompt and guide the learner who has strayed away from optimal SRL strategies.

Many of the earlier systems involving human–computer interactions were built as question-answer systems with initial initiative typically resting either with the user or the system, thus factoring out the role of mixed initiatives. This led to the allocation of control to one participant (the user or the system) [Cohen1984, Burstein2003, Boicu2003], or the creation of a passive listener [Cohen1987]. A number of mixed-initiative systems have been developed based on the notion of 'allocation of control' [Allen1999, Druzdzel1999, and Guinn1997]. There are systems that toggle the control to initiate interactions based on the competency of either the user or the system to complete the task at hand. For example, a mixed-initiative interaction interface for online website development was described by Perugini and Ramakrishnan [Perugini2003] that allowed users to specify personalization aspects out of turn to the system, allowing

[1] http://www.extremeprogramming.org/rules/pair.html

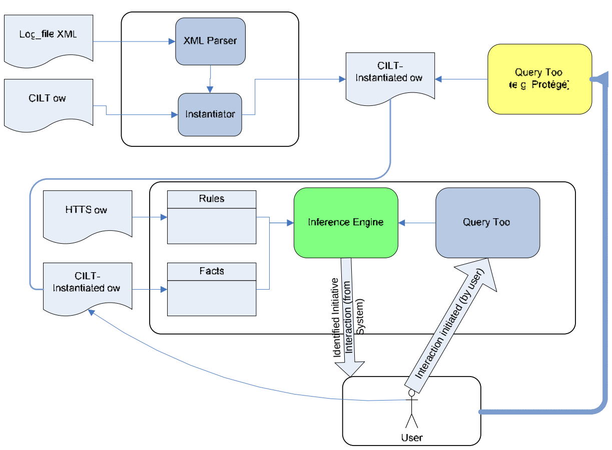
the system to modify the webpage to the needs of the user as and when required. Levels of mixed-initiative control have been defined according to when the user or the system chooses to initiate a change in the dialogue pattern [Allen1999]. Good evaluations of mixed-initiative dialogue and initiative taking mechanisms have been presented by Guinn [Guinn1999]. Systems with suggestion based mechanisms for transfer of control have been also found useful in building mixed initiative interactions [Gupta2003].

Our work is unique and distinct from the current approaches in the sense that the opportunities for initiatives are recognized based on SRL, a seminal theory in education psychology, and both the system and the learner can explain why a particular interaction has been initiated. Strategies and tactics in our domain is represented in the form of an ontology [Kumar2004]. We promote ontological representation as a solution to formally represent the principles of educational theories. The ability to recognize sequences of strategies and tactics in learner interactions with the system and the ability to match these patterns against SRL-prescribed patterns of strategies and tactics have been represented as Production Rules in JESS[2].

Architecture for MII

Our architecture for SRL-based mixed-initiative interaction is presented in Figure 1. The architecture promotes a modular and adaptable system design since the rules and facts can be fed into the system in an ontological format and reasoned with, at run time. The architecture is geared towards addressing our goals of enabling both the system and the learner to be able to explain why a particular interaction has been initiated and how such opportunities have been recognized based on the principles of SRL.

Figure 1 – System Architecture



[2] Jess is a generic rule based inference tool. http://herzberg.ca.sandia.gov/jess/

Domain Model

We experiment with MII in the domain of programming. The LearningKit Project[3] provides a study tool for the learner in Java programming. The self-regulated learning model, as described by Winne [Winne2001], consists of various tactics and strategies that students use to reach their goals during the learning process. Hadwin, et al (2005) has outlined some of the generic strategies and tactics students used in the domain of Reading. Kumar (2004b) identifies some of the means to recognize strategies and tactics employed in computer programming. We are currently designing an experiment to identify strategies and tactics used by students when engaged in learning activities in the domain of novice java programming.

We use gStudy[4], a system that promotes SRL-based reading and problem-solving activities, as the front-end. We developed an extensive ontology to capture the log of trace data of learner interactions with gStudy. The log data consists of interactions including browsing, highlighting, compiling code, text chatting, indexing, concept mapping, note taking, reviewing, collaborating, and so on. Information pertaining to these interactions is automatically instantiated in our ontology. A query interface has been built using which learners themselves review, recognize, and relate strategies and tactics that they used as part of a learning activity. Further, the system also attempts to recognize learner strategies and tactics as observed in their interaction with gStudy. The system can initiate interactions with the learner to promote specific strategies and tactics. It can also initiate interactions with the learner when it finds gaps in learner strategies and tactics. Further, it can initiate interactions with the learner with respect to the strategies and tactics employed by other students. Using these three recognizable opportunities, we provide contextualized feedback to learners, on the fly, as they study or solve problems in specific learning activities. Our research collects data on how such explainable and theory-oriented prompting and feedback promote significant, transferable, and enduring changes to learner study skills and problem solving abilities.

Ontological representation

The use of ontology as knowledge representation and knowledge sharing mechanism is a century-old notion. It has been extensively employed in the domain of online learning environments in the past decade. The use of ontology for course authoring, knowledge engineering, ontology instantiation has been an area of ongoing research. Ontology is a powerful knowledge representation scheme that can describe a vast range of complex systems using simple relations.

[3] http://www. learningkit.sfu.ca

[4] gStudy is an experimental software platform to test the principles of SRL

In our research, we have used the ontological representation of the domain knowledge and the interaction knowledge primarily because ontology allows for a formal representation of concepts and the relationships between them. The formalism that we use is based on Description Logic as formulated in OWL-DL[5].

Ontological representation formally captures SRL-specific teaching tactics and strategies. Some of these tactics and strategies are displayed in Figure 2.

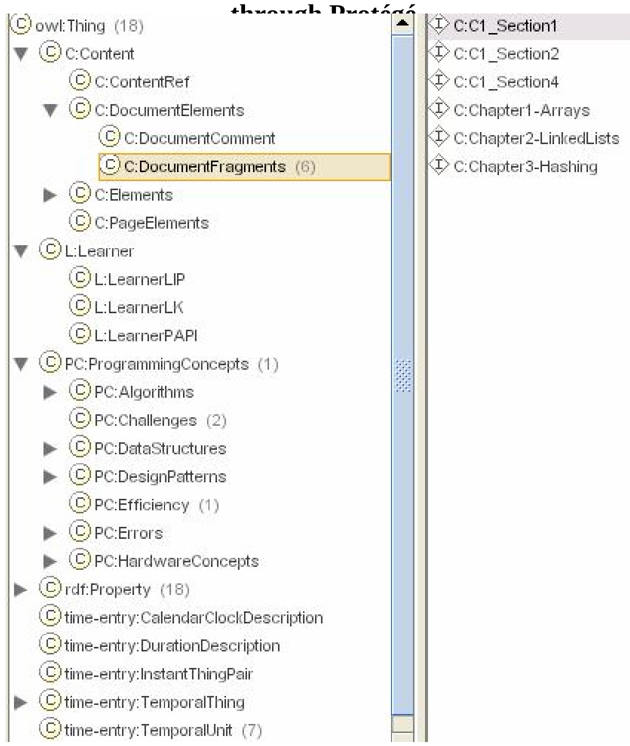
Figure 2 - Excerpt from the Teaching Tactics and Strategies Ontology (OWL file)

```
<owl:ObjectProperty rdf:about="#uses">
  <rdfs:domain rdf:resource="#SelfRegulatedLearningET"/>
  <owl:inverseOf rdf:resource="#usedBy"/>
</owl:ObjectProperty>
<owl:ObjectProperty rdf:about="#teaches">
  <rdfs:range>
    <owl:Class>
      <owl:unionOf rdf:parseType="Collection">
        <owl:Class rdf:about="#IndependdentSeatWorkTT"/>
        <owl:Class rdf:about="#DoIReallyKnowItTS"/>
      </owl:unionOf>
    </owl:Class>
  </rdfs:range>
  <owl:inverseOf rdf:resource="#isTaughtBy"/>
</owl:ObjectProperty>
<owl:ObjectProperty rdf:ID="learns">
  <owl:inverseOf>
    <owl:InverseFunctionalProperty rdf:ID="learntBy"/>
  </owl:inverseOf>
  <rdf:type rdf:resource="http://www.w3.org/2002/07/owl#FunctionalProperty"/>
</owl:ObjectProperty>
<owl:DatatypeProperty rdf:ID="hasAward">
  <rdfs:range rdf:resource="http://www.w3.org/2001/XMLSchema#string"/>
  <rdf:type rdf:resource="http://www.w3.org/2002/07/owl#FunctionalProperty"/>
</owl:DatatypeProperty>
<owl:DatatypeProperty rdf:ID="hasGoal">
  <rdfs:domain>
    <owl:Class>
      <owl:unionOf rdf:parseType="Collection">
        <owl:Class rdf:about="#SelfRegulatedLearningET"/>
        <owl:Class rdf:about="#QuestionsTT"/>
        <owl:Class rdf:about="#SelfPlanningTS"/>
      </owl:unionOf>
    </owl:Class>
```

These tactics and strategies form the production rules in the JESS inference engine. The system relies on these rules to recognize initiative opportunities and prompt feedback to learners during the learning process.

We have represented the complete application ontology as CILT (Content-Interaction-Learner-Time). This ontology represented in OWL-DL format, captures the essence of the learner's interaction of the content at a given time. An excerpt of the ontology displayed through protégé (an ontology editor) is shown the Figure 3.

Figure 3 - Sections from CILT ontology as viewed through Protégé



System Initiation Opportunities Recognition

In the pair programming model, the expert is mainly an observer with open-ended opportunities to initiate interaction. There are no specified cases or specified situations for the expert to initiate interaction. The interaction is mostly dependent on the expert programmer and the knowledge level of the novice [Jensen2003]. In an analogical approach, our system passively observes learner interactions, recognizes opportunities for system-initiated interactions, and actively initiates interactions that are based on the principles of Self-Regulated Learning.

The domain knowledge, represented as rules, is the core data in the working memory of the JESS inference engine. The learner interaction data is fed into the system in real-time, triggering the system to initiate interactions with the user when appropriate.

When learners study or solve problems, research indicates they can benefit by having access to feedback about

a. Methods they use to study/solve problems (process feedback),
b. How much they have learned (knowledge of results), and
c. How learner's peers study and what they score on tests (normative feedback).

[5] http://www.w3.org/TR/owl-guide

Because gStudy logs fine-grained data about the interactions pertaining to these types of feedback, we can mine these data to enable these feedbacks. Our system responds to queries a learner poses as well as initiate dialogues with the learner (hence, a mixed initiative dialogue) about domain topics and SRL-specific strategies and tactics.

Our mixed-initiative system is guided, in part, by sophisticated ontologies. The system has two distinguishing features. First, system-initiated queries and responses are based on data that gStudy gathers on the fly. For instance, a student can inquire about the number of times she has re-viewed a glossary term in a session where she studied technical material. Second, the topic of queries can be about content studied and about study tactics as traced by gStudy. For example, a learner will have tools to build complex queries, such as what percent of students in his/her class highlight text then immediately make a note and link that note to relevant glossary items and score more than 85% on the test covering the assignment.

Feedback categories	**System initiation opportunity**	**Rules example**
Process feedback	• Based on the student's interaction, the system can guide the student in using some more of the SRL tactics in their online learning	If student is only **highlighting**, then the system can recommend the use of **taking notes** to the highlighted text for material relevance and ease of search on topics.
	• If the student is taking notes on specific topic then the system can initiate some other reference material the student may want to review.	If the student is taking **notes only on certain topic**, then system can recommend **other document location**s that is linked to the same topic, that the learner may not be aware of.
Knowledge of results feedback	• Based on learners' accomplishment with the online course and the interactions accomplished, the system can initiate information on the learner's current knowledge status.	The system can show the **learners' knowledge status** based on the interactions and content learner had interacted.
Normative feedback	• Based on all peer interactions and accomplishments, the system can initiate comparative knowledge status and comparative accomplishment statistics	The system can show the learners' their standings in regards to the score or the learning style with respect to their peers.

Table 1 - Examples of system initiation opportunities for gStudy, based on the three feedback categories

Our system is designed to recognize opportunities and initiate interaction with the learners in the context of the three identified feedbacks. Recognition of the system initiation opportunities is based on the principles of SRL that are represented in the format of production rules. Examples of the feedback system initiation on each of the three categories are as shown in Table 1.

We are currently working on the prototype to recognize these system initiation opportunities in the domain of Java programming. We are also incorporating an asynchronous response system that uses out-of-turn recommendations to guide learners. Our design of the system requires assuming control momentarily for advising the users who have veered off optimal SRL strategies. Our system has the ability to prompt the learner by judging whether the system is competent enough to suggest a better learning strategy [Guinn 1997]. Another research direction that we explore involves system-generated pop-up interrupts as well as a dialog panel for communication between the learner and the system.

Conclusion

Our work is based on the use of ontology based knowledge representation and reasoning to identify opportunities in a Mixed-initiative environment. System-initiated interactions are aimed at process, knowledge, and normative feedback.

Opportunities for mixed-initiative interactions are recognized based on the sequences of strategies and tactics used by the learners. The system observes the fine-grained interactions of the user with the online material, translates such interactions into coarse-grained strategies and tactics, recognizes patterns of usage of strategies and tactics, matches these patterns against the optimal strategies and tactics prescribed by SRL, and triggers system-initiated interactions to prompt and guide the learner who has strayed away from optimal SRL strategies.

Our system complies with the Mixed Initiative Interaction principles advocated by Novick1997, Anderson1999, and Ramakrishnan2002 on unsolicited reporting with the goal of guiding the learner. However, a comprehensive set of characteristics of mixed-initiative interaction have not been explored in our design. Reactivity and autonomy have been the core focus of our design. Negotiation of initiation, Mode of communication and Guided collaboration and competence are some of the MII characteristics that we plan to explore in the near future.

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