# A Contextualized, Differential Sequence Mining Method to Derive Students' Learning Behavior Patterns

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Computer-based learning environments can produce a wealth of data on student learning interactions. This paper presents an exploratory data mining methodology for assessing and comparing students' learning behaviors from these interaction traces. The core algorithm employs a novel combination of sequence mining techniques to identify differentially frequent patterns between groups of students (*e.g.*, experimental versus control conditions or high versus low performers). We extend this technique by contextualizing the sequence mining with information about the student's performance over the course of the learning interactions. Specifically, we employ a piecewise linear segmentation algorithm in concert with the differential sequence mining technique to identify and compare segments of students' productive and unproductive learning behaviors. We present the results from the application of this exploratory data mining methodology to learning interaction trace data gathered during a recent middle school class study with the Betty's Brain learning environment. These results illustrate the potential of this methodology in identifying learning behavior patterns relevant to the investigation of metacognition and strategy use.

Additional Key Words and Phrases: sequence mining, differential sequence mining, piecewise linear representation, learning behaviors, metacognition, computer-based learning environments

## 1. INTRODUCTION

Cognitive scientists have established that metacognition and self-regulation are important components for developing effective learning in the classroom and beyond [Bransford et al. 2000; Zimmerman 2001]. In developing a computer-based learning environment (CBLE) called Betty's Brain, we adopt the framework for self-regulated learning (SRL), which originated from the social constructive theory of learning proposed by Bandura [1997]. In this system, students learn science topics by exploring hypermedia resources and constructing a causal map to teach the virtual Teachable Agent (TA), called Betty [Biswas et al. 2005; Blair et al. 2007]. As they teach, students can assess their agent's (and their own) learning by asking her questions and getting her to take quizzes. Overall, the combined learning and teaching task is complex, open-ended, and choice-rich, so learners must employ a number of cognitive and metacognitive skills to achieve success. Their cognitive and metacognitive activities are scaffolded through dialogue and feedback provided by

Betty and a mentor agent named Mr. Davis. This feedback aims to help students progress in their learning, teaching, and monitoring tasks.

A number of researchers (*e.g.*, [Pintrich 2000; Zimmerman et al. 1992; Zimmerman 2001]) have demonstrated that students' SRL capabilities can play a significant role in high school academic achievement. In addition, studies by Brown and Palincsar [1989] have demonstrated that through instruction younger students can acquire and apply metacognitive skills, such as planning and monitoring. However, students in typical classrooms are rarely provided opportunities to learn and exercise these strategies [Paris and Paris 2001; Zimmerman 1990]. We believe choice-rich, open-ended learning environments like Betty's Brain, where students have to work on complex learning tasks can provide these much-needed opportunities to learn and practice these skills in classroom environments.

In general, CBLEs allow researchers not only to track students' learning performance, but also many details of their learning interactions and activities. The learning activities logged by a CBLE result from a variety of internal cognitive and metacognitive states, strategies, and processes used by the student. This wealth of data provides an opportunity to more accurately assess, model, and understand student learning behaviors and strategies. To take advantage of this opportunity requires effective methods of identifying interesting learning behavior patterns in this activity data. In this paper, we present an exploratory data mining methodology using sequence mining methods for assessing and comparing students' metacognitive learning behaviors from their learning interaction traces.

In previous work, we have used hidden Markov models (HMMs) [Rabiner 1989] as a direct (probabilistic) representation of these internal states and strategies. This methodology has facilitated identification, interpretation, and comparison of student learning behaviors at an aggregate level [Biswas et al. 2010; Kinnebrew et al. 2013]. Like a student's mental processes, the states of an HMM are hidden, meaning that they cannot be directly observed, but they produce observable output (*e.g.*, actions in a learning environment). However, the aggregated descriptions often mask the exact manifestation of specific learning behaviors and strategies that students employ as they work on the system. To identify and analyze these detailed learning behaviors, we have developed sequence mining methods that provide a finer-grained analysis and more precise definitions of learning behavior differences between groups of students.

An important component of this detailed analysis of students' learning behaviors is the use of sequential pattern mining [Agrawal and Srikant 1995] to identify frequent[1] patterns of actions within a group. However, this approach can also result in a very large number of frequent patterns, especially when allowing gaps to account for "noise." For example, when we looked at activity traces of 22 $8^{th}$ grade students working on a climate change science unit in Betty's Brain, we found over 1,000 patterns that occurred in at least 80% of their interaction traces on the system, even when we limited gaps to a single action between consecutive actions in the pattern. Further, using a threshold of 80% of students resulted in overlooking many patterns that could be linked to important learning strategies employed by the majority of the group (but fewer than 80%), while lower thresholds yielded far too many patterns for consideration. In general, a major challenge in the analysis of frequent patterns is limiting the often large set of results to interesting or important patterns (*i.e.*, the *effectiveness* of a mining technique in identifying useful patterns as opposed to its *efficiency*, or speed, in finding the patterns [Agrawal et al. 1993]).

To overcome this problem, we have developed an algorithm that employs a novel combination of sequence mining techniques to identify differentially frequent patterns between groups of students (*e.g.*, experimental versus control conditions or high versus low performers) [Kinnebrew and Biswas 2011]. In this paper, we present a formal description of this algorithm and extend it by contextualizing the differential sequence mining with information about the student's performance over the course of the learning interactions. More specifically, we employ a piecewise linear segmentation algorithm in concert with the differential sequence mining algorithm to identify and compare learning behaviors during productive and non-productive periods (where productive periods are characterized by increasing performance in constructing the correct causal map). We apply this exploratory data mining methodology to learning interaction trace data gathered during a recent Betty's Brain study in a middle school classroom. These results illustrate our methodology's potential for identifying learning activity patterns relevant to the investigation of cognitive and metacognitive learning behaviors and strategies.

The rest of this paper is organized as follows. Section 2 presents a brief review of sequence mining methods that have been employed to derive and analyze students learning behaviors in CBLEs. This section also describes methods that have been employed to measure students' metacognitive and self-regulated learning behaviors. Section 3 then describes the algorithms employed in our methodology, including the differential sequence mining algorithm that identifies patterns in activity sequences and the linear segmentation technique that partitions the students' learning per-

[1]Pattern frequency in sequential pattern mining is defined as the number of different sequences (in this case the number of different student interaction traces) that include the pattern.

formance (measured by the map score) into productive and counter-productive periods. Section 4 briefly discusses the Betty's Brain learning by teaching environment, and the cognitive and metacognitive strategy model that describes the idealized learning and teaching activities in Betty's Brain. Section 5 describes the experimental study from which the sequence data was collected, and Section 6 presents the results of our differential sequence mining analysis to identify learning behaviors of high- versus low-performing students during their productive and counter-productive segments. Last, Section 7 discusses the implications of these results and outlines directions for further research.

## 2. RELATED PRIOR WORK

The focus of this paper is on the analysis of students' learning behaviors and metacognition, using data mining techniques. To find these important patterns in a comparative analysis between students' activity traces, our methodology identifies *differentially frequent* patterns and identifies productive and counter-productive phases of student activity within the traces. We discuss this methodology in section 3, but first briefly review relevant past work on measuring metacognitive behaviors in Section 2.1, and the use of sequence mining techniques to analyze student learning behaviors in Section 2.2.

### 2.1 Identifying and Measuring Metacognition and Self-Regulated Learning

The traditional approach to measuring students' metacognition and self-regulated learning (SRL) has been through the use of self-report questionnaires (*e.g.*, [Pintrich et al. 1993; Weinstein et al. 1987; Zimmerman and Martinez-Pons 1986]). The underlying assumption in these questionnaires is that self-regulation is an aptitude that students possess. For example, the questionnaire items might attempt to assess students' inclination to elaborate as they read a passage, or to determine their approach to managing available time resources [Perry and Winne 2006; Zimmerman 2008]. This approach has been useful, as the self-report questionnaires have been shown to be good predictors of students' standard achievement test scores and they correlate well with achievement levels [Pintrich et al. 1993; Zimmerman and Martinez-Pons 1986]. However, Hadwin and others [Azevedo and Witherspoon 2009; Hadwin et al. 2001; Hadwin et al. 2007; Perry and Winne 2006] have argued that while the questionnaires provide valuable information about the learners' self-perceptions, they fail to capture the dynamic and adaptive nature of SRL as students are involved in learning, knowledge-building, and problem-solving tasks.

Increasingly, researchers have begun to utilize trace methodologies in order to examine the complex temporal patterns of self-regulated learning [Aleven et al. 2006; Azevedo and Witherspoon 2009; 2009; Biswas et al. 2010; Hadwin et al. 2007; Jeong and Biswas 2008; Zimmerman 2008]. The primary notion is that metacognition and SRL are evolving events that can be better understood by observing students' learning and problem-solving activities. Perhaps the most common type of data collected are computer logs, which can record every action that the student performs in a computer-based learning environment. For example, Hadwin *et al.* [2007] performed a study that collected activity traces of 8 students using the gStudy system [Perry and Winne 2006]. The activity traces were analyzed in four different ways: (i) frequency of studying events, (ii) patterns of studying activity, (iii) timing and sequencing of events, and (iv) content analyses of students' notes and summaries. The results of this analysis were compared against students' self-reports on their self-regulated learning. One of the important findings was that many participants' self-reports of studying tactics, as determined by the MSLQ items, were not well calibrated with studying events traced in the gStudy system. The researchers found that the best matched item showed a 40% agreement, and the average agreement was 27%. The authors concluded from this study that trace data of student activity in e-learning environments are important for furthering our understanding of SRL.

More recently, trace data is being supplemented with other sources of data, such as concurrent verbal think-alouds (*e.g.*, [Azevedo and Witherspoon 2009] and measures of affect (*e.g.*, automatic recording of facial expression, posture, etc. [Burleson et al. 2004; D'Mello et al. 2007; D'Mello et al. 2008; Lester et al. 1997]. [Azevedo and Witherspoon 2009] have developed a hypermedia environment called MetaTutor to help students learn about complex and challenging science topics, such as the circulatory processes in human body systems. The system is also designed to train students in key SRL processes that relate to planning, metacognitive monitoring, learning strategies, and methods for handling task difficulties and demands. The authors used a combination of student trace data and think-aloud protocols to understand the nature of students' learning outcomes and their deployment of SRL processes. For example, one of their studies showed that students predominantly used strategies that pertained to acquiring knowledge from the multimedia resources, and they only occasionally employed monitoring strategies to check on what they have learned [Azevedo and Witherspoon 2009]. Combining trace and think-aloud protocols provides more insight into the students' thought processes that govern the use of strategies. Furthermore, they can be used to validate the results of the trace data analysis. Although we do not have think-aloud data to combine with the trace data, our methodology, presented in Section 3, contextualizes the identification of activity patterns by the student's evolving task performance (*e.g.*, productive versus counter-productive periods) over the course of the learning interactions.

### 2.2 Applying Sequence Mining to Study Student Learning Behaviors

In order to better understand learning, researchers have applied data mining techniques, such as sequential pattern mining, to a variety of educational data. For example, Perera *et al.* [2009] investigate trace data from mirroring and feedback tools that support effective teamwork among students collaborating on software development using an open source professional development environment called TRAC. In their approach, they help all groups improve their work by observing and emulating the behaviors of the strong groups. They use k-means clustering to find groups of similar teams and similar individuals, and then employ a modified version of the Generalized Sequential Pattern (GSP) mining algorithm [Srikant and Agrawal 1996] to show that leadership and group interaction are important to success.

Similarly, Martinez *et al.* [2011] discover which frequent sequences of actions characterize high-achieving and low-achieving learners. They collect electronic traces from groups of students collaborating around a shared tabletop to answer an open question posed as a mystery problem. They then apply a clustering algorithm to group similar patterns to aid in analyzing the pattern distribution across the groups. Employing sequential pattern mining allows them to identify differences between the higher- and lower-achieving groups in their manner of information gathering to solve the problem.

Like Perera *et al.* [2009] and Martinez *et al.* [2011], we compare sequential patterns derived from groups of student activity sequences. However, our differential sequence mining algorithm directly incorporates comparisons between groups in identifying interesting patterns, rather than manually performing researcher-directed comparisons after data mining. Further, in addition to sequential pattern mining metrics and constraints, we employ additional metrics, such as another frequency calculation based on episode mining, to identify differentially frequent patterns.

Other researchers have employed sequential pattern mining (with a single set of student activity sequences or subsequences) to generate student models for customizing learning to individual students. For example, Tang and McCalla [2002] propose sequential pattern mining of students' paths in a web-based environment, followed by a clustering step, to build better student models. Su *et al.* [2006] propose a method for creating personalized activity trees to be used in a Sharable Content Object Reference Model (SCORM) e-learning system. They use sequential pattern mining to extract frequent learning patterns as part of a larger process that creates a decision tree to predict the group/category for a new student.

Some researchers have also employed sequence mining with the goal of identifying learning behaviors relevant to self-regulated learning. In particular, Nesbit *et al.* [2007] employ sequential pattern mining to investigate self-regulation in gStudy, which is a software application with similarities to Betty's Brain. In this system, students learn from multimedia documents and organize their knowledge with notes, concept maps, and other objects. The authors define a set of actions from events in log files and use sequential pattern mining to find the longest common subsequences across a set of action files. Using this method, the authors hope to step beyond the question of whether a tool helps learners construct knowledge and instead investigate when and how learners use the tool as they self-regulate their knowledge construction activities. Similarly, our work investigates self-regulated learning by identifying sequential patterns of student activity. However, our data mining approach goes beyond applying sequential pattern mining to action sequences.

Unlike all of the preceding applications of sequential pattern mining, our methodology also analyzes the student's evolving performance to identify, and group, action subsequences corresponding to productive and counter-productive phases. Further, our differential sequence mining technique explicitly identifies and ranks differentially frequent patterns between these (or other) groupings of action sequences.

## 3. DIFFERENTIAL SEQUENCE MINING METHODOLOGY

To effectively perform sequential data mining on learning interaction traces, raw logs must first be transformed into an appropriate sequence of actions. Since these logs can contain a significant quantity of information about each student interaction with the system, as well as other system bookkeeping information, raising the level of abstraction from raw log events to a canonical set of distinct actions is a vital first step in effective analysis.

### 3.1 Action Abstraction with Context Summarization

Action abstraction is the first step of our data mining methodology, in which researcher-identified categories of actions define an initial alphabet (set of action symbols) for the sequences. This step filters out irrelevant information (*e.g.*, cursor position) and combines qualitatively similar actions (*e.g.*, querying an agent through different interfaces or about different concepts in a given topic).

First, log events are mapped to a sequence of canonical actions taken by each student. Sometimes abstracting the raw log traces through action categorization also strips important context from the actions in the trace sequence. For example, while differentiating the addition of each possible link in a concept map would result in an unwieldy set of distinct actions, knowing that the link added is the same as one described in a previous action involving reading source material can be important context information. To maintain a balance between minimizing the number of distinct actions in the sequences and keeping potentially important context information, we determine whether the content/object of an action is the same as the content/object of any other action in a small, configurable window of previous actions. Based on this relevance summarization we split each categorized action into two distinct actions: (1) relevant (with the "-REL" suffix) and (2) irrelevant (with the "-IRR" suffix) to recent actions [Biswas et al. 2010].

When students often perform a particular type of action (*e.g.*, reading pages of resource material) repeatedly, frequent patterns in student action sequences may include a variety of patterns that differ only by the number of repetitions of that action. To improve this exploratory analysis, our action abstraction step distinguishes a single action from repeated actions (with a given threshold on the number of repeats), which are condensed to a single "action" with the "-MULT" identifier. Using the re-transformed sequences, our differential sequence mining technique can more efficiently identify trends that could otherwise be hidden by the multitude of frequent patterns differing only by the length of a repeated action sequence [Kinnebrew and Biswas 2011].

### 3.2 Differential Sequence Mining

To identify important activity patterns in a comparison between two sets of action sequences, our methodology employs a novel combination of sequence mining techniques. In particular, sequential pattern mining [Agrawal and Srikant 1995] is used to determine the most frequent action patterns *across* a set of action sequences, while episode mining [Mannila et al. 1997] metrics are used to find the most frequently used action patterns *within* a given sequence. While these techniques can identify the frequent patterns in activity trace data, finding the patterns most important for interpreting learning behaviors or comparing between groups of students is often like trying to find a needle in a haystack.

In comparing across groups of action sequences (*e.g.*, for experiment versus control conditions, or high- versus low-performing students), the differences between the groups provide a natural criterion for identifying important patterns that may elucidate differences in learning behavior. To use this criterion for mining important frequent patterns, we first define the appropriate measure(s) of frequency and the relevant difference calculated across the groups. The sequential pattern mining frequency measure, which is important for identifying patterns common to a group of action sequences, is defined as: the number of sequences in which the pattern occurs (regardless of how frequently it occurs). We refer to this frequency measure as the *sequence support* (or s-support) of the pattern, following the convention of Lo *et al.* [2008], and we call patterns meeting a given s-support threshold, *s-frequent*.

Another important metric for comparing patterns across groups is the episode frequency, which is defined (for a single sequence) as: the number of times the pattern occurs, without overlap, in a sequence. For a given sequence, we refer to this frequency measure as the *instance support* (or i-support), following Lo *et al.* [2008]. We define the i-support of a pattern for a group of sequences as: the mean of the pattern's i-support values across all sequences in the group. Other definitions of group i-support could be employed (*e.g.*, a mean of i-support values normalized by the length of each trace or the maximum/minimum i-support of any trace in the group), but the mean i-support provides an easily-interpreted value (*e.g.*, how frequently the pattern is employed by a hypothetical average student when the comparison is between student groups) with a comprehensive view of pattern frequency for the group as a whole. Analyzing Betty's Brain interaction traces, we have found similar results using both the mean i-support value and the mean normalized i-support value for a group.

Algorithm 1 defines our differential sequence mining technique, which combines the group s-support and i-support frequency measures to identify *differentially frequent* patterns across two groups of action sequences. In this algorithm, the two groups (and their associated datasets, frequent patterns, and values) are referred to as "left" and "right," because the order of the two groups in the comparison does not matter. In this algorithm, we first employ a sequential pattern mining algorithm to identify the patterns that meet a minimum s-support constraint within each group (in lines 1-2 of Algorithm 1). One difficulty in mining frequent patterns in learning interaction traces is that the action sequences are "noisy." Students may exhibit a particular learning behavior pattern, but they may also perform additional actions interspersed with the actions that constitute the pattern. Therefore, we employ a maximum gap constraint in mining s-frequent patterns. This constraint means that between each consecutive pair of actions in a frequent pattern, the mining algorithm allows up to *gap* number of additional actions. A sequential pattern with such an optional (small) gap (*e.g.*, the pattern A $\rightarrow$ B $\rightarrow$ C) means that each subsequent action in the pattern is performed shortly after the previous action even if there were intervening actions that are not part of the pattern (*e.g.*, the student performs

**Input** : $left$ − Left dataset (set of action sequences)
$right$ − Right dataset (set of action sequences)

**Parameters**: $s_{thresh}$ − s-frequency (support) cutoff for frequent patterns
$gap$ − maximum gap allowed between actions in a pattern
$regex$ − regular expression to match for limiting patterns
$p_{thresh}$ − t-test p value for differential patterns

**Output** : Ordered lists of patterns in four categories by differential frequency

$sFreqPtrns_{left} \leftarrow \texttt{SPAMc}(left, s_{thresh}, gap, regex)$
$sFreqPtrns_{right} \leftarrow \texttt{SPAMc}(right, s_{thresh}, gap, regex)$
**for all** $ptrn \in sFreqPtrns_{left} \cup sFreqPtrns_{right}$ **do**
  $iSupport_{ptrn}(left) \leftarrow$ Count regular expression matches of $ptrn$ in each sequence in $left$
  $iSupport_{ptrn}(right) \leftarrow$ Count regular expression matches of $ptrn$ in each sequence in $right$
  **if** $\texttt{t-test}(iSupport_{ptrn}(left), iSupport_{ptrn}(right)) \leq p_{thresh}$ **then**
    **if** $ptrn \in sFreqPtrns_{left}$ AND $ptrn \in sFreqPtrns_{right}$ **then**
      **if** $\texttt{Mean}(iSupport_{ptrn}(left)) > \texttt{Mean}(iSupport_{ptrn}(right))$ **then**
        $ptrns_{bothLeft} = ptrns_{bothLeft} + ptrn$
      **else**
        $ptrns_{bothRight} = ptrns_{bothRight} + ptrn$
      **end if**
    **else if** $ptrn \in sFreq_{left}$ **then**
      $ptrns_{left} = ptrns_{left} + ptrn$
    **else**
      $ptrns_{right} = ptrns_{right} + ptrn$
    **end if**
  **end if**
**end for**
{Sort categorized patterns by i-frequency difference (left - right)}
$\texttt{SortDesc}(ptrns_{Left})$; $\texttt{SortDesc}(ptrns_{bothLeft})$; $\texttt{SortAsc}(ptrns_{bothRight})$; $\texttt{SortAsc}(ptrns_{Right})$;
**return** $ptrns_{Left}, ptrns_{bothLeft}, ptrns_{bothRight}, ptrns_{Right}$

**Algorithm 1:** Differential Sequence Mining Algorithm

A, followed by B, followed by C, in close, but not necessarily direct, succession).

Further, we employ a sequential pattern mining algorithm that allows regular expression constraints (the *regex* parameter) on the matched patterns. Specifically, we use the core algorithm (`SPAMc`) from Pex-SPAM [Ho et al. 2005], which extends the fast SPAM algorithm [Ayres et al. 2002] with gap and regular expression constraints. Incorporating regular expression constraints provides the ability to focus the comparison between groups on patterns including a specific action, subsequence of actions, or any other partial pattern of interest in an exploratory investigation. As employed in this differential sequence mining algorithm, any sequential pattern mining algorithm will generate the same set of (s-frequent) patterns, subject to any provided constraints that the algorithm can accommodate. Therefore, we refer the reader to the relevant work [Ayres et al. 2002; Ho et al. 2005] for additional details of the SPAMc algorithm.

To compare the identified frequent patterns across groups, we calculate the i-support of each pattern for each sequence in each group, which results in the vectors $iSupport_{ptrn}(left)$ and $iSupport_{ptrn}(right)$ in lines 4-5 of Algorithm 1. Again, to allow for noise in learning traces, we use a maximum gap constraint in calculating the vector of i-support values for a group of sequences. Specifically, we calculate the component i-support values as the maximum number of non-overlapping matches for the pattern (as defined for episode mining by Laxman *et al.* [2005]) in an action sequence, allowing up to *gap* number of actions between consecutive pattern actions during matching.

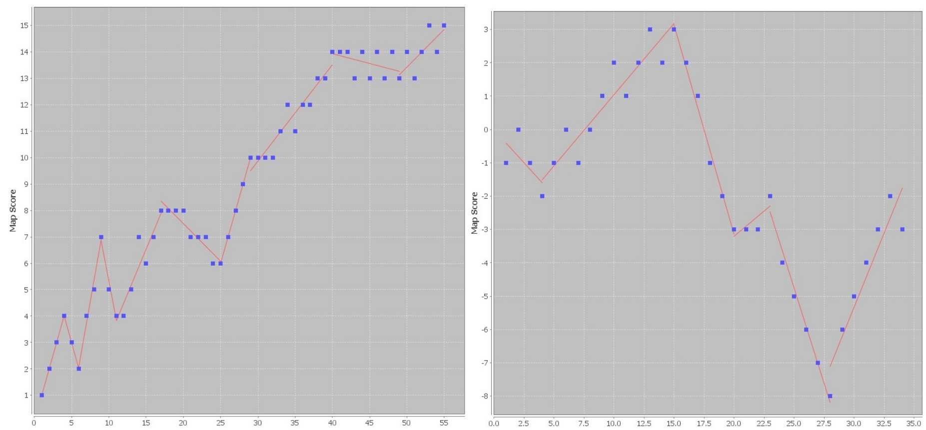
In order to identify patterns whose usage more clearly differ between the two groups, we filter the s-frequent patterns based on the p value of a t-test comparing pattern i-support between the groups (in line 6). Although this approach relies on multiple comparisons by the t-test statistic between the groups, the t-test is not used to *prove* that the two groups of sequences differ. Rather, it is employed as a heuristic for identifying more interesting patterns in an exploratory analysis. Therefore, we do not apply the Bonferroni or other corrections to the p-value threshold for rejecting the null hypothesis. Instead, determining with 95% confidence, for example, that the i-support of the pattern differs between the groups provides a useful heuristic for limiting patterns to those that are likely used differentially in the two groups, while the increased (total) chance of an occasional false positive (incorrectly identifying a difference between the groups of sequences) does not pose a major difficulty in this exploratory analysis.

Comparing the mean i-support value for each pattern between groups then allows us to focus the comparison on patterns that are employed more often by one group than the other. Although a pattern may not be s-frequent in a group of action sequences, it can still occur in some sequences in the group, so an i-support value can be calculated (or the i-support is 0 if the pattern does not occur in any trace in the group). The comparison of i-support values produces four distinct categories of frequent patterns, that are analyzed separately based on how the two groups differ with respect to those patterns: two categories where the patterns are s-frequent in only one group ($ptrns_{left}$ and $ptrns_{right}$ in lines 14 and 16), illustrating patterns primarily employed by the respective groups, and two categories where the patterns are common to both groups but used more often in one group than the other ($ptrns_{bothLeft}$ and $ptrns_{bothRight}$ in lines 9 and 11). The patterns in each of these qualitatively distinct categories are (separately) sorted by the difference in mean group i-support to focus the analysis on the most differentially frequent patterns (in line 21).

### 3.3 Performance Evolution Phase Identification

The differential sequence mining technique can be employed to analyze differentially frequent activity patterns between groups of students, but more generally it can be applied to compare any two groups of sequences. In many CBLEs, such as the Betty's Brain environment described in Section 4, a student's work can be assessed in terms of performance on a learning or problem-solving task. When this assessment can be performed repeatedly over the course of a large task, or a series of tasks, it can provide a rich source of information regarding the evolution of a student's performance and progress. Different patterns of performance evolution may be important in situating learning behaviors with respect to the student's cognitive and metacognitive activities. For example, a student might make slow, faltering progress during the early portion of a task before mastering an important skill or strategy, indicated by a generally increasing performance metric on assessments, but including occasional flat areas or small decreases. This period of slow progress might be followed by a period of rapid, more consistent progress once the student has gained more skill and familiarity with the task. There could also be periods during which the student is struggling and any increases in the performance measure are offset by commensurate (or even larger) decreases.

To more effectively identify and contextualize learning behavior patterns, we compare sequences of actions that occur during different phases of activity with respect to the evolution of a performance or progress measure. These phases are identified by generating a piecewise, linear representation (PLR) for a sequence of two-dimensional points, which correspond to the performance/progress assessments. The y-value of each point is the value of the performance metric for the




(a) High-performing student (b) Lo-performing student

Fig. 1: Example student performance evolution with identified phases

assessment, and the x-value is a cumulative measure of time or student activity (*e.g.*, the number of distinct actions taken in the system) since the beginning of the task. A real example of these points, with the performance phases identified by line segments, is illustrated in Figure 1 for two students in the study described in Section 5. In this example and the analysis presented in Section 6, the performance metric (y-value) was the current map score and each data point corresponded to a map editing action, which was the only type of action that could directly affect map score. Since the map score can both increase and decrease, depending on the students' actions, segments can easily distinguished by positive and negative slopes. However, even with cumulative performance metrics, as long as a reasonable distinction can be drawn between ranges of possible slopes, this method can be applied.

To identify these performance phases, we employ a bottom-up, time-series linear segmentation algorithm [Keogh et al. 2004]. This method begins with the finest-grained PLR in which each pair of consecutive points is a separate segment. At each step every pair of consecutive segments is considered for merging into a new segment, and the pair with the lowest error metric (for the merged segment) is merged. This process is continued until no pairs can be merged without exceeding a given error threshold. In our technique, we employ a standard linear regression to generate each segment and use sum-squared-error (SSE) as the error metric. The example in Figure 1 and the analysis presented in Section 6 employed an SSE threshold of 4, which was determined by a qualitative analysis of productive and counter-productive periods of student activity for a sample of student performance plots.

Our complete methodology consists of four major steps to compare learning behaviors between productive phases of performance and counter-productive phases for a set of students:

(1) *Action abstraction*: Logfiles are processed to produce a sequence of actions for each student by mapping sets of interaction events to canonical actions. Each canonical action is split into high ("-REL" suffix) and low ("-IRR" suffix) relevance types based on its content relation to recent, previous actions. Finally, any subsequences of a repeated action are condensed into a single repeated action ("-MULT" suffix).

(2) *Performance phase identification*: Student action sequences are split into subsequences using the time-series segmentation algorithm. These subsequences are filtered to produce two sequential datasets: a) productive action sequences corresponding to segments with a positive progress slope above a given cutoff, and b) counter-productive action sequences corresponding to segments with a negative progress slope below a given (negative) cutoff.

(3) *Differential sequence mining*: The productive and counter-productive datasets are compared to identify differentially frequent sequential patterns of action.

(4) *Interpretation*: The differentially frequent sequential patterns of action are interpreted in terms of effective and ineffective learning behaviors exhibited by students during the learning task. Investigation of pattern details (i.e., raw event details for instances of these patterns) may yield further insights into student cognition and metacognition, as well as potential flags and triggers for adaptive feedback/scaffolding in the system.

## 4. THE BETTY'S BRAIN LEARNING ENVIRONMENT

This section briefly reviews students' activities as they learn while teaching the virtual agent, Betty, and then discusses our formal cognitive and metacognitive model that outlines the general learning behaviors and strategies that we expect students to develop as they use the system. Further details of the system are presented in Biswas, et al. [2005], Leelawong and Biswas [2008], and Segedy, et al. [2013].

### 4.1 The Betty's Brain System

The Betty's Brain system emulates the learning-by-teaching paradigm to help middle school students develop cognitive and metacognitive skills as they learn in the science and mathematics domains [Biswas et al. 2005; Blair et al. 2007]. Using the visual interface shown in Figure 2, students explicitly teach Betty by constructing a causal concept map [Leelawong and Biswas 2008] that models the science topic under study (*e.g.*, climate change). The nodes in the map are relevant science concepts, and the links represent causal relations between the concepts. Students can learn the domain material that they need to teach Betty using a set of hypermedia resource documents organized into sections by scientific processes (*e.g.*, the greenhouse effect). To understand how direct causal relationships (*e.g.*, vehicle use increases fossil fuel use) can be extended to reasoning about indirect effects through a chain of relations (*e.g.*, vehicle use increases global temperature through a chain of links involving fossil fuel use, carbon dioxide, and heat reflected to the earth), learners can ask Betty questions about the information she has been taught. Betty answers questions using qualitative reasoning methods that operate through chains of links [Leelawong and Biswas 2008] from a source concept to a target concept. The learner can further probe Betty's understanding by asking her to explain her answer. Betty illustrates her reasoning through text and animation; she explains her thinking using text (*e.g.*, "The question said that Vehicle Use increases. This causes Fossil Fuel Use to increase. The increase in Fossil Fuel Use causes...") and animates her explanation by highlighting the concepts and links from the concept map that she used to generate her answer. By asking questions and following Betty's explanations, learners can reflect on and revise their current understanding of the scientific material to gain a deeper understanding of the processes under study. The student can also ask their TA to take quizzes, which are a set of questions created and graded by a Mentor Agent named Mr. Davis. The TA's quiz performance helps the students to assess and reflect on their TA's, and, therefore, their own learning performance.

We expect students using Betty's Brain to typically iterate between reading material from the resources and teaching Betty by building the causal map, while also checking and reflecting on Betty's and their own understanding of the domain knowledge. Students can use the query, explanation, and quiz features to perform this checking and then revise their maps until Betty can correctly answer all questions on the quizzes created by Mr. Davis. To complete their task, students must teach Betty a causal map that matches an expert model of the domain that is hidden from the student. When Betty takes a quiz, Mr. Davis (the mentor agent) compares Betty's answers to those generated with the expert model, and provides information about right and wrong answers. Our previous studies also show that observing Betty's quiz performance (which is actually a reflection of their own understanding) motivates students to help Betty improve her quiz score by first learning/reviewing material related to the domain and then teaching this new or revised understanding to Betty.

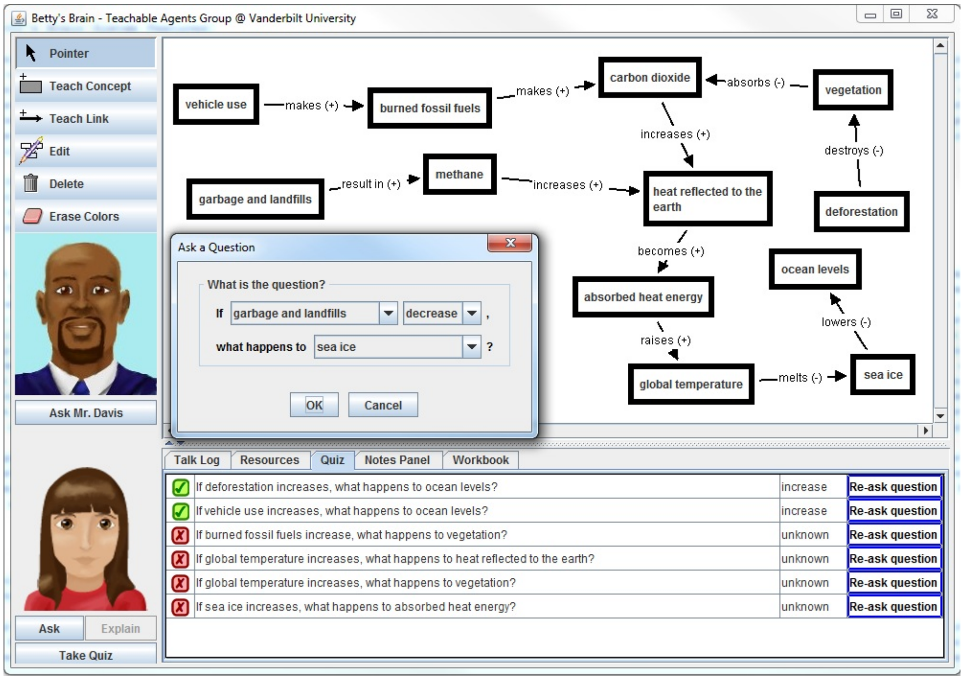



Fig. 2: Interface to the Betty's Brain system

Next, we present an idealized student activity model in the Betty's Brain environment, which provides the theoretical framing of the students' learning tasks in terms of relevant cognitive and metacognitive skills. This model is used to design the agent feedback in Betty's Brain and guides the interpretation of identified patterns from students' activity traces.

## 4.2 The Cognitive/Metacognitive Activity Model in Betty's Brain

The open-ended and choice-rich nature of the Betty's Brain learning task allows a learner to engage in many different combinations of learning activities to achieve their goals. To succeed, learners have to make appropriate decisions regarding when and how to acquire information, build or modify their causal map to teach Betty, check Betty's progress, reflect on their own understanding of both the science knowledge and the evolving causal map structure, and seek help or feedback from the Mentor agent. The variety of available activities and the need to sequence them in appropriate ways requires students to monitor and regulate their own learning processes in order to perform well as both learners and teachers.

However, a number of researchers (*e.g.*, [Schunk and Zimmerman 1997]) have pointed out that students, who are novice learners, are often poor at forethought, and their self-judgment abilities are not well developed. Metacognitive strategies can be taught, but students in typical classrooms are rarely provided the necessary opportunities to learn and master them. Betty's Brain addresses this problem by adopting a cognitive and metacognitive model that promotes a set of comprehensive skills: setting goals for learning new material and applying them to map-building tasks; monitoring one's learning progress; deliberating about strategies to more effectively facilitate learning; and revising one's knowledge, beliefs, and strategies to continually improve the learning performance [Azevedo 2005; Schraw et al. 2002; Winne and Hadwin 2008; Zimmerman 2001]. This framework has guided the design of agent-delivered feedback that encourages students to adopt effective learning strategies as they work in Betty's Brain [Segedy et al. 2012].

Figure 3 illustrates our conceptual cognitive and metacognitive model that we employ to both interpret and support student activity in the Betty's Brain system. The model is not exhaustive, but it does depict significant cognitive and metacognitive skills that have been identified as important for success in both teaching Betty and practicing self-regulated learning (for examples of such metacognitive skills, see [Butler and Winne 1995]). The cognitive layer consists of the cognitive skills that learners need to employ successfully in order to teach Betty correct information. For example, students need to be able to read and understand the resources in order to teach them to Betty. The metacognitive layer focuses on two general areas: (1) *knowledge construction* in which students choose an area of the resources to focus on, and then use that area to guide their subsequent knowledge-acquisition and map structuring activities; and (2) *monitoring* in which students monitor Betty's learning (and their own) in order to assess progress, identify deficiencies, and correct misconceptions. Within these areas of metacognition are several specific classes of strategies for directing students' use of the cognitive skills. The knowledge construction strategies include task decomposition, information seeking, and information structuring; the monitoring strategies include progress monitoring and targeted link analysis; finally, the help seeking strategies include identifying a need for help, seeking out help when necessary, and accepting help when offered. The figure also shows explicit links from the metacognitive strategies to cognitive activities. These links are indicative of ways in which students may employ metacognitive strategies using cognitive activities available to them in the learning environment.

Task decomposition involves both determining how to decompose the map construction task into segments and also linking relevant parts of the resources to each

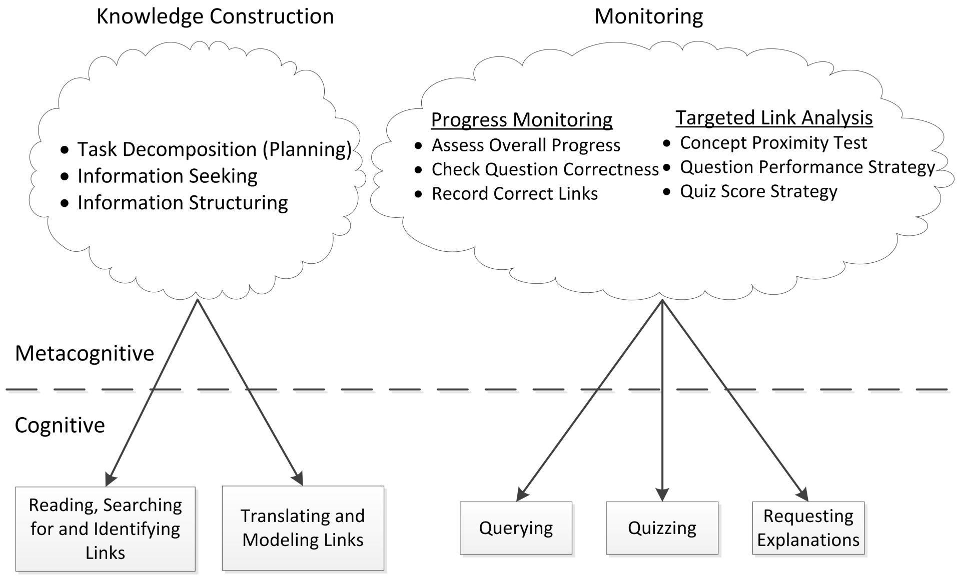



Fig. 3: Model of Cognitive and Metacognitive activities in Betty's Brain

of the segments. As an example, students may identify and focus on a small set of related concepts, and then organize their learning and teaching interactions around this set in a way that promotes efficiency (systematic reading of the resources) and progress monitoring (easier to check and track map evolution and completion). Information seeking refers to strategies for determining when and how to locate needed information in the resources during teaching. For example, if Betty answers a question incorrectly, students may need to revisit pertinent sections of the resources in order to understand her error. Information-structuring is the process by which students decide how to organize the evolving causal map structure.

Progress-monitoring describes how students monitor their progress when teaching Betty, and our model identifies three such strategies: (1) assessing overall progress, which is accomplished by periodically having Betty take a quiz and making note of her correct and incorrect answers; (2) checking question correctness, which is more specific to a particular segment of the map and can involve considering relevant quiz questions and answers, asking Betty a question and reflecting on her answer, and reading relevant resources to assess the correctness of an answer; and (3) recording correct links, which involves noting links that have appeared in one of Betty's correct answers, so the students can systematically keep track of which links on their maps are definitely correct, and which ones may need to be revised.

Targeted link analysis strategies involves using the explanation feature in Betty's Brain to lay out the chain of links used to answer a question, so that links can be checked individually. The concept proximity test strategy describes the process of searching the resources to determine specifically whether or not the two concepts connected by the link in question appear together in the text. If the two concepts don't appear together, then there most likely is not a direct relationship between them. The question performance strategy is accomplished by asking Betty questions that involve the targeted link, and then asking Mr. Davis whether or not her answers are correct. If the link in question repeatedly appears in Betty's incorrect answers, but never appears in one of Betty's correct answers, then the link in question is most likely incorrect.

The cognitive and metacognitive activity model captures the complexity of the Betty's Brain task, and also highlights the wide array of cognitive tasks that students should attend to as they are both constructing and monitoring their understanding of the science domain. Given that our middle school students are novice learners, this complexity presents a problem. In past studies, we have observed that there are many ways to fail in their learning and teaching tasks [Kinnebrew et al. 2013; Segedy et al. 2013; 2012]. Students may have trouble reading; they may not understand causal modeling; or they may have difficulty understanding, selecting, and applying the various metacognitive strategies in the model. Given these potential difficulties, we have developed a number of systematic scaffolding and feedback mechanisms based on our cognitive/metacognitive model described above to support students as they work on the system. The scaffolding and feedback are provided through conversational dialogues between the student and the agents. We do not present the structure and details of our conversational feedback mechanism in this paper, since they are covered in detail elsewhere (*e.g.*, [Segedy et al. 2013; 2012]). In this paper, we focus on the data mining algorithms that we have developed to study students' activity sequences, derive their learning behaviors, and interpret these behaviors in terms of the model presented in Figure 3.

## 5. METHODS

To illustrate our methodology, we use interaction trace data from a recent study with 40 $8^{th}$-grade students from multiple sections taught by the same teacher in a middle Tennessee school. At the beginning of the study, students were introduced to the science topic (global climate change) during regular classroom instruction, provided an overview of causal relations and concept maps, and given hands-on training with the system. For the next five days, students taught their agent about climate change and received feedback from both agents. In this version of the system, the majority of the SRL and metacognitive feedback was for knowledge construction strategies [Segedy et al. 2013]. The Mentor agent also provided some advice on monitoring strategies to help students recognize and correct errors in their concept maps.

To analyze the interaction traces from this study, we abstract student activities into actions in five categories:

(1) *READ*: students access one of the pages in the resources;

(2) *Editing*: students edit the causal map, with actions further divided by whether they operated on a causal link ("LINK") or concept ("CONC") and by whether the action was an addition ("ADD"), removal ("REM"), or modification ("CHG"), *e.g.*, *LINKREM* or *CONCADD*;

(3) *QUER*: students use a template, illustrated in Figure 2, to check their teaching by querying Betty, and she answers using causal reasoning through chains of links [Leelawong and Biswas 2008];

(4) *EXPL*: students probe Betty's reasoning by asking her to explain her answer to a query, which she does through a demonstration of her causal reasoning process with dialogue and animation on the causal map;

(5) *QUIZ*: students assess how well they have taught Betty by having her take a quiz, which is a set of questions chosen and graded by the Mentor agent.

Categorized student actions were further distinguished by their relevance to recent actions, as explained in Section 3.1. *QUIZ* actions were the one exception to this relevance summarization step because the student had no control over whether the content of a quiz was relevant to their previous actions. For this analysis, an action was considered relevant ("-REL") if it was related to at least one of the previous actions within a 3-action window, and irrelevant ("-IRR") otherwise. For Betty's Brain, a prior action is considered relevant to the current action if it is related to, or operates on, one of the same map links (or one of the same concepts if one of the actions being compared only relates to a single concept). This relevance summarization provides an indication of *informedness* for map building/refinement actions and of *diagnosticity* for map monitoring activities [Biswas et al. 2010]. Overall, the relevance summarization maintains some action context by providing a rough measure of strategy focus or consistency over a sequence of actions.

## 6. RESULTS

The results of this study presented an interesting dichotomy in student performance at constructing their causal concept maps, as defined by a map score calculated as the number of correct links (based on the expert map) in the student's map minus the number of incorrect links. 16 of the students taught their agent a correct, complete map or one very close to it (these students achieved map scores between 11 and 15, inclusive, where 15 was the maximum possible score). Another 18 students taught their agents relatively poor maps with a map score of 5 or below. Only 6 students had a map score in between these groups (*i.e.*, a map score of 6 to 10, inclusive). Therefore, we focus on an analysis and comparison of the learning activities of the high-performing ("Hi") student group and the low-performing ("Lo") student group.

| Metric | Hi Group | Lo Group | F | Sig. | Effect Size (Cohen's f) |
|---|---|---|---|---|---|
| Definition MC Gain | 0.535 (0.344) | -0.202 (0.769) | 12.448 | 0.001 | 0.624 |
| Causal Reasoning Gain | 0.130 (0.614) | -0.029 (0.414) | 0.799 | 0.378 | 0.157 |
| Short Answer Gain | 0.027 (0.241) | -0.028 (0.134) | 0.700 | 0.409 | 0.146 |
| Map Score | 14.500 (1.155) | 2.780 (1.592) | 590.171 | 0.001 | 4.314 |

Table I: High vs. Low Performers - Learning Gain and Map Score

For this study, we used three types of questions to assess students' learning gains, calculated as normalized gains ($\frac{(post-pre)}{(max-pre)}$) in pre- to post-test scores: (i) definition multiple choice questions about the science topic testing basic recall of the science material, (ii) short answer questions requiring reasoning about the science topic, and (iii) causal reasoning questions that were not directly related to the science topic. Table I presents averages and ANOVA results comparing the Hi and Lo student groups by their normalized learning gains in each of these categories, as well as their map scores. This analysis revealed a statistically significant difference on definition multiple choice gain and map score. Thus, students who achieved success in teaching Betty accurate causal maps also gained proportionally more factual information, but their gains in causal reasoning and short answer questions were not significantly different from the low-performing group. Further details of the learning gain and pre-/post-test results are available in [Segedy et al. 2012].

| Metric | High Group | Low Group | F | Sig. | Effect Size (Cohen's f) |
|---|---|---|---|---|---|
| Link Accuracy | 60.3% (7.1%) | 42.8% (10.6%) | 31.528 | 0.001 | 0.992 |
| Link Creation Effort | 11.630 (8.196) | 20.665 (5.942) | 12.745 | 0.001 | 0.652 |
| Action Relevance | 53.3% (8.4%) | 40.6% (12.2%) | 12.401 | 0.001 | 0.622 |

Table II: High vs. Low Performers - Knowledge Construction Metrics

Further, we analyzed the students' effectiveness and efficiency in teaching their agent using the causal map representation [Segedy et al. 2012]. Table II displays the means (and standard deviations) for: (i) link accuracy - the percentage of links added to the map that were correct; (ii) link creation effort - the total number of student actions divided by the number of correct link edits, a measure of the effort by the student in order to produce a correct link edit; and (iii) action relevance - the percentage of student actions that were relevant (as described in Section 5) to at least one of the three previous actions[2]. These results indicate that students in the Hi group were more accurate in their map edits and generally more efficient in their learning and teaching activities. Further, they tended to employ a somewhat more systematic approach to the task, as indicated by their higher action relevance score. However, the results also highlight the fact that even students in the Hi group struggled with link accuracy; almost 40% of their link operations (adds, edits, and deletes) were incorrect. The relatively low link accuracy in the Hi group suggests that monitoring behaviors, including the ability to identify and correct erroneous links, may have played an important role in their success.

To identify and compare learning behaviors illustrated by these students' interaction traces, we applied the differential sequence mining technique described in Section 3.2. Because almost all of the most frequent activity patterns in both the Hi and Lo student groups were the same or very similar, this technique allowed us to identify a variety of interesting learning behaviors that were not apparent from separately considering s-frequent or i-frequent patterns. To illustrate these results, Table III presents the top five patterns (that contained at least two actions) in each of the differential categories detailed in Section 3.2. In this analysis, we employed an s-support threshold of 50% to analyze patterns that were evident in the majority of either group of students and employed a cutoff of $p < 0.05$ for a reasonable confidence that pattern usage differed between the two groups. In all of the differential sequence mining results presented here, we employed a maximum gap threshold of 1, to allow for "noise" from irrelevant or interchangeable actions in the learning activity sequences, as described in Section 3.2.

The Hi group's differentially frequent patterns in Table III suggest a greater tendency to check low-relevance additions of causal links (possibly links added based on prior knowledge or guesses) by taking quizzes or by reading relevant resources, as described in the progress-monitoring strategies in Section 4.2. Further, Hi students

[2]In all presented results, we employed a 3-action window to calculate action relevance. Qualitative analysis of interaction traces and talk-aloud sessions has suggested that using a window of more than approximately three or four actions also captures a variety of only incidentally related actions.

| Pattern | I-Support Diff (Hi - Lo) | t-test (p value) | S-Frequent Group |
|---|---|---|---|
| QUIZ → READ-REL | 4.57 | 0.000 | Hi |
| QUIZ → LINKREM-REL | 4.08 | 0.003 | Hi |
| LINKREM-REL → QUIZ | 3.92 | 0.001 | Hi |
| QUIZ → READ-REL-MULT | 3.33 | 0.002 | Hi |
| LINKADD-IRR → QUIZ → LINKREM-REL | 3.14 | 0.004 | Hi |
| LINKADD-IRR → QUIZ | 5.80 | 0.001 | Both |
| LINKADD-IRR → LINKREM-REL | 3.72 | 0.013 | Both |
| LINKADD-IRR → READ-REL | 3.61 | 0.013 | Both |
| QUIZ → LINKADD-IRR | 3.24 | 0.022 | Both |
| QUIZ → QUER-REL | 3.08 | 0.006 | Both |
| QUIZ → READ-IRR-MULT | -1.18 | 0.026 | Both |
| READ-IRR → READ-REL → READ-IRR-MULT | -2.06 | 0.049 | Both |
| QUIZ → READ-IRR-MULT → READ-IRR-MULT | -0.77 | 0.005 | Lo |
| READ-IRR-MULT → READ-IRR-MULT → CONCADD-IRR | -0.84 | 0.007 | Lo |
| READ-IRR → READ-IRR-MULT → READ-IRR-MULT → READ-REL | -0.85 | 0.040 | Lo |
| READ-IRR-MULT → READ-REL-MULT → READ-IRR → READ-IRR | -0.93 | 0.047 | Lo |
| READ-IRR → READ-IRR-MULT → READ-IRR-MULT | -0.99 | 0.048 | Lo |

Table III: High vs. Low Performers - Differentially Frequent Patterns

were more likely than Lo students to follow quizzes with link removals, suggesting that they were attempting to correct errors in their map. The LINKADD-IRR → QUIZ → LINKREM-REL pattern, which was not observed at all in the majority of Lo student action sequences, combines these two trends in monitoring and removing links when they were not related to recent reading or other actions. The Hi group was also more likely to follow a quiz with relevant reading or queries, while the Lo group was more likely to follow a quiz with unrelated reading. Overall, these results suggest a differential effort by the Hi group to use monitoring strategies that made more effective use of the quiz results. These approaches to monitoring may indicate that the Hi students paid more attention to the feedback from Mr. Davis or were better able to understand and implement the monitoring feedback.

To further investigate which monitoring and other learning behaviors may have contributed to the high performers success, we identified differentially frequent patterns when students were productive as opposed to being counter-productive dur-

| Pattern | I-Support Diff (Inc - Dec) | t-test (p value) | S-Frequent Group |
|---|---|---|---|
| READ-REL-MULT → READ-REL | 0.74 | 0.043 | Inc |
| READ-REL → READ-REL-MULT | 0.55 | 0.085 | Inc |
| READ-IRR-MULT → READ-REL | 0.48 | 0.037 | Inc |
| READ-REL → READ-IRR-MULT | 0.35 | 0.039 | Inc |
| LINKADD-REL → READ-REL | 0.32 | 0.016 | Inc |
| READ-REL-MULT | 1.18 | 0.033 | Both |
| READ-REL-MULT → READ-IRR | 0.78 | 0.100 | Both |
| READ-IRR-MULT | 0.67 | 0.036 | Both |
| LINKREM-IRR | 0.58 | 0.000 | Both |
| LINKADD-REL | 0.54 | 0.026 | Both |
| QUER-REL → LINKADD-IRR | -0.17 | 0.032 | Dec |
| LINKADD-IRR → QUER-REL | -0.20 | 0.093 | Dec |
| QUIZ → LINKADD-IRR | -0.20 | 0.073 | Dec |
| LINKADD-IRR → LINKADD-IRR | -0.24 | 0.008 | Dec |

Table IV: Productive vs. Counter-productive Segments (High Performers) - Differentially Frequent Patterns

ing their map building activities. The method for extracting the productive versus counter-productive phases was described in Section 3.3, and we included all segments with a slope greater than or equal to 0.4 in the productive set and all segments with a slope less than or equal to -0.4 in the counter-productive set. The slope cutoff of 0.4/-0.4 was determined by qualitative analysis of a sample of student map score plots to distinguish generally productive/counter-productive segments from ones that were only fluctuating around a stable value. For the differential sequence mining analysis of these segments, we employed a lower s-support threshold because the sequences were significantly shorter than the complete student activity sequences. Specifically, we employed an s-support threshold of 20% to analyze patterns that occurred with some regularity (*i.e.*, in at least one out of every five subsequences). Similarly, given the limited length and number of sequences, we employed a relaxed cutoff on the t-test comparison of $p < 0.10$.

Table IV presents an overview of the results of analyzing productive and counter-productive phases of performance in the Hi group. Of particular interest, these results indicate that extended sequences of reading (both of high and low relevance) were more frequent during productive periods. Further, the addition of links relevant to recent actions were more common in these periods and more often followed by additional reading. Conversely, unrelated reading, especially in conjunction with querying and quizzing was more frequent in the counter-productive periods. These results provide tentative confirmation of the intuition that a systematic approach of reading and teaching information related to one topic or area of the map at a time are generally productive activities in the learning task.

| Pattern | I-Support Diff (Hi - Lo) | t-test (p value) | S-Frequent Group |
|---|---|---|---|
| LINKADD-IRR → QUIZ | 0.38 | 0.000 | Hi |
| QUIZ → READ-REL-MULT | 0.34 | 0.000 | Hi |
| QUER-REL → EXPL-REL | 0.31 | 0.001 | Hi |
| EXPL-REL | 0.31 | 0.062 | Hi |
| QUIZ → QUER-REL | 0.24 | 0.006 | Hi |
| QUIZ | 0.78 | 0.001 | Both |
| LINKADD-IRR | 0.63 | 0.027 | Both |
| LINKREM-IRR | 0.49 | 0.004 | Both |
| LINKREM-REL | 0.31 | 0.081 | Both |
| READ-IRR-MULT → READ-REL-MULT | -0.61 | 0.085 | Both |
| READ-REL-MULT → READ-REL → READ-IRR-MULT | -0.29 | 0.053 | Lo |
| READ-IRR-MULT → READ-REL-MULT → READ-IRR | -0.38 | 0.096 | Lo |
| READ-IRR-MULT → READ-IRR-MULT → READ-REL | -0.40 | 0.068 | Lo |
| READ-IRR-MULT → READ-IRR-MULT | -0.43 | 0.075 | Lo |
| READ-IRR-MULT → READ-REL-MULT → READ-REL | -0.48 | 0.044 | Lo |

Table V: High vs. Low Performers (Productive Segments) - Differentially Frequent Patterns

To gain further insight into the most productive learning behaviors exhibited by the students in the Betty's Brain environment, we employed the differential sequence mining technique to identify patterns differentiating the productive subsequences of the Hi and Lo groups. Specifically, all subsequences corresponding to productive segments in the Hi group were compared with all subsequences corresponding to productive segments in the Lo group, with the results presented in Table V. The LINKADD-IRR → QUIZ, QUIZ → READ-REL-MULT, and QUIZ → QUER-REL monitoring patterns were already identified in the general comparison of Hi to Lo students (Table III), but the results of this analysis suggest some additional behaviors that may have contributed to the success of the Hi students. In particular, employing explanations to investigate Betty's answer to a query suggests a more careful approach to monitoring Betty's understanding. This behavior also suggests that Hi students made a greater effort to implement the targeted link analysis strategies suggested by Mr. Davis, although additional investigation is required to understand why the Lo students were less likely to implement these strategies. Further, both relevant and irrelevant link removals were more frequent in Hi performers' productive periods, which provides additional support to the notion that awareness of the need for monitoring and a willingness to revise one's understanding of the material are important for success in the open-ended Betty's Brain learning environment.

## 7. DISCUSSION AND CONCLUSIONS

In this paper, we presented an exploratory data mining methodology for identifying and comparing learning behaviors from students' learning interaction traces. This novel methodology combines action abstraction, a sequence mining technique to identify differentially frequent activity patterns, and piecewise linear segmentation of activity phases with respect to the evolution of a performance or progress measure. Results from a recent classroom study with Betty's Brain illustrate the effectiveness of this integrated methodology for: (1) identification of important learning behaviors employed differentially between student groups, and (2) analysis of learning behaviors distinguished by their relationship to productive or counter-productive phases of activity.

Although the vast majority of frequent action patterns that can be identified in these interaction traces are common to both high-performing students and low-performing students (and occur throughout the course of students' interaction with the system), the results presented here illustrated some important learning behaviors that are related to either more or less successful performance in the learning environment. In particular, a variety of monitoring learning behaviors employing assessment of progress and recent actions distinguished high-performing students from low-performing students, especially during more productive phases of activity. Further, some behaviors such as the combination of queries and adding links that were unrelated to recent actions, may provide warning signs of counter-productive phases of activity that could be used to provide corrective feedback.

Naturally, the presented data mining methodology is not applicable to analysis of all possible learning interaction traces. In particular, the differential sequence mining algorithm is limited to the comparison of two, mutually exclusive groups of students or activity subsequences (*e.g.*, activity subsequences corresponding to specific phases or other identifiable segments of learning activities) at a time. Further, this methodology requires the definition of meaningful student actions that are relevant to learning behaviors, and the relevance summarization may not be applicable or easily calculated in all learning environments. The identification of productive and counter-productive phases with piecewise linear segmentation is limited to learning environments in which student performance or progress can be periodically assessed with a scalar metric. In addition, this methodology requires some parameters for which there is no general value that can be expected to work across all datasets: the sequence mining gap constraint, the t-test p-value cutoff, the segmentation SSE threshold, and the segmentation slope cutoffs. Although these parameters provide flexibility in this exploratory methodology, they may have to be assigned through qualitative assessment of the data or rules of thumb for learning environments that differ significantly from Betty's Brain.

This data mining methodology is designed to be exploratory in nature by identifying potentially important activity patterns for further investigation. Therefore, we intend to analyze specific instances of the patterns identified here to gain a better understanding of their relationship to successful/unsuccessful learning and metacognition. In addition, we will investigate the generality of the identified patterns by determining whether they are identified with students performing similar learning tasks in different domains. Based on these analyses, we will expand and revise the feedback triggering conditions and student modeling to improve metacognitive strategy feedback from the Betty's Brain agents.

In future work, we also intend to expand upon the presented data mining techniques through a variety of enhancements and additional applications. We will enhance the existing summarization of action-relevance to include determination of the relationship between the specific actions in all subsequences matching the identified patterns. For example, this enhanced action-relevance summarization will allow us to determine how frequently a pattern like LINKADD-IRR → QUIZ → LINKREM-REL involves removing the specific link added in the first action, following a quiz that used the same link in an incorrect answer. Relating identified patterns of action back to specific details and context in the interaction traces could provide significant benefits for more efficient and effective interpretation of learning behaviors. Further, we plan to directly integrate the action abstraction process with the differential sequence mining to autonomously determine the most detailed/specific level of action abstraction (for hierarchically defined/categorized actions) and features (*e.g.*, relevance score and length of reading actions) for which a pattern is differentially frequent.

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