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A Process Mining Approach to Linking the Study of Aptitude and Event Facets of Self-regulated Learning

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ABSTRACT
Research on self-regulated learning has taken two main paths: self-regulated learning as aptitudes and more recently, self-regulated learning as events. This paper proposes the use of the Fuzzy miner process mining technique to examine the relationship between students’ self-reported aptitudes (i.e., achievement goal orientation and approaches to learning) and strategies followed in self-regulated learning. A pilot study is conducted to probe the method and the preliminary results are reported.

Categories and Subject Descriptors
K.3.1[Computers and Education] Distance Learning

General Terms
Human Factors, Measurement

Keywords
Self-Regulated Learning, Clustering, Learning Patterns, Process Mining

1. INTRODUCTION
Existing research on self-regulated learning has taken two main paths: self-regulated learning as aptitudes and more recently, self-regulated learning as events [1]. Aptitudes are theoretical constructs underlying the observed differences between individual learners in specific contexts such as motivational factors, learning styles and epistemic beliefs [2]. They provide as the basis of standards that students use to regulate their learning. More specifically, they influence how learners metacognitively monitor and then control their learning by enacting certain cognitive tactics and strategies in action. Self-reported questionnaire is a common method of measuring aptitudes.

Self-regulated learning can also be conceived in terms of events, the actual actions learners execute rather than underlying mental states that is caused by them [3]. Recent advances in technology-enhanced learning enables for capturing fine-grained trace data of learners’ actions in online learning environments. Investigating occurrence, temporal sequence or regular patterns of events that are products of learners’ cognitive activities and strategies allows for tracing aptitudes in practice [1].

Several studies looked at occurrence and sequence of self-regulated learning actions using the concordance analysis [4], activity transition graph [5] and sequence mining [6]. It is argued that self-regulated learning behaviors, although weakly sequenced, can be assumed to be driven by an underlying holistic model [1]. A recent study introduced adoption of process mining techniques to uncover regular patterns governed by the holistic process [7]. The reported study examined differences in the self-regulated learning strategies and activities and students that have different aptitudes measured by two different constructs.

1.1 Aptitude Measures
In this paper, we specifically focus on the two aptitude measures: achievement goal orientation and approaches to learning. Achievement goal orientation is a common motivational construct which describes “the purpose of engagement in an achievement behavior” [8]. Mastery goal orientations focus on the development of task competence, whereas performance goal orientations emphasize on the illustration of performance competence [9] (with respect to self or others [10]). In terms of valence, these achievement goals may be further distinguished by approaching success and avoiding failure in a certain competence [11]. Prior research has examined association of achievement goal orientations with self-regulated learning behaviors and strategies mostly through self-report instruments measuring constructs such as strategy use [12] or learning outcome [13].

Another aptitude construct describes students’ preferred approaches to learning for a specific task, in a particular teaching context with respect to two dimensions – motives and strategies [11]. Surface study approaches have a preference towards rote learning which is motivated by failure avoidance. Whereas, deep approaches have an orientation towards comprehending and sense making with intrinsic motivation [14]. Relevant literature, has investigated influence of personal and context factors on study approaches [15], as well as how study approaches affect learning outcome and processes through self-report questionnaires [16].

1.2 Research Questions
To our best knowledge, in the context of self-regulated learning, process mining techniques have not yet been applied to identify learning patterns with respect to different aptitudes (e.g., achievement goal orientations and study approaches). This study uses process mining to examine the relationship between students’ self-reported aptitudes and how they self-regulate their learning in action. More specifically, we aim to address the following questions:

- Can we identify groups of students with similar self-reported study approaches/achievement goal orientations?
• Do groups of students with different self-reported study approaches/achievement goal orientations follow different learning strategies and perform different study activities?

To probe a research method that can address the above research questions, we carried out a pilot study with undergraduate students who were asked to conduct a research project and write an essay in an online tool for self-regulated learning.

2. METHOD

2.1 Participants

Participants were third year undergraduate students of an interdisciplinary Interactive Arts and Technology program (n=22) at a research-intensive university in Canada (Female:27%, Male:73%; Age 18 to 24: 14%, 25 to 34: 86%).

2.2 Course and Learning Task

The study was conducted in the context of a course dedicated to internet computing technologies. The course was mainly about the software development with XML and Web 2.0 technologies. Students’ learning was assessed through several assignments, quizzes, final exam and a research project. As a learning task within this study, the students were asked to perform an independent research project on the topic of their choice and write a report in the length of 1200-1500 words. The outcome was evaluated in terms of writing, structure, quality of sources and argumentation and was worth 5% of their final grade. Participation in the study was voluntary and a bonus of 3% counted towards the final grade was offered in return for participation. The participants were asked to fill out several questionnaires and submit those electronically prior to the learning task. Then, they were asked to use the nStudy tool [17] to perform their research and write a report. The students were introduced to nStudy during a lecture session and were advised to use it on their own and seek help if needed.

2.3 Instruments

The R-SPQ-2F questionnaire was adopted to evaluate students approaches to study [14]. It is composed of 20 items, grouped into 4 sub-scales corresponding to study approaches dimensions (surface motive, surface strategy, deep motive, and deep strategy). The students gave responses on a Likert-type scale, from 1 (never or only rarely true of me) to 5 (always or almost always true of me). Out of all students, 20 completed this questionnaire.

The 3×2 AGQ questionnaire was also used to investigate students achievement goals [10]. It consists of 18 items, grouped into 6 categories corresponding to achievement goals (task-approach, task-avoidance, self-approach, self-avoidance, other-approach, and other-avoidance), whereby self and task represent mastery goals and other represents performance goals. The responses were recorded on a Likert-type scale, from 1 (not at all true of me) to 7 (very true of me). Nineteen students completed this questionnaire.

2.4 nStudy Tool

nStudy is a learning tool offered as a Firefox add-on. It is primarily designed to help learners organize and process information as they self-regulate their study of online materials (Figure 1) [17]. It also captures log data of learners’ activities within the environment. A summary of all learning activities is provided in Table 1. In this study, the participants were asked to use nStudy within their research project to bookmark and organize online resources, highlight and quote key points, take notes, define terms and write the final report document. Time-stamped trace data of participants’ interaction with nStudy was collected for analysis. Twenty students used nStudy for their research project.

Figure 1: nStudy Tool
Table 1. nStudy Learning Activities

<table>
<thead>
<tr>
<th>Action</th>
<th>nStudy Object</th>
<th>Learning Activity Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Create</td>
<td>All Artifacts, Chat</td>
<td>Generate a new instance</td>
</tr>
<tr>
<td>Delete</td>
<td>All Artifacts, Chat</td>
<td>Delete an existing instance</td>
</tr>
<tr>
<td>Permanently Delete</td>
<td>All Artifacts, Chat</td>
<td>Delete an existing instance permanently</td>
</tr>
<tr>
<td>Undelete</td>
<td>All Artifacts, Chat</td>
<td>Undo deletion of an existing instance</td>
</tr>
<tr>
<td>Edit Content</td>
<td>Document, Note, Quote, Term, Chat</td>
<td>Modify content text of an object</td>
</tr>
<tr>
<td>Edit Title</td>
<td>All Artifacts</td>
<td>Modify title text of an object</td>
</tr>
<tr>
<td>Expand</td>
<td>All Artifacts, All System Components</td>
<td>Open on the sidebar tree structure</td>
</tr>
<tr>
<td>Collapse</td>
<td>All Artifacts, All System Components</td>
<td>Close on the sidebar tree structure</td>
</tr>
<tr>
<td>Include</td>
<td>All Artifacts</td>
<td>Include as child of other components on the sidebar tree structure</td>
</tr>
<tr>
<td>Exclude</td>
<td>All Artifacts</td>
<td>Exclude child from parent components on the sidebar tree structure</td>
</tr>
<tr>
<td>Switch To</td>
<td>Bookmark, Webpage, nStudy Page</td>
<td>Switch the active page</td>
</tr>
</tbody>
</table>

Note. A learning activity is referred to an action applied on an nStudy object.

+ System Objects: Chat, (root) Collection (of folders), History (of Bookmarks) and Trash

In order to implement above principles, two fundamental metrics were used:

- **Significance**: It measures relative importance of an event class ( Unary Significance) or a relationship ( Binary Significance).
- **Correlation**: It is used for relationships ( Binary Correlation) and computes "how closely related two events following one another are" [12, p.333].

Table 2: Mapping nStudy learning activities to self-regulated learning strategies

<table>
<thead>
<tr>
<th>Learning Activity</th>
<th>Learning Strategy Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Action</td>
<td>nStudy Object</td>
</tr>
<tr>
<td>Create</td>
<td>Bookmark/Quote</td>
</tr>
<tr>
<td>Create</td>
<td>Document/Folder</td>
</tr>
<tr>
<td>Create</td>
<td>Note/Term</td>
</tr>
<tr>
<td>Delete</td>
<td>(any applicable) object</td>
</tr>
<tr>
<td>Undelete</td>
<td>(any applicable) object</td>
</tr>
<tr>
<td>Permanently Delete</td>
<td>(any applicable) object</td>
</tr>
<tr>
<td>Edit Content</td>
<td>Note/Quote/Term/Document</td>
</tr>
<tr>
<td>Edit Title</td>
<td>Bookmark/Document/Folder/Note</td>
</tr>
<tr>
<td>Edit Title</td>
<td>Term</td>
</tr>
<tr>
<td>Expand</td>
<td>(any applicable) object</td>
</tr>
<tr>
<td>Collapse</td>
<td>(any applicable) object</td>
</tr>
<tr>
<td>Include</td>
<td>(any applicable) object</td>
</tr>
<tr>
<td>Exclude</td>
<td>(any applicable) object</td>
</tr>
<tr>
<td>Switch to</td>
<td>Bookmark/Webpage</td>
</tr>
<tr>
<td>Switch to</td>
<td>nStudy Page</td>
</tr>
</tbody>
</table>

Then the following steps were applied to simplify process model according to the principles:

- **Edge Filtering**: If utility of an edge is below a configured threshold then the edge is removed from the output model. The utility of an edge is computed as the weighted sum of Binary Significance and Binary Correlation. The weight is called Utility Ratio:
  \[
  \text{Util} = \text{UtilRatio} \times (\text{BinSig}) + (1 - \text{UtilRatio}) \times (\text{BinCorr})
  \]

- **Node Filtering and Aggregation**: If utility of a node is below a configured threshold then the node is either removed or clustered with other nodes as follows: 1) Low utility nodes with low Binary Correlation are removed. 2) Low utility nodes with high Binary Correlation are clustered together. The utility of a node is equal to Unary Significance.

The following parameter settings were used in our process mining analysis: Significance and Correlation were computed based on the frequency and routing measures for Unary, the frequency and distance measures for Binary, and the temporal proximity for Correlation [12]. The significance cut off for the node filter was set to 0.25. The edge Utility Ratio was fixed at 0.75. The edge cut off was set to 0 for the Learning Strategy level and 0.2 for Learning Activity level.

3. RESULTS

Trace files included 6758 interactions of 20 participants generated over the period of 3-9 study sessions each lasting 20-120 minutes. In total, 718 artifacts were produced using nStudy (Table 3).

Table 3: Descriptive statistics of nStudy artifacts produced

<table>
<thead>
<tr>
<th>nStudy Artifact</th>
<th>M</th>
<th>SD</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quote</td>
<td>15.5</td>
<td>14.28</td>
<td>310</td>
</tr>
<tr>
<td>Bookmark</td>
<td>13.2</td>
<td>7.22</td>
<td>264</td>
</tr>
<tr>
<td>Folder</td>
<td>2.15</td>
<td>2.6</td>
<td>43</td>
</tr>
<tr>
<td>Term</td>
<td>2.05</td>
<td>2.95</td>
<td>41</td>
</tr>
<tr>
<td>Document</td>
<td>1.7</td>
<td>1.26</td>
<td>34</td>
</tr>
<tr>
<td>Note</td>
<td>1.25</td>
<td>1.71</td>
<td>25</td>
</tr>
</tbody>
</table>

3.1 Cluster Analysis

The result of cluster analysis revealed two clusters based on the study approaches. As presented in Table 4, these two clusters (i.e., Surface Learners and Deep Learners) had significantly different scores on the surface and deep approach scales. However, no significant difference was found in the nStudy variables describing the use of different functionalities.

Clustering based on the achievement goal orientation scale scores did not yield satisfactory results as the difference between valences of same competence were not salient within a cluster.
Thus, no further analysis of the learning strategy and learning activities was possible using process mining.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Cluster 1: Surface Learners</th>
<th>Cluster 2: Deep Learners</th>
<th>t-test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
<td>M</td>
</tr>
<tr>
<td>Surface Ap</td>
<td>0.67</td>
<td>0.70</td>
<td>-0.86</td>
</tr>
<tr>
<td>Deep Ap</td>
<td>-0.51</td>
<td>0.99</td>
<td>0.63</td>
</tr>
</tbody>
</table>

N=18; Surface Learners (n=10); Deep Learners (n=8); **p<.01, ***p<.001

3.2 Process Mining

Figure 2 shows the resulting model with events coded on the Learning Strategy level. Rehearsal strategies had the highest utility in both models. Deep Learners (Figure 2, b) manifested a slightly higher utility of Elaboration strategies and a lower utility of Organization strategies than Surface Learners (Figure 2, a). In addition, Surface Learners demonstrated more transitions between strategies. Both models show a one-way loop from Rehearsal to Elaboration, then to Organization and at last back to Rehearsal. However, for Surface Learners there is an additional strong transition from Organization to Elaboration. On the other hand, process mining at the Learning Activity level did not uncover substantial differences between the two groups of learners.

Our findings suggest that process mining techniques are useful for exploratory analysis of self-regulated learning data. They can uncover sequential and temporal relationships that are not otherwise observable through conventional methods of analysis. However, they do not provide causal explanations. In the case of fuzzy miner, the output is a descriptive transition diagram and therefore, cannot be subjected to a statistical significance test. Hence, significance of any observed difference between output models of the two groups of students cannot be statistically confirmed [7].

Several limitations might have affected both external and internal validity of the findings. First, the small sample size might have affected the statistical power. Moreover, with small number of cases, minor changes in parameter configuration of process mining result in considerable variations in the output process model.

Second, the study did not cover a separate learning session where students can familiarize themselves with the tool at hand before the actual experiment. Therefore, trace data includes both the learning phase and actual testing phase which might have influenced the accuracy of findings since students did not have sufficient time to regulate their tool use [22].

Third, post-study surveys about students’ experience with the tool uncovers moderately low tool acceptance. Technical issues and low usability of the tool had negatively affected the perceived ease of use (M= 2.05 of 5). Two students withdrew from using the tool halfway through the study. Further interviews with one of the
participant revealed low perceived usefulness in comparison to similar available tools[23].

Fourth, students’ self-reports of their aptitudes through close-ended questionnaires are not necessarily accurate. Very often responses are influenced by cognitive illusions, such as prior experience, and are not tuned to the learning task at hand[24]. In addition, students’ aptitudes can change over the course of an experiment. Surveys fail to capture temporal shifts[1], particularly with study approaches where additional factors such as teaching and task context have high influence[14].

Despite these limitations, our methodology suggests a new venue for analysis of learning strategies and processes followed in self-regulated learning. Investigating a temporal sequence of events, which is assumed to be governed by a learning process, is in agreement with theoretical models for self-regulated learning[25]. The proposed method needs to be validated with larger sample sizes than the one in the present study and with alternative measures of aptitudes such as the trace data-based measures of achievement goal orientation as suggested by Zhou and Winne[26].

5. REFERENCES