Discovering Policies using Activity Models of Self Regulated Learners

Jordan Aiko Deja and Rafael Cabredo
De La Salle University
Center for Complexity & Emerging Technologies
Manila, Philippines
{jordan.deja, rafael.cabredo}@dlsu.edu.ph

ABSTRACT

Self-Initiated Learning Scenarios are environments that enable students to learn on their own without the supervision of a teacher. Self-regulated learners are students who can greatly benefit from these environments. In this paper, their activities are tracked in order to generate a model for positive learning habits, a set of policies that, if followed, can serve as best practices in sustaining motivation. With the use of an annotation tool called *Sidekick*, these learners undergo a process referred to as self-reflection where they reflect and improve on their learning habits and at the same time label data for scientific use. Twenty five undergraduate computing students who participated in the study immersed themselves in such environments where they were categorized based on their level of self-regulation. A model is created based on their interaction data following a machine learning task. A general model spanning all users and specific models for each category were built based on the interaction logs. These logs were also used to generate a set of rules called policies, employing a profit-sharing algorithm. A set of policies were generated depending on the classification of a student's level of self-regulation which furthermore agree with the generated models. These policies enable the self-regulated learner to discover which among their activities when followed maintain their level of motivation.

CCS Concepts

•**Human-centered computing** → *HCI theory, concepts and models;*

Keywords

Self-Regulated Learners; User Modelling; Behavior Recognition; Profit-Sharing Algorithm

1. INTRODUCTION

Self-regulated learners are students who have established a habit of having initiative of learning on their own even without the need or supervision of a teacher or an agent [25]. As such, personal learning can be considered as part of their personal development or of educating one's self or even both. These self-regulated learners are better than typical learners because of the need to plan out their schedule on how they will learn - simply managing one's time of learning during the actual learning process. Self-regulated learners have the ability to initiate and plan their learning sessions apart from the learning activity per se. The learning process is therefore extended with the tedious task of managing one's time, schedule and resources. Learning becomes self-oriented which is usually aided by motivation [18].

In this process the learner either enjoys or feels motivated to pursue studying on his or her own. Motivation encourages the student to continue learning even without the presence of an actual reward system. In such scenario, the task of ensuring motivation and attention is a bigger task in itself aside from learning the actual subject at hand. The activity in itself poses a greater challenge to the learner. The process of managing one's learning activities, reflecting or evaluating a student's previous actions have been considered an integral part of being a self-regulated learner [12]. In this paper, we refer to policies as a set of activities that a learner performs where their motivation levels, in the form of the weight function, are captured. This enabled the authors to identify if a certain set of activities contributes to the over-all goals of the learner for a certain learning session.

This paper also discusses the techniques employed towards discovering these policies. More importantly, it addresses the problem of how can the activities of self-regulated learners can be modelled into a set of policies that can best help them learn further. These policies describe how their motivation levels have changed based on a set of activities they have performed across multiple learning sessions. Related work on self-regulated learners are seen followed by the framework in this study. Models and algorithms employed towards discovering policies are mentioned afterwards followed by the results and some future work that need to be tackled.

2. RELATED WORK

Several studies have investigated self-regulated learners: starting from what activities define them [26], how to teach a learner into becoming a self regulated learner [9, 21, 22], and on discovering the natural attributes into becoming a self regulated learner [3, 5]. When self regulated learners are immersed in on-line environments, their activities and transitions become an actual subject of inquiry [2, 13, 17]. Most of these studies have only measured motivation levels given differences in gender and levels of academic level (graduate vs undergraduate). While a number of studies have investigated self-regulated learners and their attribute measures – usually on setups supervised either by a teacher or an agent – there are limited studies that have investigated on self-regulated learners, learning totally on their own. The learning activities the students undergo to and how many off-activities are planned in between play a key factor in the management of both their learning and planning activities [23].

There have been many studies that investigated the activities of regulated learners, especially those partaking in online sessions or learning on their own [4, 10]. These were made possible by the tracking of their interaction logs (a combination of keystrokes, mouse gestures, information on the running background applications). The self-reflection phase was also employed allowing students to annotate their own performance after a learning session. Policies were generated from this given data. A data collection tool made specifically for self-regulated learners called *SideKick* was used. This tool enables students to immerse themselves in a learning session approximately running for an hour each and while doing so, their data is being collected in the background. From the given interaction logs, both transition and policy data were created using a set of combination and rules as defined in the study by [19]. From here, it was postulated that self regulated learners perform a set of activities that do not go beyond the definition of being independent and regulated learners.

3. METHODOLOGY AND FRAMEWORK

This research had three major phases, namely, (1) Data Collection and Preparation, (2) Data Modeling and (3) Policy Construction. See Figure 1 for the scope of activities undertaken in this research.

3.1 Data Collection and Preparation

A sample of 25 undergraduate computing students enrolled in the same course attended a one-hour presentation about Sidekick where they were oriented, instructed and given a demonstration on how to use the software. Prior to this, they were given a Pre-Session questionnaire as patterned from the study of [6]. This questionnaire aimed to measure their level of self-regulation, the results of which were used to categorize them as students with low, medium or high self regulation. They were given consent forms regarding the data collection process, especially on the privacy and usage of their data. In return, participating students were given incentives at the end of the course when all the data have been successfully-completed.

The students volunteered to install and use the data collection tool SideKick to have their interaction logs submitted. The students were requested to let SideKick run in the background while they are performing a specific academic task with the use of the computer. No other instructions were given to ensure a controlled but less obtrusive learning experience for the students. These had to be ensured to allow the most authentic self-regulated learning experience for the students. Part of the SideKick tool measured and assessed their level of self regulation determined thru a coefficient called an *autonomy index* [7]. The methodology allowed students to use sidekick whenever it is possible and convenient. This would work best especially when they are doing tasks related to the programming course. Each of the participants used sidekick for a minimum of ten sessions where each session lasted for at least an hour. Which activities to perform were up to them, and later they have to label under which categories these activities fall, as defined by [11].

After a two to three week period of data collection, the students submitted their local copy of the database which contained the repository and the individual Personal Interaction Data (PID), Personal Transition Data (PTD), and Personal Policy Data (PPD) in their machines. These were collated and organized based on the needed models to be produced in the study. The data were accessible with the use of a Hypersonic 2 (h2.jar) that served as the database management system of the said repositories. Without the credentials and login information, the data would just appear gibberish to anyone unauthorized to access them.

Students performed their learning activities with SideKick running in the background recording their interaction logs. These were all stored in the PID. At the end of each learning session, students performed self-reflection thru the annotation of their activities. In this process they got to: (1) identify the task that they have done during the session by highlighting and labeling based on the given choices and predefined activities; (2) identify the affect they were experiencing during the said highlighted activity from the affects identified by [8], and (3) measure how the identified activity has contributed to the goals of that specific learning session. Following this approach, the students were able to contrast two or more activities during a single session where they got to label the type of activity they were doing: the affect they were feeling during the said activity and the rate (between 1 to 7) of how useful the activity was to their learning goal in a session.

The Personal Interaction Data (PID) contained the raw data acquired from the interaction logs of each user. It contained information regarding the activities of each user such as the number of key presses per second, mouse movement traveled (in dots per inch), mouse wheel movement (positive for upwards, negative for downwards), and facial captures to name a few. These interaction data were also exported per session per student in order to be able to acquire a fine-grained analysis of the interactions. The said data sets were prepared in a CSV (comma-separated values) format so that they can be imported and fed into the data modelling stages of this study. All these interaction logs were not only automatically-collected but were annotated by the students themselves.

The Personal Transition Data (PTD) were computed data transformed from the interaction logs. These were interaction log entries that were grouped into one activity, repre-

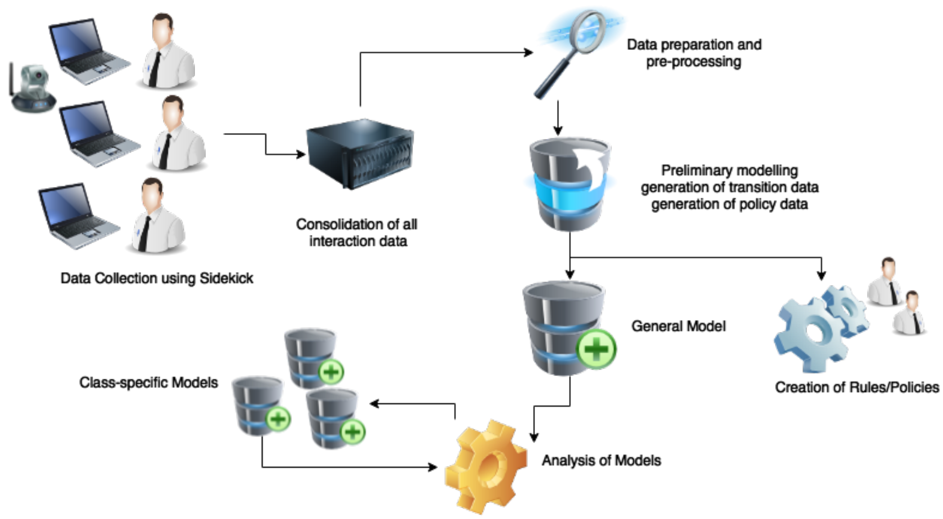

Figure 1: Framework of the research

senting a certain transition in the learning session. When the learners performed self-annotation of their activities, highlighted segments in the timeline group recorded interactions (in seconds) as one transition block. The students got to label the type of task they have defined from a set of choices. These choices represented the typical activities that a self regulated learner usually partake in when they are in a learning session [19].

The Personal Policy Data (PPD) processed the interaction and transition logs of the students. More details on the policies will be discussed in the Policy creation subsection of this paper.

This data collection process subscribed to the self regulation framework by Zimmerman [24] as augmented by Inventado's addition of retrospection phase [14] as seen in Figure 2. The self-evaluation and self-reflection phases were reflected in the annotation schemes with the use of the tool *Sidekick*.

3.2 Data Modeling

From the consolidated interaction logs of the students, two more data sets were derived, namely, the Process Transition Data (PTD) and the Policy Data. The individual activities of each student respondent were identified as historical learning behaviors. These were best represented by the transitions. The policies, following a profit-sharing algorithm, described how a certain activity performed by a learner has been useful to his or her learning goal. This is usually seen by the numerical value we refer to as *weight*. An increase in the weight value in the policy would signify an increased rate of usefulness, thus describing the activity's contribution in the learning session. The conversion of transition and policy logs are referred to as Contextualized Action Sequences. These sequences can run on a model-free environment without compromising data quality and enabling multiple domains to converge while eliminating the need for a Markovian property [1]. This approach was selected with the understanding that the data were acquired in an un-

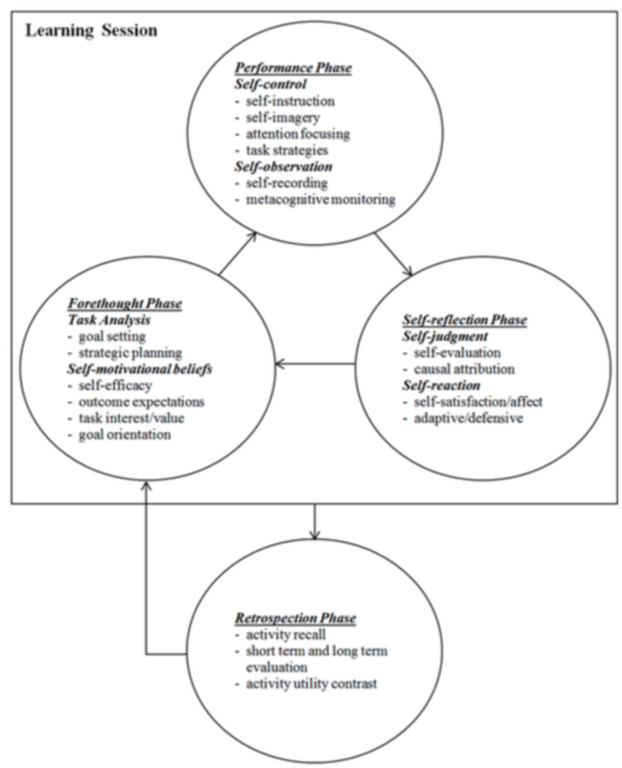

Figure 2: Addition of Retrospection phase by Inventado to the Model of Self Regulation by Zimmerman.

controlled environment. Despite the self-regulation level of each respondent, there is still an uncertainty in dealing with human behavior using a fully deterministic approach.

This is where the Profit Sharing Algorithm comes in with the treatment and modeling of the activities, in contrast with the motivation levels of the students alongside their transitions in consideration. An observation-action pair (O_t, A_t) is received as an input of sequences, where O_t is the observed from a performing action A_t. O_t refers to the state of a student as described by the activity it is in [13] . The activities A_t were categorized as follows:

- Short - activities performed for less than five (5) minutes
- Medium - activities performed between five (5) to ten (10) minutes
- Long - activities performed beyond ten (10) minutes

In return, these observation pairs were given a function returning a value specified by reward R as seen in the ARCS model [1]. A weight W_n which measures the motivation level of the students is returned, as seen in the mapping and equations below.

$$W_{n+1} \leftarrow W_n(O_t, A_t) + f({}_{n}^{T}, t) \tag{1}$$

$$f(R_t, t) = R(\frac{1}{L})^{T-t} \tag{2}$$

$$L \sum_{j=0}^{t} f(R_j) < f(R, t),\ \forall t = 1, 2, \cdots, T. \tag{3}$$

$f({}_{n}^{T}, t)$ is the variable used for a credit returned from an assignment function where t is the rule's position of time with respect to the current episode T. Following this approach, the resulting weight values W_n may tend to be updated more than once since there are multiple instances of t with respect to T. Following this approach, the specific policies are then generated and seen with their weight values. It is important to note that policies are considered a rational and guaranteed convergence to the solution following the credit assignment function [1]. This satisifes the rationality theorem as seen in the equations above. The variable L represents the number of possible actions in a certain state configuration.

To provide an improved illustration of the profit-sharing algorithm, we refer to Figure 3 as illustrated by [11] in his study. The process iterates the computation of the profit sharing algorithm starting from an initial state. In here, the student feels Engaged as the affect while he makes a learning plan for the current session. Given this example it can be seen that the student feels that the task of creating a learning plan might not be contributing much to his current learning task. Following a given short time, the student decides to proceed to performing a different action depicted by A_t (searching for information as a new task). The parameters are then updated as the observation and activity pairs changes, thus with the help of the profit-sharing algorithm

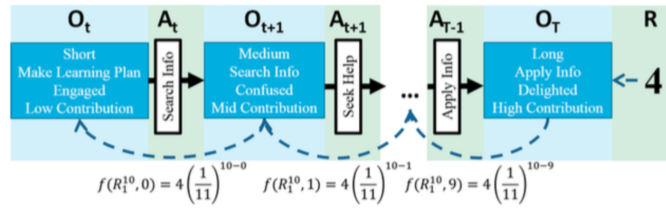

Figure 3: Observation-Action Pair Updating Cycle by Inventado

adjusting the computed resulting weight until a final weight or policy is arrived at. All these values are relative to the ARCS scale initially defined by [16]. These values particularly mean:

- Attention - engagement of the student to the said activity
- Relevance - relation of the activity to the student's goals and intentions
- Confidence - level of achievement by the student
- Satisfaction - how the said activity applies to the real-life applications

It is important to note that with this function, the values of the weights in the policy may change over time. In consideration of this, the latest value of the policy can be used as a reference point to evaluate the learning session the student is in, and this can be used to measure how his motivation levels have changed over the series of activities. All these policies and weights were computed per student respondent and generalized into another dataset. These formed the Process Policy Database (PPD) as earlier mentioned.

On a different note, all the interaction data from the PID were compiled as earlier mentioned. The interaction data set was fed into a machine learning classifier specially-designed for contextualized action sequences. The MLP was a classifier which was further modified to fit this study. Specifically, the typical multilayer perceptron (MLP) employs the sigmoid function as categorized by the equation below:

$$\gamma(v_i) = tanh(v_i) \tag{4}$$

which can be approximated by the function

$$\phi(v_i) = (1 + e^{-v_i})^{-1}, \tag{5}$$

where the former describes a hyperbolic tangent while the latter describes a logistic function ranging from 0 to 1, which is similar in shape. The specialized MLP network employs the same function but allows non-nominal and string-based data such as the labels of sequences and tasks to be part of the attributes in the data set. The standard values for learning rate, the number of hidden nodes, and momentum were set with the use of RapidMiner. The experiment, training and testing were deployed on a process which consists of a 10-fold cross validation with 500ms as the minimum training time per iteration. Additionally, several machine learning tasks were employed to provide a benchmark on

Interaction Data	Average	Max	σ
mouseclick count (per sess)	43	796	1.3
mouse movement dist (dpi)	40287	819982	1350.7
key input count (per sess)	415	21250	5.7
contribu level (per sess)	3.1	4	0.8
face captures (in secs)	197	3149	0.5

Table 1: Interaction Data Statistics

the results and performance of the model. These included the Naive-Bayes and decision tree classifiers on all groups of the data sets.

4. RESULTS

4.1 Policy Creation and Data Analysis

A bipolar classification was performed on the students depending on their level of self regulation: (1) students with low self-regulation and (2) students with high self regulation. As a result, 13 students were classified into the lower half of the self regulation scale and the remaining 12 were classified into the upper half of the said scale. In the data collection for the self reflection phase, the students were to recall their activities by annotating them with the use of Sidekick. Students spent an average of 58.1 minutes in every learning session. On average, they have annotated 4.4 transitions in each session. The most used activity per student is the Practice Skills task which on total consumed 47.8 minutes per student (80% of a session on average for the entire 10 sessions). Students in general spent the least time on Taking down Notes; such task took a total of 21 minutes per student (35% on average for the entire 10 sessions). This can be directly-linked to the presence of the Internet connection, the ubiquity of information and the modernization of the use of slides in contrast to the use notebooks and writing by pen and paper. Additionally, the most noted affect was the Engaged affect which appeared in a total of 500 instances. Table 1 below show other details on the interaction data of the respondents.

The results presented in Figure 4 show that among the 11 categories of activities, students spent the most time practicing their skills as evidenced similarly in Figure 5. However, it is also notable that Off-tasks form a large average time spent by these self-regulated learners. In the latter part of this analysis, it can be understood further why and how Off-task category is prevalent and is related to maintaining motivation among these self-regulated learners. In conclusion, even if the Practicing Skills category is the most-used useful task, it is difficult to ignore that these self-regulated learners spent an ample amount of time doing off-task things on their own. This can lead us to conclude that the data collected can be reflective of real scenarios and that this can testify on the actual self-regulation level of each of our respondents.

Another portion of this study is to determine the different activities that students undertake. These were derived by combining the policy and transition data of the interaction of the students while using Sidekick. With the use of the data modeling techniques, the following attributes were pulled out to form a behavior model:

- Session Number
- Initial state on that session number
- Final state on that session number
- Type of activity currently being performed
- Affect during the said activity or task
- Weight of the said activity in relation to the motivation of the students

The effectiveness of the reflection phase performed by the students while on each learning session were captured. These were fed into the ARCS model of computing using the Profit-Sharing Algorithm [16] where the ratings were computed at the end of each learning session. These ratings were tabulated and evaluated per student to determine the over-all effect in the self-regulation of a particular student. The derived weight values are what we refer to as *policies* with the help of the profit sharing algorithm. Among the 25 respondents, the highest recorded policy weight is 15.3 ($\overline{x} = 0.5$). Students categorized with having low and high self-regulation were observed to have the following behavior data in the form of policies (see tables below):

Table 2 presents these policies featuring their motivation levels from the 1st, the 5th and the 10th sessions of their learning activities. The original data covered multiple instances of the activities performed by the students and their corresponding weights. What was captured describes the change in their motivation from the time they started their learning (1st session) all the way to their last (10th) learning session. The values that contained the highest weights and is common among the same type of learners were acquired and used as the value for the state description. The source state describes the state where the description began. The Action Performed column describes the succeeding activity the student performed from the activity described from the state description column. The weight indicated the level of motivation that the described activity has made the student feel.

The table shows the changes in the learning policy of the students over different sessions. The 1st session was the initial session, the 5th session was the midway breakpoint and the 10th session was an assessment reference point to determine if there has been a change in the values and motivation levels of the learners across all past sessions. Analyzing the review patterns of Student Type 1 (or with low self-regulation), it can be observed that their motivation levels begin at a zero point . Since these are low regulated students who are not highly motivated compared to their counterparts, it is safe to assume that the typical activities that self-regulated learners dwell into may be confusing for these borderline self-regulated learners. Which is why, as seen in Table 2, a pattern is observed where it usually took them a long time modifying their learning plans (MLP refers here to the task of modifying the learning plan), and this task on most cases gave them the confused affect. It is by the end of the first session that the learners saw a need to modify their learning plans further: an indication that they might still be practicing the task of making learning plans towards becoming a more self regulated learner. There

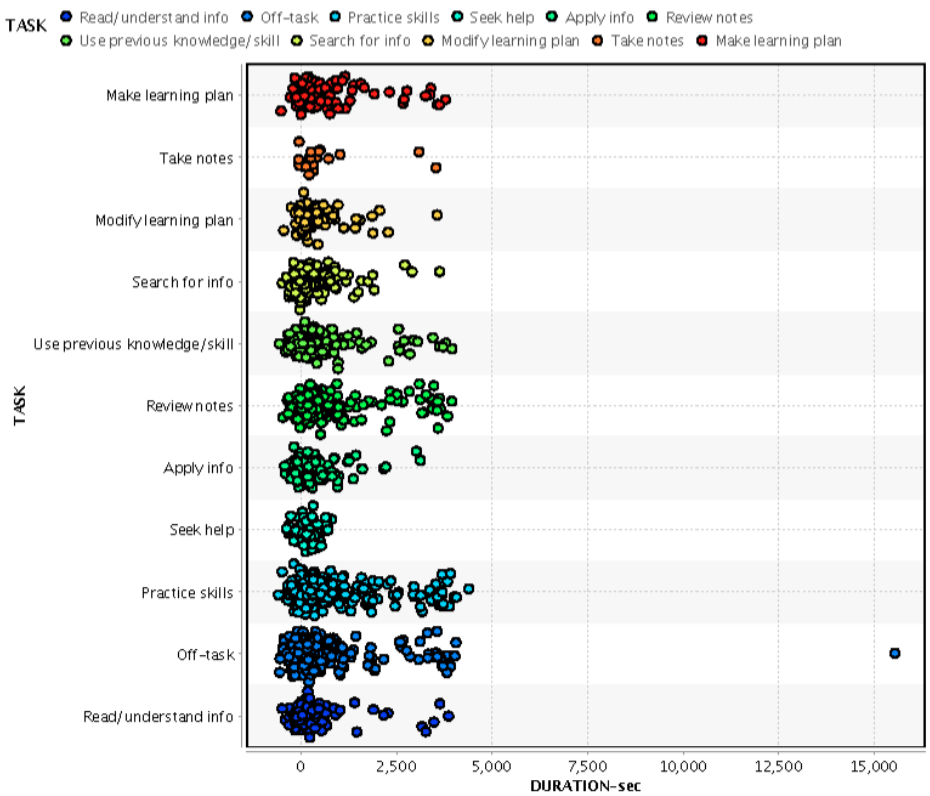

Figure 4: Scatterplot of Transitions and their average duration

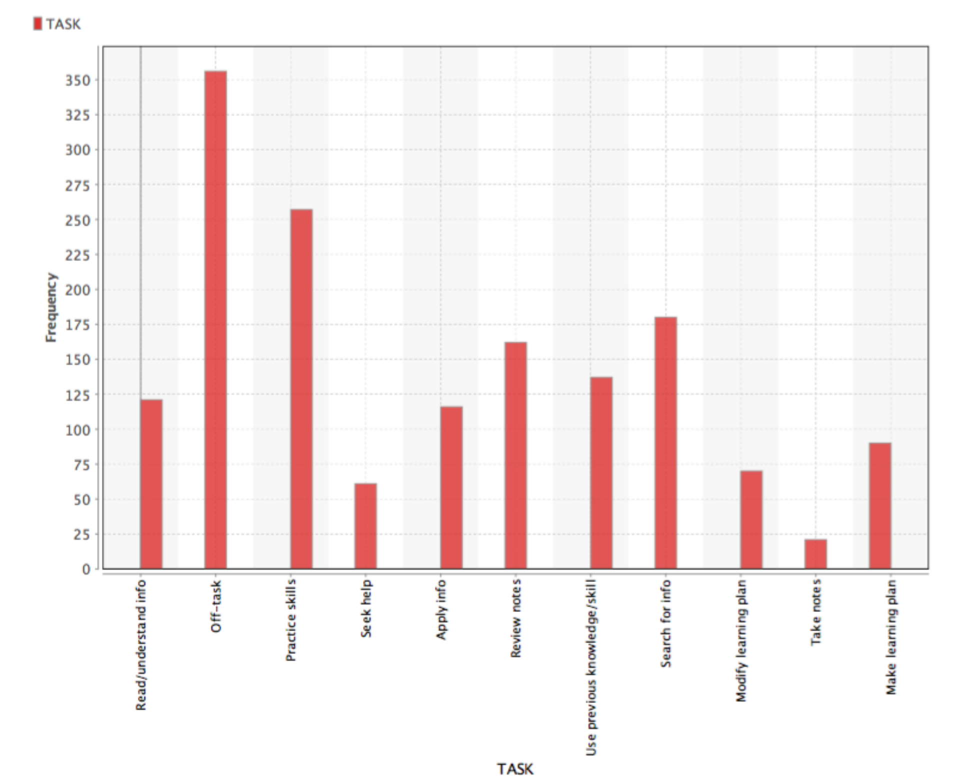

Figure 5: Histogram of Transitions and Average Time Spent per student

Low Self Regulation							
Session No.	Source State	Length of Activity	Activity Performed	Rate	Affect	Action Performed After	Weight
1	Initial	Long	MODIFY	2	Confused	MODIFY	0.0
1	Final	Short	MODIFY	2	Bored	MODIFY	0.0
5	Initial	Long	MODIFY	2	Frustrated	MODIFY	0.0
5	Final	Medium	MODIFY	3	Confused	MODIFY	0.3
10	Initial	Long	MODIFY	3	Bored	MODIFY	3.0
10	Final	Long	PRACTICE	3	Confused	PRACTICE	15.3
High Self Regulation							
Session No.	Source State	Length of Activity	Activity Performed	Rate	Affect	Action Performed After	Weight
1	Initial	Short	OFFTASK	4	Bored	OFFTASK	3.2
1	Final	Short	MAKE	4	Enggd	OFFTASK	3.2E-12
5	Initial	Medium	MODIFY	3	Enggd	OFFTASK	0.003
5	Final	Short	MODIFY	4	Enggd	SEARCH	0.0003
10	Initial	Short	OFFTASK	3	Neut	READINFO	0.00002
10	Final	Long	READINFO	4	Enggd	SEARCH	3.5

Table 2: Policies generated for students with both low and high self-regulation

was no significant change in motivation levels so far. The same learner progressed thru the 5th session and attempts to continuously modify the learning plan was still present. The assumption here was that they have finally understood the rationale to have an established learning plan in order to keep themselves motivated. It is observed that though their affects switched from frustrated to confused, there is a significant jump in their motivation from the absolute zero state. Progressing towards the 10th session, there was a flux of motivation levels as these learners become more concerned with their learning plans, yet the task has shifted focus towards completing the learning task at hand and not on focusing on creating the learning plan. The long period spent on creating and modifying their learning plans have taught the students enough motivation to lead them towards practicing their skills on long periods of time, as seen with a great jump of motivation to a value of 15.3. See Figure 6. What is noticeable about these self-regulated learners is that the confused affect followed by a bored affect provided a boost in their motivation levels. These changes in affect displayed a self-regulated factor among these students that might indicate that they want to get the job done no matter what.

The other half of the learners were clustered together because of their high autonomy index scores. This means that they are highly self regulated learners as compared to their counterparts. They begin with an above zero score of motivation (3.25) on their first learning session - an obvious difference from the other group of learners who began with motivation levels below zero. Interestingly, the length of their activities go through across all three types from short to medium to even long tasks. It can be observed with these durations that they are regulated enough to know which tasks should be given greater focus and which should not be. The shift from the 1st session to the 5th session displayed that the learning plan created was not too effective, as seen with the drop of motivation and upon modification of it gave a rise to the said value (see Figure 7). The number of off-tasks was significant which indicated a similar approach done by normally self-regulated learners who wished to reward themselves from time to time. Given the 10th session data, a transition from reading additional information boosted not only the motivation level but also the affect (affects shifted between Neutral to Engaged).

Considering the motivation levels between the different types of self-regulated learners, additional data would be necessary to establish the existence of plateau values for the motivation levels in attempts to significantly increase these levels from time to time. Notable differences between these types of learners can be seen as: (1) their initial motivation level when beginning a learning session, (2) the growth and spikes in their motivation along the different learning sessions, and (3) the threshold value to where these motivation values are limited. Low self-regulated learners who began with a zero motivation value later made a big jump to a score of 15.3 (the highest recorded motivation weight in this study). On the other hand, the highly self-regulated ones had intermittent below-zero values of motivation, yet managed to maintain a momentum in the values that range between non-extreme values. Highly self-regulated learners are keen on exploring multiple types of activities as seen in their activity duration and types of tasks performed. Exploring other activities can give students a helping boost in discovering states and transitions that make them more productive [15].

4.2 Data Modeling

The Interaction data, composed of all the collated interaction data of each respondent was prepared in one data set and was fed with a classifier specially-trained for contextualized sequences. A modification of the multilayer perceptron pattern was created to accommodate contextualized sequences. On the over-all, the perceptron employed additional hidden nodes to accept sequences and numeric labels without the need to use a sigmoid network. The training and validation of the model took around 15.9 hours to complete with the use of RapidMiner (covering almost 705,000 instances, 17 attributes and 1 label). Table 3 shows that the general model performed with an accuracy of **42.08%** and a kappa statistic value of **0.3**. The combined interaction data from all types of self-regulated learners forming the generalized model performed below average than expected. The borderline kappa statistic of 0.3 indicates that even if it is

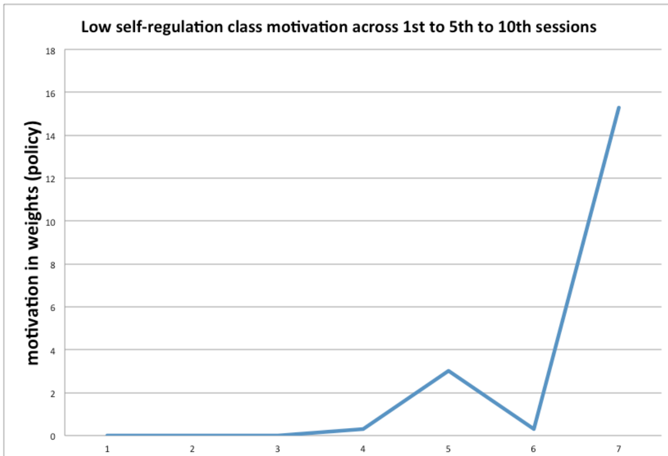

Figure 6: Changes in Level of Motivation of Low Self-Regulation Learners

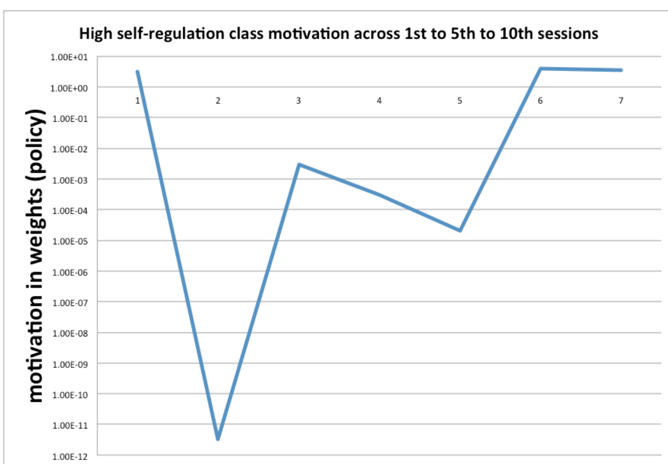

Figure 7: Changes in Level of Motivation of High Self-Regulation Learners

Category	Classifier	% Accuracy	Kappa
Low SR	Decision Trees	79.01%	0.7
Low SR	Naive-Bayes	28.03%	0.1
Low SR	Multi Layer Perceptron	51.4%	0.4
High SR	Decision Trees	29.8%	0.07
High SR	Naive-Bayes	16.6%	0.04
High SR	Multi Layer Perceptron	46.7%	0.4

Table 3: Two-Way Interaction Data Models

at an acceptable range [20], it can be assumed that the data was not perfectly fit to work for the range of self regulated learners.

The combined interaction data could be divided with a simpler approach that provide a two-way overview of how the data was spread out. Grouping the students on the upper and lower half of the self regulation scale created models with different performance scores proved to have produced better results as seen below:

5. CONCLUSION AND FUTURE WORK

5.1 In Summary

Self regulated learners performed self-reflection by annotating their activities according to the affect, as categorized by [19], and the level of contribution they thought the learning session task has done to their overall goal of learning. The effect of the retrospection phase enabled the two types of self-regulated learners to have their own clustered learning policies [11, 25]. Each category was able to produce a total seven rules following the policy and the profit-sharing algorithm. Upon discovery of these learning behavior patterns, it has been observed that motivation levels spiked and fluxed at varying points, hereby establishing that their motivation levels, their current affect and their productivity can be influenced by the type of activity that they are performing. In other existing research papers, policies were computed based on simulated data, whereas in this study, these were computed using actual data provided and annotated by the learners themselves. As such it has been observed that the relationships between the student's motivation ratings and the performance of *optimal* actions, when followed, enhanced the motivation of learners across the learning sessions. The learning behavior patterns have shown that the level of self-regulation is directly proportional to the number of activities and combinations of tasks that a learner can perform in a session. Several types of activities were performed by students who were more of regulated learners as compared to their less-regulated counterparts. A pattern among highly self-regulated learners have also been found that hints at a plateau value or a consistent rate of motivation when a set of activities are strictly-followed. This last observation is yet to be further investigated.

Upon creation of a unified data set containing the interactions covering all types of self-regulated learners, a machine learning task was employed to evaluate and validate its correctness. With the use of a multi-layer perceptron that is context-aware, the output model performed below average with an accuracy rating of 42% only and with a borderline acceptable [20] kappa statistic of 0.3. It can be inferred that both the data and the model performed below average because of its diversity, its completeness (since it covered two types of self-regulated learners all in one data set), and its complexity. Intermediary information describing background applications have been added as an attribute but this was not enough to help improve the performance of the model.

With the performance of the model from the unified data set and the diversity of the rules among the two types of self-regulated learners, and in order to model correctly and further the activities of these self-regulated learners, the design, development and use of a class-specific model, instead of a general model, would be more appropriate. Upon performing clustering on the existing interaction data, better results arose. The divided two sets, based on the level of self regulation were used on a machine learning task and yielded results that were not only average and acceptable but also consistent with rules generated from the policy data. The activities whose class labels fall under what were defined in the classifier where highlighted, and these closely agree with the activities and sequences identified to be notably motivation-inducing as dictated by the policies. These activities had notably high precision and recall scores which provided a good indicator for these models. The methodologies and techniques employed in the study were able to generate and identify the learning patterns of self-regulated learners covering two specific classes (low and high self-regulation). The data has also demonstrated that a unified general model cannot be easily created covering these types of learners and instead requires the formulation of a possibly distinct but class-specific model.

5.2 Future Work

This research can be directed into several directions, depending on which area of the results would have to be explored. Given the limited number of participants, it is recommended that the experiments be performed on a larger set of participants.

The identified policies and rules in this study can be further modelled into temporal likelihood transitions [8] which can be enabled to determine the changes in the learning behavior should there be more than 10 sessions. This likelihood function is defined by the equation below:

$$L(A_i, A_{i+1}) = \frac{P(A_{i+1}|A_i) - P(A_{i+1})}{1 - P(A_{Ai+1})} \tag{6}$$

The learning behaviors and the resulting changes in these activities can be most likely predicted. The said activities and learning behavior patterns of these self-regulated learners can be modeled into temporal transition likelihood graphs which can enable us to understand further the changes in their actions from the 10th session and beyond.

One aspect that was not tackled in this research is incorporating the concept of feedback which can be used to train non-regulated learners and potentially improve type 1 or low self-regulation learners. With the incorporation of the policy and providing a feedback facility module that interacts with a student beyond the learning session along with further assessment techniques that can be used to determine if a student had an improved level of self-regulation.

The tool *Sidekick* can be improved where with the identification of the learning behavior patterns and with the creation of user-specific models, the annotation can be semi-automated at the instance when the effort of self-annotation is less. These and all without compromising the self-reflection phase that students undergo when they annotate their data.

Finally, the approach and tools presented in this paper can be used to evaluate the productivity levels of employees and rank and file workers who use computers. By adjusting a few parameters and using a different instrument to measure self-regulation among adults, the study can be imported to help managers and policy makers determine which activity patterns produce the most motivated and productive employees.

6. ACKNOWLEDGMENTS

The authors would like to thank the Institute of Information and Computing Sciences of the University of Santo Tomas for allowing them to conduct data gathering on the said self-regulated learners. Also, the authors would like to acknowledge the support and guidance given by Dr. Paul Salvador Inventado for the thoughts and insights he has shared throughout the study. This would have not been possible without the funding and support from De La Salle University.

7. REFERENCES

[1] S. Arai and K. Sycara. Effective learning approach for planning and scheduling in multi-agent domain. In *Proceedings of the Sixth ISAB: From Animals to Animats*, volume 6, pages 507–516, 2000.

[2] A. R. Artino and J. M. Stephens. Academic motivation and self-regulation: A comparative analysis of undergraduate and graduate students learning online. *The Internet and Higher Education*, 12(3):146–151, 2009.

[3] G. Biswas, H. Jeong, J. S. Kinnebrew, B. Sulcer, and R. ROSCOE. Measuring self-regulated learning skills through social interactions in a teachable agent environment. *Research and Practice in Technology Enhanced Learning*, 5(02):123–152, 2010.

[4] S. Craig, A. Graesser, J. Sullins, and B. Gholson. Affect and learning: an exploratory look into the role of affect in learning with AutoTutor. *Journal of educational media*, 29(3):241–250, 2004.

[5] N. Dabbagh and A. Kitsantas. Personal Learning Environments, social media, and self-regulated learning: A natural formula for connecting formal and informal learning. *The Internet and higher education*, 15(1):3–8, 2012.

[6] E. L. Deci and R. M. Ryan. *Self-determination*. Wiley Online Library, 2010.

[7] E. L. Deci, R. M. Ryan, and G. C. Williams. Need satisfaction and the self-regulation of learning. *Learning and individual differences*, 8(3):165–183, 1996.

[8] S. D'Mejallo. Monitoring affective trajectories during complex learning. In *Encyclopedia of the Sciences of*

Learning, pages 2325–2328. Springer, 2012.

[9] B. K. Hofer, S. L. Yu, and P. R. Pintrich. Teaching college students to be self-regulated learners. *Self-regulated learning: From teaching to self-reflective practice*, pages 57–85, 1998.

[10] P. S. Inventado, R. Legaspi, R. Cabredo, and M. Numao. Student learning behavior in an unsupervised learning environment. In *Proceedings of the 20th International Conference on Computers in Education*, pages 730–737, 2012.

[11] P. S. Inventado, R. Legaspi, K. Moriyama, K.-i. Fukui, and M. Numao. Sidekick: A Tool for Helping Students Manage Behavior in Self-initiated Learning Scenarios. *International Journal of Distance Education Technologies (IJDET)*, 12(4):32–54, 2014.

[12] P. S. Inventado, R. Legaspi, and M. Numao. Helping Students Manage Personalized Learning Scenarios. In *Educational Data Mining 2013*, 2013.

[13] P. S. Inventado, R. Legaspi, M. Suarez, and M. Numao. Investigating transitions in affect and activities for online learning interventions. In *Proceedings of the 19th International Conference on Computers in Education. Chiang Mai, Thailand: Asia-Pacific Society for Computers in Education*, 2011.

[14] P. S. Inventado and M. Numao. Supporting student self-regulation in unsupervised learning environments. In *Proceedings of the 20th International Conference on Computers in Education*, pages 1–4, 2012.

[15] P. S. B. Inventado. Helping Students Manage Learning Behavior in Self-initiated Learning Scenarios. 2011.

[16] J. M. Keller. Using the ARCS Motivational Process in Computer-Based Instruction and Distance Education. *New directions for teaching and learning*, 1999(78):37–47, 1999.

[17] P. A. Kirschner and A. C. Karpinski. Facebook® and academic performance. *Computers in human behavior*, 26(6):1237–1245, 2010.

[18] H. J. Klein, R. A. Noe, and C. Wang. Motivation to learn and course outcomes: The impact of delivery mode, learning goal orientation, and perceived barriers and enablers. *Personnel Psychology*, 59(3):665–702, 2006.

[19] D. Laurillard. *Rethinking university teaching: A conversational framework for the effective use of learning technologies*. Routledge, 2013.

[20] R. S. Michalski, J. G. Carbonell, and T. M. Mitchell. *Machine learning: An artificial intelligence approach*. Springer Science & Business Media, 2013.

[21] G. R. Roberts et al. Technology and learning expectations of the net generation. *Educating the net generation*, pages 3–1, 2005.

[22] R. D. Roscoe and M. T. Chi. Understanding tutor learning: Knowledge-building and knowledge-telling in peer tutors' explanations and questions. *Review of Educational Research*, 77(4):534–574, 2007.

[23] J. S. Rubinstein, D. E. Meyer, and J. E. Evans. Executive control of cognitive processes in task switching. *Journal of Experimental Psychology: Human Perception and Performance*, 27(4):763, 2001.

[24] B. J. Zimmerman. *Developing self-fulfilling cycles of academic regulation: An analysis of exemplary instructional models.* Guilford Publications, 1998.

[25] B. J. Zimmerman. Becoming a self-regulated learner: An overview. *Theory into practice*, 41(2):64–70, 2002.

[26] B. J. Zimmerman, S. Bonner, and R. Kovach. *Developing self-regulated learners: Beyond achievement to self-efficacy.* American Psychological Association, 1996.