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Modeling Self-Planning and Promoting Planning Skills in a Data-Rich Context

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Abstract: Students' learning behaviors in an online learning environment can be automatically recorded by learning systems. Such learning records provide new opportunities to model students' learning process. On the other hand, it has become more common to see students having wearable devices that assist in tracking their personal physical activities. These activity tracking can be integrated into a data-rich context for training students for developing their data-informed self-direction skills. We are building the GOAL (Goal Oriented Active Learner) system to support the development of self-direction skills using learning and health activity data. A key phase in any self-directed activity is goal setting and planning. This paper will introduce how to build a new model for self-planning and support the acquisition of planning skills in the GOAL system. We combine learners' data from the self-directed activity and their interaction trace to build the model in the GOAL system. The modeling involves computing of trend value and degree of plan difficulty, then diagnosis of planning skills using a 5-point scoring criteria. An adaptive support is selected based on the computed score. The contribution of this work is modeling planning and promoting planning skills in a data-driven manner. Our approach grounds the theory of self-direction skills and enables learners to develop the skills in everyday life.

Keywords: Planning skills, self-direction, learning analytics, activity tracking, ubiquitous and mobile computing

1. Introduction

Self-direction Skills (SDS) are acquired through experience, training, and effort. The benefits of experience and training will depend on the degree to which people engage through volitionally initiated thought processes. Since it is a cognitively and behaviorally complex task to execute SDS, diagnosing learners in underdeveloped skills and subsequently designing support for promoting the skills are essential.

Although there are multiple approaches to capture data on learner's self-direction or self-regulation, self-report measures have still stayed dominant so far. The recent availability of large and fine-grained datasets has led to investigations of self-regulation by applying learning analytics (LA). The assessment of frequencies and sequences of regulatory activities in learning environments provides a novel perspective on self-regulation that complements and potentially supersedes traditional self-report measures (Bannert & Sonnenberg, 2014; Li et al., 2018). On the other hand, the increased availability of the activity tracking data gives individuals more opportunities for establishing benchmarks in objective metrics and improving achievements through the experience of reality (Swan, 2013). The research and design of data quantification have grown as an interest area in information and learning sciences (Lee, 2019).

This leads us to build the GOAL (Goal Oriented Active Learner) system to support the development of SDS with integrating the learning records and self-tracked data (Majumdar et al., 2018). The GOAL system not only leverages the rapidly increasing activity data but also creates data-driven feedback loops for the acquisition of SDS. In this paper, we will introduce how to build a new model for self-planning and support the acquisition of planning skills in that data rich context.

2. Related Work

2.1 Self-Direction Skills

According to P21 (Partnership for 21st Century Skills, 2016) framework, *Initiative and Self-Direction* requires monitoring one's understanding and learning needs, demonstrating initiative to advance professional skill levels, defining, prioritizing and completing tasks without direct oversight and demonstrating commitment to lifelong learning. It requires learners to handle multiple environments, goals, and tasks while understanding and adhering to organizational or technological constraints of time, resources, and systems. The framework gives a general criterion for a self-directed learner.

Self-directed learning (SDL) and self-regulated learning (SRL) are two most frequently used of the terms in today's educational discourse on learning process (Brockett & Hiemstra, 2018; Candy, 1991; Winne et al., 2006; Zimmerman, 2008). Literature highlights their commonality and differences (Saks & Leijen, 2014). Both SDL and SRL have 4 key phases: Task definition – Setting goals and Planning – Enacting strategies – Monitoring and Reflecting. SDL due to its adult education roots is mostly used for describing the learning activities outside traditional school environment. SRL, on the other hand, is mostly studied in the school environment.

Technological innovation in the field of data logging and rapidly increasing digital world have expanded the intersection of SDL and SRL. The processes of executing and developing SDL and SRL can be captured. For our work, we proposed a five-phase process model, DAPER which synthesizes the SDL and SRL models to conceptualize data-driven self-direction skill execution and acquisition.

2.2 Planning Skills in Self-Direction

A key phase in self-direction and self-regulation is goal setting and planning (Brockett & Hiemstra, 2018; Winne et al., 2006). Previous studies of self-direction and self-regulation has highlighted learner agency regarding how they learn and the superiority of autonomous motivation for learning (Stockdale & Brockett, 2011). Here we follow that paradigm and let students choose their own goal and direct their own plan.

Self-directed learners are expected to actively and autonomously engage in goal setting and planning (Wang, Shannon & Ross, 2013). They demand a high level of goal setting and planning skills during the self-direction process. Compared with assigned goals and plans, personal goals and plans produce higher goal commitment since the learners who are aware of their goals have high learning and achievement expectations. Therefore, self-planning skills required taking full responsibility for personal plans. They should check current status of any activity before planning and then create plans to change that status to a more desirable one when they are ready.

2.3 Support Planning in Self-Direction

In comparison to executing assigned plans, setting and striving personal plans provide individuals with less support on how to define personal plans and continuously improve them. Learners may lose their directions if without reliable, revealing and relevant data that support decision-making for planning. Following the learning analytics process model learners need to translate awareness into action (Bodily et al., 2018). They need a 'representative reference frame' to interpret the data (Wise, 2014). Both the context data and process trace data can be valuable ways to create such a reference frame. We have proposed a measurement rubric as a basis of adaptive support (Majumdar et al., 2019).

Therefore, this paper explores how to design a data rich context for self-planning, how to model self-planning, and how to provide support for promoting planning skills.

3. Our Context: Activity Data, DAPER Model, GOAL System

3.1 Activity Data in the Context of Learning and Physical Activities

Activity tracking involves some process or system to collect data generated by an individual during their execution. A variety of everyday life activities can be tracked by the currently available behavior sensors. We synthesize activity data in learning and physical activity context to involve individuals in self-directed practices. For learning activities, data is from learning logs in our learning platform which include digitized reading logs, status of course assignments, and answers of quizzes (Flanagan & Ogata, 2017). For physical activities, records are collected through native mobile health applications like Apple Health or Google Fit containing data regarding runs, workouts, sleep, steps taken, weight, heart rate, and calories burned.

3.2 DAPER Model

The DAPER (data collection-analyze-plan-execution monitoring-reflect) model conceptualizes the process of data informed SDS execution and acquisition (see Fig. 1). It has five phases, the initial phase of data collection which gives learners the initiative, followed by other four phases: data analysis, planning, execution monitoring, and reflection.

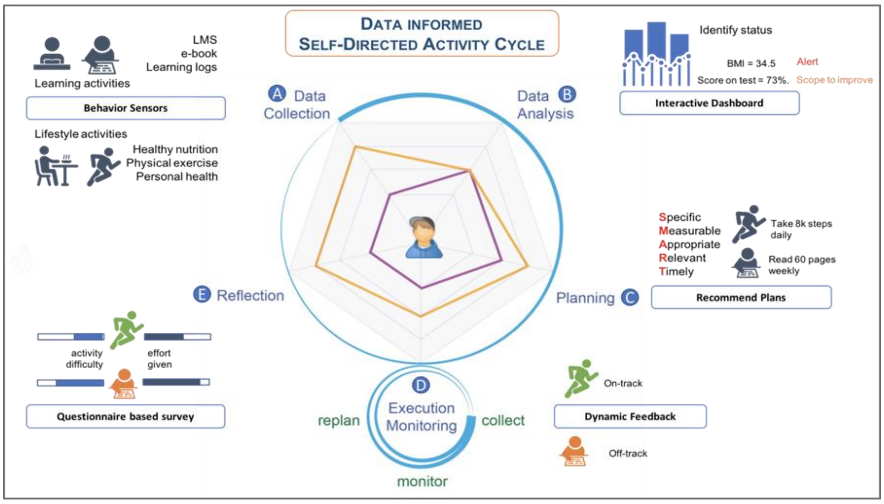

Figure 1. DAPER Model of Self-Direction Skills Execution (Majumdar et al., 2018)

3.3 GOAL System

The Goal Oriented Active Learner (GOAL) system integrates data during learners' learning and physical activities, and implements DAPER model with the functionalities required in each phase. The system further records individual's interaction log data. The GOAL architecture is given in Figure 2.

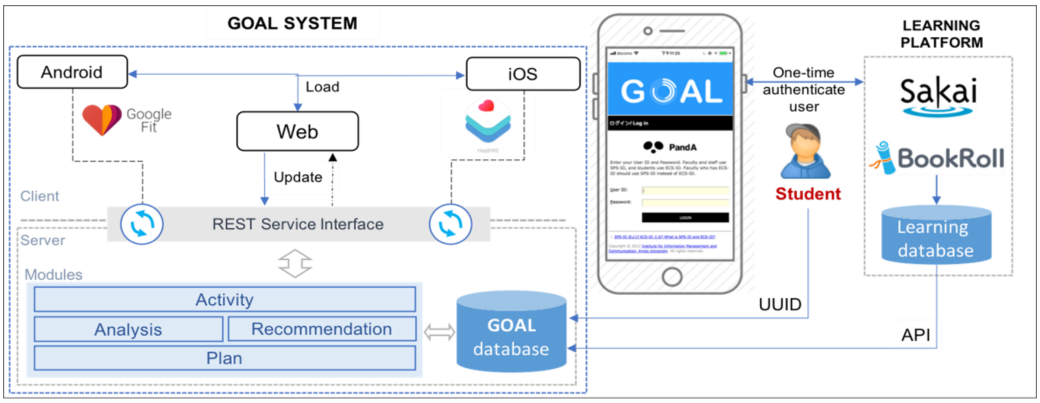

Figure 2. Architecture of the GOAL System (Majumdar et al., 2018)

The GOAL system includes cross platform applications and an analysis server. Learners can link automatically their learning activity data from the LMS and other linked e-learning tools. For physical activity data, students authenticate to synchronize that data directly from native mobile health apps like Apple Health or Google Fit. Furthermore, we log interactions between learners and the GOAL system as eXperience API (xAPI) statements in the analysis server of GOAL system (Li et al., 2019).

4. Modeling Self-Planning

Our proposed self-planning model is shown in Figure 3. First, the trend value of activity is computed from the activity data using autoregressive (AR) model. Second, the degree of plan difficulty is calculated from the trend value and planned value. Third, the planning skills are diagnosed using a 5-point scoring criteria. Finally, an adaptive support is generated based on the score of planning skills.

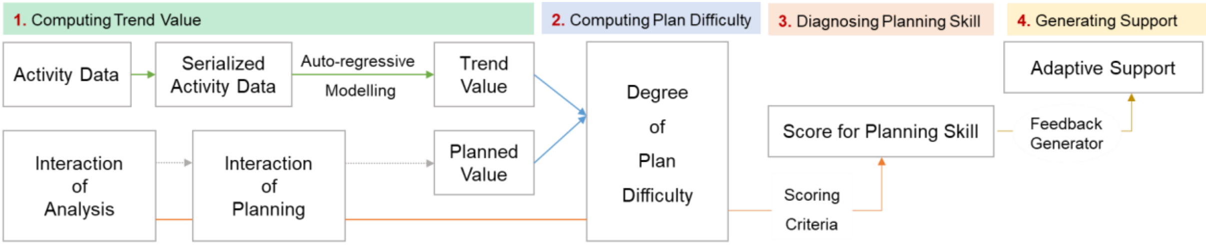

Figure 3. Modeling Self-Planning

The action type, variable, definition, and example for modeling are shown in Table 1. Activity data is data logged during an activity session, which synchronized from learning platforms or health apps. Serialized activity data is a time series data, which accumulated from activity data on the same unit over a fixed period (hour, day, week, etc.). It's used for further computing the trend value as input data. GOAL interactions mean interactions between learners and the GOAL system. They are tracked by the eXperience API, including actor, verb, object, and timestamp.

Table 1: *Action Type, Variable, Definition, and Example*

Type	Variable	Definition	Example
Activity	Activity data	Data logged during an activity session	"Reading 10 pages in e-book from 2:00 pm to 2:25 pm"
	Serialized activity data	Activity data accumulated over periods in a time series	"0, 10, 0, 0, 20, 0, 0 (pages read/day)"
GOAL interactions	Interaction of planning	Interaction of creating a plan in the system	"John created a plan that taking 8,000 steps per day for the next week at 8:00 am"
	Interaction of analysis	Interaction of executing preparatory analysis in the system	"John checked his activity data for last 7 days at 7:00 am"
	Planned value	Value set in the interaction of planning	"8,000 (steps)"

4.1 Computing trend value

The auto-regressive (AR) model is adopted to predict the trend value of activity from previous serialized activity data at the last p time value:

$$A_t = \beta_0 + \beta_1 A_{t-1} + \beta_2 A_{t-2} + \cdots + \beta_p A_{t-p} + u_t$$

Where A_t is the value of A in period t, data set of A_{t-1}, A_{t-2}, …, A_{t-p} are time series value in periods t-1, t-2, …, t-p. β_0, β_1, …, β_p are coefficients found by optimizing the model. For example, the trend value of steps taken for the next day could be predicted given the previous serialized activity data in daily scale for 7 days. For each activity, the trend value is computed with daily, weekly, monthly scales. The trend value in scale is a baseline value for self-planning in daily, weekly, or monthly activities.

4.2 Computing Degree of Plan Difficulty

The degree of plan difficulty (DPD) is calculated by comparing the planned value to the trend value. If the planned value is less than the trend value, DPD is zero. If the planned value is more than the trend value, DPD is the relative increase with respect to the trend value. For instance, if the trend value is 1,000 steps per day and the planned value is set as 1,500 steps per day, then the DPD is set to 0.5.

4.3 Diagnosis of Planning Skills using 5-point Scoring Criteria

Three parameters are considered for the diagnosis of planning skills: interaction of planning (IP), interaction of analysis (IA), and DPD. The planning skills are measured as a 5-point scoring. Table 2 indicates the scoring criteria for planning skills with action description and scoring parameters.

Table 2: *Scoring Criteria for Planning Skills*

Score	Action Description	Parameters
4	Set appropriately challenging plan after analysis	IP=1, IA=1, $0 < DPD \leq \mu$
3	Set too difficult plan after analysis	IP=1, IA=1, $DPD > \mu$
2	Set too easy plan after analysis	IP=1, IA=1, $DPD \leq 0$
1	Set plan without analysis	IP=1, IA=0
0	No plan is set	IP=0

IP: Interaction of planning, IA: Interaction of analysis, DPD: Degree of plan difficulty, μ: Threshold $\mu = 0.2$ in the initial plan, which will be adjusted by individual's achievement

4.4 Adaptive Support based on Skill Scores

Learners are classified into 5 groups based on the scoring criteria for planning skills. They are given adaptive support using a feedback generator (see Table 3). The feedback contains a suggested action and a brief description of current skill level for learners.

Table 3: *Adaptive Support for Learners based on Planning Skills*

Stage	Planning Skill	Feedback
S4	Set challenging plan after analysis	You have set appropriately challenging plan You already master the skill of planning
S3	Set too difficult plan after analysis	Please decrease the difficulty level of the plan to achieve timely You have partly mastered the skill of planning
S2	Set too easy plan after analysis	Please increase the difficulty level of the plan to challenge yourself You have partly mastered the skill of planning
S1	Set plan without analysis	Please analysis activity data before plan for it You have initiated to acquire the skill of planning
S0	No plan is set	Please try to create a plan You have not shown the skill of planning yet

5. Conclusion and Discussion

In this paper we proposed a novel model for self-planning and support the acquisition of planning skills in a data rich context. The diagnosis of planning skills helps learners to further understand how they engage in planning, it's important to better understand which feedback could be provided. Benefits from using the adaptive support are to facilitate the transfer of control between system and learners. The learner who is in underdeveloped skills is partially guided by system and then exerts more control over the direction as a fully self-directed learner.

The contribution of this paper is modeling planning and promoting planning skills in a data-driven manner. 1) *The rationality of modeling*. The data for modeling is the activity tracking data in learning and health, which gives learners the initiative to advance themselves. We confirm the fundamental assumption of self-direction that learner's agency is central in autonomous learning (Stockdale & Brockett, 2011). Our model could be applied in everyday activities across the contexts. For instance, potential activities could be vocabulary remembering in language learning, gym training in health, piano practice in music learning. 2) *The flexibility of adaptive support*. Because learners are divided according to the relative value of activity data and interaction trace data, the adaptive support is provided based on dynamic groups. The model could help learners who are ready to develop planning skills, and also help learners who just want to identify current status.

For future work, we will conduct the study in K-12 and higher education settings to evaluate the effects of the skill diagnosis and adaptive support on the improvement of engagement and planning skills. The differences of effects across different settings and activities will also be examined. The research project aims to explore a data-driven paradigm to develop SDS, and support learners while they become more autonomous in learning and in life.

Acknowledgements

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