Analytics of Behavior Semantics for Understanding Constraint Conditions Hidden in Formative Process of Real-world Learning

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Abstract
An alternative to classroom learning is situated learning by behavior in the world (e.g., environmental learning in a natural setting). Among the various types of human intelligence, this research is interested in understanding the process mechanism by which human intelligence is formed through learner–learner and learner–environment interactions. Here, we assume that a learner's cognition, interpretations, and behavior in the world are positively or negatively affected by various levels of constraint conditions determined by his/her body, cognition, and surroundings. For example, a learner may not generate a certain type of effective real-world behavior if he/she does not have basic knowledge (i.e., a cognitive-level constraint). In a place where interesting objects do not exist, a learner's active inquiry will be restricted (i.e., environment-level constraint). To mine a learner's prospective behavior for obtaining a multi-view understanding of the world, we developed technologies (1) to multidirectionally sense a learner's behavior in the world, (2) to parameterize time-series behavior with various different semantics, and (3) to extract constraint conditions hidden in the formative process of real-world learning. We applied our analytical framework in experiments on environmental learning with 30 participants in an experimental forest. Our initial results showed that the semantic-level data of behavior enabled us to understand the cognitive state and constraints of learners, and to find the change points of the learning situation. These results illustrate that our framework can be a theoretical basis for understanding the mechanism of situated intelligence emerging in the real world.

Keywords: Real-world Learning, Situated Intelligence, Behavior Semantics, Multimodal Analytics

Introduction

There are two different types of learning when a person acquires knowledge. The first includes classroom learning as a typical example of learning methods by which learners learn from teaching materials or teachers. Classroom learning is a traditional learning method through which a learner receives guidance and knowledge from teachers and books. Classroom learning has been widely studied all over the world (Weinstein, C. E., Acee, T. W., & Jung, J. 2011; Berger, J. L., & Karabenick, S. A. 2011; Felder, R. M., & Silverman, L. K. 1988).

The second type is real-world learning (e.g., environmental learning in a natural setting), which is a type of situated learning (Lave, J., & Wenger, E. 1991) by interacting with the real world. In real-world learning, learners can acquire knowledge derived from various situations by their behavior in the real world. However, for real-world learning, many research issues remain because it is not known how to assess mutual influence among the real-world situation, environmental objects, and the learner's behavior. Among the various types of human intelligence, the present study focused on real-world learning and was aimed at understanding the process mechanism by which human intelligence is formed through learner–learner and learner–environment interactions.

In this study, we consider that human intelligence has the above structure in which humans behave so as to learn from real-world situations. Thus, our study was aimed at understanding how human intelligence emerges from the generation structure of a learner's behavior. The main focus of our analysis is the interaction between the real world and the learner, with special attention on the generation structure of the learner's behavior.

As a basis of our analysis, we assume that a learner's cognition, interpretations, and behavior in the world are positively or negatively affected by various levels of constraint conditions determined by his/her body, cognition, and surroundings. For example, a learner may not generate a certain type of effective real-world behavior if he/she does not have basic knowledge (i.e., cognitive-level constraint). In a place where interesting objects do not exist, a learner's active inquiry will be restricted (i.e., environment-level constraint).

Let us consider this point in detailed. In real-world learning, different interests are elicited at different locations and the exhibited behaviors are based on those interests in order to acquire different knowledge (Okada, M., & Tada, M. 2012). For example, when studying in the area shown in the left photograph in Figure 1, learners will see autumnal trees and ponds. As a result, learners may be wondering, "Why do trees turn red?" and "What kind of aquatic organisms live in the pond?" On the other hand, when studying in the area shown in the right photograph in Figure 1, learners will see tall trees and protrusions growing from the ground. In this setting, the learner will not think about the aquatic organisms that he/she had previously focused on. Instead, he/she will think, "What are the protrusions growing around the tree?"

As explained above, in real-world learning, it is thought that there is a structure that promotes or restrains different questions and behaviors. However, these constraint conditions are difficult to observe from the outside, and a framework for research and analysis has not been established. In this paper, we propose a research method for understanding the structure of the constraint conditions that generate and determine a learner's behavior. In addition, we will explain our technical implementation of our method for practical data analysis.

Figure 1: Real-world learning as a typical example of situated learning.

Research Framework

Modeling human intelligence to understand constraint conditions in real-world learning

We propose a real-world oriented research framework for understanding the constraint conditions in real-world learning. Under the proposed framework, a researcher first creates hypotheses and models for real-world phenomena, and then reconstructs a better model by obtaining new knowledge while experimentally evaluating the first assumed model. The present paper explains the findings acquired by implementing the proposed framework.

At phase 1 of our framework, participant observation (DeWalt, K.M. & DeWalt, B.R. 2011) is conducted by going on site to where real-world learning is taking place. In this observation, we watch to determine what kind of behavior is performed and what learners are thinking. Based on the results, we form a qualitative hypothesis about the learner's actual behavior, and then modeled it as a computational expression to be integrated into our analytical method (phase 2). At phase 3, we plan and carry out experiments to evaluate the model. Phases 4 and 5 are for evaluating the appropriateness of our assumed model in the actual setting of the world, which promotes the re-design of our research method (phase 6). These phases are conducted in an environment with ecological validity (i.e., an experimental setting that there is no external control over the learner's behavior, such as no interventions by experimenters or no pre-defined scenario that the learner has to strictly follow). The next section concretely explains how we actually conducted our research procedure, beginning from phase 1.

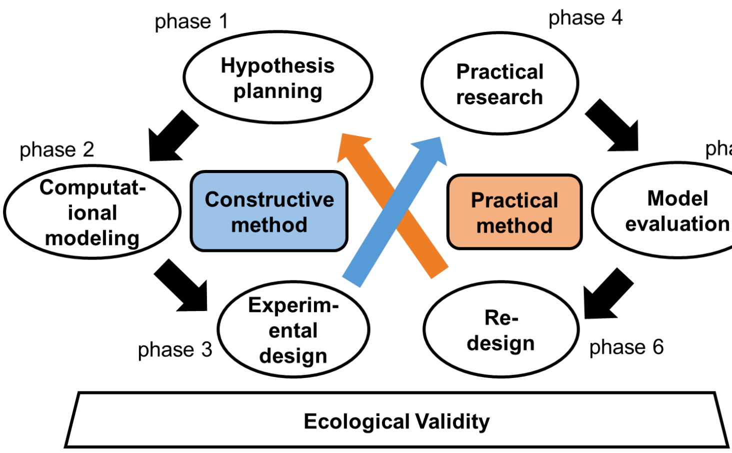

Figure 2: Real-world oriented research framework.

Hypothesis as the basis of computational modeling

Based on our participant observation at phase 1 in Figure 2, we formed the following two hypotheses. The first hypothesis is that the role of a learner's sensory functions and his prior knowledge determine the learning. As a simple example, we often found that when learners were walking along the waterside, they observed the fact that there was no moss there. We consider that this observation behavior was influenced not only by the range of vision when the learners are at the water's edge but also by their existing knowledge that water is necessary for plant growth.

The second hypothesis is that learners' behavior is constrained by their surrounding environment. As a typical example, we found that after the observation at the waterside, learners hypothesized that the moss was adapted to a different environment, and then moved to other places to look for different features of the growth of moss. We consider that the observation result that moss was not seen at the waterside became a new constraint condition of learners. This constraint condition encouraged learners to make a hypothesis and to generate behaviors to verify it.

From these hypotheses, we achieved the idea that a behavior is made under a generation structure with multi-step constraint conditions. Figure 3 shows our model of behavior generation based on multi-step constraint conditions. First, we assume that a learner acquires real-world information from the real world based on human-derived restrictions ((i), (ii) of Figure 3), such as restrictions on the visual range and the range of movement of the body. Based on real-world information, the learner interprets his/her situations using prior knowledge and hypotheses ((iii) of the model). Then, the learner internally produces a list of possible behaviors for the situation ((iv) of the model). However, in the real world, not all behaviors can be performed under the various restrictions, such as those on the body, time, and place. He/she predicts how his/her possible behavior will work ((v), (vi) of the model), and then uses the prediction results as a new constraint to select and perform one behavior that is expected to be the most effective ((vii) of the model).

Importantly, each step of human real-world processing is limited and promoted by various constraints derived from the world, a learner's internal cognitions, and his/her behavioral situations (Const. 1-4 in the figure).

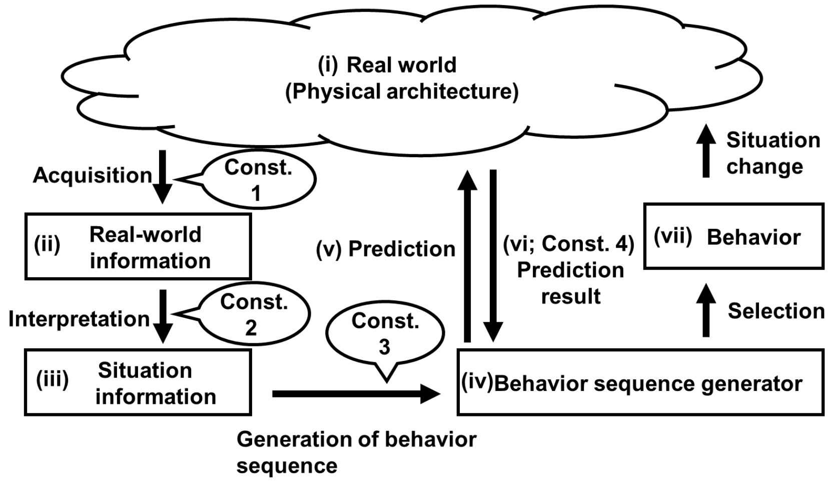

Figure 3: Model of behavior generation based on multi-step constraint conditions.

Technological Development

By considering the behavior generation structure with multi-step constraint conditions, phase 2 of our research was conducted to make computational modeling at the level of behavior semantics, not just at the level of body motion.

Methods to reproduce and analyze the formative process of real-world learning

To mine a learner's prospective behavior for obtaining a multi-view understanding of the world, we defined the requirements as follows: (1) to multidirectionally sense a learner's behavior in the real world, (2) to parameterize time-series behavior with different semantics, and (3) to extract constraint conditions hidden in the formative process of real-world learning.

Our activity map and audio-visual recording can be used as a basis to capture cognitive and behavioral activities of real-world learning (Okada, M., & Tada, M. 2012; Okada, M., Kuroki, Y., Nagata, K. & Tada, M. 2020). To perform advanced data mining, this present paper has developed three additional methods to reproduce and analyze the formative process of real-world learning. The first is the real-world jigsaw method, and the second is the real-world introspection method (Figure 4). In addition to our previous techniques, these two methods were complementarily used in the experiment for the purpose of encouraging a learner to externalize his/her cognitive processing. As a third, we developed a method to express behavior semantics for the purpose of representing behavioral data in a computable format (Figure 4).

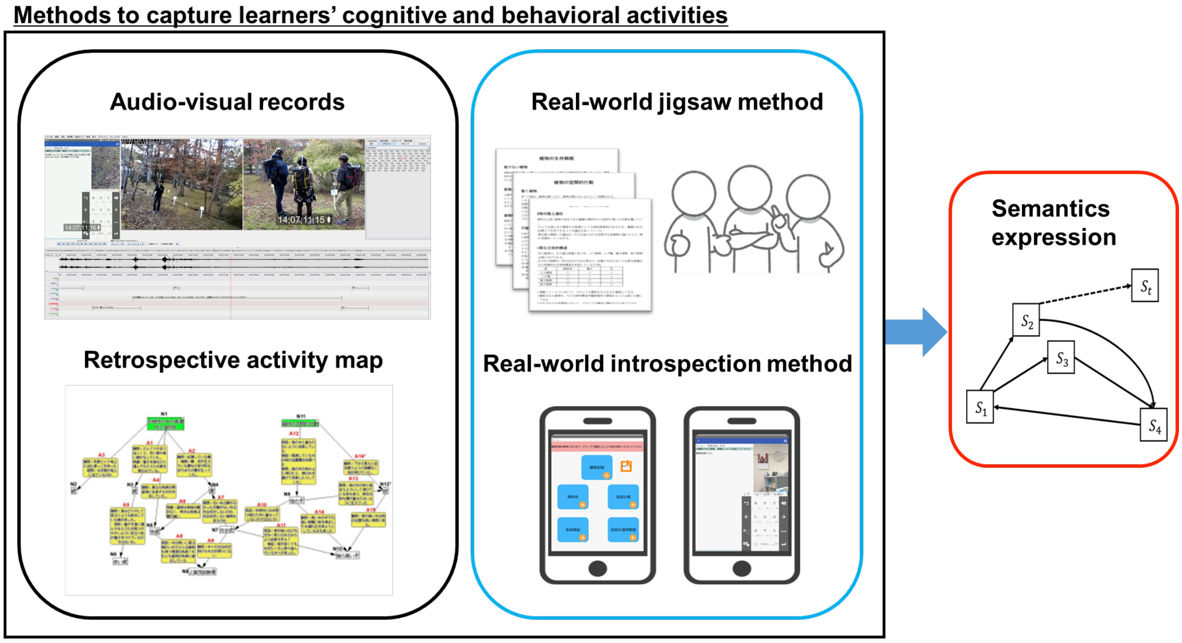

Figure 4: Methods to extract the semantics of real-world learning.

Method to externalize the learner's cognitive processing

By extending the conventional jigsaw method (Aronson, E. & Patnoe, S. 1997) frequently used in classroom learning, we developed a real-world jigsaw method. Our real-world jigsaw method provides each learner with a separate memo to be used in real-world situations. Each memo includes the academic theories of real-world phenomena. Importantly, the memos differ between learners; specifically, the memo contents that different learners can view in the real world do not overlap. The contents of the memo are, for example, the survival strategy of a plant and the community ecology of plants. This experimental control provides each learner with information from different perspectives and information at different abstraction levels. This task is designed to be used as a part of the experimental design at the phase 3 process in Figure 2.

Next, the real-world introspection method requires each learner to carry a tablet device in order to take notes of what they consider and observe during real-world learning. A learner's introspection can be written in separate UI (User Interface) fields corresponding to the essential phases of real-world learning, such as observation records, relationship findings, hypothesis construction, hypothesis verification, and the applicability of a hypothesis. We adopt this method to our experimental design so that each learner can be encouraged to meta-cognize the tasks included in the learning separately. The method also promotes the learner externalizing each cognitive process occurring inside him/her.

These first two methods capture the internal state of a learner who acquires and examines real-world information from multiple perspectives.

Method of expressing behavior semantics

Third, regarding the method of expressing behavior semantics, note first that semantics in the present study is considered as structured expression of the essence of a target for the purpose of calculating the characteristics and relationships of the information to be modeled. For this study, we developed a parameter vector for semantic expression based on the findings of our participant observations. We subdivided and defined the different roles played in the behavior generation process in order to perform a practical analysis of a behavioral generative model.

Trial Analysis

Objective

We made an initial trial analysis as phases 4 and 5 of our research framework so that we could obtain basic and qualitative findings about the mechanism of real-world learning.

Method

We applied our analytical framework to experiments of environmental learning involving 30 participants in an experimental forest. Specifically, our experiment took place at the Kamigamo Experimental Station, Kyoto University, Japan. The 30 experimental subjects were adults (20–29 years old) who all participated voluntarily. The target task of the experiment utilized our real-world jigsaw method. Learners formed groups for collaborative learning in the real world (three learners per group). The duration of each experiment was 1 hour for each group. For our hybrid analysis, we constructed the data of the process and result of real-world learning from the experimental data by the following three methods.

The first method is formative evaluation of multimodal data such as video and audio records (Figure 5). Multimodal data were acquired using the wearable sensor set developed in our previous research (Okada, M., Kuroki, Y., Nagata, K. & Tada, M. 2020). In addition, data on human cognitive processing were obtained using our real-world introspection method with a tablet device. Based on these data acquisitions, we analyzed how behavior and real-world information at a certain point affected the learner's activities.

The second method is summative evaluation of the retrospective learning data collected by which each learner summarized his/her on-site activities in a structured format. These retrospective data were obtained in the form of our activity map, which is a network style representation of a learner’s knowledge (Okada, M., & Tada, M. 2012). This summative evaluation is for quantitatively and qualitatively analyzing the final learning results. By considering the aim of the real-world jigsaw method, we evaluated the data from the viewpoint of whether a learner could obtain a multi-viewpoint and integrated description.

Finally, we compare and integrate the results of the above two evaluations, construct a sequence of parameter vectors of behavioral semantics, and extract the constraint conditions hidden in the real world. Then, we analyzed how formative assessment of time-series learning process was related to the summative assessment of the learning result, and vice versa. We examined how various behaviors changed the learner's cognitive state and influenced the learning results.

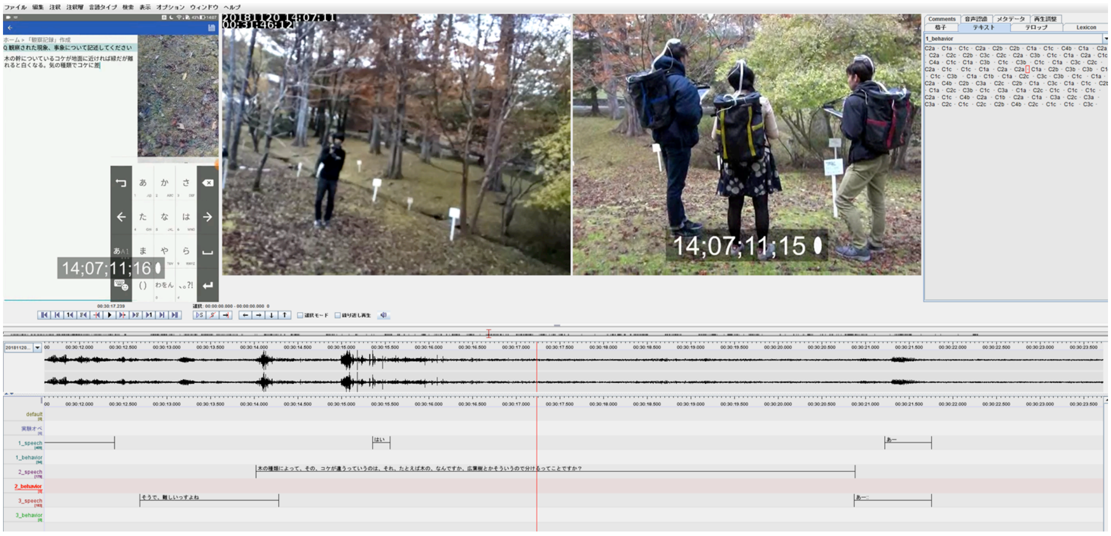

Figure 5: Hybrid evaluation of time-series multimodal data.

Results

One basic achievement of this study was that we could frequently observe that our new task utilizing the real-world jigsaw method promoted the learner actively and autonomously behaving so as to construct, compare, and integrate hypotheses among the learners and generating new collaborative knowledge to explain the mechanism of real-world phenomena from multiple perspectives. The fact that our new task design was effective is important as a research basis for examining the self-directed mechanism of real-world learning in a natural setting with ecological validity, which is different from well-defined classroom learning or laboratory experiments. We consider that our real-world introspection method was helpful not only for encouraging each learner to realize what step he/she is engaged in, but also what he/she should do at his/her current or subsequent steps. We expect that this type of enhanced meta-cognition is effective for learners to generate behavior adapted to his/her learning state.

Let us consider how each of our techniques worked. Video-based observation enabled us to trace the time series of behavior externalized as a learner’s body movement. Learners’ activity maps enabled us to read the semantic relationships describing how learners formed their cognition, thinking, and behavior in the real world, for example, the observed objects and phenomena, and the theories and hypotheses that connect the observation results. Our real-world introspection method enabled us to read learners’ internal cognitive processing consisting of multi-step cognitive activities such as examination of the relevance of observation results, generation of hypotheses, hypothesis verification, etc. These were our ground data to construct the semantics of information processing ((i), (ii), (iii) in Figure 3) and behavior generation ((iv)-(vii) in the figure) that were both performed under multi-level constraints 1-4.

Behavior semantics data constructed by our multimodal measurement enabled us to understand the cognitive state and constraints of learners, and to find the change points of the learning situation. For example, we extracted several patterns of the main behavior sequences to explain the success or failure of a real-world learning task. When learners performed particular types of behavior corresponding to the different constraint levels illustrated in Figure 3, their intellectual achievement of learning was heightened. When they did not conduct enough time amount of such types of behavior, their achievement levels were low. To be concrete, learners could behave so as to obtain high intellectual achievements when they compared and integrated others' hypotheses, questions, and predictions as a means for clarifying their own cognitive grounds to reflect on real-world phenomena. This comprises the co-related functions of behavior generation under multi-step constraints (assumed in Figure 3).

In the current paper, we have outlined the development of our research framework and technical measurement methods for capturing the constraint conditions in real-world learning. Currently, our research is at the stage of accumulating evidence about the applicability of our model through qualitative observations of actual learner behavior. As initial achievements of us, we found that (1) it is possible to measure internal cognitive data for estimating semantic-level data of behavior by encouraging introspection during real-world learning, (2) behavior semantics can be expressed from the correspondence between learning results and internal or representational behavior, and (3) semantic-level data of behavior enables us to extract and understand the constraint conditions hidden in the formative process of real-world learning.

Our model of the interaction process in Figure 3 was a clue for considering how the process of real-world learning is affected by the double constraints of both human–environment physical interaction and a human's cognitive perspectives of real-world observation. This means that our model can be a theoretical prediction for understanding the mechanism of situated intelligence emerging in the real world. We expect that this model will supply basic knowledge for context-aware learning support in the world, but quantitative verification of the model is important future work.

Conclusion

We consider that human intelligence is formed through learner–learner and learner–environment interactions. Thus, we conducted research with the idea that learners' behavior is determined by various constraint conditions imposed on the body and cognition. In order to extract and understand the constraint conditions hidden in the formative process of real-world learning, we developed and put into practice the following methods: a method for reproducing and analyzing the formative process of learning and a method for expressing behavioral semantics by formative and summative evaluation of learning. Based on these techniques, we acquired findings essential for supporting context-aware learning in the world.

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