Proceedings of Machine Learning Research 273:221–229, 2025 iRAISE Workshop at AAAI 2025

A Personalized AI Coach to Assist in Self-Directed Learning

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Abstract

Personalized learning is a powerful tool in online education, yet its application in inquiry-based modeling environments remains underexplored. Previous work has shown that learners that engage in a cycle of construction, parameterization, and simulation, which we refer to as the exploration cycle, create models with higher complexity and variety. In order to further study these findings we present an "exploration coach" that provides personalized feedback within the Virtual Experimental Research Assistant (VERA)—an interactive learning environment for conceptual modeling of complex systems that evaluates models through agent-based simulations. Our architecture, which classifies learners into groups using clustering techniques, allows us to determine what type of feedback would be useful to a learner at any point in their modeling journey. The coach then uses procedural scaffolding to guide learners through the exploration cycle. Lastly we illustrate how these categorizations and the exploration cycle map onto the cycle of self-directed learning.

Keywords: Personalized Learning, Machine Learning, Self-Regulated Learning

1. Introduction and Background

Unlike traditional instructional methods that often emphasize the passive acquisition of knowledge, inquiry-based learning encourages active learning Chi and Wylie (2014) by placing users at the center of the learning process. This approach encourages users to engage in domain exploration, question formation, and problem-solving within open-ended environments. This approach not only enhances critical thinking and creativity but also promotes deeper understanding through hands-on experience Chi and Wylie (2014); Chi et al. (2018) Inquiry-based learning is crucial in helping students develop the skills necessary to tackle open-domain problems–situations where multiple approaches may be viable, and no single correct solution exists.

While personalized learning is a powerful approach for in-person instruction Bloom (1984), it has the potential to enhance the effectiveness of online education settings Means et al. (2009). By providing users with real-time, tailored feedback, personalized learning systems have the potential to transform teaching and learning outcomes Bloom (1984); Shute (2008); VanLehn (2011); Joyner and Goel (2015). Meta-analyses have demonstrated personalized learning systems help users remain engaged and motivated Koedinger et al. (1997); Means et al. (2009); Kinnebrew et al. (2013). However, there have been limited studies that have explored how personalized learning can be leveraged to support inquiry-based modeling environments, where the learning process in inherently open-ended and exploratory Joyner et al. (2013); Joyner and Goel (2015); Bauer et al. (2017).

We explore the effects of integrating a personalized AI coach in an inquiry-based modeling environment called VERA (Virtual Experimental Research Assistant). VERA An et al. (2018, 2020) is an interactive learning environment in the field of ecology. It allows users to engage in conceptual modeling of complex systems, and evaluate these models through agent-based simulations to deepen their understanding of ecological concepts and modeling.

The design of our coach is based on a study in VERA called "Understanding Self-Directed Learning in An Online Laboratory", in which An et al. (2022) found that learners in VERA are most successful when they engage in a complete cycle of constructing, parameterizing, and simulating models. First, we define learners who adequately complete this cycle as "full-explorers". An et al. (2022) identified two other clusters of learners, each of which can be thought of as lacking as in some part of the exploration cycle; "constructors" effectively create nodes and edges in their model without effectively parameterizing and simulating, while "observers" adequately simulate their model without engaging in enough construction or parametrization. From this information, we propose the "exploration coach" to tailor feedback to these three types of learners, getting them closer to completing the full exploration cycle and creating more intricate models.

2. Methodology

The Virtual Experimental Research Assistant (VERA) application will be used for this research. VERA is an ecological modeling application where learners can create, parameterize, and simulate conceptual models of ecological systems. Every model has components (nodes) and relationships (edges). Components can be either biotic or abiotic, where biotic components are specific taxa. Relationships relate two components together, with an example being "component A affects component B". Relationships include "produces", "consumes", "destroys", "affects", and "becomes on death". Each component has tunable parameters associated with it, such as lifespan and body mass. See Fig. 1 for an example of a VERA model and its corresponding simulation.

We propose a metacogntive AI coach in VERA called the "exploration coach". The exploration coach uses procedural (metacogntive) scaffolding to encourage learners to engage in greater exploration. When the exploration coach goes to give feedback to a learner, it first classifies the learner as either a constructor, observer, or full-explorer. This is done through the following steps: a pre-processing step where VERA models' associated log activities are clustered into the three groups, and a real-time step where the exploration coach uses the clustering to classify a learner into one of the groups.

Starting with the clustering step, we employ a process identical to the one used by An et al. (2022) when they performed clustering to identify the learner groups of "constructors", "observers", and "full-explorers". We take a user's log behavior while working on a particular model and process it into an *activity sequence* that reduces actions to being one of construction, parameterization, and simulation. We define an activity sequence as a string consisting of sequences of "c", "p", and "s", each corresponding to one unit of construction, parameterization, and simulation respectively. For example, a sequence of

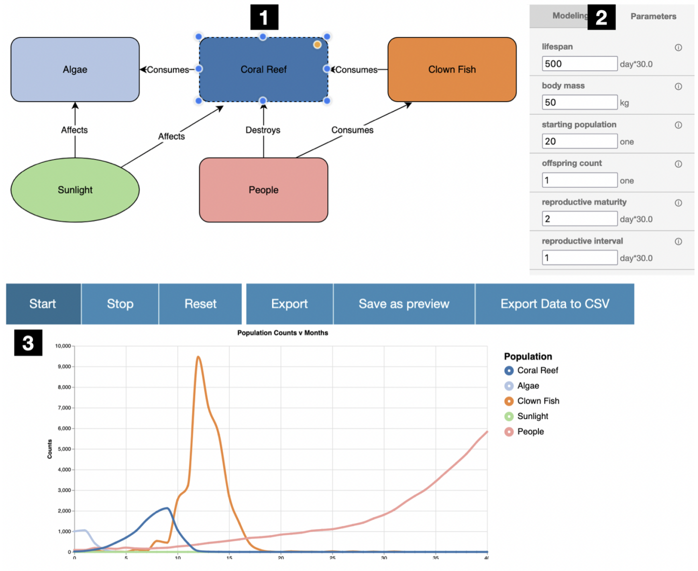

Figure 1: An example of a model in VERA created by a learner. The portion labeled by 1 shows a model that has been constructed, the portion labeled by 2 shows the ability to change parameters in the model, and the portion labeled by 3 shows a simulation of the model. An et al. (2022)

"ccps" would correspond to a sequence of two construction actions, one parameterization action, and one simulation action.

We then define a metric of similarity between two action sequences to be able to perform clustering. We use the Levenshtein distance, which measures the distance between two sequences by computing the minimum number of edits required to convert one sequence to the other. With this similarity metric, we use hierarchical agglomerative clustering to separate user activity sequences into the construction, observation, and full-exploration groups. We also need to normalize for sequence length, so we split user sequences into different length groups, and then perform the clustering on each length group.

With these clusters processed and stored, the exploration coach can utilize them to determine in real-time whether a learner is a constructor, observer, or full-explorer when they request feedback. Constructors, observers, and full explorers all receive personalized feedback to their classification, which we describe below. If a learner is categorized as a constructor, then we know that they are likely not doing enough paramerization and simulation. As such, the task we want to give them (in the context of procedural scaffolding) is to parameterize and simulate their model. As they conduct parameterization and simulation, we also want them to further understand how the changes of certain parameters directly affect the simulation output of their model and what the underlying relationships are between these components. Accordingly, we have the feedback template for constructors shown in Fig. 2.

Hey! I noticed that you've been constructing your model, but you haven't been changing many of the parameters. To gain a greater understanding of how your model works, I suggest completing the following steps:

1. For your **nodeName** node, change the **paramName** parameter to **paramVal1**.
2. Predict what will happen when you simulate your model with the new change. What will happen to the **nodeName** population?
3. Simulate your model. What do you observe? Was your prediction correct? Why did you see what you observed?
4. Now change the **paramName** parameter to **paramVal2**. Again, predict what will happen when you simulate your model.
5. Simulate your model again. Was your prediction correct? What seems to be the general trend between the **paramName** parameter and the output of the simulation? Is the trend linear? Are there multiple peaks? Do you need to test more values?
6. Reflect on this activity. What did you learn about this parameter and the system as a whole?

Figure 2: The design of the feedback given by the exploration coach for constuctors. The bolded terms are variables that differ depending on the learner receiving feedback

In this feedback, we accomplish the following: getting the learner to engage in the full exploration process and getting them to reflect on their models. The parameters in this feedback is chosen by the following methodology: we run kernel density estimation on all VERA models to determine commonly-used values for different parameters, and we recommend commonly-used values that the learner has not tried before (or deviates the farthest from). Kernel density estimation is a widely-used technique for estimating the probability density function of a distribution from sample measurements Weglarczyk, Stanislaw (2018), and we use this technique to find multiple peaks in parameter value distributions. By suggesting values from different peaks, we address the possibility that a learner has found a local maximum for some parameter, but is unaware that a global maximum/minimum exists elsewhere. In addition to this, we recommend parameters to change that have been relatively "unexplored"; if a parameter has been changed extensively, then a different one is recommended.

If a learner is classified as being an observer, then we infer that they are engaging in parameterization and simulation behavior while not engaging in a sufficient amount of construction. As such, we want to recommend that a learner creates a new node or edge in their model so that they can improve in this area. Template feedback for this is shown in Fig. 3. It includes the task of creating a node or edge in the model, but it also includes steps for the learner to change parameters in the node/edge and simulate their model so they can add the node/edge in a way that makes sense in the context of their model. As usual, the feedback includes metacognitive questions that get the learner to try to understand what creating the new node/edge did for their model.

Finally, if a learner is classified as a full-explorer, then they have been identified as completing the full cycle of constructing, parameterizing, and simulating their model. Since this is considered optimal behavior, we want to give positively-reinforcing feedback that

Hey! I noticed that you've been observing your model well, but you haven't been creating many nodes or edges or changing the structure of it. To gain a greater understanding of how your model works, I suggest completing the following steps:
1. Create another node or edge in your model.
2. Change any parameters in the new node/edge to fit your model.
3. Predict what may happen when you simulate your model with the new node/edge.
4. Simulate your model. Were your predictions correct? How did the populations of the existing biotic nodes change?
5. Reflect on this activity. What did adding the node accomplish, and why did it do that?

Figure 3: The design of the feedback given by the exploration coach for observers.

affirms the learner's idea of how to conduct the conceptual modeling process. The idea of including positive reinforcement in feedback for full-explorers is affirmed by a study titled, "Understanding Self-Directed Learning in An Online Laboratory", which investigated the effect of an affective (emotion-based) coaching agent that includes positive reinforcement when correct answers are given, as the study found the system to be significantly conducive towards learning in comparison to a control group Mondragon et al. (2016). Accordingly, the design for full-explorer feedback is shown in Fig. 4. The feedback encourages the learner to continue their optimal behavior, and it also goes into detail about how their behavior is optimal such that the learner has more explicit and solidified knowledge of the construction-parameterization-simulation process. In the future, we will combine this positive reinforcement with procedural scaffolding steps that help the learner even further (i.e. micro-optimizing their behavior).

Hey, I noticed that you are exploring with VERA well! You have done a good job of constructing your model, tuning parameters, simulating your model, and repeating until you find quality results. Keep up the good work!

Figure 4: The design of the feedback given by the exploration coach for full-explorers.

3. Discussion

Self-regulated learning is a well studied phenomenon, with its roots in constructivist theory, which describes learners as engaging in a cycle of planning, implementation, and evaluation, see Fig. 5. Learners with better self-regulated learning ability, also known as metacognitive ability, have better educational outcomes and higher levels of academic achievement Chen and Wang (2020). Furthermore, it is understood by the literature that that self-regulated learning skills can be taught and scaffolded through coaching. For this reason, many intelligent tutoring systems including Betty's Brain Kinnebrew et al. (2013), MetaTutor Azevedo et al. (2009), and VERA An et al. (2018, 2020) are all built to encourage users to engage in a loop of self-regulated learning. The exploration cycle maps onto the cycle of self-regulated learning in the following ways:

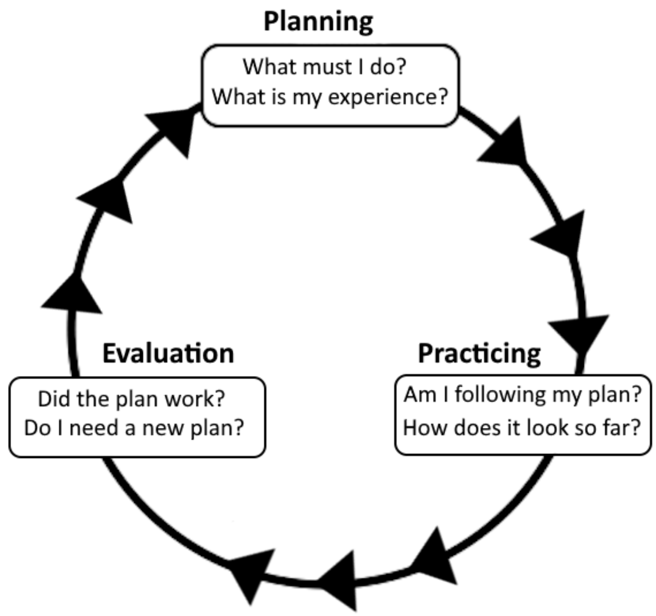

Figure 5: This figure illustrates the cycle of self-regulated learning describing planning, practicing (implementation), and evaluation. van der Graaf (2023)

1. **Planning**, as found in the self-regulated learning cycle, is a process that occurs fully in the mind. For this reason, we do not have action logs that correspond to the planning phase.

2. **Practicing**, in the self-regulated learning cycle is when a learner is taking steps toward completing their plan. This corresponds to constructors who focus solely on the practice step of the cycle by only constructing within VERA.

3. **Evaluation**, typically occurs after the learner has taken steps toward their goal in the self-regulated learning cycle. Observers in VERA are continuously evaluating their current model by simulating without planning or practicing.

To the best knowledge of the authors, there does not exist a self-directed learning coach for open-domain inquiry-based modeling platforms. Betty's Brain serves as a useful point of comparison, in that while it is an inquiry-based learning platform, it focuses on students learning scientific concepts from textbook readings. Working in Betty's Brain, Munshi et al. (2023) have previously developed procedural scaffolding for self-regulation based learning strategies. The scaffolding, however, is entirely focused on the correctness of a learner's answer, which is inapplicable to modeling in VERA. Other recent research into personalized self-regulated scaffolding has been investigated in the domain of reading and writing by Lim (2023). However, this research differs from our own due to the fact they use a rule-based approach to evaluate a learner's engagement with the cycle of self-directed learning which is different than our machine learning driven method.

Notably, the research done by An et al. (2022) was specifically focused on the actions of self-directed learners in an online laboratory. The three different categories of users were identified (Constructors, Observers, and Full Explorers), but no work was done to map these users, or their actions onto the cycle of self-directed learners. By creating a mapping from the three categories of users and their actions onto the self-directed learning cycle, we are able to identify which learners are engaging in proper self-regulated learning behavior. On this basis, we are able to establish that our coach by design dynamically encourages users to engage in self-regulated learning.

4. Conclusion

In this work, we propose an AI coach in VERA called the "exploration coach", which uses procedural scaffolding to encourage learners to engage in a full cycle of construction, parameterization, and simulation when conducting inquiry-based modeling. We then map the exploration cycle to the cycle of self-directed learning. We have deployed this coach into two classes, and future work includes an analysis and discussion of the results.

5. Acknowledgments

This research has been supported by NSF Grants #2112532 and #2247790 to the National AI Institute for Adult Learning and Online Education. We thank members of the VERA project in the Design Intelligence Laboratory for their contributions to this work.

References

Sungeun An, Robert Bates, Jennifer Hammock, Spencer Rugaber, and Ashok Goel. Vera: popularizing science through ai. In *Artificial Intelligence in Education: 19th International Conference, AIED 2018, London, UK, June 27–30, 2018, Proceedings, Part II 19*, pages 31–35. Springer, 2018.

Sungeun An, Robert Bates, Jen Hammock, Spencer Rugaber, Emily Weigel, and Ashok Goel. Scientific modeling using large scale knowledge. In *Artificial Intelligence in Education: 21st International Conference, AIED 2020, Ifrane, Morocco, July 6–10, 2020, Proceedings, Part II 21*, pages 20–24. Springer, 2020.

Sungeun An, Spencer Rugaber, Jennifer Hammock, and Ashok K. Goel. Understanding self-directed learning in an online laboratory, 2022.

R. Azevedo, A. Witherspoon, A. Chauncey, C. Burkett, and A. Fike. Metatutor: A metacognitive tool for enhancing self-regulated learning. *2009 AAAI Fall symposium series*, October 2009.

A. Bauer, J. Flatten, and Z. Popovic. Analysis of problem-solving behavior in open-ended scientific-discovery game challenges. *Analysis of Problem-Solving Behavior in Open-Ended Scientific-Discovery Game Challenges*, 2017.

Benjamin S Bloom. The 2 sigma problem: The search for methods of group instruction as effective as one-to-one tutoring. *Educational researcher*, 13(6):4–16, 1984.

C. M. Chen and W. F. Wang. Mining effective learning behaviors in a web-based inquiry science environment. *Journal of Science Education and Technology*, 29:519–535, 2020.

Michelene TH Chi and Ruth Wylie. The icap framework: Linking cognitive engagement to active learning outcomes. *Educational psychologist*, 49(4):219–243, 2014.

Michelene TH Chi, Joshua Adams, Emily B Bogusch, Christiana Bruchok, Seokmin Kang, Matthew Lancaster, Roy Levy, Na Li, Katherine L McEldoon, Glenda S Stump, et al. Translating the icap theory of cognitive engagement into practice. *Cognitive science*, 42 (6):1777–1832, 2018.

David A Joyner and Ashok K Goel. Improving inquiry-driven modeling in science education through interaction with intelligent tutoring agents. In *Proceedings of the 20th international conference on intelligent user interfaces*, pages 5–16, 2015.

David A Joyner, Ashok K Goel, and David M Majerich. Metacognitive tutoring for scientific modeling. In *AIED Workshops*, 2013.

J. S. Kinnebrew, K. M. Loretz, and G Biswas. A contextualized, differential sequence mining method to derive students' learning behavior patterns. *Journal of Educational Data Mining*, 5:190–219, 2013.

Kenneth R Koedinger, John R Anderson, William H Hadley, and Mary A Mark. Intelligent tutoring goes to school in the big city. *International Journal of Artificial Intelligence in Education*, 8:30–43, 1997.

L. et al. Lim. Effects of real-time analytics-based personalized scaffolds on students' self-regulated learning. *Computers in Human Behavior*, 139, 2023.

Barbara Means, Yuki Toyama, Robert Murphy, Marianne Bakia, and Karla Jones. Evaluation of evidence-based practices in online learning: A meta-analysis and review of online learning studies. 2009.

Aydée Liza Mondragon, Roger Nkambou, and Pierre Poirier. Towards an effective affective tutoring agent in specialized education. In Alessandro Micarelli, John Stamper, and Kitty Panourgia, editors, *Intelligent Tutoring Systems*, pages 402–408, Cham, 2016. Springer International Publishing. ISBN 978-3-319-39583-8.

A. Munshi, G. Biswas, R. Baker, J. Ocumpaugh, S. Hutt, and L. Paquette. . analysing adaptive scaffolds that help students develop self-regulated learning behaviours. *Journal of Computer Assisted Learning*, 39:351–368, 2023.

Valerie J Shute. Focus on formative feedback. *Review of educational research*, 78(1):153–189, 2008.

J. et al. van der Graaf. How to design and evaluate personalized scaffolds for self-regulated learning. *Metacognition and Learning*, 18:783–810, 2023.

Kurt VanLehn. The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational psychologist*, 46(4):197–221, 2011.

Weglarczyk, Stanislaw. Kernel density estimation and its application. *ITM Web Conf.*, 23:00037, 2018. doi: 10.1051/itmconf/20182300037. URL https://doi.org/10.1051/itmconf/20182300037.