Computational Thinking through Modeling and Simulation

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In this whitepaper I argue for a computational modeling and simulation approach to introducing computational thinking (diSessa, 2000; Papert, 1996; Wing, 2006) into a wide range of contexts, both in and out of school. Computational modeling has the potential to give students means of expressing and testing explanations of phenomena both in the natural and social worlds. There are two approaches traditionally used to give explanations of phenomena: mathematical formulae and textual descriptions. Both of these have important deficiencies in an educational context. Mathematical formulae are not easily constructible by students or jpfs. As such they can be transmitted to students, but very few students will be able to understand the assumptions hidden in the formula nor challenge or critique the formula and offer a different formula as explanation. Moreover, mathematical formulae are brittle in that they apply under very specific conditions and if the conditions are not met, the formula cannot be easily adjusted to account for the new phenomenon. In contrast, textual descriptions are constructible by students and can be easily modified, but they suffer from a lack of testability. If two textual accounts of a phenomenon contradict each other, there are not clear ways to put them to the test to determine which is a better account. Computational modeling can help students overcome both these problems. Clearly, contradictory computational models, as executable, can be put to the test. In so doing, students can uncover the assumptions behind the models and assess their adequacy. Computational models are more transparent and their assumptions are easier to detect and understand. While, as yet, there is not enough widespread computational modeling literacy for jpfs to construct their own models, it is clearly an easier task that devising a formula, requires much less formal training, and a start can be made that can be iteratively debugged and refined. There is now also a body of research that shows that typical middle school and higher students can construct, modify and critique computational models within the context of regular school classrooms (Blikstein & Wilensky, 2009; Klopfer, 2003; Repenning, Webb, & Ioannidou, 2010; Sengupta et al, 2013; Wilensky & Reisman, 2006).

At Northwestern's Center for Connected Learning and Computer-Based Modeling, we have created computational modeling tools that employ an agent-based approach. ABM is a rapidly growing methodology used in a wide range of content domains (Epstein, 2006; Miller & Page, 2007; Wilensky & Rand, in press). In agent-based modeling, you give computational rules to individual agents and then observe, explore analyze the resultant aggregate patterns. Our NetLogo ABM environment (Wilensky, 1999) includes a low-threshold (Papert, 1980) computer language designed to background syntax and foreground modeling and computational thinking. We have also designed a large number of school-based activities that integrate ABM into curriculum at almost al levels ranging from elementary school to graduate school. We have designed ABM-based units for high school in both the natural and social sciences. Our high school units and activities have been downloaded by tens of thousands of users. There are now thousands of university courses employing our NetLogo ABM environment, in virtually very subject area including physics, chemistry, biology, psychology, sociology, philosophy, music, theatre, materials science, industrial engineering, civil engineering, medicine, law and business. Thousands of scientific articles now employ ABM (see e.g., http://ccl.northwestern.edu/netlogo/references.shtml) and professionals in business, medicine, law, policy employ ABM in their work (An, 2009; Guzy et al, 2008; Rand & Rust, 2010) which furthers the case for schools to integrate it into curriculum.

Furthermore, the educational research shows that students learning with an ABM-based approach learn their subject material more deeply (Blikstein & Wilensky, 2009; Centola et al, 2000; Klopfer, 2003; Levy & Wilensky, 2009; Sengupta et al, 2013; Wilensky & Reisman, 2006) – they increase their computational thinking skills and that CT gives them greater insight into the mechanisms of action that lead to patterns in nature and society. This has been shown in a wide range of disciplines such as electricity, population biology, evolution, kinetic molecular theory, materials science, sociology, and psychology. Furthermore, non-high achieving students and members of underrepresented groups have shown increased motivation and understanding using ABM approaches (Abrahamson et al, 2007; Stroup et al, 2007). This educational advantage combined with the increased use by scientist positions ABM to achieve significant penetration in schools, exposing all students to computational thinking, even those with no interest in computer science.

Our use of ABM in educational environments comprises many different modalities. In some contexts, the learners are given the rules of a pre-built model and explore the parameter-space of its possible behaviors. Another modality is to critique the assumptions of a model and create modified rules for the model and compare the revised model to the original. In some contexts, where there is more time, students design and implement their own models from scratch. Another modality involves networked participatory simulations in which students control their own agents that interact with each other and with robotic agents with programmed rules (Ares et al, 2004; Klopfer, Yoon & Perry, 2005; Stroup et al, 2007; White & Brady, 2010; Wilensky & Stroup, 2000). Yet another modality combines bits and atoms, in so-called "bifocal modeling" (Blikstein & Wilensky, 2007; Rand et al, 2006) in which ABMs are receiving data from the real world and the modeling activity involves calibrating the model to the data and exploring possible rule-sets that will generate the observed data.

All scientific explanations involve models. There are many advantages to computational models. The computational representations are more expressive, dynamic and easier to learn than mathematical representations. Thus expressing content using computational representations allows a restructuration (Wilensky & Papert, 2010) of the knowledge domains, both altering the content to be learned and democratizing access.

References

Abrahamson, D., & Wilensky, U. (2007). Learning axes and bridging tools in a technology-based design for statistics. *International Journal of Computers for Mathematical Learning, 12*(1), 23-55.

An, G., & Wilensky, U. (2009). From artificial life to in silico medicine: NetLogo as a means of translational knowledge representation in biomedical research. In A. Adamatzky & M. Komosinski (Eds.), *Artificial Life Models in Software (2nd Ed.)*. Berlin: Springer-Verlag.

Ares, N., Stroup, W. M., & Schademan, A. (2004). *Group-level development of powerful mathematical discourses: Networked classroom technologies as mediating artifacts*. Paper presented at the annual meeting of the American Educational Research Association, San Diego, CA.

Barr, V., & Stephenson, C. (2011). Bringing computational thinking to K-12: what is Involved and what is the role of the computer science education community? *ACM Inroads*, *2*(1), 48–54.

Blikstein, P., & Wilensky, U. (2009). An atom is known by the company it keeps: A constructionist learning environment for materials science using multi-agent simulation. International Journal of Computers for Mathematical Learning, 14(2), 81-119.

Centola, D., Wilensky, U., & McKenzie, E. (2000). *A hands-on modeling approach to evolution: Learning about the evolution of cooperation and altruism through multi-agent modeling - The EACH Project.* Proceedings of the Fourth Annual International Conference of the Learning Sciences, Ann Arbor, MI.

College Board (2011). Advanced Placement (AP) Exam Data 2011, available at http://professionals.collegeboard.com/data-reports-research/ap/data .

diSessa, A. A. (2000). *Changing minds: Computers, learning, and literacy*. Cambridge, MA: MIT Press.

Epstein, J. (2006). *Generative social science: Studies in agent-based computational modeling*. Princeton, NJ: Princeton University Press.

Grover, S., & Pea, R. (2013). Computational Thinking in K-12: A Review of the State of the Field. *Educational Researcher*, *42*(1), 38–43. doi:10.3102/0013189X12463051

Guzdial, M., & Soloway, E. (2003). Computer science is more important than calculus: The challenge of living up to our potential. *SIGCSE BULLETIN*, *35*(2), 5–8.

Guzy, M. R., C. L. Smith, J. P. Bolte, D. W. Hulse and S. V. Gregory. 2008. Policy research using agent based modeling to assess future impacts of urban expansion into farmlands and forests.

Klopfer, E. (2003). Technologies to Support the Creation of Complex Systems Models -Using StarLogo Software with Students. Biosystems, 71, 111-123.

Klopfer, E., Yoon, S., & Perry, J. (2005). Using palm technology in participatory simulations of complex systems: A new take on ubiquitous and accessible mobile computing. Journal of Science Education and Technology, 14(3), 285-297.

Levy, S. T., & Wilensky, U. (2009). Crossing levels and representations: The Connected Chemistry (CC1) curriculum. *Journal of Science Education and Technology, 18*(3), 224-242. doi: 10.1007/s10956-009-9152-8

Margolis, J. (2008). *Stuck in the shallow end: Education, race, and computing*. The MIT Press.

Margolis, J., & Fisher, A. (2003). *Unlocking the clubhouse: Women in computing*. The MIT Press.

Miller, J., & Page, S. (2007). *Complex adaptive systems: An introduction to computational models of social life.* . Princeton: Princeton University Press.

National Research Council. (2010). *Report of a Workshop on The Scope and Nature of Computational Thinking*. Washington, D.C.: The National Academies Press.

National Research Council. (2011). *Report of a Workshop of Pedagogical Aspects of Computational Thinking*. Washington, D.C.: The National Academies Press.

Papert, S. (1980). *Mindstorms: Children, computers, and powerful ideas*. New York: Basic books.

Papert, S. (1996). An Exploration in the Space of Mathematics Educations. . *International Journal of Computers for Mathematical Learning, 1(1)*, 138-142.

Rand, W., Blikstein, P., & Wilensky, U. (2006, June). *Widgets, planets, and demons: The case for the integration of human, embedded, and virtual agents via mediation*. Proceedings of the annual meeting of the Swarm Development Group, South Bend, IN.

Rand, W. a. R., R. (2010). Agent-based modeling in marketing.

Repenning, A., Webb, D., & Ioannidou, A. (2010). Scalable game design and the development of a checklist for getting computational thinking into public schools. In *Proceedings of the 41st ACM technical symposium on Computer science education* (pp. 265–269).

Sengupta, P., Kinnebrew, J. S., Basu, S., Biswas, G., & Clark, D. (2013). Integrating computational thinking with K-12 science education using agent-based computation: A theoretical framework. *Education and Information Technologies*, 1–30.

Sengupta, P., & Wilensky, U. (2009). Learning electricity with NIELS: Thinking with electrons and thinking in levels. *International Journal of Computers for Mathematical Learning, 14*(1), 21-50.

Settle, A., Franke, B., Hansen, R., Spaltro, F., Jurisson, C., Rennert-May, C., & Wildeman, B. (2012). Infusing computational thinking into the middle- and high-school curriculum. In *Proceedings of the 17th ACM annual conference on Innovation and technology in computer science education* (pp. 22–27). New York, NY, USA: ACM. doi:10.1145/2325296.2325306

Settle, A., Goldberg, D. S., & Barr, V. (2013). Beyond computer science: computational thinking across disciplines. In *Proceedings of the 18th ACM conference on Innovation and technology in computer science education* (pp. 311–312). New York, NY, USA: ACM. doi:10.1145/2462476.2462511

Stroup, W. M., Ares, N., Hurford, A., & Lesh, R. A. (2007). Diversity by design: The what, why and how of generativity in next-generation classroom networks. In R. A. Lesh & J. J. Kaput (Eds.), *Foundations of the Future: Twenty-first century models and modeling*: Lawrence Erlbaum.

White, T., & Brady, C. (2010). *Space and Time in Classroom Networks: Mapping Conceptual Domains in Mathematics through Collective Activity Structures*. Proceedings of the International Conference of the Learning Sciences.

Wilensky, U. (1999). NetLogo [computer software] (Version. Evanston, IL: Center for Connected Learning and Computer-Based Modeling, Northwestern University. http://ccl.northwestern.edu/netlogo.

Wilensky, U. (2001). Modeling nature's emergent patterns with multi-agent languages. In *Proceedings of EuroLogo* (pp. 1–6). Linz, Austria.

Wilensky, U., & Papert, S. (2010). *Restructurations: Reformulations of knowledge disciplines through new representational forms*. Proceedings of the Constructionism 2010 Conference, Paris, France.

Wilensky, U., & Reisman, K. (2006). Thinking like a wolf, a sheep, or a firefly: Learning biology through constructing and testing computational theories— an embodied modeling approach. *Cognition and Instruction*, *24*(2), 171–209.

Wilensky, U., Stroup, W. (2000) Networked gridlock: Students enacting complex dynamic phenomena with the HubNet architecture. In B. Fishman & S. O'Connor-Divelbiss (Eds.), Proceedings of the Fourth Annual International Conference for the Learning Sciences (pp. 282-289). Mahwah, NJ: Erlbaum. June 14 - 17.

Wilensky, U., & Rand, W. (in press). Introduction to agent-based modeling: Modeling natural, social and engineered complex systems with NetLogo. Cambridge, MA: MIT Press.

Wing, J. M. (2006). Computational thinking. *Communications of the ACM*, *49*(3), 33–35.

Wing, J. M. (2011). Research Notebook: Computational Thinking—What and Why? *The Link*, (Spring). Retrieved from http://link.cs.cmu.edu/article.php?a=600