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 jpps. 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 jpps 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
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