Bifocal Modeling: a Framework for Combining Computer Modeling, Robotics and Real-World Sensing[1]

Paulo Blikstein, Uri Wilensky

Center for Connected Learning and Computer-Based Modeling – Northwestern University 2120 Campus Drive – Evanston, IL, USA – 60208 [paulo, uri]@northwestern.edu

Abstract

Multi-agent modeling has been successfully used in a large number of distinct scientific fields, transforming scientists' practice. Education researchers have come to realize its potential for learning. Studies have suggested that students are able to understand concepts above their expected grade level after interacting with curricula that employ multi-agent simulation. However, most simulations are 'on-screen', without connecting back to the physical world. Real-time model validation is challenging with extant modeling platforms. Therefore, we designed a technological platform that would enable students to connect computer models and sensors in real time, to validate and refine their models using real-world data. We will focus on both technical and pedagogical aspects, describing pilot studies that suggest a real-to-virtual reciprocity that spurs further inquiry toward deeper understanding of scientific phenomena.

Objectives and Theoretical Framework

A powerful means of applying technology to improve education has been to bring the most advanced tools from research labs and adapt them for use in schools. One such well- known application is the LOGO computer language, proposed by Seymour Papert (Papert, 1980) and colleagues almost forty years ago, which encapsulated the most powerful ideas in Computer Science at the time and made them available for children. The same happened to robotics in the late nineties and early 21st century (Eisenberg, 2002; Martin, 1996, 1993; Resnick, 2000, 1991; Sipitakiat, 2000). Through the introduction of robotics kits such as LEGO Mindstorms, many new learning opportunities in Engineering and Science were made available for children of all ages, opportunities that would have been unimaginable just some years before when such robotics were only available in advanced laboratories at engineering schools. Mechanical advantage, gearing, mechanism design, data sensing, control, and feedback are just some examples of the powerful ideas made available to learners.

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[1] This paper was slightly modified to correct errors in the original document.

Multi-agent modeling and simulation (e.g., "Repast", Collier, 2001; "Swarm", Langton & Burkhardt, 1997; "NetLogo", Wilensky, 1999b), too, went through a similar path. Multi-agent methods have been used with great success in fields such as biology, sociology, chemistry, physics, economics, psychology, and engineering (Raabe, Roters, Barlat, & Chen, 2004; Rand & Wilensky, 2006; Thornton & Mark, 2005; Wolfram, 2002). Instead of departing from often very complicated "aggregate" behaviors, scientists started to use massive computational power to simulate systems with thousands of very simple agents, behaving according to simple rules. This approach has dramatically changed scientists' mindsets and practices, enabling theoreticians to assign rules of behavior to computer "agents," whereupon these entities act independently *but* are responsive to local contingencies, such as the behaviors of other agents. Typical of agent-based models is that the cumulative (aggregate) patterns or behaviors at the macro level are not premeditated or directly actuated by any of the lower-level, micro-elements. For example, flocking birds do not intend to construct an arrow-shaped structure (Figure 1), and molecules in a gas are not aware of the Maxwell- Boltzmann distribution. Rather, each element (agent) follows its local rules, and the overall pattern arises as epiphenomenal to these multiple local behaviors i.e., an overall pattern emerges. In the late eighties and early nineties, Wilensky & Resnick started to realize that agent-based modeling could have a significant impact on learning (Resnick, 1994; Resnick & Wilensky, 1993; Wilensky, 1999a; Wilensky & Resnick, 1995). Wilensky & Resnick adapted languages and techniques heretofore used only with supercomputers and brought them into the classroom. Powerful ideas such as emergence, self- organization, and randomness were put in the hands (and minds) of children. In the ensuing decade and a half, ABM, like computer programming and robotics, has been translated for use in the educational context. Wilensky and colleagues have produced a large body of research showing the power of this technology for learning (Abrahamson & Wilensky, 2004c, 2005; Blikstein & Wilensky, 2004, 2005, 2006; Levy, 2004; Resnick & Wilensky, 1998; Sengupta & Wilensky, 2005; Stieff, 2003; Wilensky, 1995, 1999a; Wilensky, Hazzard, & Froemke, 1999; Wilensky & Reisman, 2006; Wilensky, 1999a). In the 2000s, many other researchers have continued this work and have documented learning gains through interaction with curricula developed using multi-agent simulation (Abrahamson & Wilensky, 2004; Charles & d'Apollonia, 2004; Jacobson & Wilensky, 2006; Klopfer, 2003; Wilensky, 2001; Wilensky & Reisman, 2006) For instance, to study the behavior of a chemical reaction using multi-agent simulations, a student would observe and articulate only the behavior of individual molecules, with the chemical reaction construed as emerging from the myriad interactions of these molecular agents. When constructing an agent-based model, the modeler assigns to agents local, micro-rules, and then sets them into motion, watching the overall patterns that emerge.

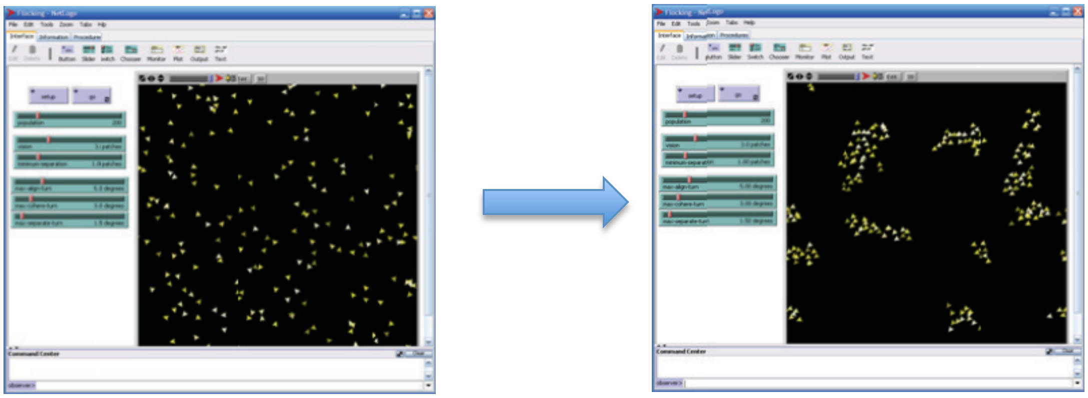

Figure 1: An agent-based model of the flocking behavior of birds

In order to build a model, one must determine the elementary rules within a system. Despite their compartmentalization in the traditional school curriculum, Physics, Chemistry, and Biology are 'out-there-in-the-world', entangled in a complex web of phenomena. Most are invisible to human vision and time scale. Many patterns in nature are too long, too fast or too small for learners to extract and understand their underlying rules and structures. Canonical examples include weather behavior, chemical reactions, housing and traffic patterns, particle physics, and population ecology. Conventional school laboratories are not well equipped to support students in developing hypotheses about the information they gather. For example, a student studying a chemical reaction in a Chemistry laboratory might discern the chemical elements involved and even hypothesize as to the relations between them; however, the investigation cannot go much further. Later, in the classroom, s/he will learn equations and theories that bear little resemblance to the phenomenon observed in the laboratory. They are missing tools that provide continuity between observation and model-building, providing the 'missing link' between data-gathering and the construction of theories using computational representations. That is, to make the study of these phenomena accessible to students, we need new technological tools that foreground and unveil deep structures in the virtual and physical world.

This paper describes a research agenda that attempts to find the "missing link" between these two last traditions, thus merging robotics/sensing and multi-agent computer simulations.

Traditional computer modeling environments do not communicate with the world, while educational robotics aims to construct autonomous devices with local, limited processing power.

Moreover, since multi-agent simulation uses simple rules to generate complex behaviors, data sensing could potentially be much simpler: instead of complex sensors, students could just detect simple physical interactions between the agents.

The platform we designed enables learners to connect virtual and physical models in order to validate, refine, and debug their computer models using real-world data. We will present proof-of-concept models that demonstrate the potential of such an approach, and the results of our two-year user study, which show the potential learning benefits of this design framework. As this modeling platform enables seamless integration of the virtual and the physical worlds, permitting modelers to focus simultaneously on their 'on-and' off-screen' models, we call it bifocal modeling.

The Technological Platform

The typical activity for our pilot-studies was for students to build using the NetLogo (Wilensky, 1999b) modeling-and-simulation environment, a *computer algorithm* of a particular scientific phenomenon, such as heat transfer or gas laws, and a *physical apparatus* equipped with electronic sensors. We developed special software components to link the models in real time through an open-source, low cost analog-to-digital interface – the GoGo Board (Sipitakiat, Blikstein & Cavallo, 2004). Then, learners would create a computer interface to visualize outcomes side-by-side (Figure 2), comparing their results, and debugging their algorithm until it adequately matched the real-world data.

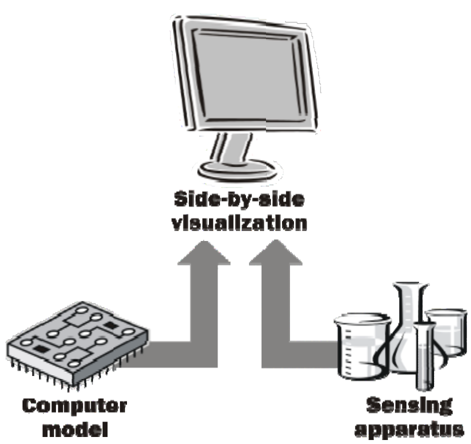

Figure 2: Basic architecture of a bifocal system

The computer screen becomes a display for two distinct 'models': the computer model, which is a proceduralization, through programming, of equations, text, or other representations of scientific content; and a display of the real-world phenomenon, which is discretized by means of sensors and other laboratory apparatus to fit into the scale (temporal and physical) of the computer model (see Figure 3). Because the computer models are carefully constructed to imitate the phenomenon's visual language, the bifocal methodology minimizes interpretive challenges typical of multi-media research. That is, the seen and the hypothesized are displayed such that their perceptual differences are backgrounded, making procedural differences more likely to be revealed. By utilizing the power of computation and representation, bifocal modeling constitutes a multi-disciplinary research tool that offloads aspects of both the interpretive and procedural burdens of scientific practice, freeing cognitive, discursive, and material resources that can instead be allocated to validating of the hypotheses. The adaptable quality of the NetLogo multi-agent modeling- and-simulation environment enables users to keep calibrating their proceduralized hypotheses until their visualization reaches compelling micro/macro similarity to the real-data, such that there are grounds to assume that the proceduralized model indeed emulates this phenomenon.

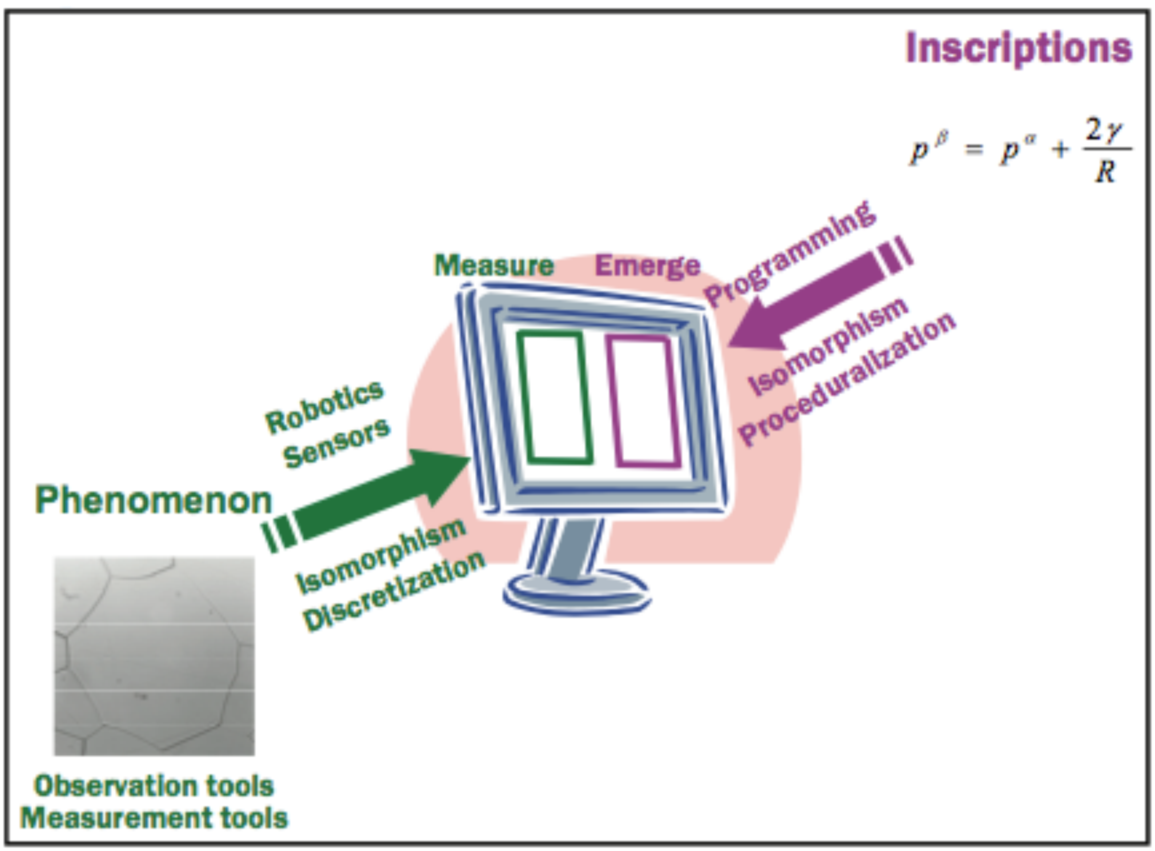

Figure 3 – The Bifocal modeling framework: Inscriptions and the phenomenon meet in the computer screen.

We built proof-of-concept systems for *bifocal* explorations in heat transfer, gas laws, chemical reactions, and Materials Science. Figure 4 (top) shows a model to investigate heat transfer using a multi-agent approach. Each cell in the hexagonal grid is an agent. The physical counterpart is a grid of 19 hexagonal cells and a lid with temperature sensors. Cells are filled with water at different temperatures. The sensors are connected to the analog-to-dialog interface, and the data are fed directly into the computer visualization, where students can compare both results (from the sensors and from their computer model). The second example figure (Figure 4, bottom) investigates gas laws using pressure, temperature, and volume sensors. As the volume of the syringe changes, the computer model varies accordingly, and students evaluate the match between sensor values and the results supplied by their own algorithms.

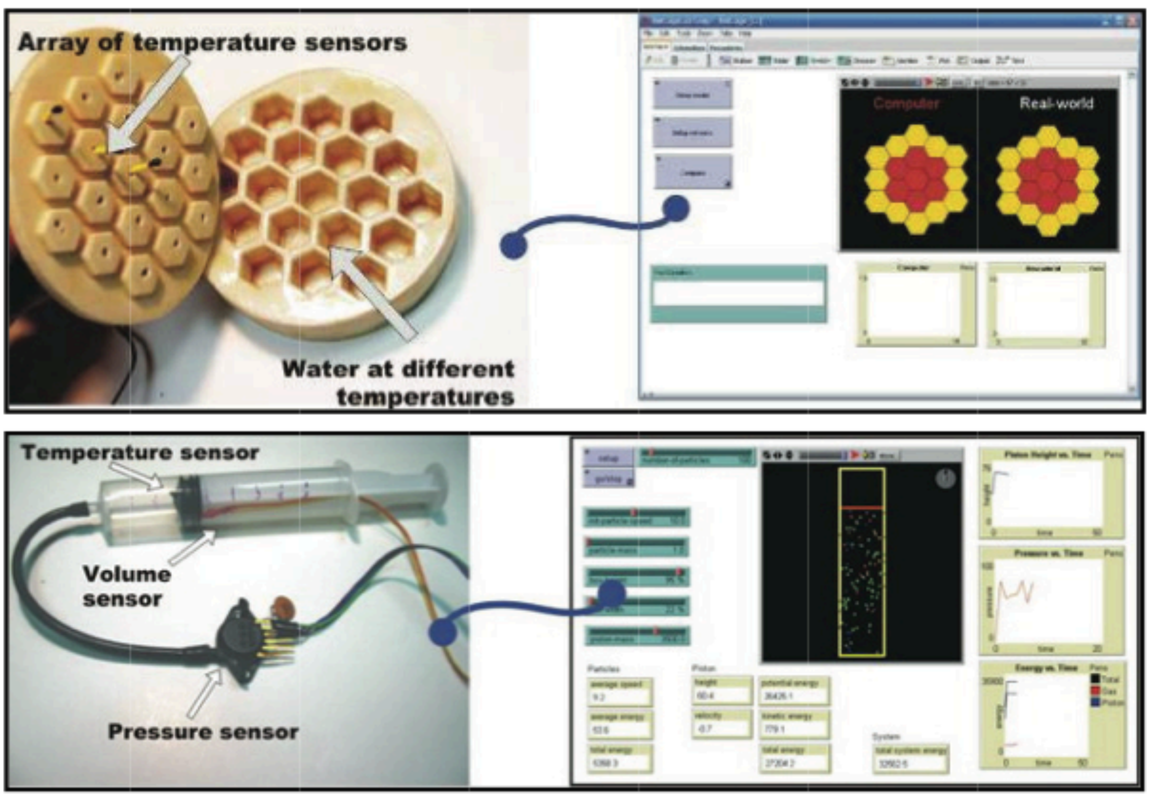

Figure 4 – Two proof-of-concept bifocal models: heat transfer and gas laws.

The two models reveal some of the new challenges modelers experience in the bifocal framework. The heat transfer model requires the discretization of the physical phenomenon: to be able to map the on-screen agent to sensors, those sensors need to enclose or represent a finite and discrete amount of matter. Spatially, the discretization needs to be geometrically and functionally equivalent to its virtual counterpart. In heat transfer, agents should have radial symmetry, i.e., heat should spread equally in all directions. In a purely virtual model, shapes can represent the agents (circle, square, etc.), even shapes which are not symmetrical – as it is a virtual ‘world’, distances and symmetry can be overridden by software. However, in the physical world, we cannot use software to fix design problems. Using a circular shape, for example, would result in walls with non-uniform thickness, which would certainly impact heat flow. The only option realizable in the real world is the hexagon, a space-filing and radially-symmetric shape. This example illustrates how this ‘dialogue’ between real and virtual models can impact both the ‘off-screen’ construction and the ‘on-screen’ programming.

The Gas Laws model also reveals some important discretization challenges. In the ‘virtual’ world, linear, exponential, and logarithmic behaviors can be freely converted and transformed. Boundary conditions can be dealt with using simple conditional commands. In the world of sensors, however, the constraints are much stiffer. Each type of sensor has its own scale, range, and boundary conditions. While pressing the syringe half-way, the pressure sensor will detect its full range. The temperature sensor will typically utilize just 0.5% of its range, while the volume sensor will exhibit non-linear behavior. Extracting and harmonizing data from all these sources requires a significant effort from the modeler in terms of software and hardware development, and will reveal not only the workings of the natural phenomena being explicitly analyzed (Gas Laws, in this case), but also, all of the sensors as physical models themselves. We will see more examples of such issues in the section titled Data and Discussion.

User Studies: Methods

In the three pilot studies conducted in 2005, 2006 and 2007, we compared artifacts generated by undergraduate and graduate students under two distinct conditions. In the first one, students created purely virtual multi-agent models. In the second, students built models with sensors. All students built their models as an assignment in a ‘Learning Environments Design’ course. In 2005 and 2006, we had 14 participants (two groups of seven). In 2007, we conducted a shorter model-building workshop for undergraduate and graduate students enrolled in a ‘Learning Environments Design’ course. In this workshop, three students built bifocal models. We conducted and videotaped interviews with students during the construction of the projects, and a longer individual post-interview took place after final projects were presented. Our data include field notes, transcriptions of interviews, and students’ artifacts. For most projects described in the next section, the complete model-building activity (constructing the physical and computer models) took approximately two weeks.

User Studies: Data and Discussion

Our data analysis will focus on particular constructs to which students in the second group (physical + virtual models) attended to more than the students in the first group. Below, we summarize the main dimensions along which students exhibited the most significant differences, followed by insights gathered from our observations and interviews.

Motivation, gender barriers, and problem-solving strategies

The process of building sensor-equipped devices was engaging for all students. Students came to school over the weekends to keep working on their projects, and invested long hours into their construction. One surprising observation throughout the work was related to the stereotypical gender barrier regarding mechanical and electrical construction. Especially in the second year of the study, the two groups were led by females, who also took over the soldering tasks and most of the construction. Carol, a 24-year old graduate student in education who had never before touched a soldering iron, reported the experience as 'liberating'. Her father was an electrical engineer himself and told her to never touch electronics or tools, because they were not "for females." Being immersed in an environment in which physical construction was part of a valued intellectual activity (creating computer models) led her to experiment with such tools for the first time. Soon, she was leading the group in both the construction and modeling tasks.

But the physical construction was not only engaging and 'liberating', but also significant in its cognitive implications. Students engaged with virtual + physical modeling attended to phenomenal factors that they would likely have overlooked if they were engaged solely with virtual modeling (though such factors were not mentioned by students in the first group), such as energy loss, reversibility, synchronicity, and precision. Some new problem-solving avenues were also explored: for example, a group designing a sensor-equipped American Sign Language recognition glove (Figure 7, top left) was struggling to write flexible and reliable code for gesture recognition. They ended up realizing that it would be far more efficient to write a program to enable each user to train the system with real-world data from their actual gestures, then applying some statistical filtering to the data. Therefore, instead of writing a complex program to recognize all possible variations of gestures, they designed a much simpler algorithm, made possible due to the availability of physical sensors as 'extensions' of the computer model. In a project studying earthquake wave patterns (Figure 7, top center and top right), learners analyzed the propagation of multiple waves in a gelatin model they built, which helped them realize many of the errors and limitations of the previously designed wave propagation algorithm. Similar findings were detected in other groups as well, such as the group that built systems to study tsunami wave propagation (Figure 7, bottom left).

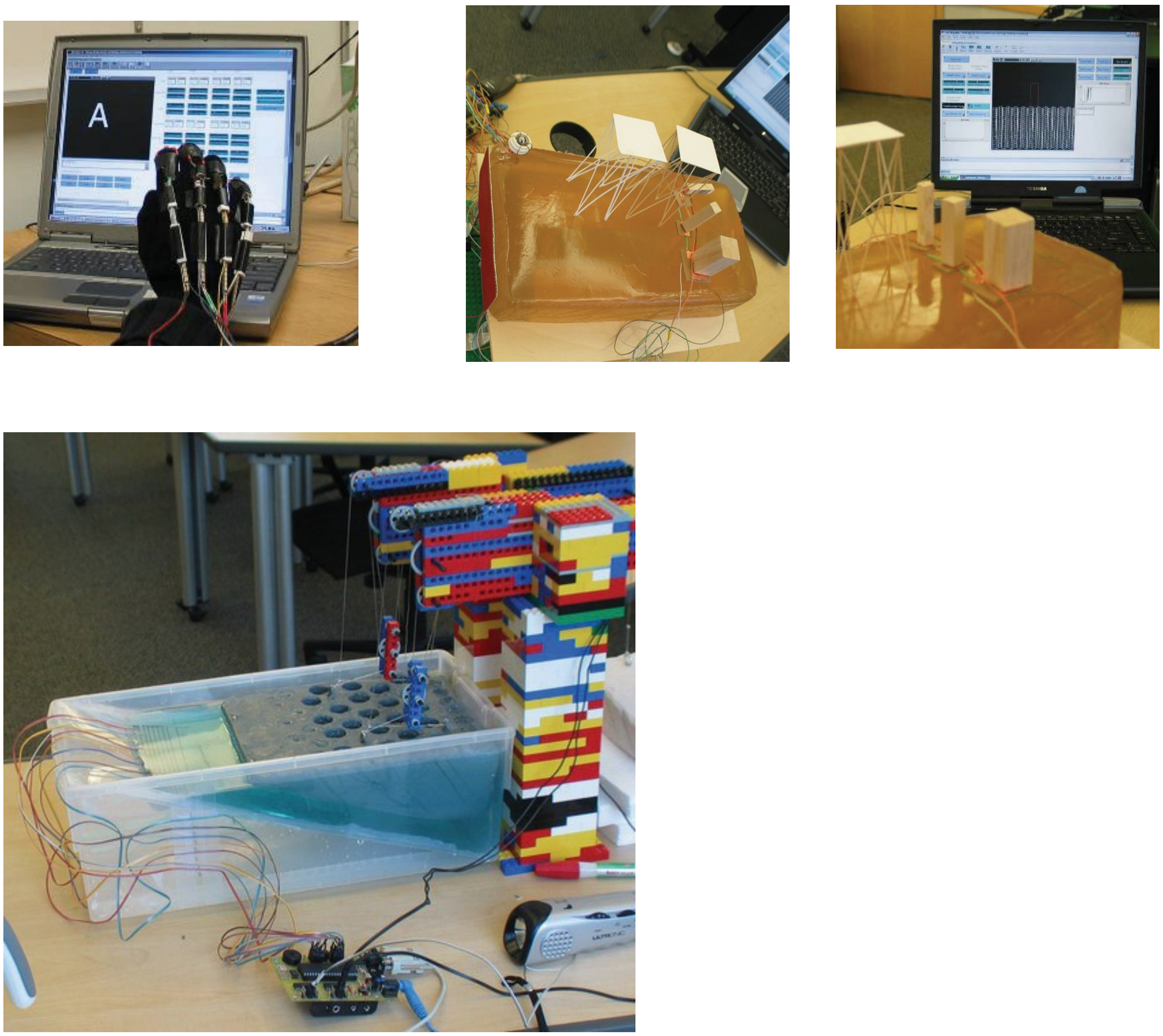

Figure 5. An ASL recognition glove (top), and models for investigating earthquakes waves (middle, on the left, the physical gelatin model, on the right, the computer model), Tsunami wave patterns (bottom left).

Scale

Bob, a student building an acid-base reaction model (Figure 8) started to get interested in calculating the real-world scale of the virtual chemical reaction, which involved only 100 molecules. After several calculations with Avogadro's number, he was startled by the orders of magnitude of difference between what was contained in one drop of water as compared to the number of molecules in the computer model. This insight changed his view on the limitations of the computer model. After the calculation, he stated that, given the current algorithm and number of molecules in the computer model, no computer in the world would be fast enough to simulate the to-scale speeds of the 100 molecules that were shown in the screen. Alternatively, no computer would be able to simulate what takes place in a real drop of water. This discussion triggered Bob to reflect on modeling itself: do we need to simulate the whole drop of water? If not, how much of it do we need to simulate? If just 100 molecules could mimic what billions do, what would be the implications for the work of a scientist?

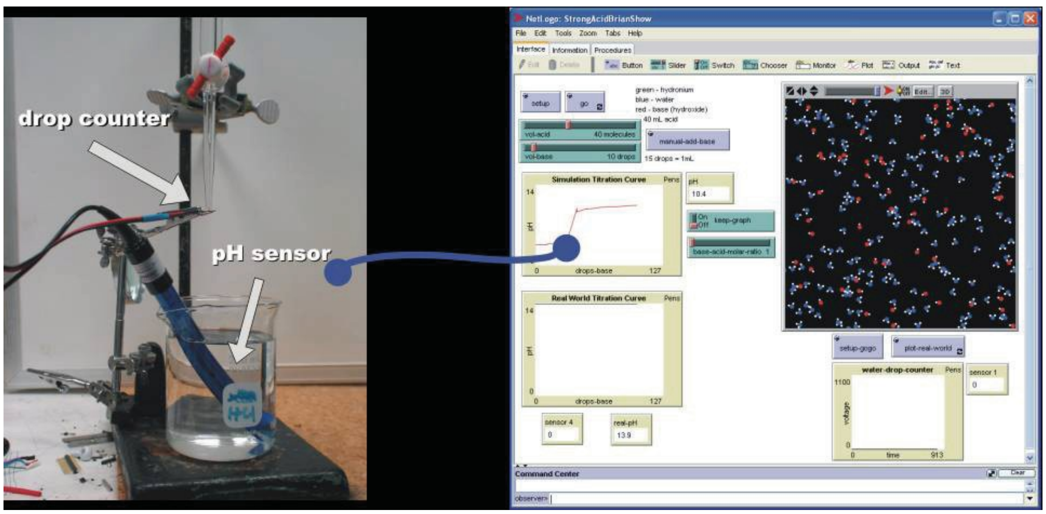

Figure 6 – A model of acid-base reactions

Coefficients, precision

Students in the virtual + physical group were more careful in coming up with adjustment coefficients for their models. Carol and Charles, two graduate students in education, took an existing NetLogo model (the fire model [Wilensky, 1997] of forest fire spread) and created a physical apparatus to incorporate 'real' wind speed into the model. They built an elaborated anemometer with a perforated cardboard wheel, a light sensor, a flashlight, and a Lego fan; the wind was generated with a hair dryer. When they started to incorporate the sensor data into the forest fire model, one immediate problem was the conversion of the measured wind speed to the scale of the computer model. Their anemometer measured wind speed in rotations per minute, but the forest fire model contained several hundred virtual trees. The computer model, in the real world, would measure several square miles. Their first step was to conduct complex calculations to convert the rotational speed of their anemometer to linear wind speed. But that was not enough – the actual hair dryer wind speed would hardly move a branch in a real forest. Thus, Carol and Charles engaged in the elaborate task of selecting a conversion coefficient for wind speed that would be meaningful when applied to a large-scale forest while being careful not to step into non-linear regions of airflow. For example, switching the hair dryer from low- to high-power would double the resulting airflow – but they wondered: would doubling the forest fire air speed be physically meaningful? In thinking about this question, they realized that their coefficient might be a *function*, and not simply a *number*. In contrast, students in the first group (no sensors) oftentimes resorted to "unexplained" coefficients to make the simulation run faster or according to their previous expectations.

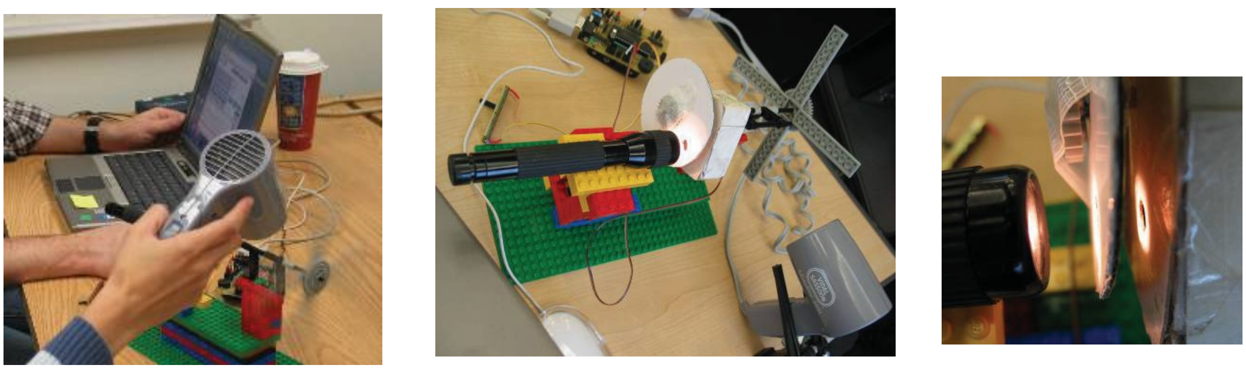

Figure 7 – A forest fire spread model with a wind generator (a hair dryer, left), the mechanism of rotation speed detection with a flashlight and a light sensor (center), and a detail of the rotation detection apparatus (right).

Energy loss

Computer models can easily ignore one fundamental process of physics: energy loss. On-screen agents can move freely in the virtual world without ever experiencing any friction unless the modeler decides to include it in the model. When dealing with the physical world, students do not have that option: energy loss and friction are facts of nature that have to be dealt with. Peter and Ann, who decided to build a model to simulate Newtonian motion, started the project sure that it would be a straightforward task; after all, Newtonian motion is a well-known part of physics and its equations are relatively simple. They built the device shown in Figure 7.

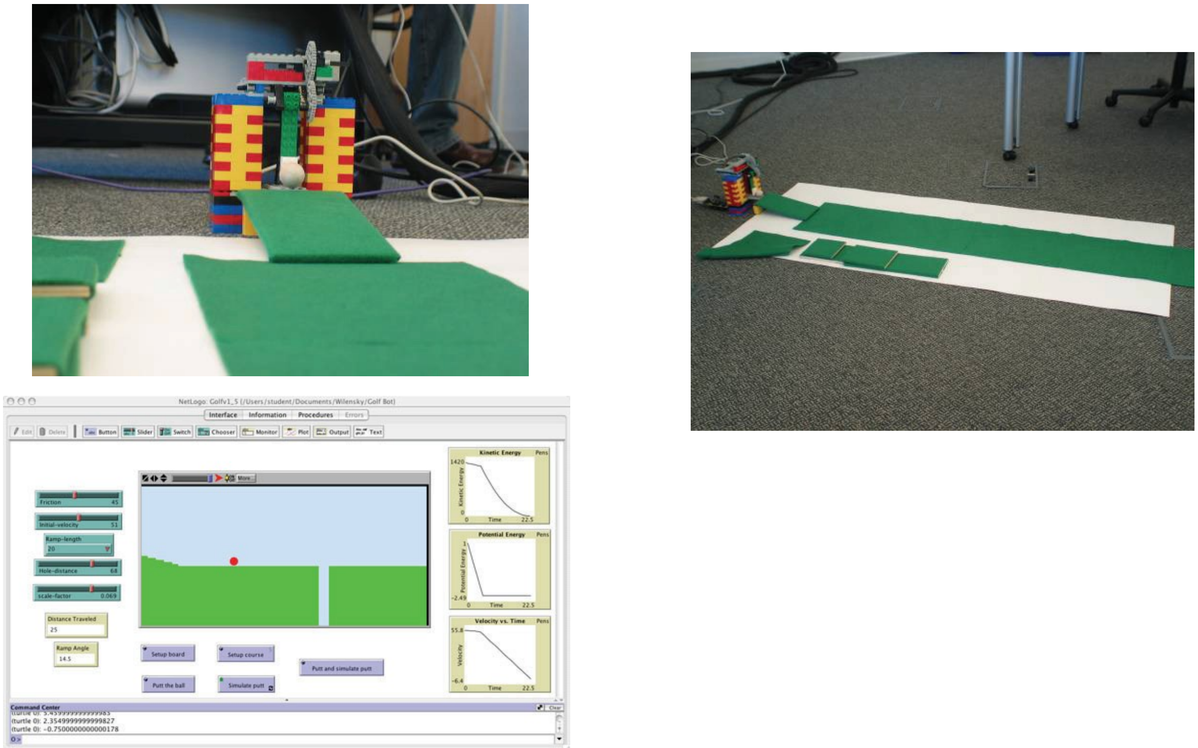

Figure 8 – The Newtonian motion apparatus (top), in which a sphere is launched at the top of the ramp by a robotic arm, rolls down the ramp, and eventually stops in the green carpet, and the corresponding NetLogo model (bottom)

After some hours trying to match their physical and virtual models, Peter and Ann were frustrated. The conventional Newtonian equations seemed to be insufficient to predict how far the real sphere would travel, compared to the virtual sphere. Upon closer investigation, they started to gather a list of possible causes for the mismatch, most of which are typically overlooked in introductory Physics courses. There was air resistance, irregularities in the texture of the green mat, variability in the initial impulse of the robotic arm, slight changes in the inclination of the whole apparatus depending on the floor of the room, discontinuities in the ramp-mat transition, and problems with the path of the sphere movement (it was never completely rectilinear). The number of new variables was overwhelming.

The group was startled to realize how much Newtonian physics as taught in the classroom differs from the actual physical phenomenon, and understand the importance of various sources of energy loss in a system. Unable to measure and model all possible variables, they decided to group all energy loss sources into one "catch-all" variable. However, unlike the students who did not build physical models, Peter and Ann were very aware of the dangers and limitations of this approach. They realized, for example, that some sources of energy loss have quadratic variations on speed, while some are linearly dependent, and others, invariant. The catch-all variable, thus, was their artifact to get the model finished on time, but with the awareness of the complexities of Newtonian motion in the physical world.

Synchronicity/time scales

Marcel was inspired by the heat transfer model (see Figure 4) to build his own model to investigate this phenomenon. However, he wanted to test how different metals would behave when heated. Coming in to the project, he harbored two hypotheses about the nature of each of the foci of bifocal modeling. Marcel supposed that it should be relatively straightforward to build: (a) an artifact that enables the measurement of the target phenomenon; and (b) a computer-based procedure that emulates this phenomenon. Both hypotheses proved incorrect. He relentlessly shifted foci back and forth between the physical and virtual, until he negotiated a common ground of logical (i.e. structural rationale) and visualization (i.e. interface) properties that enabled bifocaling. As he stated, "By comparing the dynamics of the model and the wire, I iteratively debugged my conceptual model for heat flow." The unsettling element in Marcel's model that triggered the frustration of his expectations was *time*. Upon completing the physical model and connecting it to the computer model, he realized that there was a fundamental (and hard) problem to be addressed: synchronicity. Sensors were sending temperature data twenty or thirty times a second, but the computer was calculating new temperatures for the virtual agents several thousands of times a second. Which "side" should be in control? Should the computer model be slowed down to match the real-world data, or should the sensor data be manipulated by the software to fit into the timing scheme of the computer model? Both options have significant implications for modeling and speak to the modeling endeavor itself. If the computer's timing were to prevail, the sensor data would be greatly 'stretched', and perhaps become meaningless. In the physical model, the inch that separated two temperature sensors contained billions of atoms. In the computer model, that same distance contained just a couple of agents. The nanosecond events taking place in the real material would have to be somehow converted to the model scale.

Marcel spent a significant part of the workshop thinking about this issue. Being a graduate student in education and therefore very engaged in thinking about issues of learning, he observed that the bifocaling experience had impacted his thinking with respect to the meaning of modeling itself. He had the opportunity to ground in firsthand experience the literature on pedagogy—in particular the epistemology of modeling. He then posed the following questions, which have direct implications for design: What, in fact, is the objective phenomenon that is being modeled? Is it 'what happens when you heat a wire' or is it 'the concept of heat flow?' In traditional textbooks, chapter titles disclose 'what is to be learned,' such that learning is concept-driven, whereas his experience was phenomenon-driven (see Papert, 1996 on the 'project-before-problem' principle). He wondered: can one speak of an objective phenomenon at all, or are all phenomena constructed mentally?

In the end, he synchronized his computer model so as to be regulated by the physical data, adding a "model-delay" slider to it. He also had to add computer procedures to calibrate the sensors so as to take room temperature into consideration, and built visualization mechanisms to compare the data side-by-side.

Conclusions and future work

Our data suggests that there are particular concepts which students of the second group were more attentive to: friction/energy loss, precision, scale, time, coefficients, scale conversion, and synchronicity. The *bifocal* approach enabled students to rapidly investigate their hypotheses and observe alternative outcomes, debugging their own models and algorithms. This modeling framework is an appropriate solution for some types of investigation and content, especially when the aforementioned topics (energy loss, etc.) are relevant. Also, as what is seen and what is hypothesized are displayed simultaneously, their perceptual differences are backgrounded and, therefore, procedural differences are revealed. By using the power of computation and representation, bifocal modeling constitutes an inquiry tool for students which offloads aspects of the interpretive and menial encumbrance of scientific practice, freeing cognitive resources that can be allocated to the validation of the hypotheses.

We are currently planning middle and high school implementations to extend this work to younger students, as well as improving the hardware and software platforms.

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