Learning Complexity: Agent-Based Modeling Supporting Education Research on Student Cognition in Social Contexts

Dor Abrahamson (Organizer), Paulo Blikstein, Michael Cole, David Hammer, James Levin, Uri Wilensky (Chair), and Richard Lesh (Discussant)

Embodied Design Research Laboratory, University of California - Berkeley
Center for Connected Learning and Computer-Based Modeling, Northwestern University
Physics Education Research Group, University of Maryland
Laboratory of Comparative Human Cognition, University of California - San Diego
School of Education, Indiana University

contact: dor@berkeley.edu

The symposium presents exemplars of the potential power of complexity-studies methodology, embodied in agent-based modeling, for engaging in research on psychological phenomena involving individual learners in social contexts. Working in the NetLogo environment (Wilensky, 1999), we explore the debate between Piagetian and Vygotskian accounts of learning, the development of student reasoning on Piagetian conservation tasks, and student’s implicit argumentation strategies in science inquiry. Also, we reflect on the artifacts of ABM as mediators of distributed research effort. ABM lenses could enable education researchers to explore, articulate, and share intuitions we have struggled to study and express -- that individual intelligent behavior emerges from multi-componential cognitive interactions and, one “level up,” that individuals and communities are interdependent through myriad dynamic reciprocities.

Introduction

This symposium presents a new methodology for conducting research on education theory, agent-based modeling. Agent-based modeling (hence ABM) has been increasingly used by natural scientists to study a wide range of phenomena such as the interactions of species in an ecosystem, the interactions of molecules in a chemical reaction, the percolation of oil through a substrate, and the food-gathering behavior of social insects (Sole & Goodwin, 2000; Bonabeau Dorigo, & Théraulaz, 1999; Troisi, Wong, & Ratner, 2005; Wilensky & Reisman, 1998; 2006). Such phenomena, which lend themselves to two or more layers of description—e.g., collisions of particles in a gas chamber are the “micro” events, and pressure is the “macro” event—have been termed complex, and are collectively studied in a relatively young interdisciplinary field called complex systems or complexity studies (Bar-Yam, 1997; Holland, 1995; Kauffman, 1995; Axelrod, 1997). Typical of complex phenomena 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. Rather, each element (“agent”) follows its “local” rules, and the overall pattern arises as epiphenomenal to these multiple local behaviors—the overall pattern emerges.

Specialized computer-based environments (e.g., ‘NetLogo,’ Wilensky, 1999; ‘Repast,’ Collier &

Sallach, 2001; ‘Swarm,’ Langton & Burkhardt, 1997) have been developed as research tools for investigating complex phenomena (Gilbert, 2005; North et al, 2002; Wilensky, 2001; Wilensky & Reisman, 2006). The agents can be instantiated in the form of a computer program that specifies their rule-based behaviors. ABM is thus particularly powerful for studying complex phenomena, because once the modeler assigns agents their local rules, the modeler can set these virtual agents into motion and watch for any overall patterns that arise from the agents’ interactions. For example, the modeler might assign a group of virtual birds a set of rules and then watch their interactions to see whether typical flock structures emerge (Reynolds, 1987; see also Wilensky, 1998).

Whereas initially complex-systems methods and perspectives arose from the natural sciences, complexity, emergence, and micro and macro levels of description of phenomena are all highly relevant to research in the social sciences. Indeed, the recent decades have seen a surge in social-science studies employing ABM (Epstein & Axtell, 1996; Diermeier, 2000; Axelrod, 1997). Learning, too, we argue, can be construed as a complex phenomenon, and thus ABM is a potentially powerful research tool conducive to the investigation of patterns, including structures and rules, underlying the emergence of learning. We support our argument by looking at specific projects in which members of the panel are applying ABM (using ‘NetLogo,’ Wilensky, 1999) to express putative theoretical models and “run” them so as either to generate simulated data or to analyze real data from laboratory and classroom studies. These examples pertain to: (a) the debate between Piagetian and Vygotskian accounts of learning, in which the agents are individual learners and the emergent phenomenon is “classroom” dynamics (Abrahamson, Wilensky, & Levin); (b) the development of student reasoning on Piagetian conservation tasks, where the agents are an individual’s cognitive elements and the emergent phenomenon is intelligence (Blikstein, Abrahamson, & Wilensky); and (c) student’s implicit argumentation strategies in a science inquiry classroom, in which the agents are a student’s cognitive resources, and the emergent phenomenon is a coherent argument (Blikstein, Wilensky, & Hammer). Levin and Cole (this symposium) apply a distributed-learning perspective on the emergence of collaborative-research practice from the interaction of researcher—agents: they foreground the roles of ABM artifacts, the simulations, as mediating these interactions.

A vision of the NetLogo development effort is that building simulations will become common practice of natural/social-sciences scholars investigating complex phenomena: the scholars themselves—not hired programmers—build, run, and interpret the simulations (Wilensky, 2003; Tisue & Wilensky, 2004). The new lenses of ABM, we believe, will enable education researchers to explore, articulate, and share intuitions we have struggled to study rigorously and express coherently: the intuitions that individual intelligent behavior emerges from multi-componential cognitive dynamics and, at a “level up,” that individuals and communities are interdependent through myriad dynamic reciprocities (e.g. Cole & Wertsch, 2002; Fischer & Rose, 1999; Fuson & Abrahamson, 2005; Greeno, 1998, 2006; Minsky, 1985; Wilensky & Abrahamson, 2006).

The symposium will begin with a ten-minute introduction by the chair. Following, each presenter will highlight the unique contribution of their respective paper. Finally, our discussant, Richard Lesh, will comment on the presentations, and then we will open the floor to questions and comments from the audience. Following, below, are the four papers.
This paper is a proof-of-existence empirical paper. That said, it is also a methodological paper. The methodology is agent-based modeling, a computer-supported mode of inquiry into complex phenomena, such as weather fronts, market fluctuations, or participation patterns in a middle-school mathematics lesson. We have previously shown that agent-based simulation can express theoretical models of learning (Abrahamson & Wilensky, 2005; see also Smith & Conrey, 2007). In that paper, we claimed that a promising attribute of simulation-based research into learning is that it fosters scholarly critique and engaging collaboration. It is that claim that is herein proven to stand. The proof lies in the collaborative criticism offered by the third author, Jim Levin, to the first two authors, Dor Abrahamson and Uri Wilensky, concerning their agent-based simulation of learning, which was first presented at the 2005 annual meeting of the Jean Piaget Society and was then made available online, along with its underlying computational procedures that were laid out for scrutiny. The 2005 paper explicitly invited fellow researchers to critique the simulation and possibly modify it so as to accommodate their own perspectives and possibly enable their own investigations. Indeed, the critique received from Levin took a unique form—he improved the computer-based model such that it better simulates the target constructs. Such co-constructive critique, we argue, is a hallmark of the promise of agent-based modeling. So we submit that this proof of existence, if anecdotal validation, may be a harbinger of a new mode of research in the learning sciences and beyond—a mode that builds on constructionism (Papert, 1991): constructionist collaboration.

**Background**

We have argued (Abrahamson & Wilensky, 2005) that ABM has potential to contribute to the advancement of theory in at least three major ways: (a) explicitizing—ABM computational environments demand an exacting level of clarity and specificity in expressing a theoretical model and provide the tools, structures, and standard practices to achieve this high level; (b) emergence—the computational power of ABM enables the researcher to mobilize an otherwise static list of conjectured behaviors and witness any group-level patterns that may enfold through multiple interactions between the agents who implement these conjectured behaviors; and (c) intra/inter-disciplinary collaboration—the *lingua franca* of ABM enables researchers, who otherwise use different frameworks, terminology, and methodologies, to understand and critique each others’ theory and even challenge or improve the theory by modifying and/or extending the computational procedures that underlie the model. It is the latter attribute of ABM that enabled the third author to readily engage in discourse with the first two authors, following their initial presentation of the “I’m Game” Piagetian–Vygotskian model (Abrahamson & Wilensky, 2005).

In this paper, we begin by recapping the Abrahamson–Wilensky paper and model (hence, A–W) and then present Levin’s proposed improvement on the A–W model as a case study of the A–W call for model-based constructive critique. We end with a cautionary remark on the limitations of ABM, the importance of recognizing these limitations, and the relevance of this caution for the field’s understanding, and prospective incorporation, of ABM as a viable means of propelling research into the mechanisms of learning.
The “I’m Game!” model (see Figure 1, above), built in the NetLogo agent-based modeling environment (Wilensky, 1999), implements sketches of “Piagetian” and “Vygotskiiian” interpretations of human learning into a single model and examines learner–agents’ performance under “Piagetian,” “Vygotskiiian,” and combined “Piagetian–Vygotskiiian” conditions. “Players” (circled arrows) stand in a row (Figure 1a). They each roll a marble toward a target line. Some players undershoot the line, some overshoot it (Figure 1b). Players collect their marbles, adjust the force of their roll—based either on their own performance (“Piagetian”) or on their neighbors’ (“Vygotskiiian”)—and, on a subsequent trial (Figure 1c), improve on their first trial—they have “learned” as individuals. Gradually, the group converges on the target line (see Figure 1d-1f, for three later attempts).
We have run the model under a wide range of conditions so as to evaluate its capacity to simulate reliably core features of the embedded theoretical model. For example, Figure 2 (above) shows results from running the simulation within a particular parameter space (see the sliders and switches) under the three experimental conditions and a fourth, control condition (“random”). Group mean performance (distance from target) was ranked as “Piagetian–Vygotskiian” (nearest, so best), “Piagetian,” “Vygotskiian,” and “Random” (furthest, so worst). We thus express one possible interpretation of the complementarity of the Piagetian and Vygotskiian perspectives (e.g., Cole & Wertsch, 1996).

Proof of Existence: LCHC Responds to CCL’s Call for ABM-Based Theory-of-Learning Collaborative Research

As part of an effort to study distributed learning, members of the Laboratory of Comparative Human Cognition (LCHC) at the University of California, San Diego began using NetLogo as a modeling environment for learning and examined the Abrahamson–Wilensky (A–W) model of Piagetian and Vygotskiian learning. LCHC draws heavily on cultural historical activity theory developed by Vygotsky and others, and so they were especially interested in the expression of Vygotskiian learning embedded in the A–W model. The A–W model was introduced at a weekly laboratory meeting in several ways. First, the model was shown to the whole group while it ran through a series of simulations of learning. The parameters made available through the interface were explored. The underlying code was examined, but the amount of code and the relative unfamiliarity with NetLogo code by most of the Lab limited the utility of this examination. A printout of a subset of the code was distributed to the Lab members, with the core code...
expressing the theory highlighted. Even though members of LCHC by and large did not know how to interpret NetLogo statements, a textual explanation of the core code was given by two members of the Lab who were familiar with NetLogo.

During the discussion, it became clear that the A–W implementation of the concept of “Zone of Proximal Development” was “simplex” – that is, learning in the ZPD embodied in the model depended on changes by the less skilled member of a pair of learners without any changes by the more skilled member. Several members of LCHC pointed out how the dynamic construction of a ZPD is “duplex,” that it involves both the learner and the “teacher” (the more skilled person). It occurred to Jim Levin that a relatively simple change to the model would implement a way in which teachers change their behavior depending on their knowledge of the level at which their students are performing. In this way, the members of LCHC were accepting the challenge in the Abrahamson & Wilensky (2005) paper describing this model: “We would welcome a critique that uses the existing model as a basis for expressing these constructs” (p. 28).

![Figure 3](image_url): Interface of the “I'm Game!” A-W model as modified by Jim Levin to improve the Vygotskian learning.

Levin implemented a modification to the A–W model in which the better performing player modified their next move to be within the ZPD of the less well performing play, making a play
that was worse than they knew how to make, in order to help the less well performing player learn to play better. The modification is called the “-T” version (“T” for “teacher”), and a screenshot of the model after about 50 runs is shown in Figure 3, above.

While members of LCHC who viewed this modified model at a later meeting then raised further concerns about the model, especially about the potential for oversimplification with this simulation, they were also fairly impressed with the ease of modification. For researchers who are new to modeling-based inquiry, it is clearly easier to modify an existing model than to construct one.¹ And it is even easier to explore the parameter space of an existing model.

A close examination of Figures 2 and 3 will reveal that not only does Figure 3 have two additional learning strategies but it also has different parameter values for three of the four parameters that take a range of numeric values, “ZPD,” “error,” and “#-Vygotskiian-neighbors”. If we set those three parameters to have the same values as in Figure 2, we see quite different results, as shown in Figure 4, below.

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¹ NetLogo was designed so as to enable even children to be able to easily construct their own models. In the pedagogy developed at the CCL, we have found that an important step in the process of learning to construct one’s own model is to modify an existing model.
Note that in this run of the modified A–W model, the Piagetian strategy does well, but not as well as the combined P-V or P-V-T strategies. The Vygotskiian strategy does less well, and the Vygotskiian-t version does worse than the “Random” strategy. So it matters quite a bit which set of parameters are chosen in comparing these learning strategies. The Abrahamson & Wilensky paper (2005) explores some of the multi-dimensional parameter space, using NetLogo’s BehaviorSpace research tools (Wilensky, 2001; Tisue & Wilensky, 2004). But it is not surprising that the figures in that paper, presented to the Jean Piaget Society, show the model operating with parameters in which the “Piagetian” strategy does well, while the parameters shown in Figure 3 are chosen for the Levin & Cole (2007) paper which is part of this symposium.

So an important lesson is that parameterized models such as these are open to many different interpretations, depending on which regions of the parameter space you elect to explore. Further enhancements to ABM environments could facilitate this exploration by offering users interactive tools for navigating in the conceptual space expressed in the combinatorics of the parameters selected for modeling (for a very first sketch of possible development directions, see Appendix A for the entire code of the “-T” model, with print-based orientation coding to help constructionist collaborators navigate through procedures).

Conclusion
We have presented a case study—a proof of existence—of an agent-based model that enabled constructionist collaboration of two research groups in the refinement of a theoretical model. The following attributes of agent-based modeling enabled and supported the collaborative research.

Agent-based modeling:

a. compels clear articulation of conceptual models and, *inter alia*, catalyzes personal refinement of these models (Papert’s “debugging principle,”1980);
b. clearly circumscribes the theoretically known—the unknowns are expressed in the form of “patchy” procedures that hard-code emergence into the simulation;
c. introduces modularity into the theoretical model, i.e., the program’s procedures isolate each of the modeler’s conceptual assumptions. Thus, reviewers can readily locate each of the assumptions and implement modifications to the modeling code such that it agrees with their own theoretical assumptions;
d. constitutes a *lingua franca* that transcends and cuts across the ever-ramifying niches of academic expertise (Jacobson & Wilensky, 2006);
e. stimulates and facilitates collaboration, including focused critique and modification (Levin & Cole’s “distributed research” principle, this symposium). In particular, ABM invites researchers who have not collaborated before to partake in a distributed constructionist project.

Finally, the exteriorization of the model as a conceptual object with a felt agency of its own (“it’s alive!”) is perhaps more conducive to collaboration than are idiosyncratic models. Thus, ABM invites co-construction but not at the cost of constructive criticism.

Our point of departure was that learning is a complex phenomenon and is therefore suitable for study through agent-based modeling. And yet, the emergence of a modeling *lingua franca* for
studying learning can itself be studied through the lenses of complexity studies. In particular, ABM is an inherently interdisciplinary form of inquiry, because the meta-principles of diverse phenomena can be articulated from the perspective of numerous agents acting locally with more-or-less common rules (Jacobson & Wilensky, 2006). Therefore, we see a game-theoretical advantage for multiple researchers within and between disciplines to share a mode of inquiry. Collaborative research, a form of learning, is itself complex, and we perceive agent-based modeling as advantageous to all researcher–agents.

The Illusion of Agency: On What Agent-Based Modeling Is and What It Is Not

In closing, we wish to submit the following remark that may help in further clarifying our perspective on the nature of agent-based modeling vis-à-vis more traditional forms, especially with regards to its standing as embodying a form of inquiry. This remark should be taken as preemptive—it responds to anecdotal, rather than well-articulated, sentiments toward ABM that we have encountered as we share our work.

From the view-point of pre-ABM, Graham Cairns-Smith, a chemist focusing on evolution and consciousness, for whom modeling is an essential modus operandi, supposes that any educated consumer of models can distinguish between what a model is and what it is not:

Good analogies are like in some respects that are clearly understood; and unlike in other respects that are clear also. The organic chemist’s models, for example, are thought to correspond to real molecules with respect to distances between atoms and so on, but not literally in all respects, and usually the distinctions are clear enough. Maybe the little sticks are made of steel and they go rusty, but there is no danger at all of this being taken as a blinding new insight about the nature of molecules….Of course you should never believe models, they only have an ‘as if’ status and they are likely to let you down any time” (Cairns-Smith, 1996, pp. 46-47).

Any agent-based model is primarily no more and no less than a model. Granted, ABM incorporates avatars that often bear greater iconic resemblance to their phenomenal correlates than do static diagrams; agents are dynamic and interactive such that they induce a compelling anthropomorphic sense of agency; and agents operate fast, in parallel, and iteratively such that an uninformed model user is likely overwhelmed by the magnitude of perceptual information—it is as though the agent-based model takes on a life of its own, as though it is not an ‘as-if’ but ‘the thing itself.’ Indeed, we have observed many middle-school students cheering as a green triangle and a blue triangle compete against each other in a stochastic race across the computer interface. Students’ suspension of disbelief, projection of self, and syntonic embodiment of the stark geometrical forms appears vastly facilitated by the self-propelled motion (see Papert, 1980, on syntonicity). It needn’t take a Tamagochi reality pet to induce reality—blobs moving across the screen can do it, too. Thus, the naïve phenomenology, if not the critical rationalization, of viewing a “run” of an agent-based model appears to share much in common with viewing that which is modeled therein.

However, no matter how great the verisimilitude, the complexity, and unpredictability of a model; however transfixing its dynamism; however enticing, engaging, and immersive its syntonic narrative…it is still a model. Indeed, one important reason that ABMs have proved so...
powerful for learning is this verisimilitude. But this verisimilitude can have a cost of making people forget that they are working with a model, essentially the same kind of beast as an equation. Just as a quadratic equation can model ballistic motion but would not ever be expected to describe the texture of the projectile, so one should not expect an ABM to model the entire richness of a social interaction, only the aspects chosen to be modeled. As such, agent-based models—like any other model employed in the sciences and social sciences—is an expression only of carefully selected aspects of a phenomenon—aspects that are assumed to operate individually and in concert so as to factor into the key phenomenon of interest. Beyond that, appearances are meant only ostentatiously—they tag the avatar as ‘a model of X’—and this ostentation may cause confusion or frustration when the avatar does not deliver the richness of what X does in reality. This beguiling property of models is to be understood by the model user. The modeler certainly does not purport to offer a virtual animistic fetish—a Golem or Gollum—it is the viewer, and not the modeler, who invests the avatar with life and so expects this life to live to the brim. We hope this clarification will assist in fostering a critical yet productive use of agent-based modeling in collaborative scientific discourse.

References
Appendix A – NetLogo Procedures of the “I’m Game” Model “-T,” With Proposed Print-Based Orientation System Supporting Constructionist Collaboration

;; Coded for core vs. infrastructure
;; Core theory content coded for high confidence, normal confidence, and less confidence

;; Modifications to the model by Dor Abrahamson & Uri Wilensky added by J A Levin 5 Feb 06
;; Further mods added by J A Levin 27 Apr 06
;; Original model available at:
;; http://ccl.sesp.northwestern.edu/research/conferences/JPS2005/JPS2005.nlogo
;; This modification is available at:
;; http://tepserver.ucsd.edu/~jlevin/JPS2005-t.nlogo

globals [ target ;; the target line in the middle
  max-dist ;; the maximum distance to that wall
  runcount ;; the number of times the ball has been thrown since the start
  ticks-left ;; the number of runs left of the current strategy
  pavg vavg pvavg rvavg vavgt pvavgt ;; lists of each run's distance halfway through ticks-left
  ;; ex. pavg = [ 2 3 17 ... ]
  ;; for comparison

  current-strategy
  result
]
turtles-own [ max-moves ;; the max-moves of the current throw
  best-max-moves ;; the best throw of the agent (or, if no memory, the current throw)
  best-max-moves-private ;; best throw, even if current throw different for teaching reasons (JAL)
  moves-left ;; the number of moves left until the ball comes to rest
  score ;; the current score (how far from target... lower is better)
  best-score ;; best score (or, if no memory, current throw)
]

to setup
  ca
  set runcount 0
  set-default-shape turtles "circle-arrow"
  crt number-of-players
  ask turtles [ set color color + 0.1 ] ;; to make trails a little easier
  set pavg [0] set vavg [0] set pvavg [0] set rvavg [0] set vavgt [0] set pvavgt [0]
  ;; initialized with zeros so i can use mean from the start
  rerun
end

to rerun
  cp
  set runcount runcount + 1
  ;; random strategies lets you keep the simulation running picking from the available strategies
  ;; at random
  if ( randomize-strategy-on-setup? ) [ 
    let new-strategy random 6
    if ( new-strategy = 3 ) [ set strategy "Random" set current-strategy 3]
    if ( new-strategy = 2 ) [ set strategy "Piagetian" set current-strategy 2]
    if ( new-strategy = 1 ) [ set strategy "Vygotskian" set current-strategy 1]
    if ( new-strategy = 0 ) [ set strategy "P-V" set current-strategy 0]
    if ( new-strategy = 4 ) [ set strategy "Vygotskian-T" set current-strategy 4]
  ]
end
if ( new-strategy = 5 ) [ set strategy "P-V-T" set current-strategy 5 ]

] set ticks-left 30 ; set ticks-left 16 ;; we use this one to stop each run half-way through. (see graph) This gives us the info we need ;; ; because the histogram represents values from half way through the run. For presentation, though, use "30"

set max-dist ( world-width )
setup-plots
setup-target
setup-turtles
display
end

to setup-plots
set-current-plot "avg distance"
set-plot-y-range 0 max-pxcor ;; most will fall within this range (all after a couple of steps)
set-current-plot-pen strategy ppu plotxy -1 0 ppd
set-current-plot "strategy avgs"
if length ravg > 1 [set-current-plot-pen "Random" plot-pen-reset plotxy 0 precision mean butlast ravg 2]
if length pavg > 1 [set-current-plot-pen "Piagetian" plot-pen-reset plotxy 1 precision mean butlast pavg 2]
if length vavg > 1 [set-current-plot-pen "Vygotskiiian" plot-pen-reset plotxy 2 precision mean butlast vavg 2]
if length pvavg > 1 [set-current-plot-pen "P-V" plot-pen-reset plotxy 3 precision mean butlast pvavg 2]
if length vavgt > 1 [set-current-plot-pen "Vygotskiiian-T" plot-pen-reset plotxy 4 precision mean butlast vavgt 2]
if length pvavgt > 1 [set-current-plot-pen "P-V-T" plot-pen-reset plotxy 5 precision mean butlast pvavgt 2]
end
to report get-strategy-color
ifelse ( strategy = "Random" )
[ report green ]
[ ifelse ( strategy = "Piagetian" )
  [ report blue ]
[ ifelse ( strategy = "Vygotskiiian" )
  [ report red ]
[ ifelse ( strategy = "Vygotskiiian-T" )
  [ report magenta ]
[ ifelse ( strategy = "P-V-T" )
  [ report cyan ]
  [ report grey ]
  ]
  ]
  ]
end
to setup-target
;; the target is the line in the center of the screen, 2 patches thick
set target patches with [ abs ( pxcor ) < 1 ]
ask target [ set pcolor get-strategy-color ]
end
to setup-turtles
  ask turtles
    ;; spread out the turtles evenly
    set size (world-height / count turtles)
    setxy min-pxcor ((who * world-height / count turtles)) + 2
    set score 100000
    set best-score score
    set heading 90

  ;; their max-moves are randomly distributed over the length of the playing field
  set max-moves random max-dist
end
to go
  ;; the score is their distance from the target
  ask turtles [ set score evaluate-score ] ;; the score is the distance of the turtle from the target line (evaluate-score is a reporter that provides this distance)
  ask turtles [ adjust ] ;; act according to the strategy, e.g., in Vygotskiian, you compare your scores to a neighbor and possibly update your score
reset

  ;; move all the turtles forward to their max-moves spot.
  ;; we can't just say "fd max-moves" because we want them to bounce off the wall
  ;; + leave a dissipating trail
  ask turtles [ set moves-limit-legal-distance max-moves ]
  let moving-turtles turtles with [ moves-left > 0 ]
  while [ any? moving-turtles ]
    set moving-turtles turtles with [ moves-left > 0 ]
    ask moving-turtles [ move
      if (trails?) [ set pcolor (color - 5) + (10 * (max-moves - moves-left) / max-moves) ]
    ]
  ]
do-plots

;; if sum (sentence length pavg length vavg length pvavg length ravg) >= 5 [stop]
if (ticks-left < 0) and limited-run? [ display stop ]
if (ticks-left < 0) and not limited-run? [ display rerun
  if ( strategy = "Random" ) [ if length ravg > 1 [ set result precision mean butlast ravg 2 ] ]
  if ( strategy = "Piagetian" ) [ if length pavg > 1 [ set result precision mean butlast pavg 2 ] ]
  if ( strategy = "Vygotskiian" ) [ if length vavg > 1 [ set result precision mean butlast vavg 2 ] ]
  if ( strategy = "P-V" ) [ if length pvavg > 1 [ set result precision mean butlast pvavg 2 ] ]
  if ( strategy = "Vygotskiian-T" ) [ if length vavgt > 1 [ set result precision mean butlast vavgt 2 ] ]
  if ( strategy = "P-V-T" ) [ if length pvavgt > 1 [ set result precision mean butlast pvavgt 2 ] ]
]

set ticks-left ticks-left - 1
end
to move-x
    set moves-left moves-left - 1
    fd 1
    if ( pxcor >= (max-pxcor - 1) )
        [ set heading 270 fd 2 ]
end

to-report evaluate-score
    report ( distancexy-nowrap 0 ycor ) ; the target has x-coordinate of 0, so this gives the horizontal distance of this turtle to the target
end
to-report limit-legal-distance [ val ]
    report ( min ( list ( max-dist - 1 ) max ( list 0 val ) ) )
end
to do-plots
    set-current-plot "avg distance"
    let curr-mean mean values-from turtles [ evaluate-score ]
    plot curr-mean
    ;; we sample after 15 steps. later than that, we lose information
    if ( ticks-left = 1 ) [
        if strategy = "Piagetian" [ set pavg fput round curr-mean pavg ]
        if strategy = "Vygotskiian" [ set vavg fput round curr-mean vavg ]
        if strategy = "P-V" [ set pvavg fput round curr-mean pvavg ]
        if strategy = "Random" [ set ravg fput round curr-mean ravg ]
        if strategy = "Vygotskiian-T" [ set vavgT fput round curr-mean vavgT ]
        if strategy = "P-V-T" [ set pvavgT fput round curr-mean pvavgT ]
    ]
end
to reset
    cp
    setup-target
    ask turtles [ set heading 90 set xcor min-pxcor ]
    display
end
to adjust
    if strategy = "Random" [ 
        r-adjust
            set max-moves best-max-moves
            stop
        ]
    if strategy = "Piagetian" [ p-adjust ]
    if strategy = "Vygotskiian" [ v-adjust ]
    if strategy = "Vygotskiian-T" [ v-adjust-t ]
    if strategy = "P-V" [ pv-adjust ]
    if strategy = "P-V-T" [ pv-adjust-t ]
    if ( strategy = "Vygotskiian" ) or ( strategy = "Vygotskiian-T" ) ;; or ( strategy = "P-V-T" ) [
        set max-moves limit-legal-distance
            ( best-max-moves + ( random-normal 0 ( error * best-score / max-dist ) ) )
    ]
stop

ifelse ( xcor > 0 ) [
  set max-moves limit-legal-distance
  ( best-max-moves ⫹ (- abs random-normal 0 ( error * best-score / max-dist ) ) )
] [
  set max-moves limit-legal-distance
  ( best-max-moves + (abs random-normal 0 ( error * best-score / max-dist ) ) )
] end
to p-adjust
  ;; if your score is better, that's your new best, otherwise stick with the old
  if (score < best-score) [
    set best-score score
    set best-max-moves max-moves
  ]
end
to v-adjust-1 ;; modified from v-adjust by JAL.
  if (abs((max-pxcor / 2) - best-max-moves) > abs((max-pxcor / 2) - best-max-moves-private)) [set best-max-moves best-max-moves-private] ;; restore best knowledge
  let fellow nobody
  while [ fellow = nobody or fellow = self ] [ set fellow turtle (who + ( - (#-Vygotskiian-neighbors / 2) ) + random (1 + #-Vygotskiian-neighbors ) ) ]
    ;; look randomly to one of your neighbors
    ifelse (best-score ≥ best-score-of fellow) and (best-score - ZPD <= best-score-of fellow) ;; if other is better and within ZPD
      [ set best-score best-score-of fellow
        set best-max-moves best-max-moves-of fellow
      ]
    [ set best-score score
      set best-max-moves max-moves
    ] ;; below is the new code that attempts to model the "teacher's" awareness of the "student" (JAL)
    set best-max-moves-private 0
    if (best-score < best-score-of fellow) ;; better than other (ie. closer to the target)
      set best-max-moves-private best-max-moves ;; save own knowledge of own best move, since we're going to move suboptimally for teaching purposes; assumes perfect memory, which is of course questionable (JAL)
      ifelse (best-max-moves < best-max-moves-of fellow)
        [ set best-max-moves max (list best-max-moves ((best-max-moves-of fellow) - ZPD )) ;; target is to the left
          set best-max-moves max (list best-max-moves ((best-max-moves-of fellow) + ZPD )) ;; target is to the right
        ]
    end
Abrahamson & Wilensky v-adjust (JAL)

let fellow nobody
while [ fellow = nobody or fellow = self ] [ set fellow turtle (who + ( - (#-Vygotskian-neighbors / 2) ) + random (1 +
#-Vygotskian-neighbors )) ]
;; look randomly to one of your neighbors

ifelse (best-score >= best-score-of fellow) and (best-score - ZPD <= best-score-of fellow)
[
  set best-score best-score-of fellow
  set best-max-moves best-max-moves-of fellow
]
[
  set best-score score
  set best-max-moves max-moves
]
end

PV-adjust-t :: modified pv-adjust with added Vygotskian "teacher" effect (JAL)
if (abs((max-pxcor / 2) - best-max-moves) > abs((max-pxcor / 2) - best-max-moves-private)) [set best-max-moves
best-max-moves-private] ;; restore best knowledge (JAL)
let fellow nobody
while [ fellow = nobody or fellow = self ] [ set fellow turtle (who + ( - (#-Vygotskian-neighbors / 2) ) + random (1 +
#-Vygotskian-neighbors )) ]
;; look randomly to one of your neighbors

if (score < best-score )
[
  set best-score score
  set best-max-moves max-moves
]

else (best-score > best-score-of fellow) and (best-score - ZPD <= best-score-of fellow)
[
  set best-score best-score-of fellow
  set best-max-moves best-max-moves-of fellow
]
[
  set best-score score ;; present in v-adjust but not in pv-adjust? (JAL)
  set best-max-moves max-moves ;; present in v-adjust but not in pv-adjust? (JAL)
]

;; below is the new code that attempts to model the "teacher's" awareness of the "student" (JAL)
set best-max-moves-private 0
if (best-score < best-score-of fellow) ;; better than other (ie. closer to the target)
[
  set best-max-moves-private best-max-moves ;; save own knowledge of own best move, since we're going to move
suboptimally for teaching purposes, assumes perfect memory (JAL)
  set best-max-moves max (list best-max-moves ((best-max-moves-of fellow) - ZPD )) ; target is to the left
]
[
]
set best-max-moves min (list best-max-moves ((best-max-moves-of fellow) + ZPD)) ; target is to the right
end

to pv-adjust ;; original pv-adjust from Abrahamson & Wilensky (JAL)
let fellow nobody
while [ fellow = nobody or fellow = self ] [ set fellow turtle (who + ( : (#-Vygotskiiian-neighbors / 2) ) + random (1 + #-Vygotskiiian-neighbors) ) ]
;; look randomly to one of your neighbors

;; maximize your own score and...
if ( score < best-score )
[ set best-score score
set best-max-moves max-moves
]

;; check it against your neighbor's score
if (best-score ≥ best-score-of fellow) and (best-score - ZPD <= best-score-of fellow)
[ set best-score best-score-of fellow
set best-max-moves best-max-moves-of fellow
]
end

to r-adjust
;; random strategy changes max-moves to a random number x if it's not at the wall
;; where 0 < x < max-dist
;; if it is at the target, it stops changing.
ifelse ( (abs pxcor) ≥ 0 )
[ set best-max-moves ( random max-dist )
]
[ set best-max-moves ( max-dist / 2 ) ≥ 1
]
end
Multi-Agent Simulation as a Tool for Investigating Cognitive–Developmental Theory

Paulo Blikstein
Northwestern University
paulo@northwestern.edu

Dor Abrahamson
UC Berkeley
dor@berkeley.edu

Uri Wilensky
Northwestern University
uri@northwestern.edu

Abstract
We discuss an innovative application of computer-based simulations in the study of cognitive development. Our work builds on previous contributions to the field, in which theoretical models of cognition were implemented in the form of computer programs in attempt to predict human reasoning (Newell & Simon, 1972; Fischer & Rose, 1999). Our computer serves two distinct functions: (1) illustrate the Piagetian theoretical model and (2) simulate it departing from clinical interview data. We focused on the Piagetian conservation experiment, and collected and analyzed data from actual (not simulated) interviews with children from 4 to 10 years old. The interviews were videotaped, transcribed, and coded in terms of parameters of the computer simulation. The simulation was then fed these coded data. We were able to perform different kinds of experiments:

1) Playback the interview and the computer model side-by-side, trying to identify behavior patterns;
2) Model validation: investigate whether the child’s decision-making process can be predicted by the model.
3) Evolving cognitive structures departing from purely simulated data.

We conclude with some remarks about the potential for agent-based simulation as a methodology for making sense of the emergence of self-organized hierarchical organization in human cognition.

Introduction
We discuss an innovative application of computer-based modeling in the study of cognitive development. Our work builds on previous seminal contributions to the field, in which theoretical models of cognition were implemented in the form of computer programs in an attempt to predict human reasoning (Newell & Simon, 1972; Fischer & Rose, 1999). One particular type of computer modeling offers powerful methods for exploring the emergence of self-organized hierarchical organization in human cognition: agent-based modeling (ABM; e.g., ‘NetLogo,’ Wilensky, 1999; ‘Swarm,’ Langton & Burkhardt, 1997; ‘Repast,’ Collier & Sallach, 2001) enables theoreticians to assign rules of behavior to computer “agents,” whereupon these entities act independently but with awareness of 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), or 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., the overall pattern emerges. In the mid-nineties, researchers started to realize that agent-based modeling could have a significant impact in education (Resnick & Wilensky, 1993; Wilensky & Resnick, 1995). For instance, to study the behavior of a chemical reaction, the student would observe and articulate only the behavior of individual molecules — the chemical reaction is construed as emerging from the myriad interactions of these molecular agents. Once the modeler assigns agents their local, micro-rules, the model can be put into motion and the modeler can watch the overall patterns that emerge.

Whereas initially complex-systems methods and perspectives arose from the natural sciences, complexity, emergence, and micro and macro levels of description of phenomena are all highly relevant to research in the social sciences. Indeed, the recent decades have seen a surge in social-science studies employing ABM (Epstein & Axtell, 1996; Diermeier, 2000; Axelrod, 1997). We argue that ABM has potential to contribute to the advancement of theory in multiple ways that we illustrate in this paper: (a) explicitizing — ABM computational environments demand an exacting level of clarity and specificity in expressing a theoretical model and provide the tools, structures, and standard practices to achieve this high level; (b) dynamics — the computational power of ABM enables the researcher to mobilize an otherwise static list of conjectured behaviors and witness any group-level patterns that may enfold through multiple interactions between the agents who implement these conjectured behaviors; (c) emergence — investigate intelligence as a collection of emergent, decentralized behaviors and (d) intra/inter-disciplinary collaboration — the lingua franca of ABM enables researchers who otherwise use different frameworks, terminology, and methodologies to understand and critique each others’ theory and even challenge or improve the theory by modifying and/or extending the computational procedures that underlie the model.

In this paper we focus on the potential of ABM as a research tool for formulating and critiquing cognitive development theory. ABM has been used to illustrate aspects of cognitive development (see Abrahamson & Wilensky, 2005, Blikstein, Abrahamson & Wilensky, 2006) and collaboration and group work in classrooms (Abrahamson, Blikstein & Wilensky, 2007). We, too, propose to use ABM to simulate human reasoning, yet we move forward by juxtaposing our simulation with real data using the Bifocal Modeling framework (Blikstein & Wilensky, 2006).

Previous research on cognitive modeling has generated many frameworks to model different tasks, such as shape classifications (Hummel & Biederman, 1992), language acquisition (Goldman & Varma, 1995), memory (Anderson, Bothell, Lebiere, & Matessa, 1998), as well as more general-purpose models (Anderson, 1983; Anderson & Bellezza, 1993; Anderson & Lebiere, 1998; Just & Carpenter, 1992; Polk & Rosenbloom, 1994). But it was in Minsky’s “Society of Mind” theory (1986), elaborated in collaboration with Seymour Papert, that we
found an adequate foundation of our agent-based models of cognition, due to its dynamical, hierarchical, and emergent properties, enabling the use of simple, programmable agent rules. We chose the classical Piagetian conservation task to model, because Minsky and Papert modeled this task with his theory; and we worked with children in both transitional and stable phases so as to elicit richer data. We will provide examples of step-by-step bifocal narratives – computer simulation vs. videography – of children’s performance on a conservation task. In the remainder of this paper, we will introduce Minsky’s and Papert’s theory, explain our experiment (a variation on the classical conservation-of-volume task, Piaget, 1952), and present case studies where simulation and real data are juxtaposed.

The Society of More Model

Conservation of volume is probably the best known Piagetian experiment. It has been extensively studied and reproduced over the past decades (Piaget, Gruber, & Vonèche, 1977). Minsky & Papert (1986) proposed a computational algorithm to account for children’s responses during this experiment. It is based on their construct of the intelligent mind as an emergent phenomenon, which grows out of the interaction of non-intelligent cognitive agents. Minsky’s theory has been particularly influential for overcoming the ‘homunculus’ paradox: if intelligent behavior is controlled by more primitive intelligent behaviors, we get enmeshed in a recursive explanation which cannot ultimately account for a reasonable theory of the mind. Minsky, therefore, insists on using agents that are essentially non-intelligent and obey simple rules – intelligence, therefore, emerges from these interactions.

The simplicity of Minsky’s model is, actually, its main strength – and a perfect fit for the agent-based modeling paradigm. The first important principle in his model is that agents might conflict. For example, at a given time, a child might have Eat, Play and Sleep as predominant agents. Play could have subagents, such as Play-with-blocks and Play-with-animals. If both of these subagents are equally aroused (in other words, the child is equally attracted to both activities), the upper agent, Play, is paralyzed. Then a second important principle comes into play: non-compromise. The longer an agent stays in conflict, undecided, the weaker it gets compared to its competitors. If the conflict within Play is sustained long enough, its competitors will take control (in this case, Eat or Sleep).

Minsky’s fundamental rule is, thus: “whenever in conflict, a mental entity cannot (or takes longer to) decide”. Although relatively simple, this model, as we will see, is surprisingly powerful and opens up many interesting possibilities for investigation, some of which will be described in the paper.

Minsky’s and Papert’s model of Piagetian experiments stresses the importance of structure to cognitive evolution, especially its reorganization (the ‘Papert Principle’). Within the context of the conservation task, younger children would have ‘one-level’ priority-based structures: one aspect would always be more dominant (tall would always take priority over thin and over confined - see Figure 1) and compensation, which requires a two-level structure, is thus inexistent. Minsky suggests that, as some perceptual aspects would be more present in the child’s life at a particular age, they would be more prevalent. For example, being more or less ‘tall’ than parents or other children would be a common fact for children since a very early age. On the other hand, being more fat or thin would not be as prevalent.
Later, states Minsky, the child develops a new “administrative” layer that allows for more complex decisions: in Figure 2, for example, if tall and thin are in conflict (i.e., both agents were activated by the child’s cognitive apparatus), the “appearance” administrator cannot decide and shuts off, then the history administrator will take over the decision, as it has one **one** activated agent below it.

**Experiments/Methods**

Our interviews were based on the conventional format of the conservation of volume Piagetian experiment. Two elongated blocks of clay of same shape but different color are laid before the child. One is “the child’s,” and the other is “the experimenter’s.” After the child agrees that both are the same size, the experimenter cuts one block in two, lengthwise, and joins the two parts so as to form a block twice as long, then cuts the other block in two, widthwise, to form a block twice as thick as before. The child is asked whether the blocks are still “the same” or whether either person has more than the other. According to the child’s response, the interaction then becomes semi-clinical, with the experimenter pursuing the child’s reasoning and challenging him/her with further questions.
The approximate time of each interview was 20 minutes. All interviews were videotaped and transcribed, and the data were coded in terms of parameters of the computer simulation (see Table 1). The simulation was then fed these coded data. We were able to perform different kinds of experiments:

- **Playback the interview and the computer model side-by-side**, trying to identify behavior patterns and couch them in terms of the simulated model;

- **Model validation**: investigate whether the child’s decision-making process can be predicted by the model. We set the model with the child’s initial responses, “run” it through to completion, and try to identify whether the simulated cognitive development matches the processes observed.

- **Emergence of structures**: investigate if some “society of mind” structures are more prone to emerge than others. For example, would a large number of agents organized into a one-level ‘society’ be more efficient than a less numerous population of agents organized in two levels?

### The computer model

The model tries to reproduce the clinical interview situation. We first define the “society of mind” (SOM) structure of a ‘virtual child’. Then this virtual child is presented with random pairs of virtual blocks, and evaluates if one of the two is ‘more’, ‘less’, or ‘same’. The model is able to automatically run multiple times, presenting the virtual child with different blocks, and also changing the rigidness of the structure (in other words, introducing random variations in each branch of the structure). In Figure 3, we have a screenshot of the model. Figure 4 shows the details of the main window.
To use the model, the first step is to draw a structure in the central area of the screen (a ‘society-of-more’). The drawing tools on the bottom right enable users to add nodes and edges, as well as change their labels, shapes, and sizes.

There are four possible types of nodes, each with a different shape and role:

- **RESULT (eye icon)**: the final destination of the ‘turtles’, normally placed at the top part of the structure. This node will show the result of the computation, i.e., the final
response of the virtual child. The default label for a result is “I don’t know”, which might change to “more!!”, “less!!”, or “same!!”. They can have agents or managers attached to them.

- **Manager or administrator (triangles):** these nodes might have cognitive agents attached below them, and a result node attached above.

- **Cognitive agents (rounded squares):** these agents represent some perceptual element, such as “tall”, “thin” or “number”.

- **Cognitive agents’ status (small dot and a word):** the status of an agent, which can be “more!!”, “less!!”, or “same!!”.

Once the structure is built, the second step is to “activate” the correct agents. This can be done manually or automatically:

- **Manual mode of activation:** the user assigns the correct word to the agent status (‘more!!’, ‘less!!’, or ‘same!!’, one by one, using the drawing tools), clicks on “Activate”, and clicks on the agents that should be active. Upon activation, a new “messenger” will be created under the agent, with a green label. For example, in Figure 3, all of the three agents are activated (note the three green words), as if the child did evaluate length, thinness and mass at the same time. Those green words are messengers that will travel upwards along the connecting lines when the model runs.

- **Automated mode of activation:** No user intervention is necessary. In this mode, pairs of blocks are randomly picked from a preprogrammed ‘block repository’ and displayed in the blue area inside the window (see Figure 4). The model automatically ‘sees’ the blocks and activate the correspondent agents.

Finally, for the computer to ‘see’ and evaluate each pair of blocks, each configuration of blocks has an associated list of 5 parameters, which are automatically compared by the model. They are: [length of each piece, width of each piece, length of the whole arrangement, width of the whole arrangement, number of pieces] (see Table 1). By comparing the parameters of each block, the
model is able to determine which block is ‘more’ in total length, width, number of pieces, and mass.

Table 1. Parametrization of the blocks

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Description</th>
<th>Appearance of block</th>
</tr>
</thead>
<tbody>
<tr>
<td>[ 8 1 8 1 1 ]</td>
<td>Each block is 8 units long, 1 unit thick, the full arrangement is also 8 x 1, and there is just one block</td>
<td></td>
</tr>
<tr>
<td>[ 1 1 5 1 8 ]</td>
<td>Each block is 1 unit long, 1 unit thick, the arrangement occupies the total area of is 15 x 1, and there are 8 of them.</td>
<td></td>
</tr>
<tr>
<td>[ 2 2 5 2 2 ]</td>
<td>Each block is 2 units long, 2 units thick, the total area they occupy is 5 x 2, and there are 2 of them,</td>
<td></td>
</tr>
<tr>
<td>[ 4 1 4 1 1 ]</td>
<td>Each block is 4 unit long, 1 unit thick, the total area occupied is 4 x 1m and there is just 1 unit,</td>
<td></td>
</tr>
</tbody>
</table>

**First study: qualitative bifocal validation of the model**

The goal of the first experiment is to validate the model qualitatively, i.e., evaluate if the model can minimally account for the different stages of cognitive development seen in the interviews. Below, we show the results, using ‘bifocal’ data (computer simulation alongside human behavior). We will show how the different models (programmed with data from the interviews with three children) yield a surprisingly similar probabilistic cluster of responses as the interviews themselves.
<table>
<thead>
<tr>
<th>Computer model (screen captures)</th>
<th>Transcriptions/pictures</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Child 1</strong></td>
<td></td>
</tr>
<tr>
<td>From Child1’s (6yo) interview, we inferred the simple model below. Cognitive agents presumed to be active are marked with a green outline. Dominance is represented in the model by the vertical distance to top. For this child, whenever Number -- the cardinal dimension of the stimulus -- is contextually salient, it dominates the decision-making process. Also Tall appears to dominate Thin.</td>
<td>“Because you cut in half, so there is <strong>two pieces</strong>, but... It's <strong>not as fat as that</strong>. This is kind of fat, but this is taller. I have more”.</td>
</tr>
<tr>
<td><img src="image1.png" alt="Diagram of computer model" /></td>
<td><img src="image2.png" alt="Screen capture of child" /> <img src="image3.png" alt="Screen capture of researcher" /></td>
</tr>
<tr>
<td><strong>Number</strong> is absent from this second interaction. Even when two other measurements conflict, one is always dominant. In this case, Tall is more salient.</td>
<td>Researcher: Who has more? Child1: It’s hard to tell now. [tries to measure the fat one with his fingers, then compares his fingers with the thin and tall one]. This one [the taller].</td>
</tr>
<tr>
<td><img src="image4.png" alt="Diagram of computer model" /></td>
<td><img src="image5.png" alt="Screen capture of child" /> <img src="image6.png" alt="Screen capture of researcher" /></td>
</tr>
</tbody>
</table>
In the third interaction, the experimenter reintroduces **Number** by cutting his piece in four: as predicted by the model, **number** takes priority again over **tall** and **thin**. When **number** is present, the child does not even try to measure the two sets of blocks.

> “You have more, because you have four quarters, I have only two halves.”

**Interpretation:** The ‘priority’ model can account for the responses of Child1: he cannot coordinate two or more measures. In the computer model, also, two measures cannot be coordinated. Given the same inputs, the computer model and the interview data yield comparable results.
Child 2 (8yo) has a model with Minsky’s “administrators” (appearance and history of the transformations). With one in conflict, the other takes control. If the Tall agent reports ‘more’ and the Thin agent reports ‘less’, then the Appearance administrator will say nothing - it is in conflict and cannot decide. However, this child provided different answer to similar block configurations. He would alternate between a mass-conservation explanation (no material was taken away or added) and a ‘joinable’ one (two previously cut pieces can be joined together to form the original object). It appears that, even having a more developed SOM structure, this child is also in a transitional phase, in which ‘mass’ and ‘joinable’ take turns dominating.

“If you put them back together, you’ll have the same”

Child 2 has a level of administrators, which enables him to background the appearance and focus on the history of the objects. The blue is ‘re-joinable’, so both blocks are the same. During the interview, Child 2 occasionally said that nothing was added or taken away - a static, rigid model is insufficient to account for those oscillations, as we will later discuss. The model, again, correctly determines the combinatorial space and predicts response frequency distribution.
Child 3 backgrounds appearance from the start (see, in the model, that these agents are lower than others) and focuses on confinement (nothing was taken away or added), and thus concludes that the blocks are still the same.

In this part of the study, we were able to describe the cognitive development of child 1, 2 and 3 solely in terms of the variables of the computer model: the number of layers in the structure and the relative prominence of certain agents. Child 1’s responses could be fit into a one-level structure, Child 2’s responses fit into a two-level structure but without a clear ‘leveling’ of the agent – which we will only see in Child 3. Moreover, in both Child 1 and 2 we observed elements of a transitional phase, which the model can also account for, by promoting slight random variations in its own structure, until a stable configuration is reached (see next section).

**Second study: understanding the interviews with non-rigid computer models**

To investigate in more depth the relationship between the computer model and the performance of Child 1, we coded the whole interview in terms of computer-understandable parameters. We used the same parameterization employed in the model to describe each pair of blocks laid before the child. Thus, if the child was presented with a 4 x 2 and a 1 x 8 blocks, the coding would be \[ [4 2 4 2 1] \] and \[ [1 8 1 8 1] \], following the convention already mentioned in this paper. Then we rated the child’s answer as right or wrong, and also noted which block was considered to be ‘more’. The result for Child 1 is in the Table 2. (Under the “Blocks” column, the child’s choice for the ‘more’ block has a light green background.)

<table>
<thead>
<tr>
<th>Blocks</th>
<th>Correct?</th>
<th>Transcription</th>
</tr>
</thead>
<tbody>
<tr>
<td>[4 2 4 2 1]</td>
<td>[1 8 1 8 1]</td>
<td>[4 2 4 2 1] and [1 8 1 8 1]. following the convention already mentioned in this paper. Then we rated the child’s answer as right or wrong, and also noted which block was considered to be ‘more’. The result for Child 1 is in the Table 2. (Under the “Blocks” column, the child’s choice for the ‘more’ block has a light green background.)</td>
</tr>
</tbody>
</table>
We fed the computer model with the same 9 pairs of blocks, and rated the performance of the computer model in comparing the blocks. Four different structures were tested (see Table 2):

1) Agents: “long”, “thin” and “mass”, no administrative layer
2) Agents: “number”, “long”, “thin” and “mass”, no administrative layer
3) Agents: “long”, “thin” under appearance, “mass” under history.
4) Agents: “long”, “mass” under appearance, “thin” under history. (note the displaced position of “mass” and “thin”)

We further tested each structure with different relaxations – a total of 21 simulations with the level of ‘relaxation’ increasing from 0 to 100% in steps of 5%. In the model, the ‘relaxation’ corresponds to randomly deforming the distances which the agents have to travel upwards. In practical terms, the more ‘relaxed’ the structure (closer to 100%) the less determinant the structure is.

In the following plots, the black line represents the accuracy (in percent) of the model. The blue line represents the score of the actual child, and the green line is the trend line of the model’s performance curve.

<table>
<thead>
<tr>
<th>Blocks</th>
<th>Correct</th>
<th>C1 Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>4 2 4 2 1</td>
<td>Yes</td>
<td>“It's the same.”</td>
</tr>
<tr>
<td>4 2 4 2 1</td>
<td>No</td>
<td>“Who has more?” C1: “I have more. This is two, but it's smaller.”</td>
</tr>
<tr>
<td>8 1 8 1 1</td>
<td>No</td>
<td>C1: “I have more. Look at this. We cut it in half and it got taller. This is kind of fat but this is taller.”</td>
</tr>
<tr>
<td>8 1 8 1 1</td>
<td>No</td>
<td>C1: “It's hard to tell. It's hard to tell [measures with his fingers the thickness of both] This one [the longer and thinner].”</td>
</tr>
<tr>
<td>8 1 8 1 1</td>
<td>No</td>
<td>C1: “You have four quarters, I only have two halves. If I would do that [join], we would have the same amount.”</td>
</tr>
<tr>
<td>4 2 4 2 1</td>
<td>Yes</td>
<td>C1: “I have more. I have two halves, you only have one. I could break it apart.”</td>
</tr>
<tr>
<td>4 1 4 1 1</td>
<td>No</td>
<td>C1: “You have more. Because that's 1, 2, 3, 4, 5, 6, 7, 8 [counting]. And the other is 1, 2. But if we cut that there, that there, that there, it will be the same amount (cutting the 2 pieces into 8).”</td>
</tr>
<tr>
<td>1 1 5 1 8</td>
<td>Yes</td>
<td>C1: “[Counting] 1, 2, 3, 4, 5, 6, 7, 8, and 1, 2, 3, 4, 5, 6, 7, 8. It's even.”</td>
</tr>
</tbody>
</table>

Child 1: 30% (3/9) correct
Table 3 - Different levels of relaxation for different structures

| Structure 1 | As relaxation increases, the model gets more accurate. The relaxation compensates for the inadequacy of the model to evaluate situations in which ‘long’ is not determinant of ‘more’. With relaxation up to 30%, the model scores as well as the child. After 30%, it gets better, but the gain tapers off – at some point, it is just as good as chance. |
| Structure 2 | Adding ‘number’ to the structure, the overall accuracy increases from approximately 35% to 55%. Interestingly, in this more complete model, increased randomness causes accuracy to decrease. A likely explanation is that “number” is an efficient “specialized” evaluator of ‘more’, at least for the population of blocks laid before the child. |
| Structure 3 | In this model with administrators, accuracy starts at 100%, and decreases with increase randomness. The average score of this model, even with high randomness levels, is far better than the child’s. |
| Structure 4 | This model is identical to Model 3, except that mass and thin were switched. Mass is under appearance, and thin under history. The overall score drops dramatically from 100% to 30%, approaching the child’s. This is corroborates Minsky’s hypotheses about the importance of having the ‘right’ agents under each administrator. If we were to ‘evolve’ a structure using standard GA algorithms, probably Model 3 would be rapidly selected over Model 4. |

Interpretation: The different effect of relaxation in the models’ performance is an important result of this experiment. Simple, one-level models increase their performance with increased relaxation. Complex, specialized, high-accuracy models lower their performance with high levels of relaxation. This result might seem trivial: deforming an accurate structure causes it to perform badly, and deforming a weak structure benefits from random correct hits. However, the usefulness of this result is that it can be used as a criterion to evolve cognitive structures.
Another consequence of this finding is that it suggests that learning might benefit from relaxation of constraints in different ways, depending on the developmental level, knowledge domain, and age. We could hypothesise that, when children are first learning principles of a knowledge domain, the learning environment should promote “random” connection, wrong moves, unlikely choices. The primitive structure would benefit from those to evolve administrators. Once administrators are in place, perhaps, a more structured environment is beneficial. To further investigate this issue, we conducted a third study with more comprehensive runs.

**Third study: effect of relaxation on different structures**

To conduct this study, we generated a repository of 16 different 2-block configurations. Those blocks were randomly selected and evaluated by the computer using different SOM structures. Relaxation ranged from 0% to 300%, with 5 runs for each data point.

**Model 1**, as expected, had its accuracy increased with increased randomness. Accuracy tapered off around 50-60%. This is probably around chance, but the number is different from the expected 33% (three random outcomes) because the distribution of long and thin blocks was not uniform. Consequently, Model 1 is very context-specific – if there are more long objects around the child, it would work more than chance, but when that is not the case, it’s worse than chance.

![Model 1](image.png)

Figure 5. Speed-randomness vs. accuracy for Model 1

**Model 3**, however, presents a different picture. It begins with 100% of accuracy, which decreases dramatically with relaxation. The following plot show results from 0 – 140% of relaxation: we can observe that accuracy declines and tapers off around 60%.
Model 4 confirmed the results from the previous study: placing the agents in wrong places in the structure has dramatic effects. In this experiment, accuracy dropped from 100% to around 35%, and increases with randomness.

Conclusions

The computer model can be a useful vehicle both to illustrate the Piagetian theoretical model and to simulate it departing from interview data. Through the lens of agent-based models, new properties of Minsky’s model are revealed. Namely, the mature, hierarchical structure of the cognitive model is stochastically determined, in the sense that across combinatorial initial conditions, and over sufficient interactions, the same meta-structures ultimately emerge.

Collecting and analyzing data from actual (not simulated) interviews is an essential phase in the ongoing improvement of the computer simulation of a theoretical model, such as Minsky’s model: The data sensitize us to the crucial components and dimensions of the interactions and to the nature of the transformations. We are currently exploring the entire combinatorial space of all
hypothetical children’s initial mental states and activating the simulation per each of these states. From that perspective, our data of real participants become cases out of the combinatorial space.

The following are some conclusions from the three experiments described in this paper:

1) Relaxation has different effects on structure with and without administrators. This suggests that relaxation, trial-and-error, and changes in the environment could be factors leading to a natural selection of structures of Minskyan non-intelligent agents.

2) Conventional “paper and pencil” representations of Piagetian structures might miss some of the dynamic factors in play. For example, we were able to identify in Child 1 and Child 2 some ‘embryonic’ agents, which were present in just part of the interaction. Child 2, for instance, would oscillate between a “re-joinable” and a “conserved-mass” explanation in many interactions. Without a probabilistic approach, we would be obliged to just assume that those children were in a transitional stage. With the computer representation, we could actually calculate the number of times that different embryonic agents are aroused, and estimate the developmental stage of the child. This data could then be fed into the computer model for further confirmation – we could even envision, for future work, simulations which could predict the appearance and evolution of embryonic explanations specific.

3) A natural and promising path for this work is to evolve SOM structures automatically. We suggested earlier that the dynamics of this simulation (see Conclusion 1) is such that favorable outcomes would be reinforced. As we observed in experiments 2 and 3, random reconnections of agents do not render random results – structure matters. The mechanism which we demonstrated shows that there is a higher probability for related agents (“long” and “thin”) to group together under one particular agent – this is the configuration that delivers the best performance. One can imagine that, along many years of cognitive development in the world, the child will group some sensorial and cognitive experiences into certain categories: i.e., “thin and long belong to appearance”, “taken-away and spilled relate to history of the transformation”. What Minsky states, and we verified, is that the actual content of such agents less irrelevant than it’s placement within the structure, if they are under a closely related agent.
Thus, the categorization process itself emergently generates intelligent behavior, without any interference from an external “intelligent” entity. This appears to be an indication that the ‘Society of Mind’ framework could be used with predictive power in Developmental Psychology, especially when coupled with clinical interview data.

References


Modeling Manifold Epistemological Stances with Agent-Based Computer Simulation

Paulo Blikstein, Uri Wilensky

Center for Connected Learning and Computer-Based Modeling – Northwestern University

2120 Campus Drive – Evanston, IL, USA – 60208 – tel. +1 (847) 491-5666
[paulo, uri]@northwestern.edu

Introduction

Agent-based modeling has been increasingly used by scientists to study a wide range of phenomena such as the interactions of species in an ecosystem, the collisions of molecules in a chemical reaction, or the food-gathering behavior of insects (Bonabeau, 1999; Wilensky & Reisman, 2006). Such phenomena, in which the elements within the system (molecules, or ants) have multiple behaviors and a large number of interaction patterns, have been termed complex and are collectively studied in a relatively young interdisciplinary field called complex systems or complexity studies (Holland, 1995). Typical of complex phenomena 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), or 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—the overall pattern emerges.

In the mid-nineties, researchers started to realize that agent-based modeling could have a significant impact in education (Resnick & Wilensky, 1993; Wilensky & Resnick, 1995). For instance, to study the behavior of a chemical reaction, the student would observe and articulate only at the behavior of individual molecules — the chemical reaction is construed as emerging from the myriad interactions of these molecular “agents.” Once the modeler assigns agents their local, “micro” rules, the model can be set into motion and the modeler can watch the overall patterns that emerge.

Whereas initially complex-systems methods and perspectives arose from the natural sciences, complexity, emergence, and micro and macro levels of description of phenomena are all highly
relevant to research in the social sciences. Indeed, the recent decades have seen a surge in social-science studies employing ABM (Epstein & Axtell, 1996; Diermeier, 2000; Axelrod, 1997). Recently ABM has been used to illustrate aspects of cognitive development (see Abrahamson & Wilensky, 2005, Blikstein, Abrahamson & Wilensky, 2006; Blikstein & Wilensky, 2006a) and collaboration and group work in classrooms (Abrahamson, Blikstein & Wilensky, 2007). We, too, propose to use ABM to simulate human reasoning, yet we move forward by juxtaposing our simulation with real classroom data using the Bifocal Modeling framework (Blikstein & Wilensky, 2006b).

We argue that ABM has potential to contribute to the advancement of theory in multiple ways that we illustrate in this paper: (a) explicitizing—ABM computational environments demand an exacting level of clarity and specificity in expressing a theoretical model and provide the tools, structures, and standard practices to achieve this high level; (b) dynamics—the computational power of ABM enables the researcher to mobilize an otherwise static list of conjectured behaviors and witness any group-level patterns that may enfold through multiple interactions between the agents who implement these conjectured behaviors; (c) emergence—investigate intelligence as a collection of emergent, decentralized behaviors and (d) intra/inter-disciplinary collaboration—the lingua franca of ABM enables researchers who otherwise use different frameworks, terminology, and methodologies to understand and critique each others’ theory and even challenge or improve the theory by modifying and/or extending the computational procedures that underlie the model.

**Relevance to learning research**

Various authors established the importance of practitioners’ mental models of the learning process itself as determinant for their classroom action (Strauss, 1993; Strauss & Shilony, 1994). Therefore, using computer models to conduct research in education and make those models approachable and accessible to teachers could influence and transform their everyday work. In addition, it could address limitations of current methodologies. First, experiments with human subjects cannot be indefinitely re-run, so replicating findings or exploring a wide parameter space are costly and oftentimes impossible tasks. Once the classroom data is collected, at most researchers can revisit the videotapes and transcriptions, but never re-live the situations. Second, as we move towards theories that conceptualize learning as a dynamic and adaptive phenomenon, the traditional media of scientific discourse—static linear text—becomes limited in its capacity to express these theories (Abrahamson & Wilensky, 2005; Blikstein, Abrahamson, & Wilensky, 2006). Both these flaws could be addressed, we contend, with a set of dynamic, adaptive computer models of learning. Thirdly, tools such as fMRIs cannot yet offer the speed and resolution needed to evaluate any complex learning process at a neuronal level. Models at the neuronal level are still far from being applicable to real classrooms. Lastly, ethnographic or micro-genetic methods cannot yet offer a solid, “runnable”, generalizable, task-independent account on how humans learn.

The ultimate goal of using agent-based simulation to explore human learning is to enable researchers to generalize and play “what-if” scenarios departing from in-depth interviews and ethnographic data, as well as investigate internal cognitive structures departing from external, observed behaviors. The two experimental obstacles mentioned above (the insufficiency and imprecision of fMRI and qualitative methods), as we will explain throughout this paper, could be overcome by employing a variable ‘grain size’ for delimitating the cognitive tasks, together with
simple interaction rules. The ABM modeling paradigm seems to lend itself extremely well for those two design principles.

Our work builds on previous seminal contributions to the field, in which theoretical models of cognition were implemented in the form of computer programs in an attempt to predict human reasoning (Newell & Simon, 1972; Rose & Fischer, 1999), in tasks such as shape classifications (Hummel & Biederman, 1992), language acquisition (Goldman & Varma, 1995), and memory (Anderson, Bothell, Lebiere, & Matessa, 1998), and other more general-purpose models (Anderson, 1983; Anderson & Bellezza, 1993; Anderson & Lebiere, 1998; Just & Carpenter, 1992; Polk & Rosenbloom, 1994). Our design, however, differs from extant approaches in two fundamental ways:

1) **Grain Size:** Selecting a unit of analysis toward bridging the micro and macro perspective on learning. Those theories, slicing human learning into diminutive pieces, when reintegrated into the larger context of classroom learning, could not account for any meaningful macro-cognitive phenomena.

2) **Accessibility:** Democratizing modeling-based research. Most computational theories of mind were so mathematically complex that only specialized researchers could discuss them – the intricacy and language of these theoretical models rendered them incomprehensible for teachers, educators, and policymakers. Conversely, the computer language with which we have developed the models, NetLogo (Wilensky, 1999), was built from the ground up for non-programmers, so that users can not only run simulations, but modify their internal rules and compare scenarios. Our models, too, were carefully conceived to follow established models for learning.

Our theoretical inspiration comes from the work of Minsky, Papert and Collins (Collins, 1978; Minsky, 1986). Our computer-based simulations of human learning postulate non-intelligent cognitive entities with simple rules from whence emerges intelligent behavior. These software tools enable researchers to initially feed a computer model with data from real-world experiments, such as classroom observations or clinical interviews, and subsequently simulate hypothesized scenarios in the safe virtual environment. Researchers from diverse disciplines (and with little, if any, programming background) can embody and articulate their theoretical models in a shared medium with shared nomenclature and shareable/reproducible data, thus facilitating interdisciplinary discourse and critique.

**Classroom data: personal epistemologies and cognitive resources**

Traditional research on personal epistemologies (Hofer & Pintrich, 2002) has conceptualized them as stable, constant beliefs. However, evidence of variability in student epistemologies suggests the need for more complex models (diSessa, 1993; Hammer & Elby, 2002). The activation of students’ different epistemological resources could depend on context, as shown by Rosenberg, Hammer, & Phelan (2006). In their case study, a brief epistemological intervention...
by an 8th-grade science teacher led to students’ abrupt shift from one epistemological ‘mode’ to another. Rosenberg et al. narrative tells the story of a group of students who were given the task of explaining the Rock Cycle. For the first few minutes, before the teacher’s intervention, they fail to engage in any productive work or to construct a coherent explanation of the Rock Cycle. Their explanations are fragmented, use the wrong vocabulary, and do not survive even simple logical inference. Rosenberg et al. state that the reason is epistemological, and that

“They are treating knowledge as comprised of isolated, simple pieces of information expressed with specific vocabulary and provided by authority.” Rosenberg, Hammer, & Phelan (2006), pp. 270.

The authors provide three pieces of evidence for this hypothesis: (i) students organize their efforts around retrieving information from worksheets; (ii) they focus on terminology, and (iii) students combine information and construct sentences to present a formal ordering rather than a causal sequence. But the narrative goes on. Realizing the ongoing failure, the teacher stops the activity, and tells students:

“So, I want to start with what you know, not with what the paper says.”

Abruptly, students change their ways of engaging in the activity. They immediately start to focus on elements of the Rock Cycle that they understand and rebuild the story from there – in few minutes, one of the students was able to come up with a reasonable explanation:

“OK, the volcano erupts, and lava comes out. Lava cools and makes igneous rock. Rain and wind cause small pieces of rock to break off. Sediments form, and rain and wind carry it away, and rain and wind slow down and deposit sediments and this happens over and over again to form layers.” Rosenberg, Hammer, & Phelan (2006), pp. 274

Particularly impressing is how students, departing from a single element of the story (“Lava comes out”), could correctly connect all the other pieces of the explanation. Even though the “Lava comes out” piece was the first to be mentioned, they realized that for lava to come out, the volcano has to erupt; similarly, if the lava comes out and it is hot, it has to cool down.

Concatenating pieces of information making sense of the connection rules was crucial for students to generate a coherent explanation, resorting even less times to their worksheets than in the previous half of the narrative.

In this paper, our goal is to employ ABM to help model what took place during those 15 minutes, answering two research questions concerning the abrupt epistemological shift observed:

1) What caused the two ‘modes’ to generate very diverse student performance?
2) How could a brief intervention effect such dramatic change?

We built a model that simulates the construction of declarative knowledge in terms of two basic cognitive operations: retrieving information from external/internal sources, then applying concatenation rules to join information “pieces” (the retriever/connector model, Blikstein & Wilensky, 2006; see Figure 8). We expect to answer the two research question aforementioned by exploring a significant part of the combinatorial space of initial conditions of the model, with different values for number, type, and efficiency of retrievers and connectors, which might result in emergent behaviors similar to those observed by Rosenberg et al.
The Agent-Based Model

In our model (see Figure 1), the world outside the mind is represented as an ocean of disconnected content pieces of various kinds. A piece could be a simple statement, such as “Lava comes out of volcanoes”, “Lava shoots up”, or “Water erodes rocks”. These pieces are retrieved by special agents, called retrievers and accommodated into the simulated mind, where they interact with pre-existing structures until they connect to one of them, making use of a third type of cerebral agent, the connectors. These pre-existing structures form an emergent, dynamic network with “hub ideas” (highly connected ideas) and peripheral ideas. Students’ explanations are the ad hoc result of pieces of content and ideas collected by retrievers outside the mind and assembled by connectors inside the mind.

In our simulated world, the content pieces can have different ‘stickiness’ to the retrievers. Therefore, the model can evaluate differently content from different sources – content ‘given from authority’ can have a different cognitive effect than ‘previous knowledge’ in the virtual child’s mind. Content from books can have a different ‘stickiness’ than content from friends, or from other sorts of media.

In the model, also, content cannot simply enter the mind as raw information. It needs to be retrieved and subsequently connected by internal agents to be internalized, which is coherent with constructivist theory (Piaget, 1952; Piaget, Gruber, & Vonèche, 1977; Piaget & Inhelder, 1969). Outside the mind, there is only information (content pieces), but not knowledge. Inside the mind, there is never information (loose pieces), but knowledge (connected pieces). Also, retrieved content pieces cannot be accessed until there are evaluated and copied by connectors. Below is a diagram of our simulated world.

Figure 8 – The three types of agents of the model: content pieces, retrievers and connectors
One important design stance was the decision to employ a simple ‘cognitive’ rule. In the real classroom situation, students would assemble a textual explanation such as:
In our model, all textual explanations are replaced with numbers, and a ‘correct’ explanation is simply an ascending sequence of integers. The model would evaluate as correct both of the options below:

And as incorrect both of the ‘sentences’ below:

As many cognitive tasks involve putting together a sequence of pieces in the correct order, we decided to make this task the basis of the computer model. We are aware, however, of the infinite variations and subtleties of this task in the real world, and the limitations of our chosen computer task. Nevertheless, as we will show throughout the paper, our design decision, while avoiding the computational cost of natural language processing, rendered a rich set of results.

**Investigations**

Contrarily to most cognitive modeling software, our model is not trying to simulate human thinking in its immense range of complexities and detail. Conversely, we selected the particular features of human learning processes that will possibly enable us to pair our data with Rosenberg et al. observations. As all we are modeling is the agents’ ability to construct correct connections between pieces, we are ultimately investigating the computational cost and accuracy in building probabilistic cognitive structures.

“Success”, in the model, is defined by the correct assemblage of a sentence with no errors, i.e., with all number in ascending order. We measure the time to completion of the sentences as well
as the error rate in building them. The final performance measure is the ratio between average time to completion and average error rate, which we call cost of accuracy.

First experiment
The first round of simulations compares retrievers with different performances, or “stickiness”. When retrievers collide with pieces, they grab those pieces. Low-performing retrievers, however, might collide with a piece but fail in grabbing it. The net effect of a low performing retriever is to bring fewer pieces to the connectors per unit time. This is loosely analogous to improving students’ short-term memorizing skills, or how much sheer information they can gather in the environment.

Figure 11. Comparison of the time to completion of task for different retriever success rates, showing very little performance gain (20 runs per data point).

One conclusion from this data is that retrievers have a small impact in overall task performance – dropping retriever success rates from 90% to 20% (a 70% drop) results in a timid 16% increase in time to completion of the task. In other words, in the model, retrievers appear not to be the controlling phase of the process. This is a key qualitative result of the model: good information retrieval skills do not cause abrupt gains in learning. Rosenberg et al. data qualitatively corroborates this hypothesis: during the first narrative, even with books and worksheets readily accessible, but with weak ‘connecting skills’, students were unable to weave a coherent explanation. From the narrative, it is clear that if students were given more time or more informational resources to complete the task, the impact in task performance would not have been significant. In other words, so far, our model replicates one of the observations of Rosenberg et al. classroom observations: the controlling phase of students’ cognitive work was not information retrieval, and the cause of students’ failure in explaining the rock cycle was not due to lack of information, lack of time to retrieve the correct information, access to information, or weak memorizing skills. Indeed, retrieving skills have at best a linear impact in the overall task performance.
Second experiment
The goal of the second experiment was to investigate the influence of connectors’ performance in overall task completion time and accuracy. Connectors, in the model, represent more elaborate cognitive elements, which can evaluate different pieces of information and link them together based on an internal rule. In the model, the internal rule is to build ascending sequences of numbers. Connectors can make mistakes, and wrongly connect the number ‘41’ to the otherwise correct ascending sequence [3 45 67]. The probability of such mistakes is controlled by an internal variable in each connector (connector-strength). The following plots show the impact on time to completion, accuracy, and computational cost of accuracy for different values of ‘connector strength’ (from 10% to 95% of probability of a wrong connection).

![Connector strength vs. Time to completion](image1)

![Connector strength vs. Accuracy](image2)

![Connector strength vs. Cost of accuracy](image3)

Figure 12. Connector strength vs. Time to completion of task, accuracy, and cost of accuracy (50 runs per data point, sentence size 2)

At first sight, looking at the “Connector strength vs. Time to completion” plot (top left), it appears to have no impact on overall performance. However, even though the time to complete the task remains roughly the same, accuracy increases significantly (top right). Combining the two plots (bottom, center), we observe that there is a very good linear fit of the computational
cost of accuracy and connector strength. Therefore, increasing the ‘skill’ of the connectors has a much greater impact on overall task performance than increasing retrievers’ skill (see previous experiment). Even though training skilled receivers and connectors might have different costs, this result is also qualitatively in agreement with the data from Rosenberg et al. narrative. When students were told to “start from what they already knew”, and evaluate the connections among the different phases of the rock cycle using previous knowledge, or just their common sense (i.e., ‘if lava is hot, it must cool down’), their performance increased significantly in a non-linear fashion.

This second experiment, therefore, hints that connecting skills are far more significant for task performance than retrieving skills. There is, still, an outstanding question: the cost of training skilled connectors in unknown, so a comparison between scenarios with unskilled but fast and skilled but slow connectors is still not conclusive. We will try to illuminate this question in the third experiment.

**Third experiment**

The third experiment was aimed at finding out the impact in performance of the complexity of the desired explanation. In the model, the complexity of the explanations is represented by the ‘sentence-size’, which is the target number of knowledge pieces which connectors need to put together. The following examples show explanations with sentence size two, three and four:

**Sentence size = 2**

```
the volcano erupts  lava comes out
```

**Sentence size = 3**

```
the volcano erupts  lava comes out  lava cools
```

**Sentence size = 4**

```
the volcano erupts  lava comes out  lava cools  lava makes igneous rock
```

The following plot shows a comparison between sentence sizes 2 and 3, for different values of connector strength.
The graph represents the time to completion of the task (i.e., an explanation construed) divided by the accuracy of the explanation, on the Y axis, and the connector strength (how well trained the connectors are to identify viable connection between two content pieces) on the X axis. Explanation comprised of few content pieces are relatively insensitive to the connectors’ training (sentence size 2, blue line), whereas the drop is more dramatic when explanations are longer (sentence size 3, red line).

A striking result is that, while the impact of increasing values of connector strength is linear for sentence size 2, it is roughly exponential for sentence size 3 (the best fit for the curve was exponential, but even a linear fit would have an much higher angular coefficient). This suggests that, for assembling ‘simple’ content, the gain that students get from improved connecting skills is much lower than when there are struggling with complex knowledge.

Again, this finding seems fitting with Rosenberg et al. narrative. Even in the first moment of the narrative, when students are trying to assemble explanations based on worksheets and other authority-based sources, with more consideration for formal ordering and a quasi-random approach, they were able to assemble a number of “sentence-size 2” explanations. The following four examples were extracted from the transcriptions of students’ dialogues:
However, in that first part of the narrative, students were never able to form “sentence size 3” explanations, which would require an extra step: connecting a relatively simple pair of pieces to a third piece, evaluating all possible pieces for their fit. In the second part of the narrative, after just some minutes, by trying to ‘enlarge’ their explanation making sense of the connection between pieces, students formed a sentence size 4 explanation, and just some minutes later a sentence size 10 explanation.

“Bethany: Listen up! OK, the volcano erupts [1], and lava comes out [2]. Lava cools [3] and makes igneous rock [4]. Rain and wind cause small pieces of rock to break off [5]. Sediments form [6], and rain and wind carry it away [7], and rain and wind slow down and deposit sediments [8] and this happens over and over again to form layers [9]. OK, so water is added to this [10]…” Rosenberg, Hammer, & Phelan (2006), pp. 274
To further investigate the role of increase sentence sizes to overall cost of accuracy, we ran the model for sentence size 4 as well. The results, comparing sizes 2, 3 and 4, are in the following three plots:

Connector strength vs. Time to completion, for Sentence Sizes 2, 3 & 4

Connector Strength vs. Accuracy

Connector strength vs. Cost of accuracy
For sentence size 4 (SS4), with low values of connector strength (CS), it is virtually impossible for agents to assemble a correct explanation: for CS 10%, increasing SS from 2 to 4, accuracy drops 100 times, from 2 to 0.02 (see data table). Increasing SS from 2 to 3, accuracy drops 5 times. Consequently, the cost of accuracy for SS 4 is 100 times higher for CS 10%. The “Cost of accuracy” plot shows that cost of accuracy (CA) drops non-linearly, in particular for CS in the 80-95% region. For example, for SS 4, increasing CS from 80% to 95% (a 15% increase) renders a 50% drop in CA (from 6633 to 3345).

Figure 15 shows that increasing sentence sizes has a dramatic impact on performance and on the important of ‘connecting skills’. For SS 3 and 4, ‘brute force’ (low CS) assemblage breaks down. For SS 2, brute force assemblage is not so costly, and the benefit of developing connecting skills is not so pronounced.

The events in Mrs. Phellan’s classroom tell a similar story. In the first half of the class, when students were using brute force methods and not investing on their own connecting skills, they couldn’t go much further than assembling simple, SS 2, explanations. When they activated their ‘connectors’, prompted by the teacher’s intervention, they switched from a brute force to a “sense-making” mode, in which most energy was spent on connecting pieces, and not retrieving them. That shift enabled them to assemble seamlessly explanations of SS as high as 10.

**Conclusion, limitations, implications**

Along this paper, we tried to pair our model data with real classroom data (Bifocal Modeling, Blikstein & Wilensky, 2006). In our three experiments, we searched for instances that would resemble what Rosenberg et al. described in their classroom observations. The model seems to validate key elements of those observations:

1) Students’ failure in the first half of the narrative was epistemological, and not due to lacking memorizing or information retrieving skills (see Experiment 1).

2) The fundamental mathematical basis of the model, from which all other behaviors emerge, is that brute-force methods are fast for short sequences, but for long sequences, as the combinatorial space increases exponentially, their performance drops accordingly. In the high
connector strength mode, however, once the connector is trained, the size of the sentence has a much lesser impact, since the evaluative rule of the connector filters out the combinatorial space, and one single successful connection (given an unlimited supply of pieces), will take the exact same computational time for any sentence size. This seems to be the case in the classroom, where students could assemble long explanations quickly, once they were in a ‘high connector strength’ mode.

3) In this simulated environment, we were able to verify that for learning intricate content (i.e., assembling long explanations), there is a significant, non-linear, payoff to invest in “sense-making skills” (connector strength) as opposed to “memorizing skills” (retrieving speed). For simple content (involving the connection of 2 content pieces), however, sheer memorizing can even outperform “sense-making skills”. The data shows that the payoff of improved connector strength only manifests itself after CS 80% (see Figure 12, Figure 13 and Figure 15).

4) Abrupt, non-linear shifts in student understanding are indeed possible even within very short periods of time, by activating different cognitive resources. If we consider “previous knowledge” as a strong connector, it follows that its activation following the teacher intervention could cause a sudden change in student performance.

Limitations
Our task is only an approximation of a real classroom task, and might not capture all of its complexities. In addition, we do not have a good methodology for evaluating the cost of training a strong connector. It could be that, in the real world, the difficulty in training connectors is also non-linear and increases exponentially in the 80-95% region, so the gains in performance could be diminished. Also, we would like to develop automated data collection techniques which would make our model-to-transcription comparison less ambiguous.

Implication for design
This work, we believe, could potentially have broad implications for the practice of curricular designers, teachers, and policy makers – by offering researchers “glass box,” accessible tools to simulate, model and test hypothesis about human cognition in social contexts, as well as to pair model data with real classroom data.

References


Simulations as Mediators for Distributed Research Activity

James A. Levin & Michael Cole

University of California, San Diego

Research is a distributed activity. While individuals play key roles in distributed research activity, the research process also involves a variety of other artifacts, including the media which allow for the interaction among individuals and that record the data, the analyses, the theories, and the interpretations of research. In this paper (itself a medium), we present a case study of using computer-based simulations as mediators of distributed research activity. We also analyze the role of simulations as a medium for an individual to express a theory (or at least a specific instantiation of a theory), as a medium for interaction among members of a co-located research group, as a medium for interaction among members of different research groups, and as a medium for conveying information to a wider audience.

We bring a "distributed activity" perspective to this analysis. Drawing upon the three different perspectives of distributed cognition (Hutchins, 1995), activity theory (Cole & Engeström, 1993), and organizational learning (Mehan, Hubbard, & Stein, 2005; Argyris & Schön, 1978), this distributed activity perspective focuses on the ways that activity is distributed (in space, in time, across people, across artifacts, etc.). Then once the distribution has been articulated, the distributed activity perspective focuses on the ways that the activity is mediated across these distributions. It also looks at ways that the mediators interact with each other, in ways that are coordinated, dis coordenated, or uncoordinated. The distributed activity perspective also suggests that the distribution and mediation of activity be examined at multiple scales of analysis, from the intra-individual the inter-individual, the intra-group, the inter-group, and analyses with even larger units of analysis.

We are learning researchers, and in analyzing our own professional activity, educational research, we can see that research is a specialized kind of learning, learning for which there is no "answer in the back of the book." After analyzing a variety of distributed learning activities, we decided to apply the same distributed activity perspective to our own activity of research on learning.

A Case Study of Using a Simulation as a Mediator of Distributed Research Activity.

In the Fall of 2005, a number of us were involved in an effort to organize a research center focusing on the science of distributed learning [http://eds.ucsd.edu/sdlc/](http://eds.ucsd.edu/sdlc/). Key members of that effort were the Laboratory of Comparative Human Cognition (LCHC) at the University of California, San Diego [http://lchc.ucsd.edu](http://lchc.ucsd.edu) led by Michael Cole and the Center for Connected Learning and Computer-Based Modeling (CCL) [http://ccl.northwestern.edu](http://ccl.northwestern.edu) at Northwestern University led by Uri Wilensky (along with 14 other groups at 5 other institutions). In exploring NetLogo (Wilensky, 1999) [http://ccl.northwestern.edu/netlogo/](http://ccl.northwestern.edu/netlogo/), a computer-based simulation environment developed by the CCL group, the LCHC group was initially surprised to learn that, among the extensive library of NetLogo simulation models in the NetLogo library and website, there were none which were simulations of learning. We then learned about the Abrahamson-
Wilensky model, which implemented models of Piagetian and Vygotskian learning, and comparing them to a "random" learning model and a combined Piagetian-Vygotskian model (Abrahamson & Wilensky, 2005). In order to better understand both NetLogo and the Abrahamson & Wilensky model, Jim Levin scheduled a presentation to the weekly LCHC laboratory meeting during the Spring of 2006, and presented NetLogo, Hubnet, some simple interaction models developed by Jim Levin, and the Abrahamson-Wilensky model. There was an extensive discussion of all of these, with the most interest in the A-W model, especially the way in which it expressed Vygotskian learning. To facilitate that discussion, Jim Levin brought in a one page handout, with the NetLogo code that expressed the Vygotskian learning circled (17 lines out of 270 lines of code that spanned 4 pages of printout). This handout is shown in Figure 1.

```plaintext
to adjust
  if strategy = "Random" [  
  "r-adjust"
  set max-moves best-max-moves
  stop
  ]
  if strategy = "Piagetian" [ p-adjust ]
  if strategy = "Vygotskian" [ v-adjust ]
  if strategy = "P-V" [ p-v-adjust ]
  if strategy = "Vygotskian"
  [ set max-moves limit-legal-distance
    ( best-max-moves + (random-normal 0 (error * best-score / max-dist)))
    stop
  ]
  ifelse (score > 0 ) [
  set max-moves limit-legal-distance
    (best-max-moves + (abs random-normal 0 (error * best-score / max-dist)))
  ]
  set max-moves limit-legal-distance
    (best-max-moves + (abs random-normal 0 (error * best-score / max-dist)))
  end
  p-adjust
  ;; if your score is better, that's your new best, otherwise stick with the old
  if (score < best-score) [
  set best-score score
  set best-max-moves max-moves
  ]
end

to v-adjust
  let fellow nobody
  while (fellow = nobody or fellow = self ) [ set fellow turtle (who + ( - (P-Vygotskian-neighbors) / 2)) + random (1 + P-Vygotskian-neighbors) ]
  ;; look randomly to one of your neighbors
  ;; if the score is better and it is within your ZPD, use their max-moves.
  ifelse (best-score > best-score-of-fellow) and (best-score - ZPD <= best-score-of-fellow)
  [ set best-score best-score-of-fellow
  set best-max-moves best-max-moves-of-fellow
  ]
  set best-score score
  set best-max-moves max-moves
end
```

Figure 1: handout of a portion of the NetLogo code of the A-W model
The discussion focused on the limited ways in which the A-W model captured the essence of Vygotskiian learning, especially that it focused totally on the less capable participant, who learned by adopting the action of a more capable participant. The model did not capture any changes in the more capable participant based on observation of a less capable participant.

The discussion also focused on the interpretation of "zone of proximal development", which in this model did not capturing the dynamic and co-constructed nature of the concept.

It occurred to Jim Levin that it would be relatively easy to modify the A-W model to deal with the unidirectional nature of the learning. In the A-W model, a participant determines whether it is doing better or worse at the task than a chosen partner. In the original model, if it is doing better, nothing else is done. In thinking of just one pair of participants, we can equate the one performing worse as a "student" and the one performing better as a "teacher." Many studies of learning have documented the ways in which a teacher will dynamically co-construct the learning environment, in many cases performing less competently than the teacher could actually perform (slower, more explicitly, etc.) in order to aid the learner. The A-W model could be modified so that a better performing participant, while still maintaining their knowledge of how to perform better, could actually perform less well in order to help the less well performing participant in the pair to improve its performance. To draw an analogy to classroom teaching, a lecturer solving a problem on a blackboard will go more slowly, include more steps, and explain more of what he or she is doing when teaching a less knowledgeable individual (or a whole class of students) than he or she would if solving that problem alone or with colleagues. Figure 2 shows the modification of the original A-W code shown in figure 1.
to v-adjust-t ;; modified from v-adjust by JAL
  if (abs((max-pxcor / 2) - best-max-moves) > abs((max-pxcor / 2) - best-max-moves-private)) [set best-max-moves best-max-moves-private] ;; restore best knowledge
  let fellow nobody
  while [ fellow = nobody or fellow = self ] [ set fellow turtle (who + (- (#-Vygotskiian-neighbors / 2) ) + random (1 + #-Vygotskiian-neighbors ) ) ]
  ;; look randomly to one of your neighbors
  ifelse (best-score > best-score-of fellow) and (best-score - ZPD <= best-score-of fellow)
  [ set best-score best-score-of fellow
    set best-max-moves best-max-moves-of fellow
  ]
  [ set best-score score
    set best-max-moves max-moves
  ]
  ;; below is the new code that attempts to model the "teacher's" awareness of the "student" (JAL)
  set best-max-moves-private 0
  if (best-score < best-score-of fellow) ;; better than other (ie. closer to the target)
  [ set best-max-moves-private best-max-moves ;; save own knowledge of own best move, since we're going to move suboptimally for teaching purposes (JAL)
    ifelse (best-max-moves < best-max-moves-of fellow)
    [ set best-max-moves max (list best-max-moves ((best-max-moves-of fellow) - ZPD )) ;; target is to the left
      ]
    [ set best-max-moves min (list best-max-moves ((best-max-moves-of fellow) + ZPD )) ;; target is to the right
      ]
  ]
end

Figure 2: the –T modified Vygotskiian learning algorithm (additions are bold)

We implemented this change, developing a "-T" version of the A-W model ("T" is for Teacher), and we presented it to the LCHC group two weeks later. We wanted to present it the following week, but there were a few bugs in the modification that delayed the presentation.
The main point of the A-W model was that combining Piagetian and Vygotskiian approaches produced improved learning over either one alone, and that point remains with the "-T" modification (see figure 3, showing the results of 40 repeated runs of the model). One of the interesting features of the "-T" modification is that even though half of the participants are doing less well at the task during each cycle (since they're reducing their performance to bring it within the "zone of proximal development" of their partners, the overall learning of all of the participants combined goes more quickly.

Figure 3: Learning results from the modified Abrahamson-Wilensky model

In this follow-up lab meeting, the discussion then focused on the nature of the task being learned, with a general consensus being that the learning task that the A-W model represented was very simple, and that it would be good to be able to model more complex tasks. We agreed that it was useful to express theoretical models in that format, as it forced the modeler to be explicit and allowed the viewers of the model to see both the specific details and the dynamic behavior of the model. The discussion turned to the nature of the learning task being modeled, especially the unidimensional nature of the task, and concerns about the ability of the model to extend to more complex learning activity. One member of LCHC, Peg Griffin, mentioned that Rembrandt's
drawing "Two Women Teaching a Child to Walk" captured more of the concept of "zone of proximal development" than the A-W model, and another member of LCHC was able to locate it on the web and bring it up for display during the discussion. That drawing is shown in figure 3.

![Figure 3: Rembrandt's "Two Women Teaching a Child to Walk"

Note that neither woman is walking normally, but instead in a way that supports the learning to walk of the child in the middle. The two women are providing a dynamic zone of proximal development for the child, allowing the child to walk (and learn to walk) even though the child could presumably not walk on his or her own. It would be a challenge to extend the A-W model (and to the -T modification to the A-W model) to represent this kind of learning.

We shared this modified model with Uri Wilensky and the CCL group at Northwestern and with Dor Abrahamson at UC Berkeley via email, and there was discussion via email of the nature of the modification and the simplification (or oversimplification) of the simulation. The CCL group put together a proposal for a symposium at AERA in the summer of 2006 and invited us to join them, and this proposal was accepted, which brings us to this presentation today. By using printouts of the code, printouts of graphs of the results, and animations of the model in action, we are better able to present to you the results of this research into distributed learning. How well this presentation enables you to learn something useful that you carry away and use in your own research, your own teaching or your own learning remains to be seen. But with this simulation medium, we can make the simulation available to you for your own close examination, including your examination of the dynamics of the model. And you will be able to further modify this model – modification of a model is much easier than generating a model from scratch, to create

Discussion

Any consideration of a new medium, in this case computer-based simulation, helps us understand more deeply the current media. How is research distributed and how are those distributions mediated? In some cases, there are individual researchers who conduct research for their own interest and with their own resources and who never communicate their results to others. Those are the rare cases. In a more typical case, a group of individual researchers work together (faculty, post-docs, graduate students, undergrads, staff, etc.), with the support of one or more institutions, and those researchers communicate their research results to others through face-to-face talk, through conferences, through written reports, email, websites, and through journal articles, book chapters, and books. They comprehend the reports of others (oral or written) and use those reports to contextualize their own research through literature reviews, to draw upon to formulate new research questions and directions, and to support or dispute their findings.

With print, research is expressed both through text and through graphics. This includes the recording of data, the reports of results of analysis, the expression of theory, and the reporting of research results. How do these conventional media compare to computer-based simulations, such as the A-W model of learning and its modification, described in the case study above? Certainly theories can and have been expressed in print and in talk. For example, Vygotsky and Piaget used talk and print as their media.

We see several advantages to using computer-based simulation as a medium for theory expression.

1) Computer-based simulations better express dynamic behavior of a model, and they allow an easier exploration of dynamic behavior of a model, as it unfolds over time.
2) They force theory builders to be explicit in ways that are easy for others to understand.
3) They are easier to exchange with others, both locally and at a distance.

We see several disadvantages to using computer-based simulations as a medium for theory expression:

1) We don't yet have good metrics (or even language) for representing and comparing the dynamic behavior of these computer-based simulations, so it is difficult to convey the dynamics other than by showing others the models in operation.
2) They force the theory builder to be explicit in ways that sometimes are not yet adequately supported by data or even by the builder's intuition.
3) The different versions are hard to track as they propagate around.

Any medium has its own unique strengths and weaknesses, and this is true with the media for expressing theories of talk, print, and computer-based simulation. We don't expect the newer medium to totally displace the others (otherwise, we would have presented this paper entirely as a NetLogo simulation). Instead, we plan to explore the unique strengths that this new medium
has, especially for representing dynamic properties, and to use that when faced with the need to develop theories that have important dynamic properties.

In applying the distributed activity framework to this case study, we can develop some plausible "next steps", that we will explore with LCHC, CCL, and any other individuals or groups that are interested. One idea is to post digitized video segments of people learning on the web to be analyzed by distributed groups and to be modeled in the NetLogo medium. Another idea is to organize a modeling seminar across institutions (but with course numbers at the participating institutions) that faculty, post-docs, grad students, and undergrad students could jointly participate in, using both synchronous and asynchronous media including NetLogo and web-shared video. We can identify the distributions present for such a seminar (spatial, temporal, organizational), but we can also identify mediators to span the distributions.

**Comprehending, modifying, creating, and collaborating with simulations.**

Simulations are a particular kind of "text", and require specific kinds of literacy skills to comprehend, modify, create, and collaborate with. They are typically created by creating a set of directive statements, implemented in computer-based simulations as a set of directives in a modeling language. They are modified by editing those directives, adding some directives, changing some directives, and deleting some directives.

To comprehend a simulation, it is helpful to distinguish between the core directives that capture some particular aspect of the domain being modeled and "infrastructure" directives that support the operation of the simulation. Sometimes this distinction is marked by the "comments" in the code (text statements that are to be read by people but ignored by the computer), but too often this distinction is left as an exercise by the reader. There are a variety of other "meta-model" information that would be helpful for the comprehender of a simulation, such as the rationale or evidence that the modeler has for an element of a model, or at the very least, the degree of confidence that the modeler has for the different parts of the model. In some cases, the modeler has high confidence in a model element; in other cases the modeler has low confidence but has to settle on something in order to complete the model. In the case where the modeler has very little confidence, he or she may explicitly designate those elements as parameters and allow the "reader" of a simulation to manipulate those parameters.

In the case of the A-W simulation examined in our case study here, the "core directives" were identified and presented in the "handout" shown in figure 1, a printout of part of the NetLogo procedures underlying the A-W model with one procedure circled. It would be useful to provide tools for providing this kind of meta-data explicitly, so that each person hoping to collaborate through the medium of the model wouldn't have to determine that for himself or herself. Figure 4 shows an attempt to annotate through formatting the core/infrastructure distinction, and for the core elements, the confidence dimension for the procedures of the A-W-T modified model describe above.
to v-adjust-t ;; modified from v-adjust by JAL
if (abs((max-pxcor / 2) - best-max-moves) >= abs((max-pxcor / 2) - best-max-moves-private)) [set best-max-moves best-max-moves-private] ;; restore best knowledge
let fellow nobody
while [ fellow = nobody or fellow = self ] [ set fellow turtle (who + ( - (#-Vygotskiian-neighbors / 2) ) + random (1 + #-Vygotskiian-neighbors ) ) ] ;; look randomly to one of your neighbors
ifelse (best-score > best-score-of fellow) and (best-score - ZPD <= best-score-of fellow) ;; if other is better and within ZPD
[ set best-score best-score-of fellow
set best-max-moves best-max-moves-of fellow
]
[ set best-score score
set best-max-moves max-moves
] ;; below is the new code that attempts to model the "teacher's" awareness of the "student" (JAL)
set best-max-moves-private 0
if (best-score < best-score-of fellow) ;; better than other (i.e. closer to the target)
[ set best-max-moves-private best-max-moves ;; save own knowledge of own best move, since we're going to move suboptimally for teaching purposes; assumes perfect memory, which is of course questionable (JAL)
ifelse (best-max-moves <= best-max-moves-of fellow)
[ set best-max-moves max (list best-max-moves ((best-max-moves-of fellow) - ZPD ) ) ;; target is to the left
]
[ set best-max-moves min (list best-max-moves ((best-max-moves-of fellow) + ZPD ) ) ;; target is to the right
]
end

Figure 4: an annotation of one of the procedures of the A-W-T simulation model

It has always been difficult to get programmers to "comment" their program code, because at the time that the programmers have written the code, the comments seem redundant. Comments are mainly useful when the programming is seen as a distributed activity. Often it is distributed
across programmers, with other programmers responsible for coordinating their code, or for maintaining the code across changes over time in the environment within which the program has to function. Sometimes it is distributed over time, in that the same programmer uses the comments at a later time to remind him/herself of what seemed obvious at an earlier time.

In a distributed research environment, we imagine that the meta-data like comments and other annotations of shared simulation models would be added by others trying to comprehend and modify the models created by others. Some annotations would express an understanding of the function or motivation of parts of the model, as now done by conventional "comments". Other might raise questions about the model, questions that might be then addressed by the original modelers or subsequent model modifiers. A truly collaborative modeling environment would embody elements of today's wiki, blog and other interactive communication environments.

**The interaction of theory and data.**

So far, we've focused on the role of simulations as a medium for expressing, communicating, and collaborating about theory. They can also be a meeting ground for bringing together theory and data. With the new capabilities for collecting and distributing digitized video, audio, and other data, we need to think deeply about how to extend computer-based simulation environments to support collaboration (and argumentation) about the fit of data to these dynamic theories. Figure 5 shows a frame of a video of two people interacting in an afterschool learning setting when jointly learning a computer game. It would be useful to think about how to bring such data into computer-based simulation environments to extend learning theory to such settings, and thus to evaluate the theories based on their fit to such learning data.

Figure 5: a frame from a digitized video of two people jointly learning a computer game.
Summary.

In the course of conducting the case study described here, we have come to understand more deeply the many ways that research activity is distributed, the crucial role that mediators of those distributions play, and the need to understand how the mediators interact with each other. We hope that by examining our own research activity in the same ways that we examining the learning activity of others, we can see ways to improve the distributed learning activity that we call research.

References


Further References From the Introductory Text That May Not Have Appeared in the Individual Papers:

http://gse.berkeley.edu/faculty/dabrahamson/publications/Abrahamson_Wilensky_JPS2005.PDF (paper)


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