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Modeling Manifold Epistemological Stances with Agent-Based Computer Simulation

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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.

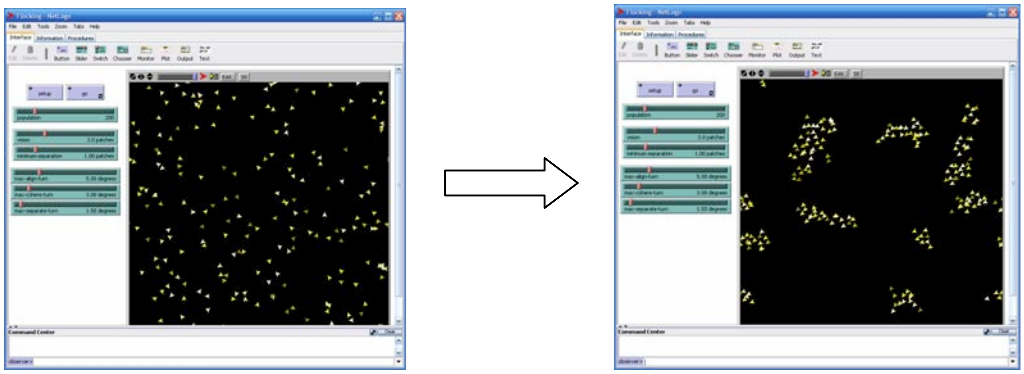


Figure 1: An agent-based model of the flocking behavior of birds.

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 field, in which theoretical models of cognition were implemented in the form of computer programs in 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/replicable 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 *el at.* 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 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 1). 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.

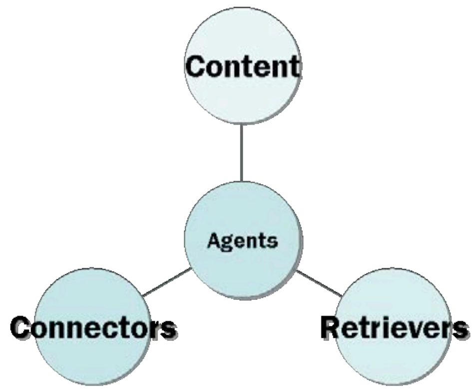


Figure 1 – The three types of agents of the model: content pieces, retrievers and connectors

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.

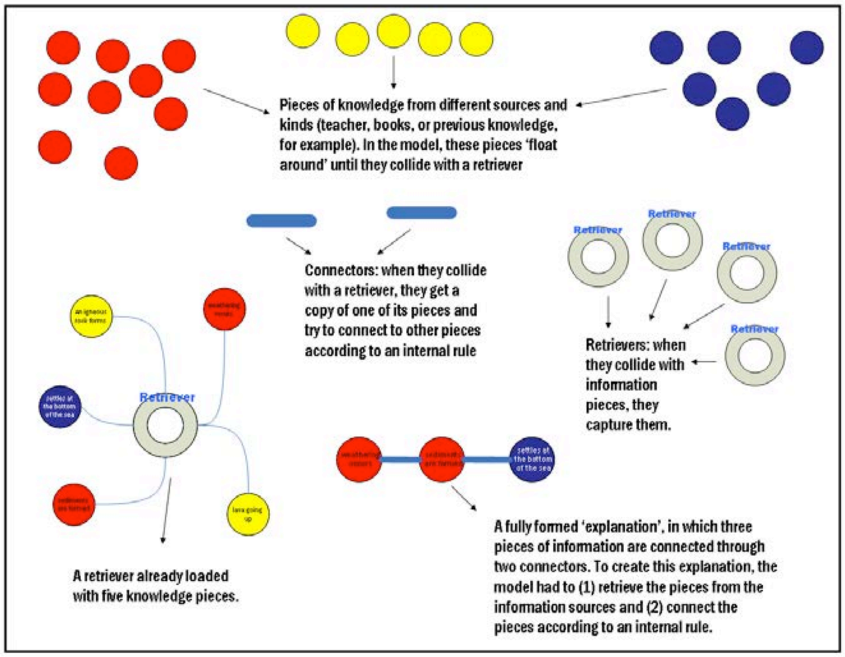


Figure 2. *Illustrated explanation of the pieces/retriever/connector computer model.*

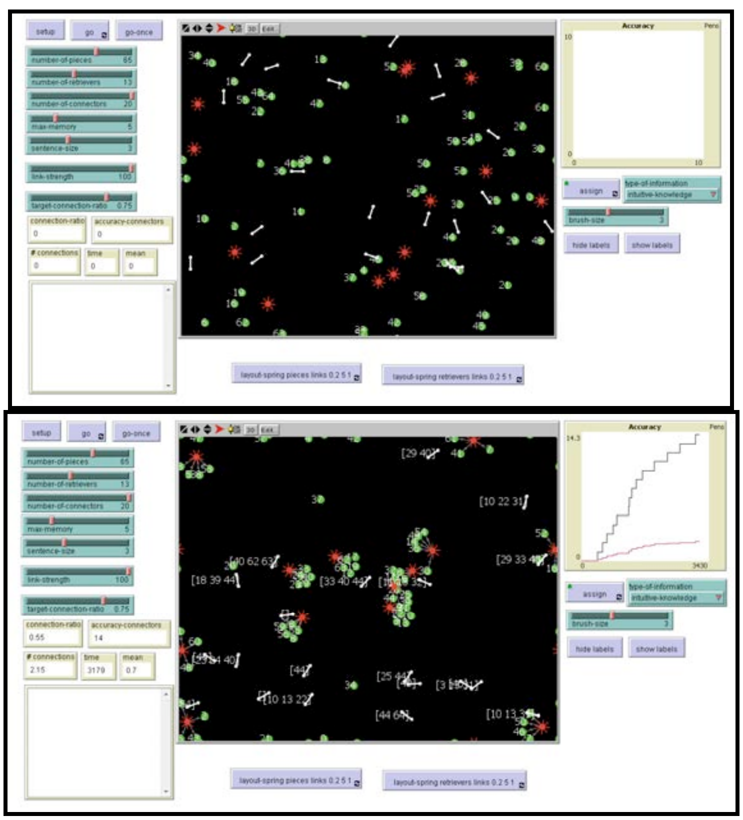


Figure 3. *The model's interface at its initial state (top), and after some steps of the simulation (bottom), in which 'clumps' of content pieces around retrievers (represented as hubs) are noticeable.*

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.

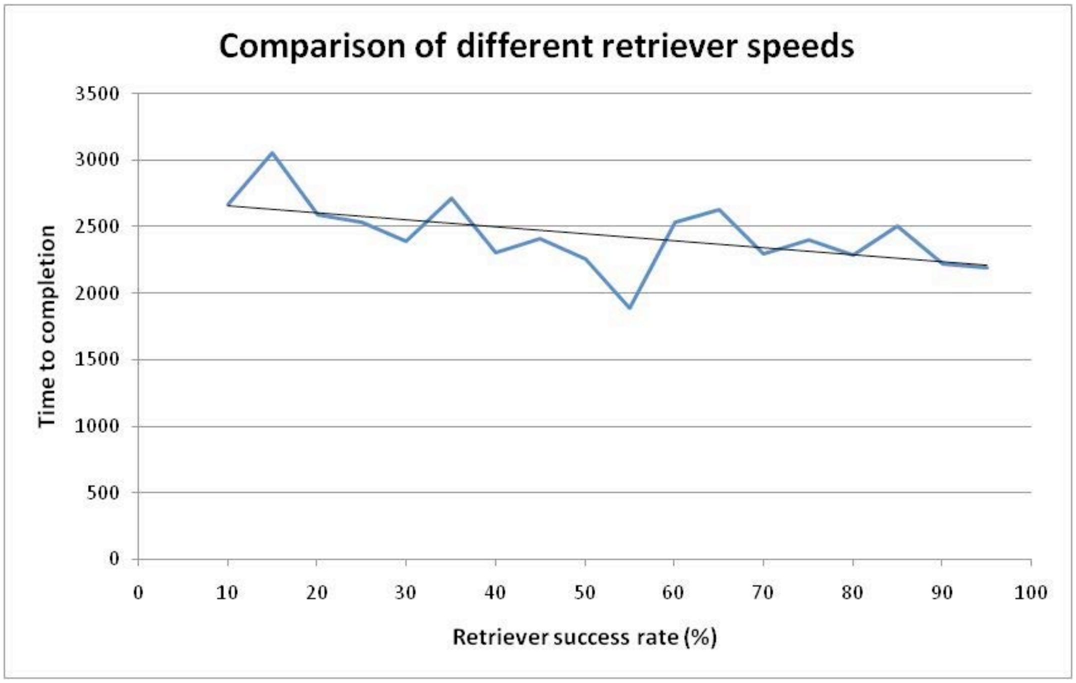


Figure 4. Comparison of the time to completion of task for different retriever success rates, showing very little performance gain (20 runs per data point).

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).

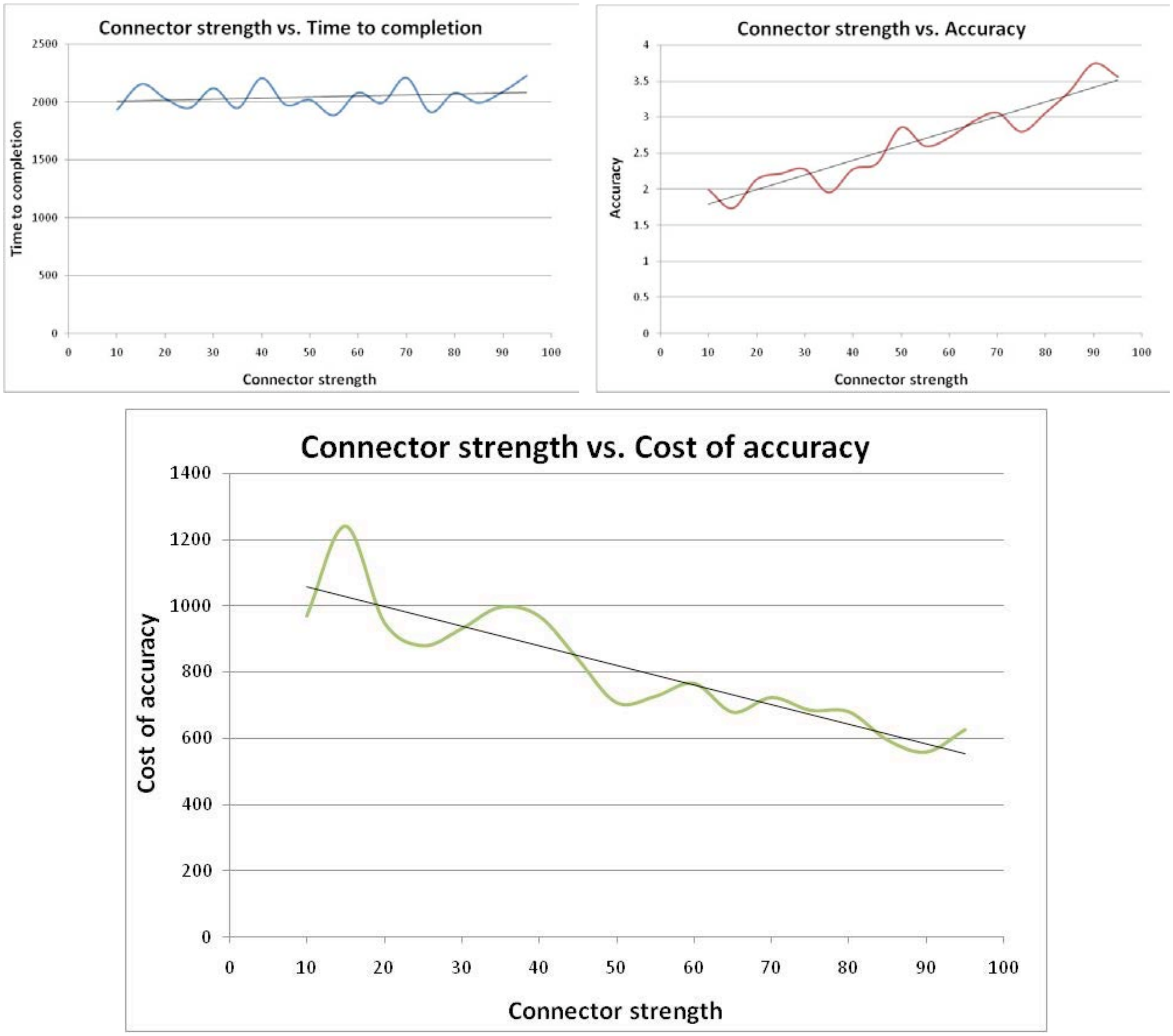


Figure 5. Connector strength vs. Time to completion of task, accuracy, and cost of accuracy (50 runs per data point, sentence size 2)

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

Sentence size = 3

Sentence size = 4

The following plot shows a comparison between sentence sizes 2 and 3, for different values of connector strength.

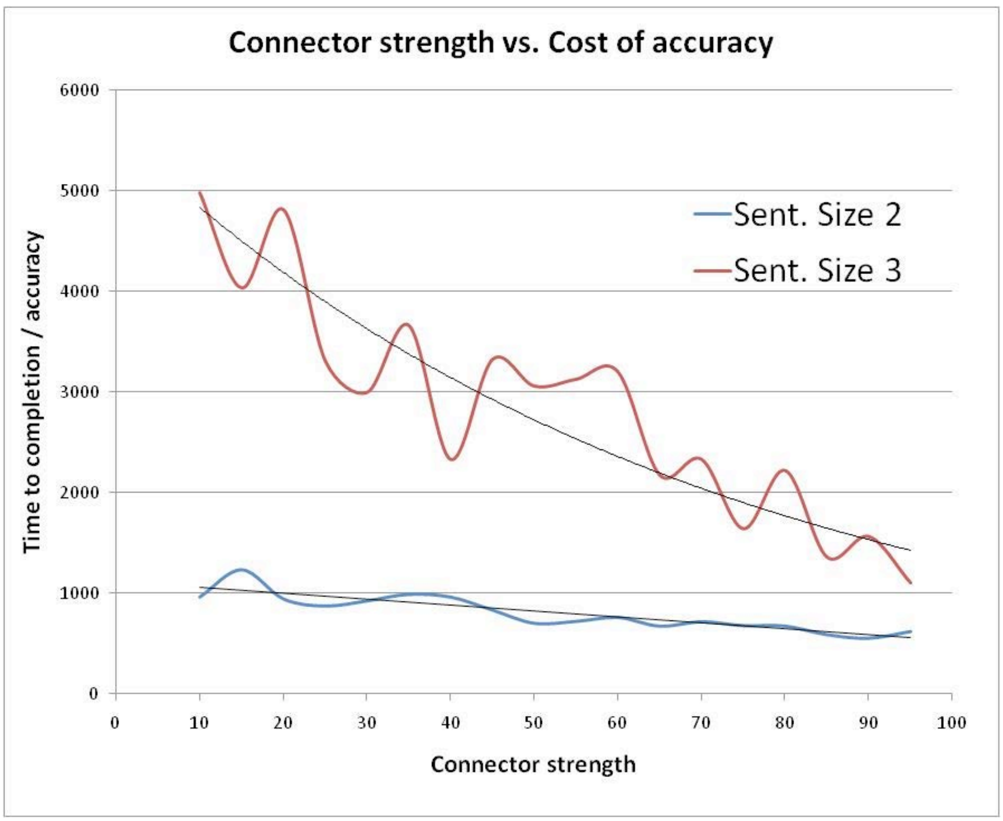
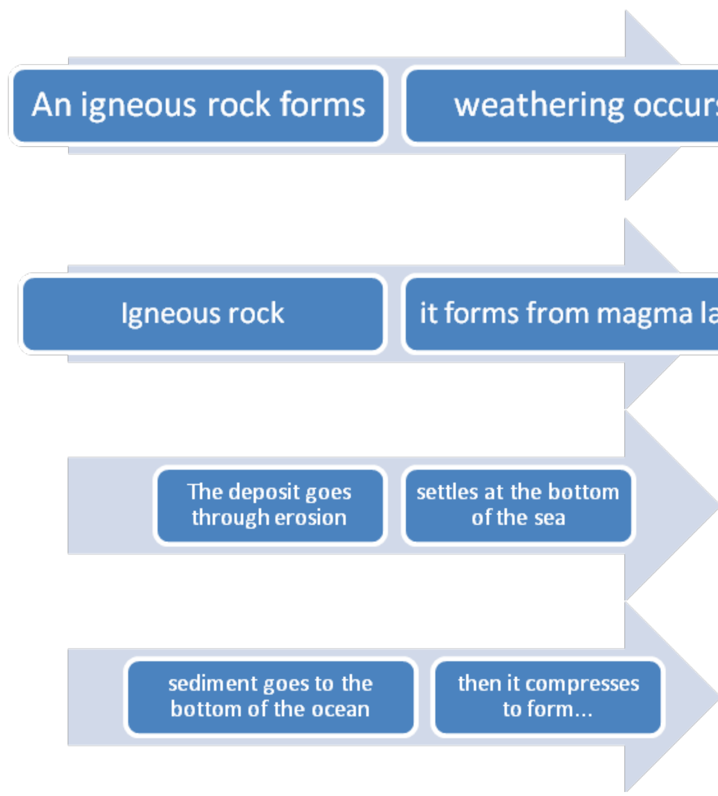


Figure 6. *The graph represents the time to completion of the task (i.e., an explanation construed) divided by the accuracy of the explanation, on the Y axis, and the connector strength (how well trained the connectors are to identify viable connection between two content pieces) on the X axis. Explanation 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.

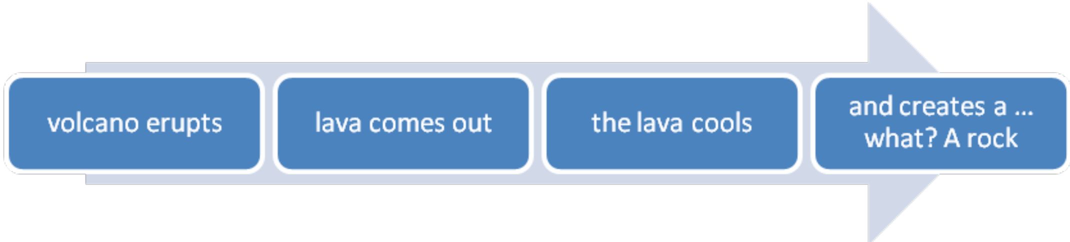
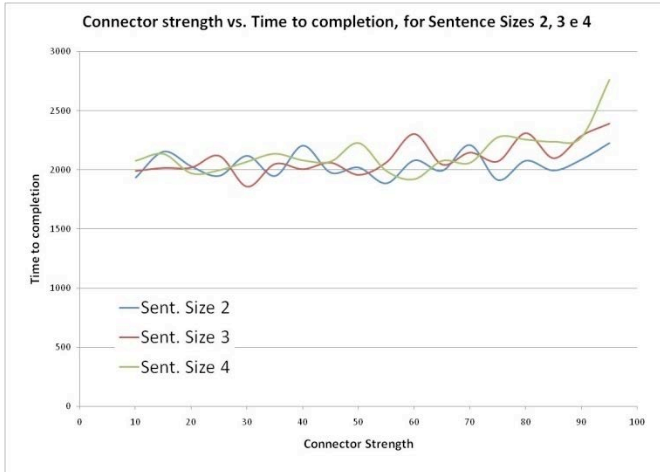
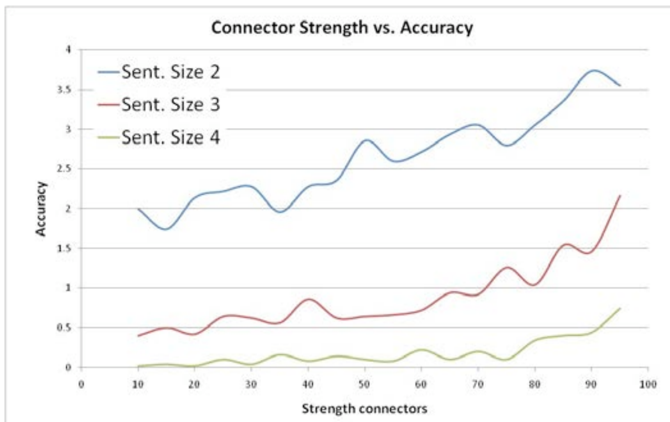


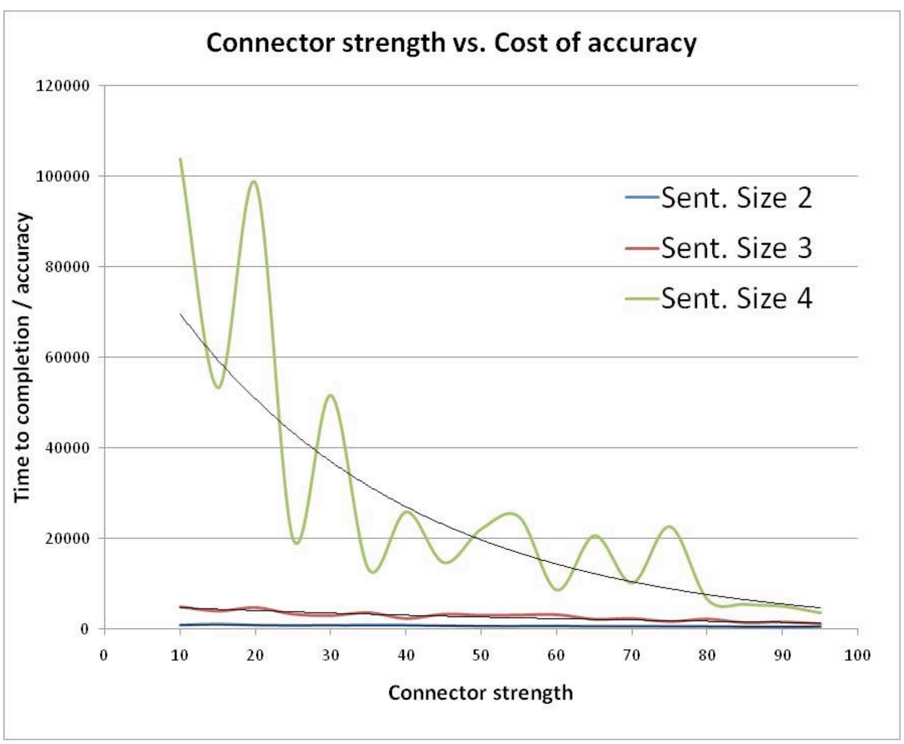
Figure 7. Students' sentence size 4 explanation (above), and sentence size 10 (below)

> "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 e 4
Time to completion
Connector Strength
Sent. Size 2
Sent. Size 3
Sent. Size 4
0
500
1000
1500
2000
2500
3000
0
10
20
30
40
50
60
70
80
90
100


Connector Strength vs. Accuracy
Accuracy
Strength connectors
Sent. Size 2
Sent. Size 3
Sent. Size 4
0
0.5
1
1.5
2
2.5
3
3.5
4
0
10
20
30
40
50
60
70
80
90
100


Connector strength vs. Cost of accuracy
Time to completion / accuracy
Connector strength
Sent. Size 2
Sent. Size 3
Sent. Size 4
0
20000
40000
60000
80000
100000
120000
0
10
20
30
40
50
60
70
80
90
100

	Time to completion			Accuracy Connectors			Time cost of connections		
Connector strength	Sent. Size 2	Sent. Size 3	Sent. Size 4	Sent. Size 2	Sent. Size 3	Sent. Size 4	Sent. Size 2	Sent. Size 3	Sent. Size 4
10	1,937.24	1,990.22	2,075.82	2.00	0.40	0.02	968.62	4,975.55	103,791.00
15	2,156.32	2,016.42	2,133.50	1.74	0.50	0.04	1,239.26	4,032.84	53,337.50
20	2,031.34	2,019.20	1,969.26	2.14	0.42	0.02	949.22	4,807.62	98,463.00
25	1,951.30	2,118.40	1,995.78	2.22	0.64	0.10	878.96	3,310.00	19,957.80
30	2,121.20	1,857.38	2,068.00	2.28	0.62	0.04	930.35	2,995.77	51,700.00
35	1,950.32	2,049.92	2,135.14	1.96	0.56	0.16	995.06	3,660.57	13,344.63
40	2,206.98	2,005.38	2,079.40	2.28	0.86	0.08	967.97	2,331.84	25,992.50
45	1,978.48	2,060.42	2,069.74	2.36	0.62	0.14	838.34	3,323.26	14,783.86
50	2,021.84	1,957.52	2,225.82	2.86	0.64	0.10	706.94	3,058.63	22,258.20
55	1,888.52	2,063.68	1,989.16	2.60	0.66	0.08	726.35	3,126.79	24,864.50
60	2,082.30	2,304.06	1,919.54	2.72	0.72	0.22	765.55	3,200.08	8,725.18
65	1,995.26	2,044.94	2,075.34	2.94	0.94	0.10	678.66	2,175.47	20,753.40
70	2,211.68	2,145.80	2,058.80	3.06	0.92	0.20	722.77	2,332.39	10,294.00
75	1,916.12	2,071.82	2,275.00	2.80	1.26	0.10	684.33	1,644.30	22,750.00
80	2,079.74	2,310.88	2,255.38	3.06	1.04	0.34	679.65	2,222.00	6,633.47
85	1,996.68	2,098.42	2,237.10	3.36	1.54	0.40	594.25	1,362.61	5,592.75
90	2,089.02	2,288.12	2,276.06	3.74	1.46	0.44	558.56	1,567.21	5,172.86
95	2,228.20	2,390.98	2,759.40	3.56	2.16	0.74	625.90	1,106.94	3,728.92
100	4,319.58	11,499.34	16,393.18	4.86	4.86	4.90	888.80	2,366.12	3,345.55
Grand Average	2,166.43	2,594.36	2,894.29	2.77	1.10	0.43	783.44	2,367.57	6,689.95

Figure 8. Connector strength vs. Time to completion of task, accuracy, and cost of accuracy (50 runs per data point, sentence sizes 2, 3 and 4), and data table.

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 8 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 5, Figure 6 and Figure 8).

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.

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