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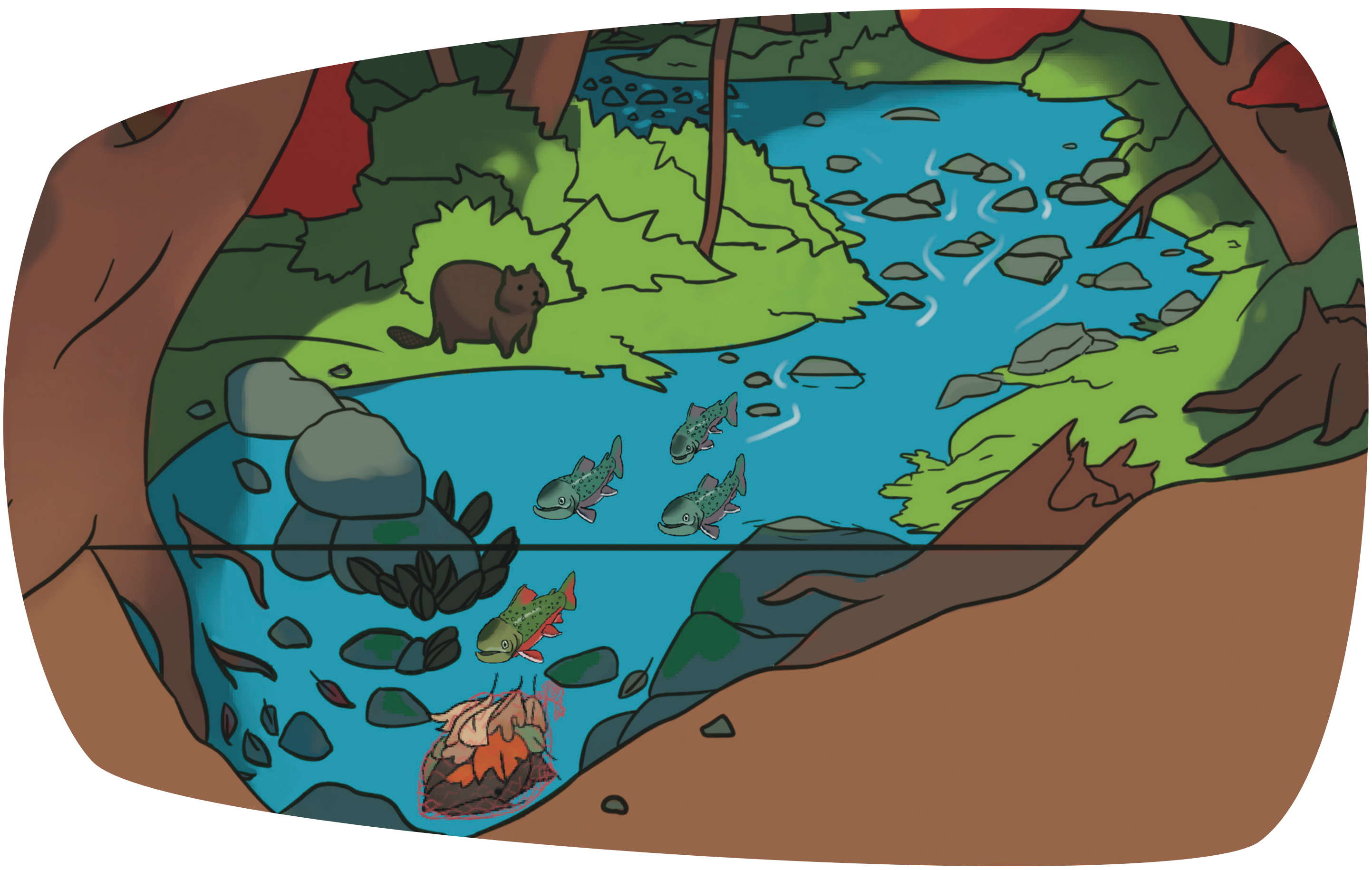
vol. 25 • no. 2 • Fall 2021



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Perspective:

Technology for Today's Innovators, and Tomorrow's

By Chad Dorsey

We are living in an exceptional new technological era. Yet looks can be deceiving. In fact, what most strongly defines our current age is *not* all the new technology we see arising, but all the technology we now take for granted. In a way no previous generation has experienced, the presence of digital technology is assumed in practically all aspects of our lives. Unfortunately, however, there is one singular, perilous exception—the way we structure and arrange teaching and learning.

We have adapted to technology's almost invisible ubiquity with breathtaking rapidity. Only a bit more than a decade ago, GPS was still a novelty. Most people didn't own cell phones. CDs and DVDs dominated their markets, and pagers and fax machines were commonplace. Today, technology has changed everything. Well, almost everything.

Sure, technology permeates our schools, but that fact is deceptive. It's the things technology has not changed about education that deserve our real attention. Despite the sudden wave of pandemic-related Chromebook purchases and the whiplash turn toward Zoom instruction, the curriculum itself has remained practically impervious to change.

Today's K-12 students exist in a world utterly defined by computation and technology. Data is everywhere. AI is on our doorstep. CRISPR, quantum computing, drones, and biosensors are the stuff of the present. Yet most students' textbooks and class syllabi could have been plucked from their grandparents' classrooms. To riff on one of my favorite of Conrad Wolfram's sayings, it's time to teach school as if computers existed.

We need to consider what it means to live and work in today's technological society—and the one just around the corner, too. Students need the competencies and habits of mind our world demands. Educators must redefine the way we approach schooling, ensuring that perspectives reflecting our technology reality reinforce everything we do.

We're already accomplishing some of this—promoting computer science and disseminating high school data science courses, for instance. But we must dive deeper and not delude ourselves into thinking that pushing a subject slightly downward from the undergraduate level into high school represents success. Similarly, elementary or middle school goals cannot be determined by merely watering down lists of current workplace skills. We must rethink K-12 learning wholesale with our eyes on new horizons.

A different approach is possible. Transformation is sweeping the workplace, and emerging professions offer an inspirational lens on the future. *MIT Technology Review*'s recent selection of "35 Innovators Under 35" is an object lesson. This incredible list's through-the-keyhole view into the future can also stand as a useful template for our educational destiny.

Partnering with artificial intelligence. Today's innovators are finding manifold ways that AI can solve tomorrow's problems, through a diversity of applications that is truly striking. From solutions to climate change to machine learning-based solutions for pain management, novel AI designs bypass existing theory and practice and aim straight at the problems they can solve. Mining large, available pools of data, AI innovators pinpoint the potential for inventive, unimagined discoveries in long-neglected corners of science and industry. Preparing learners for a world in which AI is central means seeing computers and computation as almost equal partners with humans in navigating and solving problems. From elementary school onward, students should learn not only how computing works and how to think computationally, but also gain experience identifying how computing and AI can serve as fundamental tools for approaching the world. Current research in AI education and computational thinking can help us pave the way to age-appropriate onramps for learning to apply AI to all manner of problems.

Working with DNA as a tool. Another area that begs for educational innovation is the burgeoning world of bioengineering. The advent of CRISPR technology and the recent proof of mRNA's vast utility have fundamentally shifted our orientation

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Learners must be prepared to work within a future filled with technology. We must give them opportunities to merge, mix, and mash up their knowledge and ideas.

toward biology—from seeing it as a set of systems to be observed to recognizing that it holds the active tools of our future. We need to help students see biology not as a series of facts but rather as a manipulable system. As students learn about biological processes and classification, they should be guided to see the mechanisms of biology as tools that can be used to unlock secrets, and to view medical problems as opportunities for innovative applications of miniature machines and biological building blocks. This requires significant rethinking. We must consider how to view biology education wholly differently, embracing practice-focused topics that lean into the future as much or more than they reiterate the historical past.

Seeing with sensors, and doing with drones. We must also prepare learners for a future of ubiquitous sensing and innovative action. Operating within a world where robots can be as tiny as blood vessels and sensors can be constructed from biological components demands that students see the world as a series of opportunities for both exploration and manipulation. Our curriculum must take for granted that the Internet of Things and the deluge of drones, robots, satellites, and all manner of connected machines now extend our hands and eyes to practically all scales and sites. We can monitor the entire globe from space, reach into the rubble of a disaster area, or bring the equivalent of miniature wrenches and tweezers into microscopic locations. Important new perspectives come along with this potential. Students should come to see that these tools unlock an incredible power. As soon as they understand how anything in the world functions—whether a biochemical reaction or a warehouse-scale workflow—they can turn around and apply their toolbox to directly manipulate that same process. This requires us to fundamentally rethink what "hands-on" learning means, and perhaps even to question the nature of engineering education itself.

Solving problems with data. In a future where data are everywhere, learners must be ready to use data as a medium, seeing everything around them—from music to words to photographs to brainwaves—as data. Learning how that data can be used to answer questions, shed light on the operation and interconnectedness of their world, and identify new problems to be solved is crucial. We must ensure that learners have multiple opportunities to see datasets as founts of original questions, so they are empowered and proficient at using data as a means to action. We must help them view the world as a source of data that can be used to solve problems, expose inequities, and confront social issues head on.

Putting it all together. One of the clearest lessons from the innovators of today (or any age) lies in their ability to combine disparate ideas in a way that renders them greater than the sum of their parts. Whether uniting quantum computing and agriculture or marrying innovative polymers and circuitry to solve biological problems, the innovators in MIT's lineup aren't merely working in innovative fields—they're working at the interfaces *between* them. Learners must be prepared to work within a future filled with technology. We must give them opportunities to merge, mix, and mash up their knowledge and ideas.

Bringing all of these changes about—and doing so in a way that ensures *all* learners gain rich experiences in an equitable fashion, no matter their grade level, background, or ZIP code—is the true challenge of the coming decades. And though it's indeed the task of a lifetime, taking the long view reveals that it is absolutely essential to our future, and the future of our children.

Indicators of Data Fluency

What Am I Looking For?

By Kirsten Daehler and Bill Finzer

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Data is the new "it" thing of the 21st century. From guiding traffic flow to planting crops, informing health decisions, and shaping public policies about all manner of things from incarceration to employment, data is used in countless applications and industries. Every student needs to emerge from their K–12 education having extensive data experiences. Importantly, they should be able to do things with data—explore, visualize, find patterns, identify problems, investigate sources, think about the ethical use of data, and more. These are the hallmarks of data fluency. The Concord Consortium and WestEd are collaborating on a new project funded by the National Science Foundation to promote such data fluency.

The Boosting Data Science Teaching and Learning in STEM project is developing a framework to describe the knowledge and skills teachers need to promote data fluency in their classrooms. With the help of a cadre of co-development teachers, as well as data scientists and educational researchers from across the country, the project aims to construct a Teacher Data Fluency Framework that details what teachers need to know, and be able to do, to support students in grades 5–9 to develop data fluency in science, mathematics, and computer science.

We will use this framework to guide the design of materials for teacher professional learning, then study the effects on both data science teaching and data science learning in the classrooms of teachers who have participated in the professional learning experiences. This four-year project will shape our answers to questions such as "How can teachers and students develop data fluency? What does data fluency look like? How do you know it when you see it?"

What follows are preliminary indicators that help us recognize data fluency. While these indicators serve only as a starting point, they are informed by decades of work with students and teachers using data in mathematics, statistics, and science. We've become convinced that engaging with data in a meaningful way beyond the primary grades requires technology. Using technology tools, like our Common Online Data Analysis Platform (CODAP), can make it effortless to manipulate data, conduct calculations, and make visual representations, such as graphs.

Data-rich classrooms

First, let's set the stage by peeking into a data-rich classroom. In some cases, we see students conducting their own experiments to answer a question, gathering data, constructing and analyzing graphs, and sharing their findings and the limitations of the data. In other cases, students produce a survey to gather data. More than ever before, students are also making use of countless existing publicly available datasets, and engaging as practitioners, explorers, and discoverers in every subject area.

Imagine that you and your students are thinking about income disparities, motivated by news reports on the subject. You start with data from the U.S. Census Bureau's American Community Survey, which is available at the click of a button through a plugin in CODAP (Figure 1).

Figure 1. Census microdata with income and employment for 2000 and 2017. Each row represents an individual person. People not in the labor force have been set aside.

People

people (932 cases, 1068 set aside)

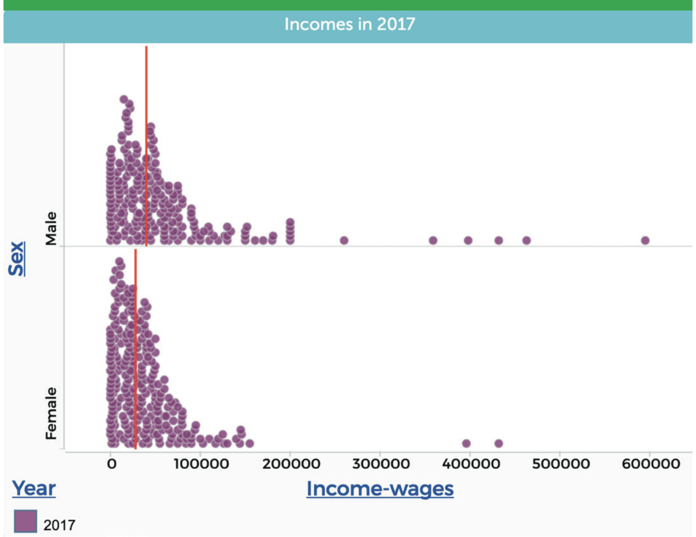
in-dex	Year	Sex	Income-wages	Age	Employment status	Usual hours worked	Weeks worked
1	2000	Female	0	16	Employed	N/A	N/A
2	2000	Female	5600	16	Employed	30	27-39 weeks
3	2000	Male	5000	16	Employed	5	27-39 weeks
4	2000	Male	2500	16	Employed	16	27-39 weeks
5	2000	Male	930	16	Employed	15	1-13 weeks
6	2017	Female	2600	16	Employed	24	1-13 weeks

Curiosity about the data is the first clue that you're in a data-rich classroom. Someone asks, "How has income changed since I was born?" or "How different are incomes for females compared to males?" One student comments, "My mom makes more money than my dad, but this data shows that men make more. Why?"

When students ***make meaning of data***—for example, by asking questions and connecting data to its origins and real-world contexts, this is a sign of data fluency.

After staring at the table of raw data, your class recognizes this is not a very efficient way to find patterns and anomalies. Students ask if there are any graphs they can look at. In the past, making graphs using paper and pencil or even a graphing calculator often felt like drudgery. Access to today's data tools changes things dramatically. You ask, "What would you like to make a graph of? What kind of graph might help us answer your question about income differences between females and males?" A student suggests comparing two graphs—income of females and income of males (Figure 2).

Figure 2. Graph of male income versus female income from 2017 census data, with median income shown as a red line.



When students ***know how (and when) to transform data and do something with the data to answer a question***—for example, by making graphs or other visual representations to reveal meaning from the data, this is a sign of data fluency.

Somewhat surprisingly, in our work with data, we have found that one of the most helpful and revealing questions to ask is "What does this point (on a graph) or row (on a table) represent?" The answer may be a person, a measurement, an experiment, a year, or a field site. Answers to this question often reveal a person's understanding of the data.

Knowing this, you drill deeper into the student's observation about their mother making more than their father by asking, "What does each point in this graph represent? Can you find a pair of data on the graphs that reflects this real-life scenario?" As students call out data points, you click on the point in the graph and CODAP simultaneously highlights the corresponding row (or case) in the data table (Figure 3).

When students can ***identify connections across data representations***—for example, by describing that a row in a data table corresponds to a point in the graph, this is yet another sign of data fluency.

There is much more students can do with the census data to begin to answer their questions. You explain that data is used to model things, usually something in the world. What we choose to record reflects both our understanding of it and the goals of our investigation. For example, a dataset of people with age, sex, employment status, hours worked, weeks worked, and income can be seen as a model for understanding wage inequality. In this way, a data table appears as a rectangle with six columns and hundreds or thousands of rows. We think of this rectangle as a flat model. However, in this situation we can better explore questions about changes over time by creating a "hierarchical representation" in which we create one group for each of two years (Figure 4).

You say, "Let's go back to our first graph of income inequality from 2017, the most recent year available in the census data." Then you describe how you made the graph comparing female and male incomes in 2017, by filtering out data about people's income in the earlier years.

Next, you ask students to work in pairs to figure out what they can do with and to the data to answer other questions, such as "What's the trend of income inequality over time? Is the gap getting bigger, smaller, or staying about the same?"

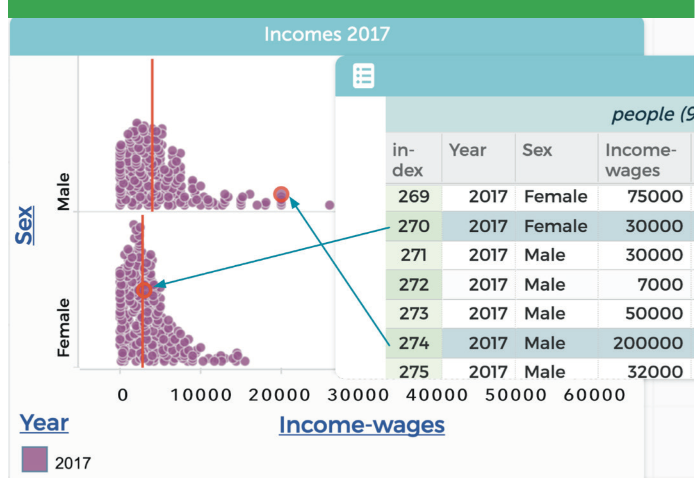
When one group calculates the median incomes by writing a formula, they learn that the gap is about $12,000 in both 2000 and 2017.

Seeing this graph, another student asks, "Is there really no change?" You suggest, "What about looking at the gap as a percentage of female income?" With this new challenge, students return to the data and make new graphs (Figure 5).

Excitedly, one group exclaims, "The wage gap is going down. Look at this. In 2000 men earned about 68% more than women, but that gap decreased to 43% in 2017."

When students ***know how (and when) to manipulate the data to answer a question and do multiple things to the data***—for example, by making "data moves" such as filtering, grouping, summarizing, calculating, merging/joining or making hierarchies, this is a good sign of data fluency.

Figure 3. Corresponding points on a graph and rows on a data table.



(continued on p.6)

(continued from p. 5)

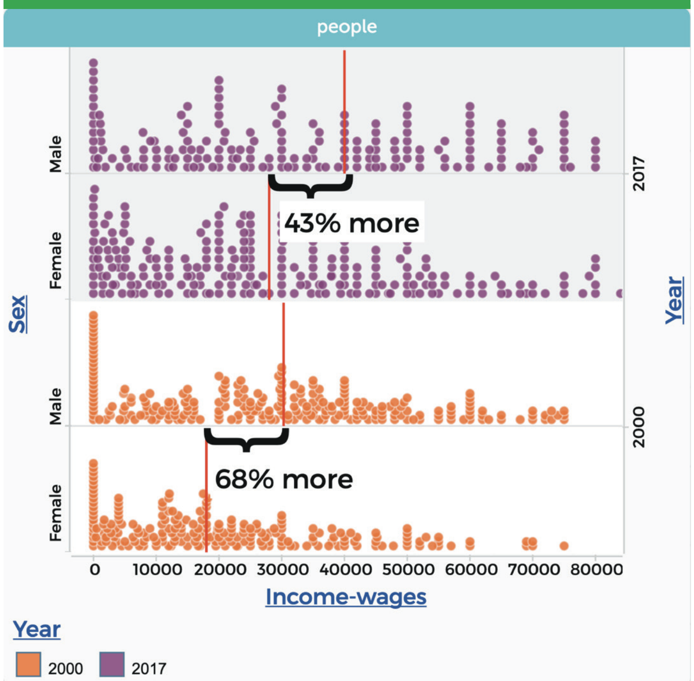
Figure 4. Rearranging data rows to show a hierarchical representation for 2000 and 2017.

People

Years (2 cases	
index	Year
1	2000
2	2017

people (932 cases, 1068 s				
index	Sex	Income-wages	Age	Employment status
456	Male	8200	70	Employed
457	Male	100000	71	Employed
458	Female	2800	72	Employed
459	Male	48100	74	Employed
1	Female	2600	16	Employed
2	Female	200	16	Employed
3	Male	730	16	Employed

Figure 5. Graph of sex versus income-wages for 2017 and 2000 with the difference between incomes calculated as a percentage of the median wage for females (and annotated in CODAP using the draw tool).



Data fluency prepares learners for the future

We hope that this glimpse into a data-rich classroom offers clues about how to boost data fluency and prepare students for lives in which they make use of data to solve problems and make discoveries. When teachers instill curiosity and excitement about data in their classrooms, they open the door to students' willingness to ask questions, try new things, think differently, and be bold when using data. Data fluency is an essential 21st century skill.

We invite you to follow our progress and to share your own classroom stories and questions about data fluency.

Common Online Data Analysis Platform

The Next Generation Science Standards (NGSS) and the Common Core State Standards (CCSS) for mathematics both emphasize the importance of analyzing and interpreting data. CODAP is free, intuitive, web-based software designed for students in grades 5 through college to visualize and analyze data. Data from public datasets, experiments, simulations, and more can be imported easily into CODAP for in-depth exploration. A growing suite of tools and plugins allows users to make their own "data moves" to group or filter data, calculate new variables and summary measures, merge datasets, and more. All data representations are dynamically linked in CODAP, so that highlighting a data point in the graph, for example, highlights the same data in a table and a map.

We invite you to build your own data fluency and explore CODAP at **codap.concord.org**. Click "Open document or browse examples" and select "Getting started with CODAP."

Continue your data exploration journey with additional tutorials, classroom activities, and discussion forums at: **codap.concord.org/for-educators**

Monday's Lesson:
Determine Stream Health

By Carolyn Staudt, Tara Muenz, and David Kline

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Fresh water scientists use several factors to determine the health of a stream, including the chemical and physical qualities of the water as well as the number and types of organisms that live below the water's surface. In this activity, you determine the health of a virtual stream by making observations about habitat, identifying and counting macroinvertebrates, and performing chemical tests.

Select a study stream

Go to https://leaf-pack.concord.org/

Select a stream by clicking one of the stream models (A, B, C, or D) at the top of the simulation. Notice the different features of each stream site and pick one that looks similar to a stream near you.

Describe the habitat

The habitat or area around the stream has a big impact on the stream's health.

1. Use the Stream Habitat Key to identify habitat features in the stream, and select the box next to each feature you see in the image (e.g., pools, riffles, trees, pavement, etc.).
2. Click page 2 of the Habitat tab and continue to mark stream features you observe.

Stream Habitat Type	Symbol
Pools	
Riffles	
Runs	

Identify macroinvertebrates

Certain aquatic macroinvertebrates are sensitive to pollution, while others are quite tolerant, so they are good indicators of stream health. To collect macroinvertebrates, scientists place packs of leaves in a stream, then collect them to see what's feeding and living on the leaves. Each virtual stream contains a leaf pack.

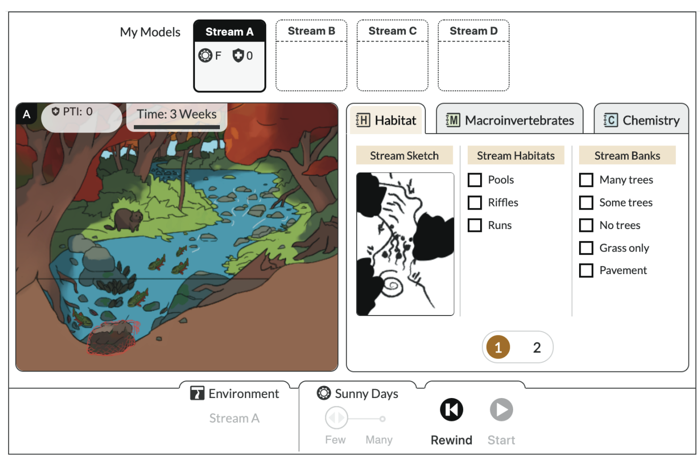
1. Set the number of sunny days in the bottom bar of the simulation (few/many), then click Start. It will run for a simulated three weeks until a Leaf Pack Sorting Tray appears.
2. Click the Macroinvertebrates tab to sort and identify the macroinvertebrates. Click and drag all the leaves to a corner of the tray. Now click an organism, then drag and drop it into the correct box on pages 1-3 of the Macroinvertebrates tab to identify it. If the sorting is accurate, the organism remains in the box and a count appears for the total number of this type found. If not, the organism reappears in the sorting tray. Optional: Use a dichotomous key to identify the organisms (stroudcenter.org/wp-content/uploads/StroudWebsiteMacroKeyFNL.pdf).
3. After identifying all the organisms, click page 4 to see the calculated Pollution Tolerance Index (PTI) from the stream's biotic factors and the stream's health rating.
4. Close the sorting tray to observe the changes in the numbers and types of observable organisms in the study stream image.

Test water chemistry

1. Click the Chemistry tab to run chemical and physical tests on a water sample.
2. Follow the directions for each test.
3. Select the number for each test in the bottom menu bar and click each step to watch the animated test. The results record automatically on the Home page.
4. For tests with a color comparator (pH, Nitrate, Dissolved Oxygen), use the slider to match the color of the sample to the color chart. (Note: Be sure to select the best color match for accurate results. The simulation does not check the accuracy of the results.)

Determine stream health

Review the results from each tab. Are they all the same (poor, fair, good, or excellent)? How healthy is your stream? What makes the stream healthy or unhealthy? Test another stream's health or complete a study on the same stream and change the number of sunny days to compare results.



LINKS

WATERS – concord.org/waters
Leaf Pack Network – leafpacknetwork.org/

The Bardic Bot:

Integrating AI and ELA Education via Poetic Meter

By Duncan Culbreth and Jie Chao

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From increasingly autonomous self-driving cars to climate change models, Artificial Intelligence (AI) has become a ubiquitous medium for understanding, explaining, and interacting with the world around us. However, opportunities to study AI at the pre-college level, if available at all, are limited to computer science classes. And yet many schools do not offer CS. This means that many students simply write off a future in AI because they aren't "math people" or don't think they can learn how to code. Our Narrative Modeling with StoryQ project aims to integrate AI into existing disciplinary studies such as English Language Arts (ELA) in order to prepare youth for the future.

Among many literary genres that students encounter in high school, poetry presents a unique opportunity for integrating AI education. Because public domain poetry texts are widely available and far shorter than novels, they make great candidates for introducing machine learning techniques in the ELA curriculum. In their 2016 paper for the International Conference on Computational Linguistics, Manex Agirrezabala, Iñaki Alegria, and Mans Hulden* apply Natural Language Processing (NLP) techniques to a selection of poetry in an attempt to identify its meter—the underlying rhythm expressed through stressed and unstressed syllables. They acknowledge that "while the rhythm in most line [sic] encountered in a work of poetry appears mundanely repetitive on the surface, poetry, while mostly a constrained literary form, is prone to unexpected deviations of such standard patterns." It is this continual setup and subversion of literary expectations that makes meter an ideal playspace for machine learning and provides an opportunity to teach AI fundamentals in the English classroom.

Identifying iambic meter

We designed a weeklong StoryQ curriculum module around iambic meter, the metrical mainstay popularized by Shakespeare and reflective of natural speech patterns in English. Teaching meter to students is a complex process, especially when the goal is to develop competence in both writing and reading poetry. Students must develop a collection of related skills: identifying syllables in words, understanding and labeling different units of meter (e.g., feet and terms for line length), and connecting these patterns with the poem's meaning. While building these skills can feel tedious and time-consuming, we believe that learning how to train machine learning models to identify the nuances of meter will engage students.

Explaining meter and scansion

In "The Bardic Bot: Training AI to Recognize Poetic Meters," we first introduce essential concepts of meter and line scanning using a glossary of important terms, including *meter, scansion, syllabification,* and *stressed* and *unstressed syllables*. Students then identify the stress patterns of words as a group, and ultimately perform scansion on lines of poetry to identify its meter. They visit the University of Virginia's *For Better for Verse* web-based learning tool to explore the meter of an entire poem, and receive automated feedback on their scansion and insight into how meter might affect the poem's meaning (Figure 1).

Alien language activity

Once students become acquainted with meter, we turn to basic concepts of machine learning, again beginning with a glossary approach, reviewing terms like *machine learning, artificial intelligence, feature,* and *target concept*. To bridge the concepts of scansion with AI, we begin with an assignment that works with patterns of stressed and unstressed syllables rather than whole words to explore how a computer might identify patterns in meter without knowing the words intrinsically. Students are presented with the following scenario:

The people of Earth have been visited by an alien race! They seem to mean no harm, but humans have been unable to understand their language. However, it seems that they are a community of performers and artists because the words coming out of their mouths sound a lot like poetry. Specifically, there are patterns in their language that sound similar to the stressed and unstressed syllables in our own speech. Shakespeare's Globe Theatre, the preservation society for William Shakespeare's literature and legacy, has commissioned you to see just how "poetic" their speech really is. They want you to identify whether or not their language is in iambic pentameter as the ultimate test of their prosody.

Training the model using StoryQ

Students look at the stressed and unstressed syllables in the alien language and decide the likelihood that they are in iambic pentameter, comparing them to annotations we provide. Students consider how a computer might process this data, and teachers can scaffold the discussion with four features developed by the StoryQ team:

1. *Does the line have four to six iambs?* Since the iamb (U/) is the fundamental unit for this target concept, this feature detects if it has a count that is within a range of five (hence, pentameter).
2. *Does the line have one or more anapests?* An anapest (UU/) is one of the two three-syllable feet.
3. *Does the line have one or more dactyls?* A dactyl (/UU) is the other three-syllable foot, arguably the least like an iamb.
4. *Does the line have two or more pyrrhics?* A pyrrhic (UU) typically is relatively uncommon in formal poetry. Nevertheless, it is also counted here.

Because AI is fundamentally about computers finding patterns in data, students now develop and train a machine learning model in our StoryQ app, which is a plugin for our Common Online Data Analysis Platform (CODAP). They are given the scansion patterns and the above four features, and are walked through the basic steps of training and testing machine learning. The model then reviews each datum and labels each of the four features or "attributes" (columns in the data table) as true or false.

Using the StoryQ app, the model produces several visualizations (Figure 2). Panel 1 shows the original scansion data and the four features that are used to judge it, the true/false label that the model proposed for each datum, and the probability that datum is in iambic pentameter, which triggers the true/false label. Panel 2 displays the four features that make up the model and how strongly each figure might affect the true/false label (known as "weight"), which is also visualized by the scatter plot in panel 5. Panel 3 shows how the model applied a predictive label to a single datum (in this case, line 10 of the dataset in Panel 1) by showing the features and their given weights, which resulted in a "true" label (three of the four are shown; the fourth was also calculated, though cannot be seen here). Panel 4 shows

```
u   /     u   /     u   /     u   /
He gazed | and gazed | and gazed | and gazed,
u   /    u   /    u   /    u   /
Amazed,| amazed,| amazed,| amazed.
```

Figure 1. The *For Better for Verse* online learning tool gives automated feedback on scansion. The stress markers are placed above the lines, and the foot separations (shown as uprights) are placed in them.

a computation matrix, displaying what proportion of the data was correctly labeled. In this case, the accuracy was good, with 100% of the actual iambic pentameter lines labeled as such, and an overall model accuracy of 80%. This means that the chosen features could be useful. The teacher then challenges students to imagine other features that might also produce an accurate model like this one.

Conclusion

The Bardic Bot merges skill development in scansion and basic machine learning concepts and paves the way for further analysis on real lines of poetry using NLP. The goal of the curriculum is to scaffold text analytics for ELA students, so they learn to understand and appreciate both poetry and AI. We hope that students also learn that while machine learning is quite successful overall, at times it fails to scan the text correctly. Artificial intelligence is a powerful, if fallible, extension of human intelligence, rather than a replacement for it.

* Agirrezabal, M., Alegria, I., & Hulden, M. (2016, December). Machine learning for metrical analysis of English poetry. In Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers (pp. 772-781).

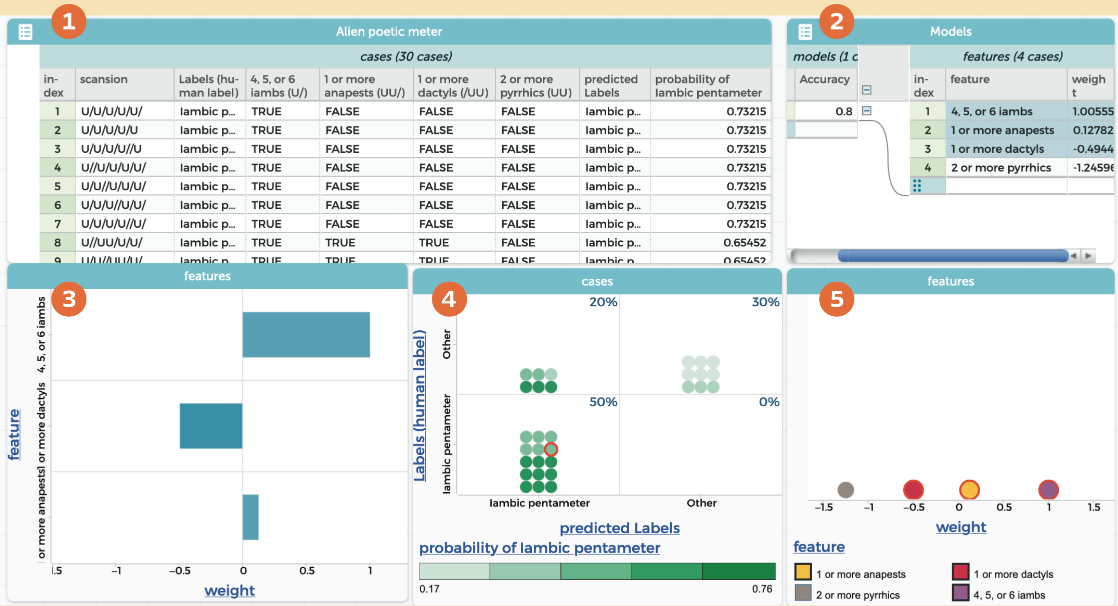

Figure 2. A dataset of 30 alien scansions that have been labeled by a machine learning algorithm via the StoryQ app.

LINKS

StoryQ
concord.org/storyq

Partnering with Seventh Graders to Design **A Community-based Life Science Curriculum Unit**

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By Frieda Reichsman and Sarah Haavind

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Reform efforts in science education frequently focus on increasing diversity and promoting access to canonical science understandings and practices. However, central to the *need* for these equity efforts is the widespread, systemic unfairness that permeates our society, including in the nation's classrooms. Historically, science class, like science in general, has not been effective in welcoming the viewpoints and cultures of minoritized students, who as a result often do not see themselves as belonging in science, even when they perform well on standardized science tests. As a result, people of color remain severely underrepresented in higher level science courses and science fields. The Bio4Community project's new curriculum approaches and pedagogies hope to disrupt this pattern.

Research on supporting minoritized youths' identity development in science points to the need to design curriculum that centers youths' lives in their communities as integral to their science learning. Such youth-centered curriculum should focus on how youth experience and embody science in their everyday lives and how those experiences align to rigorous science standards, such as the Next Generation Science Standards (NGSS). Understanding how the teaching and learning of science can foster youths' agency in using science knowledge and practices to make their lives better is as important as students' successful performance on typical measures of school science success.

The Bio4Community project, funded by the National Science Foundation, is a partnership between researchers from Rutgers University and the University of North Carolina at Greensboro and curriculum design and technology experts at the Concord Consortium. We are collaborating with middle school youth and science teachers from two predominantly Latinx middle schools in New Brunswick, New Jersey, to design a curricular unit in life science. Our goal is to support student achievement while intentionally making space for them to belong in science. The unit will help students achieve mastery towards NGSS practices, crosscutting concepts, and disciplinary core ideas in life science, and enable students to use science to address health concerns that affect their lives and the lives of people in their community.

Curriculum co-development

In building the project's Design Team, we included students with a shared concern for health issues and their community, rather than selecting students on measures of academic merit. Two teachers from two New Brunswick middle schools recruited eight 7th grade students to participate. From spring through early summer 2021 we met bimonthly over Zoom to identify a relevant health concern in the community. We will continue to meet throughout the fall.

Given the potential power dynamics between adult researchers and young students, we worked to create a trusting and collaborative environment. We tried several different interactive media, looking for one in which the young people were comfortable sharing their thinking about health with us. We adopted Discord, a popular place for young people to hang out online and share voice, video, and text. So in addition to Zoom for real-time meetings, we use Discord to post announcements and foster informal discussions. We also use Padlet, an online bulletin board where we select from relevant images, paste our own images, and use text to make comments or explain ideas. Finally, we welcome everyone to each Zoom meeting with music from a playlist that includes their contributions, and we use an emoji chart to check in at the beginning and end of each session (Figure 1).

Figure 1. Students select from an emoji chart to share their feelings.

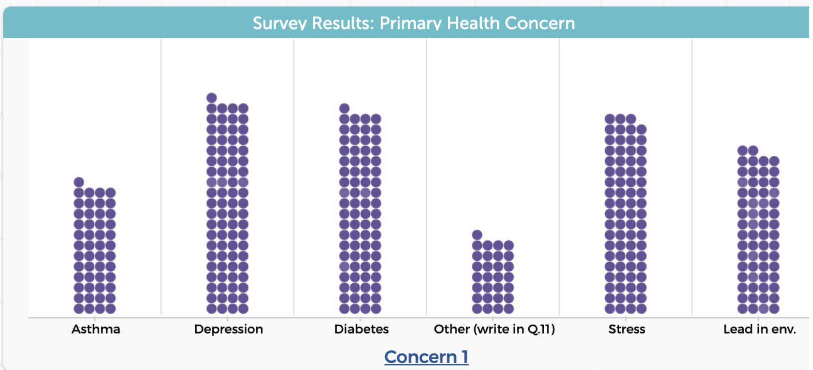

Figure 2. Results from a community health survey analyzed in CODAP.

The biology of stress

Together with participating teachers and students, we will co-design a curriculum unit that addresses stress in relation to several aspects of two NGSS disciplinary core ideas: LS1 From Molecules to Organisms: Structures and Processes and LS3 Heredity: Inheritance and Variation in Traits. The five-week unit will include the biological mechanisms of stress with a focus on long-term or chronic stressors and their effects. It will address a number of questions: How does stress affect human physiological function? Do youth react differently than older people to stress? How does a response that is beneficial in the short run become unhealthy over time, and what types of health problems result?

One way to bolster the ability of minoritized students to create an authentic identity in science is to ensure they have opportunities to engage in rigorous scientific investigations on issues that matter to them and their communities. Project software and curricular materials will support student investigation of the biological basis of environmental (social and physical) stressors as causes of chronic stress. Students will explore the presence or absence of environmental stressors, for example, racism and the lack of availability of healthy food. Students will also design real-world solutions addressing problems they identify, either via engineered technology (e.g., meditation booths in school) or social policy (e.g., making recommendations to the school regarding homework or recess policies that can reduce student stress).

Community health survey

The Design Team collaboratively created an online survey for New Brunswick students, faculty, parents, and community members about a variety of health topics. After pilot testing many of the survey questions in students' classes, we revised the survey together, and shared it with the two school communities in both English and Spanish. We received 488 responses and used our Common Online Data Analysis Platform (CODAP) to analyze the results and identify prominent health concerns.

The results indicated five primary community health issues, including asthma, depression, diabetes, stress, lead in the environment, as well as other issues (Figure 2). We noted that stress and depression might be connected, so we chose to focus on those two issues. Using Padlet, the Design Team then organized ideas, images, and comments about these health concerns (Figure 3). Not surprisingly, the loss of family members, including to COVID, came up, as did issues related to the pandemic-induced quarantine. We also viewed and discussed short videos related to challenges in the community, such as poverty and health disparities. These activities serve as background for our current work to convene a group of New Brunswick community experts on health and community challenges as we turn our focus to designing a classroom curriculum on the science related to these issues.

Next steps

Creating science curricula that foster positive science identities for minoritized students is essential to encourage underrepresented groups to enter the sciences. We hypothesize that the experience of investigating relevant local problems will help students see the power of science in benefitting their communities and see themselves as able to use science knowledge and practices for social good.

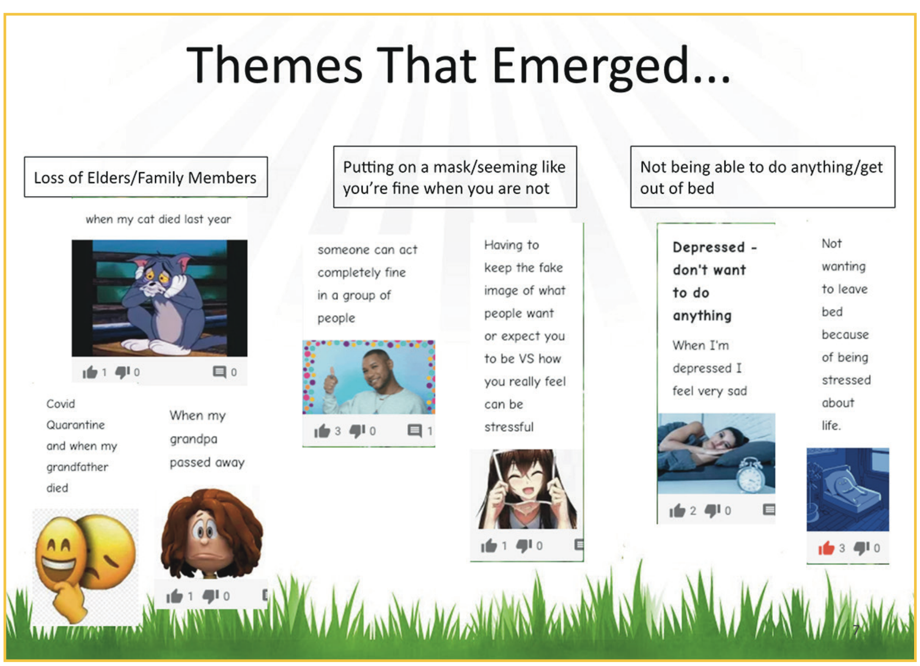

Figure 3. Students shared images and thoughts about emerging themes related to stress and depression in the community.

LINKS

Bio4 Community
concord.org/bio4community

SageModeler

Offers Two System Modeling Approaches

By Dan Damelin and Steve Roderick

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From Earth's systems to ecosystems to systems in our human bodies, the world is made of interconnected components. Using computational models to represent complex systems can greatly enhance our understanding of how systems work. Students can test their understanding of a system's complexity by sketching its structure, defining the connections within it, and running the model to see if system outputs match the real world. By comparing a model's output to observations from the real world, students can iteratively revise both their conceptual models and computational models. SageModeler offers two approaches to computational system modeling that make it a powerful learning tool for students from upper elementary through high school to build, revise, test, and share their models and their understanding.

Static equilibrium models

In SageModeler, static equilibrium models are used to represent systems that are inherently stable or can be simplified such that the state of the system is defined by the combination of inputs to that system. They help answer questions of how a change in one part of a system can cause a change in another.

Imagine that you want to create a model to help you determine how bad an epidemic will be based on several factors. In a static equilibrium approach, you first identify the elements of the system affecting the number of people who get infected, then define how each variable affects the others. The combination of susceptible people, infectivity of the virus, and infectious contacts behave similar to an algebraic equation, where a change to one variable causes all other variables to respond as defined by the relationship rules among them (Figure 1). With each change of an independent variable, the entire system immediately adjusts to a new static and stable "state."

In Figure 1 when *# of people contacted each day* is increased, a new state of the system is determined by combining this new input value with the other variables in the system, increasing *the number of infected people*. Each system state results from the set of relationships among the system components, and an adjustment to any of them causes the system to instantaneously reach a new equilibrium. Imagine taking a photograph of the population at one point in time, increasing the number of contacts, and taking another photograph. By comparing the pictures, you can analyze the effect of *# of people contacted each day* on *number of infected people*.

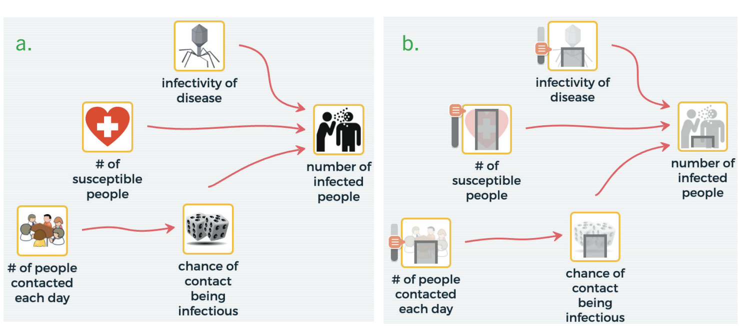

Figure 1. (a) Modeling the outcome of an epidemic. (b) During simulation bar graphs represent the value of each variable.

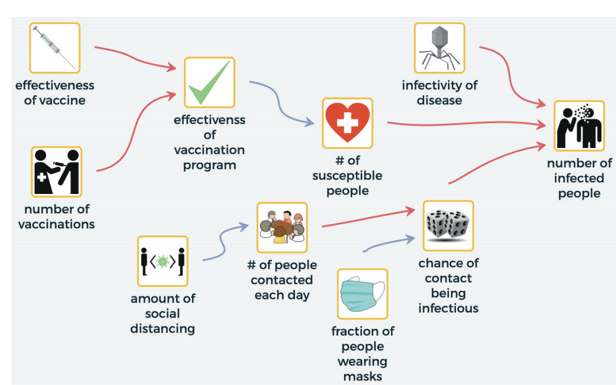

Figure 2. Broadening the epidemic model to include mitigating factors like social distancing, masking, and a vaccination program.

Static equilibrium models can be simple or built out indefinitely. For example, we can expand the epidemic model to include variables representing mitigating factors for controlling the epidemic (Figure 2), or expand the boundaries further to consider economic and social impacts. Alternatively, we could include how the virus infects and reproduces at the molecular level.

Dynamic time-based models

Like static equilibrium models, dynamic time-based models in SageModeler represent variables and connections, but with one important additional feature: the ability to represent change over time.

Let's revisit the epidemic example. Rather than modeling the overall severity of the epidemic, we may want to model how many people will get sick as the epidemic unfolds over time. This was particularly important during the COVID-19 pandemic in order to plan for expanding hospital capacity and to decide when to ease lockdown conditions.

To see an evolution of the model state over time, dynamic models include new kinds of variables—*collectors*, which can be added to or subtracted from during each model calculation cycle, and *flows*, which define the rate of change in the collectors (how much is added to or subtracted from the collectors each cycle).

In Figure 3, the *# of susceptible people* is a collector, as is the *total number of infected people* variable. The *number of people infected per day* variable represents how many people become sick during each cycle of the model, causing that number to be subtracted from the *# of susceptible people* and added to the *total number of infected people*. This flow, represented as a valve, controls the rate of transfer between the two collectors. Other variables like *chance of contact being infectious, infectivity of disease*, and *# of susceptible people* all affect the *number of people infected per day*. Over time the *# of susceptible people* decreases and the *total number of infected people* increases. However, we can see the *number of people infected per day* starts high and slows down over time (Figure 3b), due to the fact that there are fewer and fewer susceptible people over time to get infected.

Because collectors can only be added to or subtracted from, they have a "memory" of the system's state. As such, collectors make it possible for dynamic time-based models to show how feedback causes the system to influence itself. When chains of causal connections loop back upon themselves, the state of a system at one moment can provide the impetus for change into the next. In such a feedback loop, the computer first determines the model state at a given moment by noting the values of all the collectors. These values influence other system variables based on relationship rules that have been set by the student, and eventually, through a chain of cause-and-effect relationships, loop back to influence a variable that is directly connected to the collector that initiated the loop.

In Figure 4, an additional relationship has been defined between the *total number of infected people* and *chance of contact being infectious*. This connects to *number of people infected per day* and back to *total number of infected people*. Notice how the *number of people infected per day* more correctly shows the pattern we observed in the real world, when infections start slowly, reach a peak, and then taper off.

What type of model should be used?

Before deciding on the modeling approach, it is critical to clarify the model's purpose. Ask yourself, "What do I want my students to learn by building this model?" If the priority is to analyze the structure and interconnection among components in a complicated system and how a change to a system input affects other system components, static equilibrium modeling may be best.

If it is important to investigate why a particular behavior over time is observed or how a change to a variable alters the way a system develops over time, dynamic time-based modeling is the way to go. Dynamic time-based models allow students to explore feedback-induced behavioral patterns like exponential growth, growth (or decline) to a limit, S-shaped growth, and oscillations.

Both modeling approaches in SageModeler offer students the ability to test their understanding of the system as a whole. Building, revising, and sharing models provides powerful learning opportunities.

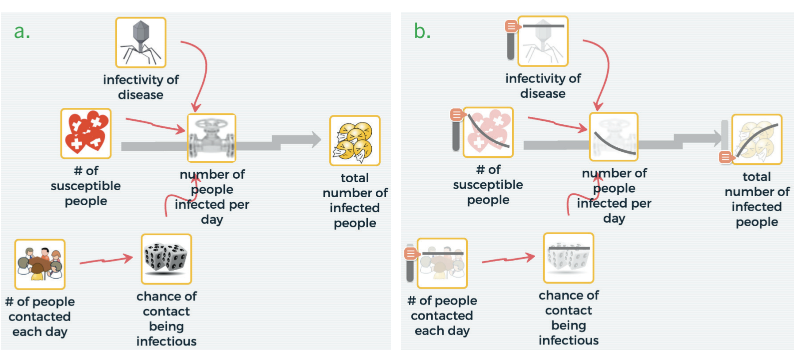

Figure 3. (a) Dynamic time-based model of a collection of susceptible people becoming infected over time. (b) When the model is run, line graphs show the values of each variable over time.

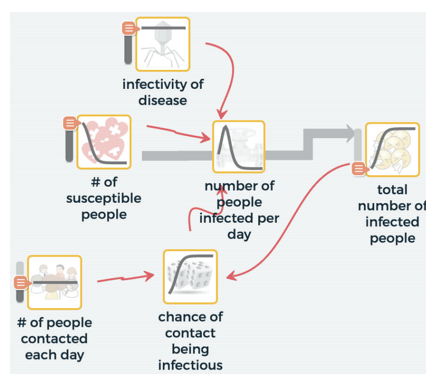

Figure 4. Feedback is added to the system by connecting the *total number of infected people* to the *chance of contact being infectious* variable, completing a loop with the *number of people infected per day*.

To see more models, including a population model with feedback loops, and links to the models featured here, see the online version of this article at https://concord.org/newsletter/2021-fall/sagemodeler-offers-two-system-modeling-approaches

LINKS

SageModeler
sagemodeler.concord.org

Under the Hood:

Three New CODAP Plugins

By Bill Finzer

Bill Finzer
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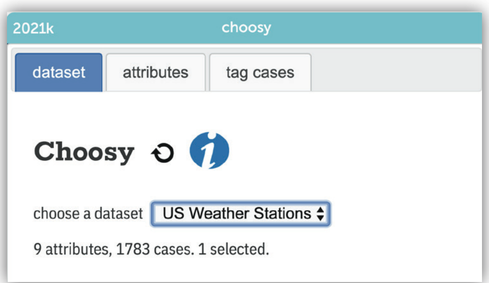
is a senior scientist.

Our Common Online Data Analysis Platform (CODAP) is both powerful and flexible. Powerful because it makes data analysis and visualization intuitive. Flexible because it's easy to add plugins to its web-based interface. In CODAP, plugins can be a source of data or a set of instructions. Importantly, plugins can also receive information from CODAP. Communication goes both ways. With a bit of JavaScript coding, you can create your own plugin and drop it into CODAP where it appears as an iFrame.

Thanks to partner collaborations, CODAP has dozens of plugins. Several have proven so useful they're built right into the CODAP Plugins menu. We're excited to announce three new plugins that have recently been embedded directly within CODAP.



Story Builder

In our Writing Data Stories project with Michelle Wilkerson at the University of California Berkeley, we're helping middle school students become "data storytellers," using data as a medium to express their understanding of important socio-scientific issues. The prototype for the Story Builder plugin was initially designed by colleague Tim Erickson, and I was excited to complete it. Students can build story "moments," with each interactive moment capturing the state of the CODAP document at a given time. Since CODAP can also embed web pages and videos, a story can be truly multimedia. Moments can be edited, deleted, and rearranged, or "locked" to prevent being accidentally changed. Stories are great for student projects and presentations, introductions to data-rich content, and even mockups of new plugin capabilities.

Choosy

Some of the datasets in the Writing Data Stories project include tens of thousands of cases and over one hundred attributes—way too big and complicated for middle schoolers! So Tim Erickson developed Choosy as a fast and efficient tool for curriculum developers or teachers who need to create simple datasets from complex ones. Teachers can hide attributes quickly and in bulk, or tag cases to set aside or delete.

Transformers

The Bootstrap project wanted to feature data moves more prominently for their curriculum resources that use CODAP, so they created this plugin with 30 transformations. It's now even easier to filter and sort attributes, and to measure, aggregate, and summarize data, among many other transformations. Users can transform datasets to produce new, distinct output datasets without modifying the original input dataset itself, thus enabling easy "what if" exploration and comparison of datasets that may represent distinct transformations performed on the same source dataset.

These three new plugins take advantage of recent enhancements to CODAP's application programming interface (API), including:

- Ask CODAP for the current state of the document.
- Pass a new document state to CODAP for it to adopt.
- Pass a formula to CODAP and get back the result.
- Ask CODAP to open a new and different plugin.
- Ask CODAP to create a case card.

Interested in trying more CODAP plugins? Check out the CODAP Data Interactive Plugins site. Want to build your own? See Getting Started with CODAP Plugins for step-by-step instructions. Contact us with questions on the CODAP Help Forum.

LINKS

CODAP
codap.concord.org/

CODAP Data Interactives Plugins
concord-consortium.github.io/codap-data-interactives/

Getting Started with CODAP Plugins
github.com/concord-consortium/codap/wiki/Getting-Started-With-CODAP-Plugins

CODAP Help Forum
codap.concord.org/forums/

Innovator Interview:
Chris Lore

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"It was beautiful under the microscope," he reports. So the next step was devastating: crushing the gemstone he'd worked so hard to create into a powder!

The Rothermel equation, which describes the rate of fire spread, has been used in fire management systems since the 1970s.* It continues to inspire Chris as a curriculum designer.

"Science is a lot of failure," reflects Chris, thinking about his master's thesis at Rensselaer Polytechnic Institute (RPI). He laughs, "I didn't have great success most of my time there." His research focused on the geochemistry of element diffusion in the Earth's crust. "Knowing the conditions like pressure and temperature that a rock formed in can be useful for many applications." His goal was to investigate the mineral tourmaline for its use in recording and preserving the conditions of pressure, temperature, and the composition of fluid in which it formed.

It took Chris a semester before he successfully grew tourmaline in the lab. "It was beautiful under the microscope," he reports. So the next step was devastating: crushing the gemstone he'd worked so hard to create into a powder! He was able to use the powdered form enriched in ^{10}B (the less abundant isotope of boron) as a marker, then simulate the heat and pressure conditions of the Earth's crust to see how far the ^{10}B diffused. Finally, he could calculate the diffusion rate.

Recognizing how much work it was to get that one number, Chris appreciates firsthand the many ideas, and experimental failures, Rothermel must have had to reach a single wildfire spread number. "The process of science can be really frustrating," he admits, "but the rewards are exciting." Chris hopes to infuse that excitement in the geoscience curriculum he helps design.

Rothermel's equation (which has been refined over the years, thanks to more sophisticated computer modeling) is used as the calculation engine behind our Wildfire Explorer model as part of our GeoHazard project. Students can run their own wildfire experiments, constraining one variable—terrain, drought levels, vegetation, wind speed, and wind direction—at a time.

"Such open-ended models give students a lot of space to explore," explains Chris, though he acknowledges that it can be difficult to get them to buy into the scientific process. He wants students to know there is always more to do: reflect on the results, ask additional questions, experiment, and start the cycle again. When teachers report their students' "aha" moments, Chris knows that he's been able to make complicated concepts accessible.

Chris had his own "aha" during a field methods course as a freshman environmental science major at RPI. During a field trip to the Bennington Bypass at the border of New York and Vermont, he saw a huge metamorphic rock cut with horizontal rock layers that suddenly and dramatically curved straight up. Awestruck by the beautiful outcrop, he changed his major to geology. "Every rock tells a story," he says, "what it is, why it's where it is, and much more." Chris now helps students learn that history in the TecRocks project, which connects rock formation to the environments and processes that generate them through an interactive 3D model.

A more recent road trip, this one across the country to relocate to Vancouver, expanded his perspective even more about both the importance of geohazard education and the scale of geology. Growing up in the Northeast, he wasn't familiar with wildfires, so the constant road signs reminding motorists about fire risks—"If you see a fire, report a fire"—surprised him.

"Geology is all around us all the time," Chris muses. Indeed, he can now see the coastal Canadian North Shore Mountains from his window, and he can't wait to start uncovering their stories.

* Rothermel, R. C. (1972). A mathematical model for predicting fire spread in wildland fuels. USDA Forest Service Research Paper INT-115. Ogden, UT: U.S. Department of Agriculture, Intermountain Forest and Range Experiment Station.

The Concord Consortium
25 Love Lane, Concord, MA 01742

The Concord Consortium is happy to announce five new projects.

MothEd

The goal of a new National Science Foundation (NSF)-funded collaboration between the Concord Consortium and Michigan State University is to understand how learning experiences and environments can support young students' participation in authentic science investigations. With practicing teachers, we are co-designing experiences for elementary and middle school students to engage in real-world scientific practices and investigations on local moth ecology. Students work individually and in small groups to construct moth traps and collect data through processes they design and enact. In partnership with entomologists and science educators, students develop and answer questions about local ecological conditions and become genuine producers of knowledge—epistemic agents—within science learning communities. We are studying features and approaches to the co-design of learning opportunities that foster student agency and identifying the ways in which teachers and students negotiate new roles in authentic science investigations.

Boosting Data Science

Boosting Data Science Teaching and Learning in STEM, a partnership between WestEd, the Concord Consortium, and Heller Research Associates, is researching the knowledge and skills middle school teachers need to support students in developing data fluency and help them overcome common roadblocks. We are developing a framework of pedagogical content knowledge for data fluency in middle school that details what teachers need to know and be able to do to support students in becoming data fluent. With a team of co-design teachers, data scientists, and educational specialists, we will use the framework to guide the design of professional learning experiences that include our Common Online Data Analysis Platform (CODAP) for teachers to learn about data science and develop resources for their students. This NSF-funded project will study the effects on both data science teaching and data science learning in the classrooms of teachers who have participated in the professional learning experiences.

Precipitating Change

The new NSF-funded Precipitating Change with Alaskan and Hawaiian Schools: Bridging Indigenous and Western Science While Modeling Mitigation of Coastal Erosion project supports Earth science learning from both Indigenous knowledge and Western-style inquiry. In a coastal erosion curriculum unit that bridges Indigenous and Western science, middle school students apply integrated Earth science, mathematics, and computational thinking. The curriculum is designed with Universal Design for Learning principles, including a multiple-representation glossary, translations for Indigenous languages, and scaffolding to assist students in understanding Indigenous and Western science terms. Project research studies how the approach prepares students to study and address socio-scientific issues.

M2Studio

The Common Core State Standards for Mathematics includes "Model with mathematics" as one of the mathematical practice standards, and notes that students should be engaged in math modeling throughout their education. But moving between the real-world domain and the mathematical domain can be challenging. A new NSF-funded project at the Concord Consortium, Clarkson University, and Pennsylvania State University aims to cultivate mathematical modeling competencies among secondary students by developing and researching M2Studio, a web-based, integrated math modeling environment. In M2Studio, students document their thought processes, uncover and test their explicit and implicit assumptions, and evaluate their solutions against real-world data. M2Studio unites our CODAP data analysis and visualization tool with our SageModeler system modeling tool to support student-generated representations of assumptions, variables, and relationships that are dynamically linked.

FABLES

With WestEd and the University of California Berkeley's Lawrence Hall of Science, the new Formative Assessment Bundling Literacy and Elementary Science in the NGSS (FABLES) project is developing and piloting a set of classroom-based assessment resources with accompanying professional learning to support early grades teachers in monitoring and enhancing students' integrated science and literacy learning. FABLES will include a suite of innovative Next Generation Science Standards-aligned assessment tasks, rubrics for interpreting student performance, teacher practice guides for engaging in classroom instruction that is informed by student learning, and professional learning for teachers. This Institute of Education Science (IES)-funded project aims to help teachers envision what evidence of NGSS learning "looks like" with an additional lens on assessing literacy in the context of STEM.

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The Concord Consortium | **Concord, MA** | **Emeryville, CA** | **978-405-3200** | **fax: 978-405-2076**
@Concord is published two times a year by The Concord Consortium, a nonprofit research and development organization dedicated to transforming STEM education through technology. This material is based upon work supported by the National Science Foundation and the U.S. Department of Education under several grants (DRL-2101049, DRL-1850051, DRL-1949110, DRL-200515, DRL-1842035, DRL-1900606, DRL-2006144, DRL-1812362, DRL-2101382, DRL-2101198, DRL-2100990, and IES-R305A210290).