# *Twenty Constructionist Things to Do With Data Science*

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## Abstract
Building on Seymour Papert and Cynthia Solomon's 1971 memo on "Twenty Things to Do with a Computer," we consider burgeoning areas of data science as a context to affirm and extend constructionist tenets concerning the power of material production in learning. Like Papert and Solomon's original treatise about computing, our considerations are motivated by the reality that much of the developmental and learning benefits of engaging with data remain out of reach for youth. Consistent with their argument, we suggest this is not because of any requisite complexity or skill but because education fields appear reluctant to progress toward more generative stances about what it means to learn from material features of data, which are distinctly emphasized in data science. The twenty things we highlight include a variety of topic contexts and epistemic pathways learners can pursue when engaging with data as material for generative inquiry and production. The things are meant to highlight what data materiality means from a constructionist viewpoint – and how data as a science might help us nuance these conceptualizations. This includes more critical consideration of the myriad ways material production fruitfully reflects learner priorities and, consequently, the social and cultural tensions accompanying outcomes. We discuss these observations in terms of their implications for constructionism and learning.

## 1. Introduction
When Seymour Papert and Cynthia Solomon, in their 1971 memo, "Twenty Things to Do with Computer," asked the world to consider how computers might be transformative, to many, it was a call to modernize education systems and the ways we understand learning among children. Fittingly, constructionists – in a field spurred partly by Papert in *Mindstorms* (1980) – have taken up the tradition of generalizing ideas in the original memo to other contexts, including block programming (Mori, 2017); life sciences (Kafai & Walker, 2020); artificial intelligence (Kafai & Morales-Navarro, 2023); and many other genres and context (Holbert, Berland, & Kafai, 2020). Consistent with the original memo, these efforts bring attention to the importance of and vast possibilities for supporting what Papert and Solomon originally described as "transactions" or "conversations" between learners and the tools they use (Schön, 1983). Notably, the collection of objects – represented together in Gary Stager's *Twenty Things to Do with a Computer Forward 50* (2021) – encourages us to consider how these tools and their productions might also serve as lenses to understand further *how* children learn.



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We build on this movement by introducing data as a material and data science as a frame that cuts across technical and academic disciplines (Jian, Lee, & Rosenberg, 2022) and reaches learners regardless of their ability or age. We hope this first attempt affirms constructionism's necessary contributions to what we know about material artifacts, learning, and their inextricably social and cultural dimensions (Brown, Collins & Duguid, 1989). "Twenty Constructionist Things to Do with Data Science" is an instantiation of the constructionist vision for learning where youth can interact deeply with processes and products. We also consider the epistemic nature of material engagement and the tensions that underlie generative acts of inquiry, which also create ramifications (both good and bad) for learners, society, and culture.

Data science in education is a crosscutting field that requires more than inquiry acts of observation, data collection, analysis, and sharing (Walker et al., 2023b) – it also involves humanistic (i.e., socially and culturally embedded) reflections, sensemaking, and decisions (Lee, Wilkerson & Lanouette, 2021; Walker et al., 2023c; Barany et al., 2024; Lee, 2025). This is to say that the choices made in data science as a context for learning, while often considered objective, are also rife with influences shaped by unique life experiences and the limits inherent to the tools used (Miller et al., 2024). Examples of this exist everywhere, including what matters to learners in how they assess or understand: the physics of designing and then "doing a trick" on a skateboard (DeVane, 2019), the "best" sewing technique for implementing the design of a programmable electronic textile bracelet to share (Peppler, 2016), or the "merits" of how data sources are collected and organized to tell a story about greenhouse gases generated across a neighborhood (Ben-Zvi & Arcavi, 2001).

Today, data science learning activities can be catalyzed by computers – it is now possible to collect, analyze, and harness data at orders of magnitude that were previously unimaginable (Giabbanelli, & Mago, 2016). These expanded ways of doing data science (sometimes called computational data science) are now accessible to children of all ages and abilities (Schanzer et al., 2022; Walker et al., 2023a; Reza et al., 2024). These developments raise concerns about what might be lost if learners do not encounter or understand the intersecting societal and cultural dimensions of why and how conclusions are drawn through epistemic acts in inquiry. In data science, constructionism helps us see and consider how data can serve as powerful "objects to think with" (Papert, 1980). One productive approach for accomplishing this can be understood from what some (Bae, 2022) have described as data "materiality." This conceptualization of data, analog or digital forms, as material from a constructionist standpoint helps clarify the possibilities and tensions for data and data science. On the one hand, this approach supports what some scholars have described as "author proximity" (Ravi et al., 2024). This is because learners are producers of data and everything derived from it, thus opening possibilities to engage on their terms (Levin & Tsybulsky, 2017).

On the other hand, it raises critical epistemic questions about the consequences that emerge when the material nature of data is shaped, maneuvered, and re-presented. These questions include concerns about who and how the data was collected, the decisions made when the data was organized, and how narratives drawn from that data are communicated or shared. These are all shaped by personal, social, and cultural needs, values, and priorities that should be disentangled and addressed upfront when considering issues about learning. We believe this is where data science, as a context for carrying out socially and culturally embedded epistemic acts, can benefit from and contribute to how we understand learning – and perhaps make visible the need and importance of moving beyond what Papert and Solomon (1971) described as “intellectual timidity” inherent to conservative and canonical ways of schooling to learn, and toward more generative learning designs and experiences.

In the next section, we present twenty things that can be done in data science from a constructionist point of view. The examples we present emphasize process and product and are organized by academic subject area. These things range from exercises that give learners opportunities to construct artifacts and ideas to opportunities to use data as material to represent their interests, society, or culture. They are drawn from learning activities from published empirical research, publicly available educator lesson plans, and anecdotal experiences from the authors. The collection is meant to highlight the vast potential data and data science have as constructionist approaches to learning.

## 2. Twenty Things to Do

### *2.1 In Math*

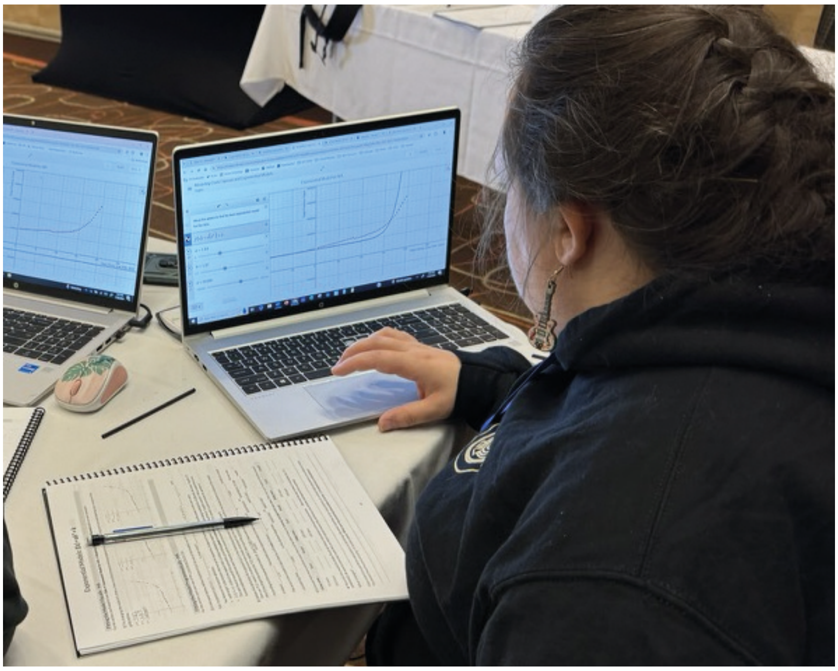

Figure 1: Analyzing Data. A learner uses the Pyret programming environment specifically designed for educational contexts.

1. Make an “Ideal” Statistic. Summary statistics are used all the time by policymakers when considering groups of people. Still, group members are typically left out of discussing what summary statistics might best describe them. This is an opportunity for young people to view those statistics as concrete artifacts that have real implications for how society perceives youth. This activity asks what is a “typical” teenager or a “typical” class? Learners consider the quantitative factors they would use to describe themselves (e.g., age, height, birthday, etc.) and attempt to summarize what is “typical” for their class. They calculate descriptive statistics and create visualizations (e.g., histograms, dot plots, and box plots) to analyze data distributions. Learners discuss how different measures of central

tendency and spread describe the data. For example, is it authentic to report on the average height of the class if the distribution is highly skewed? What is the impact of including or excluding the teacher's data as an outlier? Youth create a portrait of "typical learner" in their class, using their chosen summary statistics and choice.

2. Construct an Intuitive Visualization. Learners analyze their city or state's growth in energy consumption, population growth, or the spread of disease, describing the shape they see (Figure 1). Those unfamiliar with exponential growth can still see the pattern and draw the curve their intuition tells them is there. Then, they make predictions based on those curves and discuss exponential growth. The accessible visualization becomes the learner-created artifact showing what learners know.
3. Build a Model. Young people exist in a cultural context full of assertions. They are told that *doing more* will lead to better outcomes: studying for more hours, completing more homework, getting more sleep, and eating more vegetables. Teenagers can follow these assertions or rebel against them, but in both cases, they remain passive recipients of these claims. In this activity, learners can take the reins and question these claims by creating or collecting real-world datasets (e.g., time spent studying vs. test scores, population growth over time), and using spreadsheets or statistical tools to fit regression models. After calculating correlation coefficients and interpreting the results, students can create a guidebook of recommendations for their peers to follow – now supported by actual data! Displaying the residuals allows for opportunities to concretely discuss "fitness" for those in lower grades, while youth in higher grades can model this data with functions.
4. Use Data to Make a Simulation. Youth use simulation tools and tangible manipulatives to gather real-world data from events like coin flips, rolling dice, card shuffles, etc. They graph this data using spreadsheets or statistical tools to represent probability distributions and compare theoretical and experimental probabilities. Learners select their favorite game of chance and report on the probabilities used and how they differ in simulated compared to real-world scenarios. Data is a raw material for making a simulation to understand.
5. Design Research Questions. Students collect data from the World Health Organization (WHO) and the Organization for Economic Cooperation and Development (OECD), which tracks per-capita gross domestic product (GDP) and median life expectancy for 190 countries (WHO, 2025; OECD, 2025). Learners graph this data (Figure 2) and see a pattern – prompting questions about the relationship between wealth and health. Once the model for all 190 countries is complete, they discuss ways to split the data into sub-groups: should we split the data up and model by *continent?* Is the relationship substantially different in countries *with* universal healthcare vs. those *without? Is poverty bad for your health?* Why do wealthier people live longer? *And is more wealth always associated with a longer lifespan?* Learners analyze data and graph the relationship of median life expectancy to per-capita GDP, describing the shape they see.

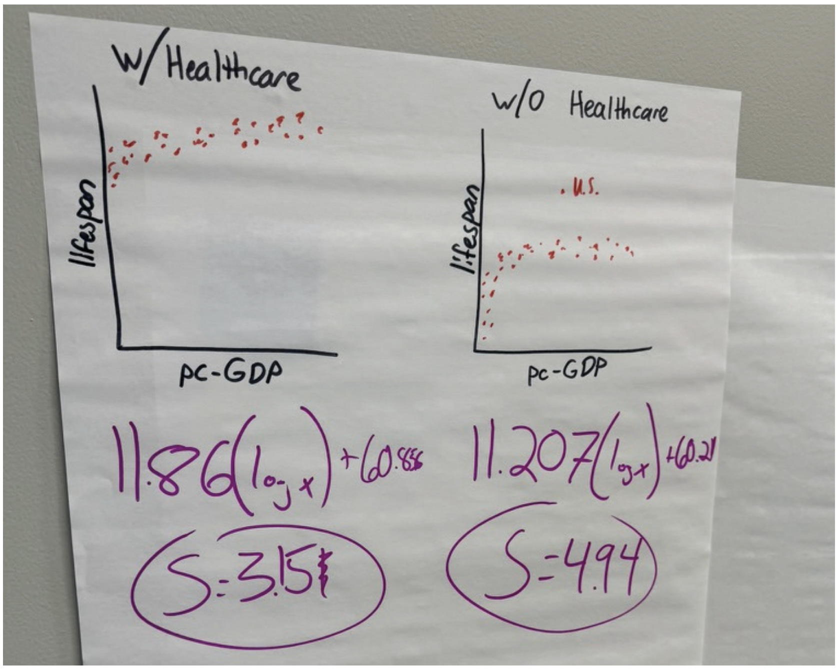


Figure 2: Modeling with Logarithms. Learners explore how their logarithmic model for countries' wealth v. life expectancy changes between those with and without universal healthcare.

### *2.2 In Physics*

6. Make Qualitative Data. In physics, data is typically used to confirm an equation or law in a textbook. However, the modeling component of data science allows this process to work in reverse: students can gather experimental data first, attempt to derive the equation or law from their collected artifacts and compare their findings to the book. In this activity, learners record and then watch videos of projectile motion (e.g., a pitch being hit) and qualitatively assess the location of the projectile frame-by-frame. Using their estimates, they first make velocity, position, and acceleration graphs and then attempt to model these relationships (Figure 3) using functions and equations. This uses actual data to motivate an exploration of kinematics, allowing students to display the real-world data from the video superimposed onto the graph of the model they derived. When the actual equation or law from the book is presented, students can question potential gaps in their model or collection of data. This activity more closely mirrors how science is conducted in the real world (equations are derived from observed data, not the other way around!), and frames the collected data and constructed model as an artifact that stands in relationship to established models in physics. The finished product is a presentation and discussion about why their initial conclusions may have paralleled or diverged from the actual laws of kinematics.

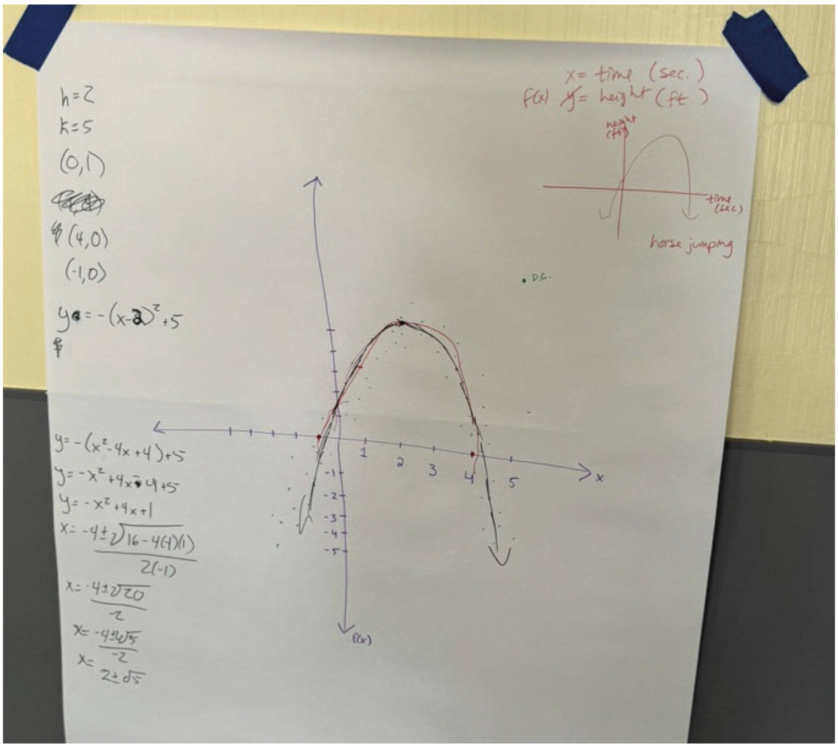


Figure 3: Understanding Parabolas. Learners attempt to model scatter plot data with a quadratic relationship.

7. Construct Creative Ideas About Motion. Learners use force sensors and motion detectors to collect data on objects being pulled or pushed. They compile force and acceleration data and fit a linear model using statistical tools or spreadsheets. The slope of the line (mass) provides empirical evidence of F = *ma*. Using what they've gained from the model, they create a "What If?" presentation that calculates the force required to pull or push fantastical objects (a single electron, Jupiter, etc.). Similar to the previous activity about kinematics, data science goes beyond simple inquiry by comparing the resulting model to established ones. This relationship allows students to question their assumptions or think more deeply to defend the accuracy of their mental models.
8. Make Data a Collection Device. Learners measure the position of a mass on a spring over time using motion sensors. They analyze the data for patterns and use it to extract the period, frequency, and damping effects. This approach allows young people to visualize and quantify harmonic motion and explore connections to wave phenomena. In this case, they learn how instruments work (or don't) in the messy data collection process.
9. Build Modeling for a Fun Experience. By graphing the relationship between energy and position, youth explore energy conservation. They use personal knowledge of this relationship to design the roller coaster of their dreams, presenting it to the class and proving that energy conservation can be a supporting design feature.
10. Design Ways to Collect Unconventional Forms of Data. Learners use audio analysis software or smartphone apps to record and analyze sounds from various sources (e.g., tuning forks, musical instruments, or their voices). They extract frequency and amplitude data and copy it into spreadsheets or statistical software, then explore various visualizations to derive relationships between pitch, loudness, and wave properties. These relationships and the tools used to uncover them are part of a finished product and/or class presentation.

### 2.3 In Social Studies

11. Make a Way to Study Trending. Learners access data from the U.S. Census Bureau (USCB, 2025) or other databases to examine changes in population demographics (e.g., age, ethnicity, migration patterns, commute times, income, home ownership, etc.) over decades. They build ways to visualize the data with line graphs, bar charts, or heatmaps to identify trends and discuss the social, economic, and political implications. They propose legislation or policy changes needed to respond to these shifts.


Figure 4: Silk Road Trade Routes. A map, showing the middle-eastern portion of the trading routes known as the Silk Road.

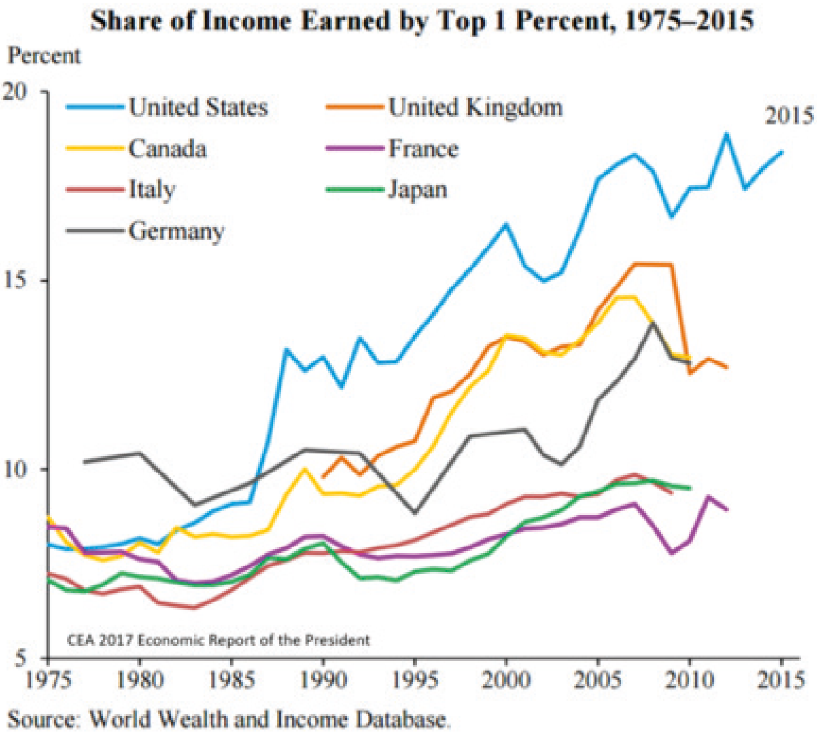


Figure 5: Income Inequality. A line graph comparing how the share of income earned by the top 1% of earners has changed over time in 7 countries.

12. Build an Election Pattern Chart. Why did a recent election turn out one way or another? The tension between a young person's sense of self and their larger community often surfaces during elections, when young people wonder whether their values are aligned with others in their community, state, or country. Learners analyze voting data from past elections, exploring turnout rates, party preferences, and demographic influences on voting behavior. Using statistical tools or spreadsheets, they make maps and charts to compare results across regions and time and predict future elections. Using push-pins, they identify places on the map where their politics are most strongly reflected, physically placing themselves in their states according to their political ideologies.
13. Construct a Historical Trade Networks Map. Learners explore how trade influenced cultural exchange, colonization, and the rise of empires, building geospatial models using historical data. The activity begins by examining trade data from historically significant routes like the Silk Road Transatlantic Trade (Figure 4) or modern economic reports. Youth then use tools like Google Maps or Tableau to create interactive maps showing trade routes, goods, and economic impacts. Learners use data to construct these maps to show how they understand the significance of these routes.
14. Make Wealth Relationship Diagrams. Learners explore datasets on wealth distribution over centuries, such as those from the World Inequality Database (WID, 2025). They analyze trends in income inequality and its correlation with historical events like wars, industrialization, or tax reforms (Figure 5). Learners diagram their findings using Gini coefficient calculations or visualizations like Lorenz curves. They use data on the *current* wealth distribution in their country and make predictions based on their historical knowledge.
15. Build a Social Impact Table. Young people are subject to the effects of legislation. They must reconcile their feelings and opinions with news reports and social media that tell them whether the legislation succeeded or failed. Data science is a tool for resolving this tension. In this activity, they select a significant piece of legislation (e.g., the Civil Rights Act, Affordable Care Act) and decide whether they believe its impact was positive. Based on their position, they consider how this impact would be quantified with data on social effects (e.g., healthcare coverage or voter registration rates). Using statistical tools and/or spreadsheets to visualize trends before and after the law's implementation, students report how data confirmed or refuted their position (or was not evident at all!).

### 2.4 In Biology

16. Making Good Purple Pigment for BioArt. Search the National Center for Biotechnology Information (NCBI) library (Figure 6) for purple pigment-expressing genes (DNA) to use in a BioArt project (NIH, 2025). Learners would identify genes and partial gene sequences from known organisms (e.g., rare *T. Liliaceae* species of purple tulips) and do a Standard Nucleotide BLAST (Basic Local Alignment Search Tool) search to find species that express the gene. Learners make decisions about what they might believe would be a "good fit" (e.g., color intensity, shade, local popularity, etc.) for their needs and also meet supposed technical parameters (e.g., "smaller" genes for handling ease, expression fidelity, etc.). Learners then try out possibilities by printing (i.e., sequencing) the genes and inserting them into host microbes (e.g., yeast cells) to make pigment and BioArt. In this process, learners compare DNA sequences and judge which gene fragments would fit their BioArt project well.

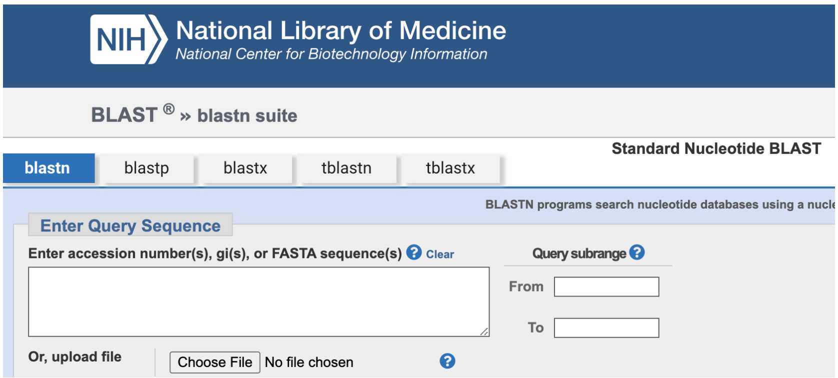


Figure 6: Standard Nucleotide BLAST. Google-like search engine that allows the public to enter DNA sequence information or gene names to compare with or find known existing genes.

17. Design a Family Trait Inheritance Chart. After learning about evolutionary phylogenetic trees, inheritance pedigree charts, and family trees, youth make something new – a family trait inheritance chart. They use cotton swabs to collect genetic material from cells lining family members' oral cavities. They also sequence the material using a sequencing service or the low-cost DNA sequencer in their local community laboratory. Learners then use the DNA sequences to identify and compare common traits (e.g., blood type, eye color, attached ear lobes, parsley taste aversion, etc.) found across family members to figure out how those traits were inherited. Because these traits are derived from multiple genes, learners must decide which, if any, are suitable indicators.


Figure 7: The BioBricks Foundation Free Genes Project. An Open Source (through Open Materials Transfer Agreement, or OMTA) repository for securing free DNA parts (i.e., gene sequences).

18. Build a Water Purification Tool that Assesses Pond Water Purity. Youth make a do-it-yourself (DIY) water filtration device to help reduce pond water contamination. To assess whether the local pond is contaminated, youth use the tool to collect water samples and use household products to isolate and identify genetic material that might exist in the specimen. Then, they sequence organisms in the sample and use a Standard Nucleotide BLAST to compare sequences in their sample to known sequences in the NCBI database to determine if genes found in the sample belong to organisms known to cause sickness in humans and/or wildlife (e.g., Staphylococcus aureus, Salmonella enterica, etc.). They deliberate about the benefits and drawbacks of sampling techniques and whether the approaches indicate "purity."

19. Make Insulin Using DNA Sequence Parts (i.e., BioBricks). Youth search the BioBricks Foundation Free Gene Parts repository (Figure 7) to order insulin-producing genes (BioBricks Foundation, 2025). They use what they've found to insert the DNA into a helpful chassis organism (e.g., *Escherichia coli*) to make low to no-cost insulin. Youths contemplate the extent to which the DNA sample made is sufficiently similar to human-derived insulin hormone and what threshold of similarity is acceptable for human use.

### *2.5 In Computer Science*

20. Program a computer to make 20 more things using data science at scale. In the current era, computers can generate data at scales and magnitudes not previously possible. Because of this, skill sets and learning experiences are not necessarily identical or transferable from traditional or analog approaches to data science (e.g., "cleaning" a data set with a thousand cases requires different considerations or heuristics than one that contains millions of cases). This requires reconsidering data science across scales (in addition to context as we present in the preceding grouped sections).

## 3. Discussion

Constructionism often emphasizes tangible materials that can be designed, organized, and represented in ways that align with learner priorities. This is reflected in recent efforts that emphasize production with computers and life sciences (Mori, 2017; Kafai & Walker, 2020; Kafai & Morales-Navarros, 2023). Here, we include a more abstract instantiation: data as material that can be molded, reshaped, and harnessed similarly. The examples we describe as constructionist exercises in data science already exist (Schanzer et al., 2022; Walker et al., 2023a) and are taken up by youth of all ages. If all learning involves inquiry exercises such as observation, data collection, analysis, and communicating ideas, then data can be another "object to think with" in this process. Data can, therefore, be understood as a social and cultural artifact that informs how one makes sense of and behaves according to how it exists or is embodied. This conceptualization affirms key ideas in constructionism, including that the nature of data's materiality is culturally embedded and is a powerful way of representing cognition (e.g., what one knows and understands) and learning (Papert, 1980). We discuss data's sociocultural, materiality, and epistemic dimensions (vis-a-vis data science) to assess how they might be implicated in constructionism and learning.

### *3.1 Data and Data Science are Social and Cultural Artifacts*

Contemporary perspectives on learning emphasize the importance of activities situated in an authentic context and practice (Brown, Collins & Duguid, 1989). This is reflected in ideas that recognize learning is not an isolated event, occurs with others, and is facilitated by available tools and practices shared in everyday life. From a humanistic perspective (Lee, Wilkerson, & Lanouette, 2021), data can be understood similarly: as an artifact inextricably threaded and embodied in our social and cultural fabric. However, learners seldom have opportunities to engage with it on these terms – to understand how sociocultural facets (e.g., sociohistorical, sociopolitical, geopolitical, socioeconomic, etc.) influence data and narratives produced in the practice of data science. For data and data science education, this occurs when learners have opportunities to engage with epistemic questions about how data is collected toward more ontological stances about whether a phenomenon exists and whether it is sufficiently captured in the data. These considerations make explicit tensions concerning data's inherent ramifications for individuals and society.

In the examples we present, data and data science provide learners with a space to engage in critical evaluations of idealized statistics and their accompanying merits. For example, students are encouraged to ask: when does the mean value of cases represent an average best in a dataset regarding public health disparities – and what is gained in a narrative where the median presents an idealized representation of what is happening in that community? From a constructionist standpoint, either path can be productive, but giving learners opportunities to contend critically with each narrative is necessary to benefit fully from insights about how data functions in society. This includes considerations about how data influences and is shaped by competing prerogatives – and the harms that result when either priority prevails. Without these considerations, learners miss opportunities to participate more generatively in socially and culturally embedded epistemic processes – and instead, are relegated to consuming or reproducing processes developed by others (Ravi et al., 2024). We believe this latter result is antithetical to constructionism and critical stances about teaching and learning.

### *3.2 Data as a Powerful "Object to Think With"*

A core tenant in constructionism is Seymour Papert's (1980) idea that objects can be powerful tools *for* and representations *of* learning. This idea underlies many contemporary instantiations of learning that emphasize hands-on activities, partly because tools help nuance how learners construct ideas about how things work. These constructions become access points for understanding how and what learners know about objects, themselves, and the world (Levin & Tsybulsky, 2017). We view data (both digital and analog) as having comparable affordances and, thus, in our view, have material features that serve as powerful objects for developing ideas.

One way to frame this is by considering data science inquiry cycles that emphasize inquiry design, data collection, processing, visualization, and communication (Walker et al., 2023b). At each of these phases, decisions must be made about how to deal with data's material affordances and constraints. Regarding inquiry designs, students are often handed a question and then asked to gather data and produce an answer. In data science, the research question is an object that learners make, and that is tied to data collection process factors. This includes considerations about what data type might be collected, when, and how. In constructionist learning, data can also be considered a raw material available for use in the inquiry or activity. This might also include how the data is processed – from raw forms to more curated or "cleaned" representations – and balanced consideration for what features are gained or lost in that process. In visualization, data science is highly concerned with how datasets can be abstracted into cognitively accessible forms such as charts, graphs, network maps, etc. This means that data, in a material sense, is transformed into something new to represent an event that can be personalized, shared, and enacted with agency (as reflected in our biology examples where data is used to make something usable). Similarly, communication in data science allows learners to construct narratives to express themselves, share their creations, and demonstrate what they have learned. In carrying out these processes, learners interact with data science on their terms (Levin & Tsybulsky, 2017) and, in that effort, nurture a sense of self and worldview that are fundamentally shaped by their interactions with the material features of data and how it exists. Consistent with constructionist traditions, these material features make data a powerful object for learning in the context of data science. This expands constructionism's applicability to include an emphasis on materials that are sometimes intangible or not physical in a traditional sense.

### *3.3 Data Science as an Ontologic and Epistemic Boundary*

Constructionism contributes to data science education in that it helps to frame how data and its use in practice are socially and culturally embedded. Constructionism also informs how we understand data as a material that can be a powerful object to learn about self, society, and beyond. As data science continues to make inroads as a productive context for teaching and learning (Jian, Lee & Rosenberg, 2022), there is an accompanying need to understand how data science might contribute to what we know about learning. As a burgeoning discipline, data science can be understood as a way of knowing (from an ontological standpoint) and doing (as an epistemic act). This serves as a good boundary point for organizing and productively characterizing what learners know and gain from using data and a set of shared disciplinary practices. In other words, data science can serve as a tacit check on ideas, practices, and dispositions that learners gain from engaging in this space. This occurs in learning designs that are structured in such a way as to encourage learners to explain what they encounter and justify how they understand those occurrences. While this is not new to learning, mainly processes emphasizing inquiry, the priorities and shared practices representing data science are distinct. In data science learning, this might look like a learner describing how they used data to produce a model or simulation – and detailing justifications for how they organized and mitigated tensions in the data set used to inform their construction.

Our examples illustrate the myriad possibilities for learning when data and data science are examined from a constructionist standpoint. We believe that emphasizing data artifacts as socially and culturally embedded materials with epistemic and ontologic characteristics is a good starting point for evidencing data science as a valuable and productive frame for constructionist learning.


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