

Invited Dialogue: "What's the Problem with Learning Analytics?" (Selwyn, 2019)

Is Data Dark? Lessons from Borges's "Funes the Memorius"

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1. Introduction

In "Funes the Memorius," Jorge Luis Borges tells the tale of an Argentinian man who falls off a horse, becomes paralyzed, and acquires the strange gift of infinite memory (Borges, 1993). Funes remembers everything, which is to say he forgets nothing. I will use Borges's story as the backdrop for my response to Professor Selwyn's critique of learning analytics (Selwyn, 2019).

My commentary is in three parts. First, I begin by stating our areas of agreement. Second, I examine Selwyn's use of the word "data." I argue that it perpetuates a number of common misconceptions about statistics and the scientific method. We cannot understand the importance of learning analytics without first clarifying these misconceptions and moving beyond them. In the course of my argument, I challenge Selwyn's central thesis that "Education is inherently social, inherently contextual, inherently subjective; it means you can't objectively rate it, measure it, indicate it." Third, I turn the tables on Selwyn. As a critic of learning analytics, Selwyn suggests that data "disadvantages large numbers of people" (Selwyn, 2019, p. 6). I argue that the root problem in education is the status quo, which Selwyn unwittingly represents, and not learning analytics. If we care about equity in education, as part of a broader interest in social justice, then learning analytics and the use of educational data can be a powerful instrument for empowering the disadvantaged.

2. Dark Times, Dark Data

Selwyn's critique of learning analytics is less an argument and more a foreboding about what ails modernity. The source of this foreboding is never articulated, but I believe it is the backdrop of Selwyn's mistrust of learning analytics. Selwyn's larger discontent, which is never stated, might be along the following lines:

We live in dark times. Democracy is on the wane worldwide. We are sliding headlong into a global ecological catastrophe. Data monopolies dominate. Free markets are anything but free. Inequality widens.

Things fall apart; the centre cannot hold;
Mere anarchy is loosed upon the world,
The blood-dimmed tide is loosed, and everywhere
The ceremony of innocence is drowned;
The best lack all conviction, while the worst
Are full of passionate intensity.

—The Second Coming, William Butler Yeats, 1920

When we look at education — and it pains me to say this — educational technology has been mostly a failure. We, its hoary advocates, have failed to deliver upon the promise. The same now appears to be case with data. Educational data has been synonymous with testing, surveillance, and performance management. As one faculty member told me recently, "When I think of analytics, I think of how data will be used against me to screw me. I don't want any of your analytics."

What are the roots that clutch, what branches grow
Out of this stony rubbish?
—The Waste Land, T. S. Eliot, 1922

Let us grant that we live in dark times. Let us grant that educational technology has been mostly a failure. Let us also grant that the use of educational data has been mostly in support of surveillance and profit. Selwyn states correctly and convincingly in his keynote that “for many people outside of the LAK community, the idea of ‘learning analytics’ is an uneasy and sometimes controversial proposition” (Selwyn, 2018, 00:09:24). I agree with Selwyn that we should be sceptical about educational technology and educational data.

The questions before us are these: Is the failure of educational technology *inevitable*? And, is educational data *inherently* dark?

3. To Think is to Forget

Borges’s “Funes the Memorius” is a fable about Big Data run amok. In the story, Funes is thrown off a horse, becomes paralyzed, and acquires the capacity for infinite remembrance. This seeming gift, however, comes at a price:

He was, let us not forget, almost incapable of general, platonic ideas. It was not only difficult for him to understand that the generic term dog embraced so many unlike specimens of differing sizes and different forms; he was disturbed by the fact that a dog at three-fourteen (seen in profile) should have the same name as the dog at three-fifteen (seen from the front; Borges, 1993 p. 89).

Funes inhabits a shadowy world of endless, streaming, and unconnected data. It is a solipsistic prison without windows and doors to the world outside, the world of knowledge. Near the end of the story, the narrator observes, “Without effort, he (Funes) had learned English, French, Portuguese, Latin. I suspect, nevertheless, that he was not very capable of thought” (Borges, 1993, p. 90). Funes’s vertiginous world of sheer particularity is a version of Hegel’s bad infinite. If we learn anything from Plato and Hegel, it is the simple truism that thought requires both the particular and the universal. Borges’s tale can be read as a *reductio ad absurdum* of the romantic view that true knowledge is wholly subjective, wholly particular, and wholly experiential.

With Borges’s fable as a backdrop, we can characterize Selwyn as an *educational romantic*. A romantic embraces the immediacy and concreteness of lived experience but is loath to move beyond it. In philosophical terms, Selwyn is a nominalist, mesmerized by the immediate and particular. Selwyn’s blithe romanticism explain statements such as: “There are not enough data points to in the world to adequately capture the complexities and nuances of who a student is ...or how a school or university functions” (Selwyn, 2018, 00:36:34). For Selwyn, using data and any and all forms of abstraction, generalization, and measurement are like Icarus’s tragic flight to reach the sun; bound for disaster. In his keynote, Selwyn’s catchall term for this hubris, the flight from particularity, is “reductionism.” “First, is a concern that anything learning analytics claims to ‘know’ about education is likely to be reductive of the actual issues” (Selwyn, 2019, p. 12). It should be noted that Selwyn often asserts the very *strong* thesis that *no use* of data in education is ever legitimate. “These concerns stretch well beyond conventional notions of data validity, and instead challenge the appropriateness of using data at all (emphasis mine) to model educational processes and practices” (Selwyn, 2019, p. 12).

I am suggesting that Funes’s and Selwyn’s worlds are the same. In both cases, vividness and immediacy are confused for insight and knowledge. The resolution to Funes’s and Selwyn’s skepticism is not to discard data, but to light the torch of thought. For data to become useful, it must be illuminated by *scientific thought*. To adapt a phrase from Kant, “Science without data is empty, data without science is blind.” Learning analytics is not just about data, nor should it be. Learning analytics is the systematic application of scientific reasoning in education. As such, learning analytics is inherently grounded in data science. In the remainder of this section, I briefly discuss two empirical pillars of data science: *statistical reasoning and model formation*.

To think at all is to forget. To know at all is to abstract. When we reason scientifically, we go further and deeper with thought. We become deliberate with what to forget and mindful of how to abstract.

3.1. Statistical Reasoning: Taming Uncertainty and Error

The starting point of all statistical reasoning is the ineradicable fact of error. The statistical picture of the world is one of the great pivots of human consciousness and it is impossible to overstate its importance for grasping modern scientific method. Statistics is a *form of reasoning* which allows us to make *reliable inferences* under *conditions of uncertainty and error*. Modern science recognizes that uncertainty acts as a fundamental brake in our quest for knowledge. This limitation is not a single thing but appears in many guises. Sometimes the limitation is in us; at other items, the limitation is in our instruments; and yet other times, the limitation is in how we reason. Each limitation imposes error. It doesn’t end there. The modern scientific picture of the world is stochastic, not deterministic. The deterministic world of Descartes and Newton was cast aside and replaced by the stochastic world of Boltzmann and Heisenberg. This means that *randomness* is an inextricable feature of the world, not

just a limitation in our knowledge of it. Given the twin facts of uncertainty and randomness, statistics provide us with a set of guideposts for reliably knowing the world. With statistics, we are able to tame — but not wholly conquer — error, randomness, and uncertainty.

We are now in a position to state a very common misconception about statistics, one that underlies much of Selwyn's critique of learning analytics and the use of data in education. Because statistics deals with individuals qua abstractions and not individuals qua individuals, it is natural to conclude that this "reductive" step means a loss of information. When we measure, we "remember" some aspects of an individual and "forget" others. Our ingrained mental model of this process is that of viewing an image as we zoom out. As the image recedes in our field of vision, details become blurry. We lose more and more information the further we move away from the picture. It is natural to think of abstraction, as Selwyn does, as a type of blurring. But this is a false picture: the right abstraction sharpens the image and increases information.

The right abstraction, seen under one aspect, means losing information; seen under another aspect, however, means gaining information. Consider the statistical step of calculating an average or mean. We discard most details, including the different circumstances in which a measurement was made, the order in which it was made, the identity of the observer, and so on. But calculating the mean also gives birth to *new information*. The measure of central tendency of a set of data points provides information not present in any of the individual data points alone. This new information also reveals *context* in the form of a relationship of a specific individual to a relevant group. If one reports the height of an individual as a solitary atomic fact, the information in itself is of no use. If one reports alongside the individual height, the mean, and standard deviation of everyone in the room, we have the beginnings of a possible insight or a possible action. The average of a set of data points can provide new information that was not available in any of the individual data points alone. Aggregation is among the simplest but most powerful of the "seven pillars of statistical wisdom" (Stigler, 2016). Statistical aggregation is paradoxical. It defies common sense: by discarding information, we also gain information. Statistics is like that.

3.2. Formal Models

Let us consider very briefly now the use of models in science. What is a model? A model is an abstract, simplified, mathematical representation of reality. The statistician George Box's famous quip captures the essence of models: "all models are wrong, but some are useful" (Box, 1976, p. 440). All models are *false* since no model is isomorphic to reality. A map is not the territory, but a good map can serve as a useful distillation of reality. Box has also emphasized that models are never the endpoint of science: "Since all models are wrong the scientist must be alert to what is importantly wrong" (Box, 1976, p. 792). This is done by a motivated iteration between theory and practice.

Why use models at all? There are many reasons, but let me highlight one that is essential to scientific reasoning. Good models sharpen our reasoning and thereby help us to *avoid errors*. Model construction requires that we identify a set of salient characteristics, in the form of variables, in order to explain some phenomenon. Models formally specify the relationship among the different variables.

How do models improve reasoning then? One way is that they can explain phenomena that contravene common sense. A famous one is Simpson's Paradox. Using formal models, we can show, for example, the possibility of subgroups having the opposite property of the parent group. In education, this actually occurred. In 1973, University of California – Berkeley's graduate school admission data showed that male applicants were significantly more likely to be admitted than female, indicating a strong possibility of gender bias. A statistical analysis showed that in fact there was no gender bias: most departments had admitted a greater percentage of women than men. Similar paradoxes crop up in many areas. Parrondo's paradox, for example, shows how it is possible for two losing bets, when played alternatively, to produce a positive expected return. Arrow's Impossibility Theorem demonstrates that no reasonably consistent and fair voting system can result in sensible results.

The world doesn't always work the way we think it does or the way we hope it does. With the aid of formal models, we can detect and correct non-obvious errors that escape the net of common sense. Science is inherently fallible, yet also reliable in the end because of how we use statistical reasoning in tandem with formal models.

When we form scientific models, we explicitly choose which details to forget (place in the background) and which details to remember (place in the foreground). Additionally, as Carolyn Penstein Rosé eloquently observes in her commentary, science is multivocal: "The key idea behind multivocality is that valuable insights into data come from juxtaposing multiple lenses" (Rosé, 2019, p. 24). One form of multivocality is the application of multiple models against the same data set. What is background in one model can be a foreground in another model. Nothing in the scientific method precludes the use of multiple models. In fact, good scientific practice encourages it (Page, 2018). Another form of multivocality is the simultaneous use of quantitative and qualitative data. For example, implementation fidelity is a key idea in assessing the effectiveness of educational interventions. Understanding the alignment of the planned intervention with the implemented intervention is crucial to assessment. But evaluating this alignment is seldom achieved by relying on quantitative data alone.

4. The Plight of the Disadvantages and the Quest for Equity

Selwyn's keynote is a timely provocation to the learning analytics community. It forces us to ask these questions: Why learning analytics? What is its wider purpose and endgame? While I cannot speak on behalf of the community, for me the answer is equity. In this final section, I justify my claim in the introduction that the *status quo* in education, and not learning analytics, "disadvantages large numbers of people." I also sketch a line of argument to suggest that data science can illuminate our understanding of inequity in education.

I begin with a trio of maxims as a way of setting the stage for my discussion. I will not defend the maxims, but accept as faith that the values they express are shared, at least partly if not wholly, by the learning analytics community.

- **Affordability:** Education should be affordable.
- **Outcomes:** Education should lead to demonstrable learning gains.
- **Equity:** Education should lead to demonstrable gains for all.

The three maxims are obviously related, especially (2) and (3) through the word "demonstrable." My use of "demonstrable" signals the fact that the terms and conditions of societal support for education has shifted radically in the past decade. This shift, I believe, is not momentary, but will continue to heighten in intensity for the foreseeable future. Whether we like it or not, education is increasingly seen as a monetary investment by society. In return, stakeholders expect evidence that the investments are worthwhile and effective. In other words, students should see the benefits of these investments and that these benefits should be demonstrable to stakeholder citizens.

For example, as late as a decade ago, the majority of public funding of higher education in the United States by state legislatures was based on head count, meaning enrollment. Today, the majority of states fund higher education based on formulas that take into account measures of achievement such as retention, graduation, and time-to-completion.

This way of stating it, the use of metrics to evaluate educational outcomes, is almost certain to invite a round of the usual objections. It will be argued that the value of education, especially in spheres such as the humanities, cannot be easily measured if it can be measured at all. Furthermore, the Return on Investment (ROI) and measurement mentality once again privileges what can be measured at the expense of what cannot be measured. While such objections have some validity, I believe, they are otiose in the present context. Whether we like it or not, we live in times of accountability. We all need to view ourselves as stewards of public resources working in behalf of the public good. The days of "just give us the money and go away" are over.

Armed with the three maxims and the observation about the increasing demand for accountability, I turn now directly to the topic of equity in education. I believe that equity in education can be framed in two senses: macro and micro. Corresponding to each, we can state an aspirational design principle for learning environments.

1. **Macro Equity:** The goal of educational equity at a macro level should be to design educational *pathways* that enable intergenerational income mobility.
2. **Micro Equity:** The goal of educational equity at a micro level should be to design instructional *environments* that close the achievement gap.

The principle of macro equity draws from the economist Raj Chetty's (2014) work on social mobility. The principle of micro equity draws from Benjamin Bloom's theory of mastery learning and his approach to educational measurement.

4.1. Macro Equity

Since its founding, American democracy has been shaped by the mythology of the "American Dream." A "mythology" in the way I am using, unlike a myth, is neither true nor false. A mythology is a set of core beliefs by which people regulate, interpret, and give meaning to their lives. The "American Dream" is the deeply rooted belief, held by most Americans, that anyone, regardless of sex, colour, gender, class, or income, "can make it from rags to riches." The way I intend to use the concept of the "American Dream," however, is independent of the United States. It expresses a fundamental ideal of social justice.

The Harvard economist Raj Chetty (2014) has shown with data that the mythology of the American Dream, at least in the United States, is a myth. The notion that American society is a level playing field is categorically false. It was certainly never true for all (e.g., African Americans). The playing field in contemporary American society is tilted heavily in favour of the wealthy. As part of his data analysis, Chetty operationalizes the term "American Dream" as intergenerational mobility. If we define "absolute income mobility" as the fraction of children who earn more than their parents did, it turns out that rates of

absolute mobility have declined precipitously from approximately 90% for children born in 1940 to 50% for children born in the 1980s. Furthermore, if we examine the fraction of children who are able to move from the lowest quintile of income to the highest, it turns out that the United States is among the very worst among developed nations. Denmark, Norway, Finland, and Canada rate as among the best.

Chetty’s examination of educational data reveals an equally disturbing pattern. A comprehensive examination of data from more than 2,000 American colleges and 30 million college students from 1999–2013 shows that colleges perform poorly in supporting intergenerational income mobility. Access to college, for example, varies substantially across the income distribution. Children with parents in the top 1% of the income distribution are 77 times more likely to attend an elite college or university than children with parents in the bottom quintile. Since higher education is a critical pathway to upward income mobility, there is overwhelming and cumulative evidence that the poor and lower income classes are effectively shut out from the “America Dream”. This state of affairs is getting worse, not better.

Statisticians care about the mean, but they also care about variability. Using sophisticated data science techniques (e.g., causal inferencing), Chetty has shown that environment matters, and there is considerable local variation in outcomes.

Social mobility varies widely both across cities and across neighborhoods within cities in the U.S. On average, a child from a low-income family raised in San Jose or Salt Lake City has a much greater chance of reaching the top than a low-income child raised in Baltimore or Charlotte.

Chetty and his colleagues have begun to apply the same causal techniques to understand the impact of educational institutions for intergenerational mobility. The CLIMB initiative is a partnership of leading economists and a set of U.S. colleges and universities that seeks to understand which colleges act as engines of intergenerational mobility. This is a first step towards understanding why some institution’s graduates are able to climb the income ladder more successfully than others.

I cite Chetty’s work as an exemplary example of how data science can be used in the service of advancing equity and social justice. Chetty’s “data” shows that the status quo has consigned an entire group, those in the bottom quintile of income, to a state of perpetual poverty and misery. Moreover, those in the second and third quintiles inhabit a turbulent and unstable middle class due to changing economic forces. Although Chetty’s analysis focuses on the US, it is likely that similar dynamics are at play in other countries.

How can we avert the coming storm? A modest proposal is to take seriously the importance of measuring and tracking social mobility as a basis (not the only basis) for educational reform. One such measure could be the “Chetty Metric,” a phrase I have coined from Chetty’s framework. The “Chetty Metric” would measure how well each higher education institution provides the skills and opportunities to its students to move up the income ladder.

For example, community and technical colleges in the United States are uniquely positioned to focus on educating and empowering the most economically disadvantaged. Mobility Track #1 (Figure 1) would take students in the bottom quintile and move them up quickly, in one or two years, to the second quintile. The bottom quintile represents poverty or those hovering in poverty. The second quintile can represent a stable, permanent job earning a living wage with benefits. For individuals in the bottom quintile climbing up even just one ladder can be transformative. At scale, it’s a game changer for families and communities.



Figure 1. Mobility Track #1

By contrast, four-year colleges are uniquely positioned to support and empower the dwindling middle class. Mobility Track #2 (Figure 2) would move people from an unstable middle class (second and third rungs) to more stable high growth and high paying professions in the fourth and fifth rungs. Traditional middle-class jobs (e.g., manufacturing) are disappearing and are not likely to be replaced by jobs requiring the same skills. But jobs are being created in the higher ladders of the income quintile.

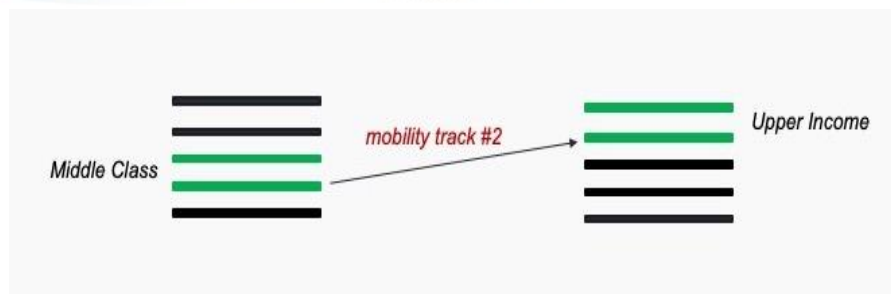


Figure 2. Mobility Track #2

Chetty's work provides a useful empirical framework for understanding the dynamics of inequity. To be sure, there is more to education than becoming economically successful. However, in today's climate it is no longer possible to survive, let alone thrive, without baseline skills. The macro picture of the status quo is alarming since as much as 50% of workers in the US occupy a precarious economic no man's land. For a significant number of them, education is not a solution, but the solution. Any attempt at educational reform, one that would empower the disadvantaged, must begin with data.

4.2. Micro Equity

Disparities or "gaps" in achievement levels or different groups of students has been a perennial concern in US education. Despite massive investments spanning five decades through programs such as The Economic Opportunity Act (EOA) of 1964, No Child Left Behind (NCLB) in 2001, and more recently, Every Student Succeeds Act (ESSA) in 2015, the problem remains unsolved. Not only has the problem remain unsolved, there is no consensus among educators or policy makers about what works and what doesn't. How is this state of affairs even possible? Here is another example where the status quo disadvantages the disadvantaged.

I define micro equity as closing the achievement gap in instruction. My approach will be to sketch a line of argument that hypothesizes how adaptive technology, also called "intelligent tutoring systems," might be part of the solution. In discussing micro equity, I will begin with a story.

In Galileo in Pittsburgh Clark Glymour (2010), a renowned philosopher of science and statistician, reflects on his long career in science and education. The chapter called "The Computer in the Classroom" describes his first-hand experience with equity in the classroom. Glymour arrived at Princeton in 1969 as a freshly minted PhD. He was called upon to teach mathematical logic to a class of about seventy students. He approached the course as most faculty do. He chose an established textbook, prepared a series of lectures, created homework assignments, and administered a midterm and final examination. "One morning at the end of the semester my graders appeared in my office to tell me I had failed every black student in the course, all seven of them. I asked if I had failed any white students. Yes — one."

For Glymour, his course in mathematical logic was eye opening. He reflected, as any good scientist would, on what might have gone wrong and then hypothesized what instructional adjustments might improve outcomes for everyone, including the black students in his course. The next semester, he had the same number of black students in his class. This time half of them received a B grade, the others received an A. Glymour writes that he discovered something:

What I had discovered was that a lot of capable students need information in small, well-organized doses, that they often do not know what do not know until they take a test, that they need a way to recover from their errors, that they need immediate feedback, that they learn at different rates, that they need a chance to ask about what they are reading and trying to do, and that, if given the chance, motivated students can and will successfully substitute sweat for background. This turns out to be about all that education experts really know about college teaching, and of course it is knowledge that is systematically ignored (Glymour, 2010, p. 29).

Glymour notes, "I also discovered that it is not physically possible to teach that way: I was ready for the hospital by the end of term." It was not humanly possible to teach by restructuring the course away from lectures and exams to one based on mastery learning and formative assessments. Glymour speculated, however, that computers were ideally suited for supporting instruction based on personalized and dynamic feedback:

But it did occur to me that this source was ideal for instruction by computer. The computer could be programmed with small modules, with interactive questions and prompts, with many penalty-free tests for each module, even with automated problem-solving aids. That would work for a lot of introductory

mathematics and for science and engineering classes, and maybe even, if sufficiently cleverly done, for history and philosophy. (Glymour, 2010, p. 29)

By experimentation, Glymour discovered the principal elements of what Benjamin Bloom characterized as mastery learning. Bloom observed, similar to Glymour, that there is considerable variation in the starting characteristics and skills of learners. He also observed that teaching all students in the same way and giving all of them the same amount of time to learn typically does not reduce the variation in outcomes. Well-prepared students do well. Those in the middle end up in the middle. And those who started behind end up doing poorly. Bloom stipulated that in well-designed learning environments, those who start behind would have the opportunity and support to catch up.

Bloom believed and demonstrated with his research that all students benefit in an instructional environment where methods and times are varied dynamically to better match student’s individual learning needs. Bloom argued that in order to overcome the input variation in incoming student abilities, background, and other characteristics, instructors must match it with instructional variation. Bloom labelled this strategy of applying instructional variation as mastery learning.

Glymour also speculated that computers are ideally suited to delivering instructional variation, especially at scale. If we think then of the well-designed adaptive systems, also called intelligent tutoring systems, the core principle is mastery learning based on instructional variation. Figure 3 shows actual data comparing the distribution of outcomes from two classes, one using an adaptive system-based mastery learning principles and another one following the traditional mode of instruction. The figure illustrates the signature pattern of what I call the “Bloom Effect” or the “Bloom Metric.”

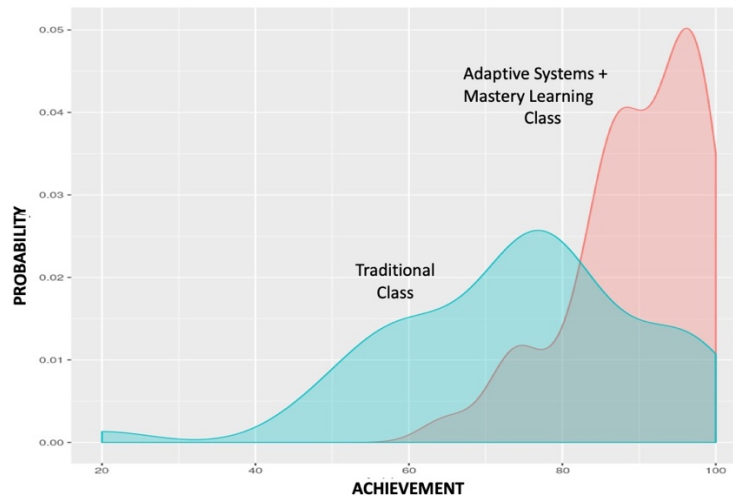


Figure 3. Illustration of the Bloom Effect through the comparison of two classes, x-axis – Probability, y-axis - Achievement

His famous paper, “2 Sigma Problem,” describes this signature effect:

The variation of the students’ achievement also changed under these learning conditions such that 90% of the tutored students and 70% of the mastery learning students attained the level of summative achievement reached by only the highest 20% of the students under the conventional instructional conditions. (Bloom, 1984, p. 4)

There is considerable evidence that well designed adaptive learning systems, based on learning science principles, can lead to significant learning gains, but also help to close the achievement gap. But the implementation of such systems at scale has remained elusive. Here is an important area where I believe learning analytics can illuminate the path forward.

5. Conclusion

Goethe famously remarked that Moses Mendelssohn, in his philosophy of aesthetics, treats beauty as entomologists treat butterflies. “He catches the poor animal, he pins it down, and as its exquisite colours drop off, there it lies, a lifeless corpse under the pin” (Berlin, 1999, p. 43). In his keynote address, Selwyn paints a similar dismal view of learning analytics.

Measurements, models, abstractions, and the myriad uses of data, pin the butterfly of education, leaving us only with its lifeless corpse. I have argued for a counterpoint, suggesting that the science and aesthetics of the butterfly each have their purpose. And in dark times we need both.

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