

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

Monolith, Multiplicity, or Multivocality: What Do We Stand For and Where Do We Go from Here?

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1. Introduction: A Reflection on Framing

As a former program co-chair of the Learning Analytics and Knowledge conference, I recalled while reading the Selwyn (2019) article that the conference has a history of inviting and welcoming critical perspectives on the field in its keynotes, and this keynote was certainly in keeping with that tradition. The author talks about the field as having a thriving industry, having a large research community, and being an integral part of the way in which institutions of learning are run. I have witnessed the emergence and growth of the field since the inception of the conference and journal that bears its name and remember a time when Learning Analytics was not yet a buzzword. I have also served once as a conference program co-chair and witnessed first-hand the intense diversity of backgrounds and perspectives within it, so it feels like a mark of achievement to hear Learning Analytics discussed in these terms, which speak of maturity and success.

I read Selwyn's write up several times and made many false starts at a commentary before settling on this one. To begin with, as an appreciator of rhetoric, I asked myself while reading, who is the projected reader of this article? What does that projected reader believe in and stand for? As that projected reader seems meant to represent the community of Learning Analytics researchers and practitioners, I further asked myself how close to that projected reader do I feel? It sounded strange in my ears to hear the term "your field." I have indeed participated actively in this community, but I see many fields represented in it. I do not identify with this as my primary field, and I wonder how many of the active participants in the community would? Some would, no doubt. However, this way of speaking makes the work of this community sound more disconnected from the many fields and disciplines the community represents than seems ideal to me. I would hold that the Learning Analytics community is much more a multiplicity than a monolith.

Cutting to the chase, it will come as no surprise that do not personally identify with the image of the projected reader found between the lines. Thus, some of my original false starts focused mainly on addressing some contentious aspects of the image of the field, its beliefs, and its values, and especially the extent to which it appears to be painted in a largely monolithic manner. What finally gave me pause in that endeavor was the fact that in the conclusion, the way forward proposed by Selwyn is nevertheless a vision that I could genuinely get behind, and I believe many in the community would share that sentiment. So, let me start with that note of affirmation. In full disclosure, I was not present at the conference when the keynote was delivered in person. Nevertheless, I feel certain that the keynote was received well overall. My interpretation of the core of what the article is critical of is the image of learning analytics as a commodity projected through hype that does not necessarily stem from the research per se. If anything, the write up of the keynote seems unnecessarily apologetic since it may not be the actual audience of the keynote or the article being critiqued. What I believe is that many in the community resonate more with the same concerns, values, and vision forward that Selwyn has offered than they do with the characterization of the field that seems implicit in the writing.

Given that the article calls for a stance that is very synergistic with the perspectives of many researchers in the field, it surprises me that early in the article the issues discussed are not ones the author sees being discussed in this field very frequently. On the other hand, Selwyn acknowledges that the concerns raised might be stating the obvious, which jives with my own sense that his questions and concerns are ones I think about all the time and I know that many of my colleagues would say the same. As this community is more a multiplicity than a monolith, I hope that this review brings out some of the juxtapositions of values, beliefs, and expertise that make this community what it is.

2. A Reflection on Quantification

The initial substantive portion of the article focuses on the results of Learning Analytics as a field. Claims are made that

Learning Analytics is associated with a reduction in understanding of education, a lack of consideration for the contexts of education, a reduction in capacity for informed decision making, and a host of biases that could pervert the use of Learning Analytics in ways that infringe upon privacy, diversity, and equity. I see two general themes here, one of which I will focus on. The first is a general concern over Learning Analytics as necessarily reductive, and the other is a concern about hidden biases and political agendas. I will focus on the first and draw from a collaboration involving other long-time members of this community around an idea referred to as multivocality (Suthers, Lund, Rosé, Teplovs, & Law, 2013).

Quantitative researchers must concede that every quantification requires a reduction from the infinite complexity of the real world. Nevertheless, sometimes the quantification appears to capture all that is important. The physical sciences more readily model visible processes and thus a strong notion of causality can be leveraged in those fields. In the learning sciences, as in the broader world of social sciences, especially as larger and larger social systems are the target of inquiry, such as groups or communities, the processes at work are much less readily observable. Frequently many confounding factors that are very challenging to tease apart obscure them. In fact, the high premium on practices for achieving experimental control within quantitative branches of the social sciences, even where smaller social systems are involved such as individuals or pairs, hearkens to the difficulty of achieving such control. Many standards for careful interpretation within the quantitative branches of the social sciences acknowledge the difficulty of capturing important social constructs and therefore always questioning the interpretation of findings. The adoption of a softer notion of causality within the behavioural sciences also hearkens to this difficulty. In particular, rather than establishing that whenever an independent variable holds, the corresponding dependent variable also holds, it is only necessary to establish that whenever the independent variable holds, the dependent variable is more likely to hold than when the independent variable does not. Quantitative branches of the social sciences acknowledge the challenges in simplification and quantification, but accept these difficulties and limitations because of a value placed on making causal inferences.

The key idea behind multivocality is that valuable insights into data come from juxtaposing multiple lenses. Lenses are drawn from a distribution where on one end (e.g., left) may reside strongly reductive approaches, where discretization and simplification are used as a means for operationalizing and isolating variables in order to measure causal relations and thus derive generalizable principles. On the other end (e.g., right) are strongly qualitative approaches, loath to reduce or simplify, but then removing the possibility of generalization or a notion of causality. Researchers may place themselves somewhere along this continuum, generally viewing researchers to their left as reductive and possibly even atheoretical and researchers to their right as possibly imprecise or even lacking in rigour. Nevertheless, within a multivocal approach, these different voices exist in productive synergy, challenging each other, and sharpening each other, perhaps “as iron sharpens iron.” Multivocality is critical because we can neither afford letting go of the concept of causality — without it we would lack the possibility of design principles or principled decision making at all — nor the concept of contextualization — without it we would oversimplify and make decisions that lack nuance and sensitivity, as the article points out. At any one position along the continuum, we are compromising to one extent on rigour and causality and to another extent on nuance and sensitivity. Since no single position along the continuum is ideal, we do best by bringing together multiple voices from different places all along the continuum. One might also consider a third dimension, possibly emergent from the interaction between the other two, which arises from an effort to build more nuance into the quantification that we strive for in order to incorporate as much contextualization as possible, which leads to increasingly complex models. This comes with many computational issues — like over-fitting — with which modellers constantly struggle. More data is required in order to avoid over-fitting in the face of the complexity introduced when considering contextual variables. The more complexity introduced, however, the more we experience models as opaque. Take the recent grow in interest in Deep Learning approaches, with well-known issues regarding lack of interpretability. We find that the less we reduce complexity and the more we consider contextual nuances, the more complex our models become, and the more opaque. These things are in tension with one another.

Taking a step back, we may ask ourselves a slightly different question now. Are analytics necessarily reductive, decontextualized, and opaque/uninterpretable/inscrutable? These qualities can certainly be true of analytics. But are they necessarily true? We have a choice about the extent to which we take up a reductive position on the spectrum in our analytics work. However, what we need to consider is that there is something to win and lose at each position. Can we afford to focus only on avoiding reduction? Can we afford to lose what we gain in that reduction? Is there truly one position associated with better decision making on its own? If not, is the concern really about learning analytics per se?

My own area of Learning Analytics is related to the analysis of language, and frequently the language I analyze is discussion data. In my own work, I have pushed to maintain as much richness in the modelling as possible, which sometimes bucks the trend. I observe a spectrum of approaches within this area of Learning Analytics. It is certainly possible to find very reductive approaches to modelling language interaction. Nevertheless, I argue that computational models of social interaction in textual form can be used to reveal layer upon layer of insight about social orientation of interlocutors towards one another as well as towards their experiences in the environment. At any given time, we must be cognizant of what nuance we retain

and lose, and if we are, we can be appropriately skeptical of our findings. Though skeptical, we can nevertheless see through a dim glass the insights for which we strive. Quantification of language can serve many purposes. It can provide a way to measure change, identify patterns, describe activity, or examine the utility of tools and interventions. Though this quantification is unarguably part of what has become the field of Learning Analytics over the past decade, the ideas are older with longer and more expansive roots than that. Some early work on quantification of language within the learning sciences community began with work on protocol analysis from cognitive psychology (Ericsson & Simon, 1993; van Someren, Barnard, & Sandberg, 1994). A set of guidelines for quantification of language bridging from the early work in protocol analysis to a broader framing within the learning sciences was published in the *Journal of the Learning Sciences* over two decades ago (Chi, 1997). A decade later, use of machine learning to automate application of coding schemes for quantifying language began to grow in popularity within the CSCL field (Rosé et al., 2008). Since the early 2000s, there has been a growing interest in the CSCL community in automating the quantification of language through applications of machine learning, and a number of reviews of such technology have recently been published (Rosé, 2017; Rosé, 2018).

Reduction is not the only concern Selwyn raises in this portion of his article. Talk of reduction transitions into concerns related to various ethical issues. Biases may be introduced into models intentionally or unintentionally at any stage as data is collected, sampled, formalized into tabular form, and then modelled. It is important to note that the same concerns may be expressed at either end of the methodological continuum introduced in this section. Just as bias may be introduced through the process of reduction in the style of quantification, it can just as easily be introduced through a different notion of reduction inherent in qualitative approaches, which nevertheless must be sampled even if the observation of the selected sample is kept as deep and thorough as possible. The fact is that, as humans, we have limited attentional capacity, and thus we must reduce in order to comprehend. Thus, we are always subject to biases. However, again I would argue that multivocality might offer some relief from concern. When we bring multiple voices and multiple perspectives to the table, we have a level of accountability that might protect us to some extent.

3. A Reflection on the Value of Data

In the second substantive portion of the article, Selwyn questions the values of the field. Most notably, he questions a value in data-driven decision making. Indeed, the entire preceding section is predicated on placing a value on data. Of course, it would be inconsistent for Selwyn to dismiss data altogether. Whatever danger there is in reduction, as discussed extensively in the previous section, then the data has value that we do not want to lose. Thus, what Selwyn discusses in particular under the heading of “blind faith in ‘data’” relates to the type of data typically used in Learning Analytics research. Specifically he refers to data traces from interactions with digital technologies.

When it comes to concern over “which data,” I believe there is a strong consensus that we frequently are not able to get the data we would like to be using, so we default to using data we can get. Sometimes this data has been referred to in even less flattering terms than “data gaze,” being referred to as “the exhaust.” Frequent discussions in the field have focused on the quandary that, on the one hand, we are not even fully aware of what exact data we need in order to make all of the measurements we would like. And one reason why we don’t know is that we haven’t seen it yet, so we can’t validate that it’s what we want through our computational methods. Thus, we don’t fully know what we would want to record as data traces. Nevertheless, I think we constantly strive for an expansion of the data we can collect and model. We are not limited to the world we can see through clicks and menu selections. Rather than focusing only in the danger in the limitations of what data we have and can model now, perhaps it would be more productive to consider the limitations in our current work that we are striving to overcome.

4. Conclusions: Where Do We Go From Here?

Selwyn’s article ends with a vision for steps forward. At this point, as mentioned early on, I see the least controversial material. I resonate very much with Selwyn’s vision that if we are reflective of potential dangers in how Learning Analytics may be (mis)understood and (mis)used, we should take a more active role in educating the public. In my own corner of Learning Analytics, I have worked to do this through raising awareness of the role of data representation and insight into what machine learning is and is not (Rosé, 2017; Rosé, 2018).

The vision forward proceeds from discussions earlier in the article questioning the “politics” behind Learning Analytics. If we ask ourselves about “politics,” we must first agree on “who” or “what” Learning Analytics is: Is it Big Brother? Is it the babysitter? Is it the snake oil that will fix our problems? Is it the auto-administrator that will do the work for us? As researchers, I think we balk at all of these characterizations. However, in my experience with discourse analytics, I sometimes feel that “customers” of Learning Analytics may be shopping for something that fits these characterizations, what I would term a “push-button solution.” Thus, in the interaction in which an individual takes up that “customer” stance, it places me (or the field?) in

the corresponding “seller” stance where what is said may not be intended to be taken as a sales pitch in line with these characterizations, but nevertheless what is said may be interpreted and cast in that light.

Overall, my biggest critique of Selwyn’s article is what comes across as a one-sided rather than a multivocal view of Learning Analytics. The article emphasizes the dangers of Learning Analytics without substantial discussion of the problem that Learning Analytics is meant to solve. We should really consider those dangers in comparison with the dangers of not going forward with Learning Analytics. Do we remember what conditions in the world prior to the inception of the field created a need for its target solution? Thus, consistent with the idea of building understanding and awareness in the public about Learning Analytics as a forward-looking goal, we should continue among ourselves to value our great diversity and work towards better understanding and appreciation of the many differences in perspective, methodology, and theoretical backgrounds in our midst. In so doing, perhaps we can protect each other from the pitfalls discussed in Selwyn’s keynote and article while not losing the tremendous value we have been working hard to achieve.

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