THE GHOST IN THE MACHINE, OR THE GHOST IN ORGANIZATIONAL THEORY? A COMPLEMENTARY VIEW ON THE USE OF MACHINE LEARNING

Journal:	*Academy of Management Review*
Manuscript ID	AMR-2021-0036-Dialogue.R1
Manuscript Type:	Dialogue
Topic Areas:	
Theoretical Perspectives:	
Abstract:	n/a for dialogue pieces

The Ghost In The Machine, Or The Ghost In Organizational Theory? A Complementary View On The Use Of Machine Learning

Dirk Lindebaum
Grenoble Ecole de Management, France
mail@dirklindebaum.EU
- dirklindebaum.EU -

Mehreen Ashraf
Cardiff Business School, UK
AshrafM2@cardiff.ac.uk

A dialogue piece written for AMR in response to this study:

Leavitt, K., Schabram, K., Hariharan, P., & Barnes, C. M. (2020). Ghost in the Machine: On Organizational Theory in the Age of Machine Learning. Academy of Management Review. doi:10.5465/amr.2019.0247

Within the span of one year only, interest in the topic of machine learning (ML) and algorithms has accelerated in AMR (see, e.g., Balasubramanian, Ye, & Xu, 2020; Lindebaum, Vesa, & den Hond, 2020). The article by Leavitt et al. (2020) on OT in the age of ML speaks to this debate. They define ML as "a broad subset of artificial intelligence, wherein a computer program applies algorithms and statistical models to construct complex patterns of inference within data". The intention is to expand their article "towards the understanding that ML can function as a powerful catalyst for the next chapter in the evolution of knowledge generation within organizational scholarship when [it] is properly matched with theory" (italics in original). To address this aim, descriptions of current approaches to ML (i.e., supervised, reinforcement & unsupervised) are provided, which are then linked to the deductive, abductive, and inductive processes we use in OT. Therefore, ML constitutes a "novel tool in our epistemological kit". Especially when ML is applied in inductive research, so it is claimed, the "tolerance for surprise results" is magnified when theorists bridge "considerations of ML to research and theory", and thereby secure possibilities for "how ML and theory may best play synergistic roles". In sum, the take-home message is that "organizational scholars must significantly adapt their theory building pursuits to the age of ML".

There is much to be admired about in their article, such as the detailed description of how the various approaches to ML can potentially be mapped onto the aforementioned epistemological processes in OT. Thus, we welcome their article as a catalyst for intellectual stimulation. Despite this, there is a need to critically interrogate some of the article's basic assumptions. Two reasons require said interrogation. First, the article is conspicuous by ontological neglect. By advocating the use of ML to advance theory, this neglect implies that the role of science is reduced to a positivist Weltanschauung only. This relates to the second issue; the article reduces the task of science to essentially prediction only, thereby not only marginalizing the branch of social science concerned with understanding, but also failing in its aim to explain social phenomena. To advance the debate, we believe it is crucial to draw clearer boundaries around the promises of using ML in OT for theory generating purposes. Overcoming these boundaries to properly 'explain' and 'understand' social phenomena will likely require technological progress to an extent we believe infeasible any time soon. We briefly elaborate on the latter two points at the end of this essay.

ONTOLOGICAL NEGLECT

Leavitt et al. (2020) emphasize ML as a new tool in our epistemological toolbox. However, since ontological questions are prior to epistemological ones (as the former constraints answers to the latter, see Guba & Lincoln, 1994), this emphasis appears premature. Explicitly recognizing the nature of social reality enables researchers to continuously scrutinise and correct the latter in order to make the world a better place (Lawson, 2019). Thus, "understanding [a phenomenon's] . . . essential properties allows us to relate to, or interact with, it in more knowledgeable and competent ways" (Lawson, 2019: 3). Practically, an ontological appreciation means to have a tool at hand to render social interventions – for which the introduction of technology qualifies (Moser, den Hond, & Lindebaum, 2021) – more likely to succeed (Lawson, 2019). In short, ontological appreciation is closely linked to being able to explain relationships between constructs in more knowledgeable ways.

The ontological problem residing in the Leavitt et al. article is the imposition of an ontological straitjacket à la positivism on OT as a whole, including the inductive tradition. Specifically, the way that ML is advocated resembles the description of three key tenets of positivism, two of which are of particular relevance in this section. The first is methodological monism, defined as the "unity of scientific methods amidst the diversity of subject matter of scientific investigation" (Von Wright, 1971: 4). No matter if theorists have deductive, abductive, or inductive dispositions, and the variety of methodological approaches that come with these traditionally, all can be subsumed under the paradigmatic strictures of positivism as programmed into ML codes. We discern three issues here. First, for inductive research, this stands in contrast to the message that "unpacking new theory requires scholars to take advantage of the breadth and variety of approaches to qualitative research" (Bansal, Smith, & Vaara, 2018: 1189). Second, some scholars worry that the application of positivist quality standards, like transparency and replicability, to qualitative data is "unhelpful and potentially even dangerous" because of the danger to inappropriately import "the logics developed largely in experimental social psychology to the field-based, qualitative, and theory-generating side of our [qualitative] field" (Pratt, Kaplan, & Whittington, 2020: 2). Third, it runs counter to recent calls to develop "interparadigmatic appreciation in action; that is, feeling at ease in moving between paradigms and the genres of writing they represent", simply because the question or topic at hand requires that (Lindebaum & Wright, 2021: italics in original). Thus, the methodological monism that shines through in Leavitt et al.'s advocacy of ML entails the loss of diversity of research approaches, a conflation of evaluative logics between quantitative and qualitative research, and a lost opportunity for dialogue amongst paradigms.

The use of ML also corresponds to another tenet of positivism, namely, that mathematics sets the "methodological ideal of standard which measures the degree of development and perfection of all the other sciences, including the humanities" (Von Wright, 1971: 4). With this in mind, it does not surprise that some argue that increased quantification represents a hallmark of scientific maturity as (a point critiqued by Guba & Lincoln, 1994). As Lindebaum et al. (2020) argue, ML operates on the assumption of formal rationally (or Zweckrationalität), which legitimizes means-end calculations and dependence on abstract and universally valid rules. When "brute calculation reigns with regard to abstract rules, decisions are arrived at "without regard to persons" (Lindebaum et al., 2020: 253). Not only that; an unbridled pursuit of the possibilities of ML can also entail that, eventually, substantive rationality (or Werterationalität) is transformed into formal rationality through formalization. It is at this juncture, for example, that human judgement based on deliberative imagination and emotional attunement to the situation at hand is substituted by 'reckoning' grounded in the calculative (formal) rationality of present-day computers (Moser et al., 2021). This is exactly what the article insinuates when, in the context of ML based on unsupervised learning applied to qualitative data (e.g., news stories), "the algorithm independently explores unlabelled data, extracting and constructing hidden patterns and structure". To detect these hidden structures, we do see potential merit in the use of unsupervised learning. For instance, in order to detect patterns of racial bias inherent in the reporting of crimes across a nation's regions

- which readily yields millions of data points[1] - it could be useful to enlist ML to probe deeper into those hidden structures concerning potential racial biases. However, while we can see that the greater computational powers that ML affords can be usefully applied to such an example, we need to underline that such applications largely remain atheoretical in kind. Next, we related the issue of ontological neglect to reduced scope for explanation and understanding.

REDUCED SCOPE FOR EXPLANATION & UNDERSTANDING

A third tenet of positivism concerns prediction and explanation (Von Wright, 1971). Here, we come full circle with Leavitt et al.'s article. They refer to the aim of 'science' as being twofold: (i) predicting variance and (ii) providing explanation for the predicted variance. While this is consistent with positivism, they offer an incomplete image of the role of social science, and it appears internally inconsistent too when one considers their article in toto.

It is incomplete because the branch of social science concerned with understanding (or verstehen) of phenomena in their historical context, or the "re-creation in the mind of the scholar of the mental atmosphere, the thoughts and feelings and motivations, of the objects of his [or her] study" (Von Wright, 1971: 6), is not recognized in the article. But it matters, because it underlines that both participants and researchers are entwined as co-producers of knowledge. The researcher attempts to establish that recreation through empathic probing designed to better understand the intentions of participants in their relative and local context (as per constructivisim), or in their social, political, or economic context as crystallized over time (as per critical theory, see Guba & Lincoln, 1994). This is consistent with the etic/emic dilemma in social science[2]. Also, while ML may screen large digital qualitative data sets, it can only ever analyse data that are 'out there at a given moment in time'. It cannot react to subtle changes in facial expressions, fluctuations in intonations, speech pauses, or nervous finger tapping on the desk that would prompt the researcher to ask a different question, or to ask the question differently, in response to these cues. Doing so

[1] See https://www.ndr.de/fernsehen/sendungen/panorama3/Polizei-nennt-Nationalitaeten-regional-sehr-unterschiedlich,polizeimeldungen102.html , accessed 23 March 2021.

[2] The etic, or outsider, perspective applied to an inquiry by a researcher "may have little or no meaning within the emic (insider) view of the studied" subject(s) as hand (Guba & Lincoln, 1994: 106). Qualitative data thus serve to reveal emic views.

would also entail a different response from participants. Thus, what is the meaning of 'data points' (i.e., specific observations), if we do not understand their contextual origin?

But the message is also internally inconsistent in their article. On the one hand, Leavitt et al. recognize the limits of ML in relation to being able to offer explanation. In their words, "algorithms generated by ML are optimized for detecting patterns, but generally fail to explain 'why' such patterns occur". However, we argue that this caveat gets crowded out in the remainder of the article, which exerts much space on touting the benefits of ML. Thus, to better inform future decisions on the application of ML to deductive, abductive and inductive research, it is crucial to elaborate that, in the case of more advanced ML algorithms, we no longer understand precisely how ML algorithms go about fulfilling their performance criteria, because they are essentially 'black boxes' in their processing of data (Lindebaum et al., 2020). What concerns us is that the calculus informing ML generated outputs is often even incomprehensible to its creators. Where does that leave our ability to explain social phenomena? How much at ease can or should we feel in 'discovering' intriguing news 'facts' that we cannot fully, or at all, explain? What is the use of developing a "tolerance for surprise results" when we cannot explain, much less understand, social phenomena? This exactly pertains to Suddaby's (2014) caution about 'dustbowl empiricism', because in the absence of a conceptual framework, dustbowl empiricism is likely to fail. That failure is due to conceptual frameworks being relegated to the backstage, rendering theory more implicit. When theories are implicit, "they discourage researchers from asking fundamental questions about the assumptions that underpin knowledge and the methods used to acquire knowledge" (Suddaby, 2014: 408). Therefore, when Leavitt et al. argue that knowledge generation in OT can powerfully proceed with the aid of ML if the latter is matched with theory, we discern a fundamental tension between their advocacy and Suddaby's (2014) concerns around the atheoretical nature of dustbowl empiricism.

In sum, Leviatt et al. have provided a timely contribution on the role of ML in OT. Yet, the ontological neglect and reduced scope for explanation (especially in terms of deductive traditions) and understanding (especially in terms of inductive traditions) that follows the use of ML puts some strain on the authors' synergetic proposal that ML can advance if matched with theory. Accordingly, we are not convinced by their claim that "ML can out-predict what theory-driven science is currently capable of" (for advocacy of theory-driven science, see Bartunek, 2020). Thus, the boundary has to be applied that any such effort concerns prediction only, where prior knowledge is harnessed to discourage atheoretical efforts and avoid post-hoc theorizing. To foster explanation and understanding through use of ML would require ML being capable of perfectly imitating the human mind in all its diversity and scope for spontaneous, creative and fresh insights. Thus, whether or not this obstacle can be overcome is a matter for computer scientists to resolve, and for now outside the theoretical conundrums we often grapple with. While we are open to technological innovations, we are not there yet, and perhaps may never be.

REFERENCES

Balasubramanian, N., Ye, Y., & Xu, M. 2020. Substituting Human Decision-Making with Machine Learning: Implications for Organizational Learning. Academy of Management Review.

Bansal, P., Smith, W. K., & Vaara, E. 2018. New Ways of Seeing through Qualitative Research. Academy of Management Journal, 61(4): 1189-1195.

Bartunek, J. M. 2020. Theory (What Is It Good For?). Academy of Management Learning & Education, 19(2): 223-226.

Guba, E. G., & Lincoln, Y. S. 1994. Competing paradigms in qualitative research. In N. K. Denzin, & Y. S. Lincoln (Eds.), Handbook of qualitative research: 105-117. Thousand Oaks: Sage.

Lawson, T. 2019. The Nature of Social Reality - Issue in Social Ontology. New York: Routledge.

Leavitt, K., Schabram, K., Hariharan, P., & Barnes, C. M. 2020. Ghost in the Machine: On Organizational Theory in the Age of Machine Learning. Academy of Management Review.

Lindebaum, D., Vesa, M., & den Hond, F. 2020. Insights From "The Machine Stops" to Better Understand Rational Assumptions in Algorithmic Decision Making and Its Implications for Organizations. Academy of Management Review, 45(1): 247-263.

Lindebaum, D., & Wright, A. L. 2021. From the editors: Imagining scientific articles and essays as productive co-existence. Academy of Management Learning & Education.

Moser, C., den Hond, F., & Lindebaum, D. 2021. Exemplary Contribution: Morality in the age of artificially intelligent algorithms. Academy of Management Learning & Education.

Pratt, M. G., Kaplan, S., & Whittington, R. 2020. Editorial Essay: The Tumult over Transparency: Decoupling Transparency from Replication in Establishing Trustworthy Qualitative Research. Administrative Science Quarterly, 65(1): 1-19.

Suddaby, R. 2014. Editor's Comments: Why Theory? Academy of Management Review, 39(4): 407-411.

Von Wright, G. H. 1971. Explanation and Understanding. New York: Cornell University Press.