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Autonomous Human Machine Teams: Data Dependency for Artificial Intelligence (AI)

William Lawless

Paine College, 1235 15th Street, Augusta, GA USA

ABSTRACT

The reliance on concepts derived from observations in laboratories combined with the assumption that concepts and behavior are one-to-one (monism) have impeded the development of social science, machine learning (ML) and belief logics by restricting them to operate in controlled and stable contexts. Even in open contexts, using ideas developed in laboratories, despite using well-trained observers to make predictions about the likelihood of outcomes in open contexts, using the same concepts and assumptions, in 2016, Tetlock and Gardner's "superforecasters" failed to predict Brexit (Britain's exit from the European Union) or Trump's presidency. Similarly, in 2022, using traditional techniques, the CIA's expert observers and the Russian military planners both mis-judged the Ukranian people by claiming that Russia's army would easily defeat Ukraine. Providing support for overturning these concepts and assumptions, however, in 2021, the National Academy of Sciences made two claims with which we fully support. First, the Academy had warned that controlled contexts are insufficient to produce operational autonomous systems. We agree; by studying real-world contexts, we have concluded that the data derived from states of social interdependence not only create data dependency, but also that interdependence is the missing ingredient necessary for autonomy. Second, a team's data dependency increases by reducing its internal degrees of freedom, thereby reducing its structural entropy production; this situation of heightened interdependence explains the Academy's second claim that the "performance of a team is not decomposable to, or an aggregation of, individual performances," consequently providing corroboration for our new discipline of data dependency. We extend the Academy's claims by asserting that the reduction of entropy production in a team's structure (SEP), indicating the fittedness among team members, represents a tradeoff with a team's performance, reflected by a team's achievement of maximum entropy production (MEP).

Keywords: Data dependency, Human-machine teams, Autonomy, Interdependence, Structural and performance entropy production

INTRODUCTION

Concepts and assumptions derived from observations and laboratories have restricted social science, machine learning (ML) and belief logics to operate in controlled and stable contexts; even still, however, by using hand-picked observers who were also well-trained in the laboratory to make predictions for the outcomes of social events occurring in open contexts, Tetlock and Gardner's (2015) "superforecasters" failed to predict Brexit or Trump in 2016 (Lawless et al., 2019); similarly, Western Russian expert observers (e.g., Jones & Wasielewski, 2022), along with Russian military planners (Risen & Klippenstein, 2022), misjudged that Russia's army would easily defeat Ukraine.

In contrast, the National Academy of Sciences (Endsley et al., 2021) has warned that controlled contexts are insufficient to produce operational autonomous systems, in particluar, for human-machine teams. We agree; by studying real-world contexts, we have concluded that interdependence is the missing ingredient necessary to achieve autonomy. Interdependence explains the Academy's second claim that the "performance of a team is not decomposable to, or an aggregation of, individual performances" (Endsley et al., 2021, p. 11).

We explain the Academy's second claim about disaggregation by noting that the data dependency (Davies, 2020) among teammates is reflected by the reduction in the degrees of freedom among them and the internal information needed to transmit and share each agent's status (e.g., a simple grunt is sufficient to alert a teammate; from Sliwa, 2021). With significantly less information needed than independent individuals can provide, these two reductions account for the failure of belief logics facing uncertainty or conflict in the field (e.g., Mann, 2018), yet recommendations to minimize interdependence persist (with experiments, see Kenny et al., 1998; for organizations, see Conant, 1976), even though the literature indicates that humans live their lives in states of interdependence (Jones, 1998), even though the source of innovation is the interdependence between culture and technology (de León et al., 2021, and even though the best science teams have been found to be highly interdependent (Cummings, 2015).

But, in addition, social science has had great difficulty replicating concepts based solely on observations of individuals alone (Nosek, 2015); e.g., the concept of implicit racial attitudes has been found to be invalid (Blanton et al., 2009); worse, explicit treatment in an attempt to change implicit racial attitudes appears to have had negligible effects (reviewed in Singal, 2023). This situation has led us to argue that users of the traditional models of teams (e.g., Cooke & Hilton, 2015) should overturn these assumptions because the independent data collected by observations alone, especially based on laboratory methods and the additional assumption that the cognitive model subsumes behavior (Thagard, 2019), cannot recreate whatever social event is being observed (viz., Shannon's, 1948, information theory and i.i.d. data preclude social interdependence; for a fuller discussion of these issues, see Schölkopf et al., 2021).

Mutual dependency is an interdisciplinary concept: In quantum mechanics, a knowledge of the whole precludes a knowledge of the parts (Schrödinger, 1935), a concept also fundamental to social psychology (i.e., the concept of the whole being larger than the sum of its parts was freely used by the founder of the discipline of Social Psychology, Lewin, 1951), and systems engineering also used the concept of the whole and its parts (Walden et al., 2015); however, System Engineers have begun to refer to this phenomenon as "emergence." But unlike Shannon (1948) information (for its use in organizations, see Conant, 1976), dependency in data poses a formidable challenge theoretically, mathematically, for engineering and information fusion systems, and the associated disciplines that depend on intuition, interpretation and meaning (e.g., for a review, see Speaks, 2021); viz., philosophy, economics and social science.

Despite these challenges, we have succeeded by treating cognition interdependently with behavior in open contexts to find that minimum team structural entropy allows a team to produce maximum team performance (Lawless, 2022a, b, c, d); and by treating beliefs as imaginary, we have rediscovered the value of debate to reduce the uncertainty and conflict that autonomous systems must be able to confront in open contexts. Regarding debate, from the U.S. Supreme Court (1970): "cross-examination [in the courtroom is] the 'greatest legal engine ever invented for the discovery of truth"'; regarding the value of appeals, from Justice Ginsburg (2011, p. 3), competing views provide an "informed assessment of competing interests"; and, in the aftermath of a tragic drone strike in Afghanistan in August 2021, from the Department of Defense (2021), "red-teaming" challenges the decisions of humans when operating in a state of heightened emotion while they are attacking targets on the ground with drone machines in combat.

Our model for autonomous human-machine teams leads us to expect that an AI machine operating interdependently with a human as a teammate, jointly challenging each other's beliefs about reality while shaping shared experiences, has a better chance to operate autonomously in open contexts. Our model exploits interdependence by requiring that teams engage in tradeoffs for agent fittedness. Surprisingly, by adding boundaries within which uncertainty and conflict could be minimized during operations allows logic to return in part, justifying Simon's (1989) bounded rationality (e.g., roundabouts with traffic; robotic surgery; no fly zones in combat; the context dependency of machine learning; and bounding uncertainty in the courtroom).

To apply Simon (1989) to the courtroom, we note that to reduce the uncertainty associated with circumstantial evidence in a criminal case, a courtroom often has two opposing officers of the court (a prosecutor and a defense attorney) face off before a judge and a jury to determine the innocence of an individual charged with a crime. The environmental uncertainty involved is further narrowed by rulings from the judge and the judge's instructions to the jury. Consequently, facing uncertainty, we conclude that debate is the primary means to ground truth (for an application of these ideas to Artificial Intelligence (AI), see Cooke & Lawless, 2021; Lawless et al., 2019; NSC, 2021; Sofge et al., 2019; and more recently, see Lawless et al., 2023).

DEVELOPING AN EQUATION TO ACCOUNT FOR THE TRADEOFFS BETWEEN THE STRUCTURE AND PERFORMANCE OF A TEAM

Briefly, we model with our equation between the uncertainty in a team's structure, ΔSEP, and its maximum entropy performance, ΔMEP:

$$\Delta SEP * \Delta MEP \geq C \quad (1)$$

Thus, as the uncertainty in a team's structure reduces to perfect coherence in the limit, its performance is allowed to become a maximum. With Equation (1), we have modeled uncertainty and conflict (where logic fails; Mann, 2018); deception; blue-red team challenges; emotion (higher emotion reduces a team's options); vulnerability; mergers (the random effects of fittedness); and innovation. In addition, Equation (1) indicates that uncertainty in a team's structure depends on how the members of a team fit together, not whether they believe they have a shared model or not, supporting the finding by the National Academies of Science that disaggregation is unable to assign individual contributions to the individual members of a team by observing a team's performance (Endsley, 2021, p. 11).

There is always a danger of autonomous teams being overseen by authoritarian regimes. But, what we have found is that authoritarians first shut down free speech, which requires them to stop or interfere with interdependence. But impeding, interferring or stopping interdependence impedes or slows innovation, requiring an authoritarian regime to steal in order to be able to innovate (Lawless, 2022d). Why do republics with strong checks and balances like the United States or Israel often lead in innovation (Lawless, 2022c)? We have found that strong republics promote the noise arising from "the circulation and mixture" of opposing ideas (Puchner, 2023), characterizing the sources of debate and conflict among ideas and concepts associated with free speech and innovation..

CONCLUSION

In this brief review, we have sought to highlight that traditional social science offers little help to produce the mathematical models of autonomy that will be needed to design and operate human-machine teams and systems. In contrast, by building upon the finding of disaggregation cited by the National Academies of Science (Endsley, 2021, p. 11), we have succeeded by exploiting the effects of interdependence under uncertainty, not the internal uncertainty in a model, but the uncertainty that is a significant part of open environments, and after much effort (Lawless, 2022a, b, c. d), we have begun to make significant strides in producing a model that works in the open (Lawless et al., 2023), away from the laboratory. In concluion, the results we have reviewed herein support the idea of a new discipline of data dependency.

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