

COVID-19 and the Futures of Machine Learning

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Perspective

TRENDS IN SCIENCE CHANGE with the sands of time and ever-shifting sociotechnical contexts in which innovations emerge. Consider, for example, the statement “big data will transform medicine” that was trending over the past decade in numerous science and technology communities. Although big data remain a cornerstone of medical research, there is a greater cognizance that sense making from big data—clinically, ecologically, and societally—is what adds value for health and society (Arga, 2019; Azodi et al., 2020; Gov and Arga, 2017; Gulfidan et al., 2020). New analysis and sense-making tools such as machine learning that can harness big data toward various applications have, therefore, emerged recently, as epitomized by expressions such as “digital transformation of medicine by machine learning” or “artificial intelligence redefining health care.”

Let us place these trends in a broader context of the history of systems science, new bottlenecks in the 21st century innovation ecosystems, as well as the current Corona Virus Disease 2019 (COVID-19) pandemic.

First, and looking back, it is helpful to remember that the rate of data production has exceeded the growth of the capacity for data analysis and computational power predicted by Moore’s law (Moore, 1965). That is, the innovation bottlenecks have been shifting from data availability to data analysis and sense making informed by the broader context of clinical and ecological metadata (data about data). For sense making from big data in a new age of machine learning and related approaches such as artificial intelligence, metadata have become crucial and timely more than ever (Özer et al., 2020; Turanli et al., 2018). It is in this overarching context that machine learning and artificial intelligence-driven algorithms and decision-making tools have been emerging in the second decade of the 21st century, be they for personalized/precision medicine, automation of health care, or applications in environmental sciences and ecology.

Second, looking into the third decade (2020–2030) and beyond in the 21st century, it is noteworthy that machine learning differs from traditional algorithms in clinical decision making based on predefined rules. Machine learning produces new rules from the input big data. In some sense similar to the traditional regression models, machine learning seeks to identify a statistically meaningful and robust combination of input variables that predict outcomes and the

dependent variables such as disease susceptibility or drug efficacy and safety signals in complex data sets. An important distinction and advantage of machine learning are, therefore, its ability to evaluate large volumes of putative predictor variables even when they (predictors) outnumber the observations and the sample size (Turanli et al., 2019). Machine learning can carry out analyses in ways that are nonlinear and interactional as well.

For example, the presently available clinical prognostic models such as Apache, Gleason, and PASI, among others, capture a relatively limited number of variables, whereas machine learning surpasses in the number of variables and the types of nonlinear analyses performed. Such differences allow machine learning to perform real-time analyses of complex and diverse data sets that differ in data volume and type and be they static or dynamic data. The machine learning approaches to sense making from highly diverse, heterogeneous, and complex electronic health records in tandem with various physiological, genomic, proteomic, and demographic predictor variables for clinical outcome forecasts would be an apt example to these ends.

With the COVID-19 pandemic, and of immense consequence for current times and future responses to pandemics, are the capacities of “Scale,” “Speed,” and “Surge,” in both national and planetary contexts around the world. Machine learning, by virtue of its capacity to examine in real-time highly diverse data sets, can help build resilience in planetary health systems in response to the present and future pandemics. Interestingly, machine learning might also prove useful in the allocation of COVID-19 aid to those who need it the most in society (Blumenstock, 2020). To succeed in machine learning approaches for the pandemic response, there is a need for regional and global coordination, and that “Every effort learns from the failures and successes of the others. Transparent and open communication is the first step” (Blumenstock, 2020).

Machine learning and the attendant biosensors, big data, and digital health approaches can be conceptualized under the overarching framework of cyber-physical systems (CPS) (Özdemir, 2019). CPS bring the virtual and physical worlds in greater proximity. Both the speed and scale of the intended beneficial effects and unintended consequences (positive and negative) of machine learning will differ in the virtual and physical worlds. This adds a new layer of complexity and opportunity to understand COVID-19 health care in the

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virtual/digital domain versus the classical physical/analog medical contexts. We can choose and pick, however, the machine learning applications and prospects that serve planetary health most optimally, whether they materialize in a virtual digital health context or analog traditional medical approaches.

As the COVID-19 pandemic evolves, all futures are plural and in the making, but the present time is singular. This point is important in that the futures are yet undecided for machine learning, depending on how we act now, and to what ends we use a new technology and analysis tool such as machine learning for COVID-19. It is useful to keep in mind that it is not the technologies that change society but rather the often opaque or invisible human values and motives that drive technologies. In this light, changes that occur in tandem with technology are sociotechnical. Technologies are created, built, and implemented by humans; examining the ends to which societies conceive and use technology can help develop foresight about the multiple futures awaiting machine learning (Frodeman, 2020).

Technology and Planetary Society

Detailed and nuanced accounts of the new ways to understand the societal repercussions of emerging technologies and ways to steer scientific discoveries toward democratic ends and responsible innovation are available elsewhere (Von Schomberg and Hankins, 2019; Von Schomberg, 2019). The knowledge of the democratic theory is helpful in this context (Lindblom and Woodhouse, 1993; Sclove, 2020) because machine learning and other technologies that aim, in part, to forecast clinical and ecological outcomes can also result in social control or concentration of power and pan-surveillance in planetary society (Koopman, 2017).

In addition, there are psychological and physiological dimensions of extreme digital connectivity and big data that machine learning relies on. For example, digital connectivity 24 h and 365 days a year has created a type of “attention economy” with potential negative effects on user health (Ward et al., 2017). Some studies suggest that the mere presence of one’s smartphone might potentially reduce cognitive capacity (Ward et al., 2017). Although the point of emphasis here is not smartphones *per se*, examining the social, physiological, psychological, and ecological dimensions of new technologies such as machine learning and smart algorithms is crucial so the technological change best serves the human and planetary health rather than *vice versa*.

Conclusions and Outlook

Machine learning specifically and the fields of bioinformatics, planetary health, and clinical decision making more broadly are in a watershed moment as we continue to face with the COVID-19 pandemic. The pandemic calls for real-time analyses of high dimensional and heterogeneous data sets. At this critical juncture, machine learning is poised to deliver scale, speed, and surge capacities in planetary health for efficient pandemic response.

Returning to the beginning of this perspective article, sense making with machine learning from big data and the CPS we are building as humanity crucially depend on the availability of robust and responsibly curated metadata. Only then we can fully make sense of big data and ensure that the machine

learning reaches its full potential and delivers on the enormous potentials it holds. The quality, veracity, and quantity of the big data that machine learning depends on are also crucial to the future success of the much anticipated intelligent decision-making algorithms. To these ends, major bottlenecks exist for metadata availability/standards, multi-omics data integration procedures and performance testing, and the limited quantity and quality of the input data.

Machine learning-driven intelligent algorithms stand to benefit and empower efficient responses to the COVID-19 pandemic while improving the prognostic models widely used in clinics around the world. This can help forecast COVID-19 health outcomes in diverse geographical and health systems settings. Machine learning will allow the planetary health scholars to move beyond employing linear relationships among a limited number of observations and thus help reduce diagnostic errors and unnecessary use of diagnostic tools through the development of rational algorithms. Indeed, the COVID-19 pandemic showed that digital health is invaluable, feasible, and not too far. The role of machine learning in medicine and digital health will continue to grow in the coming decade. Moreover, digital transformation in clinical medicine will find new applications in the course of the COVID-19 pandemic and thereafter.

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Abbreviations Used

COVID-19 = Corona Virus Disease 2019
 CPS = cyber-physical systems