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Public health response to the COVID-19 pandemic: the forecaster's dilemma and long-term consequences

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Abstract:

The global pandemic of COVID-19 exposed many flaws in public health systems, infrastructure, and the abilities of socio-political systems to interact, communicate, and act together to protect human health. For the data science professionals, the crisis pointed out where our priorities should be and what we should be able to do. These priorities include abilities to collect massive amounts of data of high fidelity, resolution, and quality; to exchange data and facilitate collaborative and transparent research; to process information in a timely fashion, and to present it clearly and comprehensively for a broad range of audiences. In my talk, I will provide examples of substantial accomplishments and persistent challenges and demonstrate the need and value for near-term forecasting and understanding the long-term consequences of the high-impact low-frequency events from a complex system thinking.

Keywords:
Complex systems; COVID-19; Forecasting; High-Impact Low-Frequency (HILF) event; Surveillance systems

1. Introduction:

The global pandemic of COVID-19 exposed many challenges in the abilities of socio-political systems to interact, communicate, and act together to protect human health. For the data science professionals, the crisis highlights the priorities for further improvements in collecting, processing, distributing, and presenting data, information, and knowledge.
The use of a complex systems approach and predictive modeling techniques are gaining a deserved recognition in public health and public health policy. Complex system thinking is a must for understanding the root causes, the processes, and the long-term consequences of the high-impact low-frequency events. The predictive modeling techniques are rapidly expanding their repertoire in the range of tools, data, and applications [1]. Ongoing research and our work demonstrate the potential of time series analysis, simulation, and combinatorial modeling for forecasting outbreak signatures using surveillance, hospital-based records, and novel data sources [2-9]. Yet the challenges and insufficient infrastructure severely limit our response and predictive capacities.

2. Methodology:

In this talk, I will review and provide examples of recently developed web-based data platforms, repositories, and dashboards at the local, national, regional, and global scales. I will use four main principles: Evidence, Efficiency, Emphasis, and Ethics, the so-called 4E-rules to access these platforms in terms of data compilation, analysis, and visualization quality. I will also define the emerging forecaster's dilemma, as an evolution of Type I and

Type II errors in a dynamic process when the proof of *no appearance* of HILF means controlling an outbreak, so when the crisis is avoided and the only evidence to point to success is in the cost of preparation [10].

3. Result:

In response to the COVID-19 pandemic, the local, regional, national, and global efforts resulted in numerous trackers, data repositories, and sources of information regarding the policy response to the crisis. Multiple models have been proposed to describe and examine the spread of COVID-19, and the factors associated with the transmission, severity, cure, etc. Data collected by public health laboratories contain the most granular and detailed information for case-specific investigation of disease rates, enabling the development of high-quality, high-fidelity, real-time, regionally focused predictive models. Yet, there is more to learn about lessons stemmed from the pandemics. The surfaced lessons pointed out that the scientific community exhibiting overall a steep learning curve on all aspects of dealing with an emerging infection; a system of rapid response with solid reliable data collection with modern technology; willingness to work in trans-disciplinary settings. The main challenges remain in risk communication, translating data to the general audience and policymakers, and developing predictive modeling capacity.

Most importantly we need to learn how to control an epidemic in real-time and protect the public in the future. In general, the forecast quality depends on the degree of data aggregation on the temporal, spatial, and demographic domains. Forecast quality could be assessed based on the six features (accuracy, reliability, balance the cost of Type1 and Type 2 errors, timeliness, sharpness, complexity). While many existing forecasts are providing some uncertainty measures, the important aspects of fidelity, such as reduction of bias and distortion introduced by lack of data or other factors, have rarely been discussed in literature or implemented in existing data platforms. The focus also should be shifted toward forecast sharpness or clarity so that predictions can be communicated to key stakeholders.

4. Discussion and Conclusion:

The complex system fields recognize the complexity of scale, uncertainty, and anticipation of unintended consequences – the critical concepts of modern thinking for solving public health problems. The complex system science is well-positioned to push forward the literacy of critical thinking, credibility, and trustworthiness desperately needed for modern governance. Nearly developed data platforms require a standardization of terms, concepts, and protocols to facilitate efficient data exchanges. Existing predictive approaches have limited capacity to produce up-to-date refined forecasts that can be customized for critical stakeholders, such as public health and healthcare professionals. Real-time local forecasts should enable continuous updating to address the ever-changing nature of the epidemic. Through our executive, professional, and academic visions and programs, we should call for action in setting new standards of gaining insights into what’s happening in the world, building capabilities and skills for solving modern challenges, promoting effective and objective science and scientific communication, considering ethical actions and long-term consequences.

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