The AI Epidemiologist

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Abstract

We propose a real-time approach for localized bio-surveillance and intervention to prevent new pandemic outbreaks. We aim to create an online method for highly-targeted, dynamic, localized lock-downs. We aim to demonstrate better efficacy plus lower cost as compared with larger-scale, blanket lock-downs and re-openings.

At any given time, there is high uncertainty about the state of the world (i.e., Who is infected? Who is contagious?), which must be determined from incomplete, anonymized, delayed data (e.g. test results, contact and location history). There are decisions which must be made under uncertainty (Who can go outside? Which businesses can open?), and hard resource constraints (We can only test 1000 people per day – who is most critical to test?). The uncertainty can be quantified (what is the *likelihood* each person is infected, even if we cannot test them, and how confident are we in this estimate?). This enables decisions to be made which maximize the usefulness of any new data received (e.g., testing people who may not have symptoms, simply because of who else they are connected to, and what information the test will reveal about the overall network).

This yields a sequential decision-making / optimal control problem: with limited knowledge and limited resources, what actions minimize economic and social costs? Costs include those due to actual infections (hospitalization expense, etc.) and due to prevention measures taken (quarantines causing unemployment and lost productivity). We frame this as a reinforcement learning (RL) problem, with agents (policy-makers, businesses, individuals) taking actions within an environment (a stochastic model of disease spread) to maximize reward (or minimize cost).

We are inspired by the AI Economist [1], which shows the potential of RL in designing dynamic tax policies to maximize a given socioeconomic objective. Along similar lines, we envision an "AI Epidemiologist" which can dynamically respond to an evolving pandemic situation, to maximize an objective function.

We also envision that such a platform may help expose which simulation parameters are most critical to model, and to resolve with high precision, thus helping prioritize efforts of the broader research community. With high uncertainty remaining in many numerical parameters (e.g. incubation period, case fatality rate, etc.), it remains unknown which parameters are most critical in projecting the large-scale behavior of an outbreak.* By putting these paremeters into a decision-theoretic context, we aim to determine which ones will have largest affect on our choice of response. This may be able to guide the scientific community as to which parameters are most worth resolving at greater precision. While typical sensitivity analysis tends to focus on which parameters affect the behavior of the *outbreak itself*, we instead propose to investigate which parameters affect the *optimal decisions* that an agent will make. This allows for the possibility that certain parameters, while they may affect disease spread significantly, may nonetheless have little affect on our response strategy.

I. Project Phases

This project would consist of any or all of the following components.

A. Simulation Environment

We propose using [2] as the underlying dynamics to simulate disease spread and the impact of interventions (but we are open to the intern using a different underlying simulator, either from within the EndCoronaVirus community or elsewhere). As a "warm-up", the intern would begin by running a few simulations in this tool, and making small changes to the simulation parameters (different disease dynamics, individualized travel patterns, different intervention measures, etc.) If the intern has deep interest in mobility dynamics and data collection, a larger task could involve integrating actual mobility data (e.g. from a source like SafeGraph—https://www.safegraph.com/) to capture realistic travel patterns, as opposed to the over-simplified travel assumptions currently being made.

B. Hand-Crafted Agent Policies

The intern would then begin investigating which intervention strategies (or "policies", in RL jargon) are the most effective in containing an outbreak, while conserving cost. Actions could include travel restrictions, contact tracing, mandatory quarantine, etc. We would hope to gain an intuitive understanding of which type of policy is likely to work best, by running a few simple examples.

C. Optimized Policies

The final and most ambitous stage would attempt to discover an *optimal* policy, as opposed to a hand-crafted one as described above. While the space of all possible interventions may in principle be small, there are likely to be continuous parameters (e.g. individual quarantine length, fraction of businesses shut-down, etc.), which can be optimized to achieve a better trade-off between containment and cost. We propose using model-based RL techniques to optimize these parameters—hopefully discovering policies that outperform anything we construct by hand. There may be value in incorporating function-approximation techniques (e.g. neural networks), in a so-called "deep RL" set-up.

Success here may require significant re-factoring of the simulation environment, in order to most effectively leverage existing libraries for ML and RL. One example could include wrapping an existing COVID simulation tool (e.g. [2]) into an OpenAI Gym environment (https://gym.openai.com/), to enable "plug-and-play" experimentation with standard RL algorithms.

*https://www.endcoronavirus.org/projects-1/what-models-can-and-cannot-tell-us-about-covid-19

II. Goals

The ideal outcome of this project would be a clear demonstration of certain interventions being more effective than others—possibly in ways that were not obvious initially. Demonstration of an online, dynamic/learned policy doing better than any static, human-designed policy would be quite notable; though, more feasibly, identifying the best policy from a set of plausible, hand-crafted policies would be worthwhile. Results will be presented in an ArXiV pre-print; perhaps along with submission to a machine learning conference, should we discover a highly compelling result. At the minimum, we will aim to write a pre-print and blog-post, possibly with a demo video to further illustrate the results. The overarching goal is to push for a more rigorous framework for optimal containment/mitigation of pandemics in general, both for COVID-19 and beyond. If the approach appears to be successful, we may consider future, hypothetical scenarios (a virus that's more contagious but less deadly; has a longer incubation period, etc.), and attempt to create a generalized approach for pandemics with different infection dynamics.

III. Learning Opportunity

This is a chance to use a variety of skills, including simulation, software engineering, and machine learning, to experiment with more rigorous approaches to pandemic response. An intern will have significant choice as to which problem(s) to focus on: data collection, software architecture, model-tuning, etc. The other researchers involved will be working on this project as well; so the intern need not work on all aspects mentioned above. Assuming stages 1 and 2 proceed well, stage 3 will offer significant opportunity to go beyond typical machine learning, and delve into reinforcement learning: an increasingly popular problem-framing which subsumes both supervised and unsupervised learning. We will be learning this area together (my knowledge in the field is mainly theoretical, with brief practical exposure that I plan to ramp up in the coming weeks).

Depending on the findings of the project, and the overlap in interests between the intern and the other researchers involved, there may be occasion to go "under-the-hood" with some of the simulation dynamics as well. The simulator in [2] uses Bayesian optimization to infer underlying disease parameters from publicly collected data, using the https://gpytorch.ai/ and https://botorch.org/ libraries. There may be occasion to think creatively about how we use these core inference/optimization algorithms, or others, in order to accomodate different types of data or interventions.

References

[1] Stephan Zheng, Alexander Trott, Sunil Srinivasa, Nikhil Naik, Melvin Gruesbeck, David C Parkes, and Richard Socher. The ai economist: Improving equality and productivity with ai-driven tax policies. *arXiv preprint arXiv:2004.13332*, 2020.

[2] Lars Lorch, William Trouleau, Stratis Tsirtsis, Aron Szanto, Bernhard Schölkopf, and Manuel Gomez-Rodriguez. A spatiotemporal epidemic model to quantify the effects of contact tracing, testing, and containment. *arXiv preprint arXiv:2004.07641*, 2020.