

Predictive Monitoring of COVID-19

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Abstract

During the current COVID-19 pandemic, there have been many efforts to forecast the infection cases, deaths and other medical indicators, with a variety of statistical or epidemiological models. Some forecasting projects have influenced policies in some countries. However, the prediction of the COVID-19 pandemic as a “wicked problem” is uncertain by nature. The uncertainty is rooted in the many unknown unknowns about the contagious virus itself and the complexity, heterogeneity and dynamism of human behaviours, government interventions and testing protocols. The wicked and uncertain nature of this pandemic makes the intent for prediction accuracy misleading. Herein, we propose to be cautious about the intent for “accurate” predictions or models, but instead, to explore the potentials of “predictive monitoring” with the aim to capture and make sense of the changes in theoretical predictions for meaningful signals of the uncertainty and changes in the real-world scenarios. Such signals from predictive monitoring are expected to make the planning, behaviours and mentality at the present time more “future-informed” and possibly initiate and guide pre-cautionary actions now to shape the real future.

Introduction

Since the outbreak of COVID-19 in January 2020, researchers around the world have adopted or developed various data-driven models to predict or forecast the next developments and trends of COVID-19 in different countries or regions. Noticeable efforts include the continually updated forecasts by Institute of Health Metrics and Evaluation (IHME) at University of Washington [1] and MRC Centre for Global Infectious Disease Analysis at Imperial College London [2], among others. Table 1 is a list of publicly accessible COVID-19 forecasting programs. Some forecasts focus on future deaths and hospitality needs [3,4,5] and infection cases and peaks [6,7,8], while others focus on the impact of social distancing, travel restrictions, and mitigation and suppression strategies [7,9,10].

Table 1. Public COVID-19 forecasting initiatives around the world, as of May 11, 2020

Organization	URL	Methods
Imperial College London	https://www.imperial.ac.uk/mrc-global-infectious-disease-analysis/covid-19/	Mechanistic transmission models
University of Geneva, ETH Zürich & EPFL	https://renkulab.shinyapps.io/COVID-19-Epidemic-Forecasting/	Statistical models
Massachusetts Institute of Technology	https://www.covidanalytics.io/projections	Modified SEIR model
Los Alamos National Laboratories	https://covid-19.bsvgateway.org/	Statistical dynamical growth model
The University of Washington, Seattle	https://covid19.healthdata.org/projections	Statistical model

The University of Texas, Austin	https://covid-19.tacc.utexas.edu/projections/	Statistical model
Northeastern University	https://covid19.gleamproject.org/	Spatial epidemic model
University of California, Los Angeles	https://covid19.uclaml.org/	Modified SEIR model

Some published studies attempted to validate the accuracy of specific prediction methods [3,4,5,6]. However, even the most cited forecasting method from the IHME has been found with model design issues [5,11] and that for 70 percent of time the actual death numbers fell outside its next-day predictions' 95 percent confidence intervals [12]. The IHME team later revised the model [4] but the prediction errors remain high. In any case, researchers are learning and improving the methods and tools on the go in order to make more and more accurate predictions on the next developments of the COVID-19 pandemic [12]. Despite the intrinsic complexity and uncertainty of COVID-19 predictions, some efforts have influenced policies or informed policy makers in some ways [13, 14].

The uncertainty that we face for work and life planning during the COVID-19 pandemic makes data-driven predictions desirable. However, it is also naturally difficult to do the predictions well. The fundamental challenge is rooted in the nature of the COVID-19 pandemic as a classic "wicked problem", formulated by Horst Rittel and Melvin Webber [15] almost 50 years ago. The wicked problems are those novel, unique, complex and evolving problems with incomplete, contradictory, and changing requirements that are often difficult to recognize. Some of the characteristics of wicked problems are below:

- Often strongly associated with moral, political, economic and professional issues;
- Involve sets of complex and interacting issues, evolving in a dynamic social context;
- Cannot be solved with traditional analytical approaches;
- Involve stakeholders with different views to understand and treat the problem;
- Have no solution that can be objectively tested or evaluated as being correct or wrong;
- It makes no sense to talk about "optimal" solutions;
- Every attempt to solve a wicked problem is a "one-shot operation";
- The effort to solve one aspect of a wicked problem may create other problems.

Wicked problems contrast with a "tame problem", which has stable agreements and requirements and can be solved by choosing and applying the correct methods. The COVID-19 pandemic is clearly wicked and naturally unpredictable in a general sense. However, this does not mean objective analyses and predictions based on science and data are totally useless. It is just that the traditional mindset for optimality and accuracy in modelling and predictions should be avoided in this context. For example, in some of the COVID-19 forecasting efforts [3,4,5,11,12], there exist obvious intents or goals to optimize the prediction models based on margins of errors, confidence intervals, hold-out sample testing, and other standard statistic techniques. Without a definitive correct answer, talking about errors and confidence intervals makes no sense and might create "false sense of certainty". Furthermore, when real-world scenarios in terms of government interventions and human behaviours are dynamically changing, it would be simply naïve and probably wrong to evaluate the accuracy of a model trained with data from a past scenario in terms of how accurately it hits the "facts" in a later and different scenario.

Instead, the wickedness of COVID-19 demands an experimental mindset, heuristic approach, and creative strategy to derive data-driven insights. Here, we experiment a heuristic approach, namely “predictive monitoring”, to address the wickedness of the context and make use and sense of the untestable data-driven predictions to understand uncertainty and capture changes, instead of certainty or accuracy. Predictive monitoring means the monitoring of the changing predictions continually updated with the latest data, jointly with the monitoring of the actual history developed to date. The fundamental assumption for predictive monitoring is that real-world scenarios are changing and thus predictions on the same variable should also change over time rather than staying fixed. Here, changes in updated predictions are not viewed as errors or inaccuracy, but valuable signals of the changes in the present real-world scenarios which are often difficult to recognize. Moreover, with acknowledging the complexity of the reality, abstractness of the model and the limitation of data, we focus predictive monitoring on patterns, such as the shape of the pandemic life cycle curve, and theoretical future events, such as the ending of the pandemic, instead of exact numbers of infection cases.

Therefore, predictive monitoring differs fundamentally from the common forecasting practices that attempt to make a prediction now that can be accurate about the future. Traditional prediction practices subconsciously view the future as fixed and are done like weather forecasts where the future weather cannot be changed by the humans as stakeholders. However, the future of COVID-19 is not fixed and can be changed by human behaviours and government interventions. Predictive monitoring is aimed to detect such changes and understand the evolution as it evolves. In addition, predictive monitoring also differs from the common monitoring of actual past cases of infection, recovery and death, which may stimulate reactive and responsive actions. By contrast, predictive monitoring may inform, initiate and guide future-informed planning, policies and actions to shape the real future. Table 2 presents a taxonomy that explicates the differences of predictive monitoring from traditional prediction and monitoring.

Table 2. The taxonomy for predictive monitoring, traditional prediction, and monitoring

		What Value Does It Deliver?	
		Future-Informed	Past-Informed
When Is It Suitable?	Wicked Problem	<i>Predictive Monitoring</i>	<i>Monitoring</i>
	Tame Problem	<i>Prediction</i>	

The Predictive Monitoring Experiment

- Theory

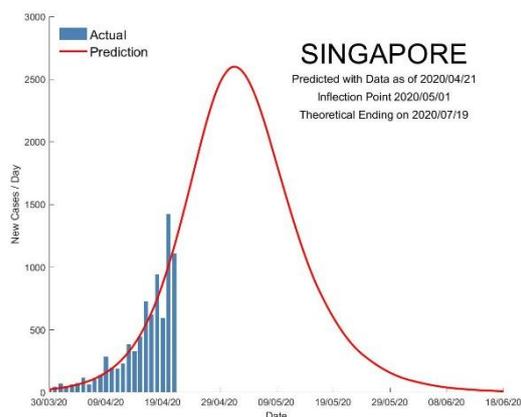
We experimented predictive monitoring in the realistic context of the on-going COVID-19, in order to explore its potentials and develop guidelines and strategies for the right use of it.

To run the experiment, the first is to choose a prediction model and data source, before we can update and monitor the predictions with daily new data coming in over time. The propagation of infectious diseases often follows a life cycle pattern, from the outbreak to the acceleration phase, inflection point, deceleration phase and eventual ending. Such a life cycle is the result of the infection process, property of the virus, the nature of a population and the adaptive and countering behaviours of agents including individuals (avoiding physical contact) and governments (locking down cities) in the population. However, the pandemic life cycles vary by countries (or regional populations), and different countries might be in different phases of the life cycles at a same point in time.

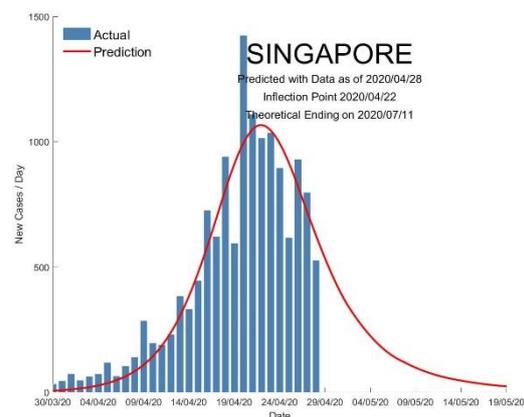
For instance, on April 21, in Singapore, Prime Minister Hsien-Loong Lee announced the extension of circuit breaker to June 1 in response to the spikes of COVID-19 cases. On the same day, Prime Minister Giuseppe Conte announced the plan to reopen businesses in Italy from May 4. Ideally speaking, such decisions and planning would be rationalized by well knowing where our own country is in its own pandemic life cycle, when the turning point is coming if it has yet come, and when the pandemic will end. Adjustments may be made according to the changes in the estimations and predictions on these fronts. The basis for such actionable estimation is the pandemic’s overall life cycle.

- Model

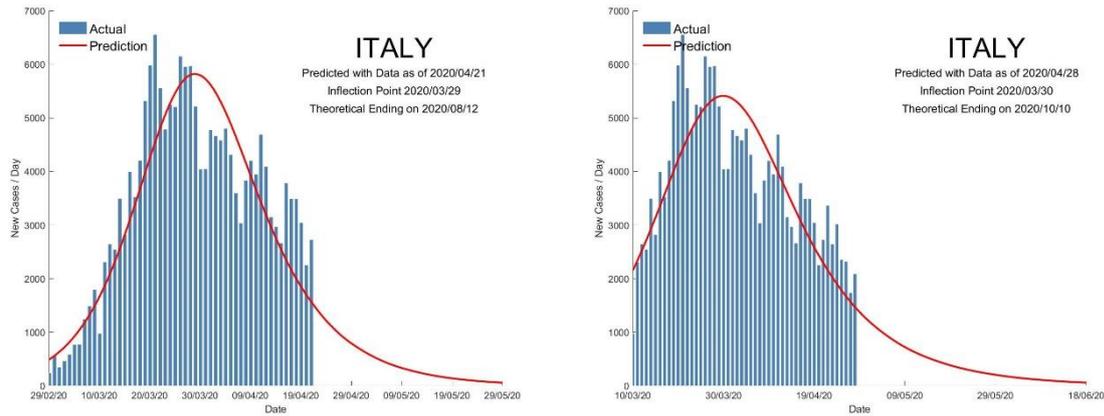
The pandemic life cycle pattern is expected to appear as a S-shape curve when one plots the accumulative count of infection cases over time or equivalently as a “bell-shape” curve of the daily counts over time (see examples in Figure 1). Note that the bell here is not expected to be symmetrical with no expectation of a normal or Gaussian distribution, but a skewed long tail to the right. Such patterns as well as the underlying dynamics have been well studied in various domains including population growth, diffusion of new technologies in the society and infectious diseases, and have theoretically established mathematical models, such as the logistic model that describes a general life cycle phenomenon and the SIR (susceptible-infected-recovered) model [16,17,18] that describes the dynamic epidemic process of the spread of infectious diseases.



A) Singapore as of April 21



B) Singapore as of April 28



C) Italy as of April 21

D) Italy as of April 28

Figure 1. Continuous Data-Driven Estimations of COVID-19 Life Cycle, Turning and Ending Dates for Singapore and Italy as of April 21 versus April 28, 2020

The SIR model is employed in this experiment for a few reasons. One, it is context-specific and models the dynamic process of inflections in a population over time. Second, it requires simple data inputs that are publicly available. Third, there are open source computer codes available for quick adoption. Here we will not repeat the details of the SIR model in this paper, which can be easily found in many mathematics textbooks. Essentially, the SIR model use three ordinary differential equations to describe the dynamic flows of people between three compartments of a population: S for the number of susceptible people, I for the number of infectious people, and R for the number of removed people (either recovered, died or immured). The SIR model incorporates two main parameters, beta and gamma. Gamma is the number of days one is contagious and a property of the virus. Beta is the average number of people infected by a previously infected person and is related to not only the interaction patterns of people in the society (which social distancing can influence) but also the infection process property of the virus.

- Implementation

The values of these two parameters determine the shape of an infectious disease's specific life cycle curve for a population. In particular, the model, which is a system of three differential equations for S, I and R in its original form, can be reduced to one function about the total infection count, or equivalently the daily new infection counts. This key variable is the sum of I and R and has publicly available data reported by official channels every day. Please refer to the paper [19] by Milan Batista for the model reduction. Therefore, only the data of the daily new infection cases over time (which can be used to derive the accumulative counts, alternatively) are required to regress the key parameters and other constants and thus train a model to derive the overall pandemic life cycle curve.

Batista also developed open-source computer codes to implement the regression [20]. In our experiments, we applied the codes of Batista to the data of daily new COVID-19 cases for each country from "Our World in Data" [21] to regress the parameters and constants of the original SIR model. Note that, more sophisticated derivative versions of the SIR model with more compartments, such as the SEIR model, have also been used in COVID-19 forecasting (such as ref. [6] and several listed in Table 1), but additional increased equations

and parameters also require more sophisticated data inputs or parameter estimates. Regressions are run for individual countries and updated daily with the newest infection case count data becoming available daily. Not the data for all countries can produce statistically meaningful regression results. Only the countries with satisfactory goodness-of-fit between model and data as measured by R^2 greater than 0.8 are accepted, analysed and reported. For these countries, the regressed model for each of them is used to estimate the full pandemic life cycle and plot the life cycle curve.

Makes Sense of Prediction Changes via Monitoring

- Monitor Predictions and Actual Data Together

As shown in the examples in Figure 1, the initial segment of the curve is fitted with the data to date and the remaining segment of the curve is “predicted”. With the estimated full life cycle curve, one can easily observe which phase of the pandemic life cycle a specific country is in (with actual data plotted together), when the inflection point (the peak in the bell-shape curve) is coming (for the interests of the countries still in the accelerating phase), and when the pandemic will end (for the interests of all countries). Our predictive monitoring is focused on such high-level transitioning characteristics of the pandemic’s total life cycle [7], instead of the specific numbers of accumulative or daily cases on a specific day, which the traditional forecasting efforts ([3,4,5] and some others in Table 1) try to predict with confidence.

The inflection point of the pandemic life cycle curve is specific and appears as the peak in the bell-shape curve. However, estimating the “ending date” is not straight-forward and may be done differently for different considerations. Most theoretically, one can define the pandemic’s end date as the day with the last infection case of the pandemic, and thus operationalize the estimation of the end date as the day with the last predicted infection at the right most end of the estimated pandemic life cycle curve. Alternatively, one may consider an earlier date when predominately most predicted infections have been actualized, e.g., the case of Australia as of May. The total predicted epidemic population size is the area under the entire curve. So, one can monitor the predicted date to reach 99% of the total expected cases, or the predicted date to reach 97% of the total expected cases. For flexibility, one may also simply exploit the estimated life cycle curve, especially its right most tail segment, to screen and sense when the pandemic gradually vanishes to which extent.

It is noteworthy that the bell-shape curve (of daily cases, instead of the S-shape of accumulative cases) is chosen to visualize the life cycle because it allows easy detection of the inflection point as the peak of the curve to distinguish countries in acceleration and deacceleration phases. For instance, Figure 1A visually reveals on April 21 Singapore was still in its acceleration phase, whereas Figure 1C shows Italy has passed its inflection point. At the time, the estimated “future” turning date (i.e., the inflection point of the curve) for Singapore would be May 1. However, as shown in Figure 1B, on April 28, Singapore has already past its inflection point based on the updated curve with newer data from April 21 to 28, earlier than the turning date predicted on 21 April (in Figure 1A). In contrast, from April 21 (Figure 1C) to April 28 (Figure 1D), the updated curve of Italy is extended more toward the right and points to later theoretical ending dates.

- Capture Changes

These changes are discovered through predictive monitoring of the actual developments and estimations together holistically. We continually monitor the predictions, not hoping the previous predictions to be true or accurate later when the real “future” comes, but for detecting the changes of the predictions over time. From a traditional perspective, the difference between a future prediction and a previous one for the same variable would be considered a bad thing and a proof of error or failure of the prediction model [11,12]. Instead, here we tend to make sense of such changes from the earlier to later predictions for meaningful signals as to what are happening in the dynamically changing real-world scenarios, based on the fundamental assumption that predictions made over time should be different when the real-world scenarios are changing. For wicked problems, such changes are often difficult to recognize, but are detectable via predictive monitoring.

For example, the changed predictions of the inflection dates and theoretical ending dates of Singapore in the last week of April (see Figure 1A and 1B) may reveal the effects of the strengthened control measures of the government and more cautions of the local citizen from Prime Minister’s announcement of circuit breaker extension on 21 April. However, the later updated estimations of Singapore became unstable and gave a prolonged pandemic life cycle. Please see Figure 2A for Singapore’s curve estimated on May 8 and Figure 3 for the volatility of the predictions for Singapore among other countries. While the estimated pandemic curves of Singapore shifted obviously from April 28 to May 8, the curves of Italy estimated on these two dates are almost the same (Figure 1D and Figure 2B). In any case, it would be wrong to expect the curve estimated with data from the previous scenario to represent the curve for a later scenario. Instead, the curves should be continually re-estimated with the latest data, the predictions based on these curves should be continually monitored, and the changes in the predictions may reveal changes in real-world scenarios over time. Monitoring and detecting such changes in the predictions provides the main value of predictive monitoring.

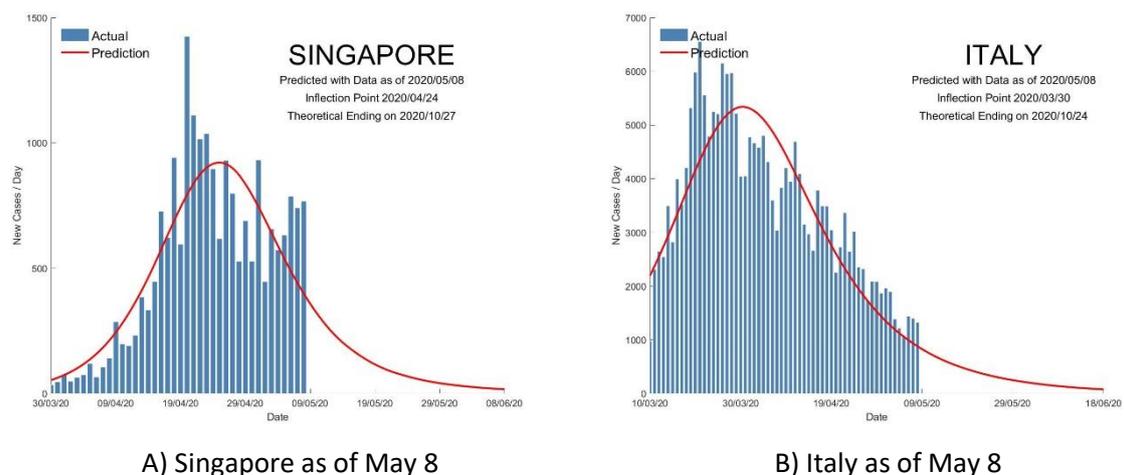


Figure 2. Continuous Data-Driven Estimations of COVID-19 Life Cycle, Turning and Ending Dates for Singapore and Italy as of May 8, 2020

In other words, our default expectation in predictive monitoring is that predictions will change, especially when the real-world scenarios, such as government policies, testing protocols and human behaviours, are also rapidly changing. In such cases, it would be unreasonable to expect the model trained with data as of today to be true for a different scenario later. It would be unreasonable to test the accuracy of a model trained with earlier data with later data. When considering the dynamics of human behaviours and government policies and other real-world scenarios that are also in the loop and the mathematical model and training data cannot fully represent, predictive monitoring is more meaningful and valuable than the traditional exercises of making a prediction now to see if it is a hit or miss in the future.

- Sense Uncertainty

The changes in the predicted theoretical future events, such as the theoretical ending dates, may also allow us to sense or measure the uncertainty rooted from the real-world scenarios on the ground. For instance, we may examine the standard deviations of the N latest and connectively predicted theoretical end dates as an indicator of uncertainty. Standard deviation measures the dispersion of values. Such a measure is often called “volatility” in finance when used to evaluate the uncertainty associated with stock prices. If the volatility of the connective predictions of theoretical ending dates is small (regardless of their accuracy), it indicates the present real-world scenarios are not changing. High volatility of connective predictions indicate radical changes in the real-world scenarios might be taking place presently on the ground. Figure 3 reports the past 5-day volatilities of the theoretical ending date estimates of some major countries with model-data (of daily new cases) fits $R^2 > 0.8$, throughout the period of examination.

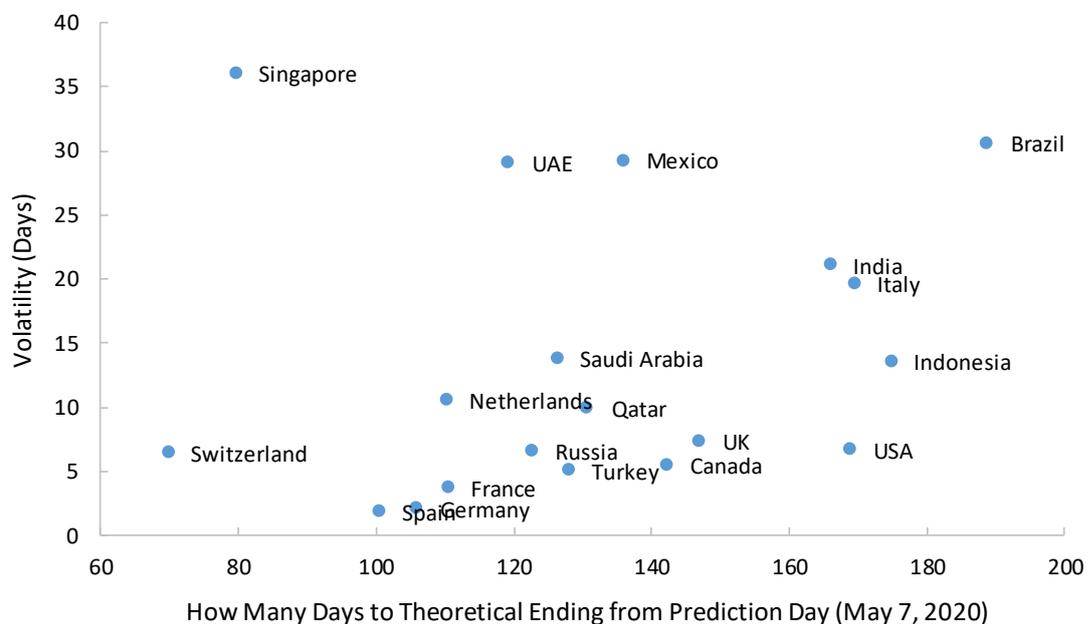


Figure 3. Prediction Volatility against Length of Time to Predicted Ending Dates

Some dots in Figure 3 are noteworthy. There appears a general correlation between the ending and volatility across countries, and also exist outliers, such as Singapore with a relatively close ending date but extremely high volatility, indicating uncertainty in the real-world scenarios, which might be related to the changing testing protocols in the contained

in dormitories of foreign workers. Also, Brazil stands out with a very far ending date and high volatility, indicating an both undesirable and uncertain real-world scenario on the ground in Brazil now and demanding cautionary actions. Figure 4A plots the estimated curves of Brazil, showing radical changes, in a week. By contrast, for the USA, its rather stable predictions all suggest a long time to reach its theoretical ending of the pandemic. Figure 4B plots the estimated curves of USA for a week together, showing a high stability, while one might still want additional policies or actions to further shorten the tails of the curves. Switzerland presents a desirable case with the closest ending date and low volatility.

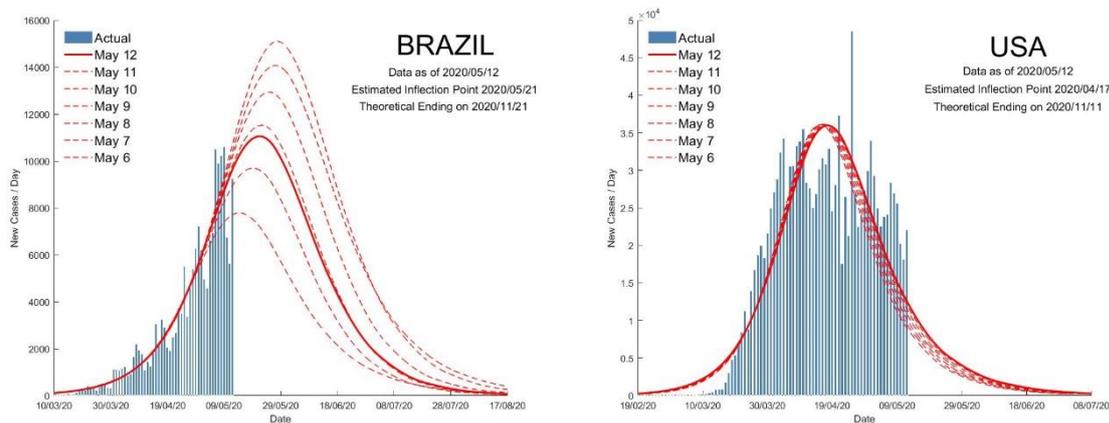


Figure 4. Predictive Monitoring of Estimated Pandemic Life Cycle Curves of Brazil and United States from May 6 to 12, 2020

Here, we have purposefully avoided such metrics as “margin of errors” and “confidence intervals”, because our assumption is the pandemic’s real-world scenarios are uncertain and evolving by nature and thus there is no target value to define an “error”. In contrast, the confidence intervals are called “uncertainty bands” in some of the ongoing COVID-19 forecasts [3,5,12]. Such a calling might be theoretically questionable and cause “false sense of certainty”. The COVID-19 pandemic has so many unknown unknowns, which results in extreme uncertainty. The concept of unknown unknowns was plausibly attributed to NASA and popularized by Donald Rumsfeld, United States Secretary of Defense at the time, in a press conference in 2002.

“There are known knowns. There are things we know that we know. There are known unknowns. That is to say, there are things that we now know we don't know. But there are also unknown unknowns. There are things we do not know we don't know.”

In the case of the COVID-19, there are many things we do not know we do not know. Such uncertainty from the unknown unknowns is not quantifiable. Only the “known unknowns” are quantifiable and are often called “risk”. Most of the “uncertainty quantification” metrics in the literature are in fact risk measures. For COVID-19 predictions, it is also a question whether the risk measures, such as “margin of errors” and “confidence intervals with 95% accuracy”, are suitable, because there exist no fixed target or fact in the wicked context. Risk measurement is only suitable when we “know” there is a definitive target but just “do not know” to what extent our solution might hit the target, i.e., known unknowns.

In sum, the foregoing sections are aimed to explicate the values and potentials of predictive monitoring to proactively address uncertainty and changes in the wicked context of the COVID-19 pandemic. We show with case examples how predictive monitoring may help

capture changes and sense uncertainty in the present real-world scenarios, despite the assumed inaccuracy of individual predictions.

Discussion

Predictive monitoring for each country should be read and interpreted together with what are happening in the real world, especially government intervention policy changes. For instance, Singapore government's strengthened restrictions in April may have bended its curve earlier than the previously predicted ones, and the early relaxation of social distancing and lockdown in Italy and Germany might increase infection rates and thus delay the pandemic ending as predicted earlier. Also, the predictive monitoring of a country should not be read in isolation, but together with the predictions and real time situations of other countries. No country is in isolation in the global pandemic.

For example, while the predictive monitoring in early May 2020 shows the pandemic life cycle curve has "theoretically" ended (despite a small number of domestic cases reported daily) in China, South Korea and Australia, it also shows many other countries (such as Brazil, USA) and the world as a whole will still suffer till the end of 2020 if we remain in our present trajectories of government policies and individual behaviours and without medical cures and vaccines for COVID-19. Therefore, the governments of China, South Korea and Australia may not want to open their international ports so soon and lift the domestic restrictions completely, until the pandemic ends in the world as whole. Although it is the time for all of us to isolate and distance physically from each other, to combat the global pandemic also demands more sharing of data, information and knowledge and more close collaboration across disciplines, professions and regions.

For countries that are still early in their own pandemic life cycles (such as Brazil still in the acceleration phase as of May 8), the prediction of the rest of the curve, inflection point and ending dates will be more teasing, but also inherently less relevant to the "real future" to come given that the actual data only cover a smaller and early portion of the total life cycle and many real-world scenarios are expected to evolve. By contrast, for countries that have been approaching ending phases, prediction is less useful whereas monitoring remains crucial. In such cases, the trained model and estimated life cycle curve are more about explaining the history. For those countries, uncertainty still exists. For example, a new epidemic wave might come if the governments and individuals lift controls and disciplines too early, especially when the pandemic is still prevalent in other countries.

Summary

The COVID-19 pandemic is a wicked problem and the predictions for its course of development are meant to be inaccurate. Especially for the countries still in the early and middle phases of their pandemic life cycles, adaptive human behaviours and responsive policy interventions are entering the loop and change the earlier predicted patterns. Here predictive monitoring is proposed to capture the changes down the road, in contrast to traditional predictions aimed for accuracy assuming a fixed future. We still need to continually experiment and explore the heuristics of predictive monitoring for novel and valuable signals of the uncertainty and changes in the evolving real-world scenarios.

In the meantime, readers must take any specific prediction with caution. Over-optimism based on some specific predictions will be dangerous because it may loosen our disciplines and controls and cause the turnaround of the virus and infection. No model and data can accurately nor fully represent the complex, evolving, and heterogeneous realities of the pandemic in different countries. Acknowledging the extreme uncertainty and wicked nature of the ongoing COVID-19 pandemic, what are eventually and fundamentally needed are the robustness, flexibility, resilience, creativity and entrepreneurship of people, organizations and governments, as well as sharing and collaboration across disciplines, professions and regions, to deal with any unpredictable undesirable future scenarios.

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