ADVANCE4COVID Qualitative Report for XPRIZE Pandemic Response Challenge Phase II
Date: February 10, 2021

Introduction

During the outbreak of the COVID-19 pandemic, many governments have issued a series of non-pharmaceutical interventions (NPI) policies to flatten the growth curve of the COVID-19 pandemic and lessen its health, economic and social impacts. Every effort is made to slow down the spread of the coronavirus and prepare medical response systems to address the pandemic crisis. As such, it is important to predict the NPI effects to support government decision-makers.

The majority of the COVID-19 NPI modeling efforts use statistical or mathematical models to evaluate the effects of candidate NPI plans on the national- and state-level cumulative reported COVID-19 cases or deaths in the future. Those efforts leverage various types of models (e.g., Bayesian-based modeling, time-series regression) to estimate the impacts of interventions on the average daily cases. However, due to the diversity and complexity of the regional situation (e.g., delay of execution, intervention effectiveness) and the ethical limitations, it is challenging to choose a balanced solution (i.e., minimizing the daily cases while minimizing the cost of the interventions) from a large number of candidate prescriptions.

However, COVID-19 has been around for over a year across the globe which gives us a good amount of data to seek the development of data-driven artificial intelligence (AI) systems for predictive modeling as well as prescribing potential intervention plans. The XPRIZE Pandemic Response Challenge has been designed exactly for this specific purpose; to assist regional governments, communities, and organizations in their implementation of potential intervention plans that minimize harm when reopening their economies.

The submission from our team (ADVANCE4COVID) includes seven prescriptions generated using a genetic programming (GP) model implemented using Distributed Evolutionary Genetic Algorithms in Python (DEAP, https://deap.readthedocs.io) and three based on a heuristic search (HS) model.

Actionability and usability

Our current model is based on the features provided by the input file according to the guideline, and it could be extended with the features in the real-world setting. For the GP model, it calls the standard XPRIZE predictor to minimize cases and stringency. For the HS model, it samples 2000 candidate prescriptions and evaluates them based on predicted cases and stringency using a simple machine learning-based predictor.

Explanation

Prescriptions based on the genetic programming (GP) model: The implementation of the GP model using the DEAP package defines the predictive task as a multi-objective optimization problem with the goal of minimizing both stringency and new cases. Specifically, each prescription is defined as an individual (solution) in the population of evolutionary algorithms. The fitness of each prescription in the population of one generation is evaluated by stringency and new case number. Then offspring are generated from the current prescription population through mating and mutating. The selection strategy is applied to select the individuals that will survive into the next generation. At last, the best prescription with optimal stringency and the new case number is selected based on iterative evaluations of the fitness of the last generation.

By using the regional evaluation function (i.e., the new case number predictor), the GP model could optimize the prescription for each region. Moreover, by adjusting the number of generations and the population in each generation, we could also balance the computation cost and model performance.

Prescriptions based on the heuristic search (HS) model: The HS model consists of a case ratio predictor and an NPI adjustment-based search model. As we observed in the real world, there is a delay between the NPI implementation and showing effect. Thus, instead of the number of 7-day average daily cases, we propose to use the case ratio of 7-day average daily cases between 7 days, namely R_d, to measure the trend of the regional epidemic, which is defined as follows:

$$R_d = \frac{7 - day\ average\ daily\ cases_d}{7 - day\ average\ daily\ cases_{d-7}}$$

With this definition, R_d less than 1 indicates a decreasing trend of the epidemic in a region, while R_d greater than 1 indicates an increasing trend. Based on the case ratio, we built a gradient boosting regression (GBR) based predictor to predict how the case ratio is affected by the prescription of N-day ago and the daily cases.

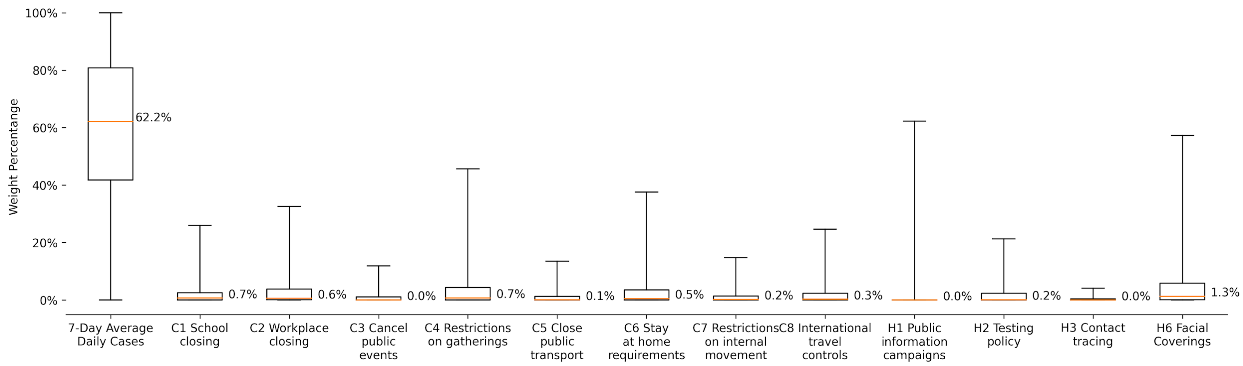

Figure 1. The effect of the features on the case ratio

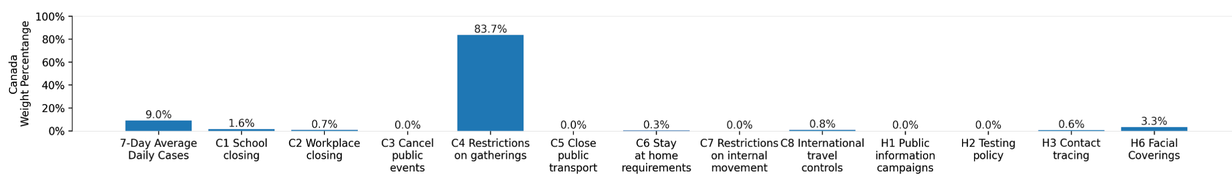

Figure 2. The effect of the features for the Canada case ratio predictor

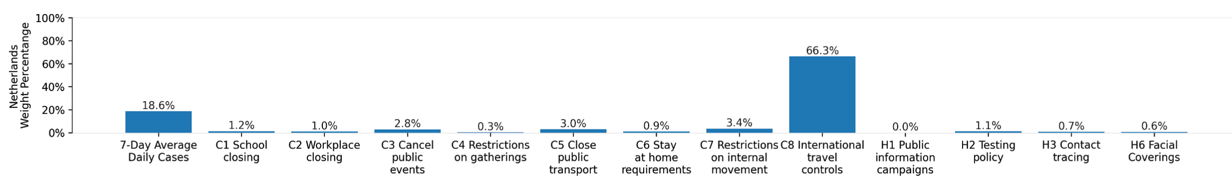

Figure 3. The effect of the features for the Netherlands case ratio predictor

We also computed the feature importance to evaluate the effect of each feature on the case ratio. For each feature, the values go from 0 to 1 where a higher value means that the feature will have a higher effect on the case ratio. As shown in **Fig. 1**, the feature of the 7-day average daily cases has a much higher effect than any other feature in our case ratio prediction in general. However, there is an obvious regional difference in the effects between features and the 7-day average daily cases are not always the most important feature. For example, the feature “C4 Restrictions on gatherings” has more effect than other features in the Canada case ratio predictor (**Fig. 2**), while the feature “C8 International travel controls” has more effects in the Netherlands (**Fig. 3**). Therefore, to get a more accurate estimation for the prescription, we trained case ratio predictor for each region separately.

To generate feasible and realistic prescriptions that could be used in the real-world setting, we propose the following algorithm to create a candidate prescription: 1) generate a candidate prescription pool with minimum adjustment on the basis of the NPI plan of yesterday; 2) predict the case ratio with our predictor model; 3) rank each prescription by the predicted case ratio and stringency; 4) select the best ranking prescription as the recommendation. To make the NPI plan effective and continuous in the real-world setting, an NPI plan will continue to be implemented for at least one week or longer without change. Therefore, we use 7 days as an implementation period (i.e., during this period, the NPI in each day remains the same as the first day of this period), and adjust the NPI plan after every 7 days until we generate a full prescription for the given date range.

When ranking the prescriptions, different weights could be applied to the case ratio and the stringency to balance the importance of each goal. In our submission, we selected three different weights to get three different prescriptions, including equal weights, heavier weights for stringency, and heavier weights for case ratio.

Addressing the challenge

Our approach is based on the historical dataset (i.e., which is used in the predictor model training and the start step of generating prescription) and general learning algorithms. It could be directly leveraged to generate NPI prescription in each region.

Inclusivity and fairness

The team was formed by an open call and we included everyone who was willing to participate voluntarily. The final team includes eight team members with diverse backgrounds. Two of them are students.

Generality

Our training approach is very general and can scale up to incorporate more features.

Consistency

We should expect the performance to be consistent across the regions and up to four weeks.

Transparency and trust

The implementation is detailed with an explanation of the approaches.

Collaborative contributions

Our team consists of informaticians, postdocs, data scientists, undergraduate and medical students, and IT professionals. The majority of the work was done as a volunteering effort. The challenge offered us an opportunity to learn from each other.

Innovation

We adopted a hybrid exploring strategy to generate the prescription recommendations. First, we adopted the GP-based algorithm to optimize the candidate prescription selection to achieve a balance between the time complexity and performance. Second, instead of 7-day average cases, we proposed to use the case ratio of 7-day average daily cases between 7 days to measure the trend of the epidemic spreads. Moreover, we adopted a heuristic method to select the prescription based on our proposed case ratio.