Kassandra's prescriptor

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Abstract

We construct prescriptive scenarios for each country/region in a weekly and greedy fashion. The proposed algorithm uses our predictor model submitted in phase 1, after having it retrained on the latest available data. For a specified interval, (typically a week) the prescription algorithm performs a search over a series of different interventions, computes the effect of each fiducial plan through the predictor and then keeps the optimal according to a weighted sum of the two objectives, i.e. minimizing the intervention cost and the new cases. Using different weight values, the Pareto front is sampled. We additionally create a website (`www.kassandras-response.net`) with a user-friendly interface, where both our predictor and prescriptor can be tested, providing the estimated new cases along with uncertainty intervals for various intervention plan scenarios. A series of prescription scenarios like random, max, and historical, as well as the prescription scenario based on our proposed algorithm can be generated and assessed by the user.

1 Explanation of the prescription algorithm

For the time interval of interest, $DayStep$, we change by at most $MaxITER$ the overall absolute level of stringency each week. Depending on whether the new cases have risen or fallen during the previous time interval, we either increase or decrease the stringency. At each iteration, we examine each intervention plan (IP) bundle (a vector of values for each plan) separately, predict the corresponding new cases, and then compute the target quantity to minimize as a weighted sum of the two objectives. We keep the bundle that minimizes the target variable and use it as the starting point for the following time interval.

In this process, any predictor could be used, with a more accurate one expected to improve the overall performance of the resulting IP strategy. However, the advantage of using our own predictor is two-fold: it is fast - 1s per country per IP bundle - and interpretable. The speed of our predictor enables the exhaustive search for the optimal intervention solution, at least locally in time. The interpretability of the predictor's coefficients (see our first report) implies that a user can modify in a straightforward and meaningful manner the behavior of the predictor making it more (or less) responsive to each intervention measure based on their expertise. We do not use any external data apart from the training data for the predictor; essentially, data are only implicitly taken into consideration through the trained predictor.

2 Actionability and usability

We constructed an interactive website, with a screenshot shown in Fig. 1, where a user can test the efficiency of various IP bundles, predict the corresponding new cases for a specified time interval and country/region, and finally visualize the prediction and its uncertainty. The values of each IP bundle are presented on the site, each with an individual slide-bar to modify its stringency. We note here that IP in action in different countries can be used with a target country - a functionality that we believe is quite innovative. The predictive model employed is in fact an ensemble of predictive models, each with its coefficients fixed. We use this to estimate and then visualize the first and third quantiles as a means to quantify the uncertainty in our forecasts. As a sanity check, we included the minimum intervention scenario (no IPs at all), and indeed the number of new cases increases for all countries/regions, while using the maximum IP values leads to a decrease in the new cases. As future extensions, we propose the ability to handle not only the prescriptor (web interface currently in development) but also to select between and manipulate various prediction models and the capability of setting the cost value for each intervention.

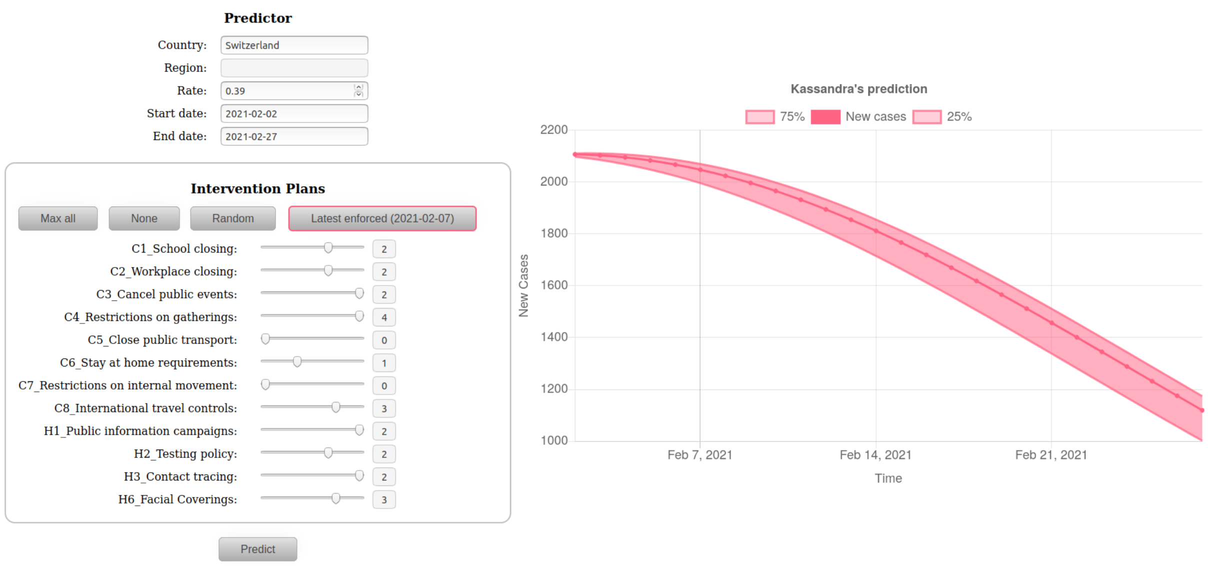

Figure 1: The website where a scenario can be created and evaluated.

3 Additional Properties of the Prescription Algorithm

3.1 Generality

The proposed prescription algorithm is general and it can be applied to any country, region or sub-region given the existence of a predictor for the particular area of interest (predictors for other countries could be used as a replacement, with the expected loss in accuracy).

3.2 Consistency

We added an additional functionality in our system that mimics the effect of the vaccination rate, or any other factor that can decrease (or even increase) the new cases. For example, the percentage of tests conducted over the entire population could be another factor that can be incorporated into this rate. In this way, we keep our predictive models constrained within an acceptable range of accuracy in the short and long term. Moreover, the behavior of the prediction/prescription system is consistent under the extreme scenarios of no or maximum stringency.

3.3 Transparency and trust

Through the graphical interface, each user can modify the stringency levels and immediately contrast and compare the effect on the new cases evolution. Such a system that behaves qualitatively in a rational way with respect to incremental changes can gain trust and be more easily adopted by policy makers. The ability to perform modifications along with the interpretability of our model make the overall system easy to comprehend and employ.

4 Possible Improvements

The use of a more accurate or a specialized-to-a-region predictor model could improve the performance of the prescription algorithm. On the other hand, given the computational speed of our predictor, an exhaustive search for the optimal intervention plan is feasible. Nevertheless, the quality of the predictor is seemingly a more crucial factor.

Appendix: Prescription Algorithm

We present the pseudo-code of the prescription algorithm below. The parameters in blue can be varied, and their values are the ones we finally chose to submit in this phase.

- DayStep = 7; (How often to recompute the intervention plans in days)
- TotalDays = 90; (Final day);
- i = 0; (Current day)
- MaxITER = 2; (Maximum number of changes in the intervention plan per recomputation)
- c(t) = "New Cases" at dat t.
- u(t) = Intervention vector at day t of dimension NoInterventions.
- lambda = {0.5, 0.75, 1, 1.25, 1.5} (penalty weight for the second objective)
- **WHILE** i<TotalDays (it's already implemented)
  - ii = 0;
  - **UNTIL** "No changes are observed" && ii≤MaxITER **REPEAT**
    - **FOR** j = 1:NoInterventions
      - **IF** c(i)-c(i-DayStep) > 0 (Increase the level of stringency when new cases increase)
        - u_temp{j}(i+1:i+DayStep) = min(u(i) + e_j, MAX_STRINGENCY_LEVEL)
      - **IF** c(i)-c(i-DayStep) < 0 (Decrease the level of stringency when new cases decrease)
        - u_temp{j}(i+1:i+DayStep) = max(u(i) - e_j, MIN_STRINGENCY_LEVEL)
      - $\tilde{c}${j}(i+1:i+DayStep) = PREDICTOR(c(i), u_temp{j}(i+1:i+DayStep))
      - TotalLoss{j}{m} = O_1($\tilde{c}${j}(i+1:i+DayStep)) + lambda{m}*O_2(W, u_temp{j}(i+1:i+DayStep), m=1,...,len(lambda)
    - j*(m) = $argmin_j$ TotalLoss{:}{m}
    - u_m(i+1:i+DayStep) = u_temp{j*(m)}(i+1:i+DayStep) (Keep the best performing intervention plan for each m)
  - ii = ii+1;
- i = i+1;