Qualitative Evaluation Phase 2 – Team Shanvi

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Phase 2: Prescriptor Development
The goal of Phase Two—Prescriptor Development is to provide useful recommendations of non-pharmaceutical interventions (NPIs) such as social distancing restrictions and school and business closures. Teams are supposed to use standard predictor (LSTM based) for the recommendation.

Data Used
Oxford University Blavatnik School of Government's data: OxCGRT_latest.csv
Standard LSTM based prediction results.
Cost of the non-pharmaceutical interventions (NPIs)

Introduction
COVID-19 pandemic has damaged global economy significantly. Many non-pharmaceutical interventions (NPIs) such as social distancing restrictions and school and business closures are in place to mitigate the community outbreaks. A balance between preventing the spread of the coronavirus while minimizing the economic cost of interventions is a challenging task. The cost assigned to the different intervention policies is different depending on the region which significantly impact policy recommendations. A good prediction model helps in developing these recommendations because it can predict the future daily new cases accurately. By analyzing these future daily new cases once can adjust the intervention plan accordingly to avoid any significant outbreaks. Four simple algorithms random1, random 2, neat and blind greedy are given that can use two different cost structures fixed or uniform random to prescribe the intervention plans in a naïve way. Blind greedy algorithm greedily chooses the lowest cost intervention plans and vary the stringency by choosing more interventions. Blind greedy algorithm performed better compared to the random 1, random 2, and neat. Teams are supposed to use machine learning algorithm to produce better recommendations compared to these algorithms.

Hypothesis
Team Shanvi hypothesized that efficient integration of the LSTM predictions with blind greedy algorithm may significantly improve the intervention plans.

Actionability and usability

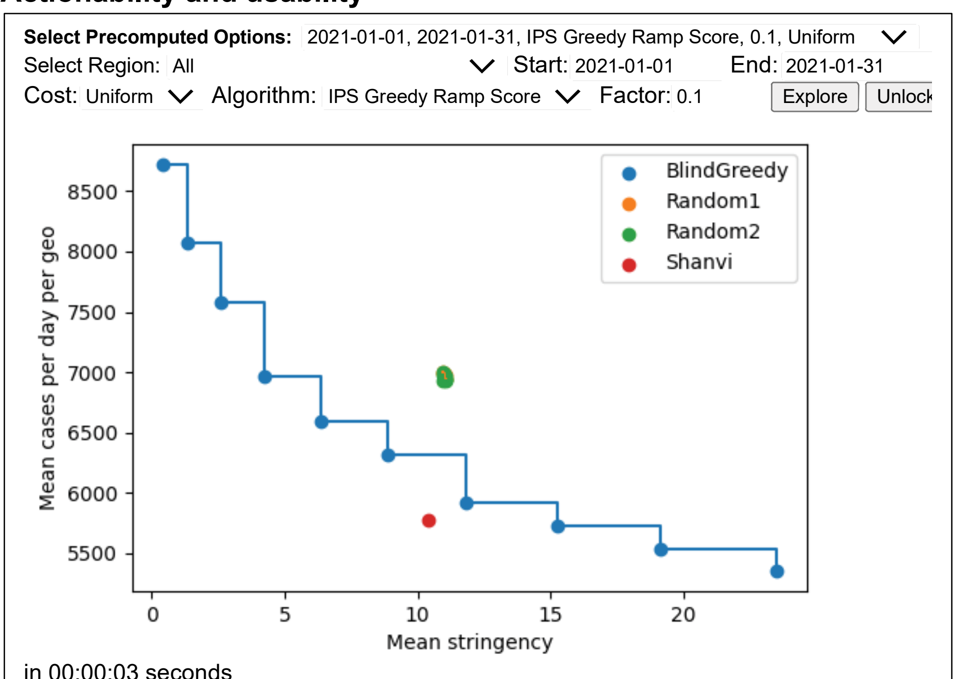

Figure 1: Shanvi Web Interface to search for better prescription.

Team Shanvi created a [web interface]() ([link]()) to search for better prescriptions. The website has a link to the interface shown in **Figure 1**. A set of pre-computed options are available at the top to explore. User can select a specific pre-computed option and click on "Explore" to get the pareto curve as a plot where results of four different algorithms are highlighted: BlindGreedy, Random1, Random2, and Shanvi. Since these algorithms are computation heavy it is hard to create a truly interactive framework where we can try different options in real time. We have optimized this process so that for the pre-computed options the results can be retrieved in 3 seconds. When the user selects a different pre-computed option, all the parameters

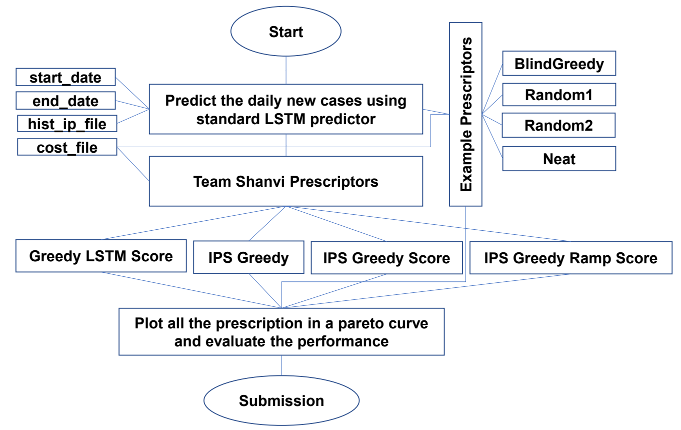

Figure 2: Flow Chart - Team Shanvi Prescriptor Development

are automatically updated so that the action of "Explore" click can retrieve the correct pareto curve. Each of the above computed options will take around 1 hours and 30 mins to finish when it is run for the first time. Thus, if we change the options and click "Explore" it could take long time to finish. Therefore, we have disabled changing critical options by default. However, for some reason if anyone wants to check the results with different parameters, they can click on the "Unlock" to enable parameter change for all. First time run is expensive but the subsequent runs are optimized to compute only Shanvi prescriptors if start-date, end-date and NPI weights (cost) was not changed which takes only 3 mins for each click.

Explanation

Team Shanvi workflow is summarized in a flow chart in **Figure 2**. The team developed four different algorithms that systematically improve the BlindGreedy strategy. The BlindGreedy strategy was provided as an example in the github. It uses the weight of the NPIs to rank them and greedily choose the lowest weight NPIs until a particular stringency is met. The BlindGreedy strategy do not use any predictors and it is solely based on the weight of the NPIs given. We decided to integrate this concept with daily new cases predicted by the standard predictor. The standard LSTM predictor was called first to predict the daily new cases in the specific data range using default historical intervention plan (IP) collected from the Oxford dataset. To design the first prescriptor, BlindGreedy strategy was combined with stringency derived from the daily new cases. The daily new cases is first normalized to a range from 0 to 35. Then, the IP choose greedily NPIs using ranking based on the specified weights (cost of NPI) just like BlindGreedy. In this strategy, more stringent NPIs were chosen when the daily cases were high and stringency of NPIs were brought down when the daily cases were low. We believe that this strategy is more efficient compared to the BlindGreedy strategy which uses the same stringencies irrespective of the daily new cases. This prescriptor is called "Greedy LSTM Score" (**Fig. 2-3**).

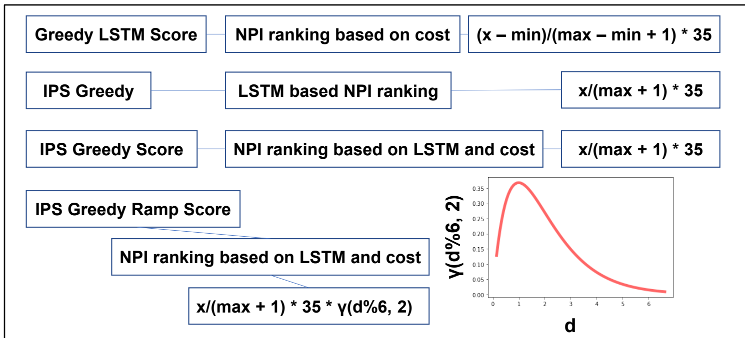

Figure 3: Shanvi prescriptors details

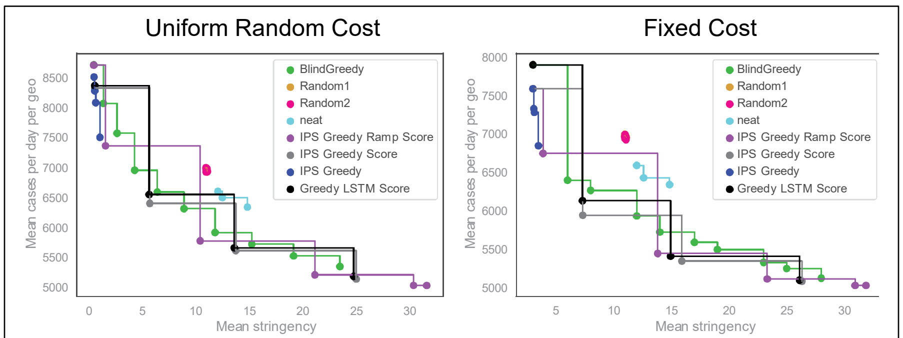

Figure 4: Pareto curves of the different algorithms. Start date 2021-01-01, end date 2021-01-31, all countries.

To improve this further, we computed the relative importance of each NPIs based on the LSTM predictor (LSTM based NPI ranking, **Fig. 3**). To compute the effect of each NPIs on daily new cases, LSTM predictor was given intervention plans for each NPIs separately. NPI who has a stronger effect in reducing daily new cases is ranked higher. The "IPS Greedy" prescriptor uses this LSTM based NPI ranking and uses stringency from the daily new cases. Strong NPIs will likely reduce the new cases aggressively. However, a balanced choice of low cost and highly effective NPI needs to be carefully controlled to optimize this further. To carefully weigh the NPIs based on both the cost and the relative importance, a new prescriptor called "IPS Greedy Score" was created. In this prescriptor, relative importance of each NPIs (range 0 to 1) were added to the cost of the NPIs to create a new NPI ranking. We also examined how ramping stringency momentarily high and bring it down in a cycle of 6 days (close to one week) has an effect on reducing the daily new cases. For ramping up the stringency, a gamma distribution with alpha = 2 and beta = 1 (red plot, **Fig. 3**) is used. The prescriptor that uses the gamma distribution is called "IPS Greedy Ramp Score". All these algorithms were evaluated with start date “2021-01-01”, end date “2021-01-31” with both fixed weights and uniform random weights scenarios (**Fig. 4**). Pareto curves were computed where the x-axis represent the stringency requirement and y axis represent the daily new cases achieved. In both cost scenarios (Fixed and Uniform) “IPS Greedy Ramp Score” appears to be superior to other algorithms in this context. The stringencies for all our prescriptors can be dialed up and down with a single parameter “factor”. Modulating the stringencies using a gamma distribution appears to help reduce daily cases.

Addressing the challenge
The standard LSTM predictor was too slow to explore many options to optimize the pareto front. However, the interactive website really helped us to narrow down a set of parameters that can work in most of the scenario. We also used 10 different compute nodes to try different options in parallel to speed up the optimization process. For 30 day duration, the LSTM prediction was taking around 3 minutes to complete. We also used four GPUs to speed up the process. However, in default run settings GPUs were comparable with CPUs. No significant speed-up was observed in GPUs.

Inclusivity and fairness
The models were solely dependent on the daily new cases as predicted by the standard predictor and the weights assigned to the NPIs. Therefore, we believe that the prescriptions are most likely fair and inclusive.

Generality
We optimized our prescriptions by using all countries together. Therefore, we believe that it may be generally applicable in all context. In our experience, 30 days prescriptions work well. We didn’t have time to perform a stepwise prescription in 30 days intervals to get better overall prescriptions for longer duration. The algorithm can be easily given appropriate inputs to mimic these scenarios. Also, it was better to normalize the daily new cases with maximum daily cases globally from all countries. Thus, it was better to include all countries to optimize for the individual countries.

Consistency: Our algorithm appears to be consistent when evaluated for 30 days. To optimize for longer duration, the algorithm can be run for 30 days interval to span the entire range. We did not have time to write a program to optimize this. However, this can be easily achieved by giving 30 days sequential inputs to pur programs.

Transparency and trust:
The code is arranged in terms of incremental improvements over four different algorithms and implemented in a object oriented manner. We feel that this strategy demonstrates better transparency and trust.

Collaborative contributions
Team Shanvi discussed and participated in the slack channel to ask important questions and provide codebase for collaborative inputs.

Innovation
Use of gamma distributions in modulating the stringencies by ramping up early and bring it down quickly is an innovative new concept. The rationale was to be strongly aggressive for a short period of time and relax for a longer period. We tried this with one, two- and three-weeks cycle where one week cycle was found to be superior. We observed that the ramp strategy helped reduce the daily new cases significantly.

Lesson Learned
In the standard LSTM based NPI ranking “C2_Workplace closing” was the most important feature followed by “C1_School closing”. “H2_Testing policy” and “C8_International travel controls” were the next two best NPIs. Workplace closing and Testing policy clearly dictates COVID-19 daily new cases. Surprisingly, “C7_Restrictions on internal movement” and “C3_Cancel public events” were the least influential NPIs. This ranking was robust globally as well as specific countries such as ‘United Kingdom’ and China.

We found that a one-week cyclic pattern of aggressive early NPIs followed by long relaxed NPIs are most effective in reducing daily new cases globally. Thus, aggressive shutdown for two days followed by relaxing for five days may be an effective strategy.

Qualitative Evaluation Phase 2 – Team Shanvi – Supplemental Materials

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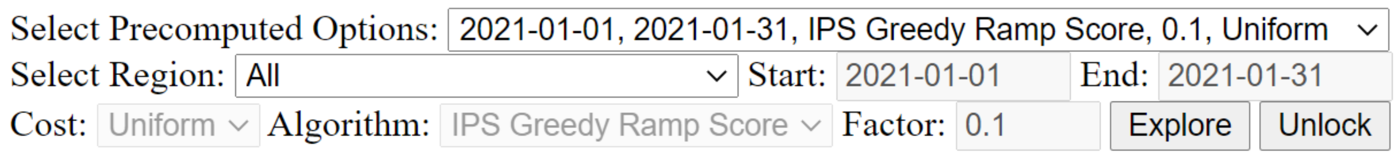
Documentation of the Interactive Website: http://hegemon.ucsd.edu/xprize

Team Shanvi

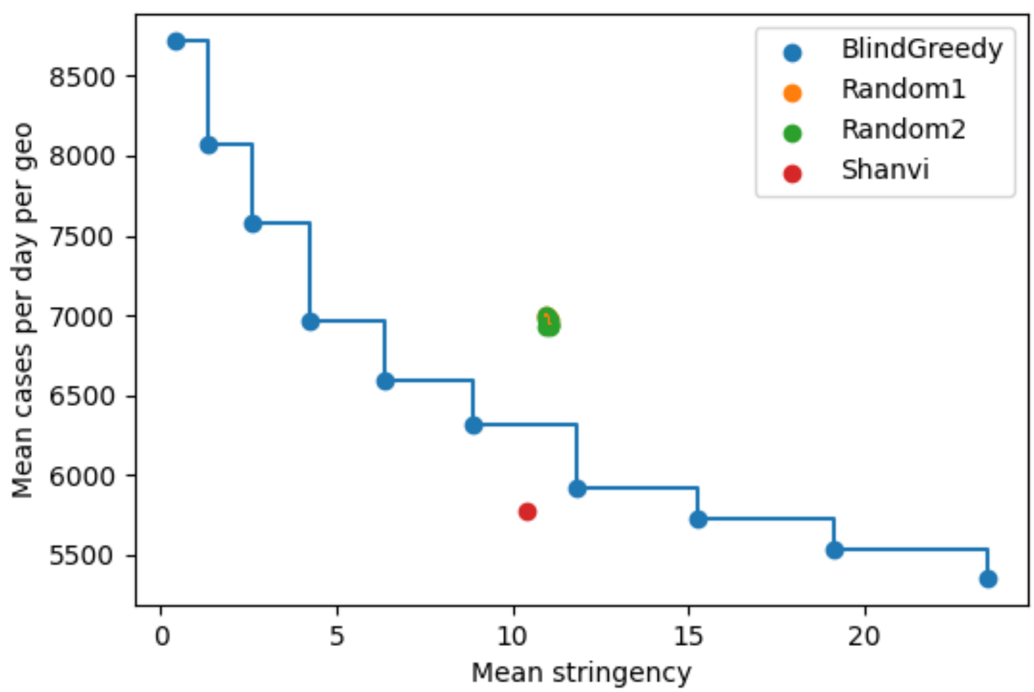
Pandemic Response Challenge

Click on the "Pandemic Response Challenge" link to see following:



Click on the "Select Precomputed Options" to see all the precomputed options. If the user change the precomputed options the parameters are automatically updated.

Click on the "Explore" button to get the pareto curves: (It takes 3 seconds on the precomputed options)



Start, End, Cost, Algorithm, and Factor parameters are deliberately disabled to avoid confusion. Changing these options are compute heavy and can take multiple hours to finish. However, subsequent change in Algorithm and Factor will take only few minutes.

To change Start, End, Cost, Algorithm, and Factor parameters click on the "Unlock" button.