확률적 프로그래밍을 통한 **COVID-19** 대응 방안

Response to COVID-19 with probabilistic programming

요약 - Abstract

Coronavirus disease (COVID-19) is an ongoing pandemic all over the world. How dangerous is COVID-19? How should the government respond to it? These are the questions that we are trying to answer in this work. We propose a method to evaluate the efficacy of the government antivirus policy and simulate their impact on the virus spread considering economic trade-off. We found that the contact-tracing and quarantine policy, if applied correctly, results in the minimum loss.

1. Introduction

Amid the COVID-19 pandemic, countries are imposing severe restrictions on their populations in a bid to stop the spread of coronavirus. The impact brought by these policies is very challenging to quantify. We aim to infer COVID-19 related parameters to simulate the virus, identify the efficacy of the policies applied by countries so far by using available data, and come up with the most optimal strategy to fight the virus. Our approach can provide a direction in improving the country policies in different sectors in order to overcome the pandemic with minimal loss.

Source code: Github; Dataset: Kaggle; Data story: Medium

(Source code and data story will be included in final version since it contains personal information and affiliation)

2. Analyze important virus statistics by Virus Model:

2.1. Mathematical model: We adapted the SEIR model from epidemiology [1]. The SEIR model assumes people carry lifelong immunity to disease upon recovery. Here S, E, I, R stand for the number of Susceptible, Exposed, Infectious and Recovered people respectively. We assume that the population stays constant over time and is equal to N. Here are differential equations to describe the model mathematically:

$$\frac{dS}{dt} = -\frac{\beta IS}{N} + \alpha R; \quad \frac{dE}{dt} = \frac{\beta IS}{N} - \epsilon E; \quad \frac{dI}{dt} = \epsilon E - \gamma I;$$

$$\frac{dR}{dt} = \gamma I - \alpha R; \quad N = S + E + I + R$$

2.2. Probabilistic Programming Model: We use Pyro's Epidemiology framework [2] for experimenting with a restricted class of stochastic discrete-time discrete-count compartmental models. We used this framework and modified it to fit the SEIR model to infer COVID-19 related parameters: reproduction number Ro, recovery time, incubation time, transmission rate, and mortality rate. For inference, we used the MCMC-NUTS algorithm.

2.3. Result: We run the model on the Sweden data before April 1st. The reason for our choice is that Sweden did not impose strict policies from the beginning. We can assume that the virus transmission rate was unaffected and can be used for a simulation experiment with no policies applied.

Table 1: Virus statistic inference result

Recovery time	16.33 days	Lock down	0.96
Incubation time	3.83 days	Tracing + Quarantine	0.76
R0	2.40	Distancing	0.60
Mortality rate	2%	Mask + Hygiene	0.34
Recovery rate	27 %		

We give the prior according to the estimation of the World Health Organization [3]. According to its estimations mild cases typically recover within two weeks, the incubation period is on average 5–6 days and R_0 is typically around 2. Mortality and recovery rates differ depending on the region and stage of the virus spread. The posterior values for Sweden's data are shown in Table 1. The results are reasonable enough to use them in our simulations.

3. Estimate policy strength by Change-Point Model

3.1. Mathematical model: Consider the case count in the log scale, the rate of transmission of the virus is represented by the slope. From the community spread onward, the graph will be essentially a steep line (rapid, exponential spread). After a policy is applied, the graph is expected to bend and become less steep (slower spread). Therefore, the graph roughly consists of 2 lines of different slopes, w_1 and w_2. If the virus statistics remain the same, the policy applied at the changing point can be estimated to have a strength of 1- w_2/w_1. We expect the policy will show effect after around 2-4 weeks after the policy establishment.

3.2. Probabilistic Programming Model: This model is adapted from Jonathan Ramkissoon [4]. We use piece-wise linear regression with StudentT noise (which is more robust w.r.t outlier than Gaussian noise):

$$y = wt + b + \epsilon \text{ where } \epsilon \sim \text{StudentT}(2, 0, \sigma^2)$$

$$\text{Let } \tau \text{ be the changing point: for } t < \tau: b = b_1, w = w_1$$

$$\text{for } t > \tau: b = b_2, w = w_2$$

Weights and biases have Normal prior and change-point has Beta prior. We used the MCMC-NUTS inference algorithm.

3.3. Experiment and Result: We run the model on the countries that strongly impose a policy. The full efficacy of the policy is assumed to be the policy strength in that country.

3.3. Results:

The full result is shown in Table 2. Figure 1 shows the posterior distribution and fitted curve for China. Other countries' figures are put in the appendix.

Table 2: Policies efficacy result

Country/Policy	Policy starts	Change-point	Policy Efficacy
China Lockdown	2020-01-23	2020-02-10	0.96
New Zealand Lockdown	2020-03-25	2020-04-02	0.96
South Korea Contact tracing & quarantine	2020-02-25	2020-03-17	0.76
Canada Social distancing	March-April	2020-04-28	0.60

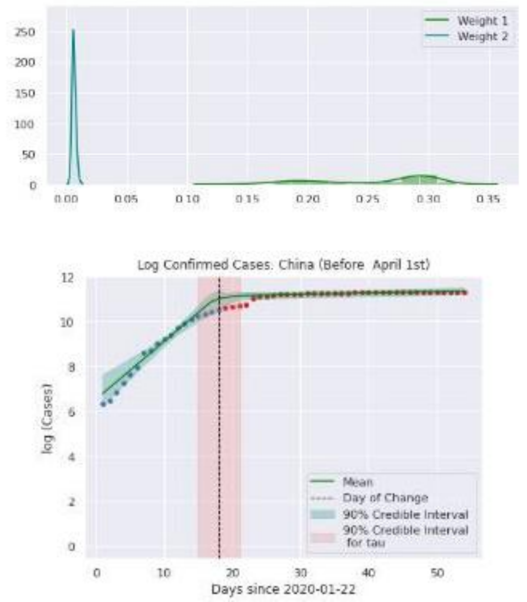


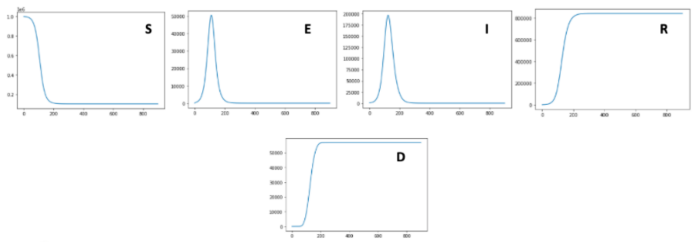
Figure 1: Posterior distribution and fitted curve for China

3.4. Effect of mandating masks and hygiene: For masks and hygiene, we compared the reproduction number R_0 of Japan before policies were applied with the one we obtained from the Sweden analysis by Virus Model. We couldn't use the Change-point model, because hygiene is hard to separate from other policies. The reason why we chose Japan lies in its cultural practices which lists the culture of wearing masks, very little "skinship" (such as hugging or shaking hands), and not wearing shoes in the house [5]. R_0 is 1.58 for Japan and 2.40 for Sweden, resulting in 0.34 efficacy.

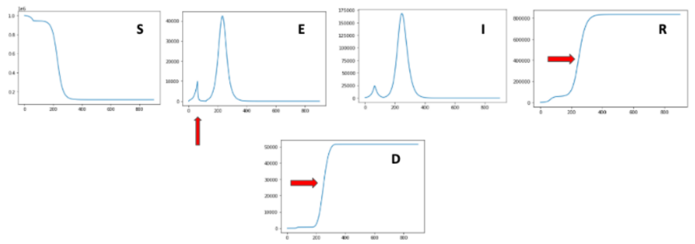
5. Simulation by Generative model

5.1. Model: We used an imaginary country with a population of 1 million and applied the same SEIR model with an extended death toll for virus simulation. In addition to the parameters we inferred from previous results we assumed that hospital capacity is 0.06% of the population and the critical case rate is 15%. The death rate for critical cases is 2% and 90% with and without medical treatment, respectively.

5.2. Lockdown only delays the virus spread: Run the model without any policy and with lockdown applied from day 60 to 120.



(1) No policy



(2) Lockdown from day 60 to 120

Figure 2: Virus spread simulation result

As you can see from Figure 2, applying lockdown for 2 months just postpones the virus spread. Another problem is that it significantly hits the economy of the country, so cannot be applied for a long time. Thus, even though lockdown is estimated to have the highest efficiency (0.96), it might not be the best policy to apply. So further experiments are required to identify how, when, and for how long the policies should be applied.

5.3. Contact-tracing and quarantine is the way to go: To compute how much government strategy against virus costs to the country, we propose to run the generative model on our imaginary nation of population 1 million with GDP per capita 30k$. We add the costs of each policy, treatment for infected, and loss of death cases. To simplify the problem, we look into the first 3-month period where a government can revise the policy in each month, and each policy can be applied fully, partially (50% efficacy), or not applied at all. The goal is to minimize the cost. We estimate the economic cost for each policy:

Lockdown: 10% of GDP per year

Distancing: 5% of GDP per year

Hygiene & masks: 2$ per day per capita.

Quarantine: 100$ per day per infected.

Infection: 300$ per infection per day (until recovered).

Death: 4.9 million$ per death

These estimations are reasonably set based on the following facts:

Research suggests that at the peak of the lockdown, global output shrinks by about 33%, with the annual impact higher than 9% of annual GDP [6].

The value of one human life is estimated to be A$4.9M ($3.48M) in Australia in 2019 [7] and $10M in America in 2017 [8].

In South Korea, the treatment's average daily cost for a mild patient is 180,000-260,000₩ ($158-$229) and for severe patients is 650,000₩ ($572) [9].

South Korea's government quarantine facility costs 100,000-150,000₩ ($88~$130) per day[1]. The price of a mask in Korea is normally set around $2, and $1.2 under the government rationing scheme [10].

Result:

The best policy identified so far is full contact tracing + quarantine in all 3 months with a loss of 65,108,814$. To better imagine it, if we do nothing, the loss in our nation is 7,592,712,053$ (scale up for the USA population, it is 2 trillion $ only for the first 3 months).

6. Conclusion

We have found that quarantine and contact tracing is the most efficient policy, even though their strength is lower than that of lockdown. The policy performs well in both slowing down the spread of the virus and preserve the economy. Indeed, we can see that countries that are most successful in controlling virus cases, e.g. South Korea, use quarantine and contact tracing as their main policies.

From the results obtained, we can conclude that the trade-off between virus prevention and the economy should be considered more accurately. Decisions regarding the policies affect the trajectory of the virus spread. It is crucial to identify efficiencies and costs of each policy and estimate what would be the best time and intensity to impose them before it is too late.

7. References

[1] Li, M. Y., & Muldowney, J. S. (1995). Global stability for the SEIR model in epidemiology. Mathematical Biosciences, 125(2), 155–164. https://doi.org/10.1016/0025-5564(95)92756-5

[2] "Epidemiology," [Online]. Available: link [Accessed 05 November 2020].

[3] WHO, "Coronavirus disease (COVID-19)," WHO, 15 April 2020. [Online]. Available: link

[4] J. Ramkissoon, "Detecting Changes in COVID-19 cases with Bayesian models," Medium, [Online]. Available: link

[5] R. Kopp, "Does Japan's culture explain its low COVID-19 numbers?," The Japan Times, 1 April 2020. [Online]. Available: link

[6] Mandel, A., Veetil, V. The Economic Cost of COVID Lockdowns: An Out-of-Equilibrium Analysis. EconDisCliCha 4, 431–451 (2020). https://doi.org/10.1007/s41885-020-00066-z

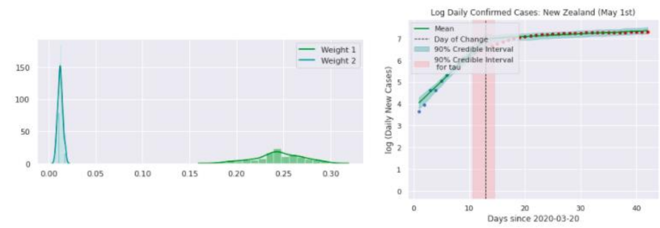
[7] "Best Practice Regulation Guidance Note," Department of the Prime Minister and the Cabinet. Available: link

[8] Kniesner, T. J., & Viscusi, W. K. (2019). The Value of a Statistical Life. In Oxford Research Encyclopedia of Economics and Finance. Oxford University Press. https://doi.org/10.1093/acrefore/9780190625979.013.138

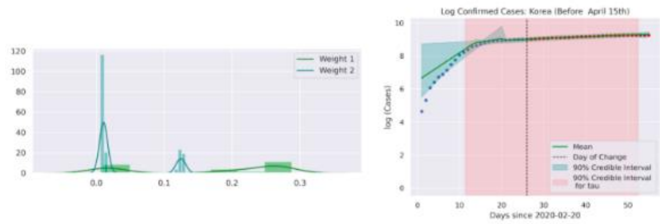
[9] L. Hansoo, "Korea's Covid-19 treatment costs far lower than US'," KBR, 17 Jun 2020. [Online]. Available: link

[10] M. Ketchell, "Price controls don't work – but mask rationing is the exception that proves the rule," The Conversation, 24 April 2020. [Online]. Available: link

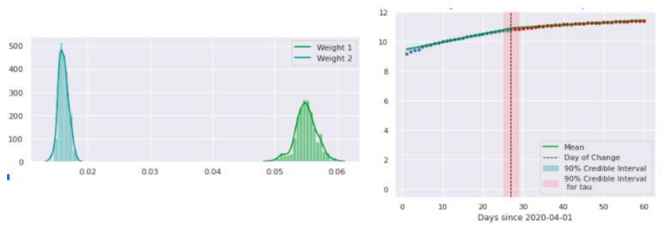
Appendix:



(1) New Zealand



(2) South Korea



(3) Canada

Figure 3: Posterior distribution and fitted curve for several countries

[1] Information available at link