Probabilistic Programming on COVID-19

#coronavirus #covid19 #togetherapart #newnormal

20180745 Mai Tung Duong | 20170906 Assem Zhunis

How **dangerous** is COVID-19?

How should government **respond**?

Pandemic & Policy

A Fatal Error

Approval Wanes for Sweden's Lax Coronavirus Policies

Popular support for Sweden's lax response to the coronavirus is waning and the situation in the country's retirement homes is concerning. The architect of the Swedish approach, Anders Tegnell, is stand

How Vietnam Contained COVID-19 and Why its Economy Will Rebound

China coronavirus: Lockdown measures rise across Hubei province

23 January 2020

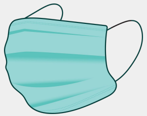
CORONAVIRUS

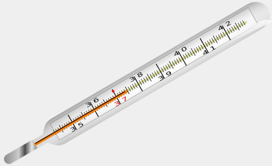
Coronavirus USA: which states are still on lockdown?

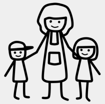
California, North Carolina and a string of U.S. cities mandated or urged mandatory mask use to get a grip on spiralling coronavirus cases as at least six states set daily records.

Countries responses to COVID-19

OUR GOAL

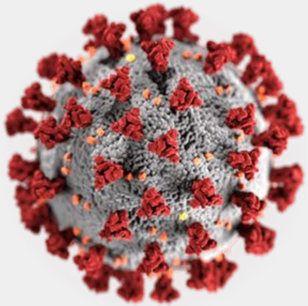




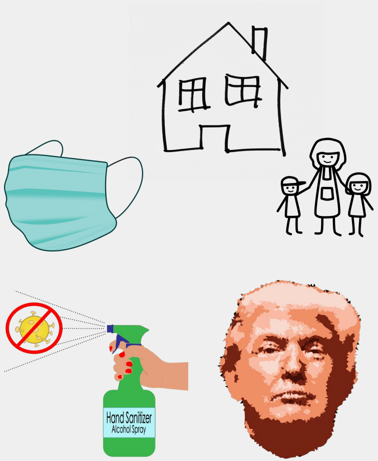


Best Policy For COVID-19?

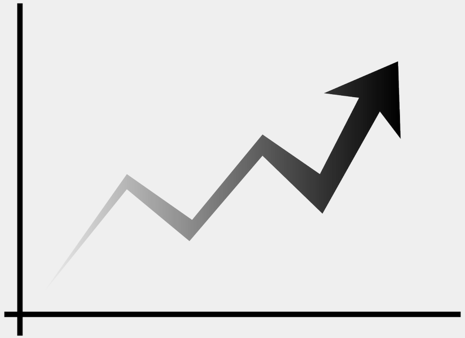
OUR GOAL



Analyze important **virus statistics**

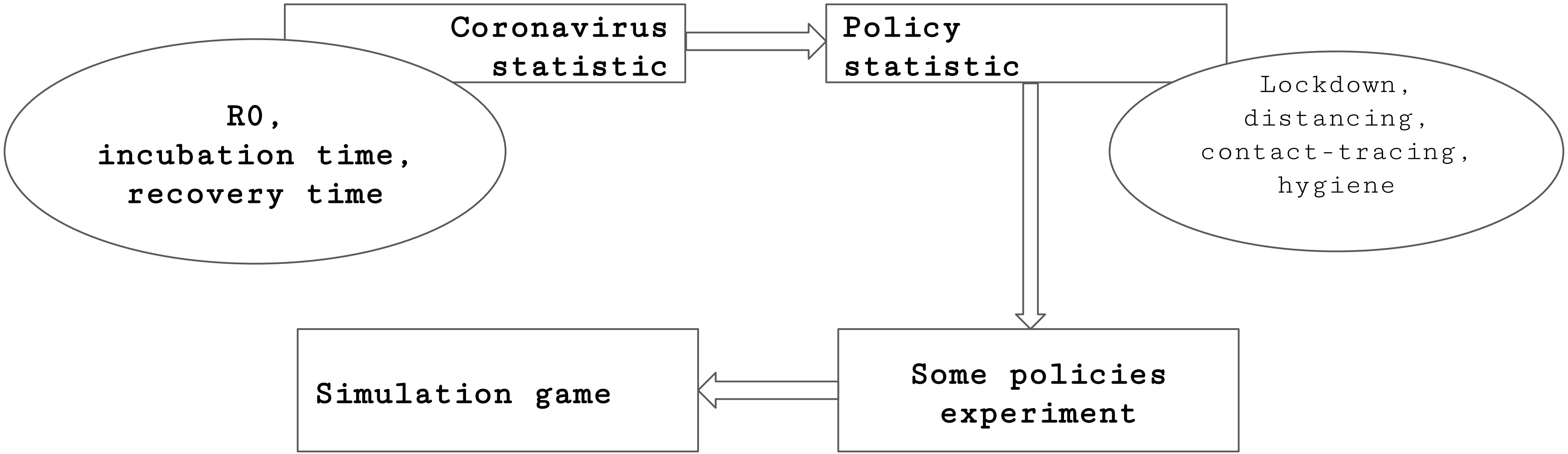


Estimate the **efficiency** of the **policies**



Simulate some policies

PIPELINE


Coronavirus statistic
R0,
incubation time,
recovery time
Policy statistic
Lockdown,
distancing,
contact-tracing,
hygiene
Some policies experiment
Simulation game

DATASET

Dataset from Kaggle: COVID-19 Dataset

Content: Number of Confirmed, Death and Recovered cases every day across the globe, divided by countries, region, province

Link:
https://www.kaggle.com/imdevskp/corona-virus-report?select=full_grouped.csv&fbclid=IwAR3ZDw5Kc9lo9kbIiw63fyrvSdV1CPSnQUbFAVXgKx9jIIxm6nWce5DFRs0

MODELS:

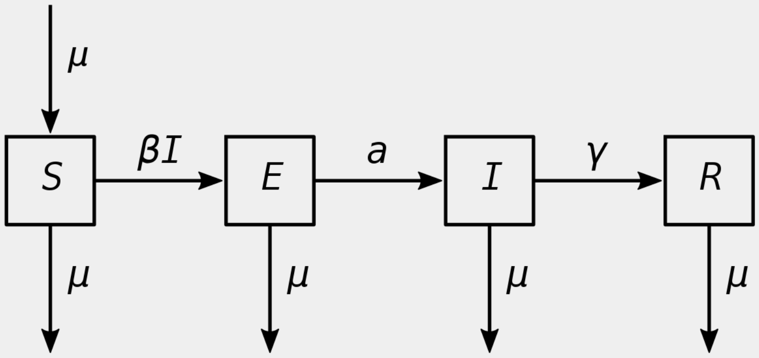
Virus Statistics Model

Policy Strength Model

Simulation Model

1. VIRUS STATISTICS MODEL

Mathematic Model: SEIR Model



$$\frac{dS}{dt} = \mu N - \frac{\beta SI}{N} + \xi R - \nu S$$
$$\frac{dE}{dt} = \frac{\beta SI}{N} - \sigma E - \nu E$$
$$\frac{dI}{dt} = \sigma E - \gamma I - \nu I$$
$$\frac{dR}{dt} = \gamma I - \xi R - \nu R$$

Assumptions:
1. recovered are immune for a lifetime
2. population is constant

1. VIRUS STATISTICS MODEL

Probabilistic Programming Model: Epidemiology Model (base model: Compartmental Model) in Pyro
Inference Algorithm: HMC with NUTS (No-U Turns) Kernel

Inferred parameter: R0, tau_e, tau_i, rho, mort_rate, rec_rate (basic reproduction numbers, recover time, incubation time, response rate, mortality rate, recover rate)

Flow:

```
state["S"] = state["S"] - S2E
state["E"] = state["E"] + S2E - E2I
state["I"] = state["I"] + E2I - I2R
```

1. VIRUS STATISTICS MODEL

Experiment:

We run data on the initial stage of Sweden (before April 1st)

Reason:

Sweden did not impose strict policies until April.
We can assume that virus transmission rate was unaffected.


The New York Times

The Coronavirus Outbreak › LIVE Latest Updates Maps and Cases What is Dexamethasone? Reopenings by State Emissions Surge Back

‘Life Has to Go On’: How Sweden Has Faced the Virus Without a Lockdown

The country was an outlier in Europe, trusting its people to voluntarily follow the protocols. Many haven’t, but it does not seem to have hurt them.

1. VIRUS STATISTICS MODEL: RESULT

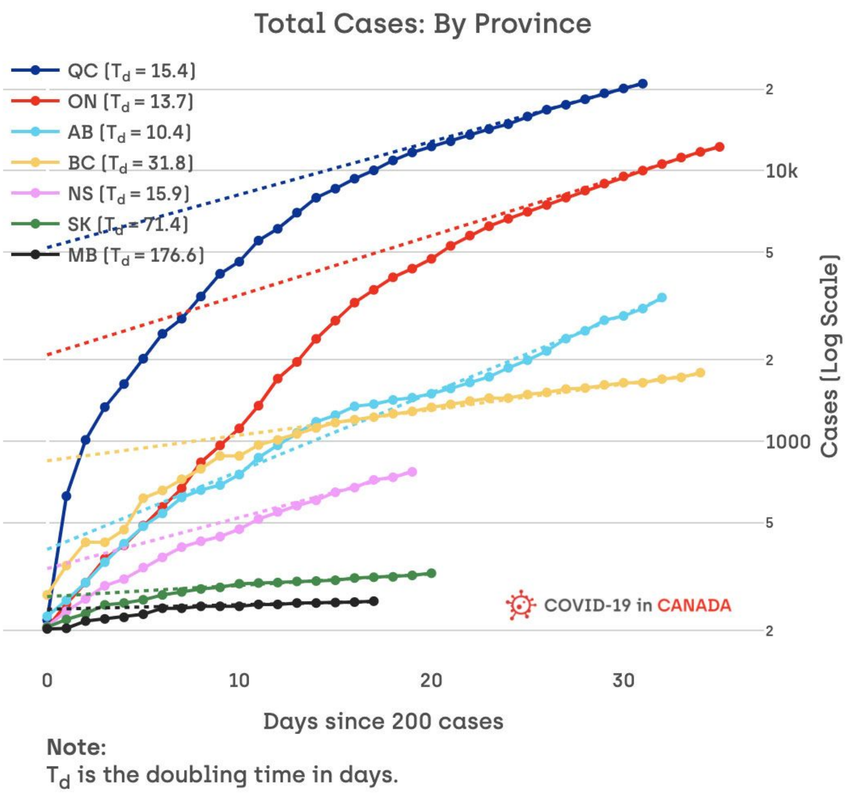
```
start_date = "2020-02-01" end_date = "2020-04-01"
```

	mean	std	median	5.0%	95.0%	n_eff	r_hat
rec_time	16.92	0.00	16.92	16.92	16.92	2.46	2.71
incub_time	3.59	0.00	3.59	3.59	3.59	2.98	1.83
R0	2.11	0.00	2.11	2.11	2.11	2.53	2.58
trans_rate	0.49	0.00	0.49	0.48	0.49	2.53	2.53
mort_rate	0.01	0.00	0.01	0.01	0.01	2.52	2.55
rec_rate	0.33	0.00	0.33	0.33	0.33		

2. POLICY STRENGTH: CHANGE-POINT MODEL

Adapted from “Detecting Changes in COVID-19 Cases with Bayesian Models” (Jonathan Ramkissoon)

Assumption: If all statistic of the virus remain the same, the **policy strength** will be reflected in the **rate of transmission** of the virus (**slope** in **log scale** of cases graph)



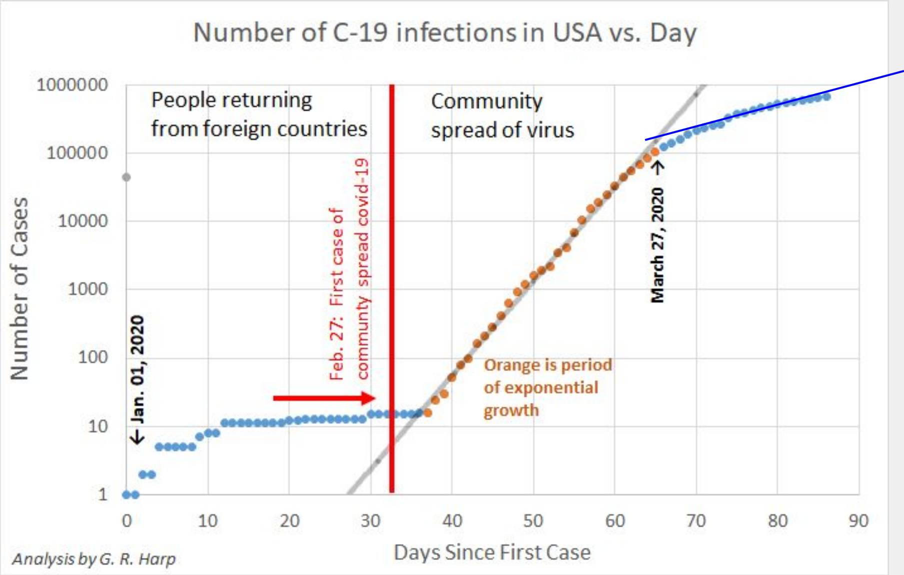
2. POLICY STRENGTH: CHANGE-POINT MODEL

Mathematical model: Segmented (piece-wise) linear model

Consider the **case count** from the **community spread** onwards in log scale.

The graph is roughly a **segmented linear** with **2 pieces** of different **slopes,** w1 and w2.

Policy Strength can be estimated by **1 - w2/w1**



2. POLICY STRENGTH: CHANGE-POINT MODEL

Probabilistic model:

Likelihood

$$y = wt + b + \epsilon\,, \qquad \epsilon \sim N(0, \sigma^2)$$

$$p(y \mid w, b, \sigma) \sim N(wt, \sigma^2)$$

Where:

$$w = \begin{cases} w_1 & \text{if } \tau \le t \\ w_2 & \text{if } \tau > t \end{cases}$$

$$b = \begin{cases} b_1 & \text{if } \tau \le t \\ b_2 & \text{if } \tau > t \end{cases}$$

Prior

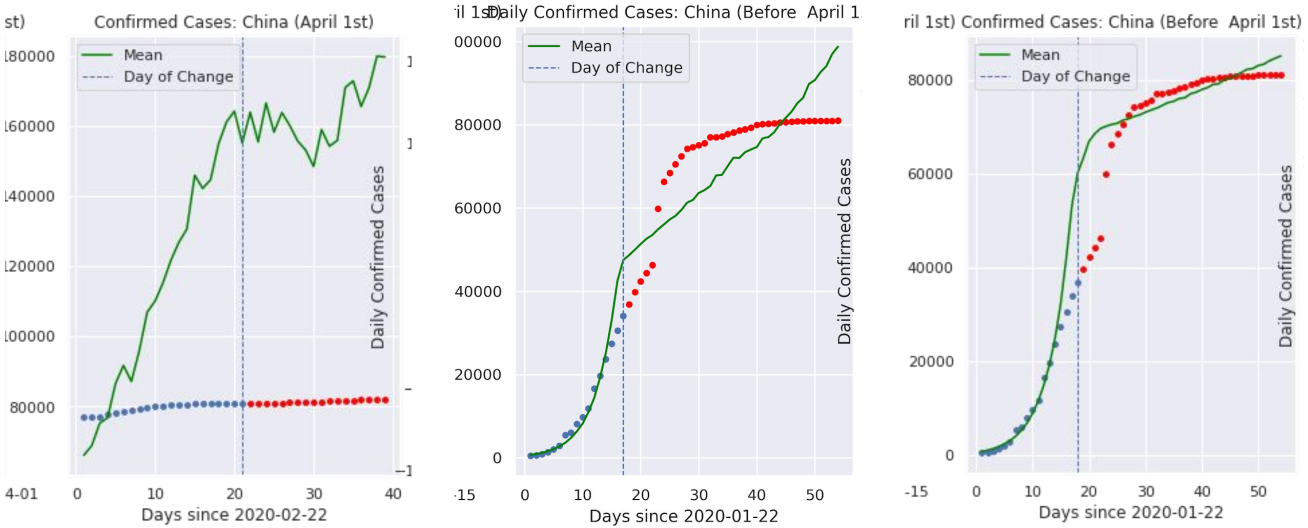
$$w_1 \sim N(\mu_{w_1}, \sigma^2_{w_1}) \qquad w_2 \sim N(\mu_{w_2}, \sigma^2_{w_2})$$

$$b_1 \sim N(\mu_{b_1}, \sigma^2_{b_1}) \qquad b_2 \sim N(\mu_{b_2}, \sigma^2_{b_2})$$

$$\tau \sim Beta(\alpha, \beta) \qquad \sigma \sim U(0, 3)$$

2. POLICY STRENGTH: CHANGE-POINT MODEL

Other design choices
Inference algorithm: MCMC with NUTS (over SVI)
Likelihood: Student Distribution (over Normal distribution)



2. POLICY STRENGTH: CHANGE-POINT MODEL

Other design choices
Inference algorithm: MCMC with NUTS over SVI
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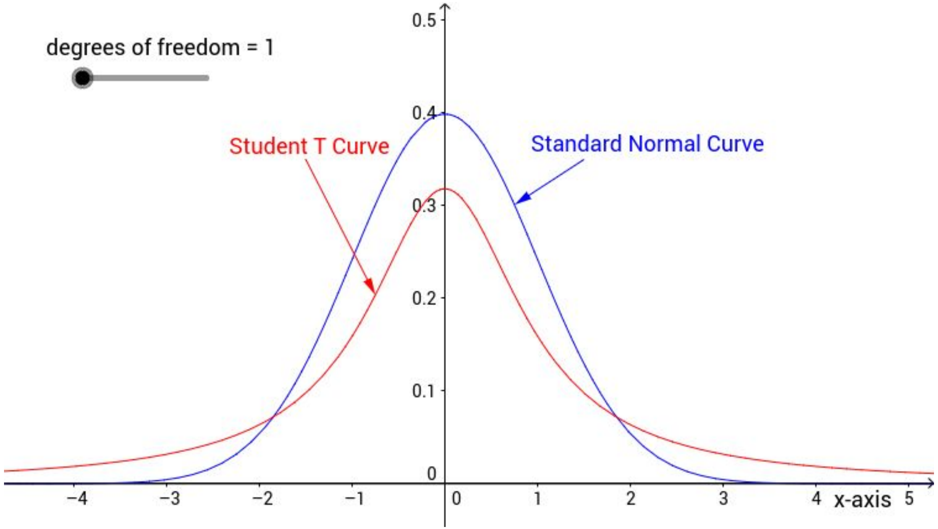


2. POLICY STRENGTH: CHANGE-POINT MODEL

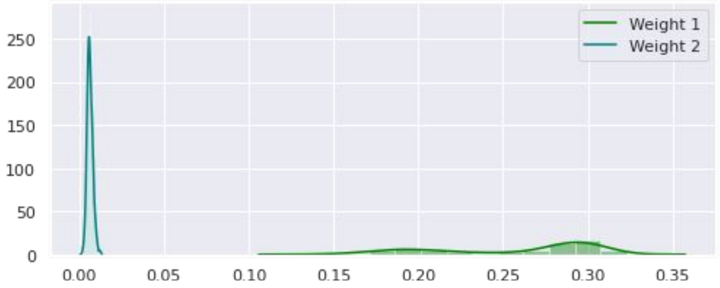
Experiment: Run the model on the countries that **strongly impose a policy.** The **full efficacy** of the policy is assumed to be **the policy strength in that country.**

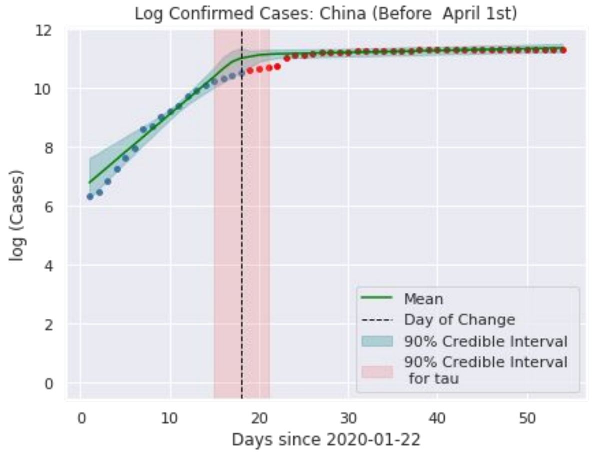
- Lockdown: **China, New Zealand**
- Contact tracing and quarantine: **South Korea**
- Social distancing: **Canada**
- Mask and hygiene efficiency: Stay tuned ^^

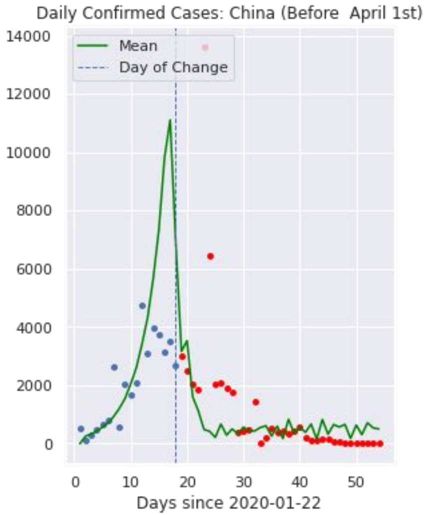
How to know our model works well:

- The date of change should be around 14 days (recommended incubation time by WHO) after the policy establishment
- Strong convergence of the algorithm and the fitness to real data
- Prior: Lockdown has very high strength ...

2. RESULT: LOCKDOWN - CHINA



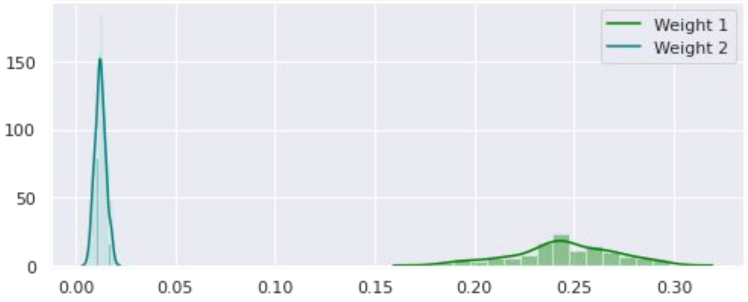


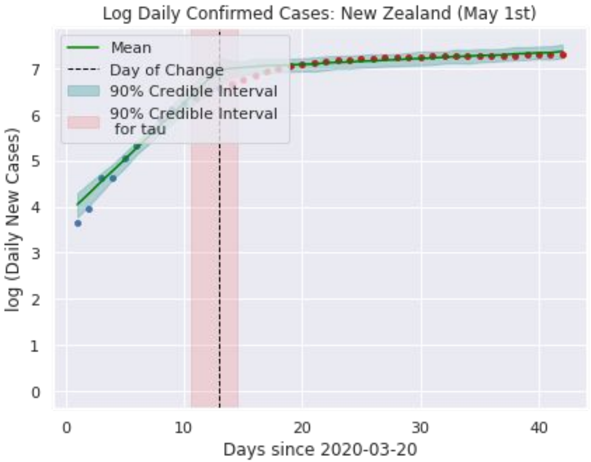


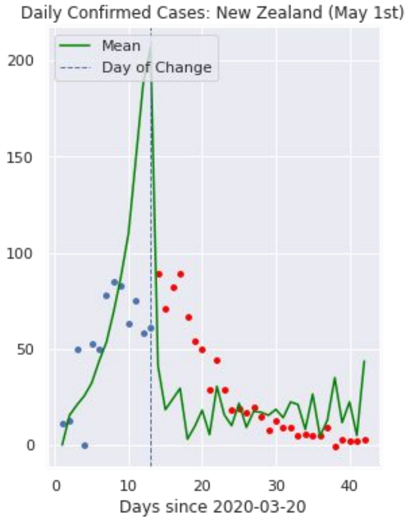
Date of change: 2020-02-09
Lockdown applied: 2020-01-23

Policy strength: 1 - 0.01/0.26 = **0.96**

2. RESULT: LOCKDOWN - NEW ZEALAND



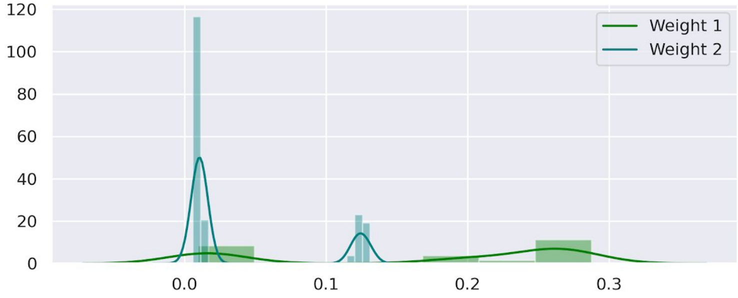


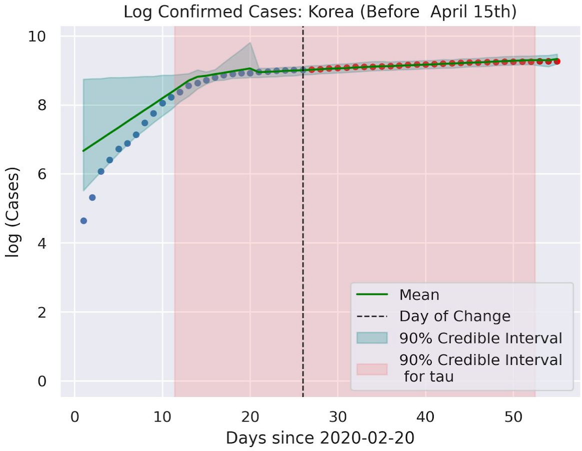


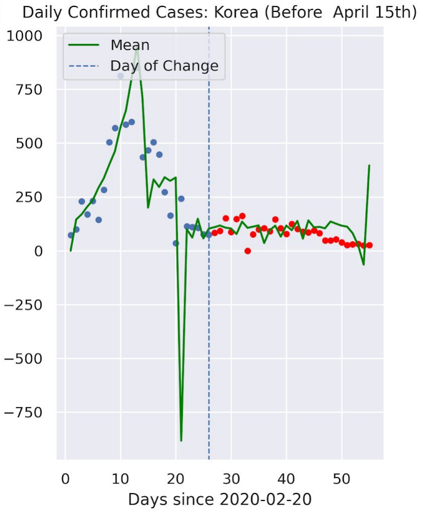
Date of change: 2020-04-02
Lockdown applied: 2020-03-25

Policy strength: 1 - 0.01/0.25 = **0.96**

2. RESULT: TRACING - SOUTH KOREA



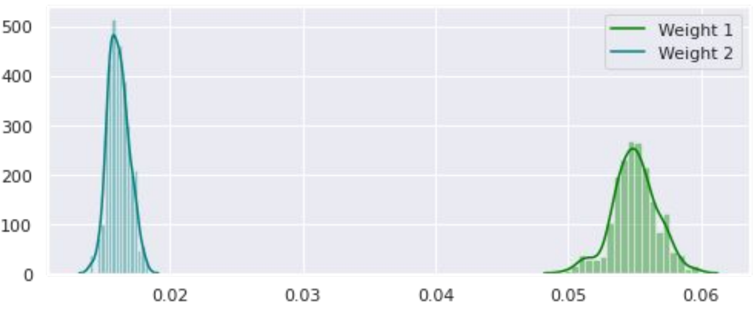


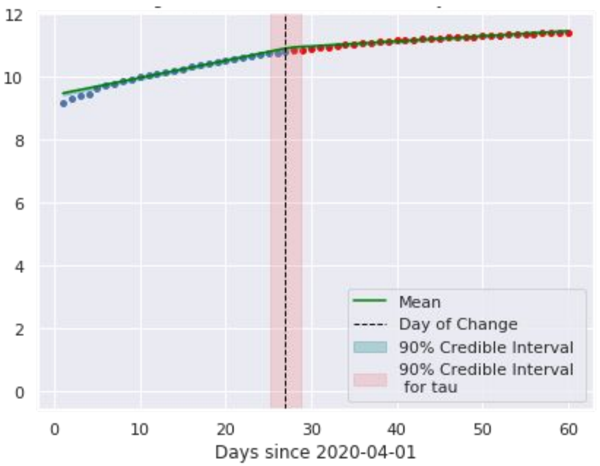


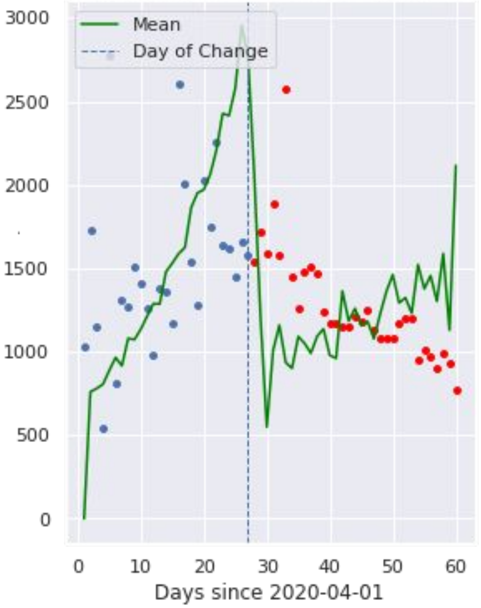
Date of change: 2020-03-17
Testing increase: 2020-02-25

Policy strength: 1 - 0.04/0.17 = **0.76**

2. RESULT: DISTANCING - CANADA







Date of change: 2020-04-28
Policy applied: March-April

Policy strength: 1 - 0.02/0.05 = **0.60**

2. RESULT: MASKS & HYGIENE- JAPAN

Note: R0 for Sweden is 2.11

	mean	std	median	5.0%	95.0%	n_eff	r_hat
rec_time	14.86	0.02	14.86	14.84	14.89	2.69	2.26
incub_time	3.99	0.01	3.99	3.98	4.00	4.12	1.47
R0	**1.72**	0.03	1.71	1.67	1.77	2.77	2.18
trans_rate	0.29	0.01	0.29	0.28	0.29	2.54	2.53
mort_rate	0.02	0.00	0.02	0.02	0.02	2.57	2.44
rec_rate	0.15	0.01	0.14	0.14	0.16	2.62	2.39

Assumption:

Japanese people were custom to wear masks even before any policy was applied.

Policy strength: 1 - 1.72/2.11 = **0.18**

2. RESULT: SUMMARY

Policy	Strength
Lockdown	0.96
Distancing	0.60
Tracing	0.76
Masks / Hygiene	0.18

3. SIMULATION: SIMPLE GENERATIVE MODEL

Inferred parameters:

- R0 : 2.11
- incubation_days : 3.59 days
- recovery_days : 16.92 days
- transmission_days : 8 days
- Mortality rate with hospitalization: 2%

- hygiene : 0.18
- distancing : 0.6
- lockdown : 0.96
- quarantine : 0.76

Assumptions:

- Population : 1 million ppl
- Hospital Cap : 0.06%
- Immunity: infinite
- Serious cases: 15%
- Mortality rate without hospitalization: 90%

3. SIMULATION: SIMPLE GENERATIVE MODEL

For S, E, I, R: The same with SEIR model

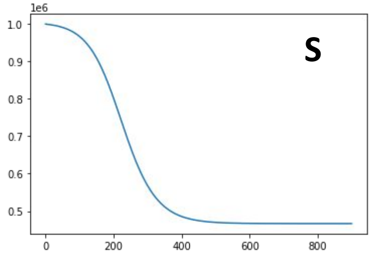
Death tolls estimation:

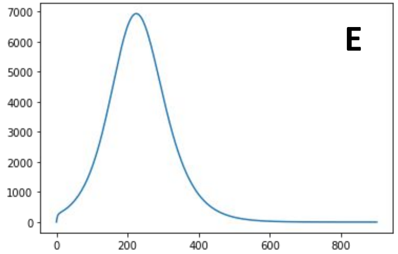
Using hospital capacity .06%, critical case rate of 15%
For critical case:

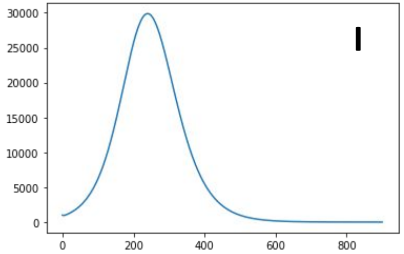
- Death rate without medical treatment: 90%
- Death rate with medical treatment: 2%

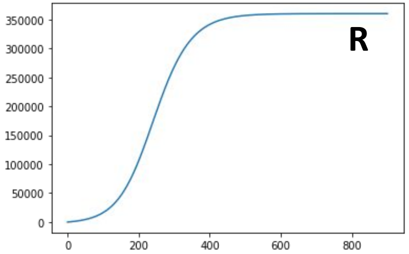
3. SIMULATION: SOME EXPERIMENT

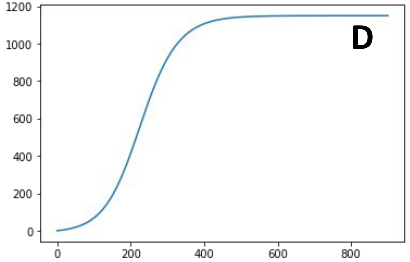
No policies:





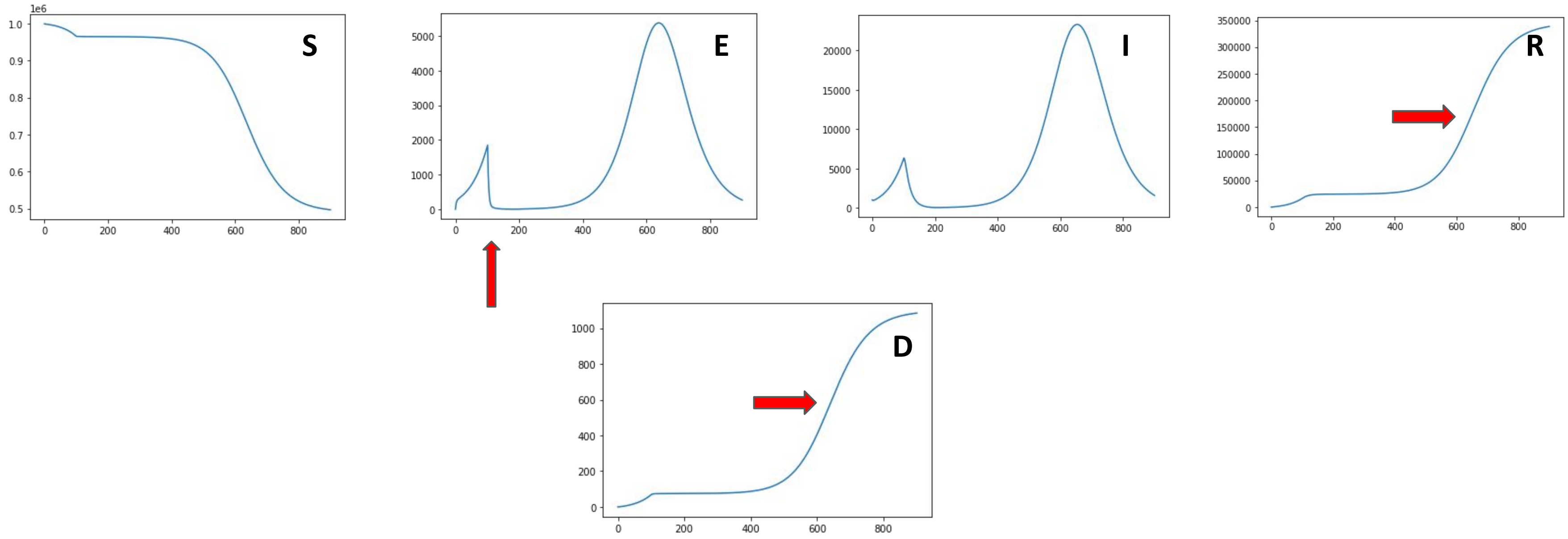






3. SIMULATION: SOME EXPERIMENT

Lockdown starting day 100-200:



3. SIMULATION GAME: ADDING REWARD

- We estimate the economic cost for each policy and give negative rewards:
  - Lockdowns: 10% of GDP per year (GDP per capita: 30k$)
  - Distancing: 5% of GDP per year
  - Hygiene: 2$ per day per capita
  - Quarantine: 100$ per day per infected
  - Infection: 300$ per infection per day (until recovered)
  - Death: 4.9 million per death
- We tried to calculate the policy with least loss / highest reward
- Assumption:
  Initially infected: 1%

3. SIMULATION GAME: EXPERIMENT

- Game mission: Derive a policy in **3 month** with **1-month interval** policy. Each policy can be applied at **x%** of its full efficacy

- **Goal: Minimize the loss**

- Original plan: **Generative modeling**, observe the score with mean 0
- **We have issue: NaN**

3. SIMULATION GAME: EXPERIMENT

- Game mission: Derive a policy in 3 month with 1-month interval policy. Each policy can be applied at x% of its full efficacy
- **Discretize** the game: 3 levels for x: full (100%), partially (50%) and none (0%)
- Goal: Minimize the loss
- Result:
  + Best policy: **Full contact tracing + quarantine in all 3 months**
  + Loss: **- 67 411 086$**
  + Loss without doing anything: **- 3 355 503 642$**

(Scale up for USA: 4 trillion $ per year)

Conclusion

- Policy affects virus a lot
- We must act early
- We must act efficiently
- We should consider health/economy trade off

References

- Simulation with JS: https://ncase.me/covid-19/?fbclid=IwAR02Xo2w7C9EAqhUchfkvt8Di0BLSapejPgltU5iuR13Q1zm_RJD28hXT-0
- Simulation with R: https://rviews.rstudio.com/2020/03/19/simulating-covid-19-interventions-with-r/?fbclid=IwAR3bgZRGxLqNhx8G4xQ-sU0DR-oy97gOK-MILX1Urpt2fp_iZDupLWbUa_I
- Change-point Model https://towardsdatascience.com/detecting-changes-in-covid-19-cases-with-bayesian-models-1b628214e8b1?gi=8f422aec39f7
- Epidemiology Model http://docs.pyro.ai/en/dev/contrib.epidemiology.html