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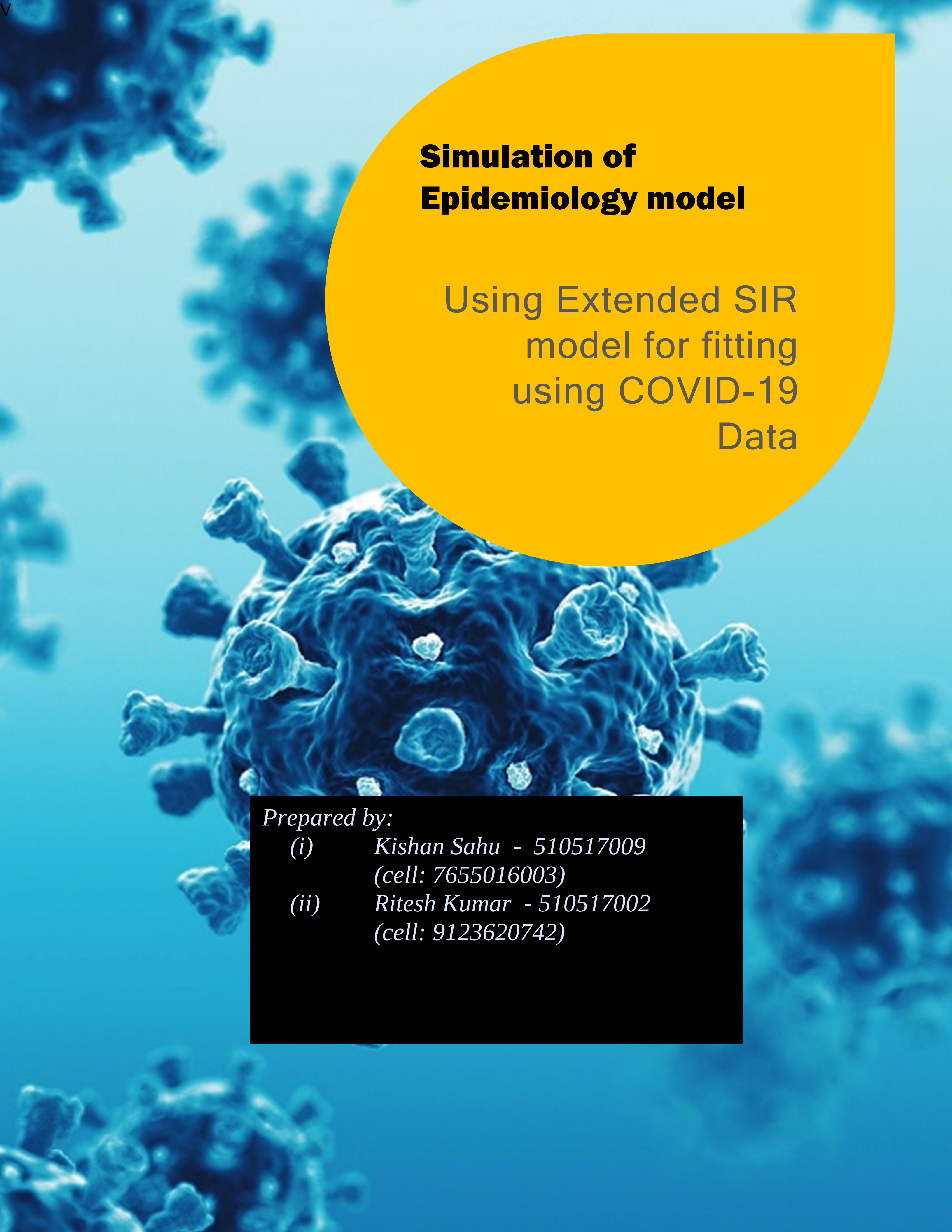

Simulation of Epidemiology model

Using Extended SIR model for fitting using COVID-19 Data

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01 Introduction:

Models are always simplifications of the real world. If you want to see a model that perfectly resembles the real world, go outside! Still — that does not mean that they cannot be interesting and generate insights.

Here I will be exploring an extension the SIR model, where Each living being is assumed to be in one of the three states at any given time: Susceptible, Infected and Recovered.

02 Assumptions:

This extended SIR model will be based on following assumptions:

- Deaths are not so high as to significantly change the population-structure.
- Only critical cases fill up the hospitals and can lead to a higher fatality rate due to shortage of available care.
- All *critical* patients that do not get treatment die.
- Individuals are immune after recovering.
- R_0 only decreases or stays constant. It does not increase.

This model consists of following compartments:

- Susceptible: They can catch Covid-19.
- Exposed: They can't yet spread the virus.
- Infected: They are infected and can spread the virus.
- Critical: They are in need of intensive care.
- Dead: Over the course of infection they die.
- Recovered: After battling with the virus they finally recover and become immune.

03 Variables:

Here is the list of variables I will be referring:

- **N:** total population
- **S(t):** number of people susceptible on day t
- **E(t):** number of people exposed on day t
- **I(t):** number of people infected on day t
- **R(t):** number of people recovered on day t
- **D(t):** number of people dead on day t
- **α:** fatality rate
- **β:** expected amount of people an infected person infects per day
- **D:** number of days an infected person has and can spread the disease
- **γ:** the proportion of infected recovering per day ($\gamma = 1/D$)
- **R_0:** the total number of people an infected person infects ($R_0 = \beta / \gamma$)
- **δ:** length of incubation period

- **ρ:** rate at which people die (= 1/days from infected until death)

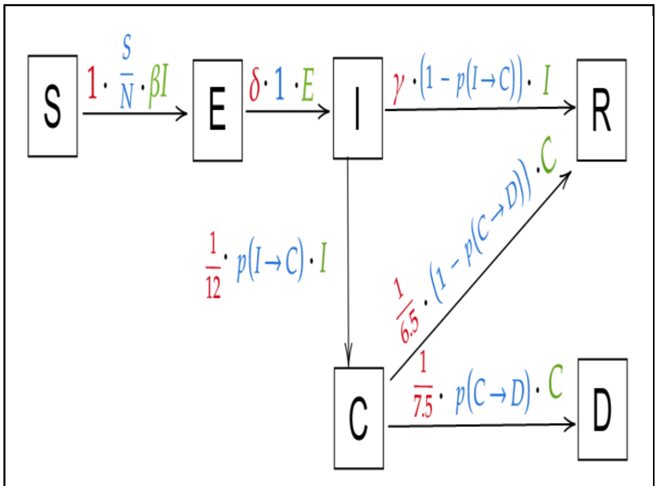
- p(I→C): Logically, the probability of going from infected to critical.

- p(C→D): We need another probability, the probability of dying while critical.

- Number of days from infected to critical: 12 (→rate: 1/12)

- Number of days from critical to dead: 7.5 (→rate: 1/7.5)

- Number of days from critical to recovered: 6.5 (→rate: 1/6.5)



1.Figure describing the transition between different compartments.

For Ro(t), we will again use the following logistic function:

For this model, we only have two time-dependent variables: Ro(t) (and thus β(t), as Ro = β / γ) and Beds(t).

$$Ro(t) = R_{0end} \frac{R_{0start} - R_{0end}}{1 + ee^{-k(x_0 + x)}}$$

03 The equations:

$$\frac{dS}{dt} = -\beta(t) \cdot I \cdot \frac{S}{N}$$

$$\frac{dE}{dt} = \beta(t) \cdot I \cdot \frac{S}{N} - \delta \cdot E$$

$$\frac{dI}{dt} = \delta \cdot E - \frac{1}{12} \cdot p(I \to C) \cdot I - \gamma \cdot (1 - p(I \to C)) \cdot I$$

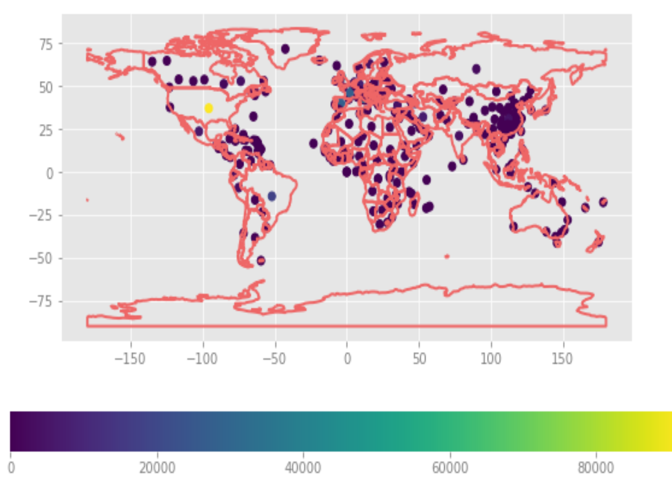
$$\frac{dC}{dt} = \frac{1}{12} \cdot p(I \to C) \cdot I - \frac{1}{7.5} \cdot p(C \to D) \cdot \min(Beds(t), C) - \max(0, C - Beds(t)) - \frac{1}{6.5} \cdot (1 - p(C \to D)) \cdot \min(Beds(t), C)$$

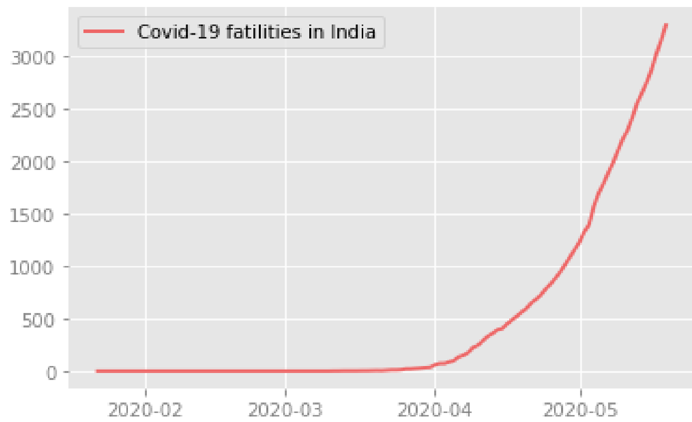
$$\frac{dR}{dt} = \gamma \cdot (1 - p(I \to C)) \cdot I + \frac{1}{6.5} \cdot (1 - p(C \to D)) \cdot \min(Beds(t), C)$$

$$\frac{dD}{dt} = \frac{1}{7.5} \cdot p(C \to D) \cdot \min(Beds(t), C) + \max(0, C - Beds(t))$$

N = S+E+I+C+R+D

04 Data visualization:

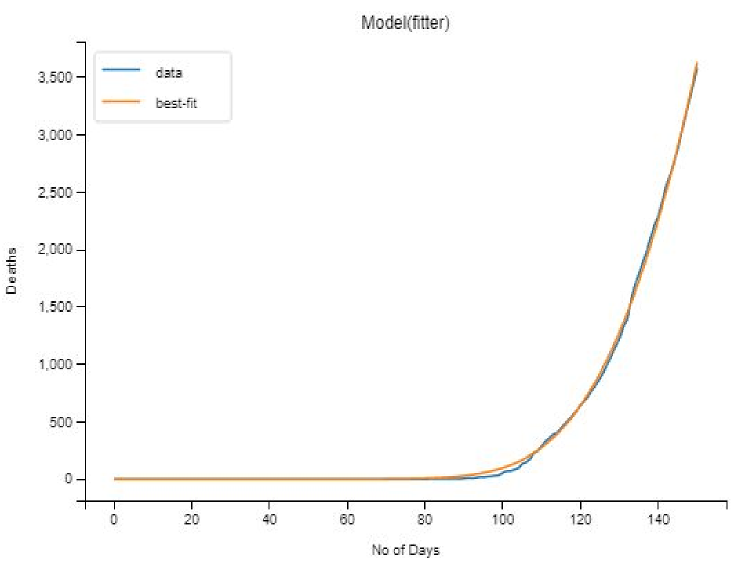




05 Curve Fitting:

For fitting, we need a function that takes exactly an x-value as first argument (the day) and all the parameters we want to fit, and that returns the deaths predicted by the model for that x-value and the parameters, so that the curve fitter can compare the model prediction to the real data. Here it is:

```
'R_0_end': 1.4265598773371855,
'R_0_start': 4.496675598412916,
'k': 0.071246531048363,
'prob_C_to_D': 0.05643141426035666,
'prob_I_to_C': 0.010000047667421689,
's': 0.003,
'x0': 94.99518409329349}
```



As we can see with the data beginning on January 21 and the outbreak shift set to 30 days, day 95 for our model is March 26. x0 is the date of the steepest decline in R0, so our model thinks that the main “lockdown” took place in India around March 26 , very close to the real date.

Some of the predicted values are:

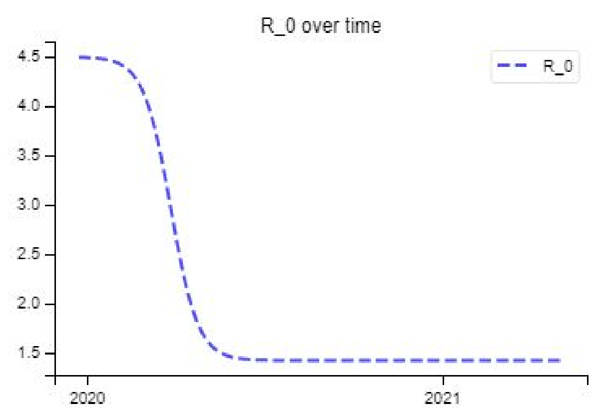
$$R_0(at\ the\ starting) = 4.49$$

$$R_0(current) = 1.43$$

$$P_{infected -> critical} = 1\%$$

$$P_{critical -> Dead} = 5\%$$

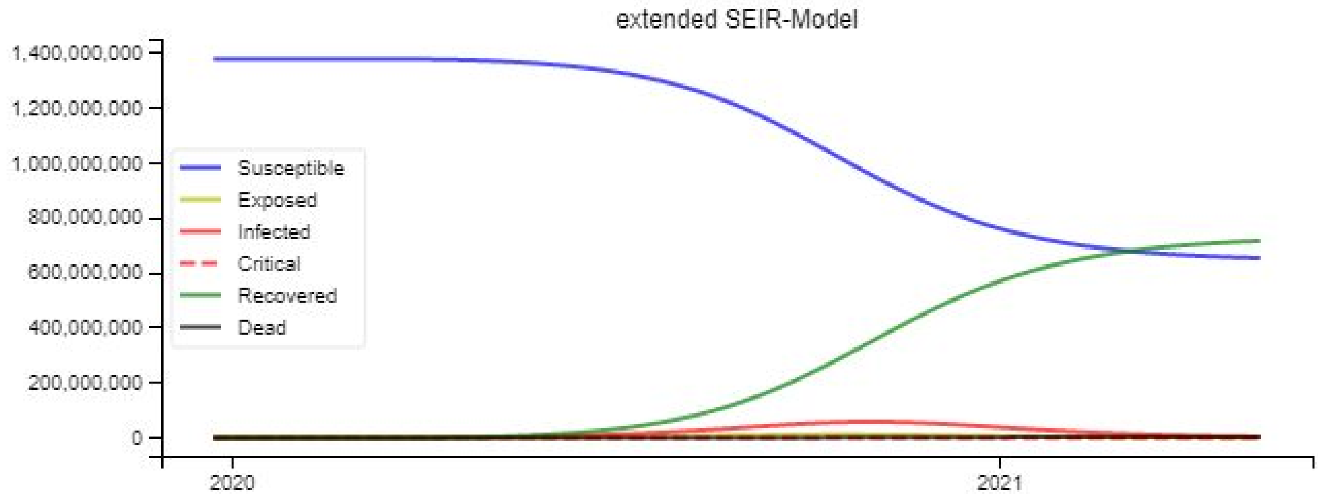
India’s R0 has shown a decline, peaking at 4, and then plunging down to 1.4, which is similar to the predicted curve



06 Simulation of The Model:

Using the best-fitting parameters,Plotted the curve to get a look at the future our model predicts.

```
Prediction for India
percentage going to ICU: 1.000004766742169; percentage dying in ICU: 5.643141426035666
```



That's all for now. In future we will build a dashboard for such a model to see the effect of different parameters in real time!

REFs:

- This project notebook can be viewed here.
- Covid-19 data was taken from here.