# **REPORT**

# **ASSIGNMENT 3**COVID-19 MODELLING

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#### **IMPLEMENTATION SUMMARY**

The following are the functions used in the program-

#### 1. projection(params)

#### Parameters-

params: list containing  $\beta$ , S(0), E(0), I(0), R(0), CIR(0)

return type: list

It returns a list containing  $\beta$ , S(0), E(0), I(0), R(0), CIR(0).

**summary:** This function makes sure that the parameters are within specified constraints. If parameters do not satisfy constraints, then the parameter is set to its limit.

#### 2. get\_training\_data():

#### Parameters-

None

**return type:** pandas.core.frame.DataFrame It returns a DataFrame containing t,  $\Delta V$ ,  $\overline{c}$ , T.

**summary:** This function returns a DataFrame containing t,  $\Delta V$ ,  $\overline{c}$ , T (where t is the day number starting from 16 March 2021.  $\Delta V$  is the number of vaccinations per day.  $\overline{c}$  is running seven-day average of  $\Delta confirmed(t)$ . T(t) is the average number of tests done during the past 7 days. The DataFrame contains data from 16 March 2021 to 26 April 2021.

#### 3. running\_average(a)

#### Parameters-

a: list of numbers.

return type: numpy.ndarray

**summary:** This function returns a numpy array containing the seven-day running average of the list a. When there are less than seven available days, the average of the available days is taken.

#### 4. SEIRV model(initial values)

#### Parameters-

initial\_values: list containing  $\beta$ , S(0), E(0), I(0), R(0), CIR(0)

return type: list

**summary:** We create four lists **S**, **E**, **I**, **R** that contain S(t), E(t), I(t), R(t) values. For each value of **t**, we calculate  $\Delta S(t)$ ,  $\Delta E(t)$ ,  $\Delta I(t)$ ,  $\Delta R(t)$  using the equations given in problem description 1.(a), and add with the previous values before storing in **S**, **E**, **I**, **R**.

In the function, some values of **S** were negative. So, a condition was added so that the negative value goes to zero, and the remaining values are scaled so that their sum is 70 million.

The function returns a list that contains S(t), E(t), I(t), R(t) values from t=0 to t=41. (t=0 refers to 16 March 2021, and t=41 refers to 26 April 2021)

#### 5. loss\_function(params)

#### Parameters-

params: list containing  $\beta$ , S(0), E(0), I(0), R(0), CIR(0)

return type: float

**summary:** The cases-to-infections ratio is calculated for t = 0 to t = 41 using the expression CIR(t) = CIR(0)\*T( $t_0$ )/T( $t_0$ ). Where T(t) is the average number of tests done during the past 7 days and t0 is 16 March 2021.

Then we calculate the running seven-day average of  $\alpha e(t)$  (where e(t) = E(t)/CIR(t))

Then we use the loss function as given in the problem description, and return the mean squared error.

#### 6. gradient(params)

#### Parameters-

params: list containing  $\beta$ , S(0), E(0), I(0), R(0), CIR(0)

return type: numpy.ndarray

**summary:** For estimating the gradient,  $\beta$  is perturbed on either side by  $\pm 0.01$ , CIR(0) is perturbed on either side by  $\pm 0.1$ , and all other parameters by  $\pm 1$ . It returns a numpy array containing the gradients for each parameter.

#### 7. gradient\_descent(params)

#### Parameters-

params: list containing  $\beta$ , S(0), E(0), I(0), R(0), CIR(0)

return type: numpy.ndarray

**summary:** The **get\_training\_data()** function is called to extract the values of  $\Delta V$ ,  $\overline{c}$ , T. Then the loss is calculated using **loss\_function**. The parameters are updated till the loss < 0.01.

Then the function returns a numpy array containing the optimal values of  $\beta$ , S(0), E(0), I(0), R(0), CIR(0).

#### 8. new reported cases()

Parameters- None return type: list

**summary:** This function returns a list of Δconfirmed values from 16 March 2021 onwards.

#### 9. plot cases(result, beta)

#### Parameters-

result: list

result contains the predictions for *S,E,I,R* till 31 December 2021.

beta: float

**summary:** Find the average CIR value for the training period. Get **E** from **result** and reported cases by using **new\_reported\_cases**(). Divide **E** by average CIR to get the number of cases. Then plot a graph that shows the number of new cases predicted on each day till 31 December 2021. It also shows the number of new reported cases till 20 September 2021.

### 10. plot\_S\_fraction(result, beta)

#### Parameters-

result: list

result contains the predictions for S,E,I,R till 31 December 2021.

beta: float

**summary:** Get **S** from **result**. Then plot a graph that shows the evolution of the fraction of the susceptible population.

#### 11. open\_loop\_control(params)

#### Parameters-

params: list containing  $\beta$ , S(0), E(0), I(0), R(0), CIR(0)

return type: list

**summary:** This is similar to **SEIRV\_model()**. But here  $\Delta V(t)$  is taken as 200000 for  $t \ge 42$ . For immunity wanning we set  $\Delta W(t) = \Delta R(t - 180) + \varepsilon \Delta V(t - 180)$ , when t is larger than 11 September 2021. In the function, some values of **S** and **R** were negative. So, a condition was added so that the negative value goes to zero, and the remaining values are scaled so that their sum is 70 million. The function returns a list that contains S(t), E(t), I(t), I(t) values till 31 December.

#### 12. closed\_loop\_control(params)

#### Parameters-

params: list containing  $\beta$ , S(0), E(0), I(0), R(0), CIR(0)

return type: list

summary: This is similar to  $open\_loop\_control()$ . But here the  $\beta$  values are updated as mentioned in the problem description. The updating starts from 27 March.

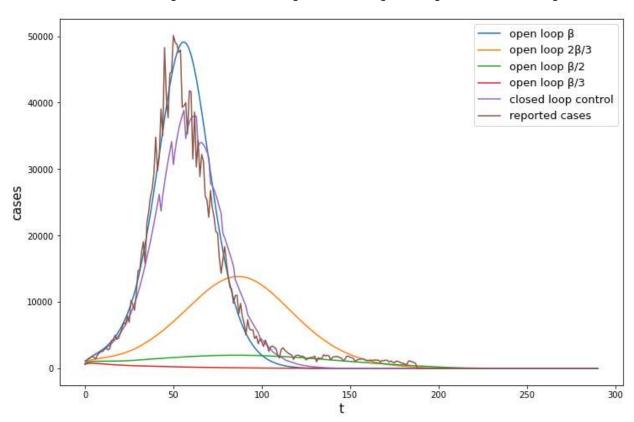
# **OUTPUT**

GRADIENT DESCENT: iterations: 34 loss = 0.007057469495405773 best\_params [0.470504737336695, 47214999.9999966, 111999.99999546476, 272999.99998825626, 22399999.99999817, 29.549793811281727]

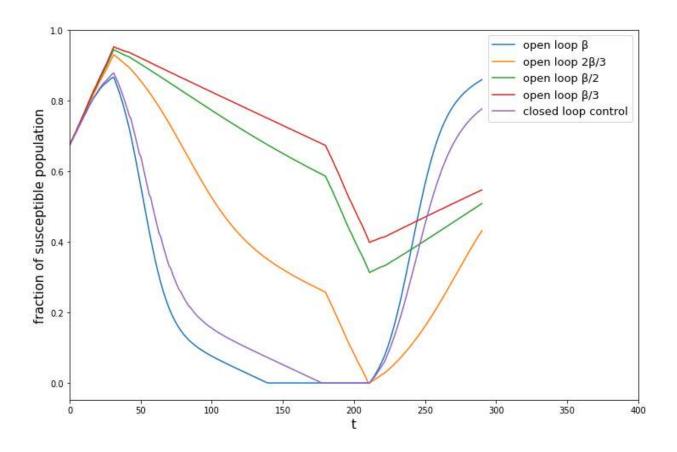
# **PLOTS**

All the plots below are from t = 0 (16 March 2021) to t = 290 (31 December 2021)

# number of new cases predicted and reported for open loop and closed loop control



# Evolution of the fraction of the susceptible population for open loop and closed loop control



# **CONCLUSION**

I learnt about different methods used to model COVID-19. I understood how the number of cases changes with different contact rates and initial values. I used pandas to create and manipulate Dataframes. I was able to get a loss of 0.007057469495405773 while fitting the model. I used the model to predict the number of new cases of infection till 31 December 2021.