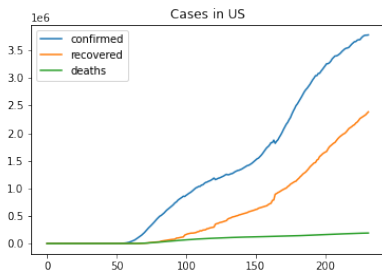


# First-principles machine learning modelling of COVID-19

Che-Chia Chang

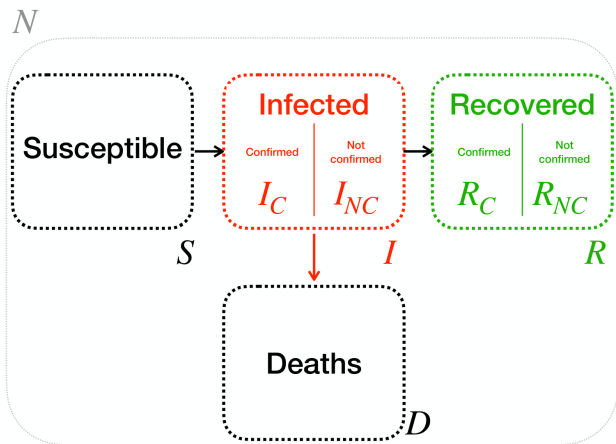
# The COVID-19 Data

- Used data: COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (<https://github.com/CSSEGISandData/COVID-19>)
- Data includes number of:
  - 1 confirmed cases
  - 2 recovered cases
  - 3 deaths casesof each day for 188 countries.



# The SIRD model

- To describe the data, we may consider the SIRD model to fit it.



- Note that here  $N = S + I + R + D$ .

# The SIRD model

The original ODE system of the SIRD model is written as:

## The SIRD model

$$\begin{aligned}\frac{dS}{dt} &= -\frac{\beta IS}{N}, \\ \frac{dI}{dt} &= \frac{\beta IS}{N} - (\mu + \gamma)I, \\ \frac{dR}{dt} &= \gamma I, \\ \frac{dD}{dt} &= \mu I,\end{aligned}$$

where  $\beta$ ,  $\gamma$ ,  $\mu$ , are rates of infection, recovery, and mortality, respectively.

- Note that here  $\beta$ ,  $\gamma$ ,  $\mu$  may be dependent of time  $t$ .

# The discrete SIRD model

We solve the ode numerically using Euler's method with step size 1, which results in the discrete SIRD model:

## The discrete SIRD model

$$S(t+1) = S(t) - \frac{\beta(t)I(t)S(t)}{N},$$

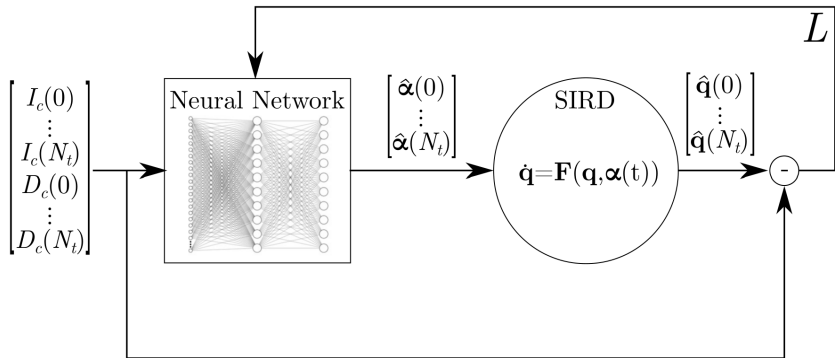
$$I(t+1) = I(t) + \frac{\beta(t)I(t)S(t)}{N} - (\mu(t) + \gamma(t))I(t),$$

$$R(t+1) = R(t) + \gamma(t)I(t),$$

$$D(t+1) = D(t) + \mu(t)I(t),$$

with  $I(0)$  and  $D(0)$  being the number of confirmed and deaths of the first confirmed day respectively,  $S(0) = N - I(0) - D(0)$ ,  $R(0) = 0$ .

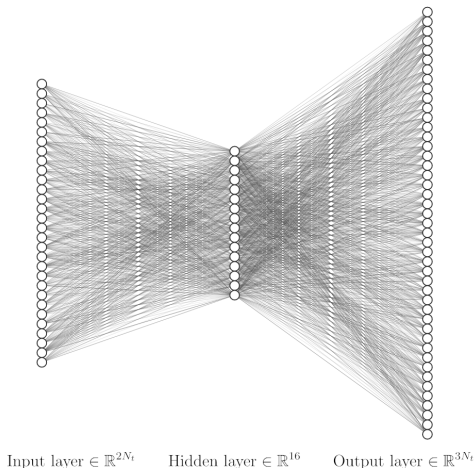
# First-principles machine learning model



- $I_c(t)$ : infected people = confirmed - recovered - deaths
- $D_c(t)$ : deaths
- $\hat{\boldsymbol{\alpha}}(t) = [\hat{\beta}(t), \hat{\gamma}(t), \hat{\mu}(t)]$ ,  $\hat{\mathbf{q}}(t) = [\hat{S}(t), \hat{I}(t), \hat{R}(t), \hat{D}(t)]$

# The neural network

- A Fully connected neural network with 1 hidden layer and sigmoid activation. Input size :  $2(N_t + 1)$ , Output size:  $3(N_t + 1)$ .



# Initialization

- We pre-train the neural network to output a constant guess of  $\beta_0, \gamma_0, \mu_0$ .
- $\beta_0, \gamma_0, \mu_0$  is found by minimizing

$$\sum_{t=0}^{\tilde{N}_t} (I_c(t) - \hat{I}(t))^2 + 100 \sum_{t=0}^{\tilde{N}_t} (D_c(t) - \hat{D}(t))^2$$

where  $\tilde{N}_t$  is the time of initial exponential growth, using optimization package. (For USA, take  $\tilde{N}_t = 70$ )

- Pre-training uses mean-squared-error with Adam optimizer and step size 0.012, 2500 iterations.



# Loss function and training

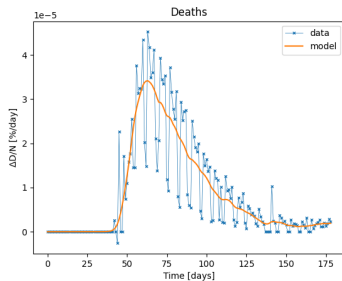
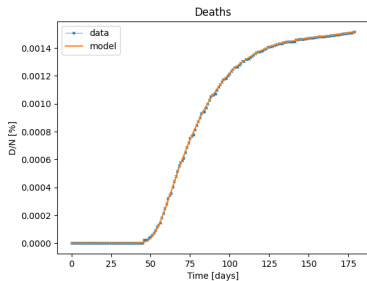
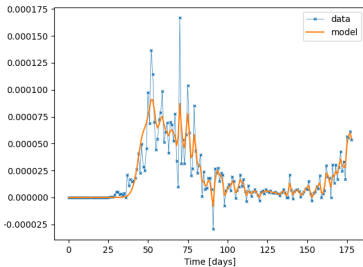
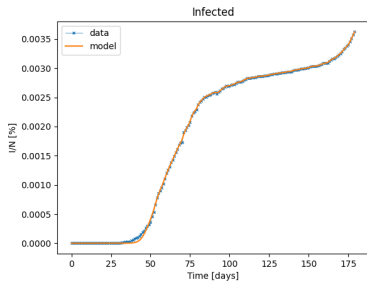
- The loss function  $L$  of the neural network is given by

$$\begin{aligned} L = & \sum_{t=0}^{N_t} \left( (\log(I_c(t)) - \log(\hat{I}(t)))^2 + (\log(D_c(t)) - \log(\hat{D}(t)))^2 \right) + \\ & 0.01 \frac{\log(\max(I_c))}{\max(I_c)} \sum_{t=0}^{N_t} \left( (I_c(t) - \hat{I}(t))^2 + (D_c(t) - \hat{D}(t))^2 \right) + \\ & 100 \frac{\log(\max(I_c))}{\max(\alpha_0)} \sum_{t=0}^{N_t-1} (\hat{\beta}(t) - \hat{\beta}(t+1))^2 + (\hat{\gamma}(t) - \hat{\gamma}(t+1))^2 \\ & \quad + 100(\hat{\mu}(t) - \hat{\mu}(t+1))^2 + \\ & 100 \frac{\log(\max(I_c))}{\max(\alpha_0)} \left( (\hat{\beta}(0) - \beta_0)^2 + (\hat{\gamma}(0) - \gamma_0)^2 + 100(\hat{\mu}(0) - \mu_0)^2 \right) \end{aligned}$$

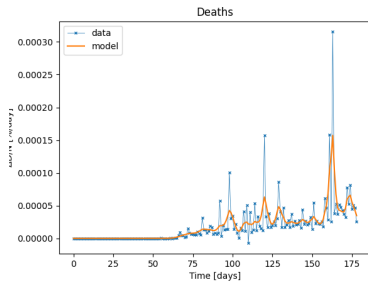
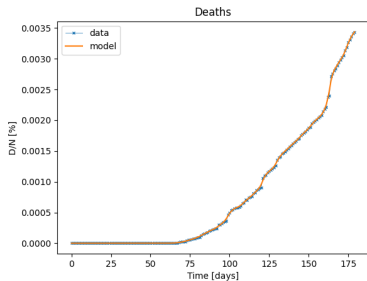
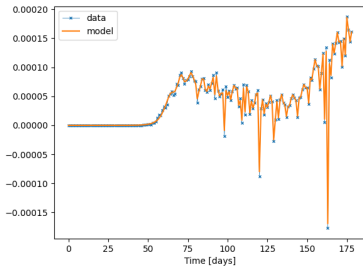
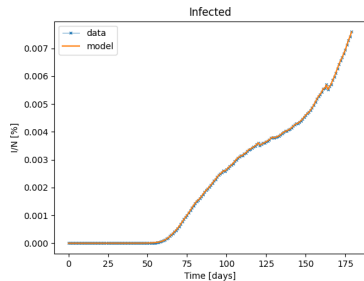
# Loss function and training

- We'll train networks of the United Kingdom, Italy, Germany, France, Spain, Belgium, US, and China. The training only involves a single data.
- We train the network using Adam and learning rate 0.00005 with 20000 iterations and 0.00001 with 20000 iterations for  $N_t = 179$ .

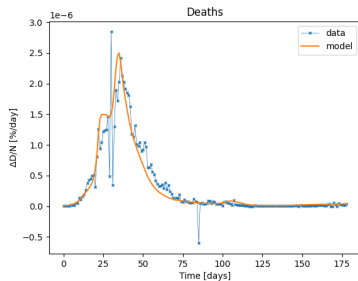
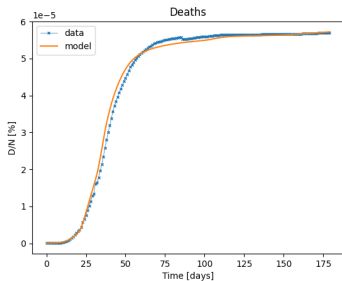
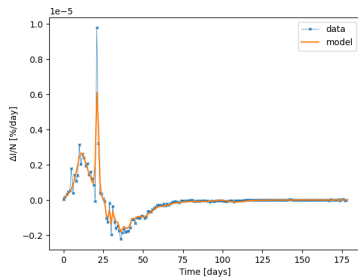
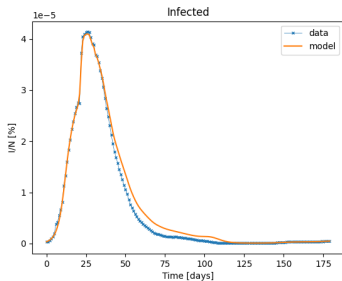
# Fitting results(Belgium)



# Fitting results(US)



# Fitting results(China)



# Parameter Results

# Non-Machine Learning methods

# Future works