

# singapore:

this is what our basic model looks like:

$$n_t = \alpha_t N_t \chi_t$$

$$N_{t+1} = N_t + n_t - \sum_i p_i n_{t-i}$$

where  $n_t$  is the new cases in day  $t$ , and  $N_t$  is the all cases in day  $t$ .  $p_i$  is the probability that a person recover after  $i$  days.  $\chi_t$  iid  $\sim E(\lambda)$ , which means:

$$f(x) = \exp(-x) dx$$

$\alpha_t$  is what the all factors can affect the virus. we assume this parameter will be the same under same condition.

so firstly we calculate  $\alpha_t$ , because  $\alpha$  can't change a lot in a short time under our assumption but can still change smoothly, so we use something like MLE but a little different to get  $\alpha$ , we change the likelihood from:

$$\sum_i \ln(p_i)$$

to:

$$\frac{\sum_{i=t-n}^{t+n} \exp(-\frac{(i-t)^2}{\tau^2}) * \ln(p_i)}{\sum_{i=t-n}^{t+n} \exp(-\frac{(i-t)^2}{\tau^2})}$$

so that for every  $t$ , we get a  $\hat{\alpha}_t(\tau)$ , if we chose  $\tau$  too large or too small,  $\alpha$  will contain nothing. we plot 10  $\alpha_t(\tau)$  chosen  $\tau$  from 1~10. then we chose manual from them to find the useful  $\tau$  and  $\alpha$ .

after getting  $\alpha$ , we will do regression between  $\alpha$  and the other factor, considering the meaning of  $\alpha$ , independent factors should affect  $\alpha$  by times each other. so that:

$$\ln(\alpha) = \sum_i f_i(\theta_i) + \epsilon$$

after regression we get some different functions  $f_i$  and can predict  $\alpha$  from different factors  $\{\theta_i\}$ , that is  $\alpha(\theta_i)$

then we predict different factors from knowledge , like we can get wathers from last year's wather , we can get the relationship between goveronment index and the total number from experience and so on.

at last we use this factors and the result of regrassion to do simulation and get the final answer in singapore.

## us or other place:

only thing different is that because of the immigration policy not that strict. increase may because cases from other country,so we change  $n_t$  a little bit:

$$n_t = \alpha_t N_t^{in} \chi_t^{in} + \beta_t N_t^{out} \chi_t^{out}$$

just like doing during get  $\alpha$  ,we can get beta similarly .

## regrassion details:

## simulation details:

## unemployment:

talking about unemployment , we believe there is 3 main reasons : macro economy , government attitude , and the covid situation . they may have correlation themselves , but they will affect unenployment independently , let U means unenployment , let i length vctor E means macro economy , let j length vctor G means goveronment's reaction toward them.

mathly speaking , because we believe unenployment can't get too high , the PDE between E,G,U must be dominated by some mechenisam that can push back the too high U.

but since assuming that PDE is a linear one is naive and unreasonable , and the PDE may also change during a long proid .

so the only thing we can do to get some info of the solution of that PDE , is to learn about the data from 2020apr on.

thanks god , after we do DFT , we observed a strong patern in the spectrum : there is nothing significant if  $v > \nu_0$  where:

$$\nu_0 = 0.1875^{-month}.$$

this means that they may probably be the noise . we can use a filter function to reduce them .

if we want a more efficient filter , we may first do interpolation on the row data . then we use a low-pass filter to reduce the noise . by choosing different interpolation method and low-pass filter function , we can get different  $U_t$  time series.

we can select the most useful one by the evaluation payoff function:

$$P = \sum_{i|u_i \text{ matches } u_{i0} \text{ in raw data}} (u_i - u_{i0})^2 * e^{-(i0-17)^2 * \nu_0^2 / 2}$$

that means for the No.k parameter  $\theta_k$  in interpolation and filter :

$$\frac{\partial P}{\partial \theta_k} = 0$$

applying this  $\{\theta_k\}$  , we get our final  $U_t$  from all of what we get.

at last we do polynomial regression on this final  $U_t \sim t$ :

$$U(t) = U(t_0) + \sum_i c_i (t - t_0)^i$$

since this is a local regression , we can't choose  $U_t$  for too long , we choose  $t$  from  $[t_0 - \Delta t]$  where:

$$(\nu_0 \Delta t)^i / (1 - \nu_0 \Delta t) < 0.1$$

if do rank i polynomial regression.

after regression , we get  $c_i$  and can predict  $U(t_0 + \delta t)$  where  $\delta t$  follow the same criteria with  $\Delta t$ .