

# Spread of Covid-19: Estimation and Simulation

Mathematical Statistics & Application in R Final Project

Date: 2020 / 04 / 23

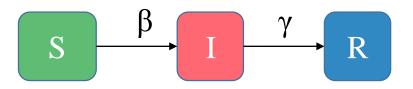
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#### **Deterministic Model: SIR**





$$\begin{array}{ll} \frac{ds}{dt} = -\beta si & s: the \ ratio \ of \ susceptible \ people \\ \frac{di}{dt} = \beta si - \gamma i & r: the \ ratio \ of \ recovered \ people \\ \frac{dr}{dt} = \gamma i & \gamma: the \ rate \ of \ transmission \\ \gamma: the \ rate \ of \ recovery \end{array}$$

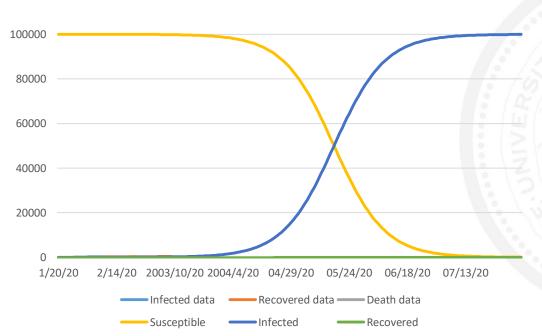
$$egin{aligned} s &= s_0 e^{-rac{
ho}{\gamma}r} \ rac{dr}{dt} &= \gamma (1-r-s_0 e^{-rac{eta}{\gamma}r}) \ t &= rac{1}{\gamma} \int_0^r rac{du}{1-u-s_0 e^{-rac{eta}{\gamma}u}} \end{aligned}$$

How to fit the real data into the model?

- 1. Solve the differential equations at every time step;
- $2. Minimize \ the \ weighted \ MSE \ for \ s, i, and r$

$$e.\,g\,min\,lpha_1(\sum_{i=1}^n(\hat{s_i}-s_i)^2+(1-lpha_1)(\sum_{i=1}^n(\hat{r_i}-r_i),set\,lpha_1=0.1$$

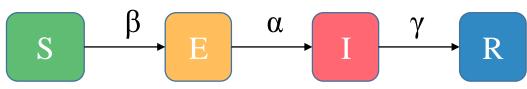
3.Get the estimated  $\beta, \gamma$ 



 $\beta$ =0.00000091,  $\gamma$ =0.00000024, r 0: 3.81126064.

# **Deterministic Model for Disease Spreading**





$$egin{array}{l} rac{ds}{dt} = -eta si & s: the \ ratio \ of \ susceptible \ people \ e: the \ ratio \ of \ exposed \ people \ (not \ infected \ but \ infective) \ i: the \ ratio \ of \ infected \ people \ (r: the \ ratio \ of \ infected \ people \ (r: the \ ratio \ of \ infected \ people \ (r: the \ ratio \ of \ infected \ people \ (r: the \ ratio \ of \ infected \ people \ (r: the \ ratio \ of \ infected \ people \ (r: the \ ratio \ of \ infected \ people \ (r: the \ ratio \ of \ infected \ people \ (r: the \ ratio \ of \ infected \ people \ (r: the \ ratio \ of \ infected \ people \ (r: the \ ratio \ of \ infected \ people \ (r: the \ ratio \ of \ recovered \ people \ (r: the \ rate \ of \ transmission \ (r: the \ rate \ of \ progression \ (r: the \ rate \ of \ progression \ (r: the \ rate \ of \ recovery \$$

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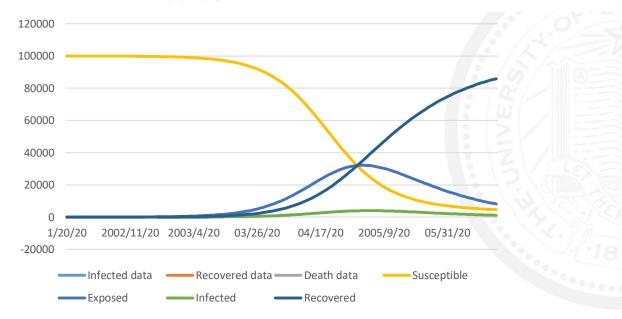
How to fit the real data into the model?

- 1. Solve the differential equations at every time step;
- $2. Minimize \ the \ weighted \ MSE \ for \ s, i, and r$

$$e.\ g\ min\ lpha_1(\sum_{i=1}^n(\hat{s_i}-s_i)^2+lpha_2(\sum_{i=1}^n(\hat{e_i}-e_i)+(1-lpha_1-lpha_2)(\sum_{i=1}^n(\hat{r_i}-r_i)$$

$$set \ \alpha_1 = 0.1, \alpha_2 = 0.1$$

3.Get the estimated  $\beta, \alpha, \gamma$ 



 $\beta$ =0.00001423,  $\alpha$ =0.05080899,  $\gamma$ =0.40000000, r\_0: 0.00003558.

### **MGF: Scale-free Network Case**

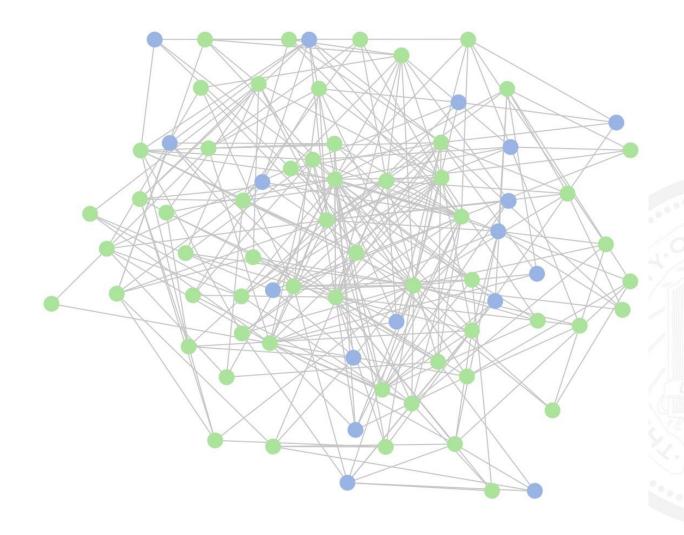


#### Network assumption:

- 1) Neighbor for every selected node is independent;
- 2) The network is huge.

#### Features:

- 1) is preferential attachment;
- 2) follows a power-law distribution or clustering coefficient distribution;
- 3) has a heavy tail..



### **Scale-free Network Case: Estimation**



 $Rewrite\ power-law\ distribution$ 

$$egin{aligned} p_k &= rac{
u-1}{k_{min}} (rac{k}{k_{min}})^{-
u} where \ c &= rac{
u-1}{k_{min}^{-
u+1}} \ z_m &= \int_{x_{min}}^{\infty} x^m rac{
u-1}{x_{min}} (rac{x}{x_{min}})^{-
u} &= rac{
u-1}{
u-1-m} x_{min}^m \end{aligned}$$

For method of moments

$$E[x] = \frac{\nu - 1}{\nu - 2} x_{min}$$

$$E[x^2] = \frac{\nu - 1}{\nu - 3} x_{min}^2$$

$$\therefore \hat{x}_{min} = \frac{\sum x_i^2 (\nu - 3)}{\sum x_i (\nu - 2)}$$

$$\therefore \hat{v} = \frac{-2(\sum x_i)^2 + 2n \sum x_i^2 \pm \sqrt{-n(\sum x_i)^2 \sum x_i^2 + n^2(\sum x_i^2)^2}}{-(\sum x_i)^2 + n \sum x_i^2}$$

For maximizing  $log-likelihood\ estimator$ With continus assumption

$$p(x)=\prod_{i=1}^nrac{
u-1}{x_{min}}(rac{x}{x_{min}})^{-
u}$$

$$logp(x) = nlog(
u - 1) - nlogx_{min} - 
u \sum_{i=1}^{\infty} log rac{x_i}{x_{min}}$$

$$rac{\partial log p(x)}{\partial x_{min}} = rac{-n}{x_{min}} + rac{
u}{x_{min}} \sum_{i=1}^{\infty} rac{1}{x_i} = 0$$

$$rac{\partial log p(x)}{\partial 
u} = rac{n}{
u - 1} - \sum_{i=1}^{\infty} log rac{x_i}{x_{min}}$$

$$u = 1 + n [\sum_{i=1}^n ln rac{x_i}{x_{min}}]^{-1}$$

With discrete assumtion

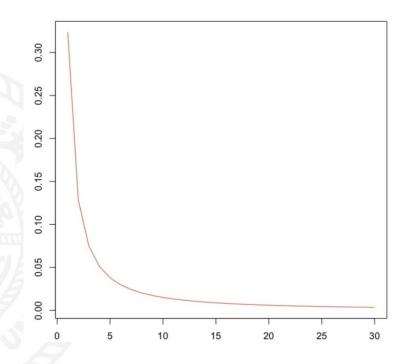
$$u = 1 + n[\sum_{i=1}^{n} ln \frac{x_i}{x_{min} - \frac{1}{2}}]^{-1}$$

$$Let~us~assume~x_{min}=1, \hat{
u}=1+rac{n}{ln(\sum x_i)}$$

#### **Scale-free Network Case**



$$P_k = C \cdot k^{-v} \quad o \quad \hat{v}_{MLE} = 1.33241$$



$$G^{(neighbor)} = G_0(G_1(\cdots G_1(x)\cdots)) \quad \dots where \quad G_1(x) = \frac{G_0'(x)}{G_0'(1)}$$

$$Z_m = rac{d}{dx} G^{(neighbor)} \Big|_{x=1} = G_0'(1) ig[ G_1'(1) ig]^{m-1} \quad o \quad Z_2 = 1321.40592$$

$$T_c = \frac{1}{G_1'(1)} = \frac{G_0'(1)}{G_0''(1)} = 0.0123764$$

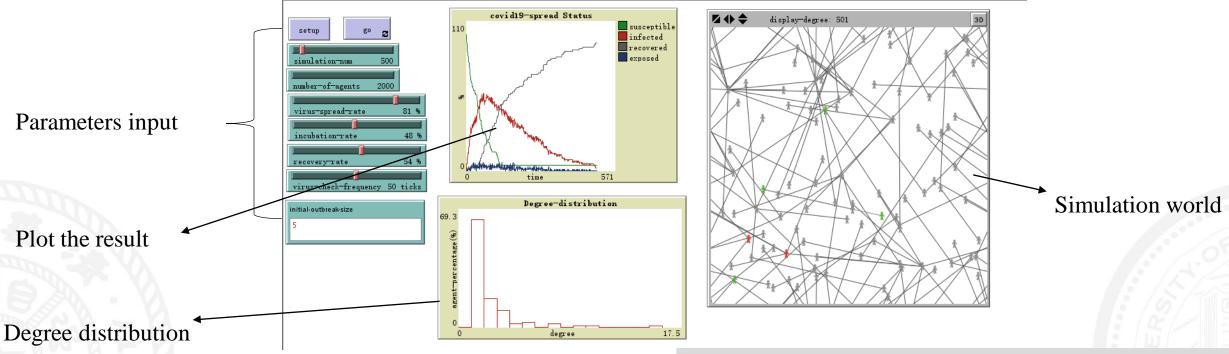
According to the public data, we know that T = 0.22.

By substituting T into the following formula, we get:

$$E[s] = 1 + \frac{T(\xi(\nu - 1))^2}{\xi(\nu)[(T+1)\xi(\nu - 1) - T\xi(\nu - 2)]}$$
= 0.7855

### **Scale-free Network Case: Simulation**





 $Simulation\ for\ parameter\ sensitivity\ test:$ 

- 1. Set ranges for parameters;
- Calculate the minimum, maximum and mean results;
- $3. Draw\ the\ experimental\ distribution\ of\ the\ outputs.$

PARAMETERS AND INITIALIZATION	RANGES
initial-outbreak-size	[1 1 5]
recovery-rate	[1 10 100]
virus-spread-rate	[1 10 100]
run the model multiple times	500
agents numbger	2000
tick-check frequency	50

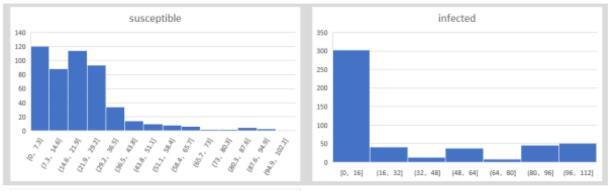
### **Scale-free Network Case: Simulation**

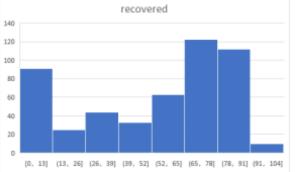


AVERAGE(%)	MIN	MAX	MEAN
susceptible	9.9720	97.0000	19.7972
infected	1.5560	78.2940	44.6495
recovered	0.0000	53.4540	35.5533
virus	1.5560	78.2940	44.6495

- The mean ratio of susceptible people, infected people and recovered people are around 19.80%, 44.65%, 35.55%;
- The experimental distribution of the ratio of susceptible people and infected people were similar to the power-law distribution while ratio of recovered people is not.

#### The experimental distribution of SIR





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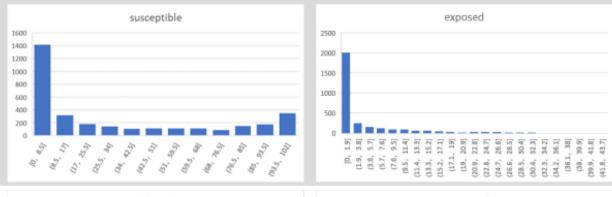
### **Scale-free Network Case: Simulation**

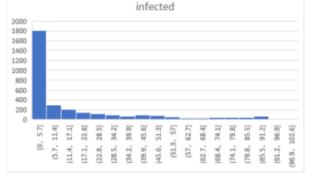


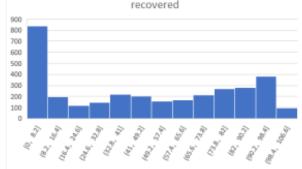
AVERAGE(%)	MIN	MAX	MEAN
susceptible	32.3918	97.8309	43.9674
exposed	0.0000	14.3373	5.7009
infected	1.2026	41.5529	21.8660
recovered	0.0000	46.8978	28.4640
virus	1.3938	48.6874	27.5569

- The mean ratio of exposed people was 5.7% which was lower than other outputs.
- This corresponds to our intuitive in the case of Covid-19.

#### The experimental distribution of SEIR







## **Conclusion**

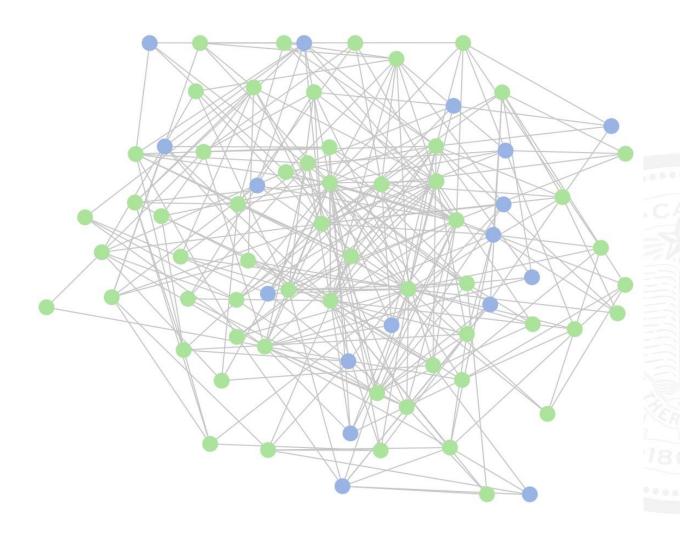


MGF 
$$\rightarrow$$
 E(s) = 0.7855

SIR 
$$\rightarrow$$
 max(infected %) = 0.78294

SEIR 
$$\rightarrow$$
 max(infected %) = 0.41553

p.s. An additional exposure state has been included in the transition state without any given data. The estimated value will be affected during solving additional one differential equations.



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