

Mathematical Modelling of Infectious Diseases for Public Health

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- 2 Catching a Glimpse of Stochastic Epidemic Models

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- (iii) Throughout the whole study period the population under consideration **is fixed in size**. There are **no births, deaths, immigration or emigration during the whole study period**.



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These assumptions reflect the situation for many diseases, such as measles or influenza, and would seem to be reasonable for computers whose anti-virus software has been updated to recognise the virus.



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An immediate implication of the assumptions is that individuals can only make two moves: from S to I and from I to R . For this reason the model is said to be an **SIR epidemic model**.



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Moreover, in this model $N = S + I + R$ does not change over time (by assumption!). The independent variable in the simple SIR Model is the time t , and the rates of transfer between compartments are mathematically expressed as derivatives with respect to time of the numbers I and S (each one viewed as a differentiable function of t). Hence, the simple SIR model is given by a system of **2 coupled non-linear ODEs**:

$$\begin{aligned}\dot{S} &:= \frac{dS}{dt} = f_1(S, I) := -\beta SI \\ \dot{I} &:= \frac{dI}{dt} = f_2(S, I) := \beta SI - \gamma I = I(\beta S - \gamma),\end{aligned}$$

where $\beta, \gamma > 0$ are positive constants, $S(t) \geq 0$ and $I(t) \geq 0$ for all $t \geq 0$.



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By potentially substituting β through βN we may assume WLOG that $S + I + R = 1$. These ODEs, together with the initial conditions $I(0) := I_0$ and $S(0) := S_0 := 1 - I_0$ for some fixed $0 < I_0 < 1$ define the model.



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Remark (Lotka-Volterra)

Coupled non-linear ODE systems of this type are very similar to the Lotka-Volterra equations, also known as the predator-prey equations, given by

$$\begin{aligned}\dot{S} &= \alpha S - \beta SI = S(\alpha - \beta I) \\ \dot{I} &= \gamma SI - \delta I = I(\gamma S - \delta),\end{aligned}$$

where $\alpha, \beta, \gamma, \delta > 0$ and S, I are defined on $[0, \infty)$.

Deterministic generalisations of simple SIR

Remark (Some deterministic generalisations of the simple SIR model)

*One can add an inflow of newborns into the class S of susceptibles to the simple SIR model, at rate μN , and - the births balancing - deaths in the classes at rates $-\mu S$, $-\mu I$, $-\mu R$ respectively, for some additional parameter $\mu > 0$. These models are known as **classic endemic models**.*

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$\{t : t \geq 0 \text{ and } \beta S(t) - \gamma > 0\}$. Moreover, $\frac{d}{dt}(S + I) = -\gamma I < 0$ on $(0, \infty)$, implying that - in any case - also the non-negative function $S + I$ is strictly decreasing on $(0, \infty)$.

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Definition

$R_0 := \frac{\beta}{\gamma} > 0$ is called **basic reproduction ratio**.



Discussion on the role of R_0 I

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Proposition

The initial value problem

$$\dot{I} = (\beta S(t) - \gamma) I, I(0) = I_0 \quad (I_0 \in (0, 1])$$

has an **uniquely determined positive** solution on $[0, \infty)$. This solution is given by

$$I(t) := I_0 \exp \left(\beta \int_0^t S(u) du \right) \exp(-\gamma t) \quad (t \geq 0).$$

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Similarly, we can see that also $S(t) > 0$ for all $t \geq 0$ (since $S_0 > 0$ by assumption). Note that *in general* we don't know whether this unique solution I is bounded from above!

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Proof.

(i) \Rightarrow (ii): Assume that $I(t) \leq I_0$ for all $t \geq 0$. Then

$\exp\left(\beta \int_0^t S(u) du - \gamma t\right) \leq 1$ for all $t \geq 0$. Hence, $\frac{1}{t} \int_0^t S(u) du \leq \frac{1}{R_0}$ **for all** $t \geq 0$. Consequently, $S_0 = S(0) = \lim_{t \rightarrow 0} \frac{1}{t} \int_0^t S(u) du \leq \frac{1}{R_0}$.

Discussion on the role of R_0 II

Proof ctd.

(i) \Rightarrow (iii): Let $S_0 \leq \frac{1}{R_0}$. Since $\dot{S} = -\beta I S$ on $(0, \infty)$ and both, I and S are positive it follows that $\dot{S} < 0$ on $(0, \infty)$, implying that S is a strictly decreasing function on $(0, \infty)$. Hence, $S(t) < S(0) \leq \frac{1}{R_0}$ for all $t > 0$. In particular, $\beta S - \gamma < 0$ on $[0, \infty)$. Consequently, $\dot{I} = (\beta S - \gamma) I < 0$ on $(0, \infty)$, implying that I is strictly decreasing on $(0, \infty)$.

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Consequently, $\dot{I} = (\beta S - \gamma) I < 0$ on $(0, \infty)$, implying that I is strictly decreasing on $(0, \infty)$. Since $\beta S_0 - \gamma < 0$ (by assumption) it follows that

$\exp(\beta \int_0^t S(u) du) \exp(-\gamma t) \leq \exp(\beta S(0) t) \exp(-\gamma t) = \exp(-\alpha t)$,
 where $\alpha := -(\beta S_0 - \gamma) > 0$. Hence, $I(t)$ decreases to 0 if

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(iii) \Rightarrow (i): trivial. □

Discussion on the role of R_0 III

Observation (Shape of the function I if $R_0 > 1$)

Let $R_0 > 1$ and $0 < t^*$ such that $S(t^*) = \frac{1}{R_0}$. Then I is strictly increasing on $(0, t^*)$. I attains its single maximum at t^* . I is strictly decreasing on (t^*, ∞) .

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Proof.

Elementary differentiation and a bit of elementary algebra induced by the structure of the SIR ODE system shows us that $\dot{I}(t) = 0$ if and only if $t = t^*$ and

$$\ddot{I} \stackrel{\vee}{=} I (\beta S - \gamma)^2 - \beta^2 I^2 S - \gamma I$$

on $(0, \infty)$. Consequently, at t^* I attains its single (and hence global) maximum.

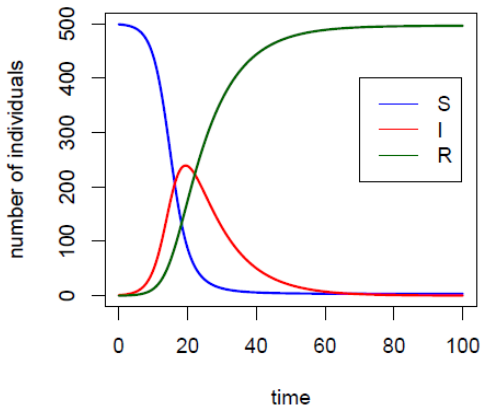
Discussion on the role of R_0 III

Proof ctd.

Let $0 < t < t^*$. Then $\frac{1}{R_0} = S(t^*) < S(t)$, implying that in fact I is strictly increasing on $(0, t^*)$. Now let $t^* < t$. Then $S(t) < S(t^*) = \frac{1}{R_0}$. Hence, I is strictly decreasing on (t^*, ∞) . \square

Shape of the functions S, I and R in the case $R_0 > 1$

Here, $N := 500$ and $S, I, R : [0, \infty) \rightarrow (0, N]$ (not the percentages!).



Discussion on the role of R_0 IV

Even if the basic reproduction ratio R_0 is not known to us the number of susceptibles today (i.e., S_0) and the percentage of remaining susceptibles $S_\infty := \lim_{t \rightarrow \infty} S(t) \leq 1$ when the epidemic is over already allows us to retrieve R_0 **at least if $S_0 \leq \frac{1}{R_0}$** , since:

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Proposition

Let $S_0 \leq \frac{1}{R_0}$ and $S(0) + I(0) = 1$. Then

$$\ln \left(\frac{S_0}{S_\infty} \right) = R_0 (1 - S_\infty) .$$

Discussion on the role of R_0 IV

Proof.

Since $\dot{S}(t) = -\beta S(t)I(t)$ for all $t \in (0, \infty)$ and $S(0) = S_0 = 1 - I_0$ we have

$$S(t) = S_0 \exp\left(-\beta \int_0^t I(u) du\right) \quad (t \geq 0).$$

Hence,

$$S(t) \stackrel{(!)}{=} S_0 \exp\left(R_0 \int_0^t (-\gamma I(u)) du\right)$$

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Hence,

$$\begin{aligned} S(t) &\stackrel{(!)}{=} S_0 \exp\left(R_0 \int_0^t (-\gamma I(u)) du\right) \\ &= S_0 \exp(R_0 (I(t) + S(t) - 1)) \quad (\text{why?}). \end{aligned}$$

Discussion on the role of R_0 IV

Proof ctd.

Equivalently written:

$$\ln \left(\frac{S(0)}{S(t)} \right) = R_0 (1 - S(t) - I(t)) .$$

Now we take limits on both sides of the latter equation (as $t \rightarrow \infty$). Since $S_0 \leq \frac{1}{R_0}$ by assumption we know that $I_\infty = \lim_{t \rightarrow \infty} I(t) = 0$ - and the claim follows. □

1 Revisiting Deterministic Epidemic Models

2 Catching a Glimpse of Stochastic Epidemic Models



A glimpse of the continuous time Markov chain SIR model I

View the class of susceptibles, respectively the class of infected as stochastic random variables, changing randomly in time.

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$\Omega \times [0, \infty) \ni (\omega, t) \mapsto S_t(\omega)$, respectively

$\Omega \times [0, \infty) \ni (\omega, t) \mapsto I_t(\omega)$, **where**

$I_t(\omega), S_t(\omega) \in S := \{0, 1, 2, \dots, N\}$ for all $\omega \in \Omega$ and $t \in [0, \infty)$.

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In addition, given the current state of the $S \times S$ -valued process $(S_t, I_t)_{t \geq 0}$ at time t , we assume that the future state of this process at time $t + \Delta t$, for any $\Delta t > 0$, does not depend on times **prior to t** (known as **Markov property**).

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In addition, given the current state of the $S \times S$ -valued process $(S_t, I_t)_{t \geq 0}$ at time t , we assume that the future state of this process at time $t + \Delta t$, for any $\Delta t > 0$, does not depend on times **prior to t** (known as **Markov property**). *“The stochastic system has no memory!”*

A glimpse of the continuous time Markov chain SIR model II

Let $s, i, k, j \in S$ and $t \in [0, \infty)$. Then the associated time-homogeneous transition probabilities

$$P_{(s,i),(s+k,i+j)}(\Delta t) := \mathbb{P}((S_{t+\Delta t}, I_{t+\Delta t}) = (s+k, i+j) \mid (S_t, I_t) = (s, i))$$

are modelled as

$$P_{(s,i),(s+k,i+j)}(\Delta t) := \begin{cases} \beta s i \Delta t + o(\Delta t) & \text{if } (k, j) = (-1, 1) \\ \gamma i \Delta t + o(\Delta t) & \text{if } (k, j) = (0, -1) \\ 1 - (\beta s i - \gamma i) \Delta t + o(\Delta t) & \text{if } (k, j) = (0, 0) \\ o(\Delta t) & \text{else} \end{cases}$$

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Unfolding the powerful machinery of Chapman-Kolmogorov equations, respectively time-homogeneous Markov semigroups one can then start to calculate transition probabilities and derived probabilities (think at multiple life insurance mathematics...).

A glimpse of the SDE SIR model of Allen I

Coupled SDE SIR Model of Allen

Let $\beta > 0$, $\gamma > 0$ and $W^{(1)}$ and $W^{(2)}$ be two independent standard Brownian motions.

$$\begin{aligned}
 dS_t &= -\beta S_t I_t dt - \sqrt{\beta S_t I_t} dW_t^{(1)} \\
 dI_t &= (\beta S_t I_t - \gamma I_t) dt + \sqrt{\beta S_t I_t} dW_t^{(1)} - \sqrt{\gamma I_t} dW_t^{(2)}.
 \end{aligned}$$

Moreover, the initial conditions are given by $I(0) := I_0$, $S(0) := S_0 := 1 - I_0$, $0 < I_0 < 1$ (as in the simple deterministic case).



A glimpse of the SDE SIR model of Allen II

One equivalent formulation of the SDE SIR model of Allen is the following one:

A glimpse of the SDE SIR model of Allen II

One equivalent formulation of the SDE SIR model of Allen is the following one:

Coupled SDE SIR Model of Allen in Vector Notation

Let $\beta > 0$, $\gamma > 0$ and $W^{(1)}$ and $W^{(2)}$ be two independent standard Brownian motions.

$$d \begin{pmatrix} S \\ I \end{pmatrix} = \begin{pmatrix} -\beta I & 0 \\ \beta I & -\gamma I \end{pmatrix} \begin{pmatrix} S \\ I \end{pmatrix} dt + \begin{pmatrix} -\sqrt{\beta SI} & 0 \\ \sqrt{\beta SI} & -\sqrt{\gamma I} \end{pmatrix} d \begin{pmatrix} W^{(1)} \\ W^{(2)} \end{pmatrix}$$

Moreover, the initial conditions are given by $\begin{pmatrix} S(0) \\ I(0) \end{pmatrix} := \begin{pmatrix} S_0 \\ I_0 \end{pmatrix}$, where $S_0 := 1 - I_0$, $0 < I_0 < 1$ (as in the simple deterministic case).

A glimpse of the SDE SIR model of Allen III

Problem

*Is the SDE SIR model of Allen **well-defined**? To answer this non-trivial question we need the whole machinery of (multidimensional) Itô calculus including theory and application of the (vector-valued stochastic) Itô integral! **Actually, SDEs are stochastic integral equations. Brownian motion paths are nowhere differentiable with probability 1!***

A glimpse of the SDE SIR model of Allen III

Problem

Is the SDE SIR model of Allen *well-defined*? To answer this non-trivial question we need the whole machinery of (multidimensional) Itô calculus including theory and application of the (vector-valued stochastic) Itô integral! *Actually, SDEs are stochastic integral equations. Brownian motion paths are nowhere differentiable with probability 1!* Do data reflect whether this model is useful in practice? Why are two independent standard *Brownian motions* used?

A glimpse of the SDE SIR model of Allen III

Problem

Is the SDE SIR model of Allen *well-defined*? To answer this non-trivial question we need the whole machinery of (multidimensional) Itô calculus including theory and application of the (vector-valued stochastic) Itô integral! **Actually, SDEs are stochastic integral equations. Brownian motion paths are nowhere differentiable with probability 1!** Do data reflect whether this model is useful in practice? Why are two independent standard **Brownian motions** used? What about the possibility of Poisson jumps? Are the solution processes S and I still semimartingales?

Only a - very - few references



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Thank you for your attention!

Are there any questions, comments or remarks?