Continuous-time stochastic models

Modern Techniques in Modelling





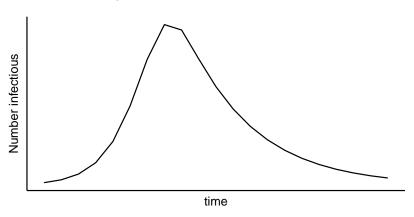


Overview

- Introduce continuous-time stochastic models (~20 minutes)
- Implement the Gillespie algorithm and analyse stochastic model output (~60 minutes)
- Implement a stochastic model with the adaptivetau package (~20 minutes)
- Discussion and concluding remarks (~20 minutes)

Deterministic models

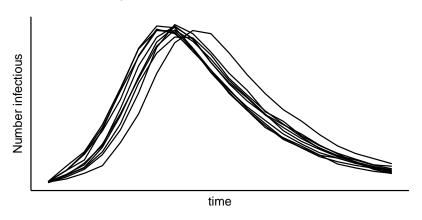
SIR model with $I_0 = 10, \beta = 1.3, \gamma = 0.3$



One set of parameters \rightarrow one trajectory

Stochastic models

SIR model with $I_0 = 10, \beta = 1.3, \gamma = 0.3$



One set of parameters \rightarrow many trajectories

Types of model

- discrete vs continuous time
- ullet compartment- vs individual-based
- $\bullet \ deterministic$ vs stochastic dynamics

Session 3: Discrete-time deterministic models

- discrete vs continuous time
- compartment- vs individual-based
- deterministic vs stochastic dynamics

$$\begin{split} S(t+1) &= S(t) - \beta S(t)I(t) \\ I(t+1) &= I(t) + \beta S(t)I(t) - \gamma I(t) \\ R(t+1) &= R(t) + \gamma I(t) \end{split}$$

Session 3: Discrete-time deterministic models

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Session 4: Ordinary differential equations

- discrete vs continuous time
- compartment- vs individual-based
- deterministic vs stochastic dynamics

$$dS/dt = -\beta SI/N$$

$$dI/dt = \beta SI/N - \gamma I$$

$$dR/dt = \gamma I$$

Session 4: Ordinary differential equations

- discrete vs continuous time
- compartment- vs individual-based
- deterministic vs stochastic dynamics

$$dS/dt = -\beta SI/N$$

$$dI/dt = \beta SI/N - \gamma I$$

$$dR/dt = \gamma I$$

Session 8: Stochastic individual-based models

- discrete vs continuous time
- compartment- vs individual-based
- deterministic vs stochastic dynamics

```
For each ts from 1 to T {
  lambda <- beta * I/N
  For each i from 1 to N {
    If individual i is susceptible:
      with prob 1-exp(-lambda·t) make infected.
    Else-if individual i is infected:
      with prob 1-exp(-gamma·t) make susceptible.
  }
  Record population state
```

Session 8: Stochastic individual-based models

- discrete vs continuous time
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Continuous-time stochastic models



Continuous-time stochastic models

- discrete vs continuous time
- compartment- vs individual-based
- \bullet deterministic vs **stochastic** dynamics

Stochastic differential equations (SDEs)

- discrete vs continuous time
- compartment- vs individual-based
- deterministic vs stochastic dynamics

$$\begin{split} dS/dt &= -\beta SI/N - \sqrt{\beta SI/N} dW_1 \\ dI/dt &= \beta SI/N - \gamma I + \sqrt{\beta SI/N} dW_1 - \sqrt{\gamma I} dW_2 \\ dR/dt &= \gamma I + \sqrt{\gamma I} dW_2 \end{split}$$

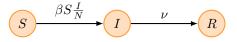
(not covered in this course)

Continuous-time discrete stochastic models

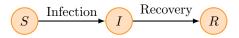
- discrete vs continuous time
- compartment- vs individual-based
- deterministic vs stochastic dynamics

We model these as a so-called **continuous-time Markov** chains.

Event-based view



Event-based view



- infection: $(S, I, R) \rightarrow (S 1, I + 1, R)$ with rate $\beta SI/N$
- recovery: $(S, I, R) \rightarrow (S, I + 1, R)$ with rate γI

Discrete time

```
for (ts in 1:steps) {
   update all compartments
}
(see Session 8: Stochastic individual-based models)
```

Continuous time

```
while (time < finaltime) {
   advance time and record next event
}
(this session)</pre>
```

Gillespie algorithm

Repeat until end time:

1. Calculate rates of all possible events

```
rates <- c(
  infection = beta * S * I / N,
  recovery = gamma * I
)</pre>
```

2. Determine time of next event

```
rexp(n = 1, rate = sum(rates))
```

3. Determine which event happens

```
sample(x = length(rates), size = 1, prob = rates)
```

and update system state according to event.

Now, put it in R



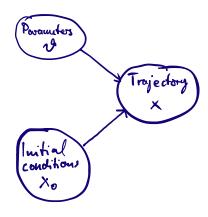
Practical structure

- Part 1: Stochastic simulations using the Gillespie algorithm
- Part 2: A faster alternative: the adaptivetau package

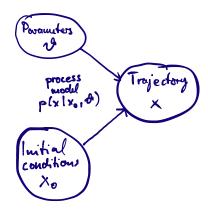
Representing uncertainty



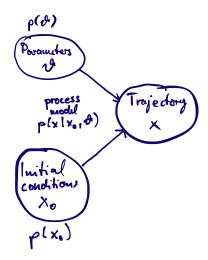
The deterministic view



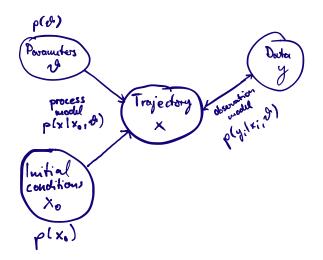
The stochastic view



Other types of uncertainty



Linking models to data



See LSHTM short course on Model Fitting and Inference for Infectious Disease Dynamics.

Further reading

- L.J.S. Allen (2017). A primer on stochastic epidemic models: Formulation, numerical simulation, and analysis. Infectious Disease Modelling, 2(2):128–142. https://doi.org/10.1016/j.idm.2017.03.001
- M.J. Keeling, P. Rohani (2017). Modeling Infectious Diseases in Humans and Animals. Princeton University Press.
- D.T. Gillespie (1976). A general method for numerically simulating the stochastic time evolution of coupled chemical reactions. J Comput Phys, 22(4):403–434, 1976. ISSN 0021-9991. https://doi.org/10.1016/0021-9991(76)90041-3
- Y. Cao, D.T. Gillespie, and L.R. Petzold (2007). Adaptive explicit-implicit tau-leaping method with automatic tau selection. J Chem Phys, 126(22):224101 URL https://doi.org/10.1063/1.2745299
- A.A. King, M. Domenech de Cellès, F.M.G. Magpantay and Pejman Rohani (2015). Avoidable errors in the modelling of outbreaks of emerging pathogens, with special reference to Ebola. Proc Roy Soc B 282(1806). https://doi.org/10.1098/rspb.2015.0347