Modern Techniques in Modelling



#### Outline



- Ordinary differential equations (ODEs)
- How do we 'solve' ODE's
  - integration
  - numerical integration
  - using the deSolve package
- Using R package deSolve
  - SI, SIR, SEIR models in R
  - time dependent parameter changes
  - events based on numbers of infection



### Reminder: Difference equations



In the previous session, we explored difference equations:

$$S(t+1) = S(t) - \beta S(t) I(t) + \beta S(t) I(t) + \beta S(t) I(t) - \gamma I(t)$$

$$R(t+1) = R(t) + \gamma I(t)$$
next
value + change
in value

These changes are the interesting part – they are what define the behaviour of the system.



#### Difference equations

$$S(t+1) = S(t) - \beta S(t) I(t)$$

$$I(t+1) = I(t) + \beta S(t) I(t) - \gamma I(t)$$

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

Ordinary differential equations have a similar structure, but only the rate of change is given:

$$dS(t)/dt = -\beta S(t) I(t)$$
  

$$dI(t)/dt = \beta S(t) I(t) - \gamma I(t)$$
  

$$dR(t)/dt = \gamma I(t)$$

The explicit dependence on time is often omitted (e.g. S is written instead of S(t))



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Mathematically, dX/dt represents the derivative of X with respect to time (i.e. the rate at which X is changing over time).

For example, is S is the number of susceptibles, t is measured in days, and we have

$$dS/dt = -\beta SI = -2$$

then this means the number of susceptibles is currently shrinking at a rate of 2 people per day, and in one day's time will have around\* 2 people fewer.

\* not exactly 2, because over the course of that day, the value of  $-\beta$  S I will change!

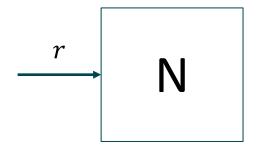
We will look at examples in the next section.

# How do we 'solve' ODE's





- Some ODE models are simple enough to solve by hand.
- —Consider a population of size N, which grows at a per capita rate r with initial population size  $N_0$ .
- —The per capita growth rate r means that each individual generates "offspring" at rate r.
- -We can formulate this model as a flow diagram:





—We are interested in the rate of change of N with respect to time t, so we can write the ODE as follows:

$$\frac{\mathrm{d}N}{\mathrm{d}t} = rN,$$

-With initial coniditions (values of the state variables at time t=0)

$$N(0) = N_0$$



– We can rearrange  $\frac{dN}{dt} = rN$  by hand to get the solution as follows:

$$\frac{1}{N} dN = r dt$$

$$\int \frac{1}{N} dN = \int r dt$$

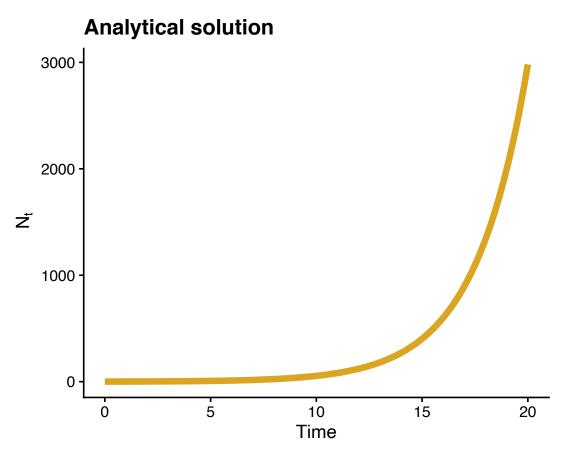
$$\log(N) = rt + c$$

$$N(t) = e^{rt+c}$$

$$N(t) = N_0 e^{rt}$$



Assume there is one animal at time 0, N(0) = 1 with r = 0.4, then for t = 0, ..., 20 the predicted growth is:



# Numerical solutions





- When you can't find the solution by hand, numerical methods are required
- Euler's method finds numerical solutions using difference equations
- This method approximates continuous time using discrete time steps



Consider the formal definition of the derivative,

$$\frac{\mathrm{d}y}{\mathrm{d}t} = \lim_{\Delta t \to 0} \frac{y(t + \Delta t) - y(t)}{\Delta t}$$

—If we set  $\Delta t$  to be some small, fixed value we obtain the following approximation

$$\frac{dy}{dt} = f(y(t), t)$$

$$\frac{y(t + \Delta t) - y(t)}{\Delta t} \approx f(y(t), t)$$

$$y(t + \Delta t) = y(t) + \Delta t f(y(t), t)$$



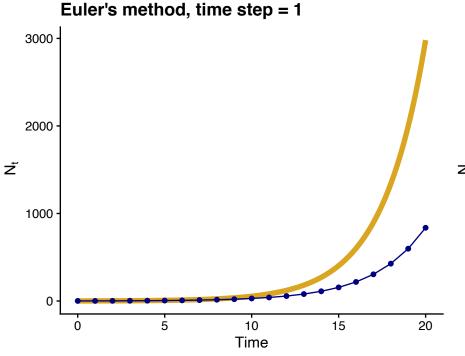
We can rewrite our population growth ODE as follows,

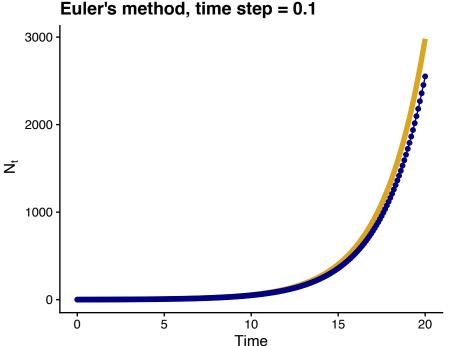
$$N(t + \Delta t) = N(t) + \frac{dN}{dt} \Delta t$$
$$= N(t) + rN(t) \Delta t$$



Using  $\Delta t = 1$  leads to a poor approximation.

Using  $\Delta t = 0.1$  is better, but does not approximate the growth well towards the end of the 20 days.





#### What alternatives are there?



- –Runge-Kutta method
- –Commonly referred to as RK4
- So called because it calculates 4 different increments in its approximation
- We will implement this using the package deSolve

### Using R package deSolve



- R package which can numerically solve systems of differential equations using different integrators
- Function ode() stands for ordinary differential equation

#### -Inputs:

- y, the initial conditions
- times the time points to solve the ODE(s)
- parms, a vector parameter values
- func, a function describing the ODE(s)

#### -Outputs:

 a matrix consisting of the numerical solution to the equations and the times



- –Inputs:
  - y, the initial conditions

We have one animal at time 0, so N(0) = 1, which we will write inside a vector as follows:

state 
$$<$$
  $c(N = 1)$ 



- –Inputs:
  - times the time points to solve the ODE(s)

Let's solve the equation over a period of 20 days, which we will write inside a vector as follows:

```
times \leftarrow seq(from = 0, to = 20, by = 1)
```



- –Inputs:
  - parms, a vector parameter values

We have just one parameter, the growth rate:

```
parameters <- c(r = 0.4)
```



#### -Inputs:

• func, a function describing the ODE(s)

pop\_model <- function(times, state, parms){
 ## Define variables

N <- state["N"]

# Extract parameters

r <- parms["r"]

# Define differential equations

dN <- r \* N

res <- list(c(dN))

return(res)</pre>



```
# Solve equations
output raw <- ode(y = state, times = times,
                 func = pop model, parms = parameters,
                 method = "euler")
# Convert to data frame for easy tion of columns
output <- as.data.frame(output ra
head(output)
## time
## 1 0 1.00000
## 2 1 1.40000
## 3 2 1.96000
## 4 3 2.74400
## 5 4 3.84160
## 6 5 5.37824
```

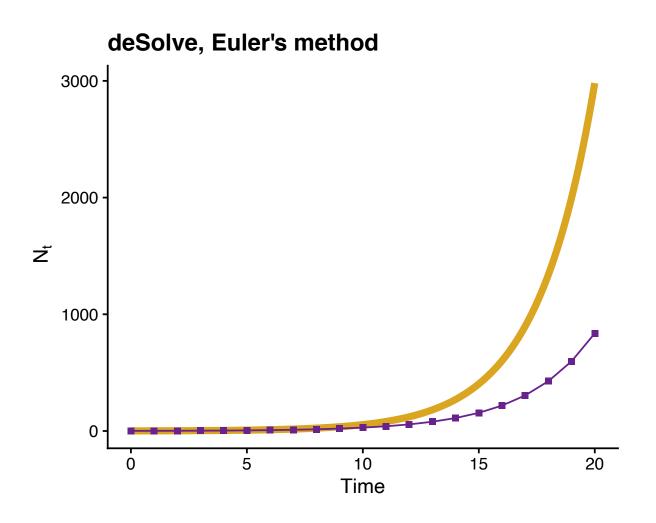


The output from ode is the same as our difference equations with  $\Delta t = 1$ .

```
N_0 <- state["N"]
N_t <- N_0 * exp(parameters["r"] * times)

plot(times, N_t, pch = 17, col = "orange")
points(output$time, output$N, type='b', lwd
= 2, pch = 19, col = "navy")</pre>
```

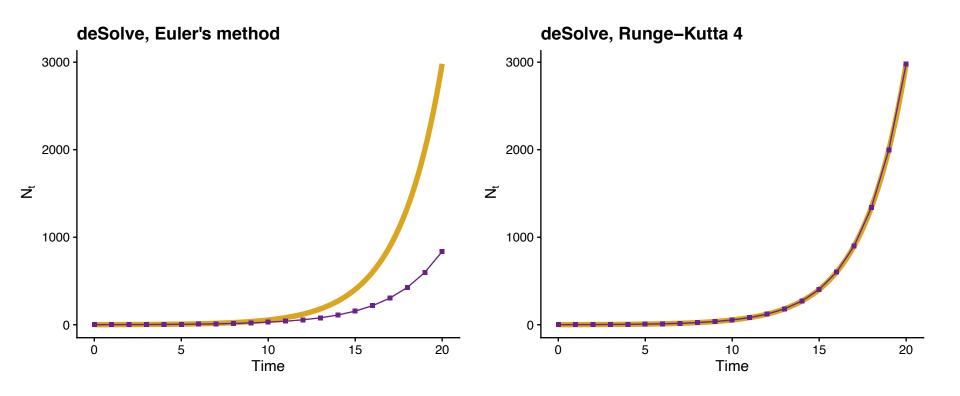






```
output raw rk4 <- ode(y = state, times = times,
                      func = pop model,
                      parms = parameters,
                      method = "rk4")
# Convert to data frame
# for easy extraction of columns
output rk4 <- as.data.frame(output raw rk4)
output raw euler <- ode(y = state, times = times,
                         func = pop model,
                         parms = parameters,
                         method = "euler")
output euler <- as.data.frame(output raw euler)</pre>
```





In the practical we will use RK4, BUT it will be up to you in your research to make sure that you know which method you are using and you why you are using it.

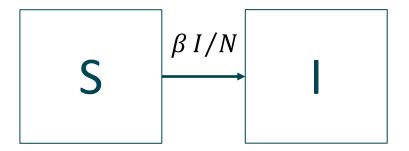
# Susceptible Infected model



### Susceptible Infected (SI) model



Individuals are either susceptible or infected



– Susceptible individuals become infected via transmission rate  $\beta$ .

$$\frac{dS}{dt} = -\beta SI/N$$

$$\frac{dI}{dt} = \beta SI/N$$



- -Inputs:
  - y, the initial conditions

Assume we have population of N = 100, with 1 infected individual:



- –Inputs:
  - times the time points to solve the ODE(s)

Let's solve the equation over a period of 50 days, which we will write inside a vector as follows:

```
times \leftarrow seq(from = 0, to = 50, by = 1)
```



- -Inputs:
  - parms, a vector parameter values

We have just one parameter, the transmission rate:

```
parameters <- c(beta = 0.4)</pre>
```



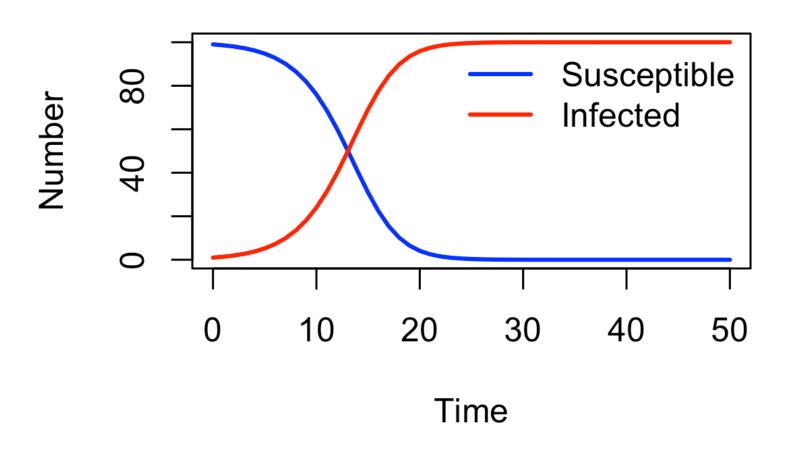
#### -Inputs:

 func, a function describing the ODE(s) SI model <- function(times, state, parms){</pre> ## Define variables S <- state["S"]</pre> I <- state["I"]</pre> N < - S + I# Extract parameters beta <- parms["beta"]</pre> # Define differential equations dS <- - (beta \* S \* I) / N dI <- (beta \* S \* I) / N res <- list(c(dS, dI)) return(res)



```
# Solve equations
output raw <- ode(y = state, times = times,
                 func = SI model, parms = parameters,
                 method = "rk4")
# Convert to data frame for easy extraction of columns
output <- as.data.frame(output raw)</pre>
head(output)
        ## time
                        S
                                 Ι
        ## 1 0 99.00000 1.000000
        ## 2 1 98.60400 1.396000
        ## 3
               2 98.05340 1.946605
        ## 4
               3 97.28991 2.710090
        ## 5 4 96.23525 3.764747
        ## 6
               5 94.78605 5.213953
```





# Practical part 1



## Practical part 1



- Open the file '04\_ODEs/01\_ODE\_SIR.R' and add your code to the existing script
- -Objective: Solve SI, SIR, SEIR models using deSolve
- Answer questions 1, 2 and 3
- Question 4 is optional

#### Practical part 1 - 04\_ODEs/01\_ODE\_SIR.R



#### Around line 215...

#### The four plot/lines commands should be:

#### Part 1 summary



- —There is a defined list of outputs that you need to tailor to your model
  - Inputs:
    - y, the initial conditions
    - times the time points to solve the ODE(s)
    - parms, a vector parameter values
    - func, a function describing the ODE(s)
- Be aware of what 'method' is being used to numerically solve your model

# Advanced use of deSolve package



## Advanced use of deSolve package



Speeding up code,

— Using Rcpp

Different types of models,

- Time dependent parameters
- Using 'events' in deSolve
  - method ="lsoda"

## Using Rcpp



- Rcpp is a CRAN package that provides a interface between R and C++
- -The func input in ode can be written in Rcpp
- -Why? speed

#### Using Rcpp



```
#include <Rcpp.h>
using namespace Rcpp;
// [[Rcpp::export]]
List SIR cpp model(NumericVector times, NumericVector state,
                            NumericVector parms) {
    // Define variables
    double S = state["S"];
    double I = state["I"];
    double R = state["R"];
    double N = S + I + R;
    // Extract parameters
    double beta = parms["beta"];
    double gamma = parms["gamma"];
    // Define differential equations
    double dS = - (beta * S * I) / N;
    double dI = (beta * S * I) / N - gamma * I;
    double dR = gamma * I;
    NumericVector res vec = NumericVector::create(dS, dI, dR);
    List res = List::create(res vec);
    return(res);
```



#### Recall the SI model is written as follows:

$$\frac{dS}{dt} = -\beta SI/N$$

$$\frac{dI}{dt} = \beta SI/N$$



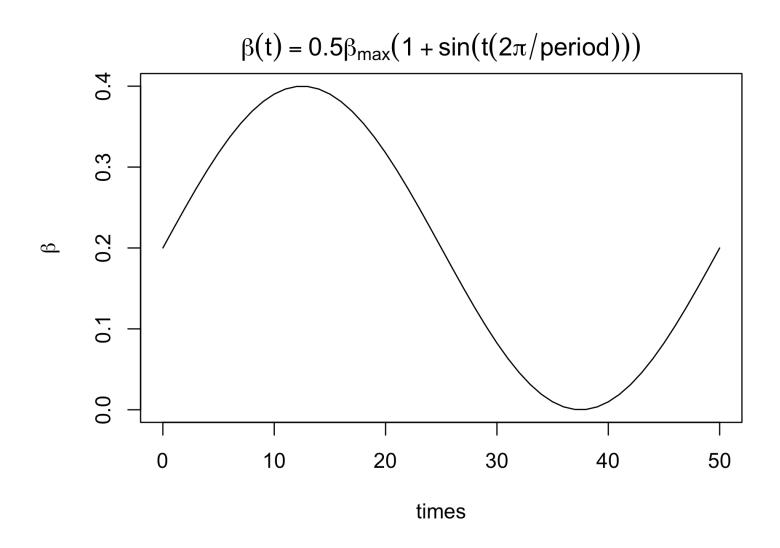
Note that S and I are also functions of time t,

$$\frac{dS(t)}{dt} = -\beta S(t)I(t)/N(t)$$

$$\frac{dI(t)}{dt} = \beta S(t)I(t)/N(t)$$

What if a model parameter, i.e. the transmission rate was a function of time?







```
SI seasonal model <- function(times, state, parms) {
  ## Define variables
  S <- state["S"]
  I <- state["I"]</pre>
 N < -S + T
  # Extract parameters
  beta max <- parms["beta max"]</pre>
  period <- parms["period"]</pre>
  # Calculate time dependent transmission rate
  beta <- beta max / 2 * (1 + sin(times * (2 * pi /
period) ) )
  # Define differential equations
  dS <- - (beta * S * I) / N
  dI <- (beta * S * I) / N
  res <- list(c(dS, dI))
  return(res)
```

#### method = "lsoda"



- -deSolve has a useful method option called lsoda
- switches automatically between stiff and non-stiff methods
- what is a stiff problem?
  - broadly, rapid changes in state variables
- why is it a problem?
  - some numerical methods will lead to poor approximation
- We will use this in events



- deSolve has the capability to include 'events'
- This can be used when you want to change the value of a state variable based on some condition
- Events can be specified as a data.frame, or in a function.
- Events can also be triggered by a root function.
  - use a data.frame to specify times at which events occur
  - use root function to trigger an event based on some condition



- -Let's look at an example of using a root function
- We want to predict infection in a livestock population
  - managed births, i.e. birth rate is a function of some target farm size K
  - assume that death occurs at longer time scale than infection, so we don't include it

$$\frac{dS}{dt} = bN(K - N)/K - \beta SI/N$$

$$\frac{dI}{dt} = \beta SI/N$$

where N = S + I.



We have our model function,

```
SI open model <- function(times, state, parms) {
  ## Define variables
  S <- state["S"]
  I <- state["I"]</pre>
  N \leq -S + T
  # Extract parameters
  beta <- parms["beta"]</pre>
  K <- parms["K"]</pre>
  b <- parms["b"]
  # Define differential equations
  dS \leftarrow b * N * (K - N) / K - (beta * S * I) / N
  dI <- (beta * S * I) / N
  res <- list(c(dS, dI))
  return(res)
```



- Our event is going to be a herd cull at rate  $\tau$ .
- Firstly, we need to write a function which changes the appropriate state variables

```
event I cull <- function(times, state, parms) {</pre>
  ## Define variables
  I <- state["I"]</pre>
  # Extract parameters
  tau <- parms["tau"]
  I <- I * (1 - tau) # cull the infected</pre>
population
  state["I"] <- I
  return(state)
```



Secondly, we need to write a function which triggers the event

```
root <- function(times, state, parms){</pre>
  ## Define variables
  S <- state["S"]
  I <- state["I"]</pre>
 N \leq -S + T
  # Extract parameters
  K <- parms["K"]</pre>
  # Our condition is if more than half of the
target herd size becomes infected
  condition <- !(I > K * 0.5) # This is a logical
condition (TRUE/FALSE)
  return(as.numeric(condition)) # Make this
numeric, event occurs if root==0
```



What does the output look like?

# Practical part 2



#### Practical part 2



- Download the file '04\_ODEs/02\_ODE\_Extras.R' and add your code to the existing script
- Objective: implement SIR with time dependent transmission and use the events function in deSolve
- Answer questions 1,2
- Question 3 is optional

#### Summary



- Baseline structure of `deSolve`
- Be aware of what `method' is being used to solve your ODEs
- `deSolve` has many different types of extensions!
- Soetaert, K., Petzoldt, T. & Setzer, R.W. (2010) Solving differential equations in R: Package deSolve. Journal of Statistical Software, 33, 1–25.