

# System Dynamics Modeling with R

An Interactive Workshop

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## System Dynamics Modelling with R *An Interactive Workshop*

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<https://github.com/JimDuggan/SDWorkshop>

# Overall Goals – Focus on breadth!



1

- Understand data frames and plot simulation data using **ggplot2**

2

- Analyse sensitivity runs with **dplyr**

3

- Build a model using **deSolve**

4

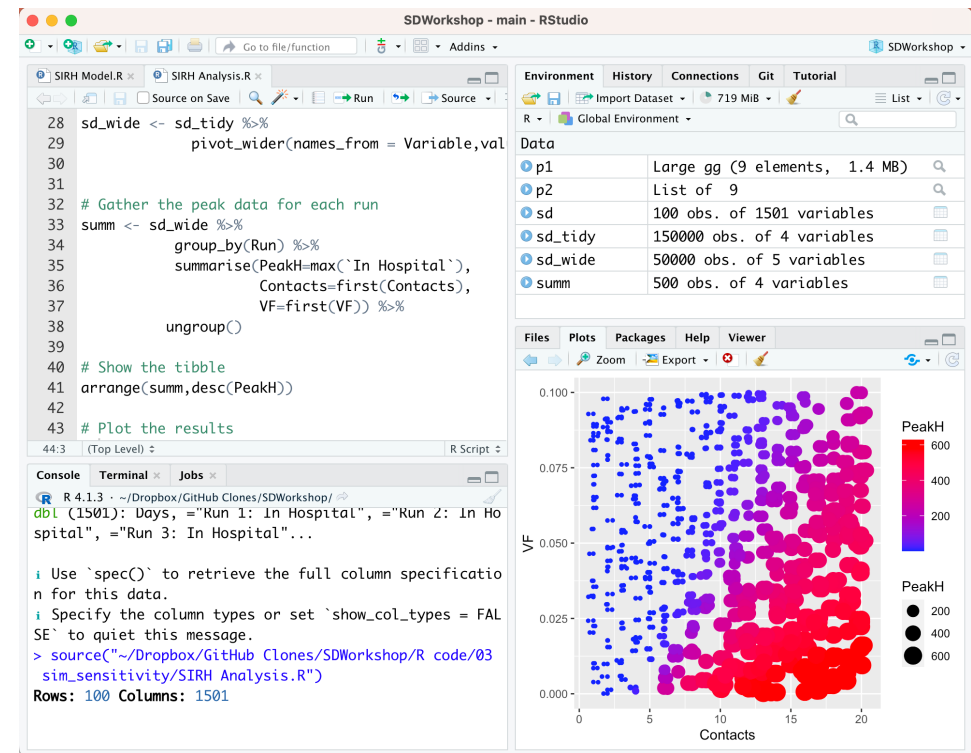
- Run sensitivity sweep with **purrr**, **deSolve** and **dplyr**

5

- Create interactive simulation app using **Shiny**

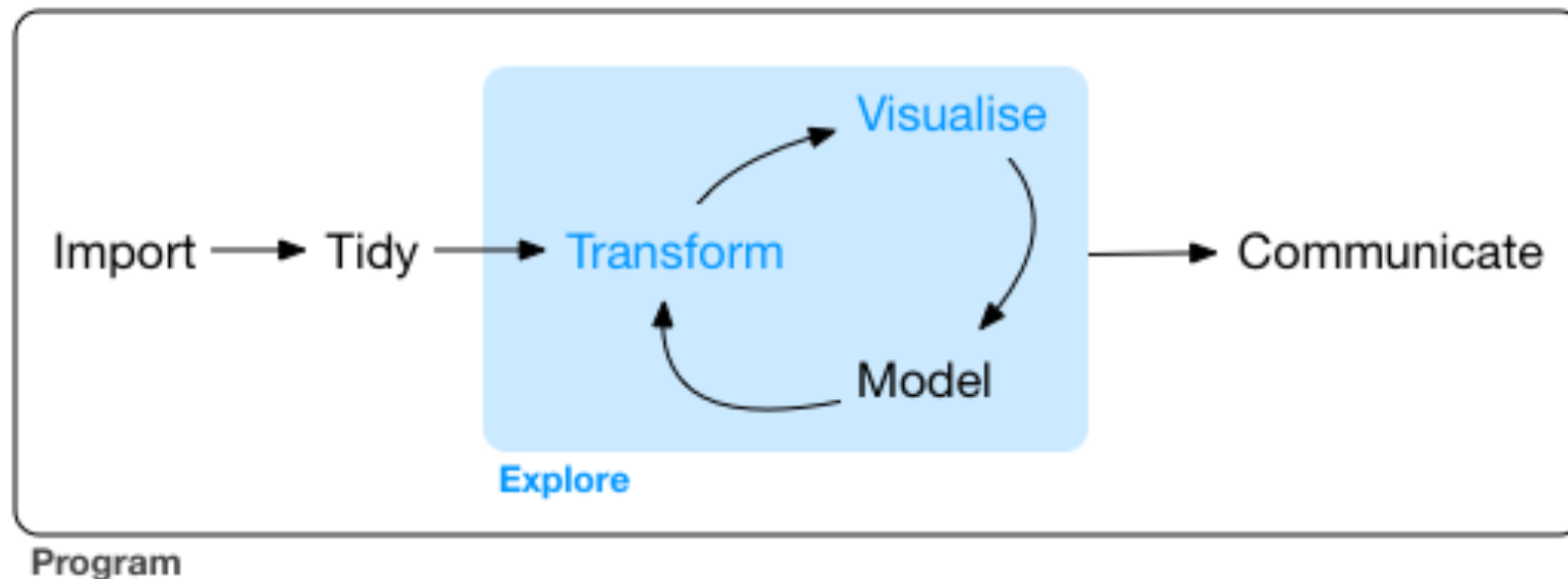
# R

- R's *mission* is to enable the best and most thorough exploration of data possible (Chambers 2008).
- It is a dialect of the S language, developed at Bell Laboratories
- ACM noted that S “*will forever alter the way people analyze, visualize, and manipulate data*”

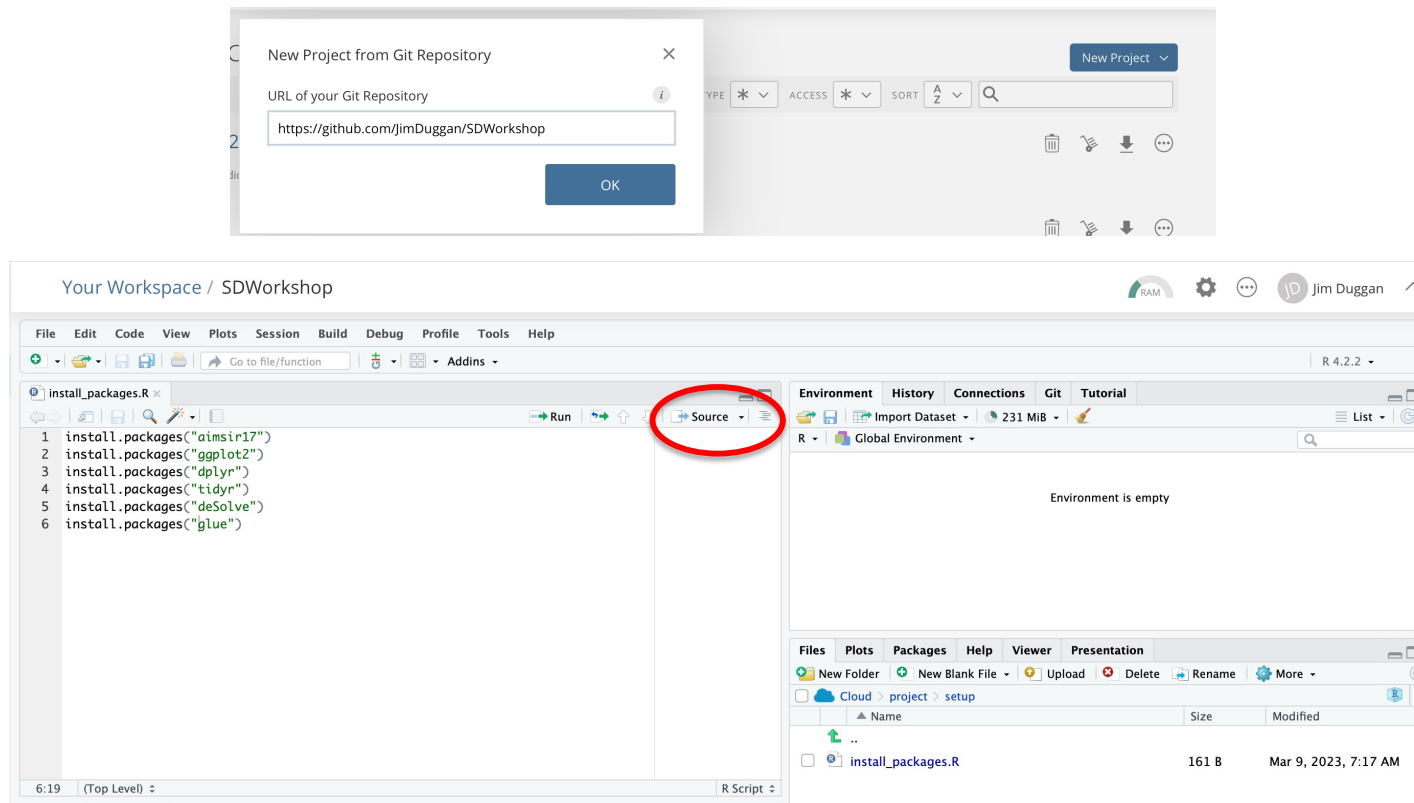


# Data Science Process and Workflow

“Data exploration is the art of looking at your data, rapidly generating hypotheses, quickly testing them, then repeating again and again and again.” (Wickham and Grolemund 2017).



# Access to workshop resources and setup





- Introducing the data frame (rectangular data)
- Plot graphs
- Import a simulation run from a CSV file (e.g. Stella/Vensim output)
- Plot simulation data

# Data Frames/Tibbles – mpg

- The most common way of storing data in R
- A two-dimensional structure, with rows (observations) and columns (variables)

```
> mpg
# A tibble: 234 × 11
  manufacturer model      displ  year   cyl trans      drv    cty   hwy fl    class
  <chr>         <chr>    <dbl> <int> <int> <chr>    <chr> <int> <int> <chr> <chr>
1 audi         a4          1.8  1999     4 auto(l5) f       18    29 p    compact
2 audi         a4          1.8  1999     4 manual(m5) f       21    29 p    compact
3 audi         a4          2    2008     4 manual(m6) f       20    31 p    compact
4 audi         a4          2    2008     4 auto(av) f       21    30 p    compact
5 audi         a4          2.8  1999     6 auto(l5) f       16    26 p    compact
6 audi         a4          2.8  1999     6 manual(m5) f       18    26 p    compact
7 audi         a4          3.1  2008     6 auto(av) f       18    27 p    compact
8 audi         a4 quattro  1.8  1999     4 manual(m5) 4       18    26 p    compact
9 audi         a4 quattro  1.8  1999     4 auto(l5) 4       16    25 p    compact
10 audi         a4 quattro  2    2008     4 manual(m6) 4       20    28 p    compact
# ... with 224 more rows
# Use `print(n = ...)` to see more rows
```

# Sample Code (engines.R)

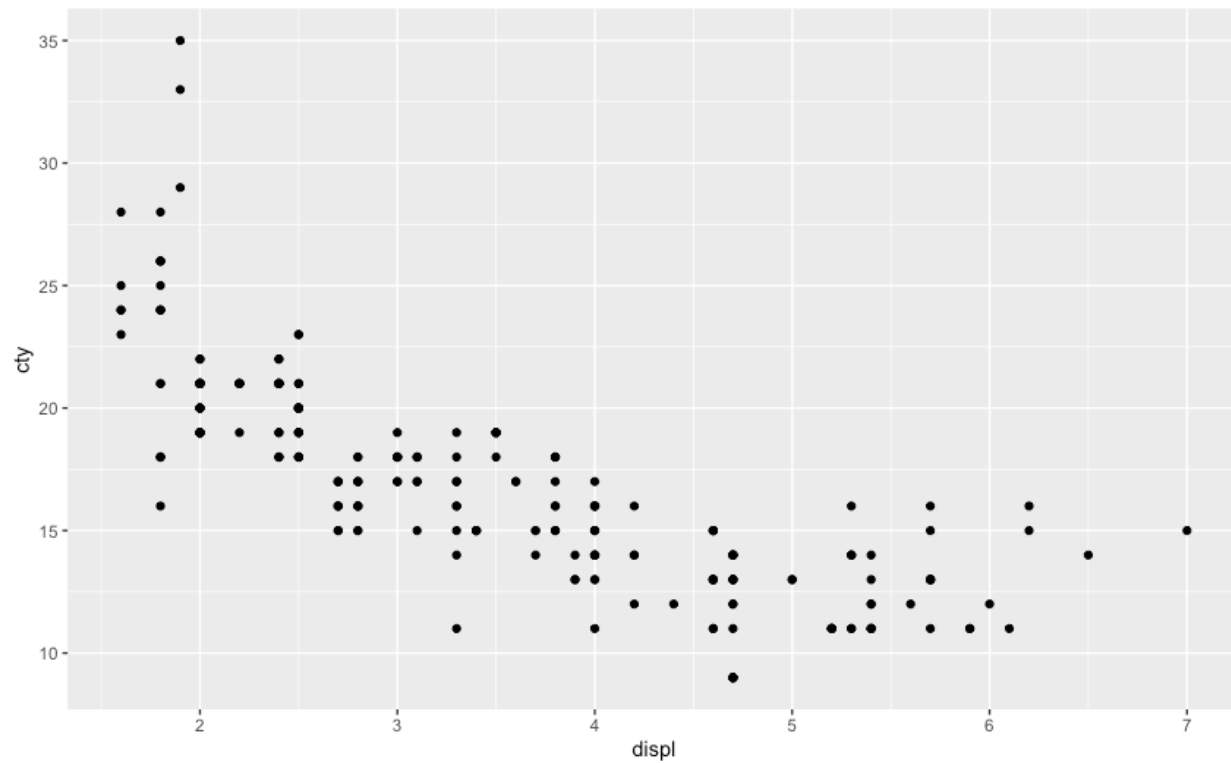
```
1 library(ggplot2)
2
3 summary(mpg)
4
5 ggplot(mpg,aes(x=displ,y=cty))+geom_point()
```

```
> summary(mpg)
```

manufacturer	model	displ	year	cyl	trans
Length:234	Length:234	Min. :1.600	Min. :1999	Min. :4.000	Length:234
Class :character	Class :character	1st Qu.:2.400	1st Qu.:1999	1st Qu.:4.000	Class :character
Mode :character	Mode :character	Median :3.300	Median :2004	Median :6.000	Mode :character
		Mean :3.472	Mean :2004	Mean :5.889	
		3rd Qu.:4.600	3rd Qu.:2008	3rd Qu.:8.000	
		Max. :7.000	Max. :2008	Max. :8.000	
drv	cty	hwy	fl	class	
Length:234	Min. : 9.00	Min. :12.00	Length:234	Length:234	
Class :character	1st Qu.:14.00	1st Qu.:18.00	Class :character	Class :character	
Mode :character	Median :17.00	Median :24.00	Mode :character	Mode :character	
	Mean :16.86	Mean :23.44			
	3rd Qu.:19.00	3rd Qu.:27.00			
	Max. :35.00	Max. :44.00			



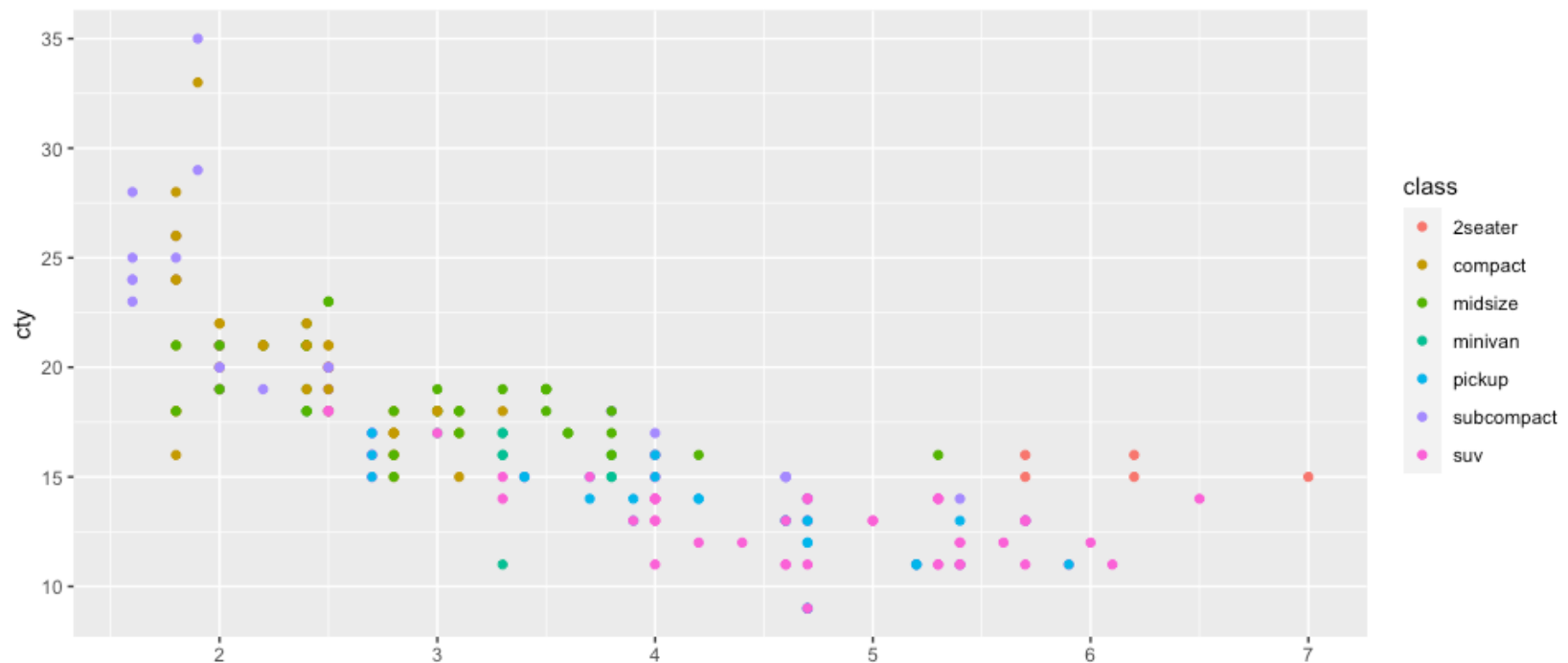
“The simple graph has brought more information to the data analyst’s mind than any other device.” – John Tukey



```
ggplot(mpg, aes(x=displ, y=cty)) + geom_point()
```

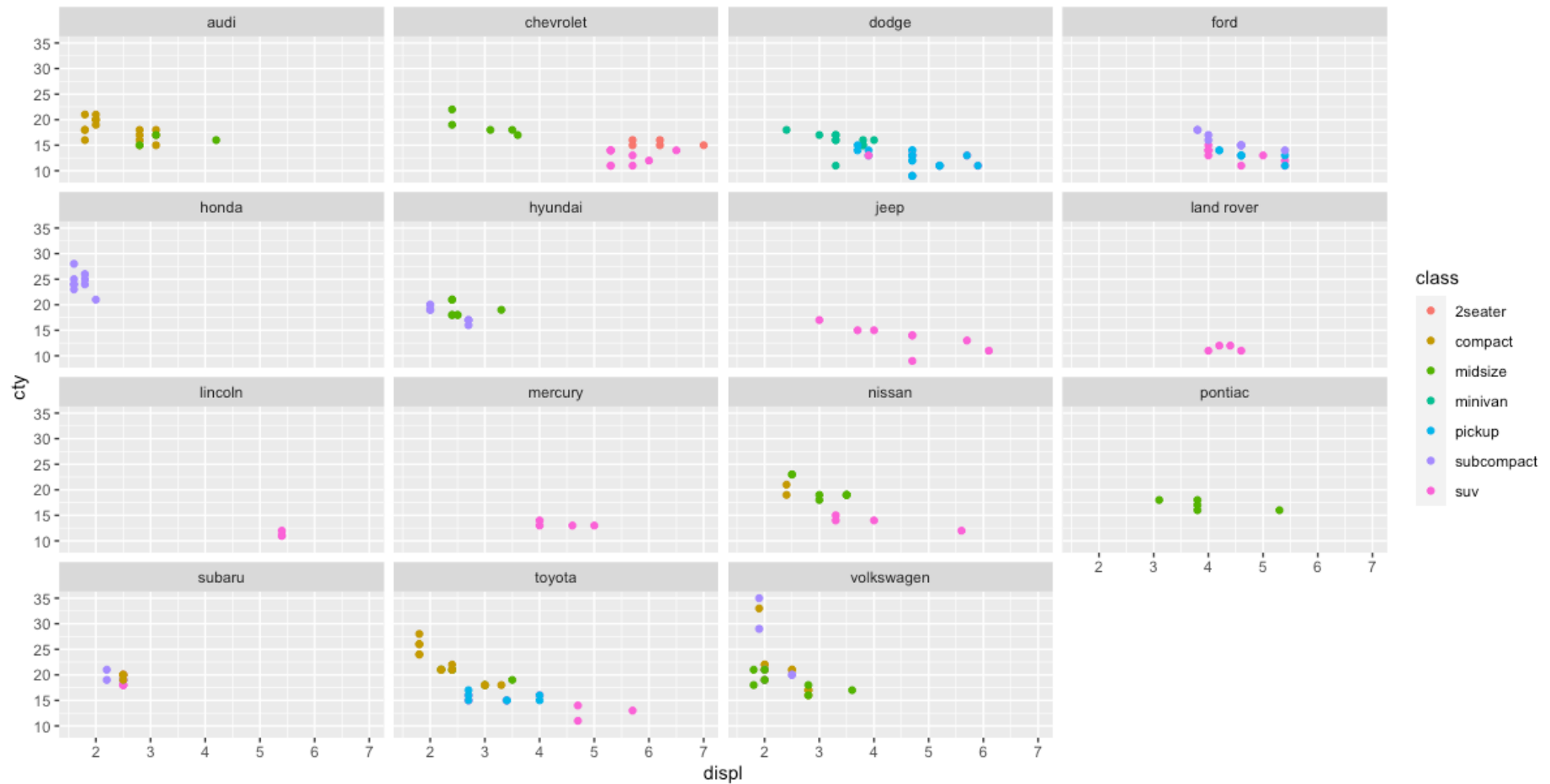
“The greatest value of a picture is when it forces us to notice what we never expected to see” – John Tukey

*A third variable can be added to a 2-D plot by mapping it to an aesthetic: colour, size or shape*

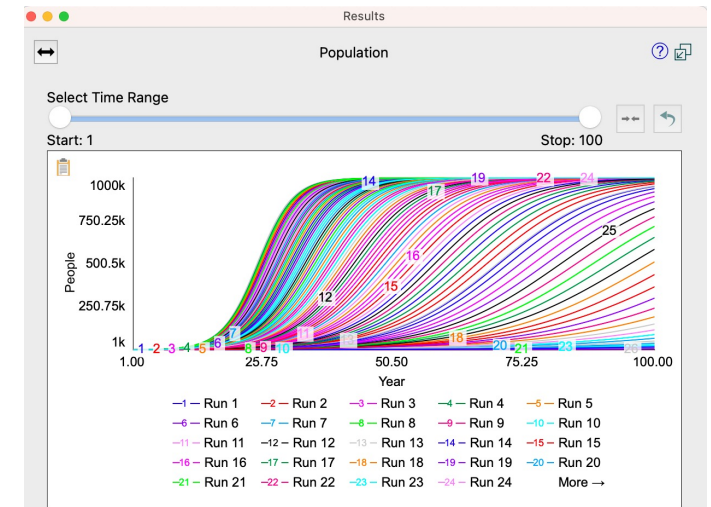
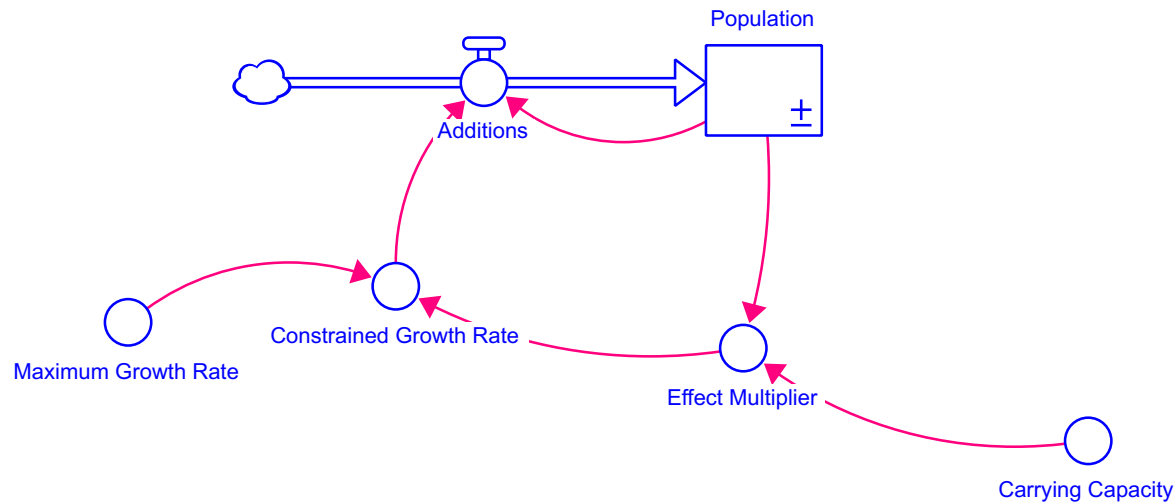


```
ggplot(mpg, aes(x=displ, y=cty, colour=class)) + geom_point()
```

```
ggplot(mpg, aes(x=displ, y=cty, colour=class)) + geom_point() + facet_wrap(~manufacturer)
```



# Simulation Output – CSV File

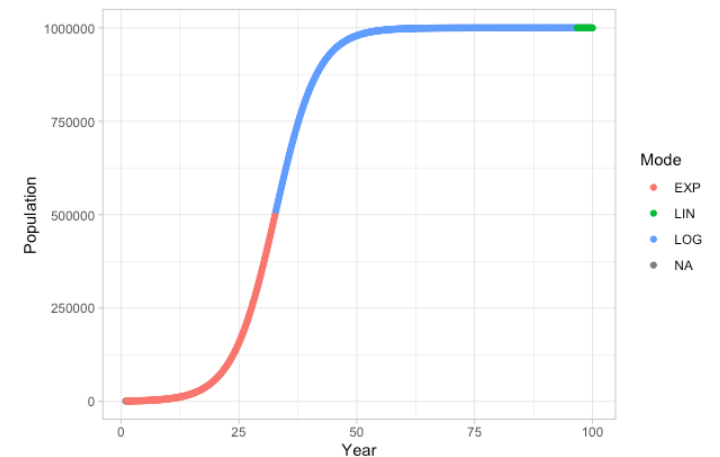
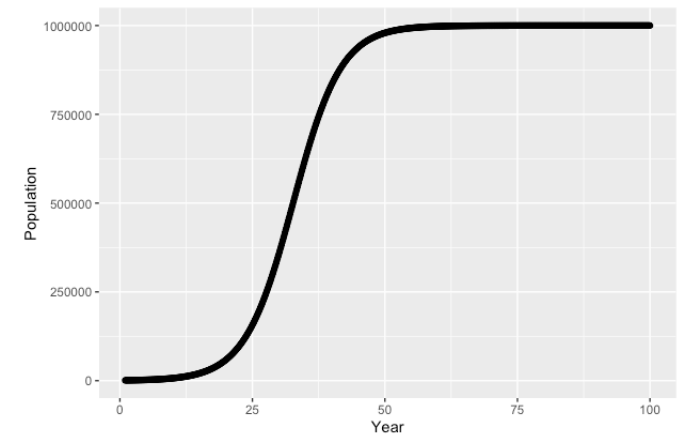


A	B	C	D	E	F	G
Year	Additions	Carrying Capacity	Constrained Growth Rate	Effect Multiplier	Maximum Growth Rate	Population
1	220.2795	1000000	0.2202795	0.999	0.2205	1000
1.125	226.3386436	1000000	0.220273429	0.998972465	0.2205	1027.534938
1.25	232.5641055	1000000	0.22026719	0.998944173	0.2205	1055.827268
1.375	238.9604315	1000000	0.22026078	0.998915102	0.2205	1084.897781
1.5	245.5322907	1000000	0.220254194	0.998885232	0.2205	1114.767835
1.625	252.2844784	1000000	0.220247426	0.998854541	0.2205	1145.459371

```

1 library(ggplot2)
2 library(readr)
3 library(dplyr)
4
5 d <- read_csv("datasets/single runs/LTG.csv")
6
7 ggplot(d,aes(x=Year,y=Population)) +
8   geom_point()+geom_line()
9
10 d <- d %>%
11   mutate(ModeValue=round(c(NA,NA,diff(abs(diff(Population))))),3),
12          Mode=as.factor(ifelse(ModeValue>0,"EXP",
13                                ifelse(ModeValue<0,"LOG","LIN"))))
14
15 ggplot(d,aes(x=Year,y=Population,colour=Mode)) +
16   geom_point()+theme_light()
17 > d
18 # A tibble: 793 x 9
19   Year Additions `Carrying Capacity` `Constrained Growth Rate` Effect ...1 Maxim...2 Popul...3 ModeV...4 Mode
20   <dbl>   <dbl>         <dbl>          <dbl>    <dbl>    <dbl>    <dbl>    <dbl> <fct>
21 1 1      220.         1000000        0.220    0.999    0.220    1000    NA    NA
22 2 1.12   226.         1000000        0.220    0.999    0.220    1028.    NA    NA
23 3 1.25   233.         1000000        0.220    0.999    0.220    1056.    0.757 EXP
24 4 1.38   239.         1000000        0.220    0.999    0.220    1085.    0.778 EXP
25 5 1.5    246.         1000000        0.220    0.999    0.220    1115.    0.8    EXP
26 6 1.62   252.         1000000        0.220    0.999    0.220    1145.    0.821 EXP
27 7 1.75   259.         1000000        0.220    0.999    0.220    1177.    0.844 EXP

```



## A behavioral approach to feedback loop dominance analysis

David N. Ford<sup>a</sup>

linear atomic behavior pattern

exponential atomic behavior pattern

logarithmic atomic behavior pattern

$$\partial(|(\partial x/\partial t)|)/\partial t = 0$$

$$\partial(|(\partial x/\partial t)|)/\partial t > 0$$

$$\partial(|(\partial x/\partial t)|)/\partial t < 0$$



- Visualisation is an important tool for insight generation, but it's rare that you get the data in exactly the right form you need (Wickham and Grolemund 2017)
  - Create new variables
  - Create summaries
  - Order data
- **dplyr** package is designed for data transformation

# dplyr Basics: 5 key functions

Function	Purpose
<b>filter()</b>	Pick observations by their values
<b>arrange()</b>	Reorder the rows
<b>select()</b>	Pick variables by their names
<b><i>mutate()</i></b>	<i>Create new variables with functions of existing variables</i>
<b><i>summarise()</i></b>	<i>Collapse many values down to a single summary</i>

- "A grammar of data manipulation" <https://dplyr.tidyverse.org>
- All verbs (functions) work similarly
  - The first argument is a data frame/tibble
  - The subsequent arguments decide what to do with the data frame/tibble
  - The result (data frame/tibble) supports chaining of steps – NOTE the "pipe operator" which we will cover later.

# Process Sensitivity Data (Stella)

A	B	C	D	E	F	G	H	I	J
Year	Run 1: Population	Run 2: Population	Run 3: Population	Run 4: Population	Run 5: Population	Run 6: Population	Run 7: Population	Run 8: Population	Run 9: Population
1	1000	1000	1000	1000	1000	1000	1000	1000	1000
2	1104.372133	1108.19136	1172.035949	1231.861465	1056.806787	1249.957467	1271.978986	1001.499482	1085.448046
3	1219.624672	1228.073885	1373.62837	1517.403111	1116.837003	1562.298647	1617.814294	1003.00121	1178.188937
4	1346.888976	1360.907683	1609.840283	1869.011748	1180.273137	1952.539704	2057.489958	1004.505187	1278.843588
5	1487.413409	1508.087943	1886.596445	2301.911204	1247.307964	2440.02602	2616.353021	1006.011418	1388.085504

```

> head(sd)
# A tibble: 6 × 203
  Year = "Run ...1" = "Run...2" = "Run...3" = "Run...4" = "Run...5" = "Run...6" = "Run...7" = "Run...8" = "Run...9" = "Run...X" = "Run...X" = "Run...X"
    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>
1     1      1000      1000      1000      1000      1000      1000      1000      1000      1000      1000      1000      1000
2     2    1104.    1108.    1172.    1232.    1057.    1250.    1272.    1001.    1085.    1017.    1152.    1179.
3     3    1220.    1228.    1374.    1517.    1117.    1562.    1618.    1003.    1178.    1033.    1326.    1390.

1 library(readr)
2 library(dplyr)
3 library(ggplot2)
4 library(stringr)
5
6 # Load in the sensitivity data
7 sd <- read_csv("datasets/sensitivity runs/LTG_Sensitivity.csv")

```



# Convert wide data to tidy data

```
> sd_tidy
# A tibble: 20,200 × 4
  Run   Year Variable  Value
  <int> <dbl> <chr>      <dbl>
1     1     1     1 Population  1000
2     2     2     1 Population  1000
3     3     3     1 Population  1000
4     4     4     1 Population  1000
5     5     5     1 Population  1000
6     6     6     1 Population  1000
7     7     7     1 Population  1000
8     8     8     1 Population  1000
9     9     9     1 Population  1000
10    10    10     1 Population  1000
# ... with 20,190 more rows
```

- The tidy data standard is designed to:
  - Facilitate initial exploration and analysis of data
  - Simplify the development of data analysis tools that work well together
- Rules
  - Each variable must have its own column
  - Each observation must have its own row
  - Each value must have its own cell

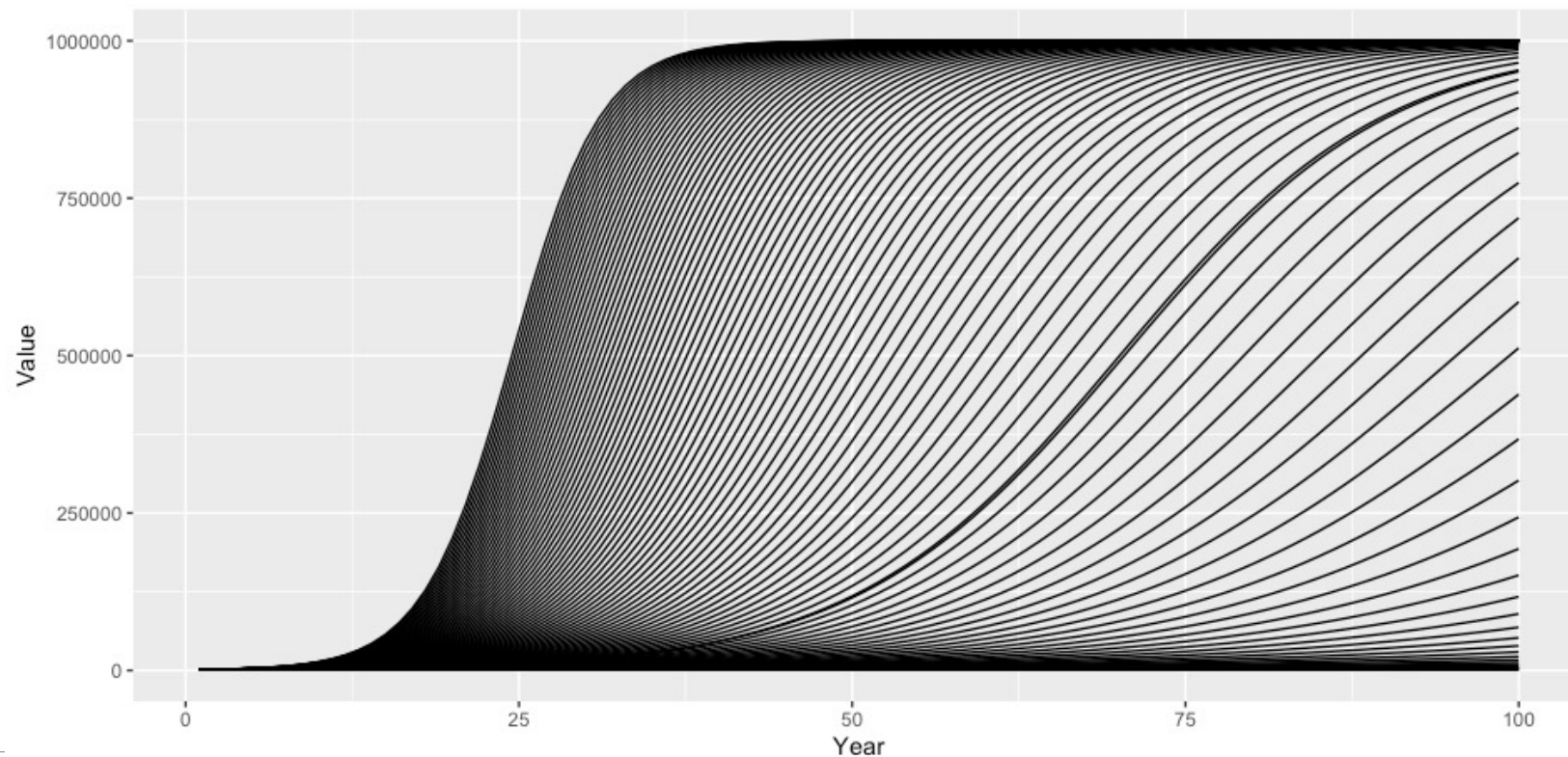
## Code (tidyr and dplyr)

```
9 # Convert to tidy data format
10 sd_tidy <- sd %>%
11     pivot_longer(cols=!Year,names_to="Variable",values_to="Value") %>%
12     mutate(Variable=str_replace_all(Variable,'\\\"','\"'),
13           Variable=str_replace(Variable,"=", "")) %>%
14     separate(Variable,into=c("Run","Variable"),sep = ":") %>%
15     mutate(Variable=trimws(Variable)) %>%
16     separate(Run,c("TempRun","Run"),sep = " ",convert = TRUE) %>%
17     select(Run,Year,Variable,Value)
```

*Tidy data makes it easier to leverage tools such as ggplot2 and dplyr*

# Plotting multiple runs with ggplot2

```
19 ggplot(filter(sd_tidy, Variable=="Population"), aes(x=Year, y=Value, group=Run)) + geom_line()
```



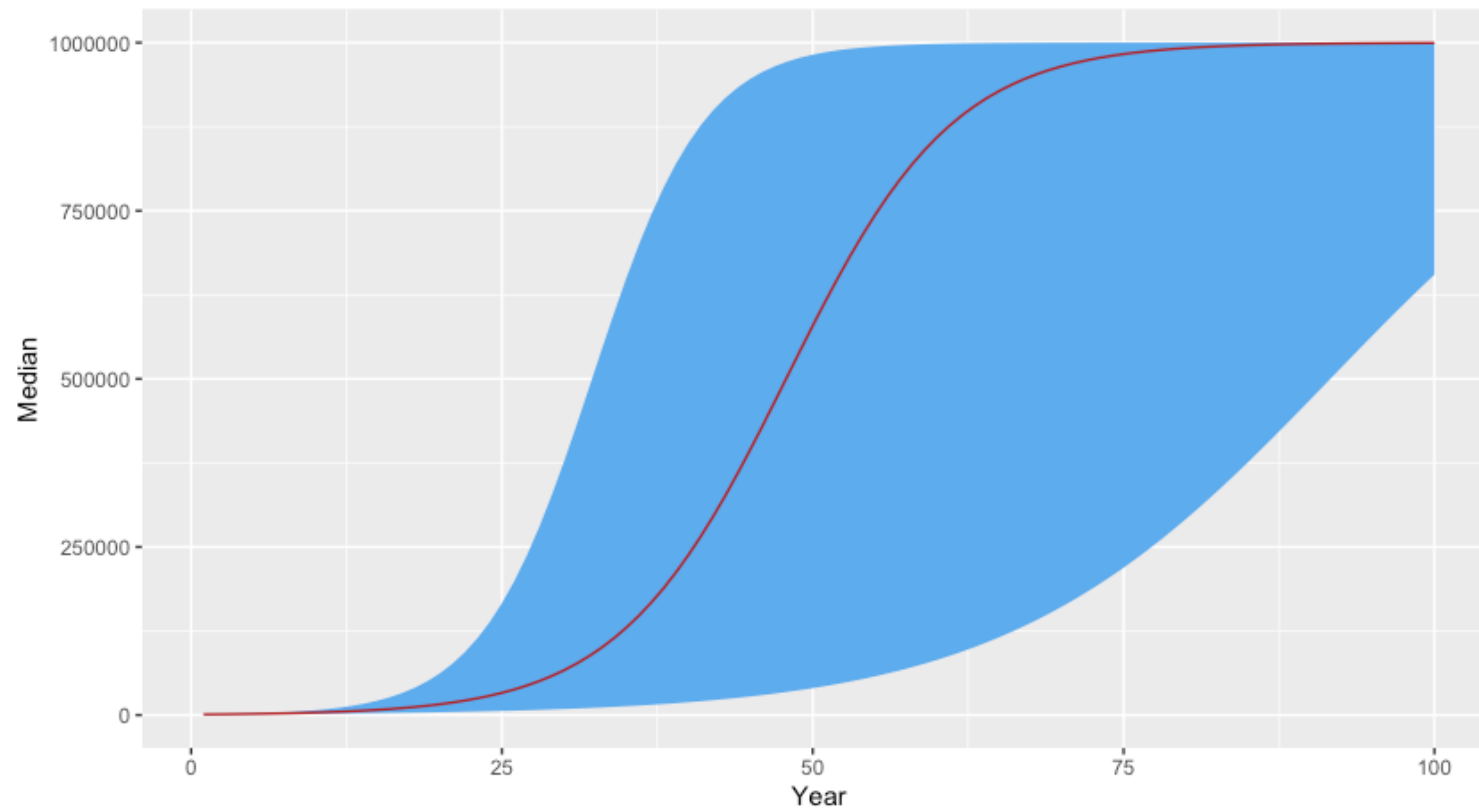
## Finding summary data - quantiles

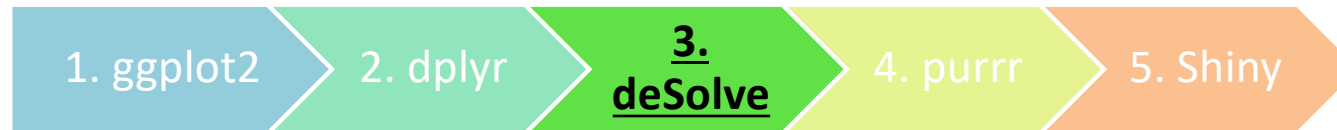
```
21 sum_runs <- sd_tidy %>%  
22   filter(Variable=="Population") %>%  
23   group_by(Variable,Year) %>%  
24   summarise(Q75=quantile(Value,0.75),  
25             Q25=quantile(Value,0.25),  
26             Median=median(Value),  
27             Mean=mean(Value))
```

# Finding summary data - quantiles

```
> sum_runs
# A tibble: 100 × 6
# Groups:   Variable [1]
  Variable    Year   Q75    Q25 Median  Mean
  <chr>      <dbl> <dbl> <dbl> <dbl> <dbl>
1 Population    1  1000  1000   1000  1000
2 Population    2  1246. 1079.  1158. 1163.
3 Population    3  1553. 1164.  1342. 1362.
4 Population    4  1936. 1256.  1554. 1607.
5 Population    5  2412. 1356.  1800. 1909.
6 Population    6  3005. 1463.  2085. 2282.
7 Population    7  3743. 1578.  2414. 2745.
8 Population    8  4662. 1703.  2796. 3322.
9 Population    9  5805. 1837.  3238. 4043.
10 Population   10  7227. 1982.  3749. 4945.
# ... with 90 more rows
# i Use `print(n = ...)` to see more rows
```

```
30 ggplot(sum_runs,aes(Year, Median)) +  
31   geom_ribbon(aes(ymin = Q25,ymax = Q75),fill = "steelblue2") +  
32   geom_line(color = "firebrick")
```





R's deSolve package solves initial value problems written as ordinary differential equations (ODE), differential algebraic equations (DAE), and partial differential equations (PDE)



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February 2010, Volume 33, Issue 9. <http://www.jstatsoft.org/>

### Solving Differential Equations in R: Package deSolve

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Ecology

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Technische Universität  
Dresden

R. Woodrow Setzer  
US Environmental  
Protection Agency

*The model is implemented as an R function, and called via ode()*

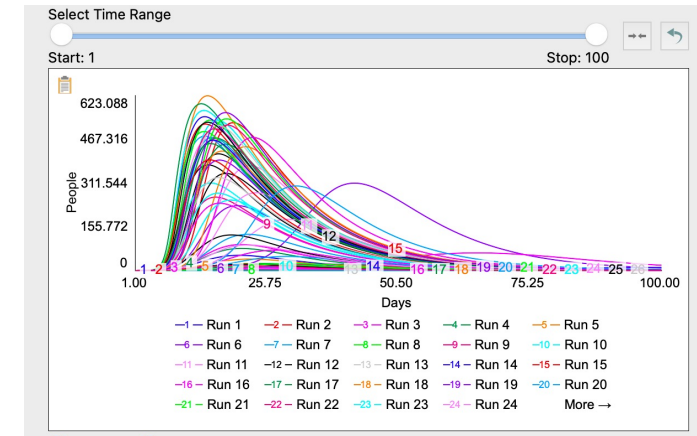
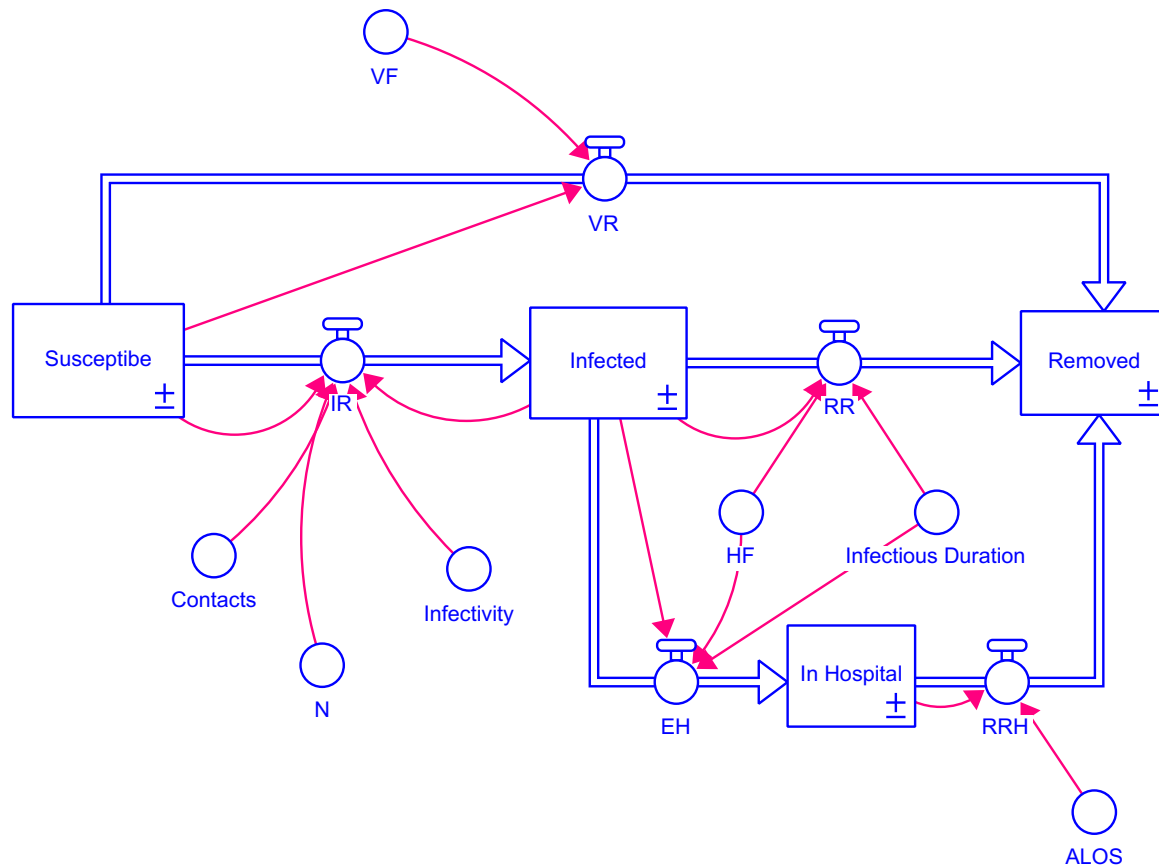
# ode function in deSolve

Argument	Description
y	The initial (state) values for the ODE system, a vector. If y has a name attribute, the names will be used to label the output matrix
times	Time sequence for which output is wanted; the first value of times must be the initial time
func	<ul style="list-style-type: none"><li>• An R function that computes the values of the derivatives in the ODE system at time <i>t</i>. It must be defined as: <code>func &lt;- function(t, y, parms,...)</code>, where <i>t</i> is the current time point in the integration and <i>y</i> is the current estimate of the variables in the ODE system.</li><li>• If the initial value <i>y</i> has a names attribute, the names will be available inside <i>func</i>.</li><li>• <i>parms</i> is a vector or list of parameters; ... (optional) are any other arguments passed to the function.</li><li>• The return value of <i>func</i> should be a list, whose first element is a vector containing the derivatives of <i>y</i> with respect to time, and whose next elements are global values that are required at each point in times. The derivatives must be specified in the same order as the state variables <i>y</i>.</li></ul>
parms	Parameters passed to <i>func</i> .
method	Normally a string to indicate the integration method, for example, "euler", "rk4", "ode23", "ode45".
returns	A matrix of class <code>deSolve</code> with up to as many rows as elements in <i>times</i> and as many columns as elements in <i>y</i> plus the number of "global" values returned in the second element of the return from <i>func</i> , plus an additional column (the first) for the time value. This can be easily converted to a data frame object using the function <code>data.frame()</code>

```
sim <- data.frame(ode(y=stocks,
                     times = simtime,
                     func   = sirh,
                     parms  = auxs,
                     method = "euler"))
```



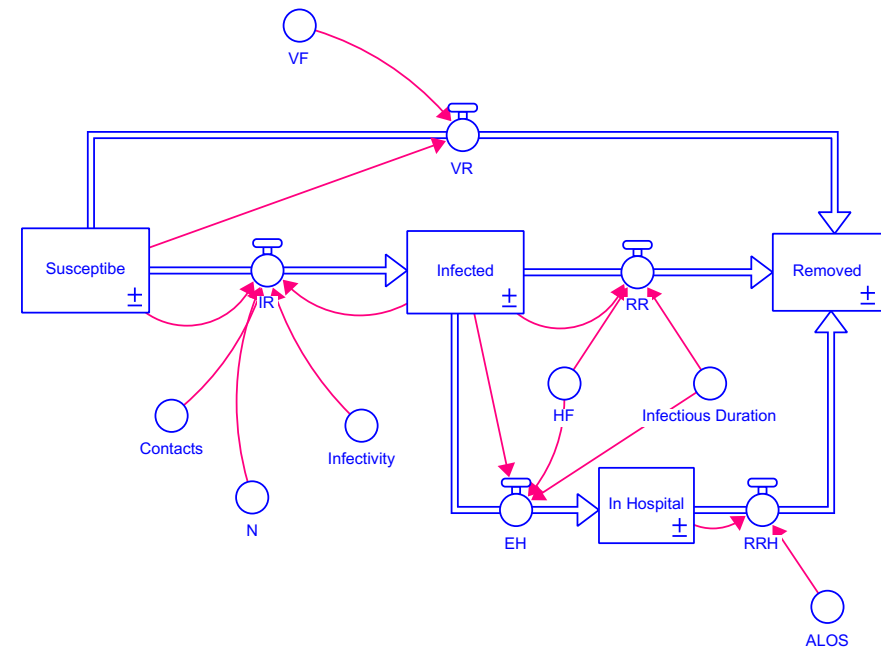
# Model Example



```

10 sirh <- function(time, stocks, auxs){
11   with(as.list(c(stocks, auxs)),{
12     IR <- contacts * S * I/N * i
13     RR <- I * (1-HF) / D
14     EH <- I * HF / D
15     RRH <- H / ALOS
16     VR <- S * VF
17
18     dS_dt <- -IR - VR
19     dI_dt <- IR - RR - EH
20     dR_dt <- RR + RRH + VR
21     dH_dt <- EH - RRH
22
23     CheckSum <- S+I+R+H
24
25     # browser()
26
27     return (list(c(dS_dt,dI_dt,dR_dt,dH_dt),
28                 IR=IR,RR=RR,EH=EH,RRH=RRH,Contacts=contacts,
29                 Infectivity=i,ALOS=ALOS,HospFrac=HF,VaccFrac=VF,
30                 CheckSum=CheckSum,N=N))
31   })
32 }

```



```

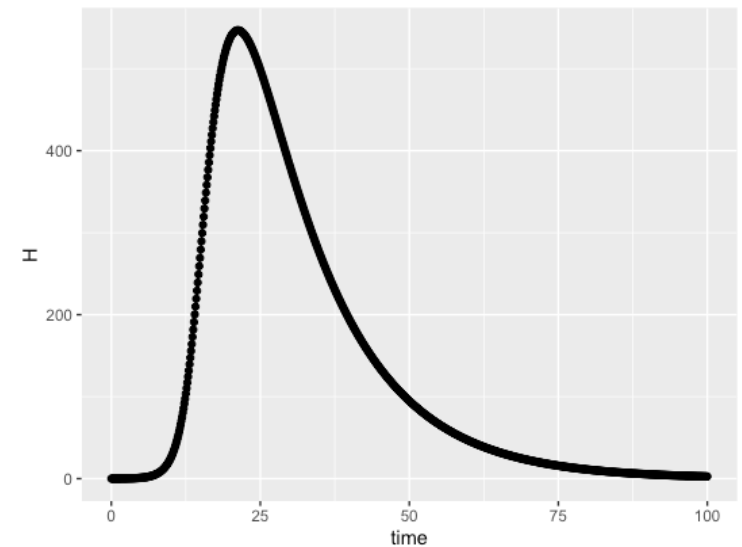
49 simtime <- seq(start, finish, step)
50 # initialise vector of stocks
51 stocks <- c(S=inits[1],
52             I=inits[2],
53             R=inits[3],
54             H=inits[4])
55
56 # initialise vector of auxiliaries
57 auxs <- c(contacts=contacts, # Contacts
58           i=infectivity,      # Infectivity
59           D=duration,         # Duration of infectiousness
60           N=N,                # Total Population
61           ALOS=ALOS,          # Average length of stay
62           HF=HF,              # Hospitalisation Fraction
63           VF=VF)              # VaccinationFraction
64
65
66 sim <- data.frame(ode(y=stocks,
67                      times = simtime,
68                      func   = sirh,
69                      parms  = auxs,
70                      method = "euler"))

```

```

78 p1 <- ggplot(sim, aes(x=time, y=H)) +
79     geom_point() +
80     geom_line()

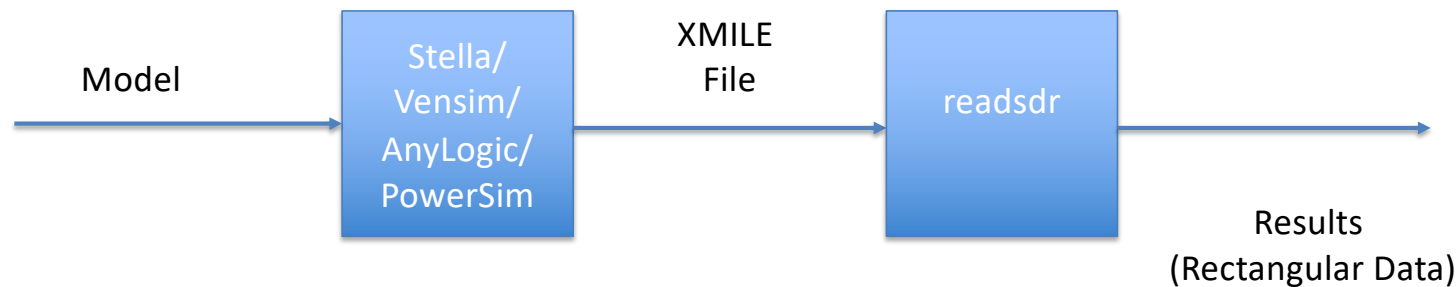
```



# Simulation output

```
> sim
# A tibble: 801 × 16
  time      S      I      R      H      IR      RR      EH      RRH Contacts Infectivity ALOS HospFrac VaccFrac Check...1      N
  <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1 0      99990    10     0     0      10.0  3.3  0.0333 0      10      0.1    14     0.01     0 100000 1e5
2 0.125 99989.   10.8  0.413 0.00417 10.8  3.57 0.0361 0.000298 10      0.1    14     0.01     0 100000 1e5
3 0.25  99987.   11.7  0.859 0.00864 11.7  3.87 0.0391 0.000617 10      0.1    14     0.01     0 100000 1e5
4 0.375 99986.   12.7  1.34  0.0135 12.7  4.20 0.0424 0.000961 10      0.1    14     0.01     0 100000 1e5
5 0.5   99984.   13.8  1.87  0.0186 13.8  4.55 0.0459 0.00133 10      0.1    14     0.01     0 100000 1e5
6 0.625 99983.   14.9  2.44  0.0242 14.9  4.92 0.0497 0.00173 10      0.1    14     0.01     0 100000 1e5
7 0.75  99981.   16.2  3.05  0.0302 16.2  5.33 0.0539 0.00216 10      0.1    14     0.01     0 100000 1e5
8 0.875 99979.   17.5  3.72  0.0367 17.5  5.78 0.0584 0.00262 10      0.1    14     0.01     0 100000 1e5
9 1      99977.   19.0  4.44  0.0436 19.0  6.26 0.0632 0.00312 10      0.1    14     0.01     0 100000 1e5
10 1.12 99974.   20.5  5.22  0.0512 20.5  6.78 0.0685 0.00365 10      0.1    14     0.01     0 100000 1e5
# ... with 791 more rows, and abbreviated variable name 1Checksum
# i Use `print(n = ...)` to see more rows
```

# readsdr package <https://github.com/jandraor/readsdr>



## Usage

```
library(readsdr)
filepath <- system.file("models/", "SIR.stmx", package = "readsdr")
mdl <- read_xmile(filepath)
summary(mdl)
#>               Length Class  Mode
#> description      4      -none- list
#> deSolve_components 4      -none- list
```

```
library(deSolve)

simtime <- seq(deSolve_components$sim_params$start,
               deSolve_components$sim_params$stop,
               deSolve_components$sim_params$dt)

output_deSolve <- ode(y      = deSolve_components$stocks,
                      times  = simtime,
                      func   = deSolve_components$func,
                      parms  = deSolve_components$consts,
                      method = "euler")

result_df <- data.frame(output_deSolve)
```



- A **map function** is one that applies the same action/function to every element of an object (e.g. each entry of a list or a vector, or each of the columns of a data frame)
- The naming convention of the map functions are such that the type of the **output** is specified by the term that follows the underscore in the function name
- Consistent with the way of the tidyverse, the **first argument** of each mapping function is always the **data object** that you want to map over, and the **second argument** is always the **function** that you want to iteratively apply to each element of the input object

- `map(.x, .f)` is the main mapping function and returns a list
- `map_df(.x, .f)` returns a data frame
- `map_dbl(.x, .f)` returns a numeric (double) vector
- `map_chr(.x, .f)` returns a character vector
- `map_lgl(.x, .f)` returns a logical vector

*map functions support iteration...*

# Sensitivity Sweep

```
82 # Sensitivity sweep, modify 2 params
83 NSIMS <- 10
84 s_contacts <- sample(3:20,NSIMS,replace = T)
85 s_vacc      <- runif(NSIMS,min=0,max = 0.10)
```

```
> s_contacts
[1] 15 19 14 17 10  5  8  4 13  9
>
>
> s_vacc
[1] 0.03728884 0.05089462 0.06664778 0.06672938 0.09171309 0.05087442 0.07575453 0.03544004
[9] 0.03325082 0.01643648
```

# R Code to support sensitivity sweep

```
37 run_sirh <- function(start=0,
38                       finish=100,
39                       step=0.125,
40                       contacts=10,
41                       infectivity=0.1,
42                       duration=3,
43                       N=100000,
44                       ALOS=14,
45                       HF=0.01,
46                       inits=c(N-10,10,0,0),
47                       VF=0.0){
48
49   simtime <- seq(start, finish, step)
50   # initialise vector of stocks
51   stocks <- c(S=inits[1],
52               I=inits[2],
53               R=inits[3],
54               H=inits[4])
```

```
56   # initialise vector of auxiliaries
57   auxs <- c(contacts=contacts, # Contacts
58             i=infectivity,     # Infectivity
59             D=duration,        # Duration of infectiousness
60             N=N,               # Total Population
61             ALOS=ALOS,         # Average length of stay
62             HF=HF,             # Hospitalisation Fraction
63             VF=VF)            # VaccinationFraction
64
65   sim <- data.frame(ode(y=stocks,
66                        times = simtime,
67                        func   = sirh,
68                        parms  = auxs,
69                        method = "euler"))
70
71   as_tibble(sim)
72 }
73 }
```



## map2 Iteration code...

```
87 count <- 1
88 # map2 is an iterator over two vectors
89 sens <- map2(s_contacts, s_vacc, ~{
90   message(glue("Sim {count} contacts {.x} vacc Fr {.y}"))
91   out_sim <- run_sirh(contacts = .x, VF = .y) %>%
92     mutate(Run=count) %>%
93     select(Run, everything())
94   count <- count+1
95   out_sim
96 })
97
98 full_sims <- bind_rows(sens)
```

# Full results

```
> full_sims
# A tibble: 200,250 × 17
  Run time      S      I      R      H      IR      RR      EH      RRH Contacts Infectiv...1 ALOS HospF...2 VaccF...3
  <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1     1 0    99990    10     0     0      18.0  3.3  0.0333 0      18     0.1    14     0.01 0.00753
2     1 0.125 99894.   11.8  94.5 0.00417 21.3  3.90 0.0394 0.000298 18     0.1    14     0.01 0.00753
3     1 0.25  99797.   14.0 189. 0.00906 25.1  4.62 0.0467 0.000647 18     0.1    14     0.01 0.00753
4     1 0.375 99700.   16.6 283. 0.0148  29.7  5.46 0.0552 0.00106 18     0.1    14     0.01 0.00753
5     1 0.5   99602.   19.6 378. 0.0216  35.1  6.46 0.0653 0.00154 18     0.1    14     0.01 0.00753
6     1 0.625 99504.   23.2 473. 0.0295  41.5  7.64 0.0772 0.00211 18     0.1    14     0.01 0.00753
7     1 0.75  99405.   27.4 567. 0.0389  49.0  9.03 0.0913 0.00278 18     0.1    14     0.01 0.00753
8     1 0.875 99306.   32.4 662. 0.0500  57.8 10.7 0.108 0.00357 18     0.1    14     0.01 0.00753
9     1 1     99205.   38.2 757. 0.0630  68.3 12.6 0.127 0.00450 18     0.1    14     0.01 0.00753
10    1 1.12  99103.   45.2 851. 0.0784  80.6 14.9 0.151 0.00560 18     0.1    14     0.01 0.00753
# ... with 200,240 more rows, 2 more variables: CheckSum <dbl>, N <dbl>, and abbreviated variable names
#   1Infectivity, 2HospFrac, 3VaccFrac
# i Use `print(n = ...)` to see more rows, and `colnames()` to see all variable names
```

# Summary, Peak Cases

```

103 summ <- full_sims %>%
104   group_by(Run) %>%
105   summarise(PeakH=max(H),
106             Contacts=first(Contacts),
107             VF=first(VaccFrac)) %>%
108   ungroup()

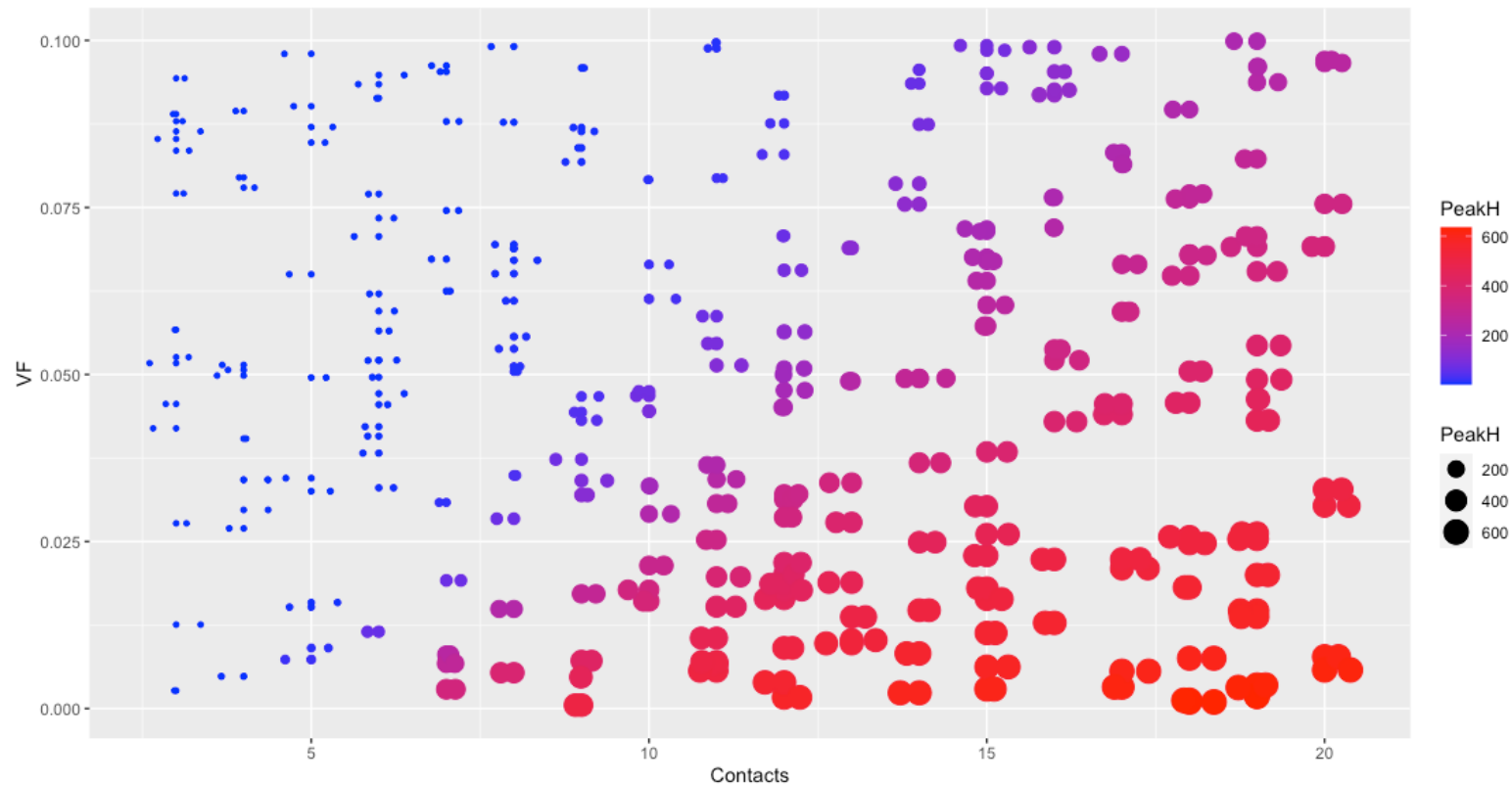
```

```

> summ
# A tibble: 250 × 4
   Run   PeakH Contacts    VF
  <dbl> <dbl>   <dbl>   <dbl>
1     1  605.      18 0.00753
2     2  439.      19 0.0463
3     3  227.      19 0.0961
4     4   7.92      8 0.0512
5     5   0.141      3 0.0943
6     6   0.827      7 0.0953
7     7  154.      17 0.0980
8     8  217.      15 0.0675
9     9  420.      9 0.00715
10    10   73.4      9 0.0373
# ... with 240 more rows
# i Use `print(n = ...)` to see more rows

```

```
p3 <- ggplot(summ,aes(x=Contacts,y=VF,size=PeakH,colour=PeakH))+
  geom_point()+
  scale_color_gradient(low="blue", high="red")+geom_jitter()
```

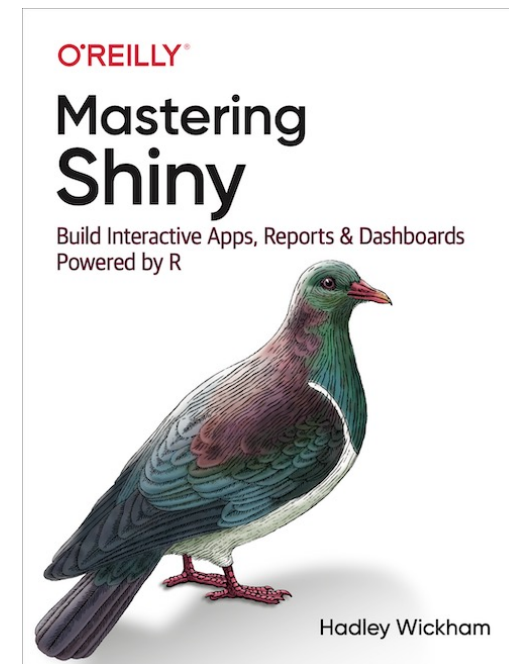




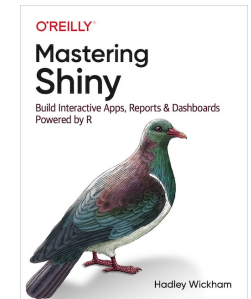
Spreadsheets are closely related to reactive programming: you declare the relationship between cells using formulas, and when one cell changes, all of its dependencies automatically update.

Hadley Wickham – Mastering Shiny

<https://mastering-shiny.org>

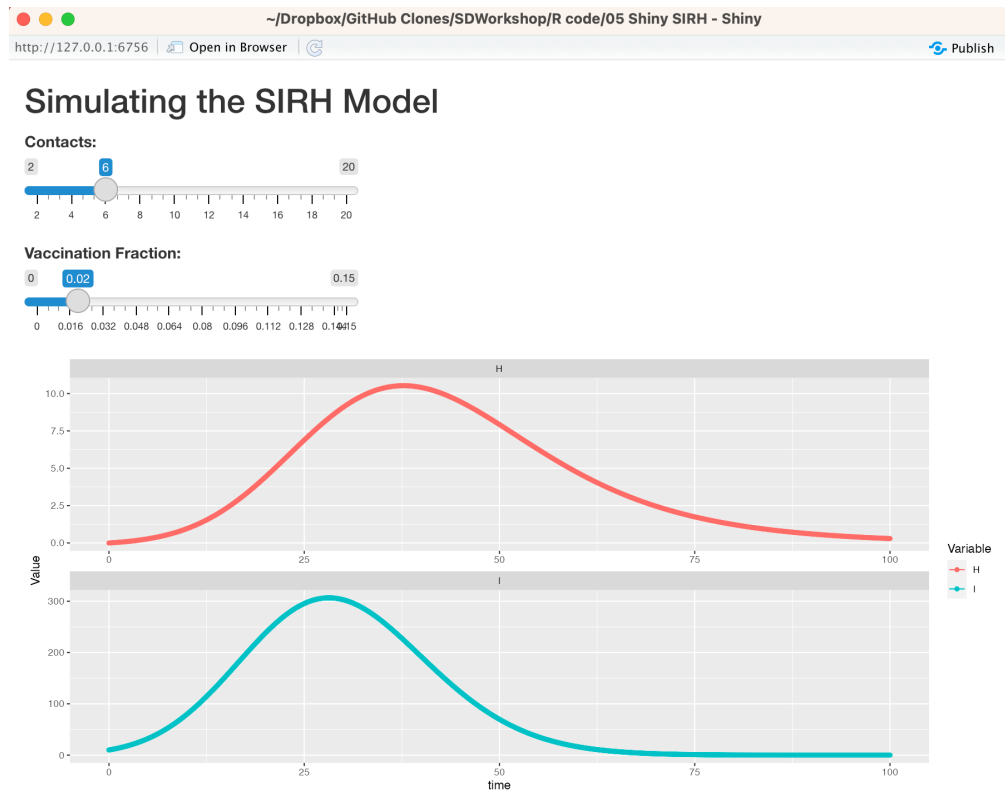


# Shiny (Wickham)



- Shiny is a framework for creating web applications using R code.
- It is designed primarily with data scientists in mind, and to that end, you can create pretty complicated Shiny apps with no knowledge of HTML, CSS, or JavaScript.
- On the other hand, Shiny doesn't limit you to creating trivial or prefabricated apps: its user interface components can be easily customized or extended, and its server uses reactive programming to let you create any type of back end logic you want.
- Shiny is designed to feel almost magically easy when you're getting started, and yet the deeper you get into how it works, the more you realize it's built out of general building blocks that have strong software engineering principles behind them

# The App



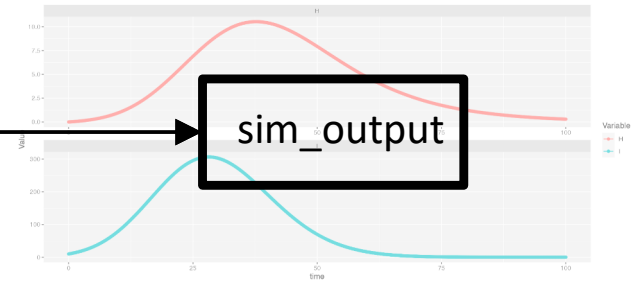
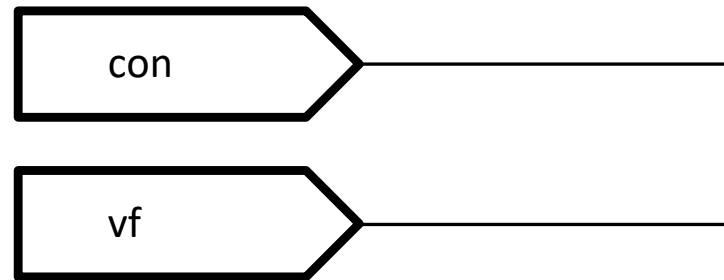
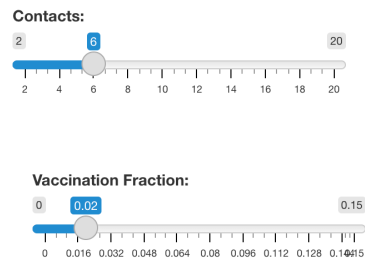
```
shinyApp(ui, server)
```

# The ui object

```
10 ui <- fluidPage(  
11   titlePanel("Simulating the SIRH Model"),  
12   sliderInput("con", "Contacts:",  
13               min = 2, max = 20, value = 6  
14   ),  
15   sliderInput("vf", "Vaccination Fraction:",  
16               min = 0, max = 0.15, value = .02  
17   ),  
18   plotOutput("sim_output")  
19 )
```



# The reactive graph – spreadsheet cell analogy

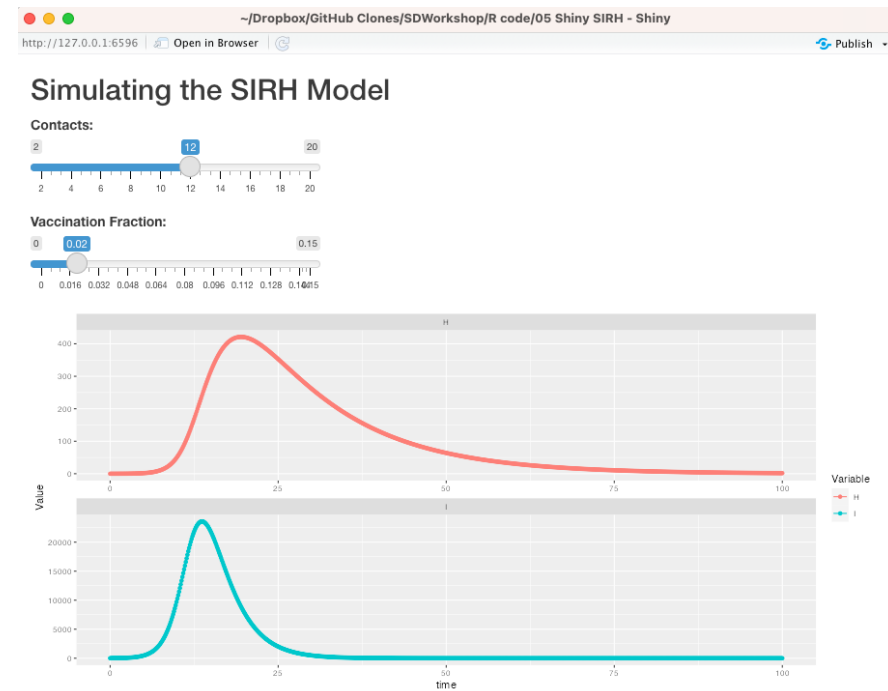
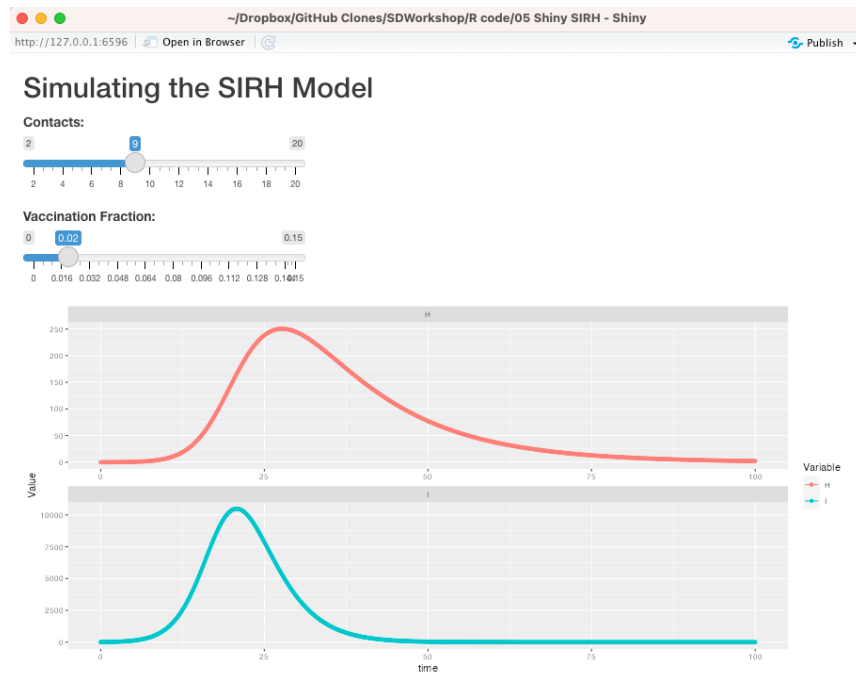


- Any change to an input control
- Leads to a reaction in the server code
- Which then updates the output

# The Server

```
21 server <- function(input, output, session){
22   message("\nStarting the server...")
23   output$sim_output <- renderPlot({
24     sim <- run_sirh(contacts = input$con,
25                   VF = input$vf) %>%
26     select(time,I,H) %>%
27     pivot_longer(cols = -time,
28                 names_to = "Variable",
29                 values_to = "Value")
30
31     ggplot(sim,aes(x=time,y=Value,colour=Variable))+
32     geom_point()+geom_line()+
33     facet_wrap(~Variable,nrow = 2,scales="free")
34   })
35 }
```

# Outputs



# Conclusion



1. ggplot2

2. dplyr

3.  
deSolve

4. purrr

5. Shiny

- R can integrate in a flexible way within your System Dynamics workflow
- Visualization, summaries, modelling, sensitivity and web apps
- Can also support calibration workflows - Andrade and Duggan 2021

## MAIN ARTICLE

### **A Bayesian approach to calibrate system dynamics models using Hamiltonian Monte Carlo**

Jair Andrade\* and Jim Duggan

