# Stockholm R useR Group: Microsimulation

#### Mark Clements

Department of Medical Epidemiology and Biostatistics, Karolinska Institutet

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#### Who am I?

- Lektor in Biostatistics at Karolinska Institutet (colleagues with Alex Ploner)
- I did my undergraduate in statistics at the Department of Auckland in New Zealand (where was developed)
- Ruser since 1998

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- Quser since 1998
- Currently using microsimulation to model prostate cancer screening for a large randomised controlled trial planned for Stockholm

#### **Disclaimers**

- This is work in progress!
- This is a health-centric (chronic diseases) view of microsimulation

I welcome comments during the presentation.

#### Table of Contents

- Background
- 2 R implementation of microsimulation
- Random number streams
- 4 C++ implementation of microsimulation
- 6 Additional material

## Cross-classification by the following factors

- Group-level (G) versus individual-level (I)
- Markov (M) versus non-Markov (nM)
- Discrete time (DT) versus continuous time (CT)

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#### Some examples

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- (I,nM,DT) = Agent-based simulation
- (I,nM,CT) = Discrete event simulation

#### What is Microsimulation?

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- The International Microsimulation Association defines microsimulation as a modelling technique that operates at the level of individual units such as persons, households, vehicles or firms.
- In health sciences, microsimulation refers to a type of simulation modeling that generates individual life histories.
  - The technique is used when 'stock-and-flow' type modeling of proportions (macrosimulation) of the population cannot sufficiently describe the system of interest.
  - This type of modeling does not necessarily involve interaction between individuals and in that case can generate individuals independently of each other, and can easily work with continuous time instead of discrete time steps.

# Microsimulation in health: Two common approaches

- Discrete time, Markov
  - Popular with health economists, who like their Markov models (e.g. TreeAge software)
  - Alex Ploner is working on such a framework for modelling cervical cancer, with model specification and post-processing in
    - and the simulation engine in C
  - The TraMineR package is very useful for visualising discrete time life histories

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    - and the simulation engine in C
  - The TraMineR package is very useful for visualising discrete time life histories
- Continuous time, non-Markov
  - Most generally implemented as a discrete event simulation
  - We are working on an prostate cancer



implementation for

Conceptually, we have an event queue which is ordered by event times, where events are defined by their type and time<sup>1</sup>.

<sup>&</sup>lt;sup>1</sup>Law AM. (2007) *Simulation Modeling and Analysis*. Fourth edition. New York: McGraw-Hill.

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Initialise an empty event queue; insert initial events into the queue

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- Initialise an empty event queue; insert initial events into the queue
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  - (i) Retrieve the event at the head of the queue
  - (ii) Process the event, possibly updating any variables, or insert/delete events from the queue

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- 2 Repeat until the queue is empty:
  - (i) Retrieve the event at the head of the queue
  - (ii) Process the event, possibly updating any variables, or insert/delete events from the queue
- Finalise the simulation (e.g. return statistics).

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#### Discrete event simulation: Software

- Proprietary: Arena, Extend, GPSS, SIMSCRIPT, etc.
- Open source: NS-2, Omnet++, Simpy, SSJ, etc.
- Only one simple example by Norm Matlof (http://www.esg.montana.edu/R/revent.pdf)

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```
R
```

```
> eq <- EventQueue$new() # R5 class (to be defined)</pre>
> eq$insert(3, "Clear drains")
> eq$insert(1, "Solve RC tasks")
> eq$insert(2, "Tax return")
> while(!eq$empty()) {
 print(eq$pop())
+ }
[1] "Solve RC tasks"
attr(,"time")
[1] 1
[1] "Tax return"
attr(,"time")
\lceil 1 \rceil 2
[1] "Clear drains"
attr(,"time")
[1] 3
```

```
1 EventQueue <- function() {</pre>
    times <- events <- NULL
    insert <- function(time, event) {</pre>
      ord <- order(newtimes <- c(times, time))
      times <<- newtimes [ord]
      events <<- c(events, list(event))[ord]
    pop <- function() {</pre>
      head <- structure (events [[1]], time=times [1])
      events << events [-1]
      times <<- times [-1]
      return (head)
    empty <- function() length(events) == 0</pre>
    list(insert = insert, pop = pop, empty = empty)
16
```

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      events <<- c(events, list(event))[ord]
    pop <- function() {</pre>
      head <- structure (events [[1]], time=times [1])
      events << events [-1]
10
      times <<- times [-1]
      return (head)
13
    empty <- function() length(events) == 0</pre>
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    list(insert = insert, pop = pop, empty = empty)
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```

# R: Event queue (using an R5 class)

```
EventQueue <-
  setRefClass("EventQueue",
               fields = list(times = "numeric", events = "list"),
               methods = list(
                 insert = function(time, event) {
                   ord <- order(newtimes <- c(times, time))
                   times <<- newtimes [ord]
                   events <<- c(events, list(event))[ord]
                 pop = function() {
                   head <- structure (events [[1]], time=times [1])
                   times <<- times [-1]
                   events <\!\!< events [-1]
                   return (head)
                 empty = function() length(times) == 0
```

#### Comments

- R5 classes and closures look very similar!
- Closures provide a simple approach to working with fields and methods
- R5 classes allow for inheritance (see next), but they are slow.



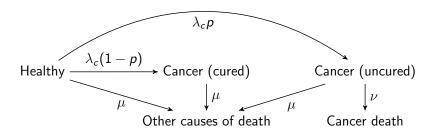
# Running the simulation

```
> set.seed(123)
> sim <- Simulation$new()</pre>
> sim$run()
[1] "Cancer diagnosis"
attr(,"time")
[1] 55.76424
[1] "Cancer death"
attr(,"time")
[1] 59.29142
> sim$run()
[1] "Death due to other causes"
attr(,"time")
[1] 59.96818
```

# Outline of the BaseDiscreteEventSimulation class

- Inherit from the EventQueue class (with methods: insert, pop and empty)
- Define init() to set up the initial events
- Schedule events using scheduleAt(time, event), where event can be any object (e.g. a list or a character string)
- Define handleMessage(event) to respond to different events, possibly scheduling other events or clear()ing the queue
- Define final() to finish the simulation (if required)
- After the model is defined, run() the simulation

# Simulation: Concrete example



where p=0.5, and  $\mu$ ,  $\lambda_c$  and  $\mu$  are rates for Weibull distributions. In practise for competing risks, we sample from the event time distributions and take the first event.

# R: Concrete class example

```
Simulation <-
    setRefClass("Simulation",
                 contains = "BaseDiscreteEventSimulation")
  Simulation methods (init = function() {
    clear()
    scheduleAt(rweibull(1,8,85), "Death due to other causes")
    scheduleAt(rweibull(1,3,90), "Cancer diagnosis")
  Simulation $methods (handle Message = function (event) {
    now <- attr(event, "time")</pre>
    if (event %in% c("Death due to other causes", "Cancer death")) {
      clear()
      print(event)
14
    else if (event = "Cancer diagnosis") {
      if (runif(1) < 0.5)
16
        scheduleAt(now + rweibull(1,2,10), "Cancer death")
      print(event)
18
19
20
```

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18
19
20
```



# R: Discrete event simulation (R5)

```
BaseDiscreteEventSimulation <-
    setRefClass("BaseDiscreteEventSimulation",
                 contains = "EventQueue",
                 methods = list(
                   clear = function() {
                     times <<- numeric()
                     events <<- list()
                   scheduleAt = function(time, event) insert(time,
                       event),
                   init = function() stop("VIRTUAL!"),
                   handleMessage = function(event) stop("VIRTUAL!"),
                   final = function() {},
                   run = function() {
                     init()
14
                     while(!empty()) {
                       event <- pop()</pre>
                       handleMessage (event)
18
                     final()
20
```

#### Some class extensions

- Define fields for currentTime and previousEventTime
- Define a utility function now() for the current time
- Include a report field for returning statistics

## Running the simulation

```
R
```

```
> set.seed(123)
> sim <- Simulation$new()</pre>
> system.time(for (i in 1:5000) sim$run())
        system elapsed
  user
          0.02 15.03
  14.96
> subset(sim$report,id<=4)
  id
       state begin
                           end
                                                  event.
   1 Healthy 0.00000 55.76424
                                        Cancer diagnosis
   1 Cancer 55.76424 59.29142
                                           Cancer death
3
   2 Healthy 0.00000 59.96818 Death due to other causes
   3 Healthy 0.00000 43.61622
                                       Cancer diagnosis
5
   3 Cancer 43.61622 80.36382 Death due to other causes
6
   4 Healthy 0.00000 31.80345
                                        Cancer diagnosis
      Cancer 31.80345 38.04237
                                           Cancer death
```

```
Simulation <-
  setRefClass("Simulation",
              contains = "BaseDiscreteEventSimulation2", # See
                  Additional material
              fields = list(id = "numeric", state = "character",
                  report = "data.frame").
              methods = list (initialize = function (id = 0)
                  callSuper(id = id)))
Simulation $ methods (init = function() {
  clear()
  id \ll - id + 1
  state <<- "Healthy"
  scheduleAt(rweibull(1,8,85), "Death due to other causes")
  scheduleAt(rweibull(1,3,90), "Cancer diagnosis")
```

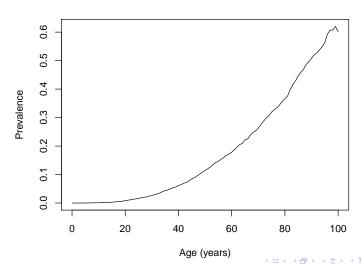
## R: Concrete class example 2

```
Simulation $ methods (handle Message = function (event) {
  report <-- rbind(report, data.frame(id = id,
                                       state = state.
                                       begin = previousEventTime,
                                       end = currentTime.
                                       event=event.
                                       stringsAsFactors = FALSE)
  if (event %in% c("Death due to other causes", "Cancer death")) {
    clear()
  else if (event = "Cancer diagnosis") {
    state <<- "Cancer"
    if (runif(1) < 0.5)
      scheduleAt(now() + rweibull(1,2,10), "Cancer death")
```

# Life histories: calculating prevalence using SQL

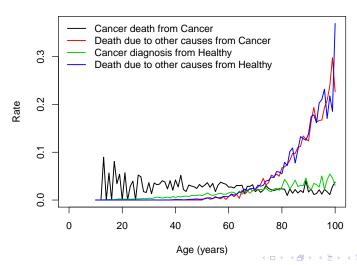
```
R
> require(sqldf)
> report <- sim$report
> ages <- transform(data.frame(lhs = seq(0,100,1)),</pre>
                    rhs = lhs + 1
+
> prev <- sqldf("select t.*, a.lhs as age
       from report as t
        inner join ages as a on t.begin <= a.lhs and a.lhs < t.end")
> xtabs(~state+age, prev, subset = age %% 10 == 0)
         age
                 10
                      20 30 40
                                     50 60
                                               70
                                                    80
                                                         90
                                                             100
state
  Cancer
                6
                      43
                          132
                               302 539 769
                                              909
                                                   788
                                                        374
                                                              59
  Healthy 5000 4991 4947 4836 4589 4173 3536 2546 1362
                                                              39
```

## Life histories: Prevalence of cancer



# Life histories: calculating rates using SQL

#### Life histories: Rates



#### Microsimulation: Outline of tasks

- Define the microsimulation model
- For different scenarios:
  - Define the input parameters
    - Possibly initial histories based on observed individuals (e.g. a survey or registers)
    - Transition probabilities or time to event distributions
  - Run the microsimulation (in cancer, for 10<sup>5</sup> to 10<sup>7</sup> individuals)
  - Summarise the results

# Microsimulation: Calibration/estimation

- Define
  - Microsimulation model
  - Fixed input parameters
  - Prior distributions for the uncertain input parameters
  - Calibration targets (i.e. data to fit)
- Sample from the posterior distribution
  - Run the microsimulation (in cancer, for 10<sup>5</sup> to 10<sup>7</sup> individuals)
  - Calculate the likelihood for the calibration targets
- Summarise the posterior distribution

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#### Common random numbers and variance reduction

- For calibration/estimation and comparing scenarios in microsimulation, we want to reduce the Monte Carlo variation.
   Best practice advises the use of common random numbers
- The simplest approach for common random numbers is to have a different random seed for each individual
- A better approach is to have a different random seed for each individual for each "random process"

#### Random streams and sub-streams

Imagine that we have a random number generator that produces a long, independent series of random numbers:



#### Random streams and sub-streams

Imagine that we have a random number generator that produces a long, independent series of random numbers:

Now, we split this series into a set of streams:

00000000000000

00000000000000

00000000000000

#### Random streams and sub-streams

Imagine that we have a random number generator that produces a long, independent series of random numbers:

Now, we split this series into a set of streams:

00000000000000

00000000000000

999999999999

And we can split the streams into a set of sub-streams:

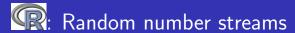
99999 99999 99999 99999

#### Random streams and sub-streams: microsimulation

 $\bullet \ \, \mathsf{Streams} \to \mathsf{random} \,\, \mathsf{processes}$ 

#### Random streams and sub-streams: microsimulation

- Streams  $\rightarrow$  random processes
- ullet Sub-streams for a given stream o individuals



- Random number streams are implemented in the parallel core package (see also the rlecuyer, rstream and rsprng packages)
- parallel uses the "L'Ecuyer-CMRG" random number generator, which has a period of around  $2^{191}$  (=3138550867693340381917894711603833208051177722232017256448; the default "Mersenne-Twister" RNG has a period of  $2^{19937}-1$ )
- Each stream is a subsequence of the period of length  $2^{127}$  which is in turn divided into substreams of length  $2^{76}$
- The parallel package adapts and simplifies the RngStreams C package, losing some useful functionality

## RNGStream object

- open, close and with methods for using an RNGStream object
- resetSubStream, resetStream, nextSubStream and nextStream methods for changing the object seed



# R: Example of random number streams

```
R
                                            R
                                            >
> set.seed(101)
                                            > s1$resetStream()
> s1 <- RNGStream(nextStream=FALSE)</pre>
                                            > s2$resetStream()
> s2 <- RNGStream()
                                            > with(s1,rnorm(2))
> with(s1,rnorm(1))
                                            T11
                                                 2.1891887 -0.6045821
[1] 2.189189
                                            > with(s2,rnorm(2))
> with(s2,rnorm(1))
                                            [1] 0.5205894 0.8820710
[1] 0.5205894
                                            > s1$nextSubStream()
> s1$nextSubStream()
                                            > with(s1,rnorm(2))
> with(s1,rnorm(1))
                                            [1] -1.4611126 -0.8230108
[1] -1.461113
```

# RNGStream object

```
require (parallel)
2 RNGkind ("L' Ecuyer-CMRG")
3 RNGStream <- function(nextStream = TRUE) {
    current <- if (nextStream) nextRNGStream (.Random.seed) else</pre>
        Random seed
    .Random.seed <<- startOfStream <- startOfSubStream <- current
    structure(list(open = function() .Random.seed <<- current,</pre>
                    close = function() current <<- .Random.seed ,</pre>
                    resetSubStream = function() .Random.seed <<-</pre>
                         current <<- startOfSubStream .
                    resetStream = function() .Random.seed <<- current</pre>
                         <<- startOfSubStream <<- startOfStream ,</pre>
                    nextSubStream = function() .Random.seed <<--</pre>
                         current <<- startOfSubStream <<-
                         nextRNGSubStream (startOfSubStream),
                    nextStream = function() .Random.seed <<- current</pre>
                        <<- startOfSubStream <<- startOfStream <<--</pre>
                         nextRNGStream(startOfStream)),
               class="RNGStream")
```

## with method for RNGStream object

```
with.RNGStream <- function(stream, expr,...) {
    stream$open()
    out <- eval(substitute(expr), enclos = parent.frame(), ...)
    stream$close()
    out
}</pre>
```

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# Why C++?

• Ris too slow!

# Why C++?

- is too slow!
- Good GPL'd libraries in C and C++ available for:
  - Discrete event simulation (SSIM)
  - Random number streams (RngStreams of course!)
- But...

# Why C++?

- Ris too slow!
- Good GPL'd libraries in C and C++ available for:
  - Discrete event simulation (SSIM)
  - Random number streams (RngStreams of course!)
- But...
  - We like
  - We may miss "s dynamic typing, closures, extensive packages, etc.
  - We may not really want to program in C++

# Entrez: Rcpp

- ullet An elegant C++ framework for passing data and structures between R and C++
- Increasingly popular solution for dealing with large and slow computational tasks in
- We can now do all of our pre- and post-processing with and use C++ as the engine



#### Good advice

Do everything for two reasons



## Running the simulation

```
R
> require(microsimulation)
Loading required package: microsimulation
Loading required package: Rcpp
> set.seed(123)
> system.time(df <- callSimplePerson(100000))</pre>
        system elapsed
   user
 0.688 0.016 0.705
> head(df)
   endtime
                  event id startTime
                                       state
1 55.76424
               toCancer 0
                             0.00000 Healthy
2 59.29142 toCancerDeath 0
                            55.76424
                                      Cancer
3 59.96818 toOtherDeath 1 0.00000 Healthy
4 43.61622
               toCancer 2
                             0.00000 Healthy
5 80.36382 toOtherDeath 2
                            43.61622
                                      Cancer
```

toCancer

6 31.80345

0.00000 Healthy

#### Discussion

- Ongoing work
  - Methods for calibration (with Alexandra Jauhiainen)
  - Application to prostate cancer (with Hatef Darabi)
  - Statistics collection in C++
  - Visualisation; the Biograph package looks very interesting
- Issues and challenges
  - User-defined random number generators use one C function (double \*user\_unif\_rand ()) → name conflict??
  - How to encourage R programmers to learn C++?
- The microsimulation package is available at <a href="https://github.com/mclements/microsimulation">https://github.com/mclements/microsimulation</a>

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#### "Process-oriented" discrete event simulation

- The concept on the previous slide describes event-oriented simulation
- At a higher level, we can consider a process-oriented simulation, where we have a process that includes a series of events. The processes run as "continuations".

14

16

## R: Discrete event simulation 2

```
BaseDiscreteEventSimulation2 <-
  setRefClass("BaseDiscreteEventSimulation2",
              contains = "BaseDiscreteEventSimulation",
               fields = list(currentTime = "numeric",
                 previousEventTime = "numeric"),
              methods = list(
                 now = function() currentTime,
                 run = function() {
                   previousEventTime <<- 0.0
                   init()
                   while(!empty()) {
                     event <- pop()</pre>
                     currentTime <<- attr(event, "time")</pre>
                     handleMessage (event)
                     previous Event Time <<- current Time
                   final()
                 }))
```

## microsimulation

```
1 setOldClass("RNGStream")
  Simulation <-
    setRefClass("Simulation",
                 contains = "BaseDiscreteEventSimulation2",
                 fields = list(id = "numeric", state = "character",
                     report = "data.frame", rng = "RNGStream"),
                 methods= list(initialize = function(id = 0) {
                   callSuper(id = id)
                   rng <<- RNGStream(nextStream = FALSE)</pre>
  Simulation $ methods (init = function () {
10
    clear()
    id \ll - id + 1
    state <<- "Healthy"
    scheduleAt(with(rng,rweibull(1,8,85)), "Death due to other
14
        causes")
    scheduleAt(with(rng,rweibull(1,3,90)), "Cancer diagnosis")
15
  Simulation $methods (final = function() rng $nextSubStream())
```

# : Common random numbers in a

microsimulation II

```
Simulation $ methods (handle Message = function (event) {
    report <<- rbind(report, data.frame(id = id,</pre>
                                          state = state.
                                          begin = previousEventTime,
                                          end = currentTime,
                                          event=event.
                                          stringsAsFactors = FALSE)
    if (event %in% c("Death due to other causes", "Cancer death")) {
      clear()
    else if (event == "Cancer diagnosis") {
      state <<- "Cancer"
      if (with(rng, runif(1)) < 0.5)
        scheduleAt(now() + with(rng, rweibull(1,2,10)), "Cancer death
14
```

# C++: A simple microsimulation example (R code)

```
enum <- function(obj, labels)</pre>
    factor(obj, levels = 0:(length(labels)-1), labels=labels)
  callSimplePerson <- function(n=100) {
    stateT <- c("Healthy", "Cancer", "Death")</pre>
    eventT <- c("toOtherDeath", "toCancer", "toCancerDeath")</pre>
    out <- . Call("callSimplePerson",
                  parms=list(n=as.integer(n)),
                  PACKAGE="microsimulation")
10
    out <- transform (as.data.frame(out),
                       state=enum(state, stateT),
                       event=enum(event, eventT))
    Out
```

```
// include headers for microsimulation and Rcpp
2 #include "microsimulation.h"
3 #include <Rcpp.h>
5 using namespace std:
  enum state_t {Healthy, Cancer, Death};
9 enum event_t {toOtherDeath, toCancer, toCancerDeath};
11 // for returning life histories
12 | map<string , vector<double> > report;
14 #define Reporting(name, value) report[name].push_back(value);
```

```
class SimplePerson: public cProcess
  public:
    state_t state;
    int id:
    SimplePerson(const int i = 0) : id(i) {};
    void init();
    virtual void handleMessage(const cMessage* msg);
10
  void SimplePerson::init() {
11
    state = Healthy;
    scheduleAt (R::rweibull (8.0,85.0), toOtherDeath);
    scheduleAt (R::rweibull (3.0,90.0), toCancer);
14
15
```

```
void SimplePerson::handleMessage(const cMessage* msg) {
    double dwellTime, pDx;
    Reporting ("id", id);
    Reporting ("startTime", previousEventTime);
    Reporting ("endtime", now());
    Reporting ("state", state);
    Reporting ("event", msg->kind);
9
    switch(msg->kind) {
    case toOtherDeath:
    case to Cancer Death:
      Sim::stop_simulation();
      break:
13
    case to Cancer:
14
      state = Cancer:
      if (R:: runif(0.0, 1.0) < 0.5)
16
         scheduleAt(now() + R:: rweibull(2.0,10.0), toCancerDeath);
      break:
18
    default:
19
      REprintf("No valid kind of event\n");
20
      break:
```

```
RcppExport SEXP callSimplePerson(SEXP parms) {
    SimplePerson person;
    Rcpp::RNGScope scope;
    Rcpp::List parmsl(parms);
    int n = Rcpp::as<int>(parmsl["n"]);
    for (int i = 0; i < n; i++) {
        person = SimplePerson(i);
        Sim::create_process(&person);
        Sim::run_simulation();
        Sim::clear();
    }
    return Rcpp::wrap(report);
}</pre>
```