NIHR | Yorkshire and Humber Patient Safety Translational Research Centre

NHS Bradford Teaching Hospitals NHS Foundation Trust

SIMULATION MODELLING WITH R-SIMMER

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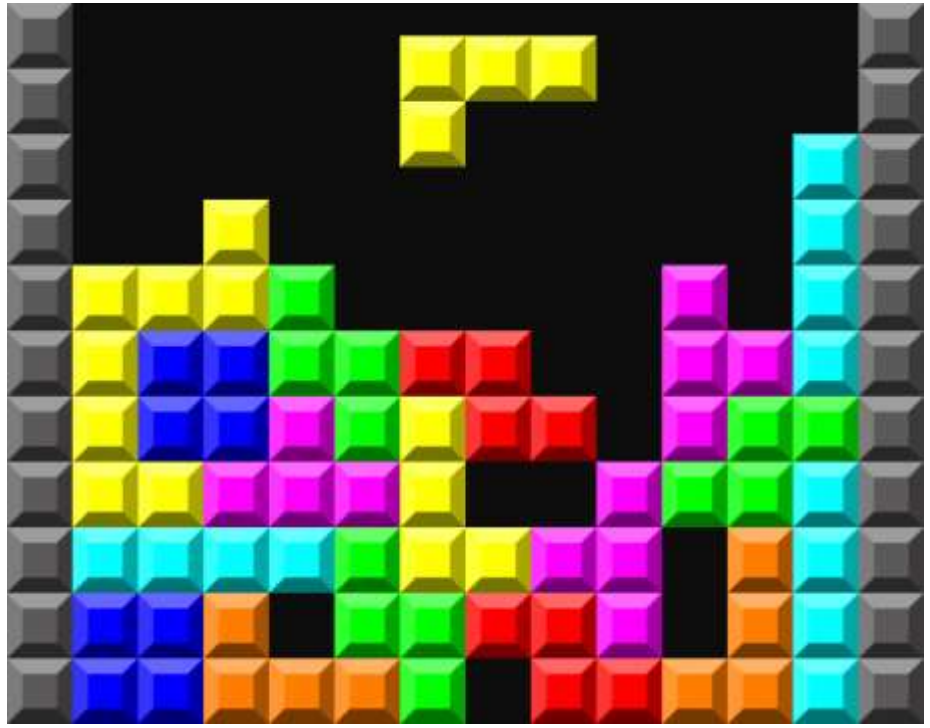
Improvement Academy

The Health Foundation

Modelling – The Need

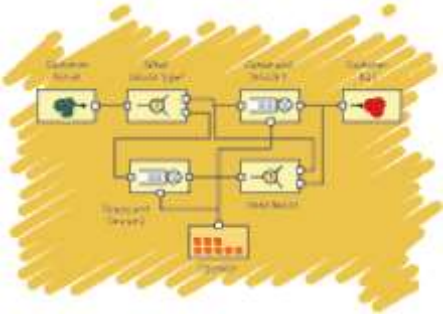
- **16 beds x 365 days**
  - Does NOT neatly provide 5840 days of care
  - Can't just "slot" patients together as they don't arrive on demand

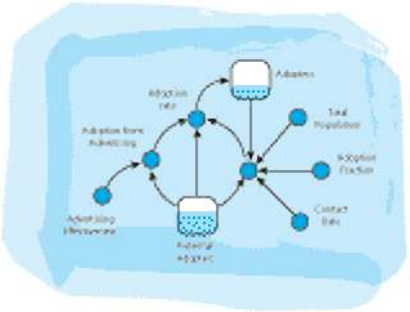
Row Labels	Average of LOS
Planned local surgical admission	3.8
Non Planned Admission	5.9
Grand Total	*5.4*

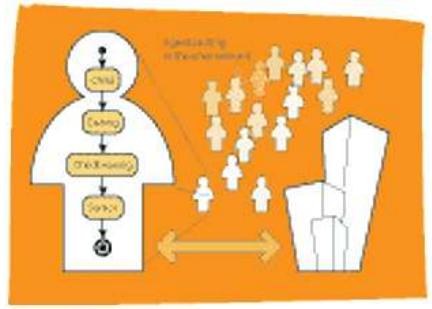


Modelling - Types

- **Discrete Event Simulation**
  - Entities (patients) moving between states. Queues and servers
  - Stochastic, individual. Probability (Markov chain) vs data driven
- **System Dynamics**
  - Stocks (patients) and flows and/or time series approaches
  - Aggregate, deterministic. Hybrid approach with DES/ABS
- **Agent Based Simulation**
  - Agents (patients) are active rather than servers
  - Stochastic, can be used with DES







Maidstone R. Discrete Event Simulation, System Dynamics and Agent Based Simulation: Discussion and Comparison. System. 2012 Mar 7;1(6):1–6

r-simmer “DES for R”

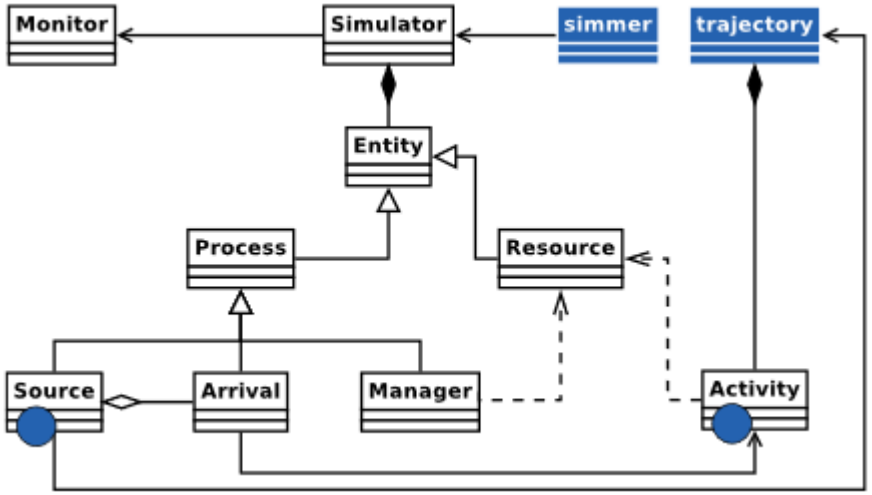
- **Trajectory**
- **Resource** (Server & Queue)
- **Arrival**

- **Arrivals**

  Generator, Attributes, Priority

- **Activities**

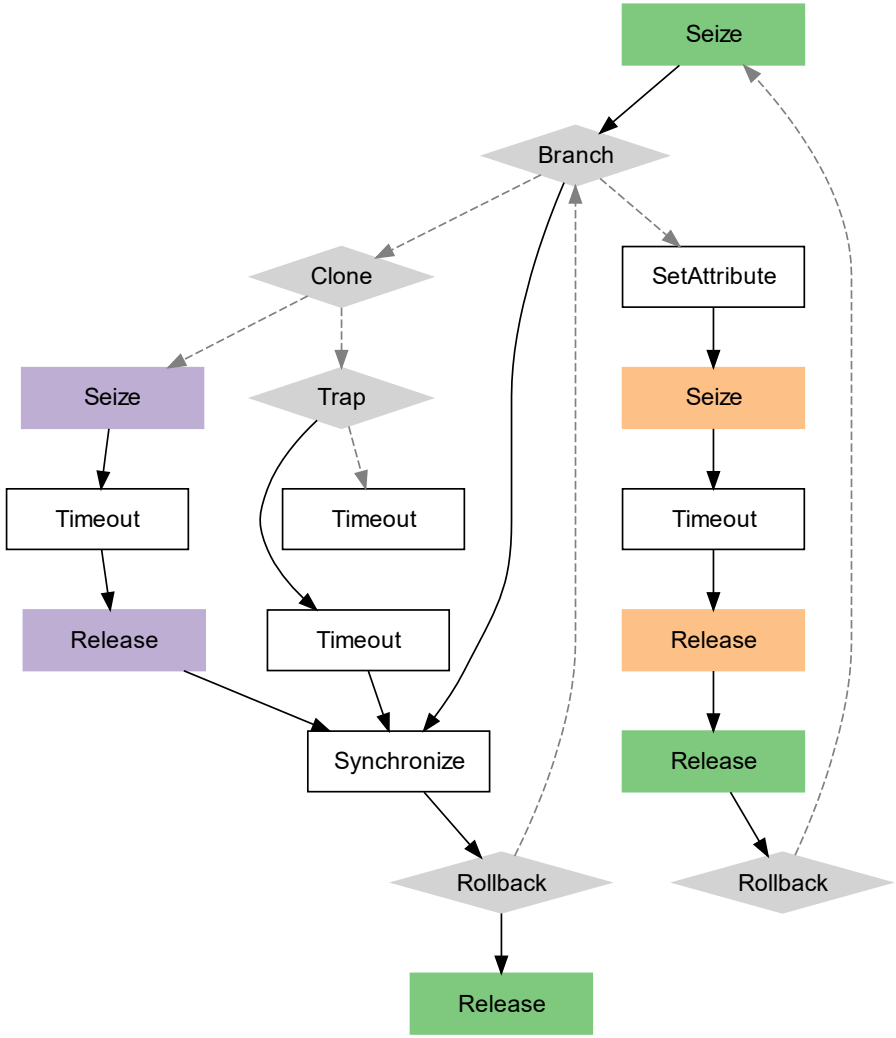
  Select, Seize, Release, Timeout, Renege, Branch, Clone, Trap, Rollback



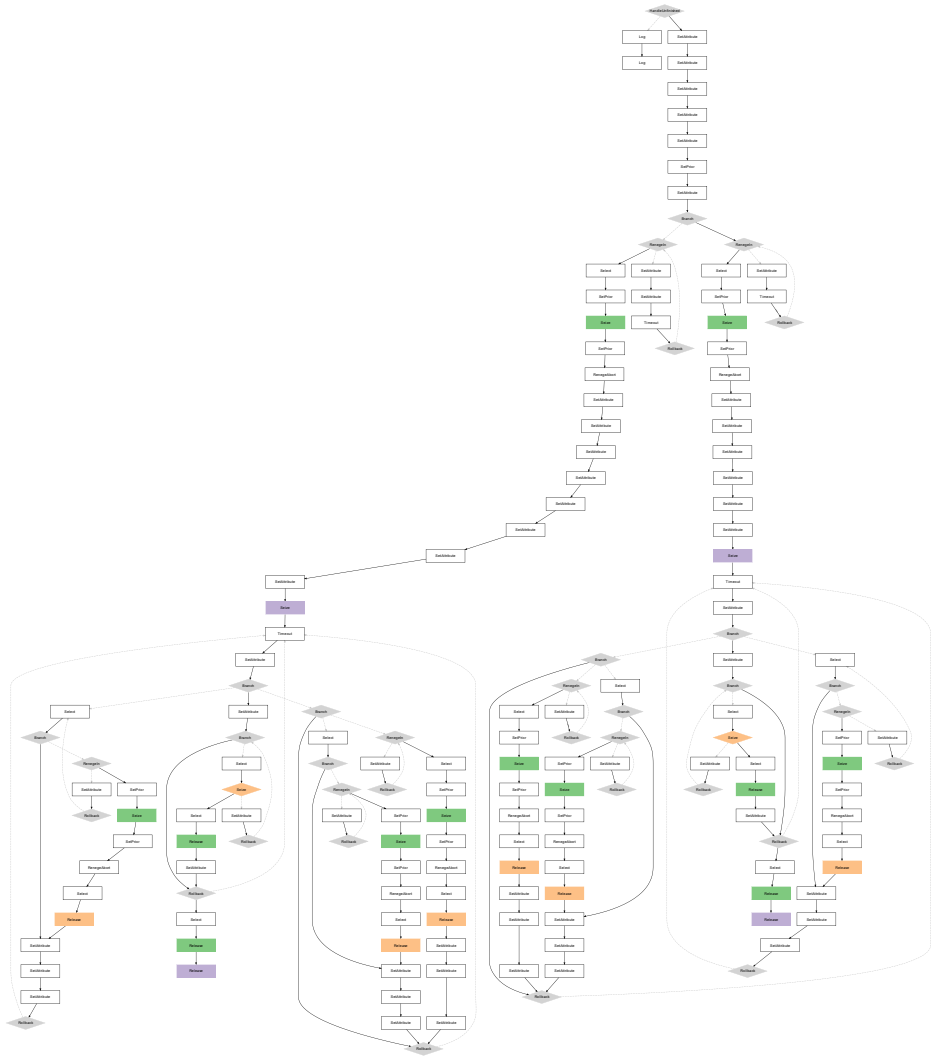
Ucar I, Smeets B, Azcorra A. simmer : Discrete-Event Simulation for R. Journal of Statistical Software. 2019;90(2)

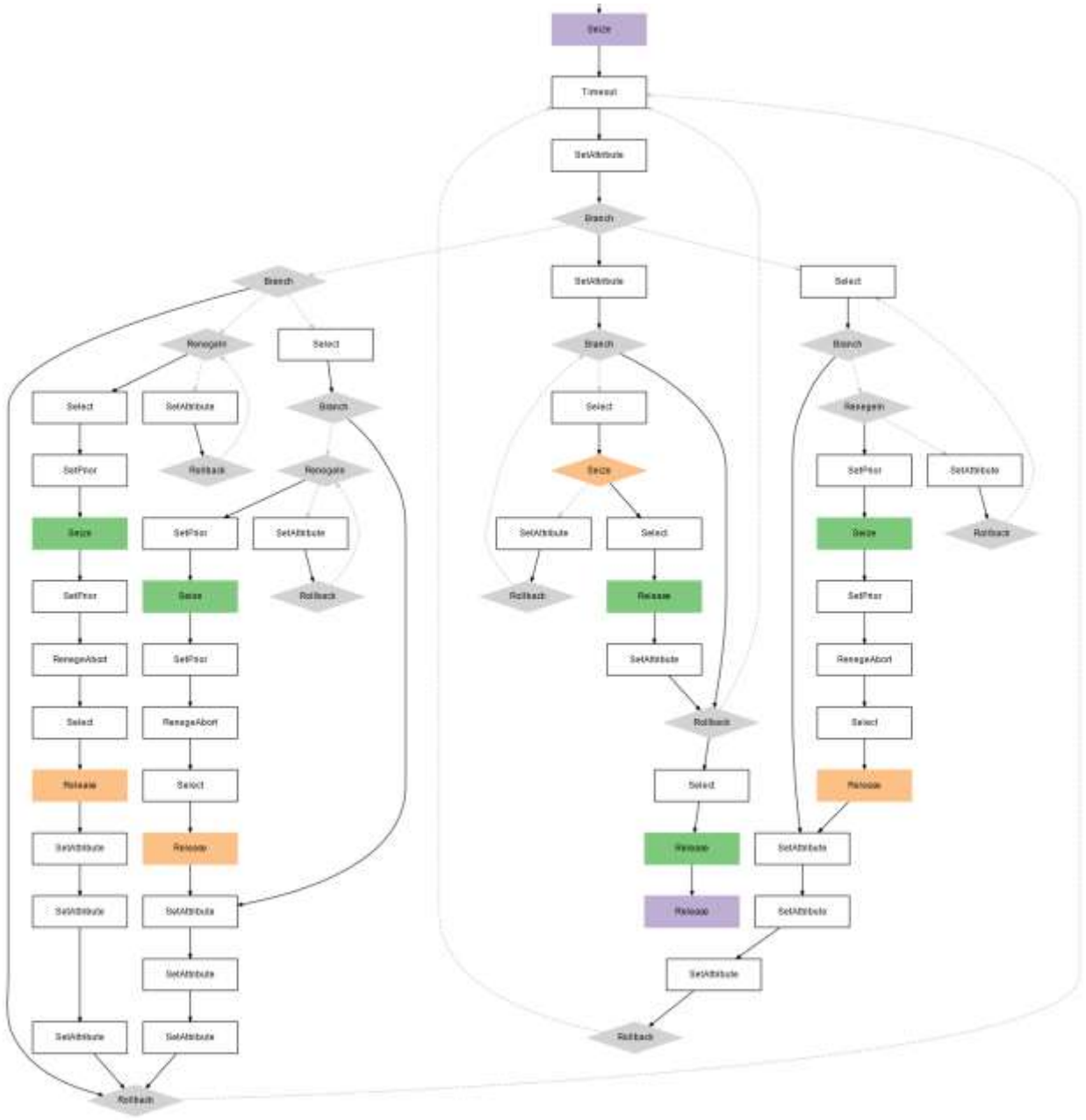
Trajectories

```
t0 <- trajectory() %>%
  seize("res0", 1) %>%
  branch(function() 1, c(TRUE, FALSE),
         trajectory() %>%
           clone(2,
                 trajectory() %>%
                   seize("res1", 1) %>%
                   timeout(1) %>%
                   release("res1", 1),
                 trajectory() %>%
                   trap("signal",
                        handler=trajectory() %>%
                          timeout(1)) %>%
                   timeout(1)),
         trajectory() %>%
           set_attribute("dummy", 1) %>%
           seize("res2", function() 1) %>%
           timeout(function() rnorm(1, 20)) %>%
           release("res2", function() 1) %>%
           release("res0", 1) %>%
           rollback(11)) %>%
  synchronize() %>%
  rollback(2) %>%
  release("res0", 1)
```



Trajectories



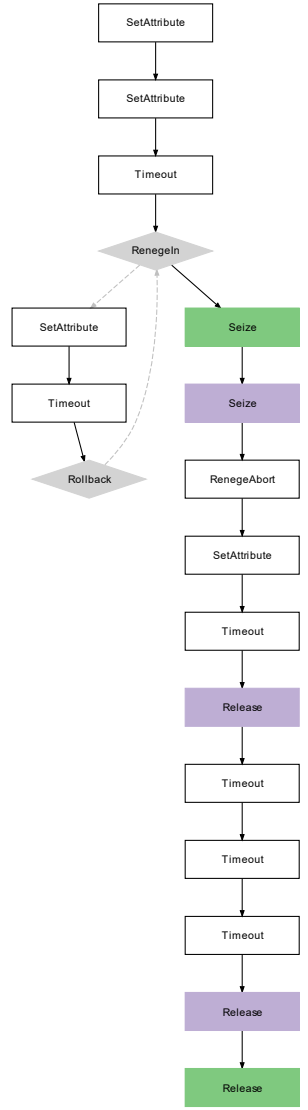


Modelling technique

- **Mixed, mostly data driven technique**
- **Inputs** traditionally modelled

  (Poisson/exponential)
- **Patients (demand)** sampled from real data
- **Rules** to govern interaction with the system

  System may not be identical to the one which “generated” the data
- **Monte-Carlo:** Repeatedly generate a single year



Lawton T, McCooe M. Policy: A novel modelling technique to predict resource requirements in critical care – a case study. Future Healthcare Journal. 2019 Feb 1;6(1):17–20

ICU Rules

- **Patient Types**
  - **Emergency** – no control
    - *“Unplanned Local Admission”*
    - Can be transferred out to other hospitals (this is bad)
  - **Elective** – need operation but could be delayed
    - *“Planned Local Surgical Admission”*
    - Deferral for usually a week
  - **Repatriations** – people we’ve transferred out (clinical/non-clinical)
    - They will usually ask for a bed daily
  - **Transfers In** - from other hospitals
    - Can be rejected

ICNARC Data (CCMDS)

- **Level 3** – sickest patients with most support (ICU)
  1:1 nursing
- **Level 2** – less unwell but still too demanding for ward (HDU)
  1:2 nursing
- **Level 1** – could be managed on ward with extra input (discharge)
  1:4 nursing in theory, 1:2 usually in practice
- **Level 0** – delayed discharge
  Usually treated as level 1
- **Modelling: must assume a "direction of travel"**

Model Environment Suggestions

- **Tick Rate**
  - Days
- **Resources**
  - Beds (16)
  - Half-A-Nurse (24)
- **Trajectories**
  - Initial trajectories for each patient type
    - (**emergency**, **elective** main ones)
  - Common trajectory to select a real patient
  - Common trajectory to use resources (suggest L3>L0)

Generator Suggestions

- **Poisson distribution**

  `rpois(1,x)`

- **Each day –** real values indexed by:

  Admission type

  Day of week (`weekdays()`) or business day (`is.bizday()`)

- **r-simmer needs inter-arrival gaps (-1 to end)**

  `from_to()` helper function

  More advanced: use of closure to store current date & last patient

Trajectory suggestions

- **Set up appropriate patient**
  - Store L3,2 etc days in attributes?
  - Or store key to an external dataframe?
- **Seize bed, appropriate nursing resource**
  - Failure (`renege_in()`) – record event. Retry?
- **Timeout**
  - L3,2,1,0 days
  - Remember to release nursing resource on L3->2 transition
- **Release**
  - `release_all()`

Coding

- https://r-simmer.org/

  Articles - **“The Bank Tutorial”**

- https://github.com/thigger/ICU-Model
- **`ICNARC Test Data.csv`**

  Date, admission type, days of care L3-L0

- **`ICUModel.R`**

  An example final model

github examples

- **`WORKSHOP.md`**

  Instructions and suggestions for workshop

- **`1 - Partmodel-BedsOnly.R`**

  Trajectory and random generators defined. Models beds only

- **`2 - Partmodel-AddedNurses.R`**

  Random generator, random days. Nurses added

- **`3 - Partmodel-ElectiveAndEmergency.R`**

  Separate trajectories for elective and emergency patients

github examples

- **`4 - Partmodel-DaysAsAttributes.R`**

  Attributes defined for days at different levels

- **`5 - Partmodel-PoissonGenerator.R`**

  Generator upgraded to a closure with variable Poisson process

- **`6 - Partmodel-DataDriven.R`**

  Generator and attributes pull from real data. Monte-Carlo

- **`ICUModel.R`**

  Full model including repatriations/transfers in