

Simulation Experiments in R

Helene Wagner, University of Toronto

Goals:

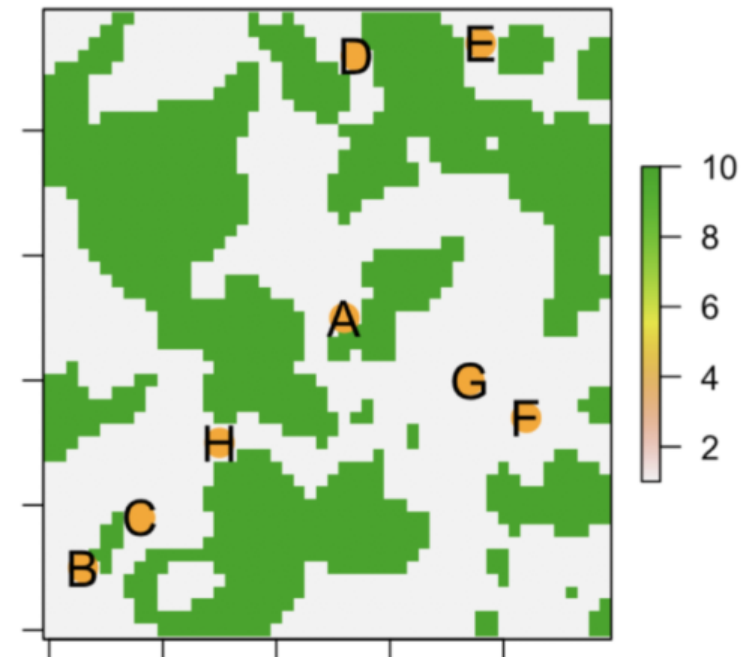
- Simulate a metapopulation on a resistance landscape
- Compare performance of partial Mantel test and Sunder

Methodological Challenges:

Video 1:

- Workflow of a simulation experiment
- Testing statistical methods with simulations
- Partial Mantel test vs. Sunder

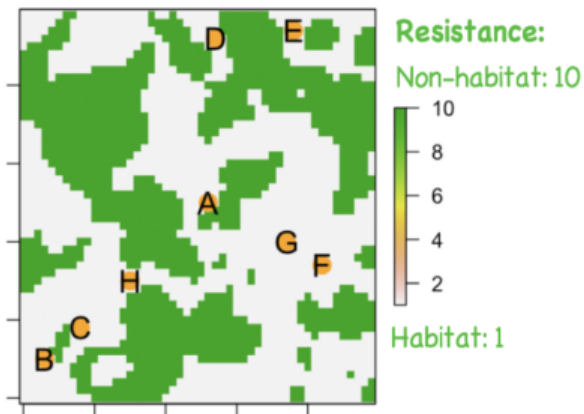
Video 2: Efficient R



Simulation Workflow

1. Initialize

- Landscape map **constant**
- Populations (A - H) **constant**
- Individuals (genotypes) **variable**



Create random maps with 'secr':

- Habitat amount (A)
- Habitat aggregation (p)

2. Time step

- Demographic model
- Mating and reproduction
- Dispersal and recruitment

```
> str(para)
List of 15
 $ n.pops      : num 8
 $ n.ind       : num 100
 $ sex.ratio   : num 0.5
 $ n.cov       : num 3
 $ n.offspring : num 2
 $ mig.rate    : num 0.1
 $ disp.max    : num 50
 $ disp.rate   : num 0.05
 $ n.allels    : num 10
 $ n.loci      : num 20
 $ mut.rate    : num 0.001
```

3. Run a single simulation

- Initialize genotypes
- Run for many time steps
- Collect genotype data
- Summarize results

Fst: degree of differentiation
Decide: IBD or IBR?

4. Batch run simulations

- Replicate runs with same parameters
- Run scenarios across parameter space
- Store results and settings

Parameter space:

- time: # generations
- rep: # replicate sims

```
> para.space
      rep time
1     1     5
2     2     5
3     3     5
4     1    25
5     2    25
6     3    25
7     1    45
8     2    45
9     3    45
```

5. Synthesize results

- Extract summary data
- Visualize in parameter space
- Sensitivity analysis

Robust vs. sensitive

Partial Mantel Tests

IBD

IBR

```
PopGenReport::wassermann(eucl.mat = eucl.mat, cost.mats = list(cost=cost.mat),  
  gen.mat = gen.mat, plot=F)$mantel.tab
```

	model <chr>		r <chr>	p <chr>
1	Gen ~cost Euclidean	IBR IBD	0.5366	0.041
2	Gen ~Euclidean cost	IBD IBR	-0.4753	0.983

Some issues with (partial) Mantel tests:

- Low statistical power?
- Inflated type I error rates if spatial autocorrelation?

Use simulations to test and compare methods!

Alternative with 'Sunder'

'Bedassle' (Bradburd et al. 2013), alternative implementation in 'Sunder' (Botta et al. 2014)

Run the analysis (parameter settings: <http://www.nbi.dk/~botta/Sunder.html#overview>)

IBD
IBR
Iterations

```
D.G <- as.matrix(dist(para$locs))
D.E <- cost.mat
nit <- 10^3 ## just for the example, should be much larger, e.g. 50000
output <- Sunder::MCMCCV(Array,D.G,D.E,
  nit=nit,thinning=max(nit/10^3,1),
  theta.max=c(10,10*max(D.G),10*max(D.E),1,0.9),
  theta.init=c(1,2,1,1,0.01),
  run=c(1,1,1), ud=c(0,1,1,0,0),
  n.validation.set=dim(Array)[1]*dim(Array)[2]/10,
  print.pct=FALSE)
```

```
print(output$mod.lik)
````
```

Likelihood

|  |           | IBD       | IBR       |
|--|-----------|-----------|-----------|
|  | G+E       | G         | E         |
|  | -9050.244 | -9058.499 | -8974.353 |

```
> names(which.max(output$mod.lik))
[1] "E"
```

# Testing Method Performance

Assessing error rates requires MANY replicate samples!

Resistance values

|   |   |   |   |   |
|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 1 |
| 1 | B | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 | 1 |
| A | 1 | 1 | 1 | C |

## Type I error rate

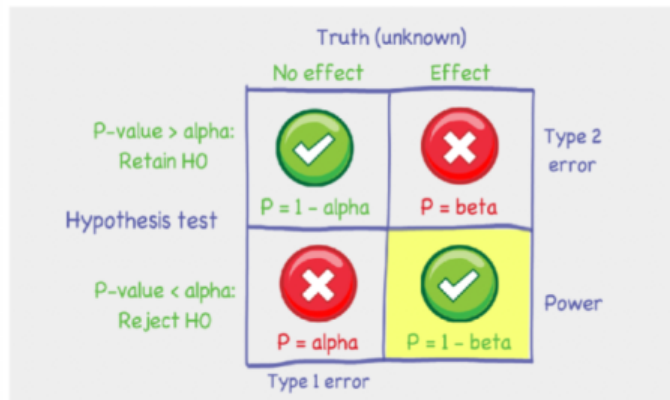
- Simulate under null hypothesis
- Expect alpha % false positives

## Statistical power to detect effect

- Simulate under alternative hypothesis
- Assess True Positive Rate (TPR)
- Larger effect size -> higher power
- Larger sample size -> higher power

|   |   |   |   |   |
|---|---|---|---|---|
| 3 | 3 | 7 | 7 | 7 |
| 3 | B | 2 | 7 | 3 |
| 1 | 1 | 2 | 2 | 3 |
| 1 | 5 | 5 | 2 | 1 |
| A | 5 | 5 | 5 | C |

## Statistical Power



Compare power between methods!

# Where is my Stuff?

R has 3 homes !

`getwd( )`

Current working directory

`"/Users/Helene/  
Desktop/MyProject"`

`Sys.getenv("HOME")`

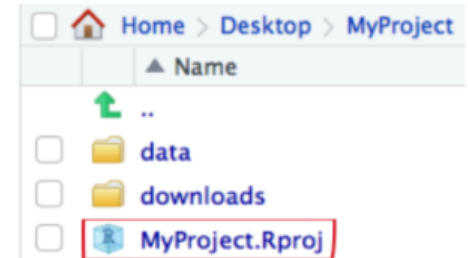
User's home directory

`"/Users/Helene"`

`R.home( )`

Where R is installed

`"/Library/Frameworks/  
R.framework/Resources"`



## Default working directory?

- Console in regular R session: Varies! Use `'setwd( )'`
- Console in R project: Project folder
- R Notebook: Notebook file location

`"/Users/Helene/Desktop/MyProject/downloads"`

## Advice

- Always work in an R project
- Use path names relative to project folder
- Use `'here :: here( )'` in R Notebooks

`file.path( here :: here(), "data", "myFile.csv" )`

`"/Users/Helene/Desktop/MyProject/data/myFile.csv"`  
`"/data/myFile.csv"`  
`"/Users/Helene/Desktop/MyProject"`



# Input / Output

## File System

|                   |                              |
|-------------------|------------------------------|
| List all files    | <code>dir()</code>           |
| Create directory  | <code>dir.create()</code>    |
| Download from web | <code>download.file()</code> |
| Unzip archive     | <code>unzip()</code>         |
| File size         | <code>file.size()</code>     |
| Remove file       | <code>file.remove()</code>   |



## R Workspace

|                            |                  |
|----------------------------|------------------|
| <code>ls()</code>          | List all objects |
| <code>object.size()</code> | Object size      |
| <code>rm()</code>          | Remove object    |

## Text files: csv

|                            |                           |                            |
|----------------------------|---------------------------|----------------------------|
| <code>base ::</code>       | <code>read.table()</code> | <code>write.table()</code> |
| <code>base ::</code>       | <code>read.csv()</code>   | <code>write.csv()</code>   |
| <code>readr ::</code>      | <code>read_csv()</code>   | <code>write_csv()</code>   |
| <code>data.table ::</code> | <code>fread()</code>      | <code>fwrite()</code>      |

Package 'rio':  
Fast import / export for any file type

`import()`  
`export()`

## Binary files

|                         |                             |                              |                       |
|-------------------------|-----------------------------|------------------------------|-----------------------|
| <code>base ::</code>    | <code>load()</code>         | <code>save()</code>          | <code>.RData</code>   |
| <code>base ::</code>    | <code>readRDS()</code>      | <code>saveRDS()</code>       | <code>.rds</code>     |
| <code>feather ::</code> | <code>read_feather()</code> | <code>write_feather()</code> | <code>.feather</code> |

`rds`: Small, fast, flexible object format  
`feather`: Compatibility with Python

**Warning: check handling of text (character or factor?) and missing values!**

# Why is my Code Slow?

R was not designed to be fast!

## 1. Identify bottlenecks

Simple:

- Knit, monitor R Markdown pane
- Name each chunk in R Notebook
- Which chunks take a long time?

Advanced: profiling

- Convert .Rmd to .R: 'purl'
- Source script with 'source'
- Profile with 'lineprof' or 'profvis'
- Visualise time, memory use

| Code                          | File                | Time (ms) |
|-------------------------------|---------------------|-----------|
| ▼ source                      |                     | 113850    |
| ▼ withVisible                 |                     | 113840    |
| ▼ eval                        |                     | 113840    |
| ▼ eval                        |                     | 113840    |
| ▶ PopGenReport::run.poggensim | Week8_vignette_A... | 73970     |
| ▶ getSunder                   | Week8_vignette_A... | 19060     |
| ▶ PopGenReport::wassermann    | Week8_vignette_A... | 7910      |
| ▶ mmod::pairwise_Gst_Nei      | Week8_vignette_A... | 3540      |
| ▶ secr::make.grid             | Week8_vignette_A... | 2910      |

## 2. Use faster functions

Simple:

- Vectorized: 'lapply' > 'for' loop
- Integrated: tidyverse > R base
- Optimized: CRAN task views

Advanced: benchmarking

- Package 'microbenchmark'
- Define each method as a function
- Compare speed: 'microbenchmark'
- Differences in precision, behavior?

Unit: milliseconds

| expr                  | min      | lq       | mean     | median   |
|-----------------------|----------|----------|----------|----------|
| import("gen.RData")   | 36.56224 | 39.62443 | 40.76476 | 40.21394 |
| import("gen.rds")     | 40.00667 | 40.12891 | 42.14960 | 41.90262 |
| import("gen.feather") | 45.26174 | 45.96569 | 46.91915 | 46.63800 |
| import("gen.csv")     | 73.59831 | 80.19661 | 90.62875 | 81.40790 |

## 3. Speed up your code

Simple:

- Preallocate result vectors
- Don't duplicate large objects
- Use binary data files

Advanced:

- Use 'data.table', 'bigmemory'
- Compile functions: 'cmpfun'
- Parallelize: use multiple cores
- Distribute: cluster computing

mclapply()

foreach()





# Bash R scripts 101

myBashFile.sh

## Navigate the shell

- Default: same as ' Sys.genenv ( "HOME" ) '
- In RStudio: project folder
- List folder content: ' ls '
- Move to folder with relative path:  
' cd ./myFolder /subFolder '
- Move up one level: ' cd .. '

## Execute a Bash R script

- Must change file permission
- Execute file
- Specify arguments

```
chmod +x myBashFile.sh
./ myBashFile.sh 5 0 1
```

## Write a Bash R script ...

```
#!/bin/bash
R --slave << EOF

Your R code:
myFunction <- function (n, m, s)
{
 rnorm (n, m, s)
}
args <- c(5, 0, 1)
myFunction (args)

EOF
```

```
knitr :: purl ("myNotebook.Rmd")
creates file: myNotebook.R
```

## ... with arguments!

```
#!/bin/bash
R --slave --args $@ << EOF

Your R code:
myFunction <- function (n, m, s)
{
 rnorm (n, m, s)
}
args <- as.numeric (commandArgs ())
myFunction (args)

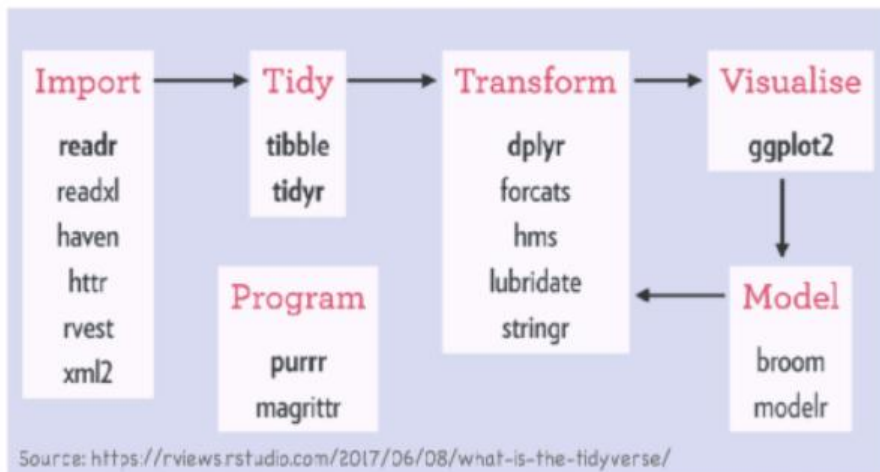
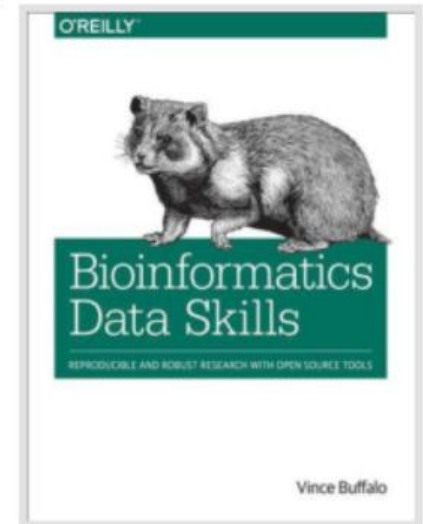
EOF
```

Remember what arguments to provide!  
Arguments read as 'character' by default.

# Further Reading

## Books

Efficient R programming (Gillespie): <https://csgillespie.github.io/efficientR>  
Advanced R (Wickham): <http://adv-r.had.co.nz>  
R for Data Science (Wickham): <http://r4ds.had.co.nz>



## Tidyverse

- Coherent system of packages for data manipulation, exploration and visualization
- Make data scientists more productive: workflow, communication, reproducible research

## Blogs

<https://www.r-bloggers.com/faster-higher-stronger-a-guide-to-speeding-up-r-code-for-busy-people/>  
<https://www.r-bloggers.com/r-with-parallel-computing-from-user-perspectives/>  
<https://datascienceplus.com/strategies-to-speedup-r-code/>  
<https://support.rstudio.com/hc/en-us/articles/218221837-Profiling-with-RStudio>  
<https://research.computing.yale.edu/sites/default/files/files/efficientR.pdf>

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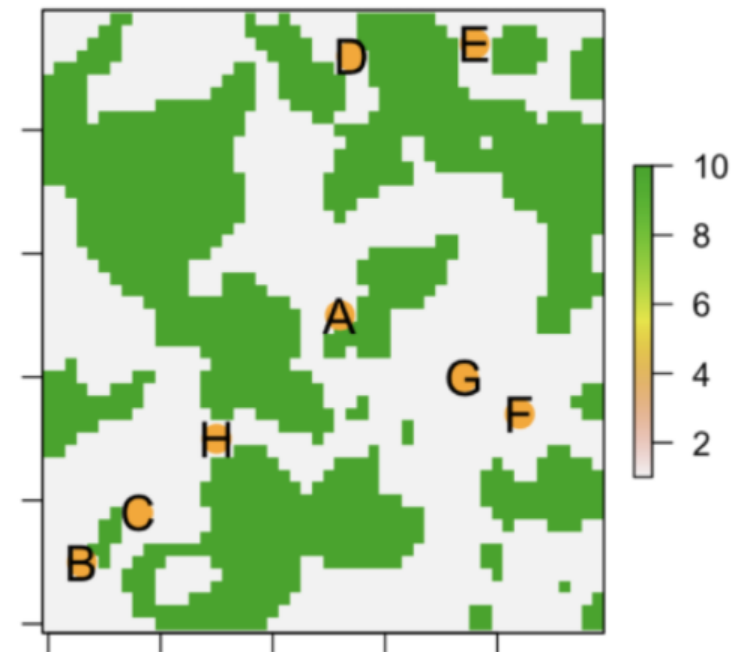
## Methodological Challenges:

### Video 1:

- Workflow of a simulation experiment
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- Partial Mantel test vs. Sunder

### Video 2: Efficient R

- Where is my stuff?
- Why is my code slow?



Interactive R tutorial: generating data, string manipulation  
Worked example: landscape genetic simulation experiment  
Bonus material: file manipulation, benchmarking, Bash R script