



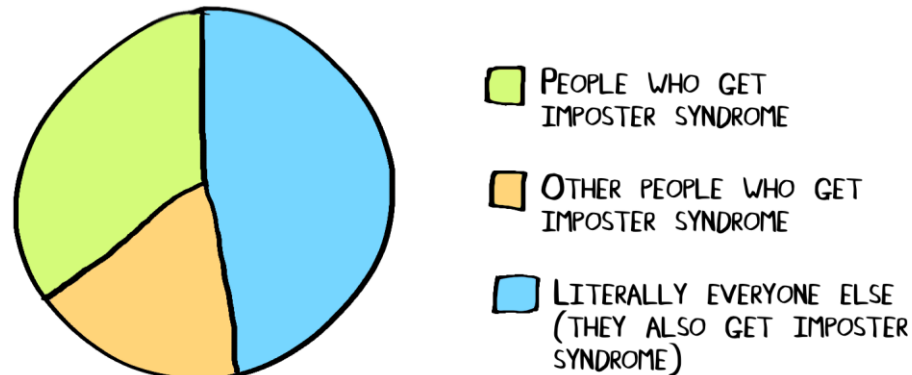
# Improving the speed of a discrete event simulation model in breast cancer screening...

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# ...the experience of an intermediate level R user!

- Caveats

- Learnings from an ongoing process
- Huge amount of work went into original code
- Very happy to hear additional suggestions
- I apologise in advance for my novice markdown copy and pasting!



EVERYONE FEELS LIKE AN IMPOSTER  
SOMETIMES, AND THAT'S OKAY

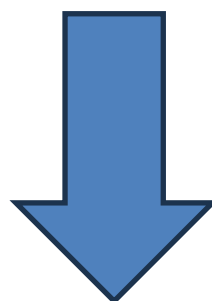
ERRANTSCIENCE.COM

# Evaluation of a Stratified National Breast Screening Program in the United Kingdom: An Early Model-Based Cost-Effectiveness Analysis



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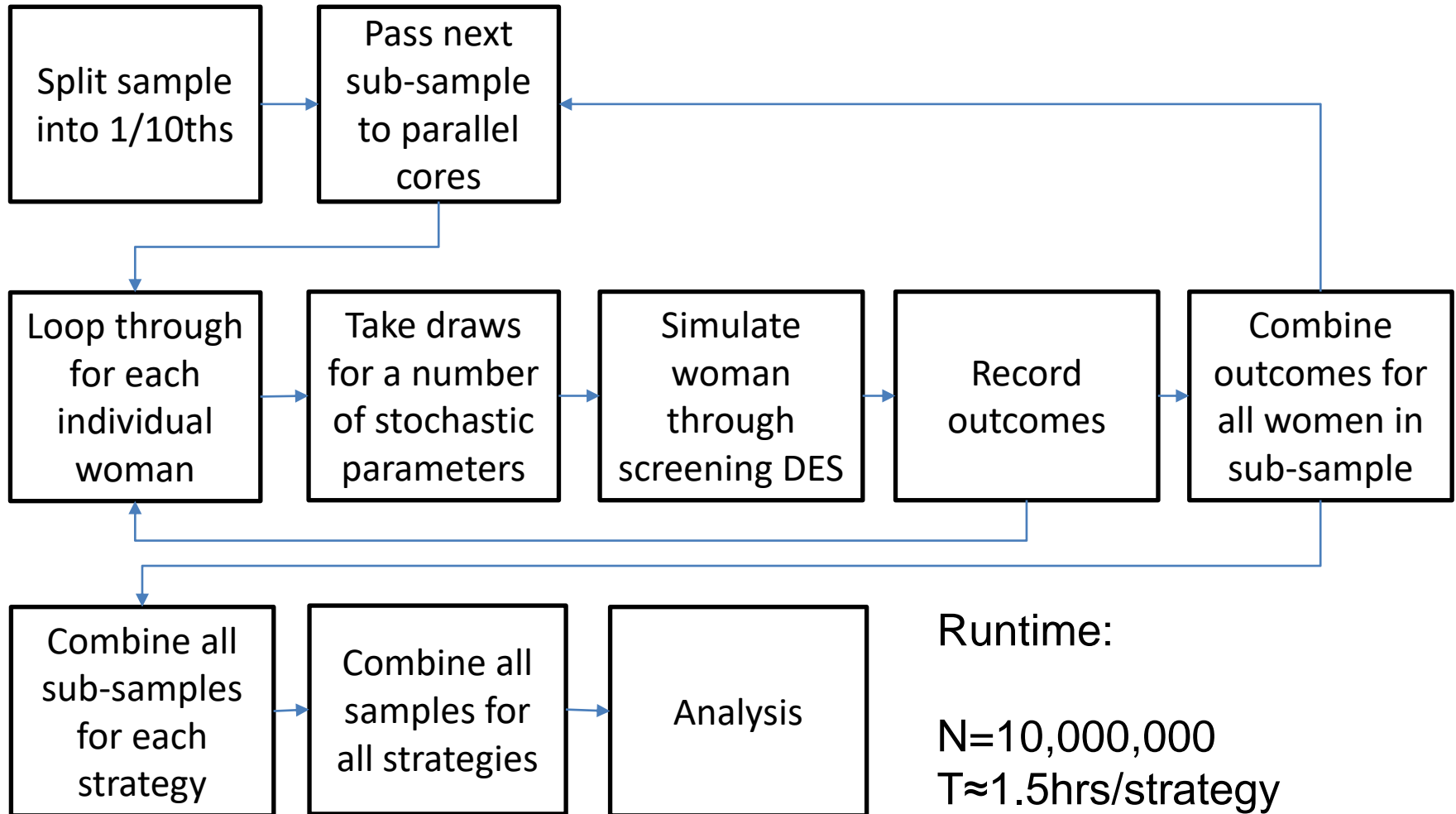
Applied Health Economics and Health Policy (2024) 22:527–542  
<https://doi.org/10.1007/s40258-024-00887-z>

## ORIGINAL RESEARCH ARTICLE

### A structured process for the validation of a decision-analytic model: application to a cost-effectiveness model for risk-stratified national breast screening

Stuart J. Wright<sup>1</sup> · Ewan Gray<sup>2</sup> · Gabriel Rogers<sup>1</sup> · Anna Donten<sup>1</sup> · Katherine Payne<sup>1</sup>

# Rough Outline of Original Structure



# Key Approaches to Speeding Up a Model

- Improve model code -> increase speed per run
- Reduce unnecessary variance -> reduce total N
- Improve computational power -> increase speed per run/improve parallelisation


# Improve Model Code

- Everything in a loop is done  $i$  times
- Check for redundant code and where possible take these things out of a loop:
  - Defining new parameters
  - If statements (particularly if complex)
  - Objects that increase in size

# Example: Function to see if cancer detected

- Function is called at every screening event
- That's around 4-5 times per individual

Don't need to define this vector 40mil times!



```
Sen_VDG<-c(0.85,0.776,0.695,0.61)
dense_OR <- (Sen_VDG[VDG]/(1-Sen_VDG[VDG]))/(Sen_VDG_av/(1-Sen_VDG_av))
Sensitivity <- ((Sensitivity/(1-Sensitivity))*dense_OR)/(1+((Sensitivity/(1-Sensitivity))*dense_OR))
```

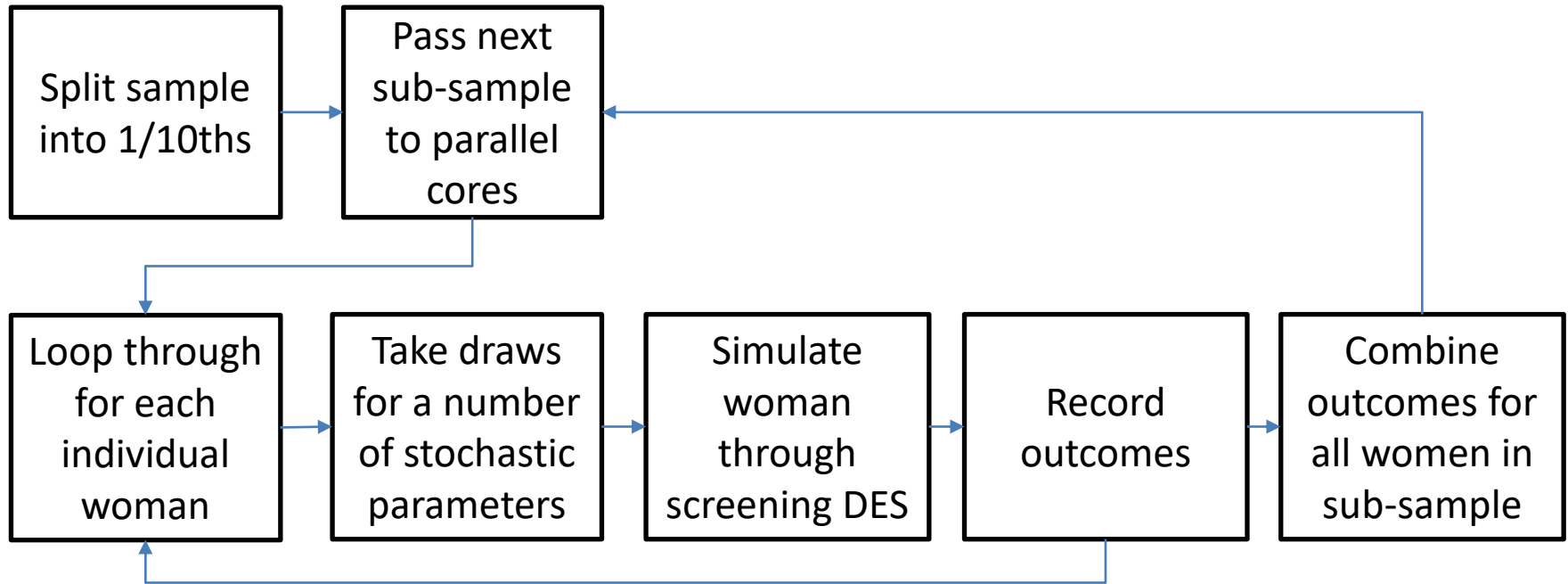
# The Big One!

Pre-create a sample (data.frame) of individuals  
with pre-drawn stochastic parameters

Iterate over each row of the data.frame



# The Problem



A: We have to do multiple individual draws from parameter distributions for each woman

B: Each sample of women for each strategy is different – they vary in ways that won't affect the results

## A Useful Rule for Stochastic Models (inc PSA)

It is much quicker to take  $X$  random draws from a distribution than to do individually draw from the distribution  $X$  times

```
library(tictoc)
probdraw<-numeric(length(1000000))
tic()
for (i in 1:1000000){
  probdraw[i]<-rbeta(1,50,50)
}
toc()
```

Vector of probabilities  
is different every time  
code is run

```
## 1.65 sec elapsed
```

```
probdraw<-numeric(length(1000000))
fairprobdraw<-numeric(length(1000000))
tic()
probdraw<-rbeta(1000000,50,50)
for (i in 1:1000000){
  fairprobdraw[i]<-probdraw[i]
}
toc()
```

Vector of probabilities  
is the same every time  
code is run

```
## 0.33 sec elapsed
```

**BONUS!**  
By setting the seed,  
reviewers should be  
able to reproduce  
exact results

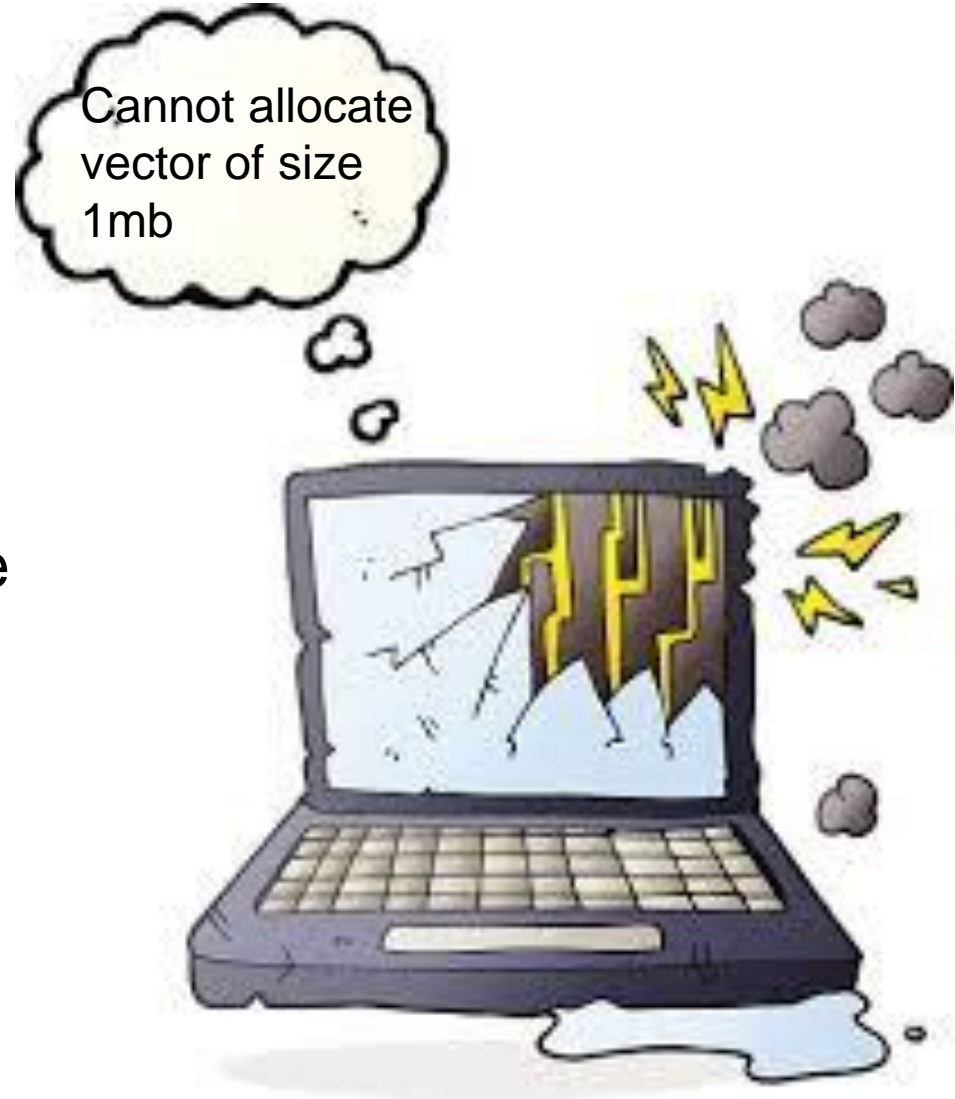
	^ X1.VBD ^	^ X1.tenyrrisk ^	^ X1.liferisk ^	^ X1.risk_group ^	^ X1.VDG ^	^ X1.MRI_screen ^	^ X1.US_screen ^	^ X1.risk_predicted ^	^ X1.feedback ^
1017	14.39705	4.267940	16.76400	0	3	0	0	0	0
13499	13.06310	9.807890	31.36680	0	3	0	0	0	0
9941	9.16390	3.561810	17.07960	0	3	0	0	0	0
12204	5.87783	3.760580	15.05710	0	2	0	0	0	0
3476	5.31918	2.953430	10.84650	0	2	0	0	0	0
4633	7.46740	3.675890	16.67480	0	2	0	0	0	0
9888	11.69403	1.748370	7.24550	0	3	0	0	0	0
14835	3.45438	2.428690	12.04680	0	1	0	0	0	0
465	9.08413	1.458280	7.69616	0	3	0	0	0	0
13453	5.56860	2.646900	13.00200	0	2	0	0	0	0
14950	3.66738	1.181120	4.89676	0	1	0	0	0	0
6763	20.73423	3.004370	14.00670	0	4	0	0	0	0
6273	6.73515	1.403050	5.81391	0	2	0	0	0	0
501	5.35525	1.110270	4.53265	0	2	0	0	0	0
3747	3.93368	2.828720	11.45760	0	1	0	0	0	0
9509	11.15860	1.712360	8.74569	0	3	0	0	0	0
5939	3.11133	1.445100	5.97387	0	1	0	0	0	0
8943	8.11435	3.430440	13.11100	0	3	0	0	0	0
6611	12.95128	2.625970	12.90230	0	3	0	0	0	0
1101	3.66703	2.085600	8.47259	0	1	0	0	0	0

The parameters above this box are all generated with if statements – now outside the loop

# BUT...

1. R holds data in RAM – making a huge data.frame means it will run slowly or not at all

2. Iterating over the rows of the frame rather than over a simple sequence of numbers requires a bit of a tweak



# Solution 1: Chunking

- Split the big data.frame into chunks of smaller ones
- Save the chunks to drive
- Remove the data.frames from memory
- In the outer loop load one of the chunks
- Run through model
- Save results
- Load next chunk...

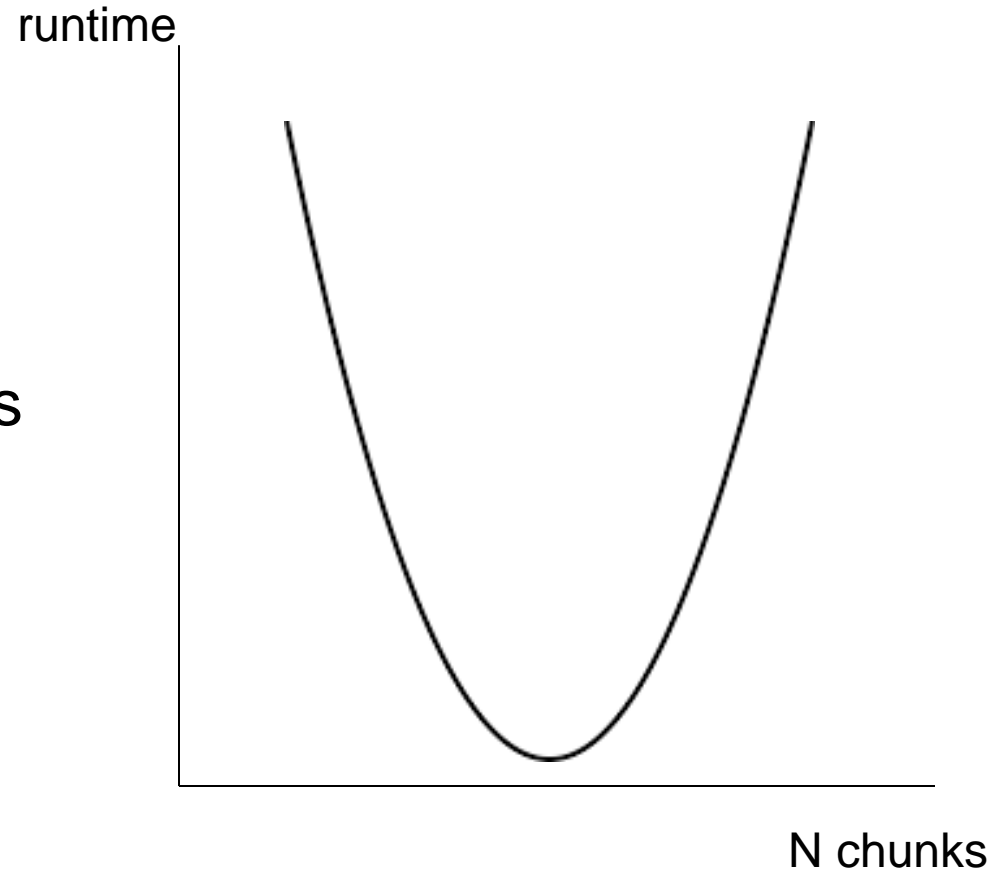
Chunk

~~My R Code~~  
Sloth



# A note of caution on chunks

- More chunks means less data in memory
- BUT running each chunk requires two slow processes
  - Loading data in R
  - Initialising the parallelisation
- So need to find the optimal number of chunks which depends on  $N$



# Solution 2: Parallelising a data.frame

```
results <- foreach(i=n/chunks,.combine = 'rbind',.packages = c('MASS','dqrng','tidyverse')) %dopar% {
```

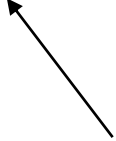


-This is called an iterator

-Essentially R makes a sequential vector with the numbers 1:n/chunks

-PROBLEM: each core gets the same rows (1:n/chunks)

-Actually need each core to work on separate set of rows



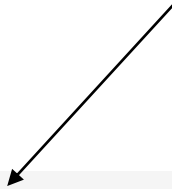
Tip: supposedly a faster random number generator than in base R



# Different iterators

- Using the iterators package you can iterate over different types of objects

Chunk of main data.frame



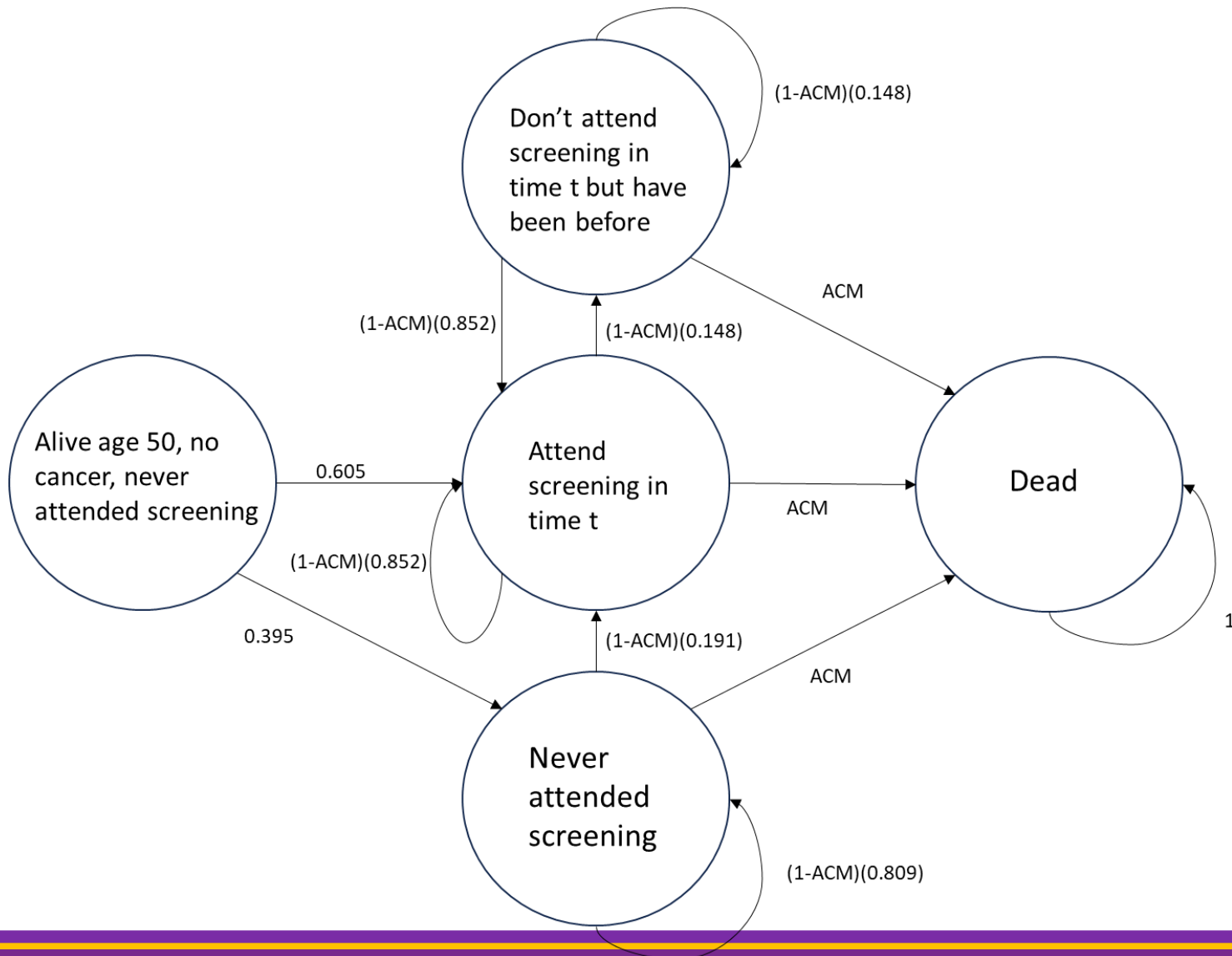
```
itx<-iter(splitsample,by="row")  
results <- foreach(i=itx,.combine = 'rbind',.packages = c('MASS','dqrng','tidyverse')) %dopar% {
```

- This one line took me about a 6 months to figure out

# Results

	Original Model	MANC-RISK-SCREEN
N per strategy	10,000,000	3,000,000
Run time per strategy (mins)	~90	10-15 depending on complexity

# ~87% of women in the model don't get cancer



## **Screening models: pushing the limits of R?**

- Building a cervical cancer screening model
- Infectious disease model of HPV transmission
- Dynamic effect of vaccination over time
- Pre-cancer and cancer growth model
- Very complex screening and triage strategies
- Considering using Python for data generation, R for analysis

Thank You!