Conclusion 00

# Unit (and other) testing of stochastic code

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### INTRODUCTION

We've recently been working on epidemic modelling

- Simulation of stochastic processes on networks
- Large scale (10<sup>5</sup> nodes), lots of repetitions at different points in a parameter space

Developing and maintaining a codebase for stochastic processes has raised some interesting questions about how to engineer such systems

This talk

How we optimised, what went wrong, questions that arise about software engineering for stochastic codes

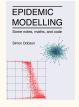
## Epidemic modelling on one slide

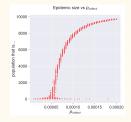
"Compartmented" disease models 1

- e.g., Susceptible-Infected-Removed
- ► Maintain sets of SI edges and I nodes
- Draw random element and change edge states, node compartments
- Sequential, several million operations

### Scale

- Simulate for different disease parameters
- Exact results are stochastic, but follow distributions that are known for common processes (and not for others)





<sup>&</sup>lt;sup>1</sup>S. Dobson. Epidemic modelling - Some notes, maths, and code. Independent Publishing Network, 2020. ISBN 978-183853-565-0. URL https://simoninireland.github.io/introduction-to-epidemics/

## The optimisation

Core operation is drawing a random element from a set

- Python's inbuilt sets don't support this
- $\Rightarrow$  re-code as balanced binary trees
- "Book" solution involves lots of random numbers
- ► ⇒ developed an optimisation that reduced this significantly
- Massively faster at the cost of introducing a slightly biased choice, some elements slightly less likely to be drawn

Question: Is this optimisation safe?

### Let's do some experimental science

Distribution of SIR and other processes are known

- We were already aggressive about testing, with a full CI infrastructure in place
- Analytic prediction of the location of the phase transition
- ► ⇒ run a set of sample experiments, compare empirical to theoretical distribution
- $\chi^2$  goodness-of-fit test (or other statistical magic)

Therefore although we know that there *is* bias, it isn't being observed by the disease process

### Everything always works, until it doesn't

Several months later, combine disease process with addition-deletion process

- Dynamic population of nodes, changing population of edges
- Addition-deletion has a known final degree distribution<sup>2</sup>
- ...and our implementation doesn't follow it

## Much debugging later

- ► The addition-deletion process *does* observe the bias
- (Still not entirely sure why...something to do with the time nodes are resident in the sets)

<sup>&</sup>lt;sup>2</sup>C. Moore, G. Ghoshal, and M. Newman. Exact solutions for models of evolving networks with addition and deletion of nodes. *Physical Review E*, **74**, September 2006. URL doi://10.1103/PhysRevE.74.036121

#### Local solutions: better unit tests

Stochastic code needs specific kinds of test

 A result isn't right or wrong *on it's own*, and therefore isn't (on its own) a suitable unit test

Each test samples the distribution of possible results

- ► Take samples, compare to what's expected
- (We've written a library to do this, obviously)

Challenges

- You need to run lots of samples, which may be individually expensive
- ► (Do you *really* want to *need* a compute cluster for testing?
- May not know the distribution you should expect

## Where are the stochastic elements?

In our case we knew we had stochastic effects

 We were looking at the shapes of distributions (although not in the place that affected them)

What happens when you *don't* know?

- ► Race conditions can be very subtle
- ► (Does your OS thread scheduler affect your results?)
- More importantly, these effects can come from the interactions between components rather than from the components themselves

## When is stochastic code stochastic?

The interactions are themselves stochastic

- Some processes observe bias, some observe variance
- ...and some don't

The risks

- The composition of two correct components may not be correct – a massively larger surface area for testing
- ► By definition less likely to observe low-probability events
- We have a weak understanding of these effects
- How does a stochastic operation map the distributions of its inputs to those of its outputs?

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## Specifying test suites

Was there something we could have done differently?

- How to design suites that catch these effects?
- You can only deliberately test something you can observe (and know you want to)

#### More-than-unit tests

- We took to reproducing the results of known and "classic" papers, in whose results we had confidence
- Do our simulations get the same results?
- This then threw up some major questions about reproducubility and the adequacy of the scientific paper as a communication tool...

# Conclusion

We need to look at this further

- Changes the way we think about testing
- Changes the testing infrastructure
- Makes automation/devops/CI even more important (but potentially more resource-intensive)

How much stochastic code is out there?

- We don't know
- Comes up very obviously in simulation, which is perhaps something we need to teach more of
- Important as an application area, but also illuminates issues of general software engineering interest

# References



S. Dobson. *Epidemic modelling – Some notes, maths, and code*. Independent Publishing Network, 2020. ISBN 978-183853-565-0. URL https://simoninireland.github.io/introduction-to-epidemics/.

C. Moore, G. Ghoshal, and M. Newman. Exact solutions for models of evolving networks with addition and deletion of nodes. *Physical Review E*, 74, September 2006. URL doi://10.1103/PhysRevE.74.036121.