

# What is infectious disease modelling

# Who am I?

- Bachelor's degree from FAM program 2009-2013
- Master's degree in theoretical particle physics 2015
- PhD in nuclear physics 2019
- Data scientist at Telenor 2019-2021
- Infectious disease modeller (“seniorforsker”) at Folkehelseinstituttet since 2021, mostly working on covid-19

# Outline

1. Infectious disease modelling: The problem
2. Agent-based models
3. Compartmental models
4. Briefly on fitting the model to data

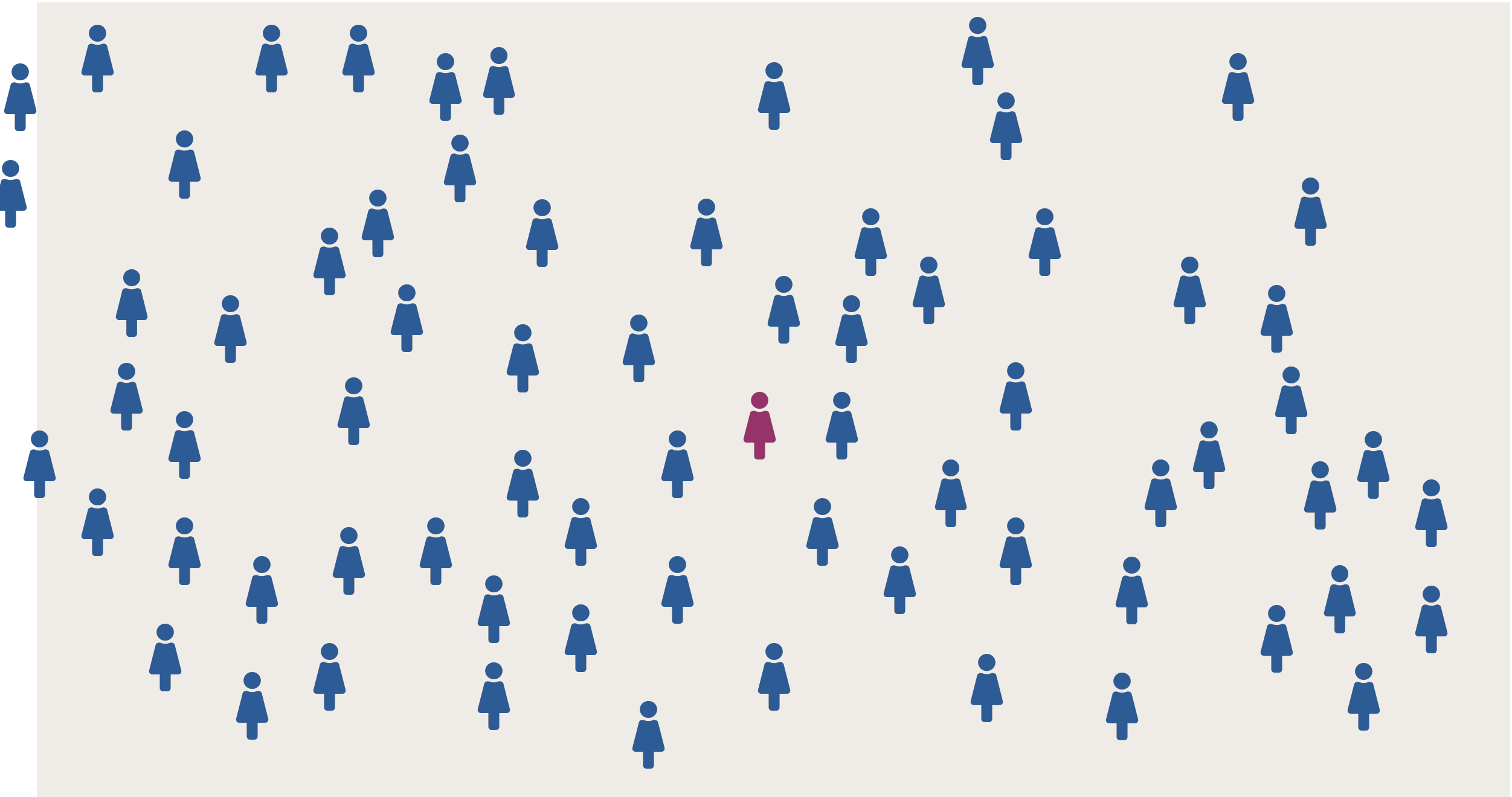
# Infectious disease modelling

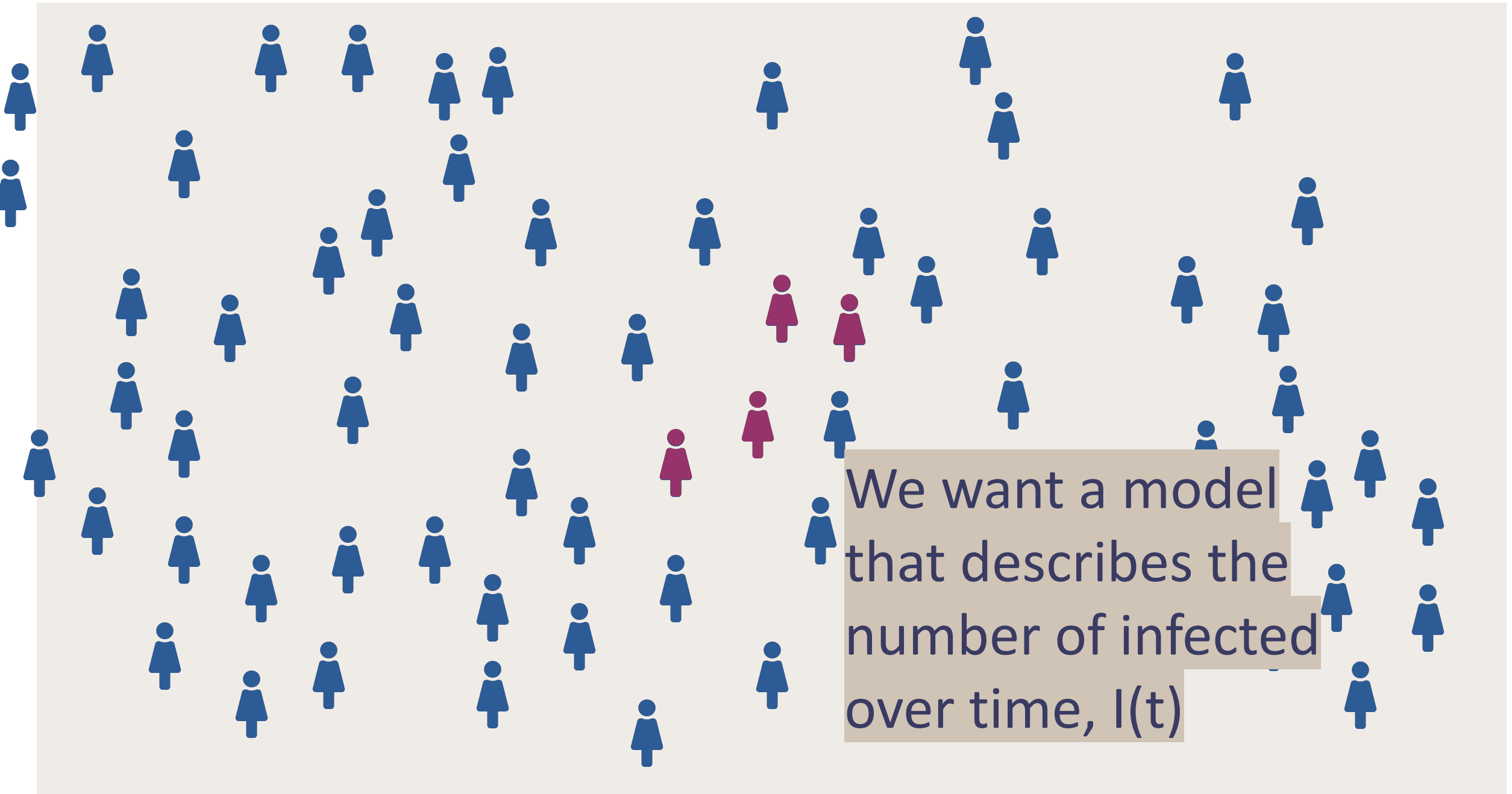
# Infectious diseases

- Sars-Cov-2 / covid-19
- Monkeypox
- Ebola, SARS, MERS
- Influenza, common cold, norovirus, ...
- Sexually transmitted diseases (HIV, gonorrhea, chlamydia, ...)
- Vector-borne diseases (malaria, dengue fever, ...)
- Animal diseases, e.g. foot and mouth disease

**They transmit from individual to individual upon contact.**

**This is what we want to model.**





We want a model  
that describes the  
number of infected  
over time,  $I(t)$

Don't forget recoveries

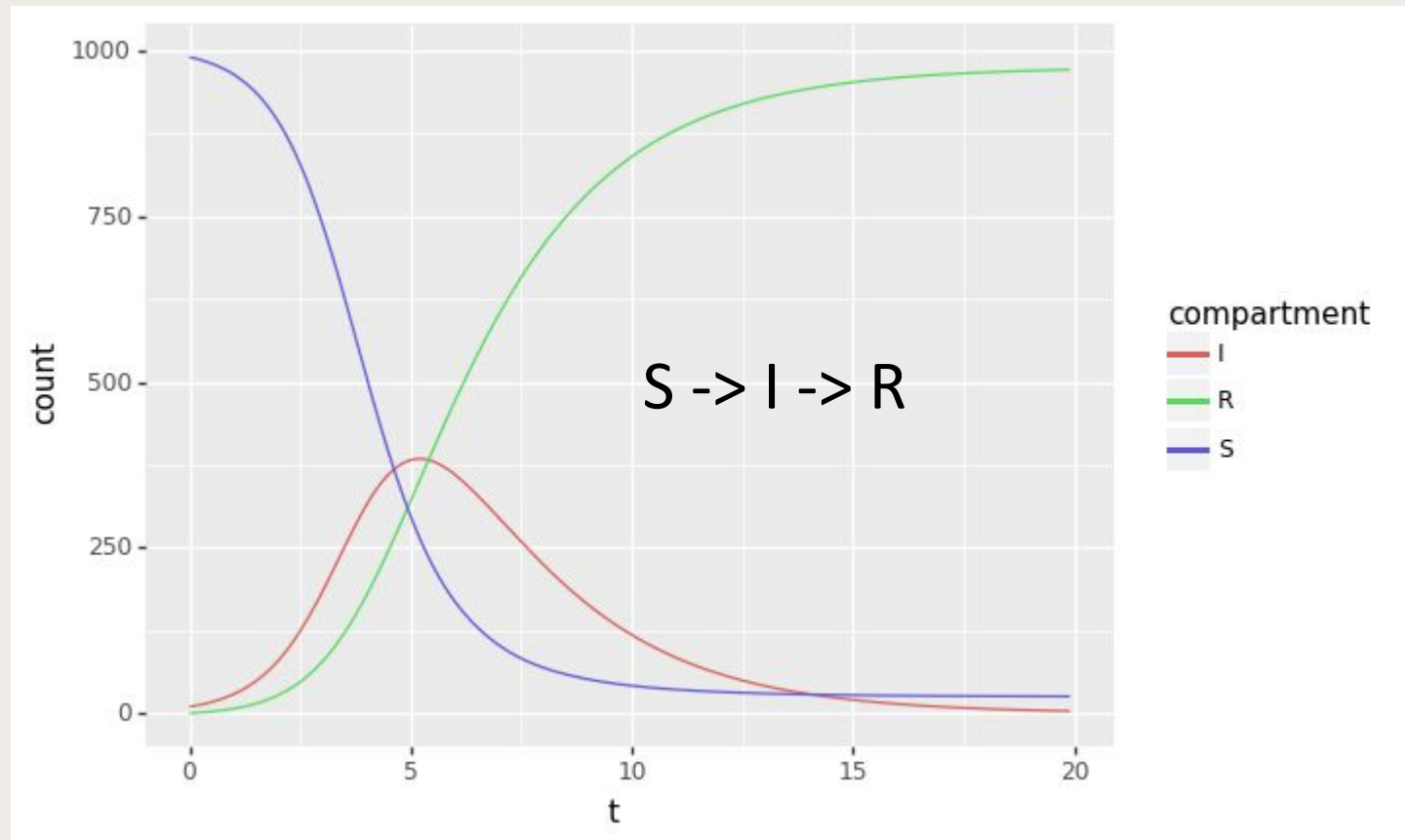




Don't forget recoveries



# The SIR model



# Some necessary terminology

- S: Susceptible
- I: Infected (infectious)
- R: Recovered (removed)
  
- *Incidence*: Number of new infections per day
- *Prevalence*: Total number presently infected
  
- $\beta$  (*beta*): The standard variable name for the infectiousness parameter (of the virus) in the model

# More than SIR

- The SIR model assumes that infection gives sterilising immunity forever - works for measles (meslinger), chickenpox (vannkopper) etc
- This is approximately true for covid-19 on a short timescale (<~1 year)
- You can make any flavour you like:
  - SEIR (E = exposed, presymptomatic period - actually important for covid)
  - SIRS (waning of immunity over time)
  - SIS (no immunity, e.g. gonorrhea)
  - $SE_1E_2I_aR$
  - Also add vaccination to the mix

# Why so many physicists?

Much overlap in methods and skills

- Numerical tools
  - programming
  - data analysis
  - visualisation
- Way of approaching a modelling problem
- Statistical proficiency
- Monte Carlo methods

# Agent-based models

# Agent-based models

A physicist's preferred approach (?)

Microscopic model keeping track of individual agents and their behaviour and infectious status

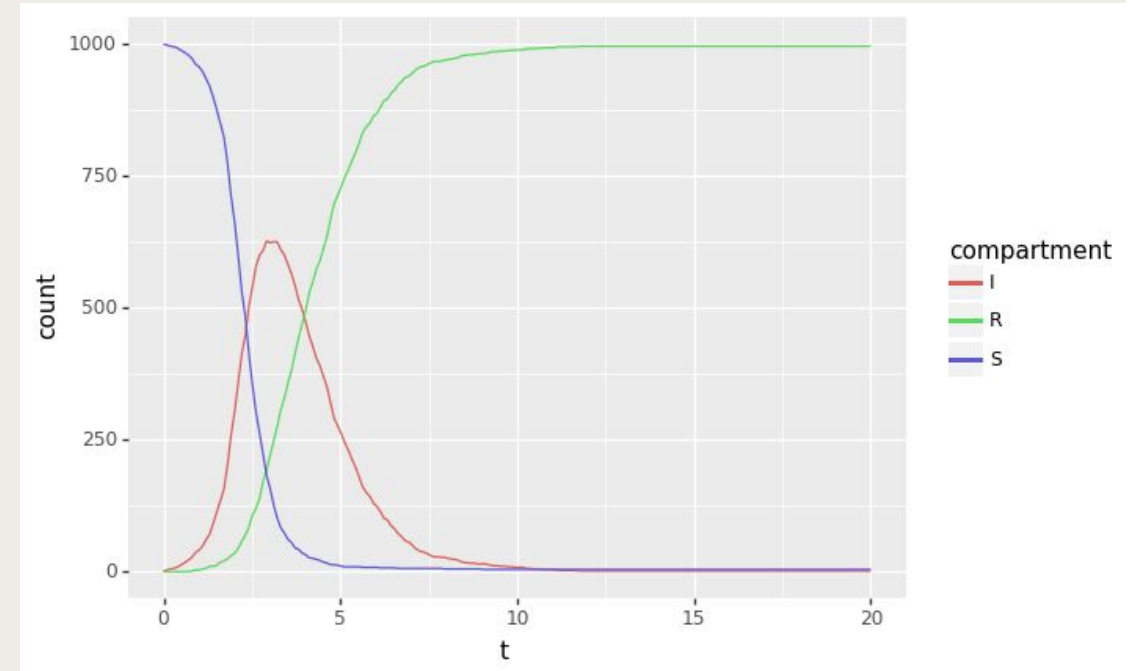
- Straightforward to increase complexity
  - Age, gender, risk behaviour
  - Contact networks (households, schools...)
  - Superspreading events
- High computational cost

# A simple agent-based SIR model

[github.com/jorgenem/smittemodellar](https://github.com/jorgenem/smittemodellar)

Assuming  $N$  individuals indexed  $i=0, \dots, N-1$ , each having status  $S$ ,  $I$  or  $R$

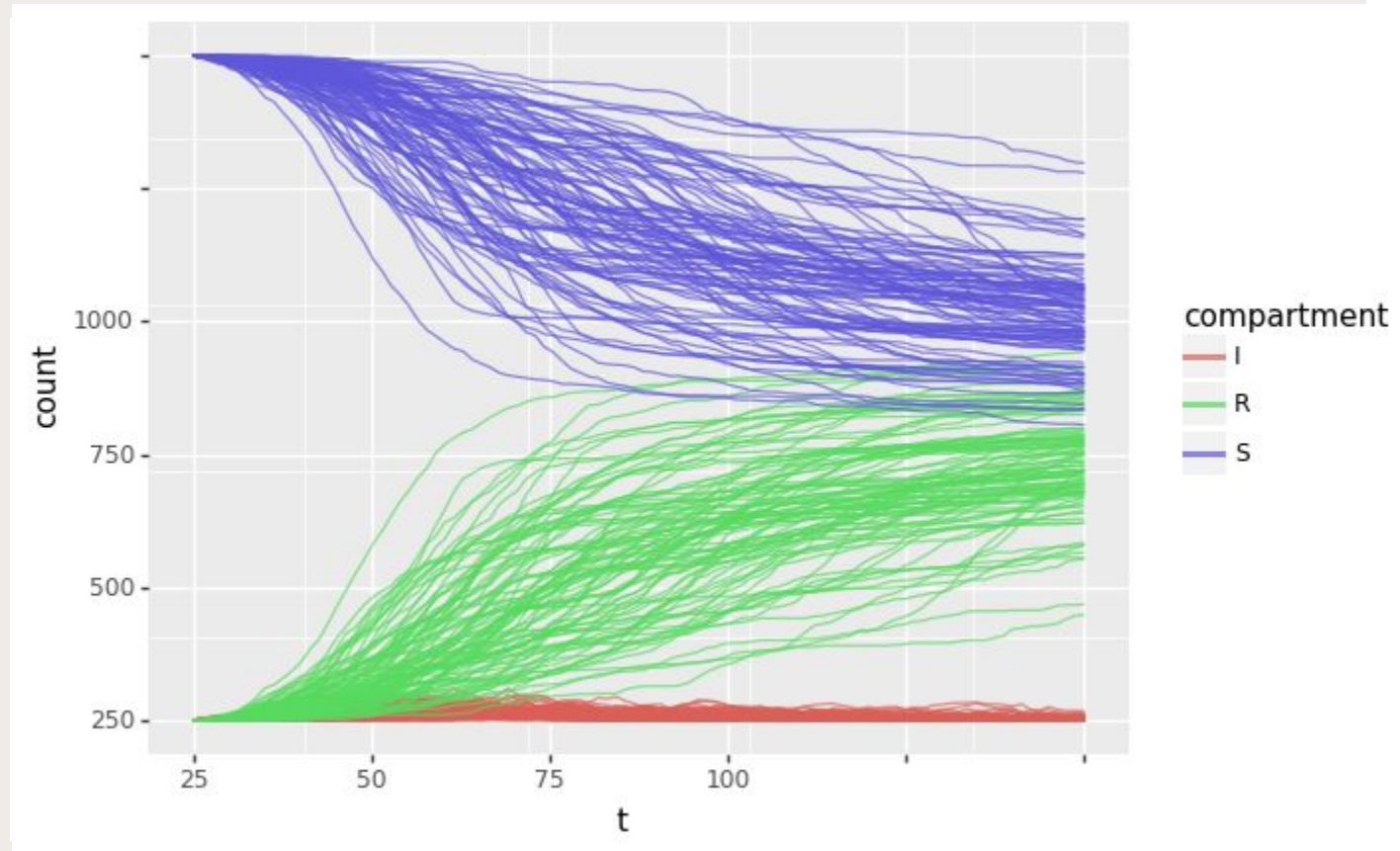
1. For each individual that is  $I$ , draw random other individuals to be their *contacts*
2. For each contact
  - a. Check if they are  $S$
  - b. Draw a random yes/no whether they will be infected
  - c. Update their status to  $I$  if yes
  - d. Draw time of recovery from a distribution
3. Repeat at next timestep with updated  $I$  population





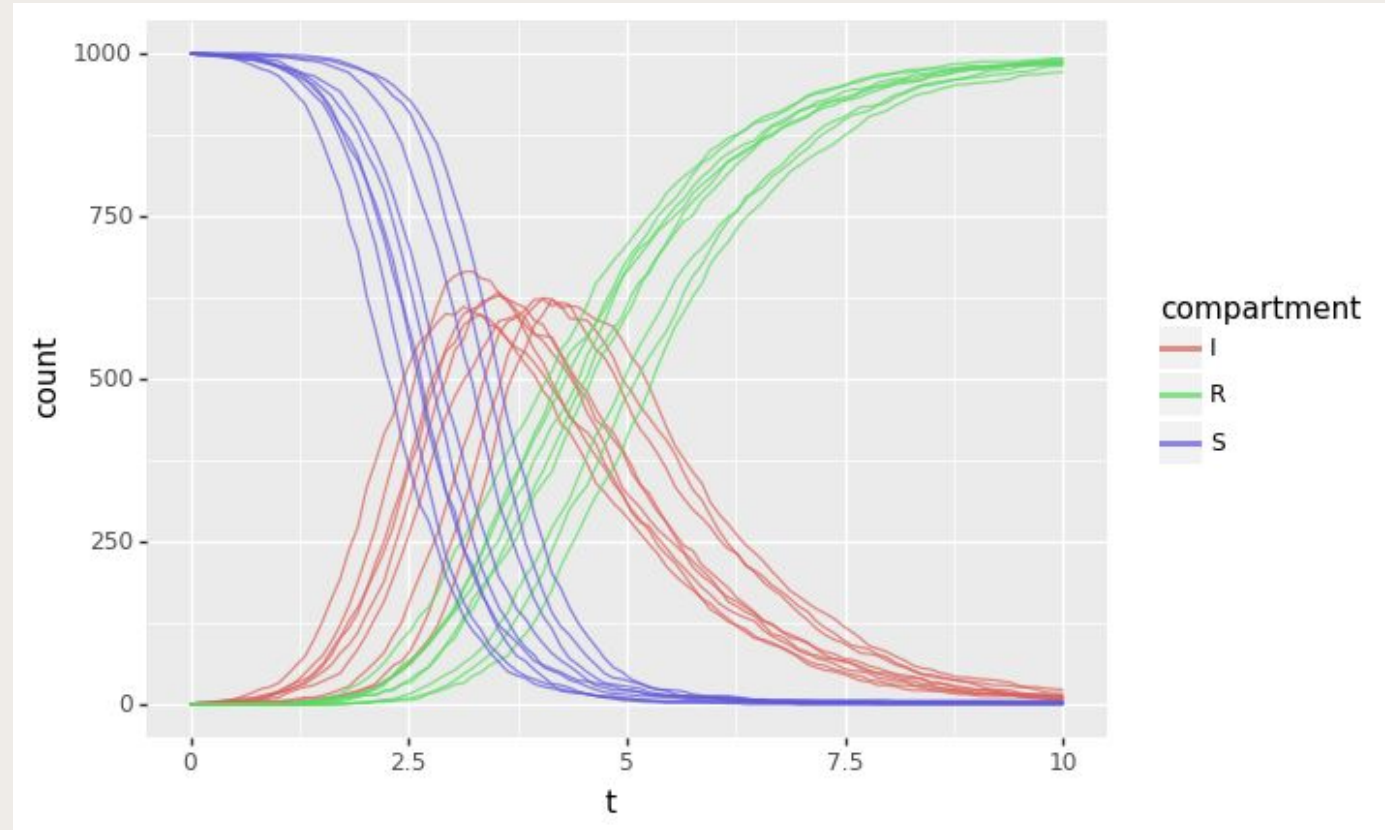
# Stochastic effects emerge

- There is inherent randomness in the model
- Run it many times for each parameter value
- Infection seeding and superspreader events



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2 minute read · December 3, 2021 7:05 PM GMT+1 · Last Updated a year ago

## Omicron outbreak at Norway Christmas party is biggest outside S. Africa - authorities

By Gwladys Fouche and Nerijus Adomaitis



# Our big ABM at FHI

## Individual features

- Location
- Age
- Occupation
- Epidemiological status
- Hospitalization status
- Vaccination status (SYSVAK)



## Households

Synthetic, based on census data



## Transmission settings



kindergartens  
Schools, grades 1-13  
Universities



Households

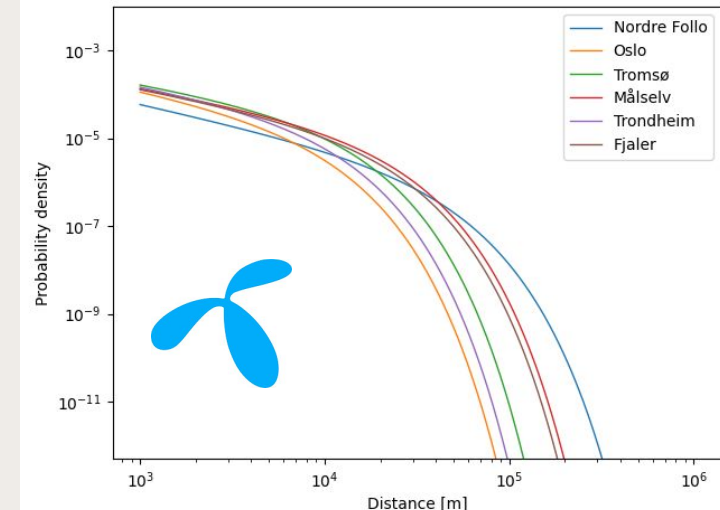
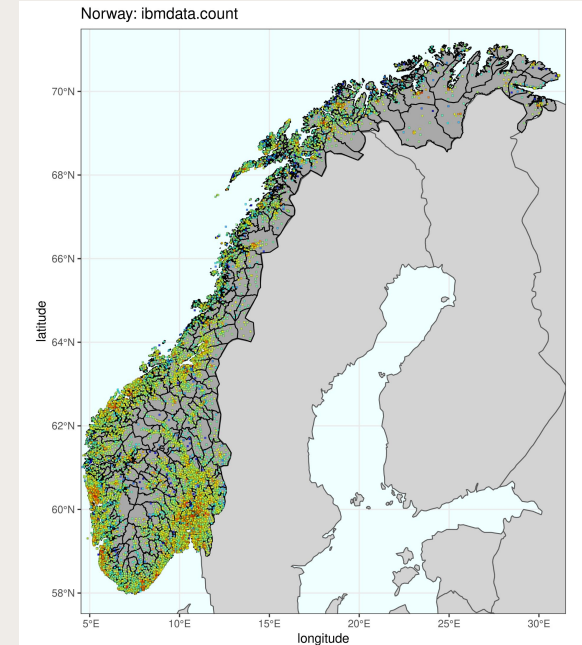


Workplaces



Community

One beta parameter for each setting



# Compartmental models

# Compartmental models

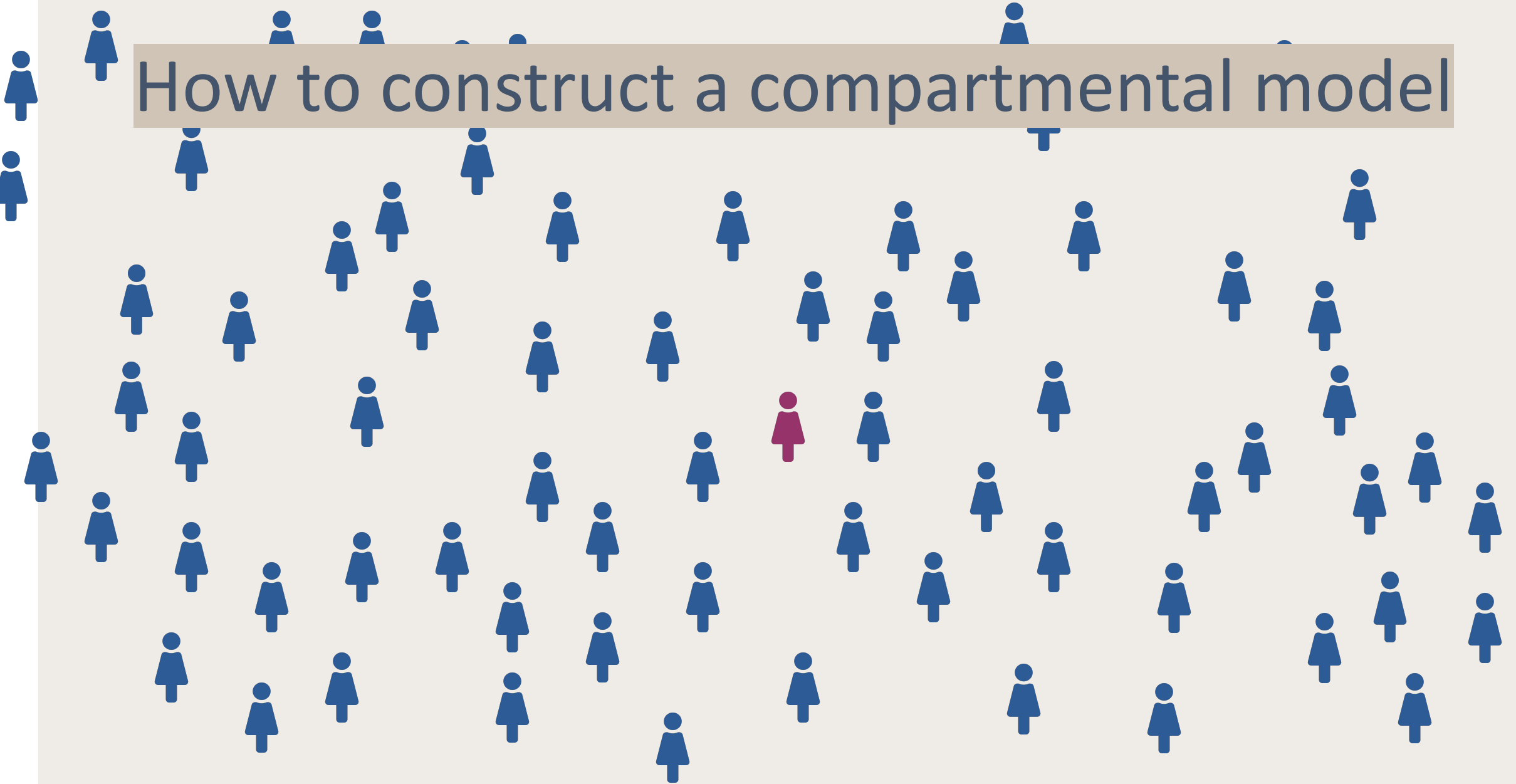
- “Mean-field models” (fancy word for average)
- Based on differential equations governing the behaviour of each *compartment* ( $S$ ,  $I$  and  $R$ )
- Stochastic or deterministic

$$S' = -\beta S I$$

$$I' = +\beta S I \\ -\gamma I$$

$$R' = +\gamma I$$

# How to construct a compartmental model







# How to construct a compartmental model

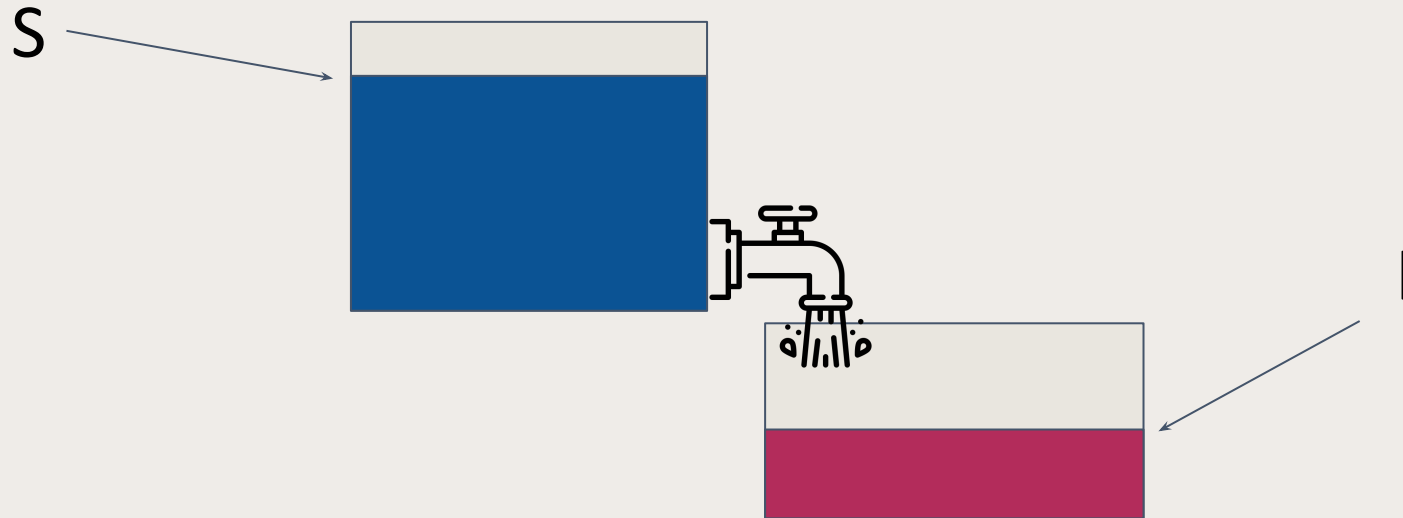
We want a model that describes the number of infected over time,  $I(t)$



# Simplify to average behaviour



How about modelling the population as a... tank of water?  
And infections as a running tap?



Change in I =

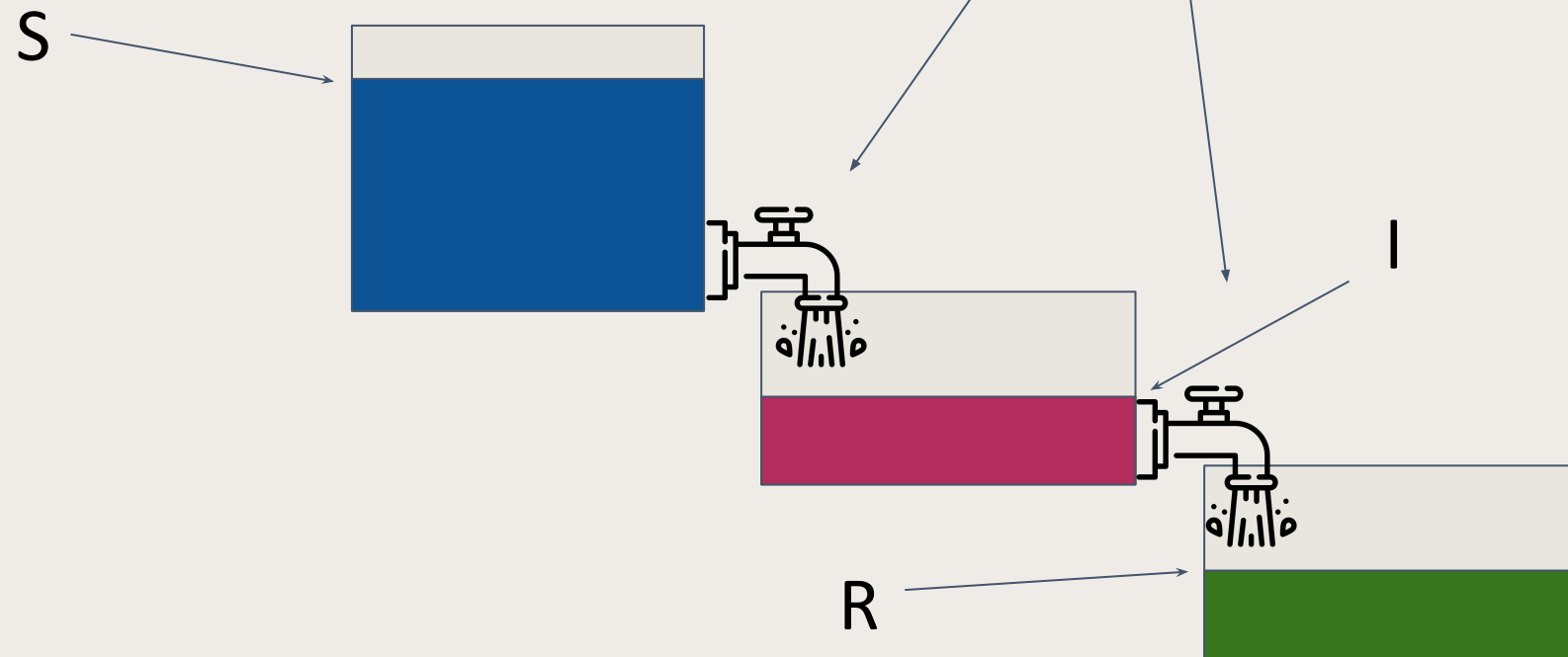
$$I' = \beta S I$$

Don't forget recoveries



Don't forget recoveries



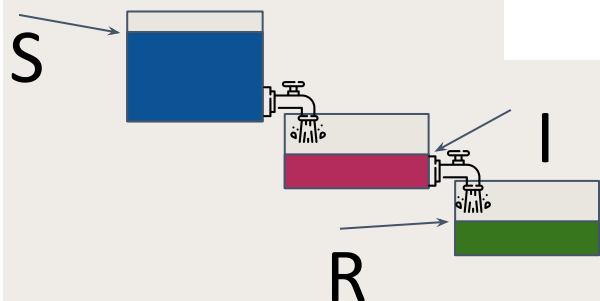
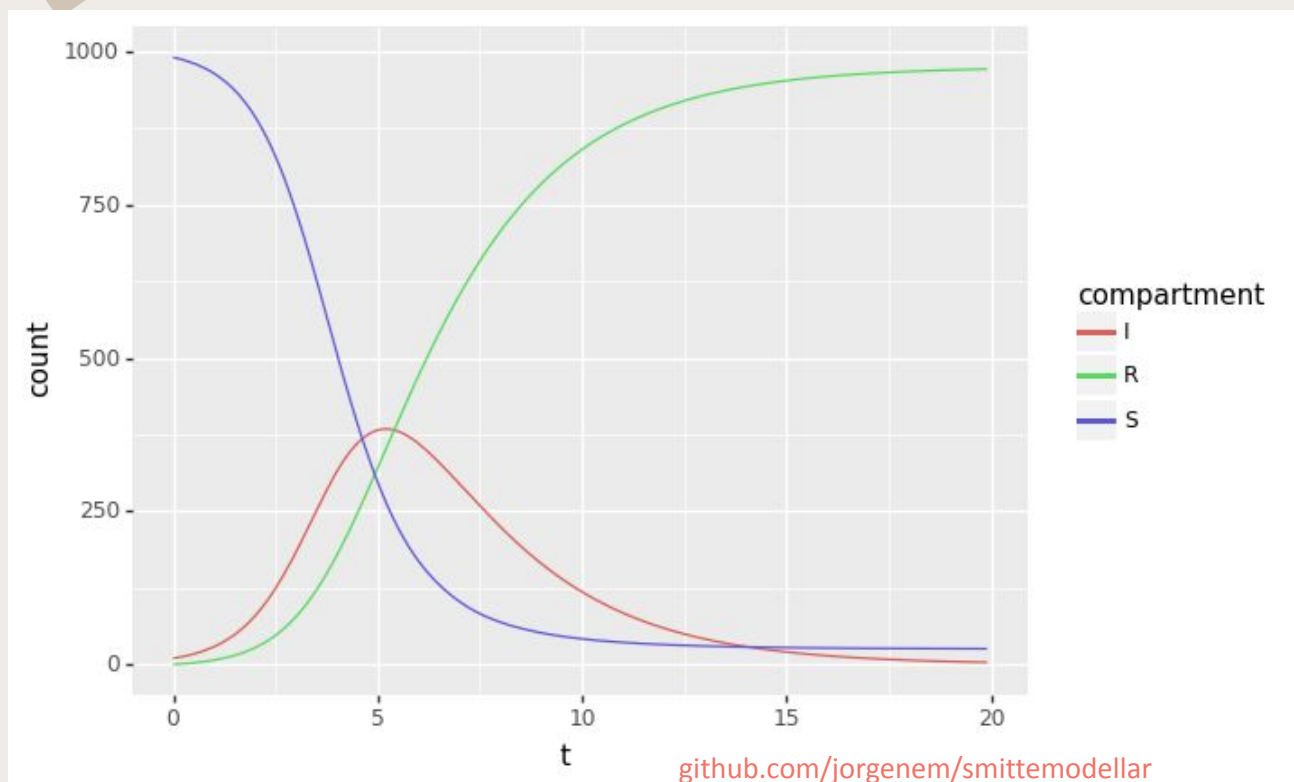
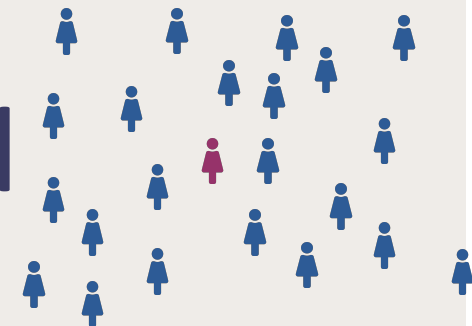


Change in  $I =$

$$I' = \beta S I - \gamma I$$

# This is the compartmental SIR model

deterministic



$$S' = -\beta S I$$

$$I' = +\beta S I$$

$$-\gamma I$$

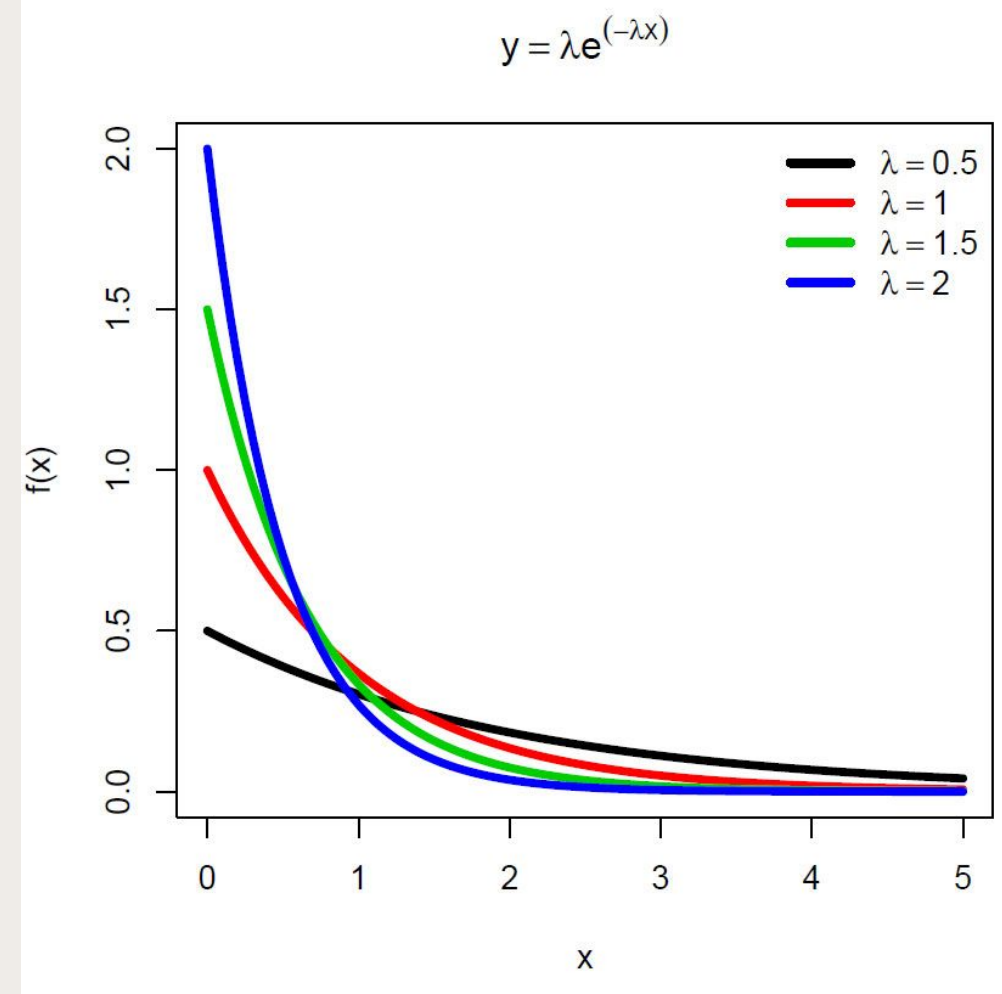
$$R' = +\gamma I$$

# Beware of implicit assumptions

In addition to the explicit assumption of averaging over individuals, the equations bake in *implicit assumptions*. Importantly:

*The transition times of individuals from S to I to R are **exponentially** distributed.*

This is **wrong** for e.g. covid, but models still work fine on the big picture. If needed, techniques exist to amend by adding extra compartments.



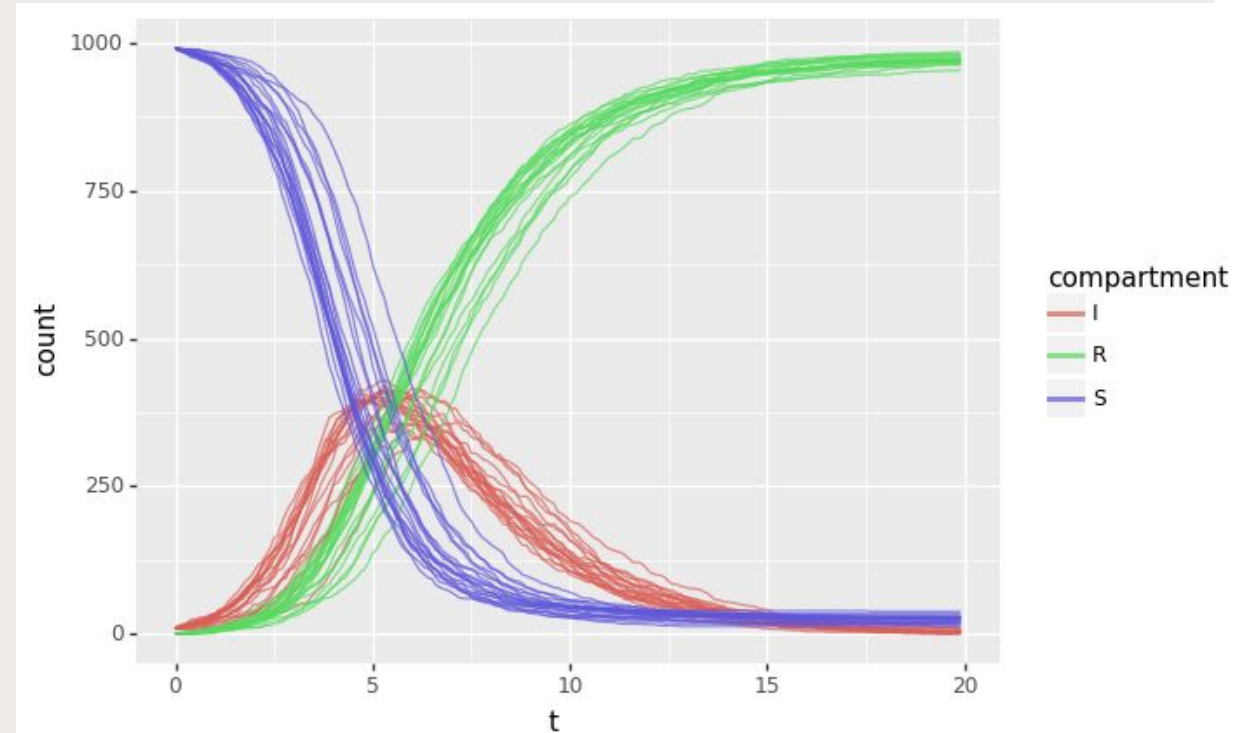
# Stochastic compartmental models

- Real world infectious disease spread is highly *stochastic*, i.e., random
  - As in the agent-based model
- Replaying the Wuhan outbreak might not have resulted in a pandemic -- certainly not the exact same one
- To mimic this, one can add stochasticity (randomness) to the compartmental model equations
- We then write a discrete-time difference equation with a random draw from a *binomial distribution* at each timestep:

$$I_{i+1} \propto \text{binom}(S_i, p_{\text{indiv}})$$

# Stochastic compartmental models

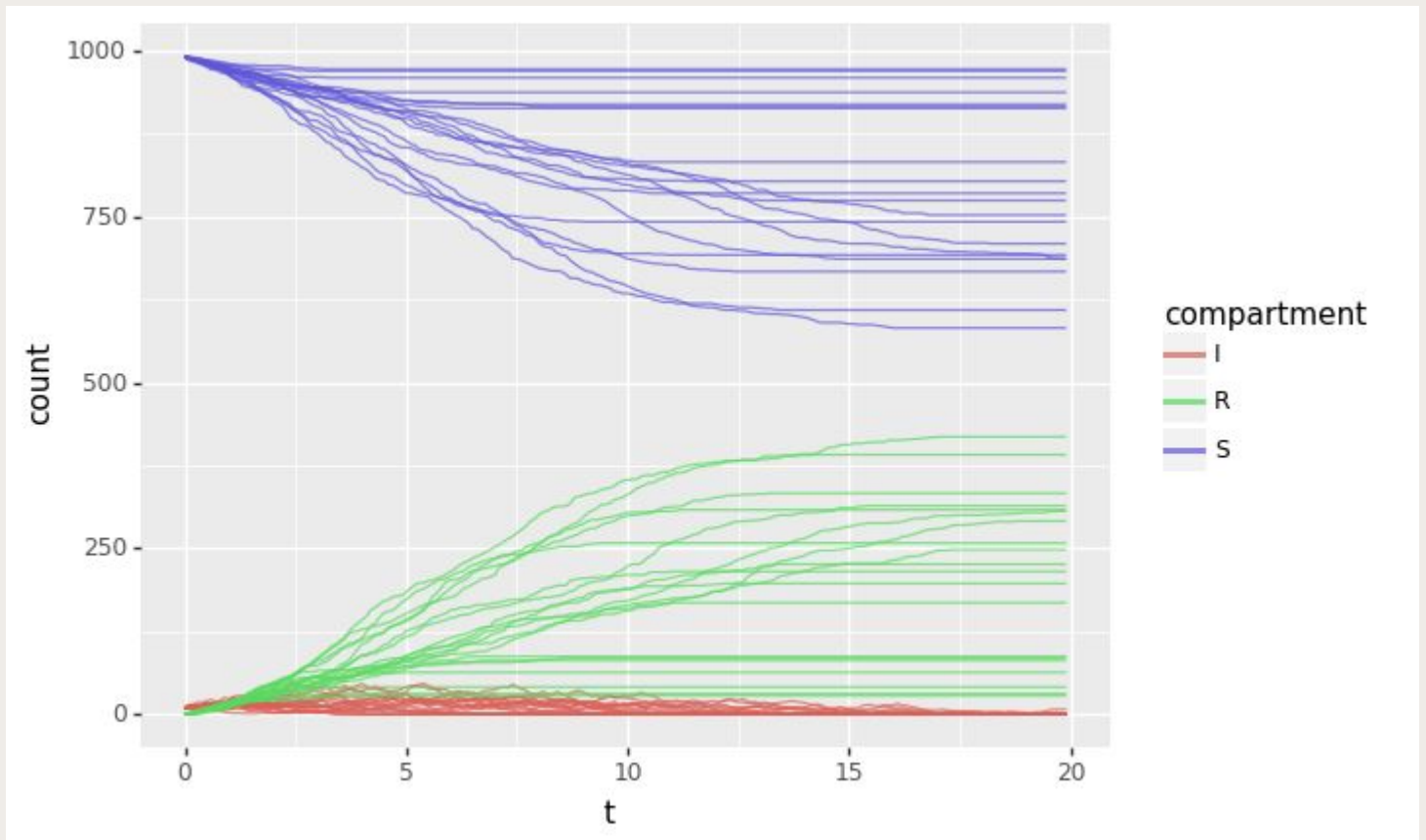
```
def rhs(self, y):  
    """Right-hand side of the equation set.  
    Args:  
        y = [S[i], I[i], R[i]]  
    Returns:  
        [S[i+1], I[i+1], R[i+1]]  
    """  
    p_SI = 1 - np.exp(-self.beta * y[1] / self.N * self.dt)  
    p_IR = 1 - np.exp(-self.gamma * self.dt)  
    n_SI = self.rng.binomial(y[0], p_SI)  
    n_IR = self.rng.binomial(y[1], p_IR)  
    ynew = np.array([  
        y[0] - n_SI,  
        y[1] + n_SI - n_IR,  
        y[2] + n_IR  
    ])  
    return ynew
```





# Threshold effects

Does a seeded case  
lead to an outbreak?  
Initial randomness can  
decide.



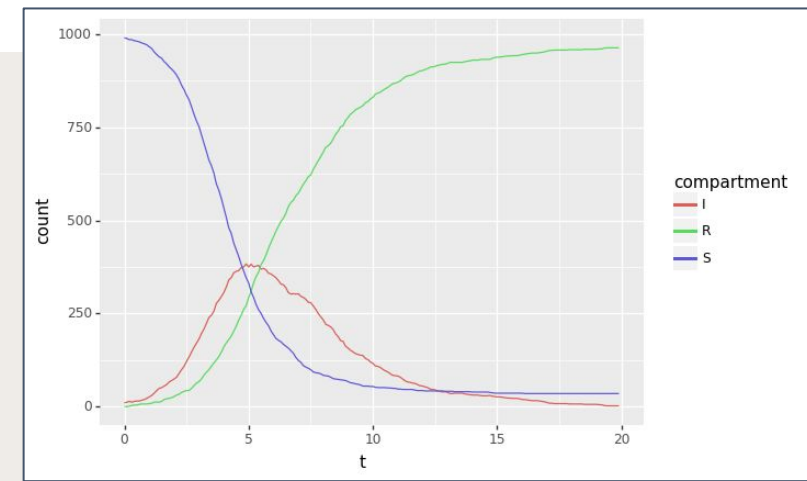
# Markov chain

Technically, this is by assumption a *markov chain*:

At each timestep  $t$ , the system is in a certain state described by the three numbers  $[S(t), I(t), R(t)]$ .

The state at timestep  $t+1$  depends solely on the state at  $t$ .

This has implications for what kind of solvers, approximate methods etc. are applicable.



# Some final points

# The tools we use in practice

- Not always cost-efficient to write code from scratch - pre-written libraries are extremely valuable!
  - Much can be done in Python these days
- Our ABM is written in C, from scratch, by my colleague Francesco di Ruscio. However, to infer its parameters we use a layer on top, written in R and leveraging statistical libraries
  - I might have been tempted to try Python with Numba or something if I was writing another one now
  - Don't underestimate the value of a high-level language interface to your model
- For compartmental models, we often use a set of R libraries called *odin*, *dust* and *mcstate*. These allow specifying arbitrary models in R-like syntax, which are compiled to run fast and automatically interfaced with MCMC, SMC tools etc.

See [https://mrc-ide.github.io/mcstate/articles/sir\\_models.html](https://mrc-ide.github.io/mcstate/articles/sir_models.html)

- TeX (since we have a critical mass of physicists++ - but nobody else understands...)
- Unix/linux
- Supercomputers and parallelisation (MPI and OpenMP)
- Git

# Statistical inference

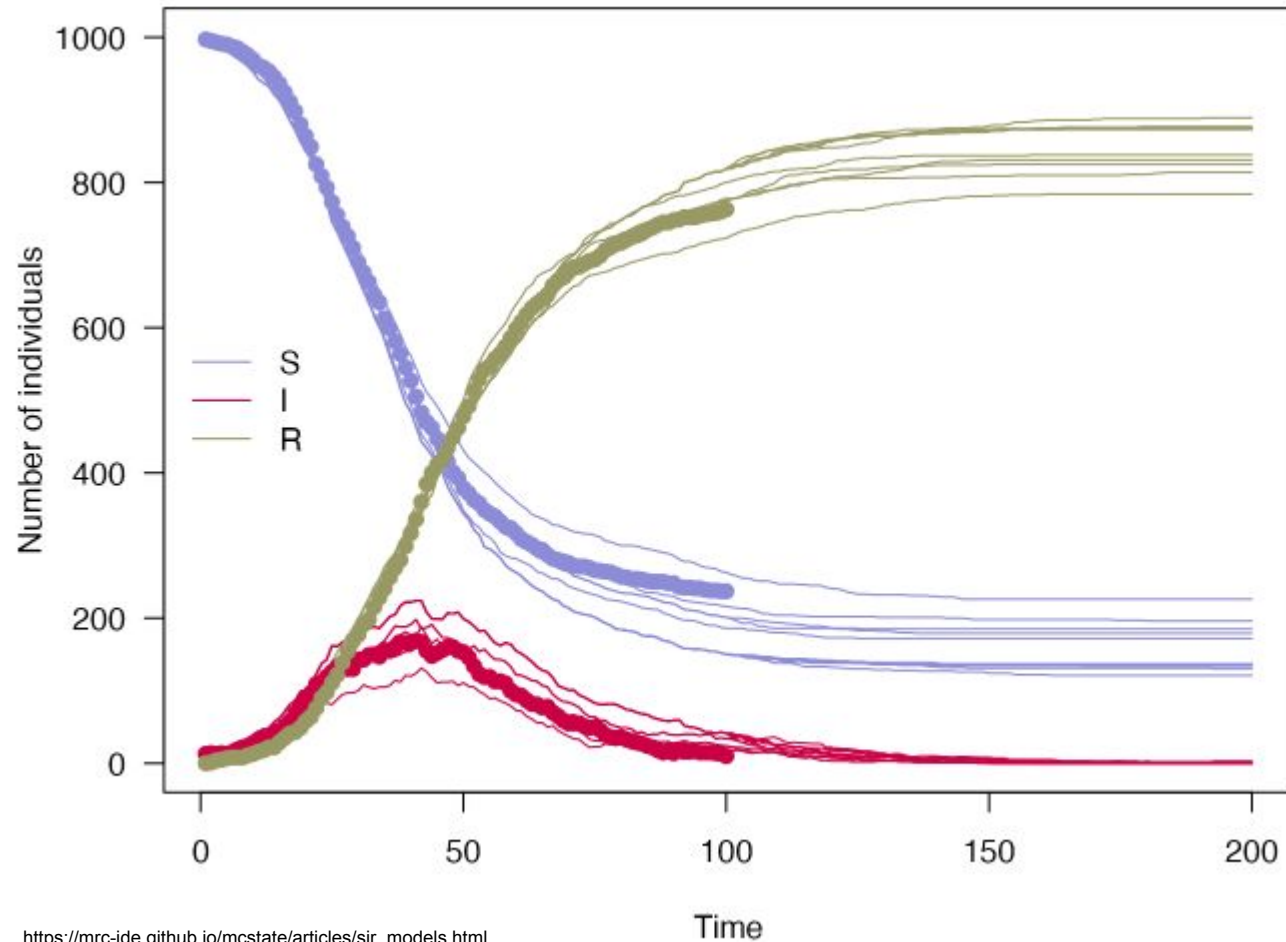
A model is nothing without data!

$$p(\theta|\mathcal{D}) \propto \mathcal{L}(\theta, \mathcal{D})\pi(\theta)$$

Input - assumptions

Model - simulation

Output - consequences

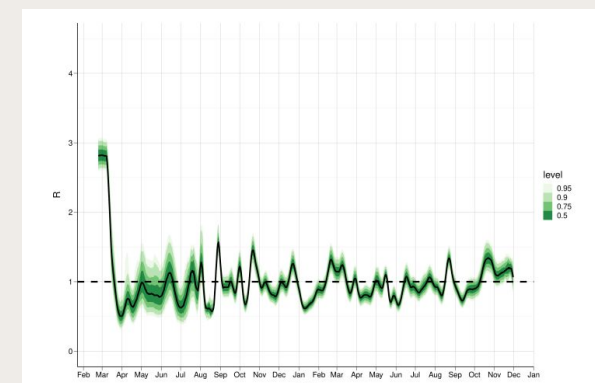
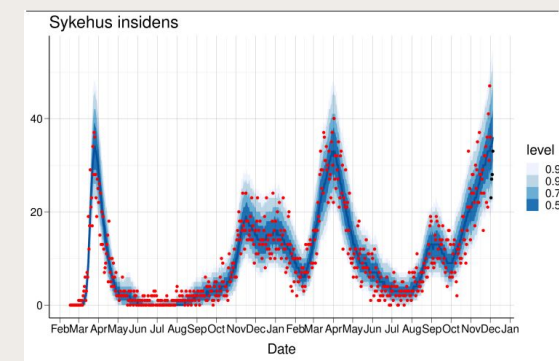


[https://mrc-ide.github.io/mcstate/articles/sir\\_models.html](https://mrc-ide.github.io/mcstate/articles/sir_models.html)

# Calibration (fitting) techniques

All those we use are based on a Monte Carlo approach within a Bayesian framework

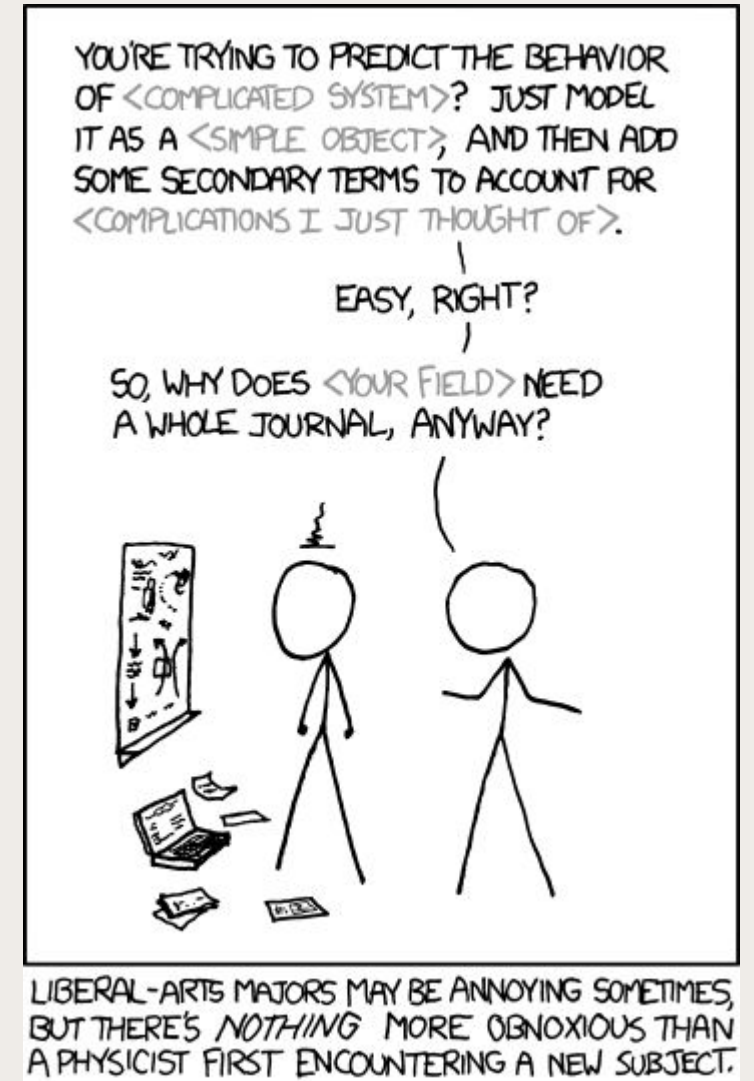
- Changepoints
- Approximate Bayesian Computation (ABC)
- Sequential Monte Carlo / “particle filter”
- Latin Hypercube Sampling (grid scan)
- MCMC
- HMC / NUTS [a fast MCMC, requires gradient] (Stan or pymc)
- History matching



# Working in a new field

Advice from a physicist to fellow physicists: Never underplay the importance of domain knowledge

- Physicists are **great** at modelling, computations and solving complex problems
- There are also many things we do not know, and it's important to be curious (and humble)



Also, always remember:

All models are wrong, but some are useful.

-George Box