Dynamic Calibration for a Microsimulation of Disease Spread

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Context

- Disease spread: highly complex system
- Individual-level models are ideally suited
- We built a COVID microsimulation
- BUT model and simulation will naturally diverge
- The most reliable predictions will combine a model and observations (c.f. weather forecasting, using "all the available information")
- Ideally (future work) we would implement data assimilation to update our model state
- But this is hard, so in the meantime we're using dynamic calibration (i.e. re-calibrate the model as new data arrive)

Aims

- Use ABC to dynamically update a COVID microsimulation in response to new data
- Explore how parameter values change during the simulation (this might tell us something about the dynamics of the disease and social responses to it)
- Show that short-term future predictions will be more accurate if we use the most recent data

Dynamic Microsimulation for Epidemics (DyME)

- Simulates activities (shopping, working, schooling) of individuals in England, and associated disease transmission

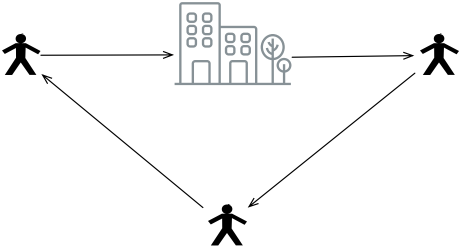

Figure 1: Dynamic Workflow

Dynamic Microsimulation for Epidemics (DyME)

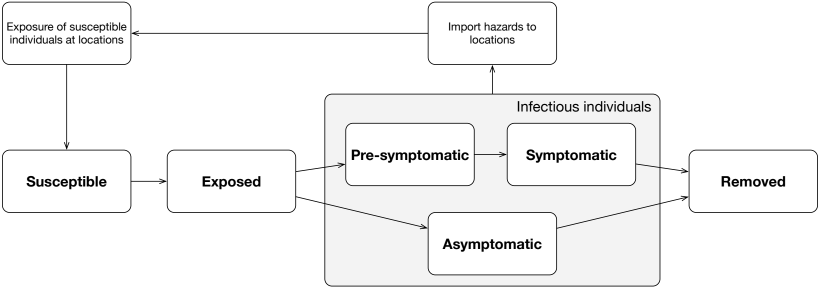

Figure 2: Disease Status Upates

Parameters

The model has loads of parameters; we are just calibrating:

- Location hazards (the 'riskyness' of visitting a place)
    - `retail`
    - `primary_school`
    - `secondary_school`
    - `work`
- Disease parameters (the transmisibility of the disease at different disease states
    - `presymtomatic`
    - `symptomatic`
    - `asymptomatic`

Dynamic Calibration with ABC

Data

- We have daily COVID cases per MSOA throughout the course of the pandemic (although we only simulate 100 days from 1st April)

Method:

- Begin by using ABC to roughly calibrate the model so it isn't starting totally from scratch (this is kind of cheating!)
- Then use data assimilation (ish) forecast-update windows:
  1. Collect case data for the current day
  2. Calibrate the simulation running from 1st April up to the current day
  3. Make predictions for the next week(s)
  4. Repeat (1) after in 7 days

Results (Example): Posteriors in each window

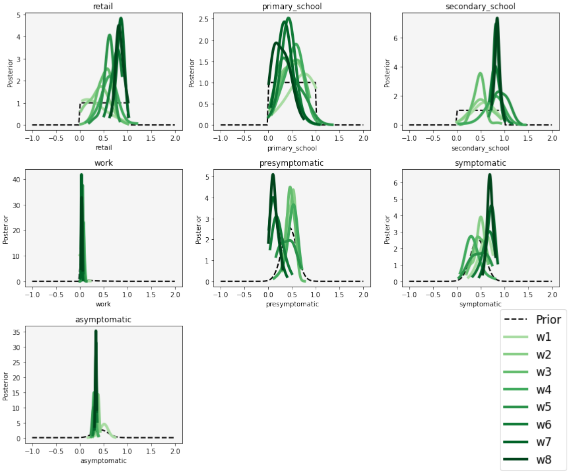

Figure 3: Posteriors

Results (Example): Comparison to real data

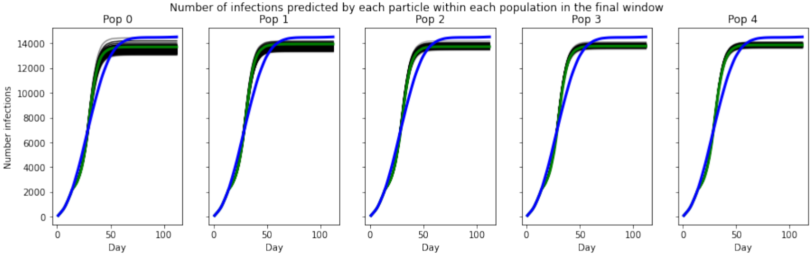

Figure 4: Compare to data

Results (Example): Quality of short-term predictions

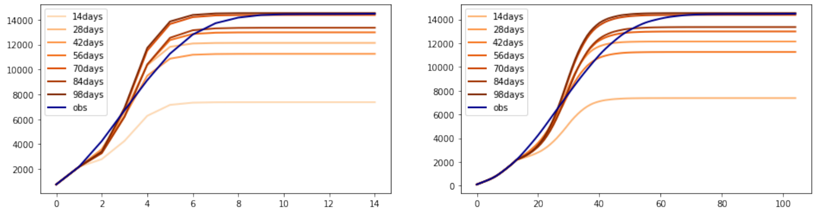

Figure 5: Predictions

Results (for discussion)

The results are quite sensitive to the ABC parameters (e.g. number of particles, number of populations, etc.)

Examples:

- 5 populations, 100 particles
- 10 populations, 100 particles
- 10 populations, 200 particles