Ensemble-based Data Assimilation for epidepiological agent based models

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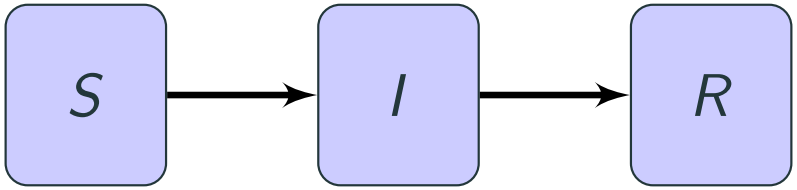
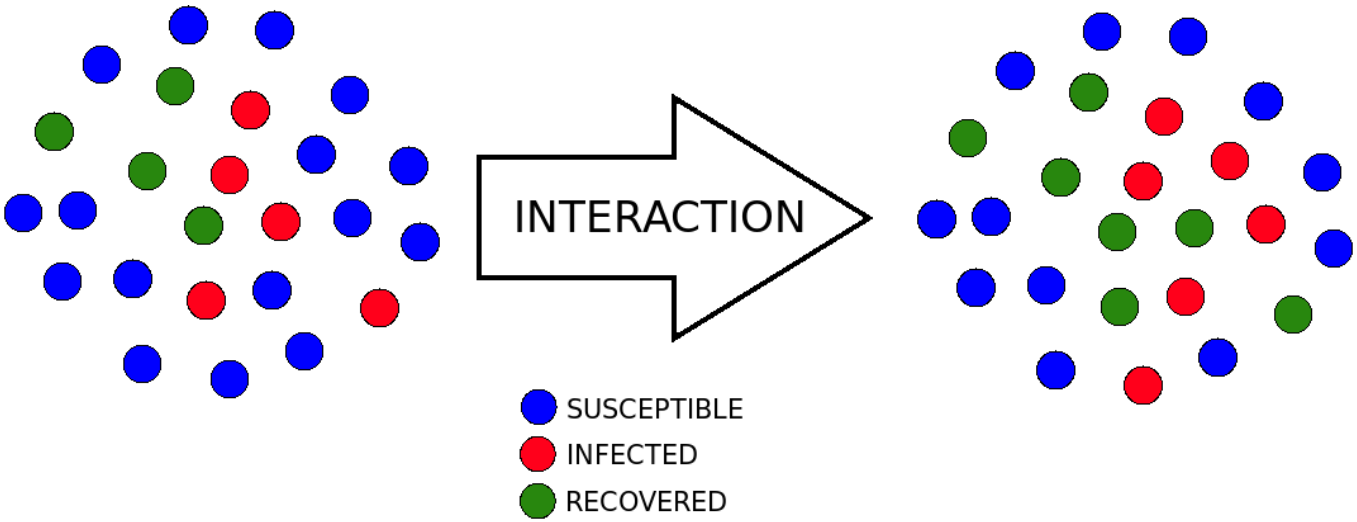
Compartimental epidemiological model

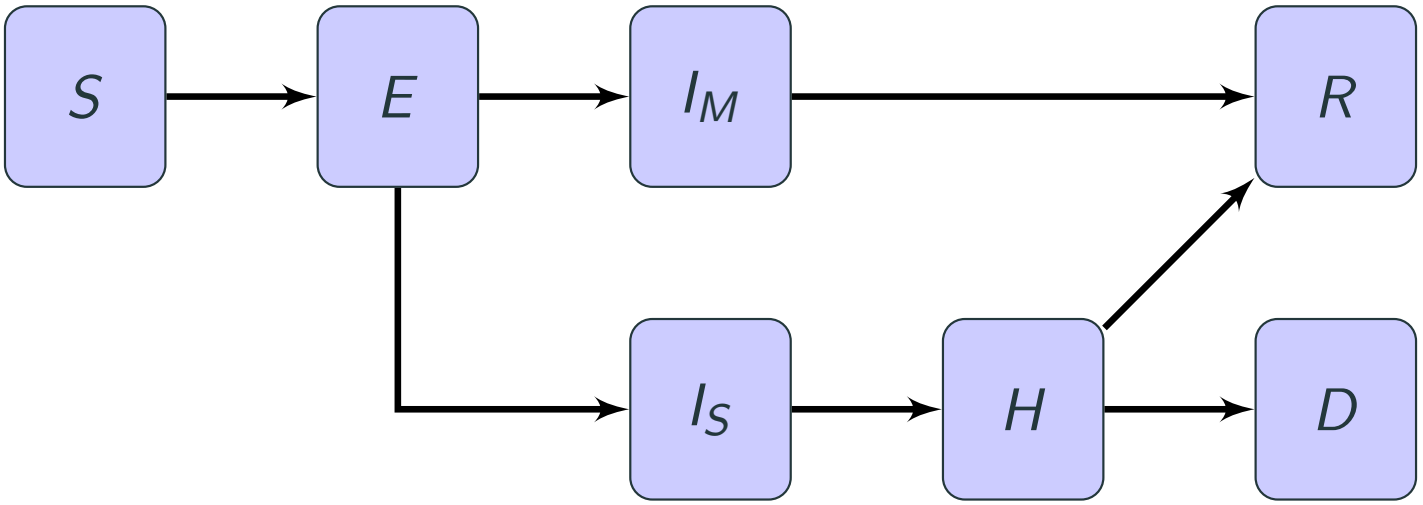


$$\begin{cases} \frac{dS}{dt} & = -\beta \frac{SI}{N} \\ \frac{dI}{dt} & = \beta \frac{SI}{N} - \gamma I \\ \frac{dR}{dt} & = \gamma I \\ N & = S + I + R \end{cases}$$

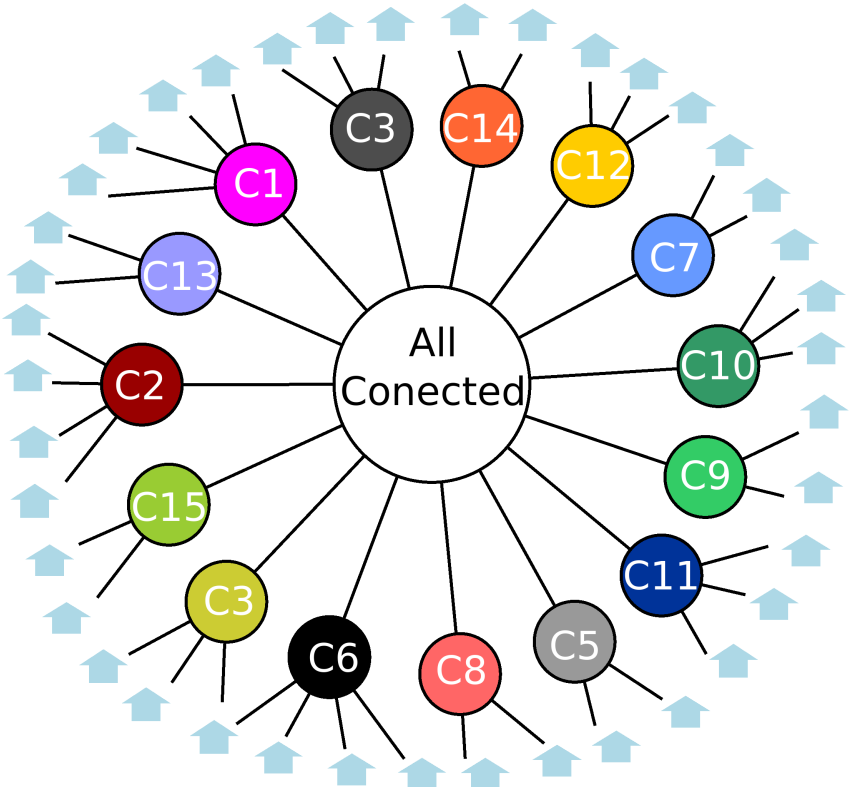
Agent based models

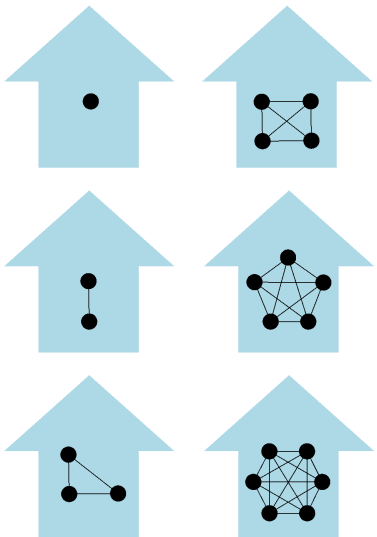


SEIHRD

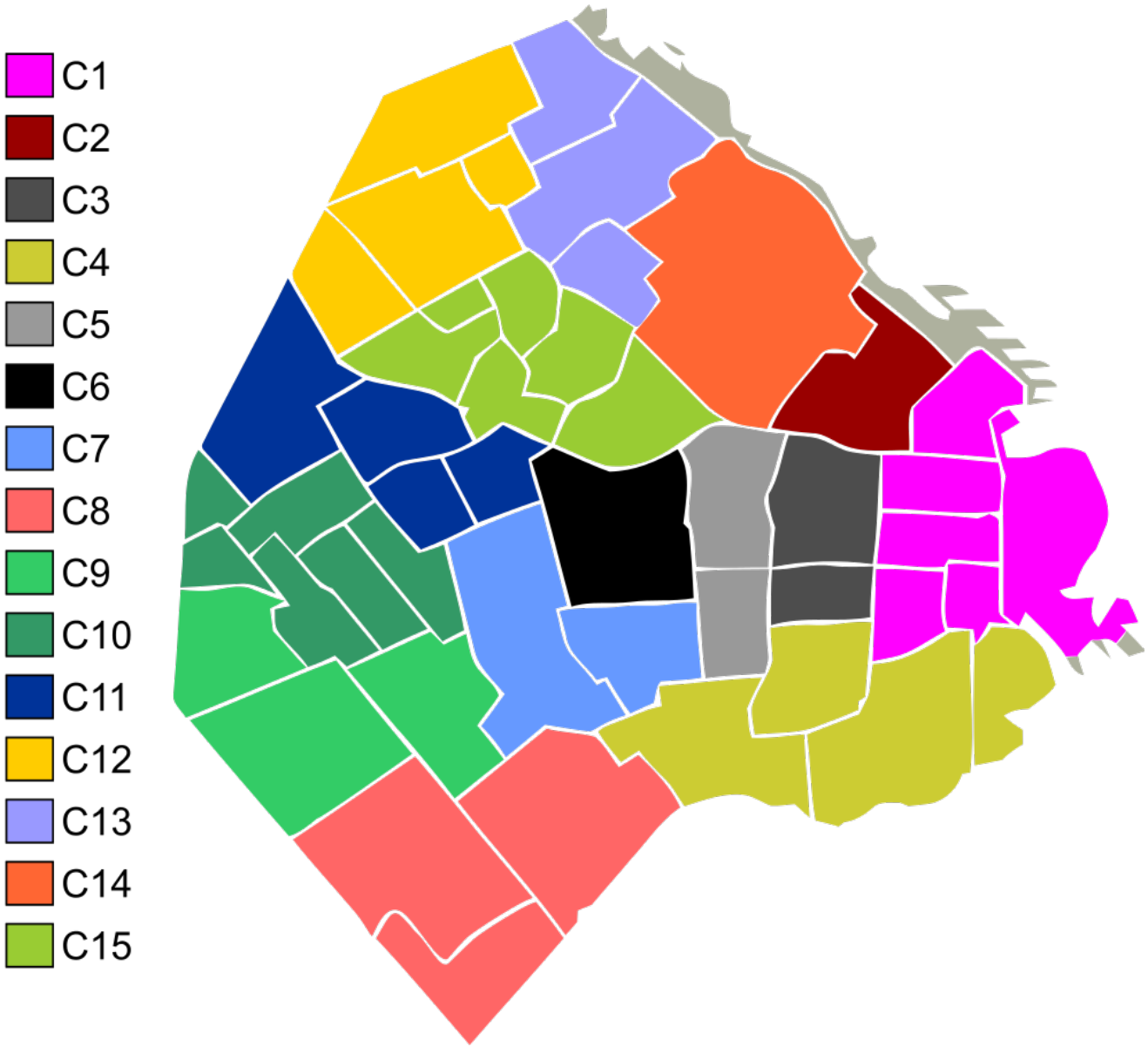


Contact network





CABA comunes



Agent interaction

- Contact network with two levels structure: comune and household.
- Each agent has $n_c \sim Poisson(\lambda)$ contacts per day.
- Each contact can be casual or domestic with chances p_C y $1 - p_C$ respectively.
- Domestic contacts are between cohabitants of the same house.
- Casual contacts are potentialy with any other agent.
- An agent from comune i contacts an agent from comune j with probability C_{ij}

Agent data type

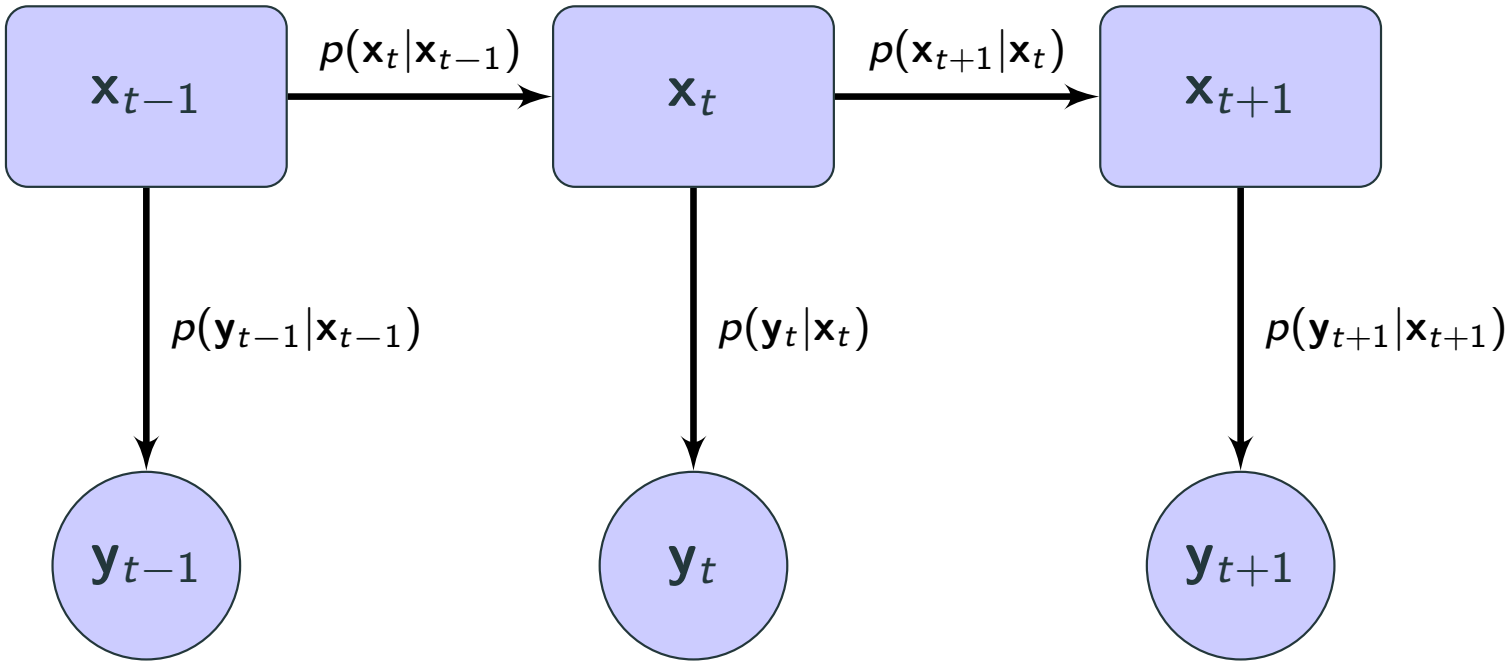
```
1  typedef struct agent{
2    int id;
3    int location;
4    int household;
5    int state;
6    float epi_state_time;
7  } Agent;
8
```

Aggregation or summarization

$$\phi : (\mathbb{Z} \times \mathbb{Z} \times \mathbb{Z} \times \mathbb{Z} \times \mathbb{R})^{N_{agents}} \rightarrow \mathbb{R}^{7N_{loc}}$$

$$\begin{aligned}
\phi(A_t) = \mathbf{x}_t = (S_t^1, &\ldots, S_t^{N_{loc}},\\
E_t^1, &\ldots, E_t^{N_{loc}},\\
I_{M\,t}^1, &\ldots, I_{M\,t}^{N_{loc}},\\
I_{S\,t}^1, &\ldots, I_{S\,t}^{N_{loc}},\\
H_t^1, &\ldots, H_t^{N_{loc}},\\
R_t^1, &\ldots, R_t^{N_{loc}},\\
D_t^1, &\ldots, D_t^{N_{loc}})
\end{aligned}$$

Partially observed systems



Transition, observational and initial distribution probabilities:

$$\mathbf{x}_t = f(\mathbf{x}_{t-1}, \boldsymbol{\theta}_t)$$

$$\mathbf{y}_t = g(\mathbf{x}_t, \boldsymbol{\theta}_t)$$

$$\mathbf{x}_0 \sim p(\mathbf{x}_0)$$

Ensemble-based DA – General scheme

Algorithm 1: General forecasting-filtering scheme for ensemble DA

Sample initial particles: $\{\mathbf{x}_0^{a(j)}\}_{j=1}^{N_p} \sim p(\mathbf{x}_0)$

for $t = 1, ..., T$ **do**

  for $j = 1, ..., N_e$ **do**

    $\mathbf{x}_t^{f(j)} = f(\mathbf{x}_{t-1}^{a(j)})$ using f

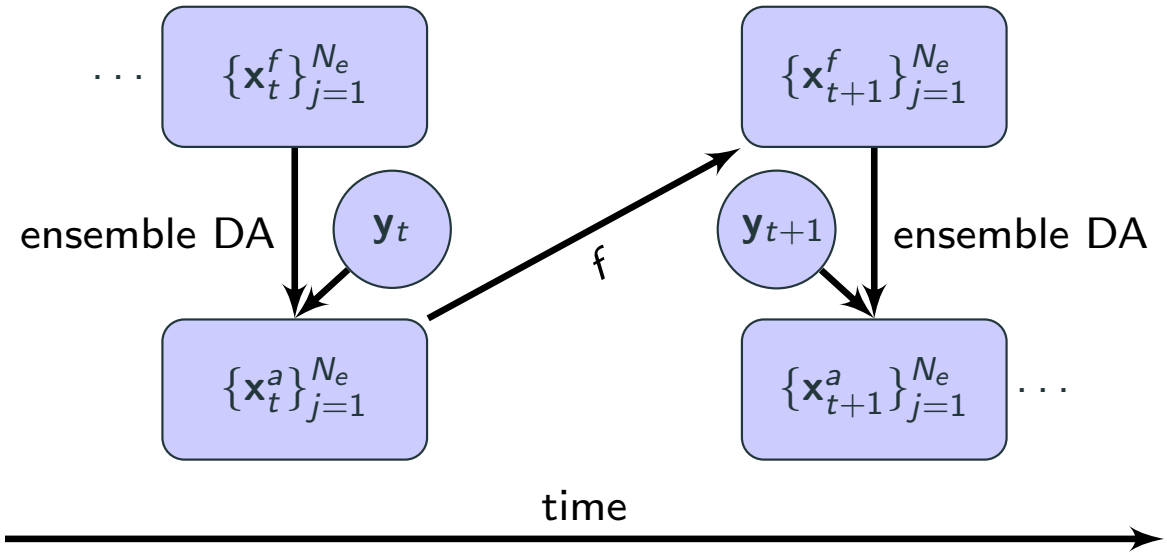
  end

  Transform $\{\mathbf{x}_t^{f(j)}\}_{j=1}^{N_p}$ into $\{\mathbf{x}_t^{a(j)}\}_{j=1}^{N_p}$ using $\mathbf{y}_t$

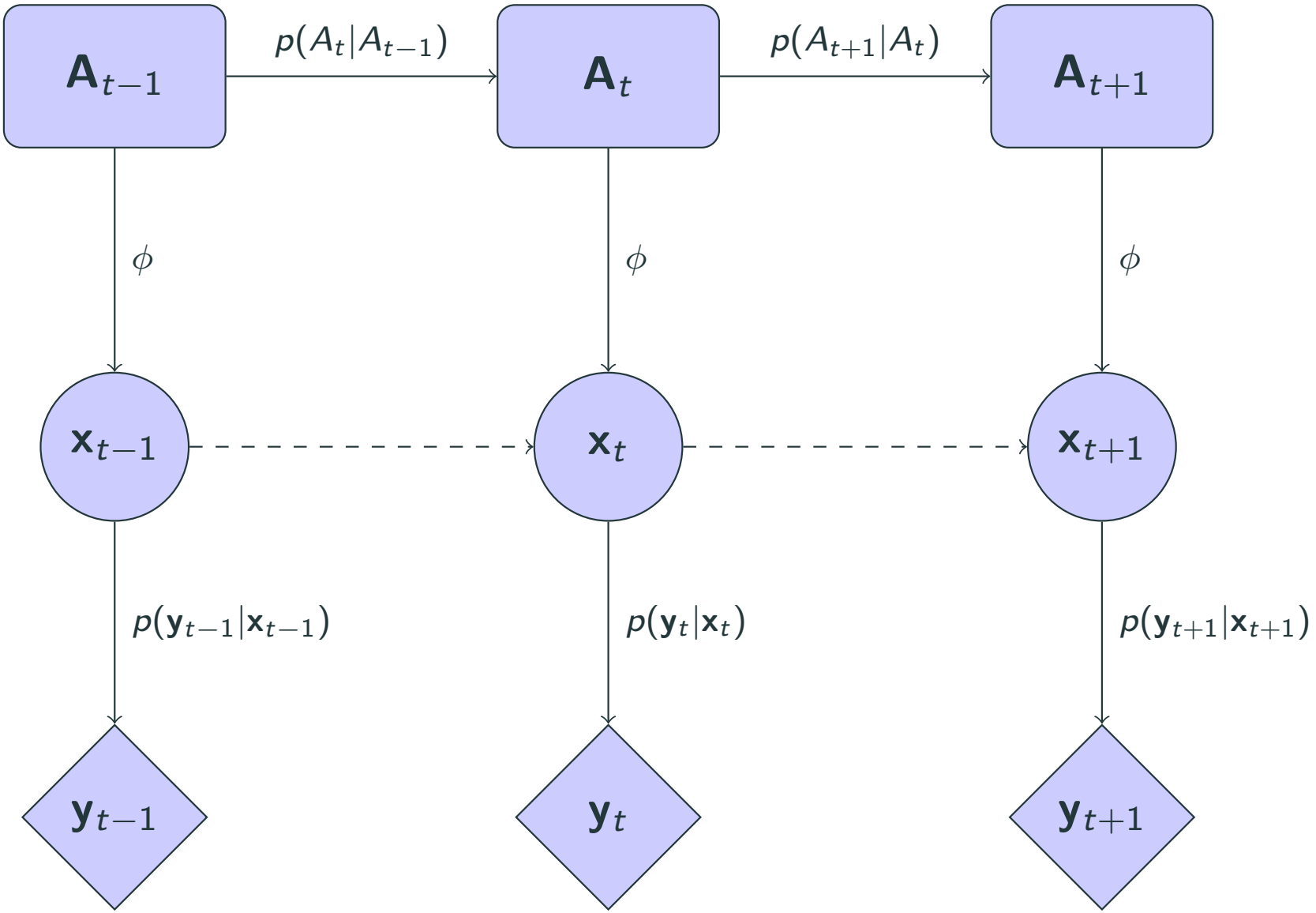
end

This has the advantage that the forward model can be treated as a black box.

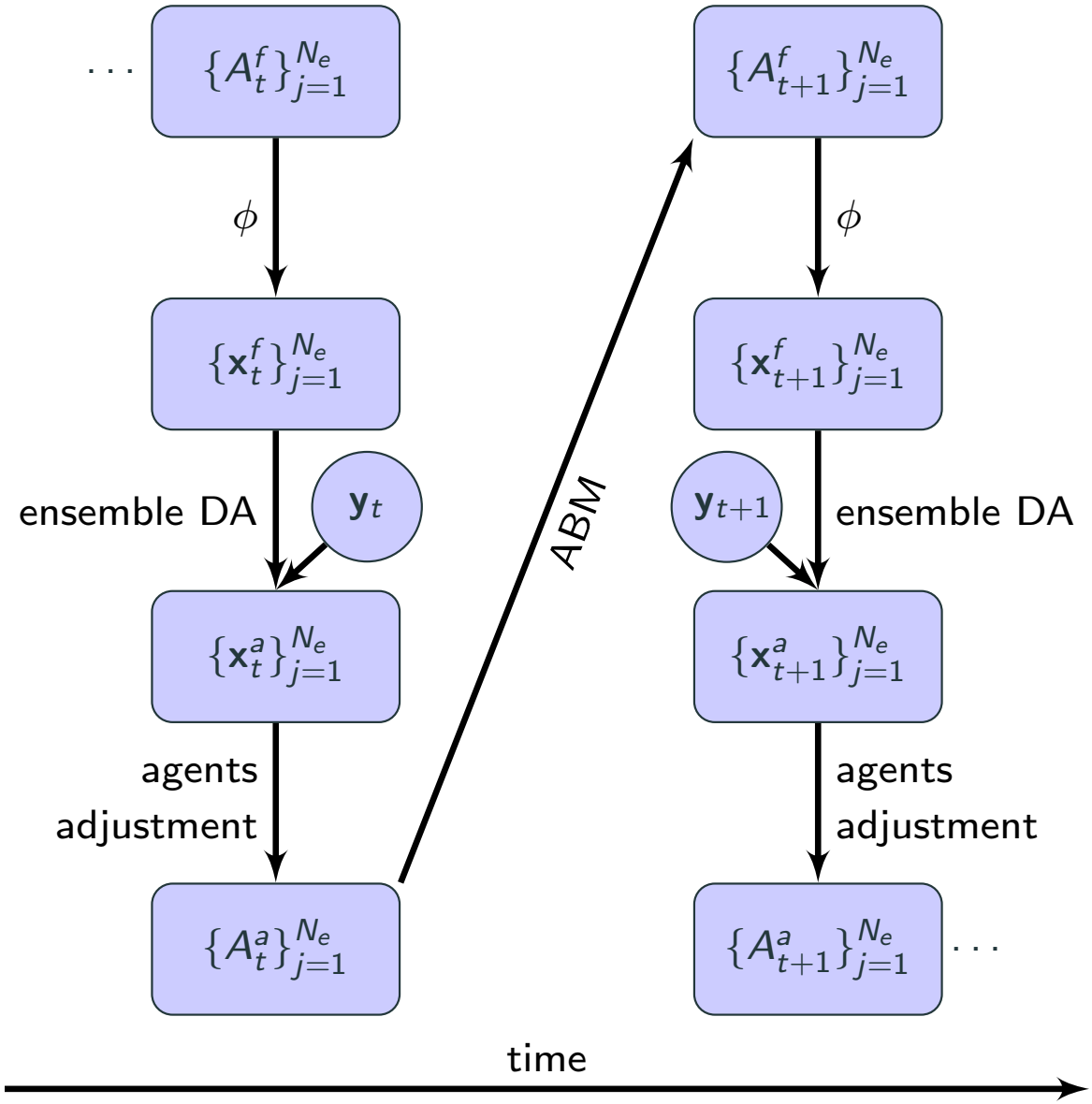
Ensemble-based DA – General scheme



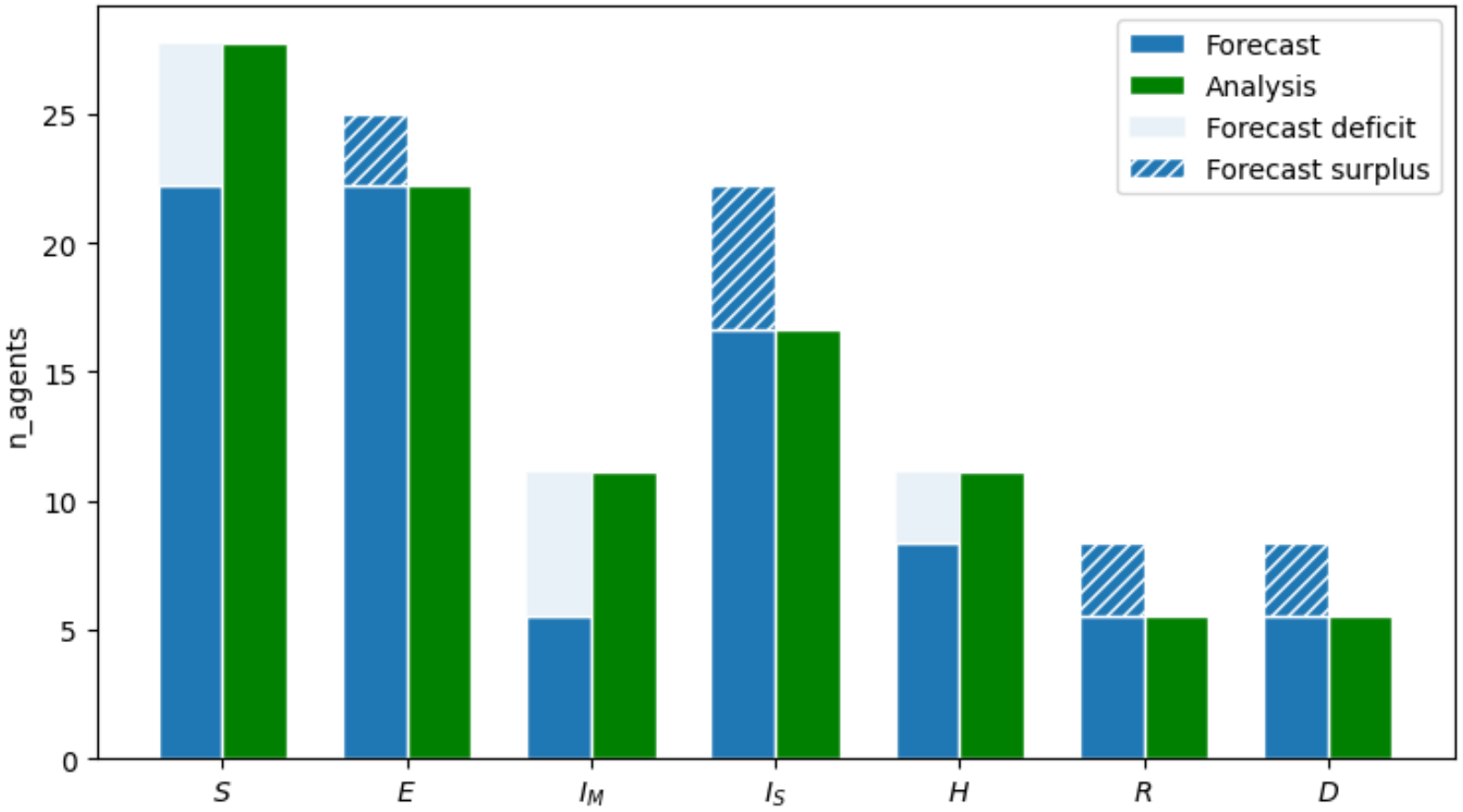
Partially observed ABM



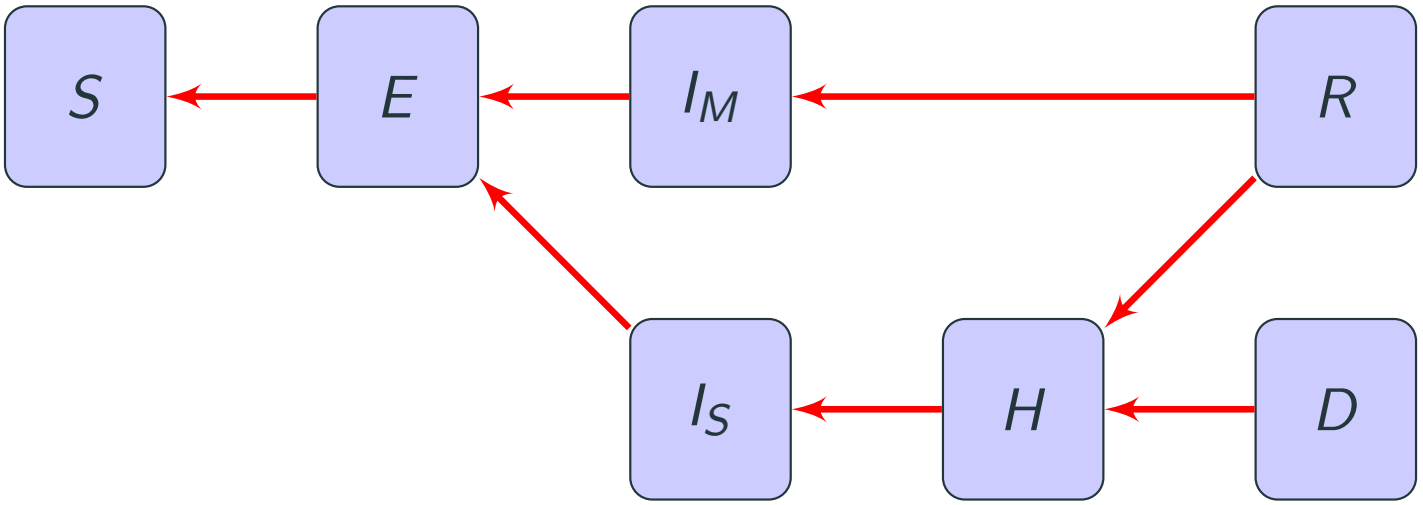
Ensemble DA for ABMs



Agents correction for SEIHRD – randomized redistribution



Agents correction for SEIHRD – cascade redistribution



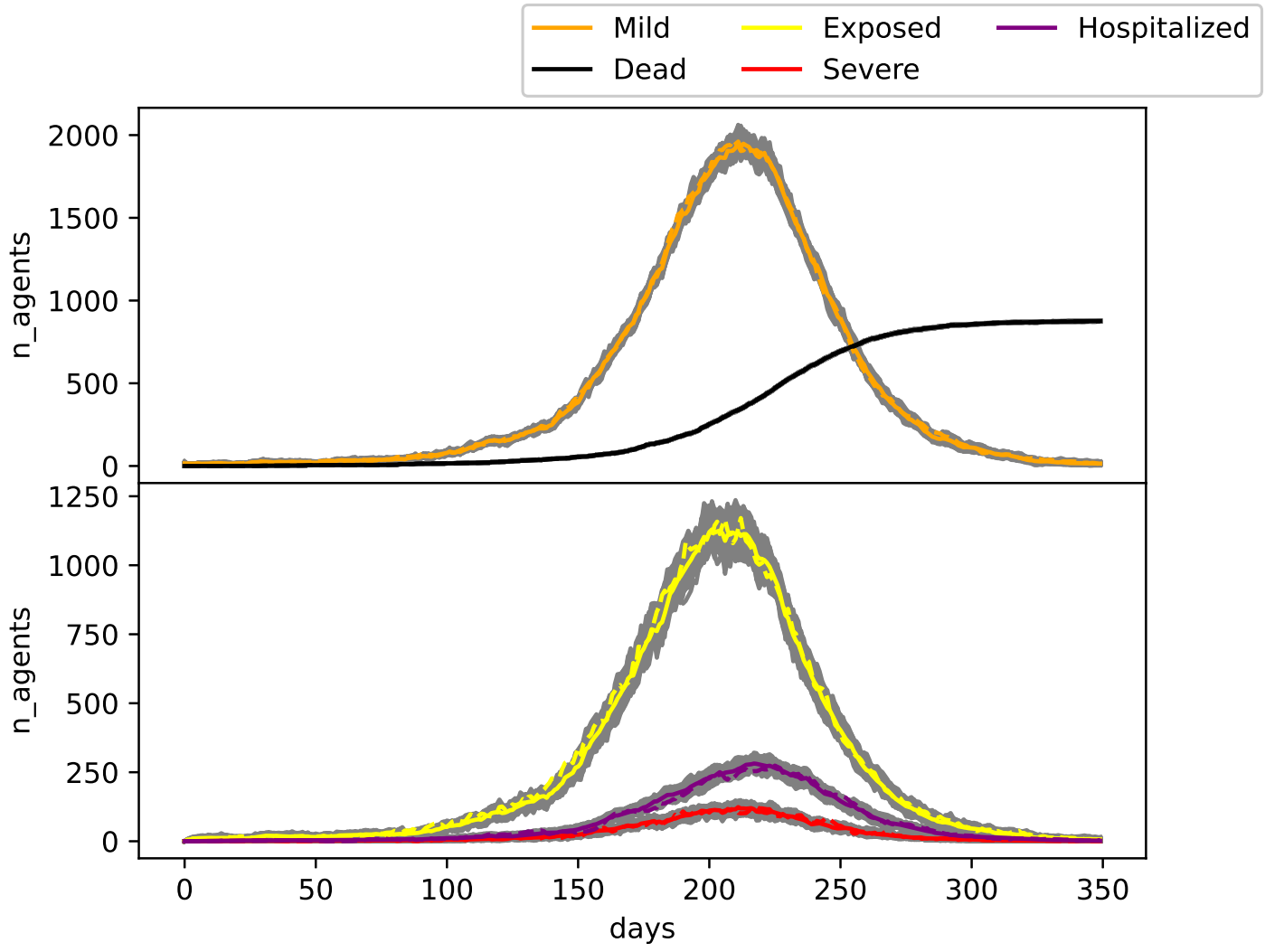
Experiment – Synthetic observations

Observed variables:

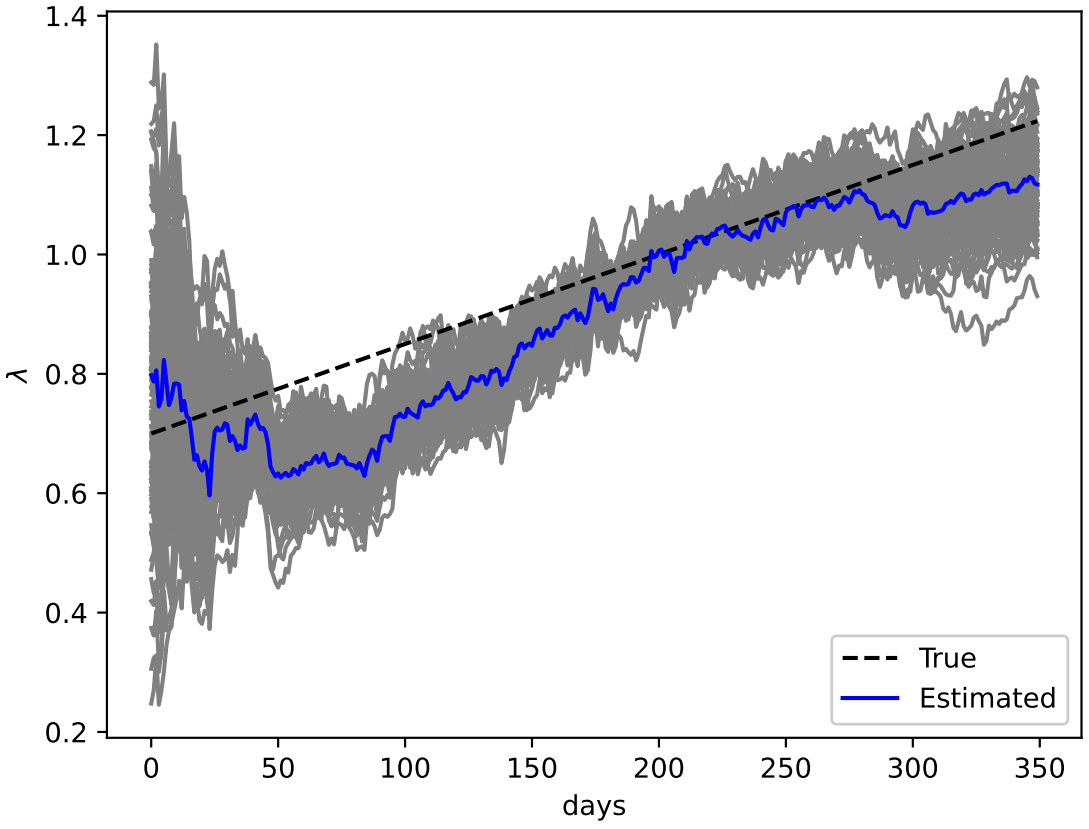
- Cumulative confirmed per comune:
  $\delta {I_M}^i + {I_S}^i + H^i + R^i + D^i$ for every comune i.
- Cumulative deaths per comune:
  D^i for every comune i.

We use 4 comunes, 30k agents and 100 ensemble members. λ is conidered to evolve linearly in time and is estimated through state augmentation.

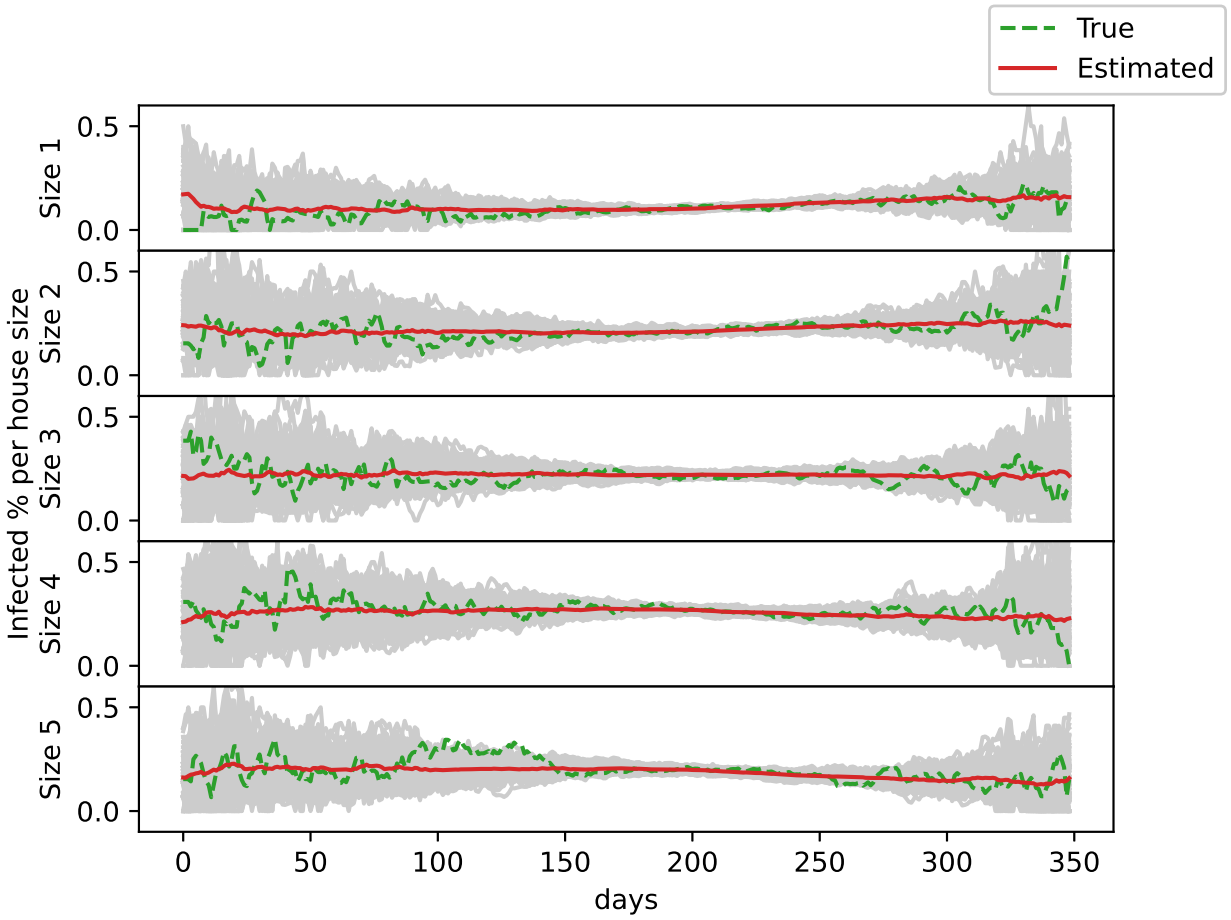
Results – Synthetic observations



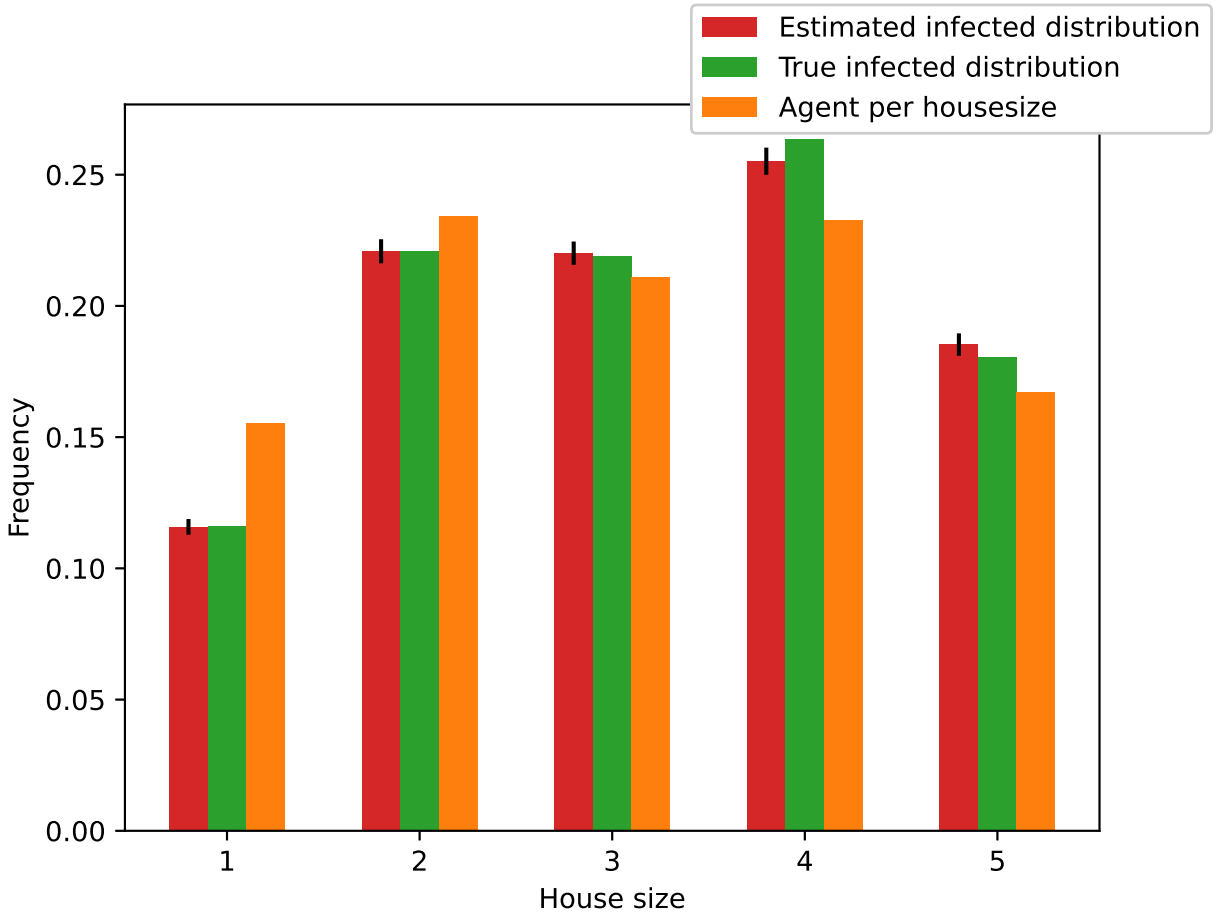
Results – Synthetic observations



Results – Synthetic observations



Results – Synthetic observations



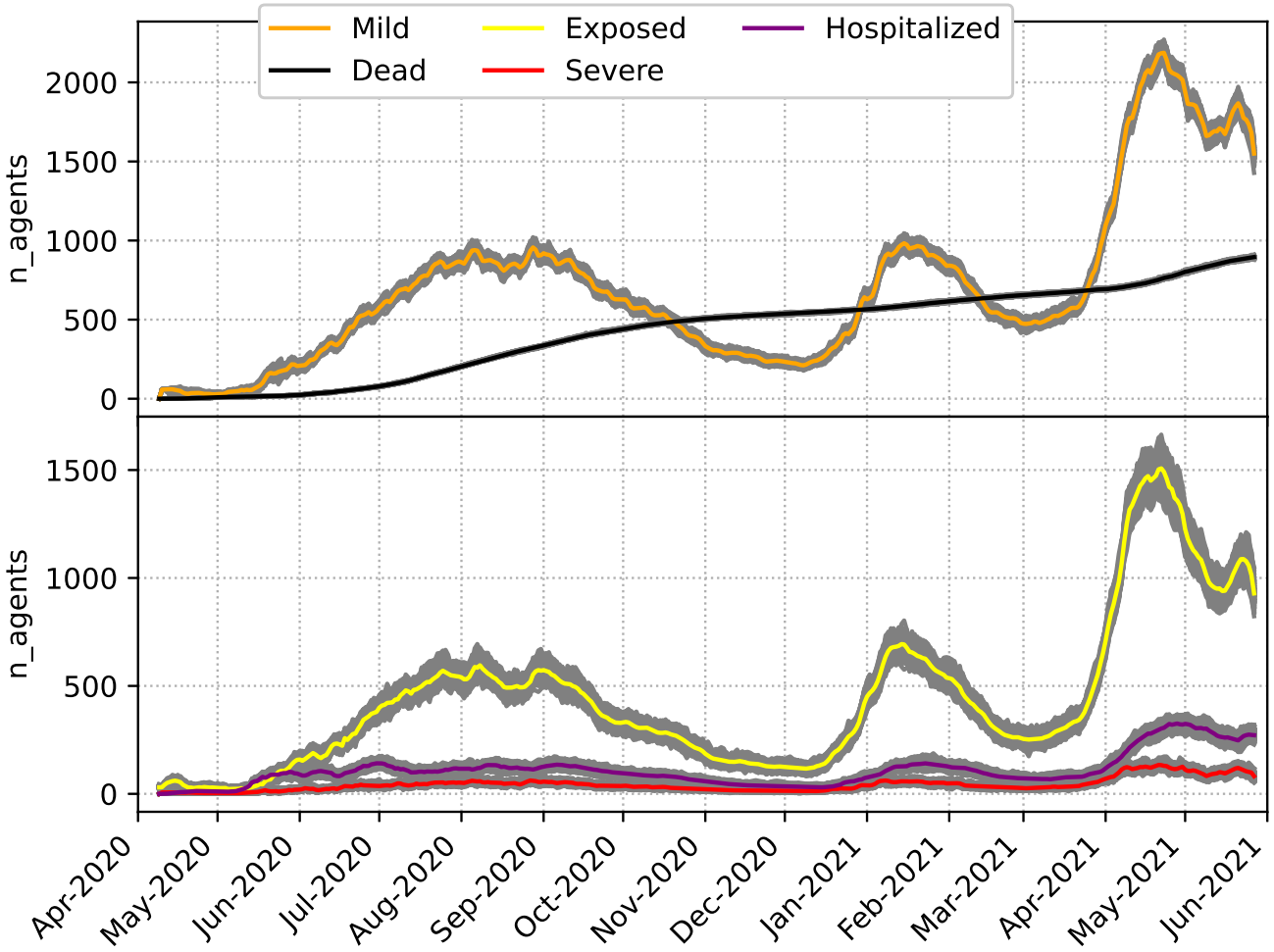
Experiment – Data from CABA

Observed variables

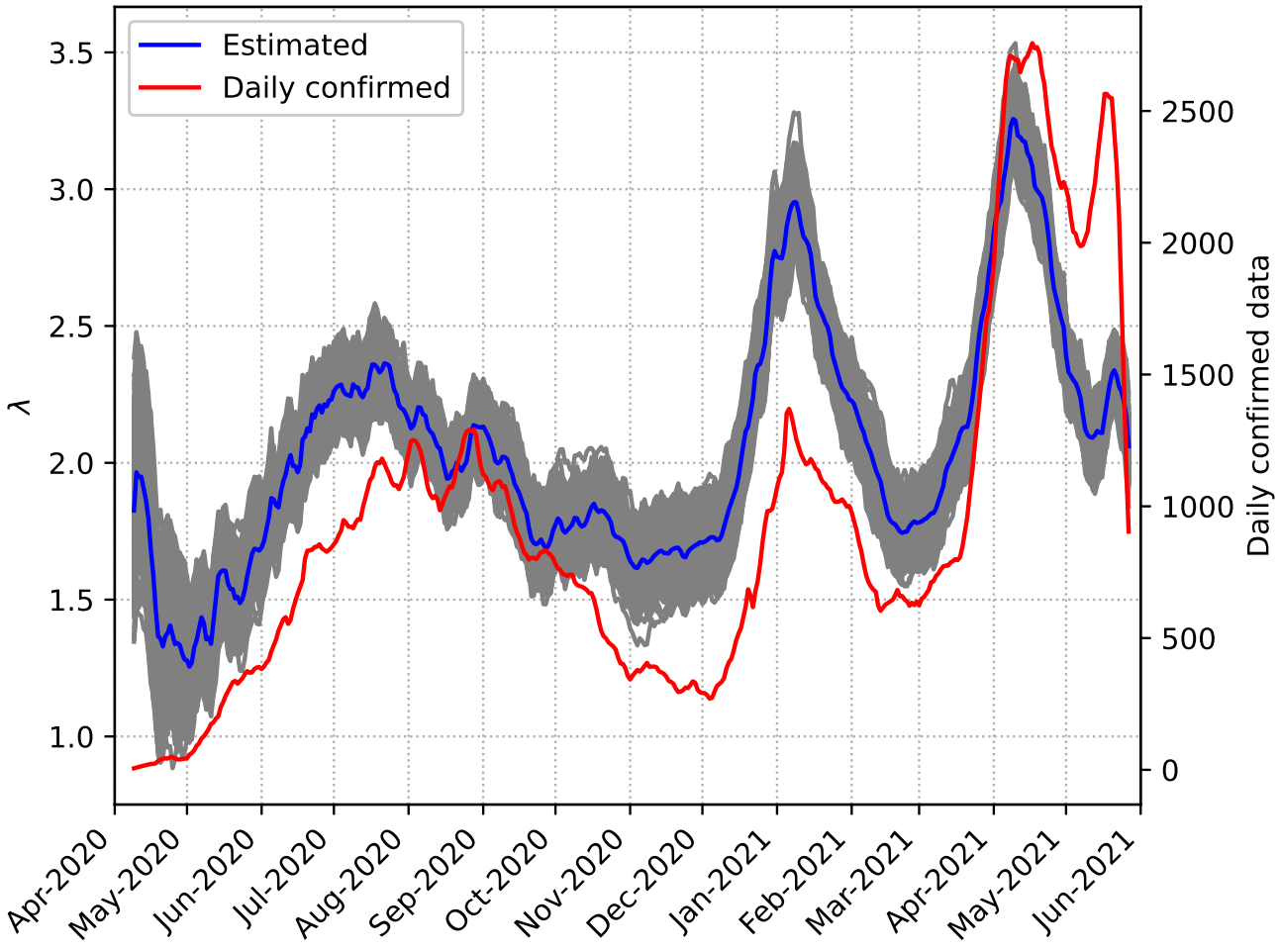
- Cumulative cases per comune:
  ${I_M}^i + {I_S}^i + H^i + R^i + D^i$ for each comune i.
- Cumulative deaths per comune:
  D^i for each comune i.

We use all 15 comuns, 300k agents and 400 EnKF ensemble members.

Results – Data from CABA



Results – Data from CABA



Observations

- Underreportig because of asymptomatics
- Inference on microstate (specific attributes of agents)
- Offline inference (eg.: ESMDA, pMCMC, variational)

Bibliography

- Kerr, C. C., et al (2020). Covasim: An agent-based model of covid-19 dynamics and interventions. *medRxiv*
- Evensen, G., et al. (2020). An international assessment of the covid-19 pandemic using ensemble data assimilation. *medRxiv*
- Ward, J. A., et al. (2016). Dynamic calibration of agent-based models using data assimilation. *Royal Society Open Science*, 3 (4), 150703