

Agent-based epidemiological models: Importance of disaggregation in SARS-CoV-2 models for policy decision making

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Research seminar

Motivation

Challenges

- Lockdown across the world due to SARS-CoV-2 manifest the need of **robust** and **dynamic** models, to guide decision making.
- Accounting for individual behaviour through an epidemic outbreak by using **large scale models**.
- Datasets are growing in size and are becoming available in continuous streams.
- Difficulty of finding **disaggregated data** to **validate** the model.
- Allows to **assess the impact** that a certain policy has on **different segments of the population**.

Research gaps

Limitations

- Lack of data leads to add aggregated parameters inside the agent-based models, [TYK⁺20].
- Agent-based models in order to define more targeted and less disruptive interventions. Results are achieved using real-time data-driven analysis, [AMCB⁺20].
- Clear methodology to know which variables are meaningful inside an epidemiological model, for example income or residence place, [CPK⁺21].
- Make the probabilities time dependant, since an early adoption can potentially allow to contain the epidemics, [MBCV20].

Agent-based epidemiological models, [HD19]

Activity-based model
(human mobility)

SIR model
(epidemic spreading)

Outline of this talk

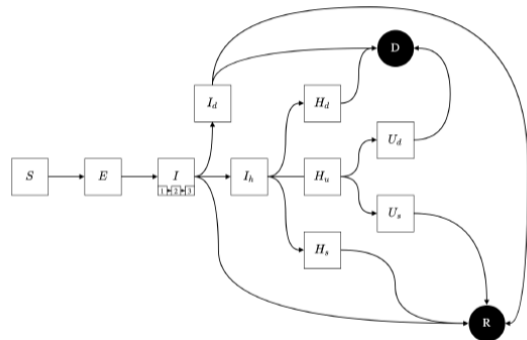
- 1 Added value of using disaggregate models for modelling SARS-CoV-2 spreading. ¹
- 2 Importance of including dependency on socioeconomic, time, and location in the conditional probability of infection. ²
- 3 Potential of these models to study SARS-CoV-2 policy decision making. ³

Literature:

- ¹ A. Aleta, D. Martín-Corral, M. Bakker, A. Piontti, M. Ajelli, M. Litvinova, M. Chinazzi, N. Dean, M. Halloran, I. Longini, A. Pentland, A. Vespignani, Y. Moreno, and E. Moro. Quantifying the importance and location of sars-cov-2 transmission events in large metropolitan areas, 12 2020.
- ² S. Chang, E. Pierson, P. Koh, J. Gerardin, B. Redbird, D. Grusky, and J. Leskovec. Mobility network models of covid-19 explain inequities and inform reopening. *Nature*, 589:1–6, 01 2021.
- ³ M. Mancastropa, R. Burioni, V. Colizza, and A. Vezzani. Active and inactive quarantine in epidemic spreading on adaptive activity-driven networks. *Physical Review E*, 102, 08 2020.

Agent-based epidemiological models

- insight on transmission and intervention that will complete what can be obtained with usual compartmental models (SIR).
- Added value of these models ...
 - The **interactions** between agents are **nonlinear, discontinuous or complex**.
 - When the space is crucial and we do **not have fixed positions**.
 - Population is **heterogenous** with different socioeconomic characteristics.
 - Agents have **complex behaviour**.
 - Topology of **interactions** is **complex**.



Schematic diagram of COVID-19 transmission and hospitalisation process, [LPSA⁺20].

Activity-based models

Activity-based model

- They allow more complex policies to be evaluated.
- The phenomena are understood as the result of the interaction of multiple agents, each guided by individual norms/intelligence.
- This interaction results in a complex system, consisting of many sub-systems and agents (applicable to many disciplines: ecology, economics, computer simulation...).
- It uses microscopic simulation.
- Examples: MATsim, TRANSIMS...

Model Formulation

See [CN05], based on [AdPL93] and [CSH75].

Utility of a plan S_{plan}

$$S_{plan} = \sum_{q=0}^{N-1} S_{act, q} + \sum_{q=0}^{N-1} S_{trav, mode}(q)$$

The utility of an activity q :

$$S_{act, q} = S_{dur, q} + S_{wait, q} + S_{late.ar, q} + S_{early.dp, q} + S_{short.dur, q}$$

Epidemiological models

Epidemiological models

They solve the problem that we aggregate purely individual relationships and assume that collectives will behave accordingly.

- The transitions at each time step Δt are:

$$p_{\text{expose}} = 1 - \exp\left(-\Delta t \cdot \beta \cdot \frac{I_1 + I_2 + I_3}{H}\right)$$

$$p_{\text{infect}} = 1 - \exp(-\Delta t \cdot \sigma)$$

$$p_{\text{recover}} = 1 - \exp(-\Delta t \cdot \gamma)$$

Transition	rate parameter	Unit
$S \rightarrow E$	$\beta = \frac{R_0 \cdot \gamma}{k}$	d^{-1}
$E \rightarrow I_1$	$\sigma = \frac{1}{5.2}$	d^{-1}
$I_1 \rightarrow I_2$	$\gamma = \gamma_s \cdot k$	d^{-1}
$I_2 \rightarrow I_3$	$\gamma = \gamma_s \cdot k$	d^{-1}
$I_3 \rightarrow R$	$\gamma = \gamma_s \cdot k$	d^{-1}

- S: Susceptible
- E: Exposed
- I: Infected
- R: Recovered

Epidemiological models

Issues:

- SEIR models work on an aggregate level.
- Not transferable to different epidemics.
- Crucial parameters might not be available.
- Exponential is a strong assumption.

In order to relax the exponential assumption:

- $k = 3$ compartments of infected cases, I_1, I_2, I_3 .
- infectious period shaped as Erlang distribution.

Model formulation

The serial interval SI , which is the interval between two subsequent infections.
The basic reproductive number R_0 representing the number of newly infected per infected.

SI (COVID-19 is currently estimated to be in range 6.5-8.2).
 R_0 is drawn each timestep to obtain β .

$$SI = \frac{1}{2} \left(\frac{1}{\gamma \cdot k} \right) + \frac{1}{\sigma}, \beta = \frac{R_0 \cdot \gamma}{k}$$

Binomial distribution drawn each timestep

$$N_{I_1 \rightarrow I_2}(t) = \text{Binom}(I_1, 1 - \exp(-\delta t \cdot \gamma))$$

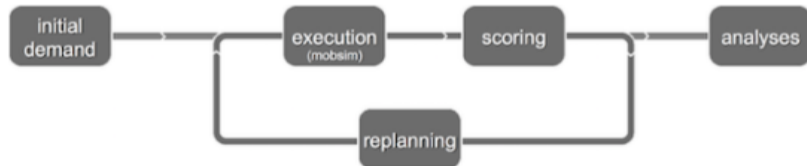
Agent-based epidemiological models

What is Matsim, [Abo]

Definition

- Multi-agent transport simulation tool.
- The framework consists of several modules which can be combined or used stand-alone.
- Modules can be replaced by custom implementations to test single aspects of your own work.

MATSim Framework



Episim

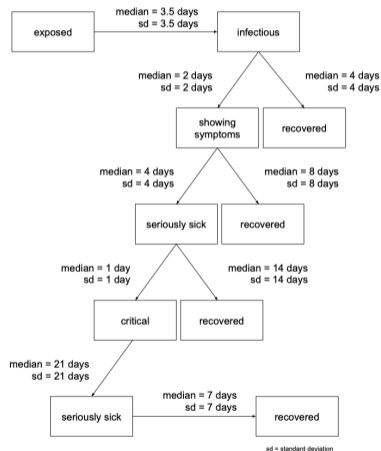
- Episim is an open source framework which can be used to simulate, based on MATSim events, an epidemic outbreak.
- The model has states exposed, infectious, showing symptoms, seriously sick(= should be in hospital), critical (= needs intensive care), and recovered.
- The durations from one state to the next follow log-normal distributions.

SIR model used in Episim, [MBC⁺20]

- The probability for person n to become infected by this process in a time step t in [MBC⁺20]:

$$P_{n,t} = 1 - \exp \left[-\Theta \sum_m q_{m,t} \cdot c_{i_{nm},t} \cdot i_{n,t} \cdot \tau_{nm,t} \right]$$

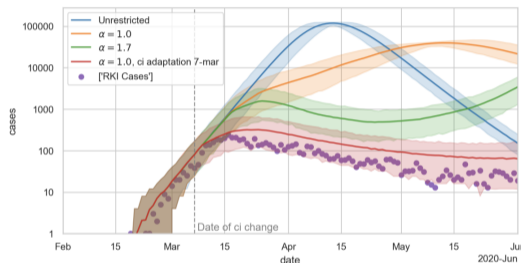
- Main issues of this probability:**
 - Parameters unknown for COVID-19, so set to *value* = 1,
 - All multiplying so it might be independent modifying one or another,
- We want to create dependence on not only individual and time but also on the location.



Case study: Berlin scenario - Baseline

$$P_{n,t} = 1 - \exp \left[-\Theta \sum_m q_{m,t} \cdot ci_{nm,t} \cdot in_{n,t} \cdot \tau_{nm,t} \right]$$

- Θ is the equivalent to the infectious rate β of a compartmental model.
- $q = ci = in = 1$
- Θ in the base case calibrated so that the number of cases doubles every three days.

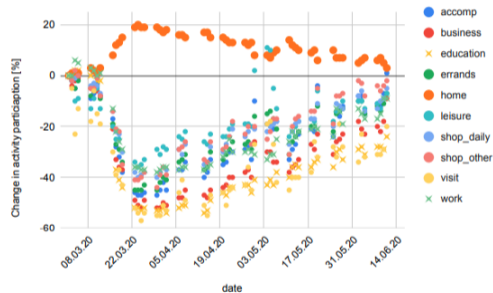


RKI case numbers together with simulated result for different values of α , and final calibration result, [MBC⁺20].

Case study: Berlin scenario - Baseline

The reductions in activity participation can be simulated by:

- Removing an activity from a person's schedule, plus the travel to and from the activity.
- Reduction in activity participation from data (for example Google data [com]).



Reduced activity participation over the course of the epidemics in Germany, [MBC⁺20] .

Case study: Berlin scenario

Research objective:

- Make the model completely disaggregated and compare it to the baseline scenario.
- Include ci in the infection probability, making it dependant on the number of people performing an activity at the same time.
- Include place dependency and socioeconomic variables on the conditional infection probability.
- Find disaggregated data to build a model and validate it.
- Policy testing, taking advantage of the agent level. Test policies by dividing populations according to socioeconomic variables, or according to places or the interaction of both. Also, useful to determine the perfect timing to implement them.

Thank you

References I

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Model Formulation

Waiting:

$$S_{\text{wait},q} = \beta_{\text{wait}} \cdot t_{\text{wait},q}$$

Performing an activity:

$$S_{\text{dur},q} = \beta_{\text{perf}} \cdot t_{\text{typ},q} \cdot \ln(t_{\text{dur},q}/t_{0,q})$$

Late arrival :

$$S_{\text{late.ar},q} = \begin{cases} \beta_{\text{late.ar}} \cdot (t_{\text{start},q} - t_{\text{latest.ar},q}) & \text{if } t_{\text{start},q} > t_{\text{latest.ar},q} \\ 0 & \text{else} \end{cases}$$

Early departure :

$$S_{\text{early.dp}} = \begin{cases} \beta_{\text{early.dp}} \cdot (t_{\text{earliest.dp},q} - t_{\text{end},q}) & \text{if } t_{\text{end},q} < t_{\text{earliest.dp},q} \\ 0 & \text{else} \end{cases}$$