Disaggregation of a SIRD model for policy testing in targeted groups of the population

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ETH Workshop

Agenda

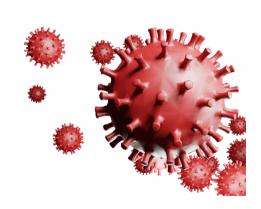
- Introduction and Motivation
- State of the Art
- SIRD Disaggregated Model
- Results
- Conclusion



Motivation

Challenges

- Accounting for individual behaviour through an epidemic outbreak by using large scale models.
- Difficulty of finding disaggregated data to validate the model.
- Capturing spread of the disease through daily activities.
- Allows to assess the impact that a certain policy has on different segments of the population.
- Epidemiological datasets are becoming available.



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].



Outline of this talk

- Added value of using disaggregate models for modelling SARS-CoV-2 spreading. ¹
- ② Description of the preliminary considerations and presentation of a model that accounts for virological and socio-economic variables.²
- Openation of these models to study SARS-CoV-2 policy decision making.³

Literature:

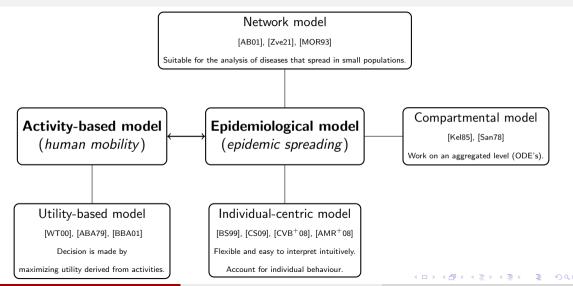
- ¹ A. Aleta, D. Martin-Corral, M. Bakker, A. Piontti, M. Ajelli, M. Litvi-nova, M. Chinazzi, N. Dean, M. Halloran, I. Longini, A. Pentland, A. Vespignani, Y. Moreno, and E. Moro. Quantifying the importance and location of sars-cov-2 transmission events in large metropolitan areas, 12 2020.
- ² S. Chang, 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. Mancastroppa, 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.



State of the Art



State of research



Compartmental models

The SIR epidemic model can be written in the following way(c.f [KMS17]):

• The transitions at each time step Δt are:

$$\frac{\partial S}{\partial t}(t) = -\lambda I(t) \frac{S(t)}{N}$$
$$\frac{\partial I}{\partial t}(t) = \lambda I(t) \frac{S(t)}{N} - \gamma I(t)$$
$$\frac{\partial R}{\partial t}(t) = \gamma I(t)$$

•	S:	Susce	ptible
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- I: Infected
- R: Recovered

Compartmental model

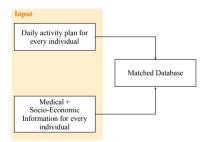
[Kel85], [San78]

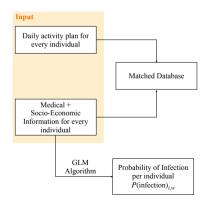
Work on an aggregated level (ODE's).

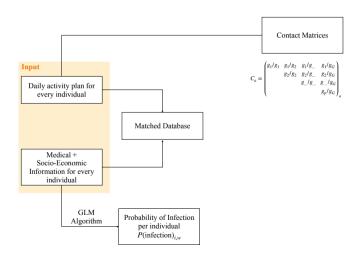
Notation	Parameters
λ	Contagion rate between S and I.
$1/\gamma$	Length of the infectious period for population <i>I</i> .

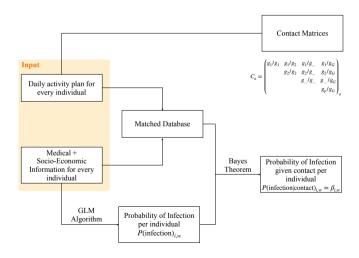


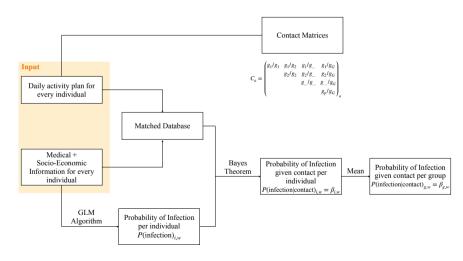


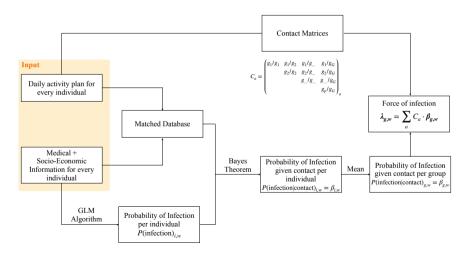


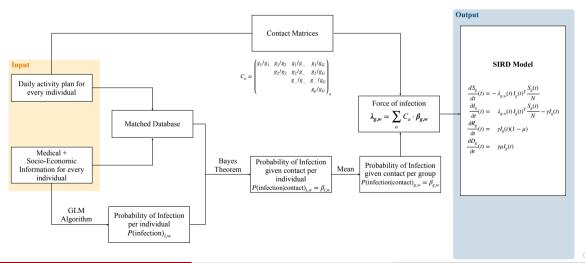


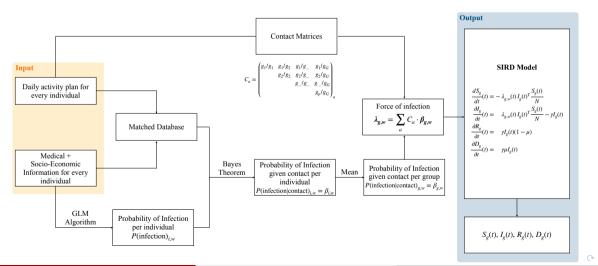








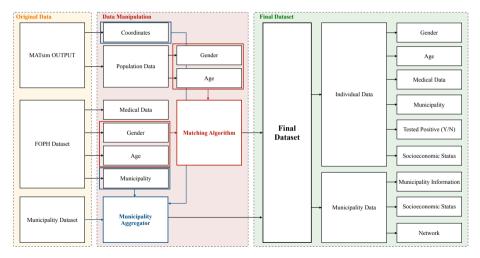




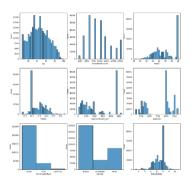
Results

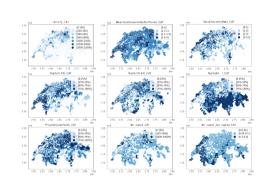


Pre-process [HB21], [RPA+21], [BFS22]



Pre-process





Activity Contact Matrix

- We stratify the model into 4 age groups:
 - C = the individuals younger than 18 years old,
 - A1 = individuals between 19 and 35 years-old,
 - A2 = individuals between 36 and 55 years-old
 - E = individuals over 56 years-old

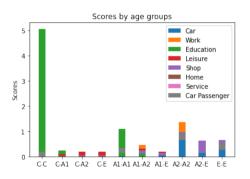
 The segmentation endows our model with high flexibility for policy testing on the different population groups. The contact matrix C_a becomes:

	child (C)	adult1 (A1)	adult2 (A2)	elderly (E)
child	child / child	child / adult1	child / adult2	child / elderly
adult1	-	adult1 / adult1	adult1 / adult2	adult1 / elderly
adult2	-	-	adult2 / adult2	adult2 / elderly
elderly	-	-	-	elderly / elderly

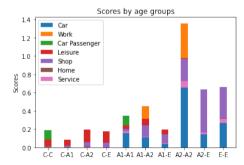
Table: Contact matrix structure for each activity

Activity Contact Matrix

All activities



Education removed



Generalized Linear Model Regression

$$P(\text{infection})_{i,1} \sim \beta_{\Lambda} \log(\Lambda) + \beta_{\chi} \log(\chi) + \beta_{\Upsilon} \log(\Upsilon) + \beta_{\kappa} \log(\kappa). \tag{1}$$

$$P(\text{infection})_{i,2} \sim \beta_{\Lambda} \log(\Lambda) + \beta_{\chi} \log(\chi) + \beta_{\Upsilon} \log(\Upsilon) + \beta_{\kappa} \log(\kappa) + \beta_{\Phi} \Phi. \tag{2}$$

Where:

- The age of the individual: Λ.
- ullet The percentage of the population above 65 years old for a specific municipality: χ .
- The percentage of the population between 20 and 65 years old for a specific municipality: Υ .
- The population density per km: κ .
- The income: Φ.

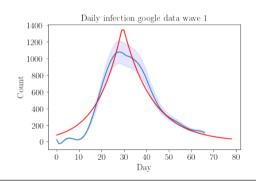


SIRD Disaggregated Model Output

Assumptions:

We reduce the activities the 24th of March 2020 to:

- 100% Education.
- 90% Leisure and Services.
- 80% Work.
- 70% Shop.
- 60% Car and car passenger.



Conclusions and future work

- The most significant contributions are:
 - We capture how the socio-economic characteristics of an individual define the force of infection
 - We obtain a self-explanatory model, defined by the estimates of the variables that characterize the spreading event
 - We obtain high goodness of fit of our model with Google data.
- The future work includes:
 - Improve and validate the current model
 - Scale it up to more groups.
 - Include it in an optimization framework to use it for policy analysis.



Thank you

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Generalized Linear Model Regression

Summary of statistics list of covariates

Table: Summary statistics of the list of covariates

	1 st WAVE			2 nd WAVE		
Stratified by infection	0	1	SMD	0	1	SMD
n	269642	414		281576	14499	
$\Lambda(mean(SD))$	44.42 (20.99)	50.91 (20.24)	0.315	44.43(21.05)	43.33(19.68)	0.054
$\Upsilon(mean(SD))$	3.89 (3.27)	65.17 (3.07)	0.0400	63.63(3.30)	63.91(3.25)	0.086
$\kappa(mean(SD))$	2399.74 (1760.49)	3123.01 (1733.89)	0.414	2222.49(1771.15)	2401.70(1751.82)	0.102
$\chi(mean(SD))$	16.89 (2.50)	16.26 (2.29)	0.0264	17.04(2.56)	16.84(2.48)	0.077
$\Phi(mean(SD))$) í	` ,		0.02(0.13)	0.02(0.12)	0.002

Generalized Linear Model Regression

Summary of the estimates using Causal Inference

Table: Coefficients using Matching score algorithm

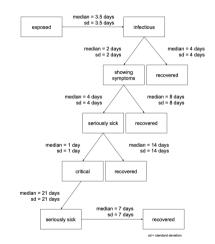
	1 st WAVE				2 nd WAVE			
Variable	Est.	SE	z-val.	p-val.	Est.	SE	z-val.	p-val.
$log(\Lambda)$	0.641	0.101	6.321	2.590e - 10	0.0301	0.0143	2.100	0.0358
$\log(\chi)$	1.395	0.773	1.806	0.0701	-0.386	0.107	-3.608	0.000309
$\log(\Upsilon)$	7.388	2.893	2.554	0.0106	-2.0381	0.391	-5.211	1.880e - 07
$\log(\kappa)$	0.281	0.109	2.594	0.00950	0.187	0.0141	13.246	$< 2\mathrm{e} - 16$
Φ					-0.0556	0.0261	-2.131	0.0331

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]:

$$P_{n,t} = 1 - \exp\left[-\Theta\sum_{m}q_{m,t}\cdot ci_{nm,t}\cdot in_{n,t}\cdot au_{nm,t}
ight]$$

- 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.





Activity-based model [AG92]

- 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 or 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...

Epidemiological models

Compartmental models

Issues:

- SEIR models work on an aggregate level: neglects the imperfect mixture.
- Not transferable to different epidemics.
- Crutial parameters might not be available.
- Exponential is a strong assumption.

Network models

The graph G is defined by n vertices, and m edges:

$$\{G_1, G_2, \dots, G_n\}$$
, where $n = (M \ m)$ with $M = N(N-1)/2$.

The probability of picking each graph is the same:

1/n.

Network models

Issues:

- Complex to find the correct adjacency matrix.
- Difficult to use them in densely populated areas.
- Quality of the contacts between two individuals. The adjacency matrices are binary.
- Static character of network models.

Individual-centric models

If an individual is susceptible and it has contact with an infected agent, it becomes infected with a probability: *p*.

This probability can be defined as desired. For example in [Smi09], the probability for person n to become infected by this process in a time step t is defined as:

$$P_{n,t} = 1 - \mathsf{exp}\left[-\Theta \sum_{m} q_{m,t} \cdot \mathit{ci}_{nm,t} \cdot \mathit{in}_{n,t} \cdot au_{nm,t}
ight]$$

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.

Individual-centric models

- ullet 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.