

From agent-based scenario simulations of disease dynamics to expert support on public health interventions

Prof. Dr. Michael Moeckel

WCE 2024, Cape Town, SA
25th of September 2024
Oral abstract presentation



TH Aschaffenburg
university of applied sciences

Thanks to project collaborators / paper



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IT Support



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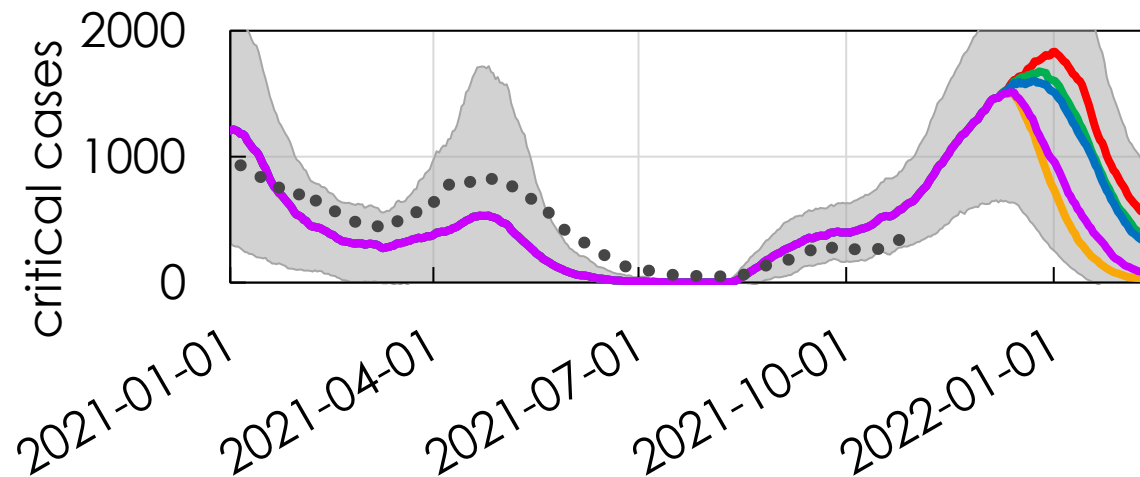
Harnessing multi-output machine learning approach and dynamical observables from network structure to optimize COVID-19 intervention strategies

Caroline Alves, Katharina Kuhnert, Francisco Aparecido Rodrigues, Michael Moeckel
doi: <https://doi.org/10.1101/2024.09.23.24313636>

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State of art @ Covid-19: Scenario based disease modeling

- Tools were made to predict disease dynamics
- Scenario techniques used to probe possible future developments and the effects of public health interventions



medRxiv
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<https://www.medrxiv.org/content/10.1101/2021.08.31.21262915v1>

<https://www.medrxiv.org/content/10.1101/2021.11.28.21266959v1>

- Comparisons between different interventions difficult

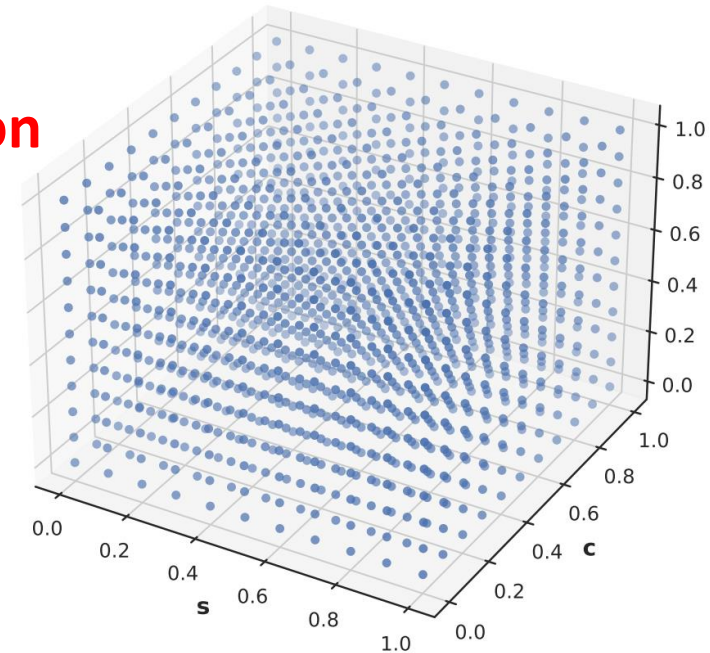
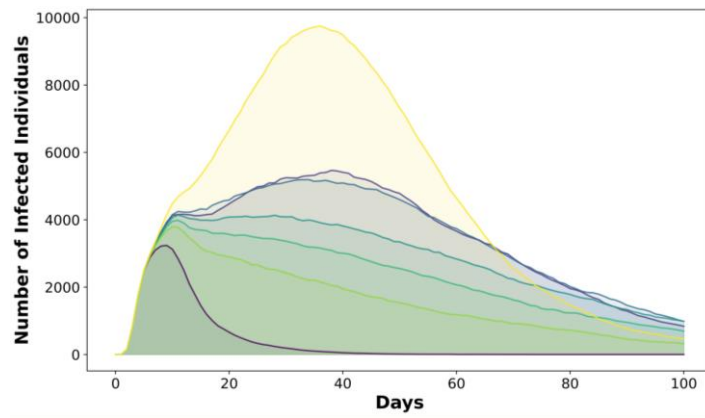


Key message of the talk: Actual question is different!

From:
**Prediction of
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To:
**Representation
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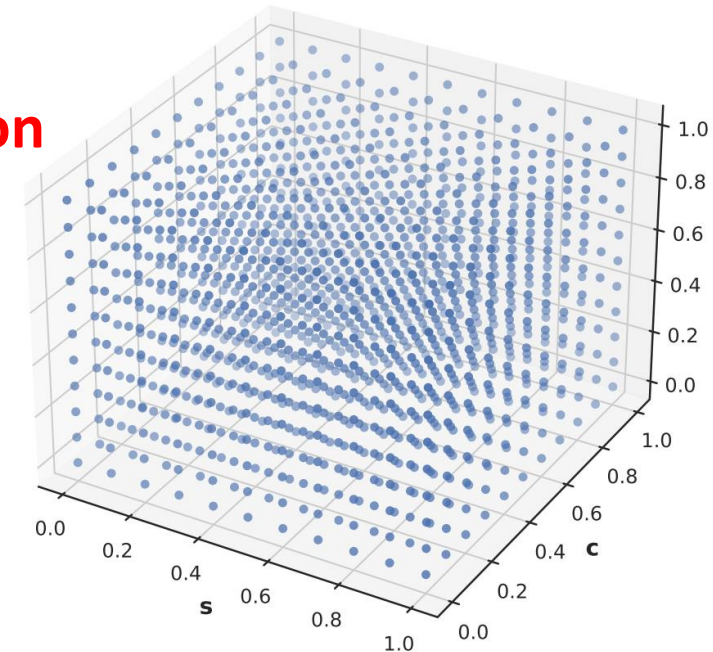
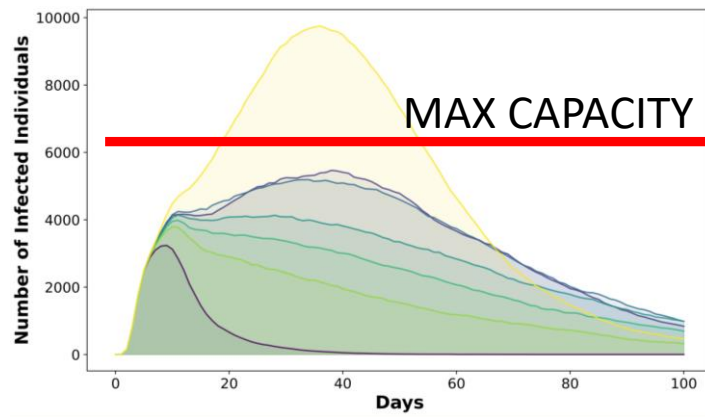


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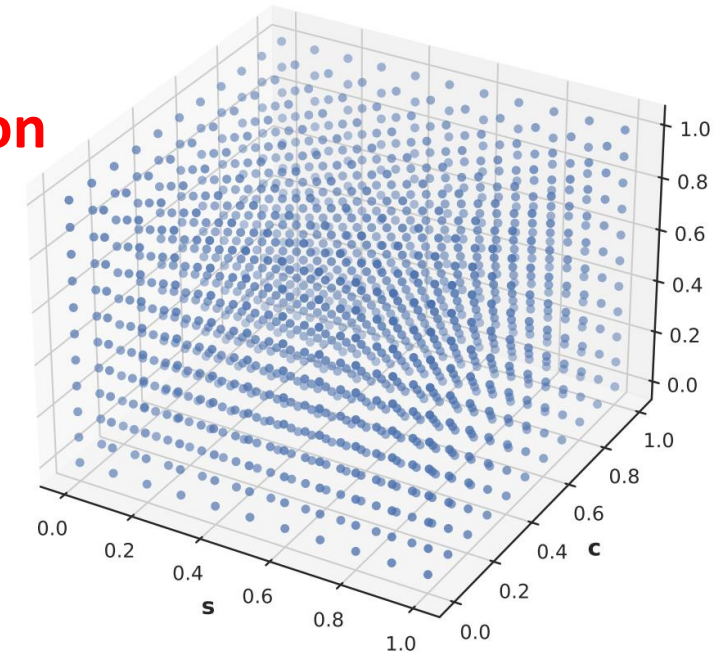
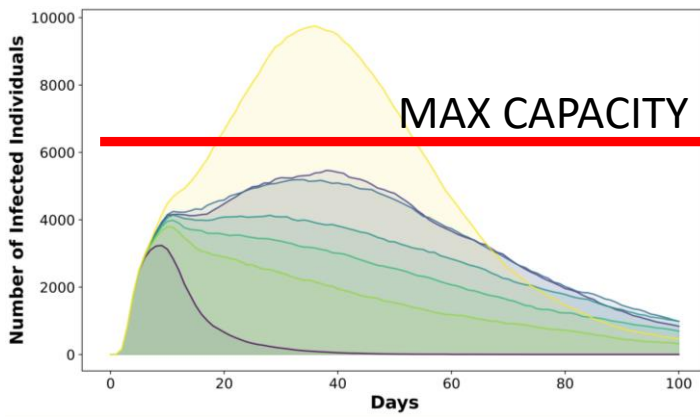
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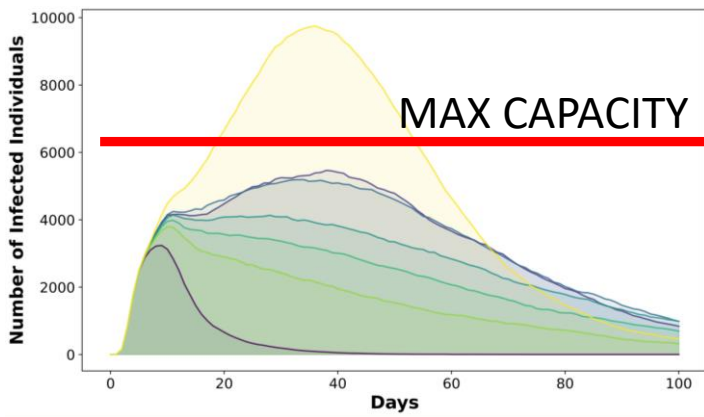
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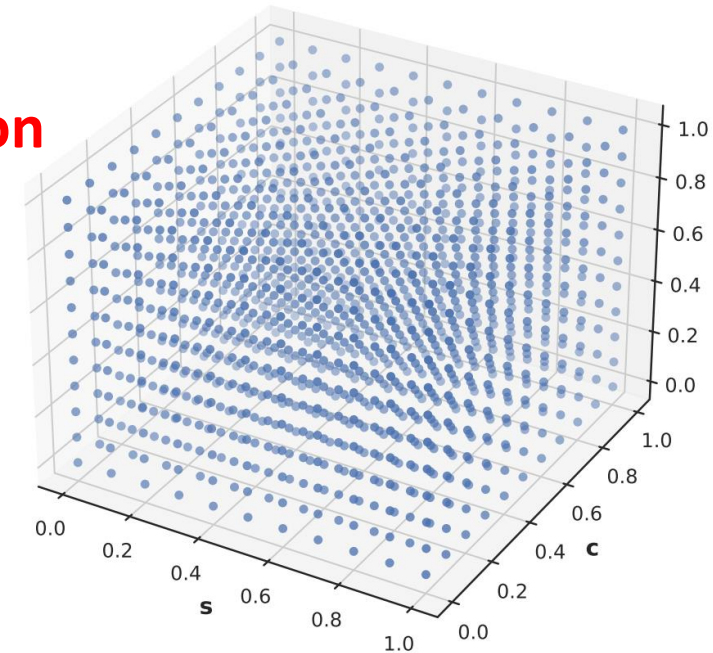
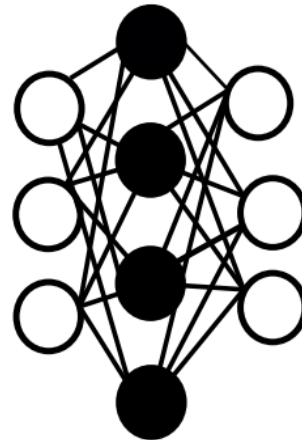
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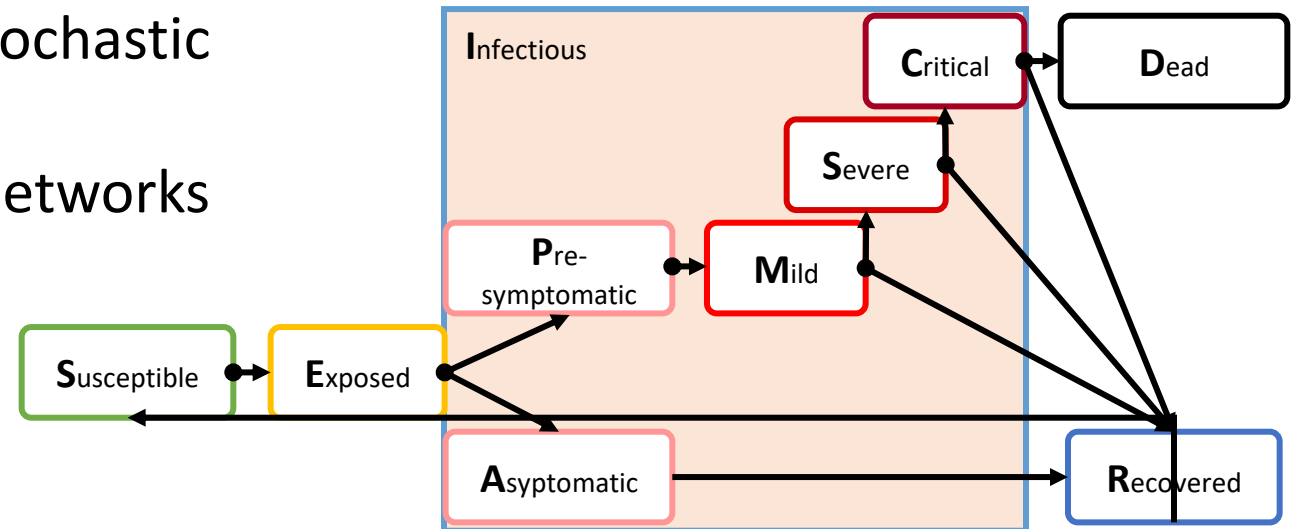
Machine Learning



**Selection of permissible dynamics
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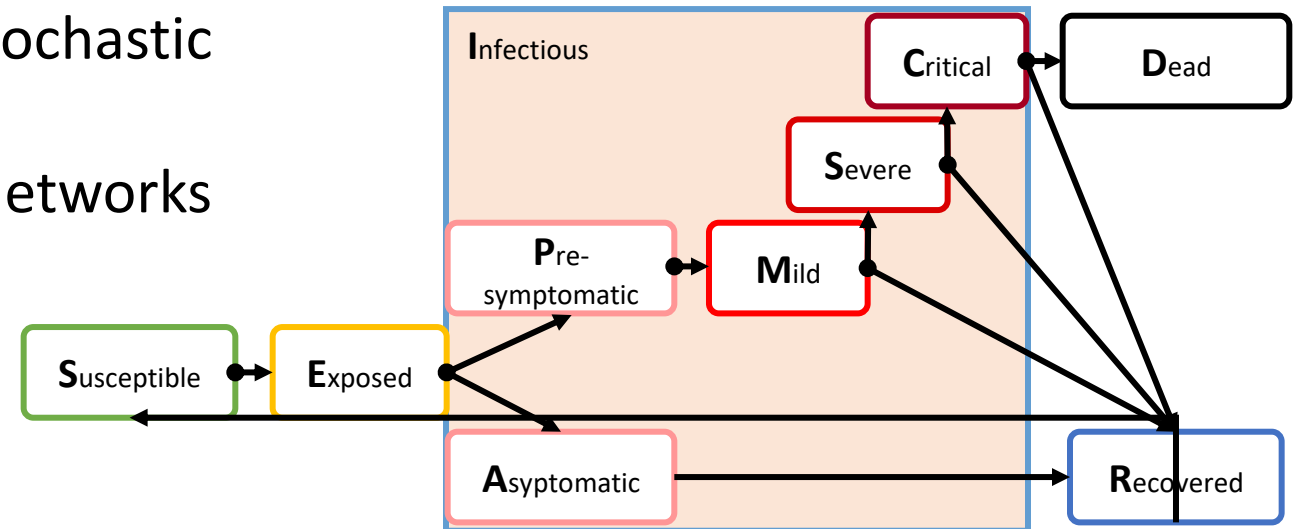
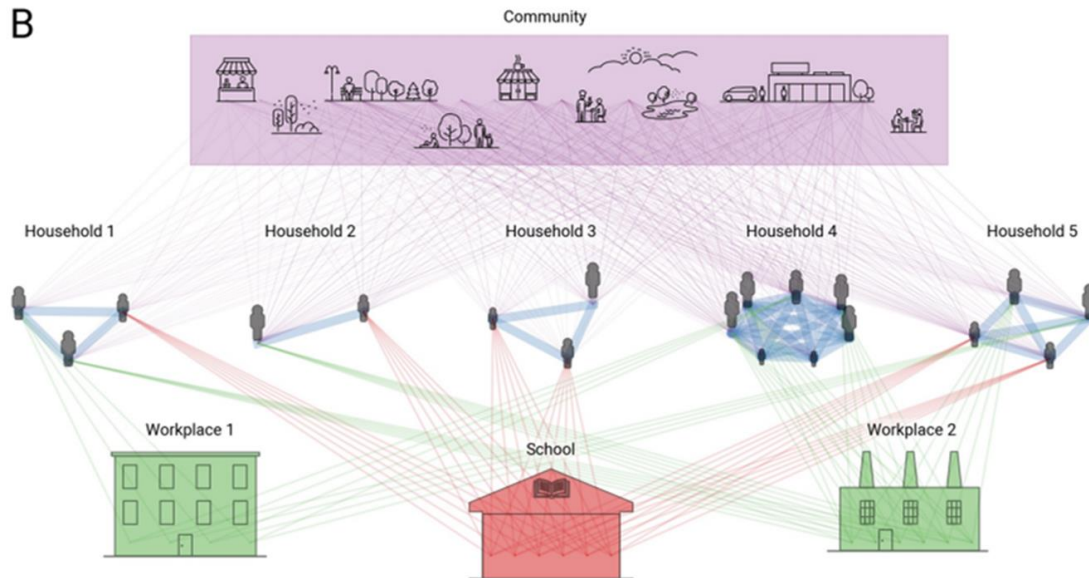
Agent-based stochastic simulators: compartments & contact networks

- Infectious dynamics modeled by a stochastic random process of agents
- Agents are represented on contact networks (multi-pgraph networks)



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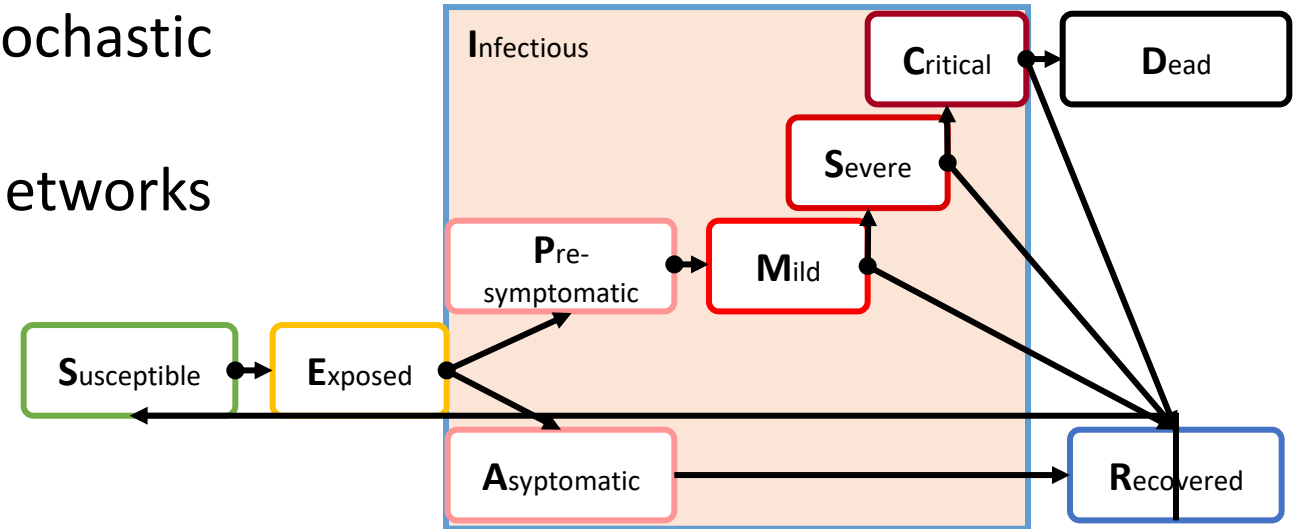
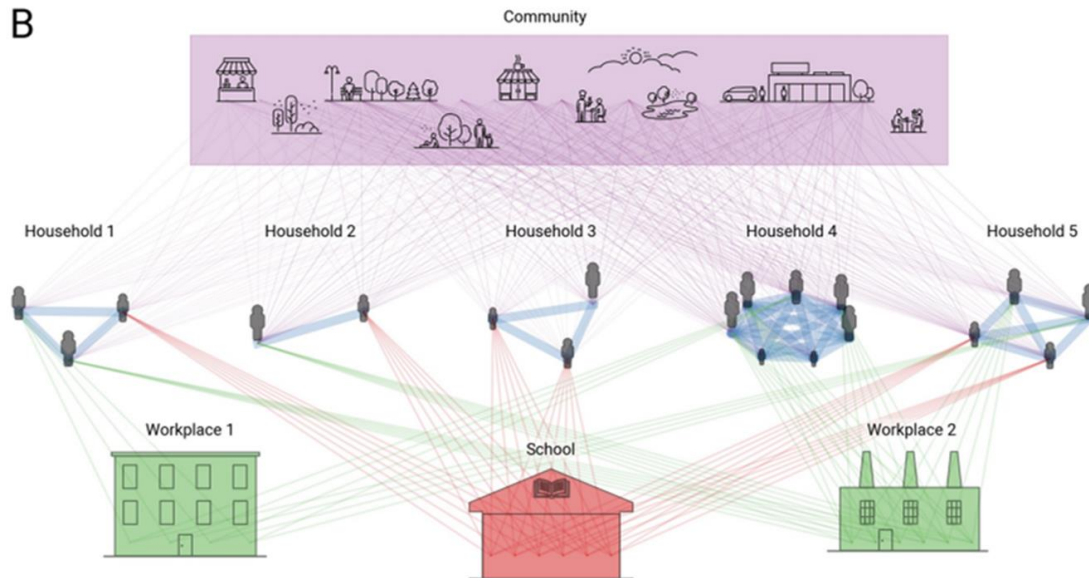


Agent-based stochastic simulators: compartments & contact networks



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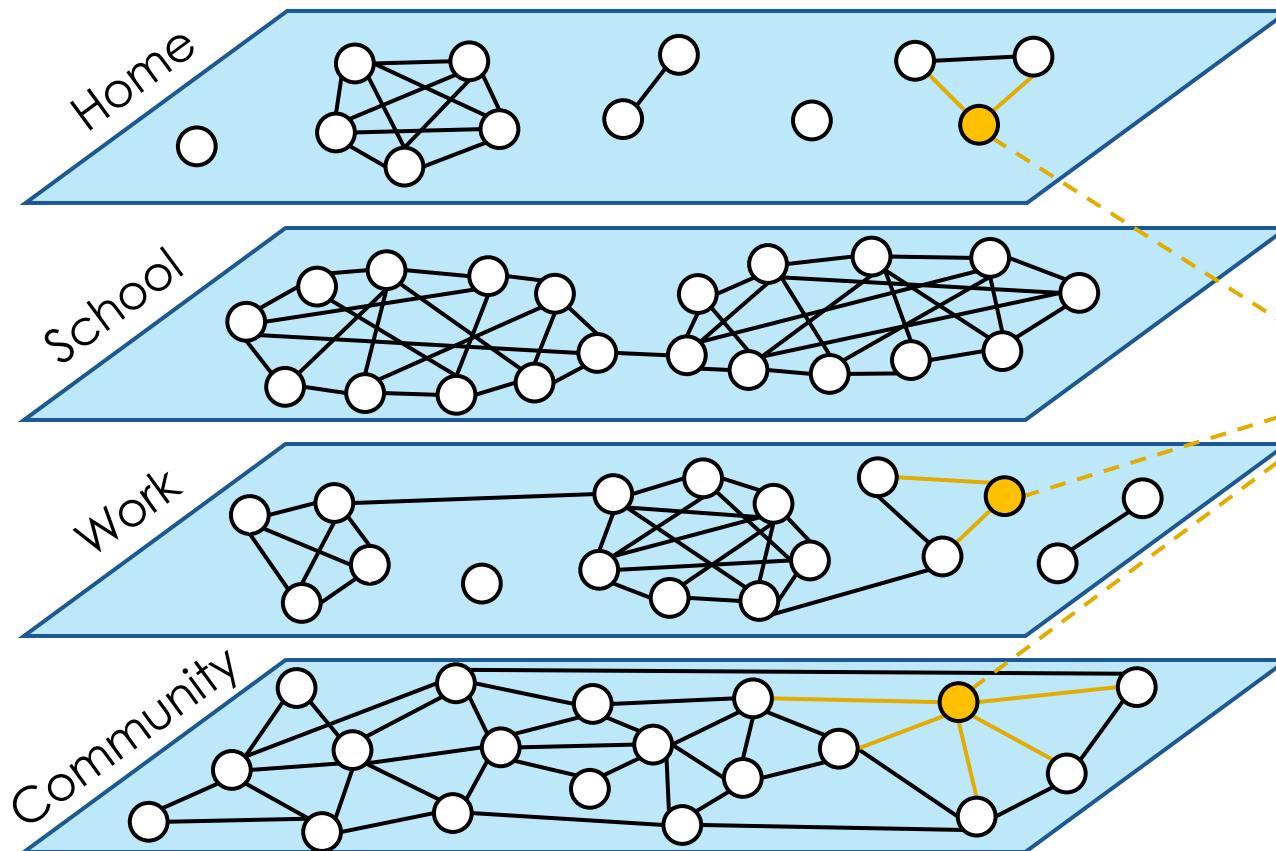
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Multi-graph structure of contact networks

Home, school, work, community

Contact layers:

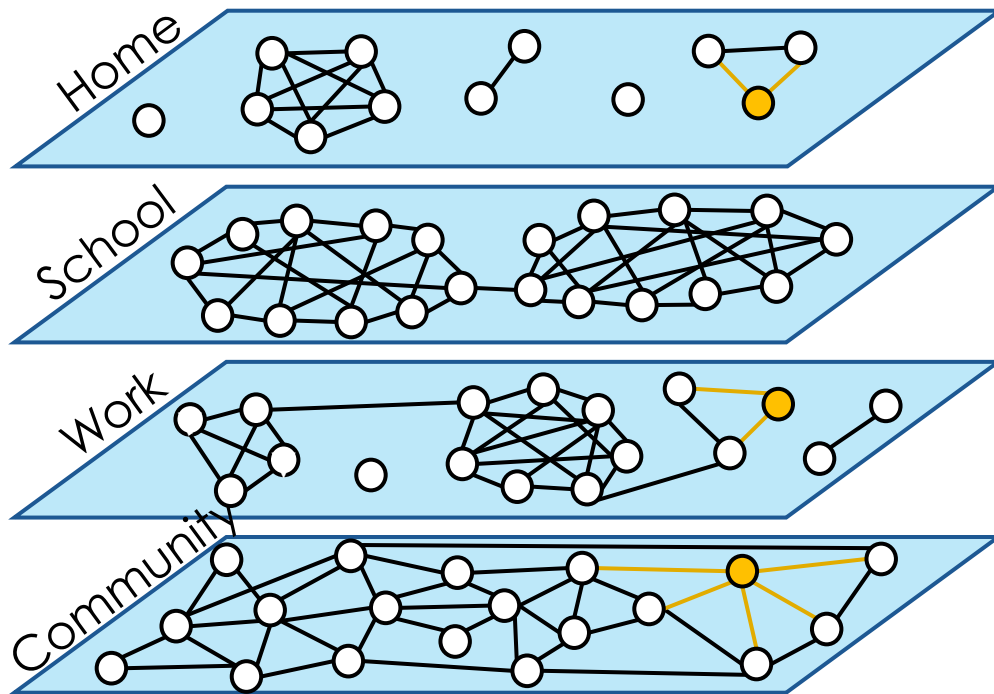


Agent State:

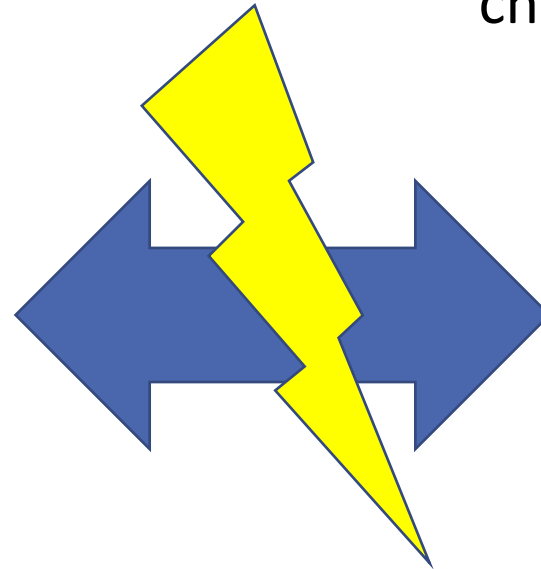
| | |
|-----------------|--------------------------|
| ID | 19573 |
| age | 46 |
| sex | male |
| contacts | {h: [...], s: [...],...} |
| infectious | False |
| ... | |
| severe_prob | 0.049 |
| death_prob | 0.273 |
| ... | |
| date_infected | '2020-10-12' |
| date_recovered | '2020-10-26' |
| date_vaccinated | '2021-05-05' |
| ... | |

Numerical complexity: Multi-graph problem for all configurations

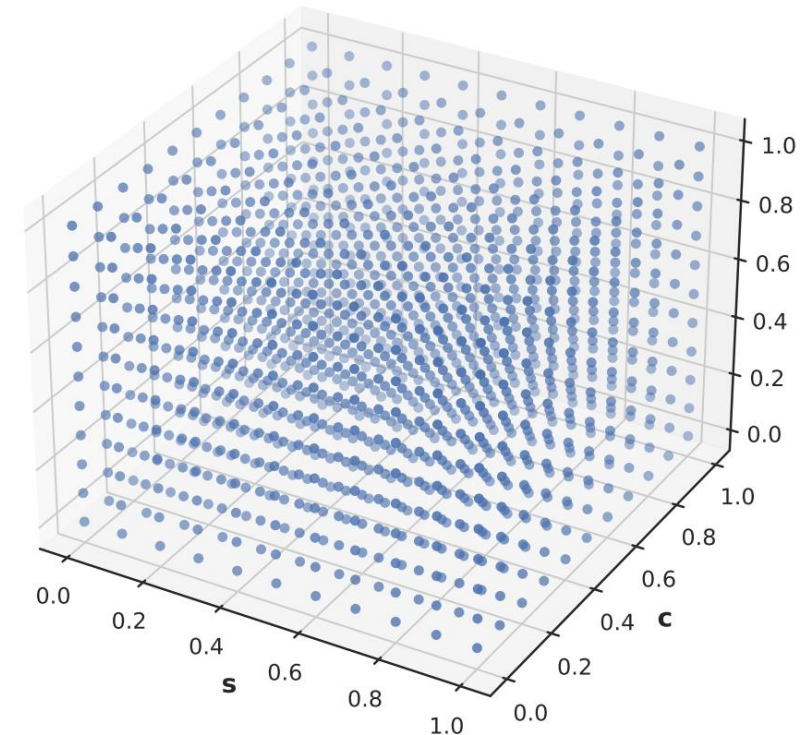
Contact network subgraphs
represented by a adjacency matrix



Interventions (contact restrictions)
change contact networks:

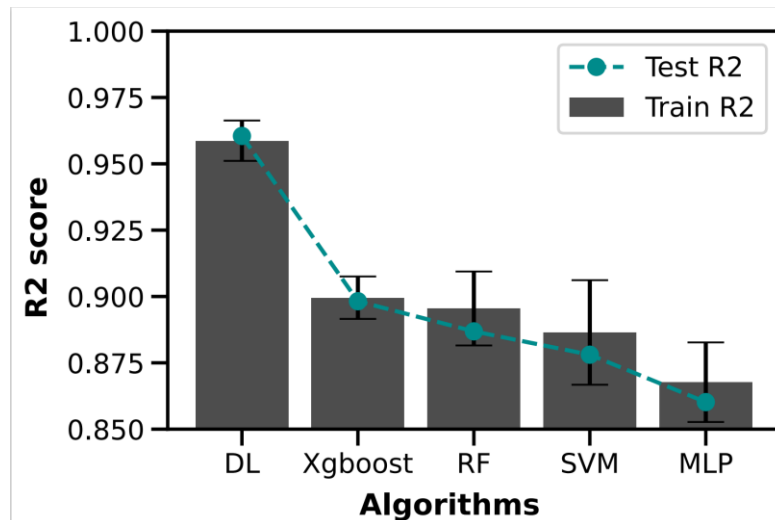
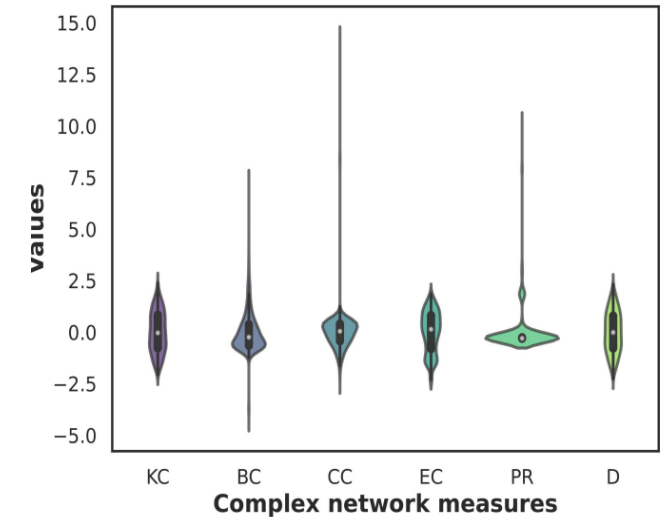


Numerical complexity
Simplifications needed



Reduced (sufficient) network characterisation by complex network measures

- Create synthetic dataset from COVASIM runs
- Extract complex network measures from adjacency matrix
- Their values differ depending on chosen restrictions

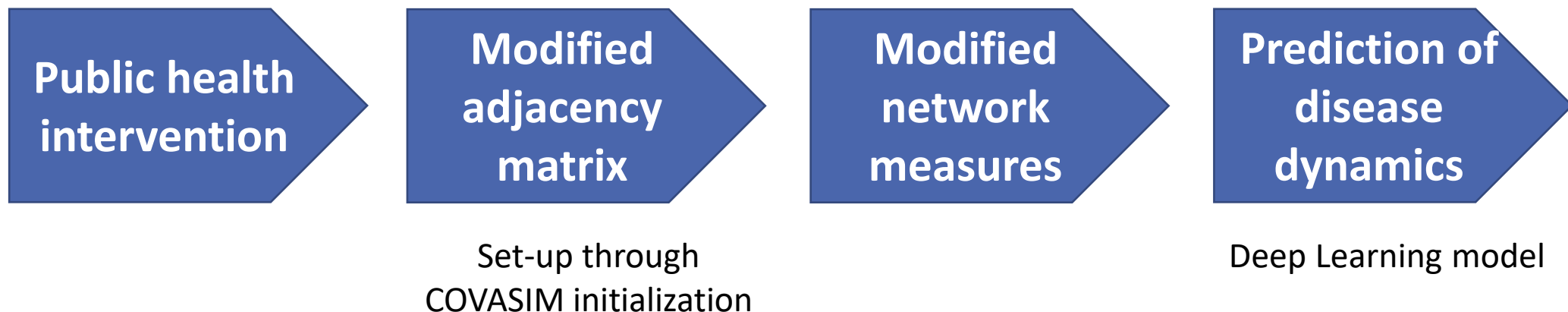


- They have predictive power on the disease dynamics
- Shown empirically by testing various machine learning models (deep learning performs best, >1000 simulation runs used)



1st result: complex network measures are a helpful simplification for contact modeling

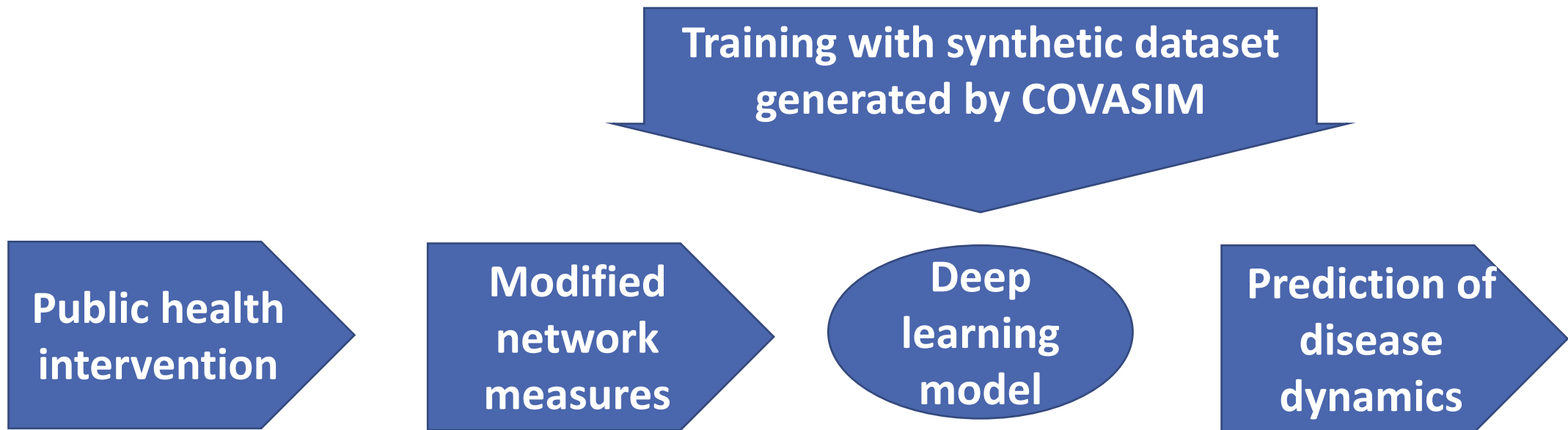
- Contact restrictions imposed by public health interventions modify contact networks
- Global interventions (e.g. by public orders) change the contact network in a global way which is captured by modified values of complex network measures





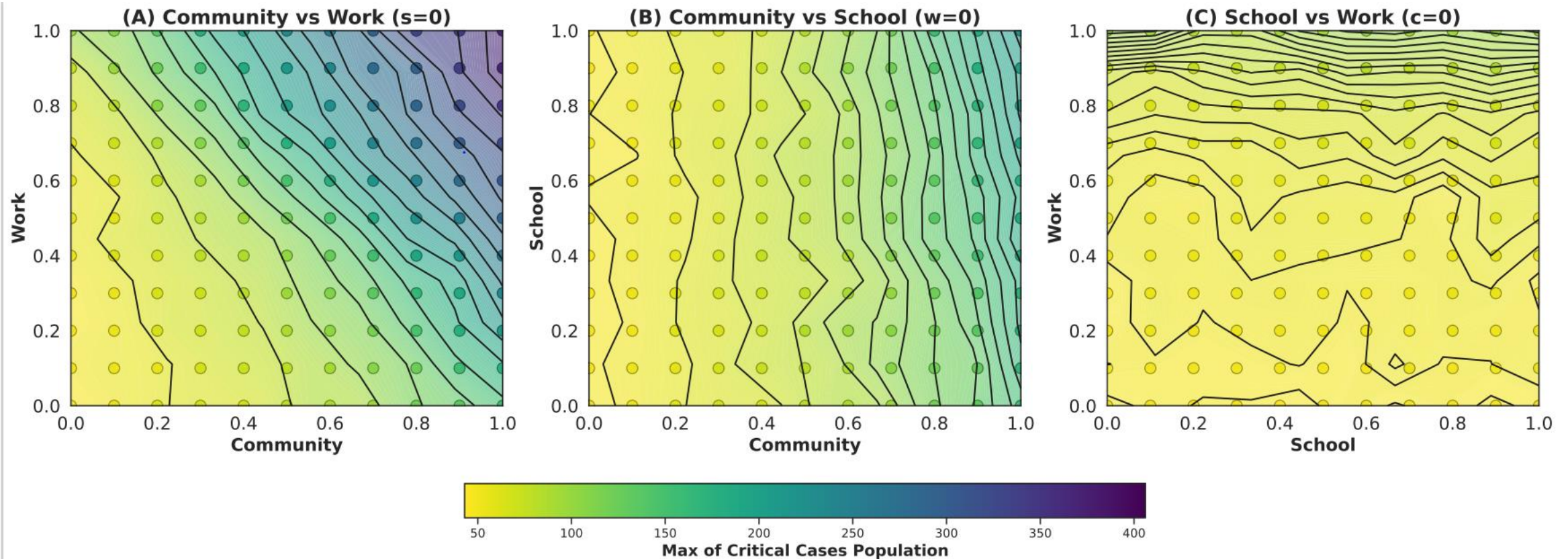
Speed-up of phase space scanning

- Machine learning methods are powerful tools for interpolation
- Training a substitutional neural network allows for quick evaluation of further configurations



2nd result: manifold of equivalent interventions mapped out

Intersections of intervention phase space





Discussion & Outlook

Next steps:

- Extension to other public health interventions
- Improved tools for manifold representation in intervention space
- Collaborations welcome!

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