

PanSim + Sim-2APL: A Framework for Large-Scale Distributed Simulation with Complex Agents

Parantapa Bhattacharya[†], A. Jan de Mooij[‡], Davide Dell'Anna[‡],
Mehdi Dastani[‡], Brian Logan[‡], and Samarth Swarup[†]

[†]University of Virginia, USA

[‡]Universiteit Utrecht, The Netherlands

EMAS Workshop 2021

Companion publication

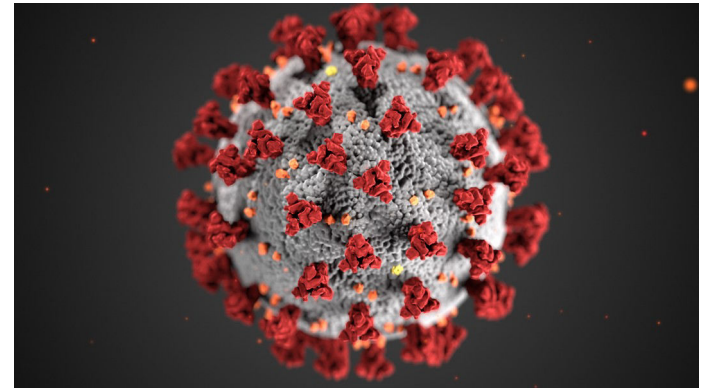
“Quantifying the Effects of Norms on COVID-19 Cases
Using an Agent-based Simulation”

Jan de Mooij, Davide Dell'Anna, Parantapa Bhattacharya,
Mehdi Dastani, Brian Logan, and Samarth Swarup

MABS Workshop 2021

A Covid-19 Epidemic Simulation with norm-aware complex agents

- Non-pharmaceutical interventions has been heavily used to manage spread of Covid-19
- Important to understand the efficacy of these interventions
- Agent based simulation is an effective tool for this



Related Work

- Fast epidemic simulation platforms for HPC
 - Barrett et al. [2008], Bisset et al. [2009], Bhatele et al. [2017]
 - Simple agent models
- Slow complex agent models
 - Barrett et al. [2013]
- Covid-19 Simulations
 - Single node: MATSim Episim (Müller et al. [2021]), COMOKit (Gaudou et al. [2020])
 - HPC based: CityCovid [www.anl.gov/dis/citycovid]

What is PanSim?

- PanSim: The Pandemic Simulator
 - A distributed agent based simulation framework
 - Discrete time simulator
 - Runs on distributed memory clusters
- Simulates two contagions concurrently on top a dynamic contact network
- Simple contagion
 - SIR like model, fully describable declaratively
 - In the current work: Covid-19 disease model
- Complex contagion
 - Custom code must be provided
 - In the current work: A BDI based behavior model written using Sim-2APL

What is Sim-2APL?

- 2APL is a BDI based multi-agent programming framework
 - supports development of complex reasoning agents
 - defines the concepts of beliefs, goals, plans, and reasoning rules
 - dictates the interaction between them
- Java-2APL is a java base re-implementation of 2APL
 - Context: captures the agent's information or beliefs
 - Triggers: capture events or goals the agent may react to
 - Plans: capture specific parts of behavior that agents can perform
 - Plan Schemes: match triggers to a suitable plan to be executed
- Sim-2APL: Extension of Java-2APL to support discrete time simulations

Behavior Aware Covid-19 Simulation

- Agent state
 - Socio-psychological behavior state
 - Disease state
- Agent behavior
 - Disease Modifier behavior
 - Wearing masks, social distancing, ...
 - Visible attribute behavior
 - Showing symptoms
 - Displaying political/religious affiliations, ...

```
# PanSim Disease Model
```

```
unit_time = 300.0
```

```
states = [ "succ", "expo", "isymp", "iasymp", "recov" ]
```

```
behaviors = [ "base", "mask", "sdist", "mask_sdist" ]
```

```
exposed_state = "expo"
```

```
[susceptibility]
```

```
succ = 1
```

```
[infectivity]
```

```
isymp = 4.81e-05
```

```
iasymp = 2.40e-05
```

```
[progression]
```

```
expo = { isymp = 0.6, iasymp = 0.4 }
```

```
isymp = { recov = 1.0 }
```

```
iasymp = { recov = 1.0 }
```

```
[dwell_time]
```

```
expo = { isymp = "dist1", iasymp = "dist1" }
```

```
isymp = { recov = "dist2" }
```

```
iasymp = { recov = "dist2" }
```

```
[distribution]
```

```
dist1 = { dist = "fixed", value = 6 }
```

```
dist2 = { dist = "fixed", value = 14 }
```

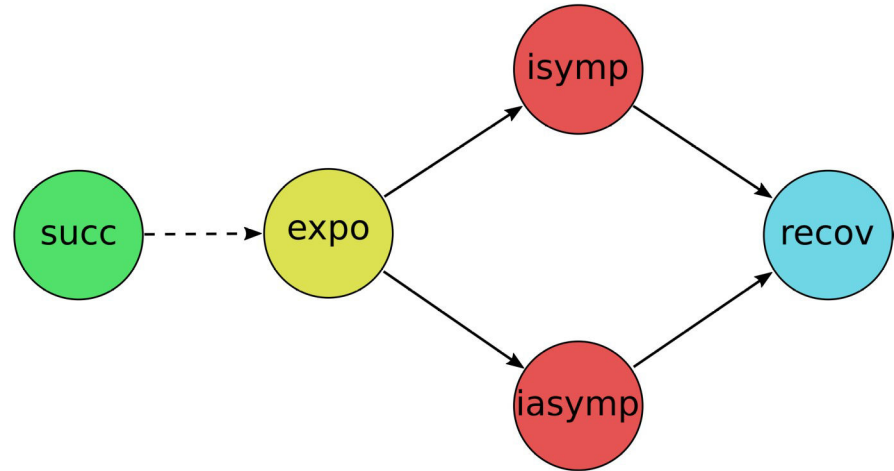
```
[behavior_modifier]
```

```
base = { base = 1.0, mask = 0.5, sdist = 0.5, mask_sdist = 0.25 }
```

```
mask = { base = 0.5, mask = 0.25, sdist = 0.25, mask_sdist = 0.15625 }
```

```
sdist = { base = 0.5, mask = 0.25, sdist = 0.25, mask_sdist = 0.15625 }
```

```
mask_sdist = { base = 0.25, mask = 0.15625, sdist = 0.15625, mask_sdist = 3.906e-3 }
```



Data driven simulation

- Realistic synthetic population
 - Aggregated from multiple sources: American Community Survey (ACS), National Household Travel Survey (NHTS), various location and building datasets
 - Individual attributes: County, Occupation, Work Hours, Shopping location, Shopping time, ...
- Mobility Data
 - Anonymized and privacy enhanced cellphone based mobility data
 - Provided by Cuebiq
- Covid-19 Case data
 - County level data from Covid Facts
- Executive orders in Virginia

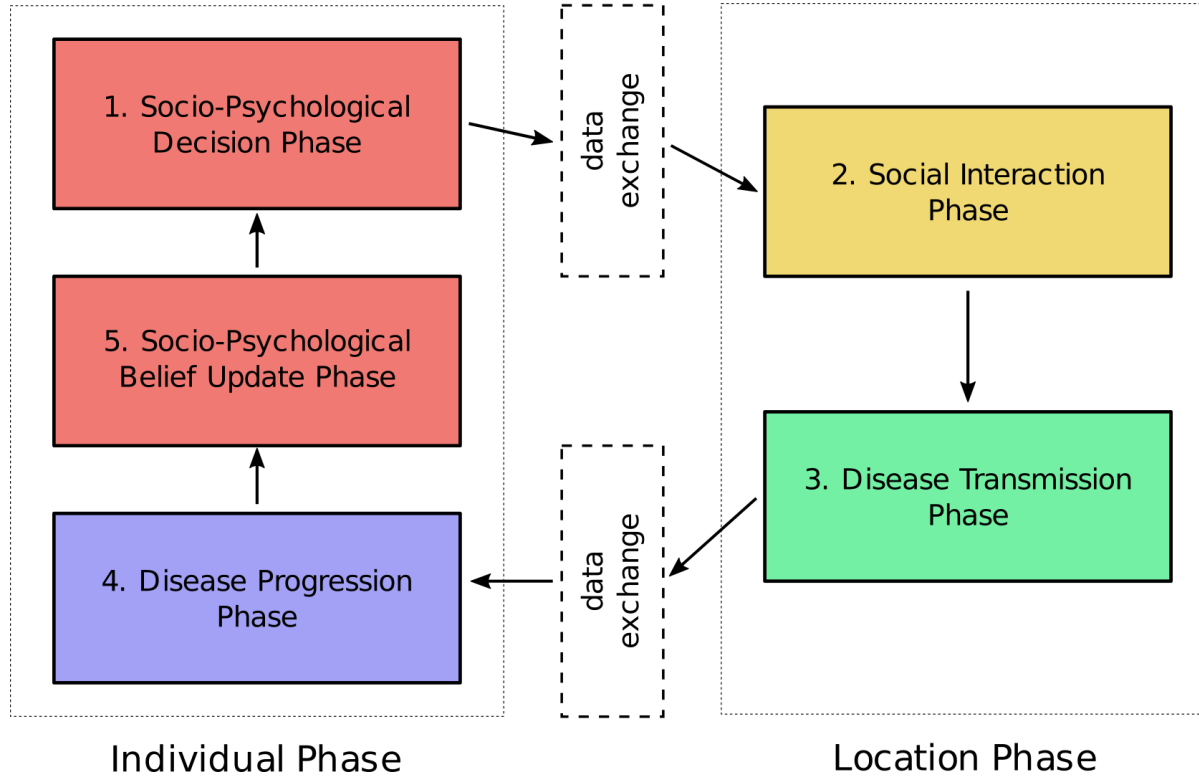
Norm aware Sim2APL agents

- 11 norms: A subset of executive orders in Virginia
- Regimented norms (agents must follow)
 - e.g. business closure, employees wear masks, ...
- Non-regimented norm (agents can ignore)
 - e.g. mask wearing, social distancing, ...
- Violating or obeying a norm
 - Trust in governmental institutions
- More details in companion paper

PanSim System Implementation

- Agents and locations partitioned across ranks
- Simple greedy partitioning
- Implemented in
 - Python, C++, MPI
- Uses Apache Arrow for interfacing with Behavior module
 - Supports: C, C++, Java, Python, R, ...

Phases of a PanSim simulation



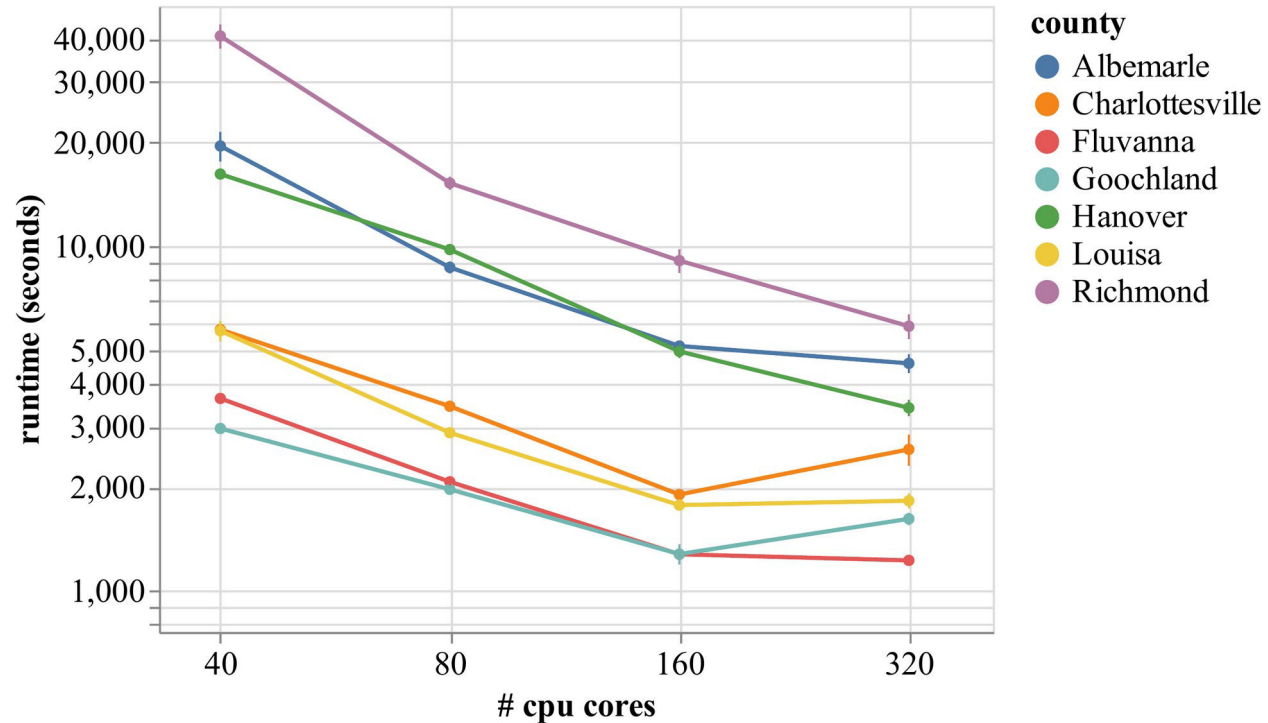
- Discrete time simulation
- Bulk synchronous parallel design
- Each timestep consists of multiple phases
- Within a phase computation is done in parallel

Sim2APL+PanSim: Scaling Experiments

- 7 counties in the state of Virginia, USA
- 180 days (starting March 1, 2020)
- Compute node configuration
 - 384 GB DDR4 RAM
 - 2 x 20 core Intel Xeon Gold 6148 CPUs
 - Mellanox Connect-X 5 adaptors
- 10 replicates of each simulation

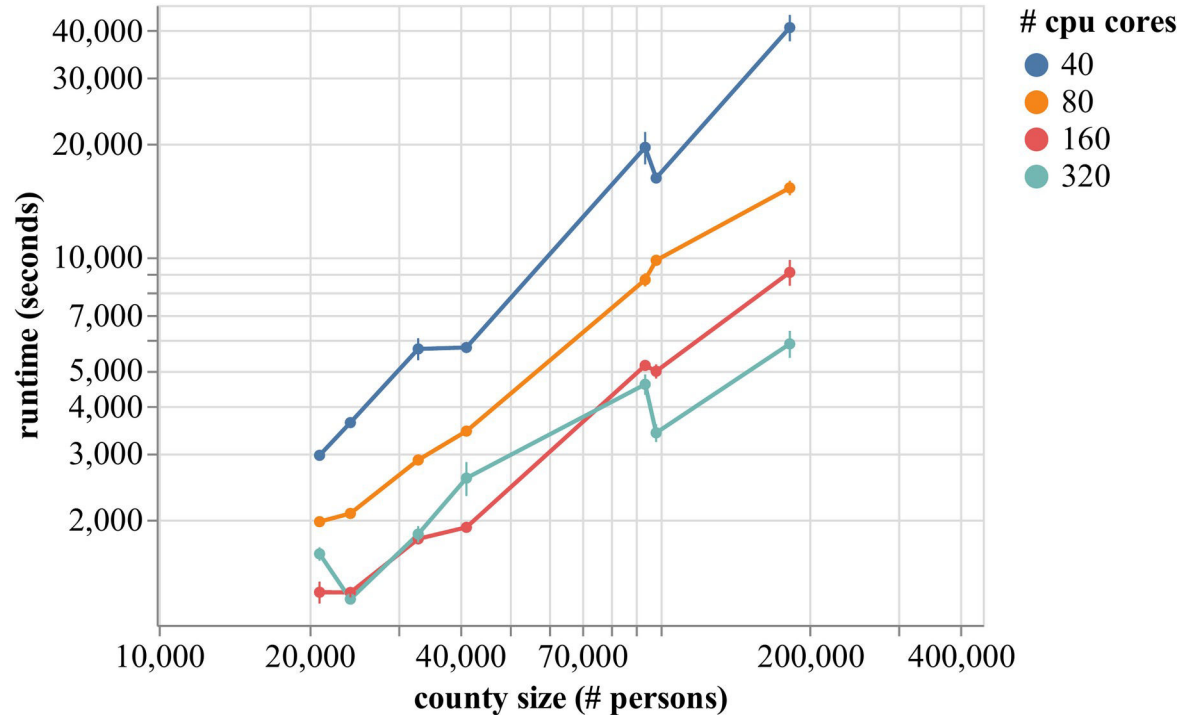
County	Persons	Households	Visits
Goochland	20,923	8,240	680,571
Fluvanna	24,110	9,776	779,337
Louisa	32,938	13,398	1,066,179
Charlottesville	41,120	18,377	1,335,596
Albemarle	93,570	39,920	3,047,807
Hanover	98,435	38,149	3,204,317
Richmond	181,975	89,146	5,920,569

Scaling Sim2APL Covid-19 simulations with PanSim



The mean run time of PanSim+Sim-2APL simulations for seven counties of the state of Virginia compared with increasing number of CPU cores

Scaling Sim2APL Covid-19 simulations with PanSim



The mean run time of PanSim+Sim-2APL simulations when using different number of CPU cores for increasing population sizes

Conclusion

- We presented a new simulation framework for designing and developing agent based simulations with complex cognitive agents.
- Our system can scale to 320 CPU cores given a large enough region to simulate.
- Further details about the simulations can be found in our companion paper.

References

- Christopher Barrett, Keith Bisset, Shridhar Chandan, Jiangzhuo Chen, Youngyun Chungbaek, Stephen Eubank, Yaman Evrenosoglu, Bryan Lewis, Kristian Lum, Achla Marathe, Madhav Marathe, Henning Mortveit, Nidhi Parikh, Arun Phadke, Jeffrey Reed, Caitlin Rivers, Sudip Saha, Paula Stretz, Samarth Swarup, James Thorp, Anil Vullikanti and Dawen Xie. “Planning and Response in the Aftermath of a Large Crisis: An Agent-based Informatics Framework”, WSC 2013.
- Christopher L. Barrett, Keith R. Bisset, Stephen G. Eubank, Xizhou Feng and Madhav V. Marathe. “EpiSimdemics: an Efficient Algorithm for Simulating the Spread of Infectious Disease over Large Realistic Social Networks”. IEEE/ACM Supercomputing 2008.
- Abhinav Bhatele, Jae-Seung Yeom, Nikhil Jain, Chris J. Kuhlman, Yarden Livnat, Keith R. Bisset, Laxmikant V. Kale, Madhav V. Marathe. “Massively Parallel Simulations of Spread of Infectious Diseases over Realistic Social Networks”. IEEE/ACM CCGRID 2017.
- Sebastian A. Müller, Michael Balmer, William Charlton, Ricardo Ewert, Andreas Neumann, Christian Rakow, Tilmann Schlenker, and ProfileKai Nagel. “Predicting the effects of COVID-19 related interventions in urban settings by combining activity-based modelling, agent-based simulation, and mobile phone data”, <https://doi.org/10.1101/2021.02.27.21252583>
- Gaudou, B., Huynh, N. D., Philippon, D., Brugière, A., Chapuis, K., Taillandier, P., Larmande, P., and Drogoul, A. (2020) COMOKIT: a modeling kit to understand, analyze and compare the impacts of mitigation policies against the COVID-19 epidemic at the scale of a city . Front. Public Health. doi: 10.3389/fpubh.2020.563247

Thank You