City-scale Agent-based Simulator for Modelling COVID-19 Spread

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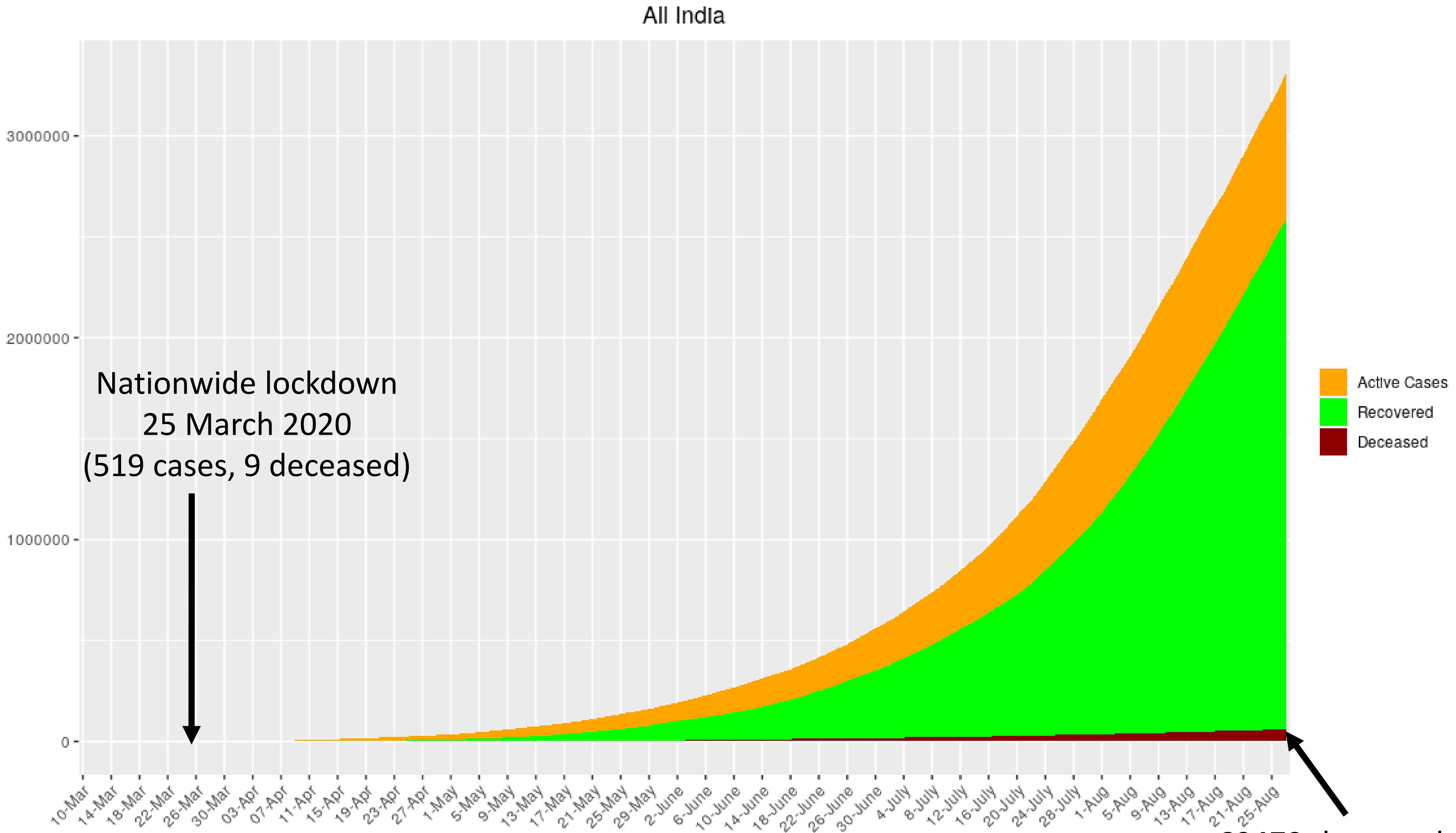
Joint effort with TIFR Mumbai Colleagues

28/08/2020

COVID-19 India data

Web search:
incovid19 ISI

Courtesy:
Siva Athreya and team



60472 deceased
27 August 2020

Our COVID-19 response

- Tools
  - Agent-based city-scale simulator (open source) https://cni.iisc.ac.in/simulator
  - Workplace readiness indicator (open source) https://covid.readiness.in
  - Swabs-to-labs (in progress) https://swabs2labs.readiness.in/
- For whom?
  - City/state administrators – e.g., KSDMA (Bengaluru), BMC (Mumbai)
  - Organisations (e.g., MSMEs, government offices, IT offices)
  - Karnataka health department, BBMP for efficient transfer of swabs to labs
- Studies
  - Mumbai containment zones / trains
  - Bengaluru opening of schools

Mumbai: Containment effectiveness and trains

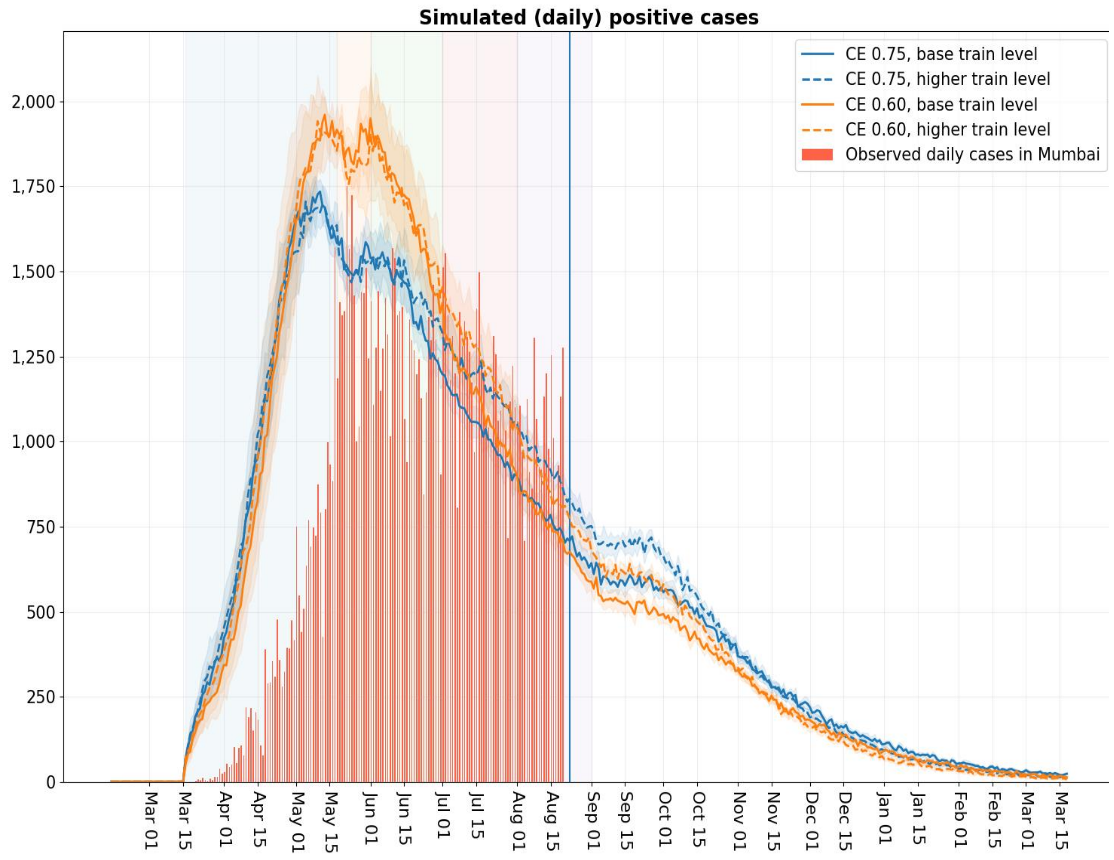
From our TIFR colleagues

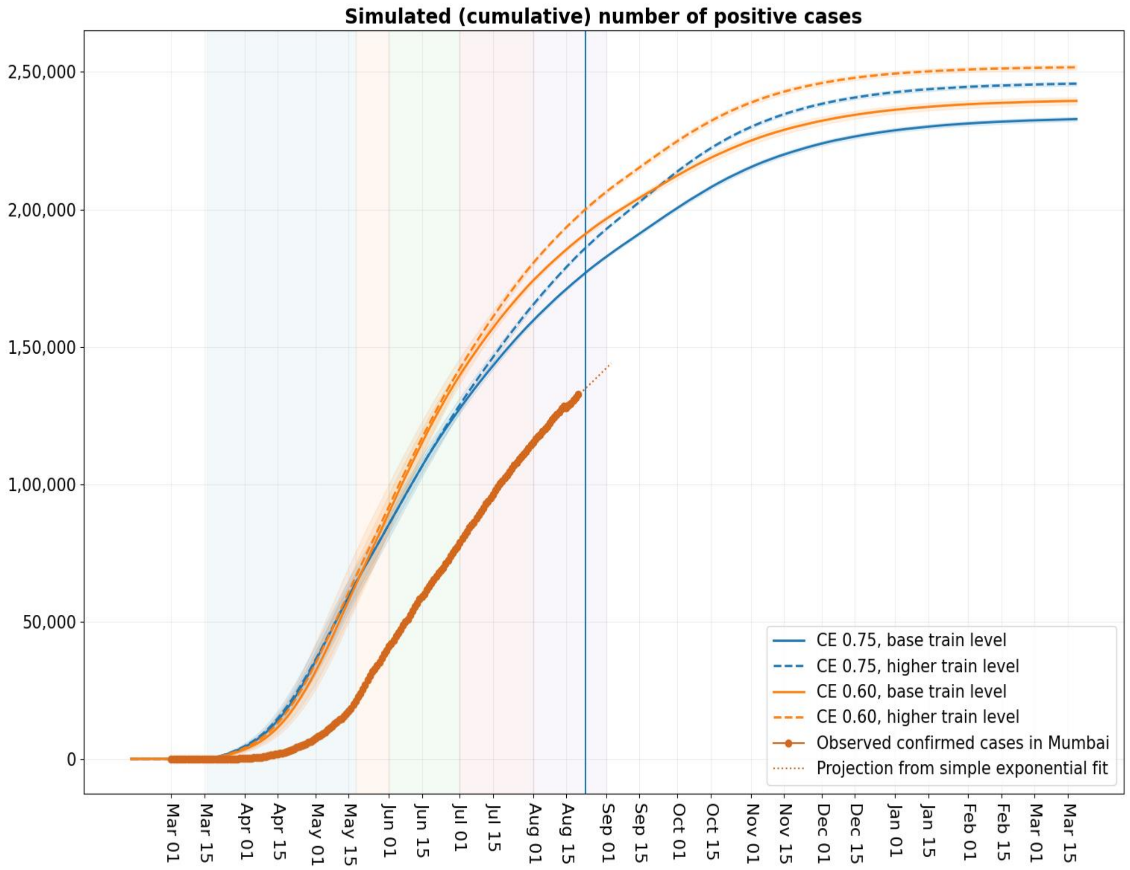
- Containment of a neighborhood (100 m around a case) proportional to number hospitalised
  - Containment Effectiveness 75% => 3 out of 4 movements constrained.
  - What if effectiveness is 60%?

- To manage infections from transport (trains), open economy gradually
  - Trains open 30% in September
  - 60% in October
  - 100% November
  - Offices are opened similarly
  - Stagger office times, use shifts to aid in social distancing precautions
  - What if trains interaction is 50% more than the 'base level'?

Predictions for Mumbai

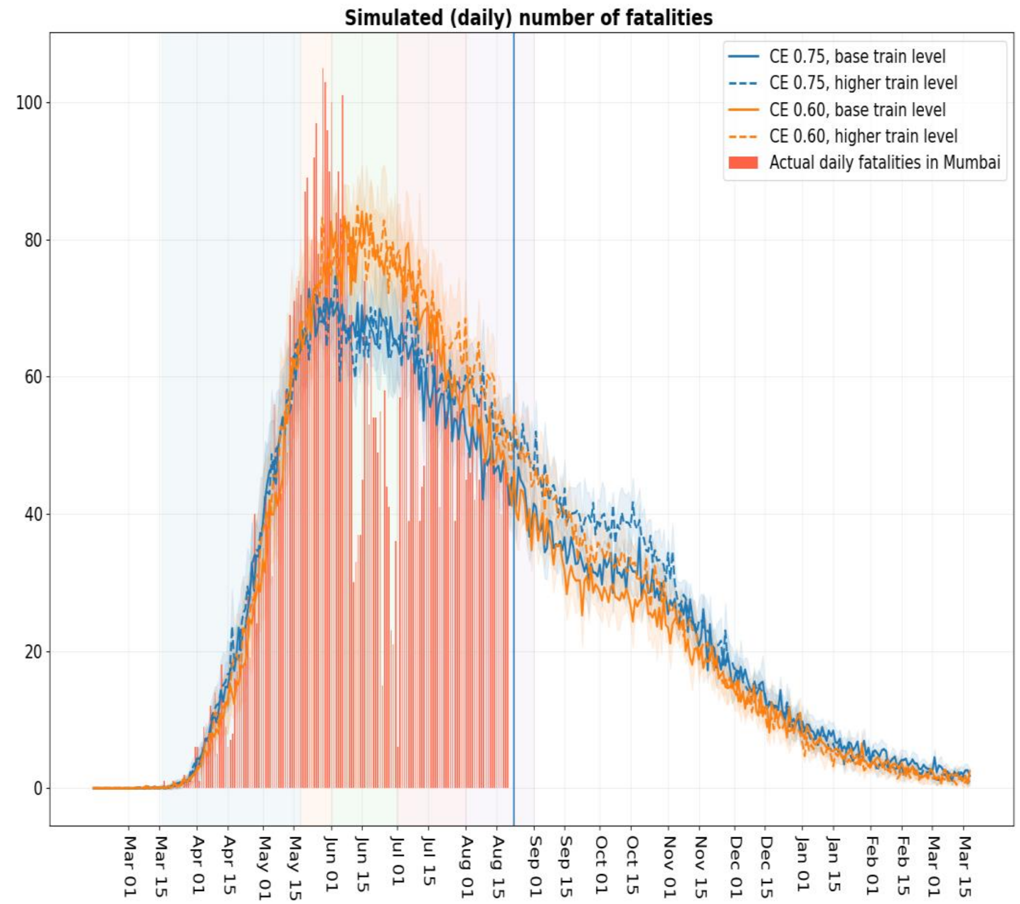
Under various levels of ‘containment effectiveness’ (CE) and train contact levels

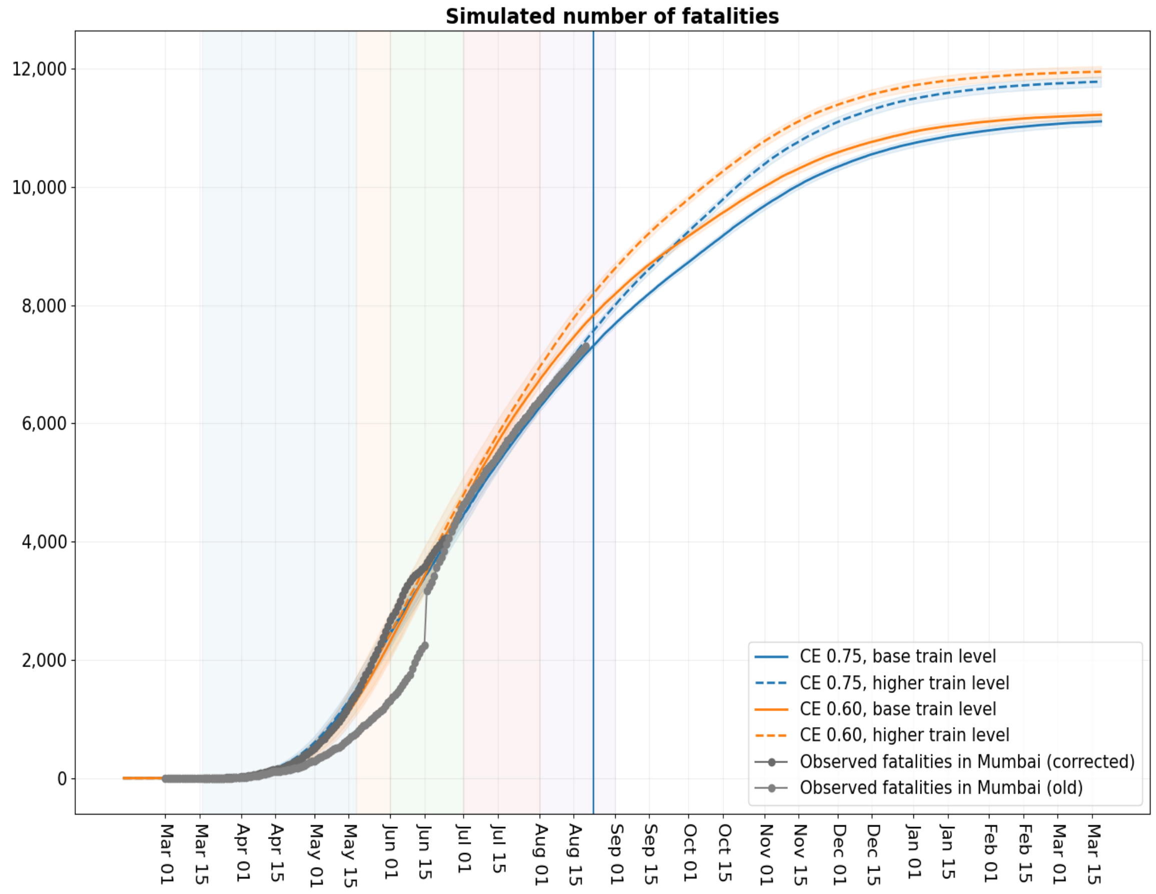




Predictions for Mumbai

Under various levels of ‘containment effectiveness’ (CE) and train contact levels





Modelling

- While we eagerly await vaccines, we have turned to timely case identification, case management (isolation/monitoring/treatment), and other non-pharmaceutical interventions for addressing the pandemic

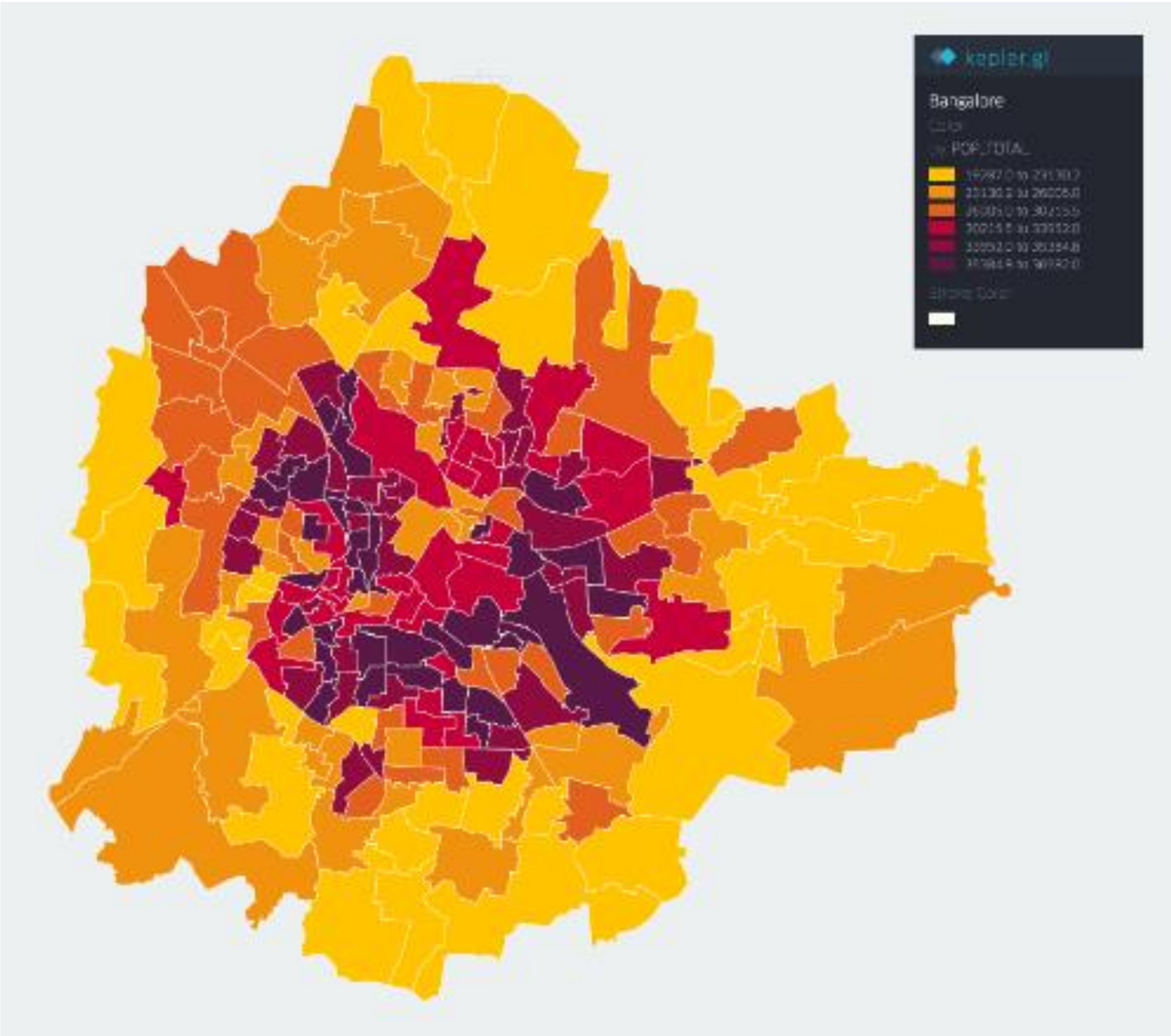
- Simulations can help us with scenario exploration and can help in decision making

- Today’s discussion
  - Agent-based simulator
  - Some outcomes of our agent-based model

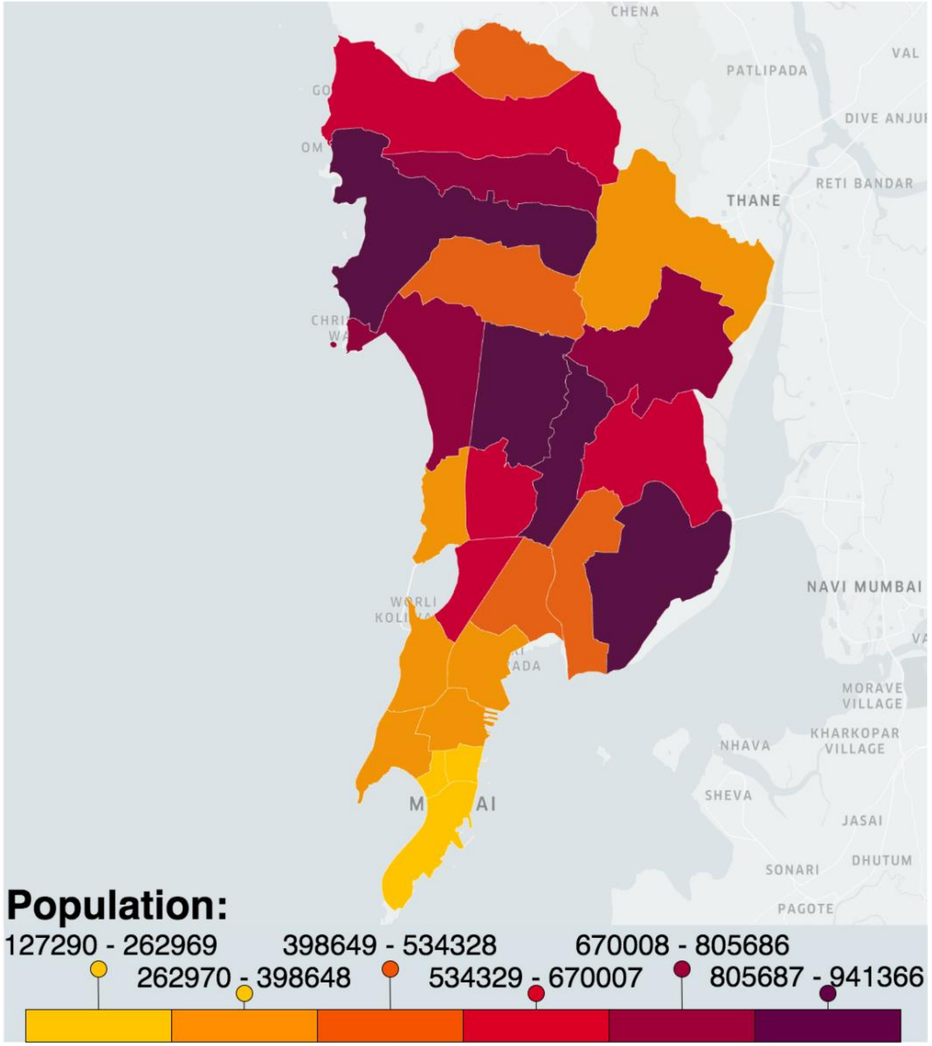
Agent-based simulators

Create a synthetic population of agents
Model the disease dynamics
Model interventions
Simulate the spread in the synthetic population via a Markov chain

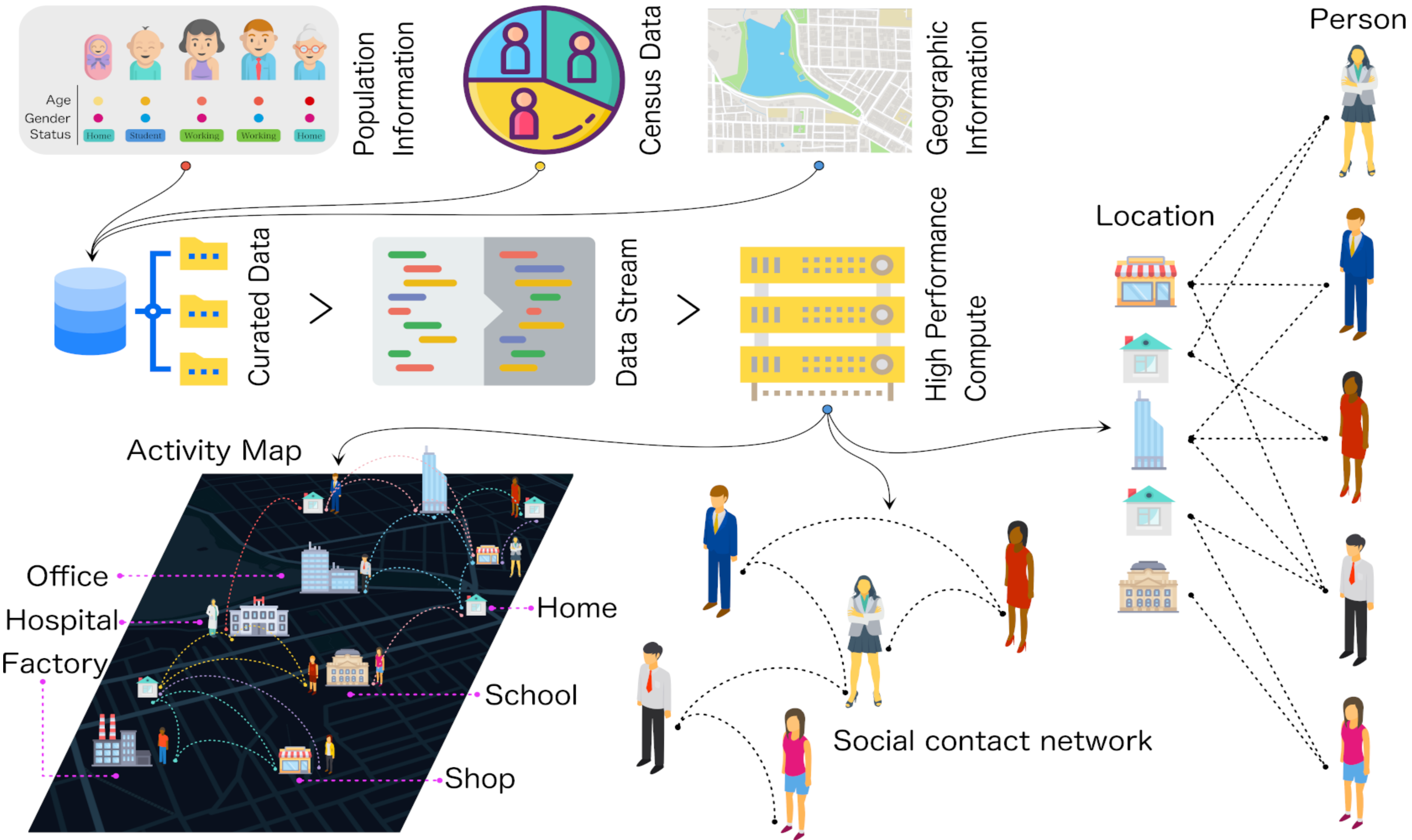
Bengaluru and its 198 wards
1.23 crore agents (12.3 million)



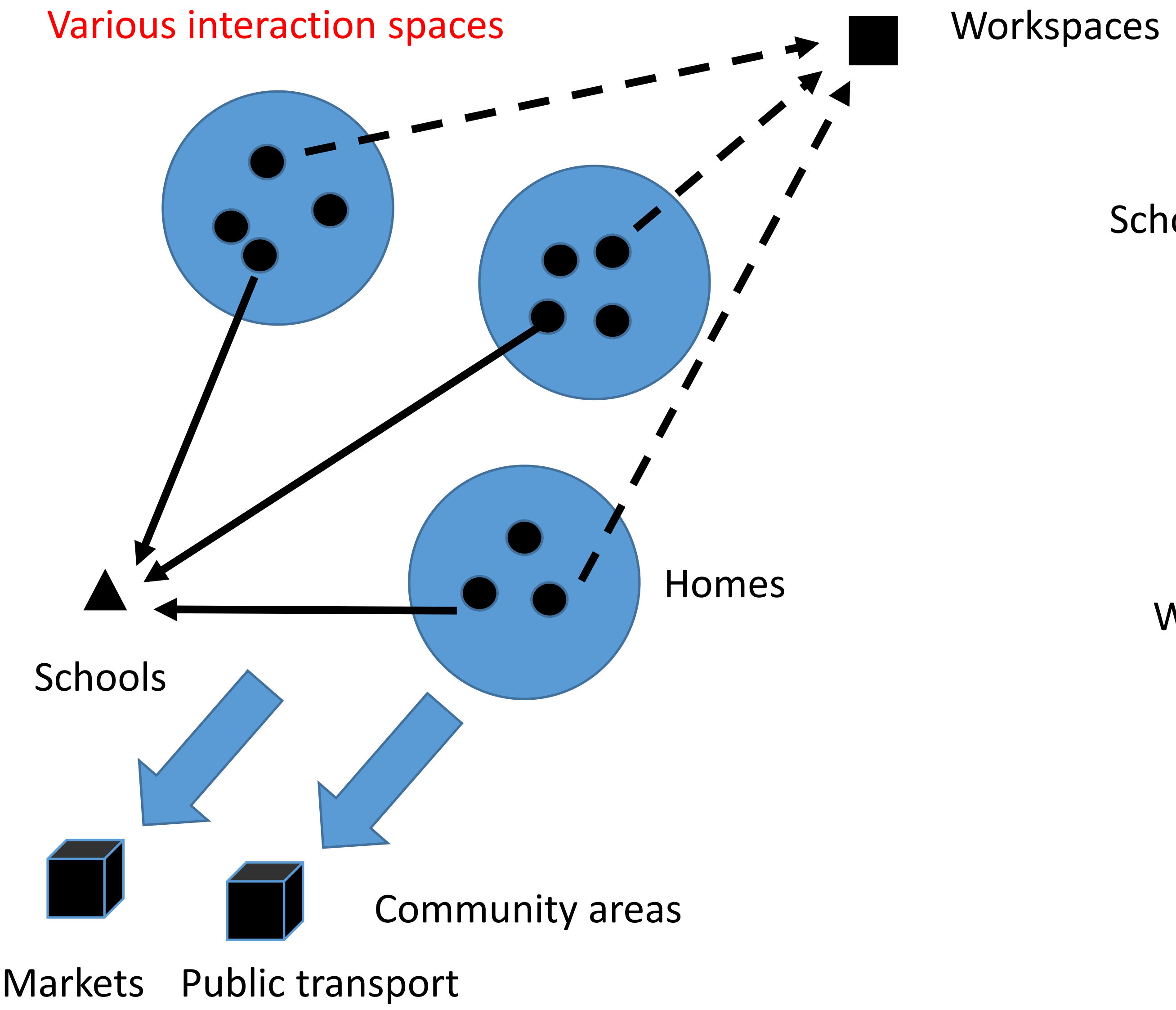
Mumbai (BMC) and its 24 wards
1.24 crore agents (12.4 million)

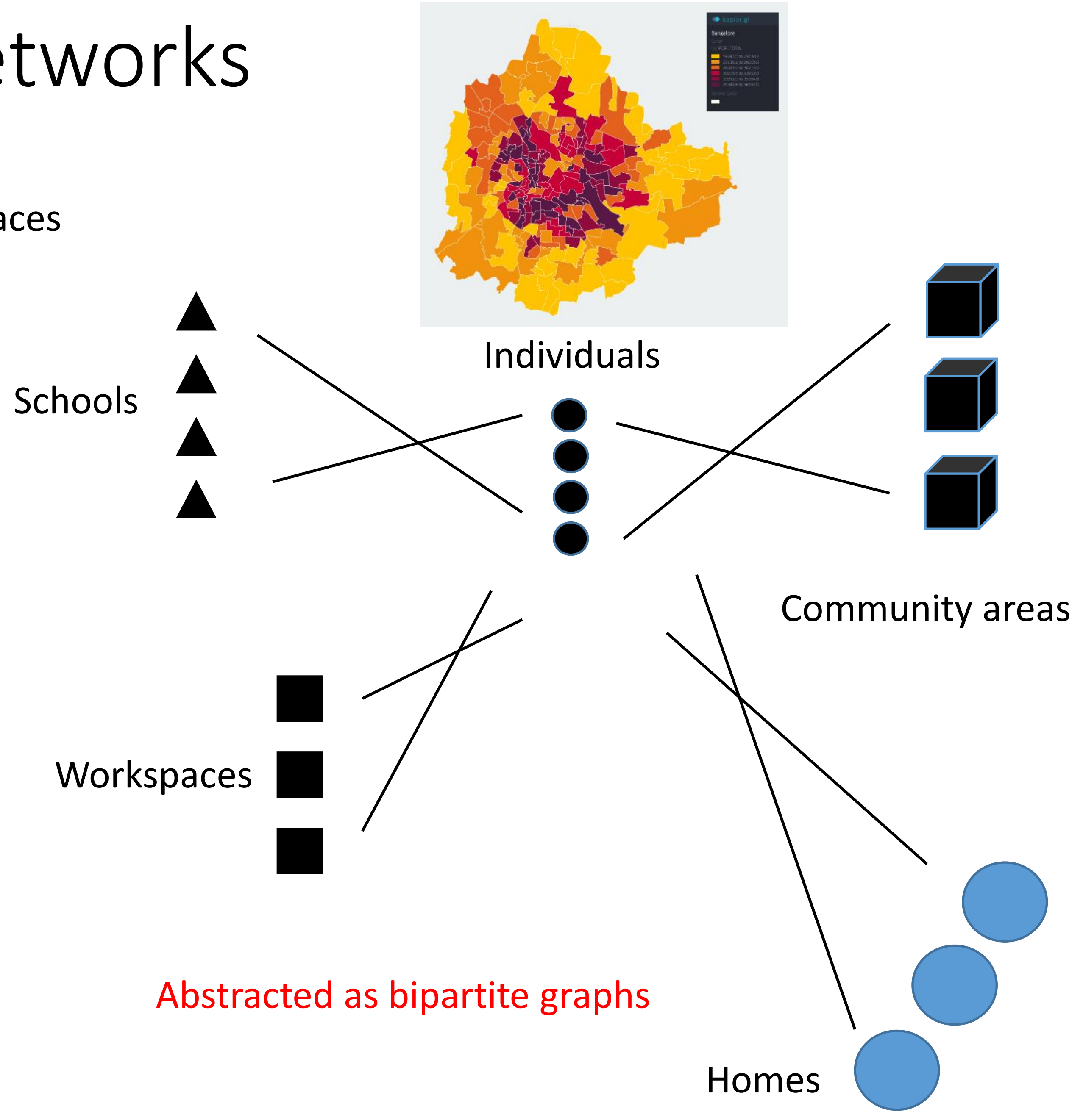


AGENT-BASED MODEL AND CITY-SCALE SIMULATOR

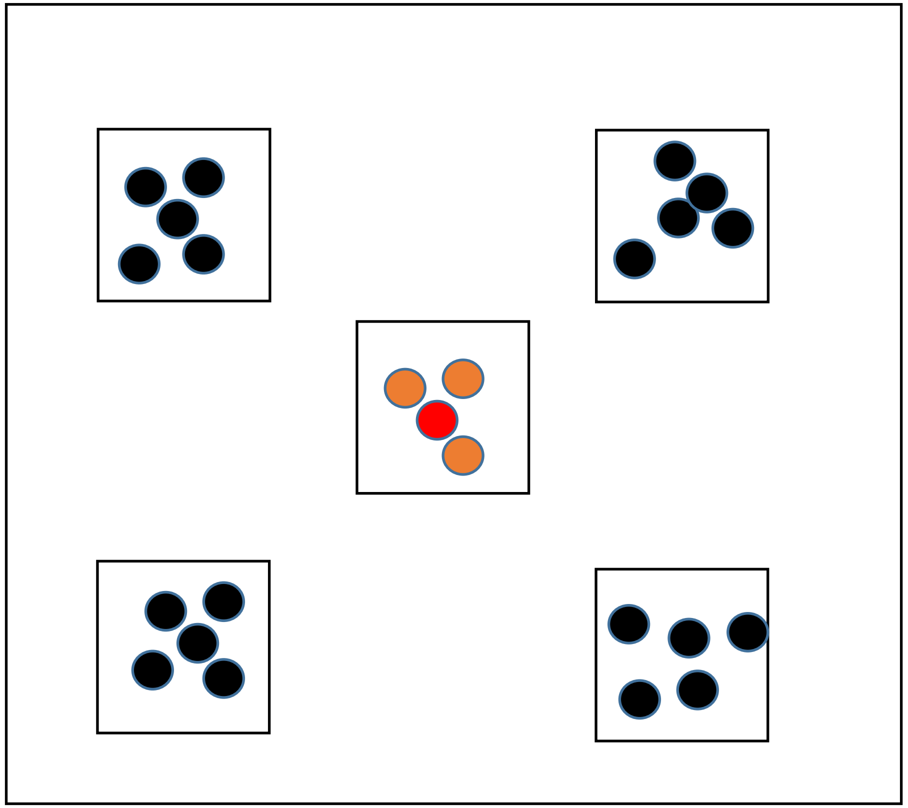


Multiple interacting social networks

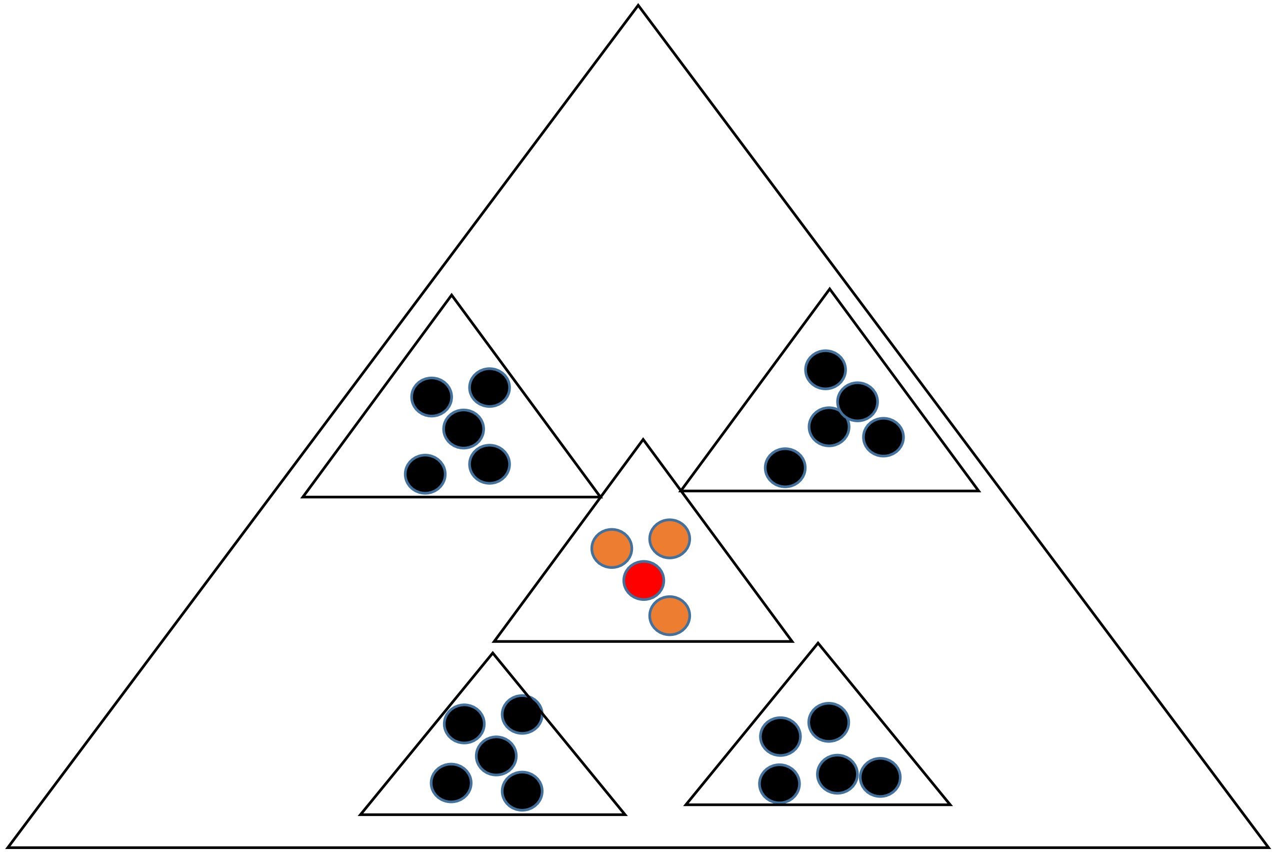




Scales of interaction

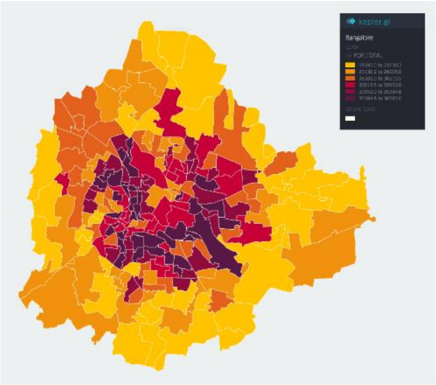


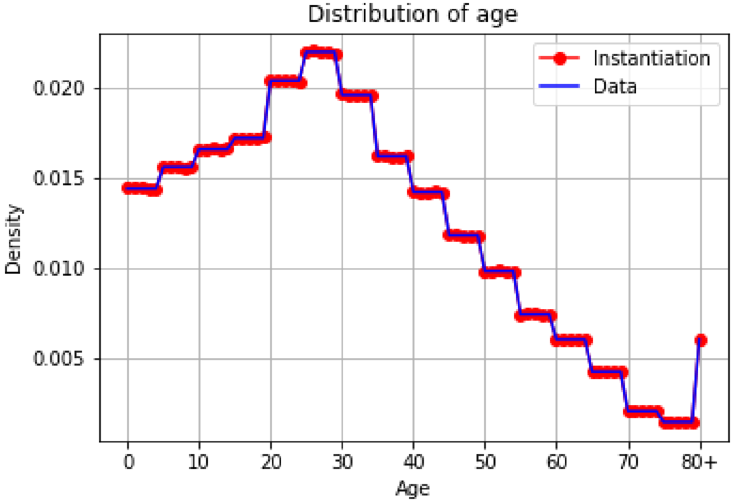
Workplace network structure

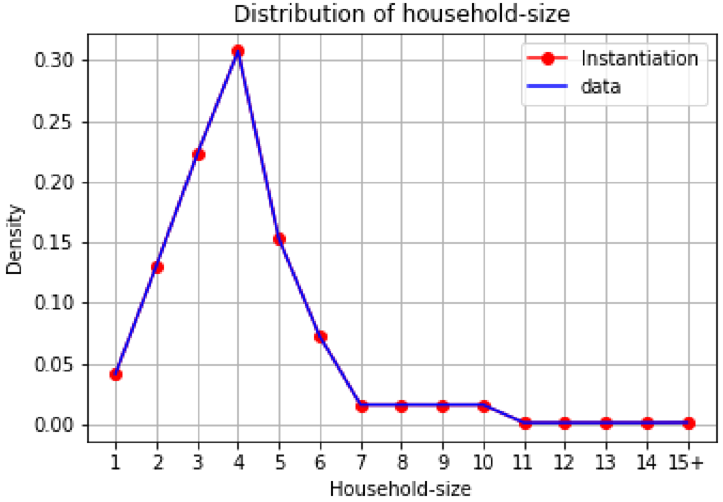


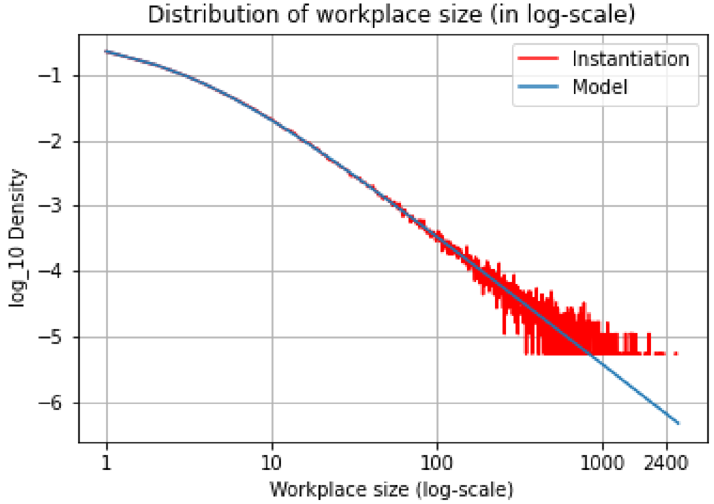
School network structure

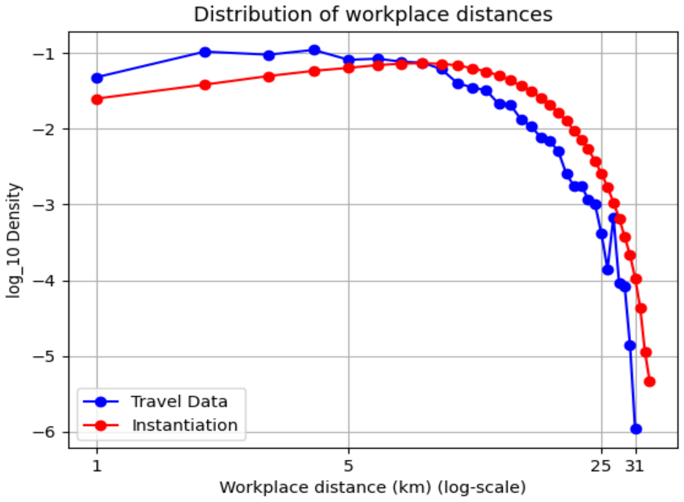
Real and synthetic Bengaluru

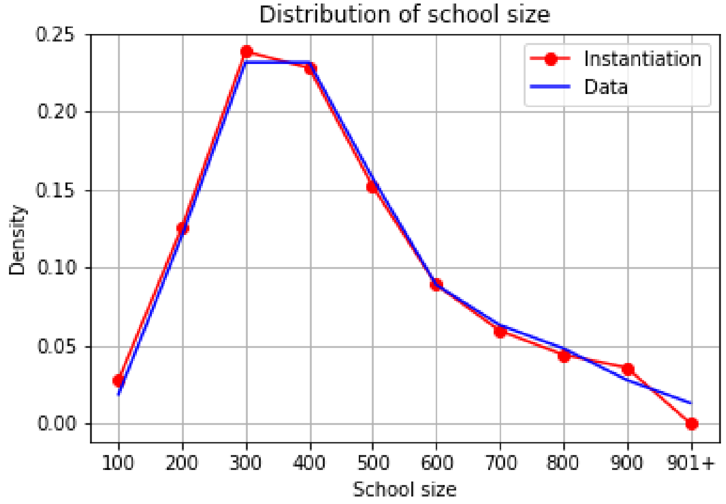






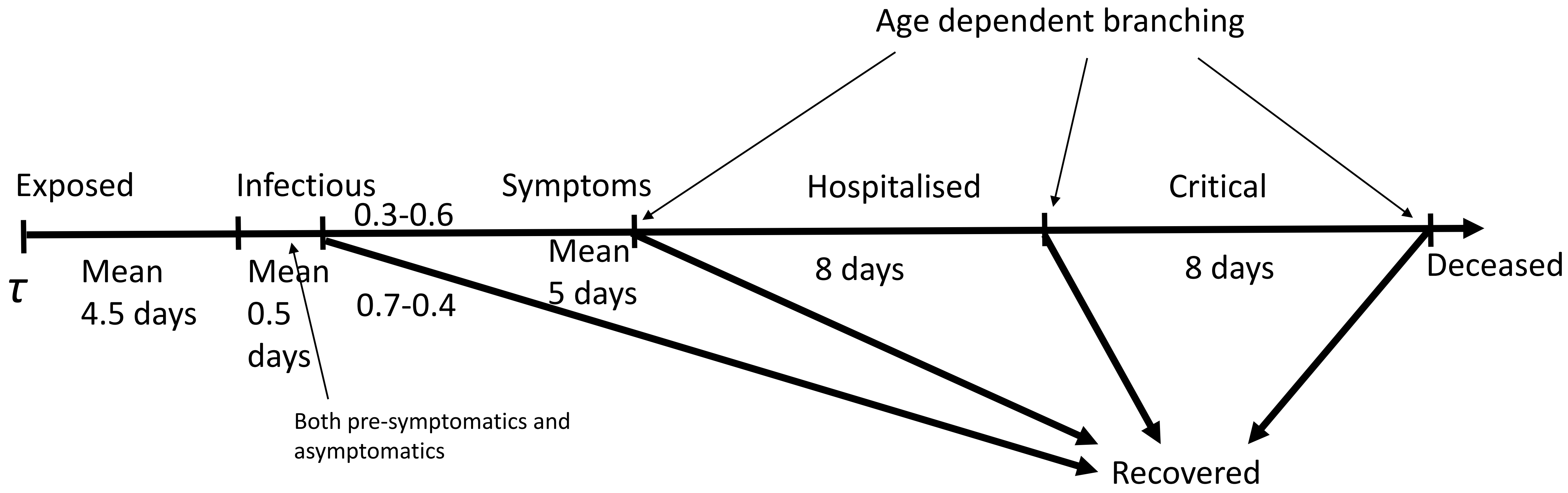






Heterogeneity within an individual: Infection progression

(COVID-19, current understanding)



- Elderly are more susceptible
- Comorbidities

Age-dependent branching
Verity et al. 09/03/2020 estimates

Age group	% symptomatic cases requiring hospitalisation	% hospitalised cases requiring critical care	% critical cases deceased
0 - 9	0.1%	5.0%	40%
10 - 19	0.3%	5.0%	40%
20 - 29	1.2%	5.0%	50%
30 - 39	3.2%	5.0%	50%
40 - 49	4.9%	6.3%	50%
50 - 59	10.2%	12.2%	50%
60 - 69	16.6%	27.4%	50%
70 - 79	24.3%	43.2%	50%
80+	27.3%	70.9%	50%

Comorbidities

Guan et al. 14/05/2020 estimates, based on data from 1590 patients from China

Comorbidity	% with ailment that needed ICU, invasive ventilation, and/or deceased	% without ailment that needed ICU, invasive ventilation, and/or deceased
Hypertension	19.7%	5.9%
Cardiovascular diseases	22.0%	7.7%
Cerebrovascular diseases	33.3%	7.8%
Diabetes	23.8%	6.8%
Chronic obstructive pulmonary disease	50.0%	7.6%
Chronic kidney diseases	28.6%	8.0%
Malignancy	38.9%	7.9%

$$\lambda_n(t) = \sum_{n':h(n')=h(n)} \frac{1}{n_{h(n)}^{\alpha}} \cdot I_{n'}(t)\beta_h \kappa(t-\tau_{n'})\rho_{n'}(1+C_{n'}(\omega-1))$$

Home

$$+ \zeta(a_n) \sum_{n':\mathscr{H}(n')=\mathscr{H}(n)} \frac{1}{n_{\mathscr{H}(n)}} \cdot \zeta(a_{n'}) I_{n'}(t)\beta_h^{*} \kappa(t-\tau_{n'})\rho_{n'}(1+C_{n'}(\omega-1))$$

$$\text{(larger neighbourhood interaction)}$$

Larger neighbourhood

$$+ \frac{\zeta(a_n) f(d_{n,c(n)})}{\sum_{n':\mathscr{C}(n')=\mathscr{C}(n)} f(d_{n',c(n')})} \times \sum_{n':\mathscr{C}(n')=\mathscr{C}(n)} f(d_{n',c(n')})\zeta(a_{n'}) I_{n'}(t)\beta_c^{*} \kappa(t-\tau_{n'})\rho_{n'}(1+C_{n'}(\omega-1))$$

$$\text{(close friends' circle interaction)}$$

Friends and family across the city

$$+ \sum_{n':s(n')=s(n)} \frac{1}{n_{s(n)}} \cdot I_{n'}(t)\beta_s \kappa(t-\tau_{n'})\rho_{n'}(1+C_{n'}(\omega\psi_s(t-\tau_n)-1))$$

School

$$+ \sum_{n':\mathscr{S}(n')=\mathscr{S}(n)} \frac{1}{n_{\mathscr{S}(n)}} \cdot I_{n'}(t)\beta_s^{*} \kappa(t-\tau_{n'})\rho_{n'}(1+C_{n'}(\omega\psi_s(t-\tau_n)-1))$$

$$\text{(class network interaction)}$$

Within a class

$$+ \sum_{n':w(n')=w(n)} \frac{1}{n_{w(n)}} \cdot I_{n'}(t)\beta_w \kappa(t-\tau_{n'})\rho_{n'}(1+C_{n'}(\omega\psi_w(t-\tau_n)-1))$$

Workplace

$$+ \sum_{n':\mathscr{W}(n')=\mathscr{W}(n)} \frac{1}{n_{\mathscr{W}(n)}} \cdot I_{n'}(t)\beta_w^{*} \kappa(t-\tau_{n'})\rho_{n'}(1+C_{n'}(\omega\psi_w(t-\tau_n)-1))$$

$$\text{(project network interaction)}$$

Within a group/project

$$+ \frac{\sum_{n':\mathcal{T}(n')=1} A_{n',t}}{\sum_{n'} \mathcal{T}(n')} \times \sum_{n':\mathcal{T}(n')=\mathcal{T}(n)} \left(\frac{d_{n',w(n')} I_{n'}(t)\beta_{\mathcal{T}} M_{n'}}{\sum_{n':\mathcal{T}(n')=\mathcal{T}(n)} d_{n',w(n')}} \right)$$

Transport

$$+ \frac{\zeta(a_n)\cdot f(d_{n,c})}{\sum_{c'} f(d_{c,c'})} \sum_{c'} f(d_{c,c'}) h_{c,c'}(t)$$

Markets/restaurants/theatres/religious locations/events

Why model these interaction spaces and heterogeneities?

Closer to reality: Disease spread is in social interaction spaces, and these are heterogeneous

Spatial heterogeneity comes in naturally in the agent-based models

Connectivity due to daily mobility to workplace automatically taken into account

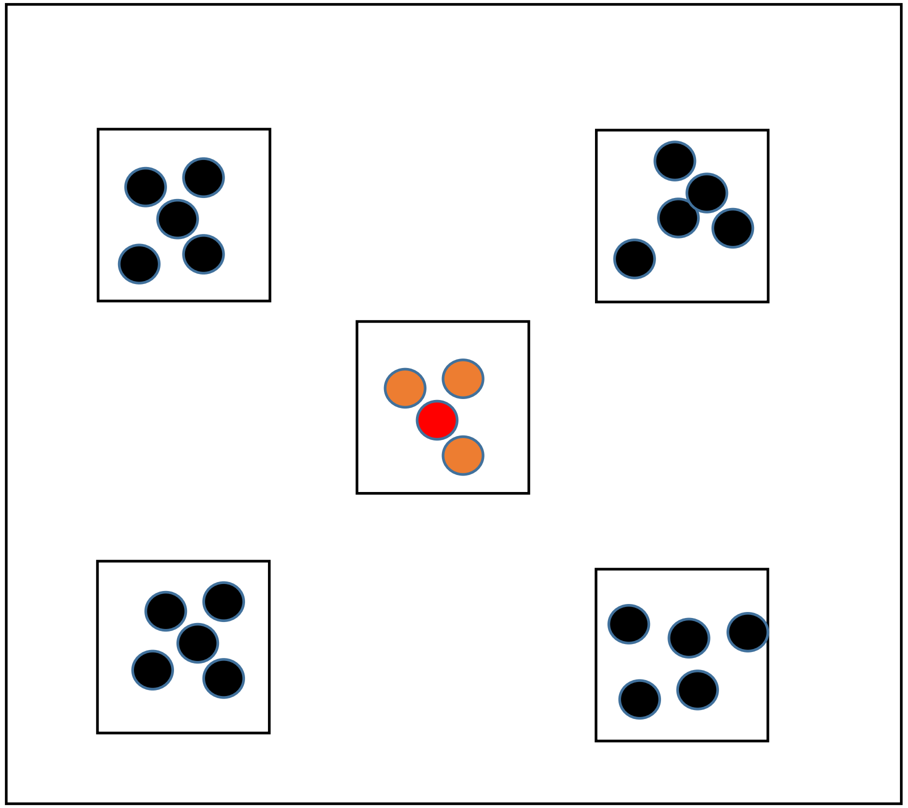
Enables study of targeted interventions

- Case isolation, home quarantine, social distancing of elderly, school closures
- Phased opening of transport, type of containment zone, offices, schools, etc.

Interventions

Label	Policy	Description
NI	No intervention	Business as usual.
CI	Case isolation in the home	Symptomatic cases stay at home for 7 days, reducing non-household contacts by 75%. Household contacts remain unchanged. Assume 70% of the household comply.
HQ	Voluntary Home Quarantine	Following identification of a symptomatic case in the household, all household members remain at home for 14 days. Household contact rates double during this quarantine period, contacts in the community reduce by 75%. Assume 90% of the household comply with the policy.
SC	Schools and colleges closed	…
SDE	Social distancing of the elderly	…

Quarantine induced by contact tracing



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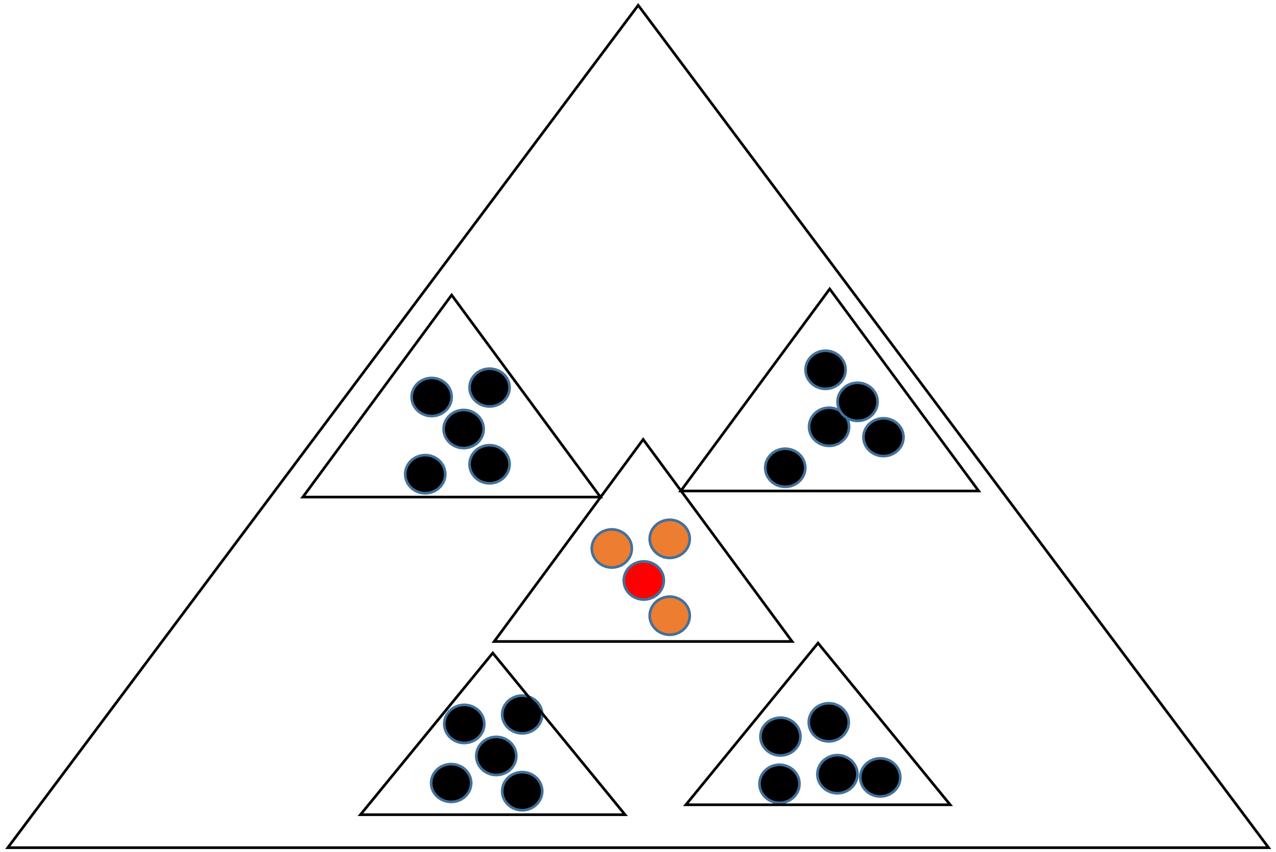
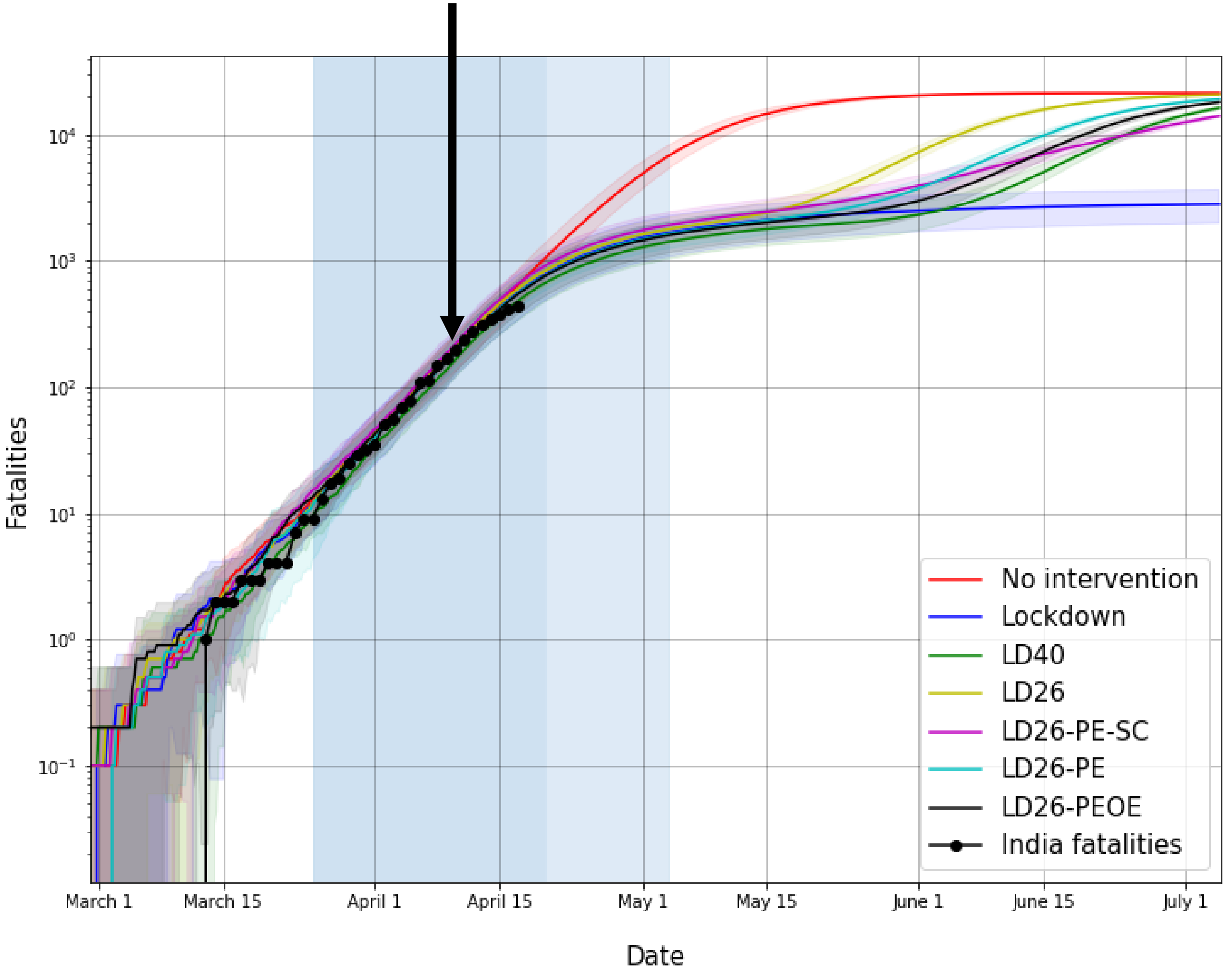


School network structure

Calibration

- Seed 100 nodes with infections in the city
- Calibrate contact rates and start date so that:
    - 1/3, 1/3, 1/3 infection rates from home, workplace, schools
    - match the initial no-intervention time series of fatalities until 09 April 2020 (200 deaths)
- Calibrate compliance levels to match subsequent growth rates

Calibration based on India data up to 09 April 2020



“ABMs can be calibrated to say anything”

- In defence of ABMs, they are constructed bottom-up
  - City census data, household size distribution, household age mix, commute distance distribution, school size distribution, office size distribution, unemployment rate
  - Disease parameters based on clinical studies
  - Past flu cohort studies suggest relationships between school and office contact rates
- Contact rates, seeding, compliance parameters, testing parameters - calibrated to data
  - Home, office, community, number to seed, and seeding date
  - Calibrate on an independently generated smaller system (1 million) and only in the early part of the disease (time series of the first 200 deaths in India).

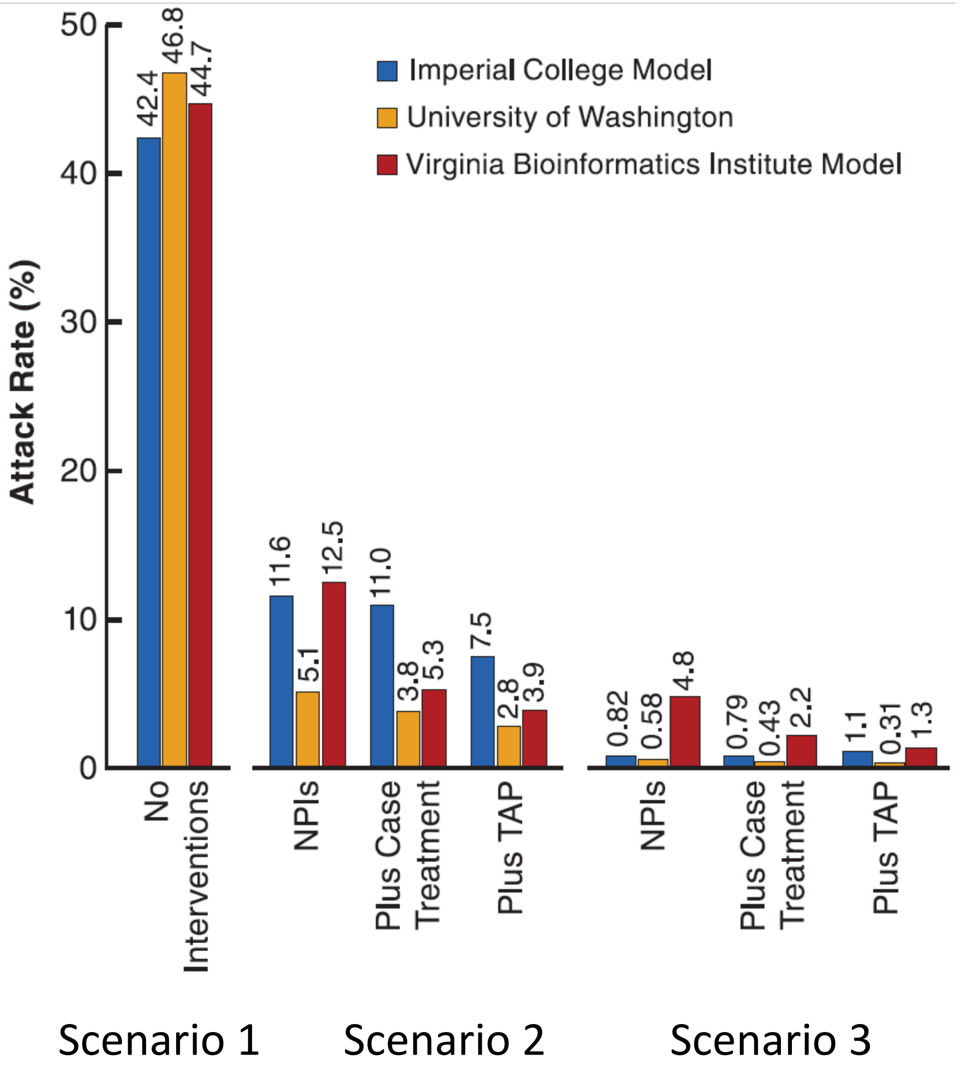
A comparative study

- Three models from Imperial College, UW, and Virginia Polytechnic

  Halloran et al., 2008. Modeling targeted layered containment of an influenza pandemic in the United States. *Proceedings of the National Academy of Sciences*, *105*(12), pp.4639-4644.

- NPI, + case treatment, + targeted antiviral prophylaxis

- Scenarios
  - 1 = No intervention
  - 2 = some intervention + low compliance
  - 3 = some intervention + high compliance



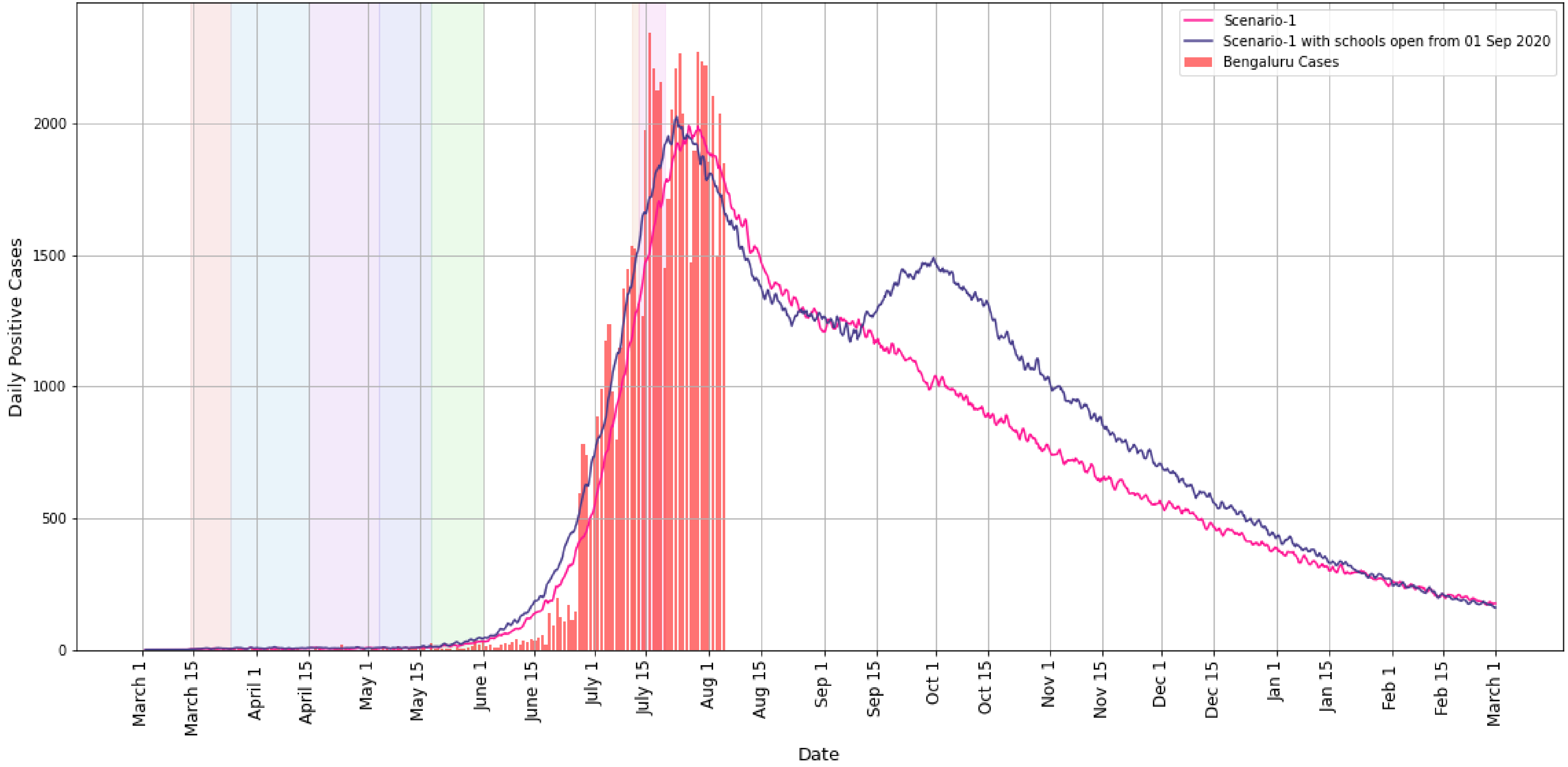
City-scale simulation studies - 2

The opening up of schools from September 01.

Simulated Bengaluru interventions on 1.23 crore agent-based simulator

Period	**Scenario-1**	Compliance
01 – 13 March 2020	No intervention	N/A
14 March – 24 March 2020	Prelockdown	70%
25 March – 03 May 2020	40 days of National lockdown	70%
09 April – onwards	Masks ON	70%
04 – 17 May 2020	Phased opening. Voluntary home quarantine, social distancing of elderly, case isolation, schools and colleges closed, 50% occupancy at workplaces.	60%
18 May 2020 - 11 July	**Unlocked Bengaluru** with only ICMR-guideline contact tracing and associated quarantining and case isolations. Schools/Colleges closed.	60%
12 - 13 July	Same as above	60%
14 July - 21 July	Same as above	60%
22 July - 31 July	Same as above	60%
01 Aug onwards	Same as above	60%
01 Sep onwards	Same as above, but schools and colleges open/closed	60%
Throughout	**Ward containment enabled**	60%

Bengaluru daily cases
without schools and with schools from 01 September 2020



Takeaway: School opening will lead to a short resurgence around 01/10/2020.

Summary

- We looked at agent-based models for COVID-19
    - Can model heterogeneity at the individual level
    - Can bring in behavioural adaptations
    - Can model heterogeneity in interactions
    - Interventions
    - Future – testing strategies, vaccination prioritisation, etc.
- We highlighted some of our studies
    - Trains restart, schools restart
- Other domains – traffic studies, effectiveness of the now-on now-off odd-even strategy in New Delhi, etc.

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