Agent-based simulators for the study of COVID-19 spread

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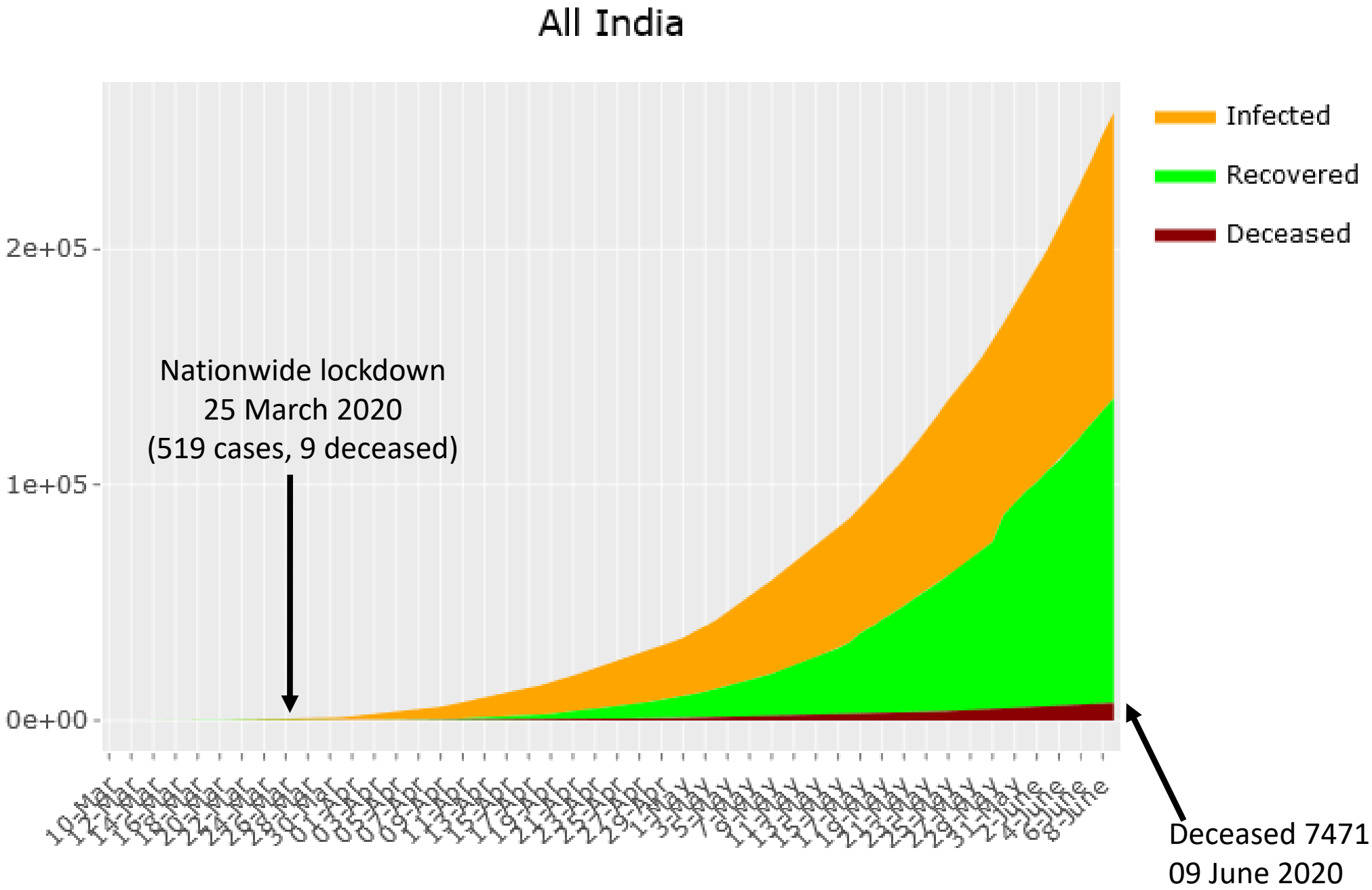
Joint effort with TIFR Mumbai Researchers

10/06/2020

COVID-19 India data

Web search: incovid ISI
(Courtesy: Siva Athreya and team)



Introduction

- **Lockdown**‘s initial goal was to suppress the transmission of COVID-19

- We needed tools to evaluate unlocking strategies

- Tools
  - Agent-based city-scale simulator (open source) https://cni.iisc.ac.in/simulator
  - Workplace readiness indicator (open source) https://covid.readiness.in

- For whom?
  - City/state administrators – e.g., KSDMA (Bengaluru), BMC (Mumbai), other cities
  - Organisations (e.g., MSMEs, government offices, IT offices)

- Studies
  - Report-1: 19 April 2020, Unlocking the lockdown in India, IISc, TIFR, various phased emergences
  - Importance of compliance
  - Report-2: 05 June 2020, Phased emergence from the lockdown in Mumbai
  - What type of containment zones? Ward-wise or 100m radius zone?

Getting familiar with pandemics

- 1918 Spanish flu, Bombay fever, Influenza A virus known as H1N1, 5 crore fatalities
- 1957 Asian flu, Influenza A virus known as H2N2, 10-20 lakh fatalities
- 1968 Hong Kong flu, Influenza A virus known as H3N2, 10-40 lakh fatalities, mostly elderly
- 1970s/80s West Africa, HIV, 7.5 crore infected, 3.2 crore fatalities and mostly due to secondary illnesses.
- 2002 China SARS, virus is known as SARS-CoV, about 8,000 cases, 774 fatalities, no vaccines
- 2009 Swine flu, Influenza A known as H1N1, vaccines available
- 2012 MERS Saudi Arabia, virus is knowns as MERS-CoV, no vaccines yet
- 2014 Ebola West Africa, virus known as Zaire EBOV, no vaccines
- 2019-20 COVID-19, virus known as SARS-CoV-2, no vaccines yet

Just how severe is COVID-19?

2017-18 Influenza (A,B) in the USA

- 4.8 crore cases
- 9 lakh hospitalised (1.88%)
- 80,000 fatalities (0.17%)

COVID-19 in the USA till 07 June 2020

- ~20 lakh confirmed (est. ~1 crore)
- Severe hospitalised cases, est. 4%
- 1.11 lakh fatalities (est. 0.5 – 1.0%)

1918 Influenza A (H1N1)

- Fatalities: 6.75 lakh in USA, 1.2 crore in India, 5 crore worldwide (case fatality 10%)

SARS-CoV case fatalities were about 10%

Our knowledge of SARS-CoV-2 virus and COVID-19 as on 09/06/2020

- Close to SARS-CoV of the 2002 outbreak in China
- Overwhelming evidence that it is zoonotic
- Infectious, R0 is estimated between 2-3
- Only circumstantial evidence that it may show, like other flu viruses, lower virulence during summer
- Transmission mostly through respiratory droplets.
- Enters the body through mouth, nose, eyes.
- The virus has been detected in some printers, keyboards, doorknobs used by infected individuals in Chinese studies. There is also circumstantial evidence from a Singapore investigation of “fomite” transmission
- There are recorded cases of presymptomatic transmission. Virus presence in asymptomatics is known. But no recorded case of truly asymptomatic transmission, although models suggest this as a possibility.
- Is every one susceptible? Not clear. There is large variation in severity across individuals. Factors for this individuality are not yet understood
- Mostly affects the respiratory system.
- Currently no evidence that mutations accumulated since December 2019 affect disease characteristics
- Mutations that may affect testing RT-PCR detection assays have been reported but are rare.
- Testing, test for the virus during infection, then test for antibodies IgM and IgG
- Happy hypoxia, cytokine storm leading to ARDS
- At present, there is no proven medicine for prevention or treatment. Studies ongoing for Remdesivir, HCQ, convalescent plasma treatments

Modelling

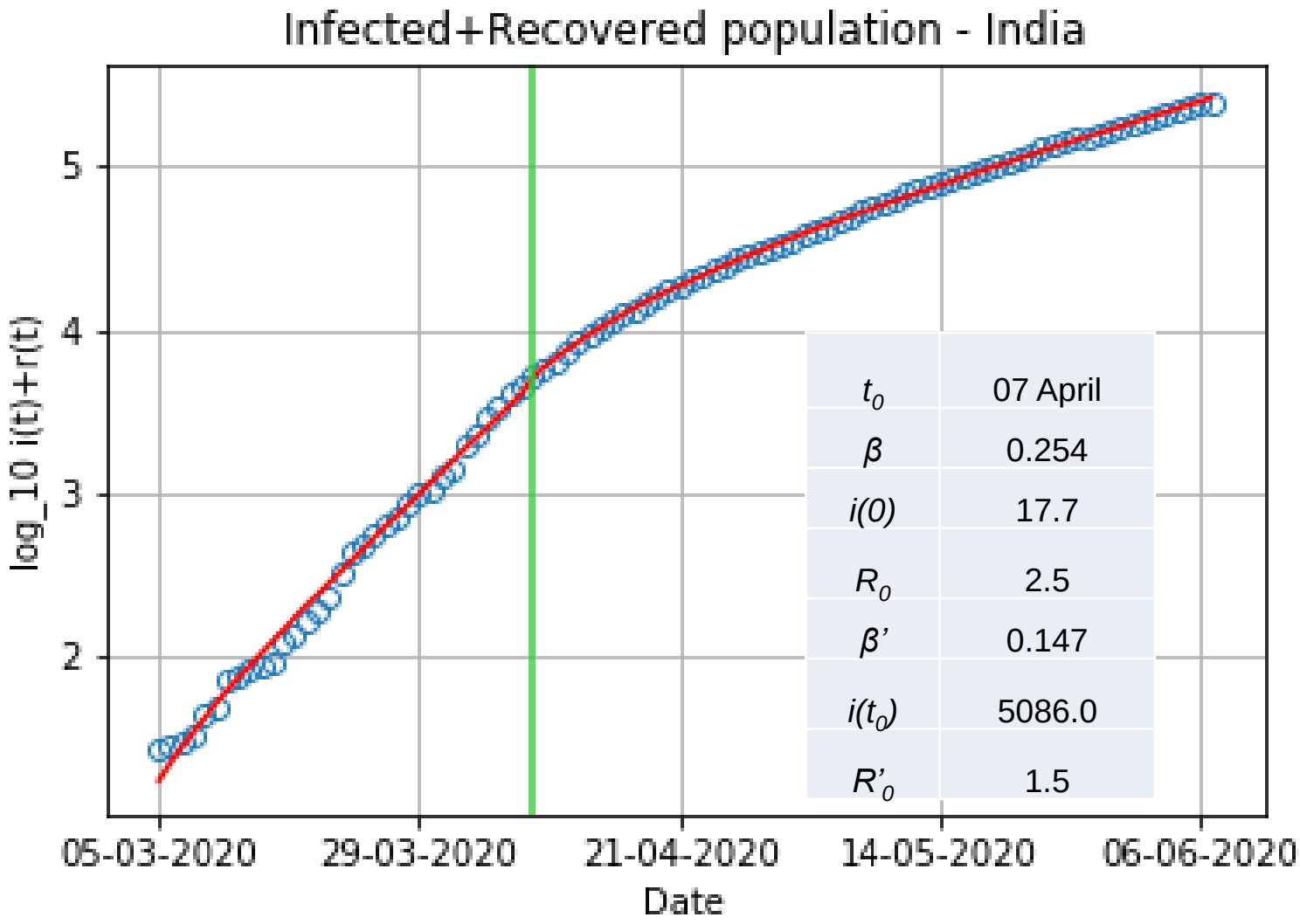
- While we continue to wait for vaccines and medicines, we have turned to case identification, case management, and other non-pharmaceutical interventions for addressing the pandemic
- Models have guided the use of such interventions, by scaring the wits out of us
- Today's discussion
  - Agent based models
  - Some outcomes of our agent-based model

An SIR model

$$\frac{ds}{dt} = -\beta i(t)s(t)$$

$$\frac{di}{dt} = \beta i(t)[s(t) - \frac{\mu}{\beta}]$$

$$\frac{dr}{dt} = \mu\, i(t)$$



Doubling time 4.5 days prior to national lockdown.
Doubling time 14.7 post national lockdown.

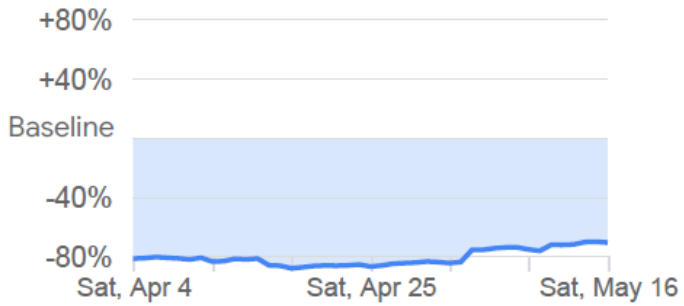
Karnataka

Google's mobility data for Karnataka, 16 May 2020

t_0	07 April
β	0.254
$i(0)$	17.7
R_0	2.5
β'	0.147
$i(t_0)$	5086.0
R'_0	1.5

Retail & recreation

-70% compared to baseline

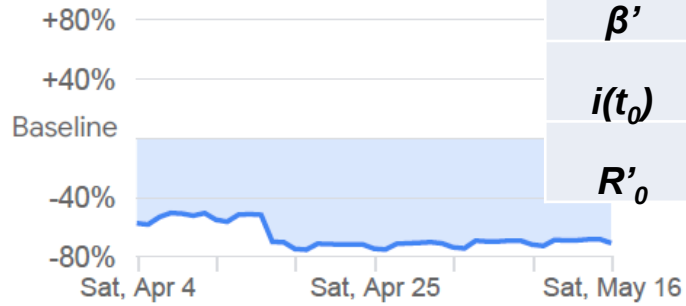


Grocery & pharmacy

-16% compared to baseline

Parks

-71% compared to baseline

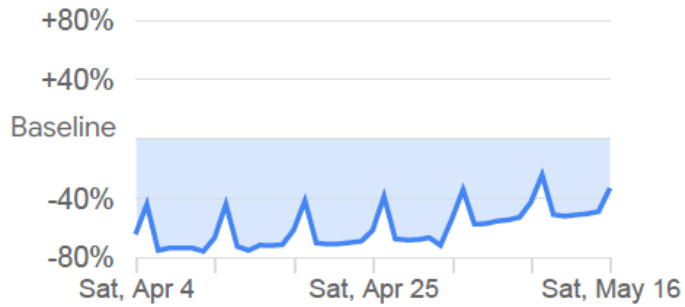


Transit stations

-41% compared to baseline

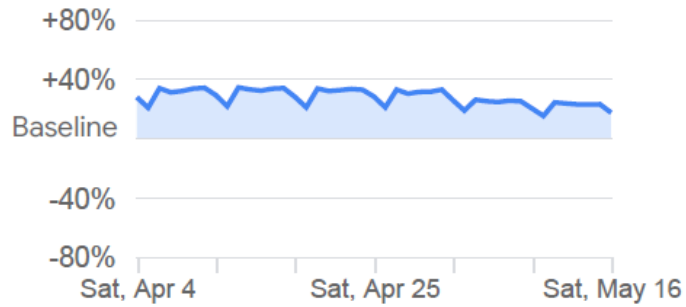
Workplaces

-33% compared to baseline



Residential

+18% compared to baseline



Need actionable insights

- Is protecting the vulnerable an effective strategy?
- At the beginning and near the end, spread is stochastic. If at the beginning, what's the chance of a pandemic?
- What interventions to prescribe?

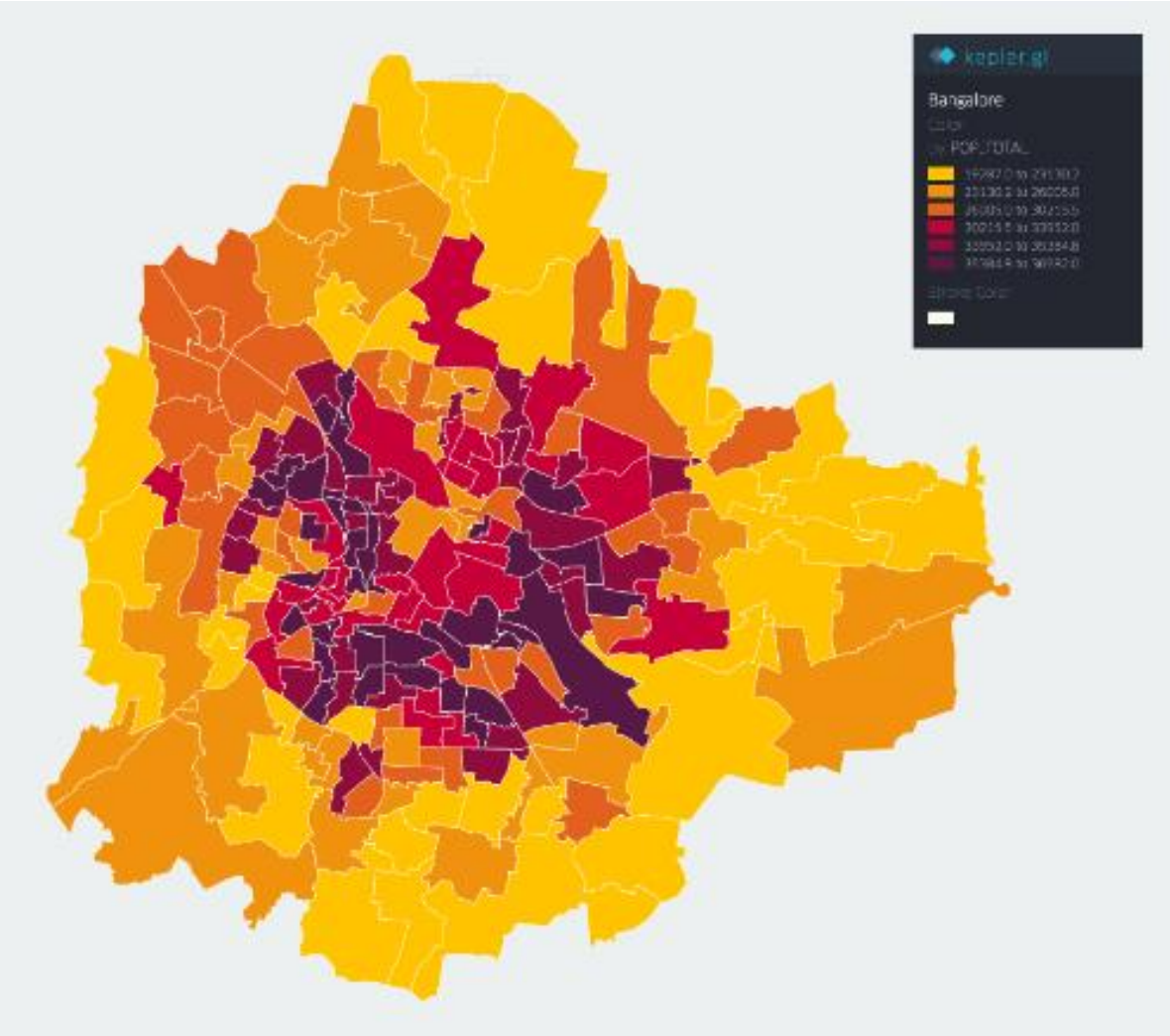
Enter: Agent-based modelling

Create a synthetic population of agents

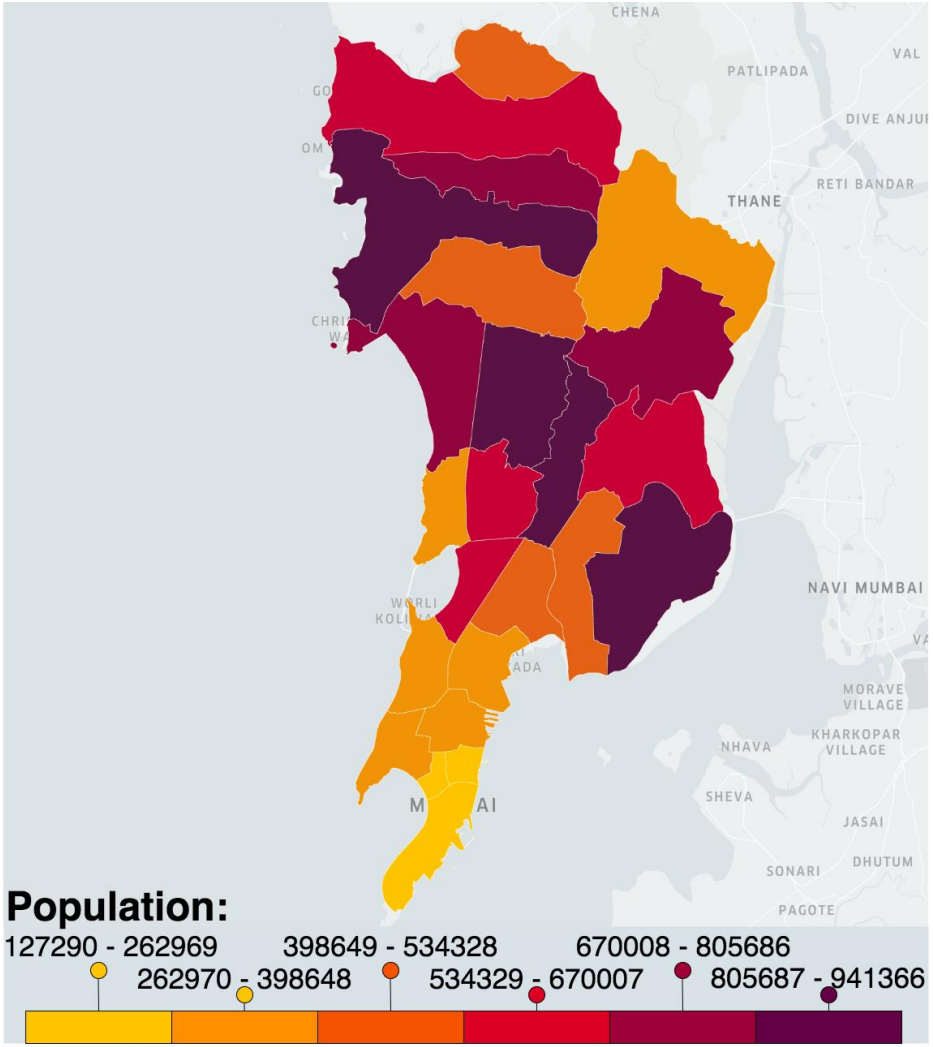
Model the disease dynamics

Simulate the spread in the synthetic population via a Markov chain

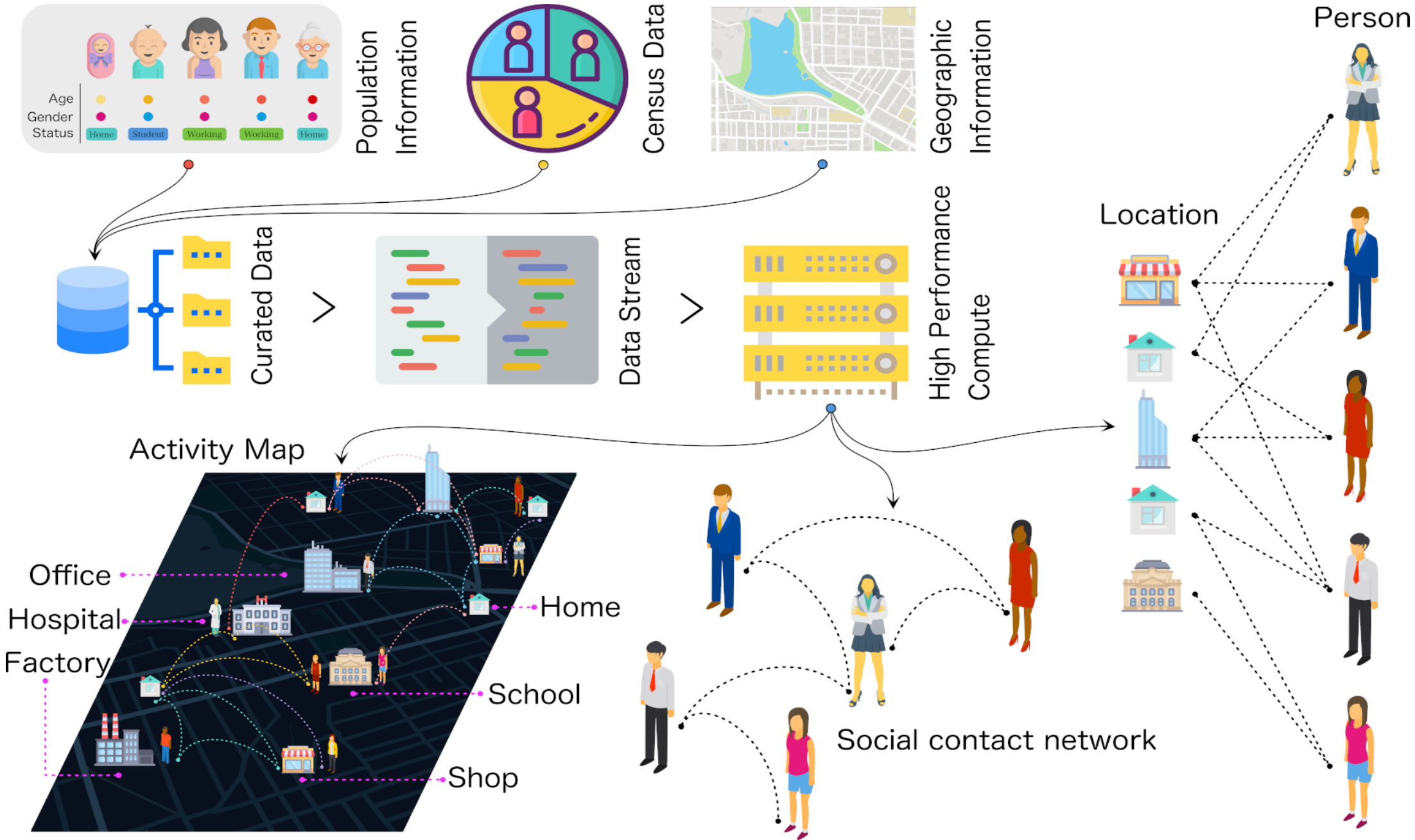
Bengaluru and its 198 wards
1.23 crore agents



Mumbai (BMC) and its 24 wards
1.24 crore agents

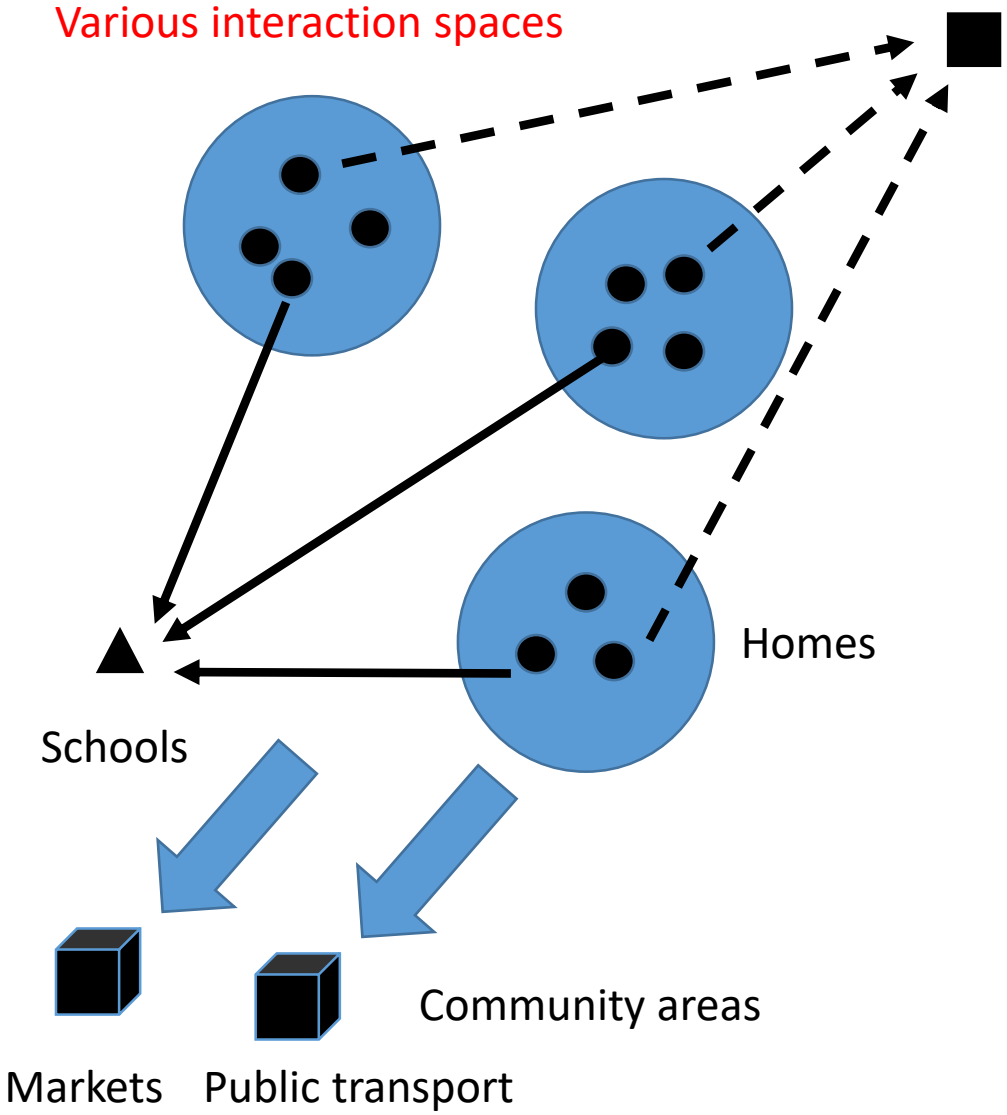


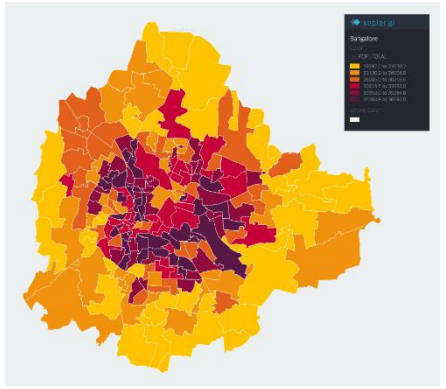
AGENT-BASED MODEL AND CITY-SCALE SIMULATOR

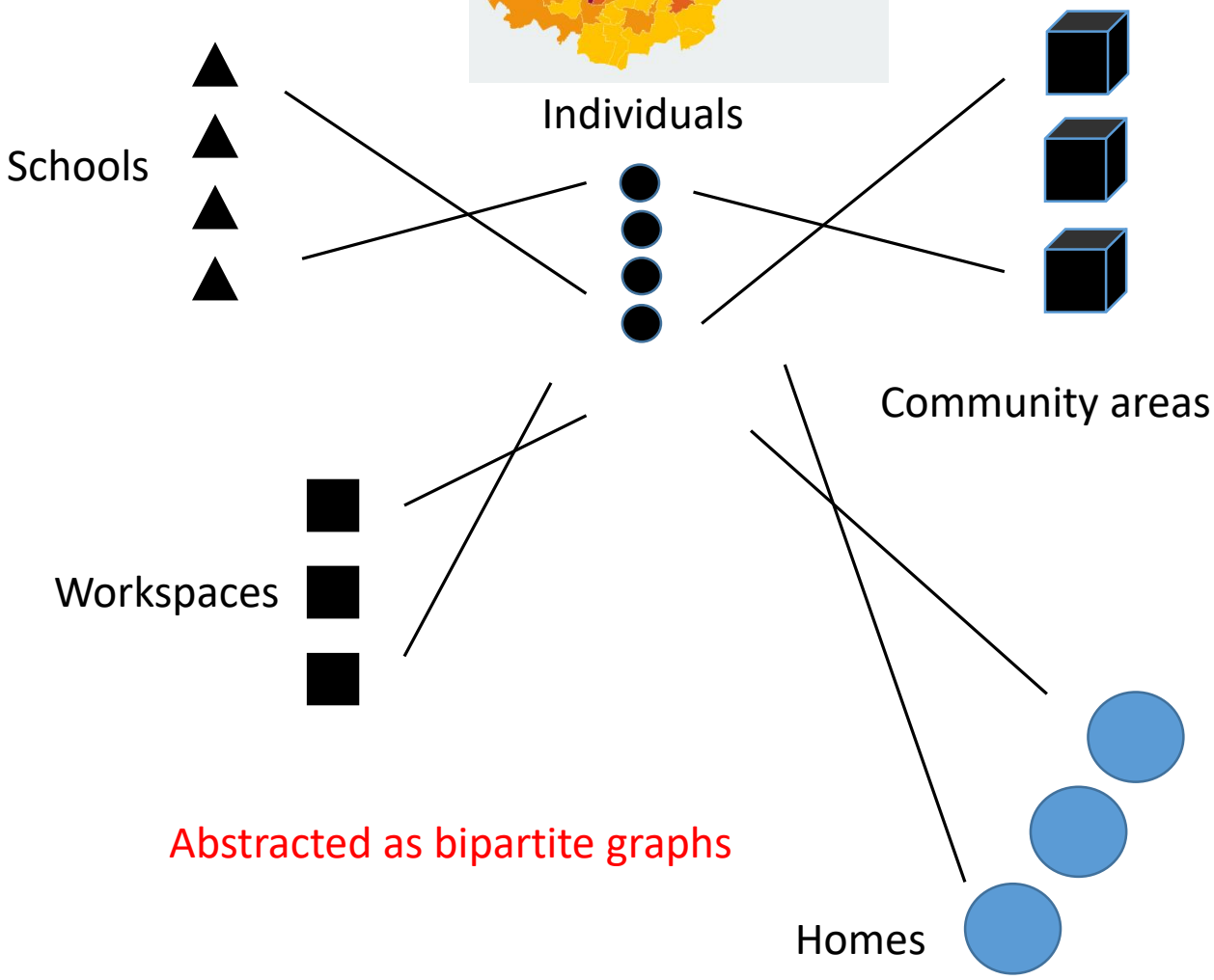


Multiple interacting social networks

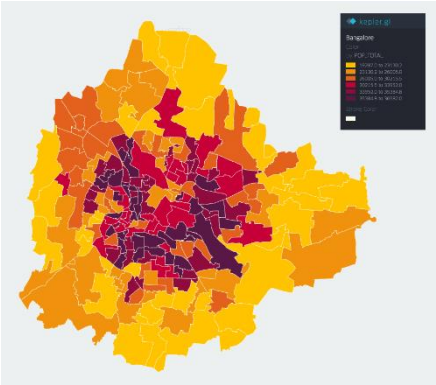
Various interaction spaces



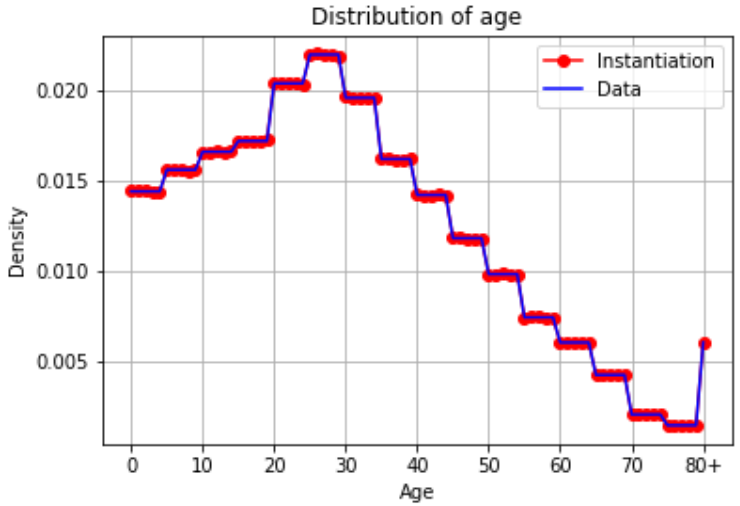


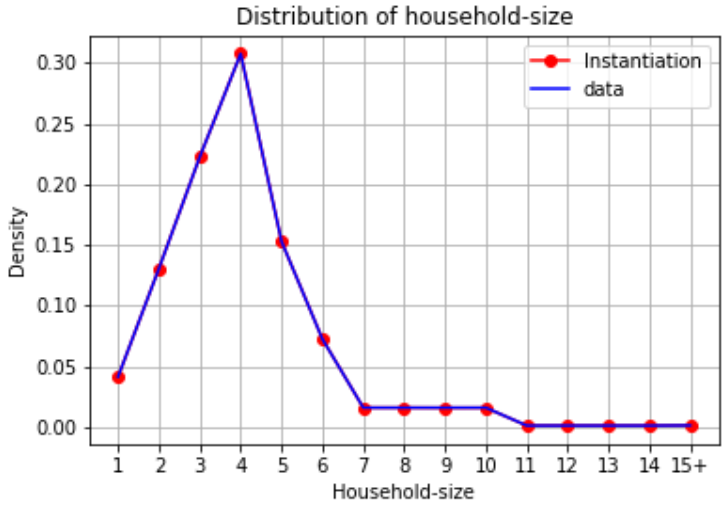


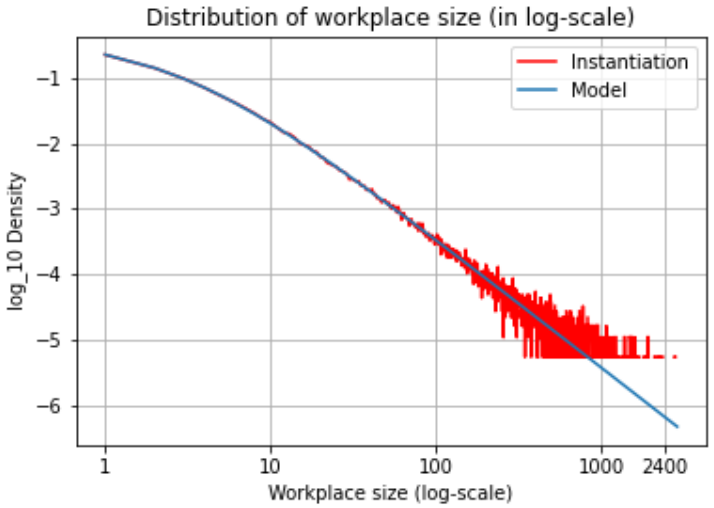
Abstracted as bipartite graphs

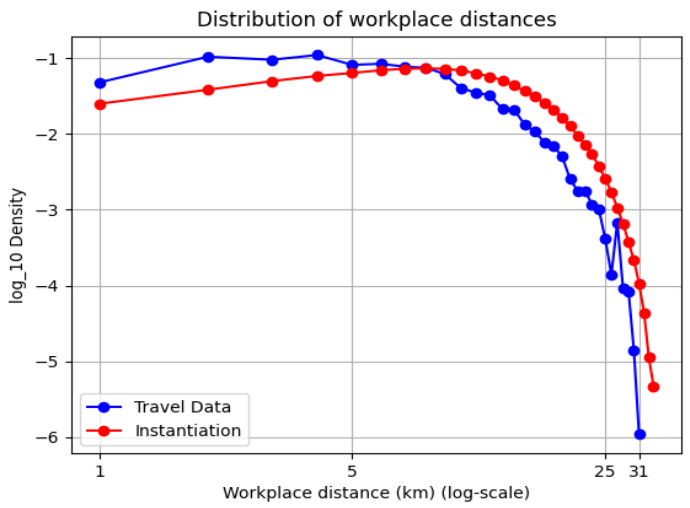


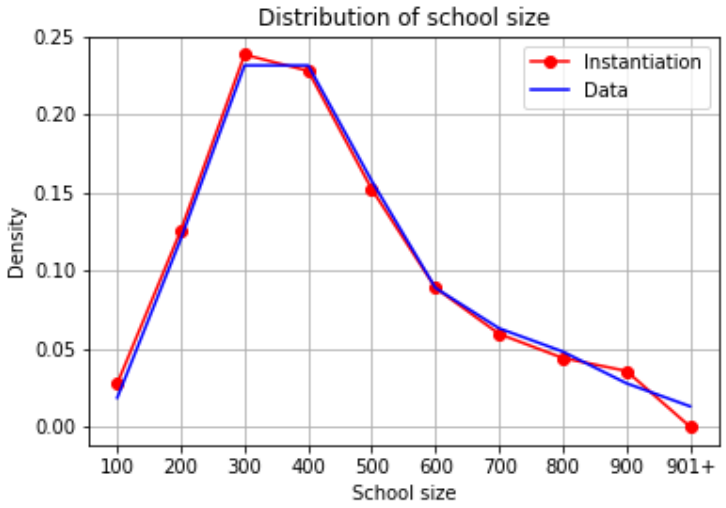
Real and synthetic Bengaluru









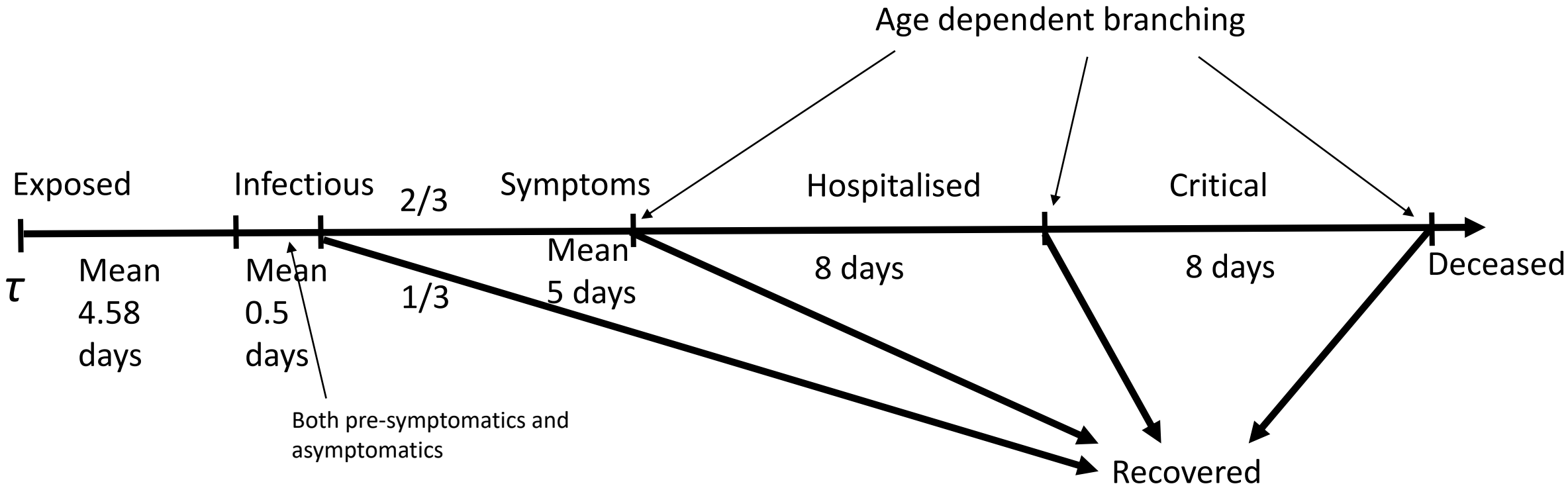


Question for the BPS types

- Individuals have been assigned to homes. Assign school-goers to schools and office-goers to offices so that the following are respected:
    - School-size distribution
    - Office-size distribution
    - Commute distance distribution
- It must be computationally efficient

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%

Other kinds of heterogeneity in contacts:
Not every infected individual spreads equally

- We already saw heterogeneity based on social network: whether an individual goes to work or school or is unemployed, or size of workplace, or whether the agent uses public transport
- Heterogeneity based on socio-economic factors, crowded households, crowded communities
- Severity induced absenteeism
  - The more severe the infection, the more likely that the individual stays at home, absenteeism
  - This absenteeism leads to reduced contacts at workplace and schools
- Infectiousness varies significantly across individuals
  - PHFI doctors seem to suggest that 20% of the infected individuals have caused 80% of the spread. Model infectiousness as a random variable
  - Infectiousness higher while exhibiting symptoms compared to the pre-symptomatic period
  - Infectiousness may also vary during the symptomatic period (not in ours)

Why model these?

Why model these interaction spaces and heterogeneities?

Tries to be a little more realistic

Enables study of targeted interventions

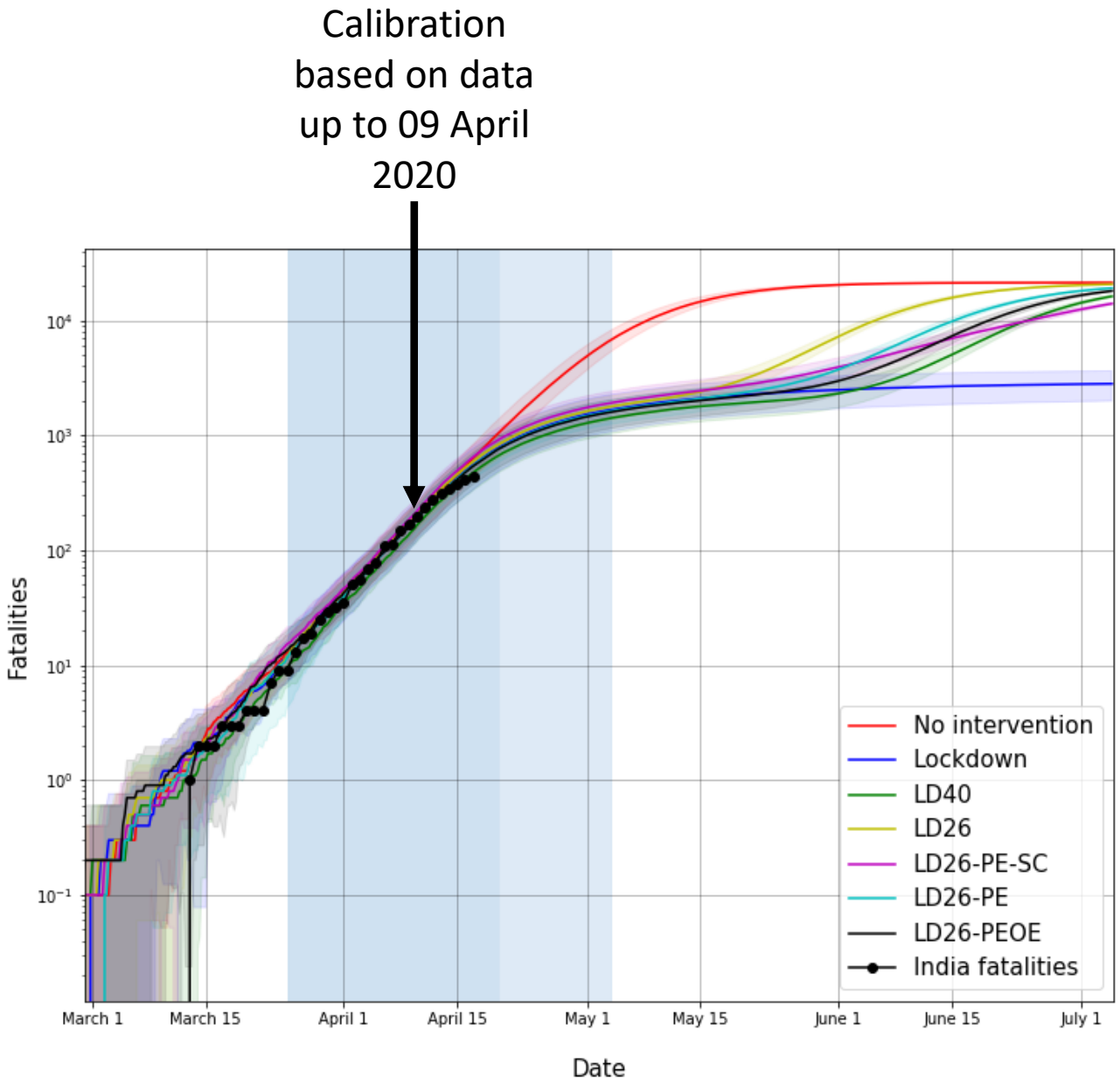
- Case isolation, home quarantine, social distancing of elderly, school closures
- Phased opening of some industries, transport, type of containment zone, etc.

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 50% of the household comply with the policy.
SC	Schools and colleges closed	…
SDE	Social distancing of the elderly	…

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)



“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 and seeding are the only 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).

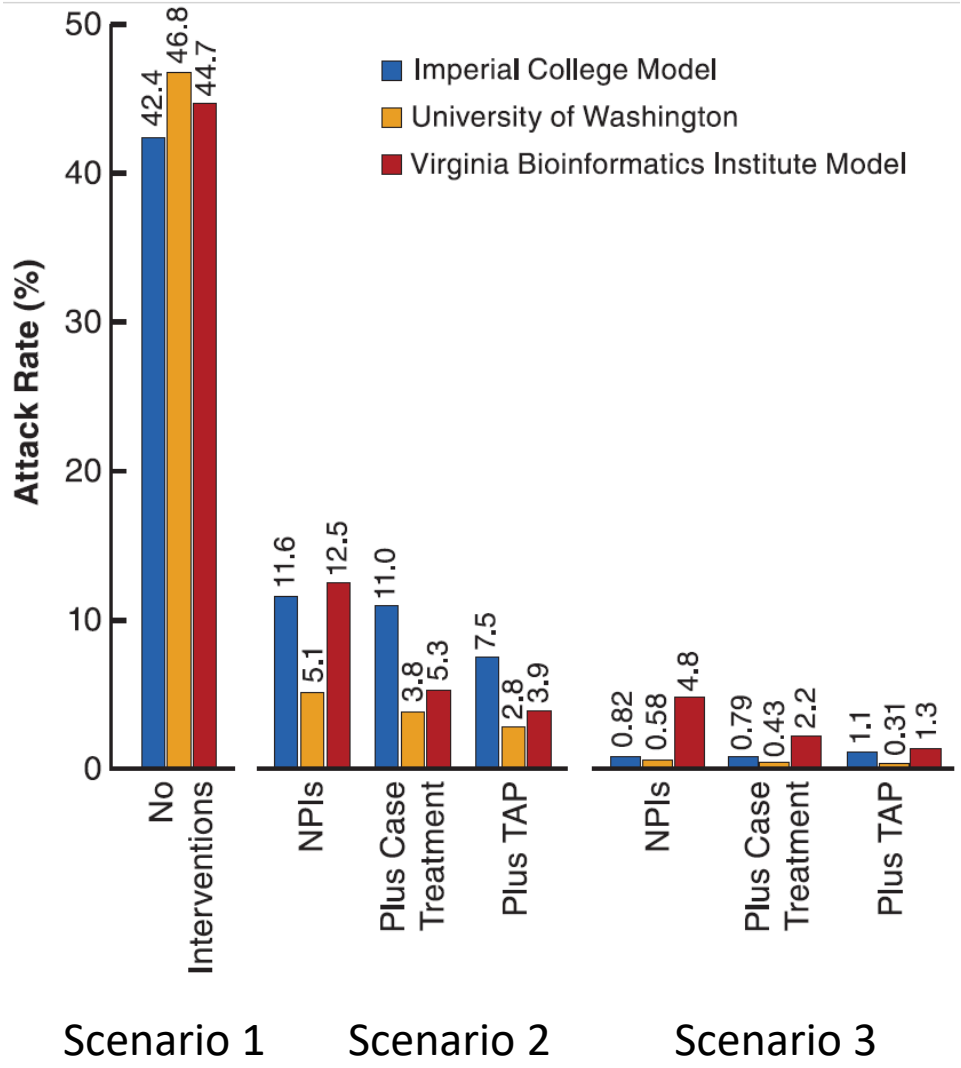
A comparative study

- 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



COVID-19 fatalities predicted by agent-based models

Model	City/Country (Pop.)	No intervention	Under proposed intervention	Observed as on 07/06/2020
Imperial College	UK (6.78 crores)	5,10,000	24,000 (middle value)	40,465
Imperial College	USA (33.10 crores)	22,00,000	Not available	1,09,802
University of Wash.	USA	Not yet available	Not yet available	1,09,802
University of Virginia	USA	Not yet available	Not yet available	1,09,802
Oxford University	USA	Not yet available	Not yet available	1,09,802
Uppsala	Sweden (1.01 crore)	96,000	25,000 (mandated social distancing)	10,699
IND-SCISIM – agent-based	India	Not available	Not available	6,929
IISc-TIFR	Mumbai (1.24 crore)	27,790	530 (90% compliance)	1,518
IISc-TIFR	Bengaluru (1 crore)	21,200	30 (90% compliance)	15

City-scale simulation studies - 1

Importance of compliance

MHA Order of 15/04/2020

- Many restrictions continued to apply nation-wide until 03 May 2020
- A few activities were permitted between 20 April 2020 and 03 May 2020, but decisions left with state administrations
  - IT and IT enabled services can operate at 50% strength
  - GoI and state/UT offices: critical function offices can operate, others can operate at 33% attendance.
  - Manufacturing and other industrial establishments with access control in SEZs and EoUs, industrial estates, industrial townships may operate (some restrictions apply)
- Comparative study of the public health impact of allowing these relaxations

Lockdown fatigue

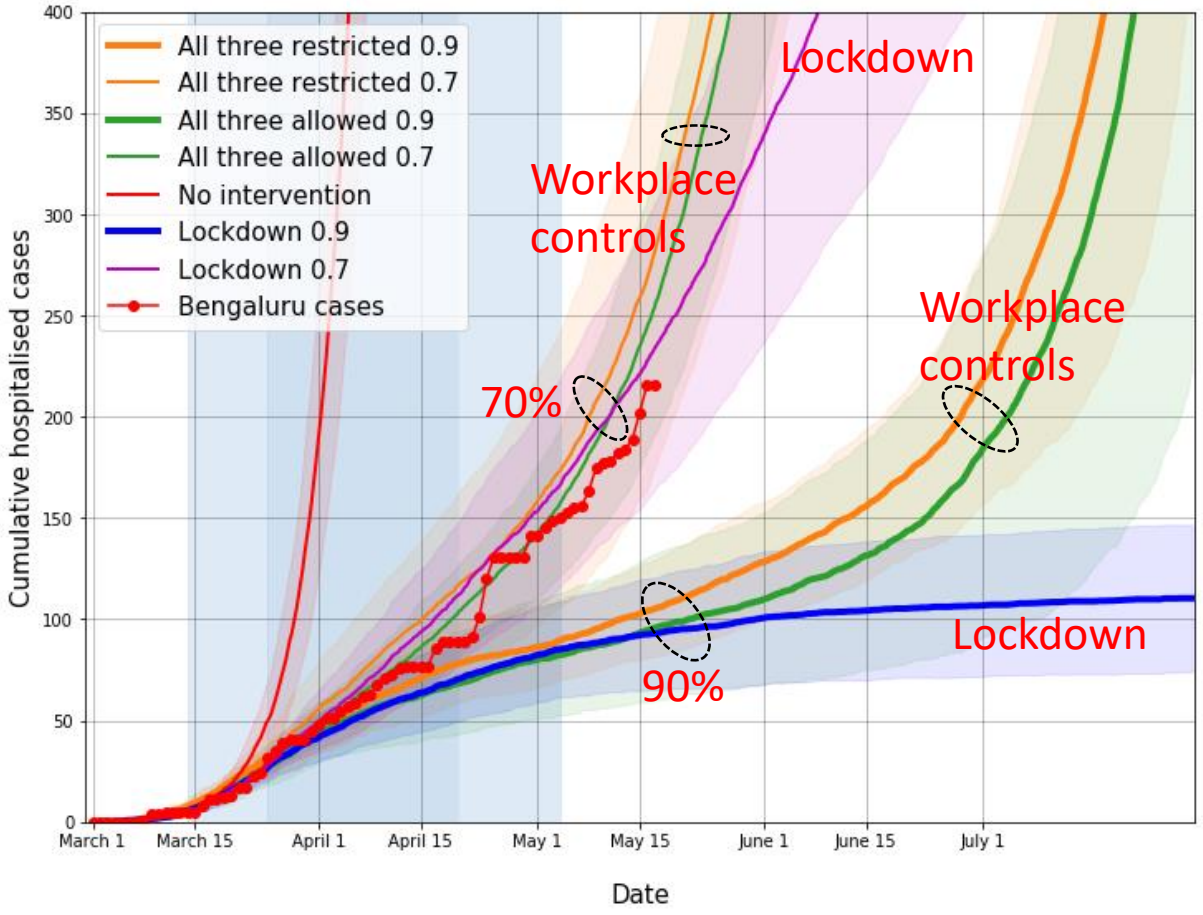
- Google mobility data provides some indication of lockdown fatigue

- We explored two compliance scenarios:
  - Lockdown but 70% of the households
  - Phased opening, but 90% of the households comply.

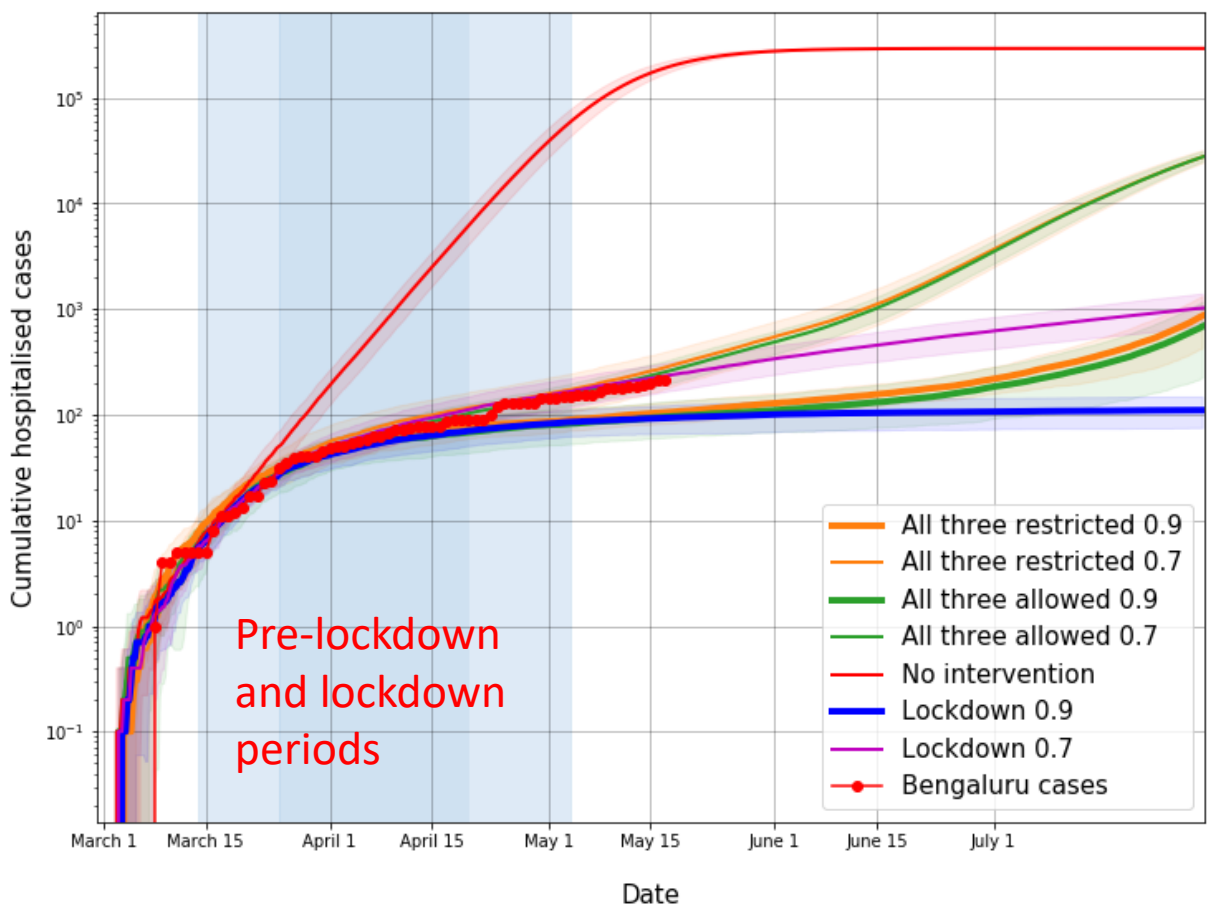
Bengaluru – compliance vs. allow/disallow 3 workplaces

(estimated hospitalised cases based on model, with standard error indications)

Linear scale plot of cumulative hospitalised



Log scale plot of cumulative hospitalised



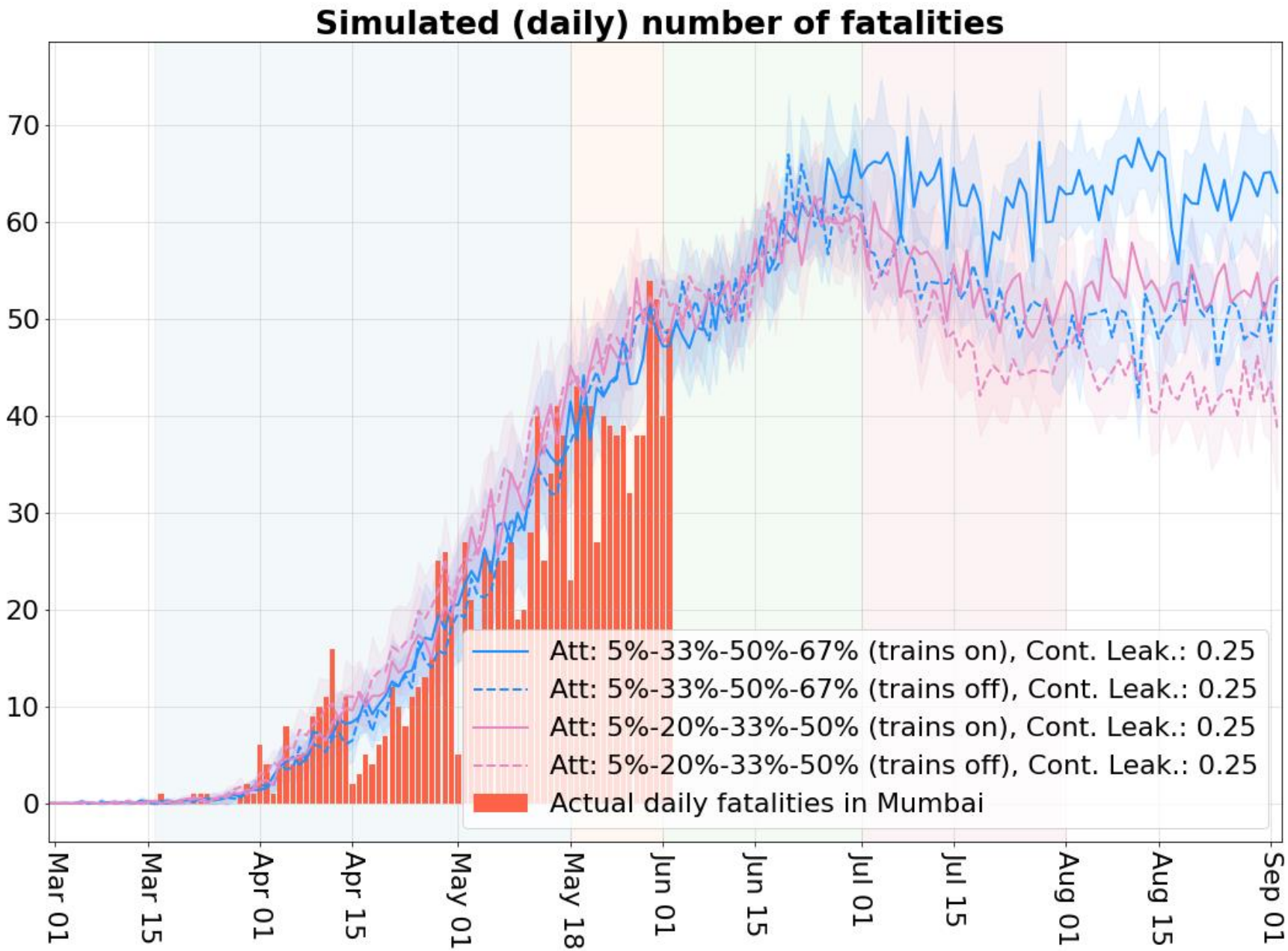
Take away: Allowing/disallowing these workplaces does not lead to much variation in the estimated cases.
But compliance plays a big role.
Bengaluru trend captured well between 70%-90% compliance.

City-scale simulation studies - 2

Mumbai trains and phased emergence (slides from our TIFR Mumbai colleagues)

Relaxations considered. Lockdown till May 17

Scenario	May 18 – May 31	June 1 – June 30	July
	During the lockdown 60% compliance in some areas, 40% in high-density areas. Soft containment zones active with the above compliance. Local lock at 0.1% hosp. Face masks modelled after 09 April. Strict case-Isolation (10%), home-quarantine post lockdown, 65 and older restricted to stay at home. Trains may be on or off at a suitable level after 01 June.		
1 with trains on 1 with trains off	Offices operate at 5% capacity.	Offices operate at 20% capacity	Offices operate at 33% capacity
2 with trains on 2 with trains off	Offices operate at 5% capacity	Offices operate at 33% capacity	Offices operate at 50% capacity


Simulated (daily) number of fatalities
70
60
50
40
30
20
10
0
Mar 01
Mar 15
Apr 01
Apr 15
May 01
May 18
Jun 01
Jun 15
Jul 01
Jul 15
Aug 01
Aug 15
Sep 01
Att: 5%-33%-50%-67% (trains on), Cont. Leak.: 0.25
Att: 5%-33%-50%-67% (trains off), Cont. Leak.: 0.25
Att: 5%-20%-33%-50% (trains on), Cont. Leak.: 0.25
Att: 5%-20%-33%-50% (trains off), Cont. Leak.: 0.25
Actual daily fatalities in Mumbai

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
    - Stochasticity in the beginning and at the end of the epidemic
    - Interventions
    - Study strategies for testing of contacts (in resource constrained settings)
- We highlighted some of our studies
    - Compliance, trains restart
- Other domains – traffic studies, effectiveness of the now-on now-off odd-even strategy in New Delhi, etc.

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  - Nidhin K Vaidhiyan, Nihesh Rathod, Preetam Patil, Sarath.A.Y., Sharad Sriram, Narendra Dixit, Aditya Krishna Swamy

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