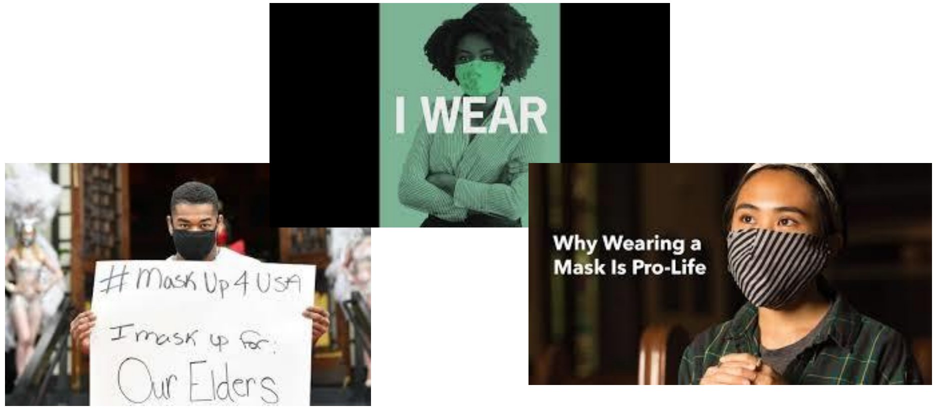
Towards Population-Scale Models of Pandemic Attitudes and Behaviors

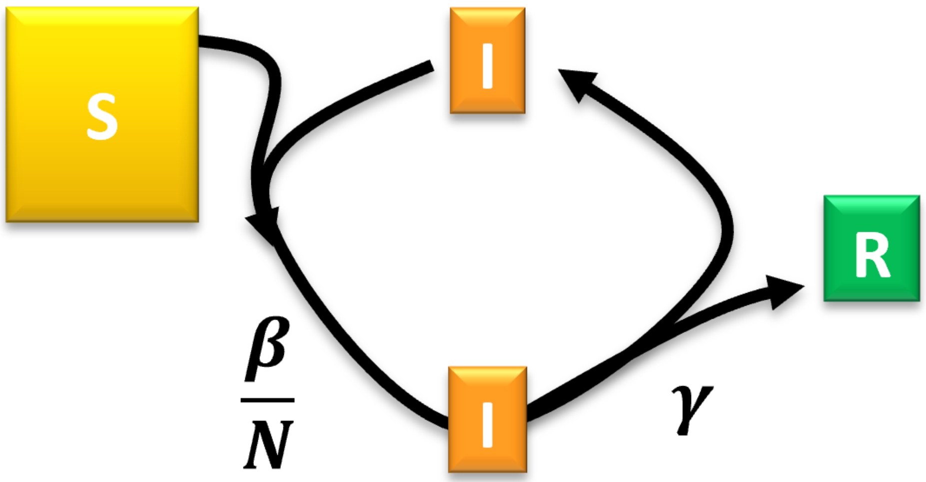
Peter Pirolli, Konstantinos Mitsopoulos,
Choh Man Teng, Christian Lebiere, Mark Orr

Individual Psychology Matters in the Prediction of Population-level Response to Pandemics



- **People have different mindsets and capabilities, they respond differently to behavior-change interventions**, and those responses change over time.

SIR Models (Compartmental Models; ODE Models)



Population is in different states or compartments:

- S = Number Susceptible
- I = Number Infectious
- R = No. Removed (immune or deceased)

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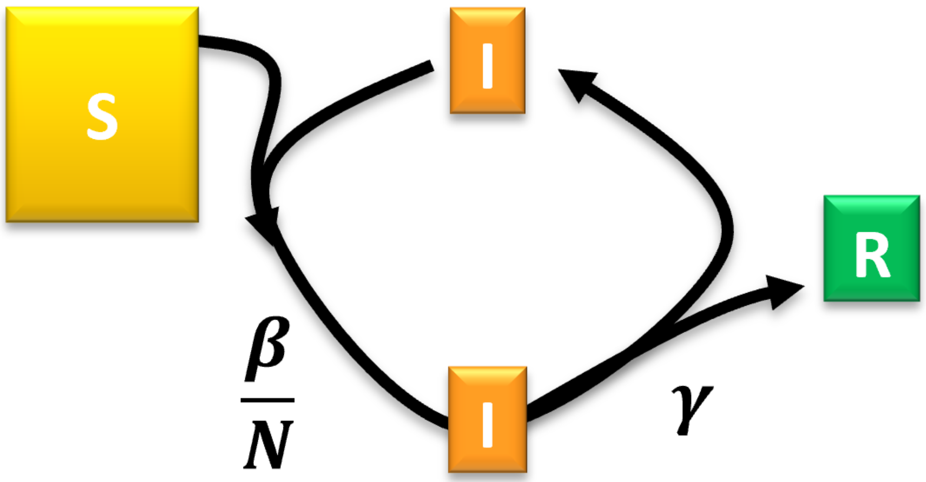

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A set of ordinary differential equations characterize the transitions

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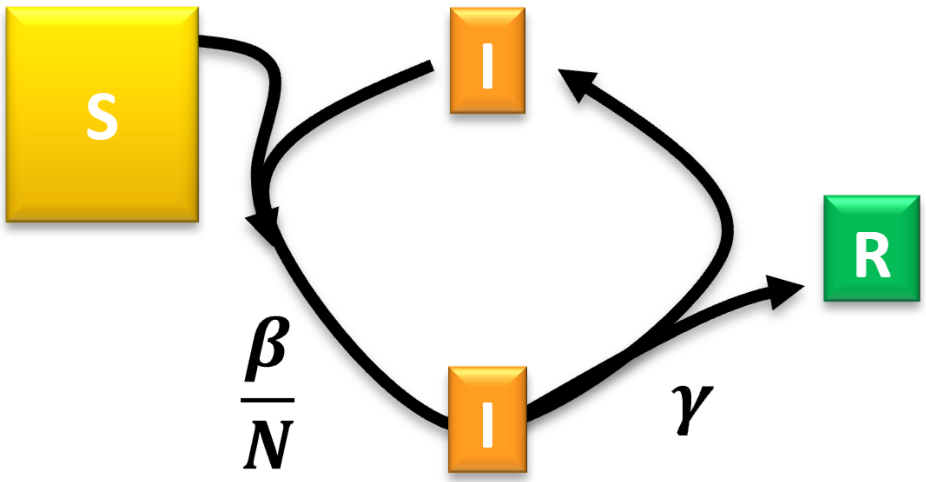

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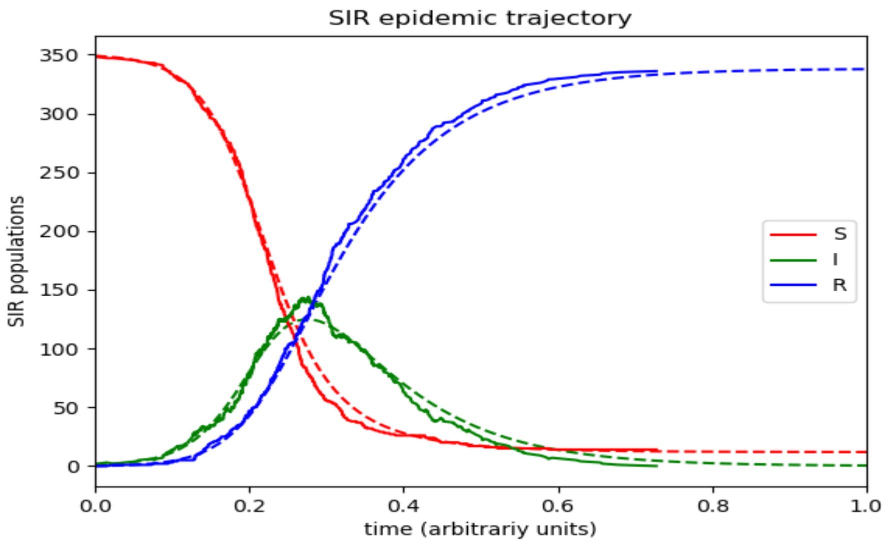
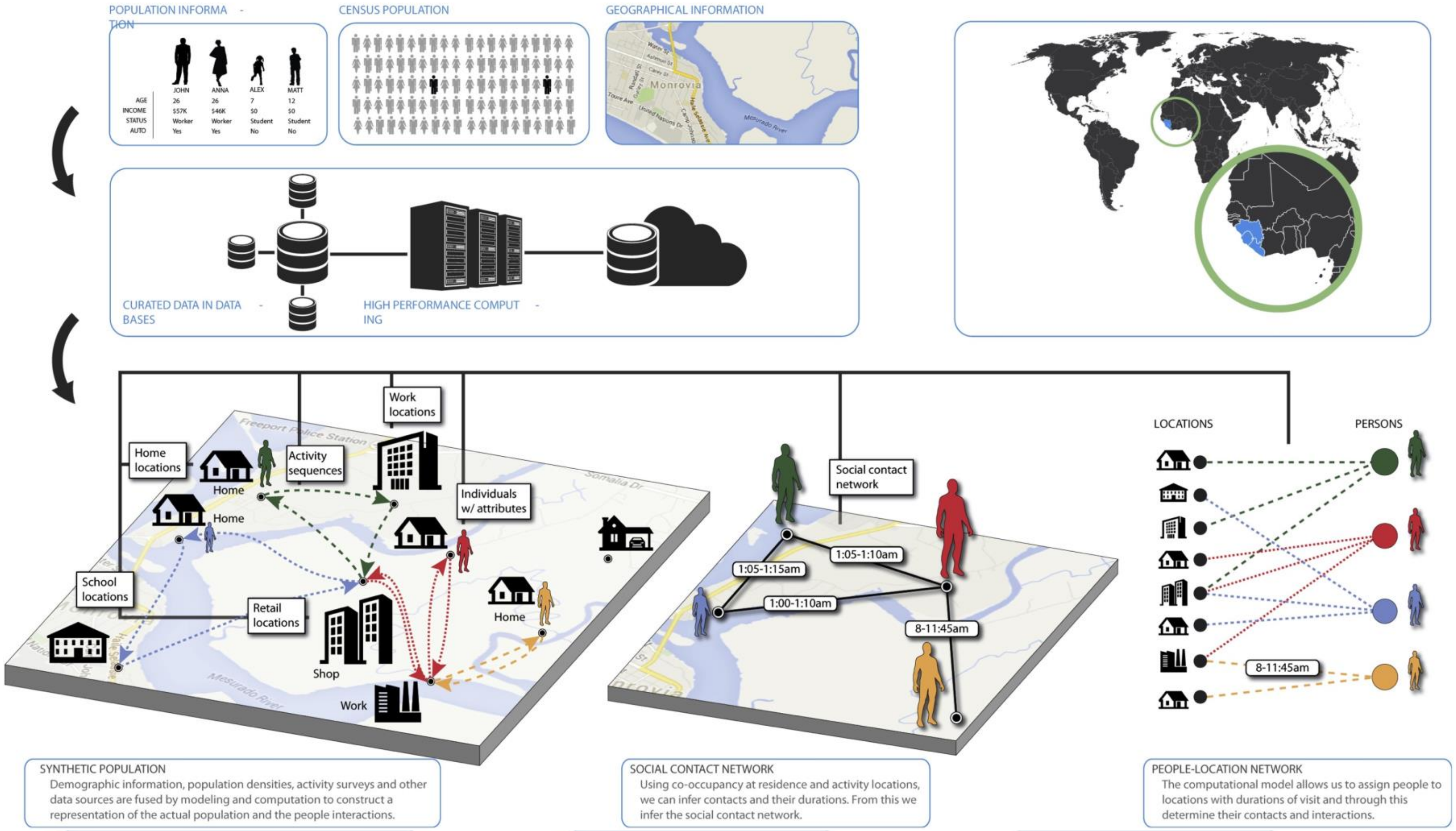


Agent Based Models

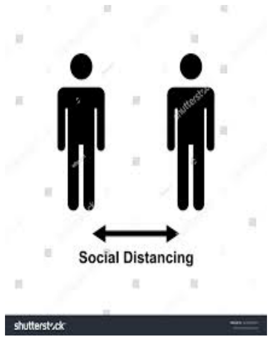


Venkatramanan, S., Lewis, B., Chen, J., Higdon, D., Vullikanti, A., & Marathe, M. (2018). Using data-driven agent-based models for forecasting emerging infectious diseases. *Epidemics, 22*, 43-49. doi:10.1016/j.epidem.2017.02.010

Individual-level behavior-response strength profile

Hand washing

Mask wearing

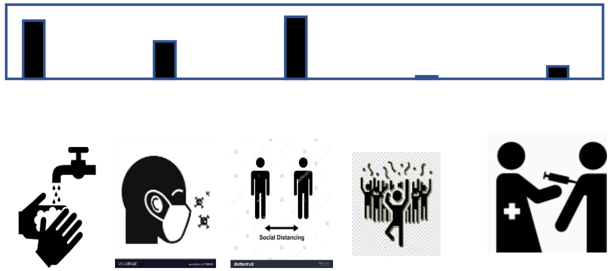


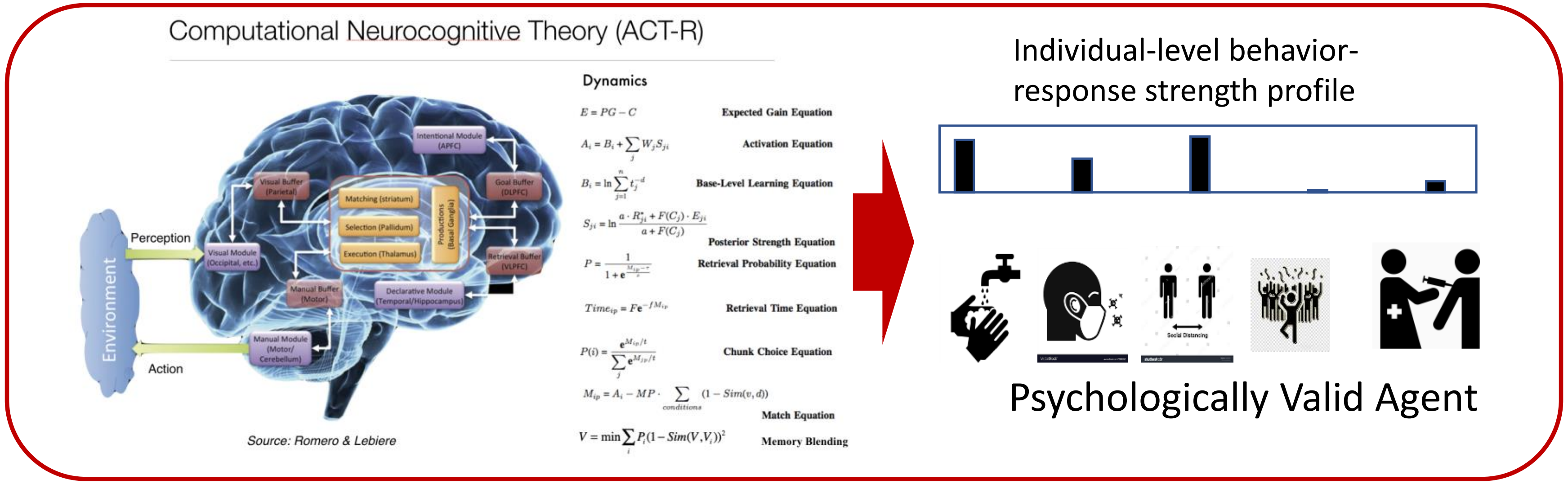
Social distancing

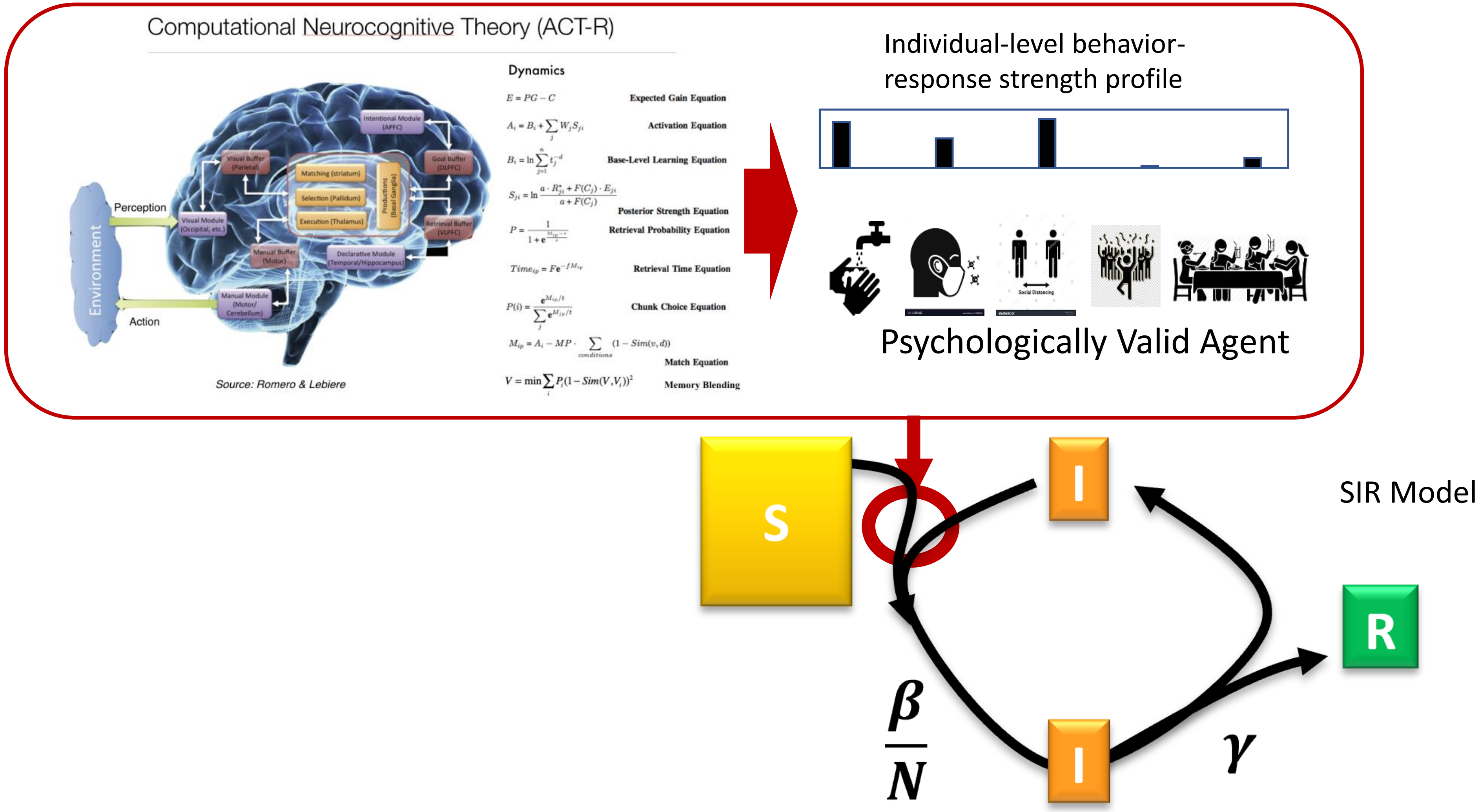
Nonessential visits

Vaccination

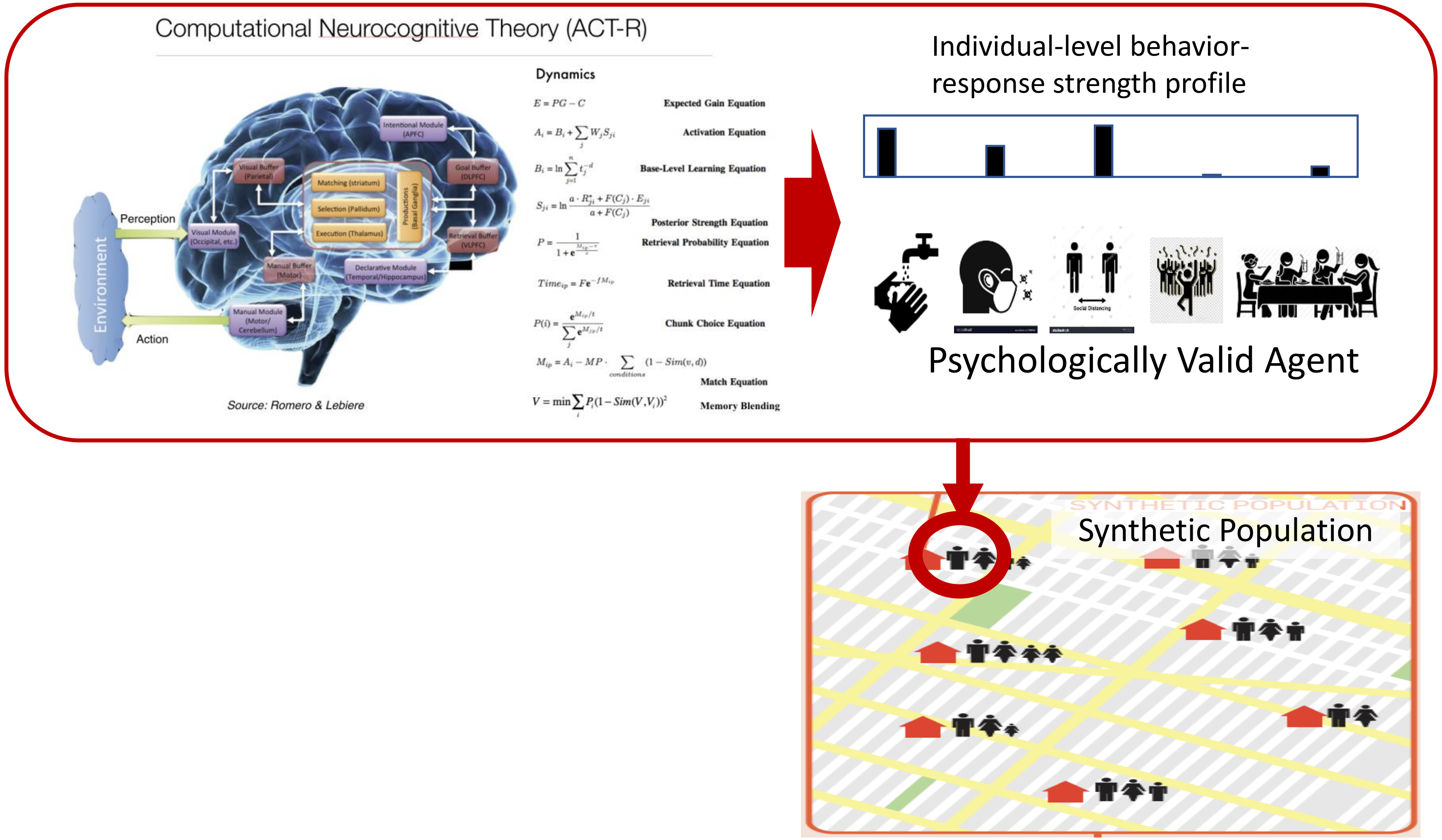
Individual-level behavior-response strength profile



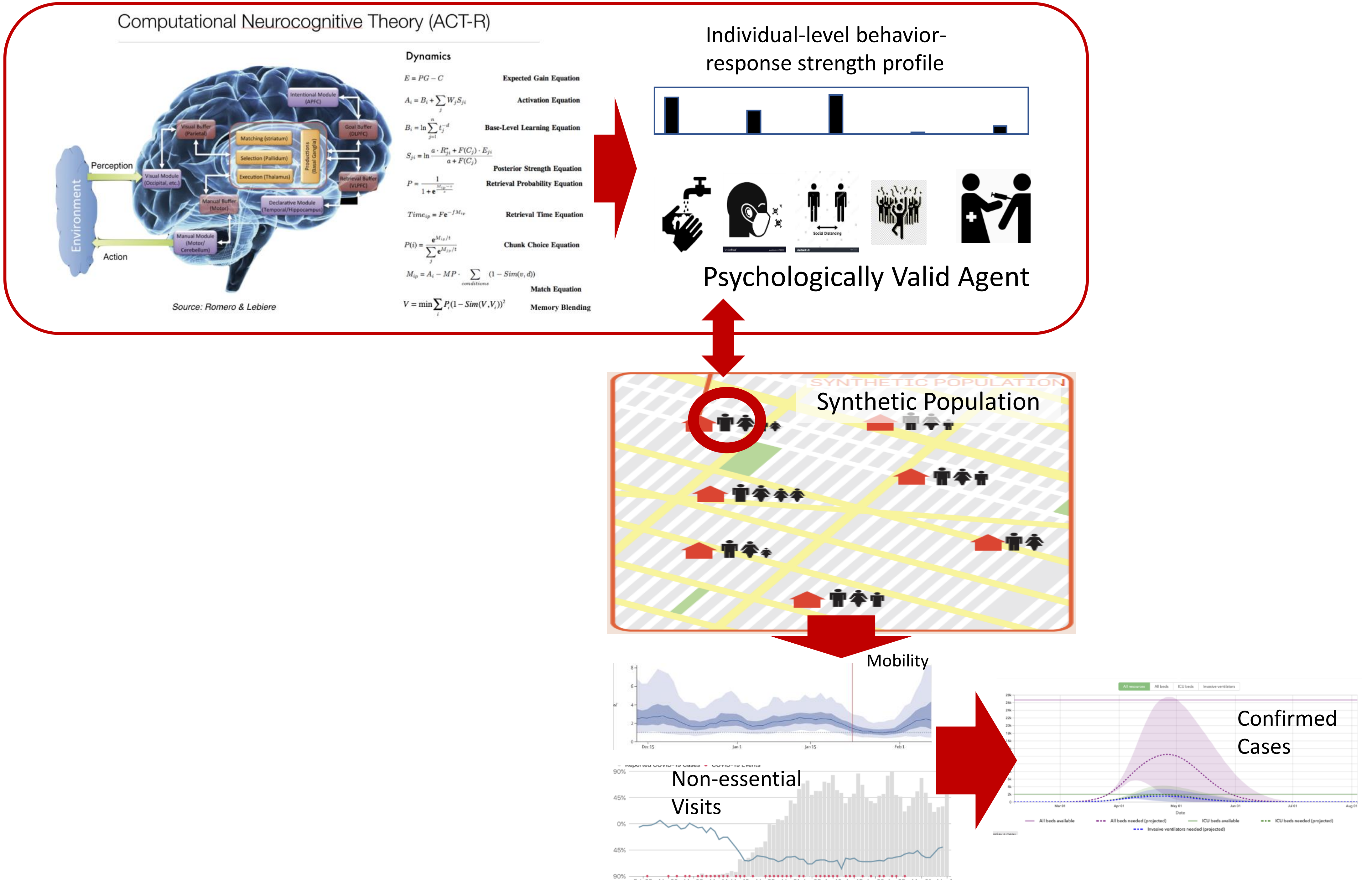

Computational Neurocognitive Theory (ACT-R)
Dynamics
Expected Gain Equation
Activation Equation
Base-Level Learning Equation
Posterior Strength Equation
Retrieval Probability Equation
Retrieval Time Equation
Chunk Choice Equation
Match Equation
Memory Blending
Environment
Perception
Action
Intentional Module (APFC)
Visual Buffer (Parietal)
Goal Buffer (DLPFC)
Matching (striatum)
Selection (Pallidum)
Execution (Thalamus)
Productions (Basal Ganglia)
Visual Module (Occipital, etc.)
Retrieval Buffer (VLPFC)
Manual Buffer (Motor)
Declarative Module (Temporal/Hippocampus)
Manual Module (Motor/ Cerebellum)
Source: Romero & Lebiere
Individual-level behavior-response strength profile
Social Distancing
Psychologically Valid Agent



Embed <u>Psychologically Valid Agents</u> in an SIR Model of a given region and period



Embed Psychologically Valid Agents *in an agent-based simulation of a given region and period*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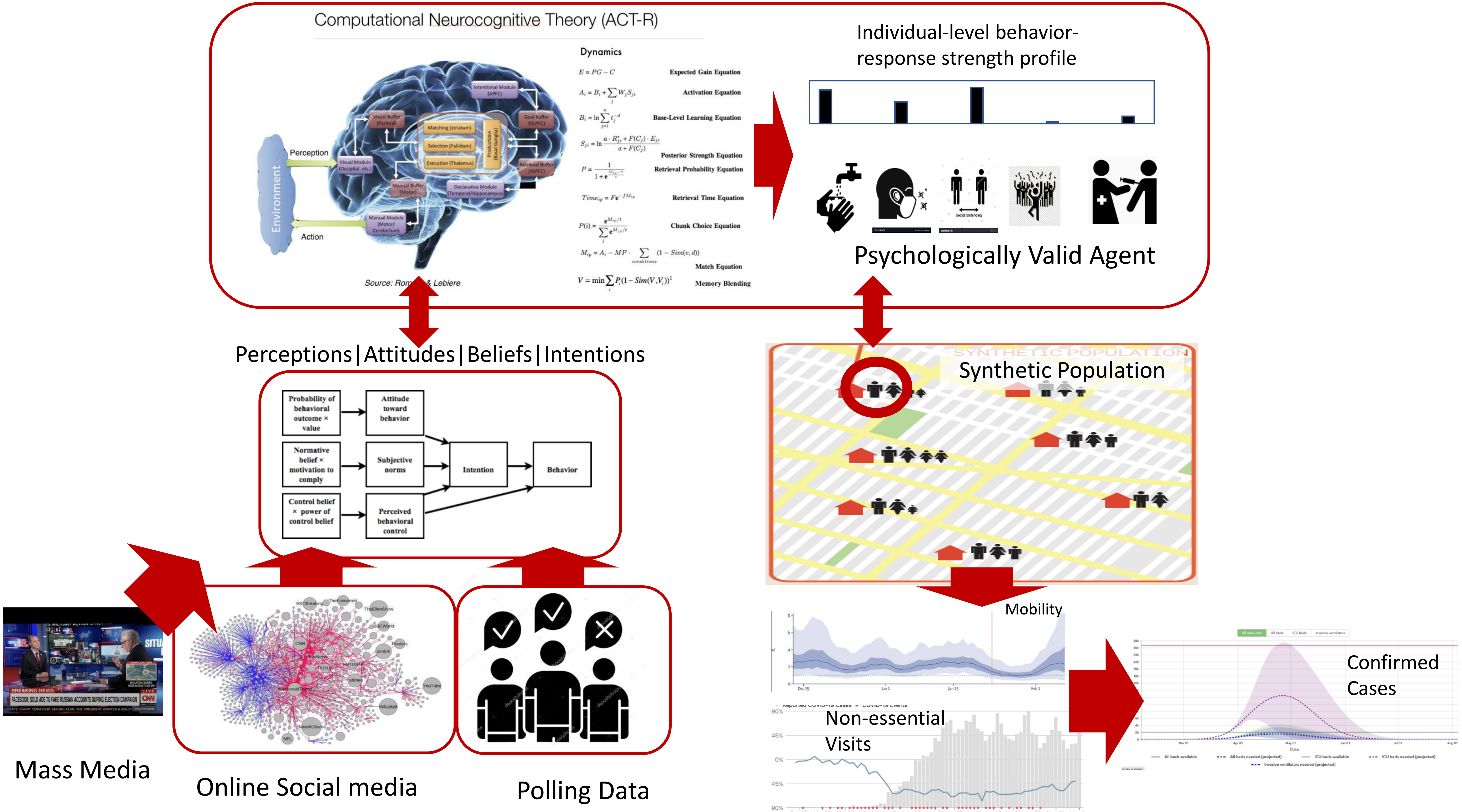
Individual-level behavior-response strength profile
Psychologically Valid Agent
Synthetic Population
Mobility
Non-essential Visits
Confirmed Cases



Computational Neurocognitive Theory (ACT-R)
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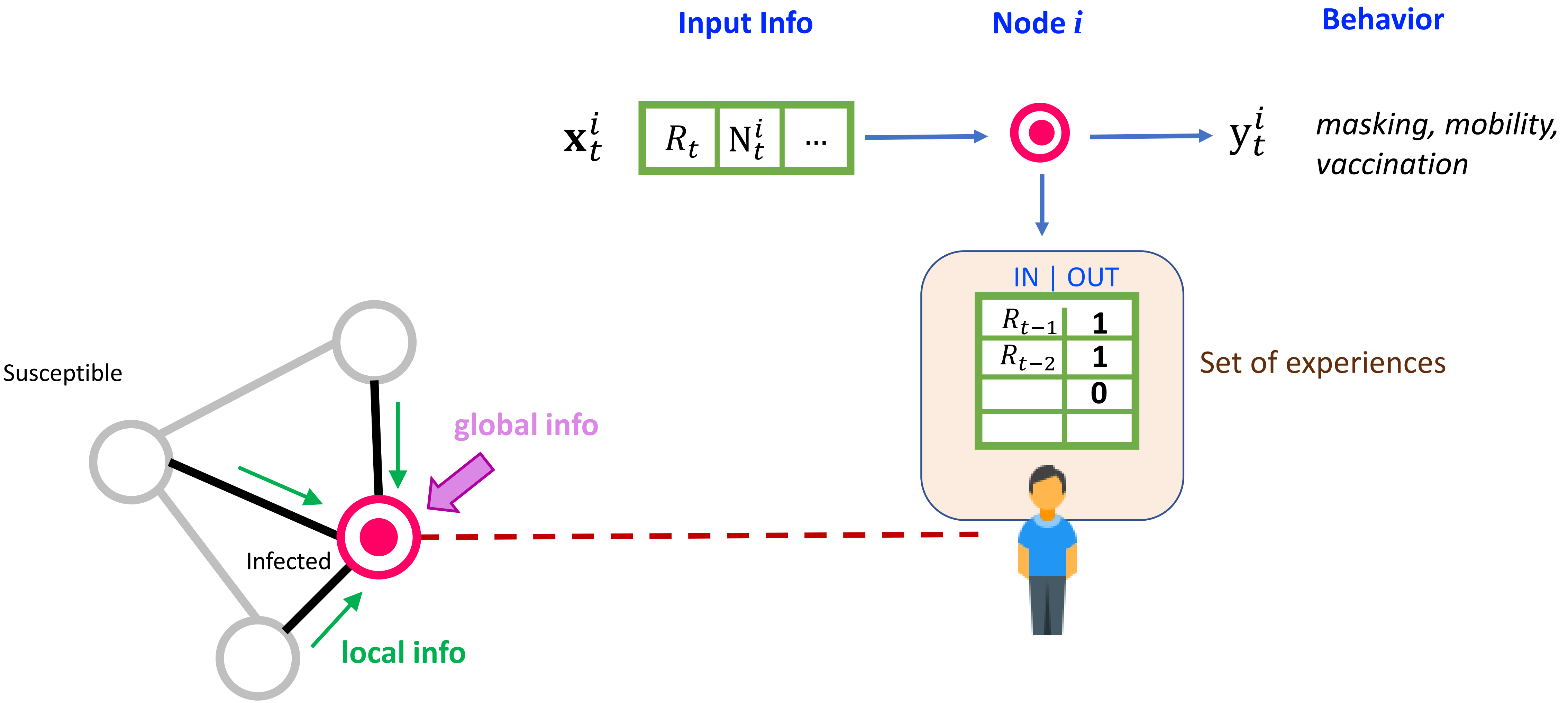
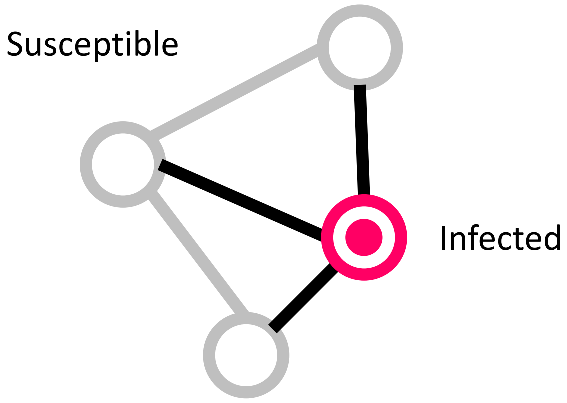
Individual-level behavior-response strength profile
Psychologically Valid Agent
Perceptions|Attitudes|Beliefs|Intentions
Probability of behavioral outcome × value
Attitude toward behavior
Normative belief × motivation to comply
Subjective norms
Intention
Behavior
Control belief × power of control belief
Perceived behavioral control
Synthetic Population
Mobility
Non-essential Visits
Confirmed Cases
Mass Media
Online Social media
Polling Data

Data-informed Agents in Epi-Networks

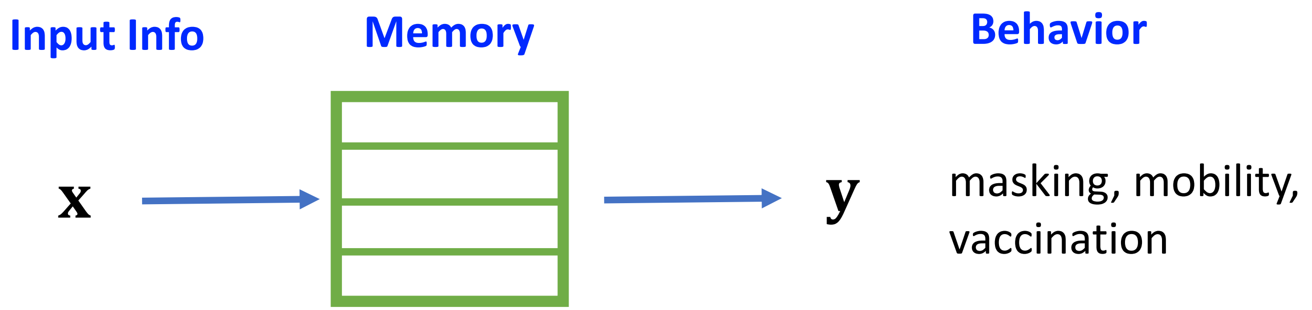


Types of Data-Informed Agents

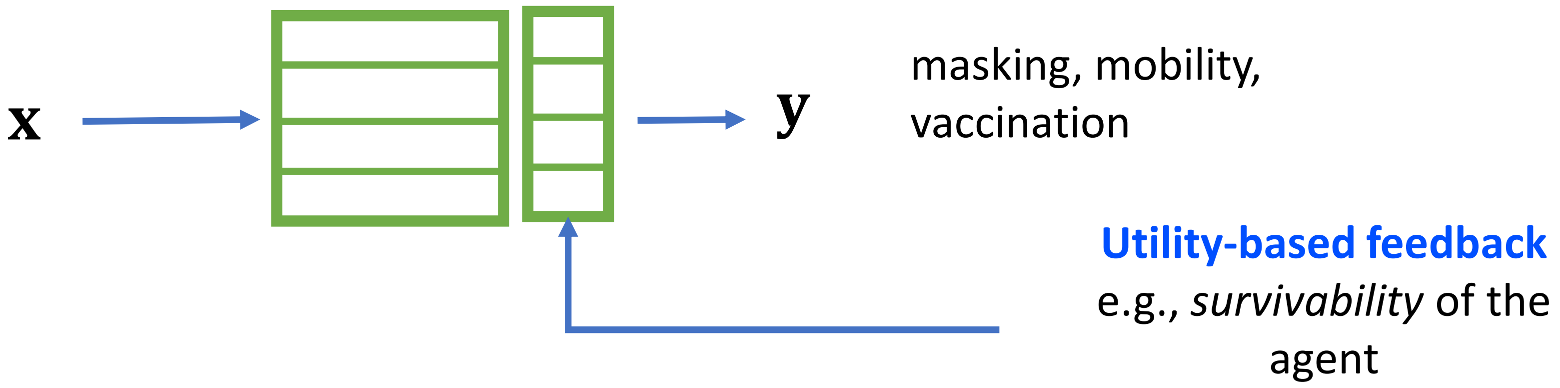


Agents core module is based on a <u>**Cognitive Architecture**</u> that performs Instance-based Learning.

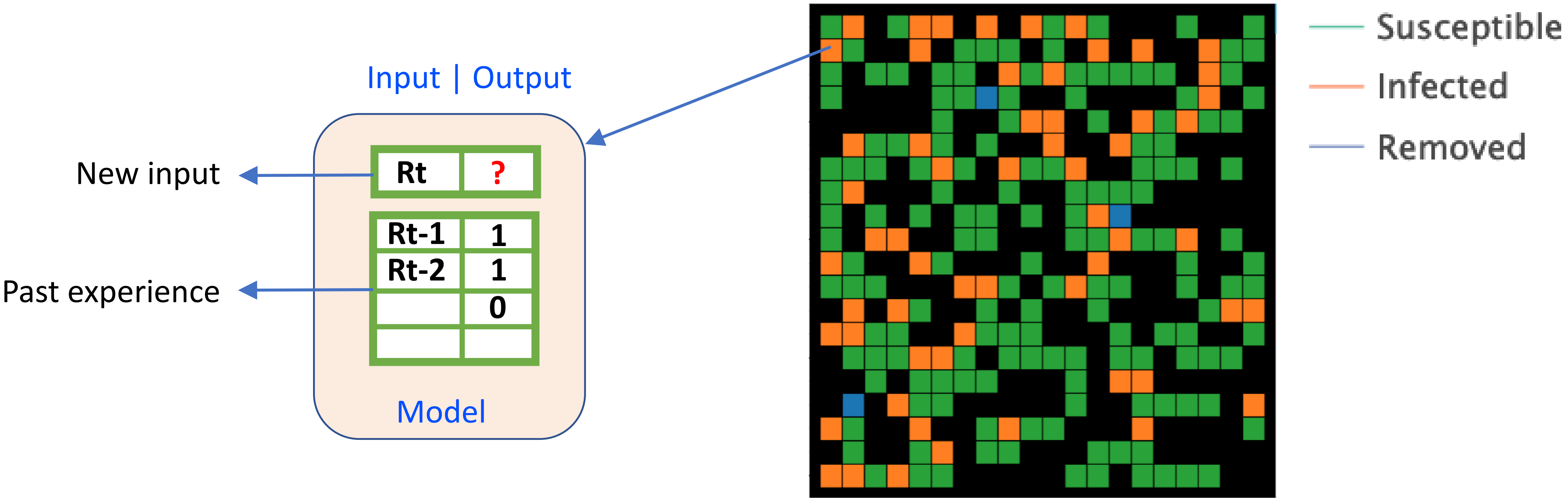
A. Experience-based Behavior



B. Utility-based Behavior



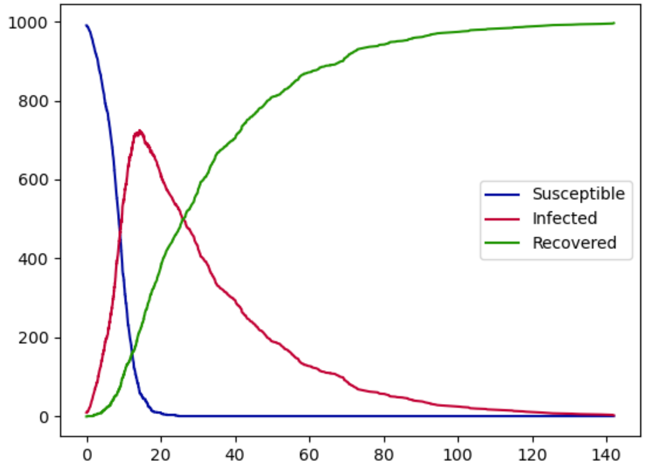
Simple Scenario with Global Information



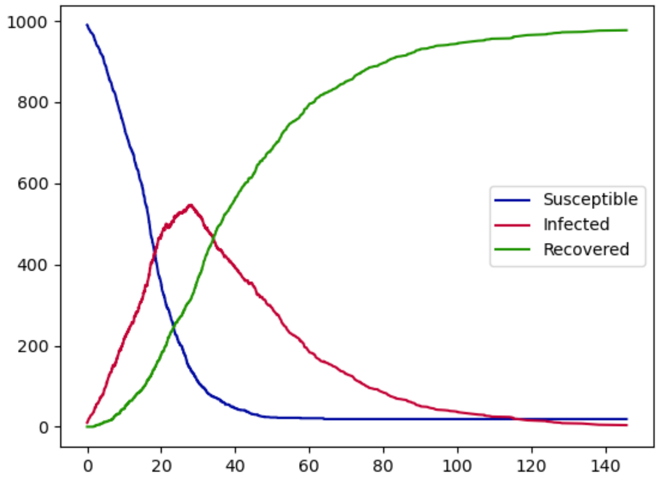
Rt → Model → 😷 → Epidemic Model → Rt+1 → …

Running Scenarios

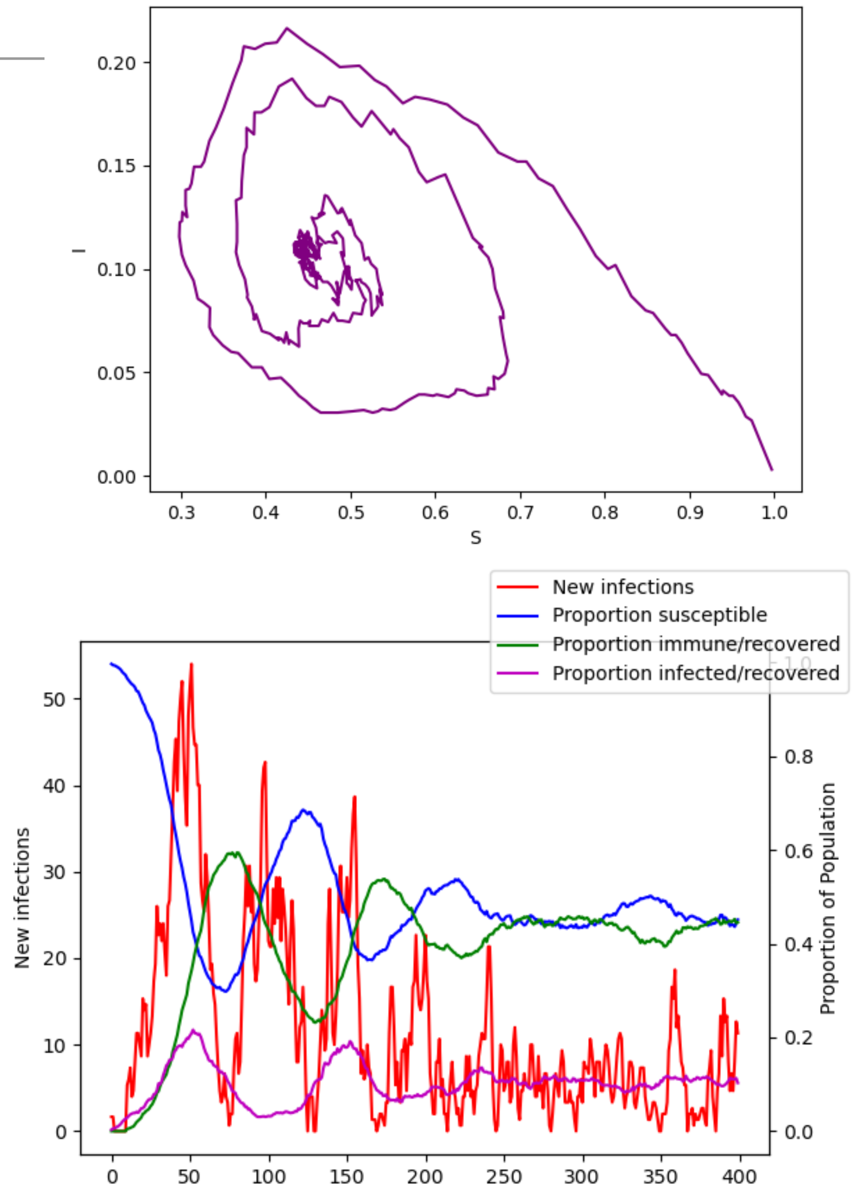
No masking



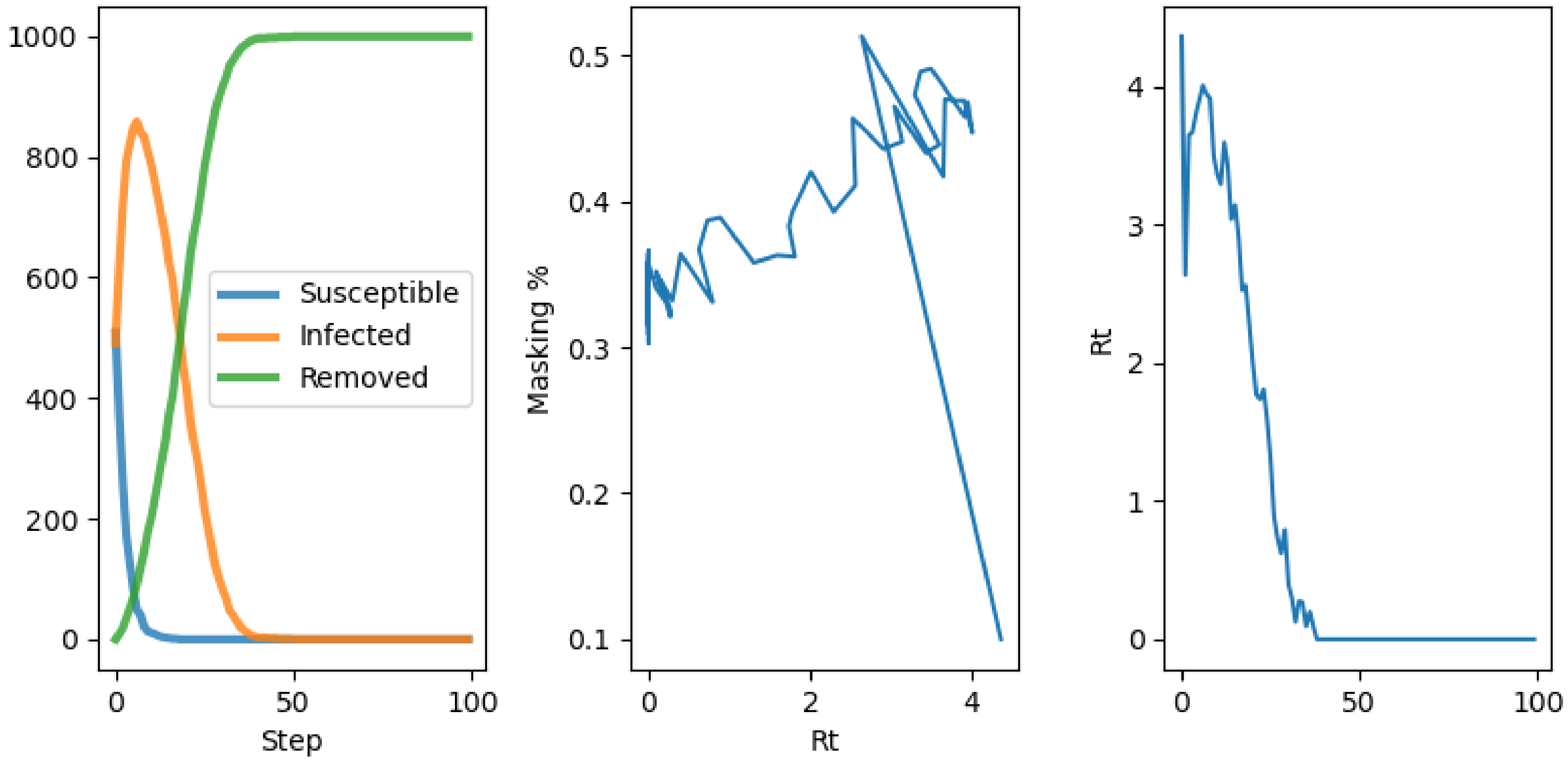
Masking



SIRS with varying immunity



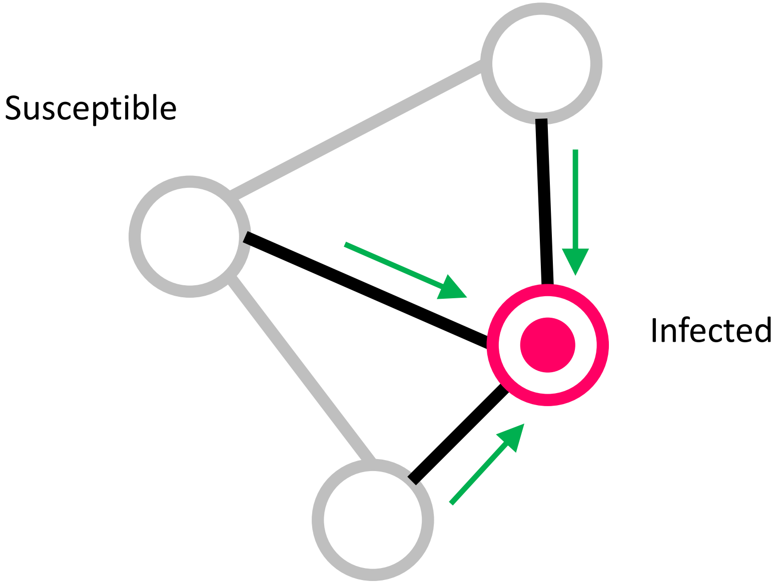
Running Scenarios with Experience-based Agents



Simple Scenario with Local Information and Realistic Network

Input Info **Node *i*** **Behavior**

$\mathbf{x}_t^i$ $\boxed{\mathrm{N}_t^i}$ $\longrightarrow$ ◉ $\longrightarrow$ y_t^i masking, mobility, vaccination



Network approximates a synthetic population network of **Portland** (10K nodes).

Avg num of neighbors: 11

Population parameters

'Asym.prop',
'Critical.prop',
'Die.in.icu.prop',
'Hosp.prop',
'MonthsOfImmunityDuration',
'Severe.prop',
'd.asym',
'd.hos',
'd.icu.mult',
'd.incum',
'd.sym.mild',
'd.to.death.not.hosp',
'd.to.hos',
'incum.non.infec.proportion',
'm.Sm',
'm.Ss',
'm.h',
'severe.die.hosp.shut',
'tau',
'prob.tran.base',
'mult.trans',
'daily.vacc.rate',
'vacc.eff.prev.trans',
'daily.prob.randomly.testing',
'false.positive.rate',
'false.negative.rate',
'pos.test.mixing.reduction',
'variant.prob',
'variant.trans.drift',
'variant.count',
'variant.history',
'tau.eff',
'R0',
'status_init'

t=0

	id	sex	household_id	age	inf.status	test.day	trans.factor	disease.trans.day	pos.test	vaccinated	variant	path	R.count	R.count.transformed	strength	vacc.priority.score
2000261	2000261	2	2000076	57	Susc	nan	1.00000	nan	False	False	nan	1	0.00000	0.00000	0.01820	5568.00000
2000262	2000262	1	2000076	23	Susc	nan	1.00000	nan	False	False	nan	1	0.00000	0.00000	0.05794	6503.00000
2000263	2000263	1	2000076	32	Susc	nan	1.00000	nan	False	False	nan	1	0.00000	0.00000	0.03788	6160.00000
2000264	2000264	2	2000076	26	Susc	nan	1.00000	nan	False	False	nan	1	0.00000	0.00000	0.06993	7577.00000
2000413	2000413	2	2000122	36	Susc	nan	1.00000	nan	False	False	nan	1	0.00000	0.00000	0.02172	4604.00000

t=30

2007066	2	2002564	41	Inf.Sm	750110.00...	0.20000	31.00000	False	False	1.00000	Inf.Sm	0.00000	0.00000	0.05749	8338.00000
2007067	2	2002564	18	Susc	nan	1.00000	nan	False	False	nan	1	0.00000	0.00000	0.02937	3434.00000
2007068	1	2002564	17	Susc	nan	1.00000	nan	False	False	nan	1	0.00000	0.00000	0.01117	1315.00000
2007189	2	2002598	49	Susc	nan	0.20000	nan	False	False	nan	1	0.00000	0.00000	0.04795	8332.00000
2007190	2	2002598	18	Susc	nan	1.00000	nan	False	False	nan	1	0.00000	0.00000	0.04712	4853.00000
2007191	1	2002598	16	Susc	nan	1.00000	nan	False	False	nan	1	0.00000	0.00000	0.01526	1691.00000

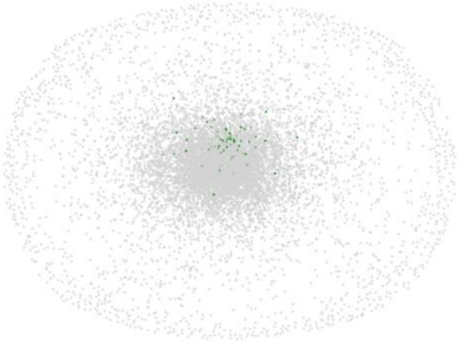
from	to	data
2000261	2000262	{'weight': 0.01849580767861203, 'edge_id': 1}
2000261	2000263	{'weight': 0.01849580767861203, 'edge_id': 2}
2000261	2000264	{'weight': 0.01849580767861203, 'edge_id': 3}
2000261	2029128	{'weight': 0.01849580767861203, 'edge_id': 4}
2000261	2189707	{'weight': 0.01849580767861203, 'edge_id': 5}
2000261	2668730	{'weight': 0.01849580767861203, 'edge_id': 6}
2000261	2000260	{'weight': 0.01849580767861203, 'edge_id': 7}
2000262	2000263	{'weight': 0.01849580767861203, 'edge_id': 8}
2000262	2000264	{'weight': 0.01849580767861203, 'edge_id': 9}
2000262	2006030	{'weight': 0.01849580767861203, 'edge_id': 10}
2000262	2026136	{'weight': 0.01849580767861203, 'edge_id': 11}
2000262	2030942	{'weight': 0.01849580767861203, 'edge_id': 12}

Algorithm 1 ABM Epidemiological Simulation

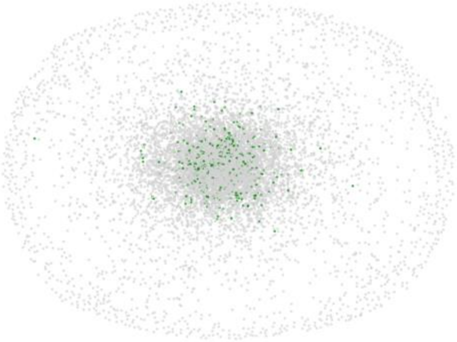
```
robjects.r[source](abm_run_init.R)                      ▷ Run initialization script in R
g_sim_r ← robjects.r[g_sim]                             ▷ g_sim is from R workspace
p ← robjects.r[p]                                       ▷ population params
g_sim_py ← convert_to_python(g_sim_r)
G ← create_network(g_sim_py)
create_decision_makers(G)

for t in range(num_periods) do
    g_sim_r ← robjects.r[RunAbm](g_sim_r, p, days = 7)  ▷ simulation in R
    g_sim_py ← convert_to_python(g_sim_r)
    G ← update_network(G, g_sim_py)
    mask_decisions(G, criterion)
    g_sim_r ← revert_network_to_r(G, g_sim_r, g_sim_py)
end for
```

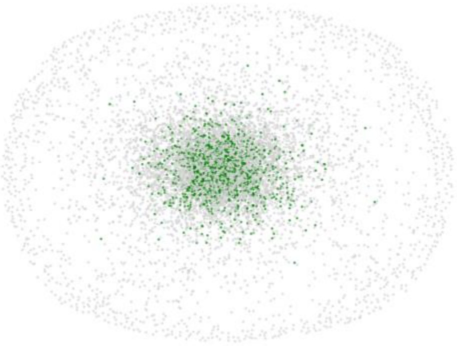
t=0
R=2.5



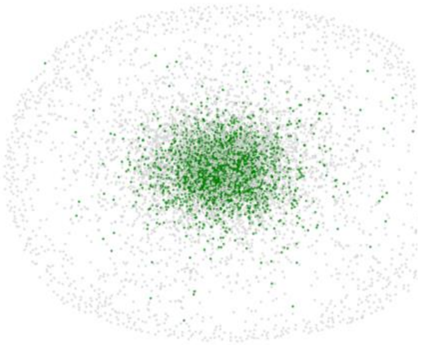
t=14



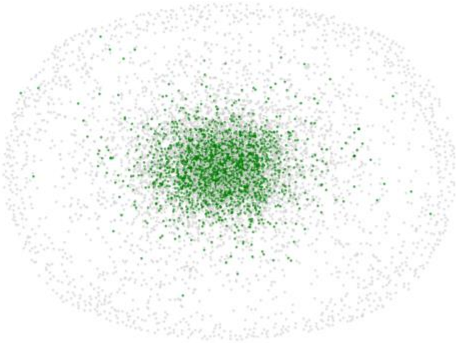
t=21



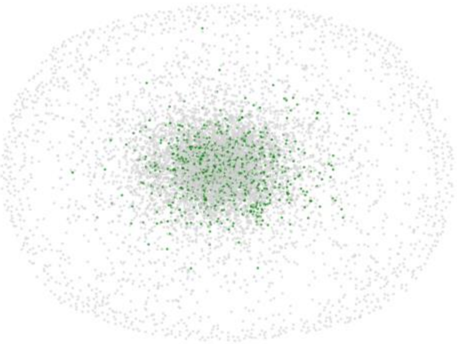
t=28



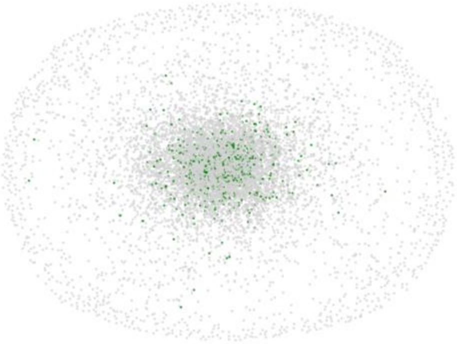
t=35



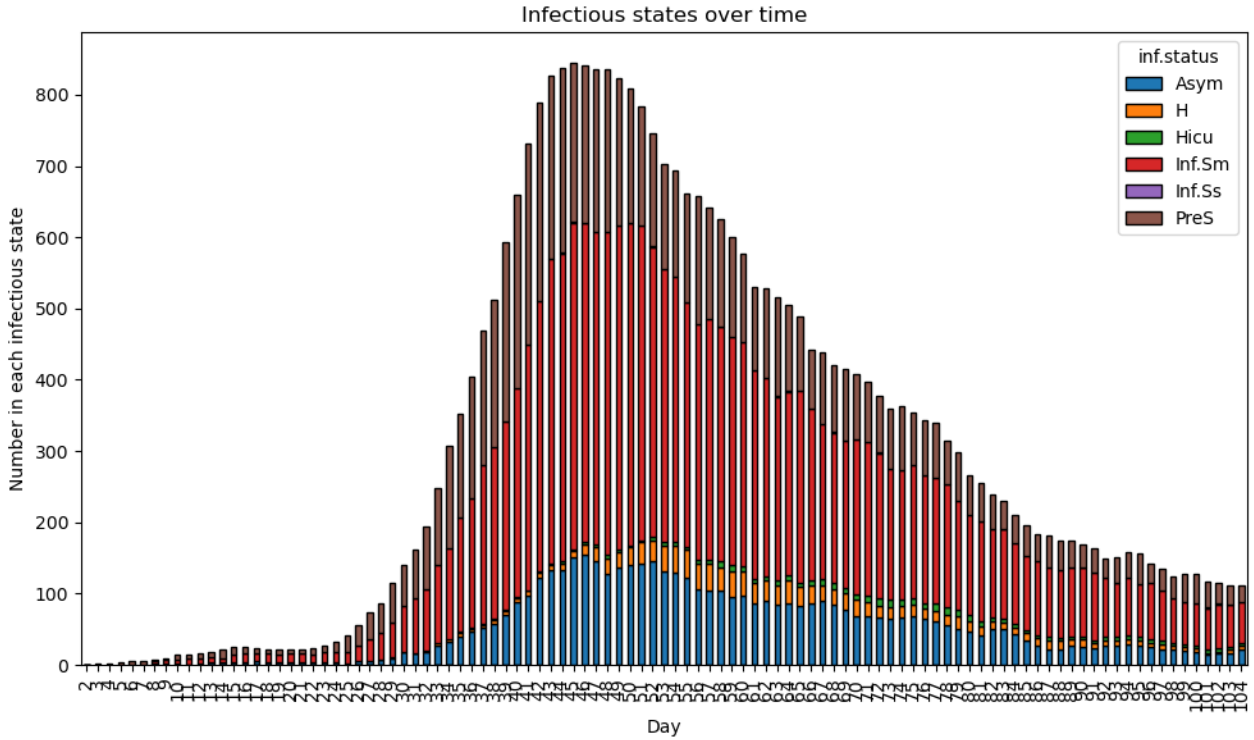
t=49
R=1.77



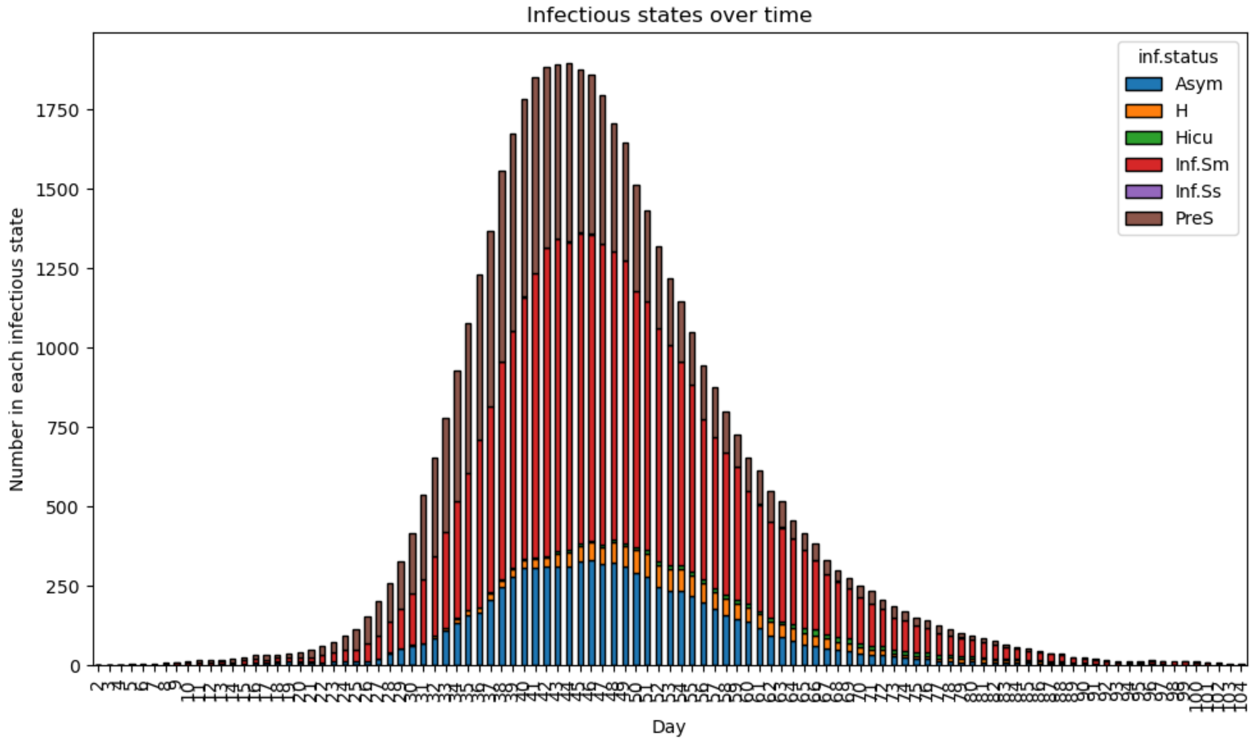
t=77



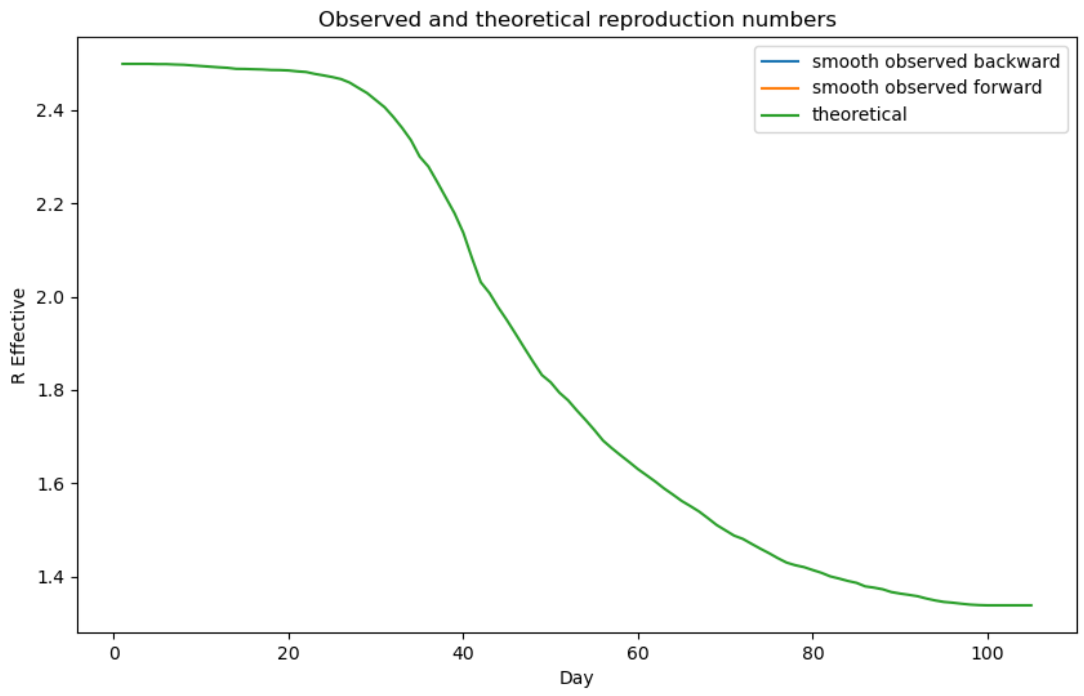
t=98
R=1.33



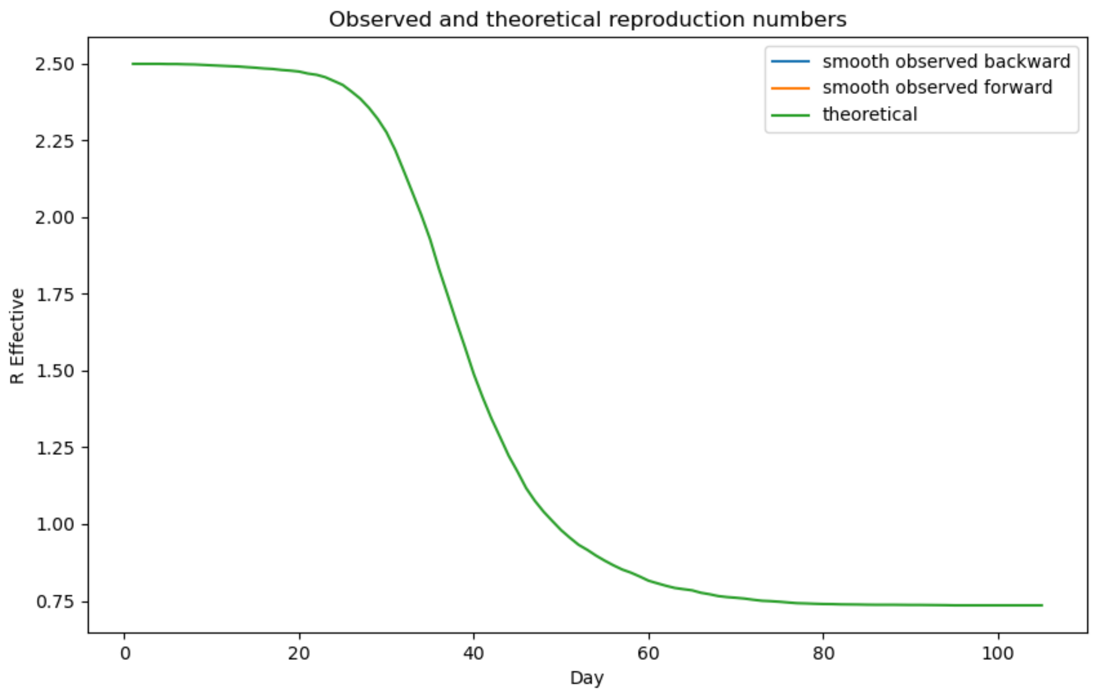
Masking



No Masking



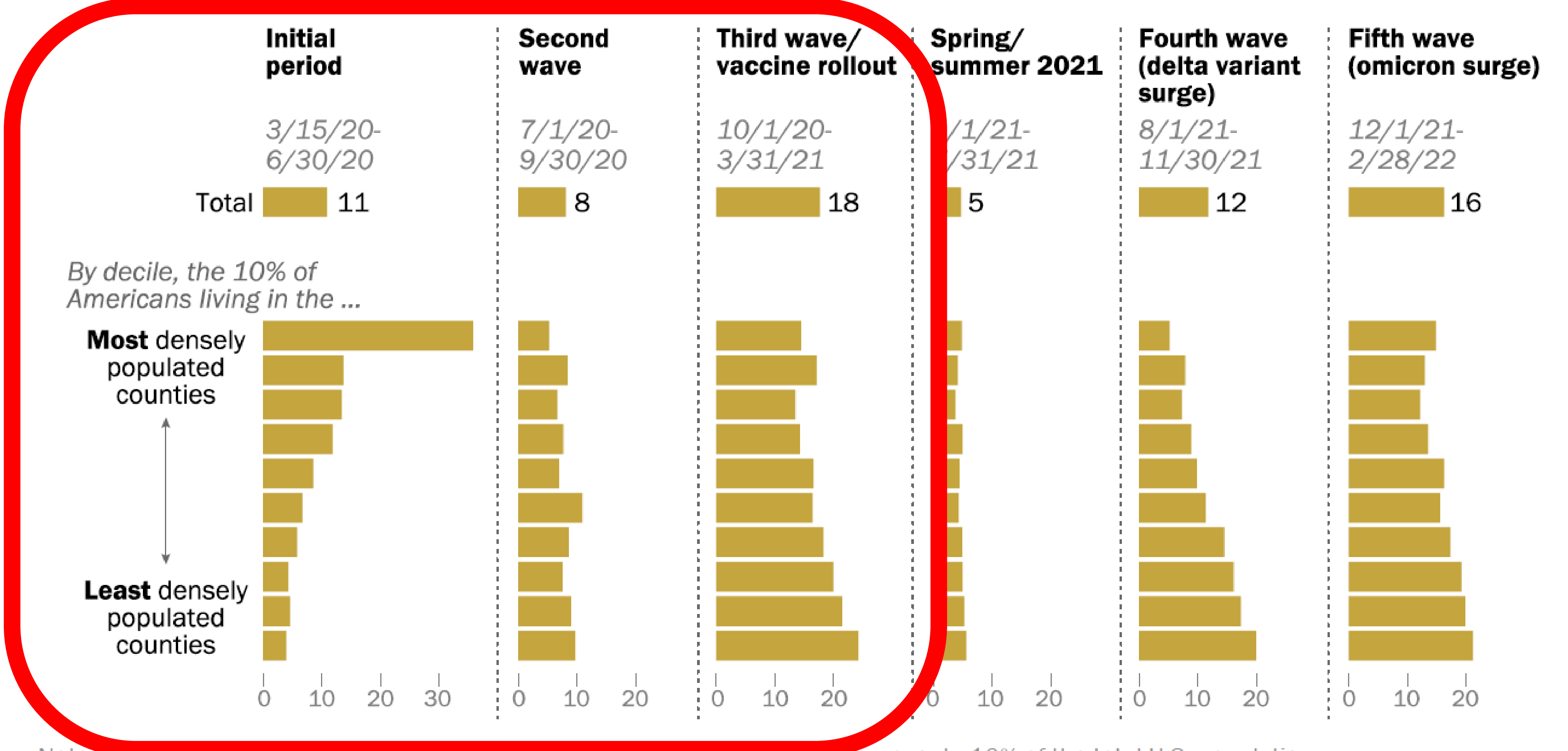
Masking



No Masking

COVID-19 initially ravaged the most densely populated parts of the U.S., but that pattern has changed substantially over the past two years

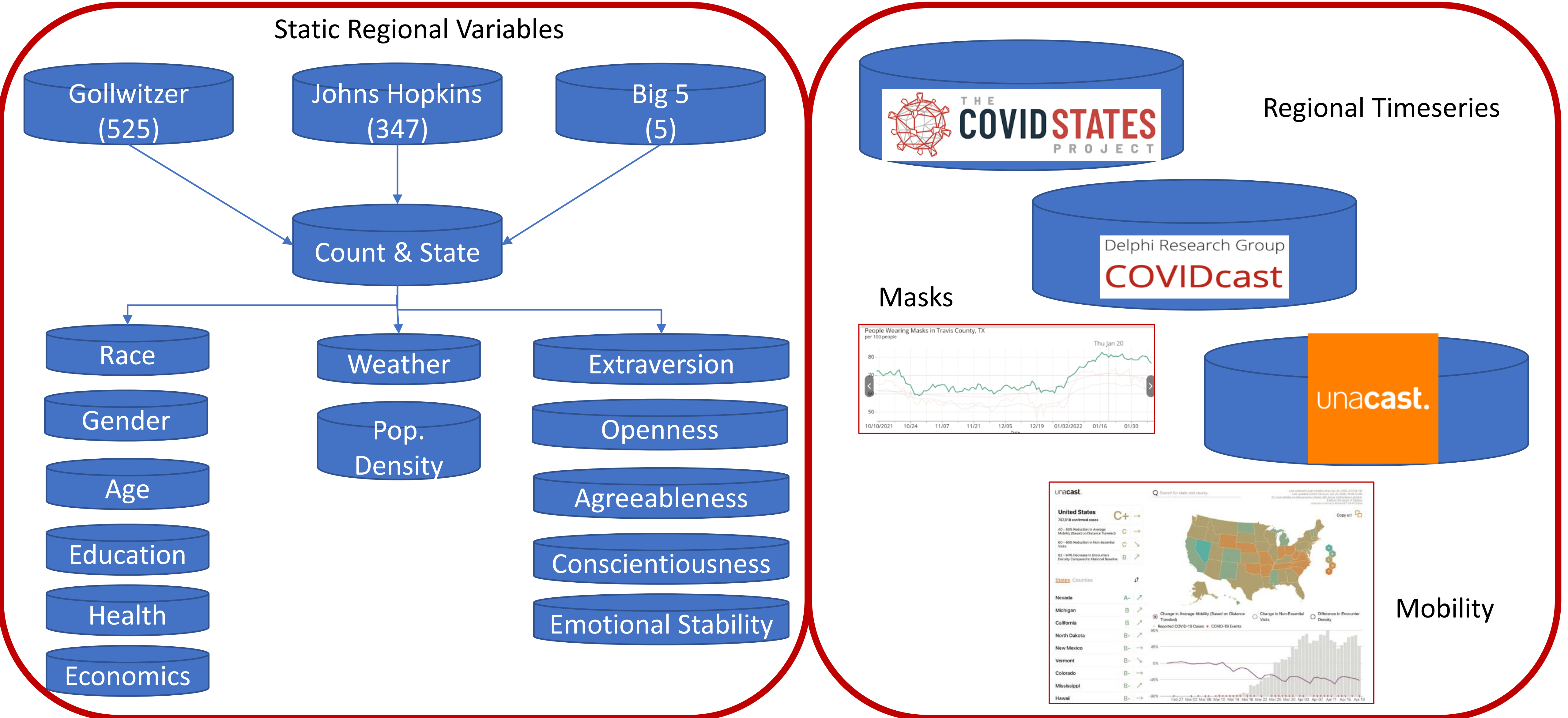
Average monthly reported coronavirus deaths per 100,000 U.S. residents



Note: Counties are grouped into deciles by population density. Each decile represents 10% of the total U.S. population.
Source: Pew Research Center analysis of COVID-19 data collected by The New York Times as of Feb. 28, 2022. See methodology for details.

PEW RESEARCH CENTER

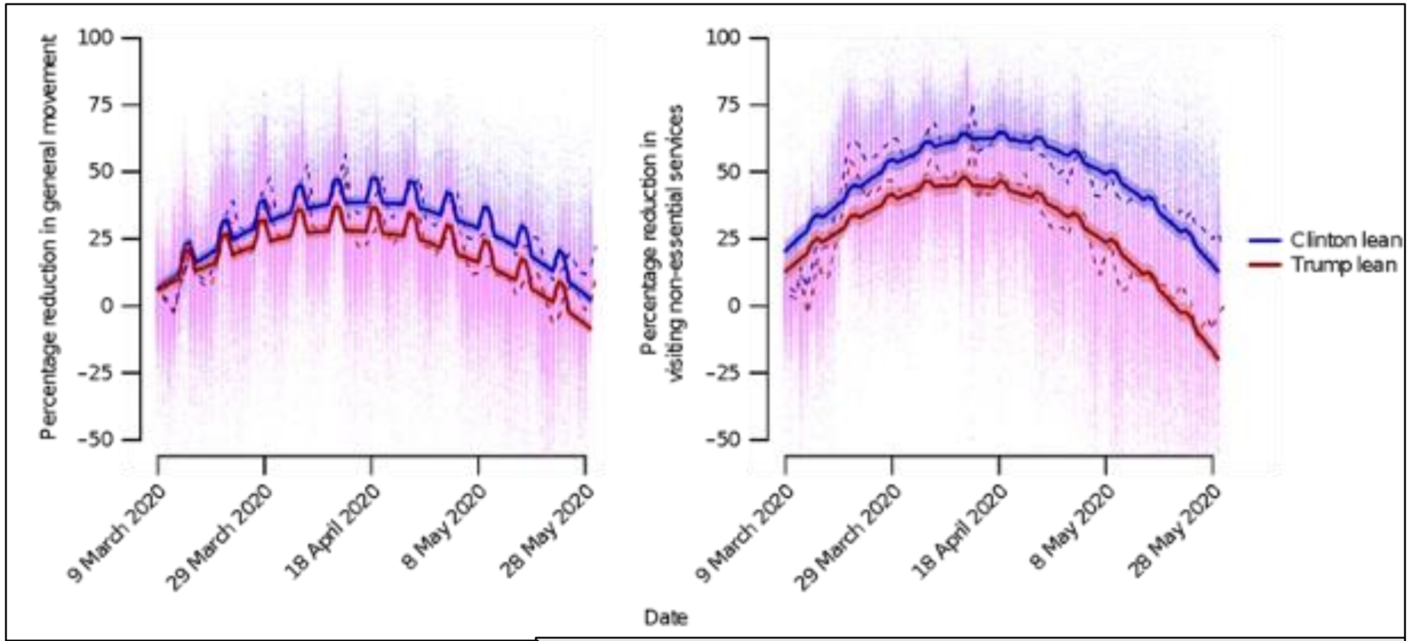
Data Pipeline



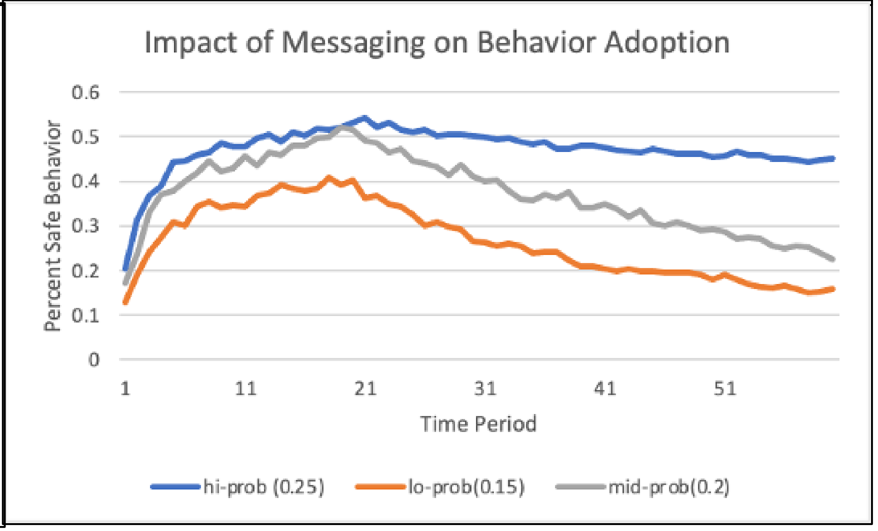
Norms and norm amplification

Gollwitzer, A., et al. (2020). Partisan differences in physical distancing are linked to health outcomes during the COVID-19 pandemic. *Nature Human Behaviour, 4*(11), 1186-1197. doi:10.1038/s41562-020-00977-7

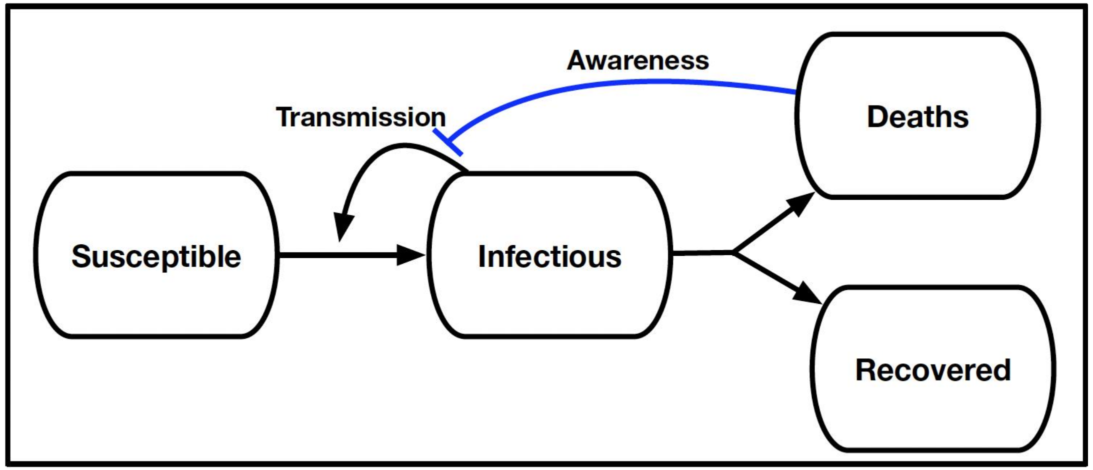
- Compliance with non-pharmaceutical interventions (NPIs) or vaccination involves decision making about risk-reducing options
- Different individuals/regions have different norms
- Differences in norms amplified over time by experience & memory sampling bias



A_s		wear	0.0
A_i		wear	-10.0
A_n		dont	1.0
A_r		dont	-10.0

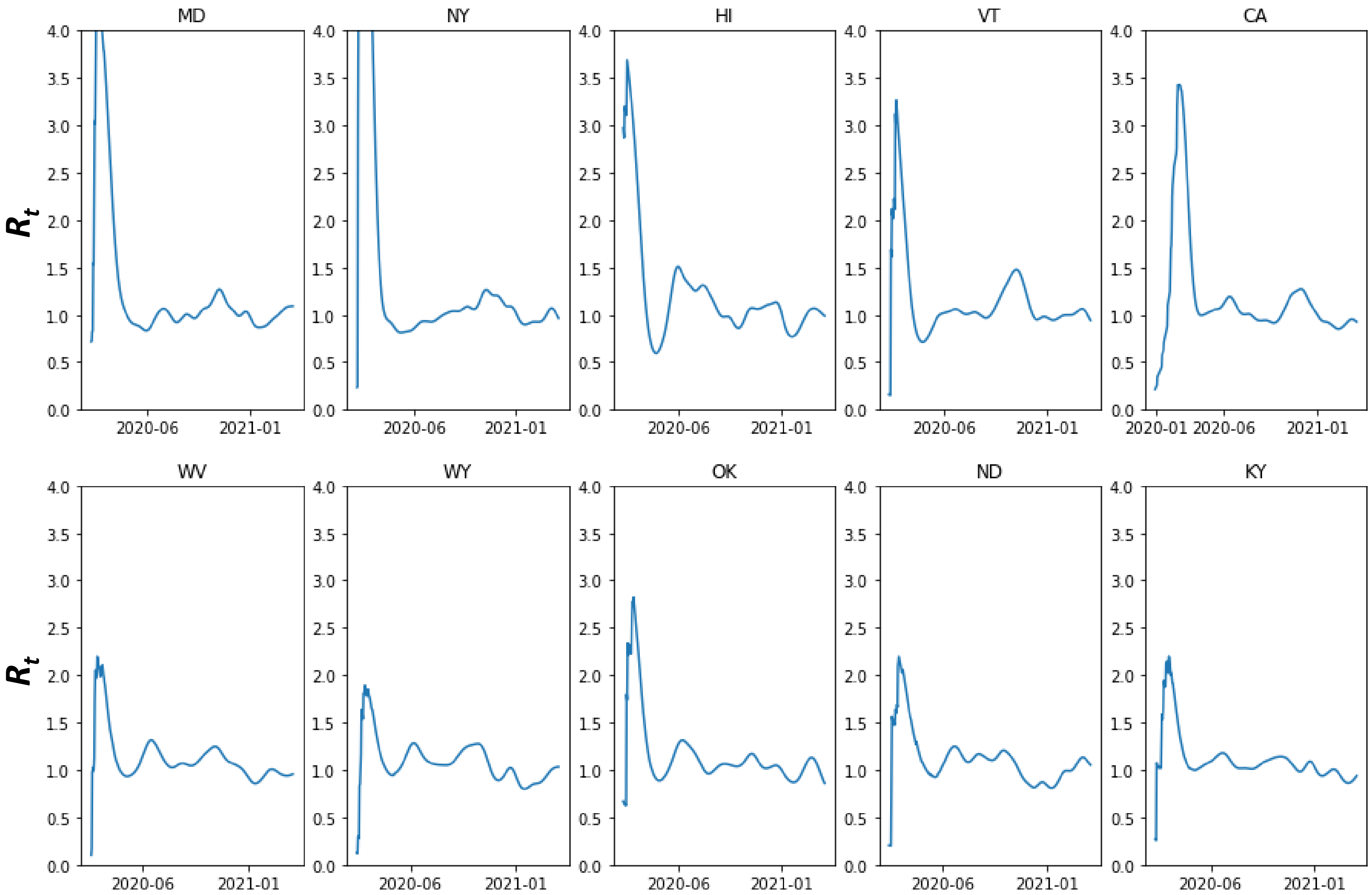


Awareness-driven reactions drives the shape and dynamics of epidemics

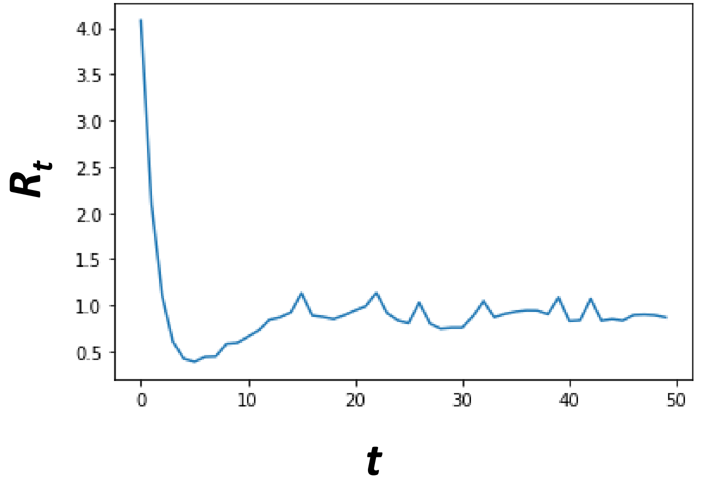


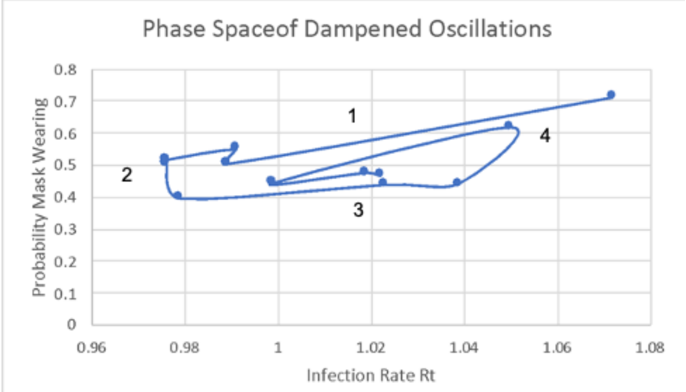
- Proximal experience, news, social media etc. give indication of cases and death
- These perceptions influence attitudes, intentions, behavior
- Behavior modulates transmission
- There are delays between infection, fatality, and awareness
- This results in oscillatory dynamics

Dampened Oscillation of Effective Transmission Number (R_t)

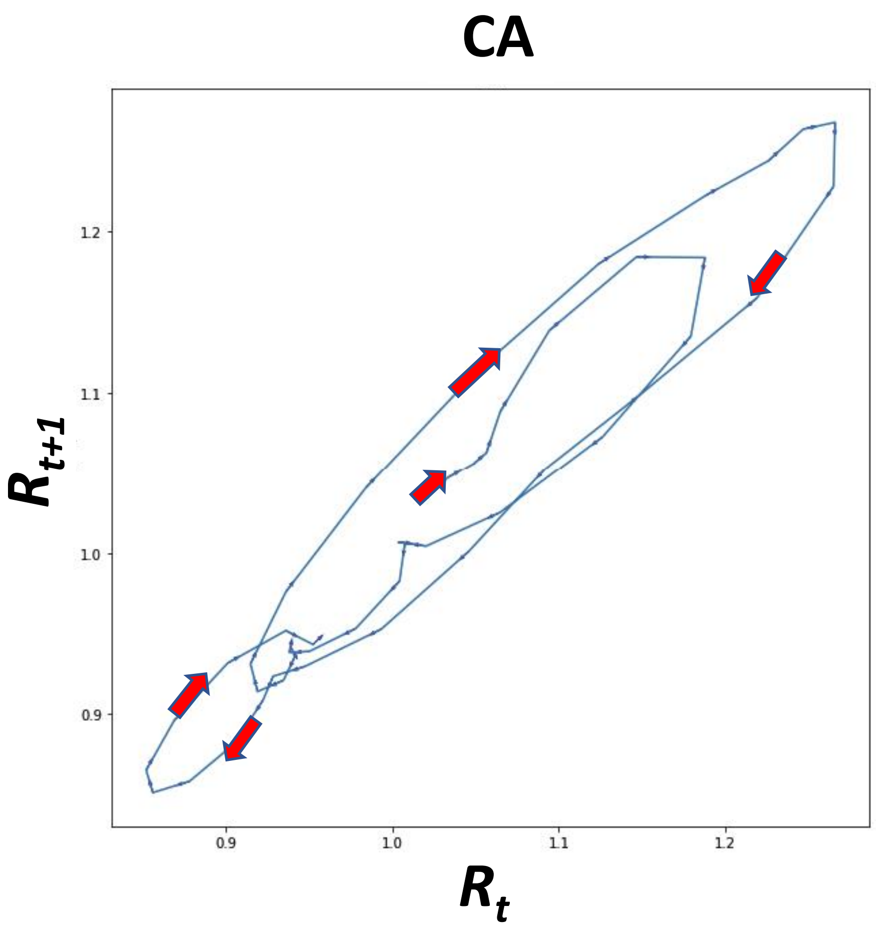


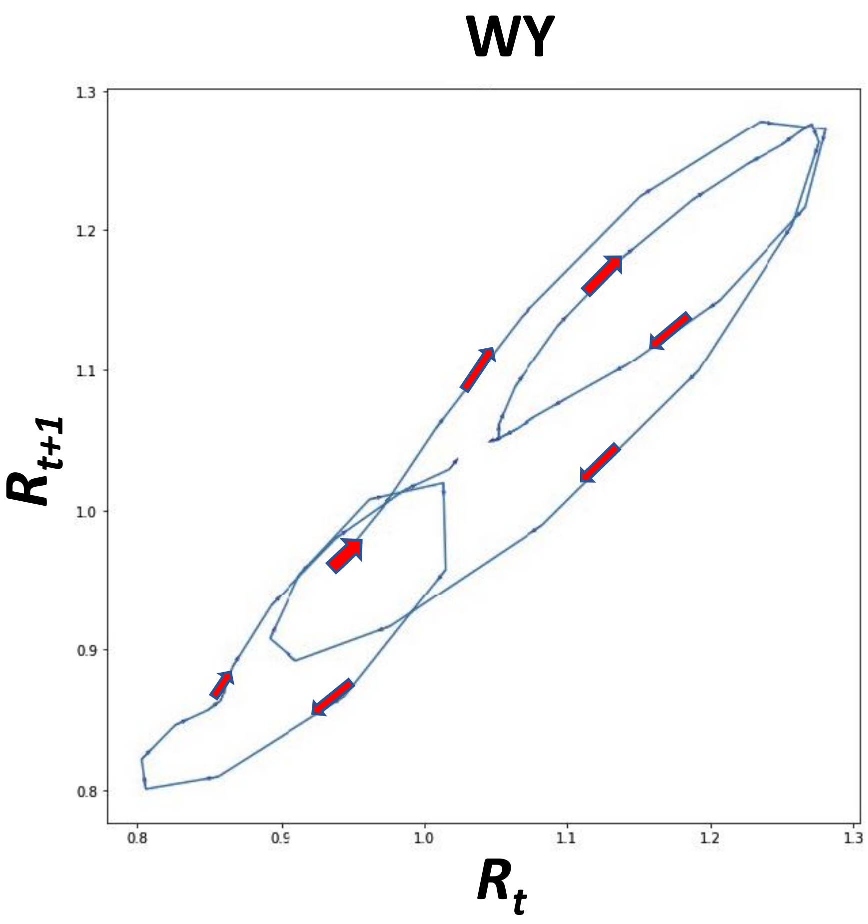
Simple ACT-R Model



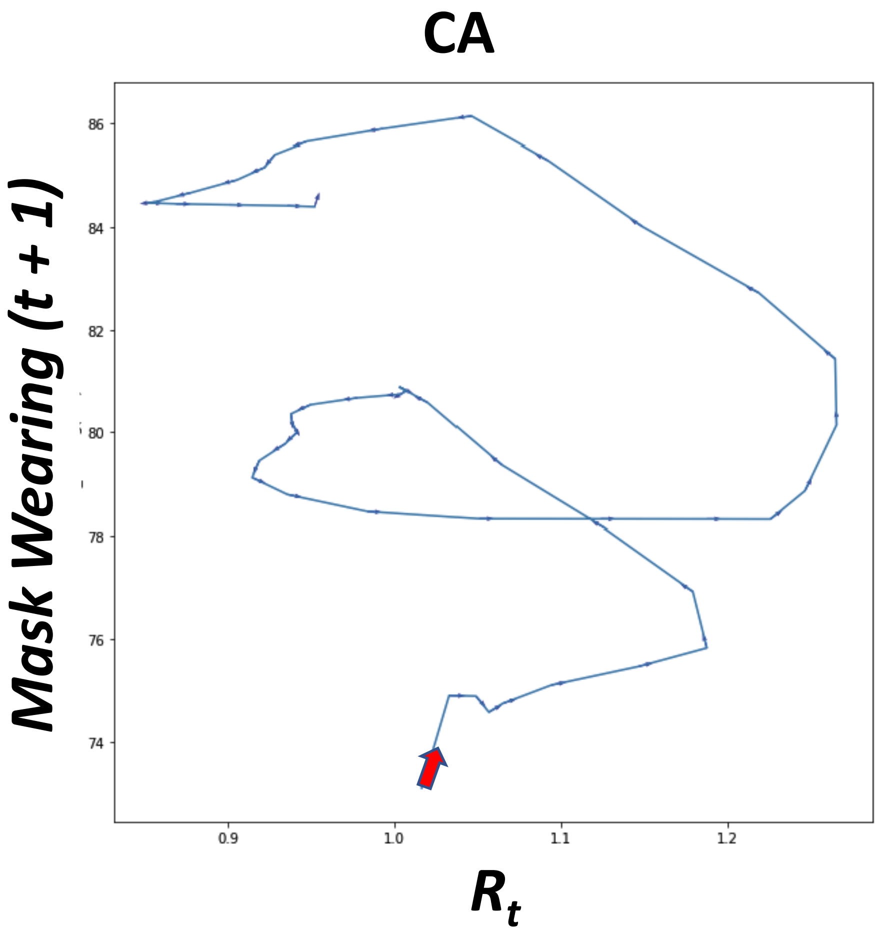


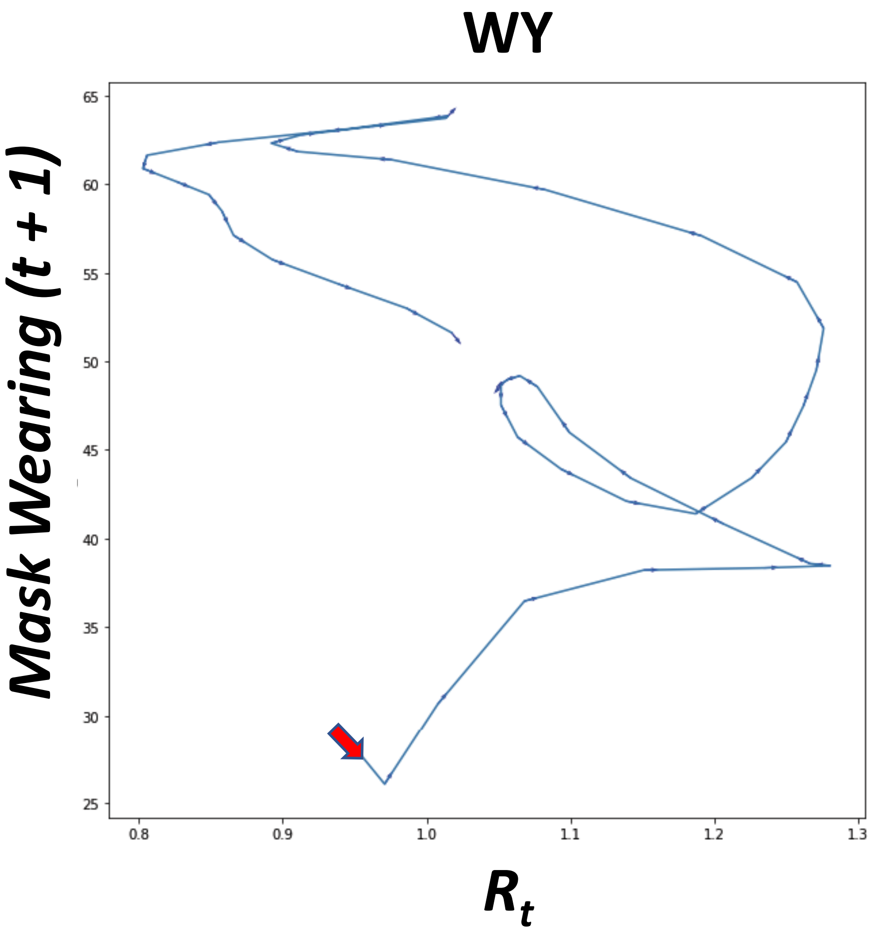
Dampened Oscillation of R_t





Oscillation of R_t and Mask Wearing Exhibits a Learning Effect



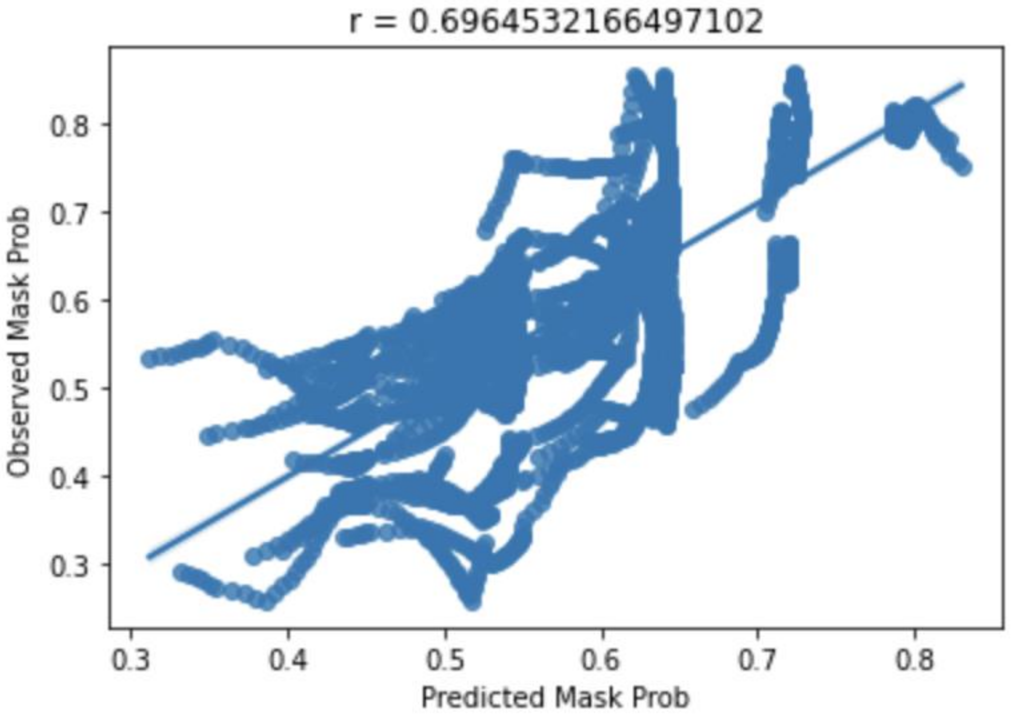


Example 1:
50 State Agents, Estimate Subjective Utilities of Wearing Masks

- Curve-fitting exercise that is analogous to typical policy & econometric analysis that use surveys to estimate factors affecting risk perceptions and behavioral preferences
- Revealed preferences as opposed to stated preference
- Goal: Find the subjective utility values for the model that best predict the observed data
- Data = 50 states, daily mask wearing, waves 1,2,3 (3-15-2020 to 3-31-2021)

Example 1:
50 State Agents, Estimate Subjective Utilities of Wearing Masks

- Assume
  - Prob(mask) = exp(V)/(1+exp(V))
  - Prob(mask) = .5 when V = 0 logits
  - Where V is some blending of mask-wearing utilities U(i)
- State agents have normative utilities
  - Mask, no-mask wearing
  - Utility chunks added in proportion to demographic variables—e.g., percent voting Trump in 2016
- State agents have awareness-based reactions
  - Utility of risk reduction of mask wearing is high when Rt is high and low when Rt is low
  - Utility chunks added in proportion to observed proportion of people wearing masks (”fear”) or not (“freedom”)
  - Use blending to predict mask-wearing utility based on current day’s Rt value

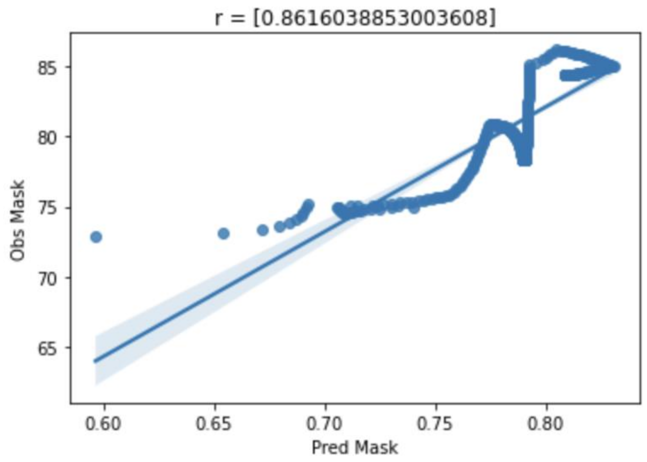


+Trump	-2.69
-Trump	+2.64

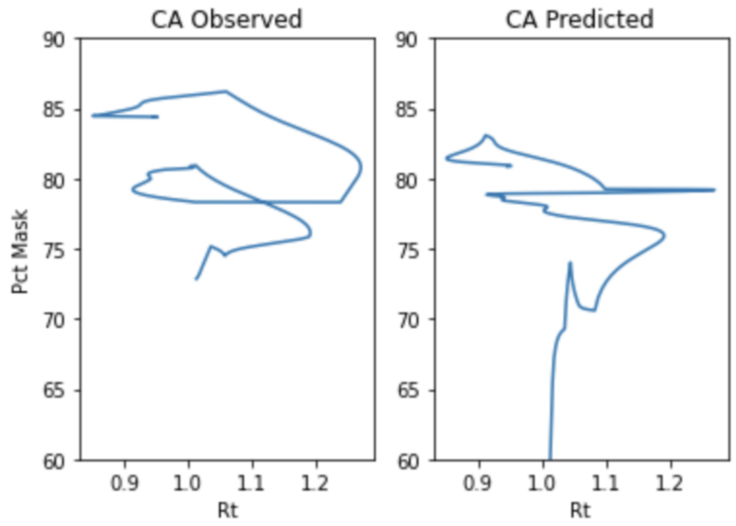
Freedom	-1.40
Fear	+1.93

Example 2: 50 State Agents
Behavioral outcomes stored directly with regional features

- Train norms for each state using N = 10 initial days of data
  - F1, … Fk demographic & psychographic variables
  - Outcome ~ [0, 1]
  - Learn <F1, …, Fk, outcome> for each state
- State agents have awareness-based reactions
  - Use blending to predict mask-wearing outcome based on current day's Rt value



Specific state dynamics



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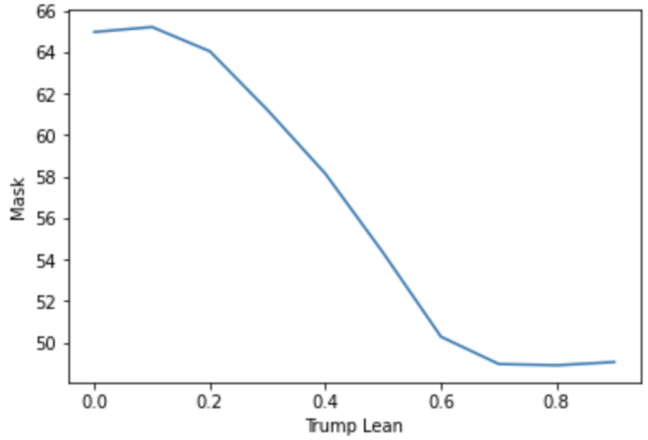
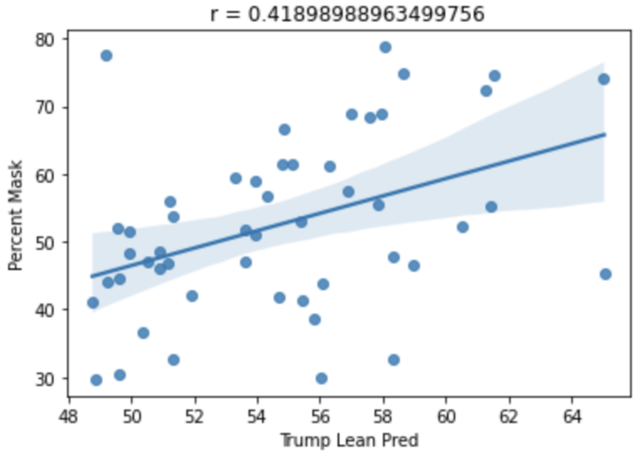


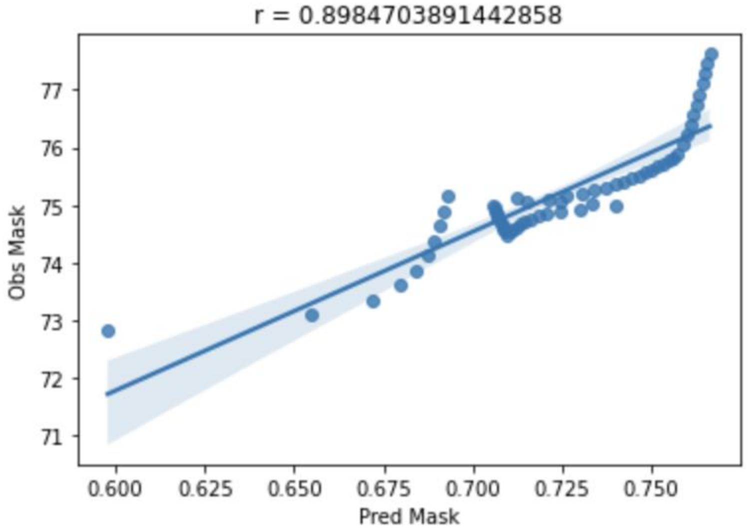
Probe for effects of specific features



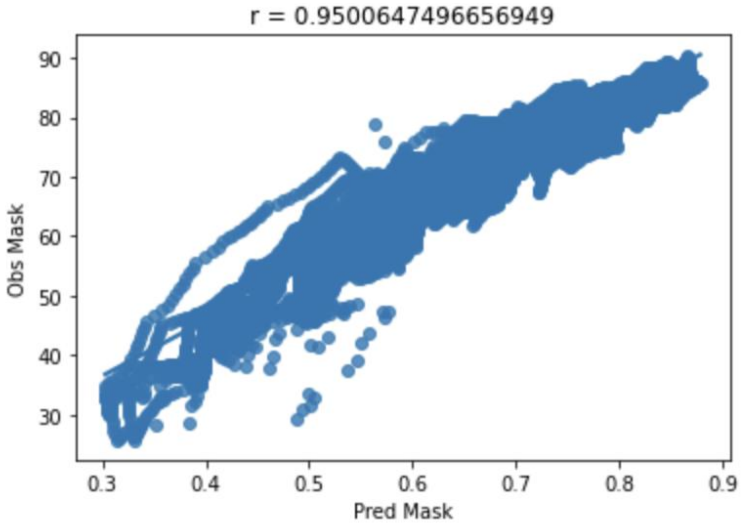
Probe for predicted masking given known state feature

Example 3: One agent containing all state info

- Norms and reactions in chunks that contain all demo- and psycho-graphic factors as well as state labels
- Blending can query values based on factors or state labels



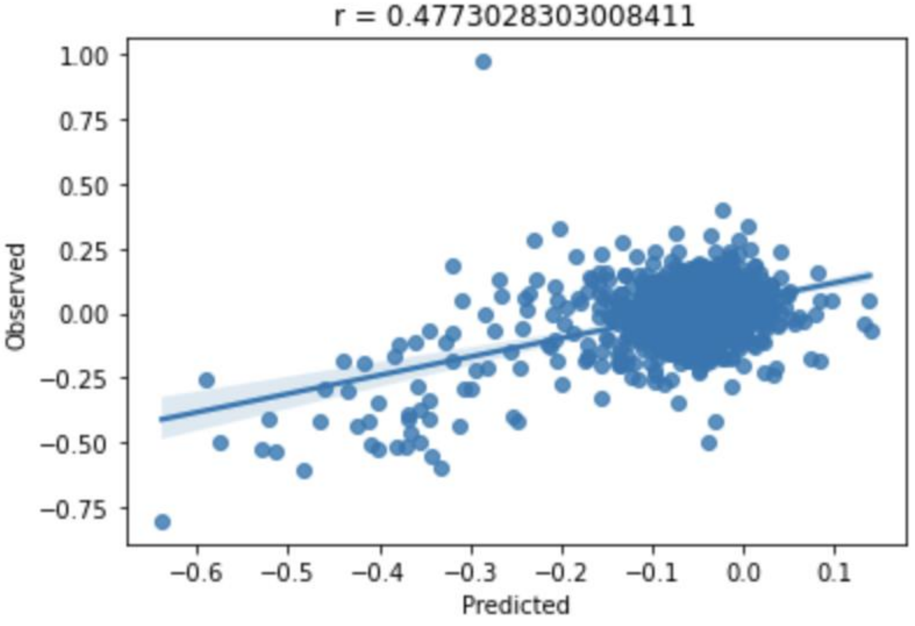
California Waves 1,2,3



All states Waves 1,2,3

Example 4: County level, Reduction in non-essential visits (social distancing)

- Similar to state model. One big agent for all counties (N = 1999)
- Richer demo- /psycho—graphic features
  - Demographics
  - Weather
  - Big 5 personality



Conclusions

- Psychologically Valid Agents can be used to predict behavior change
  - Exhibit norm amplification & awareness-driven transmission oscillation
- Previous work has used ML and NLP analysis of Twitter to seed the models with attitudes
- Technical issues for ACT-R
  - Can IBL salience be used as a robust measurement of the effects of a change in an input factor X on a dependent behavior Y?
  - The structure of similarity space is currently ad hoc
- Theoretical challenges
  - Are we modeling individuals, types of individuals, populations (regions, networks…)?
  - When are we doing cognitive modeling and when are we using architectures for data science?
- Plenty of available data and phenomena to address:
  - Information flows and consumption, effects of mass media, regional media consumption
  - Eye-of-the-beholder: How people interpret/react to experiences, messages, guidance, mandates.
  - Complexities and dynamics of source credibility and information flow in reaction to waves of cases and mandates

Predictive Intelligence for Pandemic Prevention (PIPP)

- IHMC + CMU + UVA is one of 26 teams in $26 million NSF program to support interdisciplinary investigations and collaboration to predict and prevent the next infectious disease outbreak
- Increase our ability to anticipate the role of human behavior and information sharing, and development of mitigation strategies and policy recommendations.

<u>IHMC+CMU+UVA Grand Challenge</u>

An interdisciplinary science of computational theories and models needs to address the mutually adaptive dynamics of (mis)information flows, human behavior, and the transmission and evolution of pathogens

Thanks

- Anton Gollwitzer
  - County level demographics
- Uncast
  - Mobility datsa
- Delphi Group COVIDcast
  - Mask-wearing and other psycho-behavioral data
- Tobias Ebert and Samuel Gosling
  - Regional Big 5 Personality data
- Johns Hopkins
- Andrew Parker and Raffaele Vardavas
  - Agent-based network SIR platform

Fin.

http://www.dianefarrisgallery.com/artist/currelly/ex00/images/uncharted_territory.html

Goals and Memory Chunks in ACT-R

```
GOAL-35
  ISA BEHAVIOR-GOAL
   BEHAVIOR  STATIC_LUNGE_WITH_WALL
   DIFFICULTY  -0.5437191
   ABILITY  NIL
   MOTIVATION  NIL
   UTILITY  1
```

Goal

Memory

```
BEHAVIOR-EXPERIENCE100-0
  ISA BEHAVIOR-EXPERIENCE
   BEHAVIOR  MARCHING_IN_PLACE
   DIFFICULTY  -0.013206851
   ABILITY 0.025988732
   MOTIVATION  0.242358
   UTILITY  1.0
   OUTCOME  SUCCESS
```

...

```
BEHAVIOR-EXPERIENCE5-0
  ISA BEHAVIOR-EXPERIENCE
   BEHAVIOR  PUSHUPS_OFF_WALL
   DIFFICULTY  -1.037143
   ABILITY  -1.0252459
   MOTIVATION  0.23818936
   UTILITY  1
   OUTCOME  SUCCESS
```

The Scientific Opportunity for Cognitive Science

Behavior Change in the Real World

- **Take computational psychology out of the lab, off of Mechanical Turk, and into the real ecology of everyday life**
- **Neuroscience and cognitive psychology can address the meaningful, complex activities that people perform in their everyday life**
- **Multilevel: From neurons to communities**