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)
SIR Models (Compartmental Models; ODE Models)

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- $S = \text{Number Susceptible}$
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\[
\begin{align*}
\frac{dS}{dt} &= -\frac{\beta IS}{N}, \\
\frac{dI}{dt} &= \frac{\beta IS}{N} - \gamma I, \\
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\end{align*}
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A set of ordinary differential equations characterize the transitions.
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Agent Based Models
Individual-level behavior-response strength profile

Likelihood

Hand washing  Mask wearing  Social distancing  Nonessential visits  Vaccination
Individual-level behavior-response strength profile
Psychologically Valid Agent

Individual-level behavior-response strength profile

Source: Romans & Lebreau

Computational Neurocognitive Theory (ACT-R)

Dynamics

- Expected Gain Equation
- Activation Equation
- Non-Level Learning Equation
- Posterior Strength Equation
- Retrieval Probability Equation
- Retrieval Time Equation
- Chunk Choice Equation
- Matching Equation
- Memory Branding

Psychologically Valid Agent
Individual-level behavior-response strength profile

Psychologically Valid Agent

Embed Psychologically Valid Agents in an SIR Model of a given region and period
Individual-level behavior-response strength profile

Psychologically Valid Agent

Embed Psychologically Valid Agents in an agent-based simulation of a given region and period
Mobility

Psychologically Valid Agent

Synthetic Population

Confirmed Cases

Non-essential Visits

Individual-level behavior-response strength profile
Perceptions | Attitudes | Beliefs | Intentions

Mass Media

Online Social media

Polling Data

Computational Neurocognitive Theory (ACT-R)

Dynamics

Perception

Psychologically Valid Agent

Synthetic Population

Individual-level behavior-response strength profile

Non-essential Visits

Confirmed Cases

Mobility
Data-informed Agents in Epi-Networks

Input Info

\[x_t^i \quad R_t \quad N_t^i \quad \ldots\]

Node $i$

\[y_t^i\]

Behavior

masking, mobility, vaccination

Susceptible

Infected

local info

global info

IN | OUT

\[
\begin{array}{c|c}
R_{t-1} & 1 \\
R_{t-2} & 1 \\
0 & \\
\end{array}
\]

Set of experiences
Types of Data-Informed Agents

A. Experience-based Behavior

Input Info → Memory → Behavior

B. Utility-based Behavior

Input Info → Memory → 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

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',
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'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',
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'R0',
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**Algorithm 1** ABM Epidemiological Simulation

1: `robjects.r[source](abm_run_init.R)`  \(\triangleright\) Run initialization script in R
2: `g_sim_r ← robjects.r[g_sim]`  \(\triangleright\) `g_sim` is from R workspace
3: `p ← robjects.r[p]`  \(\triangleright\) population params
4: `g_sim_py ← convert_to_python(g_sim_r)`
5: `G ← create_network(g_sim_py)`
6: `create_decision_makers(G)`
7: 
8: **for** `t` **in** `range(num_periods)` **do**
9: `g_sim_r ← robjects.r[RunAbm](g_sim_r, p, days = 7)`  \(\triangleright\) simulation in R
10: `g_sim_py ← convert_to_python(g_sim_r)`
11: `G ← update_network(G, g_sim_py)`
12: `mask_decisions(G, criterion)`
13: `g_sim_r ← revert_network_to_r(G, g_sim_r, g_sim_py)`
14: **end for**
Masking Population

t=0
R=2.5

t=14

t=21

t=28

t=35
R=1.77

t=49
R=1.33
Masking

Observed and theoretical reproduction numbers

No Masking

Observed and theoretical reproduction numbers
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

- **Initial period**: 3/15/20-6/30/20
  - Total: 11

- **Second wave**: 7/1/20-9/30/20
  - Total: 8

- **Third wave/vaccine rollout**: 10/1/20-3/31/21
  - Total: 18

- **Spring/summer 2021**: 4/1/21-7/31/21
  - Total: 5

- **Fourth wave (delta variant surge)**: 8/1/21-11/30/21
  - Total: 12

- **Fifth wave (omicron surge)**: 12/1/21-2/28/22
  - Total: 16

By decile, the 10% of Americans living in the...

- **Most densely populated counties**: [Chart]
- **Least densely populated counties**: [Chart]

Note: Counties are grouped into deciles by population density. Each decile represents 10% of the total U.S. population.

PEW RESEARCH CENTER
Data Pipeline

Static Regional Variables

- Gollwitzer (525)
- Johns Hopkins (347)
- Big 5 (5)

Count & State

- Race
- Gender
- Age
- Education
- Health
- Economics
- Weather
- Extraversion
- Pop. Density
- Openness
- Agreeableness
- Conscientiousness
- Emotional Stability

Regional Timeseries

- COVIDcast

Masks

Mobility

- Delphi Research Group
Norms and norm amplification

- 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
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

Phase Space of Dampened Oscillations
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**
  - \( \text{Prob(mask)} = \frac{\exp(V)}{1+\exp(V)} \)
  - \( \text{Prob(mask)} = .5 \) 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

<table>
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<tr>
<th>Trump</th>
<th>Fear</th>
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Example 2: 50 State Agents
Behavioral outcomes stored directly with regional features

• Train norms for each state using $N = 10$ initial days of data
  • $F_1, \ldots, F_k$ demographic & psychographic variables
  • Outcome $\sim [0, 1]$
  • Learn $<F_1, \ldots, F_k, \text{outcome}>$ 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
Example 2: 50 State Agents
Behavioral outcomes stored directly with regional features

- Train norms for each state using $N = 10$ initial days of data
  - $F_1, \ldots, F_k$ demographic & psychographic variables
  - Outcome $\sim [0, 1]$
  - Learn $\langle F_1, \ldots, F_k, \text{outcome} \rangle$ for each state

- State agents have awareness-based reactions
  - Use blending to predict mask-wearing outcome based on current day’s Rt value

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
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.

IHMC+CMU+UVA Grand Challenge

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 data
- 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
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