Wither Cognitive? Population Health Simulation & its Discontents

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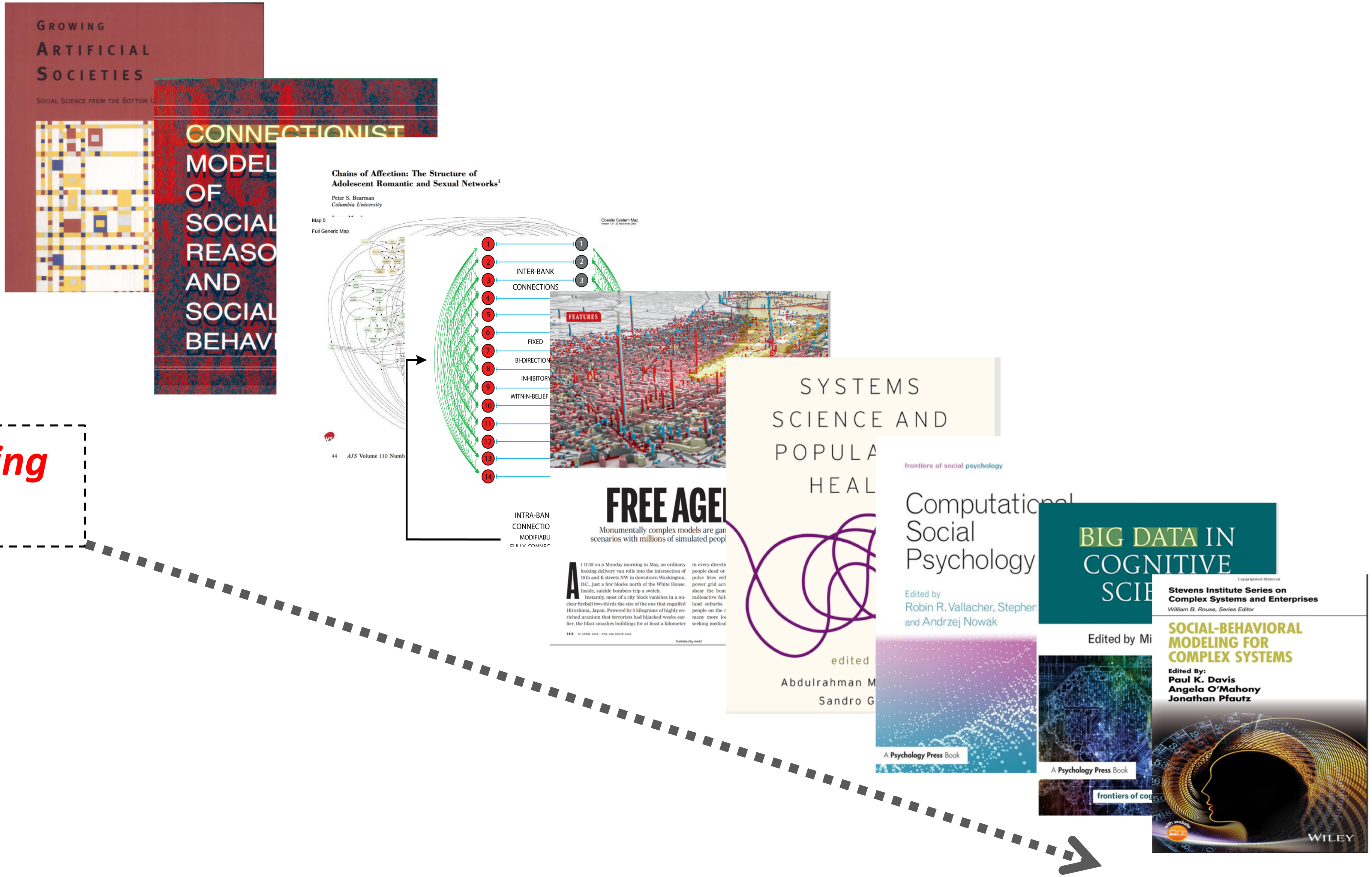
Simulation Modeling of Population Health

History and rationale, state of the art, & general issues for social modeling

Complex Systems Approaches in Population Health



Socio-Cognitive Modeling At-Scale

special article

The Spread of Obesity in a Large Social Network over 32 Years

spread of norms

Nicholas A. Christakis, M.D., Ph.D., M.P.H., and James H. Fowler, Ph.D.

influence adoption of behavior

ABSTRACT

Background
The prevalence of obesity has increased substantially over the past 30 years. We performed a quantitative analysis of the nature and extent of the person-to-person spread of obesity as a possible factor contributing to the obesity epidemic.

Methods
We evaluated a densely interconnected social network of 12,067 people assessed repeatedly from 1971 to 2003 as part of the Framingham Heart Study. The body-mass index was available for all subjects. We used longitudinal statistical models to examine whether weight gain in one person was associated with weight gain in his or her friends, siblings, spouse, and neighbors.

Results
Discernible clusters of obese persons (body-mass index [the weight in kilograms divided by the square of the height in meters], ≥30) were present in the network at all time points, and the clusters extended to three degrees of separation. These clusters did not appear to be solely attributable to the selective formation of social ties among obese persons. A person's chances of becoming obese increased by 57% (95% confidence interval [CI], 6 to 123) if he or she had a friend who became obese in a given interval. Among pairs of adult siblings, if one sibling became obese, the chance that the other would become obese increased by 40% (95% CI, 21 to 60). If one spouse became obese, the likelihood that the other spouse would become obese increased by 37% (95% CI, 7 to 73). These effects were not seen among neighbors in the immediate geographic location. Persons of the same sex had relatively greater influence on each other than those of the opposite sex. The spread of smoking cessation did not account for the spread of obesity in the network.

change a person's tolerance

areas of the brain stimulated

Conclusions
Network phenomena appear to be relevant to the biologic and behavioral trait of obesity, and obesity appears to spread through social ties. These findings have implications for clinical and public health interventions.

homophily

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General Issues

- Does at-scale social simulation need cognition?
  - Keep it simple, stupid!
  - Architecture of Complexity; Nearly decomposable systems
  - Anderson 1991 Relevance Thesis; Newell bands + extension *(a la)
- Does cognition need at-scale simulation?
  - Multi-resolution of cognitive arch; etc.
  - Big data and cognition
- Are we just doing it wrong?

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S.I.: SBP-BRIMS 2018

Check for updates

Multi-scale resolution of neural, cognitive and social systems

Mark G. Orr[1] · Christian Lebiere[2] · Andrea Stocco[3] · Peter Pirolli[4] · Bianica Pires[5] · William G. Kennedy[6]

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Abstract
We recently put forth a thesis, the *Resolution Thesis*, that suggests that cognitive science and generative social science are interdependent and should thus be mutually informative. The thesis invokes a paradigm, the reciprocal constraints paradigm, that was designed to leverage the interdependence between the social and cognitive levels of scale for the purpose of building cognitive and social simulations with better resolution. We review our thesis here, provide the current research context, address a set of issues with the thesis, and provide some parting thoughts to provoke discussion. We see this work as an initial step to motivate both social and cognitive sciences in a new direction, one that represents unity of purpose, an interdependence of theory and methods, and a call for the careful development of new approaches for understanding human social systems, broadly construed.

Keywords Cognitive modeling · Agent-based modeling · Social simulation · Multi-scale systems

1 Introduction

The degree of overlap between cognitive science and generative social science is small despite a shared interest in human behavior and a reliance on computer simulation. The former focuses, largely, on developing computational and formal accounts

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One Approach

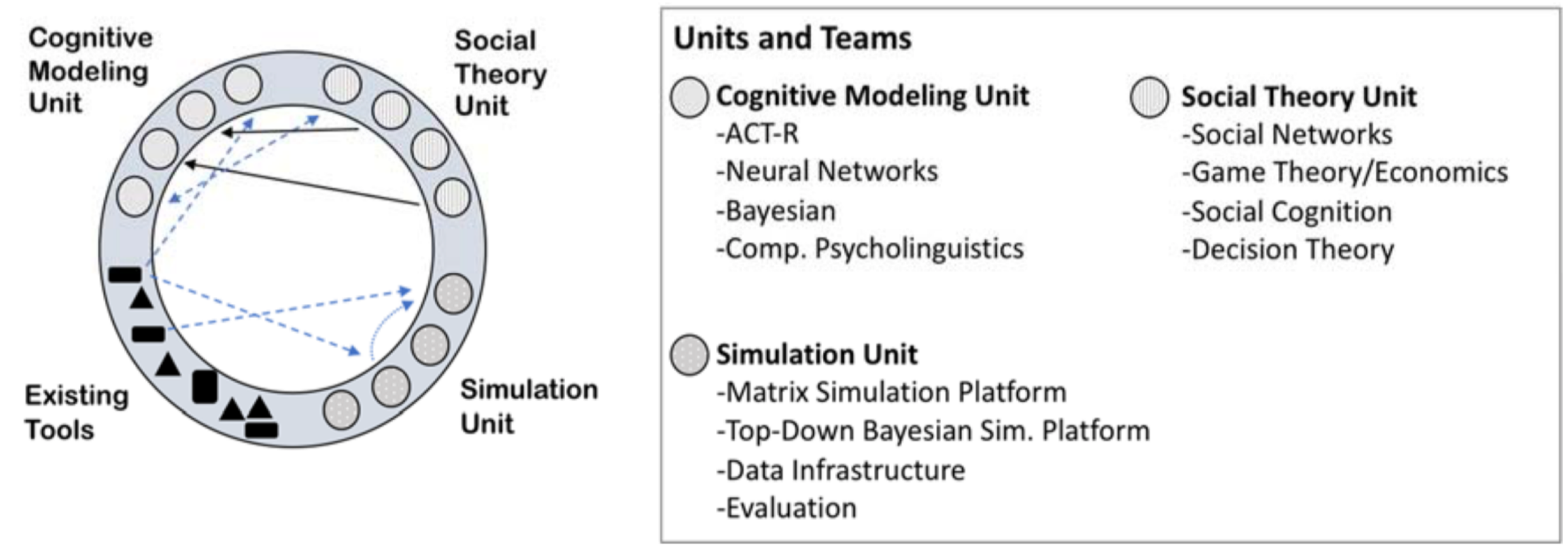


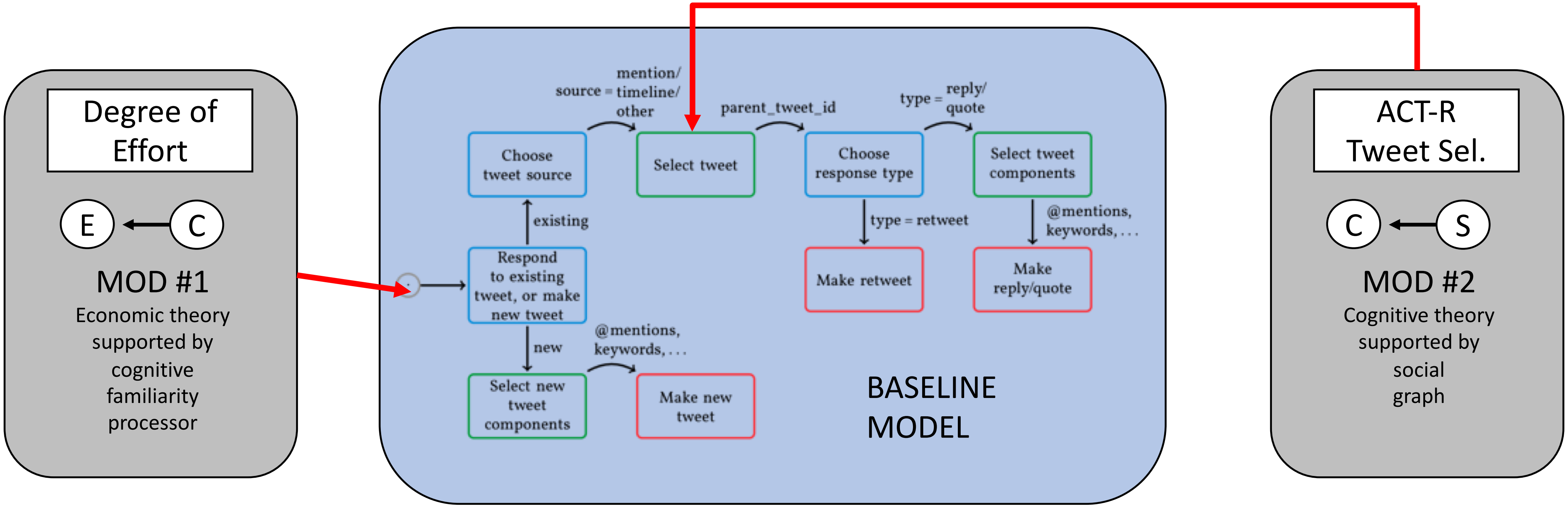
Figure 6. The organizational scheme of *Cognitio Veritas* in relation to a problem space. Considered as a dynamic graph, the *Cognitio Veritas* organization (a large technical and substantive team) responds to a given problem/challenge by the generation of the appropriate kinds of edges connecting appropriate nodes (prior existing tools can be considered nodes on the graph). Some edges transmit existing code; some provide data constructions; some are bidirectional to illustrate iterative sharing of information or resources.

Socio-Cognitive Modeling

A cognitive architectural approach to agency in at-scale social simulations

Beyond Modular Integration of Theories

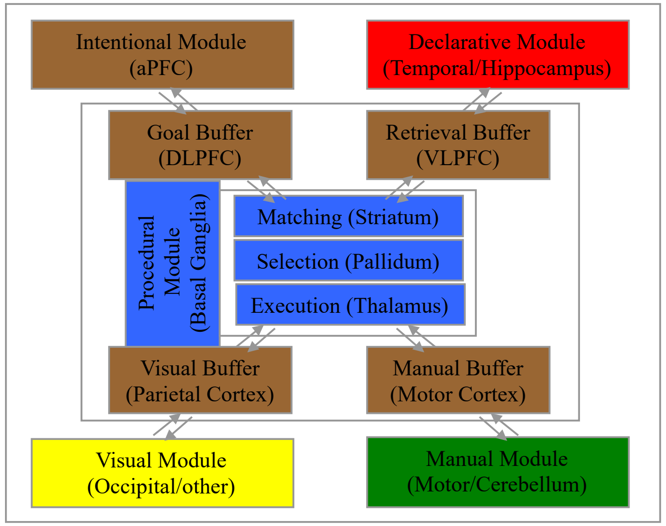
- Baseline put full challenge to each cognitive modeling team with carte blanche, social theory advised and provided some structure (e.g., social graph)
- CP1 integrated cognitive and social modeling into the Bayesian Decision Diagram formalism but with little drive for theoretical integrations (CP1 is shown in the diagram below).
- ***TAKEAWAY:*** *Modular integration between cognitive and social/economic theory is too limited*



Expanding Cognitive Architectures with Social, Economic and Neuroscience theory

- Cognitive architectures integrate learning mechanisms
  - Work together rather than in isolation
    - Future of machine learning
- Convergence between machine learning and cognitive neuroscience
  - Reinforcement learning to determine effectiveness of actions
    - Neurotransmitters and policy learning
  - Associative learning to build bottom up representations
    - Hebbian learning and deep learning
- Economic theory to constrain reinforcement learning
  - Current production utility learning requires user-supplied reward function
    - Missing architecture module to map external events into internal reward
- No current learning of associations
  - Initial Bayesian mechanism had difficulties scaling to long-term activity
  - New mechanism inspired by Hebbian spike-timing dependent plasticity

ACT-R Cognitive Architecture



Band	Scale (sec)	Time Units	System
Social	10^7	months	
	10^6	weeks	
	10^5	days	
Rational	10^4	hours	Task
	10^3	10 min	Task
	10^2	minutes	Task
Cognitive	10^1	10 sec	Unit task
	10^0	1 sec	Operations
	10^{-1}	100 ms	Deliberate act
Biological	10^{-2}	10 ms	Neural circuit
	10^{-3}	1 ms	Neuron
	10^{-4}	100 µs	Organelle

Figure 1. Bands of human cognition (adapted from Newell, 1990).

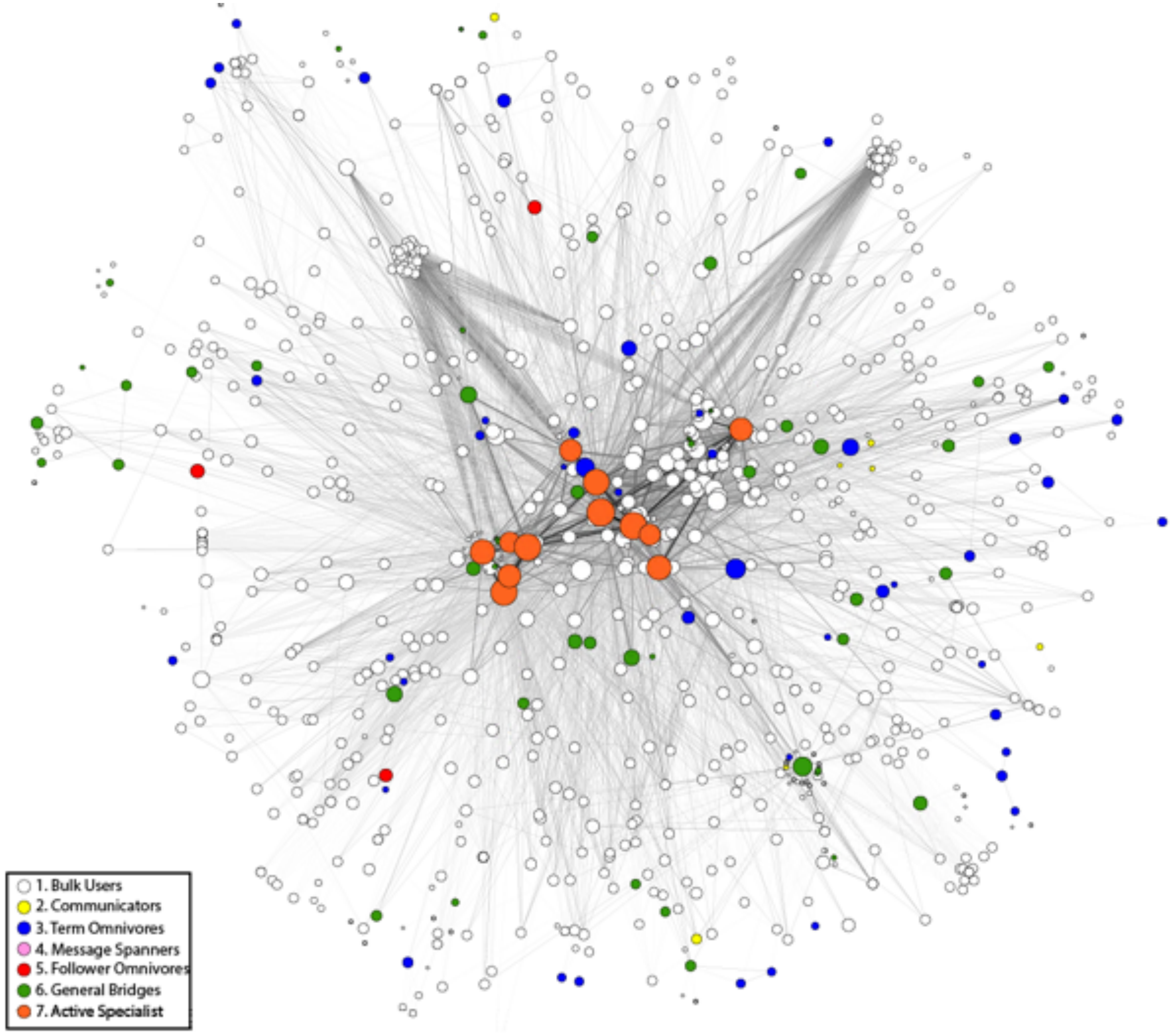
Generating Social Roles

Approach: Aim to model the relational logic of twitter users by building shared activity (term use, reacting to similar messages) and interaction (replying to or mentioning each other networks, then identifying common roles across these networks. Based on classic network ideas of White, Boorman & Breiger (1976): ***actions embody informal rules and norms, so equivalent actors should behave similarly.***

Feed into sociological agent: Active agents are assigned to one of 7 substantive roles based on contact patterns across constituent subnetworks.

Findings: About 20% of nodes are "active."

The network of active users is highly clustered across all types of ties and seems to track interest topics. There are two sorts of general users: "bulk users" are intermittently active but specific; while "Active specialists" have very high degree within their cluster. The remainder roles are variants of bridges, either to people (communicators & followers), twitter content (term omnivores or message spanners) or both (general bridges).



Sub community 1 of the largest community within the pooled all-relations summary network. N=1046 nodes. Layout uses the Fruchterman Rheingold algorithm, with post-layout adjustments for overlap and pendant (degree=1) placement. Colors track roles. Line thickness and shade capture the strength of the relation.

Estimating Role-Specific Utility

$$U_t(retweet, reply, quote) = f(tweet\ features, user\ features)$$

For each individual type (roles 1—8), 3 models are developed for each reaction type (retweet, replies, quotes) and each tweet is modeled as

$$\log(Y_i) = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_n X_{ni} + \varepsilon_i$$

where Y is a binary variable, $Y = 0$ if the tweet did not receive any reaction, $Y = 0$ if it received at least one reaction.

Independent Variables $(X_{1i}, \dots, X_{ni})$:

		Retweets	Quotes	Replies
	Intercept			
Tweet Features	IsRetweet			
	IsReply			
	IsQuote			
	IsURL			
Global Features	Activity			
	Coin Activity			
User Features	Tweet Share			
	RT Share			
	Friend			
	Follower			

$$\Rightarrow \begin{bmatrix} \widehat{\beta_t^{RT}} \\ \widehat{\beta_t^{Q}} \\ \widehat{\beta_t^{Rp}} \end{bmatrix}$$

Instance-Based Learning Cognitive Model

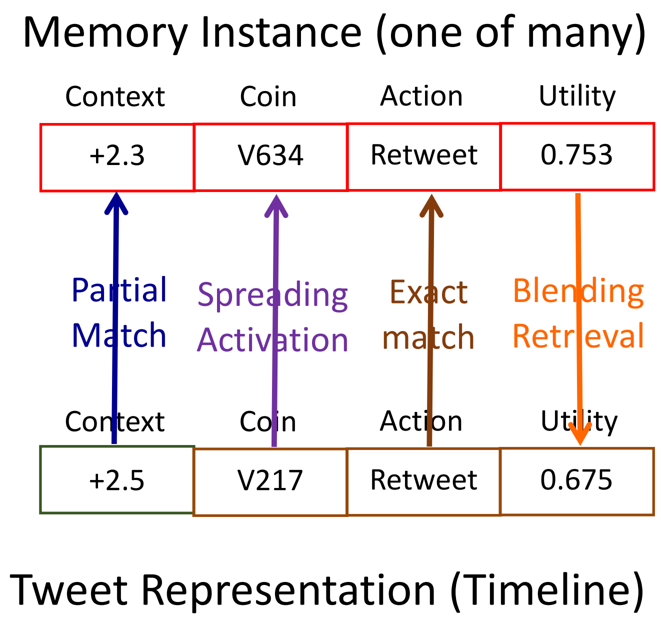
- Cognitive model of action choice
  - Choose between tweet, retweet, reply and quote
    - Considered in one step or two (new/old content)
- Instance-based learning approach
  - Model memory holds past decision instances
    - Associates decision context, action chosen, resulting outcome(s) and outcome(s) utility
- Iterative decision process
  - Iterative blending process to evaluate expected utility of each action
    - Select action with highest expected utility
- Bounded rationality and cognitive biases
  - Recency bias
    - Most recent experiences have disproportionate effect
  - Anchoring bias
    - Most common experiences persist after relevance lost
  - Sampling bias
    - Initial experience can lead to lasting risk aversion

$$B_i = \ln\left(\sum_{j=1}^{n} t_j^{-d}\right)$$

$$A_i = B_i + \sum_{j=1}^{m} W_j \times S_{ji}$$

$$M_i = A_i + \sum_{j=1}^{l} MP \times Sim(d_j, v_{ij})$$

$$V = \underset{V_j}{\operatorname{argmin}} \sum_{i=1}^{k} P_i \times Sim(V_j, v_{ij})^2$$

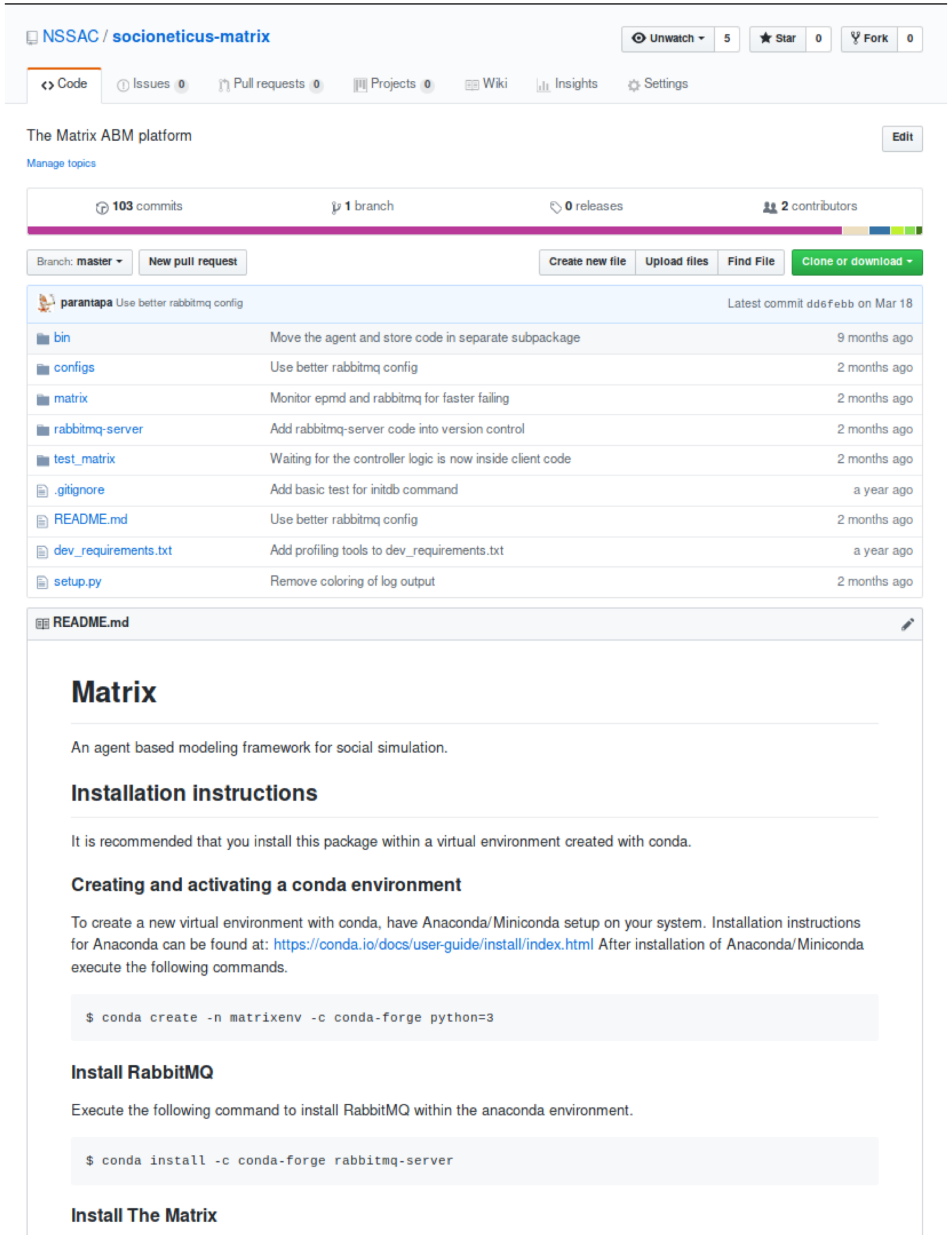


Socio-Cognitive Modeling

***The Matrix**: A social simulation platform integrating cognitive architecture at-scale*

What is The Matrix?

- The Matrix is an agent based modeling (ABM) framework
- The Matrix is free and open source software
- Specialized for `compute and data intensive' simulations
    - Such as large number individual cognitive agents



github.com/NSSAC/socioneticus-matrix

Integration of theory into ABMs

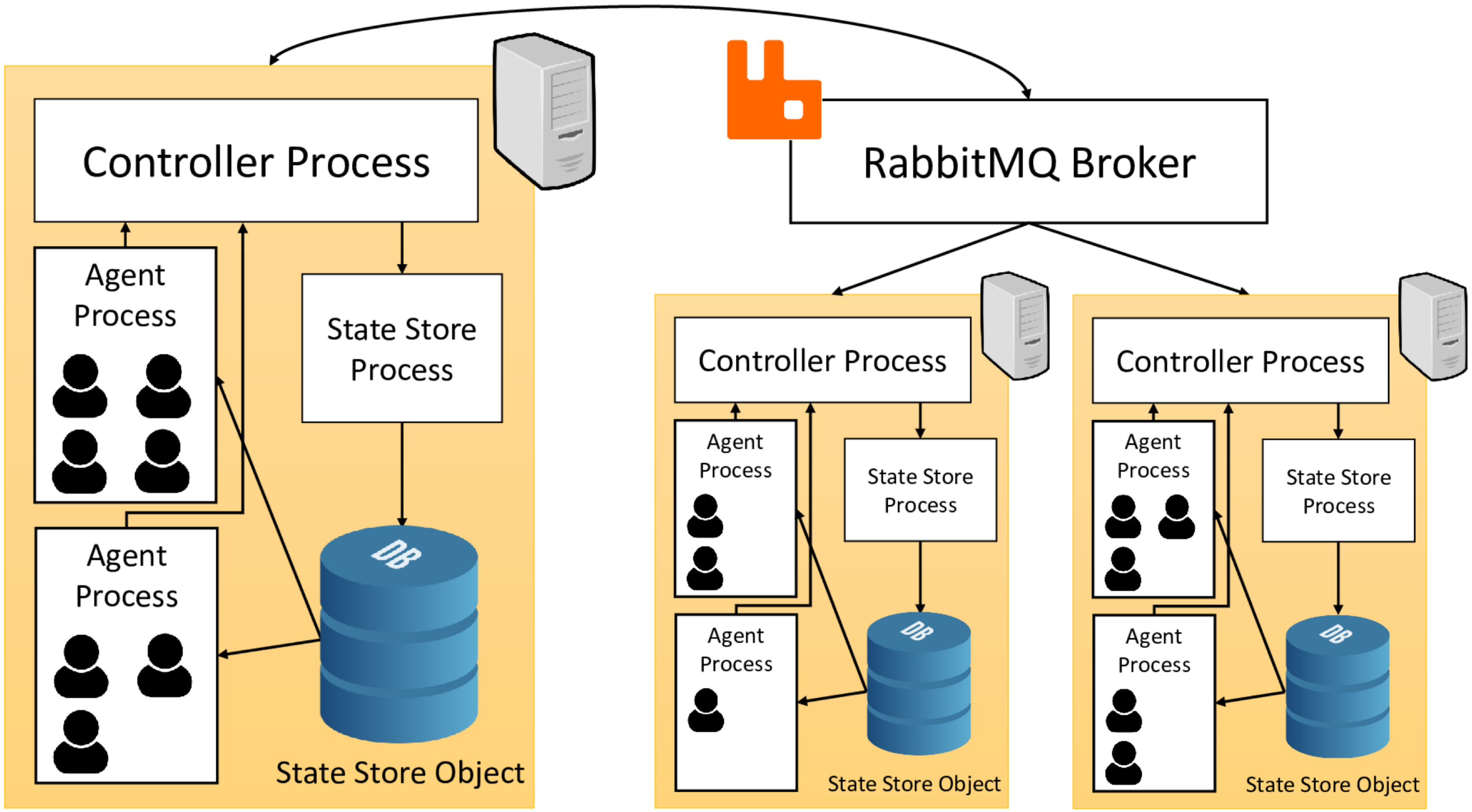
Name	**Model Type**	**Prog. Lang**
Freq-Stat	Frequentist statistical model	Python
Soc-Th	Social structure theory model	Python
CM-ANN	Artificial neural network model	C++
CM-Bayes	Bayesian cognitive theory model	R
CM-ACTR	ACT-R cognitive theory model	Common Lisp

*Some examples of past and current agent models in *The Matrix.*

Integration of theory into ABMs: Specs

- Ability to rapidly prototype and test heavyweight agent models
- Ability to write agents in popular programming languages
  - Python, R, C++, Java, Lisp, …
- Ability to use GPU units, and popular neural network libraries
  - TensorFlow, PyTorch, Keras, Lens, …
- Ability to use cognitive system libraries like ACT-R
- Ability to run simulations on commodity clusters
  - Amazon EC2, Google Compute Cloud, and Microsoft Azure
- Ability to efficiently store, update, and query large amounts of system state
  - large amounts ≈ hundreds of gigabytes
- Ability to use run simulations with millions of active agents

Overview of Matrix ABM Runtime

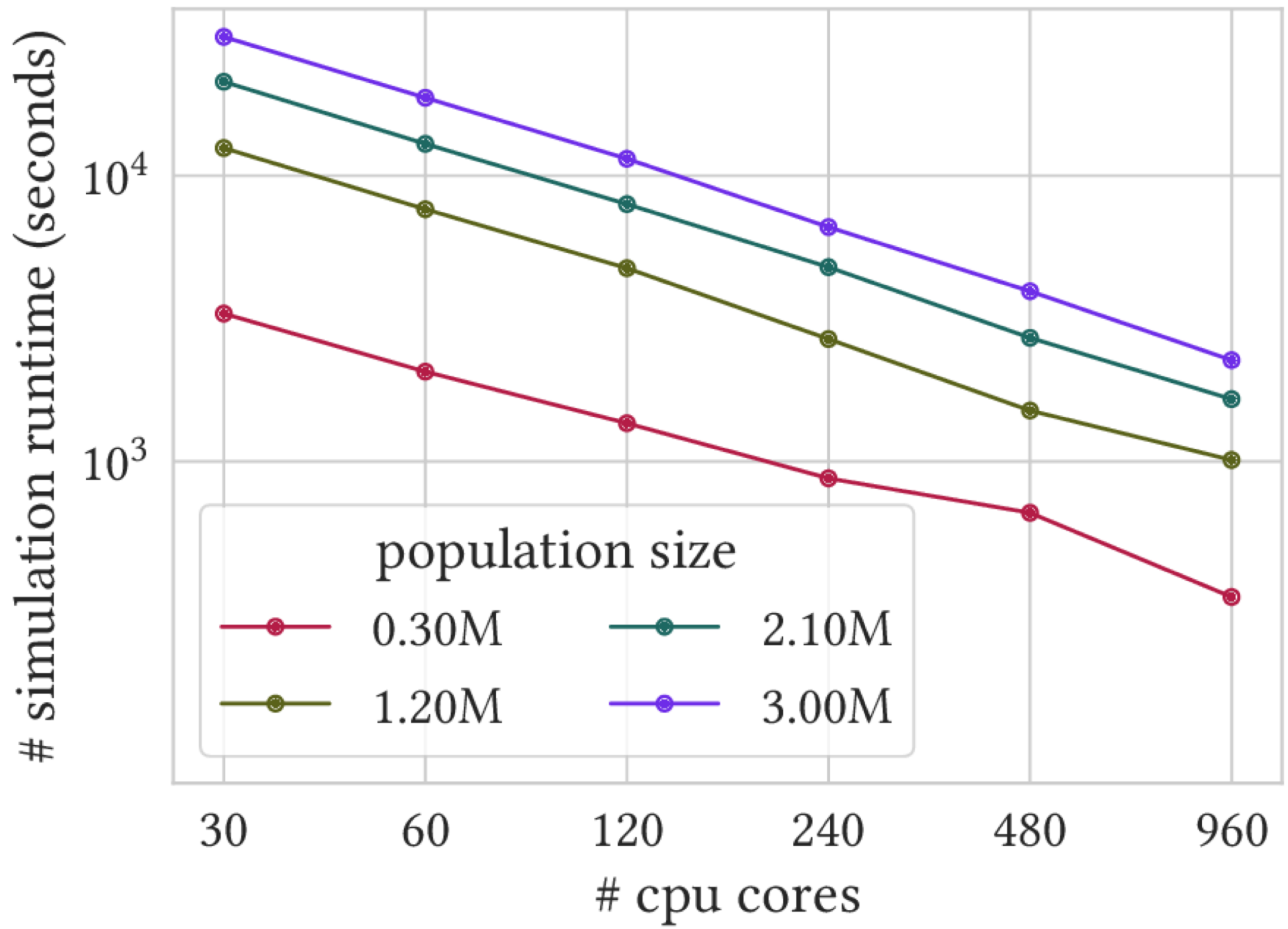


Discrete Time simulation with adjustable time scale

Matrix exposes API interface using JSON RPC over TCP/IP

Subsumes complexities of distributed computation and synchronization

Scaling up GitHub ACT-R simulation



Reduction in simulation runtime of GitHub ACTR simulation (CM-ACTR)
with increasing number of cpu cores,
for different population sizes of GitHub agents.

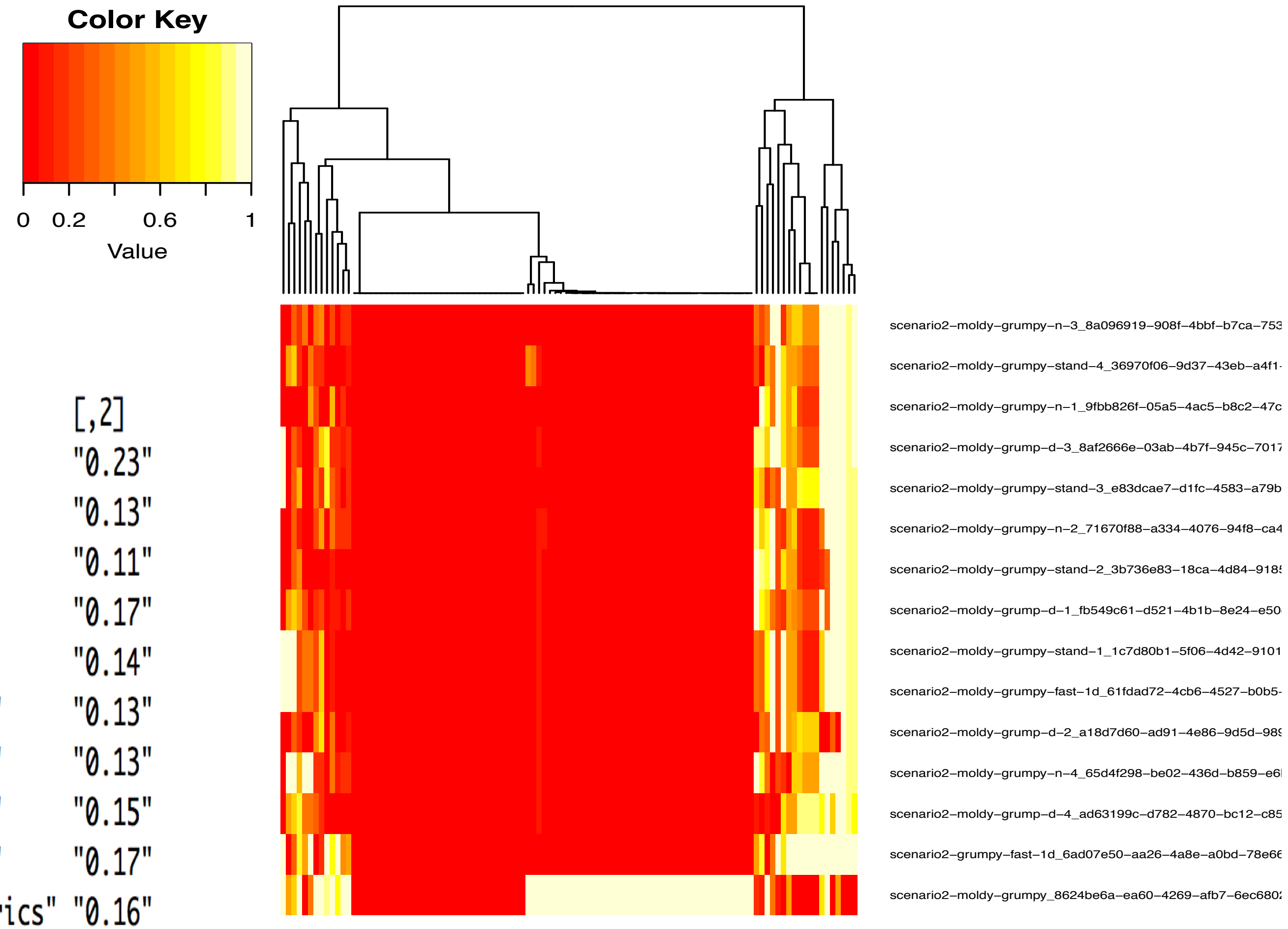
Socio-Cognitive Modeling

Does cognition matter? Implications for population health

Benefits of Socio-Economic-Cognitive Integration

Model Variants:

- *Standard*: assignment of each user to one of 8 role utility profiles + learning of expectations
- *Default role assignment*: uniform utility function for all users
- *No expectation learning*: only training and ground truth instances, no confirmation bias

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Global Synthetic Information

2 GB/M
People Storage

7Billion
Synthetic individuals

28+Billion
Interactions

40+
Databases

220 countries
Synthetic
Populations &
Networks
Constructed

50K+
Files in
Which Data
is Stored

5 Days
Compute
Time

8TB
Storage

First Data-Driven Global Synthetic Populations & Proximity networks