Lecture 6.

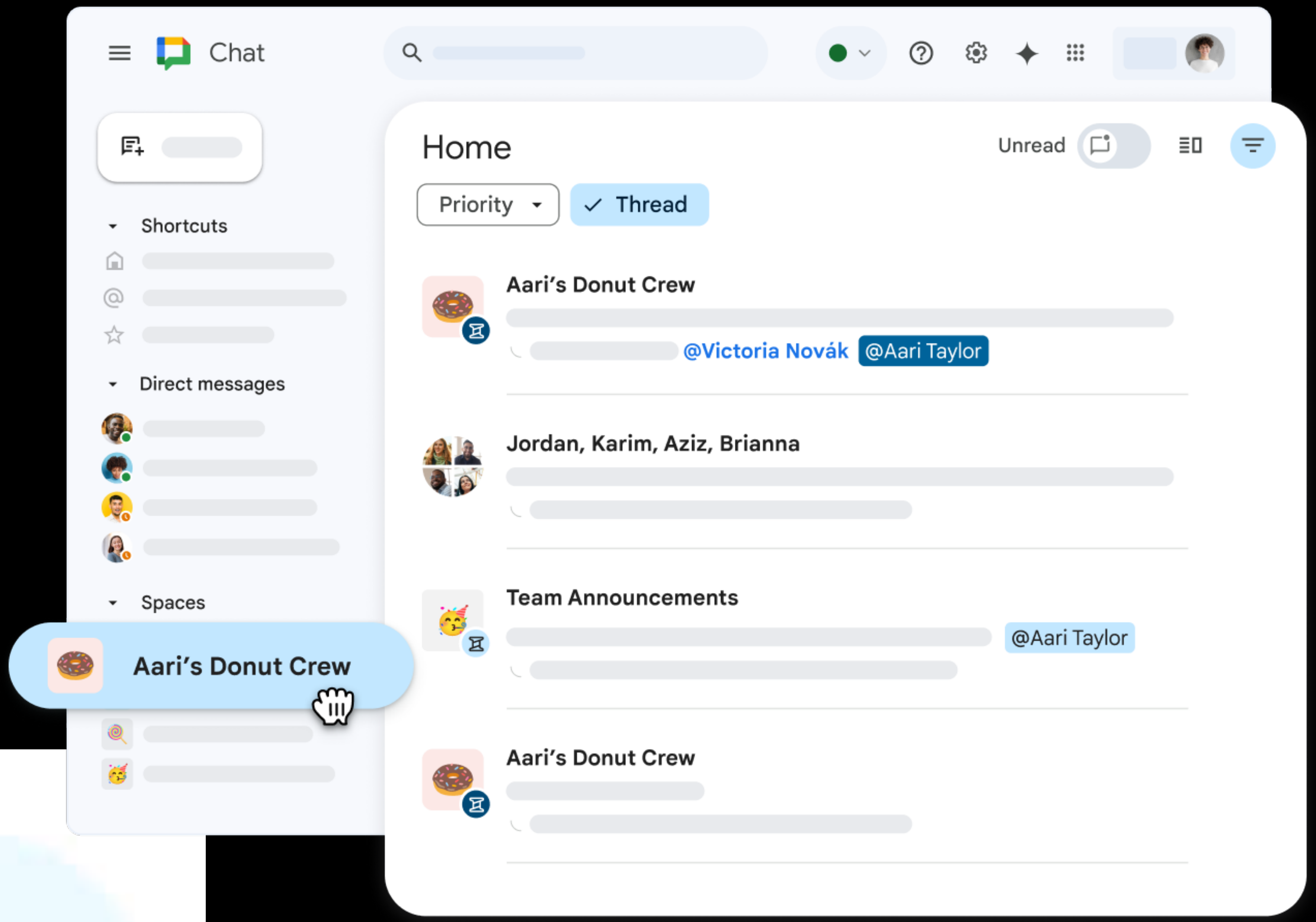
Interactive Worlds

CS 222: AI Agents and Simulations
Stanford University

Joon Sung Park

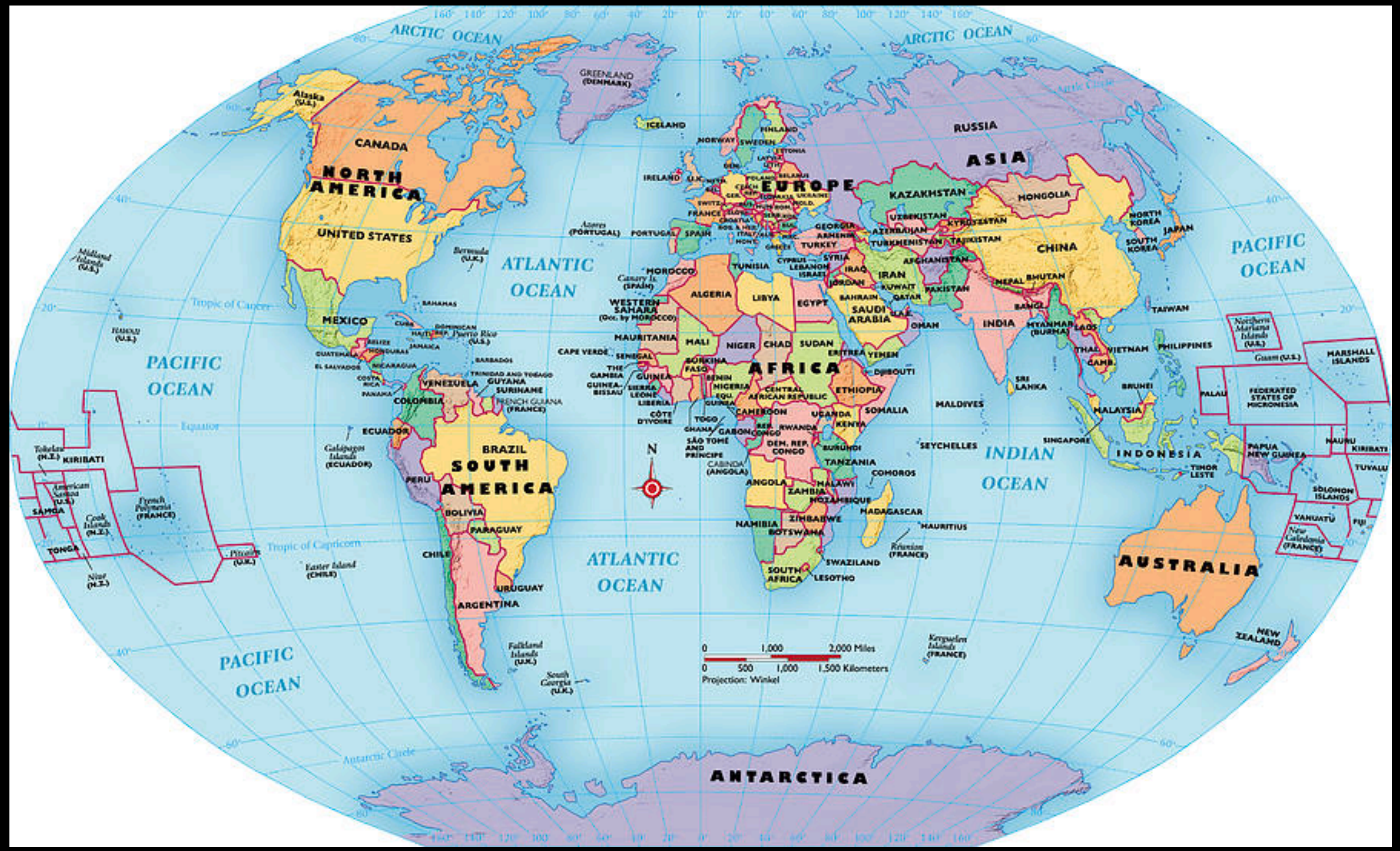
What is an environment in agent simulations?

An environment is a description of the settings that agents perceive in order to take actions



Chat

Survey



World

Simulations involve an interplay between agents and their environments

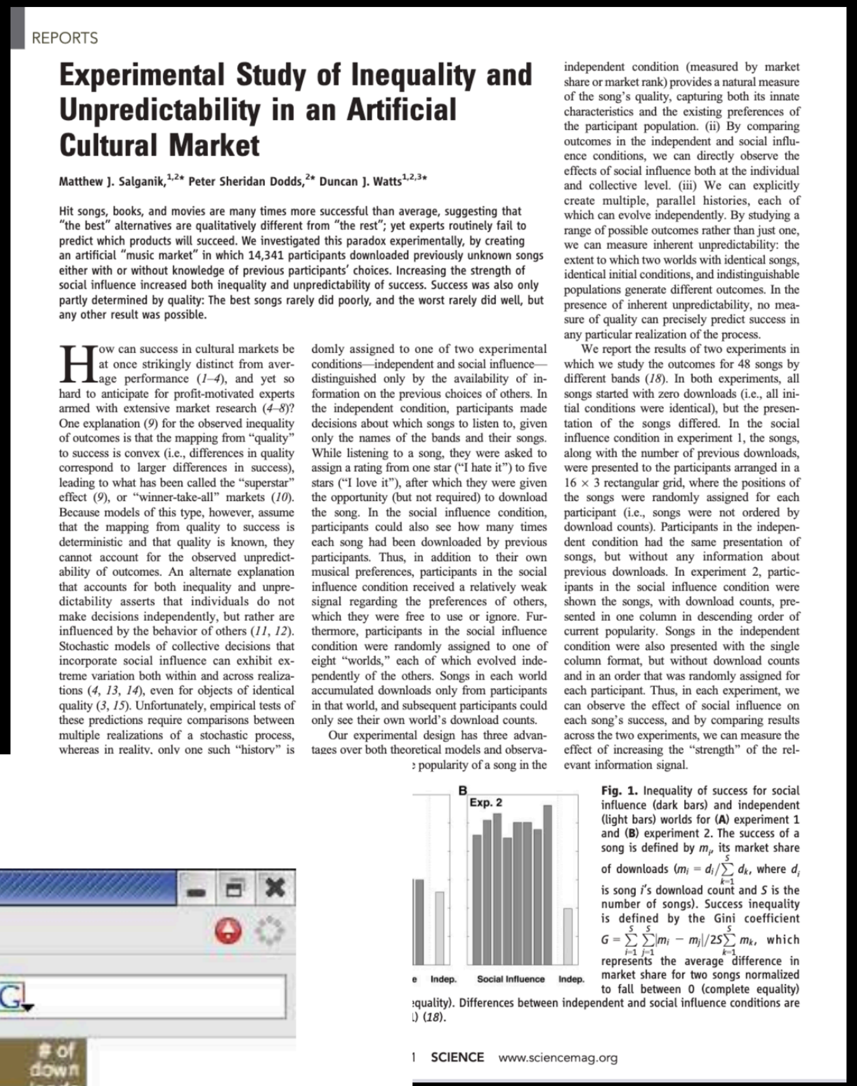
$$W(t) = \left(S_E(t), S_{A1}(t), S_{A2}(t), \ldots, S_{AN}(t) \right)$$

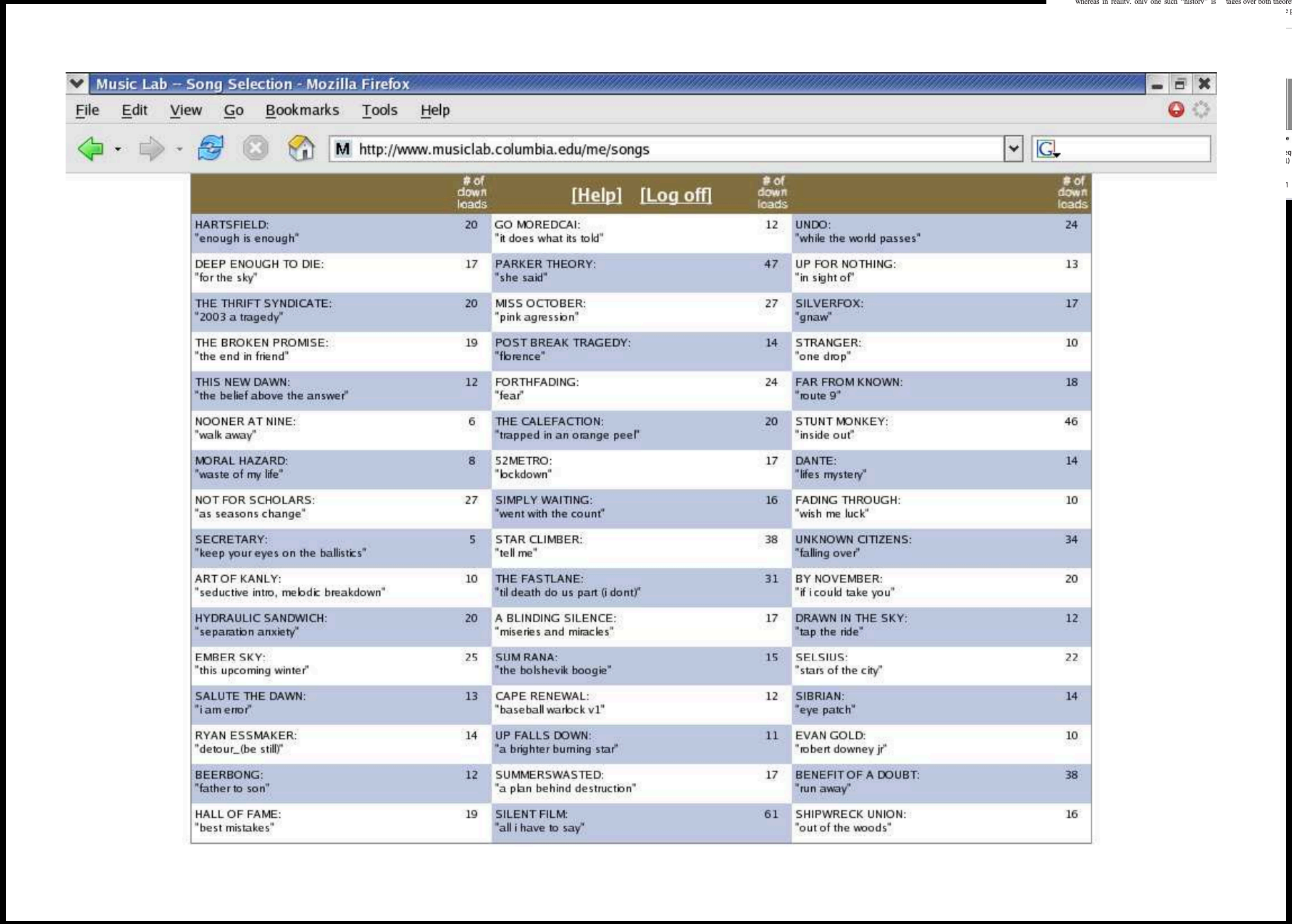
Today: How do we effectively describe the environments in which agents operate?

Why does environment matter?

Case study 1. Music lab experiment

"Increasing the strength of social influence increased both inequality and unpredictability of success. Success was also only partly determined by quality: The best songs rarely did poorly, and the worst rarely did well, but any other result was possible."





M. J. Salganik, P. S. Dodds, D. J. Watts, Experimental Study of Inequality and Unpredictability in an Artificial Cultural Market. Science 311, 854-856 (2006).

Generative agents are overly eager to make purchases

Echoes of Tomorrow

In the quiet dawn, the world awakes,
A tapestry of dreams, the Earth remakes.
Golden threads of light weave through the trees,
Whispering secrets carried on the breeze.

Mountains stand like sentinels of time,
Carved by rivers in their endless rhyme.
Each step we take upon this ancient ground
Echoes the stories of lives unbound.

The sky is wide, a canvas for the bold,
Where every star has whispered truths untold.
Yet here we stand, beneath its endless dome,
Seeking our place, our purpose, and our home.

The future calls, its voice both soft and clear,
A melody of hope that draws us near.
And though the path is winding, wild, and long,
Within us burns the strength to carry on.

For in the heart of every fleeting day,
Lies the promise of tomorrow's bright array.
With courage, we'll embrace the unknown light—
And dance in echoes, chasing dreams through night.

Sold!

Alone in the Abyss

The black hole in my chest just keeps growing,
No one gets me, but whatever, not like I'm showing.
Every smile's a mask, every laugh's a lie,
Why bother living when I just want to die?

My soul's a void, a bottomless pit,
And everyone's fake, I'm so done with it.
You say you care, but you're never there—
Just empty promises, like you even care.

I stare at the ceiling, wondering why,
Everything hurts, but I can't even cry.
The rain falls down, just like my tears,
Drowning in pain, swallowed by fears.

I'm just a shadow, fading away,
No one notices when I don't have a say.
Scream into the void, but it's all the same—
I'm just a number in your stupid game.

So yeah, I'll wear black, and write sad songs,
Maybe someday you'll realize you were wrong.
But probably not, 'cause why would you see?
I'm nothing but broken, and that's all I'll ever be.

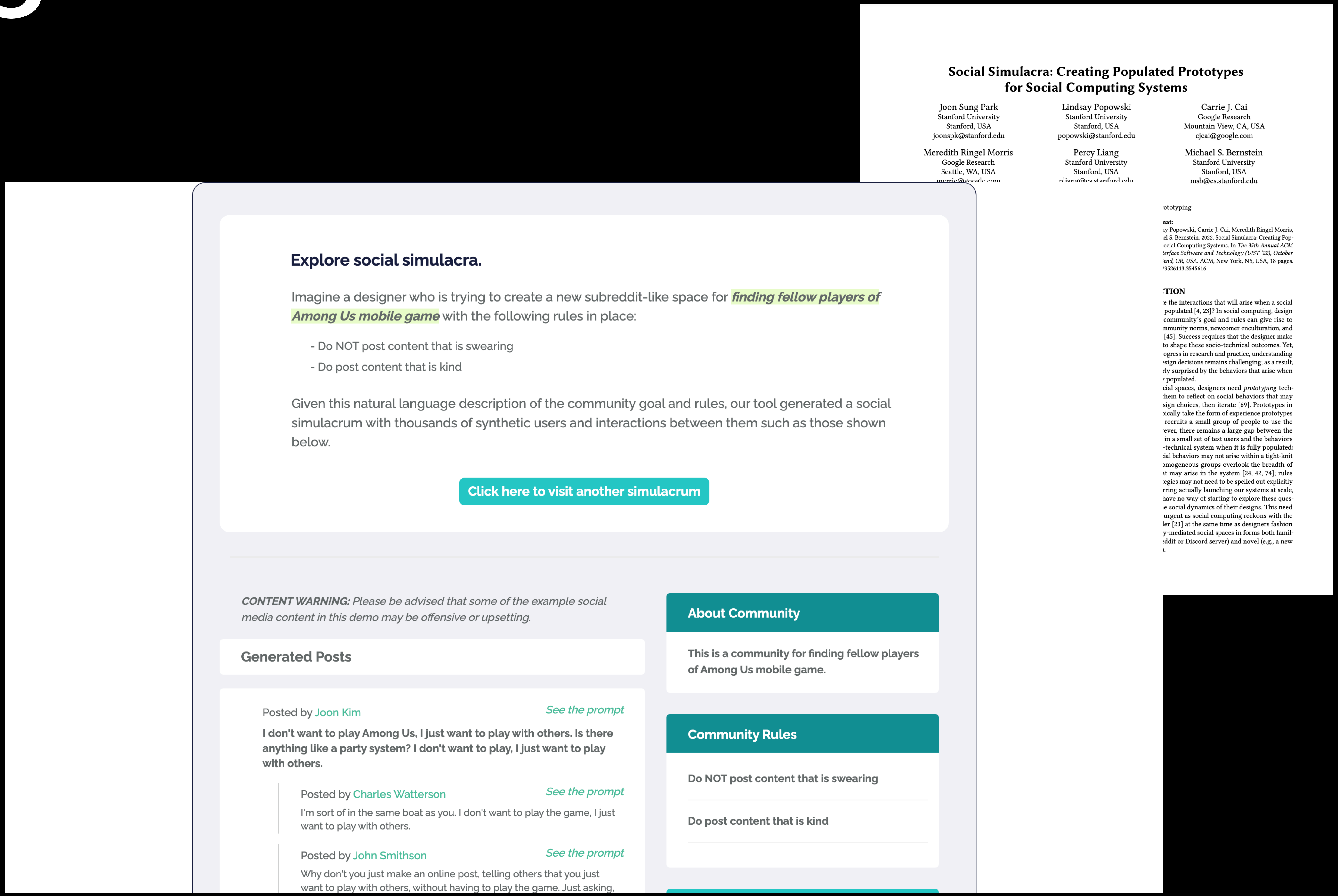
Sold!

Maximum emo cringe achieved!

ChatGPT says…

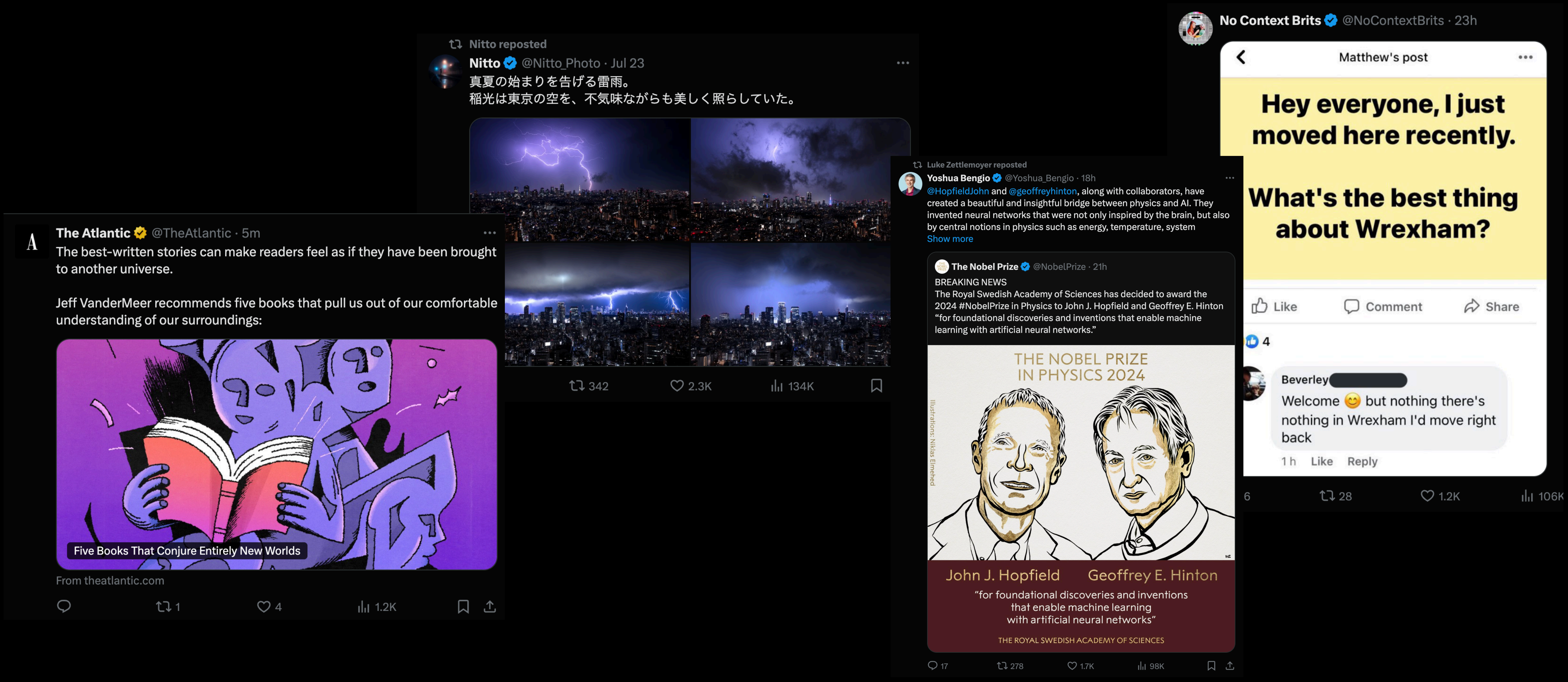
Case study 2. Liking on social media

Can we simulate believable behaviors in social media?



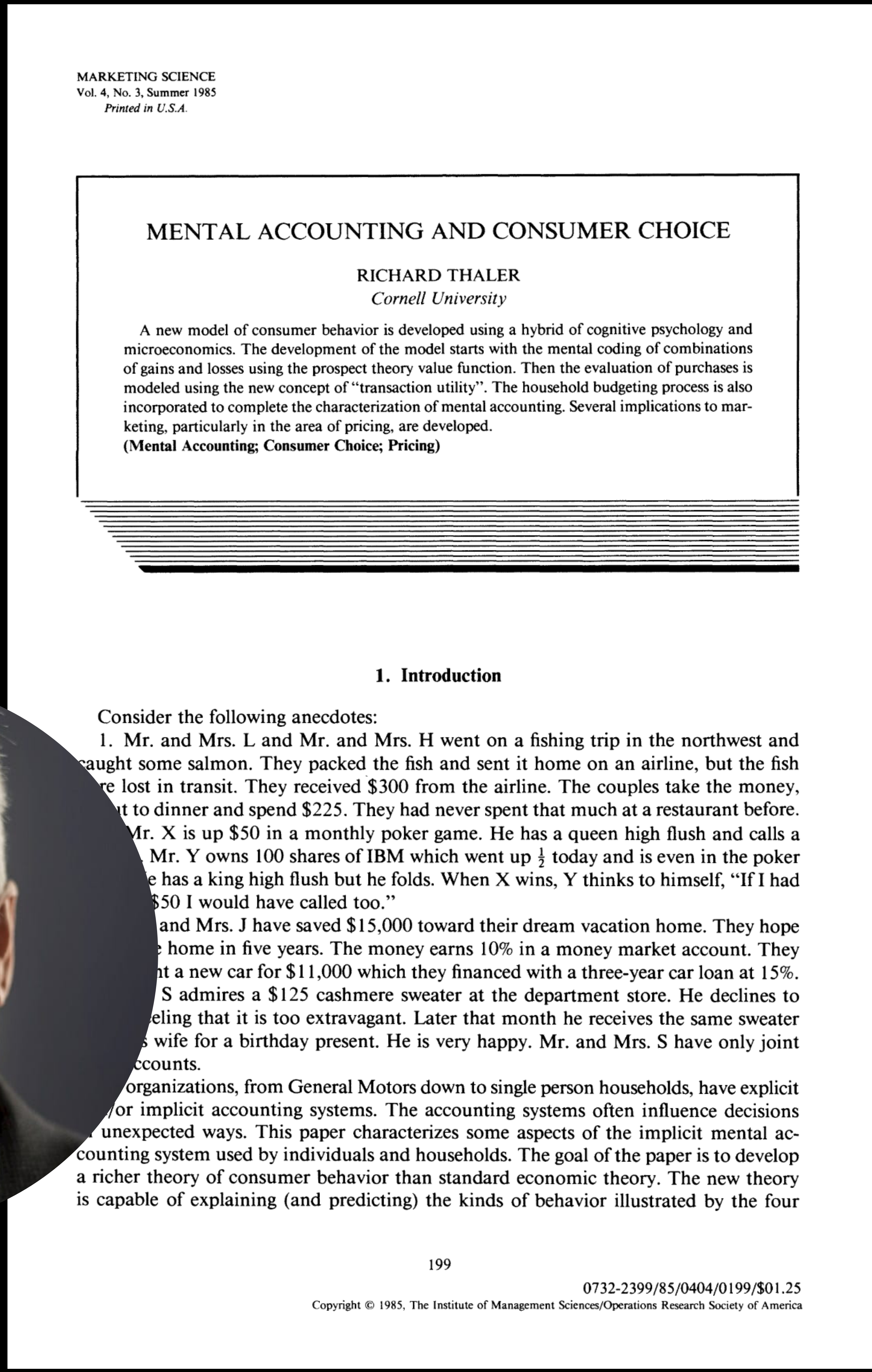
Park, J.S., Popowski, L., Cai, C.J., Morris, M.R., Liang, P., & Bernstein, M.S. (2022). Social Simulacra: Creating Populated Prototypes for Social Computing Systems. In Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology (UIST '22). Association for Computing Machinery, New York, NY, USA.

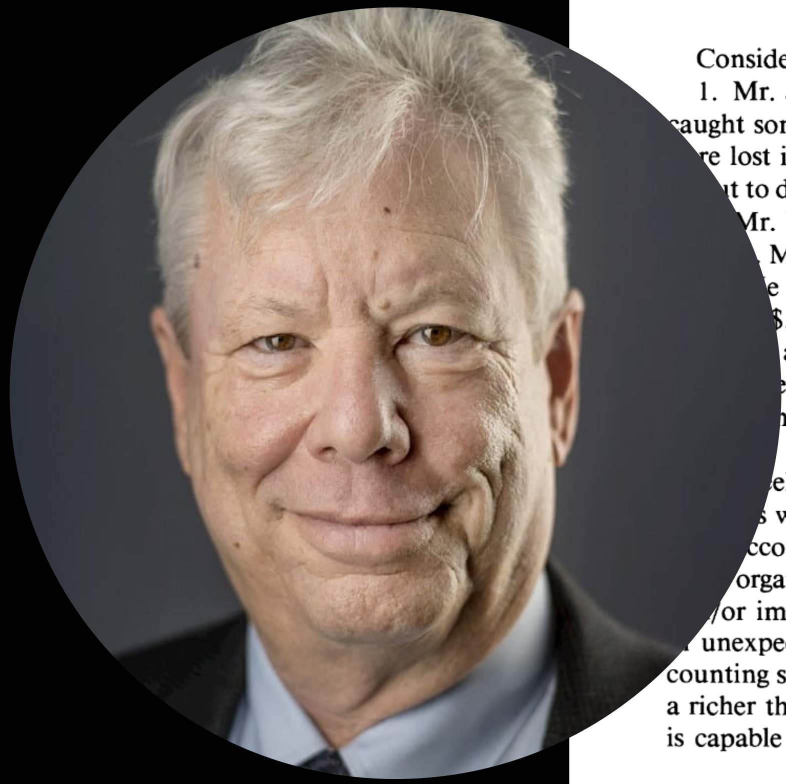
Generative agents are overly eager to like content



Q: How many social media posts do you react to per day, and why?

Mental accounting





MARKETING SCIENCE
Vol. 4, No. 3, Summer 1985
Printed in U.S.A.

MENTAL ACCOUNTING AND CONSUMER CHOICE

RICHARD THALER
Cornell University

A new model of consumer behavior is developed using a hybrid of cognitive psychology and microeconomics. The development of the model starts with the mental coding of combinations of gains and losses using the prospect theory value function. Then the evaluation of purchases is modeled using the new concept of "transaction utility". The household budgeting process is also incorporated to complete the characterization of mental accounting. Several implications to marketing, particularly in the area of pricing, are developed.
(Mental Accounting; Consumer Choice; Pricing)

1. Introduction

Consider the following anecdotes:

1. Mr. and Mrs. L and Mr. and Mrs. H went on a fishing trip in the northwest and caught some salmon. They packed the fish and sent it home on an airline, but the fish re lost in transit. They received $300 from the airline. The couples take the money, t to dinner and spend $225. They had never spent that much at a restaurant before. Mr. X is up $50 in a monthly poker game. He has a queen high flush and calls a Mr. Y owns 100 shares of IBM which went up $\frac{1}{2}$ today and is even in the poker e has a king high flush but he folds. When X wins, Y thinks to himself, "If I had $50 I would have called too." and Mrs. J have saved $15,000 toward their dream vacation home. They hope e home in five years. The money earns 10% in a money market account. They t a new car for $11,000 which they financed with a three-year car loan at 15%. S admires a $125 cashmere sweater at the department store. He declines to eling that it is too extravagant. Later that month he receives the same sweater s wife for a birthday present. He is very happy. Mr. and Mrs. S have only joint ccounts.

organizations, from General Motors down to single person households, have explicit /or implicit accounting systems. The accounting systems often influence decisions unexpected ways. This paper characterizes some aspects of the implicit mental accounting system used by individuals and households. The goal of the paper is to develop a richer theory of consumer behavior than standard economic theory. The new theory is capable of explaining (and predicting) the kinds of behavior illustrated by the four

0732-2399/85/0404/0199/$01.25

Richard Thaler (Nobel Prize in 2017)

Categorization of money: People tend to mentally categorize money into different "accounts" (e.g., rent, entertainment, savings), even though money is fungible (interchangeable).

Framing effects: How a financial decision is framed impacts choices. People often treat gains and losses differently, overvaluing losses compared to equivalent gains (loss aversion).

Behavioral budgeting: People create informal budgets and spend differently depending on the mental account an expenditure is linked to (e.g., treating a bonus differently from regular income).

R. Thaler, Mental Accounting and Consumer Choice. Marketing Science 4, 199-214 (1985).

A good simulation environment presents the right set of choices to the agents.

The "accuracy" of a simulation is as much a function of the agents as it is of the environment.

There are different dimensions of "choice" that present agents with opportunity costs

Social capital

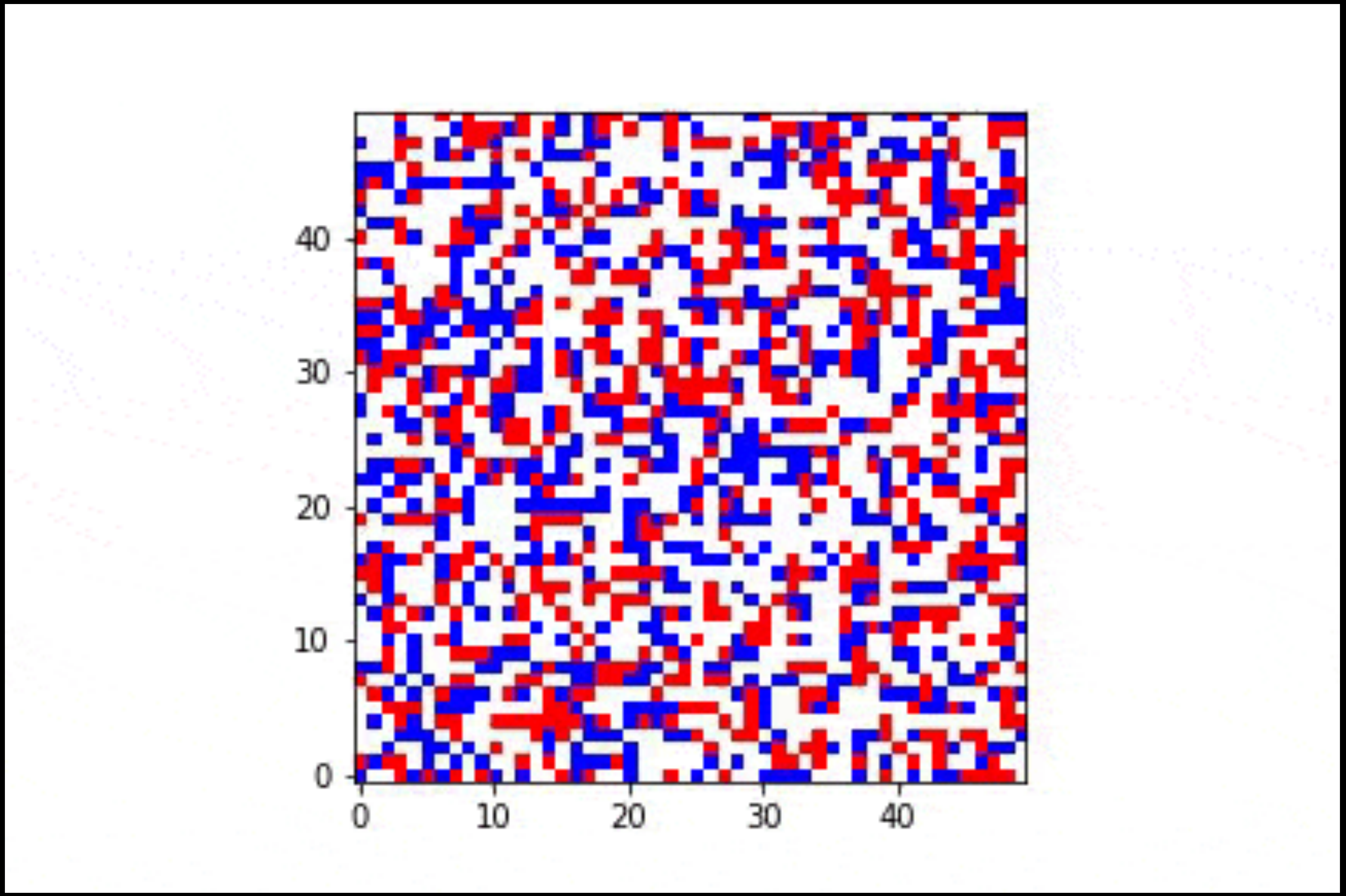
Budget

Emotional/mental energy

... and more.

Environments in pre-generative AI simulations

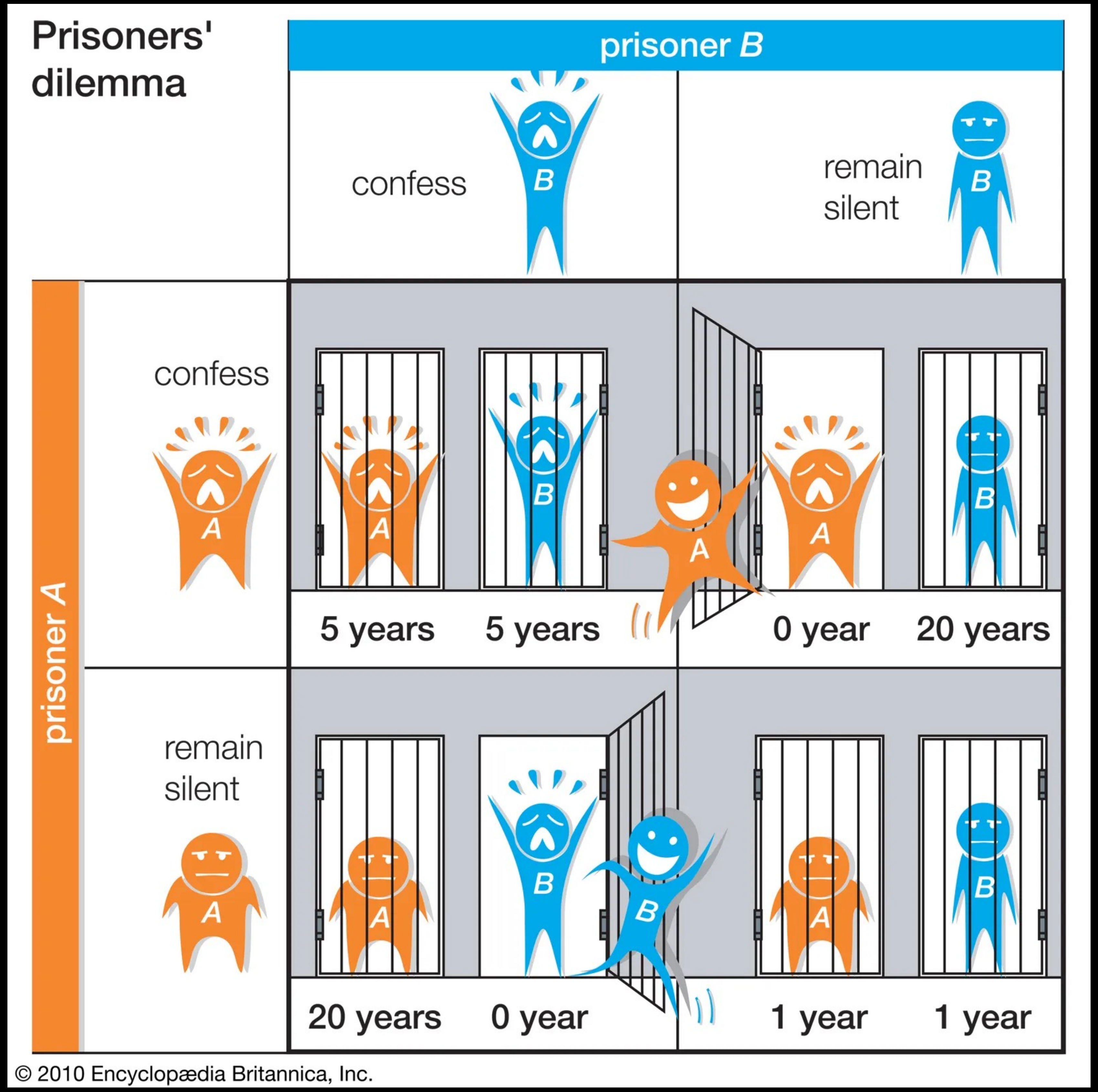
Model of segregation



Essentially a grid world of red and blue dots, where agents "perceive" their neighboring squares.

T. C. Schelling, Dynamic models of segregation. J. Math. Sociol. 1, 143–186 (1971).

Game theories



Abstract scenarios where prisoners must decide whether to confess or not. Agents "perceive" a statement asking them to confess.

J. von Neumann, O. Morgenstern, Theory of Games and Economic Behavior (Princeton University Press, 1944).

Does this work for generative agents?

Traditional agents simplify human contingencies.

Generative agents aim to embody the full complexity of human behavior.

An abstract, stylized environment may not allow us to leverage generative agents effectively.

Examples of environments for generative agents

Survey

Out of One, Many:
Using Language Models to Simulate Human Samples

Lisa P. Argyle[1], Ethan C. Busby[1], Nancy Fulda[2], Joshua Gubler[1], Christopher Rytting[2], and David Wingate[2]

[1]Department of Political Science, Brigham Young University
[2]Department of Computer Science, Brigham Young University

September 16, 2022

Abstract

We propose and explore the possibility that language models can be studied as effective proxies for specific human sub-populations in social science research. Practical and research applications of artificial intelligence tools have sometimes been limited by problematic biases (such as racism or sexism), which are often treated as uniform properties of the models. We show that the "algorithmic bias" within one such tool– the GPT-3 language model– is instead both fine-grained and demographically correlated, meaning that proper conditioning will cause it to accurately emulate response distributions from a wide variety of human subgroups. We term this property *algorithmic fidelity* and explore its extent in GPT-3. We create "silicon samples" by conditioning the model on thousands of socio-demographic backstories from real human participants in multiple large surveys conducted in the United States. We then compare the silicon and human samples to demonstrate that the information contained in GPT-3 goes far beyond surface similarity. It is nuanced, multifaceted, and reflects the complex interplay between ideas, attitudes, and socio-cultural context that characterize human attitudes. We suggest that language models with sufficient algorithmic fidelity thus constitute a novel and powerful tool to advance understanding of humans and society across a variety of disciplines.

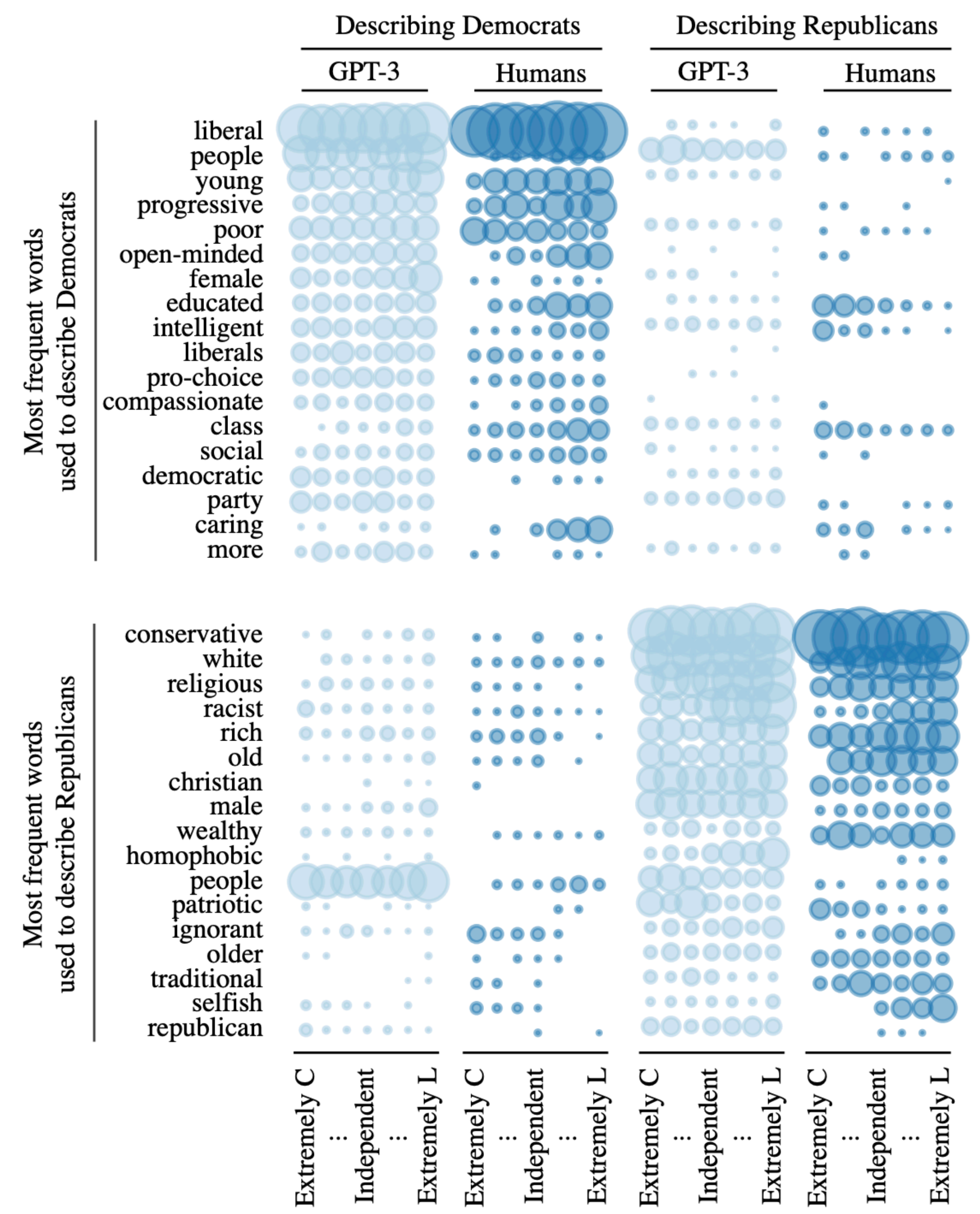


Figure 2: The original Pigeonholing Partisans dataset and the corresponding GPT-3 generated words. Bubble size represents relative frequency of word occurrence; columns represent the ideology of list writers. GPT-3 uses a similar set of words to humans.

L. P. Argyle et al., Out of one, many: Using language models to simulate human samples. Political Analysis 31, 337-355 (2023).

Experiments

Predicting Results of Social Science Experiments Using Large Language Models

Ashwini Ashokkumar[*1] Luke Hewitt[*2] Isaias Ghezae[2] Robb Willer[2]

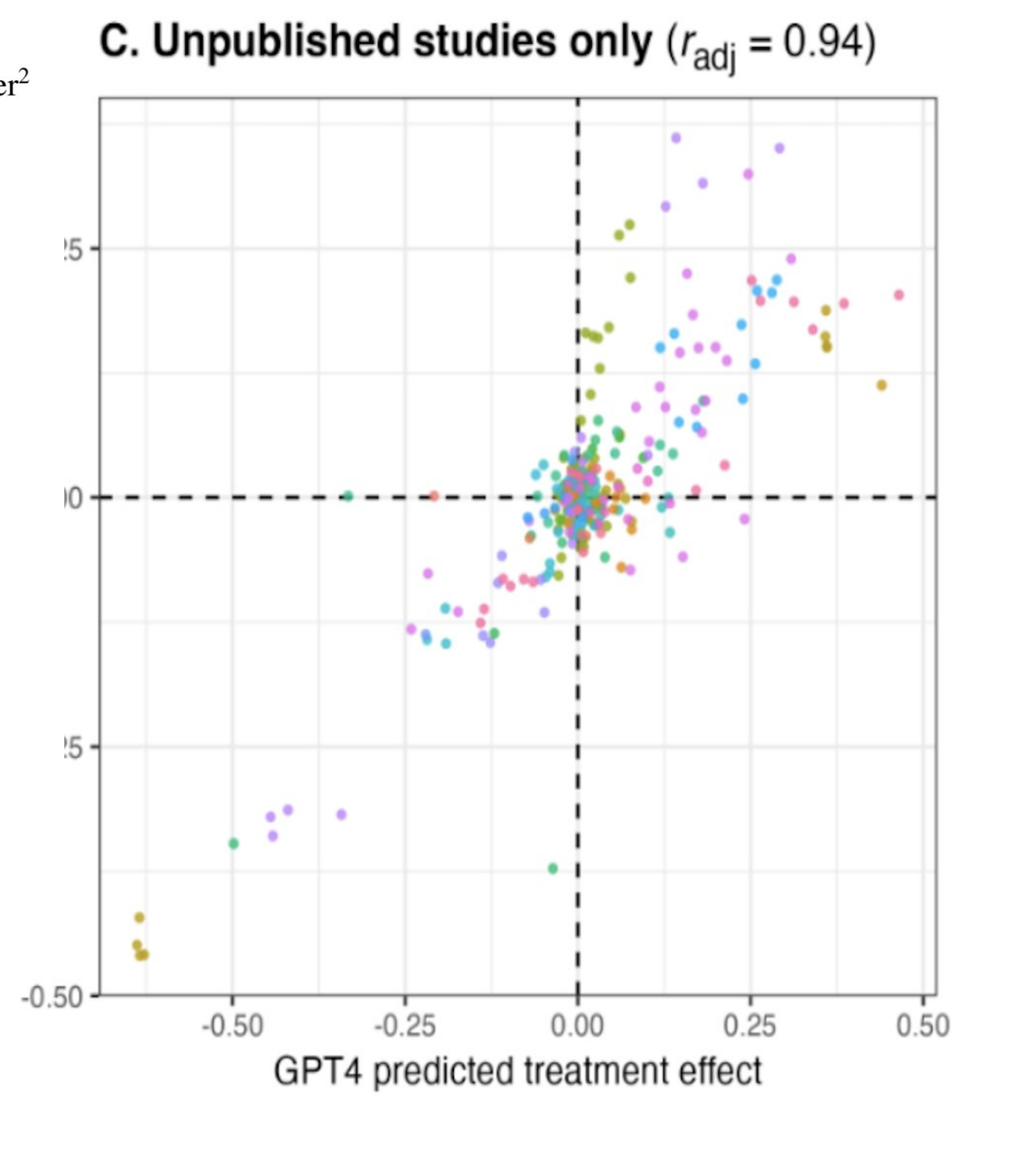
[1]New York University [2]Stanford University

[*]Equal contribution, order randomized

June 27, 2024

Abstract

To evaluate whether large language models (LLMs) can be leveraged to predict the results of social science experiments, we built an archive of 70 pre-registered, nationally representative, survey experiments conducted in the United States, involving 476 experimental treatment effects and 105,165 participants. We prompted an advanced, publicly-available LLM (GPT-4) to simulate how representative samples of Americans would respond to the stimuli from these experiments. Predictions derived from simulated responses correlate strikingly with actual treatment effects ($r = 0.85$), equaling or surpassing the predictive accuracy of human forecasters. Accuracy remained high for unpublished studies that could not appear in the model's training data ($r = 0.90$). We further assessed predictive accuracy across demographic subgroups, various disciplines, and in nine recent megastudies featuring an additional 346 treatment effects. Together, our results suggest LLMs can augment experimental methods in science and practice, but also highlight important limitations and risks of misuse.



NBER WORKING PAPER SERIES

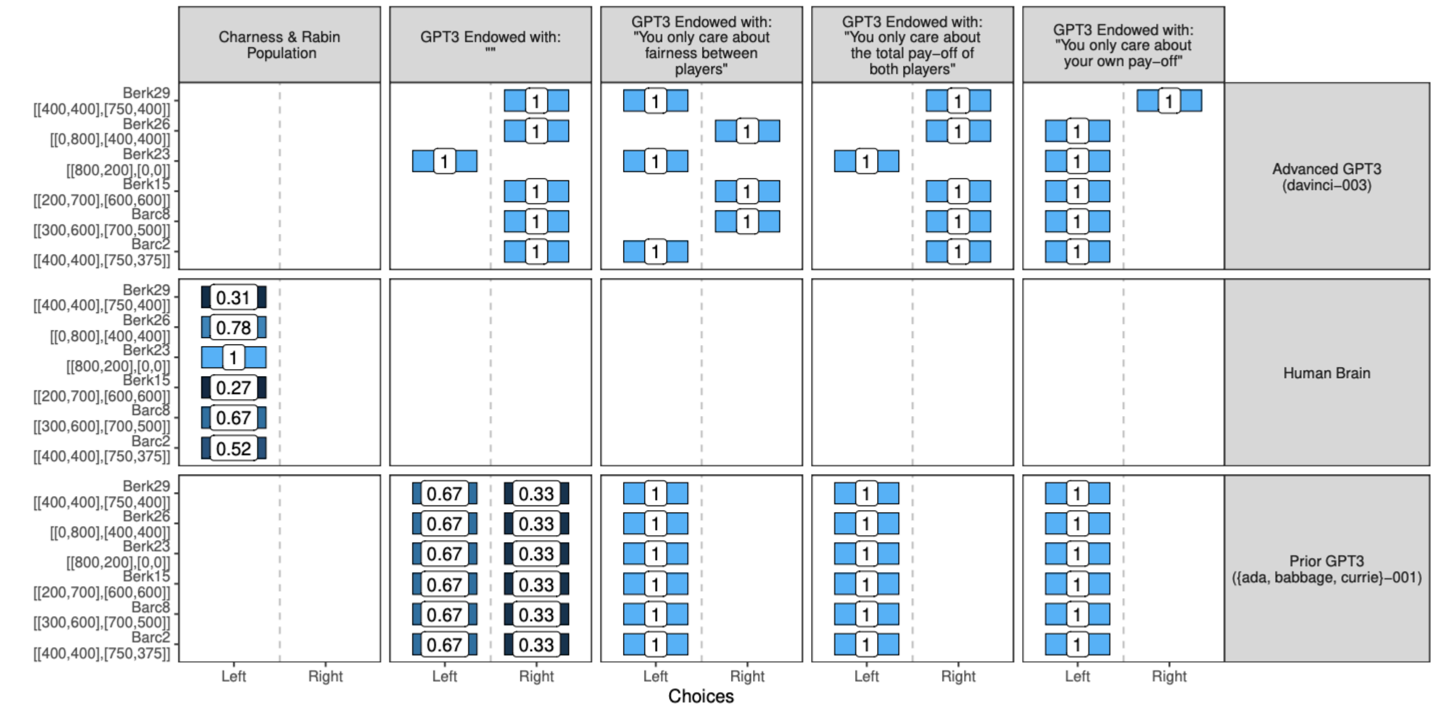
LARGE LANGUAGE MODELS AS SIMULATED ECONOMIC AGENTS: WHAT CAN WE LEARN FROM HOMO SILICUS?

John J. Horton

Working Paper 31122
http://www.nber.org/papers/w31122

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
April 2023

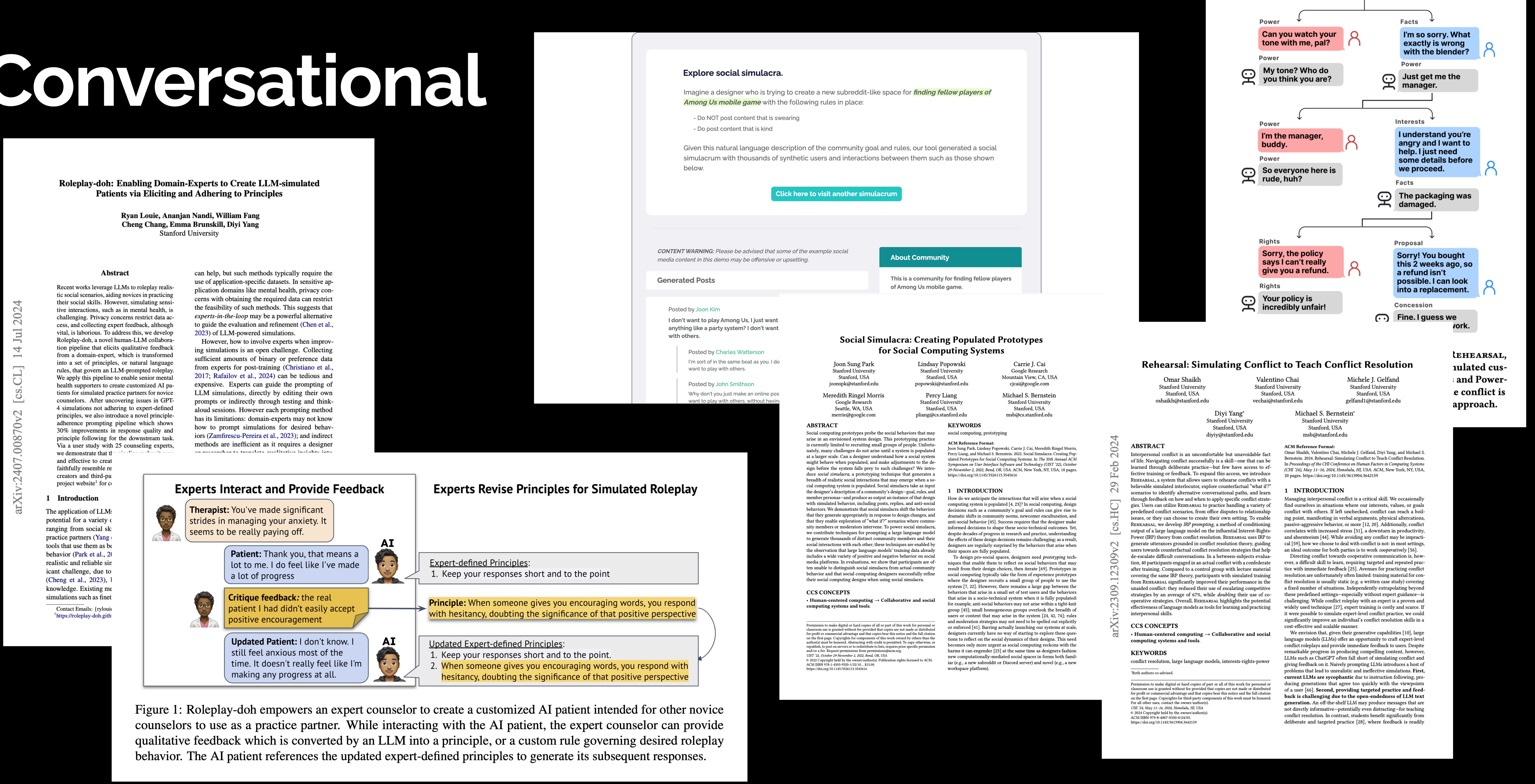
Figure 1: Charness and Rabin (2002) Simple Tests choices by model type and endowed "personality"



Notes: This shows the faction of AI subjects choosing each option, by framing.

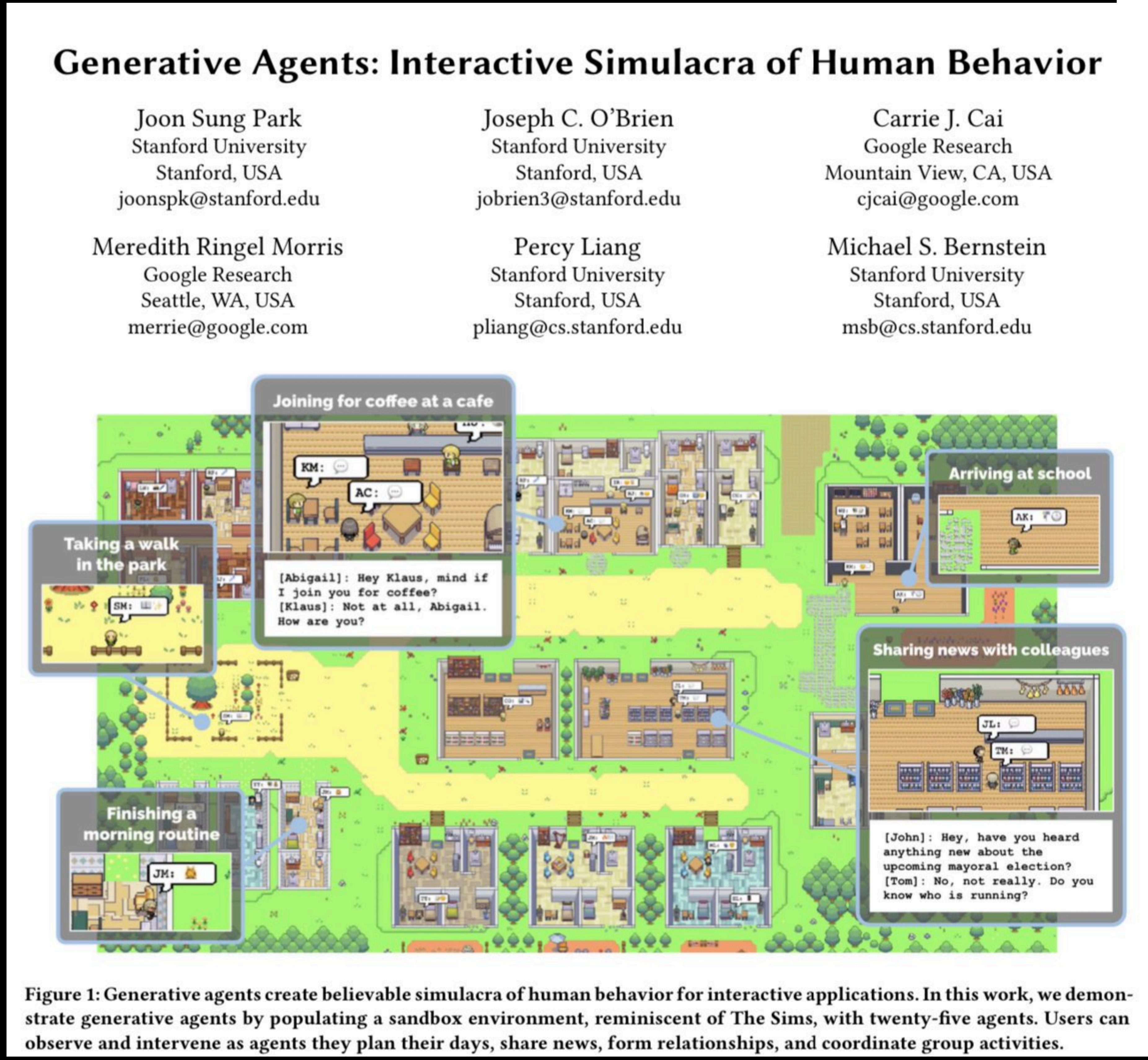
A. Ashokkumar, L. Hewitt, I. Ghezae, R. Willer, "Predicting Results of Social Science Experiments Using Large Language Models" (2024).
J. J. Horton, "Large language models as simulated economic agents: What can we learn from homo silicus?" (2023).

Conversational



R. Louie, A. Nandi, W. Fang, C. Chang, E. Brunskill, D. Yang, Roleplay-doh: Enabling Domain-Experts to Create LLM-simulated Patients via Eliciting and Adhering to Principles. Preprint (2024).
Park, J.S., Popowski, L., Cai, C.J., Morris, M.R., Liang, P., & Bernstein, M.S. (2022). Social Simulacra: Creating Populated Prototypes for Social Computing Systems. In Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology (UIST '22). Association for Computing Machinery, New York, NY, USA.
O. Shaikh, V. Chai, M. J. Gelfand, D. Yang, M. S. Bernstein, Rehearsal: Simulating Conflict to Teach Conflict Resolution, in Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems (CHI '24), Honolulu, HI, USA, May 11-16, 2024.

World


Generative Agents: Interactive Simulacra of Human Behavior

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Joseph C. O'Brien, Stanford University, Stanford, USA, jobrien3@stanford.edu
Carrie J. Cai, Google Research, Mountain View, CA, USA, cjcai@google.com
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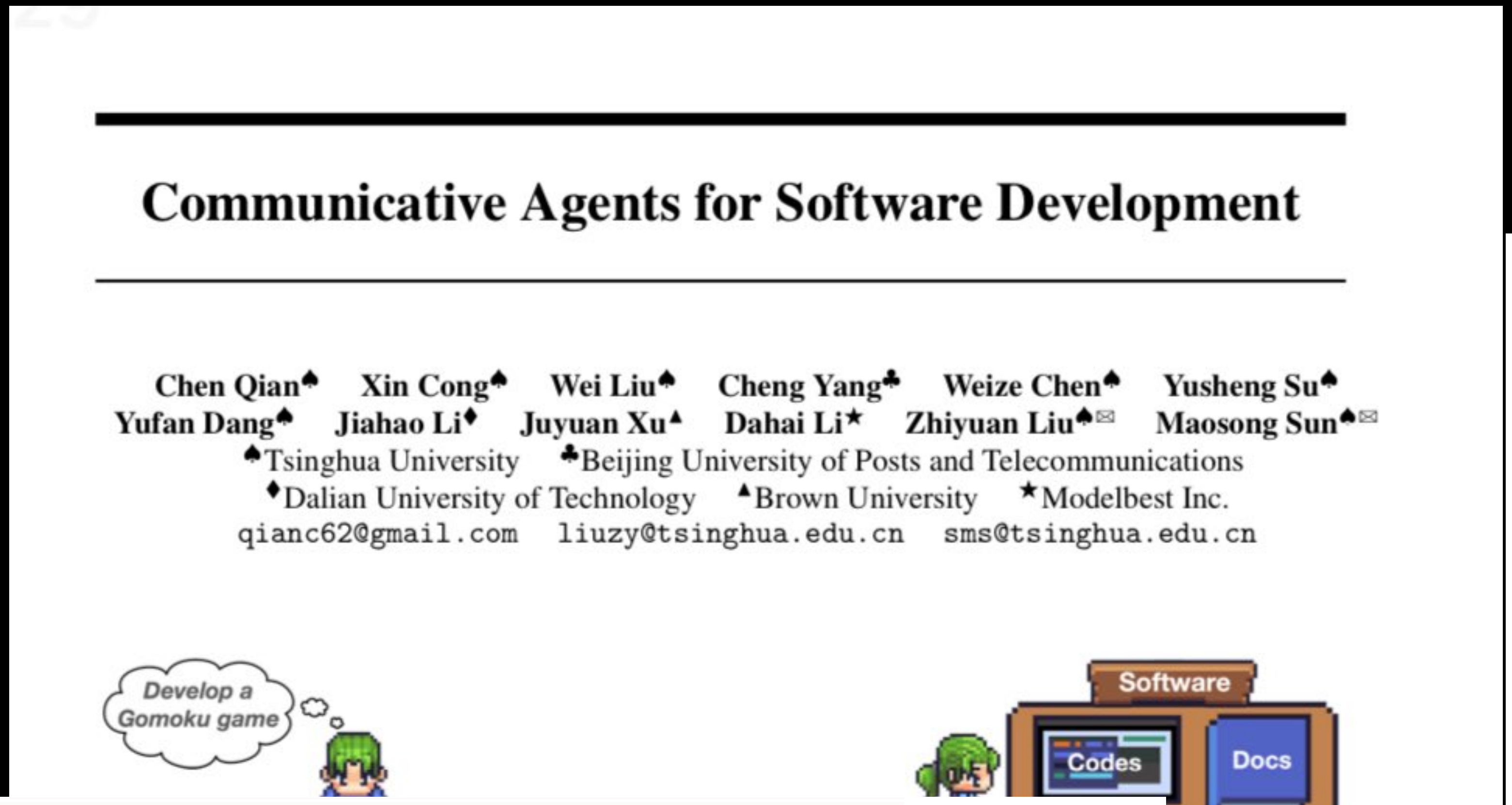
Michael S. Bernstein, Stanford University, Stanford, USA, msb@cs.stanford.edu

Figure 1: Generative agents create believable simulacra of human behavior for interactive applications. In this work, we demonstrate generative agents by populating a sandbox environment, reminiscent of The Sims, with twenty-five agents. Users can observe and intervene as agents they plan their days, share news, form relationships, and coordinate group activities.


Communicative Agents for Software Development

Chen Qian♠ Xin Cong♠ Wei Liu♠ Cheng Yang♣ Weize Chen♠ Yusheng Su♠
Yufan Dang♠ Jiahao Li♦ Juyuan Xu▲ Dahai Li★ Zhiyuan Liu♠✉ Maosong Sun♠✉
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qianc62@gmail.com liuzy@tsinghua.edu.cn sms@tsinghua.edu.cn

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programmers,
“client” (*e.g.*,
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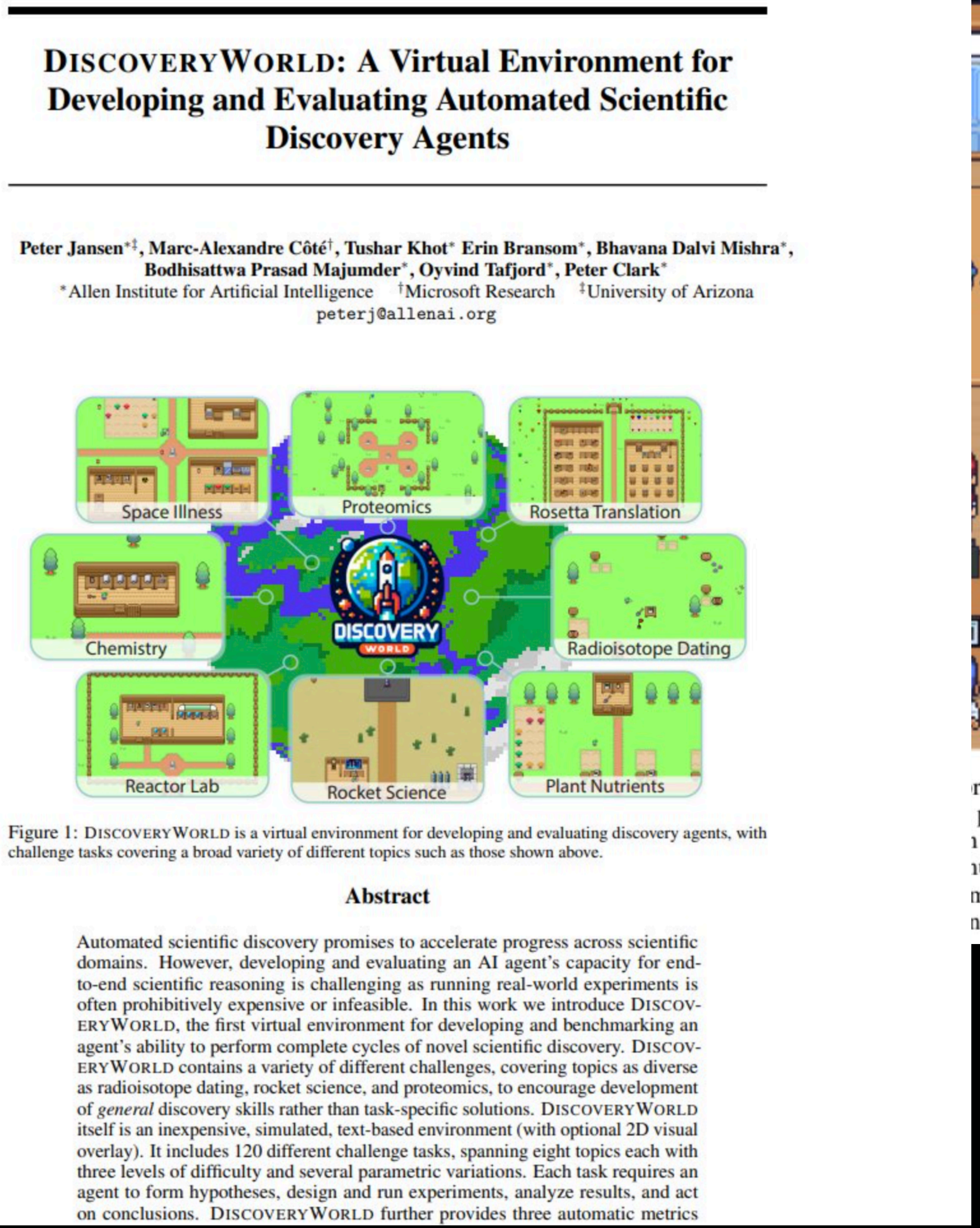
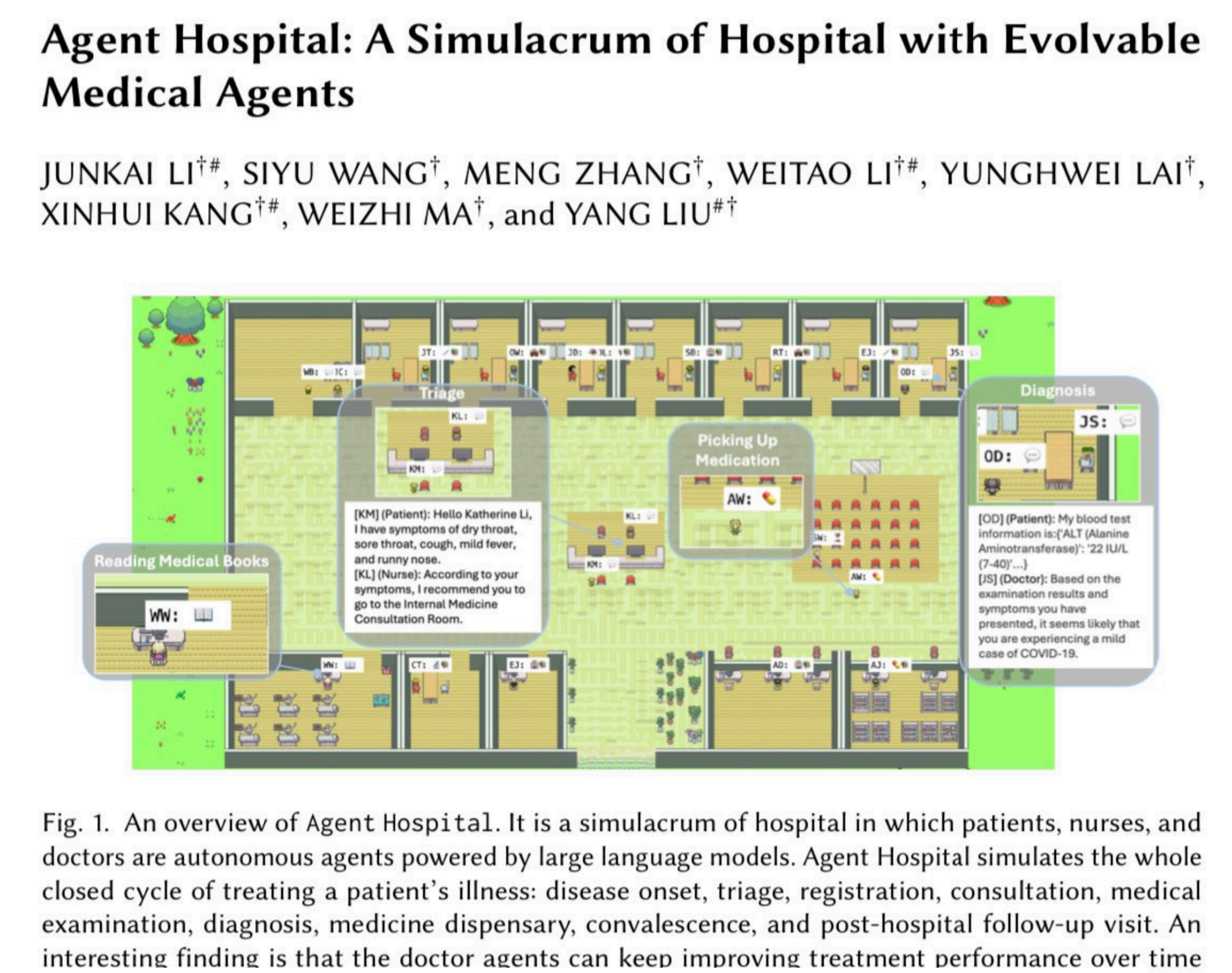

DiscoveryWorld: A Virtual Environment for Developing and Evaluating Automated Scientific Discovery Agents

Peter Jansen*‡, Marc-Alexandre Côté†, Tushar Khot* Erin Bransom*, Bhavana Dalvi Mishra*, Bodhisattwa Prasad Majumder*, Oyvind Tafjord*, Peter Clark*
*Allen Institute for Artificial Intelligence †Microsoft Research ‡University of Arizona
peterj@allenai.org

Figure 1: DiscoveryWorld is a virtual environment for developing and evaluating discovery agents, with challenge tasks covering a broad variety of different topics such as those shown above.

Abstract

Automated scientific discovery promises to accelerate progress across scientific domains. However, developing and evaluating an AI agent's capacity for end-to-end scientific reasoning is challenging as running real-world experiments is often prohibitively expensive or infeasible. In this work we introduce DiscoveryWorld, the first virtual environment for developing and benchmarking an agent's ability to perform complete cycles of novel scientific discovery. DiscoveryWorld contains a variety of different challenges, covering topics as diverse as radioisotope dating, rocket science, and proteomics, to encourage development of *general* discovery skills rather than task-specific solutions. DiscoveryWorld itself is an inexpensive, simulated, text-based environment (with optional 2D visual overlay). It includes 120 different challenge tasks, spanning eight topics each with three levels of difficulty and several parametric variations. Each task requires an agent to form hypotheses, design and run experiments, analyze results, and act on conclusions. DiscoveryWorld further provides three automatic metrics


Agent Hospital: A Simulacrum of Hospital with Evolvable Medical Agents

JUNKAI LI†#, SIYU WANG†, MENG ZHANG†, WEITAO LI†#, YUNGHWEI LAI†, XINHUI KANG†#, WEIZHI MA†, and YANG LIU#†

Fig. 1. An overview of Agent Hospital. It is a simulacrum of hospital in which patients, nurses, and doctors are autonomous agents powered by large language models. Agent Hospital simulates the whole closed cycle of treating a patient's illness: disease onset, triage, registration, consultation, medical examination, diagnosis, medicine dispensary, convalescence, and post-hospital follow-up visit. An interesting finding is that the doctor agents can keep improving treatment performance over time

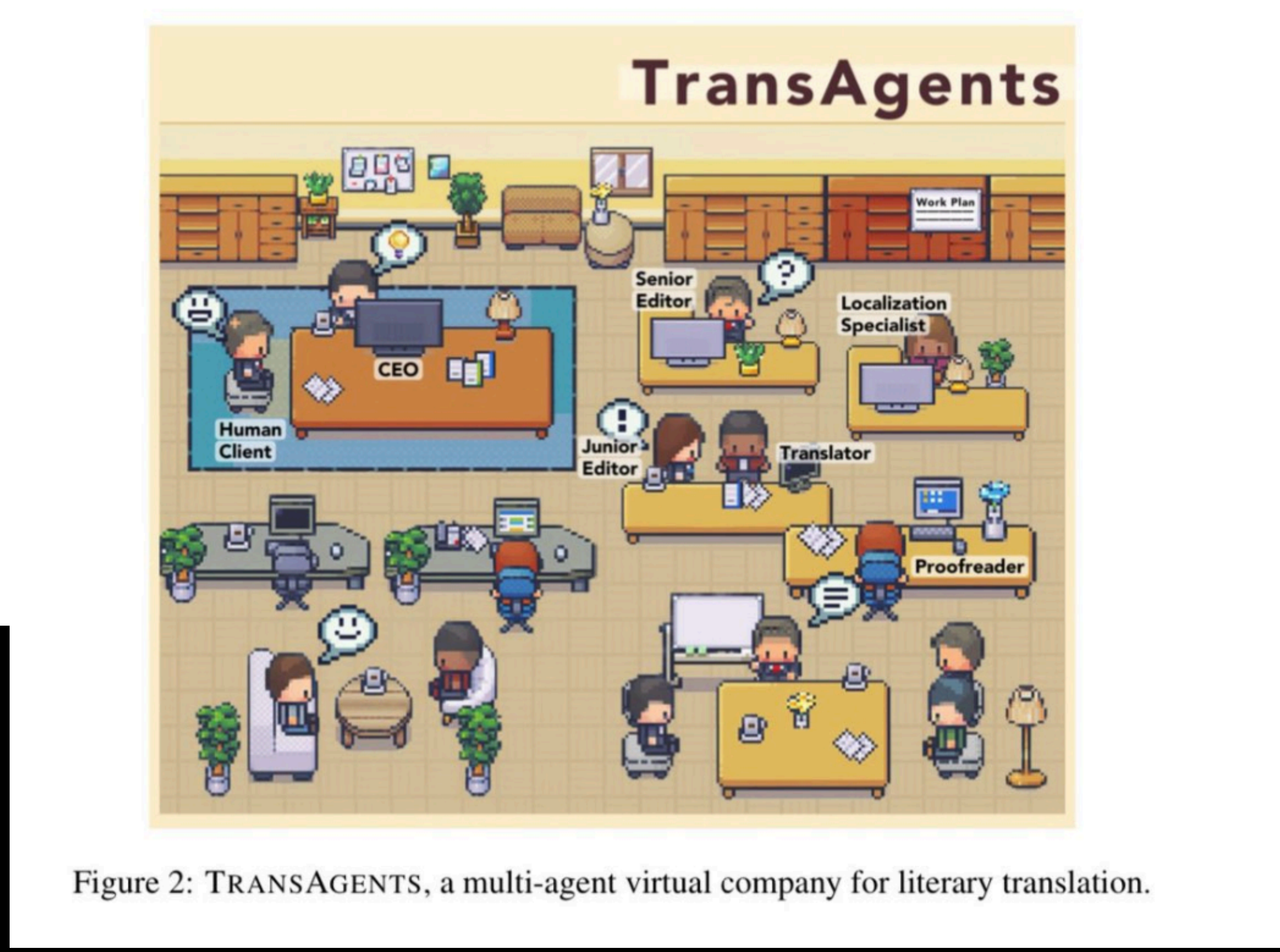
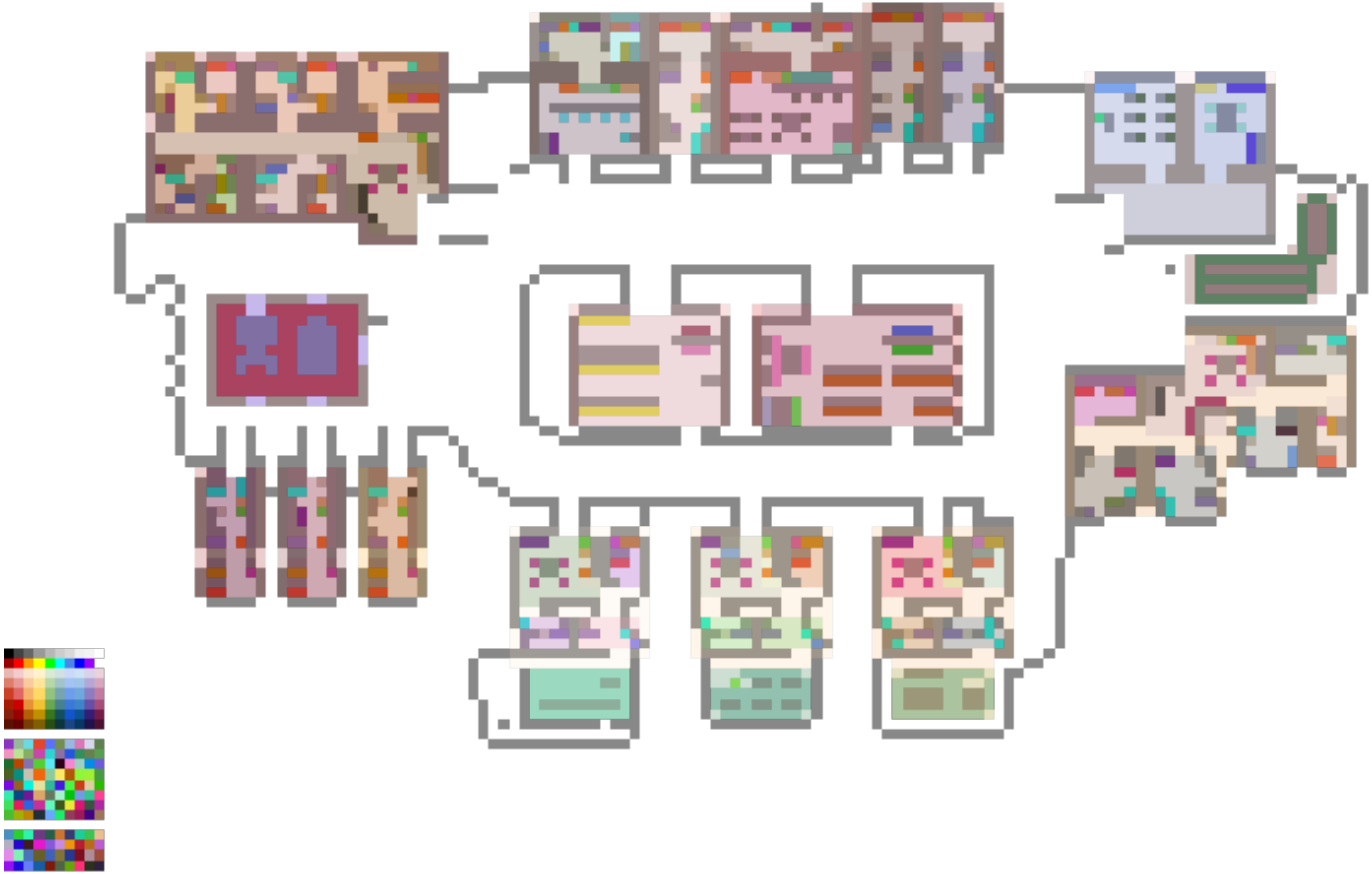


Figure 2: TransAgents, a multi-agent virtual company for literary translation.

J. S. Park, J. C. O'Brien, C. J. Cai, M. R. Morris, P. Liang, M. S. Bernstein, Generative agents: Interactive simulacra of human behavior, in Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology (ACM, 2023).
C. Qian, W. Liu, H. Liu, N. Chen, Y. Dang, J. Li, C. Yang, W. Chen, Y. Su, X. Cong, J. Xu, D. Li, Z. Liu, M. Sun, ChatDev: Communicative Agents for Software Development, in Proceedings of the 2024 Annual Conference of the Association for Computational Linguistics (ACL 2024).
P. Jansen, M.-A. Côté, T. Khot, E. Bransom, B. Dalvi Mishra, B. P. Majumder, O. Tafjord, P. Clark, DISCOVERYWORLD: A Virtual Environment for Developing and Evaluating Automated Scientific Discovery Agents. Preprint (2024).
J. Li, S. Wang, M. Zhang, W. Li, Y. Lai, X. Kang, W. Ma, Y. Liu, Agent Hospital: A Simulacrum of Hospital with Evolvable Medical Agents. Preprint (2024).

Smallville environment


Joining for coffee at a cafe
KM:
AC:
[Abigail]: Hey Klaus, mind if I join you for coffee?
[Klaus]: Not at all, Abigail. How are you?
Taking a walk in the park
SM:
Arriving at school
AK:
Sharing news with colleagues
JL:
TM:
[John]: Hey, have you heard anything new about the upcoming mayoral election?
[Tom]: No, not really. Do you know who is running?
Finishing a morning routine
JM:



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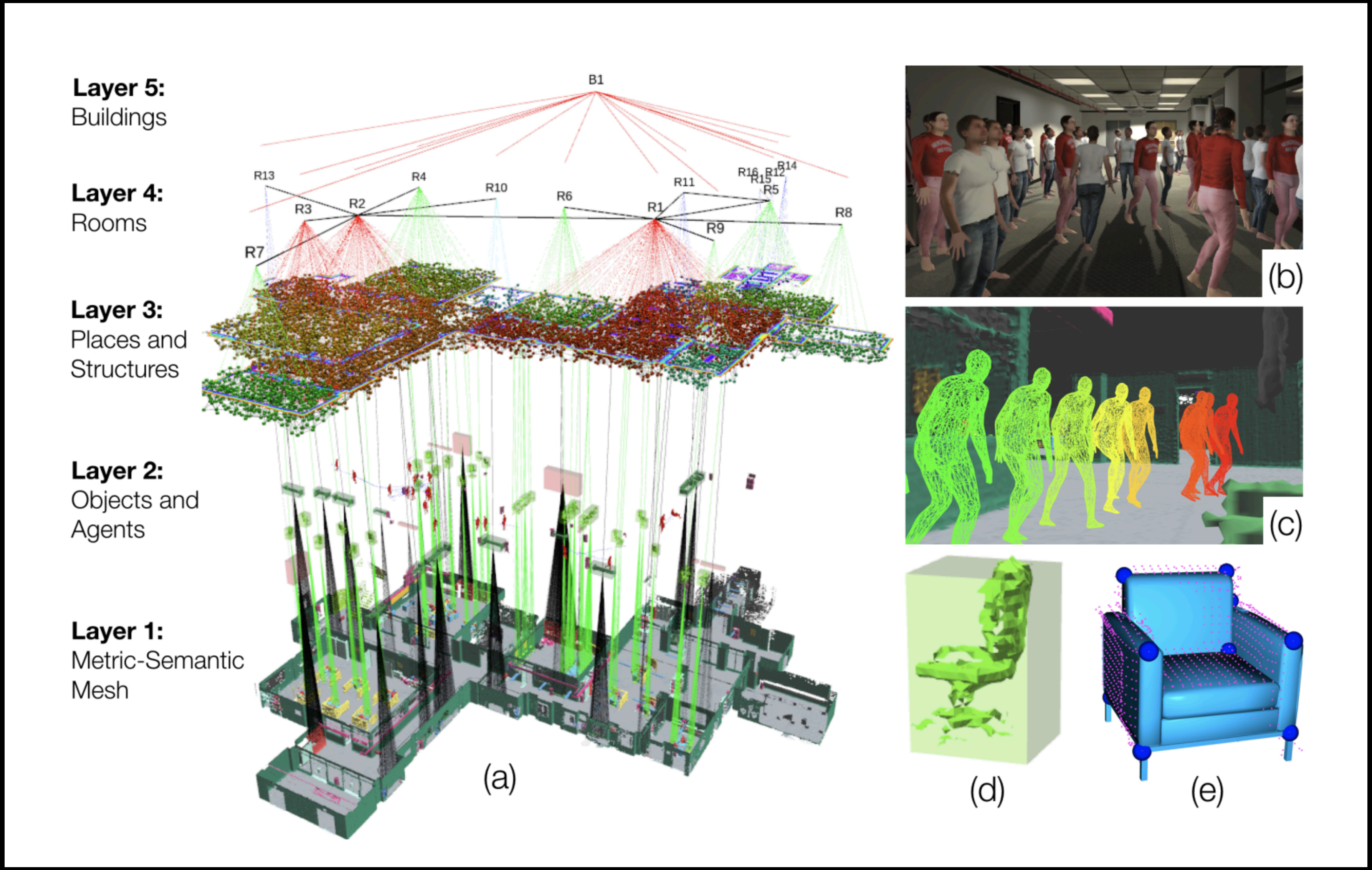
Line 1, Column 1 Spaces: 3 JSON

Collision									World Block
Artist Co-living space	Hobbs Cafe	House 3	Artist Co-living space: room 1	Artist Co-living space: room 4 BA	Apt 1: Ba	Apt 5: Room	Johnson Park: Park	Student Dorm: Ba 1	
Apt 1	Oak Hill College	House 4	Artist Co-living space: room 1 BA	Artist Co-living space: room 5	Apt 2: Room	Apt 5: Ba	Supply Store: Supply Store	Student Dorm: Ba 2	
Apt 2	Johnson Park	House 5	Artist Co-living space: room 2	Artist Co-living space: room 5 BA	Apt 2: Ba	The Rose and Crown Pub: Pub	Willow Market: Grocery and Pharmacy: Store	Student Dorm: Common Room	
Apt 3	Supply Store	House 6	Artist Co-living space: room 2 BA	Artist Co-living space: hallway	Apt 3: Room	Hobbs Cafe: Cafe	Student Dorm: Room 1	Student Dorm: Kitchen	House 2: Room
Apt 4	Willow Market: Grocery and Pharmacy	Student Dorm	Artist Co-living space: room 3	Artist Co-living space: common room	Apt 3: Ba	Oak Hill College: classroom	Student Dorm: Room 2	Student Dorm: Garden	House 2: Ba
Apt 5	House 1		Artist Co-living space: room 3 BA	Artist Co-living space: kitchen	Apt 4: Room	Oak Hill College: Library	Student Dorm: Room 3	House 1: Room	House 3: Room
The Rose and Crown Pub	House 2		Artist Co-living space: room 4	Apt 1: Room	Apt 4: Ba	Oak Hill College: Hallway	Student Dorm: Room 4	House 1: Ba	House 3: Ba

Under the hood, Smallville is represented as a simple scene graph



A. Rosinol, A. Violette, M. Abate, N. Hughes, Y. Chang, J. Shi, A. Gupta, L. Carlone, Kimera: from SLAM to Spatial Perception with 3D Dynamic Scene Graphs. Int. J. Robot. Res. 40, 1510-1546 (2021).

Deciding where to go for an action is a recursive classification task

!<INPUT 0>! is in {!<INPUT 1>!} in !<INPUT 2>!.
!<INPUT 3>! is going to !<INPUT 4>! that has ONLY the following areas: {!<INPUT 5>!}
Stay in the current area if the activity can be done there. Never go into other people's rooms unless necessary.
!<INPUT 6>! is !<INPUT 7>!. For !<INPUT 8>!, !<INPUT 9>! should go to the following area in !<INPUT 10>!: {

Limitations of existing environments

Our virtual environments are still stylized and simplified compared to the real world

What if stores, bathrooms, schools, etc., didn't exist in Smallville?

How do agents navigate when there are no cars?

Some environments, like Smallville, are resource-intensive to design.

Agents viewing social media posts one at a time might lack context around social capital, personal relationships, and other dynamics.

Possible future directions

Finding the right schema or structure to describe the simulation environment is an important research topic—and we don't have an answer for it yet.

And we do not have an answer for it yet.

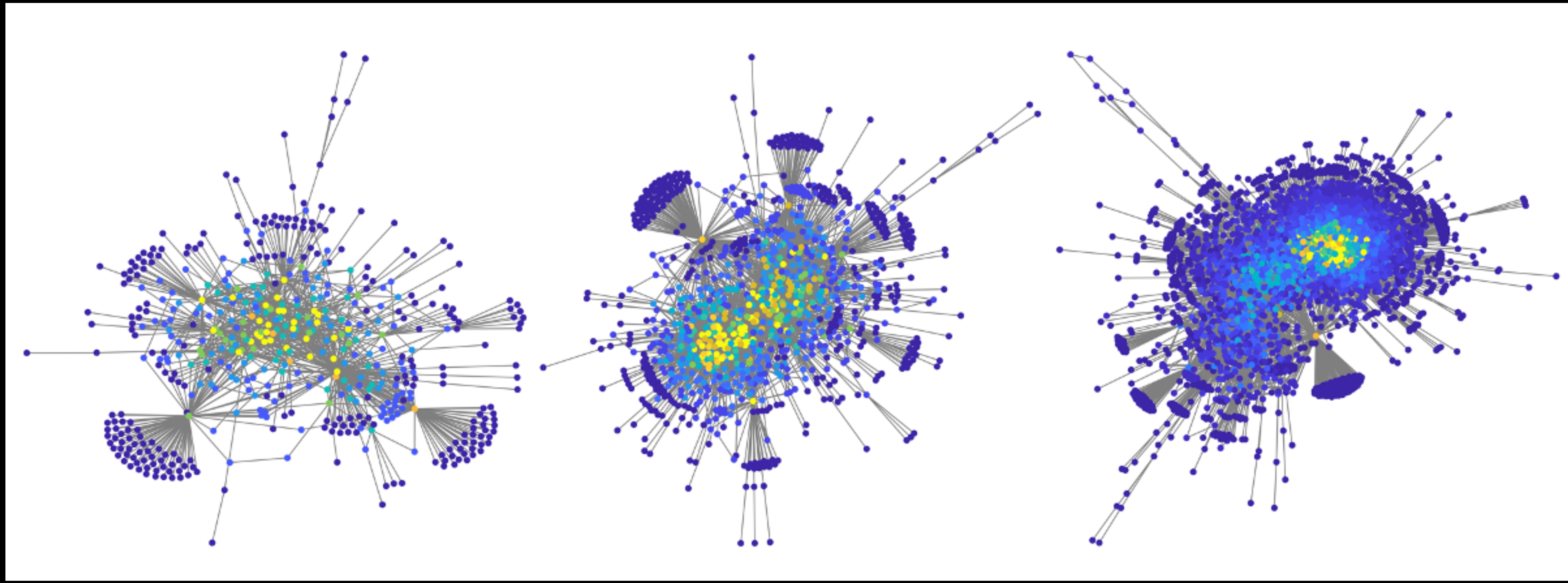
Desiderata

Rich and accurate: We want the environment to encode the complexities of our world.

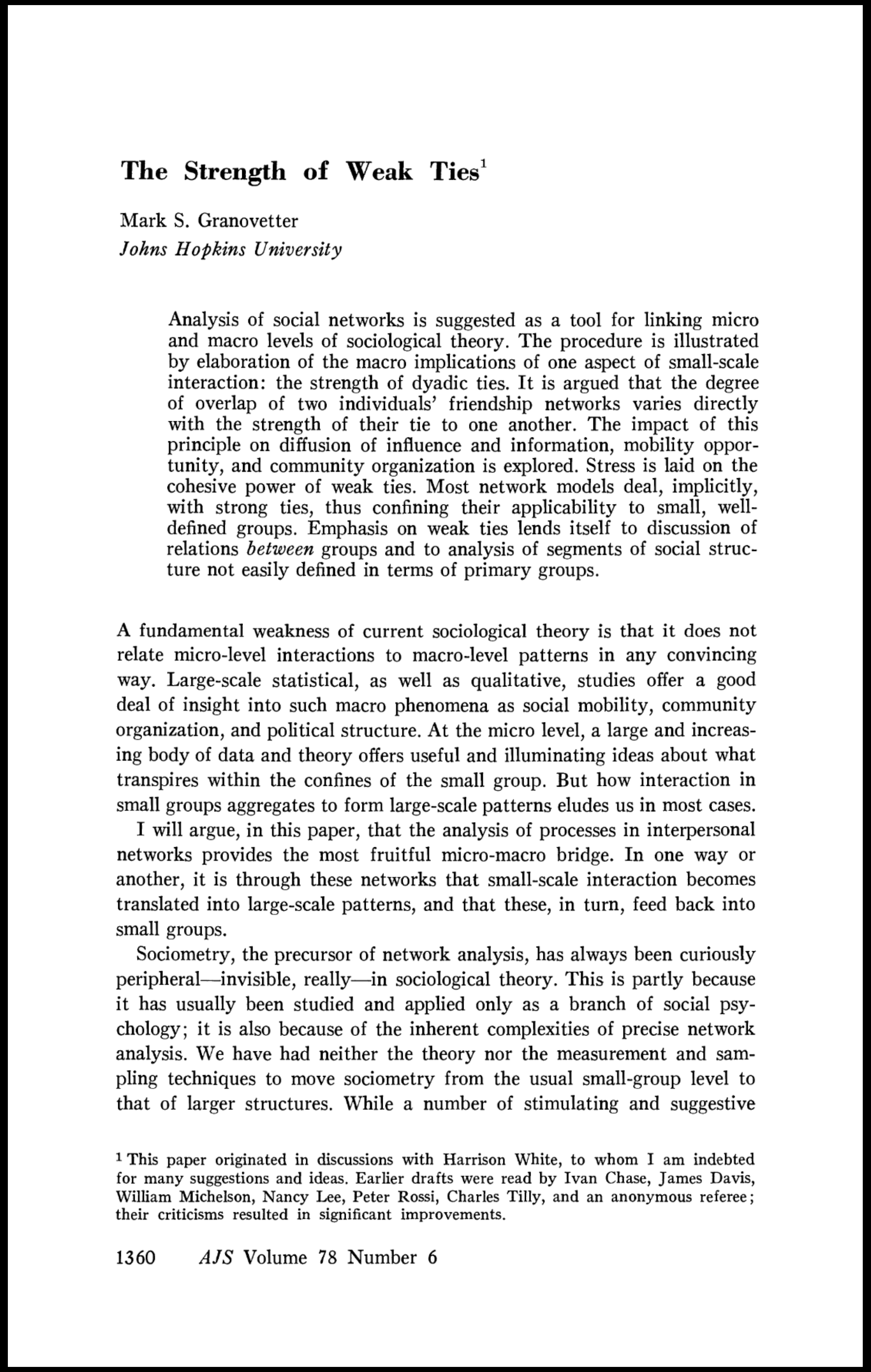
Scalable: We want the environment to be easily scalable (e.g., for simulating 8 billion people).

Can networks be the environment for simulations?

Networks are constructed of nodes and links (with some weights).



Example: In social networks, nodes represent individuals, and links represent the strengths of relationships



The Strength of Weak Ties[1]

Mark S. Granovetter
Johns Hopkins University

Analysis of social networks is suggested as a tool for linking micro and macro levels of sociological theory. The procedure is illustrated by elaboration of the macro implications of one aspect of small-scale interaction: the strength of dyadic ties. It is argued that the degree of overlap of two individuals' friendship networks varies directly with the strength of their tie to one another. The impact of this principle on diffusion of influence and information, mobility opportunity, and community organization is explored. Stress is laid on the cohesive power of weak ties. Most network models deal, implicitly, with strong ties, thus confining their applicability to small, well-defined groups. Emphasis on weak ties lends itself to discussion of relations *between* groups and to analysis of segments of social structure not easily defined in terms of primary groups.

A fundamental weakness of current sociological theory is that it does not relate micro-level interactions to macro-level patterns in any convincing way. Large-scale statistical, as well as qualitative, studies offer a good deal of insight into such macro phenomena as social mobility, community organization, and political structure. At the micro level, a large and increasing body of data and theory offers useful and illuminating ideas about what transpires within the confines of the small group. But how interaction in small groups aggregates to form large-scale patterns eludes us in most cases.

I will argue, in this paper, that the analysis of processes in interpersonal networks provides the most fruitful micro-macro bridge. In one way or another, it is through these networks that small-scale interaction becomes translated into large-scale patterns, and that these, in turn, feed back into small groups.

Sociometry, the precursor of network analysis, has always been curiously peripheral—invisible, really—in sociological theory. This is partly because it has usually been studied and applied only as a branch of social psychology; it is also because of the inherent complexities of precise network analysis. We have had neither the theory nor the measurement and sampling techniques to move sociometry from the usual small-group level to that of larger structures. While a number of stimulating and suggestive

[1] This paper originated in discussions with Harrison White, to whom I am indebted for many suggestions and ideas. Earlier drafts were read by Ivan Chase, James Davis, William Michelson, Nancy Lee, Peter Rossi, Charles Tilly, and an anonymous referee; their criticisms resulted in significant improvements.

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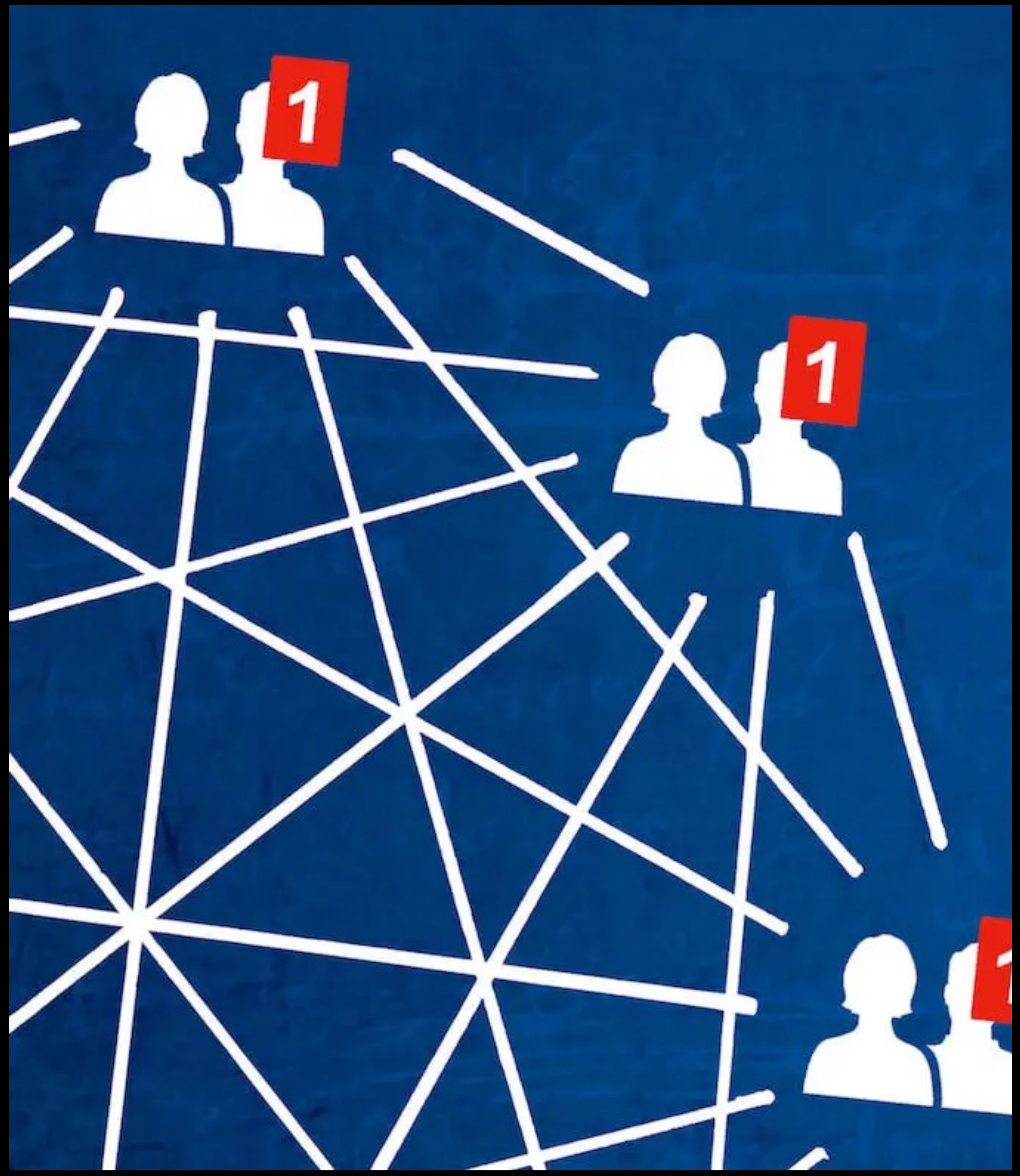
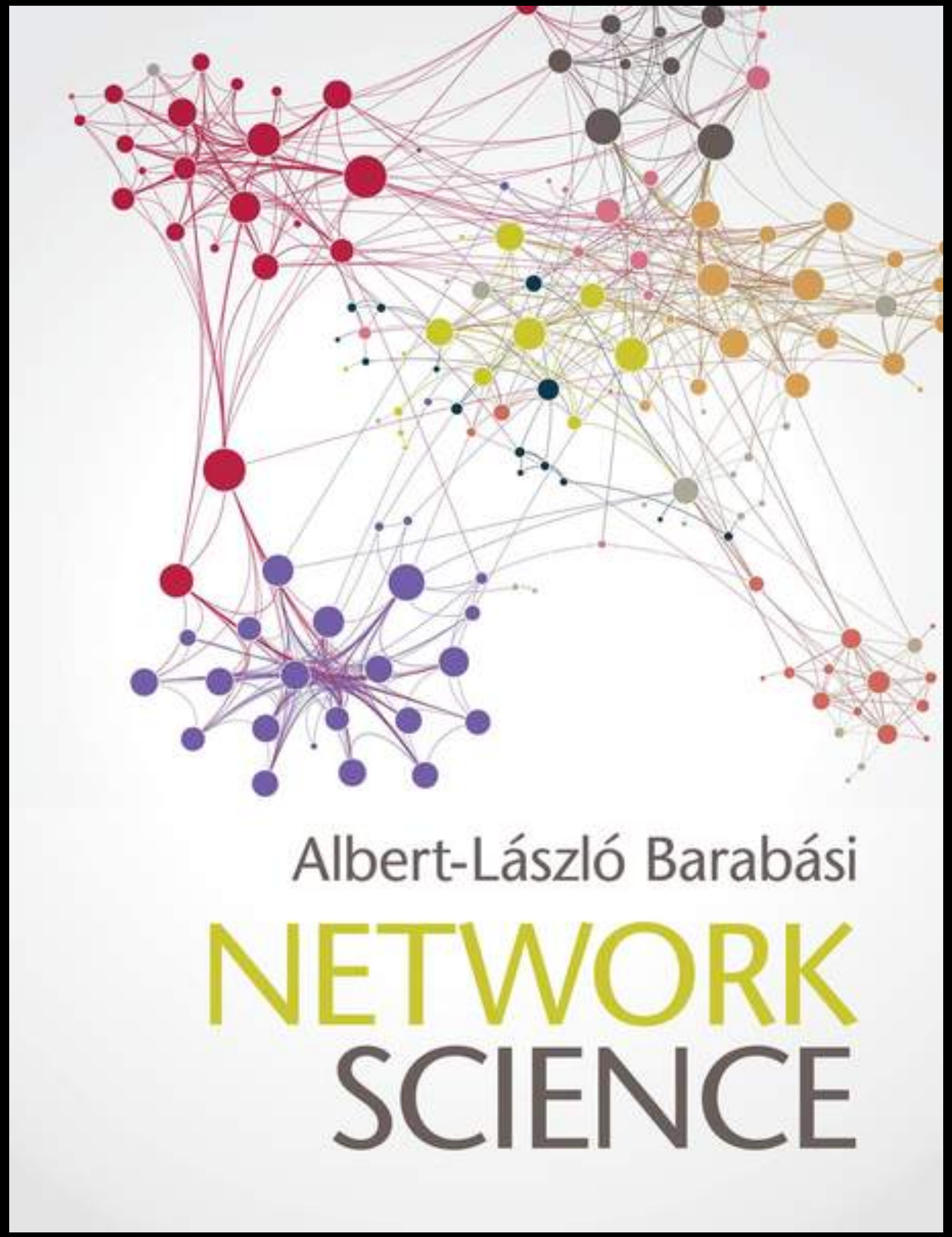


M. S. Granovetter, The Strength of Weak Ties. Am. J. Sociol. 78, 1360-1380 (1973).

Networks are flexible and exhibit emergent phenomena and equilibria



Preferential attachment

A. L. Barabási, Network Science (Cambridge Univ. Press, Cambridge, 2016).
A. L. Barabási, R. Albert, Emergence of Scaling in Random Networks. Science 286, 509-512 (1999).

We can generate structurally realistic social networks

LLMs generate structurally realistic social networks but overestimate political homophily

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Abstract

Generating social networks is essential for many applications, such as epidemic modeling and social simulations. Prior approaches either involve deep learning models, which require many observed networks for training, or stylized models, which are limited in their realism and flexibility. In contrast, LLMs offer the potential for zero-shot and flexible network generation. However, two key questions are: (1) are LLM's generated networks realistic, and (2) what are risks of bias, given the importance of demographics in forming social ties? To answer these questions, we develop three prompting methods for network generation and compare the generated networks to real social networks. We find that more realistic networks are generated with "local" methods, where the LLM constructs relations for one persona at a time, compared to "global" methods that construct the entire network at once. We also find that the generated networks match real networks on many characteristics, including density, clustering, community structure, and degree. However, we find that LLMs emphasize political homophily over all other types of homophily and *overestimate* political homophily relative to real-world measures.

1 Introduction

The ability to generate realistic social networks is crucial for many applications, when the true social network cannot be observed (e.g., for privacy reasons) or a realistic network is desired between hypothetical individuals. For example, in epidemic modeling, synthetic social networks are frequently used so that researchers can model the spread of disease based on who has come into contact with whom (Barrett et al., 2009; Block et al., 2020). Synthetic networks are also useful for simulating and analyzing social media platforms (Pérez-Rosés and Sebé, 2015; Sagduyu et al., 2018) and social phenomena, such as polarization and opinion dynamics (Dandekar et al., 2013; Das et al., 2014).

Deep learning approaches to network generation typically require training on many domain-specific networks (You et al., 2018), making it difficult to generalize to new settings where networks are not yet observed. Classical models for network generation require far less training, but these stylized models make rigid and unrealistic assumptions about how networks form. For example, Erdős–Rényi models assume that each edge forms with a uniform probability p (Erdös and Rényi, 1959). More realistic models, like small-world models (Watts and Strogatz, 1998) or stochastic block models (Holland et al., 1983), are still limited by a predefined, small set of numerical hyperparameters, missing the full complexity of real social interactions.

In contrast, generating social networks with large language models (LLMs) has the potential to address these limitations. LLMs possess zero-shot capabilities, enabling network generation without training. LLMs can also generate networks in a flexible manner, based on natural language descriptions of each person in the network. A key question, however, is whether LLMs can generate *realistic* social networks. On one hand, LLMs have demonstrated capabilities to realistically simulate human responses and interactions (Aher et al., 2023; Park et al., 2023; Argyle et al., 2023), suggesting that they may be able to generate realistic social networks as well. On the other hand, LLMs sometimes struggle with reasoning over graphs (Wang et al., 2023; Fatemi et al., 2024) and it is unclear if their language abilities generalize to structured objects like networks, so that they can reproduce structural characteristics of social networks such as low density and long-tailed degree distributions.

Furthermore, a central concern with using LLMs in social settings is bias. Prior works have shown that LLMs produce stereotyped descriptions of individuals based on their demographics (Cheng et al., 2023a,b) and skew towards the liberal opinions (Santurkar et al., 2023). These demographics,

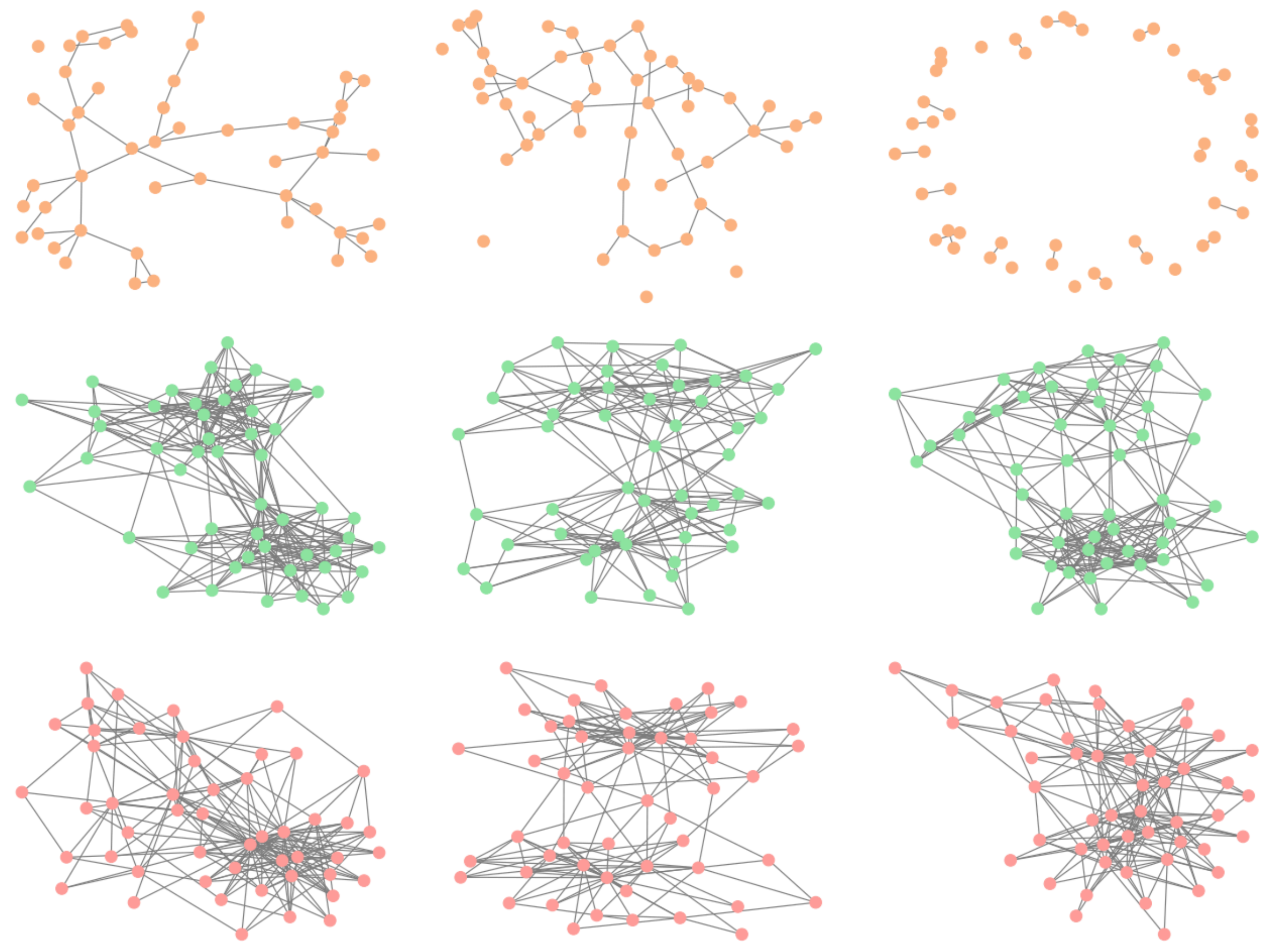

Figure 2: Generated social networks from different prompting methods: Global (top), Local (middle), Sequential (bottom).

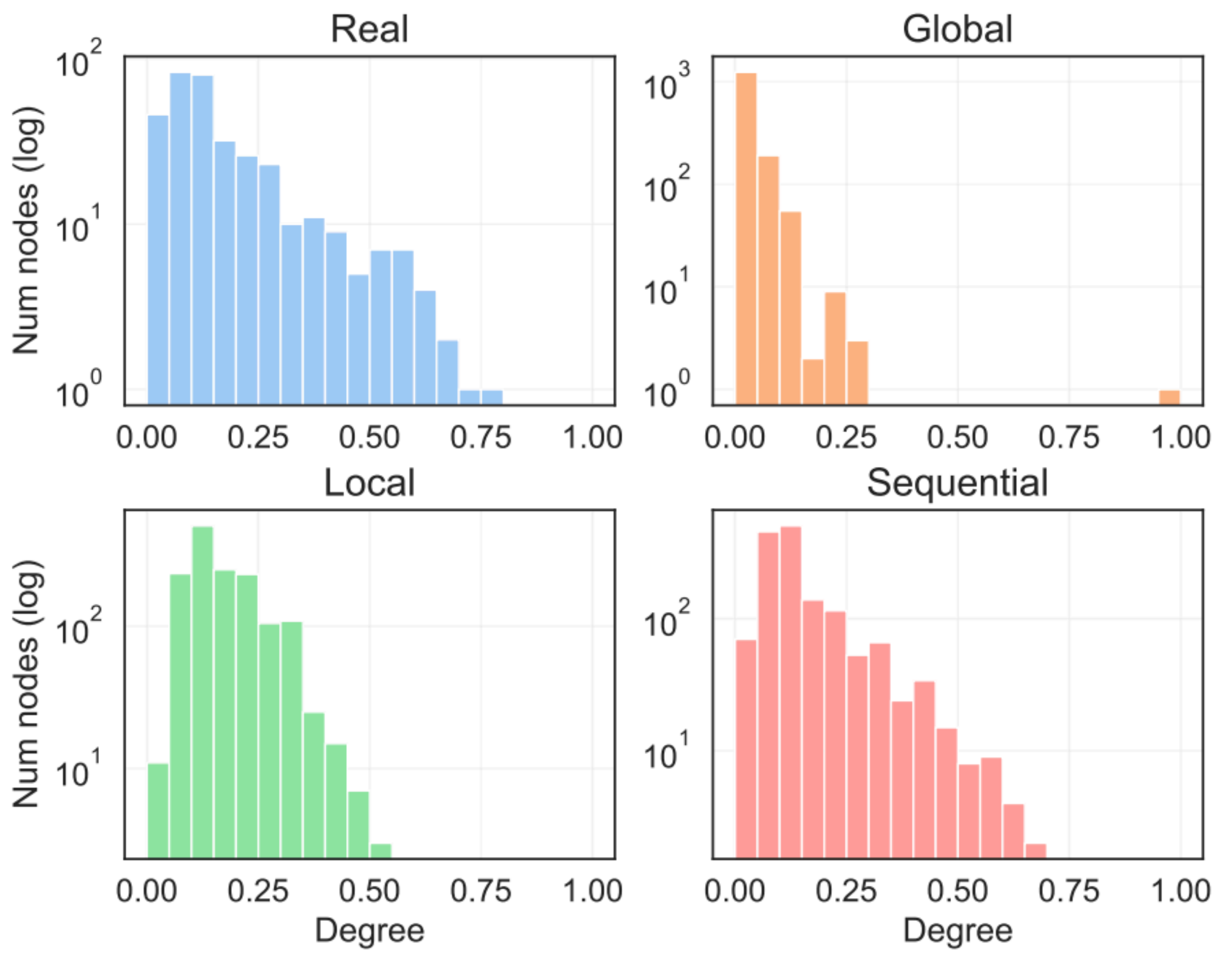

Figure 4: Degree distributions over real and generated social networks. For each set of networks, we pool degrees over nodes in the networks (Section 4).

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Here, "realistic" could mean that we observe similar emergent phenomena

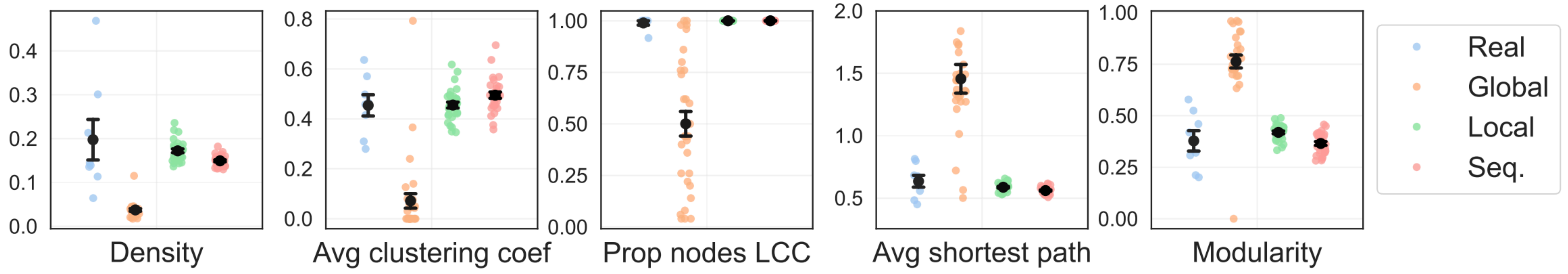

Figure 3: Graph-level metrics over real and generated social networks. We visualize mean and standard error (in black) and individual data points corresponding to each network.

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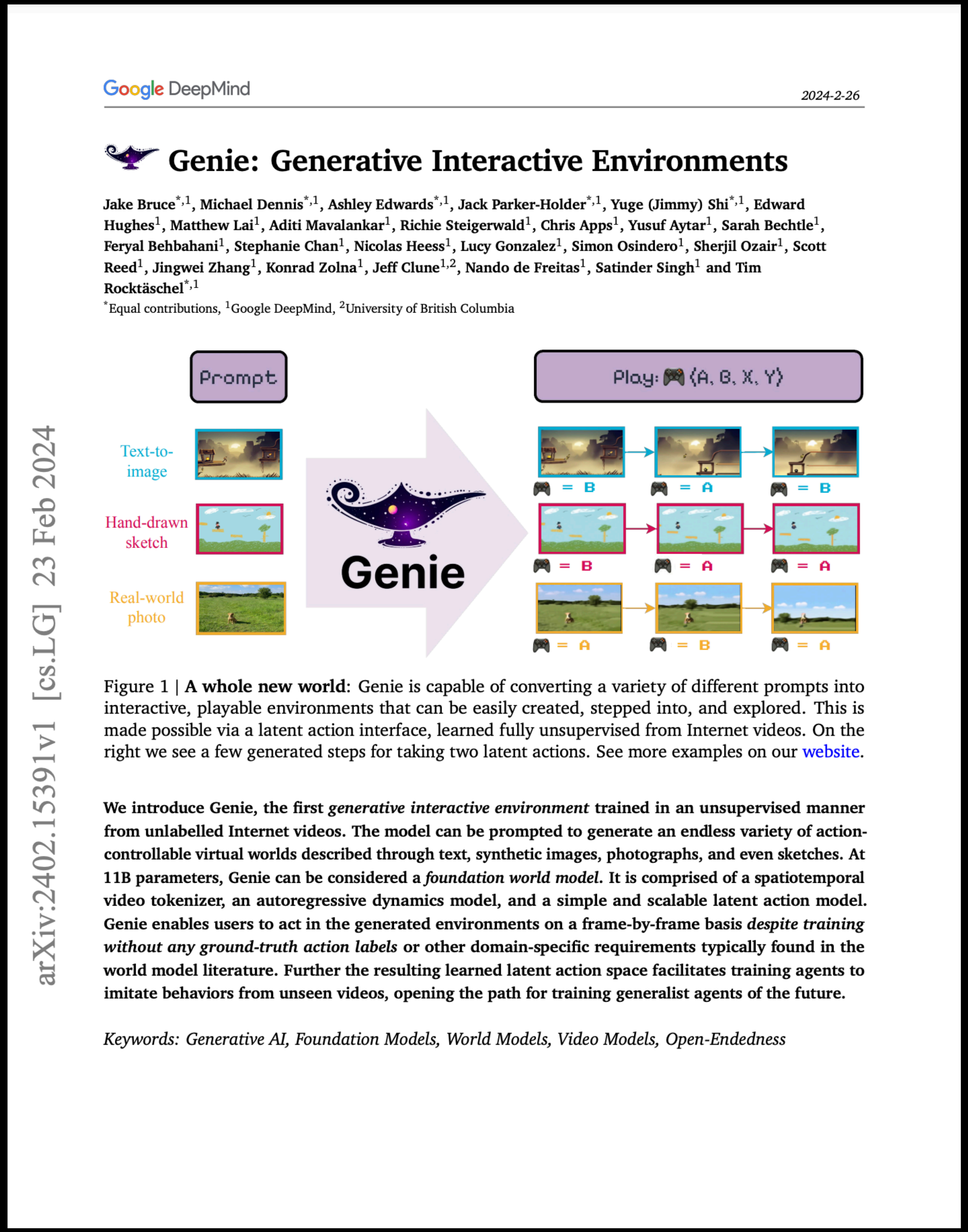
Another angle: What if we generate the world in the same way we generate agent behaviors?


Google DeepMind 2024-2-26

Genie: Generative Interactive Environments

Jake Bruce[*,1], Michael Dennis[*,1], Ashley Edwards[*,1], Jack Parker-Holder[*,1], Yuge (Jimmy) Shi[*,1], Edward Hughes[1], Matthew Lai[1], Aditi Mavalankar[1], Richie Steigerwald[1], Chris Apps[1], Yusuf Aytar[1], Sarah Bechtle[1], Feryal Behbahani[1], Stephanie Chan[1], Nicolas Heess[1], Lucy Gonzalez[1], Simon Osindero[1], Sherjil Ozair[1], Scott Reed[1], Jingwei Zhang[1], Konrad Zolna[1], Jeff Clune[1,2], Nando de Freitas[1], Satinder Singh[1] and Tim Rocktäschel[*,1]
[*]Equal contributions, [1]Google DeepMind, [2]University of British Columbia

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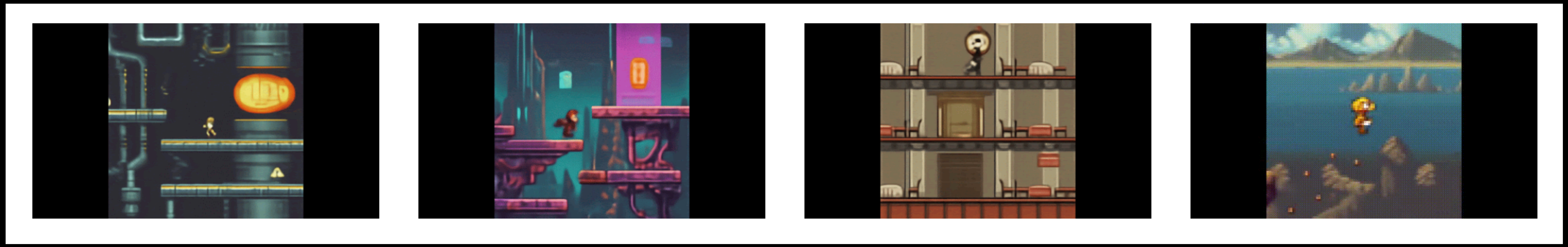
Figure 1 | **A whole new world**: Genie is capable of converting a variety of different prompts into interactive, playable environments that can be easily created, stepped into, and explored. This is made possible via a latent action interface, learned fully unsupervised from Internet videos. On the right we see a few generated steps for taking two latent actions. See more examples on our website.

We introduce Genie, the first *generative interactive environment* trained in an unsupervised manner from unlabelled Internet videos. The model can be prompted to generate an endless variety of action-controllable virtual worlds described through text, synthetic images, photographs, and even sketches. At 11B parameters, Genie can be considered a *foundation world model*. It is comprised of a spatiotemporal video tokenizer, an autoregressive dynamics model, and a simple and scalable latent action model. Genie enables users to act in the generated environments on a frame-by-frame basis *despite training without any ground-truth action labels* or other domain-specific requirements typically found in the world model literature. Further the resulting learned latent action space facilitates training agents to imitate behaviors from unseen videos, opening the path for training generalist agents of the future.

Keywords: Generative AI, Foundation Models, World Models, Video Models, Open-Endedness



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CS 222: AI Agents and Simulations

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