Theory-Informed Generative Agents for Human Mobility Modeling

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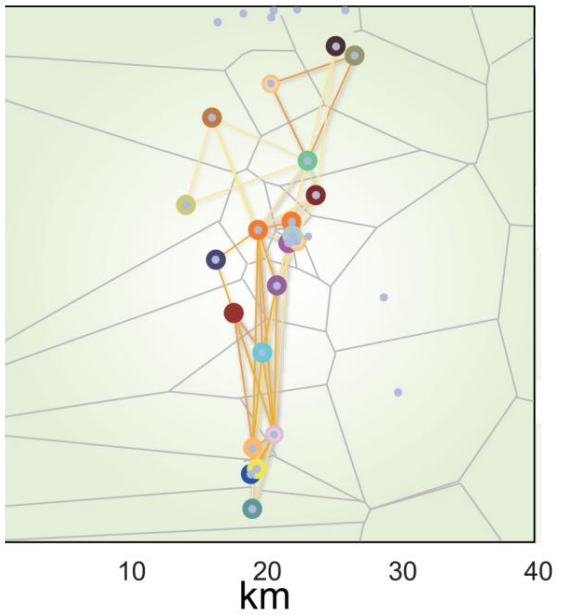
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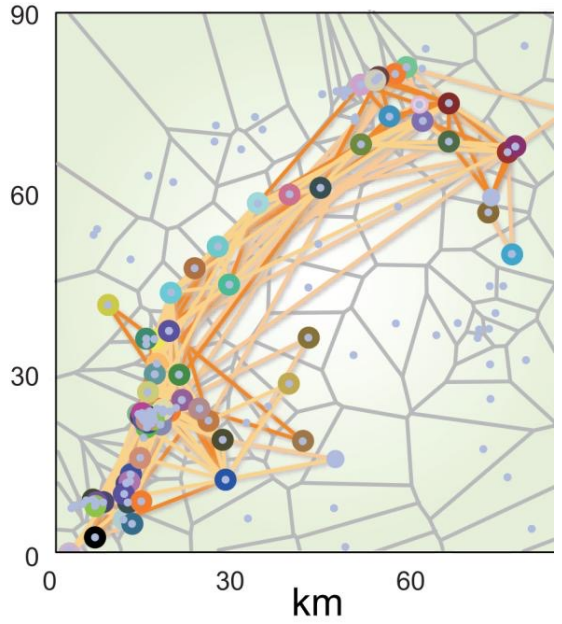
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Motivation: Population-level vs Individualized



Population level mobility modeling





Individual-level Heterogeneity

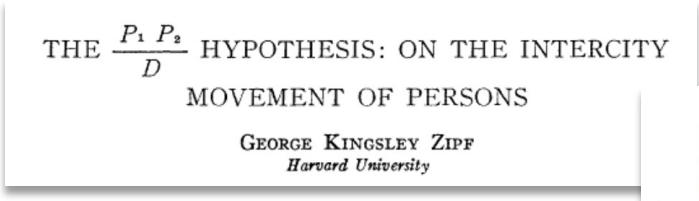
Motivation: Two Challenges in Human Mobility Modeling

Mechanism-driven Mobility Models

- Capture robust population-level mobility laws

Limitation:

Hard to model individual heterogeneity and context-dependent decisions.



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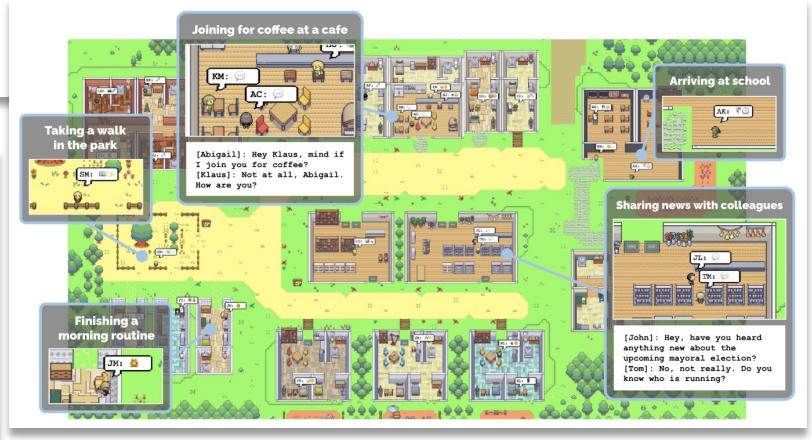
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Returners and explorers dichotomy in human mobility

Luca Pappalardo, Filippo Simini, Salvatore Rinzivillo, Dino Pedreschi, Fosca Giannotti & Albert-László Barabási



Data-driven Learning

- More accurate

Limitation:

Data-hungry, less Interpretability

LLM-based agents

- Can generate more detailed daily trajectory

Limitation:

"Black box", computationally expensive

Research Gap

How can we combine **physical mobility laws with LLM-based semantic reasoning** to model both **macro-level regularity** and **micro-level heterogeneity**?

Research Question and Contributions

Research Question

Can **LLM** **semantic reasoning** be embedded into **physical mobility theory** to simulate both ***population-level regularities*** and ***profile-level behavioral heterogeneity***?

Contributions

1. **Hybrid Framework**
   Physical mobility theory constrains movement, while *LLMs infer* profile-conditioned behavioral tendencies.

2. **Population-scale Simulation**
   LLM inference is performed at the *profile level*, not at every decision step.

3. **Social & Crisis Applications**
   TIMA is used to study *experienced segregation* and *pandemic counterfactual* mobility response.

Data and Simulation Setup

Synthetic Agent Population

- Agents are initialized at the **CBG level**
- Demographic profiles are synthesized from **ACS data**[2]

Urban Environment

- CBG boundaries
- Socio-economic context[3]
- POI category (NAICS), location (Safegraph[1])

Benchmark and Study Areas

- Four U.S. cities selected to span **diverse urban scales and morphologies**:
  - **New York City**: high-density metropolis
  - **Chicago**: large but geographically distinct city
  - **Orlando**: tourism-oriented city
  - **Norfolk–Virginia Beach**: smaller metropolitan area
- Empirical benchmark: **SafeGraph**[1] **Weekly Patterns**





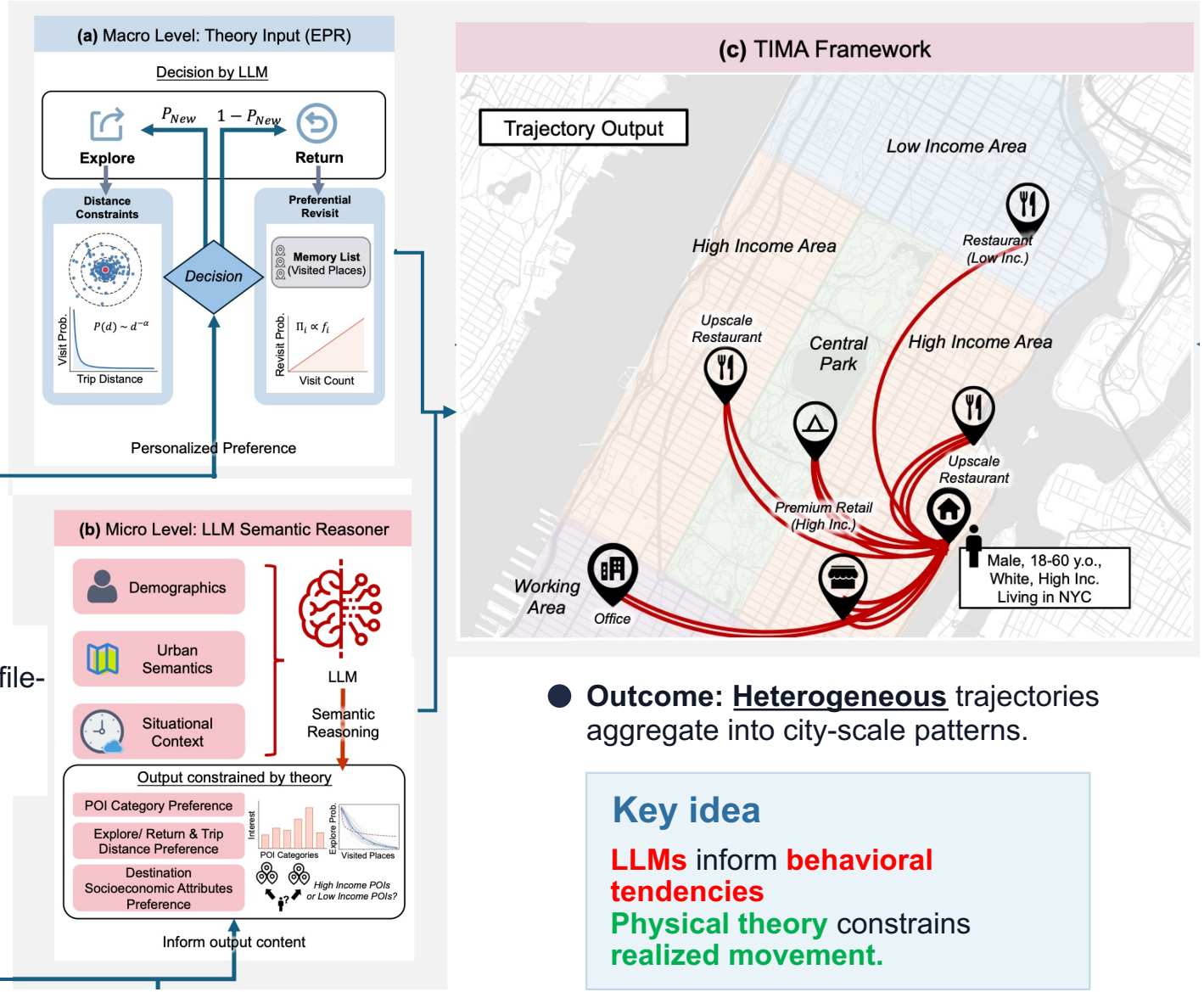




[1]SafeGraph. *Weekly Patterns* [Data documentation]. https://docs.safegraph.com/docs/weekly-patterns
[2]U.S. Census Bureau. (2020). *2019 American Community Survey 5-year estimates: Detailed tables* [Data set]. https://api.census.gov/data/2019/acs/acs5.html
[3]Xi, Y., Liu, Y., Li, T., Ding, J., Zhang, Y., Tarkoma, S., Li, Y., & Hui, P. (2023). A satellite imagery dataset for long-term sustainable development in United States cities. *Scientific Data, 10*, Article 866. https://doi.org/10.1038/s41597-023-02576-3

Theory-Informed Mobility Agents (TIMA)

- **Macro layer:** EPR **constrains** distance decay and explore-return dynamics.
- **Micro layer:** LLM **infers** profile-conditioned semantic preferences.

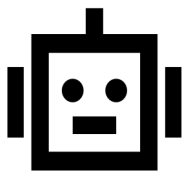


- **Outcome:** **Heterogeneous** trajectories aggregate into city-scale patterns.

Key idea

LLMs inform **behavioral tendencies**
Physical theory constrains **realized movement.**

Mobility Decision Process: From *EPR* to *TIMA*



Mobility Agent

History-conditioned exploration probability

Stage 1

Explore

Return

Which activity purpose does this agent prefer?
Decide by LLM under theory-constrained

Select a POI Category

Which type of neighborhood is this agent more likely to visit?
Farther POIs should less likely to be selected.
Decide by LLM under theory-constrained

Select specific POI

Select a previously visited POI

Stage 2

Preferential return $f_{u,l}^{t-1}$
Revisit places with higher past visit counts.

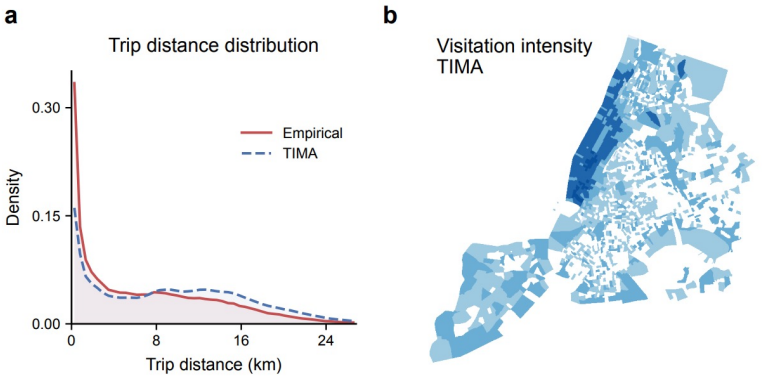
How likely is this agent to explore new places?
Decide by LLM under theory-constrained

Key idea: the LLM does not generate trajectories directly; it generates **behavioral preferences** inside a *theory-constrained* mobility model.

Result: *Population-level Metric*

		Distance Distribution	From where to where	Density Distribution	Visiting POIs with diff. functions	Different people visit different POIs
City	**Model**	**Trip Distance (KL) ↓**	**OD Flow (CPC) ↑**	**Visitation Density (MSE) ↓**	**POI Proportion (KL) ↓**	**Stratified OD (CPC) ↑**
New York City	TIMA (Ours)	**0.083**	**0.299**	**0.006**	**0.223**	**0.272**
	d-EPR	**0.091**	**0.290**	**0.006**	0.840	**0.262**
	EPR	0.415	0.256	0.007	1.160	0.238
	Social-EPR	0.447	0.184	0.007	**0.782**	0.169
	Gravity	0.395	0.248	**0.006**	1.417	0.231
Chicago	TIMA (Ours)	**0.006**	**0.401**	**0.009**	**0.234**	**0.394**
	d-EPR	**0.007**	**0.424**	0.010	**0.596**	**0.419**
	EPR	0.757	0.204	0.014	0.957	0.198
	Social-EPR	0.782	0.163	0.017	0.856	0.161
	Gravity	0.639	0.230	**0.004**	0.952	0.221
Orlando	TIMA (Ours)	**0.020**	**0.596**	**0.009**	**0.829**	**0.548**
	d-EPR	**0.044**	**0.554**	**0.009**	0.967	**0.503**
	EPR	0.565	0.445	0.014	0.960	0.419
	Social-EPR	0.563	0.423	0.014	**0.855**	0.397
	Gravity	0.520	0.390	0.013	0.918	0.354
Norfolk–Virginia Beach	TIMA (Ours)	**0.039**	**0.540**	**0.009**	**0.592**	**0.479**
	d-EPR	**0.073**	**0.541**	0.011	**0.575**	**0.482**
	EPR	0.524	0.426	0.018	0.753	0.383
	Social-EPR	0.517	0.387	0.012	0.716	0.348
	Gravity	0.464	0.385	**0.009**	0.607	0.345

The top two performances for each city are highlighted



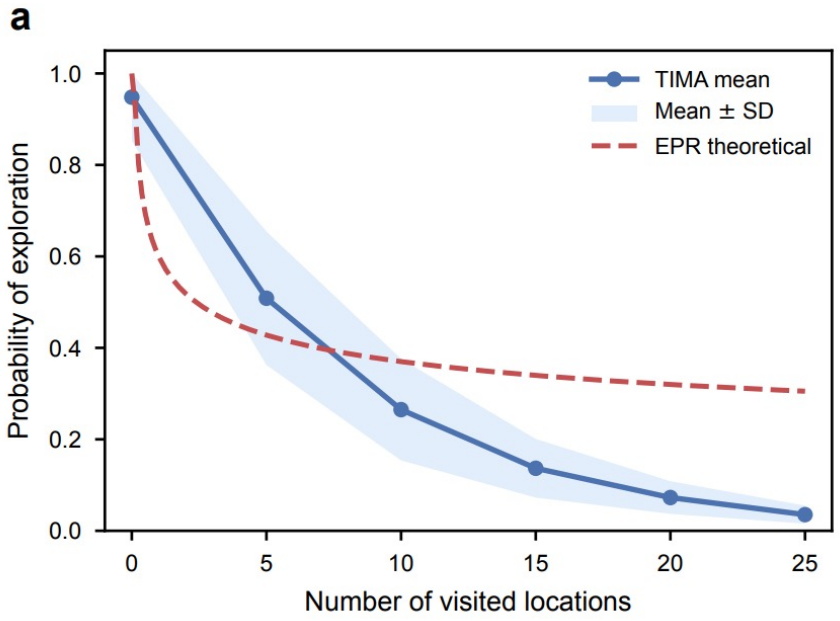
1. **Macro regularity:**
   Lowest Trip Distance KL in all four cities.

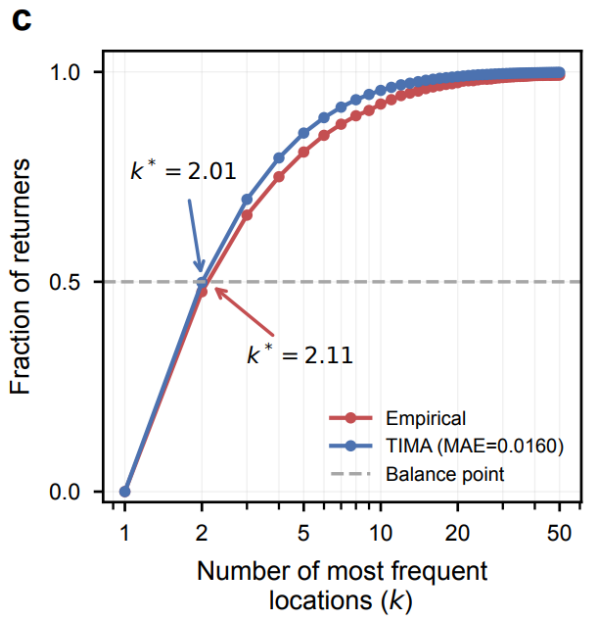
2. **Spatial structure:**
   OD Flow and Visitation Density are **consistently top-tier**

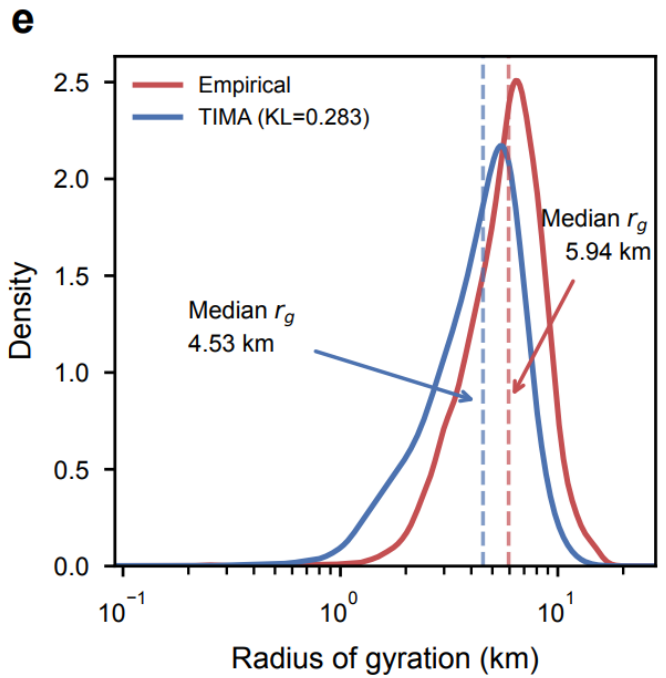
3. **Semantic heterogeneity:**
   TIMA substantially **improves POI-category proportion**

4. **Social outcome:**
   TIMA achieves **the best Stratified OD CPC** in NYC and Orlando, and remains close to *d*-EPR in Chicago and Norfolk-VB.

Result: Personalized Agents Recover Macroscopic Mobility Laws







Exploration decay — EPR law

- **Law**: people explore less as their familiar activity set grows.
- **TIMA**: LLM-inferred $P_u(S)$ **varies by profile**, but still decays with visited locations.

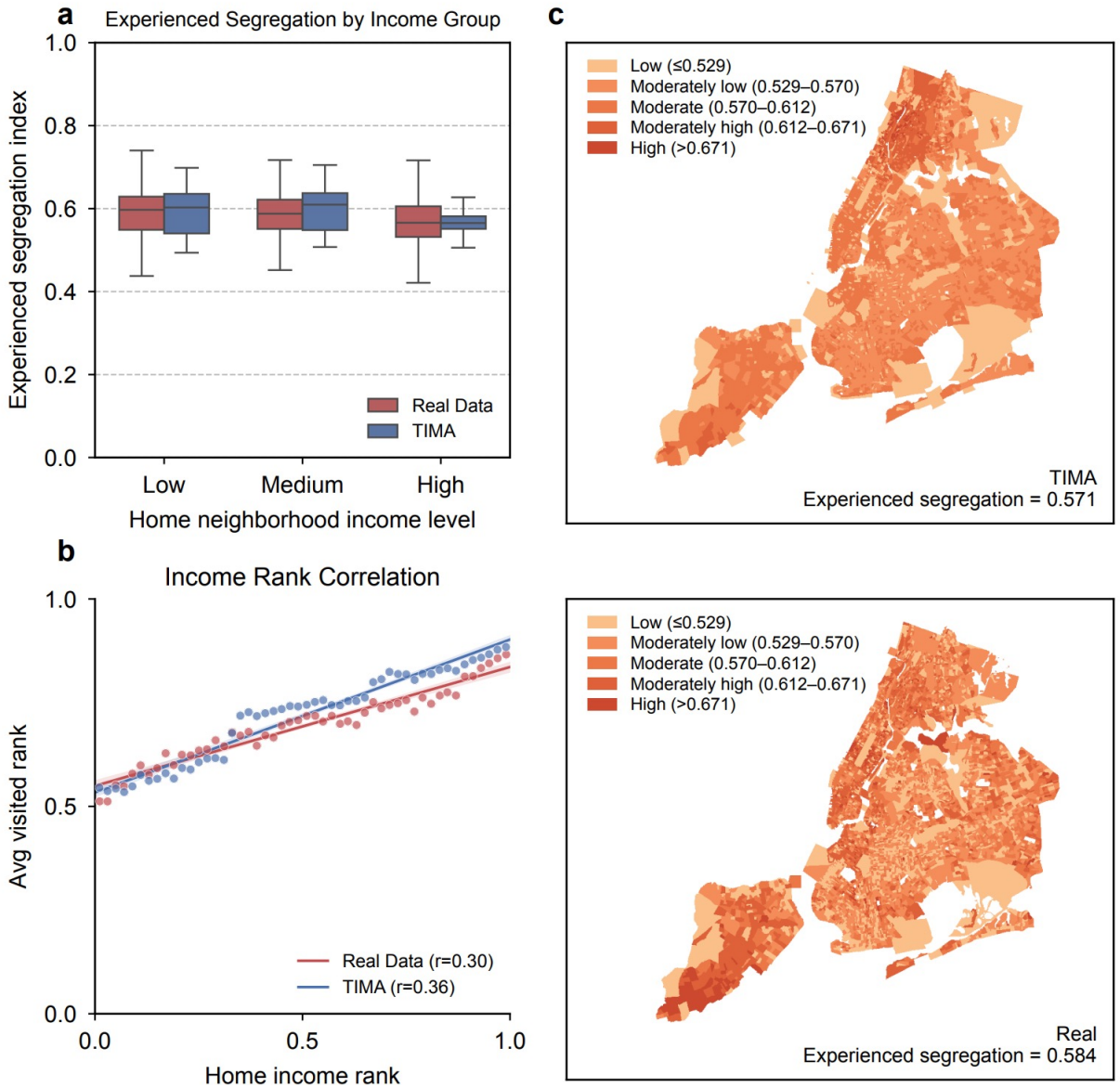
Explorer–returner dichotomy

- **Law**: people differ in whether mobility is dominated by **a few frequent locations**.
- **TIMA**: $k^*_{TIMA} = 2.01$, close to $k^*_{Real} = 2.11$.

Radius of gyration distribution

- **Law**: individuals / neighborhoods have **heterogeneous spatial mobility ranges**.
- **TIMA**: median $r_g = 4.53$km vs real 5.94km.

Result: *Emergent Experienced Segregation*



Key findings

- TIMA reproduces the **spatial distribution** of experienced segregation in NYC.
- **Income-homophilous visitation**: residents from higher-income areas tend to visit higher-income destinations.
- Segregation **emerges from profile-conditioned destination affinity**, rather than being directly fitted.

Takeaway

Generalizable to **studying broader social phenomena** and exploring how different **individual behaviors shape collective outcomes**

Scenario: External Shock

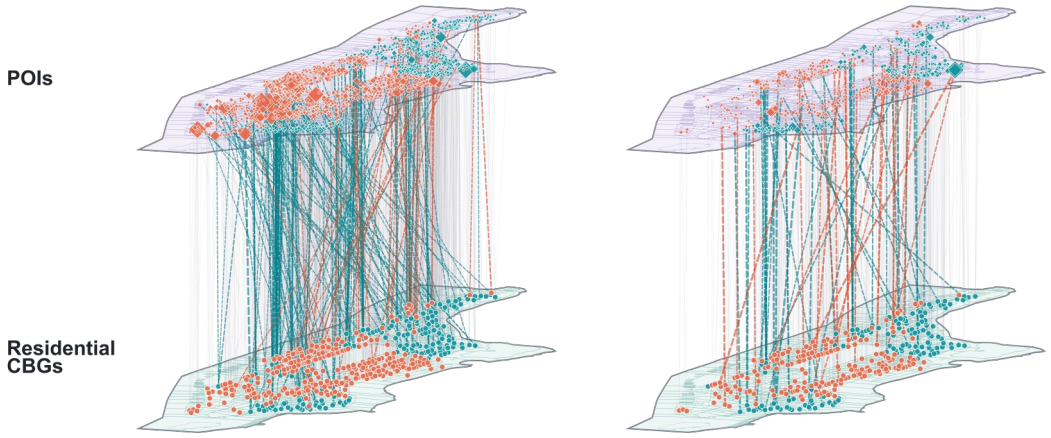
- COVID
- Weather disaster

Consider that:

- Policy (e.g. Stay-at-home order)
- Road blocked
- No public transportation…

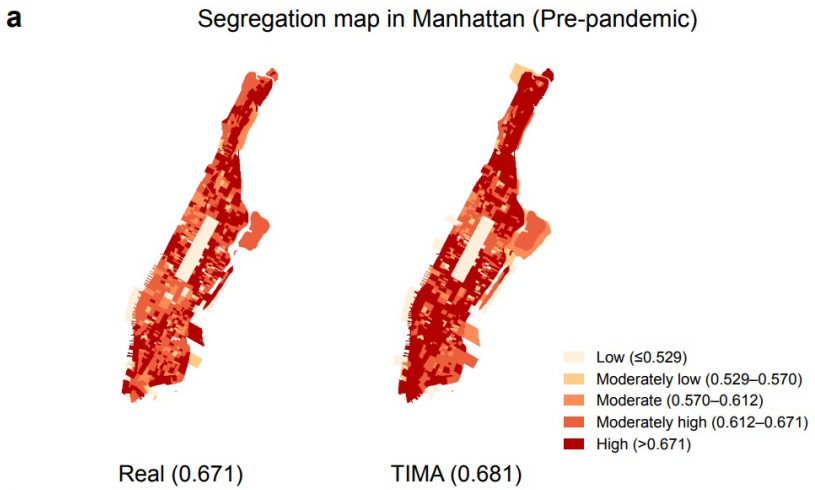


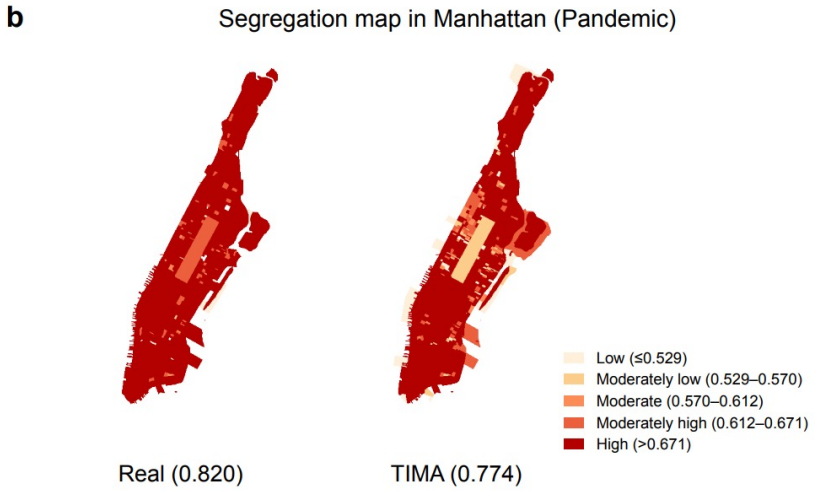
How will Human Mobility *Change*?
How will *different* people response *differently*?



Normal COVID

Result: *Personalized and Accurate Crisis Response*



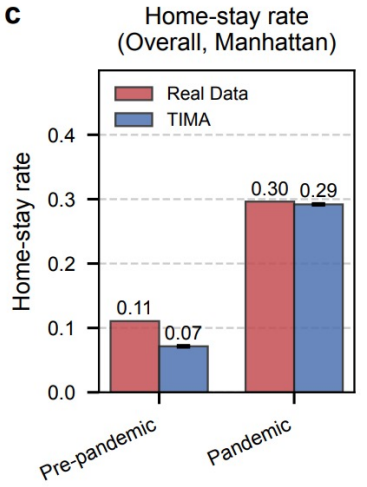


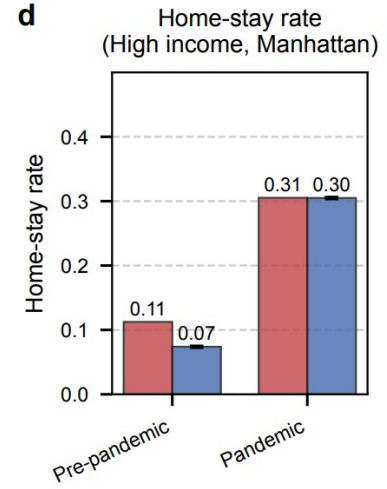
Key findings

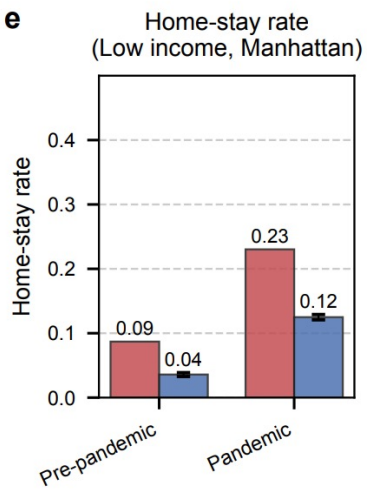
- In general, Experienced segregation **rises** during the pandemic.
- High-income group shows **stronger mobility reduction**
- Low-income group shows **constrained response**
- Align with empirical studies

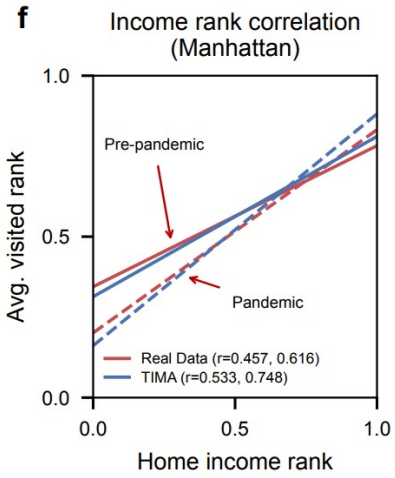
Takeaway

TIMA captures both population-level distancing and unequal mobility constraints.









Conclusion

1. **Theory grounding**
   EPR and gravity constraints preserve macro-level mobility laws
2. **Semantic heterogeneity**
   LLMs infer profile-conditioned behavioral preferences.
3. **Policy-relevant simulation**
   TIMA enables social and crisis test.

By embedding LLM reasoning inside *physical mobility theory*, **TIMA preserves population-level regularities while uncovering *interpretable, profile-aligned* behavioral heterogeneity.**

This reframes LLMs as **theory-constrained tools** for modeling human behavior, and enable social simulation on **different scenarios**.

Thanks!

For more details, please refer to the Preprint

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