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Mobility Agents: Modeling Urban Human Mobility Patterns Through Theory-guided LLM Agents

Haoyang Li@HKBU, Under the Supervision of
Dr. Hongru Du

Introduction

Motivation

- Understanding **the Human Mobility Patterns** has been a **widely discussed scientific question.**
- Many famous works have previously made important explorations in this field, with the main methods including:
  - **Mechanism-driven Model**
    - Gravity Model
    - EPR (Exploration and Preferential Return) Model
    - **Issue**: Make sense in **logic**, but not that **accurate**
    - **Issue**: Also, **over-simplifying** real situations
  - **Data-driven Model**
    - Machine Learning/ Deep Learning
    - Statistical Prediction Model
    - **Issue**: Lack of **Interpretability**
    - **Issue**: Heavily rely on historical data
- **How about LLM?**
  - Can it understand and predict human mobility **more accurately**
  - Can solve **Interpretability** issue though reasoning?

Introduction

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Study Aim

To simulate and predict urban human mobility patterns using a **theory-guided, LLM-driven Agent-Based Modeling (ABM)**.

Why theory-guided?

- Workflow of LLM Agent should be **well-designed**
  - As we can see CoT/ ReAct agents perform better than Zero-shot ones
- Many **famous work** have proposed theories and principles of human mobility and have been widely validated
  - -> Choose ***d*-EPR** here!

Why LLM-driven ABM?

- ABM is effective in simulate social dynamics,
  - many famous work were built based on ABM (EPR, *d-EPR*, …)
- LLMs can **input** demographic profiles into Agents, solve the **heterogeneity** question
- LLMs can **output** reasoning, solve the **interpretability** question
- LLMs can model and predict more accurately
- Also, **do not need many data** to train! (high-cost and poor portability)

More details later

Introduction

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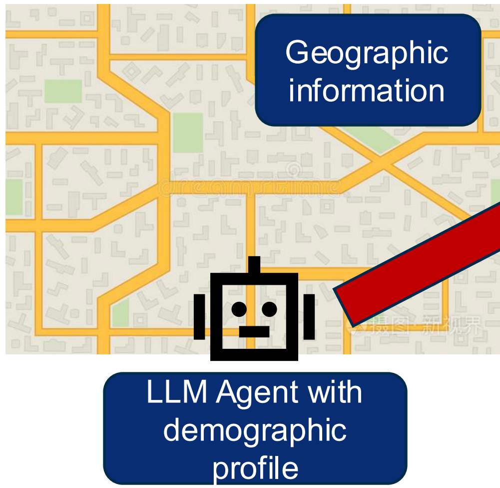
Study A

To simula ded,
LLM-driv

Why the

- Workfl
  - As nes
- Many f obility
  and have been widely validated
  - -> Choose ***d*-EPR** here!



Output Human-like reasoning and decision-making

LLM-driven ABM

Why LLM-driven ABM?

- ABM is effective in simulate social dynamics
  - many famous work were built based on ABM (EPR, *d-EPR*, …)
- LLMs can **input** demographic profiles (also **geographic** information) into Agents, solve the **heterogeneity** question
- LLMs can **output** reasoning, solve the **interpretability** question
- LLMs can model and predict more accurately
- Also, **do not need many data** to train! (high-cost and poor portability)

More details later

Literature Review

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Core Idea: Design **theoretically sense** human mobility model

Mechanism-driven Models

THE $\frac{P_1 P_2}{D}$ HYPOTHESIS: ON THE INTERCITY MOVEMENT OF PERSONS

GEORGE KINGSLEY ZIPF
Harvard University

IN THE present paper we shall show with supporting data that the number of persons that move between any two communities in the United States whose respective populations are P_1 and P_2 and which are separated by the shortest transportation distance, D, will be proportionate to the ratio, $P_1 \cdot P_2/D$, subject to the effect of modifying factors.

The data in support of the above proposition are the highway, railway and airway data for an arbitrary set of cities during intervals of measurement in 1933-34. Before presenting the data, however, we shall give a brief theoretical discussion of the proposition itself with illustrations from other kinds of observations with which the above data are intimately connected.

I. THEORETICAL DISCUSSION

In 1940 the author published the observation that the following equation of the generalized harmonic series described the recent distribution of communities in India, Germany, and certain other countries including the United States (for communities of 2,500 or more inhabitants), when the communities are arranged in the order of decreasing size, with A representing the population of the largest community, and with the denominators referring to the ranks of the communities thus arranged:[1]

$$A\ Sn = \frac{A}{1^p} + \frac{A}{2^p} + \frac{A}{3^p} + \dots + \frac{A}{n^p}$$

In Figure 1 are presented the United States urban data for 1930 and 1940, as indicated, to which an ideal line, A, with a negative slope of 1 (i.e. $p = 1$) has been added to aid the reader's eye. The linearity of the data is apparent.

In 1941 the author presented a fuller

[1] Zipf, G. K. "The generalized harmonic series as a fundamental principle of social organization." *Psychological Record*, 4 (1940), 43.

Gravity Model
a.k.a. Zipf's Law
Zipf, 1946

nature physics

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Article | Published: 12 September 2010

Modelling the scaling properties of human mobility

Chaoming Song, Tal Koren, Pu Wang & Albert-László Barabási

Nature Physics **6**, 818–823 (2010) | Cite this article

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EPR Model
Exploration and Preferential Return
Song et al., 2010

Divide human travel into two types:
- Exploration
- Preferential Return

The probability of travel is directly proportional to the **population** of the current location and the destination, and inversely proportional to the **distance**.

Literature Review

UNIVERSITY of VIRGINIA
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Core Idea: Design theoretically sense human mobility model

Mechanism-driven Models

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Gravity Model + EPR Model

=

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Article | Open access | Published: 08 September 2015

Returners and explorers dichotomy in human mobility

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

Nature Communications **6**, Article number: 8166 (2015) | Cite this article

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***d*-EPR Model**
Pappalardo et al., 2015

- Consider "Gravity" in Exploration
- Preferential Return
- Use data not public accessible

Very Famous Work, But…?

Literature Review

Core Idea: Design accurate predictor of human mobility regardless of theoretically sense

Data-driven Models

nature communications

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nature > nature communications > articles > article

Article | Open access | Published: 04 February 2025

Human mobility is well described by closed-form gravity-like models learned automatically from data

Oriol Cabanas-Tirapu,

Nature Communicatio

11k Accesses | 8 Ci

$$\log T_{od} = A\left(1 + \frac{B((m_d + C)(m_o + D))^{\beta}}{d_{od}}\right)^{\xi} \quad \text{or} \quad \log T_{od} = \log\left[A\left(\frac{B(m_d m_o + C m_d + D)}{d_{od}^{\alpha}} + 1\right)^{\gamma}\right]$$

scientific reports

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Article | Open access | Published: 13 August 2019

Reconstructing commuters network using machine learning and urban indicators

Gabriel Spadon, Andre C. P. L. F. de Carvalho, Jose F. Rodrig

Scientific Reports 9, Article number: 11801 (2019) | Cite this a

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$$\varphi_i(f, x) = \sum_{S \subseteq M \setminus \{i\}} \frac{|S|!(M - |S| - 1)!}{M!} [f_x(S \cup \{i\}) - f_x(S)],$$

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Home > ACM Journals > ACM Computing Surveys > Vol. 55, No. 1 > A Survey on Deep Learning for Human Mobility

SURVEY

A Survey on Deep Learning for Human Mobility

Machine Learning and Deep Learning Methods

- Very complex functions -> NO **interpretability**
- Rely heavily on **historical data**
- Need to **train** -> high cost

Methodology

Methodology

- Foundation: Inspired by ***d*-EPR** model, agents in our model alternate between two fundamental actions: **explore and preferential return**.
- Our agents make actions condition on
  - **Demographics**
  - **Characteristics of origin and destination** (e.g., distance, opportunity structure, education and income level).
- We also integrate a **gravity model** into the exploration mechanism to help with **spatial reasoning**.

- Data Sources: **SafeGraph** (for POI data) and **American Community Survey (ACS) data** provided by **OpenCensus** (for agent demographics).

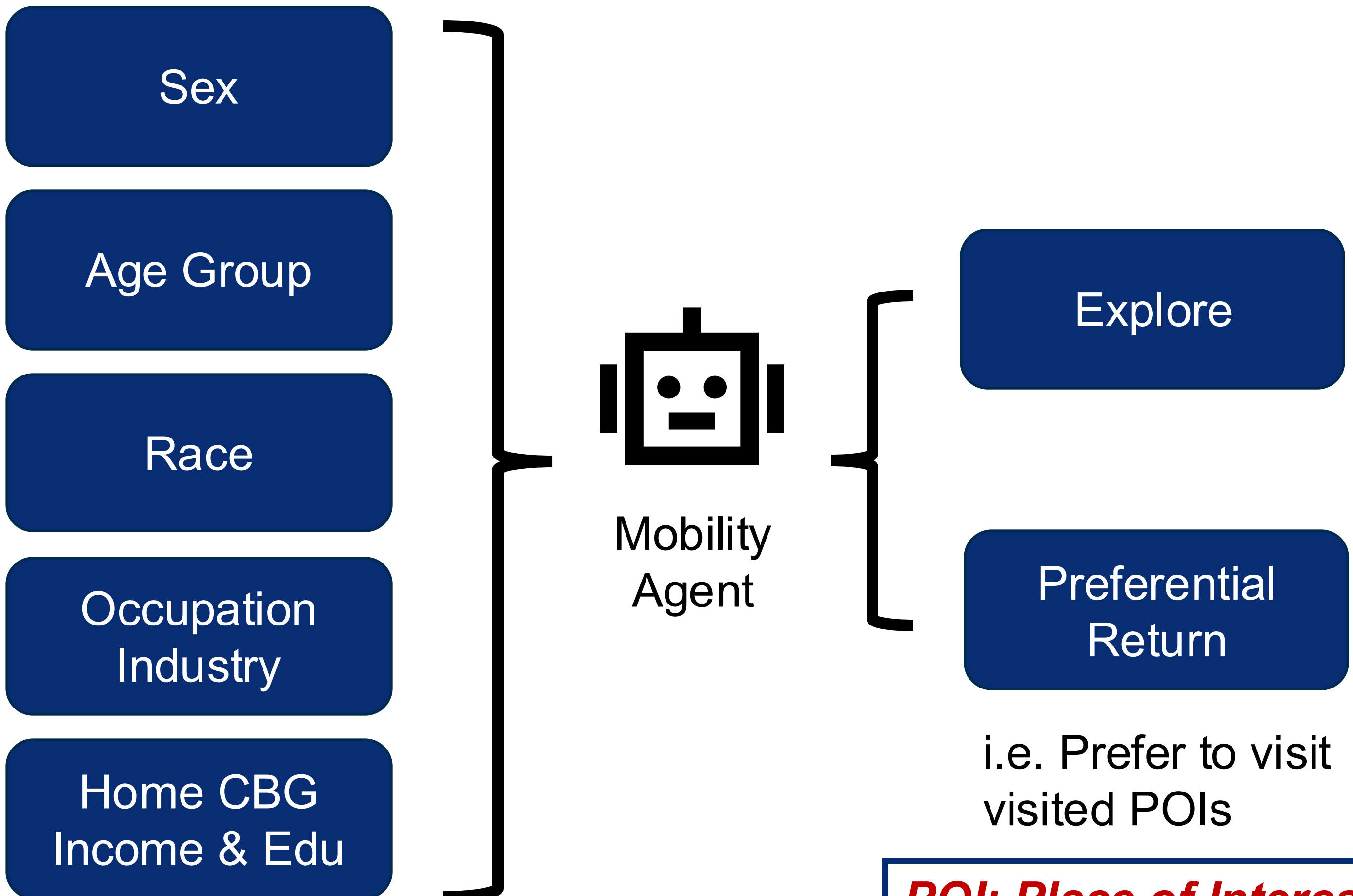
SAFEGRAPH

United States® Census Bureau

Free and Public Accessible Data

Brief Description

Methodology



POI: Place of Interest

Actions

CBG: Census Block Group

Brief Description

Methodology

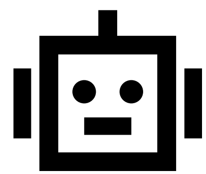
Sex

Age Group

Race

Occupation Industry

Home CBG Income & Edu



Mobility Agent

What can Mobility Agent see?
How do Mobility Agents make decisions?

Explore

Preferential Return

i.e. Prefer to visit visited POIs

CBG: Census Block Group

POI: Place of Interest

Actions

Problem Formulation

LLM-Driven Preference

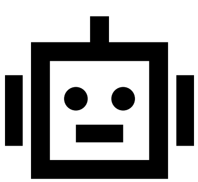
A LLM agent generates a dynamic distribution of Interest Score I_C for each POI category (C) based on the agent's profile and home CBG context.

Interest Score

- **Definition**
  The interest level of a specific population group in a specific POI category. This interest level represents **how willing they are** to visit a certain POI. The range is a decimal between 0 and 1.

- Interest Score is generated by LLM according to **specific demographic group**
- Interest Score will be used to calculate the "**gravity**" when it decide to **explore**

More details later for this



Do I interest in certain POI category?
I can give an interest score!

Brief Description

Methodology


```json
{
  "id": "0",
  "sex": "Female",
  "age_group": "18 to 60 years",
  "race": "Other",
  "industry": "Retail trade",
  "City": "New York city",
  "home_cbg_income": 64792,
  "home_cbg_edu": "Medium",
  "home_cbg_population": 931,
  "CBG": "360470405001"
},
```


Example for a mobility agent's profile

Core Prompt (Segment)

```
You are a resident living in a city, ...

---
**Your Resident Profile**

- **Your Sex:** {agent_sex}
- **Your Age Group:** {agent_age_group}
- **Your Race:** {agent_race}
- **Your Job Sector:** {agent_industry}
- **Your Home Neighborhood's Education Level:** {home_cbg_edu_level}
- **Your Home Neighborhood's Income Level:** {home_cbg_income_level}
- **Your Home Neighborhood's Vibe (for context):** A place with this mix of
POIs: {home_cbg_poi_probs_for_prompt}

---
**Your Task...

The POI types correspond to the list indices as follows:...

**Function Requirements:**
1.  **Define the function:** `def policy_function():`
2.  **Return a list:** It must return a list of 6 "interest scores".
3.  **Scores:** Each score must be a number between 0.0 and 1.0, representing
your fixed interest in visiting that type of POI.
4.  **Use Logic:** Base your logic on your resident profile. For example, a
person working in 'Educational Services' might have a higher baseline interest
in visiting POIs of that type. A younger person might be more interested in
'Arts, Entertainment, and Recreation'. Use fixed values based on your profile.
5.  **Be Realistic:** The rules should make common sense.
6.  **Add Comments:** Include brief Python comments (`#`) to explain your
thinking.
```

Brief Description

```
{
    "agent_type_key": [
        "Female",
        "18 to 60 years",
        "Other",
        "Retail trade",
        "Medium",
        "High"
    ],
    "policy_function_code": "def policy_function():\n    # Resident Profile: Female, 18-60, Retail Job, High Income Neighborhood.\n    # This policy reflects the preferences of a working adult with high disposable income.\n\n    # Baseline interest scores for each POI category.\n    # Index 0: 'Wholesale & Retail Trade, Transportation and Warehousing'\n    # Index 1: 'Others'\n    # Index 2: 'Educational Services'\n    # Index 3: 'Health Care and Social Assistance'\n    # Index 4: 'Arts, Entertainment, and Recreation'\n    # Index 5: 'Accommodation and Food Services'\n    \n    # Initialize a default list of scores.\n    interest_scores = [0.0] * 6\n\n    # Logic based on Job Sector: Retail trade (Index 0)\n    # As I work in retail, I have a high and consistent need to visit these places for work.\n    # High income also supports frequent personal shopping.\n    interest_scores[0] = 0.8\n\n    # Logic based on general needs and lack of specific drivers.\n    # 'Others' (Index 1) is a generic category, so interest is moderate.\n    interest_scores[1] = 0.3\n    # 'Educational Services' (Index 2) is a low priority for a working adult without children specified.\n    interest_scores[2] = 0.1\n\n    # Logic based on High Income Level.\n    # High income implies good access to and regular use of 'Health Care' (Index 3).\n    interest_scores[3] = 0.5\n    # High disposable income strongly correlates with spending on leisure activities.\n    # 'Arts, Entertainment, and Recreation' (Index 4) is a top priority for leisure time.\n    interest_scores[4] = 0.9\n    # 'Accommodation and Food Services' (Index 5) like dining out is also a primary social/leisure activity.\n    interest_scores[5] = 0.9\n\n    return interest_scores"
},
```

Initialize for agent profile and POI cate. list

Example for a mobility agent's output

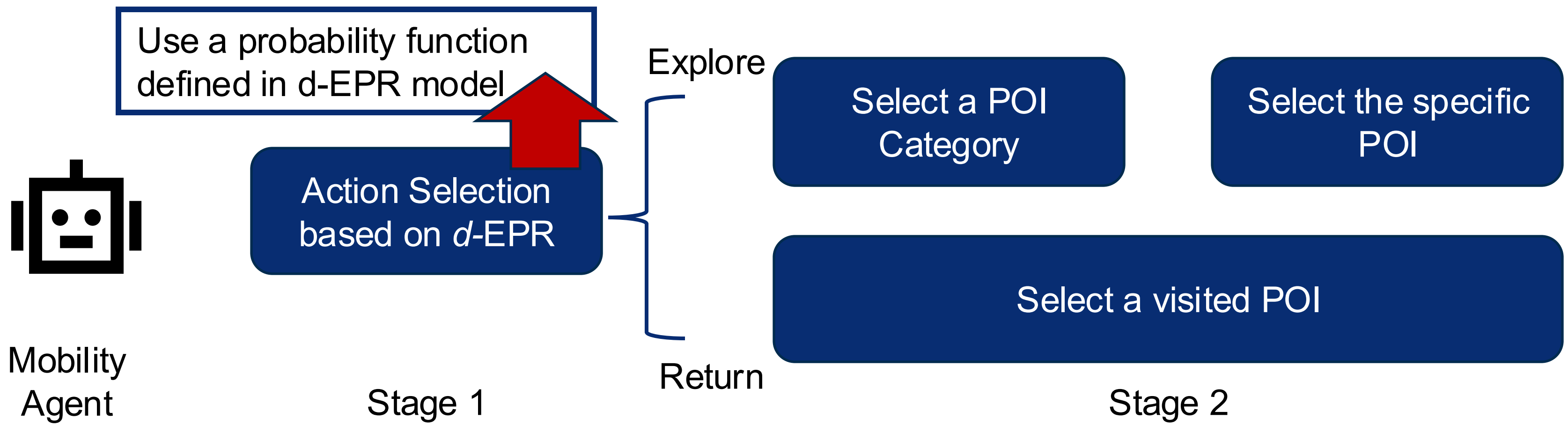
Return interest score with demographic-reasonable thinking

Agentic Workflow

Mobility Decision Process

At each time step, an agent decides its next move from a given set of potentials POIs:

- **Action Selection (*d*-EPR)**: The agent first chooses between **exploring** a new POI or **returning** to a previously visited one.
- **POI Selection (Gravity Model + Interest Score)**: Combine LLM reasoning and **physical constraints**. If exploring, the agent selects a specific POI by calculating an attraction score for all potential destinations.



Agentic Workflow

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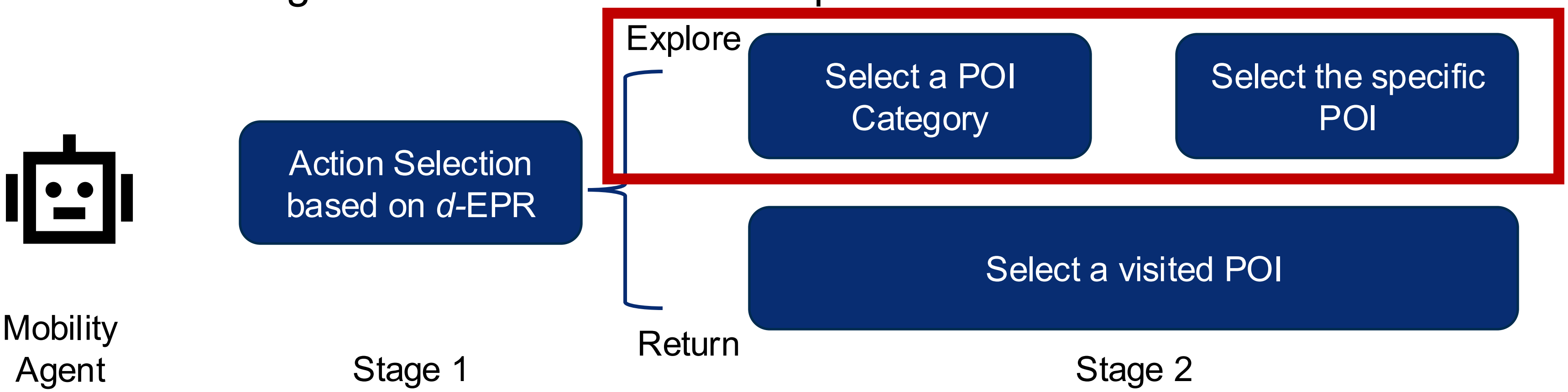
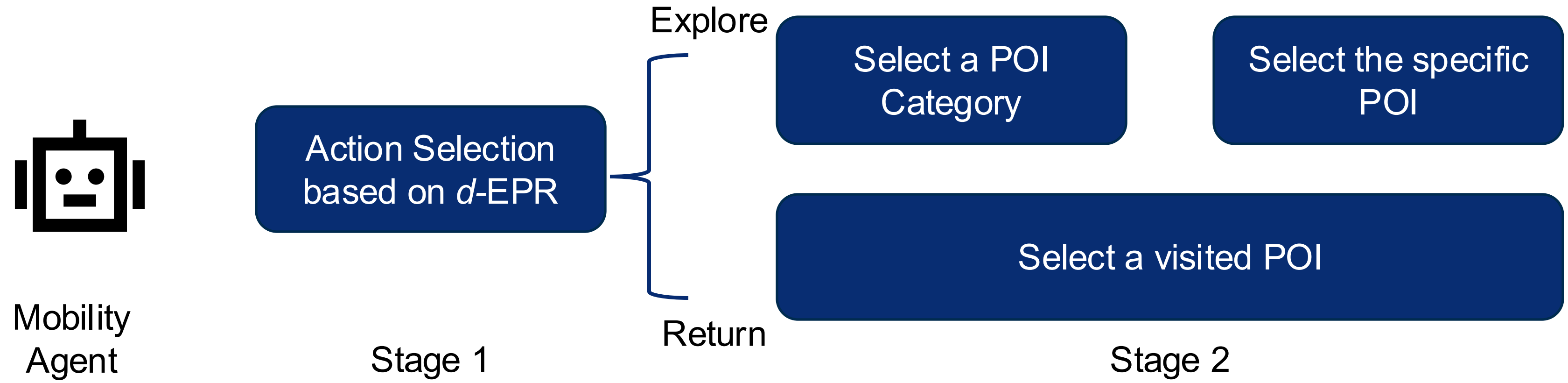
How do this work?



Agentic Workflow

Mobility Decision Process



When Exploring

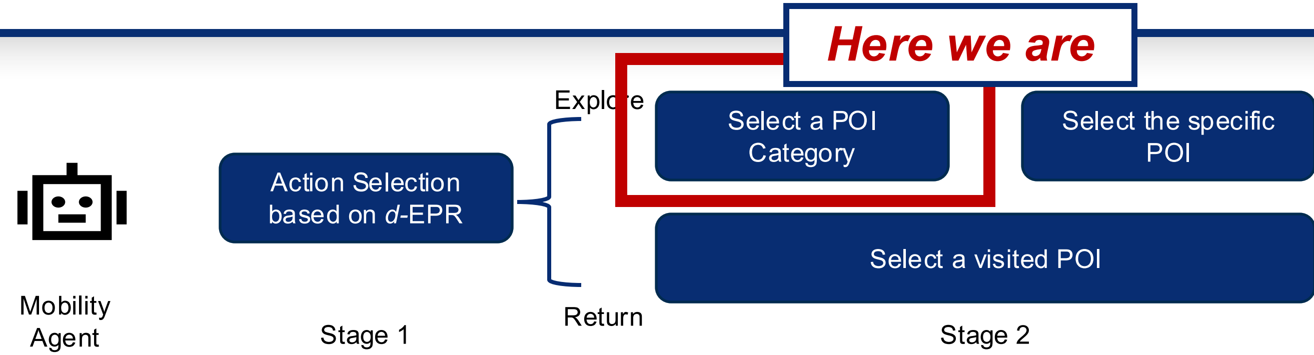
Select a POI Category

Give agent a list of a ranked POI categories , calculated by **Interest Score × POIs (specific category)** within a travel radius
Then, convert it into a probability distribution, and select a category

Select the specific POI

First, based on the selected POI category, all POIs of that category within the map range are filtered.
Then, the "**gravity**" of each POI is calculated (combining the interest score and the gravity model, the formula will be provided later), and then converted into a probability distribution to select specific POI.

Agentic Workflow



Interest Score for POI Category Selection

The attraction A_c of a POI Category c for an agent at location is defined by the following attraction formula:

$$A_c = I_c \cdot N_c$$

Where:

I_c is the agent's Interest Score for the POI category (c). **Use LLM to generate this**

N_c is the total number of POIs belonging to that category within within a travel radius D_{max} around the current position of the agent.

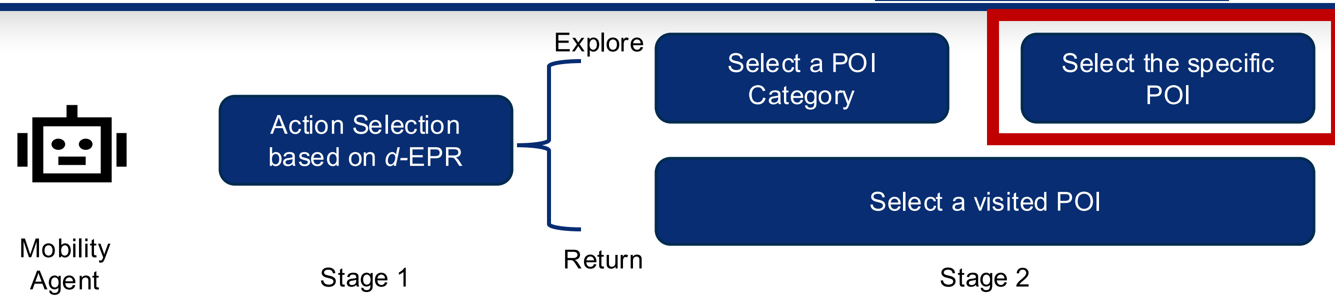
Idea: You wouldn't visit an interest place if there is no (or very less) related POIs

Note:

- POI Category is classified by **North American Industry Classification System (NAICS)** and re-aggregated into six main categories
- D_{max} is set to 5km in this project which align with the travel mode preference for driving

Agentic Workflow

Here we are



Gravity Model for POI Selection

After determining the target POI category, the decision-making process enters the second stage of selecting POI, all the POIs in the map become candidate, and the **gravity** is defined as:

$$G_i \propto \frac{I_c}{d_i^{\alpha}}$$

Where:
I_c is the agent's Interest Score for the POI category (c).
d_i^{α} is the distance between the agent's current location i and POI j.
α is the distance decay parameter, default value is 2.5 in our model.
This formula follows the core idea of gravity model since **attraction is directly proportional to interest and inversely proportional to distance**.
The probability of visiting a POI is the normalized attraction score across all candidate POIs.

Evaluation & Results

Evaluation Goal

To validate the model by comparing the simulated traffic flows from Census Block Groups (CBGs) to POI categories against empirical data.

Baseline

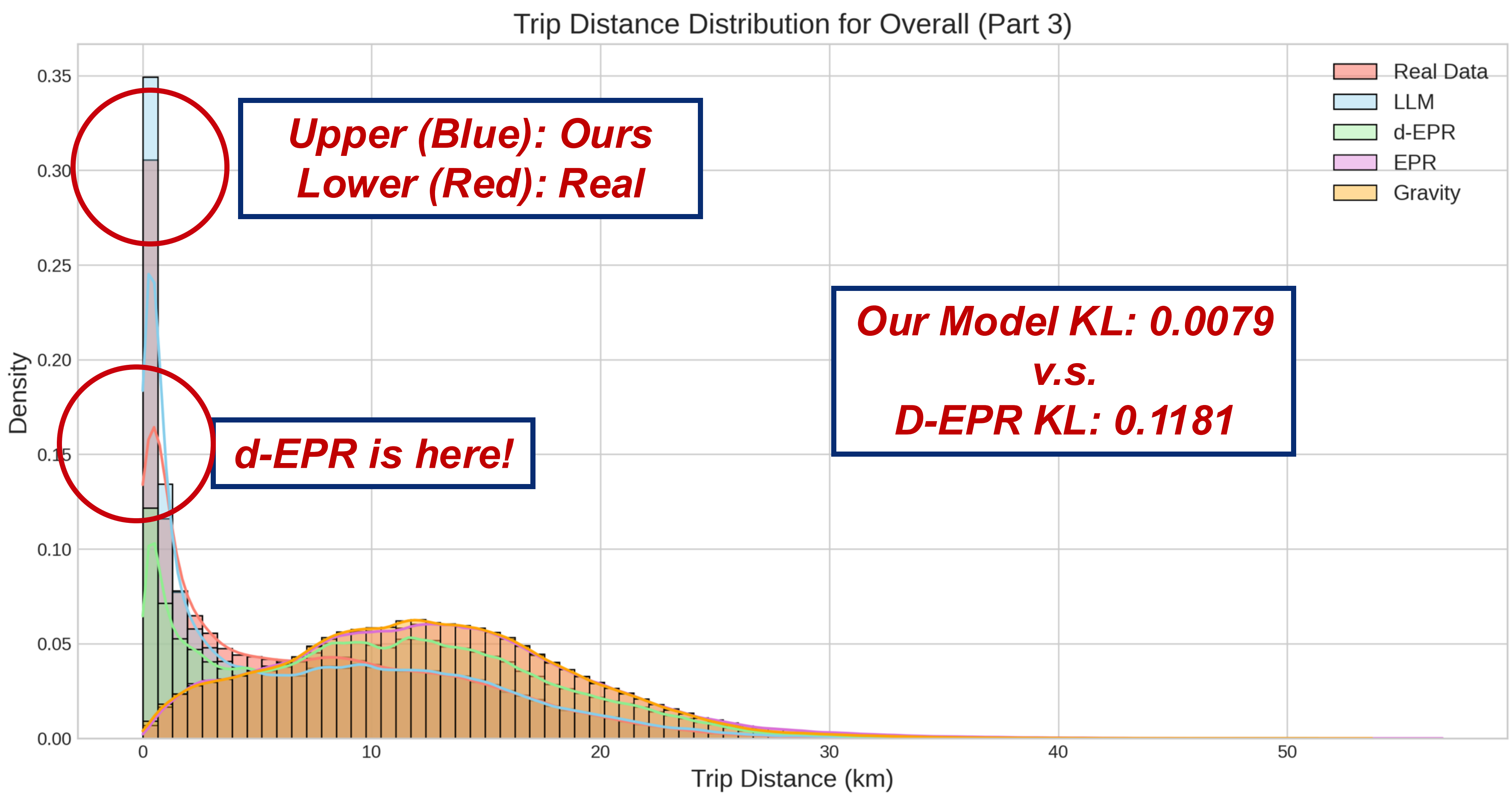
d-EPR model

Ground Truth

Randomly selected as the week of 2019-06-10
To avoid bias, also do sensitivity analysis and test different period of time

Evaluation & Results

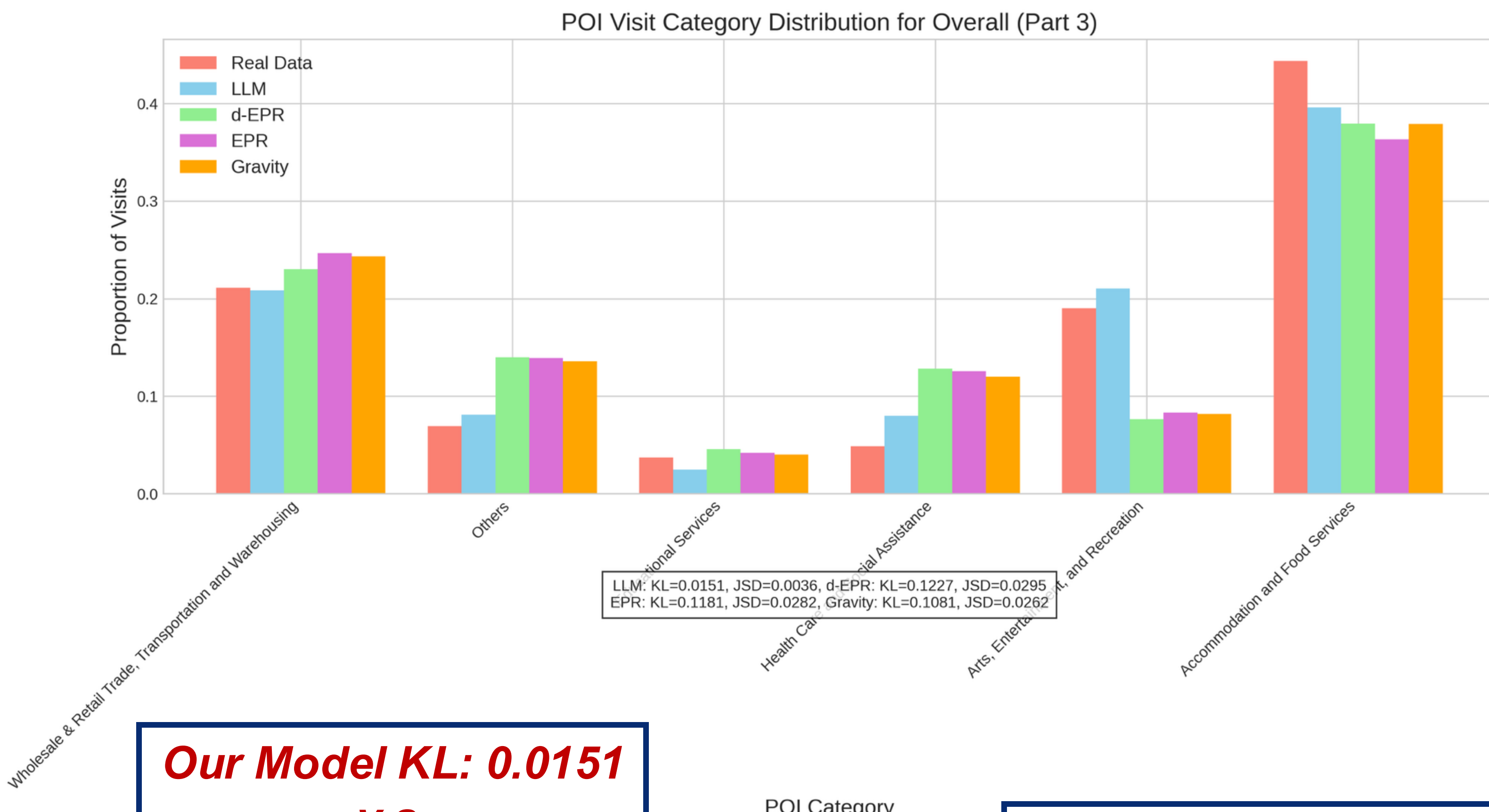
Overall Performance, Gemini-2.5-pro, Trip Distance



LLM: KL=0.0079, JSD=0.0020, d-EPR: KL=0.1181, JSD=0.0299
EPR: KL=0.4079, JSD=0.1152, Gravity: KL=0.3927, JSD=0.1112

Evaluation & Results

Overall Performance, Gemini-2.5-pro, Poi Category

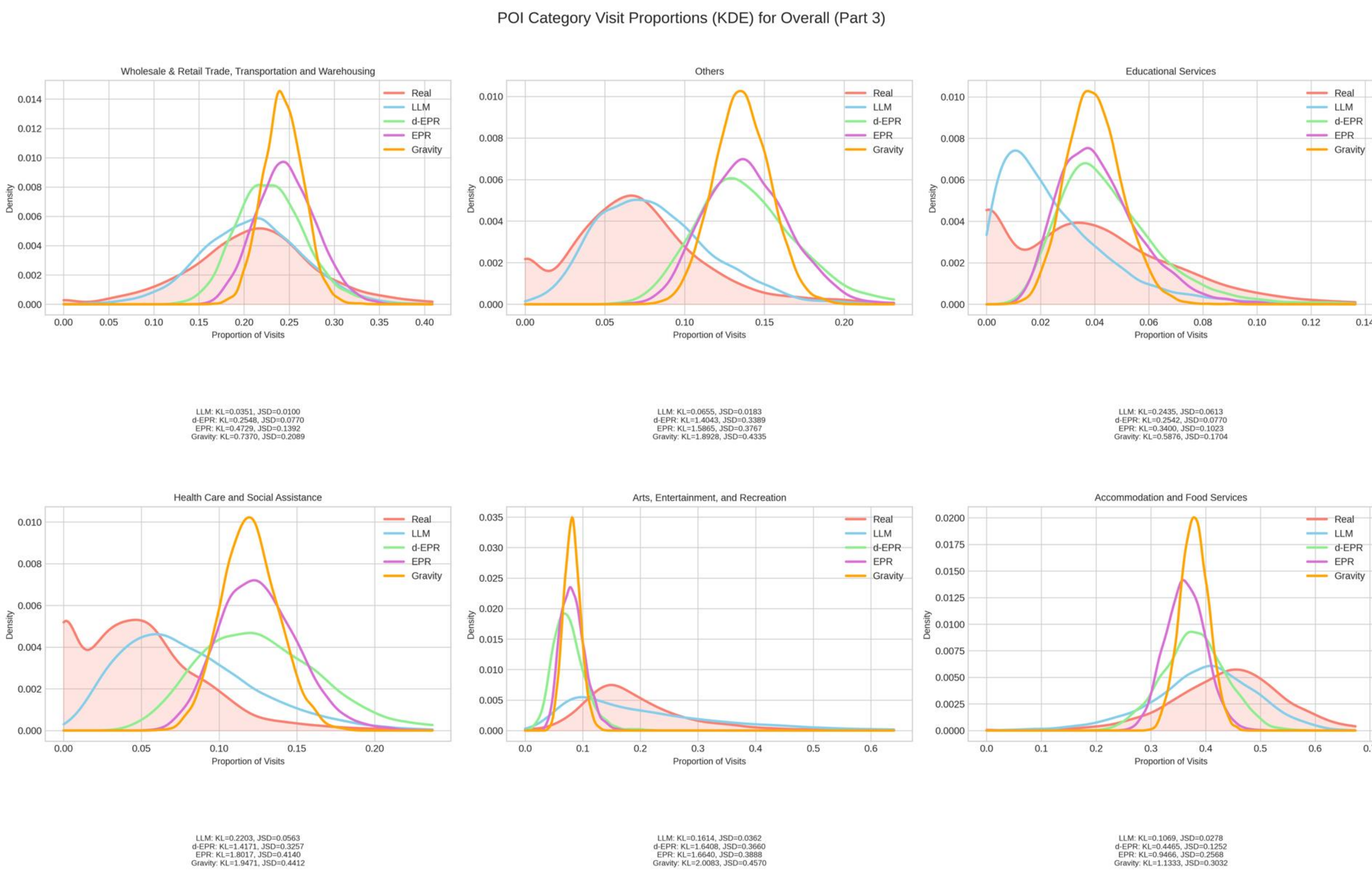


Our Model KL: 0.0151
v.s.
D-EPR KL: 0.1227

Also, fit very well!

Evaluation & Results

Overall Performance, Gemini-2.5-pro, Visit Prop. (KDE)



Evaluation & Results

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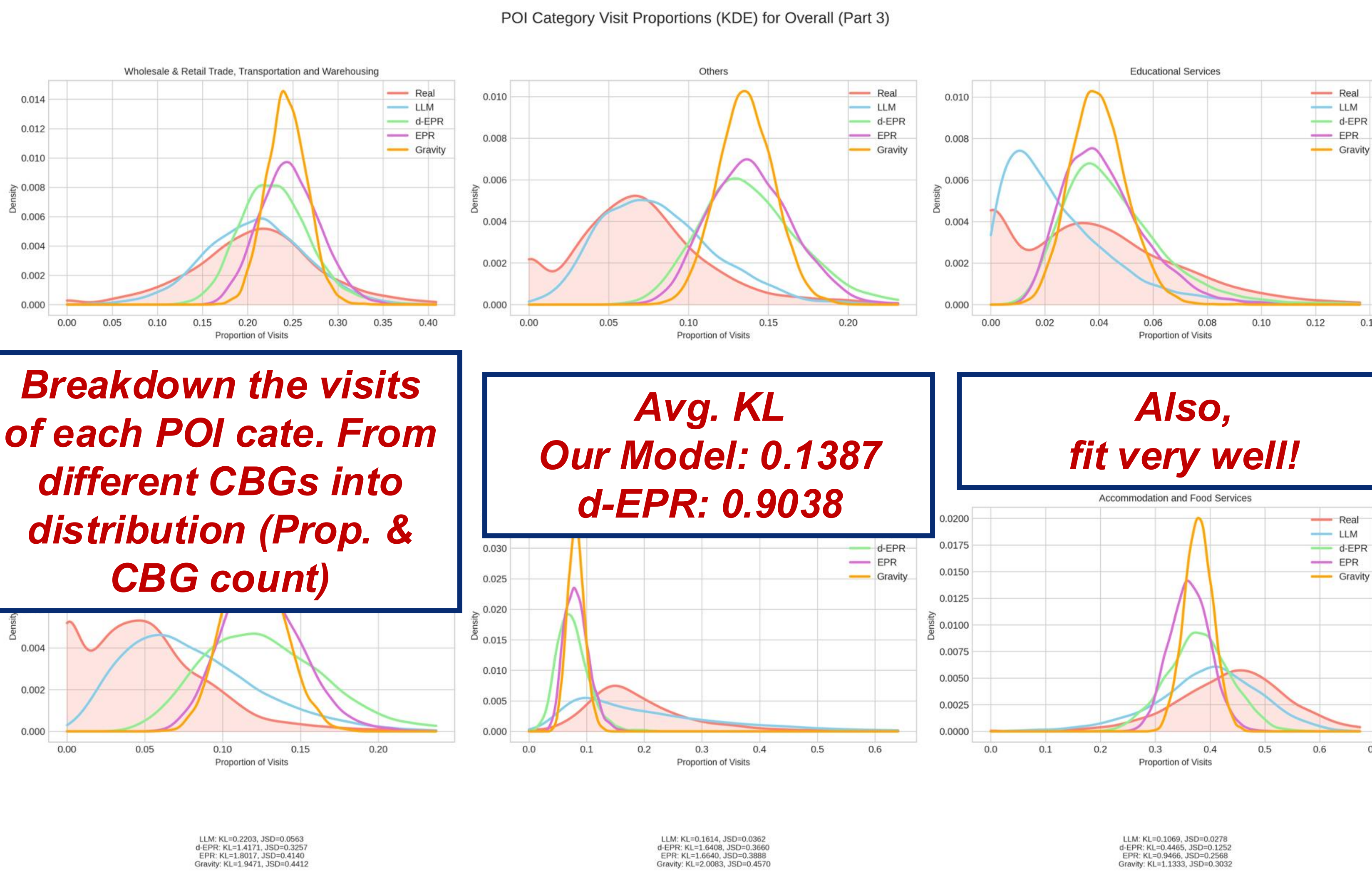
Overall Performance, Gemini-2.5-pro, Visit Prop. (KDE)



Breakdown the visits of each POI cate. From different CBGs into distribution (Prop. & CBG count)

Avg. KL
Our Model: 0.1387
d-EPR: 0.9038

Also, fit very well!

Evaluation & Results

Colocation

Treat different demographic group's visiting pattern to a certain **POI** as a vector, such as:

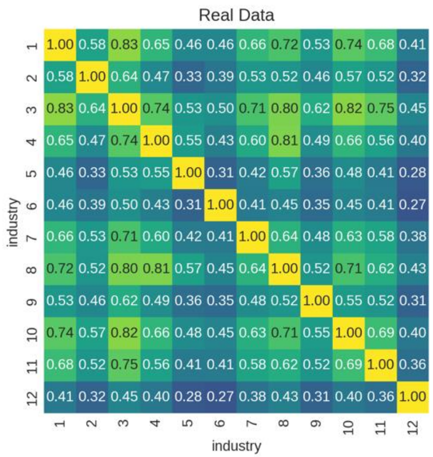
- vector_white_agents = {'poi_1': 150, 'poi_2': 0, 'poi_3': 300, ...}

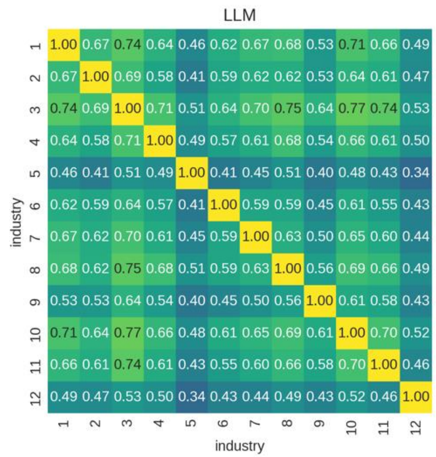
Then we can compute the similarity of visiting patterns between different demographic groups through **compute the similarity of vectors** (here we use Cosine Similarity)

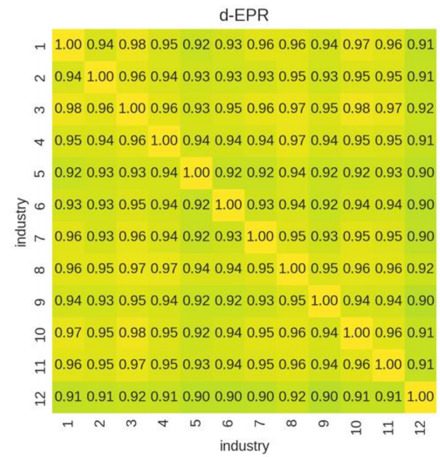
Evaluation & Results

Colocation, Gemini-2.5-pro, industry, Cosine

We can model the Heterogeneity due to LLM's reasoning with agent profile

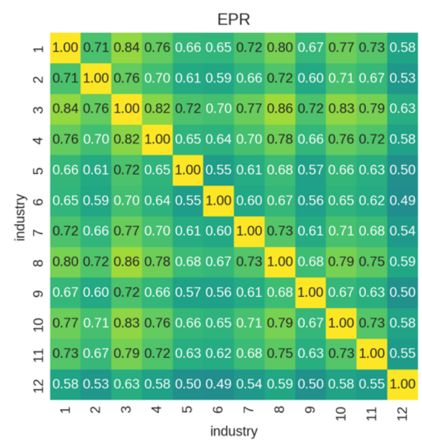


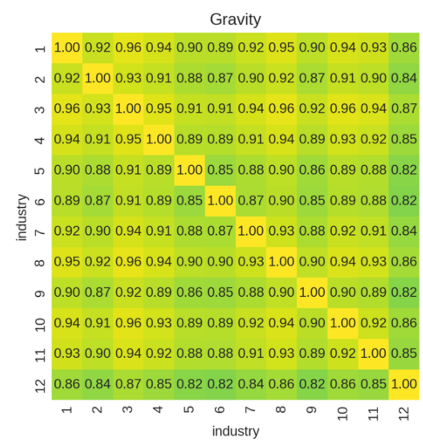




X-axis and Y-axis are agent's different occupation (industry)

The cosine similarly represent the **colocation relationship of different demographic group**





Sensitivity analysis

University of Virginia
SCHOOL of ENGINEERING & APPLIED SCIENCE

Base model: d_max = 5km, alpha=2.5, Best Performance!

Condition		Evaluation Metric (model rank)				Avg. Divergence	Rank
Paramater	Value	Trip Distance KL	POI Catregory KL	POI Category Breakdown avg. KL	Colocation (Industry) avg. Diff.		
Base Model		**0.0079**	**0.0151**	**0.1387**	**0.0622**	**0.0560**	**1**
D_max	1.0km	0.0605	0.0331	0.2067	0.0914	0.0979	7
	10km	0.0085	0.0178	0.1860	0.0502	0.0656	3
	25km	0.0237	0.0402	0.3292	0.0477	0.1102	9
	50km	0.0244	0.0402	0.3349	0.0477	0.1118	10
	+inf (N/A)	0.0245	0.0402	0.3357	0.0476	0.1120	11
alpha	1.0	0.2979	0.0187	0.1798	0.0488	0.1363	12
	2.0	0.0382	0.0142	0.1495	0.0512	0.0633	2
	3.0	0.0672	0.0223	0.1736	0.1436	0.1017	8
rho, gamma	rho = 0.8, gamma = 0.1	0.0142	0.0156	0.2243	0.0960	0.0875	5
	rho = 0.4, gamma = 0.3	0.0246	0.0237	0.1790	0.0575	0.0712	4
KL with weekly average		0.0075	0.0146	0.2685	0.0998	0.0976	6
d-EPR		0.1177	0.1227	0.9038	0.3757	0.3800	13
EPR Model		0.4079	0.1181	1.1350	0.1319	0.4482	14
Gravity Model		0.3927	0.1081	1.3838	0.3384	0.5558	15

Discussion

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Achieved Interpretability:

- Macro-level: The agent's workflow is **guided by** the classic scientific theory of ***d*-EPR**, aligning with physical intuition.
- Micro-level: Each decision is accompanied by explicit **reasoning generated by the LLM based on its profile**, conforming to human logic, completely solving the "black box" problem of traditional data-driven models.

Overcame Trajectory Data Dependency:

The framework operates **without requiring training** on large-scale historical trajectory data, relying only on publicly **available census and geographic data**.

This significantly **reduces the cost** of model application, bypasses **data privacy** barriers, and enhances model **portability**.

Successfully Modeled Heterogeneity:

By injecting demographic profiles, the LLM agent effectively captures the **diverse and nuanced travel preferences of different groups** (e.g., different income levels, occupations), something traditional rule-based models struggle to achieve.

Conclusion

- Successfully constructed and validated **Mobility Agents**, an innovative framework for **simulating large-scale urban mobility patterns using theoretically guided LLM agents**.

- Experimental results show that
  - significantly outperforms in simulating both **macroscopic travel patterns** (such as travel distance distribution) and **microscopic heterogeneous behaviors** (such as co-occurrence patterns among different groups).

- Three major advantages: 1) high **interpretability**, 2) **no need for training** with historical trajectory data, and 3) reliance solely on **publicly available data**. It provides a novel and powerful research paradigm for **integrating scientific theory and artificial intelligence to study complex social systems**.

Q&A

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Thanks!

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