

Mobility Networks for Pandemic Response & Emerging Directions with Generative AI

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Self-Intro: Serina Chang



- Assistant professor in UCB Computer Science and UCSF UCB Computational Precision Health (CPH), started in July'25
- Research in AI & human behavior
 - Simulating & inferring behaviors with AI
 - Human-AI interaction
 - Societal decision-making over large-scale behaviors, e.g., mobility
- PhD at Stanford, on the job market in 2024, postdoc at Microsoft Research

Plan for today:

I. Mobility Networks for Pandemic Response

Inferring mobility networks from location data

Modeling disease spread and pandemic policies

} PhD work

II. Emerging Directions with Generative AI

Generating mobility trajectories with diffusion models

Simulating human behaviors with LLMs

} Ongoing work
in my lab

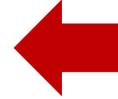
III. Job Market Discussion

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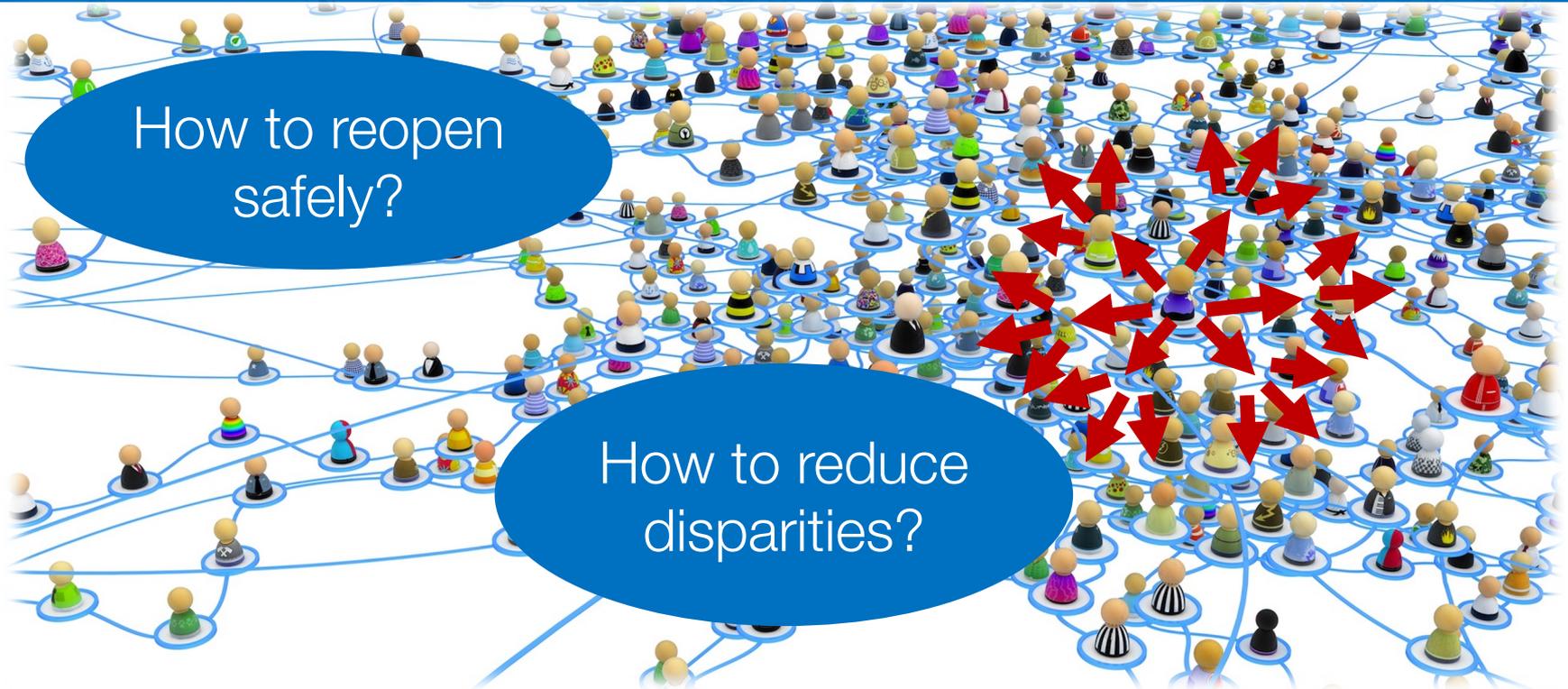
Simulating human behaviors with LLMs

III. Job Market Discussion

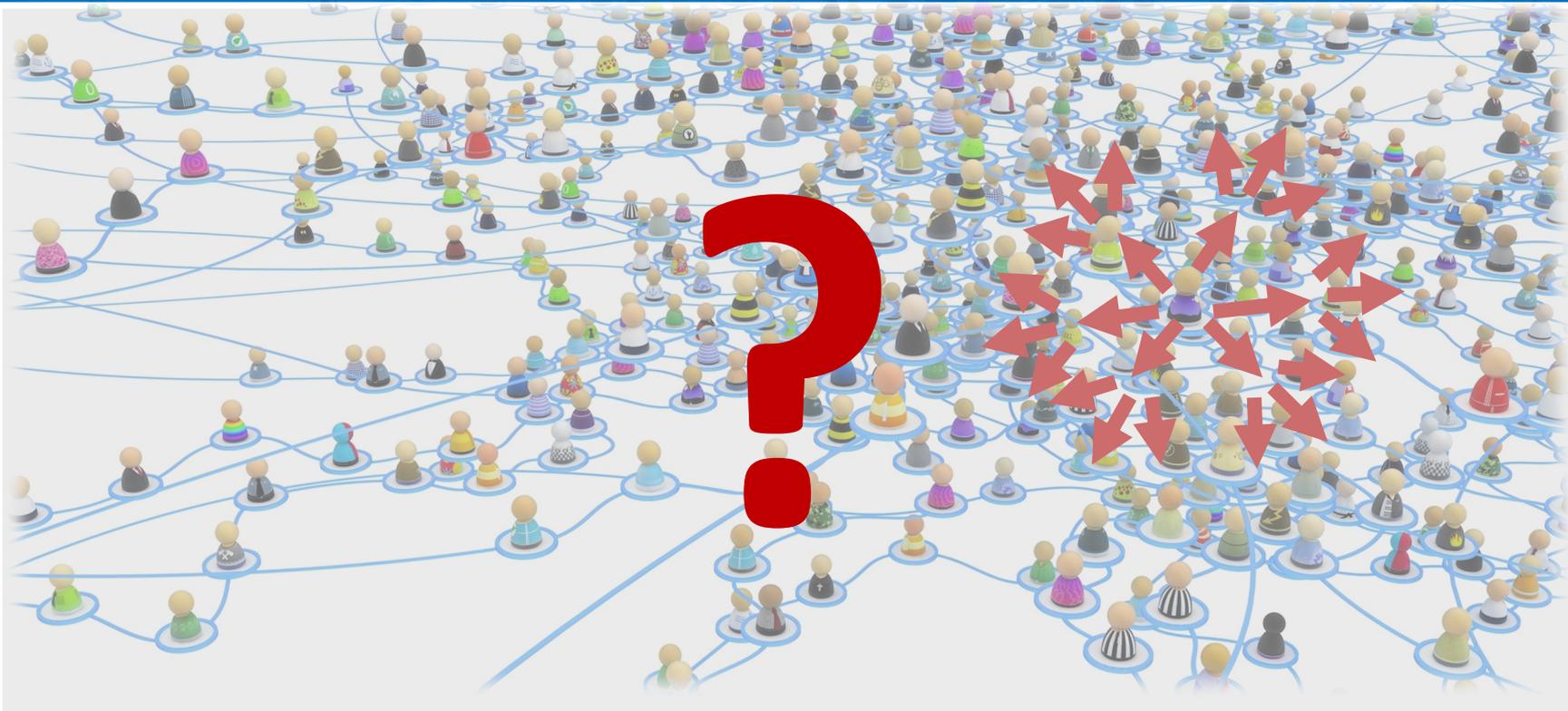
Infectious diseases spread through **contact**



Understanding **contact network** is crucial



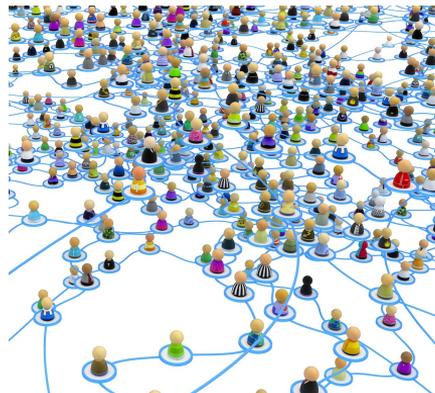
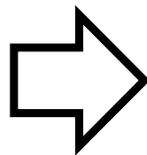
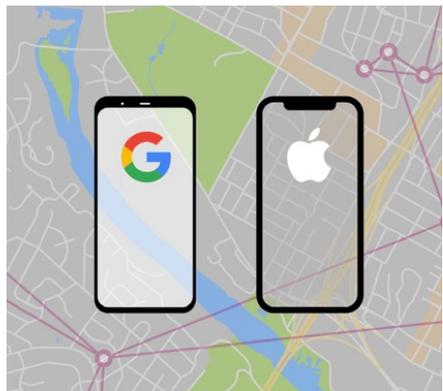
But we don't know the **contact network**



But we don't know the **contact network**

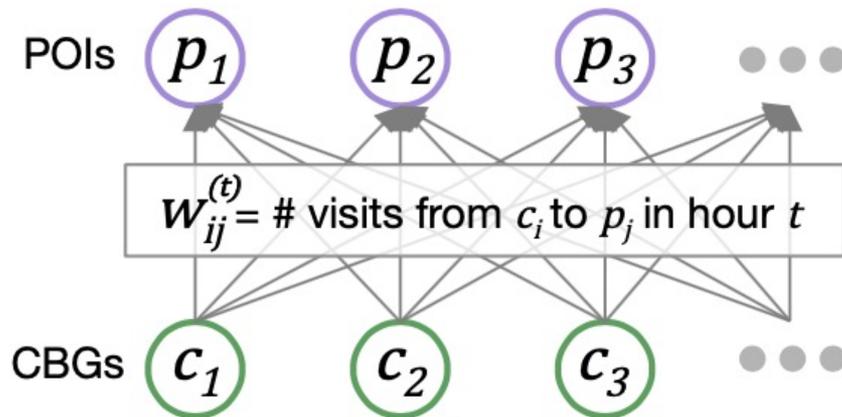
Our solution: infer fine-grained contact networks from aggregated location data during the pandemic

[**Chang** et al., Nature 2021; **Chang** et al., ICML 2024]



Network inference

What we want: hourly visits of people from census block groups (CBGs) to points-of-interest (POIs)



Network inference

What we want: hourly visits of people from census block groups (CBGs) to points-of-interest (POIs)

Idea: use iterative proportional fitting (IPF)!



Hourly visitors to POIs

x_1

x_2

x_3

...

x_m



Hourly visitors from CBGs

y_1

y_2

y_3

...

y_n

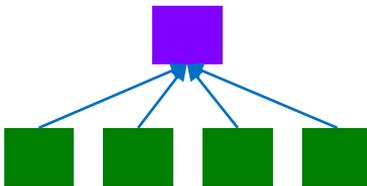


Hourly



No network

Monthly estimates of each POI's home CBGs



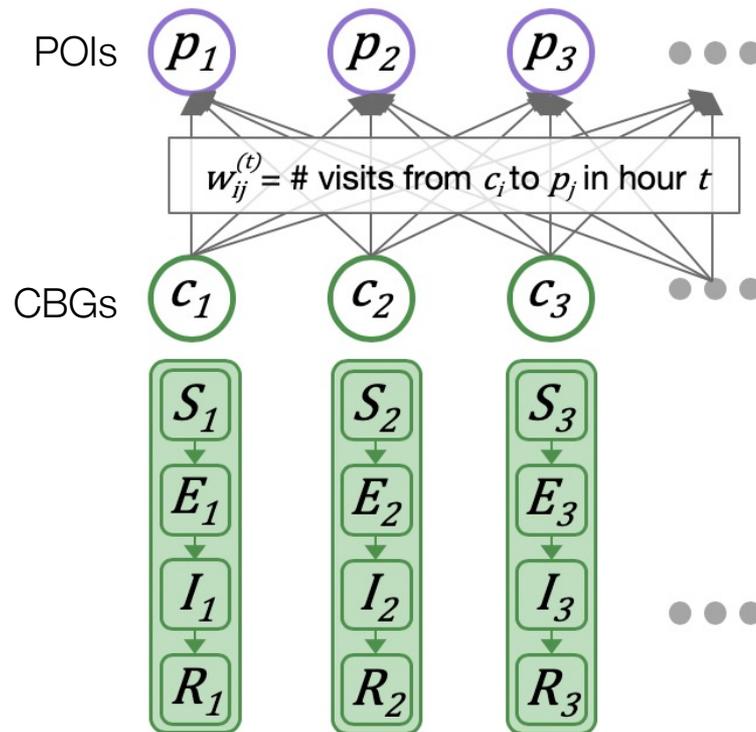
Not hourly



Has network

Epidemiological model

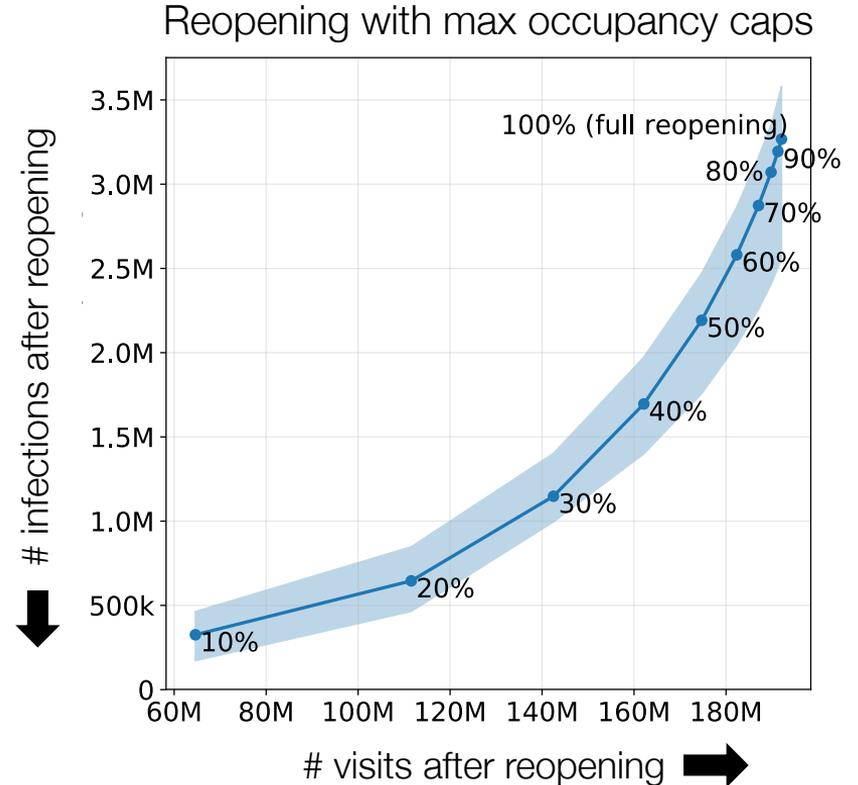
- We used IPF to infer hourly networks in 10 of the largest US metro areas: **5.4 billion hourly edges**
- Integrated networks into epi model with only **three free parameters**, fixed over time
- Networks enable our model to accurately fit daily COVID-19 cases



Epidemiological model

Example use cases

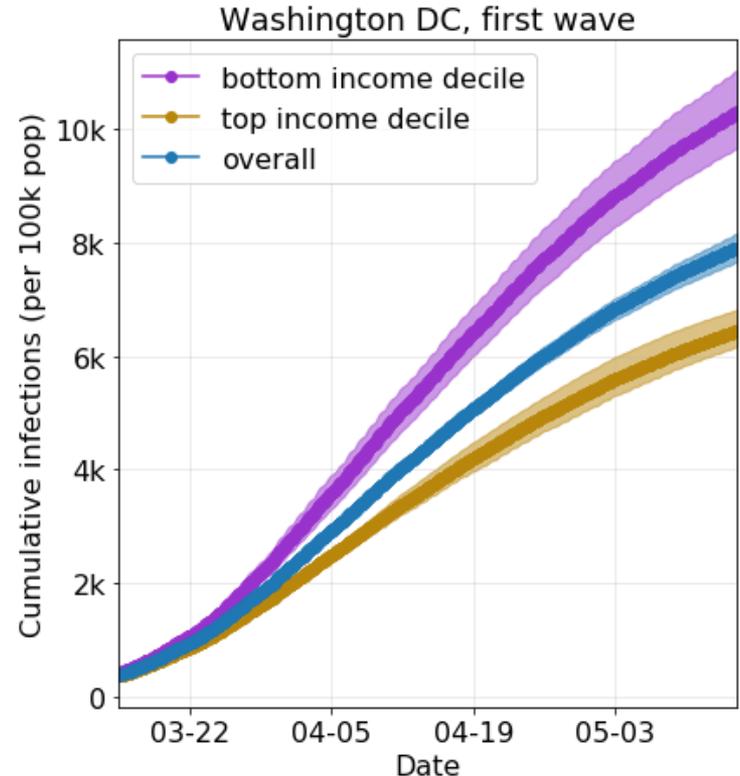
- Analyze **reopening strategies**: tradeoffs between mobility and predicted infections



Epidemiological model

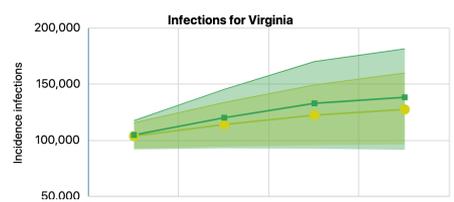
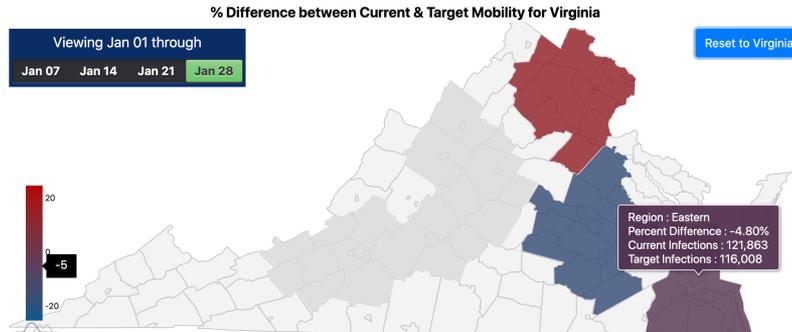
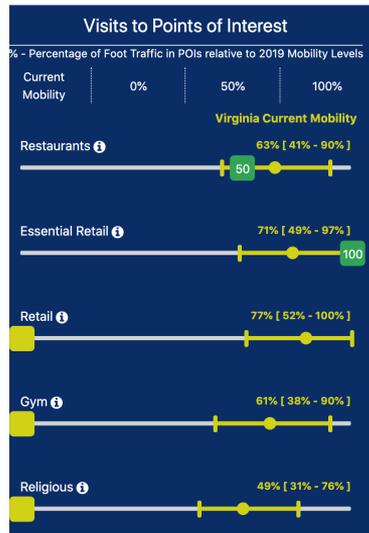
Example use cases

- Analyze **reopening strategies**: tradeoffs between mobility and predicted infections
- The model correctly learns **socioeconomic disparities** from mobility networks *alone* – what is the mechanism?



Policy impact

- Results cited by policymakers around the world, 650+ news outlets
- Deployed model as **decision-support tool** for Virginia Dept of Health [Chang et al., KDD 2021, Best Paper Award]



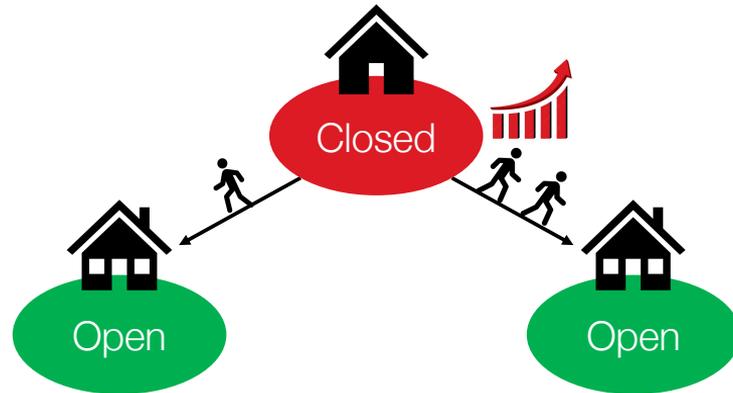
Region	Difference in Infections	Percent Difference
Richmond	-5,721	-6.33%
Eastern	-5,855	-4.80%
Washington DC	+40,112	+15.60%
Virginia	+28,536	+6.08%

Evaluating policy impacts

1.5 years later...

How do people actually react to mobility restrictions?

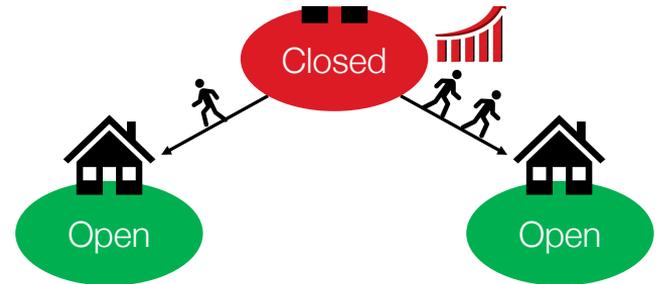
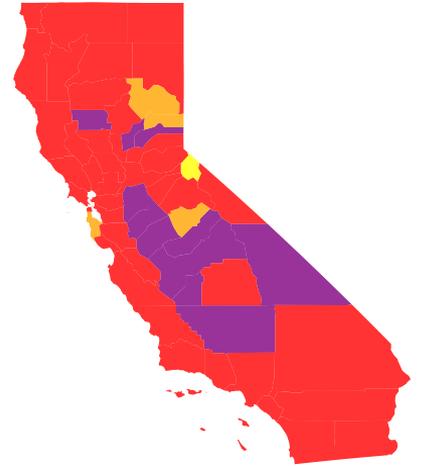
Neighboring regions with different policies → are people **spilling over** from more to less restricted areas?



Evaluating policy impacts

Are people spilling over from more to less restricted areas? **Yes!** [Chang et al., AAI'23]

- California counties assigned to tiers at the cutoffs of continuous COVID metrics → regression discontinuity design to estimate **unconfounded** spillover effects from the mobility network
- We find **significant spillover movement** from more to less restricted counties
- Under our model: county-level restrictions only **54% as effective** as statewide



Mobility Networks for Pandemic Response



Chang*, Pierson*, Koh* et al., *Nature* 2021: modeling COVID-19 spread with mobility networks

Chang et al., KDD 2021: transforming model into deployed tool for Virginia Dept of Health

Chang et al., AAAI 2023: estimating causal effects of pandemic policies from mobility networks

Chang*, Koehler*, Qu* et al., ICML 2024: statistical analysis of IPF for dynamic network inference

Come to my ITS talk on Mar 6 for details!

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Simulating human behaviors with LLMs

III. Job Market Discussion

Generating mobility trajectories

Previously: infer mobility networks from CBGs to POIs

Now: generate *individual* mobility trajectories



Applications: infectious disease modeling, transportation planning, measuring social segregation, environmental risks



Jessie Li

Generating mobility trajectories

Challenge: demographic heterogeneity – hard to observe

Our solution: method to learn demographic-conditioned trajectory generation from available data:

1. Trajectories *without* demographic information
2. Region-level mobility statistics (eg, POI visit counts)
3. Region-level demographic distributions

Generating mobility trajectories

Phase 1: train a generative AI model on trajectories

- $P(\text{trajectory})$
- BART autoencoder
- Diffusion model

Phase 2: fine-tune on region-level mobility statistics (eg, POI visit counts)

- $P(\text{trajectory} \mid \text{demo})$
- Sample from model following region's demographic distribution
- Fit based on aggregate loss between model and ground-truth statistics

Simulating behaviors with LLMs

Why simulate?

Difficult to observe

Costs

Privacy / access

Future or
counterfactual
behaviors



Why LLMs?

Natural language
inputs and outputs

Social knowledge
from pretraining

Generalization to
unseen scenarios

Simulating behaviors with LLMs



1. Generating social networks



2. Predicting public opinions



3. Simulating human-AI chats

Simulating behaviors with LLMs



1. Generating social networks

[**Chang** et al., ICWSM'25]

- We propose three prompting methods to generate social networks with LLMs
- We find that LLMs can generate social networks that match real networks on structural characteristics, e.g., density, clustering, degree distribution
- But they consistently overestimate political homophily / polarization

Simulating behaviors with LLMs



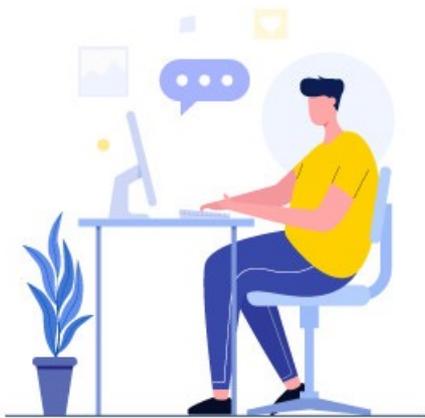
2. Predicting public opinions

[Suh et al., ACL'25; Jahanparast et al., under review]

- We fine-tune LLMs on survey data to predict demographic group-specific opinions
- We show that fine-tuning outperforms prompting by ~50% and improvements generalize to unseen questions & groups
- Probing LLM activations reveals that LLMs have more knowledge of opinions than their outputs reveal



Simulating behaviors with LLMs



3. Simulating human-AI chats

- Simulating human users of AI chatbots
- Goal: 1) interactive evaluation of AI chatbots, 2) training AI models to support humans
- [**Chang** et al., ACL'25] The gap from static benchmarks to interactive evaluation
- Ongoing work
 - Measuring political bias in AI chatbots
 - Evaluating AI chatbot mental health risks
 - Training AI models on user simulators

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My job market experience

- Went on the job market 2023-2024 (final year of my PhD)
- Interviewed with computer science, information science, and business school departments
- My job talk is online: <https://www.youtube.com/watch?v=v0XUtKtXwns>
- Framed as intersection of human networks & high-stakes decision-making
 - 1) How to infer missing networks
 - 2) Modeling processes + policy decisions over networks
 - 3) How human networks change in response to policies
- Running example of mobility networks & pandemic response

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