UCLA Mobility Lab

CENTER OF EXCELLENCE
on New Mobility and Automated Vehicles

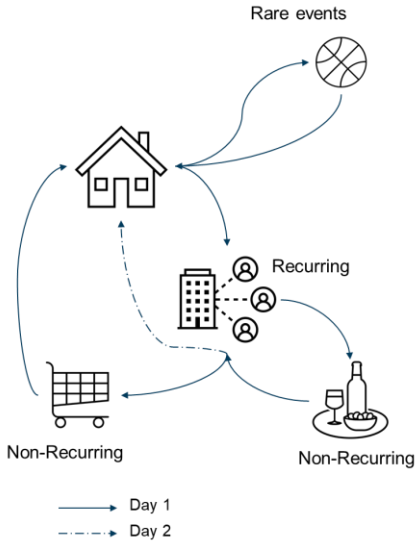
AI for Travel Demand and Mobility Pattern Generation

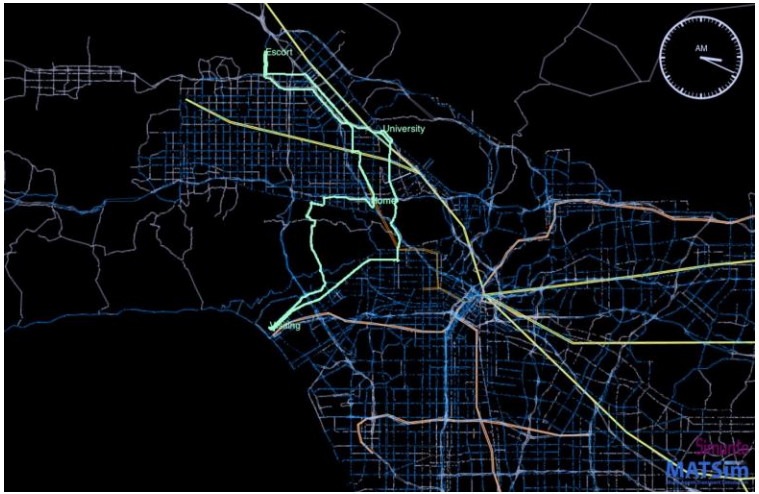
Jiaqi Ma
Professor, CEE and CS, UCLA Samueli School of Engineering
Director, FHWA/UCLA Mobility Center of Excellence

Presentation at AMPO Conference 2026
4/22/2026

Activities and Travel

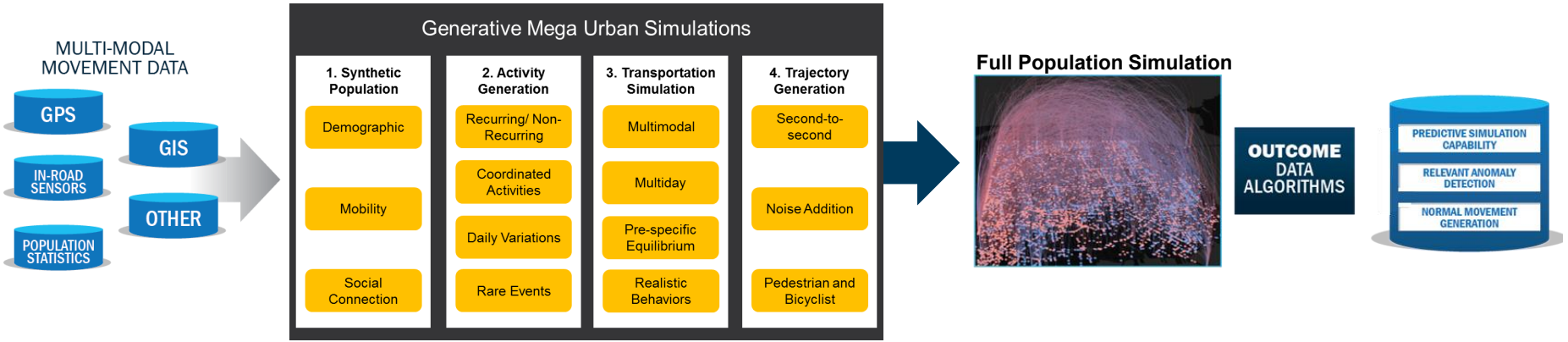
- Combination of data-driven algorithms and **top-down** models of human behaviors to create models of normal activities and contextual influence.
- Four-Layer of modeling pipeline
  - Population
  - Activity
  - Simulation
  - Trajectory





AI Agents: Deep Activity Model

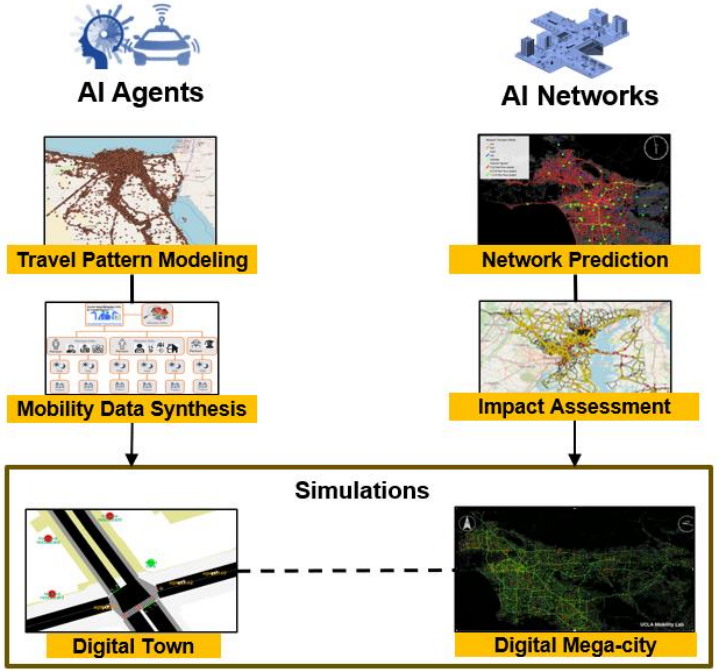
[Motivation] Model city mobility pattern to improve urban planning, mobility optimization, public safety



Human Mobility Patterns describe who does what, where, when, and how

Mobility System DT: AI Agents and Networks

[Definition] Mobility AI Agents are the digital human beings and vehicles, and mobility AI Networks are the digital the transportation networks in the Mobility System Digital Twin framework



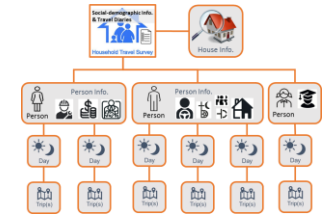
a) **AI Agents** make autonomous, real-time decisions based on environmental conditions and develop individual preferences.

b) **AI Networks** provide system condition insights and overcome the data and computation limit.

c) AI agents and the AI network mutually influence each other; agent behavior depends on network conditions, while collective behavior shapes those conditions.

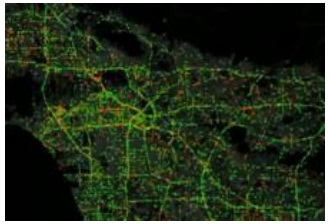
AI Agents: Deep Activity Model

[Research Goal] Build scalable and transferable generative models for mobility trajectory synthesis
[Societal Impact] Enhance urban planning, mobility optimization, public safety, and AI research

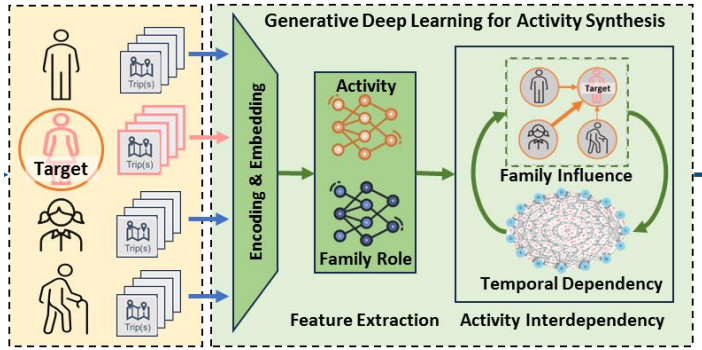


Household Data and Travel Trips

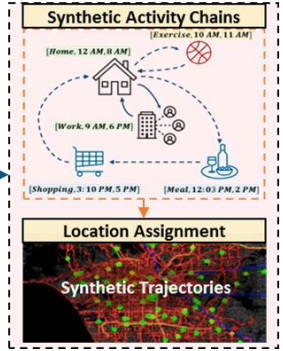
Activity Chain
$[Home, 12\ AM, 8\ AM]$,
$[Work, 9\ AM, 5\ PM]$,
$[Shopping, 5{:}30\ PM, 6\ PM]$,
$[Home, 6{:}30\ PM, 11{:}59\ PM]$



Synthetic mobility trajectories



Deep Learning-Based Human Mobility Pattern Modeling



Traffic Demand Generation and Traffic Simulation

Approach

- Implement **generative deep learning** to synthesize human activity chain based on socio-demographics
- Design location assignment algorithm to allocate human activities

Achievement

- Scalable: generate 7m chains in 3 hours
- Transferable: validated in three regions
- Realistic: tested in **large-scale simulation**

Resul

- A 0.997 cosine similarity with ground truth in **origin-destination**
- Mean Absolute Percentage Error of 5.85% for **traffic volume** and 4.36% for **speed**

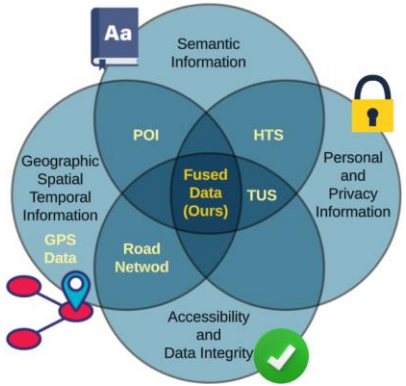
AI Agents: Cross Domain Data Fusion

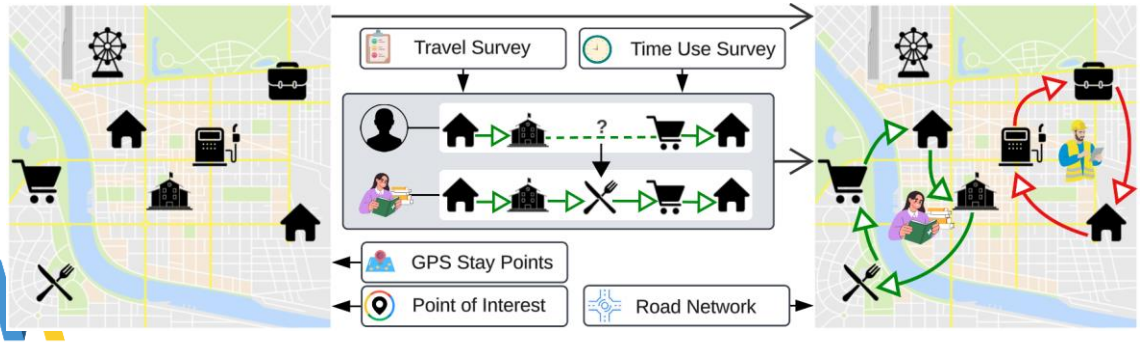
[Research Goal] Learning generic human mobility patterns through cross-domain data fusion
[Societal Impact] Enhance urban planning, mobility optimization, public safety, and AI research

Mobility pattern modeling is limited by data

- Diverse characteristics of data sources
- Limited data accessibility
- Restricted model adaptability across different geographic regions

We need a semantic enrich and unbiased mobility dataset





Approach

- Fuse multi-modal data by mobility pattern learning
- Use LLM for semantic information enrichment
- Develop deep learning with domain adaptation for different region/culture

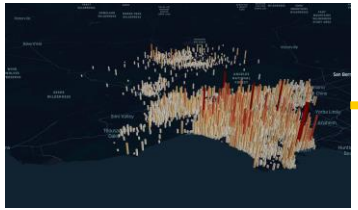
Achievement

- Synthesize mobility dataset for LA, Tokyo, and Egypt
- City-level microscopic simulation

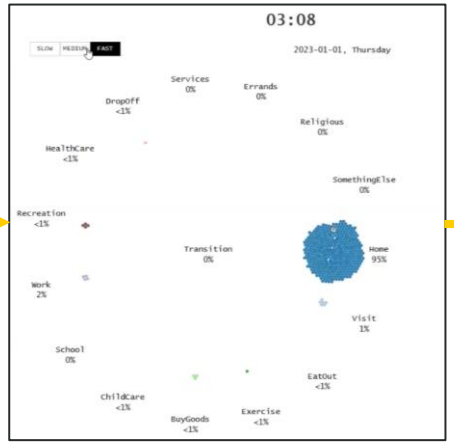
Resul

- The synthetic data supports macroscopic and microscopic simulation, reach the same accuracy as using survey data

AI Agents: Mega City Simulation – Los Angeles

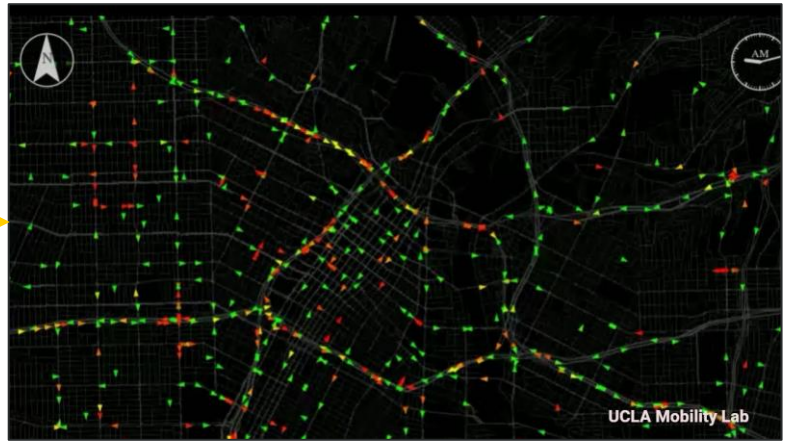


Population of Los Angeles County



Sample agent daily activities

Location Assignment

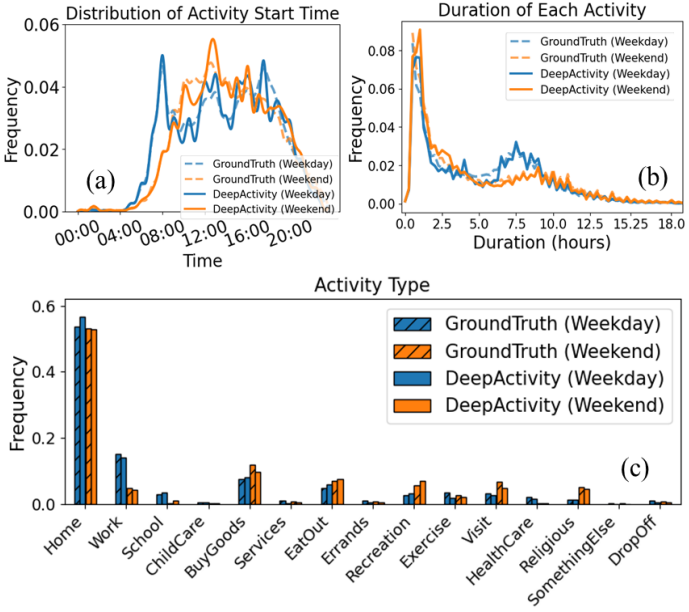


One-million population simulation

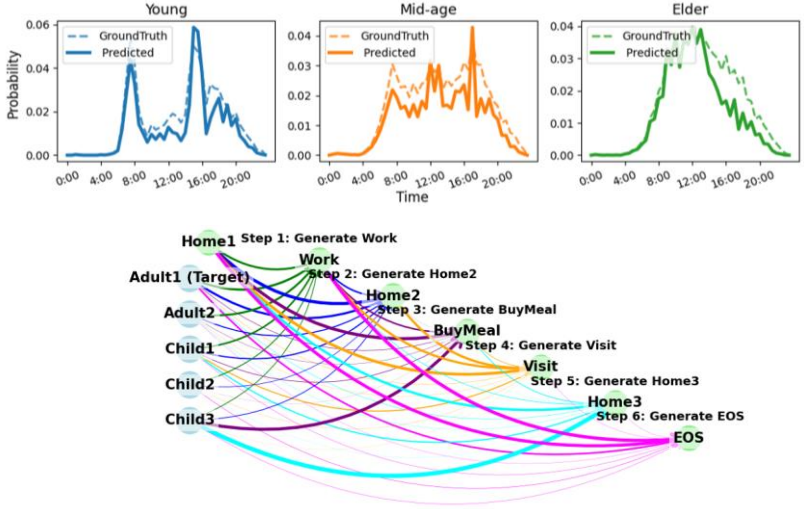
City-wide traffic simulation generates trajectories, facilitated by resident digital twins

AI Agents: Deep Activity Model

Pattern of weekend and weekday



Pattern of different age groups



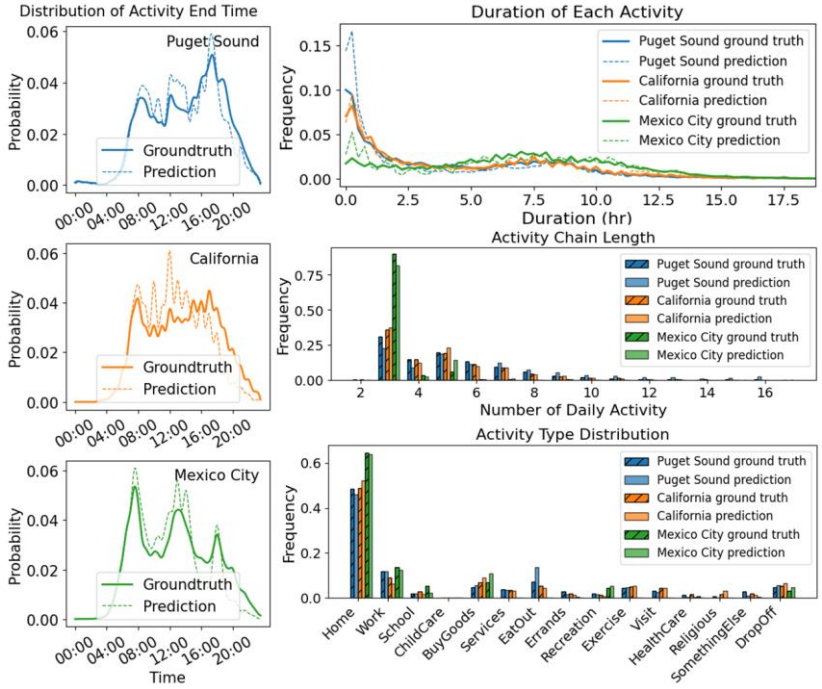
Explainability of the interdependencies among household and activities

Model captures patterns in different contexts and explains the interdependencies

AI Agents: Deep Activity Model

- Model transfer using small dataset for regions and cultures with large pattern deviation
- Test in Los Angeles, Puget Sound (Seattle), and Mexico City, Tokyo, Egypt.

Region	Len.	Start	End	Dur.	Type	EC	F-Norm
California	.004	.013	.033	.002	.007	83.6%	.460
Puget Sound	.030	.009	.051	.010	.012	79.5%	.652
Mexico City	.010	.056	.010	.006	.009	63%	.339



Deep Activity Model is transferable to other regions

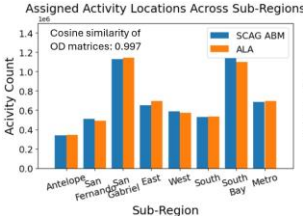
AI Agents: Deep Activity Model

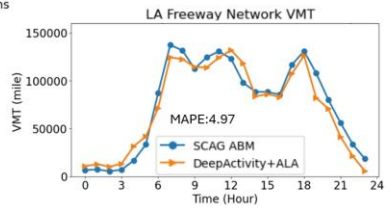
- Each activity is assigned a Traffic Analysis Zone level (e.g., blocks) **location** and load to network for **simulation**
- Result is compared with PeMS data provided by Caltrans (CA DOT) and traditional activity-based model

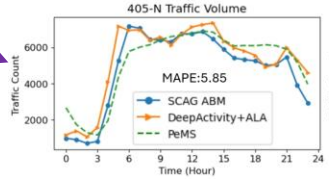
(a) Los Angeles County and 8 Sub-Regions

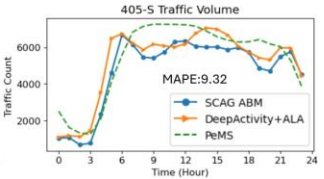
(b) Los Angeles County Freeway Network

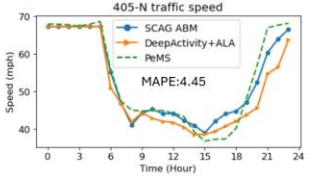

(c) MATSim Simulation Network of LA County

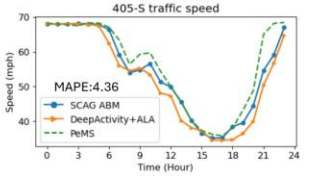












Deep Activity Model generates realistic traffic demand that aligns well with traffic data

The Solution: Actovia

Actovia turns any physical space and its demographics into a simulated world where decisions can be tested before reality pays the price.

Simulation loop

interventions reshape the world

world feedback reshapes choices

LA County: 1M synthetic agents with complete daily activity patterns interaction

Analytics tells you what happened. Actovia tells you what **would** happen.

The Problem

The world runs on decisions about how people will behave.

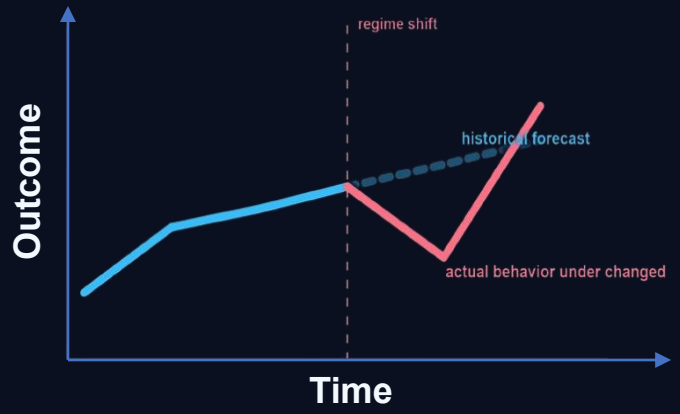
> “If I build 500 housing units here, can nearby schools and grocery stores handle it?”
> Urban Development

> “If 70,000 people leave the stadium tonight, which intersections collapse first?”
> Mega-Events / LA28

> “If this road is under construction for three months, how does daily life get disrupted?”
> Transportation / GovTech

What decision-makers actually need

- Test interventions before deployment
- See deltas, risks, and bottlenecks
- One system for routine and disrupted conditions



What customers get

Decision-ready outputs — not just raw simulation traces

Primary outputs

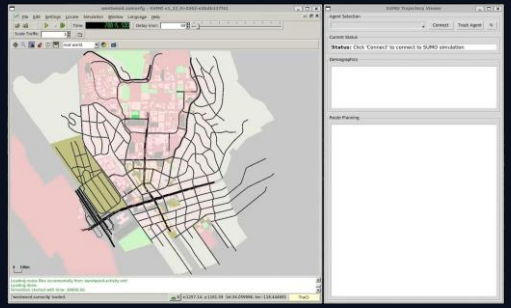
- Scenario deltas vs. baseline
- Drivers of change
- Uncertainty bands & stress tests
- Cohort / segment summaries
- Representative synthetic-agent traces
- Governance-safe published metrics

Optional differential privacy

Decision Studio Views

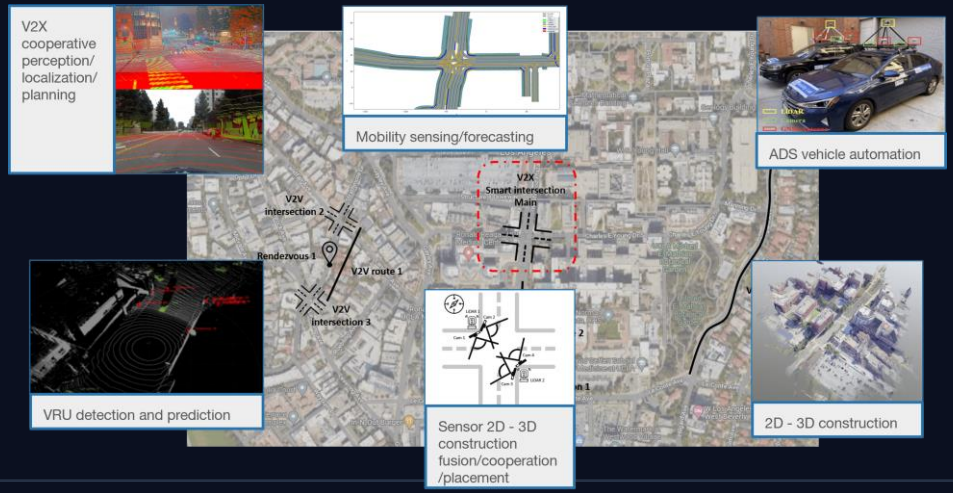
Actovia's World Model: Olympic LA28 Westwood Athletes Village

Network Simulation



Microscopic Simulation

Vehicle/Driving Simulator



High-resolution 3D Models

Built, validated, and deployed — not just theorized.

Production-grade technology with government relationships, federal funding, and a live demo environment.

10M+
Synthetic Agents
LA metro area

0.997
OD Validation
vs. PeMS ground truth

6
Cities Validated
LA · Seattle · Mexico City
Cairo · Jordan · Tokyo

3
Federal Programs
ARPA-I · IARPA · FHWA

10+
Top Conference/Journal Published
NeurIPS · CVPR · TITS · AAAI

DIGITAL WESTWOOD — LIVE DEMO ENVIRONMENT

10
V2X Sensor Nodes Deployed
V2XPnP · V2XReal

50k+
LLM-Agumented Virtual Residents
MobiVerse

2
LiDAR Equipped Multifunctional AV
UCLA

Caltrans D7
TDI architecture designed by our team. Phase 1 reference node. LA28 is the forcing function.

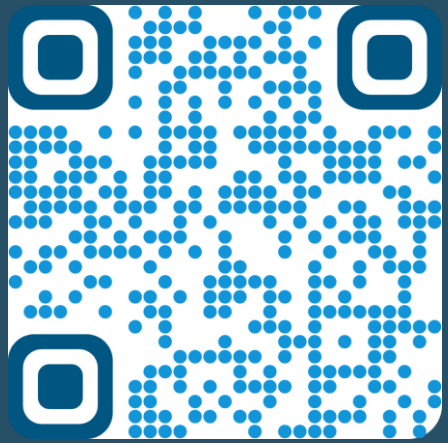
AWS Partnership
LA demo build sponsored on AWS. Solutions Architect support. Multi-service GPU pipeline in progress.

Thank You

Questions?

CENTER OF EXCELLENCE
on New Mobility and Automated Vehicles

Subscribe for Updates:



Contact:

Jiaqi Ma
jiaqima@ucla.edu
(310) 206-3212