Bridging AI and Urban Planning: My Journey Towards Smarter, More Sustainable Cities

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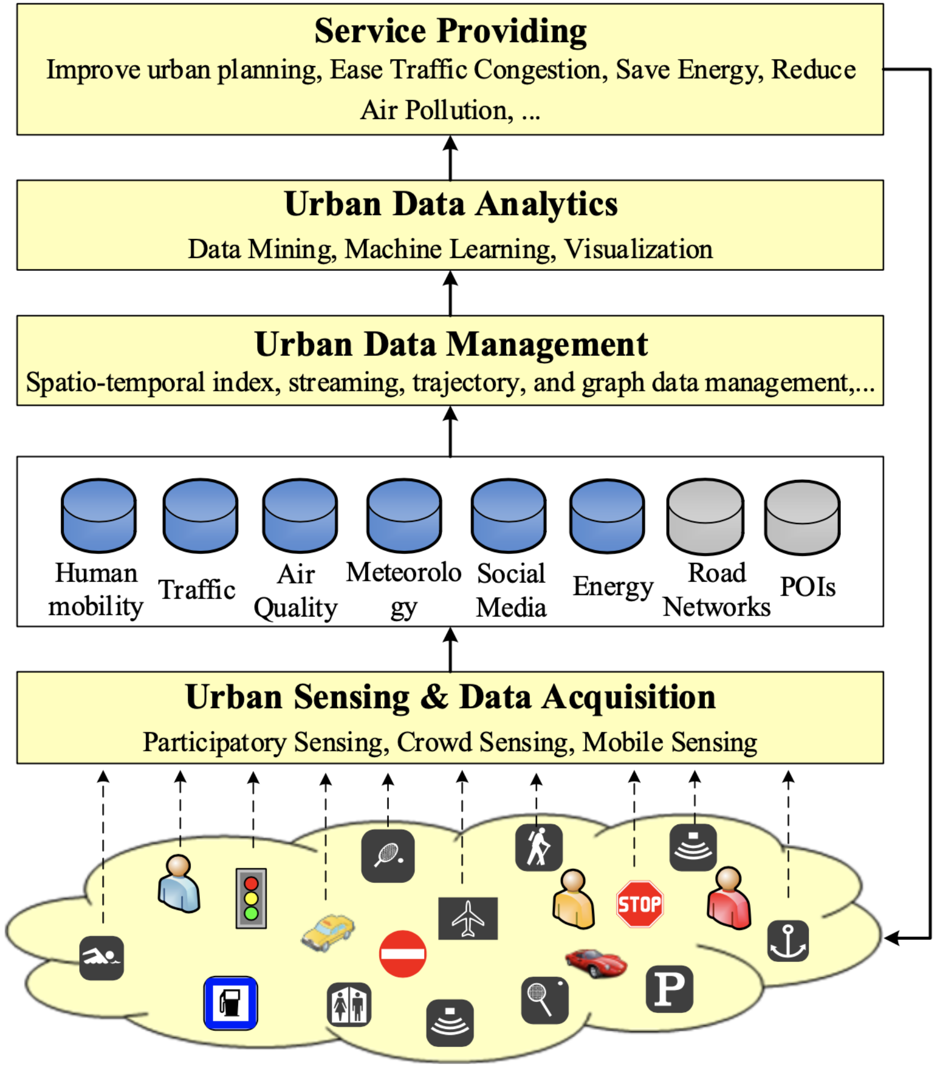
About Me

- **Associate Professor, ASU Fulton Engineering School of Computing and AI**
- **Education**
  - **2004-2008: B.E. from University of Science and Technology of China, Hefei, China**
  - **2008-2011: M.E. from Chinese Academy of Sciences, Beijing, China**
  - **2011-2016: Ph.D. from Rutgers University, NJ, USA**
- **Track Records**
  - **Awards: 2023 US NAE FOE early career engineer, 2021 US NSF CAREER award, 2018 NSF CRII award, five best paper (finalist/runner-up) in SIGSpatial20, ICDM15, 21, 20, KDD18, several university-level awards and industrial awards**
  - **Research: Google Scholar citation: around 7500+, recognized in the Stanford Elsevier 2024 World's Top 2% Scientists**
  - **Grants: 10 grants (including 7 NSF leading PI/site PI core research grants)**
  - **Teaching: 4 PhDs graduated (3 tenure track assistant professors at UMacau, UKansas, Portland State, 1 postdoc at UOxford UK), supervising 6 PhDs, average teaching rating:4.6/5**

Senseable Cities: Sensors, IoTs, Mobile Devices, Location Based Social Networks

Turning Big Data into Urban Intelligence



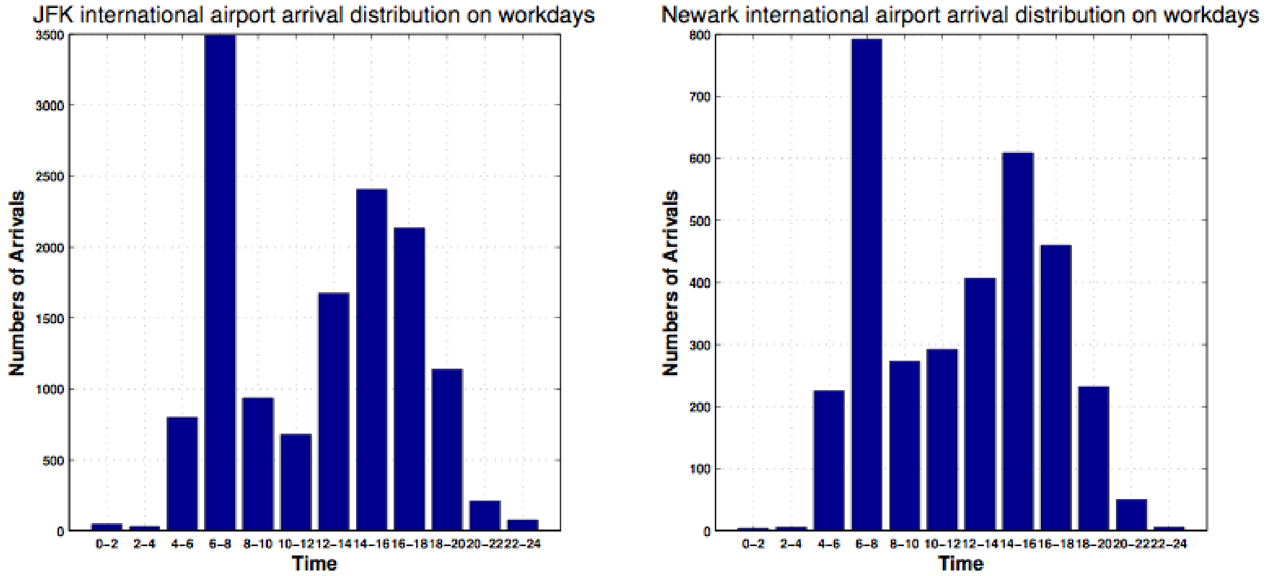
Project: Making Sense of Human Mobility Data

- Multi-source, multi-dimensional, multi-domain, multi-format, semantically-rich, collectively-related human mobility data
  - Devices, e.g., smart phones, smart watches
  - Vehicles, e.g., taxicabs, buses, subways, city bikes
  - Sensors, e.g., GPS, satellite remote sensing
  - Buildings, e.g., banks, shopping malls, restaurants
  - Human in location based services, e.g., Foursquare, Flickr, Tweeter, Facebook, Google+, Yelp

Human Mobility Modeling Research

- **Collective Modeling**
  - Geographic co-location: documents and words
  - Graph structure: dynamic graphs over time
  - Spatial diffusion: stochastic processes
  - Collaborative correlation: tensors and factorization
- **Semantic Augmentation**
  - Trajectories: what (trip purposes), where (destinations), when (trip time), who (out-of-town travelers or local residents)
  - Users: user demographics, profiles, daily activities, preferences, social groups
  - Events: spatiotemporal event detections (e.g., protests, incidents)
  - Regions: important locations, spatial configurations, urban functions
- **Human-Community Interactions**
  - Human-Transportation-Systems interactions
  - Human-Food-Services interactions

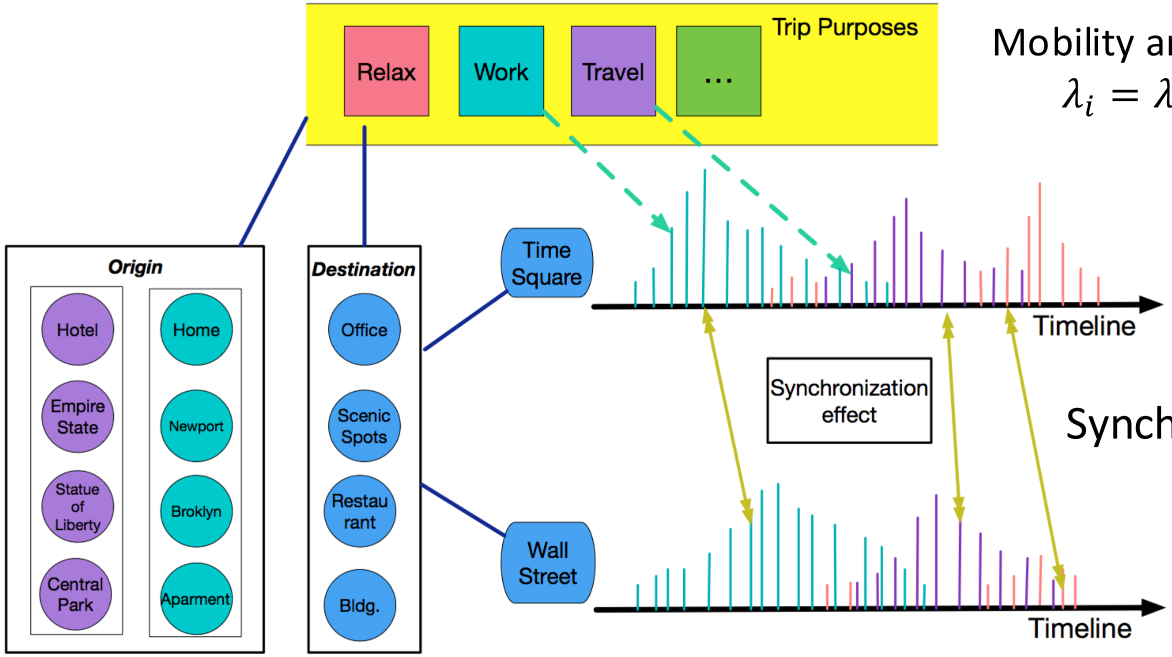
Human Mobility Synchronization and Trip Purpose Detection (ACM SIGKDD 2017)



- Taxi arrival distributions of JFK Airport and Newark Airport
- Two regions show similar arrival patterns in particular time periods if they share similar urban functions

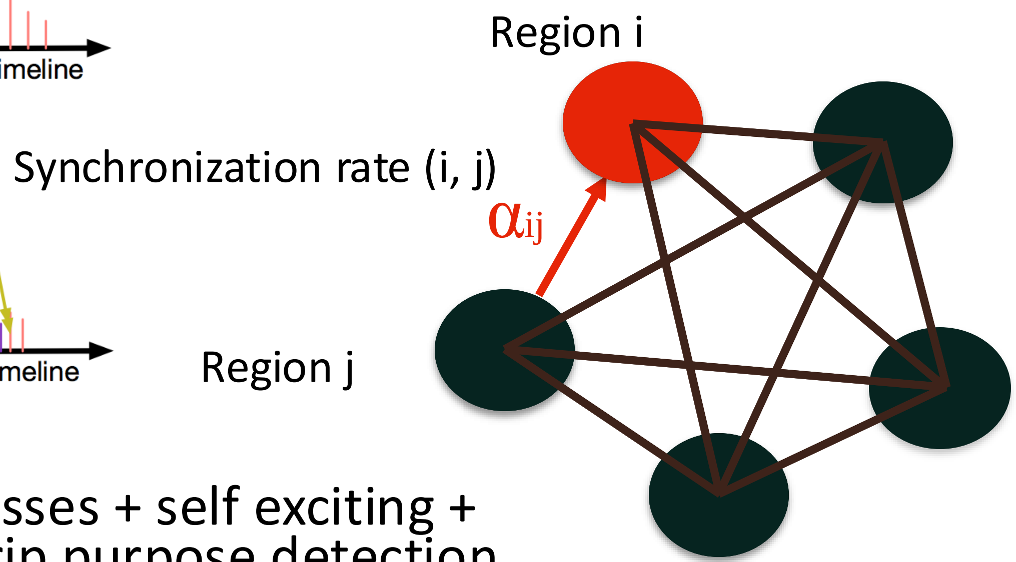
Wang, Pengfei, et al. "Human mobility synchronization and trip purpose detection with mixture of hawkes processes." *Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining*. 2017.

Linking Mobility Arrivals, Urban Functional Regions and Trip Purposes via Synchronized Mixture Hawkes Process



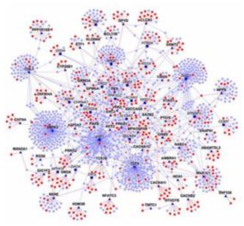
Mobility arrivals observed in the i-th region :

$$\lambda_i = \lambda_{i,eat}(t) + \lambda_{i,work}(t) + \lambda_{i,relax}(t) + \cdots$$

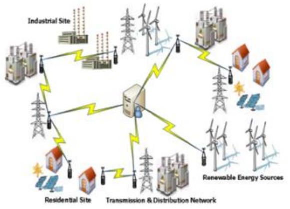


Computing insights: mixture stochastic processes + self exciting + mutual exciting effects = event modeling & trip purpose detection

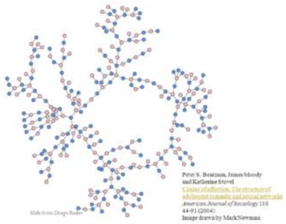
Project: Deep Geospatial Representation Learning for Region Characterization, Mobile User Profiling, Driving Behavior Analysis



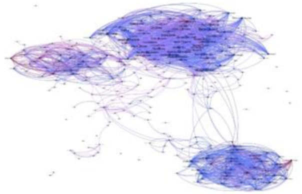
Protein-protein interaction networks



Power grid networks

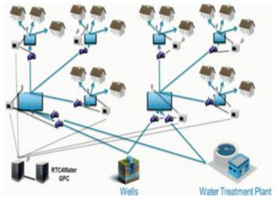


Dating networks

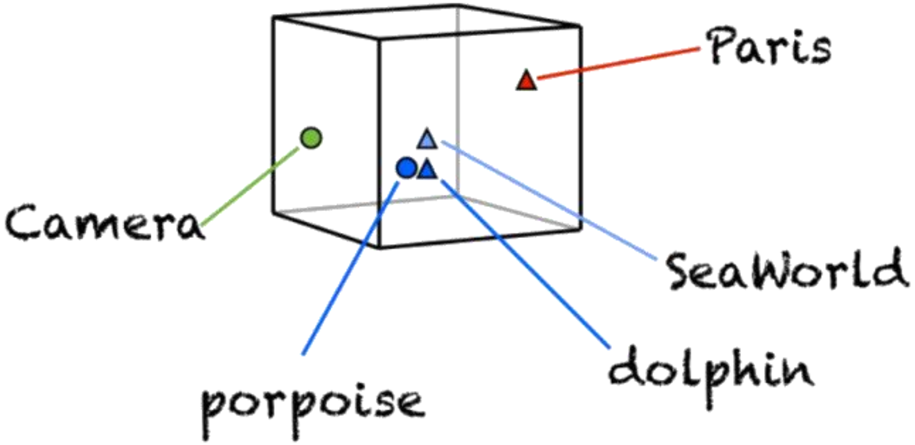


Facebook friends' networks

Retail networks



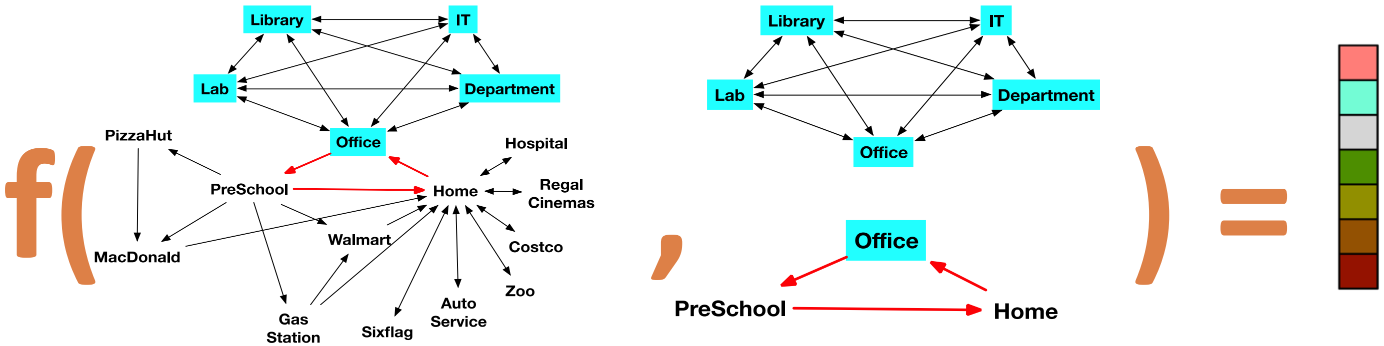
Water distribution networks



Representation Learning: mapping a spatial object to a vector for computing distances and performing machine learning

Graduated PhD: Dr. Pengyang Wang, a tenure-track assistant professor in University of Macau

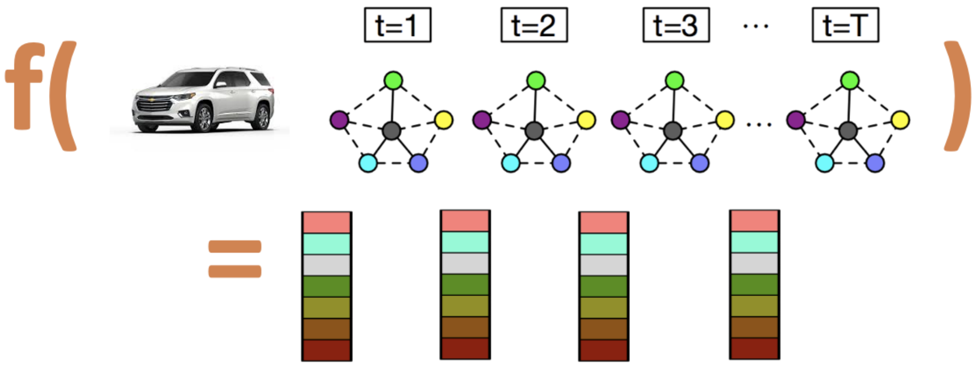
Structure-aware, Collective, Dynamic Geospatial Representation



Global Structure Patterns Substructure Patterns Representations

1) Structure-aware spatial representation learning for mobile user activity profiling and next visit prediction

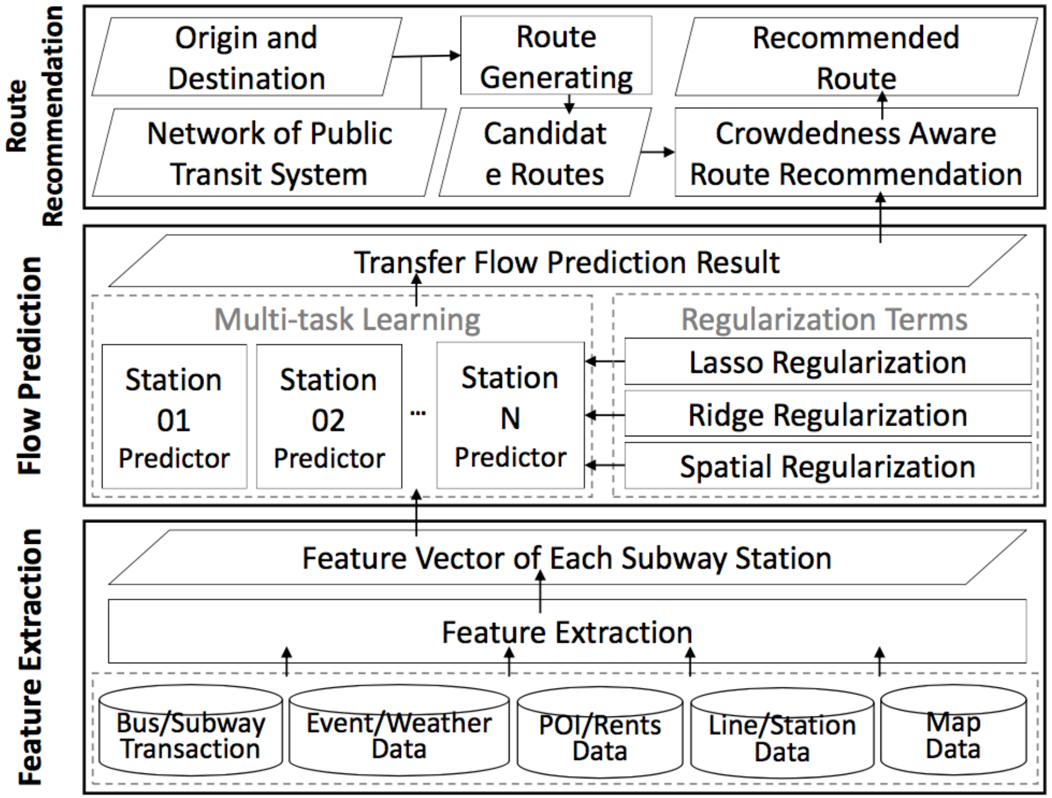
2) Collective spatial representation learning for region profiling and characterization



3) Dynamic spatial representation learning for risky driver detection

Project: Transportation, Mobility, and Crowdedness-aware Routing

- Time cost based routing or comfort based routing?
- Take the spatial temporal unbalance of passenger flow into account

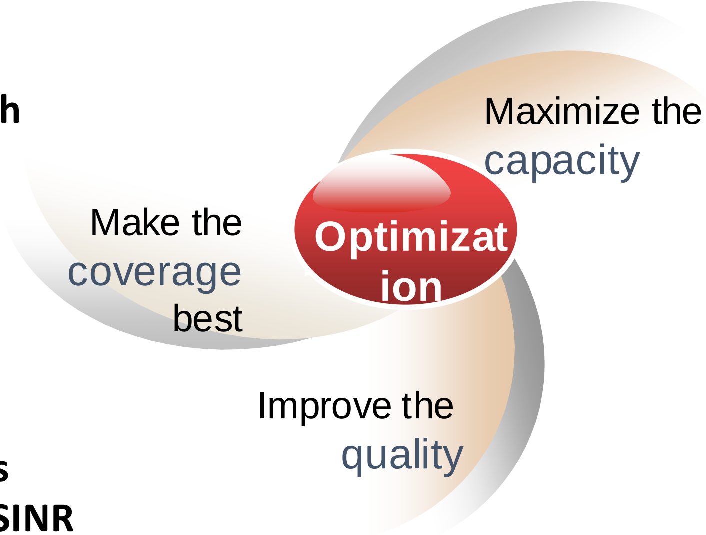


Project: Leveraging Human Mobility Modeling for Self-Optimizing Mobile Network Planning

Coverage:
1, Horizontal Azimuth
2, Vertical Tilt

Capacity:
1, Pilot Power

Quality
1, network resources such as bandwidth, SINR



- ❖ Optimize the coverage, capacity and quality of networks using the data from network monitoring (devices), human mobility (physical), and social networks data streams (cyber)
- ❖ Decision rule based methods (white box) and reinforcement learning (black box)

Project: Site Selection for Planning Gas and Bike Stations

Gas Refilling Event Detection and Gas Station Site Selection (DASFAA16)

Niu, Hongting, et al. "Exploiting human mobility patterns for gas station site selection." *Database Systems for Advanced Applications: 21st International Conference, DASFAA 2016, Dallas, TX, USA, April 16-19, 2016, Proceedings, Part I 21*. Springer International Publishing, 2016.

Bike Station Site Selection and Rebalancing (ICDM15)

Liu, Jingyuan, et al. "Station site optimization in bike sharing systems." *2015 IEEE international conference on data mining*. IEEE, 2015.

Project: Urban Vibrancy: Measurement

- Spatial characters of vibrant communities:
  - Walkable, Dense, Compact, Diverse, Accessible, Connected, Multiple land uses
- Quantification methods via socio-economic aspects
  - **Willingness to pay**
  - **Diversity and frequency of mobile activities**
  - **Social interaction intensity from social media**
- “III: Understanding Urban Vibrancy: A Geographical Learning Approach Employing Big Crowd-Sourced Geo-Tagged Data”. IIS-1755946. National Science Foundation.

Modeling Locational Insights of Vibrant Communities

Urban Geography **Human Mobility** **Community Vibrancy Rankings**

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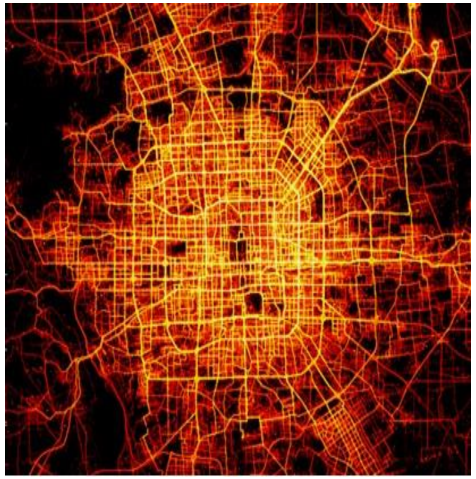
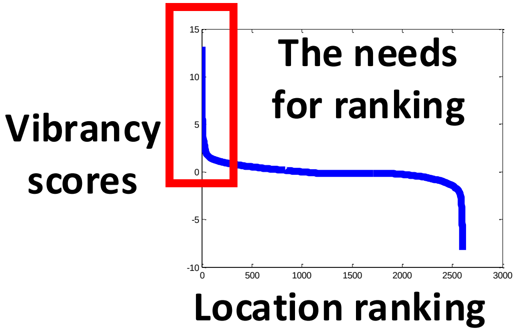
, ) =


- Geographic individual dependency (land-use data)
  - community vibrancy is related to geographic characteristics of its own neighborhood
- Geographic peer dependency (human mobility data)
  - community vibrancy is related to nearby community vibrancy
- Geographic zone/hierarchical dependency (spatial hierarchical structure)
  - community vibrancy is impacted by the vibrancy of its associated region/area

Project: Profiling Mixed Land-uses of Urban Communities

The composition of community functions

Office

Retail

Education

Transportation

Light industry

Government agencies

Residential

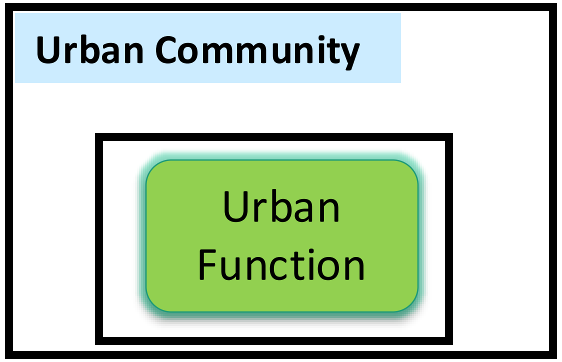
Entertainment

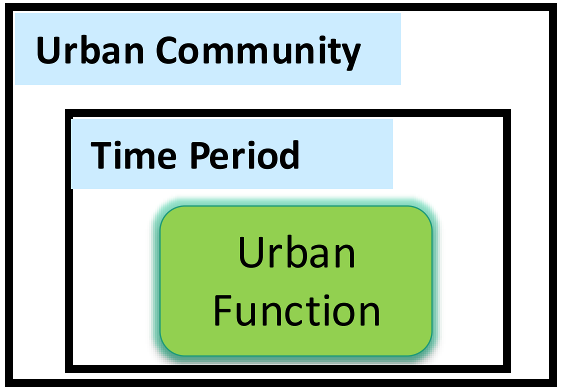
Finance and banking

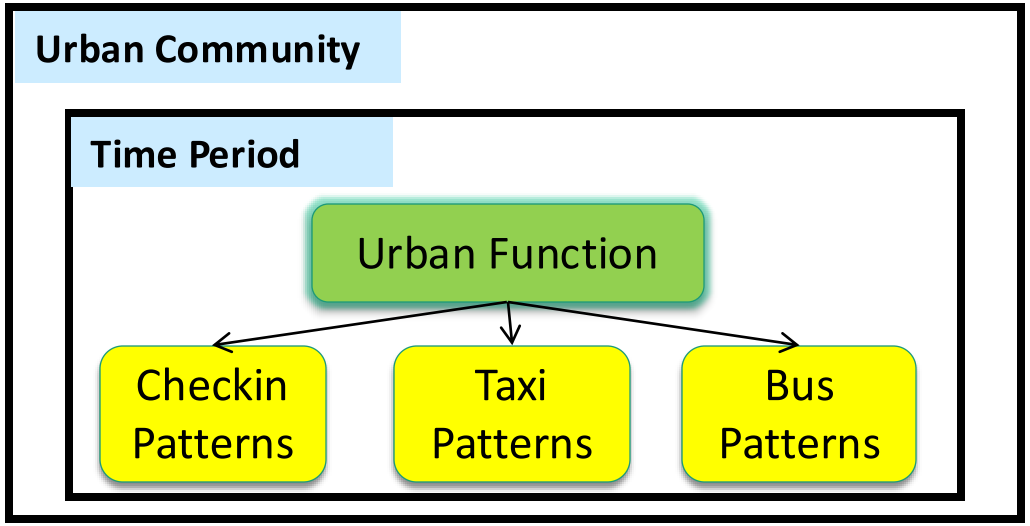
Heavy industry

- Which community functions are compatible?
  - Identify compatible urban functions that help increase vibrancy
- What is the composition of these compatible functions?
  - Learn the portfolio of these compatible functions in a community

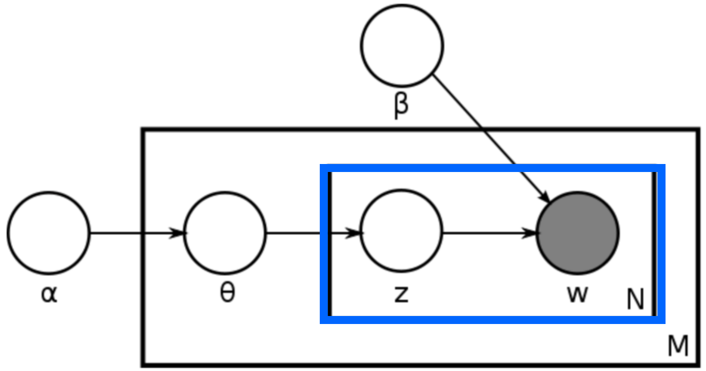
Urban Communities, Urban Functions, Temporal Effect, and Mobility Patterns: Latent Factor Models



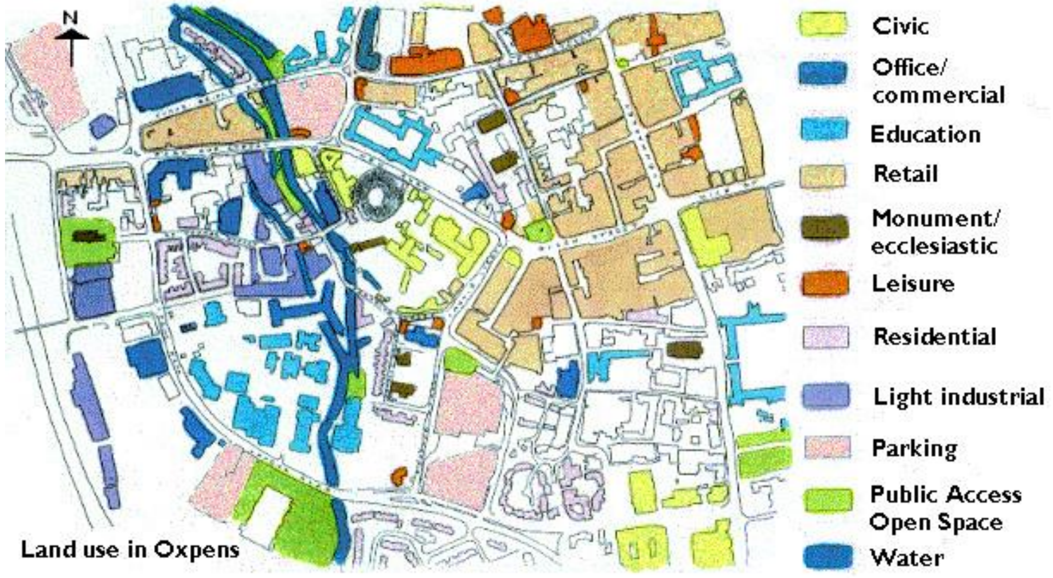




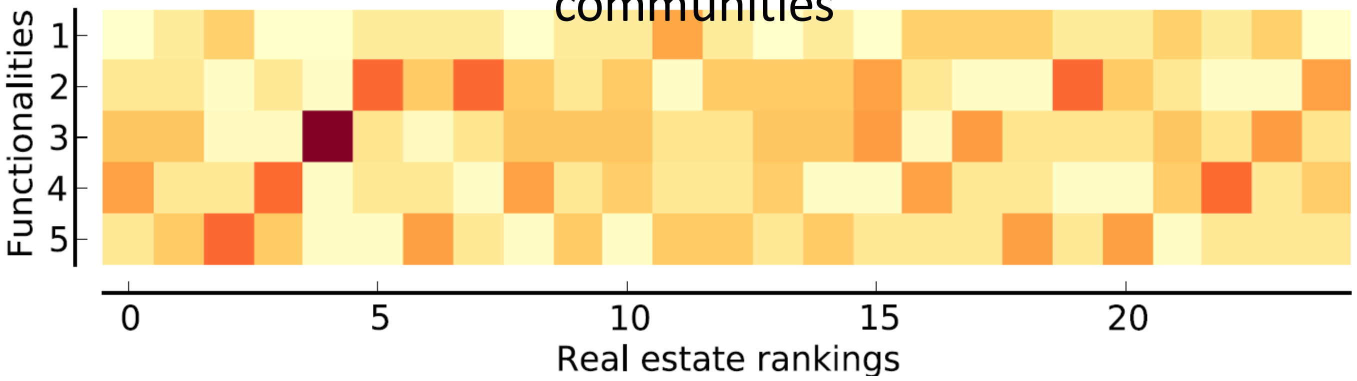
Community-Mobility Patterns	Doc-Words



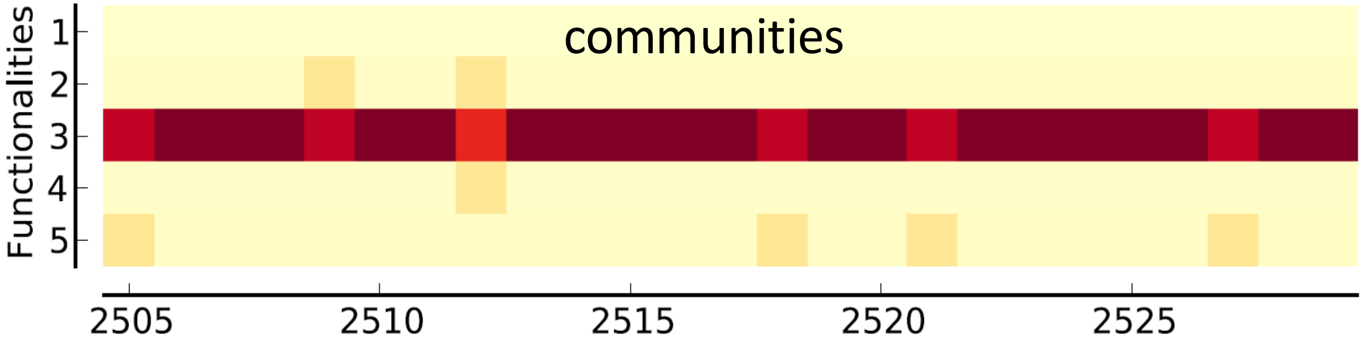
Project: Leveraging Mixed Land-uses and Diversity for Real Estate Value Prediction



The portfolios of urban functions for **high-rated** communities



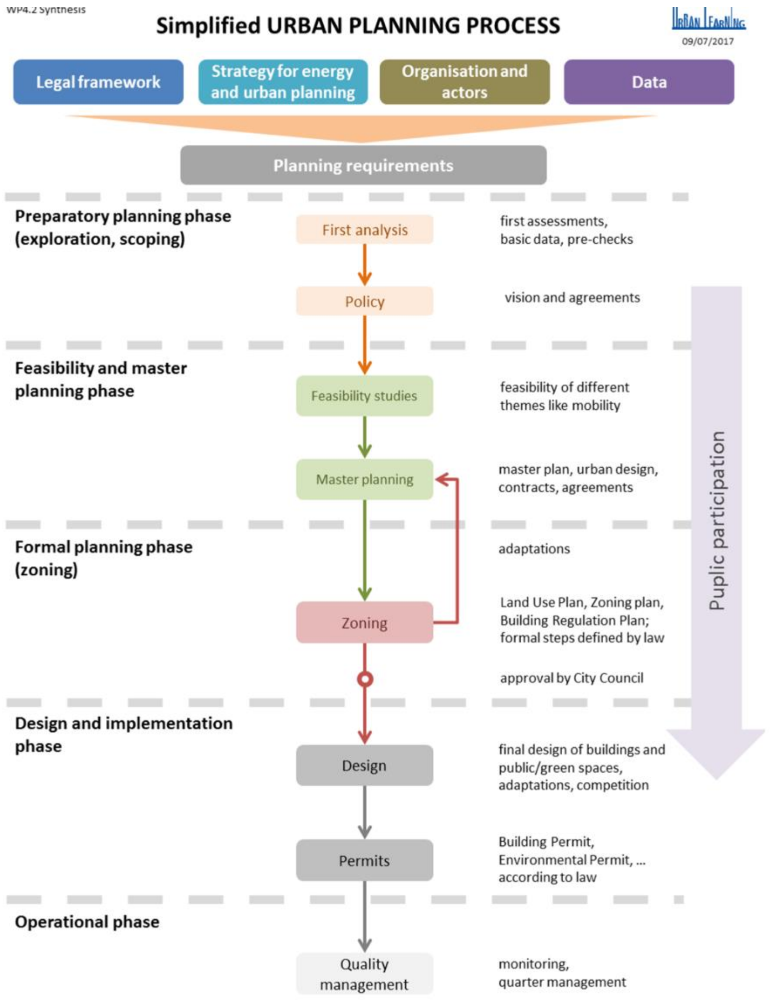
The portfolios of urban functions for **low-rated** communities



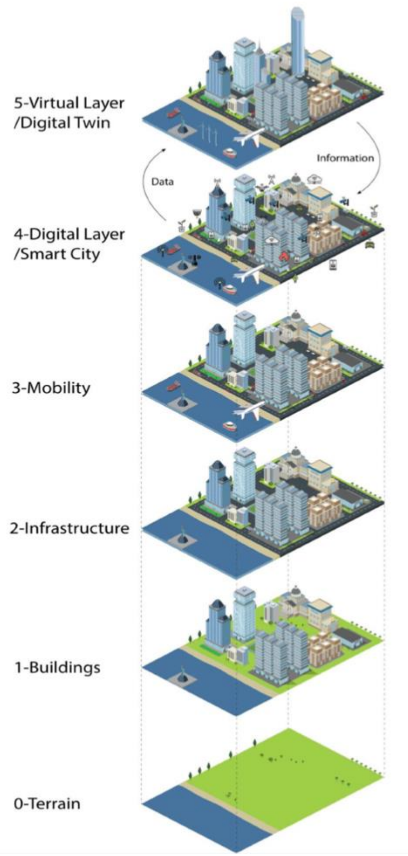
Insight: High-rated locations maximally cover balanced urban functions

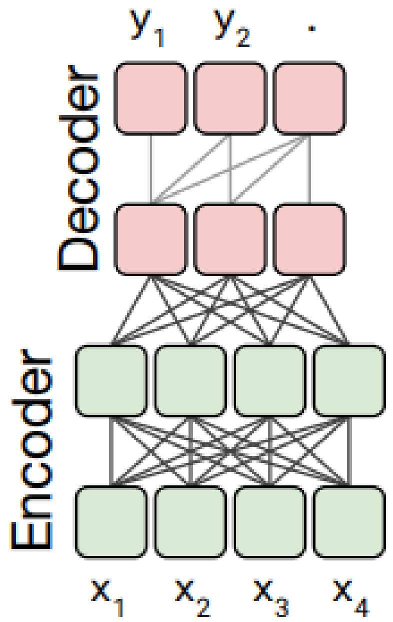
Incorporate **functional diversity** into **list-wise learning to ranking** to enhance real estate ranking

Project: Urban Planning and Generative AI



Source: City of Vienna – MA20 (Hemis)

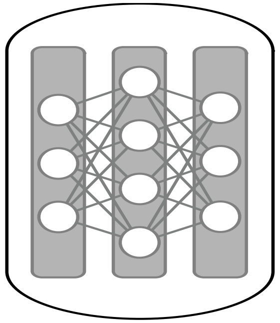




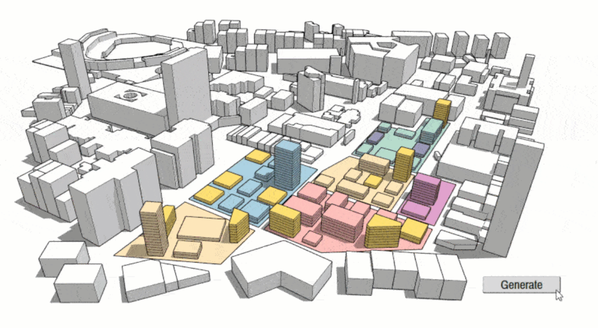
Generative Urban Planning

Human Instructions as Planning Requirements

Given: geographic, mobile, social, economic, environmental, demographics data as planning contexts

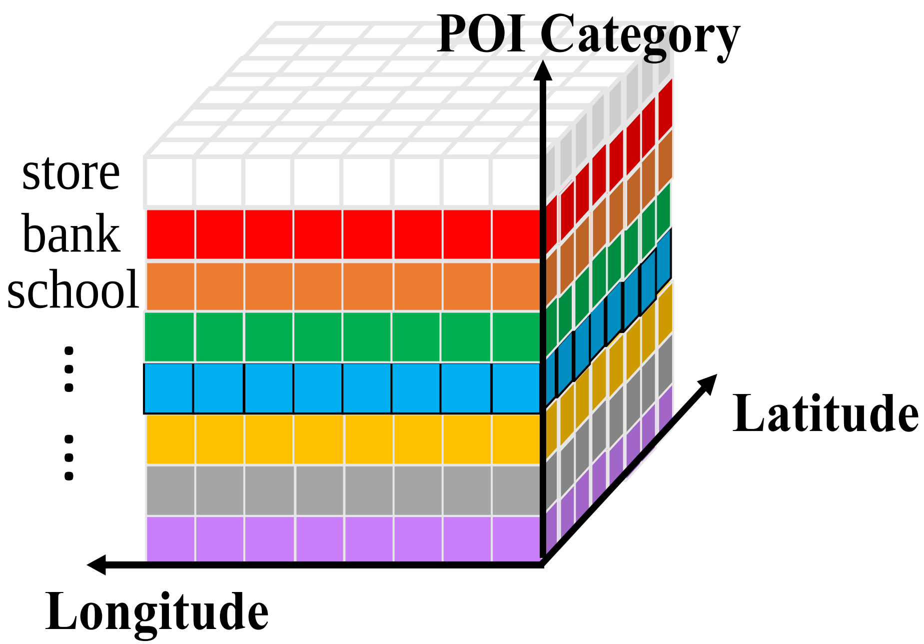


Modeling: generative AI as automated urban planner



Community Configurations: where to put buildings and how many to put?

Land-use Configuration as A Longitude-Latitude-Building Function Tensor



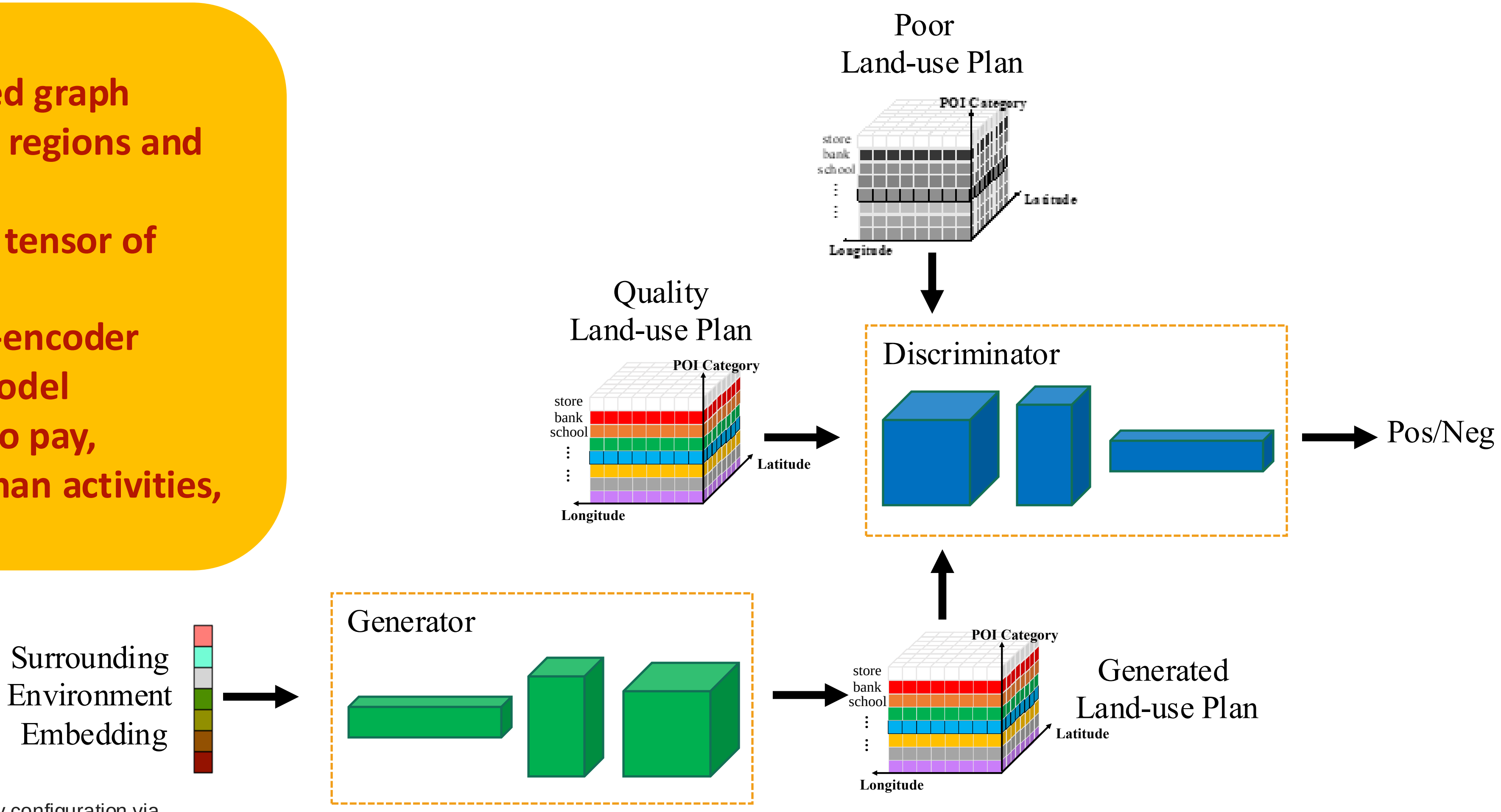
code	POI category	code	POI category
0	road	10	tourist attraction
1	car service	11	real estate
2	car repair	12	government place
3	motorbike service	13	education
4	food service	14	transportation
5	shopping	15	finance
6	daily life service	16	company
7	recreation service	17	road furniture
8	medical service	18	specific address
9	lodging	19	public service

Land use configuration: a tensor of longitude, latitude, POI function category, in which each entry's value is the number of POIs with respect to a POI function category in a specific latitude range and a specific longitude ranges

Generation: Automated Generative Planning via Adversarial Learning (SIGSPATIAL 2020 Best Paper Runner-up)

Computing Insights:

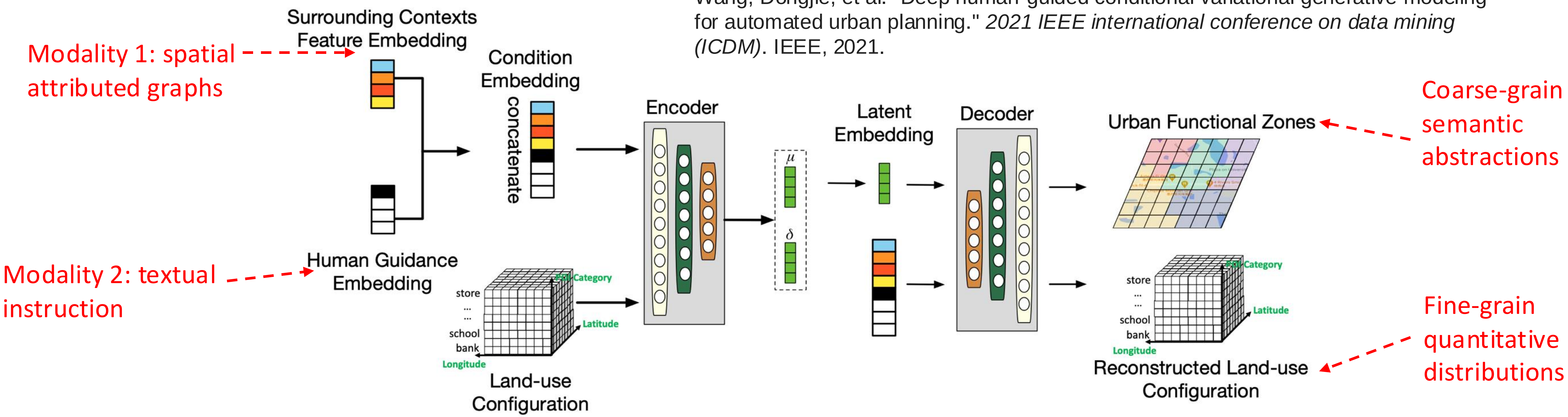
- **A region as a spatial attributed graph augmented with surrounding regions and geographic contexts**
- **A land-use configuration as a tensor of building allocations**
- **The urban planner is a graph-encoder tensor-decoder generative model**
- **Planning scores: willingness to pay, diversity and intensity of human activities, social interaction**



Wang, Dongjie, et al. "Automated urban planning for reimagining city configuration via adversarial learning: quantification, generation, and evaluation." *ACM Transactions on Spatial Algorithms and Systems* 9.1 (2023): 1-24.

Alignment: Deep Human-guided Conditional Variational Generative Modeling (IEEE ICDM 2021 Best Paper Finalist)

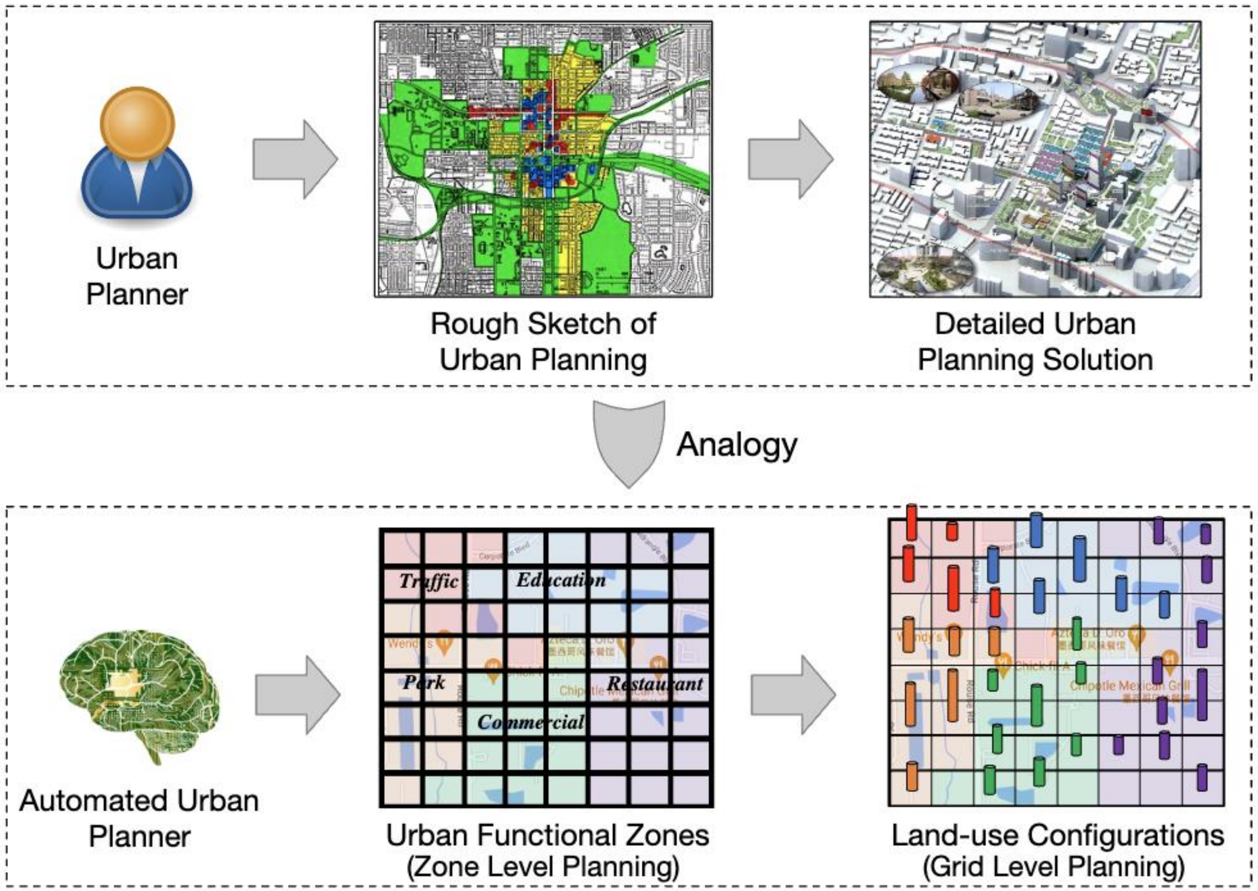
Wang, Dongjie, et al. "Deep human-guided conditional variational generative modeling for automated urban planning." *2021 IEEE international conference on data mining (ICDM)*. IEEE, 2021.



Computing Insights:

- **align planning generation: 1) between human textual guidance and surrounding contexts 2) between zone-level urban functions and grid-level land-use configurations**
- **Textual instructions as generative conditions of deep variational generative autoencoder**
- **Joint generation of zone-level urban function distributions and grid-level POI distributions as alignment**

Hierarchy: Human-instructed Deep Hierarchical Generative Learning (AAAI 2023)

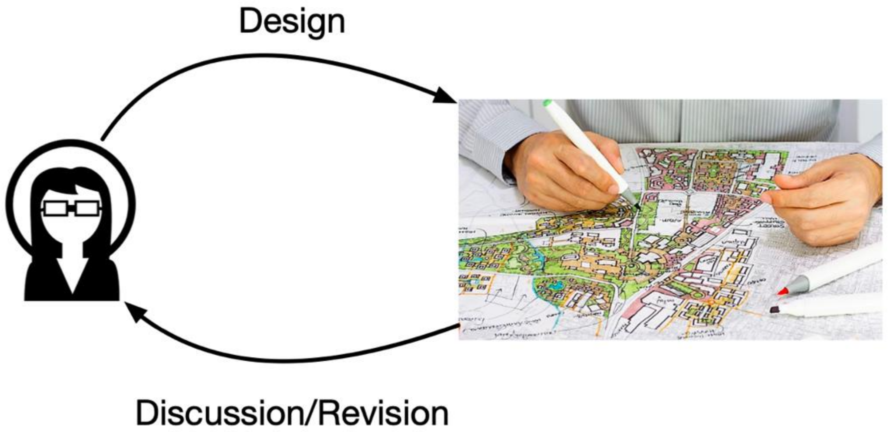


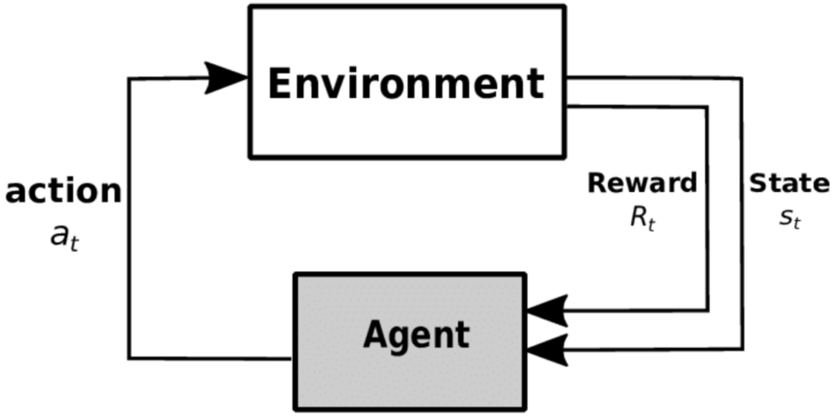
Computing insight: hierarchically generate zone-level planning then generate grid-level planning.

Wang, Dongjie, et al. "Human-instructed deep hierarchical generative learning for automated urban planning." *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 37. No. 4. 2023.

Reinforcement: Urban Planning as Reinforcement Decision Process (SIAM SDM 2023)

Where to allocate buildings?





Update spatial configuration

Reward of allocating buildings

Wang, P., Wang, D., Liu, K., Wang, D., Zhou, Y., Sun, L., & Fu, Y. (2023). Hierarchical Reinforced Urban Planning: Jointly Steering Region and Block Configurations. In Proceedings of the 2023 SIAM International Conference on Data Mining (SDM) (pp. 343-351). Society for Industrial and Applied Mathematics.

Zheng, Y., Lin, Y., Zhao, L. *et al.* Spatial planning of urban communities via deep reinforcement learning. *Nat Comput Sci* **3**, 748–762 (2023). https://doi.org/10.1038/s43588-023-00503-5

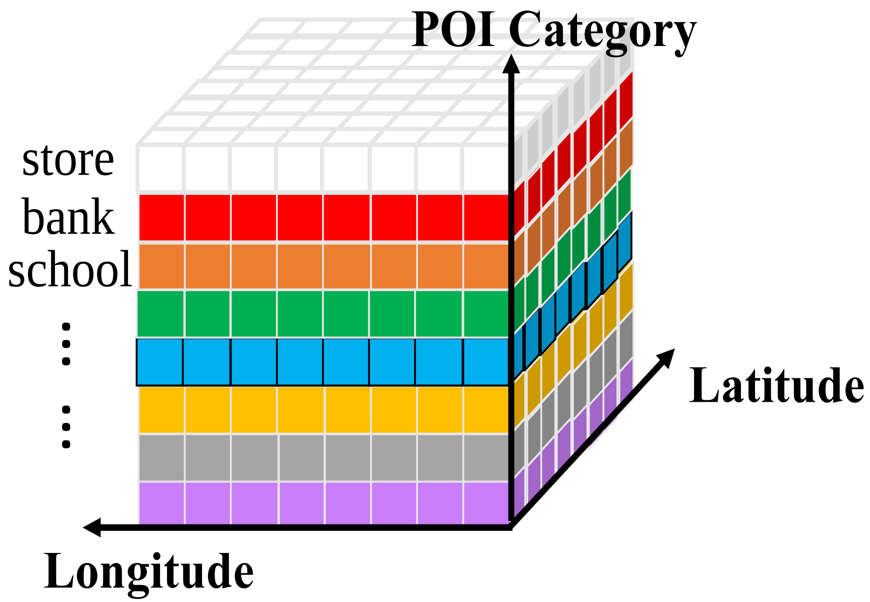
Open Challenges and Research Directions

Compromise, fix one issue but generate another issue

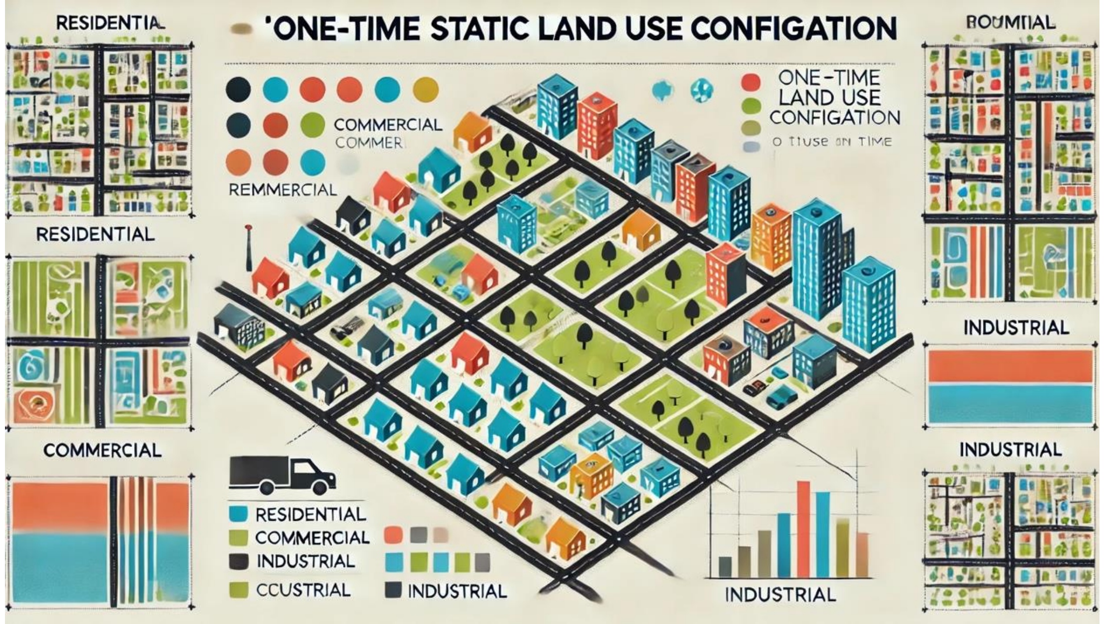
Detecting Real Human Needs for Urban Planning

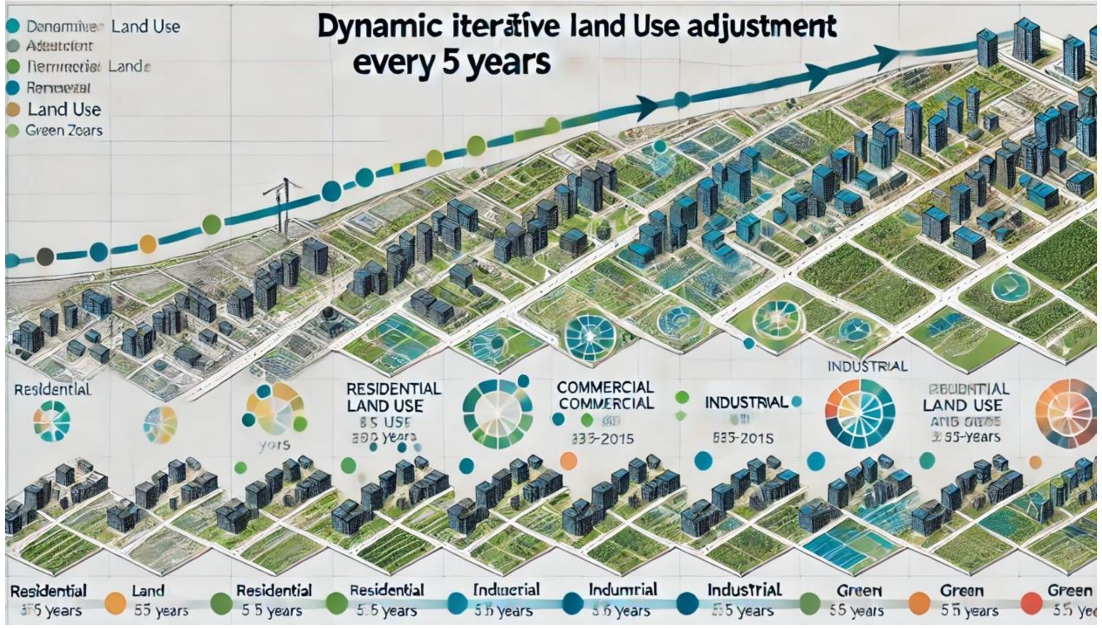
Planning Scope: Generic Global Planning versus Specific Local Planning

- Example: land use configurations versus sidewalk planning



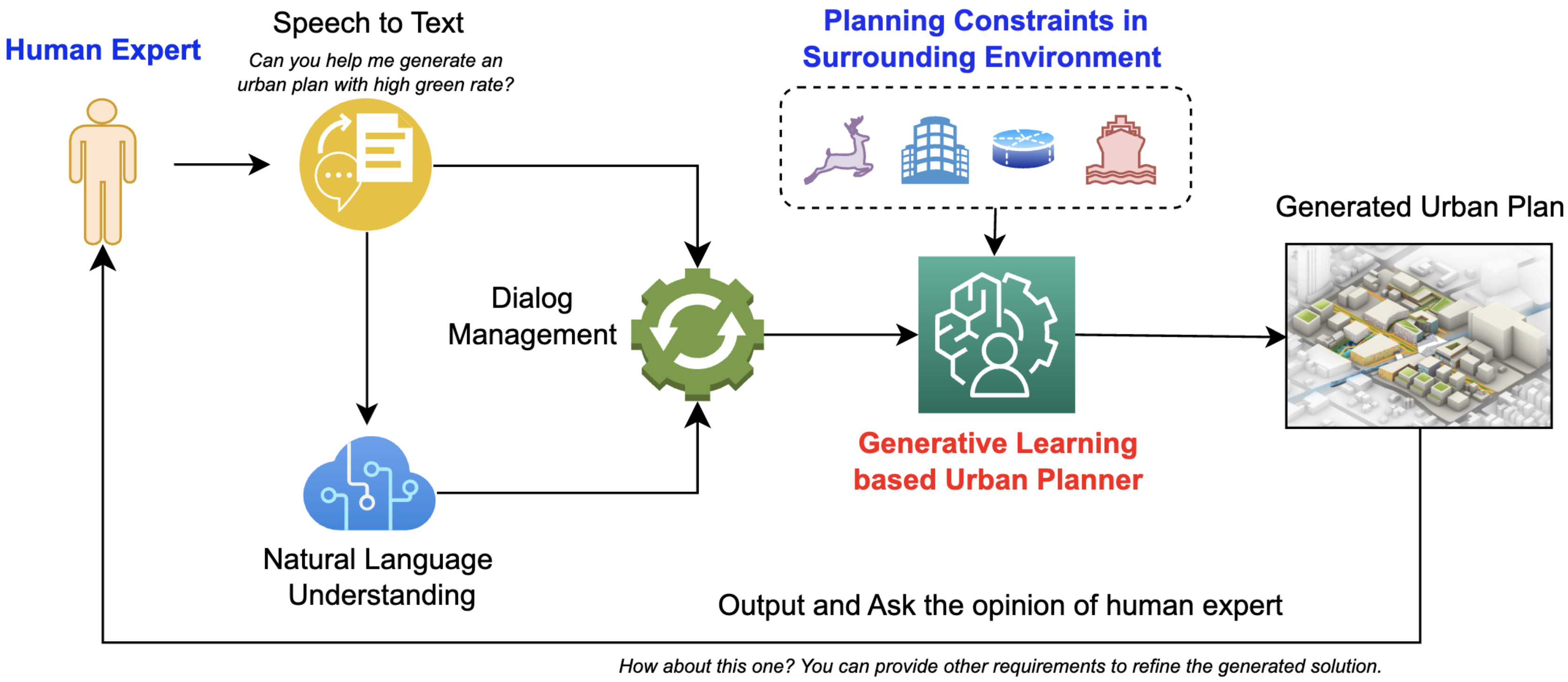
Static or Dynamic: Planning Configuration versus Planning Adjustment





CoDesign: Human-Machine Collaborative Planning

- Conversational generative AI: integrating generative intelligence and human feedback in the loop to collaborative planning



Human value aligned and human-centric urban planning

- Functionality fairness oriented planning
- Mobility and accessibility fairness oriented planning
- Environment and green sustainability oriented planning
- Diverse and intense social interaction oriented planning

Urban Digital Twins: A Close Loop of Simulation, Measurement, Planning Decisions

- It takes a long time to evaluate the social economic impacts of urban planning.
- A loop of simulation-measurement-planning
  - **Simulation**: simulate how a spatial configuration can impact the geospatial, mobility, human, social data of a place
  - **Measurement**: quantify sustainability, accessibility, vibrancy, happiness, safety, resilience with simulated data
  - **Planning decisions**: measurements as optimization feedback to learn decision policy networks of urban planning

LLM and Agentic AI for Urban Planning

Leveraging the representation, alignment, cross-modality generation, understanding, reasoning, planning, grounding, tasking abilities of LLMs over vision-text-tabular modalities

Thank You.

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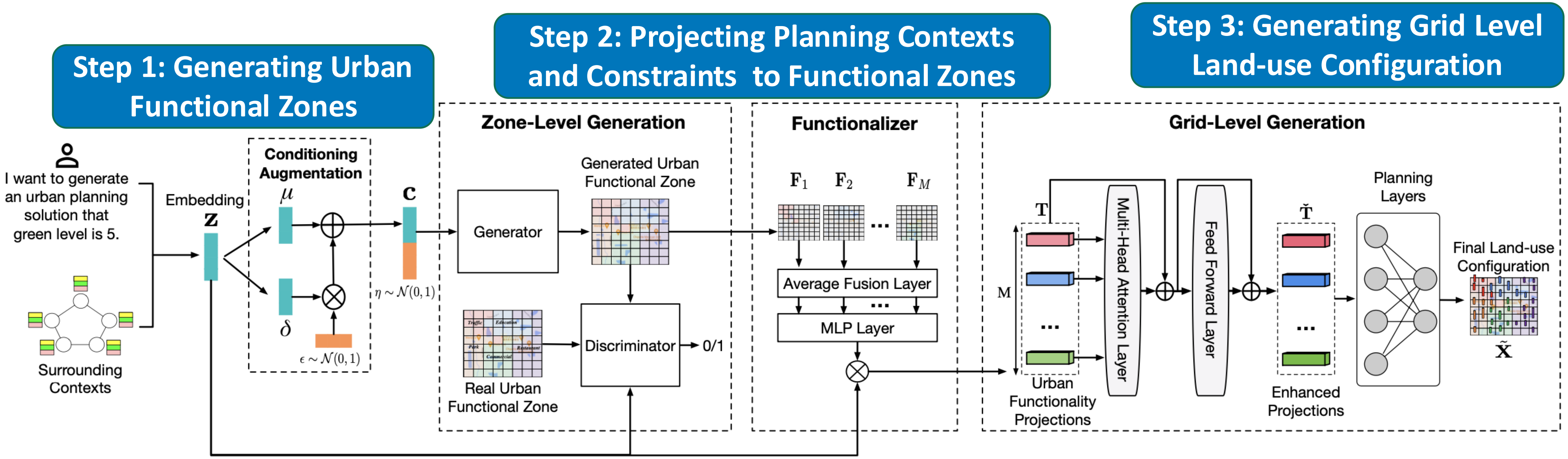
Deep Hierarchical Generative Planning: from planning functional zones to planning landuse configuration



Computing Insights:

- Spatial hierarchy to steer generation from functional zones to grid configurations
- Different planning requirements have different attentions (projections) to urban functionalities
- Functionalizer by neural selection, memory, forget to project planning requirements to zones of different functionalities

Urban Digital Twins: A Close Loop of Simulation, Measurement, Planning

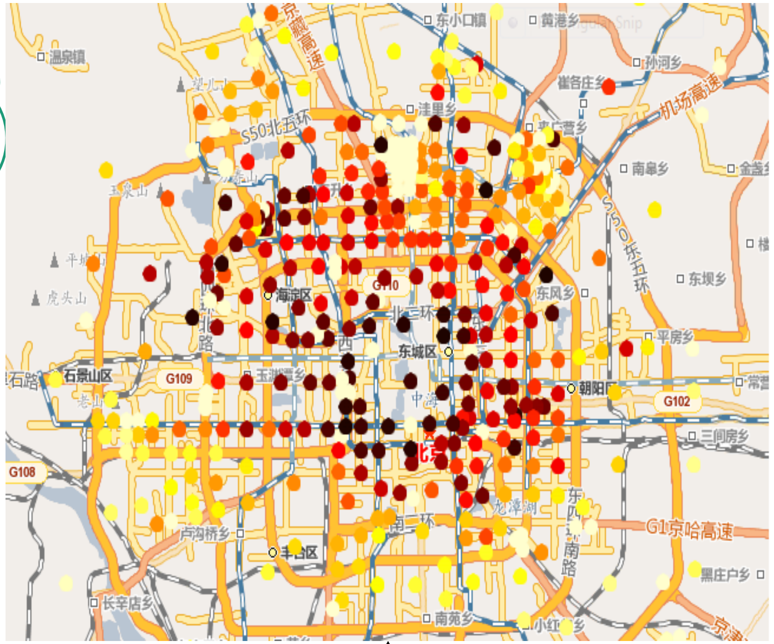
- Delayed Effects of Urban Planning
  - It takes a long time to observe how can urban planning change the social, economic, human factors of a community.
- Potential Direction: **interactive simulation-measurement-decision** for evaluating the effectiveness of urban planning
  - Using urban simulator to simulate the geospatial, mobility, human, social data of a place conditional on an urban planning
  - Measure the sustainability, accessibility, vibrancy, happiness, safety, resilience, etc. of a community with simulated data
  - Leverage measurements to provide optimization feedback to adjust urban planning for better intervention

The AI Task: Unsupervised Extraction of Compatible Urban Functions and Portfolios

- **Given**
  - Residential complexes with locations and historical prices
  - Urban geography (e.g., POIs, road networks)
  - Human mobility (e.g., taxi, bus, checkin)
  - Customer reviews of business venues
- **Objective**
  - Identify **compatible community functions** and **their corresponding portfolios** for each residential complex

How Land-use/Urban Function Diversity Impacts Community Values?

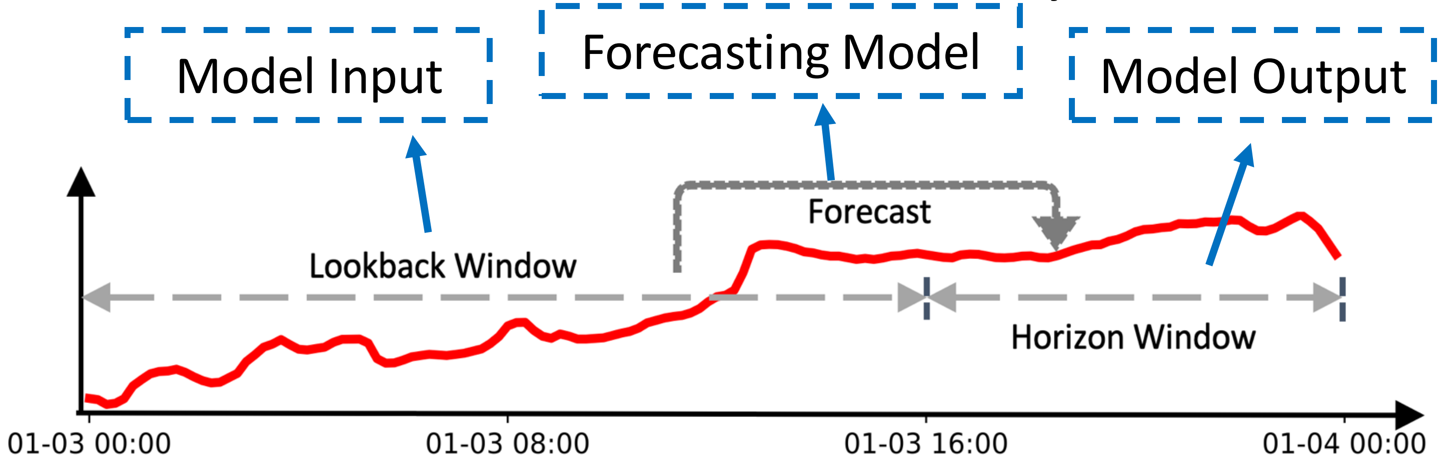
High-rated complex?

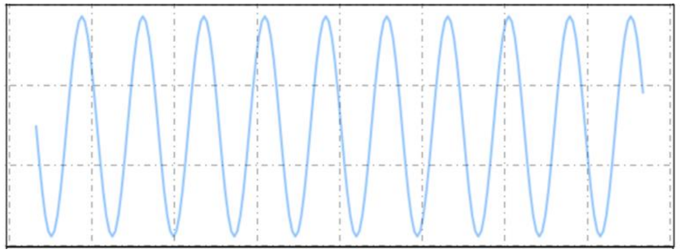


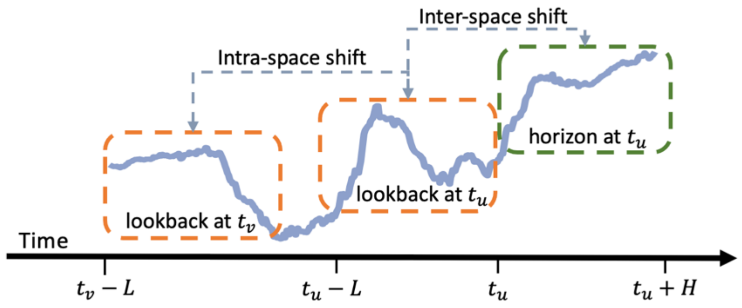
Housing Price Rating ⟷ Location ⟷ Mixed Land Use

Project 3: Deep Time Series Learning: forecasting, distribution shift, event detection, causality

- **Time Series Distribution Regularity**
  - *Periodic Time Series via **Learning** Data Distributions*
  - -- **Distribution Extraction** with Expansion Learning
- **Time Series Distribution Shift**
  - *Shifted Time Series via **Manipulating** Data Distributions*
  - -- **Distribution Scaling** with Time Series Norm-Denorm
  - **Distribution Transformation** with Time Series Normalizing Flow
- Multimodal Time Series Foundation, Alignment, Representation Models
- Time Series Casual Graph Learning







Graduated PhD: Dr. Wei Fan, a post doc at University of Oxford (time series for healthcare)