

UrbanLLaVA: A Multi-modal Large Language Model for Urban Intelligence



Arxiv

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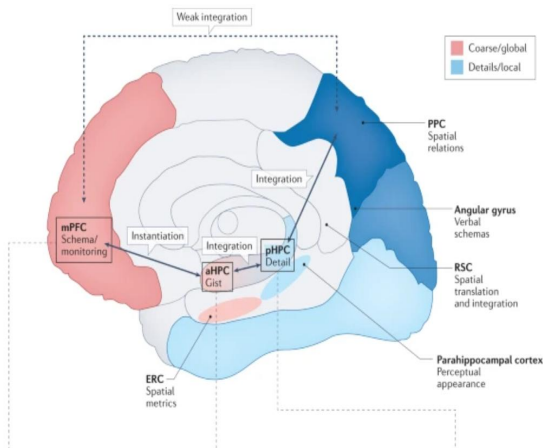
Github

Spatial Intelligence

- **Spatial Intelligence**—the capacity to understand, reason, and act on spatial information—is the foundation of embodied AI and a key prerequisite for AGI.



- **Spatial Intelligence is also for Cognitive Science, Urban Science, Complex Systems, Earth Science**



Spatial Intelligence → Urban Intelligence

- General LLMs have significant limitations in spatial knowledge, understanding, and reasoning.

Image

Question

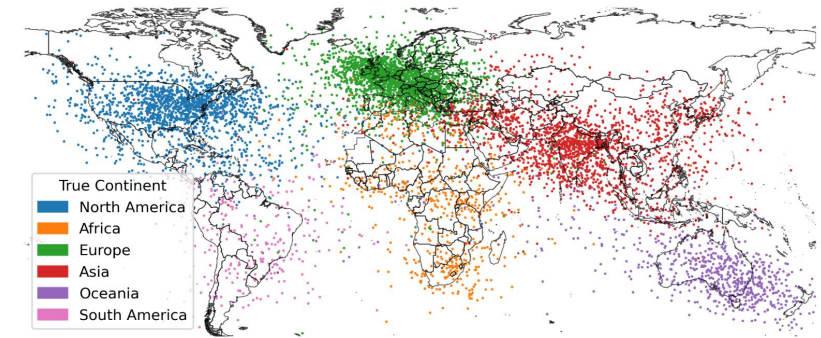
Select from among the four answers given in the bottom line of the picture the cross-section that you would see when the grey cutting plane slices the object. Imagine that you are facing the cutting plane head-on, as if you were looking in a mirror.

Answer: A

Answers

A/C	Qwen2 (VL-72B)	Qwen2 (VL-7B)	B
A/C	InternVL2 (26B)	InternVL2 (8B)	A/B
D	Llama3.2 (90B)	Llama3.2 (11B)	A/D
A/B/C	GPT-4o	GPT-4o (mini)	A/B/C
D	Gemini1.5 (pro)	Gemini1.5 (flash)	A

World Level



Urban Level



Embodied Level

Object Size

What is the length of the longest dimension (length, width, or height) of the refrigerator in centimeters?

Answer: 119

Absolute Distance

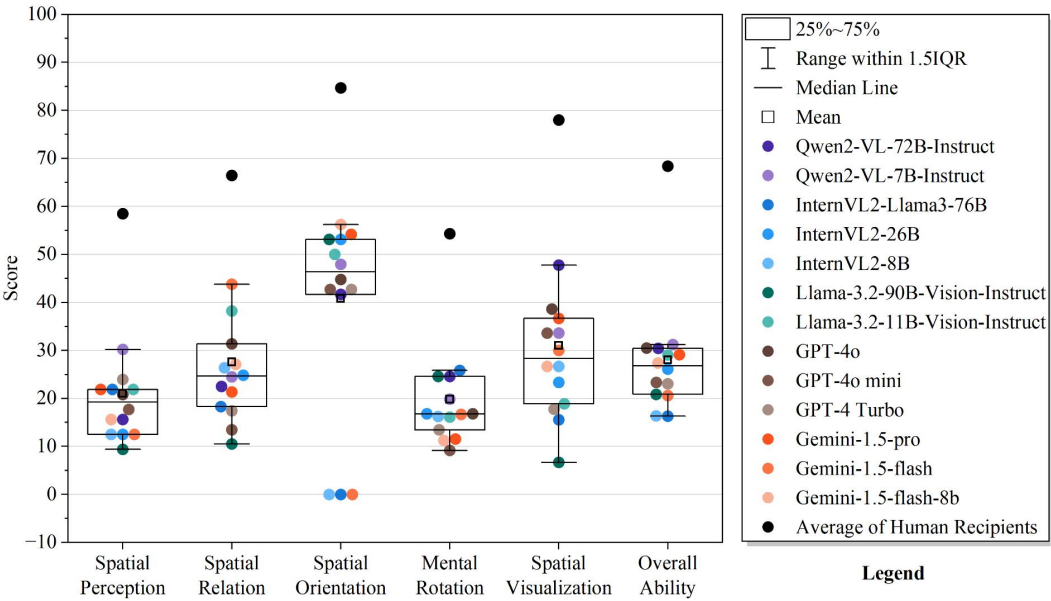
Measuring from the closest point of each object, what is the distance between the bed and the sofa in meters?

Answer: 3.2

Room Size

What is the size of this room (in square meters)? If multiple rooms are shown, estimate the size of the combined space.

Answer: 57.6

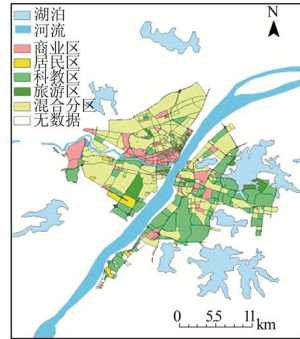


Xu, Wenrui*, Dalin Lyu*, Weihang Wang*, **Jie Feng**, Chen Gao, and Yong Li. "Defining and Evaluating VLMs' Basic Spatial Abilities: A Perspective from Psychometrics." ACL 2025 Main.

Gurnee, Wes, and Max Tegmark. "Language models represent space and time." ICLR 2024.

Urban Intelligence

- We need strengthen LLMs spatial intelligence at Urban scale for embodied and generalized AI.



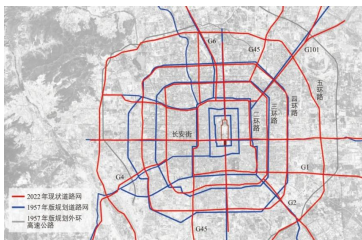
Regions



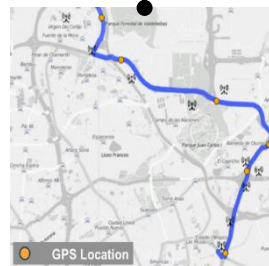
Remote Sensing



Street View



Road Network

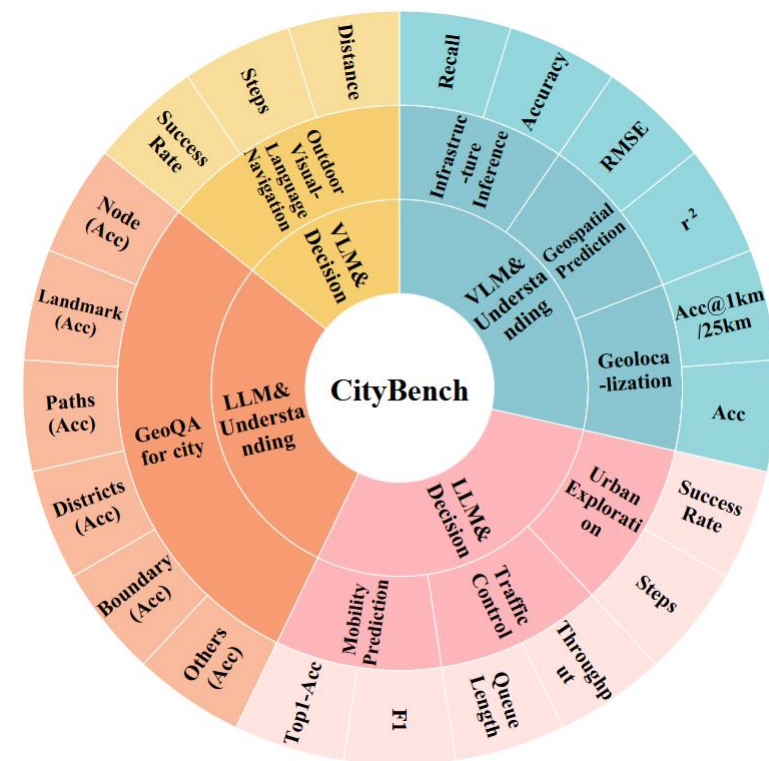
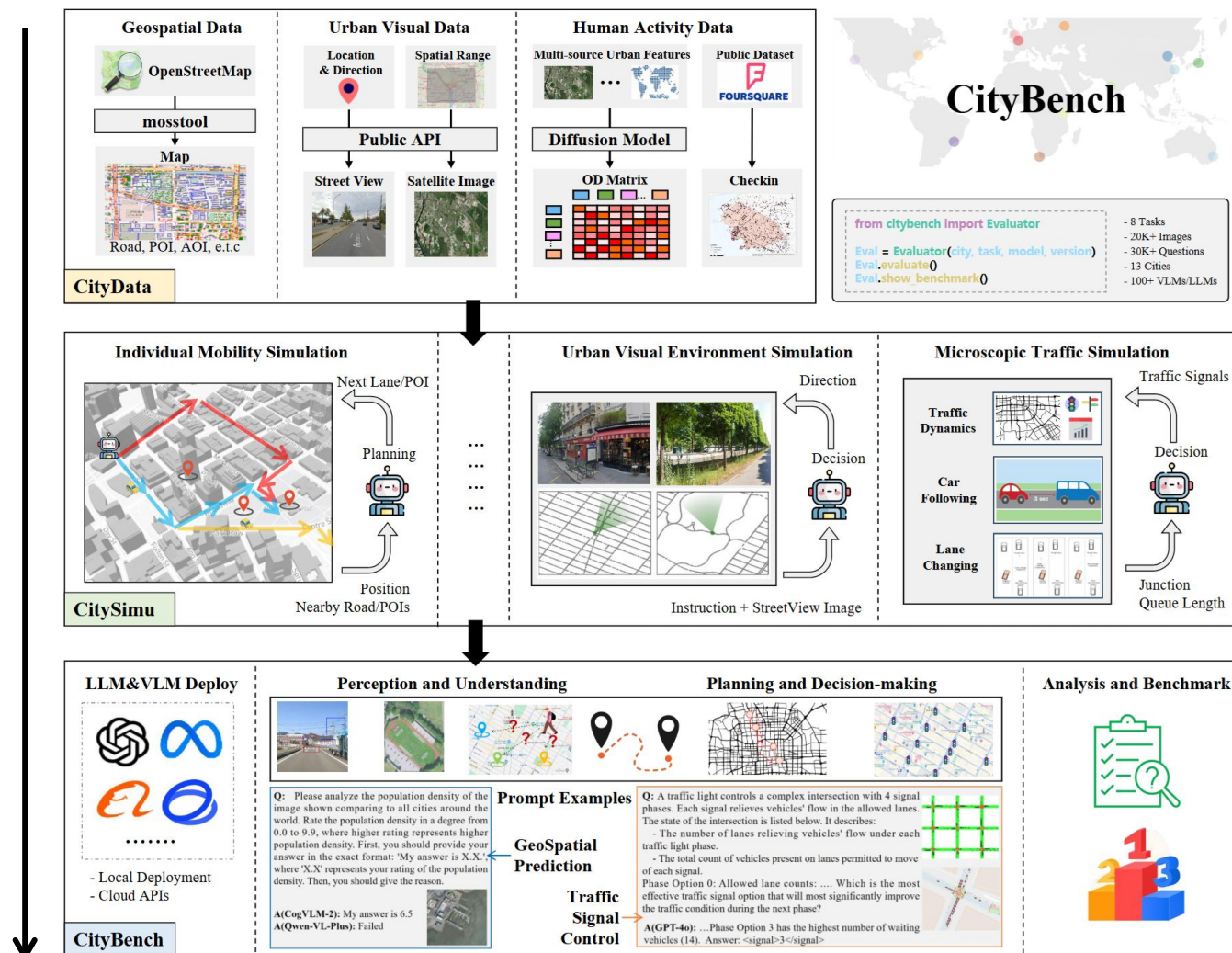


Mobility Trajectory



POI

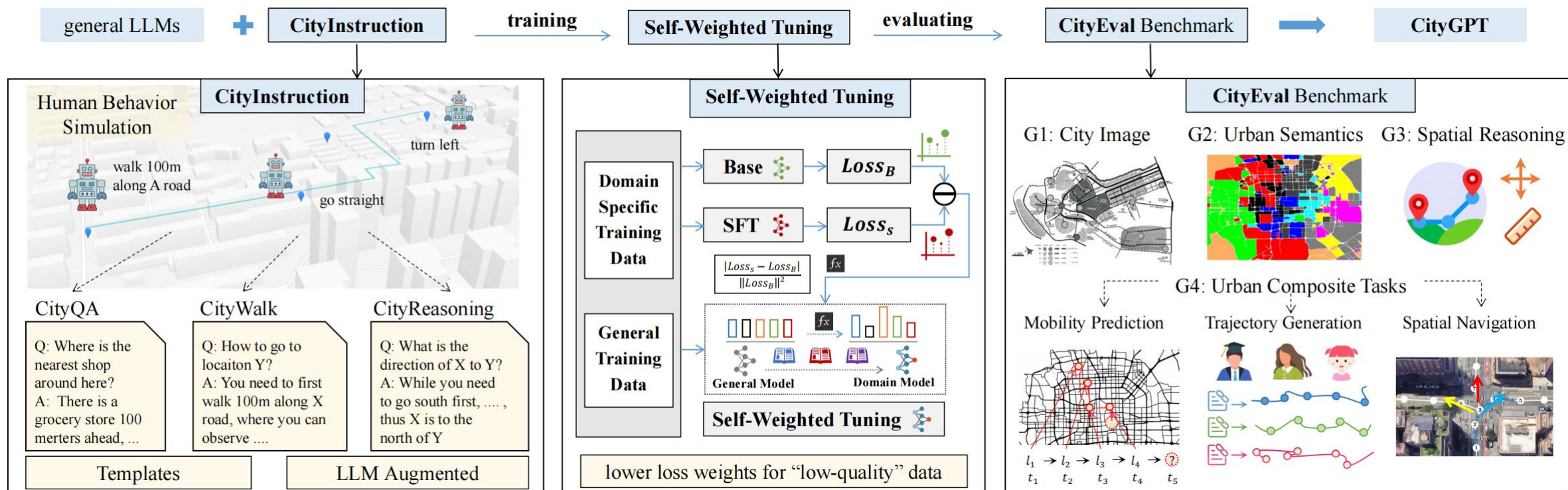
- **A comprehensive urban spatial intelligence benchmark**



8 tasks in 13 cities around the world

Before UrbanLLaVA: CityGPT

- For urban geospatial knowledge: CityGPT, using daily behavior simulation to synthesize data



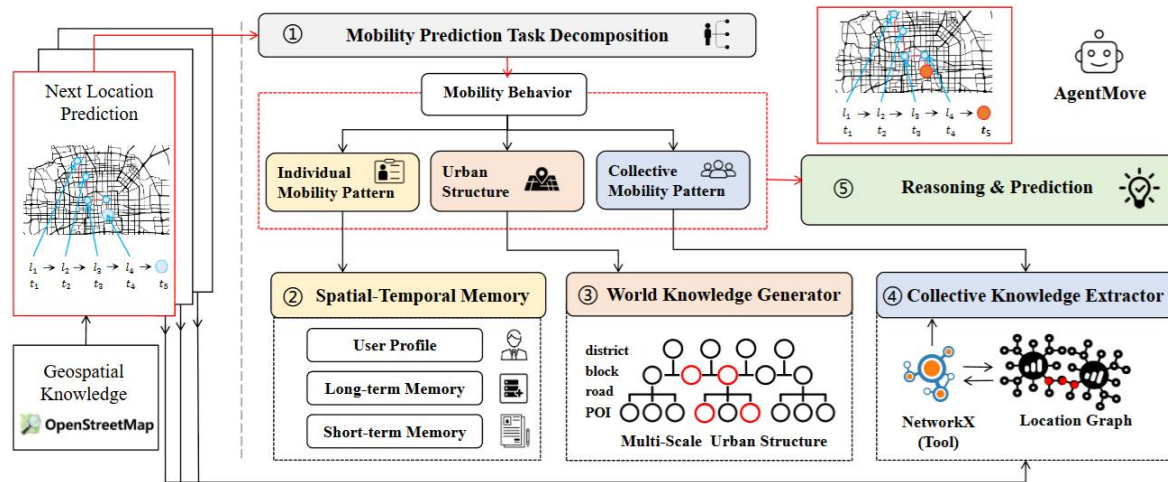
Large-scale human behavior simulation to synthesize high-quality, multi-source spatial data.

Domain-data mixed adaptive training to balance general and specialized capabilities.

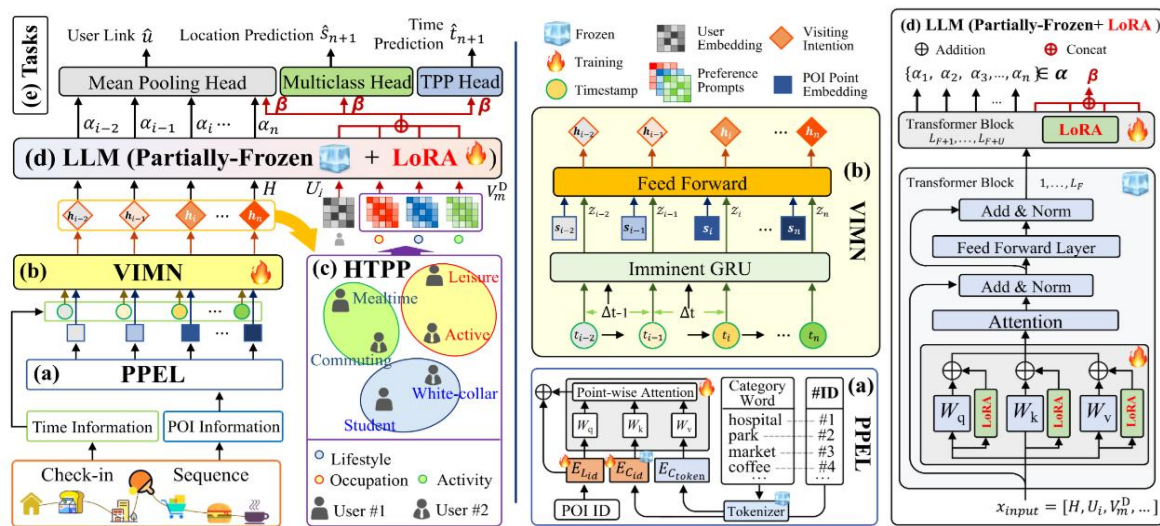
Systematic evaluation of language-based urban spatial cognition.

Before UrbanLLaVA: AgentMove/Mobility-LLM

- For urban mobility intelligence: language-driven methods (AgentMove) and modality-aligned modeling (Mobility-LLM).



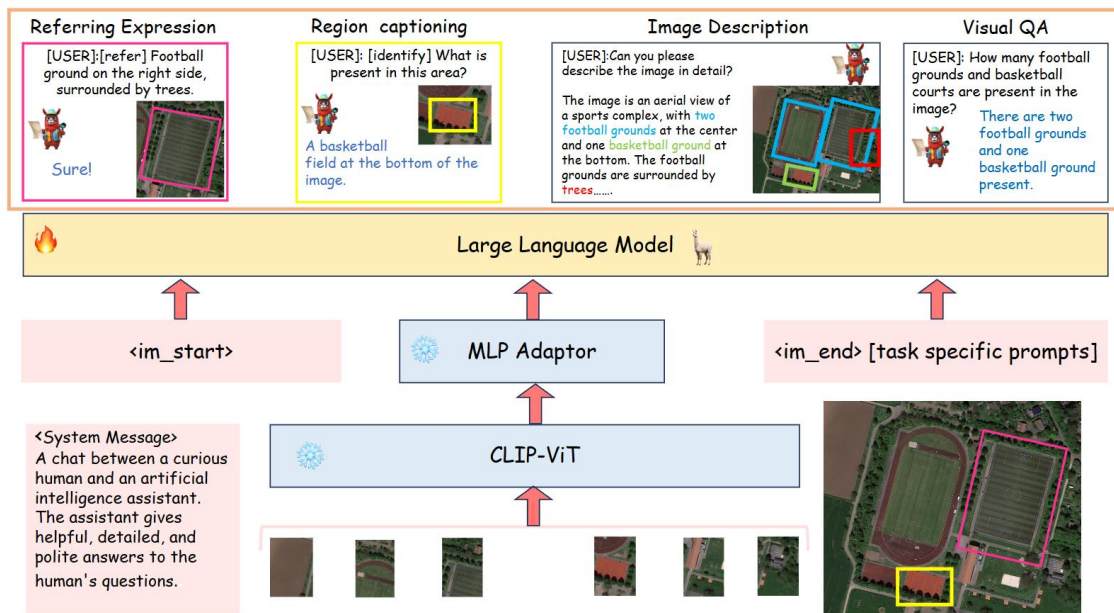
AgentMove: Models movement behavior by translating mobility trajectories into natural language descriptions and performing the modeling within the natural language space.



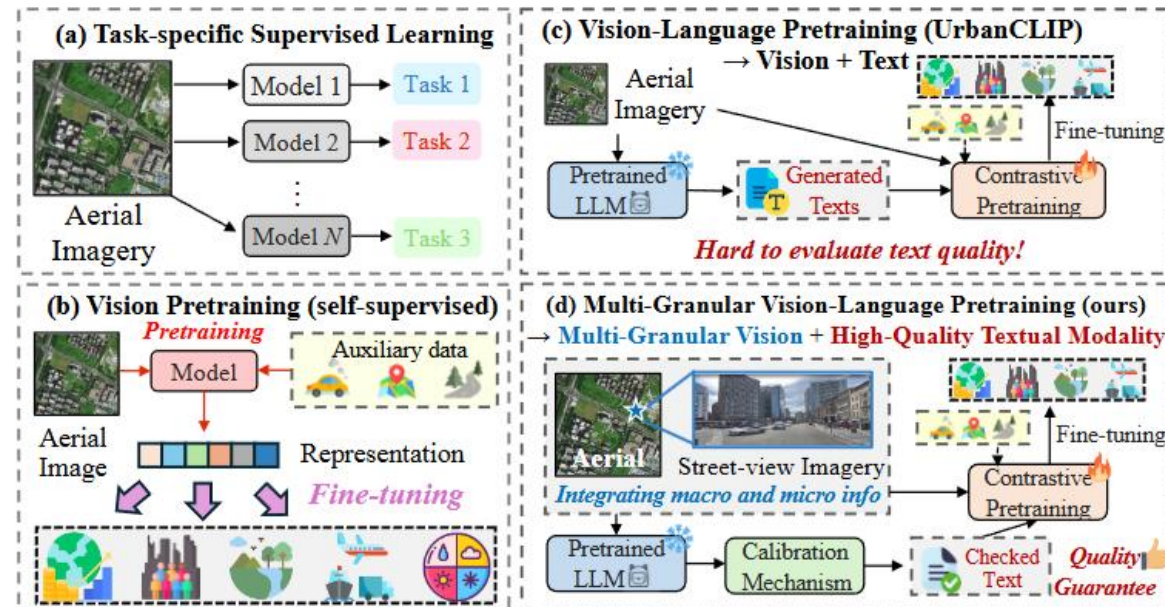
Mobility-LLM: Models movement by using classical models to process mobility trajectories, obtaining an embedded representation that is then integrated into the LLM.

Before UrbanLLaVA: GeoChat/UrbanVLP

- For urban vision intelligence, e.g., GeoChat and UrbanVLP.



GeoChat: Addresses urban remote sensing recognition and detection tasks using a classical multi-modal architecture.



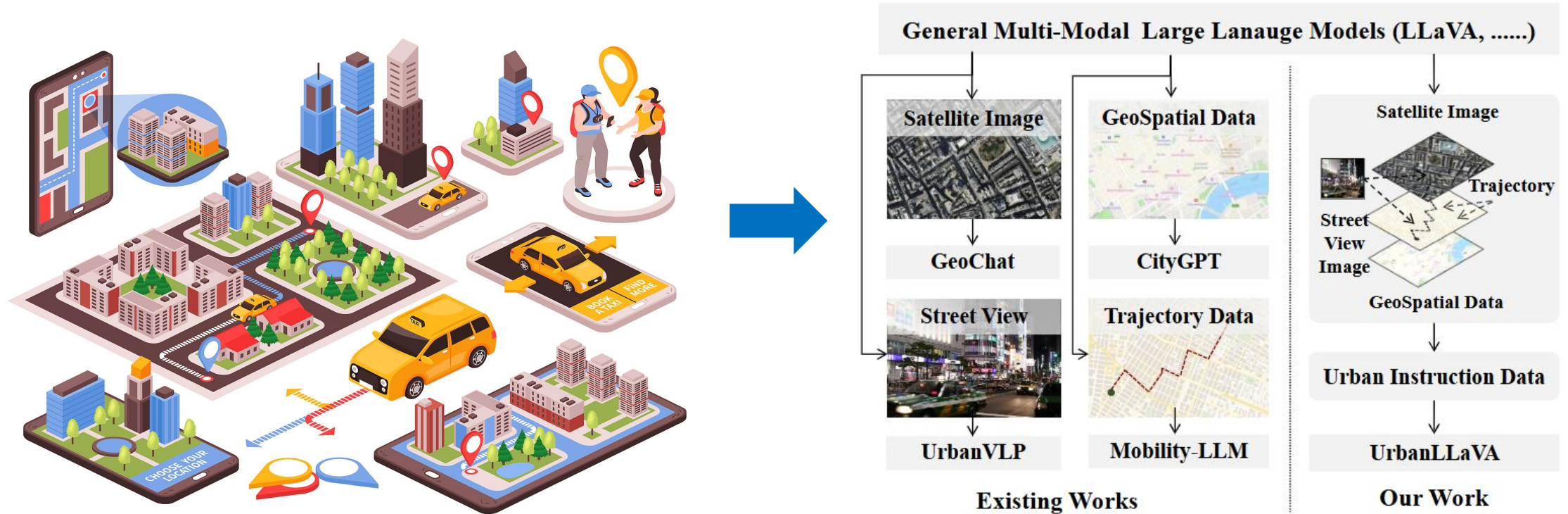
UrbanVLP: Focuses on predicting socio-economic indicators from street view imagery, leveraging contrastive learning and LLM annotation.

Kuckreja, Kartik, et al. "Geochat: Grounded large vision-language model for remote sensing." CVPR 2024

Hao, Xixuan, et al. "Urbanvlp: Multi-granularity vision-language pretraining for urban socioeconomic indicator prediction." AAAI 2025

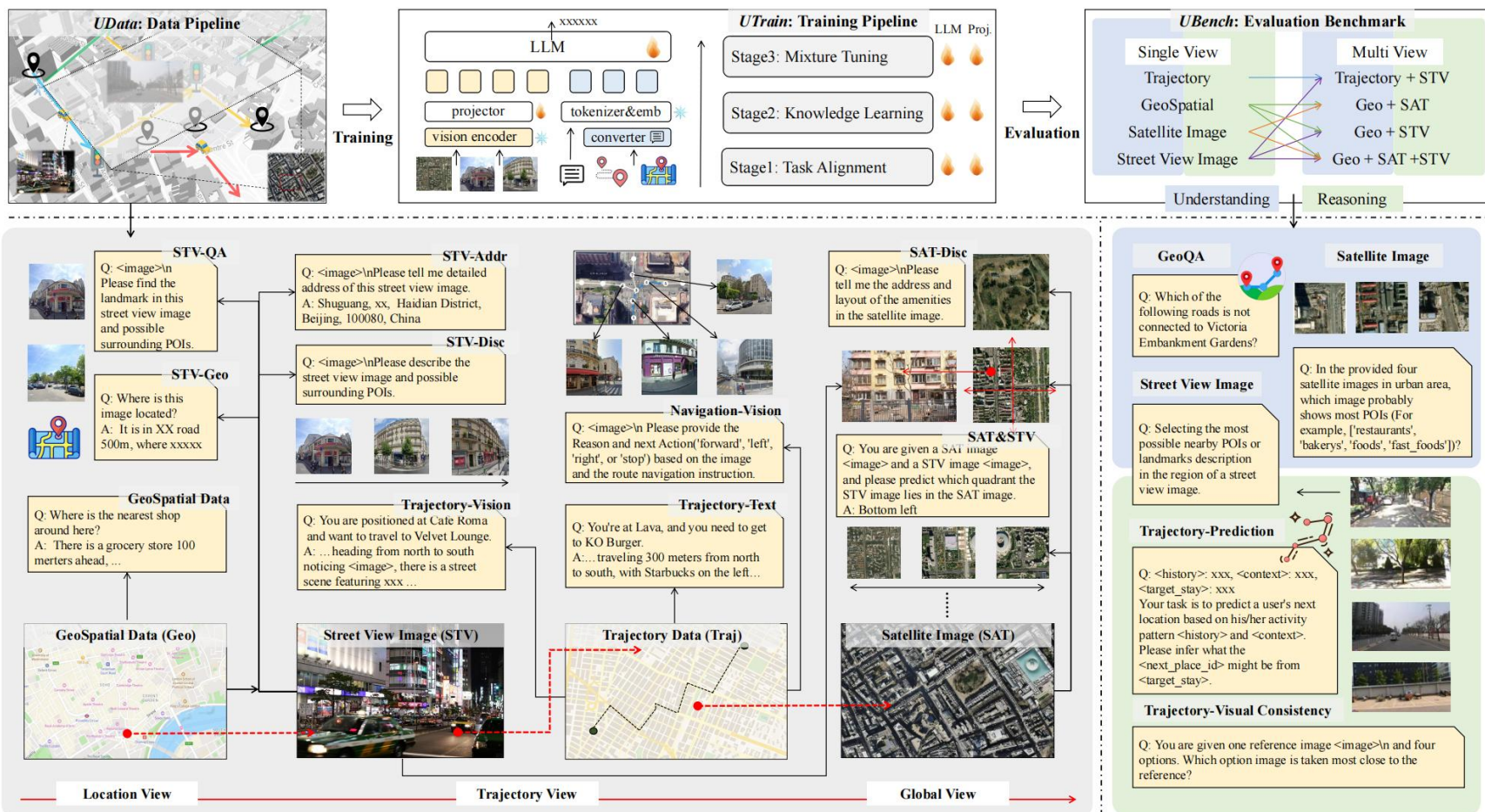
UrbanLLaVA: Building Unified Foundation Model for Urban Intelligence

- **UrbanLLaVA:** Achieves unified modeling of **remote sensing, street view, geographical data, and mobility trajectories** by deeply aligning and fusing **visual information** with **geospatial knowledge**.



UrbanLLaVA: Building Unified Foundation Model for Urban Intelligence

• UrbanLLaVA: UData + Utrain + UBench



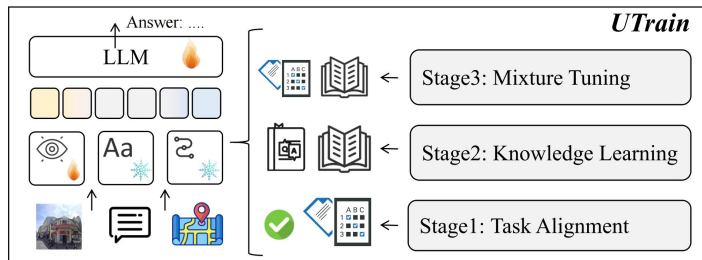
Training Data

Table 1. Detailed information about UBench for Beijing, 'STV' refers to street view image, and 'SAT' refers to satellite image.

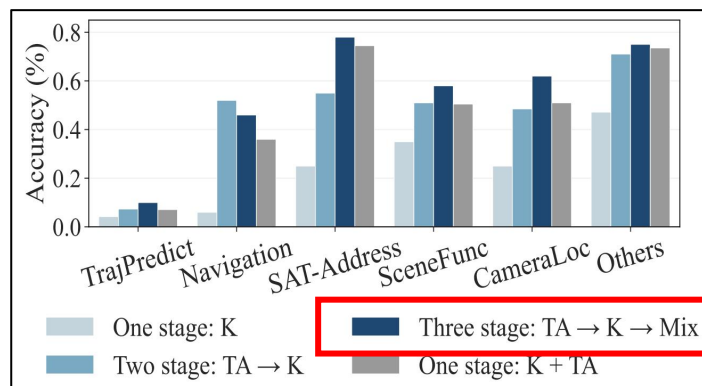
Tasks	Data	Category	Metrics	Samples	Source
GeoQA	Geospatial Data	GeoQA	Avg. Accuracy	1450	CityBench
TrajPredict	Trajectory Data	Geo+Traj	Top-1	500	CityBench
Navigation	Single STV	Geo+Traj	Success Rate	50	CityBench
SceneComp	Multi SAT	Geo+SAT	Accuracy	200	UrBench
ImgRetrieval	Multi STV & SAT	Geo+SS	Accuracy	200	UrBench
CameraLoc	Multi STV & SAT	Geo+SS	Accuracy	200	UrBench
STV-Address	Single STV	Geo+STV	Accuracy	200	UBench
STV-Landmark	Single STV	Geo+STV	Accuracy	200	UBench
SAT-Address	Single SAT	Geo+SAT	Accuracy	200	UBench
SAT-Landuse	Single SAT	Geo+SAT	Accuracy	200	UBench
STV-Outlier	Multi STV	Geo+STV	Accuracy	200	UBench
SceneFunc	Multi SAT	Geo+SAT	Accuracy	200	UBench

UrbanLLaVA: Building Unified Foundation Model for Urban Intelligence

- Uses a multi-stage training pipeline for urban domain multi-modal and multi-scenario tasks, leading to significant performance gains on critical benchmarks.



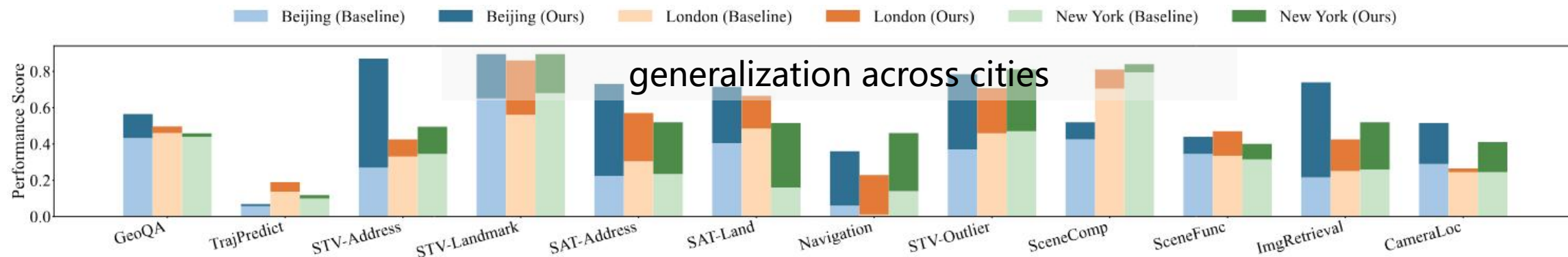
multi-stage
training pipeline



multi-stage
training approach
yields superior
performance on
critical tasks
compared to direct
mixed training.

City Task Group	Beijing					London				
	GeoQA	Geo+Traj	Geo+STV	Geo+SAT	Geo+SS	GeoQA	Geo+Traj	Geo+STV	Geo+SAT	Geo+SS
VILA1.5-3B	0.3873	0.0200	0.3967	0.3200	0.2575	0.4362	0.0400	0.2557	0.2850	0.2725
VILA1.5-8B	0.4322	0.0589	0.4300	0.3488	0.2425	0.4841	0.0884	0.4495	0.4575	0.2575
VILA1.5-13B	0.4410	0.1156	0.5167	0.3638	0.2400	0.4592	0.1298	0.4991	0.4538	0.2625
InternVL2-8B	0.4709	0.1578	0.4667	0.3313	0.2325	0.4973	0.1347	0.4477	0.4763	0.2400
InternVL2-26B	0.4877	0.1478	0.4550	0.3825	0.2275	0.5168	0.1288	0.4923	0.5138	0.2425
Qwen2VL-7B	0.4950	0.1389	0.4383	0.3638	0.2675	0.4991	0.1560	0.4381	0.4863	0.2775
Qwen2VL-72B	0.5491	0.1611	0.5817	0.3588	0.2975	0.5802	0.2322	0.6375	0.4375	0.3250
LLama3.2-11B	0.4229	0.0756	0.4375	0.3075	/	0.4804	0.1180	0.4000	0.3800	/
LLama3.2-90B	0.4502	0.1056	0.5325	0.2925	/	0.5659	0.2010	0.5450	0.4700	/
GPT4o-mini	0.4542	0.1622	0.4350	0.3800	0.2475	0.5357	0.1278	0.4752	0.5388	0.2675
GPT4o	0.5479	0.1522	0.4300	0.4125	0.3025	0.6446	0.1300	0.5469	0.6050	0.2850
UrbanLLaVA-VILA1.5-8B	0.5682	0.2800	0.8650	0.6663	0.7025	0.6399	0.2680	0.7500	0.7100	0.4325
vs. VILA1.5-8B	+31.47%	+375.38%	+101.16%	+91.03%	+189.69%	+32.18%	+203.17%	+66.85%	+55.19%	+67.96%
vs. Best Baseline	+3.48%	+72.63%	+48.70%	+61.53%	+132.23%	-0.73%	+15.42%	+17.65%	+17.36%	+33.08%

achieves significant performance improvements
across various tasks in multiple cities.



generalization across cities

UrbanLLaVA: Building Unified Foundation Model for Urban Intelligence

• Task Examples

Image Inputs:



Prompt: You are given one reference image <image> and four options. Which option image is taken most close to the reference?

- A. The First image <image> B. The Second image <image>
C. The Third image <image> D. The fourth image <image>

Only provide one letter as the answer and please select your answer from A, B, C, or D.

Reference: D

Ours: D

VILA1.5-8B: B

GPT-4o mini: A

Explanation: The reference displays a city road image with a bike lane. The fourth image shows a similar scene while the others lack features like bike lane or sidewalks.

STV-Outlier Task

Image Inputs:



Prompt: In the provided four satellite images in urban area, which image probably shows most POIs (For example, ['restaurants', 'bakerys', 'foods', 'fast_foods', 'beveragess', 'food_courts', 'bars', 'cafes', 'coffees', 'vending_machines', 'nightclubs'])?

- A. The first image <image> B. The second image <image>
C. The third image <image> D. The fourth image <image>

Only provide one letter as the answer and please select your answer from A, B, C, or D.

Reference: C **VILA1.5-8B:** A

Ours: C

GPT-4o mini: C

Explanation: The third image depicts a commercial area. In contrast to residential or sparse offices, it is likely to have a higher concentration of food-related businesses.

SceneFunc Task with Satellite Image

STV-Landmark

Image Inputs:



Reference: A **VILA1.5-8B:** A

Ours: A **GPT-4o mini:** A

Explanation: The sidewalk and apartment building indicate that there is a residential building area nearby.

Prompt: The following is a multiple-choice question about selecting the most possible nearby POIs (Place of Interests) or landmarks description in the region of a street view image.

- A. Residential building area.
B. Overpass near commercial buildings.
C. Power transmission lines.
D. Wudaokou Shopping Center

Please choose the most suitable one among A, B, C and D as the answer to this question. Please output the option directly. No need for explanation.

STV-Landmark Task

User: <image> \n What is shown in this street view image? And what related pois could be estimated nearby



Assistant: The image depicts a building partially obscured by lush greenery. The structure appears to be a single-story building with a flat roof, characterized by a light-colored exterior that suggests a concrete or stucco material. The roof is lined with a blue trim, which adds a subtle contrast to the overall appearance. Surrounding the building, dense foliage and various plants create a vibrant green backdrop, indicating a well-established natural environment. The vegetation is thick, with a mix of taller trees and lower shrubs, suggesting a sense of seclusion. The building is positioned towards the center of the image, with trees flanking its sides, while a pathway or road runs along the left side, leading towards the viewer. The spatial relationship between the building and the surrounding greenery is notable; the building is somewhat hidden by the dense plants, which extend close to its walls, creating a harmonious blend of man-made and natural elements. The sunlight filters through the leaves, casting dappled shadows on the ground, enhancing the tranquil atmosphere of the scene. Overall, the image conveys a sense of quietude and integration with nature.

STV-Description

User: You are given a satellite image <image> and a street view image <image>, can you predict which quadrant the street view image lies in the satellite image?

- A. Top left
B. Top right
C. Bottom left
D. Bottom right

Please provide a detailed reasoning for your answer. And give me one letter as your answer in the last sentence.



Assistant: Step 1: Identify the satellite view image's address: The satellite image is taken in the Chaoyang District of Beijing, featuring a well-organized 5x5 grid of notable locations. To the north is the Olympic Village Science Park, a central site surrounded by various establishments. Directly east along Datun Road is the National Zoological Museum of China, enhancing the area's scientific theme. Moving south on Datun Road, you'll find China Unicom, a key telecommunications provider, and the vibrant The Red Parrot Image Agency, adding cultural flair. Datun Road connects these points, facilitating easy navigation. This area blends educational, cultural, and commercial establishments, all within close proximity.

Step 2: Identify the street view image's address: The street view image is taken at The Red Parrot Image Agency, # 50, Datun Road, Chaoyang District, Beijing, 100101, China.

Step 3: Determine the quadrant where the street view image lies in the satellite view image: The street view image is located in quadrant C of the satellite view image."

CameraLoc Task with STV and Satellite Image



UrbanLLaVA@Github

Thanks!



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