Exploring the Roles of LLMs in Transportation Systems: A Framework and Case Study

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About me

- Tong Nie (聂通)
- Dual PhD student @ The Hong Kong Polytechnic University & Tongji University
- Supervised by Prof. Jian Sun and Dr. Wei Ma
- Interests: spatiotemporal learning, urban science, LLMs, autonomous driving
- Publication venues: **KDD, AAAI, CIKM, TR-C, TR-E, IEEE TITS**, etc.
- Funded by the National Natural Science Foundation of China (国家自然科学基金)
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TOPS

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- **Nie, T.,** Sun, J., & Ma, W. (2025). **Exploring the Roles of Large Language Models in Shaping Transportation Systems: A Survey, Framework, and Roadmap.** Preprint, arXiv:2503.21411.
- **Nie, T.,** He, J., Mei, Y., Qin, G., Li, G., Sun, J., & Ma, W. (2025). **Joint Estimation and Prediction of City-wide Delivery Demand: A Large Language Model Empowered Graph-based Learning Approach**. Transportation Research Part E: Logistics and Transportation Review, 2025.
- He, J.*, **Nie, T. *,** & Ma, W. (2024). **Geolocation representation from large language models are generic enhancers for spatio-temporal learning**, Accepted at the Thirty-Ninth AAAI Conference on Artificial Intelligence (AAAI-25).

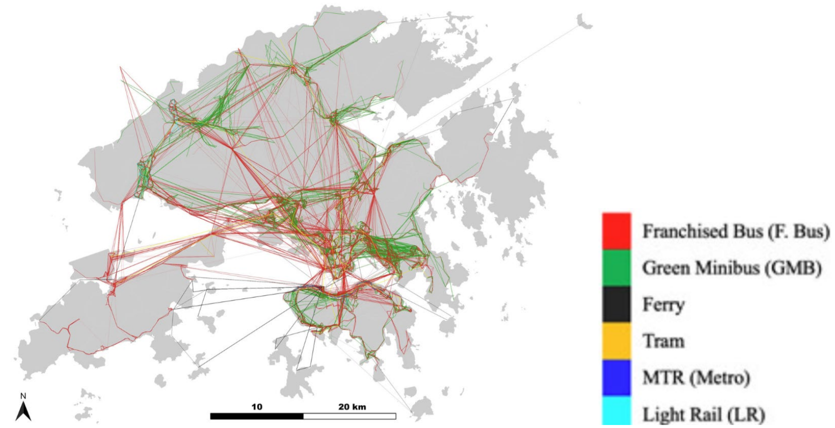
1 Motivation

☐ Growing complexity of cyber-physical-social systems

➢ Growing complexity and demand of transportation systems

- ✓ Multi-modal, multi-stakeholders
- ✓ Large-scale, high-dimensional
- ✓ Persistent challenges

Congestion, resilience, sustainability, and adaptability

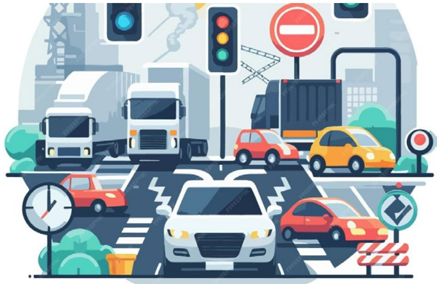


Multi-modal Transportation Systems in Hong Kong

➢ AI enabled intelligent transportation systems (ITS)


human factors

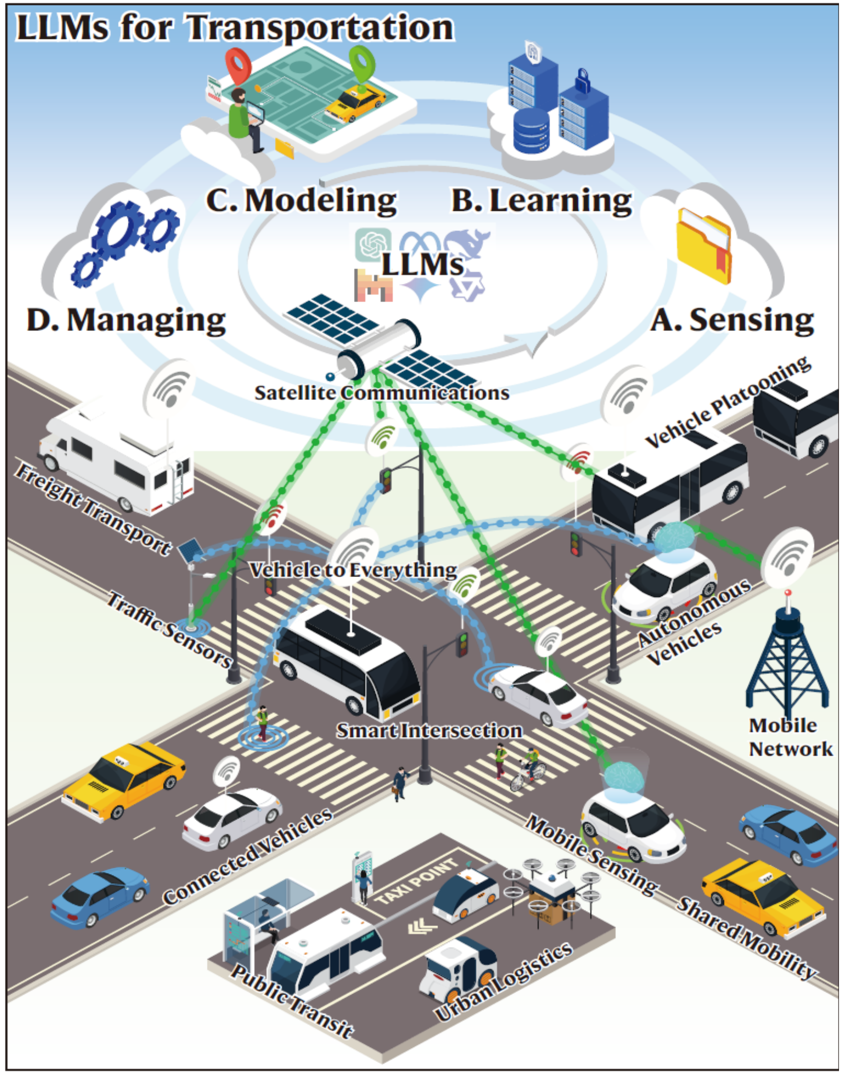
large-scale data


dynamic environment

interaction with infrastructures

1 Motivation

Growing complexity of cyber-physical-social systems



➢ Fundamental tasks in transportation systems:

✓ **Sensing:**

Acquisition of traffic data and the environmental perception process.

✓ **Learning:**

Pattern recognition and predictive analytics.

✓ **Modeling:**

Formulation and simulation of transportation systems.

✓ **Managing:**

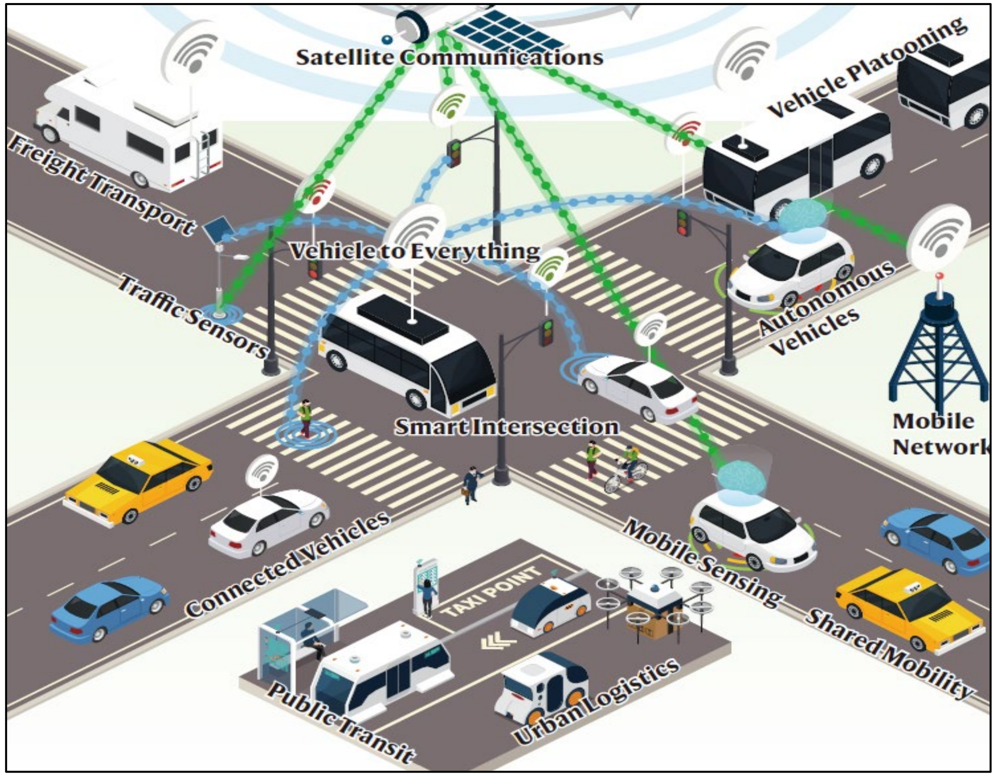
Optimization and control strategies for the operation of transportation systems.

1 Motivation

☐ Growing complexity of cyber-physical-social systems

➢ Emergence of multimodal mobility

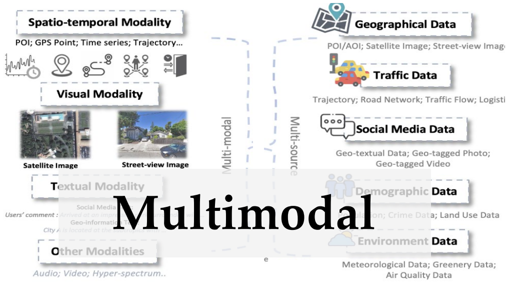
- ✓ CAVs
- ✓ Cloud computing
- ✓ Drone logistics
- ✓ Human-robot interactions
- ✓ Shared mobility
- ✓ Smart intersection control

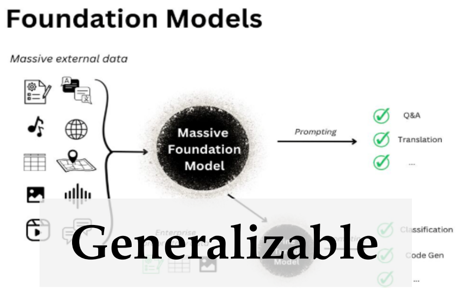


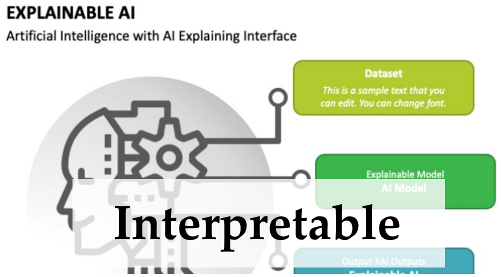
➢ Existing ITS solutions

- ✓ Static models and fragmented data pipelines
- ✓ Customizability and interpretability constraints
- ✓ Task-specific and expertized solutions

➢ More intelligent tools are needed





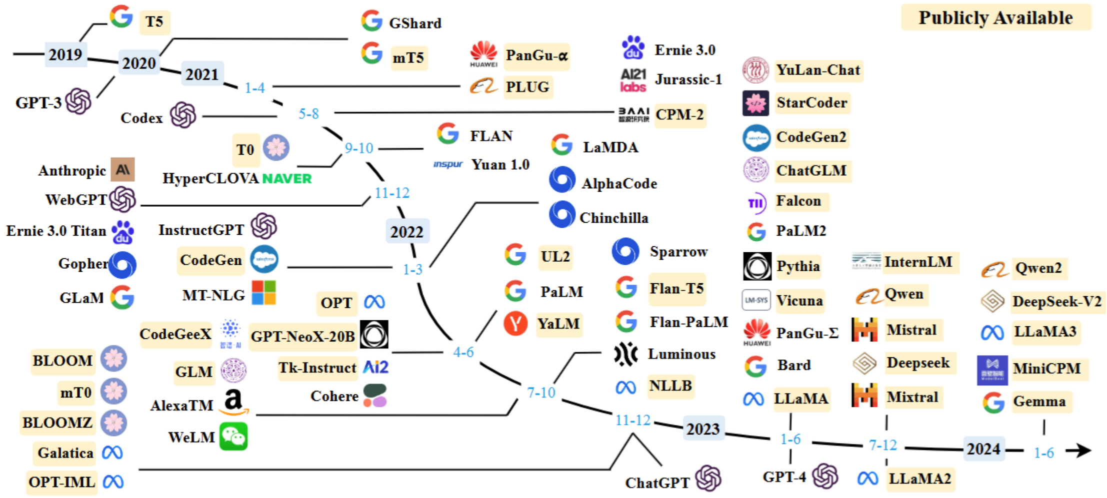


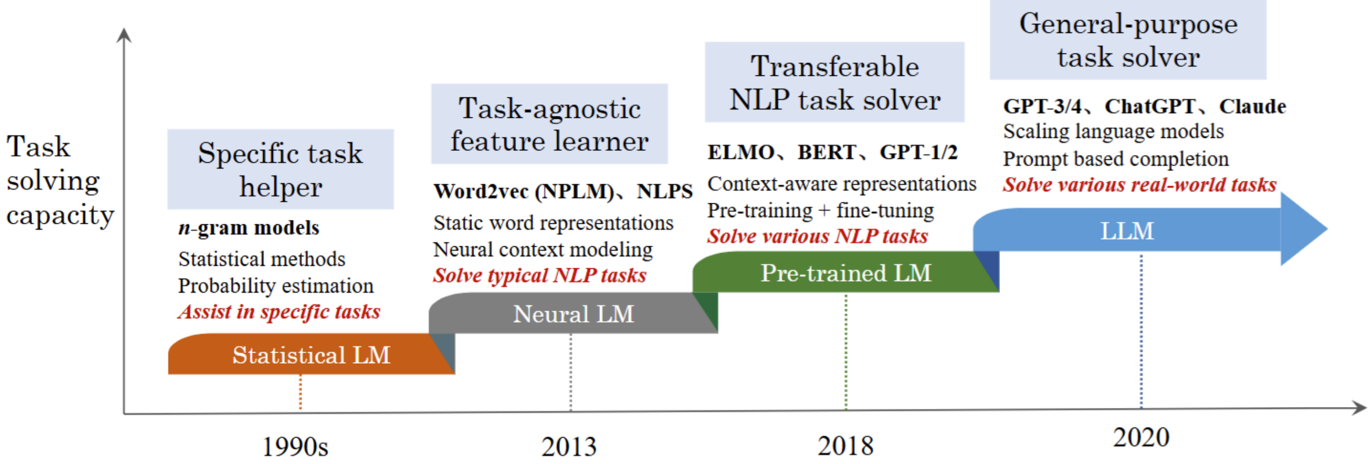
1 Motivation

Rapid evolution of powerful large language models

- Scaling LLMs to solve various real-world tasks
  - ✓ Large Language Models (LLMs)：
    Step-by-step reasoning, in-context learning, instruction following and human-like decision making.
  - ✓ From text generators to general-purpose problem solver:
    Programming, planning, generating, imaging, reasoning, …

Can LLMs help to solve domain-specific transportation problems? How?



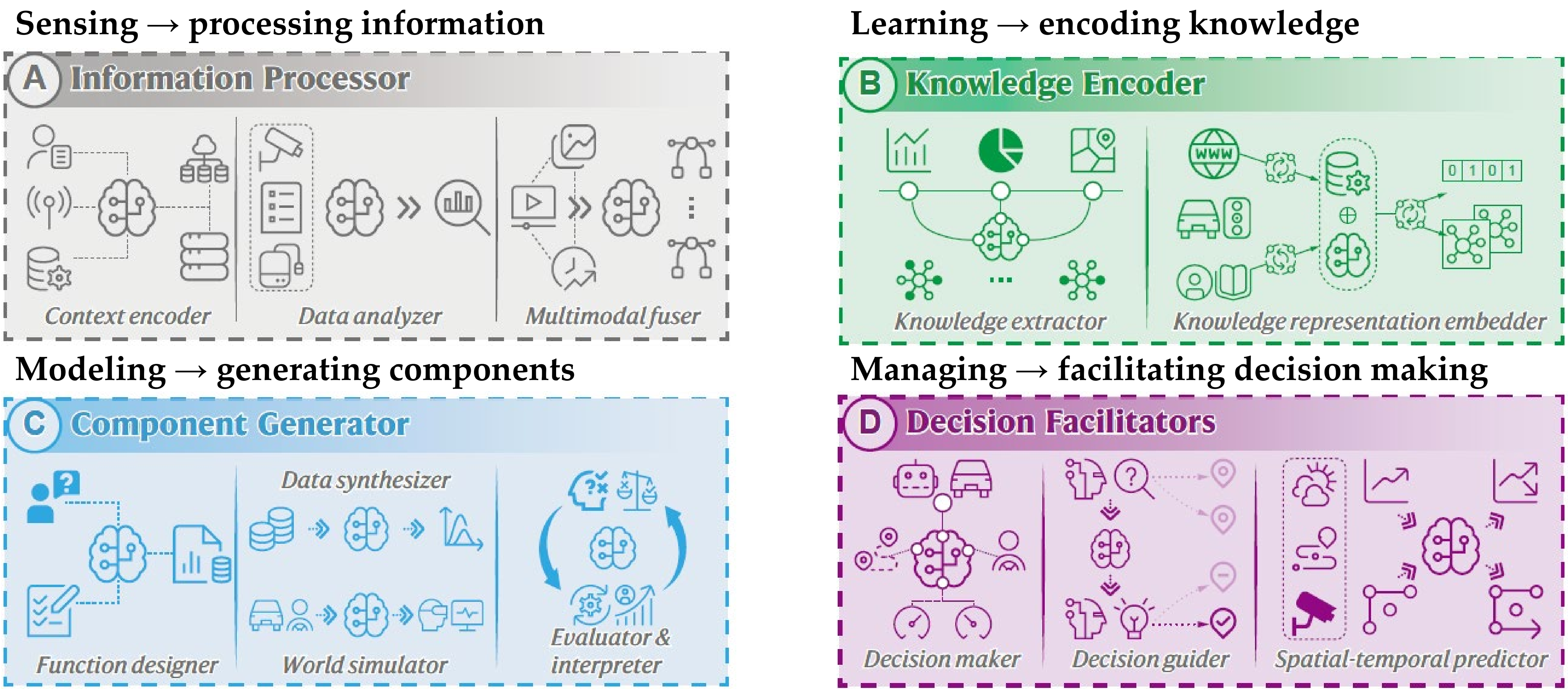


- Zhao W X, Zhou K, Li J, et al. A survey of large language models[J]. arXiv preprint arXiv:2303.18223, 2023.

2 Conceptual Framework and Taxonomy

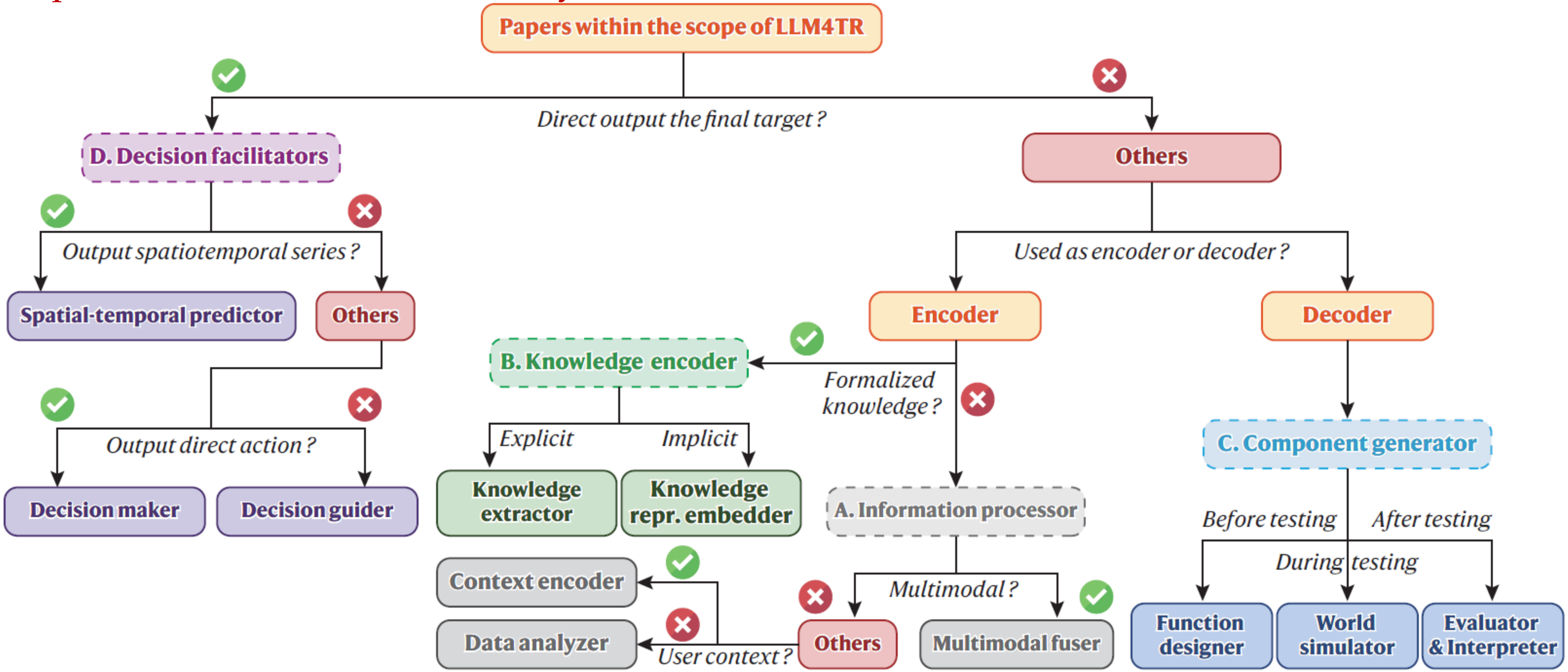
◻ The roles of LLMs in multimodal transportation systems

➢ Conceptual framework and taxonomy: LLM4TR



◻ The roles of LLMs in multimodal transportation systems

➢ Conceptual framework and taxonomy: LLM4TR



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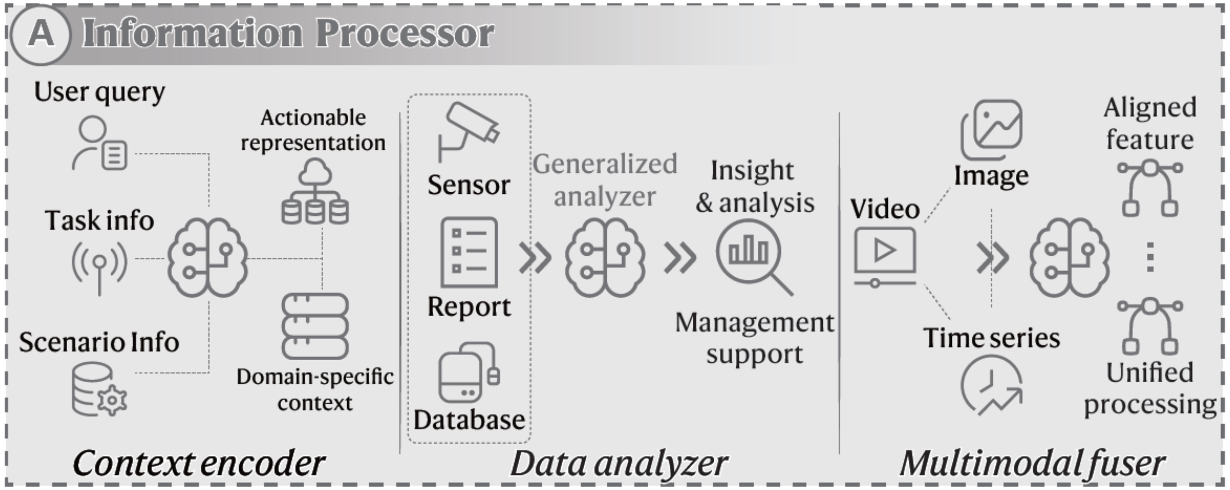
LLMs as Information Processors



Definition: LLMs process and fuse heterogeneous traffic data from multiple sources through contextual encoding, analytical reasoning, and multimodal integration.

Example: Using LLMs to analyze sensory traffic data (Zhang et al., 2024d), accident reports (Mumtarin et al., 2023) and convert user language queries to task-specific commands (Liao et al., 2024).

✓ **Context encoder**

- Translating textual descriptions of traffic information or task queries into structured encodings.

✓ **Data analyzer**

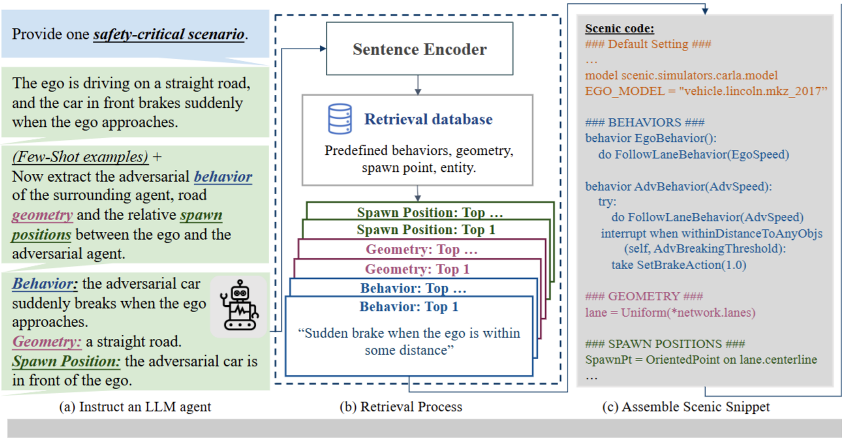
- Generalized analyzer for multimodal traffic data, such as reports, images, videos, and time series.

✓ **Multimodal fuser**

- MLLMs can convert heterogeneous types of data into aligned feature vectors or unified processing.

LLMs as Information Processors

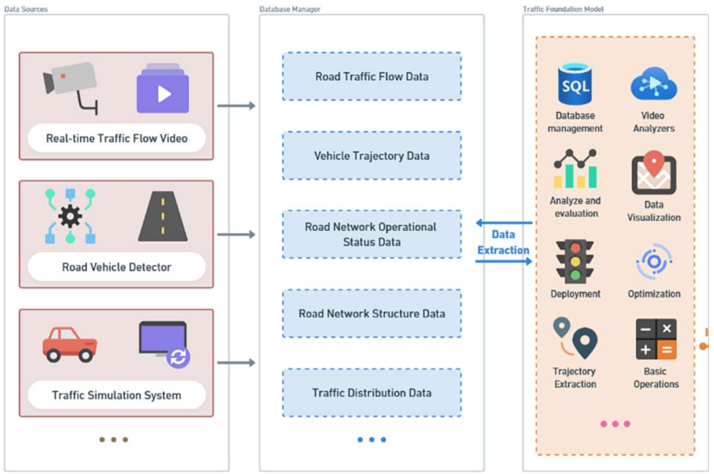
✓ Context encoder



ChatScene (Zhang et al., 2024b)

- Traffic simulation (modeling)
- Traffic scenario description → runnable code

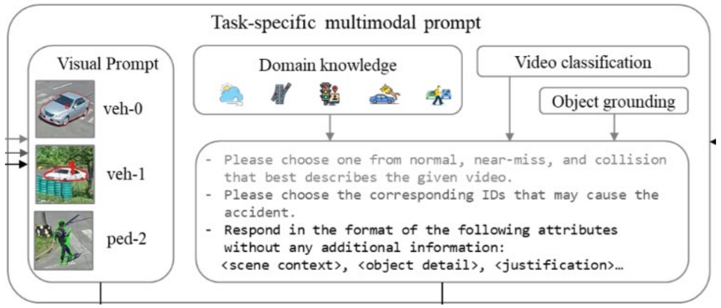
✓ Data analyzer



TrafficGPT (Zhang et al., 2024d)

- Traffic management (managing)
- Heterogeneous traffic data → actionable insights

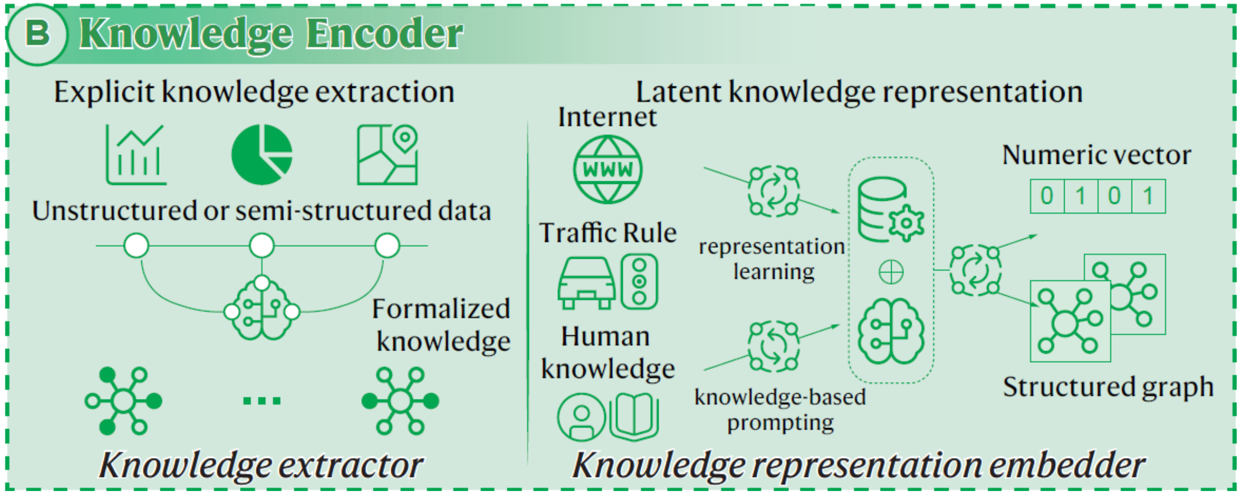
✓ Multimodal fuser



SeeUnsafe (Zhang et al., 2025)

- Safety analytics (learning)
- Using MLLMs to automate video-based accident analysis

LLMs as Knowledge Encoders



Definition: LLMs extract and formalize traffic domain knowledge from unstructured data through explicit rule extraction and implicit semantic embedding.

Example: Building a knowledge base of traffic rules (Wang et al., 2024e), formalizing scenarios as knowledge graphs (Kuang et al., 2024) and generating computable vectors for subsequent tasks (He et al., 2024).

✓ **Knowledge extractor**

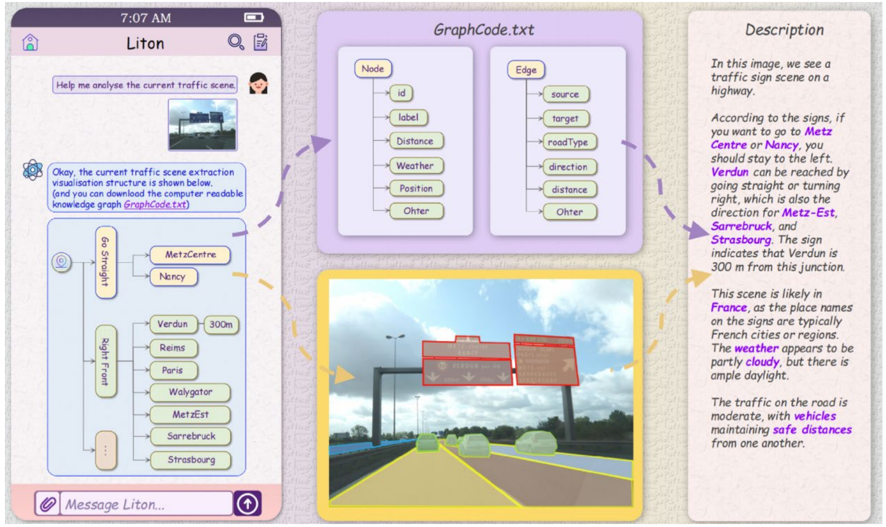
- Explicitly distill unstructured data into formalized knowledge representations such as text and knowledge graphs.

✓ **Knowledge representation embedder**

- LLMs encode transportation semantics into dense latent spaces that capture implicit relationships between entities.

◻ LLMs as Knowledge Encoders

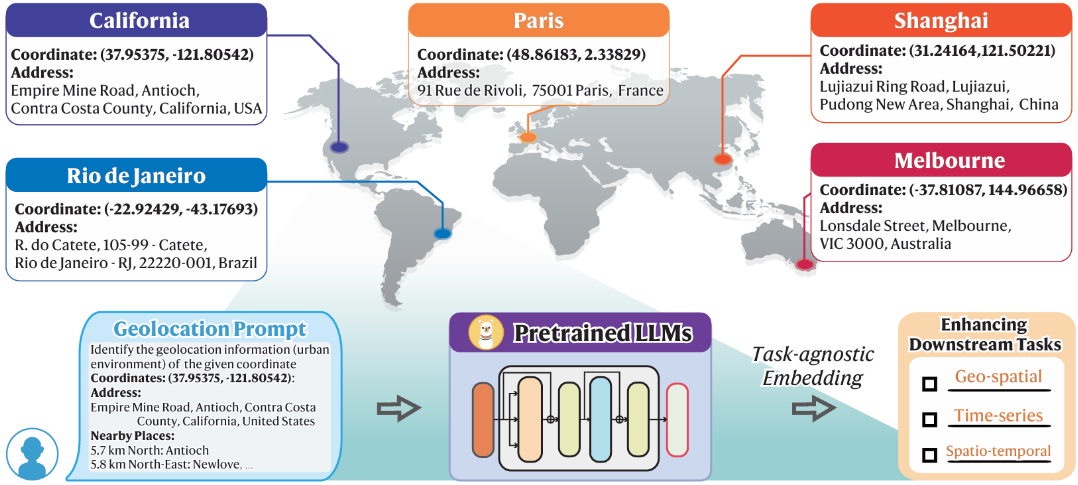
✓ Knowledge extractor



Kuang et al. (2024)

- Scene understanding (sensing)
- Generating visual traffic knowledge graphs from scene image using VLMs

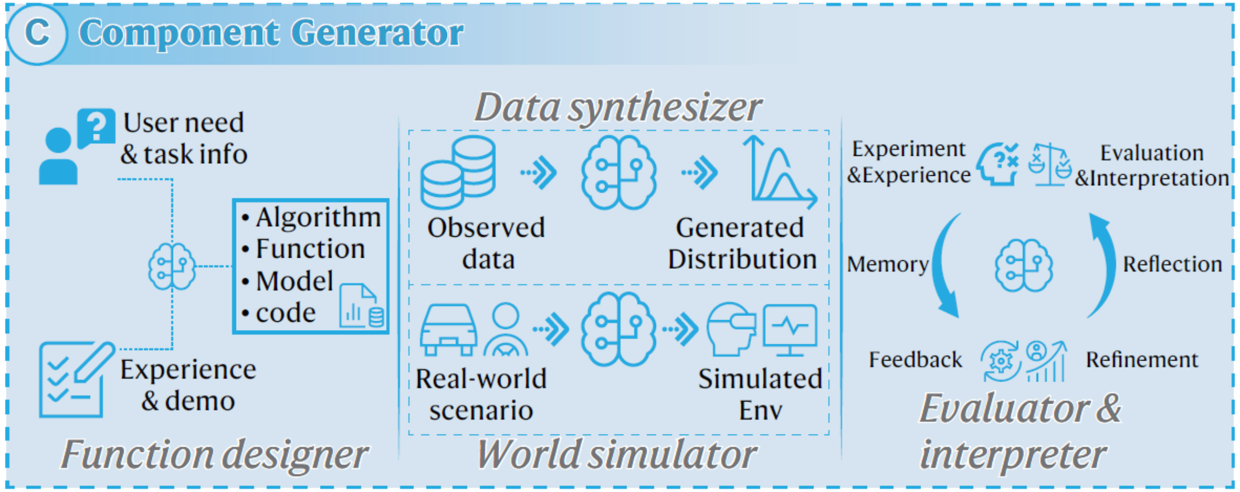
✓ Knowledge representation embedder



LLM2Geovec (He & Nie et al., 2024)

- Traffic prediction (learning)
- Knowledge from the Internet → location-specific vectors

LLMs as Component Generators



Definition: LLMs create functional algorithms, synthetic environments, and evaluation frameworks through instruction-followed content generation.

Example: Designing reward functions in reinforcement learning (Yu et al., 2024), synthesizing virtual driving environments (Zhao et al., 2024), and providing feedback for model refinement (Tian et al., 2024).

✓ **Function designer**

- Designing or refinement of code- or rule-based functions for traffic management.

✓ **World simulator**

- Simulating the environmental dynamics of real-world scenarios (generalized simulators).

✓ **Data synthesizer**

- Generative synthesis of system parameters and data engineering.

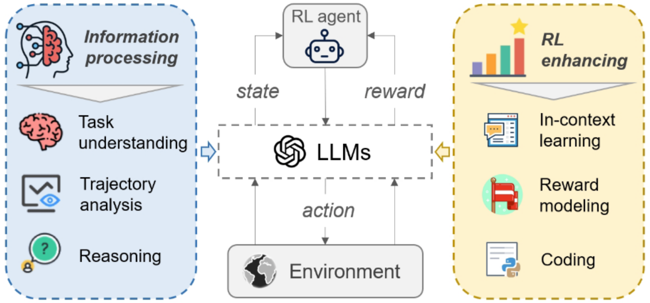
✓ **Evaluator and interpreter**

- Bringing human-like reasoning to system evaluation and decision self-refinement.

2 Conceptual Framework and Taxonomy

☐ LLMs as Component Generators

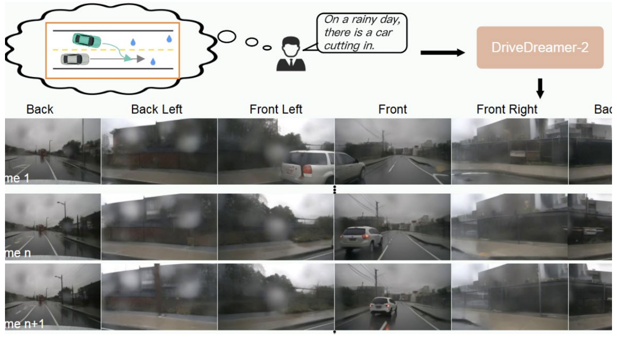
✓ Function designer



Yu et al. (2024)

Reward design for RL agent in traffic control

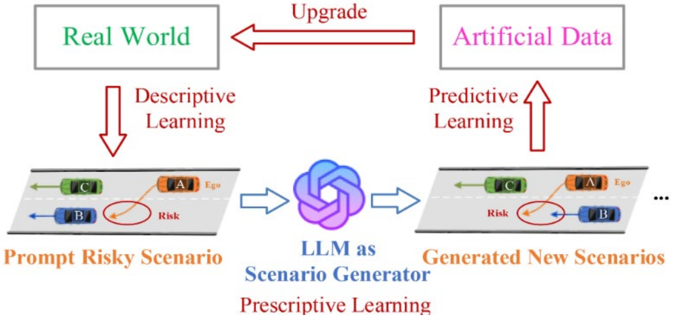
✓ World simulator



Drive Dreamer-2 (Zhao et al., 2024)

World models for high-fidelity driving simulation

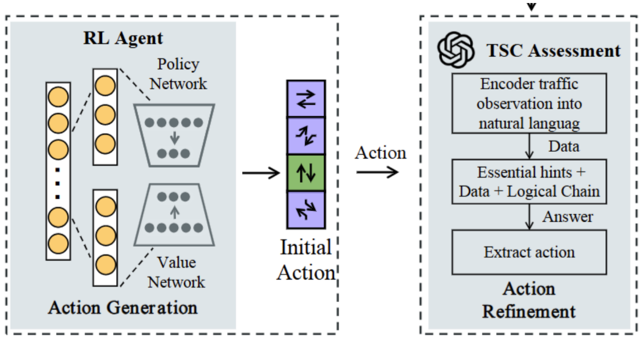
✓ Data synthesizer



LLMScenario (Chang et al., 2024)

Generating parameters for safety-critical scenarios

✓ Evaluator and interpreter

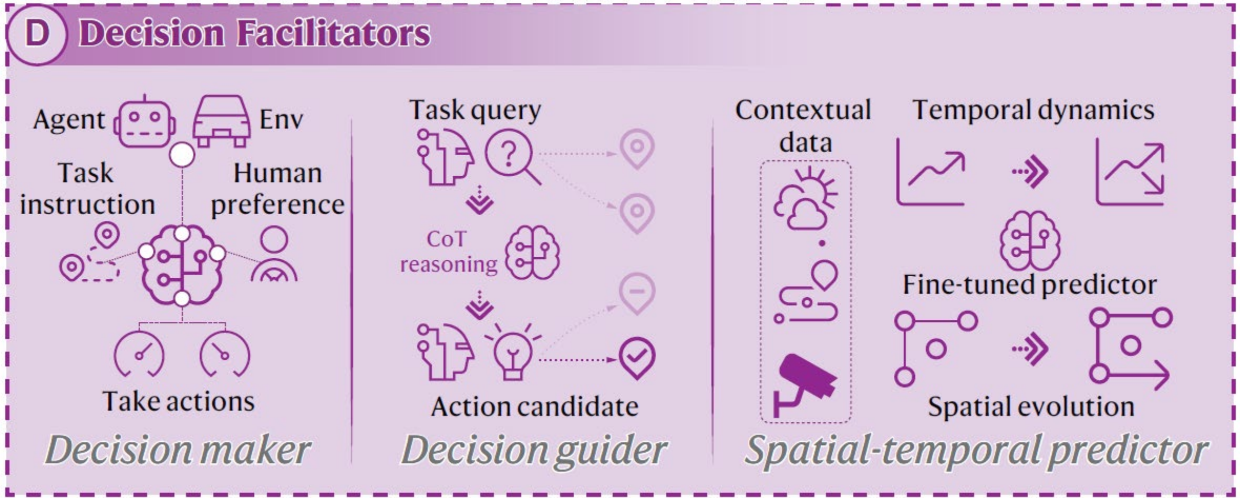


iLLM-TSC (Pang et al., 2024a)

Adjusting actions through feedbacks to align with real-world constraints

2 Conceptual Framework and Taxonomy

LLMs as Decision Facilitators



Definition: LLMs predict traffic dynamics, optimize decisions, and simulate human-like reasoning, establishing new paradigms as generalized task solvers.

Example: Making control and planning decisions for autonomous driving (Sima et al., 2024), guiding safety-critical actions (Wang et al., 2023a), and forecasting traffic states (Ren et al., 2024).

✓ **Decision maker**

- Making direct decision or predicting actions by task planning and in-context learning abilities.

✓ **Decision guider**

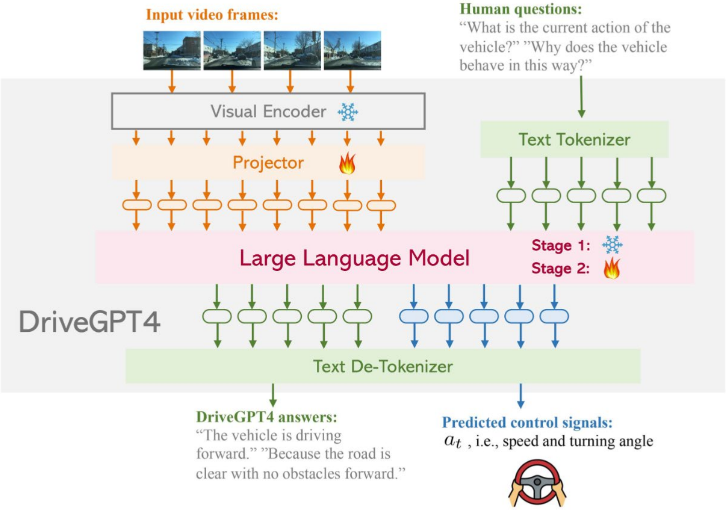
- Guiding or optimizing the decisions by generating action candidates or language instructions.

✓ **Spatial-temporal predictor**

- Forecasting spatial-temporal dynamics of traffic systems at both macro and micro scales.

LLMs as Decision Facilitators

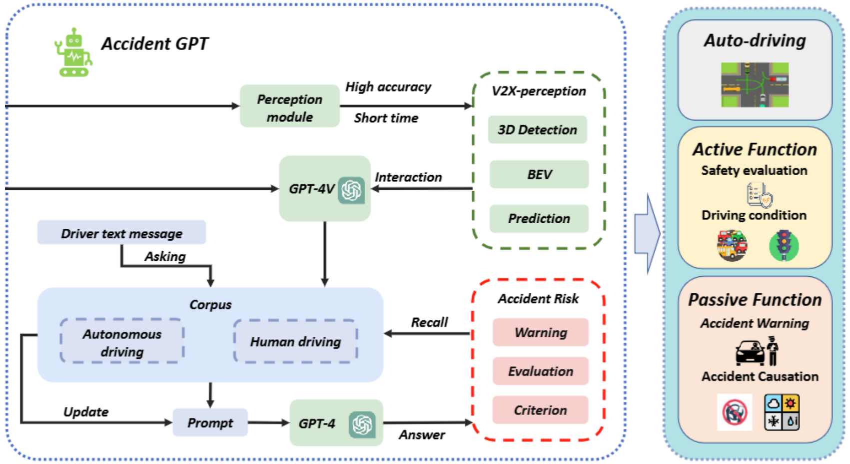
✓ Decision maker



DriveGPT4 (Xu et al., 2024)

- Autonomous driving (managing)
- VLMs process videos and textual, directly predicting low-level control signals.

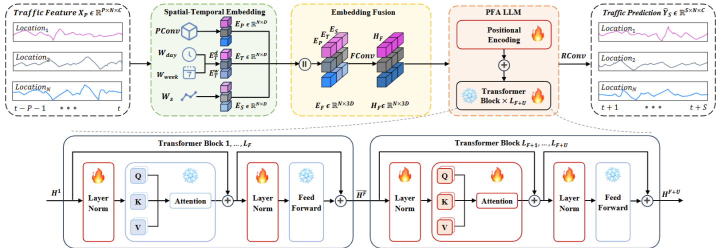
✓ Decision guider



AccidentGPT (Wang et al., 2023a)

- Accident prevention (managing)
- Safety advisor to issue long-range warnings and human-understandable guidance.

✓ Spatial-temporal predictor

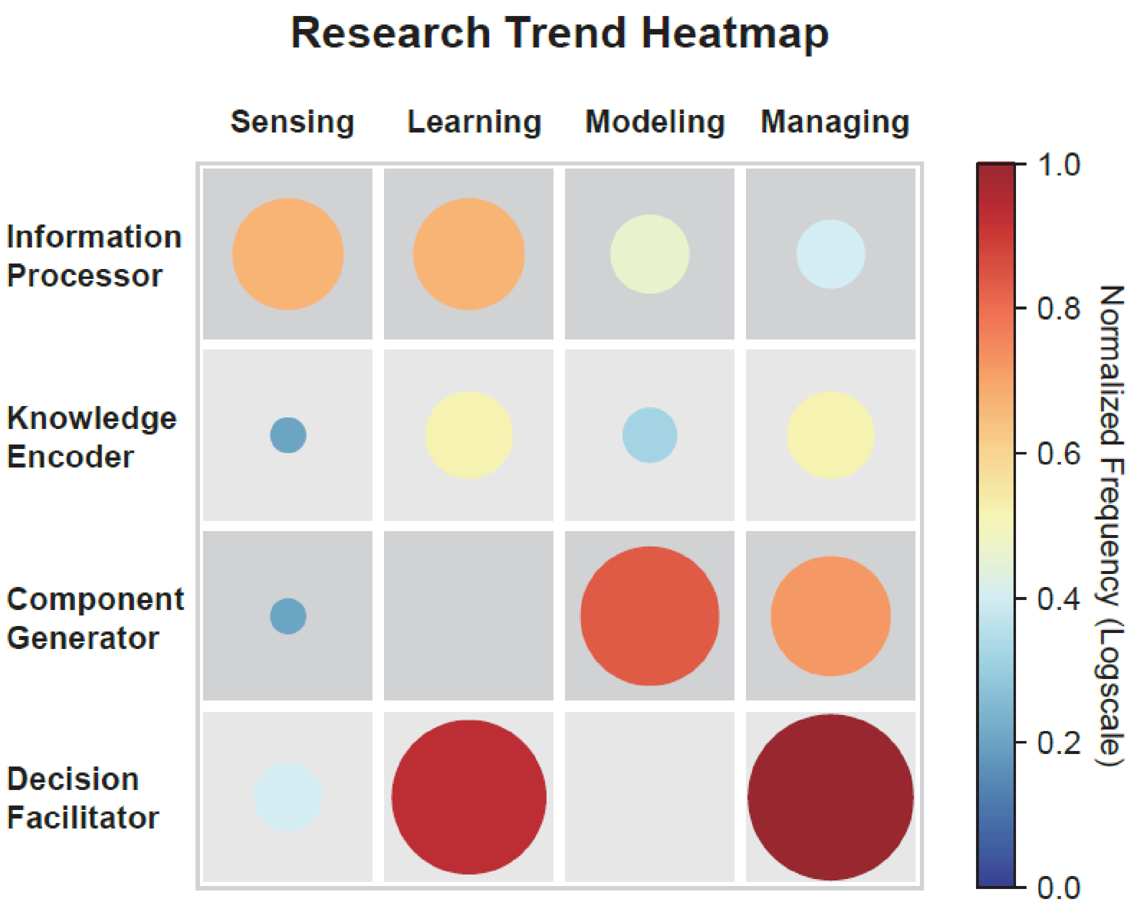


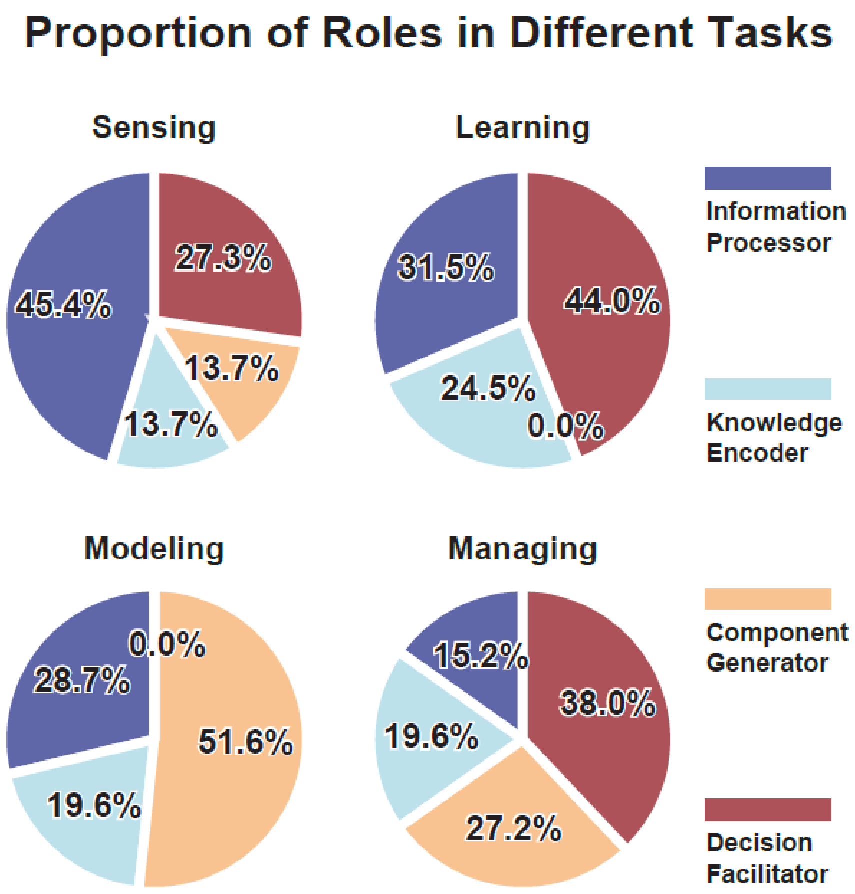
ST-LLM (Liu et al., 2024b)

- Traffic prediction (learning)
- As backbone forecasters for traffic flow, with spatial-temporal tokenization

☐ The roles of LLMs in multimodal transportation systems

➢ Research trend and future opportunities





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3 Case Study: LLM-based Geospatial Representation

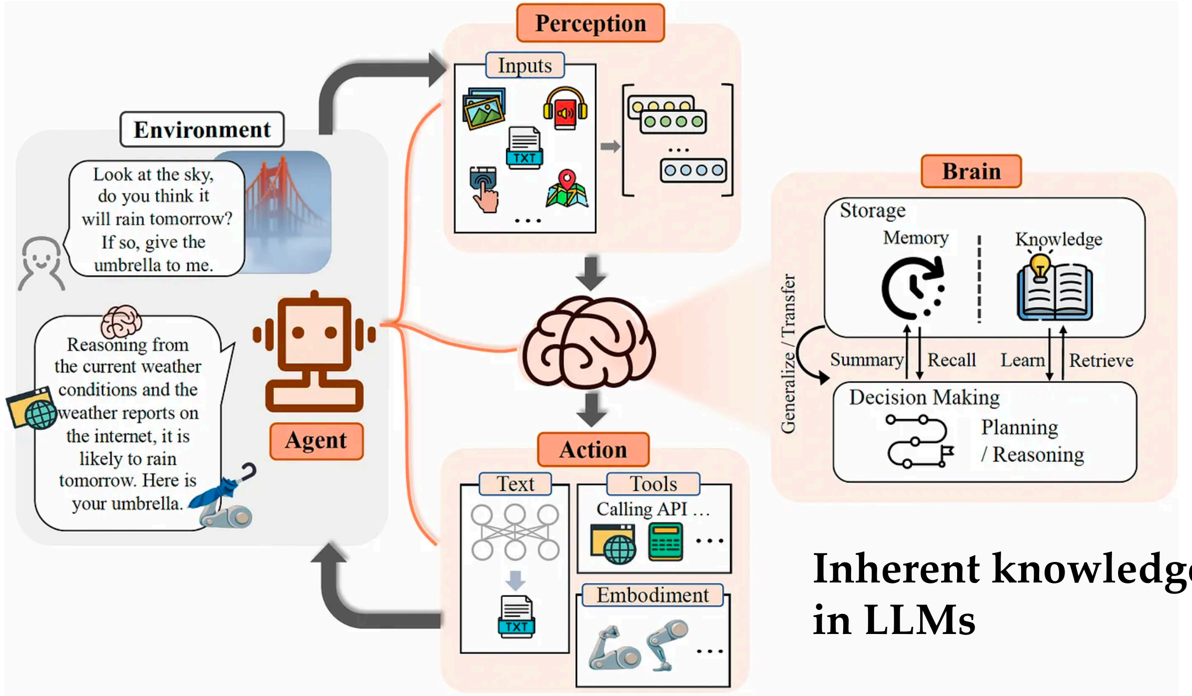
❑ Unlocking the power of large language models in predictive learning

➢ LLMs as **black-box** agents (using API)

- ✓ Understand environments
  - ❑ Perception
  - ❑ Memorization
- ✓ Analyse unstructured data
  - ❑ Text, Code
  - ❑ Image, Video
- ✓ Use external tools to take actions
  - ❑ Simulator
  - ❑ Optimizer
  - ❑ Web Search
  - ❑ Programme
- ▪ <u>Most literature: input-output</u>

➢ Intrinsic mechanisms of LLMs are unexplored

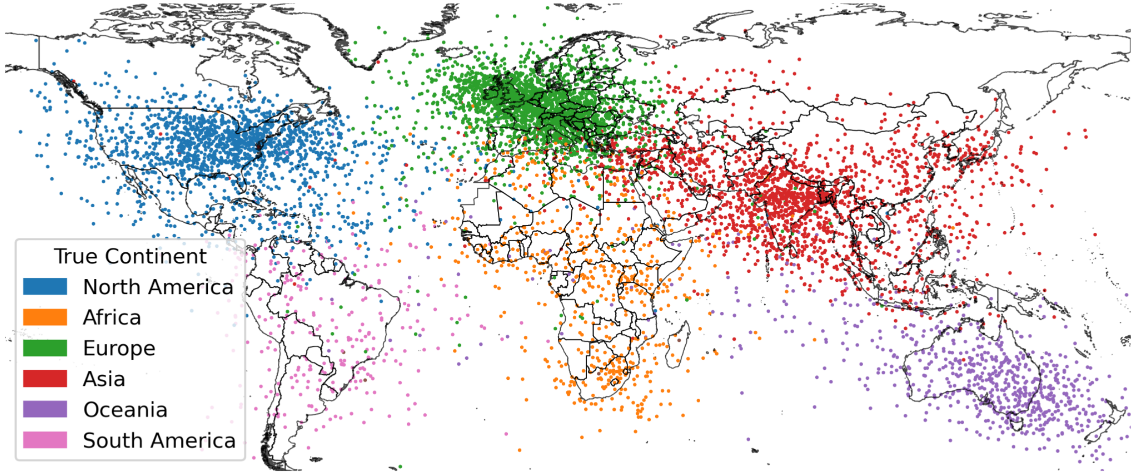
- ✓ Trained on the whole Internet with human languages → common sense and world knowledge
- ✓ Rich information → <u>**LLM as a knowledge base**</u>

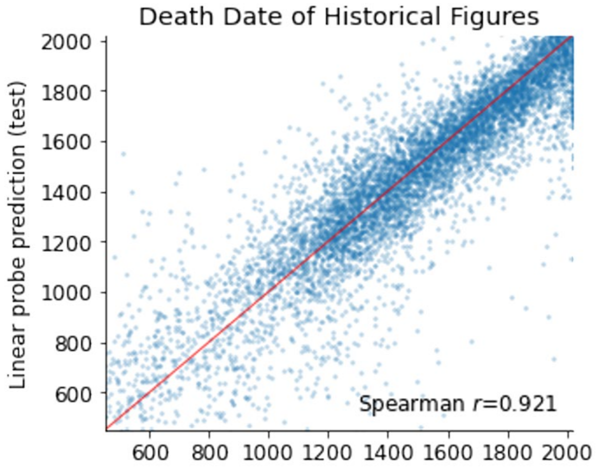


Inherent knowledge in LLMs

◻ Unlocking the power of large language models in predictive learning

- LLMs can represent space and time **(understand the world)**
  - ✓ Whether LLMs just learn an enormous collection of superficial statistics or an inherent model of the data generating process -- **a world model?**
  - ✓ LLMs learn linear representations of space and time across multiple scales
  - ✓ **How can we extract such representations from LLMs and facilitate location-based modeling?**





- Gurnee W, Tegmark M. Language models represent space and time[J]. arXiv preprint arXiv:2310.02207, 2023.

3 Case Study: LLM-based Geospatial Representation

□ LLM2Geovec: converting world knowledge to computable vectors

➢ Eliciting geospatial knowledge from LLMs

✓ **Location-based encoding** enhances spatiotemporal tasks, e.g., demand estimation

✓ Obtaining globally covered representations with readily accessible data is challenging

✓ LLMs have demonstrated extensive world and human-related knowledge

✓ **LLM-based geospatial representations as generalized location encodings**

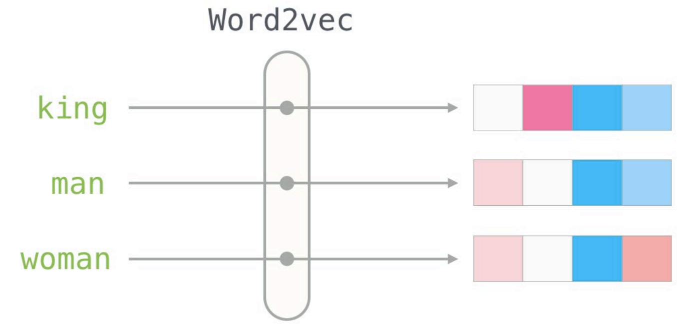
➢ Representation: object → numeric vector

✓ Word2Vec:

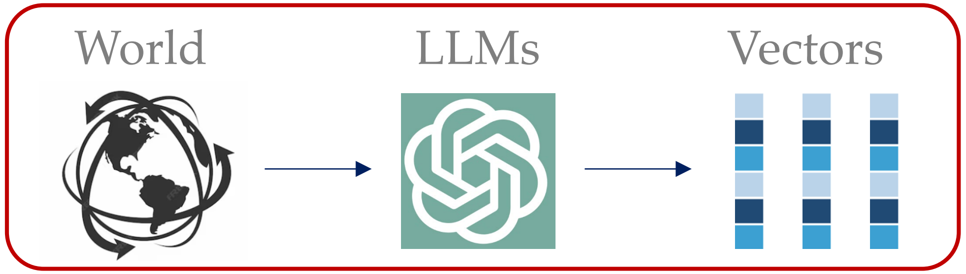
Text
- Unstructured
- non-calculable

→

Vector
- Structured
- Calculable



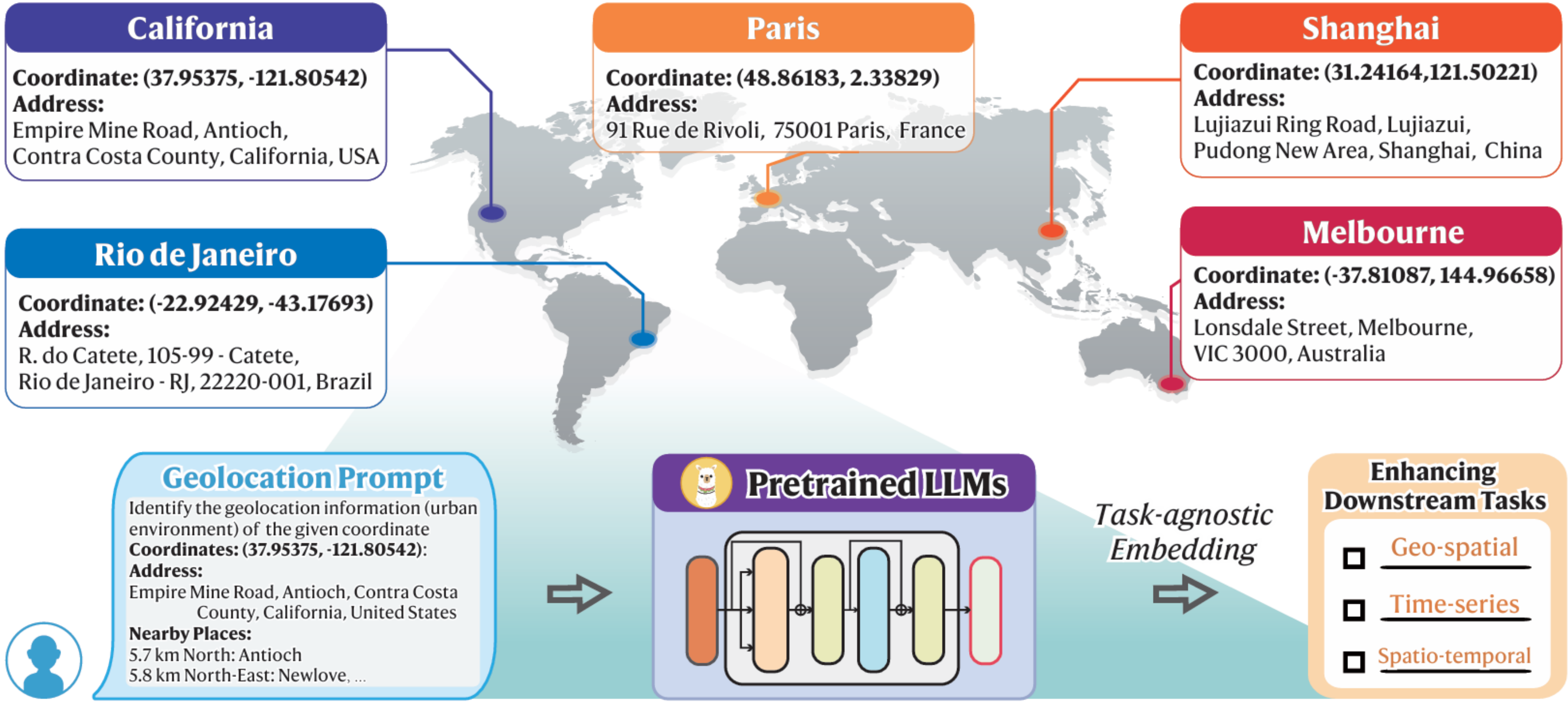
✓ LLM2Vec:



3 Case Study: LLM-based Geospatial Representation

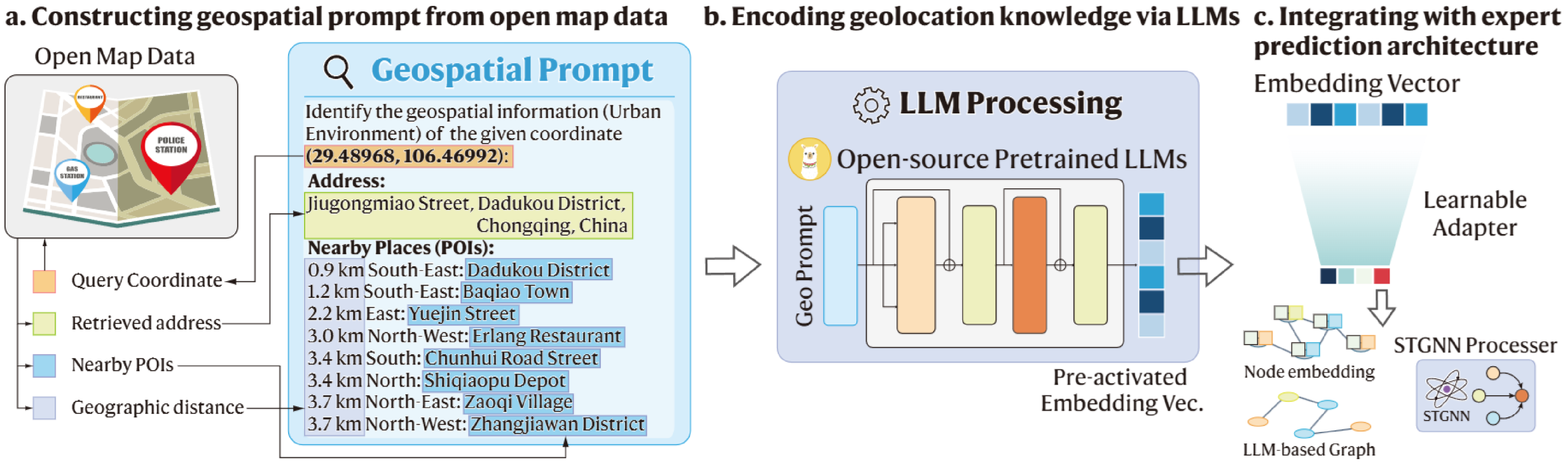
☐ LLM2Geovec: converting world knowledge to computable vectors

- **Stage 1**: generating geolocation prompts for coordinates from open map data
- Stage 2: generating representations for text descriptions from pre-trained LLMs
- Stage 3: employing representations in various downstream tasks



LLM2Geovec: converting world knowledge to vectors

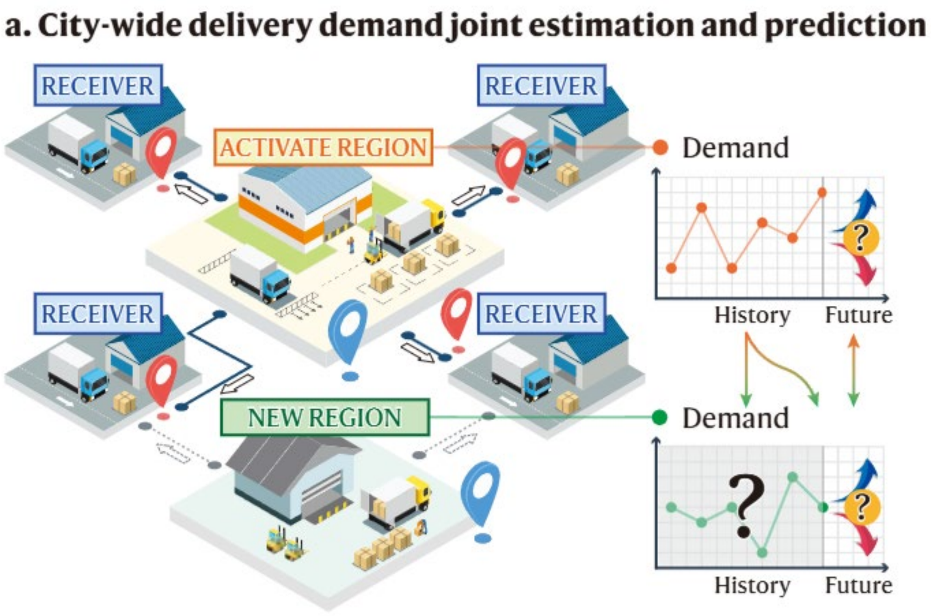
- **Stage 1**: generating geolocation prompts for coordinates from map data
- **Stage 2**: generating embeddings for text descriptions from pre-trained LLMs **(training-free)**
- **Stage 3**: employing refined embeddings in various downstream tasks



- Nie T, et al. Joint Estimation and Prediction of City-wide Delivery Demand: A Large Language Model Empowered Graph-based Learning Approach. TRE, 2025.

Application 1: Traffic demand estimation and prediction

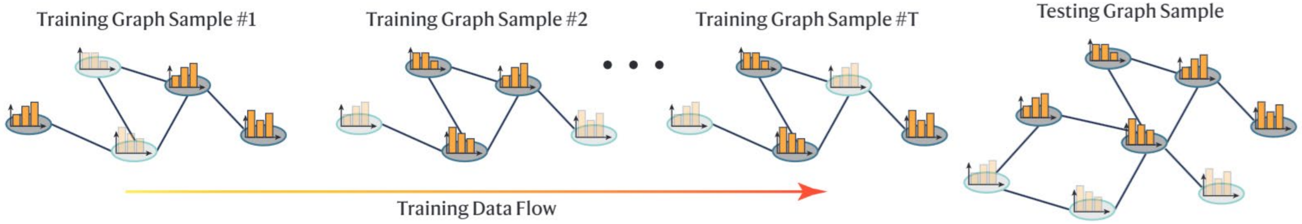
- Joint estimation and prediction of delivery demand in **new regions (w/o historical data)**
- Transferring the model from an active city to **new cities (zero-shot)**
- Modeling as a graph-based learning problem: **region-specific and region-wide patterns**.



Demand joint estimation and prediction by neural predictors

$$p(\underbrace{\{\bar{\boldsymbol{X}}^n_{\{1,\dots,T\}}\}_{n=1}^{N_u}}_{\text{unobserved demand}}, \underbrace{\{\boldsymbol{X}^n_{t+T}\}_{n=1}^{\bar{N}}}_{\text{future demand}} \,|\, \underbrace{\{\boldsymbol{X}^n_{\{1,\dots,T\}}\}_{n=1}^{N_o}}_{\text{observed demand}}, \underbrace{\boxed{\{\boldsymbol{v}_n\}_{n=1}^{\bar{N}}}}_{\text{location}}), \ \forall t \in [1, T'],$$

$$\underbrace{\boxed{\boldsymbol{\theta}}}_{\text{model-based transfer}} = \arg\max_{\boldsymbol{\theta}} \mathbb{E}[p_{\boldsymbol{\theta}}(\{\bar{\boldsymbol{X}}^n_{\{1,\dots,T\}}\}_{n=1}^{N_u}, \{\boldsymbol{X}^n_{t+T}\}_{n=1}^{\bar{N}} | \{\boldsymbol{X}^n_{\{1,\dots,T\}}\}_{n=1}^{N_o}, \{\boldsymbol{v}_n\}_{n=1}^{\bar{N}})].$$



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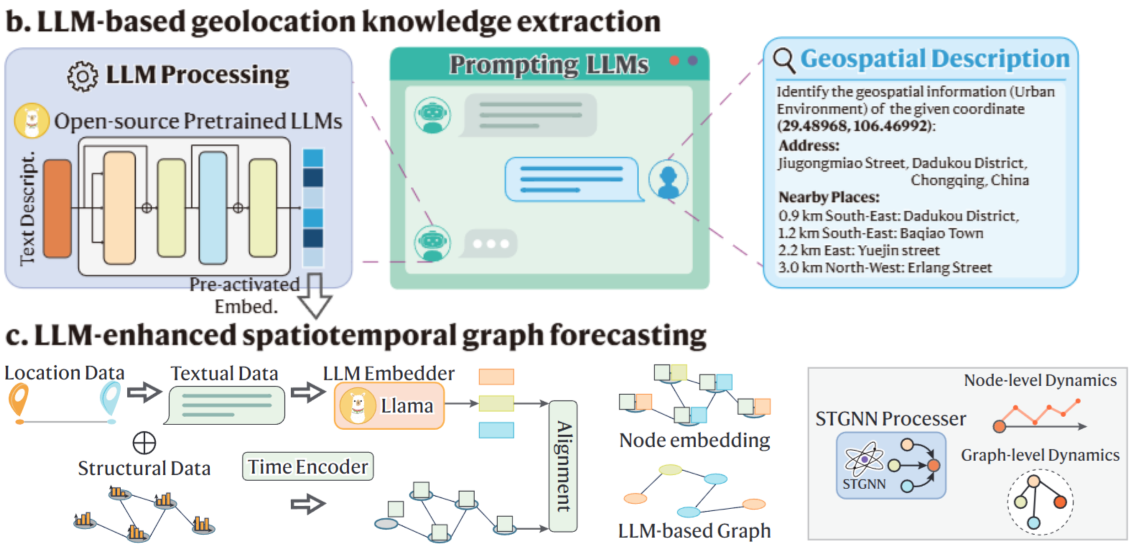
Application 1: Traffic demand estimation and prediction

- **Location-specific covariates** → in-sample accuracy
- **Cross-location covariates** → out-of-sample transferability
- LLM2Geovec can facilitate the modeling process



- Integrating LLM2Geovec into spatiotemporal demand predictor (graph neural networks)

Individual patterns: LLM2Geovec as fixed region embeddings

$$p_{\boldsymbol{\theta}_i}(\boldsymbol{x}^i_{t+h}|\boldsymbol{X}^i_{t-W:t}, \boldsymbol{U}_{t-W:t+h}, \boldsymbol{v}^i) \approx p^i(\boldsymbol{x}^i_{t+h}|\mathcal{X}_{<t}, \boldsymbol{U}_{\leq t+h}, \boldsymbol{V}),\ \forall h \in [1, H],\ \forall i \in \{1, \dots, \bar{N}\},$$

$$\boldsymbol{h}^{i,(\ell+1)}_t = \psi^{(\ell)}\left(\boldsymbol{h}^{i,(\ell)}_t, \mathrm{AGGR}_{j\in\mathcal{N}_k(i)}\{\rho^{(\ell)}([\boldsymbol{h}^{i,(\ell)}_t \| \boxed{\tilde{\boldsymbol{v}}_{\phi_i}}], \boldsymbol{h}^{j,(\ell)}_t, e^{i\leftarrow j})\}\right)_{\ell=0}^{L-1},$$

Collective patterns: functional graph construction with LLM2Geovec

$$p_{\boldsymbol{\theta}}(\boldsymbol{x}^i_{t+h}|\bar{\mathcal{G}}_{t-W:t}, \boldsymbol{U}_{t-W:t+h}) \approx p(\mathcal{X}_{t+h}|\mathcal{X}_{<t}, \boldsymbol{U}_{\leq t+h}, \boldsymbol{V}),\ \forall h \in [1, H],\ \forall i \in \{1, \dots, \bar{N}\},$$

$$\bar{\mathcal{X}}^u_{t-W:t}, \hat{\mathcal{X}}_{t:t+H} = \mathcal{F}(\bar{\mathcal{G}}_{t-W:t}, \boldsymbol{U}_{t-W:t+H}, \boxed{\boldsymbol{A}_{\mathrm{LLM}}}|\boldsymbol{\theta}),\ \boldsymbol{A}_{\mathrm{LLM}} \sim q_{\Phi}(\bar{\boldsymbol{A}}|\bar{\mathcal{X}}_{t-W:t}) \in \mathbb{R}^{\bar{N}\times\bar{N}},$$

• Nie T, et al. Joint Estimation and Prediction of City-wide Delivery Demand: A Large Language Model Empowered Graph-based Learning Approach. TRE, 2025.

3 LLM-enhanced Delivery Demand Joint Prediction & Estimation

Application 1: Traffic demand estimation and prediction

- Parameterization by graph neural networks
- Collective-individual pattern treatment considering transferability
- End-to-end transferable predictor by inductive learning

Inductive training scheme

Sampling: $\boldsymbol{m}^i_{t-W:t} \sim p(\boldsymbol{m}^i_{t-W:t}) = \mathcal{B}(\beta),\ \forall i \in \{1,\dots,N_o\}$,

Masking: $\bar{\mathcal{X}}_{t-W:t} = \{\boldsymbol{m}^i_{t-W:t} \odot \boldsymbol{X}^i_{t-W:t}\}_{i=1}^{N_o}$,

Reconstructing: $\hat{\mathcal{X}}_{t:t+H} = \mathcal{F}(\bar{\mathcal{X}}_{t-W:t}, \{\boldsymbol{A}_\tau\}^t_{t-W} | \boldsymbol{\theta}) \approx \mathbb{E}_p[p_{\boldsymbol{\theta}}(\boldsymbol{x}^i_{t+h} | \bar{\mathcal{X}}_{t-W:t})],\ \forall h \in [1, H]$

Learning: $\boldsymbol{\theta}^\star = \arg\min_{\boldsymbol{\theta}} \mathcal{L}_{\text{recon}}(\widehat{\mathcal{X}}_{t-W:t}, \mathcal{X}_{t-W:t}) + \mathcal{L}_{\text{pred}}(\widehat{\mathcal{X}}_{t:t+H}, \mathcal{X}_{t:t+H})$

$$= \arg\min_{\boldsymbol{\theta}} \underbrace{\sum_{\tau=t-W}^{t} \frac{\sum_{i=1}^{N_o} \overline{m}^i_\tau \cdot \ell(\hat{\boldsymbol{x}}^i_\tau, \boldsymbol{x}^i_\tau)}{\sum_{i=1}^{N_o} \overline{m}^i_\tau}}_{\text{reconstruction loss}} + \underbrace{\frac{1}{\bar{N}H} \sum_{h=1}^{H} \sum_{i=1}^{\bar{N}} \ell(\hat{\boldsymbol{x}}^i_{t+h}, \boldsymbol{x}^i_{t+h})}_{\text{prediction loss}},$$

Estimating: $\hat{\mathcal{X}}_{t:t+H'} = \mathcal{F}(\bar{\mathcal{X}}_{t-W':t}, \{\bar{\boldsymbol{A}}_\tau\}^t_{t-W'} | \boldsymbol{\theta}^\star),\ \bar{\mathcal{X}}_{t-W':t} = \{\boldsymbol{X}^i_{t-W':t}\}_{i=1}^{N_o} \cup \{\bar{\boldsymbol{X}}^i_{t-W':t}\}_{i=1}^{N_u}$.

Spatial-temporal message passing neural networks

- ✓ Temporal message-passing layers (TEMPENC)

$$\boldsymbol{h}^{i,\ell+1}_t = \sigma(\boldsymbol{W}^\ell_t [\boldsymbol{x}^{i,\ell}_t \| \boldsymbol{x}^{j,\ell}_{t-1} \| \dots \| \boldsymbol{x}^{j,\ell}_{t-W}] + \boldsymbol{b}^\ell_t).$$

- ✓ Spatial message-passing layers

Message Updating: $\boldsymbol{m}^{j\to i,\ell}_t = \sigma(\boldsymbol{W}^\ell_m [\boldsymbol{h}^{i,\ell}_t \| \boldsymbol{h}^{j,\ell}_t \| e^{i\leftarrow j}_t] + \boldsymbol{b}^\ell_m)$,

Edge Updating: $\alpha^{j\to i,\ell}_t = \sigma(\boldsymbol{W}^\ell_e \boldsymbol{m}^{j\to i,\ell}_t + \boldsymbol{b}^\ell_e)$,

Node Updating: $\boldsymbol{h}^{i,\ell+1}_t = \sigma(\boldsymbol{W}^\ell_n \boldsymbol{h}^{i,\ell}_t + \text{MEAN}_{j\in\mathcal{N}_k(i)} \{\alpha^{j\to i,\ell}_t \boldsymbol{m}^{j\to i,\ell}_t\})$

- ✓ Dense Feedforward Layer

$$\boldsymbol{h}^{i,\ell+1}_t = \sigma(\boldsymbol{W}^\ell_r \boldsymbol{h}^{i,\ell}_t + \boldsymbol{b}^\ell_r) + \boldsymbol{h}^{i,\ell}_t.$$

- ✓ MLP-based Multistep Output Layer

$$\hat{\boldsymbol{x}}^i_{t+h} = \text{MLP}(\boldsymbol{h}^{i,(L)}_t, \boldsymbol{U}_{t:t+h}, \boldsymbol{v}_{\phi_i}),\ \forall i \in \{1,\dots,\bar{N}\}.$$

- Nie T, et al. Joint Estimation and Prediction of City-wide Delivery Demand: A Large Language Model Empowered Graph-based Learning Approach. TRE, 2025.

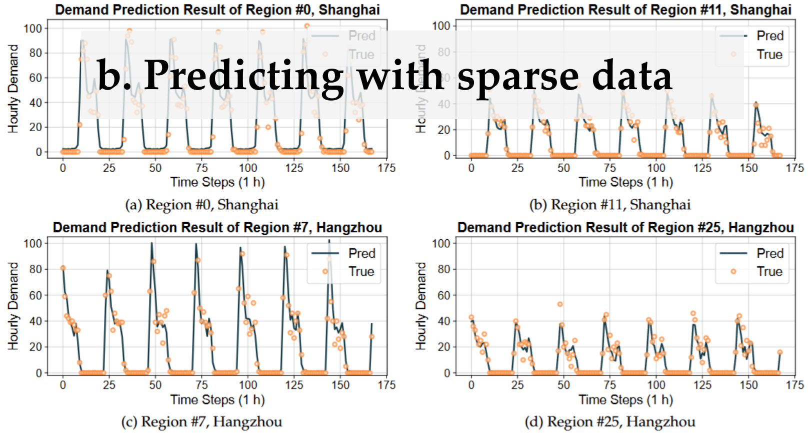
☐ Application 1: Traffic demand estimation and prediction

- **Accuracy:** outperforms SOTA baselines in all scenarios by large margins
- **Transferability**: flexible to generalize to new cities in zero-shot ways
- **Robustness**: more robust performance in online scenarios

a. Single-city comparison

Models	Shanghai		Hangzhou		Chongqing		Jilin		Yantai	
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
HA	6.96	16.41	8.94	20.56	4.00	8.85	2.27	4.85	3.82	8.42
DCRNN (Li et al., 2017)	5.65	11.86	7.33	14.59	3.53	6.15	2.05	3.37	3.21	6.17
STGCN (Yu et al., 2017)	5.07	11.62	6.38	14.26	2.99	6.00	1.53	2.84	2.80	5.79
GWNET (Wu et al., 2019b)	5.22	11.67	7.99	15.90	3.06	6.03	1.64	3.06	2.93	6.01
MTGNN (Wu et al., 2020)	5.09	11.56	6.23	13.89	2.97	5.91	1.52	2.84	2.73	5.70
IGNNK (Wu et al., 2021b)	5.22	11.50	7.25	15.06	3.22	6.06	2.22	3.71	2.97	5.93
SATCN (Wu et al., 2021c)	4.75	9.38	7.64	14.77	3.04	5.27	1.58	2.84	2.83	5.02
MPGRU (Gao and Ribeiro, 2022)	6.30	13.43	7.95	16.03	3.91	7.60	1.94	3.61	3.58	7.45
GRIN (Cini et al., 2021)	5.08	11.64	6.30	14.56	3.05	6.08	1.54	2.90	2.86	6.02
IMPEL (Ours)	**3.76**	**7.93**	**4.52**	**9.90**	**2.47**	**4.92**	**1.39**	**2.51**	**2.23**	**4.18**
Improvement (%)	20.8	15.4	27.4	28.7	16.8	6.64	8.55	11.6	18.3	16.7

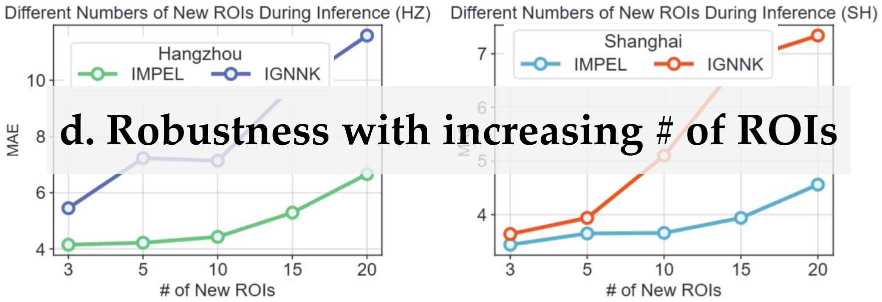
b. Predicting with sparse data



c. Cross-city transferability

Models	IMPEL (Ours)		MTGNN		IGNNK		STGCN		GRIN	
Source ↦ Target	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
Shanghai ↦ Hangzhou	3.35	6.42	4.07	7.32	5.64	9.00	5.55	9.31	3.75	7.33
Shanghai ↦ Chongqing	**2.26**	**4.44**	2.62	4.89	3.25	5.22	2.91	4.91	2.51	4.86
Shanghai ↦ Yantai	**2.21**	**4.14**	2.52	4.68	3.47	5.66	2.79	4.77	2.56	4.87
Hangzhou ↦ Shanghai	**2.90**	**6.20**	3.12	6.38	3.04	6.26	3.09	6.54	3.11	6.53
Hangzhou ↦ Chongqing	**2.10**	**4.25**	2.21	4.37	2.21	4.32	2.17	4.37	2.20	4.47
Hangzhou ↦ Yantai	**2.13**	**4.08**	2.26	4.33	2.23	4.17	2.21	4.28	2.34	4.69

d. Robustness with increasing # of ROIs



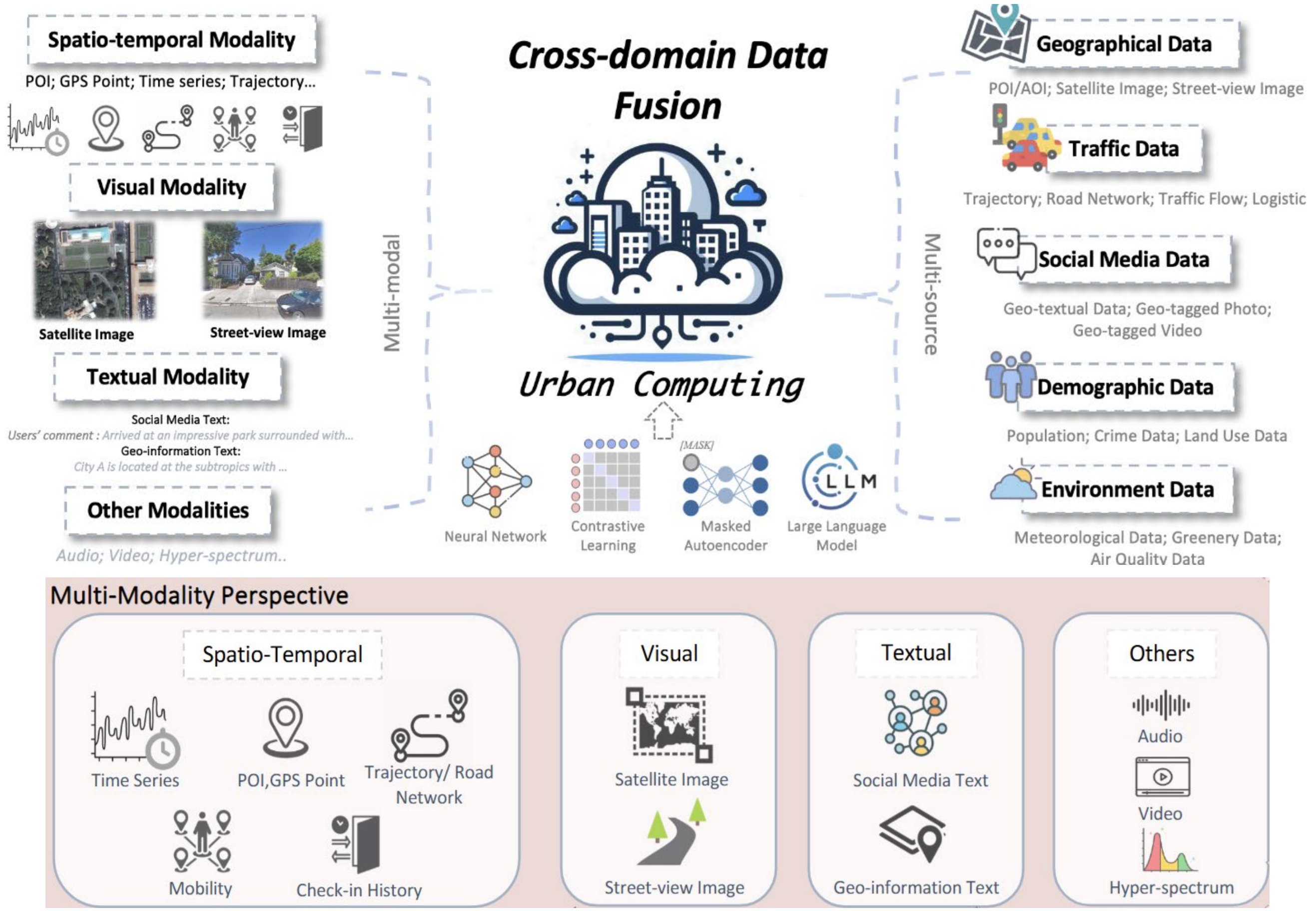
- Nie T, et al. Joint Estimation and Prediction of City-wide Delivery Demand: A Large Language Model Empowered Graph-based Learning Approach. TRE, 2025.

☐ Location-based spatiotemporal process in urban and earth systems

- ➢ From a big picture: urban systems
  - ✓ Spatial-temporal complex systems
  - ✓ **Location-based** process:

    Human mobility, social media, geographic, demographic, economic, environmental factors

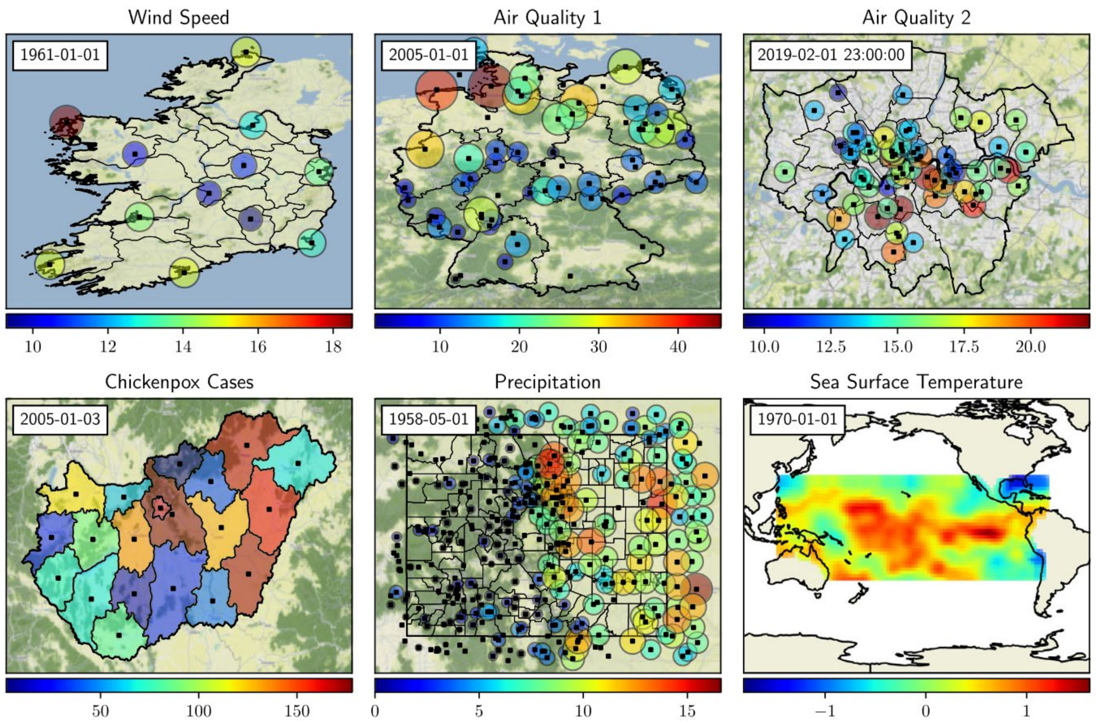
✓ Call for **generalizable, cost-effective, and equitable** methods for urban computing



- Zou X, Yan Y, Hao X, et al. Deep learning for cross-domain data fusion in urban computing: Taxonomy, advances, and outlook[J]. Information Fusion, 2025.

Application 2: Spatio-temporal learning on the earth

- Spatiotemporal learning, which consists of **spatially-referenced time series**, such as air pollution monitoring, disease tracking, and cloud-demand forecasting



Our aim:

- ✓ To leverage LLMs to generate semantically rich and **globally covered geolocation representations with readily accessible data**.
- ✓ To offer a **simple yet effective paradigm** for enhancing spatio-temporal learning using LLMs, resulting in **direct performance improvements**.

- He, J.*, Nie, T. *, & Ma, W. (2024). Geolocation representation from large language models are generic enhancers for spatio-temporal learning, AAAI-25

4 LLM-enhanced spatiotemporal and geographic Prediction

Application 2: Spatio-temporal learning on the earth

- Geographic prediction:
  - ✓ Given **ground observations** (e.g., crime rate, income level, temperature) of **partial locations**
  - ✓ Trained to predict values of unlabeled locations

- How to Enhance :
  - ✓ LLM2Geovec acts as input features of locations
  - ✓ Using simple **linear model** (ridge regressor)
  - ✓ Integrating LLM2Geovec with **existing architectures**

Tasks	Source	Scale	Attribute	Training/ Testing
Annual Air Temperature	Chelsa	Global	Climate	80k/20k
Annual Precipitation	Chelsa	Global	Climate	80k/20k
Monthly Climate Moisture	Chelsa	Global	Climate	40k/20k
Population Density	WorldPop	Global	Society	80k/20k
Nighttime Light Intensity	EOG	Global	Society	80k/20k
Human Modification Terrestrial	SEDAC	Global	Society	80k/20k
Global Gridded Relative Deprivation	SEDAC	Global	Society	80k/20k
Ratio of Built-up Area to Non-built Up Area	SEDAC	Global	Society	80k/20k
Child Dependency Ratio	SEDAC	Global	Society	80k/20k
Subnational Human Development	SEDAC	Global	Society	80k/20k
Infant Mortality Rates	SEDAC	Global	Society	80k/20k
Asset Index	DHS	Global	Society	20k/5k
Sanitation Index	DHS	Global	Society	20k/5k
Women BMI	DHS	Global	Society	40k/10k
Poverty Rate	DHS	Country	Society	5k/1k
Population Density	FaceBook	Country	Society	5k/1k
Women BMI	DHS	Country	Society	5k/1k
Population Density	NYC	City	Society	1k/424
Education Level	NYC	City	Society	1k/424
Income Level	NYC	City	Society	1k/424
Crime Rate	NYC	City	Society	1k/424

Tasks	LLMGeovec (LLaMa 3 8B)			LLMGeovec (Mistral 8 x 7B)			Bert-whitening (Bert base)			GTE-large			GTE-qwen2 7B		
	MAE	RMSE	R^2	MAE	RMSE	R^2	MAE	RMSE	R^2	MAE	RMSE	R^2	MAE	RMSE	R^2
Annual Air Temperature	**9.90**	**14.32**	**0.95**	11.05	16.03	0.94	24.03	32.73	0.76	22.23	30.15	0.80	14.05	19.99	0.91
Annual Precipitation	**2016.60**	**3021.76**	**0.86**	2176.82	3245.12	0.83	3717.73	5293.82	0.56	3519.57	5012.55	0.61	2604.86	3931.23	0.76
Monthly Climate Moisture	**1302.14**	**2021.21**	**0.55**	1345.82	2097.32	0.52	1644.56	2715.44	0.19	1619.65	2610.16	0.25	1394.10	2288.89	0.43
Population Density	**695.10**	**1020.11**	**0.85**	759.81	1115.38	0.82	1342.98	2185.67	0.30	1266.82	1986.15	0.42	896.52	1417.02	0.70
Nighttime Light Intensity	**3.55**	**4.58**	**0.97**	3.79	4.89	0.96	8.55	11.37	0.81	7.63	9.99	0.85	4.77	6.15	0.94
Human Modification Terrestrial	**0.07**	**0.09**	**0.78**	0.07	0.09	0.75	0.12	0.15	0.39	0.11	0.14	0.47	0.08	0.11	0.68
Global Gridded Relative Deprivation	**6.56**	**8.98**	**0.85**	6.70	9.15	0.84	10.43	13.60	0.65	9.83	12.95	0.68	8.13	10.86	0.78
Ratio of Built-up Area to Non-built Up Area	**8.44**	**11.07**	**0.78**	8.72	11.41	0.77	13.04	16.40	0.52	12.51	15.81	0.56	10.48	13.41	0.68
Child Dependency Ratio	**5.84**	**8.29**	**0.86**	5.88	8.34	0.88	9.50	13.12	0.64	9.11	12.47	0.68	7.17	10.09	0.79
Subnational Human Development	**5.79**	**8.20**	**0.89**	5.82	8.22	0.89	9.81	13.30	0.70	9.15	12.36	0.75	7.10	9.95	0.83
Infant Mortality Rates	**3.98**	**6.06**	**0.93**	4.02	6.14	0.93	7.42	10.76	0.77	7.24	10.20	0.80	4.97	7.50	0.89
Asset Index	**0.02**	**0.03**	**0.93**	0.02	0.03	0.92	0.06	0.08	0.53	0.05	0.07	0.62	0.04	0.06	0.78
Sanitation Index	**0.09**	**0.12**	**0.95**	0.10	0.13	0.93	0.23	0.30	0.67	0.20	0.26	0.75	0.15	0.20	0.85
Women BMI	**0.76**	**1.01**	**0.95**	0.83	1.12	0.94	1.82	2.38	0.77	1.55	2.04	0.83	1.16	1.57	0.90

- He, J.*, Nie, T. *, & Ma, W. (2024). Geolocation representation from large language models are generic enhancers for spatio-temporal learning, AAAI-25

4 LLM-enhanced spatiotemporal and geographic Prediction

Application 2: Spatio-temporal learning on the earth

- Graph-based Time Series Forecasting:
  - ✓ Given historical time-series data and the graph relational bias of locations
  - ✓ Predict **long-term or short-term** future dynamics of sensors
- How to Enhance :
  - ✓ LLM2Geovec acts as **additional covariates** of locations, concatenated on the historical signal embedding before models

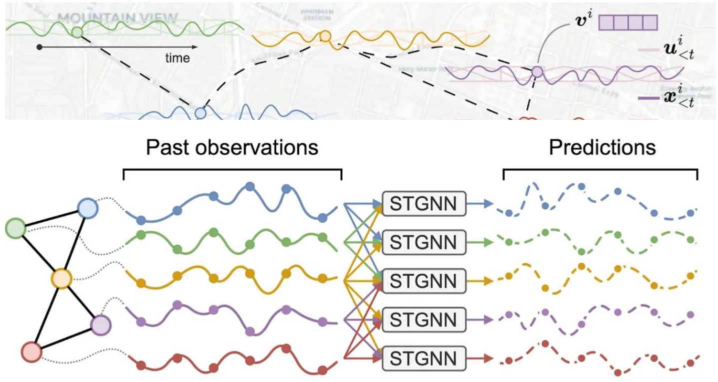


Image source: Cini et al. 2023, by authors

Short-term forecasting results

Models	SD MAE	SD RMSE	GLA MAE	GLA RMSE	GBA MAE	GBA RMSE	IMP (%)
HA	60.78	87.39	59.58	86.19	56.43	79.81	–
DCRNN	25.23	39.17	22.73	35.65	22.35	35.26	8.32%
+LLMGeovec	**18.70**	**31.36**	**21.43**	**34.76**	**21.69**	**34.37**	
STGCN	20.10	34.60	22.48	38.55	23.14	37.90	3.51%
+LLMGeovec	**19.83**	**33.21**	**22.03**	**37.45**	**22.43**	**36.51**	
ASTGCN	25.13	39.88	28.44	44.13	26.15	40.25	7.98%
+LLMGeovec	**23.89**	**38.08**	**23.74**	**38.27**	**23.24**	**37.78**	
AGCRN	18.45	34.40	20.61	36.23	20.55	**33.91**	0.60%
+LLMGeovec	**18.21**	**33.82**	**19.88**	**35.96**	**19.77**	34.12	
GWNET	19.38	31.88	21.23	33.68	20.84	34.58	3.92%
+LLMGeovec	**18.03**	**30.06**	**20.29**	**32.62**	**20.66**	**33.58**	
MTGNN	23.69	36.83	23.47	37.68	23.73	36.01	8.09%
+LLMGeovec	**19.03**	**31.17**	**21.76**	**34.58**	**22.55**	**35.77**	
MLP	27.84	43.92	29.12	45.76	29.15	45.64	26.53%
+LLMGeovec	**19.00**	**3.03**	**21.07**	**34.56**	**21.42**	**34.92**	

Long-term forecasting results

Models / Metric	iTransformer MSE	iTransformer MAE	w/ LLMGeovec MSE	w/ LLMGeovec MAE	TSMixer MSE	TSMixer MAE	w/ LLMGeovec MSE	w/ LLMGeovec MAE	RMLP MSE	RMLP MAE	w/ LLMGeovec MSE	w/ LLMGeovec MAE	Informer MSE	Informer MAE	w/ LLMGeovec MSE	w/ LLMGeovec MAE	IMP %
Global Wind	4.582	1.51	**3.979**	**1.380**	4.261	1.424	**4.132**	**1.407**	4.905	1.498	**4.180**	**1.414**	4.905	1.576	**4.844**	**1.566**	13.30%
Global Temp	13.079	2.653	**11.945**	**2.601**	12.035	2.480	**11.441**	**2.398**	13.447	2.558	**12.525**	**2.480**	**18.370**	**3.209**	18.639	3.234	5.19%
Solar Energy	0.233	0.262	**0.206**	**0.265**	0.255	0.294	**0.219**	**0.289**	0.261	0.313	**0.235**	**0.286**	0.264	**0.308**	**0.263**	0.313	11.59%
Demand-SH	0.331	0.298	**0.322**	**0.297**	0.355	0.332	**0.336**	**0.305**	0.345	0.326	**0.318**	**0.286**	0.896	**0.618**	**0.779**	0.666	2.47%
Air Quality	1.922	0.631	**1.856**	**0.619**	2.068	0.665	**1.989**	**0.650**	1.857	0.627	**1.820**	**0.613**	3.584	0.864	**2.858**	**0.771**	3.46%
Traffic-SD	0.136	0.225	**0.106**	**0.201**	0.116	0.212	**0.105**	**0.197**	0.205	0.296	**0.168**	**0.264**	0.199	0.298	**0.152**	**0.254**	22.01%

- He, J.*, Nie, T. *, & Ma, W. (2024). Geolocation representation from large language models are generic enhancers for spatio-temporal learning, AAAI-25

Harnessing LLM-based Geospatial Representations for Spatiotemporal Learning

- LLMs are surprisingly geospatially aware;
- LLM2Geovec offers linear, interpretable representations of Earth data;
- Integrating these vectors into existing models—whether GNNs or MLPs—is computationally efficient and boosts performance;
- LLM2Geovec brings little additional computational time and memory overhead, making advanced tools accessible even with limited data.

5 ITSC 2025 Invited Session Calls for Papers

IEEE ITSC 2025

IEEE Intelligent Transportation Systems Society

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Welcome to submit your paper!

Submission Deadline: May 1st, 2025

Invited session: Innovative Applications of Large Language Models in Multimodal Transportation Systems

Topics of interest (not limited to):

- **LLM-enhanced sensing:** Integrating LLMs or VLMs for multimodal traffic data acquisition, fusion, translation, and analysis.
- **Knowledge-driven learning**: Prompt engineering, domain-specific LLM fine-tuning, few-shot learning, RAG, and knowledge representation in predictive learning tasks such as traffic prediction, travel forecasting, and behavior modeling.
- **Generative modeling in ITS**: Use LLMs to generate synthetic traffic scenarios, assist in the development of digital twins and simulation systems, design heuristic algorithms and functions, and provide feedback and evaluation.
- **Intelligent decision making**: LLM-based traffic control, network optimization, mixed traffic flows, intelligent vehicles, human-in-the-loop interfaces, agent frameworks for complex tasks, and collaborative multi-agent coordination.
- **LLMs in transport operation and management:** Applying LLMs in real-time traffic management, safety analytics, public transit, shared mobility, multimodal integration, Mobility as a Service (MaaS) platform.
- **Innovative case studies**: Presentation of pioneering deployment where LLMs have been successfully integrated into real-world multimodal transportation systems.
- **Ethical and operational considerations**: Discussions on the challenges and implications of deploying LLMs, including data privacy, interpretability, bias mitigation, scalability, and computational efficiency.

Thank you for your attention!

Papers @ arXiv

More about us

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Mobility AI Lab

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