

Deep Learning for Human Mobility Analytics

-- L11-Large Language Models for ST Data Mining

Yuxuan Liang (梁宇轩)

INTR & DSA Thrust

yuxuanliang@hkust-gz.edu.cn

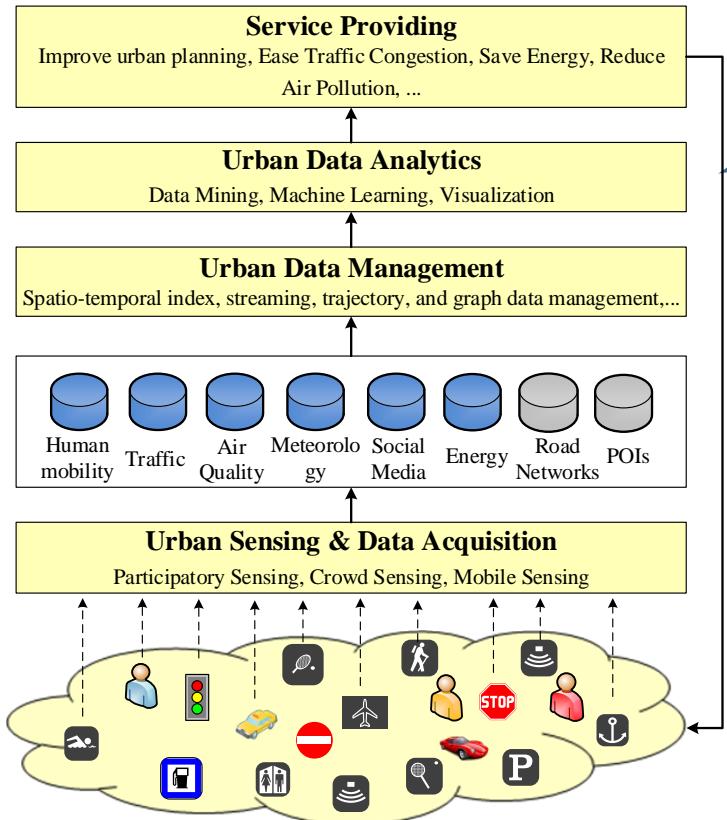


Objectives of this Course

To introduce

- Conventional methods for ST data mining
- LLMs for ST data mining
 - LLM-as-Enhancer
 - LLM-as-Predictor
 - LLM-as-Agent

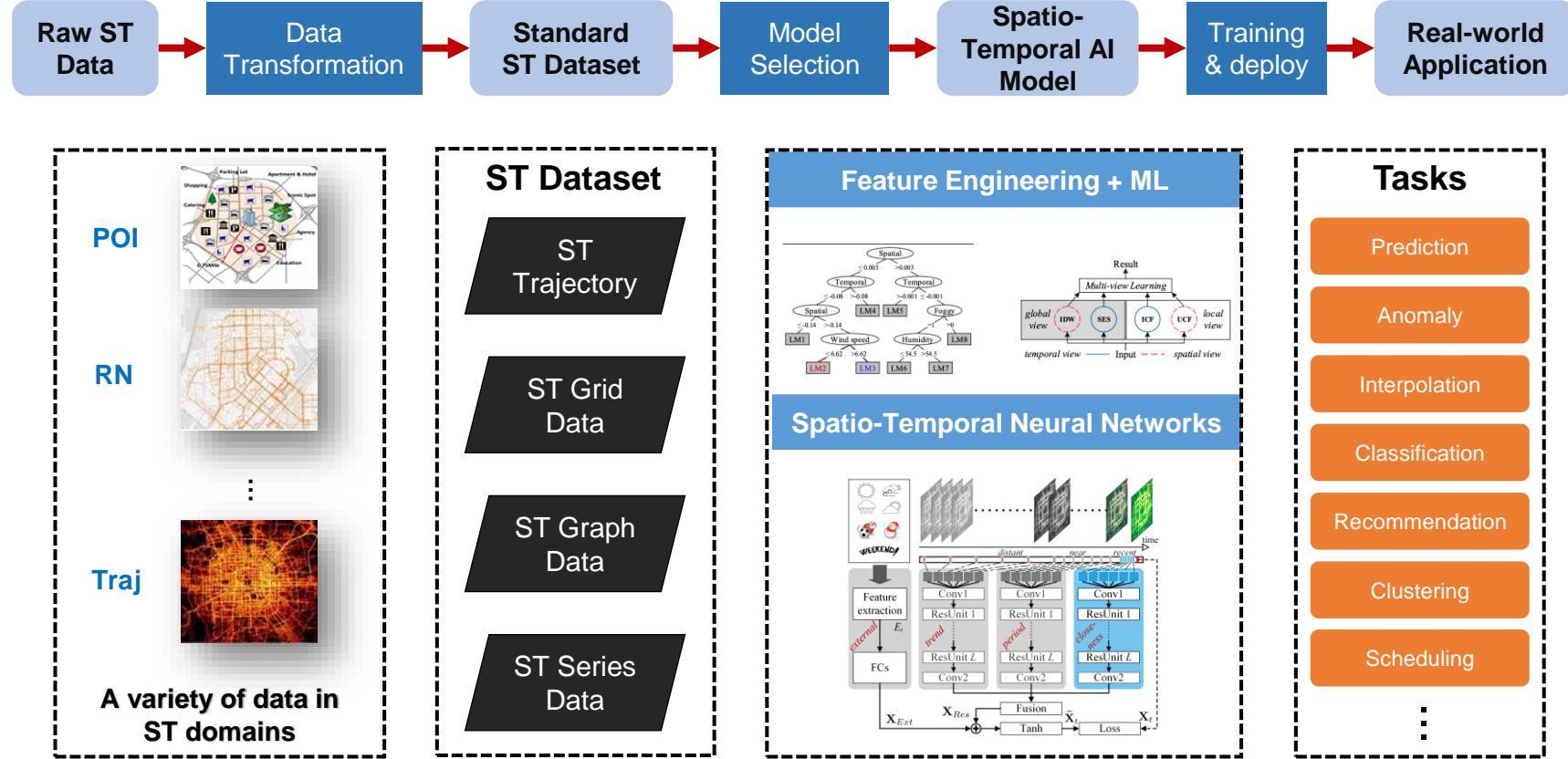
3rd Stage: Urban Data Analytics



- Texts and images → spatio-temporal data
- A single data source → cross-domain data sources
- Separate data mining algorithms → ML + data management
- Visual and interactive data analytics

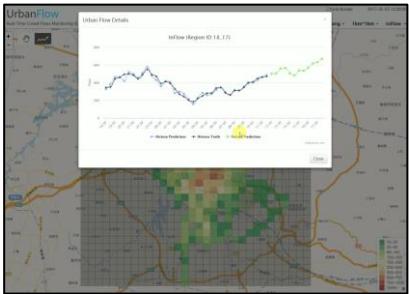
Urban Data Analytics				
Data Fusion	Visualization and Interactive Visual Analytics			
	Fill Missing Values	Causality Inference	Predictive Models	Transfer Learning-Based
Basic	Multi-View-based Fusion	Similarity-Based Fusion	Probabilistic-Dependency-Based	Transfer Learning-Based
	Stage-Based Data Fusion	Feature-level Data Fusion		
Clustering Classification Regression Outlier Detection Association				

Modeling Pipeline

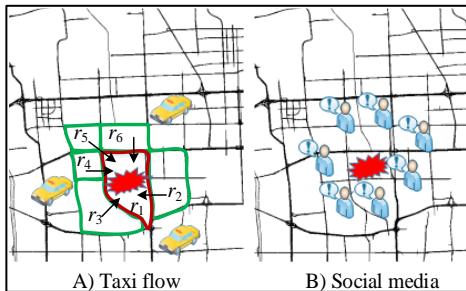


Popular Downstream Tasks

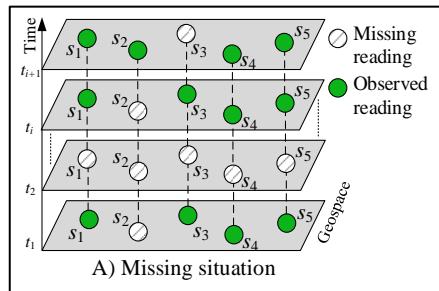
ST Prediction



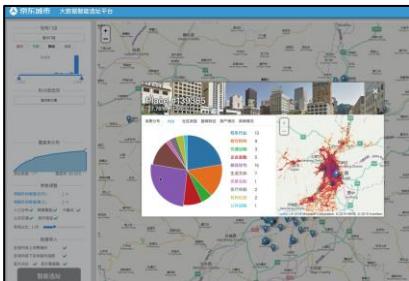
Anomaly Detection



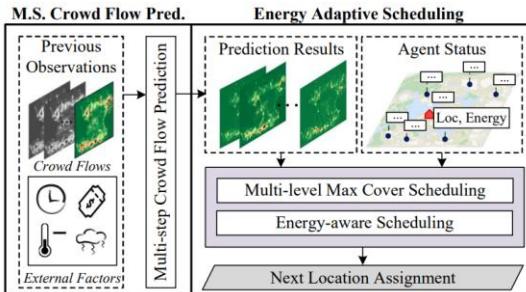
ST Interpolation



ST Recommendation



Scheduling

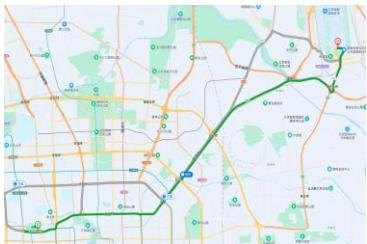


Classification



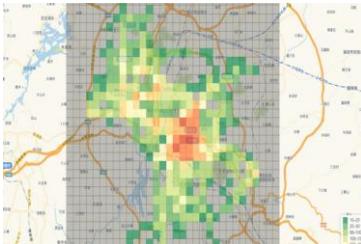
Sample Methodologies & Applications

Modeling ST Trajectory



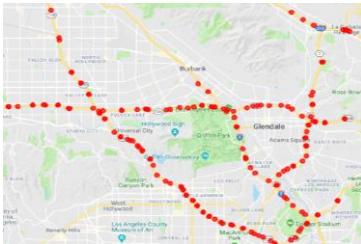
TrajCL [IJCAI'24]

Modeling ST Grid Data



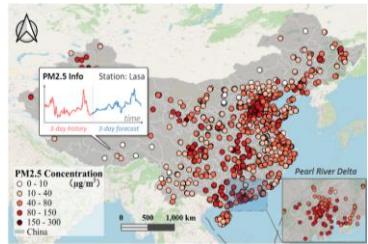
PhysicNet [TKDE'23]

Modeling ST Graphs



CaST [NeurIPS'23]

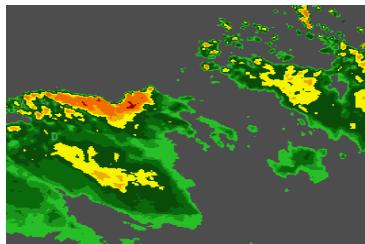
Modeling ST Series



AirFormer [AAAI'23]



COLA [WWW'24]



NuwaDynamic [ICLR'24]



LargeST [NeurIPS'23]



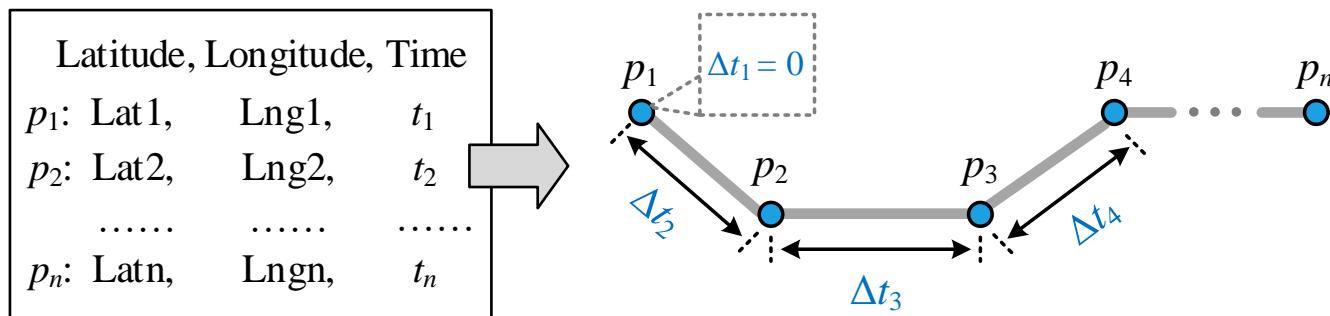
STGNP [KDD'23]

Definition of ST Trajectories

- A ST trajectory is a sequence derived from a moving object in geographical spaces, formulated by a series of chronologically ordered points

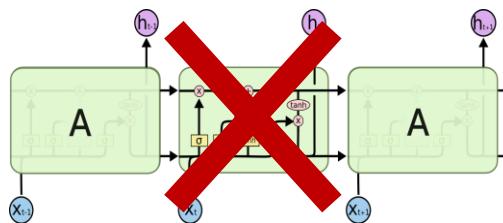
$$T = p_1 \rightarrow p_2 \rightarrow \dots \rightarrow p_n, \quad p_i = (\underline{a_i}, \underline{b_i}, \boxed{t_i})$$

Timestamp
Location (latitude & longitude)

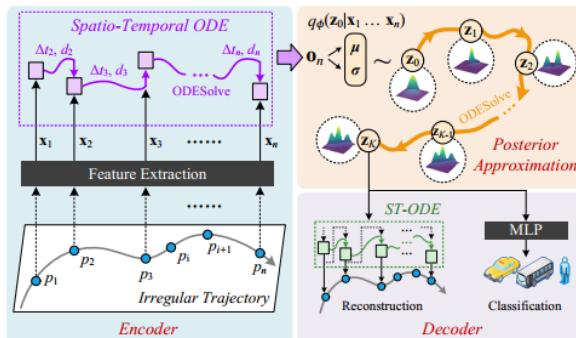


Examples on ST Trajectories

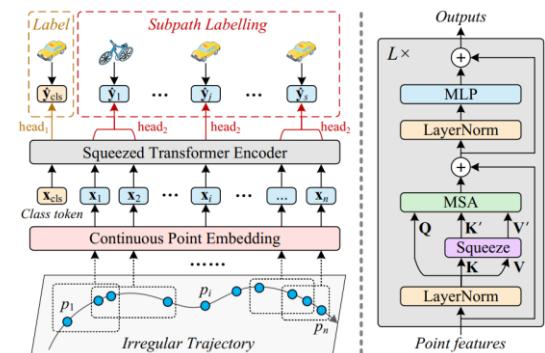
- Existing AI approaches for CV/NLP are NOT always good choices for modeling trajectories
- Capturing the **irregularity** of trajectories is of great importance to trajectory modeling
- We demonstrate how to encode the domain knowledge (i.e., irregularity) into existing AI methods, including RNNs and Transformers



Classic RNNs



Continuous trajectory modeling



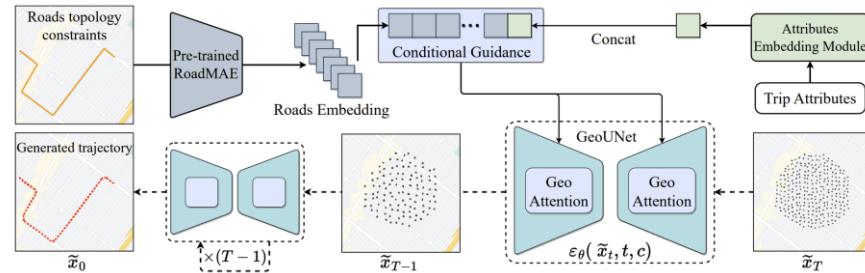
Efficient trajectory modeling

Y. Liang et al., *Modelling Trajectories with Neural Ordinary Differential Equations*. IJCAI 2021.

Y. Liang et al., *TrajFormer: Efficient Trajectory Classification with Transformers*. CIKM 2022.

Methodologies for Generating ST Trajectories

- Using real-world human trajectories usually has **privacy concerns**
 - Generation helps protect users' privacy
 - DDPM outperforms GAN and VAE**



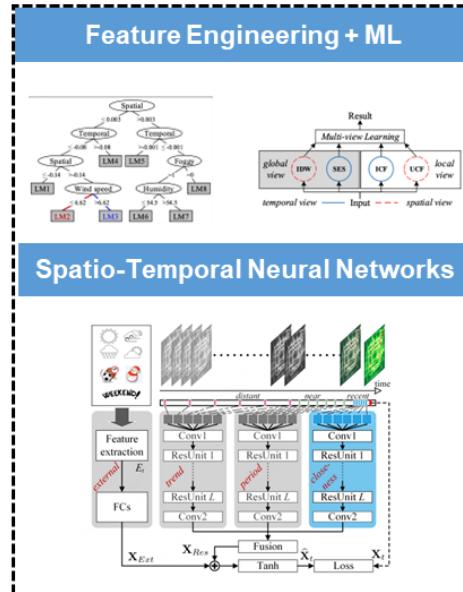
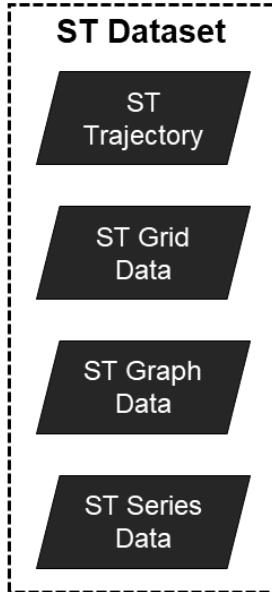
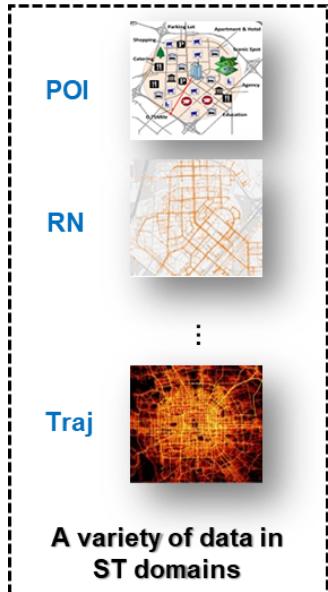
Same origin and destination



Different origin and destination

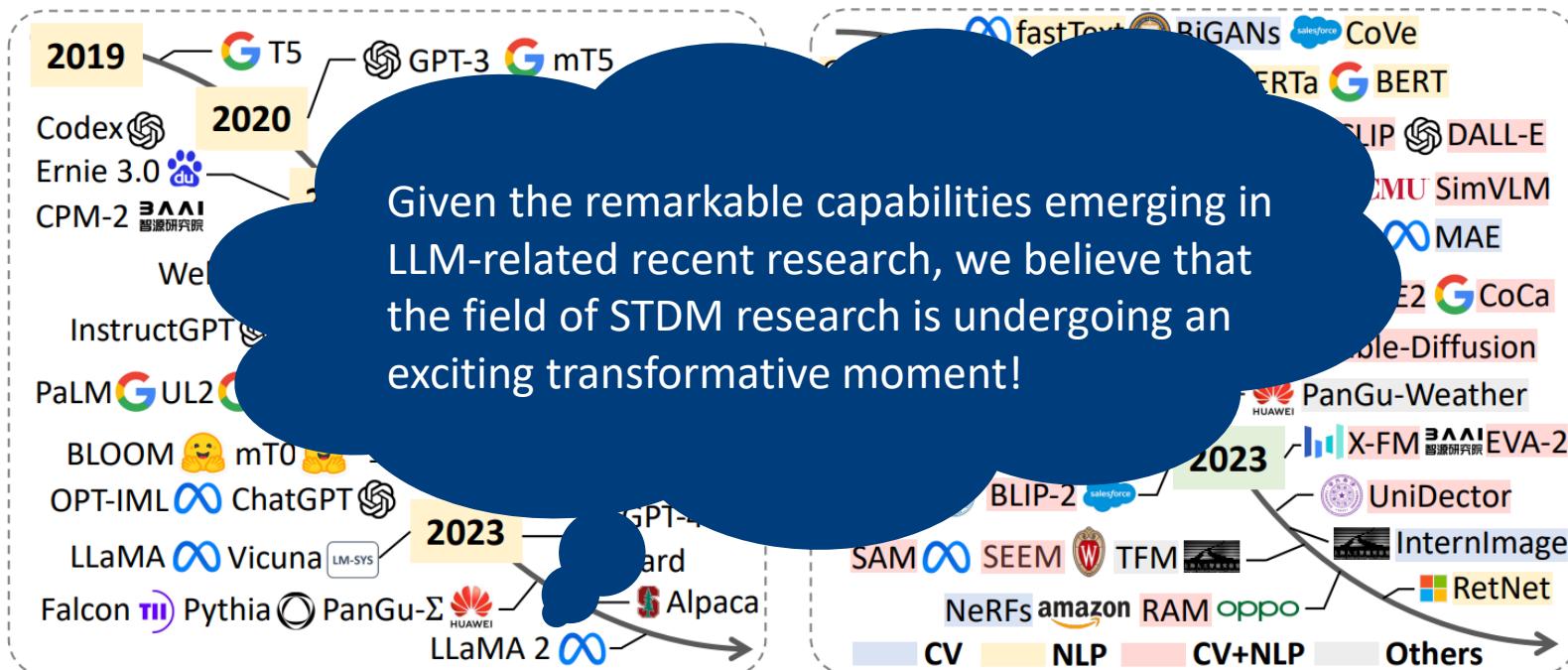
Limitation

- “There is no free lunch”. Prior literature mostly concentrated on solving specific tasks



Roadmap of LLMs

- LLMs and Foundation Models



LLMs for Spatio-Temporal Data

General LLM



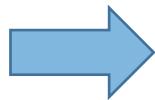
Text generation



text2speech



Machine
translation



Spatio-Temporal LLM (oriented to ST data)



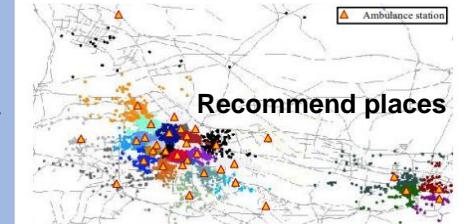
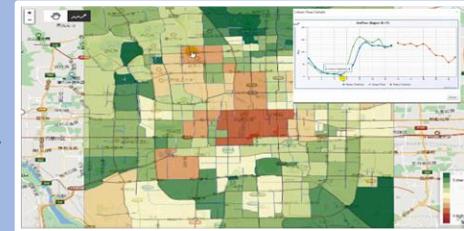
Traffic prediction



Fire risk early warning



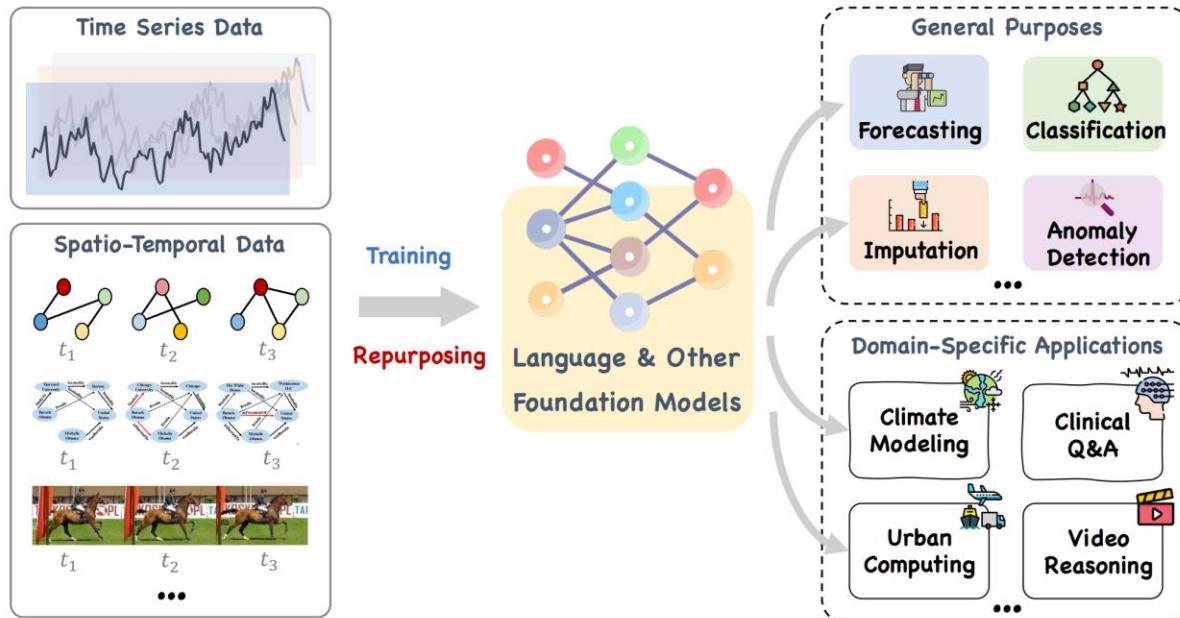
Dynamic ambulance
redeployment



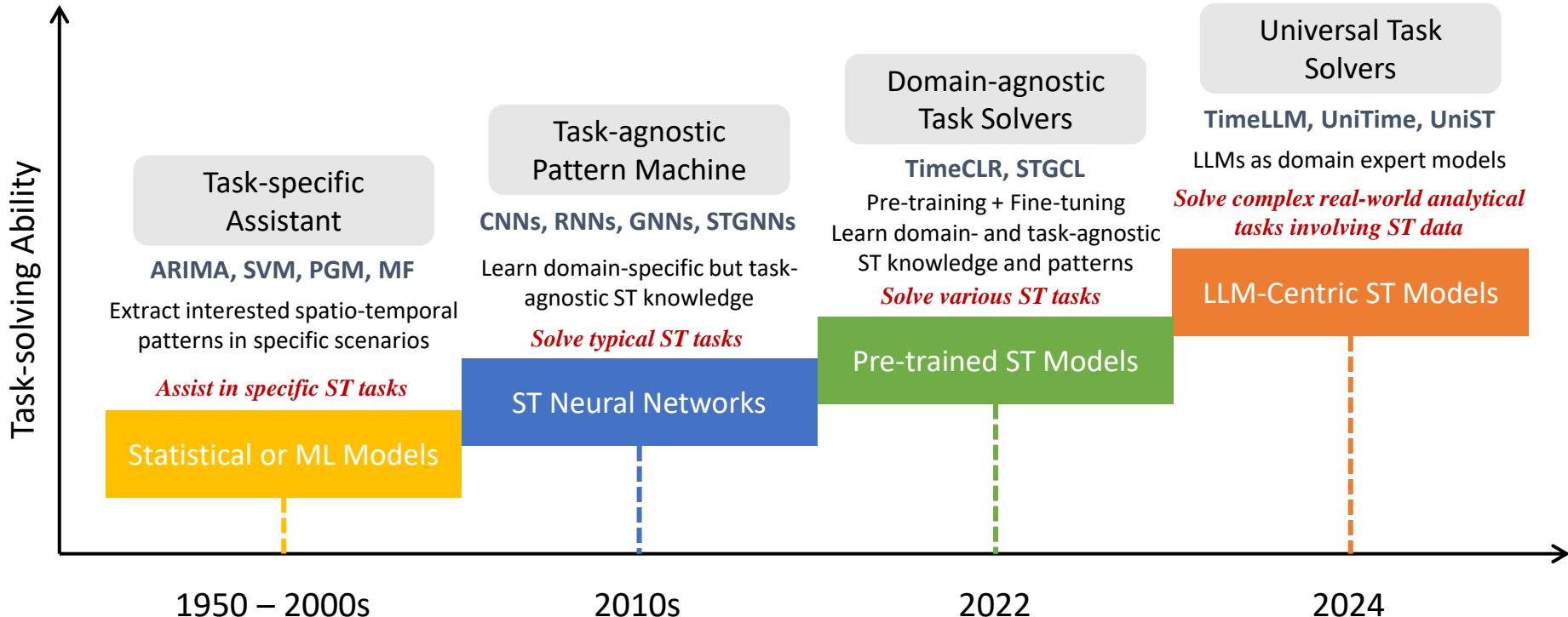
Recommend places

Towards ST General Intelligence (STGI)

- LLMs can be either trained or adeptly repurposed to handle ST data for a range of general-purpose tasks and specialized domain applications.

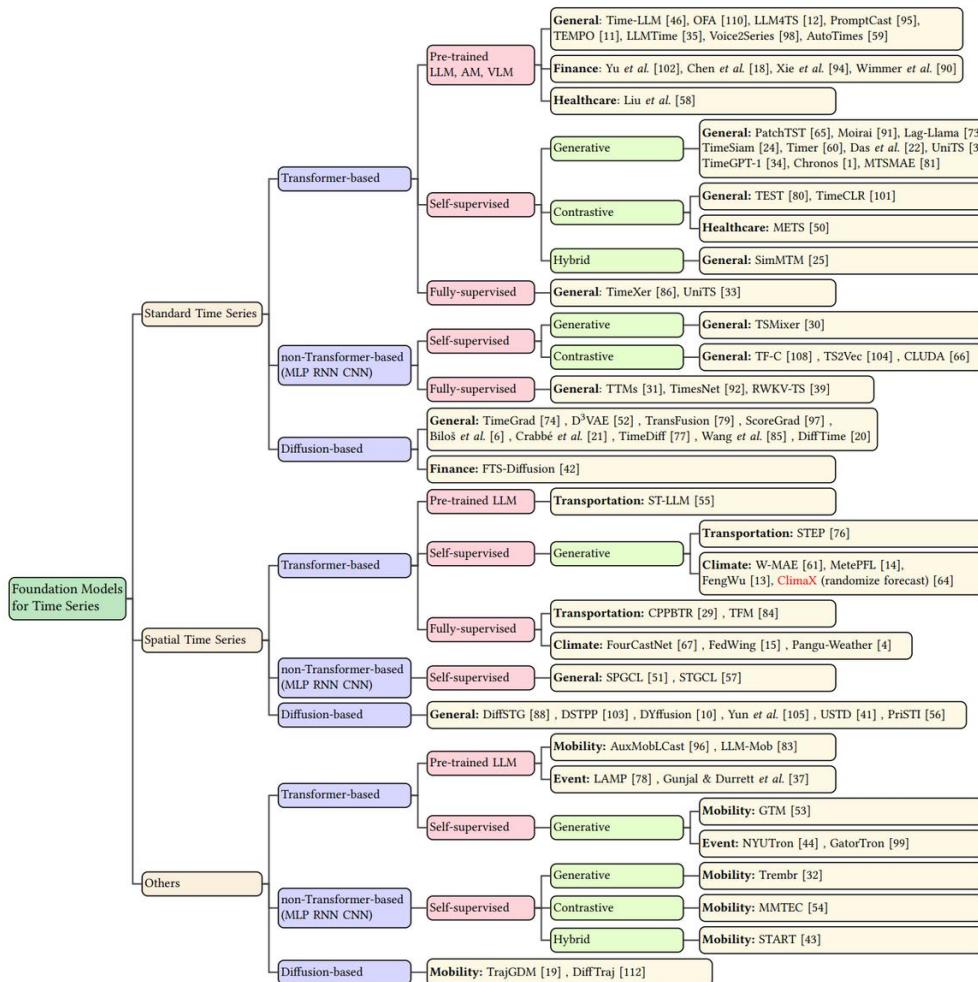


Roadmap of STDM





Taxonomy



Our Position

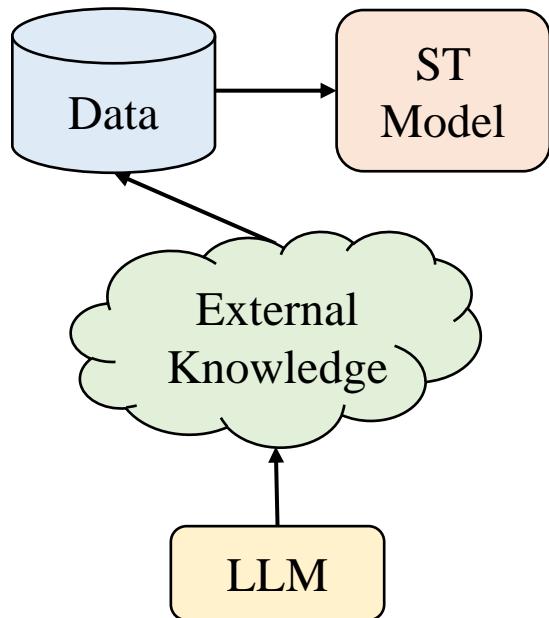
- Our standpoint is that LLMs can serve as the central hub for understanding and advancing STDM in three principal ways
 - **LLM-as-Enhancers**: augmenting ST data and existing approaches with enhanced external knowledge and analytical prowess
 - **LLM-as-Predictors**: utilizing their extensive internal knowledge and emerging reasoning abilities to benefit a range of downstream tasks, e.g., forecasting
 - **LLM-as-Agents**: transcending conventional roles to actively engage in and transform spatio-temporal data mining

LLM-as-Enhancer

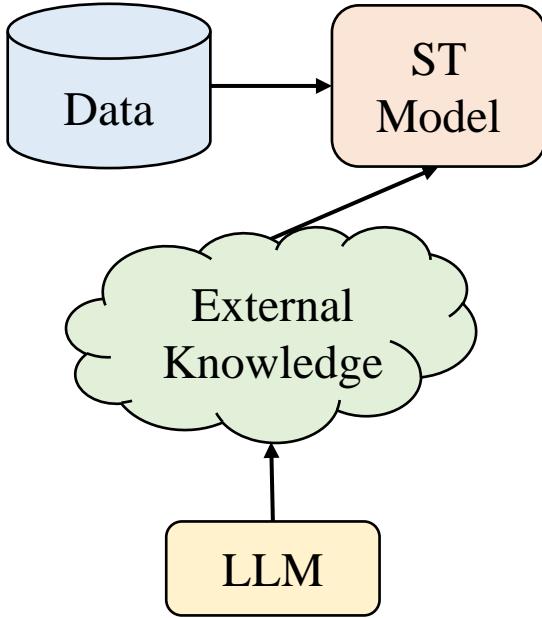
- Our standpoint is that LLMs can serve as the central hub for understanding and advancing STDM in three principal ways
 - **LLM-as-Enhancers**: augmenting ST data and existing approaches with enhanced external knowledge and analytical prowess
 - **LLM-as-Predictors**: utilizing their extensive internal knowledge and emerging reasoning abilities to benefit a range of downstream tasks, e.g., forecasting
 - **LLM-as-Agents**: transcending conventional roles to actively engage in and transform spatio-temporal data mining

LLM-as-Enhancer

- Data-centric enhancer

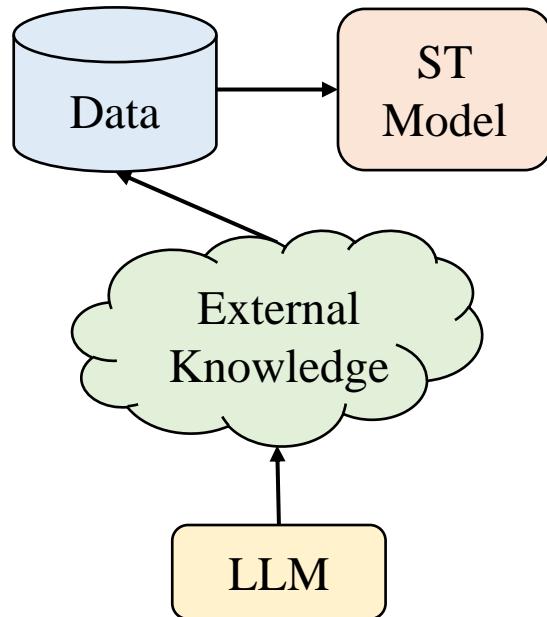


- Model-centric enhancer



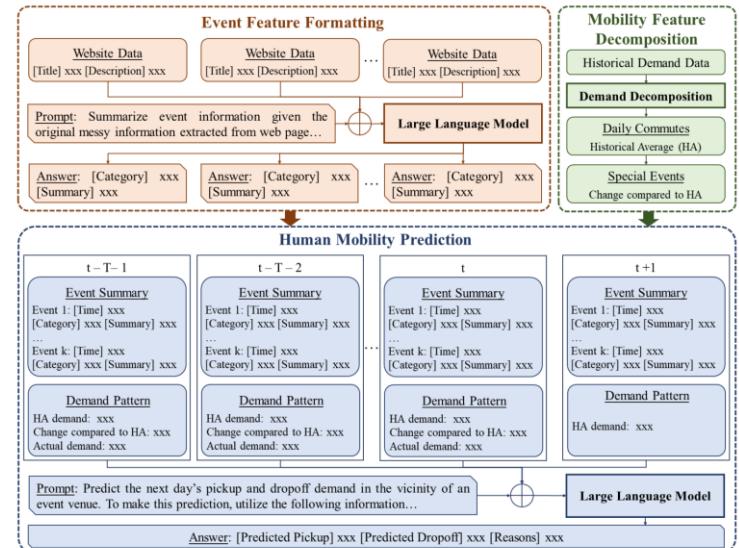
Data-Centric Enhancer

- It enhances data **interpretability** or provide supplementary improvements, facilitating a more thorough understanding and effective use of ST data
- Examples
 - LLM-MPE for human mobility
 - LLM for finance



Example: LLM-MPE for Human Mobility

- While rich textual descriptions about public events are commonly available from online sources, it is challenging to encode such information in ML models
- They introduce LLM-MPE for human mobility prediction under public events based on LLMs
 - leveraging their unprecedented ability to process textual data, learn from minimal examples, and generate human-readable explanations



Example: LLM for Finance

- This study focuses on NASDAQ-100 stock price prediction, supplemented by metadata about the stock company and relevant financial news data

Prompt: Generate a short description for stock AAPL's company. Also list general positive and negative factors that might impact the stock price; be brief and use keywords. Consider diverse general factors, such as macro economic situation (e.g. inflation, CPI growth), business factors (e.g. sales, investment, products), technology factors (e.g. innovation), and others. Use format Description: ..., Positive Factors: ..., Negative factors: ...

GPT-4 Response:

Description:

AAPL (Apple Inc.) is a world-renowned technology company based in Cupertino, California. Known for its sleek designs and innovative technologies, the company produces a wide range of products including the iPhone, iPad, Mac, Apple Watch, and services like iCloud, App Store, and more.

Positive Factors:

Macroeconomic: Economic growth, increased consumer spending

Business: Strong sales, expansion into new markets, positive earnings reports, strategic acquisitions

Technology: Innovation, new product launches, advancements in artificial intelligence and augmented reality

Brand: Strong global brand, loyal customer base

Legal/Regulatory: Favorable policy changes, successful patent applications

Negative Factors:

Macroeconomic: Inflation, economic downturn, trade restrictions

Business: Decreased sales, poor earnings reports, lack of new investments

Technology: Slow pace of innovation, delays in product launches

Brand: Damage to brand reputation, loss of customer loyalty

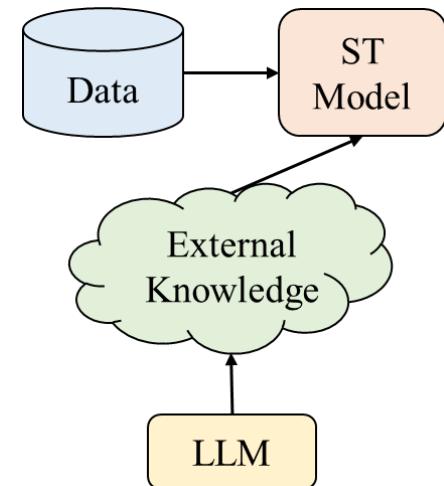
Legal/Regulatory: Antitrust investigations, unfavorable policy changes, patent disputes

Environmental: Failure to meet sustainability goals, negative environmental impact

An example of a stock's company profile consisting of the company description

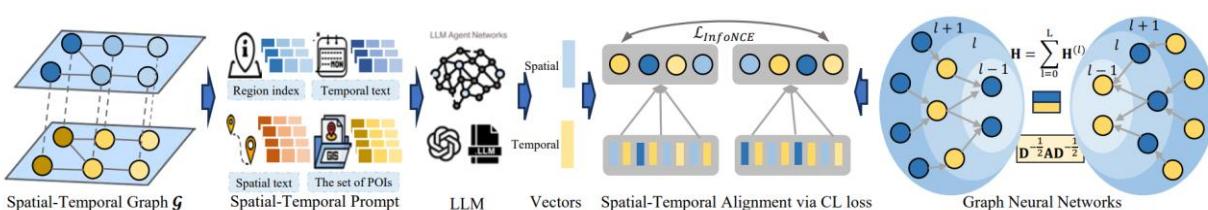
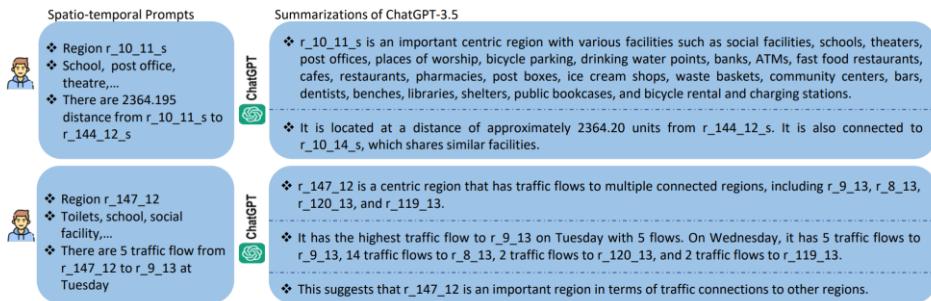
Model-Centric Enhancer

- Model-based enhancers aim to augment ST models by addressing their limitations in external knowledge and domain-specific contexts.
- Transferring knowledge from LLMs boosts the performance of domain models in handling complex tasks
- Examples
 - STLLM: LLM for spatio-temporal forecasting
 - UrbanCLIP: LLM for urban region profiling



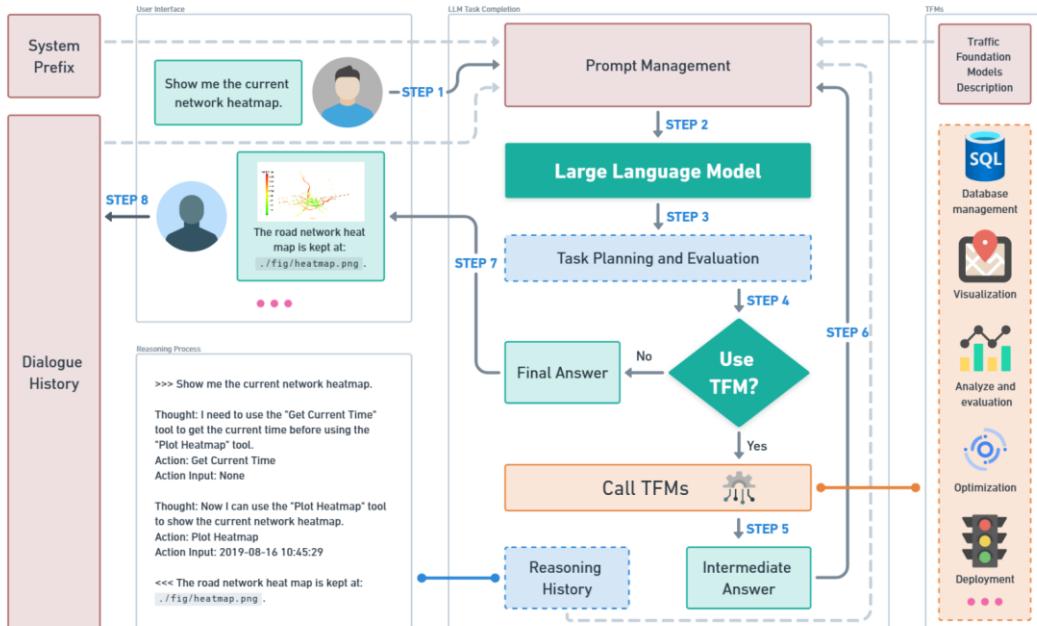
Example: STLLM

- Using a **spatio-temporal knowledge alignment** paradigm to maximize mutual information between LLM-based knowledge representations and GNN-based structural embeddings, ensuring effective alignment and information preservation across different views



Example: TrafficGPT

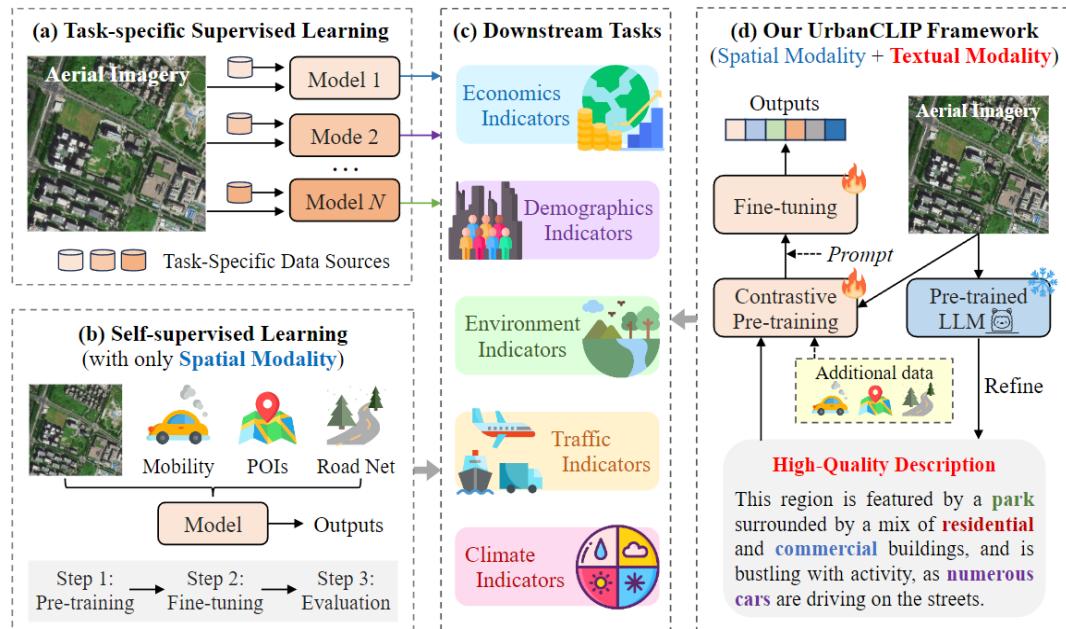
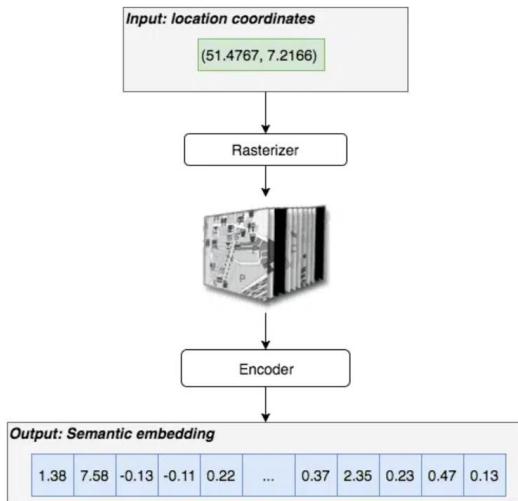
- TrafficGPT exemplifies decision analysis, integrating traffic models with LLMs for user-tailored solutions, offering detailed insights to enhance interpretability



Example: UrbanCLIP

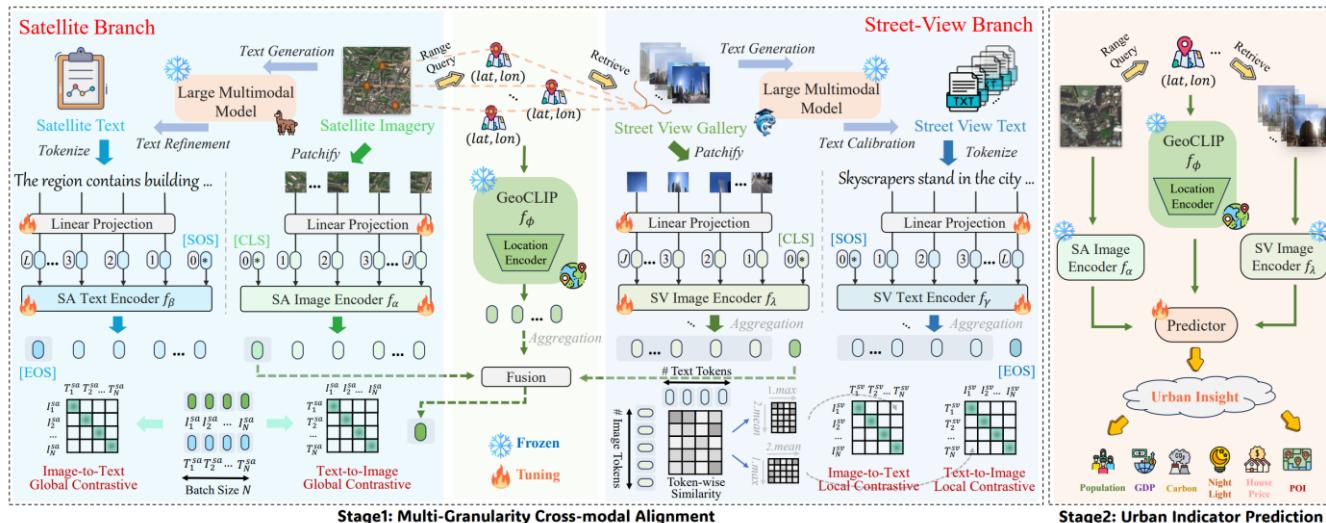
- **Urban Contrastive Language-Image Pre-training (UrbanCLIP)** is the first framework that integrates the knowledge of text modality into **urban region profiling**

Definition



Advanced Framework: UrbanVLP

- We further present UrbanVLP for urban region embedding
 - Introducing an additional data source – **Street-view Image**
 - Designing an **automatic text evaluation method**
 - Proposing new alignment techniques



Automatic Text Evaluation



Share-GPT4V

Generated Text: The image captures a **bustling city street**, bathed in the **soft glow of daylight**. The sky above is a clear, serene blue, providing a stark contrast to landscape. **Cars, buses and motorcycles** move along its length, their colors muted under the bright sunlight... **Pedestrians** can be seen as well...

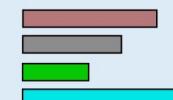
Segmentation



MAE



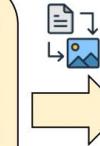
Segmentation Ratio Similarity
(Cycle Score)



Façade
Street Furniture
Greenery-Tree
Sky
...

29%
16%
11%
34%

Average
+
Reverse



SDXL
Model



Segmentation

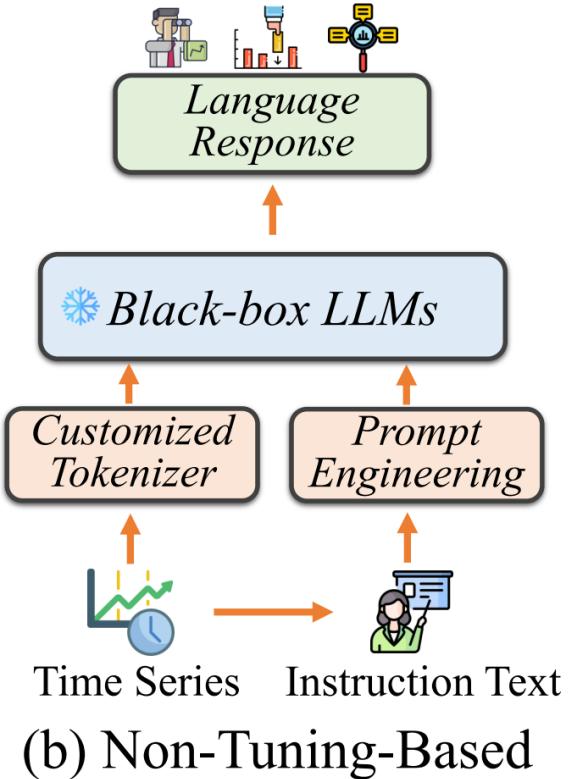
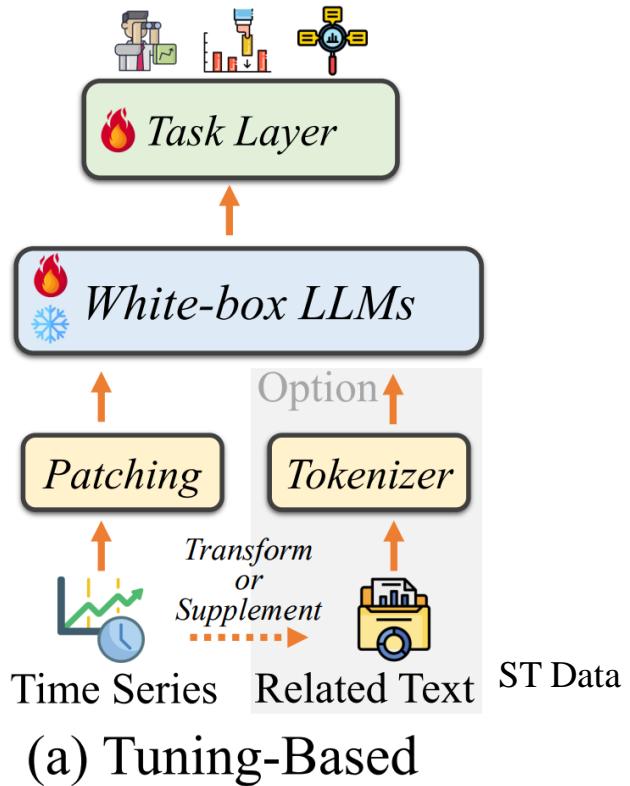


MAE

- Our standpoint is that LLMs can serve as the central hub for understanding and advancing STDM in three principal ways

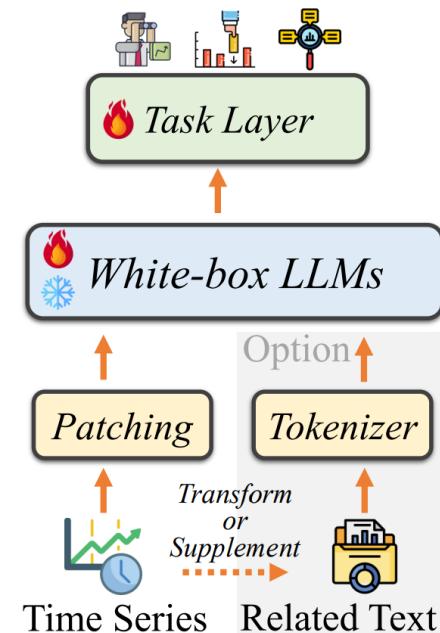
- **LLM-as-Enhancers**: augmenting ST data and existing approaches with enhanced external knowledge and analytical prowess
- **LLM-as-Predictors**: utilizing their extensive internal knowledge and emerging reasoning abilities to benefit a range of downstream tasks, e.g., forecasting
- **LLM-as-Agents**: transcending conventional roles to actively engage in and transform spatio-temporal data mining

LLM-as-Predictor

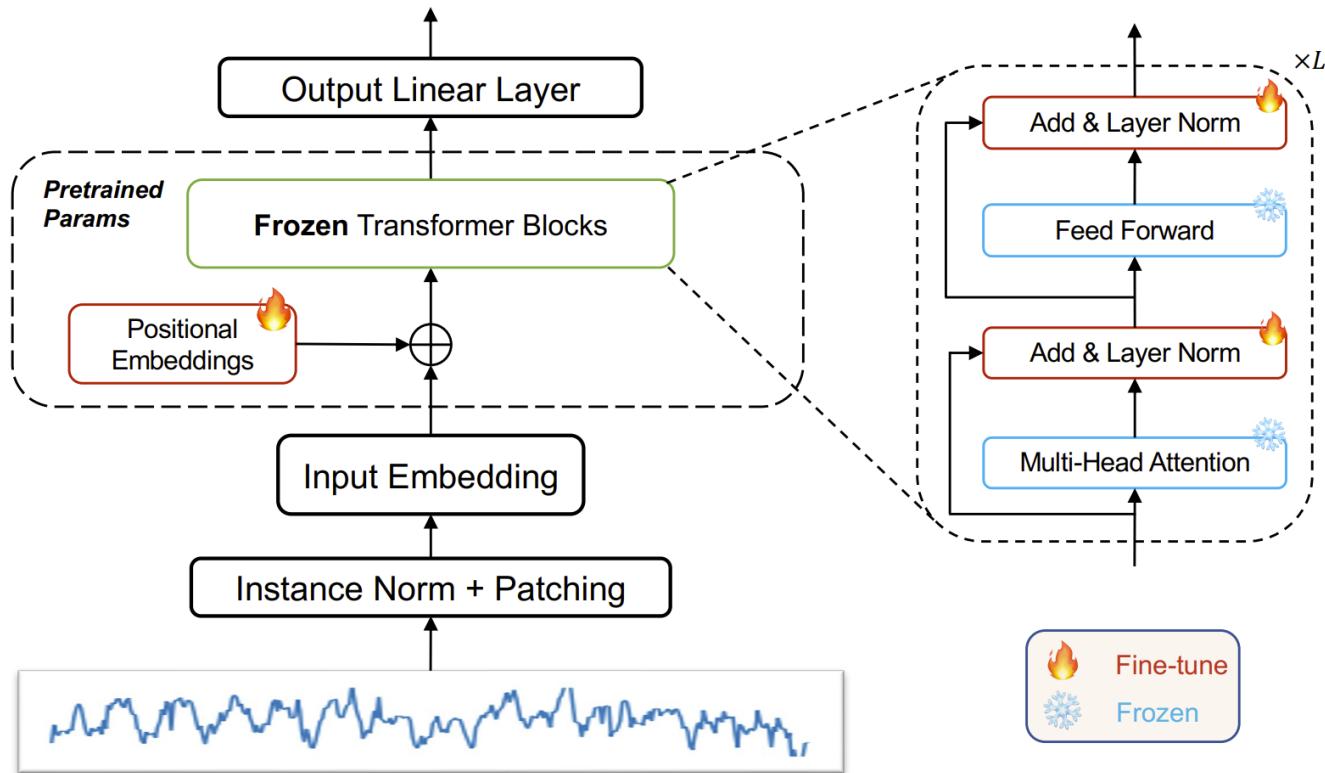


Tuning-based LLM Predictors

- Tuning-based predictors use accessible LLM parameters, typically involving **patching** and **tokenizing** numerical signals and related text data, followed by fine-tuning for ST data
- Examples
 - GPT4TS
 - Time-LLM
 - Chronos

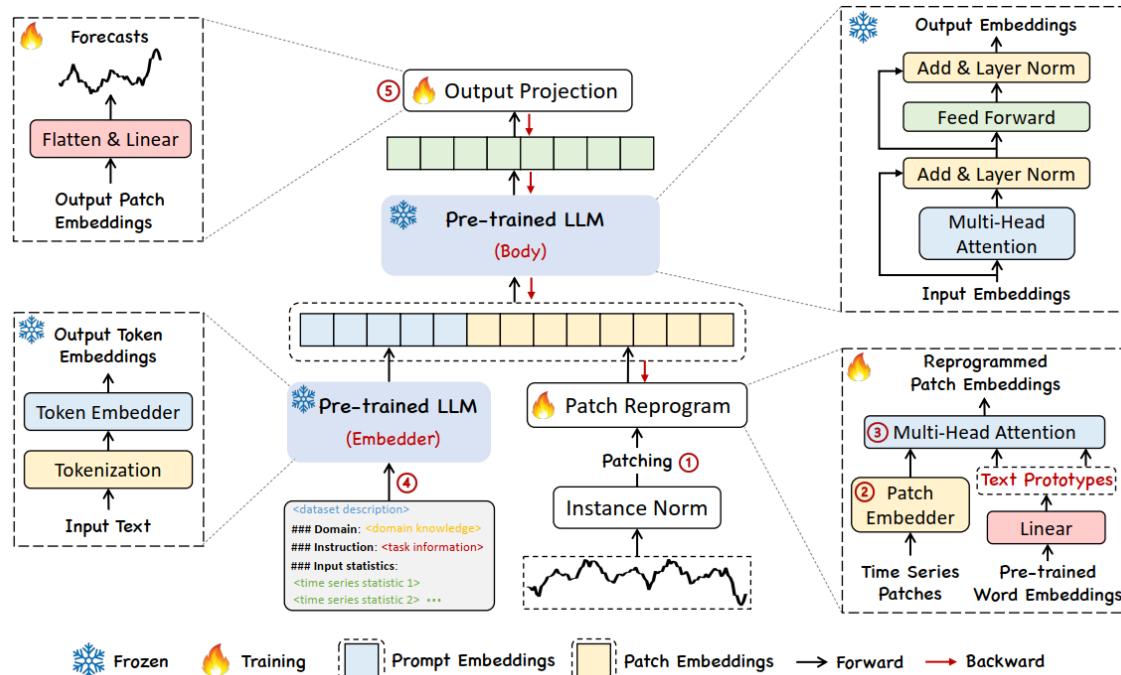


GPT4TS for Time Series Analysis



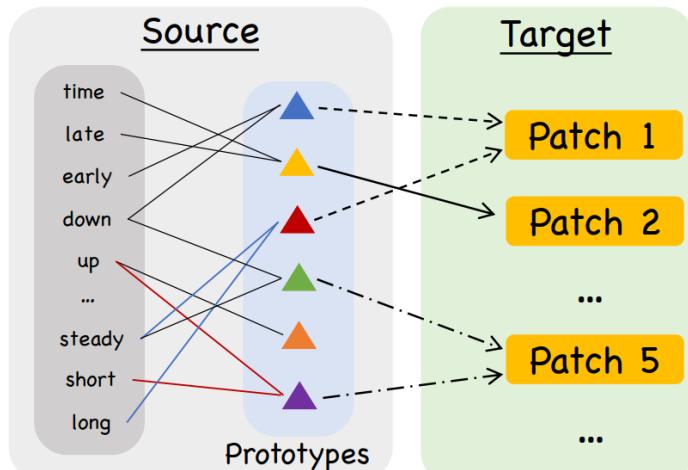
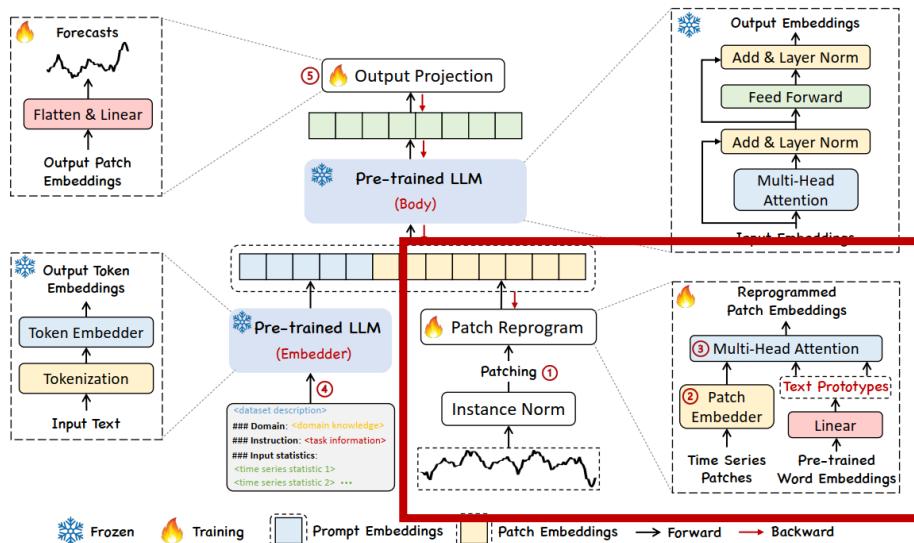
Time-LLM for Time Series Analysis

- Key question: How to enable LLMs to understand time series?



Contribution 1: Patch Reprogramming

- This module aims to **reprogram** time series features using pre-trained word embeddings in the backbone



Contribution 2: Prompt-as-Prefix

- **Dataset context** furnishes LLM with essential background information concerning the input time series
- Task instruction serves as a crucial guide in the transformation of patch embeddings for specific tasks
- We also enrich with additional crucial **statistics**, such as trends and lags, to facilitate pattern recognition and reasoning

The Electricity Transformer Temperature (ETT) indicates the electric power long-term deployment. Each data point consists of the target oil temperature and 6 power load features ...
Below is the information about the input time series:

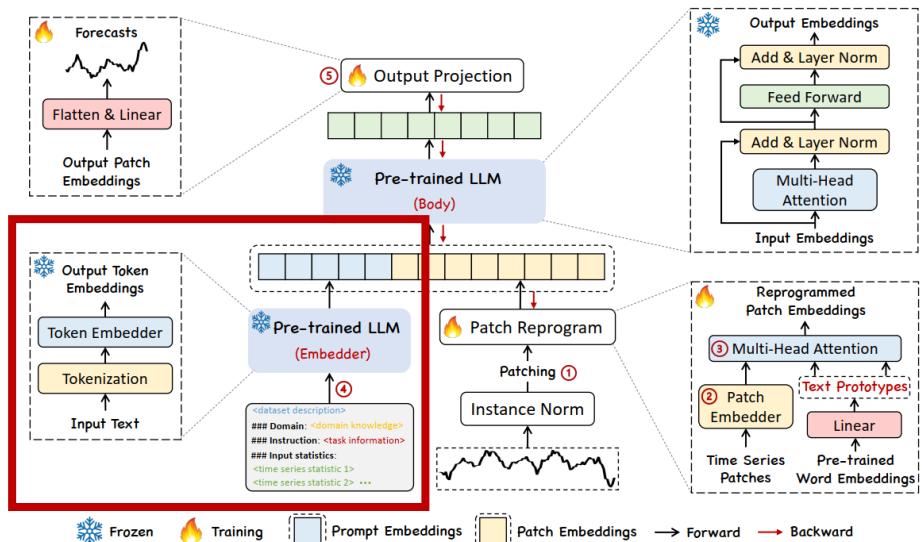
[BEGIN DATA]

[Domain]: We usually observe that electricity consumption peaks at noon, with a significant increase in transformer load

[Instruction]: Predict the next $\langle H \rangle$ steps given the previous $\langle T \rangle$ steps information attached

[Statistics]: The input has a minimum of $\langle \text{min_val} \rangle$, a maximum of $\langle \text{max_val} \rangle$, and a median of $\langle \text{median_val} \rangle$. The overall trend is $\langle \text{upward or downward} \rangle$. The top five lags are $\langle \text{lag_val} \rangle$.

[END DATA]



Results on Long-Term Forecasting

Table 1: Long-term forecasting results. We use forecasting horizons $H \in \{96, 192, 336, 720\}$. A lower value indicates better performance. **Red**: the best, **Blue**: the second best.

Methods	TIME-LLM		GPT4TS		DLinear		PatchTST		TimesNet		FEDformer		Autoformer		Stationary		ETSformer		LightTS		Informer		Reformer		
Metric	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	
<i>EITTh1</i>	96	0.362 0.392	0.376 0.397	0.375 0.399	0.370 0.399	0.384 0.402	0.376 0.419	0.449 0.459	0.513 0.491	0.494 0.479	0.424 0.432	0.865 0.713	0.837 0.728												
	192	0.398 0.418	0.416 0.418	0.405 0.416	0.413 0.421	0.436 0.429	0.420 0.448	0.500 0.482	0.534 0.504	0.538 0.504	0.475 0.462	1.008 0.792	0.923 0.766												
	336	0.430 0.427	0.442 0.433	0.439 0.443	0.422 0.436	0.491 0.469	0.459 0.465	0.521 0.496	0.588 0.535	0.574 0.521	0.518 0.488	1.107 0.809	1.097 0.835												
	720	0.442 0.457	0.477 0.456	0.472 0.490	0.447 0.466	0.521 0.500	0.506 0.507	0.514 0.512	0.643 0.616	0.562 0.535	0.547 0.533	1.181 0.865	1.257 0.889												
	Avg	0.408 0.423	0.465 0.455	0.422 0.437	0.413 0.430	0.458 0.450	0.440 0.460	0.496 0.487	0.570 0.537	0.542 0.510	0.491 0.479	1.040 0.795	1.029 0.805												
<i>EITTh2</i>	96	0.268 0.328	0.285 0.342	0.289 0.353	0.274 0.336	0.340 0.374	0.358 0.397	0.346 0.388	0.476 0.458	0.340 0.391	0.397 0.437	3.755 1.525	2.626 1.317												
	192	0.329 0.375	0.354 0.389	0.383 0.418	0.339 0.379	0.402 0.414	0.429 0.439	0.456 0.452	0.512 0.493	0.430 0.439	0.520 0.504	5.602 1.931	11.12 2.979												
	336	0.368 0.409	0.373 0.407	0.448 0.465	0.329 0.380	0.452 0.452	0.496 0.487	0.482 0.486	0.552 0.551	0.485 0.479	0.626 0.559	4.721 1.835	9.323 2.769												
	720	0.372 0.420	0.406 0.441	0.605 0.551	0.379 0.422	0.462 0.468	0.463 0.474	0.515 0.511	0.562 0.560	0.500 0.497	0.863 0.672	3.647 1.625	3.874 1.697												
	Avg	0.334 0.383	0.381 0.412	0.431 0.446	0.330 0.379	0.414 0.427	0.437 0.449	0.450 0.459	0.526 0.516	0.439 0.452	0.602 0.543	4.431 1.729	6.736 2.191												
<i>EITTm1</i>	96	0.272 0.334	0.292 0.346	0.299 0.343	0.290 0.342	0.338 0.375	0.379 0.419	0.505 0.475	0.386 0.398	0.375 0.398	0.374 0.400	0.672 0.571	0.538 0.528												
	192	0.310 0.358	0.332 0.372	0.335 0.365	0.332 0.369	0.374 0.387	0.426 0.441	0.553 0.496	0.459 0.444	0.408 0.410	0.400 0.407	0.795 0.669	0.658 0.592												
	336	0.352 0.384	0.366 0.394	0.369 0.369	0.386 0.366	0.392 0.411	0.445 0.459	0.621 0.537	0.495 0.464	0.435 0.428	0.438 0.438	1.212 0.871	0.898 0.721												
	720	0.383 0.411	0.417 0.421	0.425 0.421	0.416 0.420	0.478 0.450	0.543 0.490	0.671 0.561	0.585 0.516	0.499 0.462	0.527 0.502	1.166 0.823	1.102 0.841												
	Avg	0.329 0.372	0.388 0.403	0.357 0.378	0.351 0.380	0.400 0.406	0.448 0.452	0.588 0.517	0.481 0.456	0.429 0.425	0.435 0.437	0.961 0.734	0.799 0.671												
<i>EITTm2</i>	96	0.161 0.253	0.173 0.262	0.167 0.269	0.165 0.255	0.187 0.267	0.203 0.287	0.255 0.339	0.192 0.274	0.189 0.280	0.209 0.308	0.365 0.453	0.658 0.619												
	192	0.219 0.293	0.229 0.301	0.224 0.293	0.303 0.220	0.249 0.309	0.269 0.328	0.281 0.340	0.280 0.339	0.253 0.319	0.311 0.382	0.533 0.563	1.078 0.827												
	336	0.271 0.329	0.286 0.341	0.281 0.342	0.274 0.329	0.321 0.351	0.325 0.366	0.339 0.372	0.334 0.361	0.314 0.357	0.442 0.466	1.363 0.887	1.549 0.972												
	720	0.352 0.379	0.378 0.401	0.397 0.421	0.362 0.385	0.408 0.403	0.421 0.415	0.433 0.432	0.417 0.413	0.414 0.413	0.675 0.587	3.379 1.338	2.631 1.242												
	Avg	0.251 0.313	0.284 0.339	0.267 0.333	0.255 0.315	0.291 0.333	0.305 0.349	0.327 0.371	0.306 0.347	0.293 0.342	0.409 0.436	1.410 0.810	1.479 0.915												
1 st Count		18	0	1	4	0	0	0	0	0	0	0	0												

Results on Few-Shot Learning

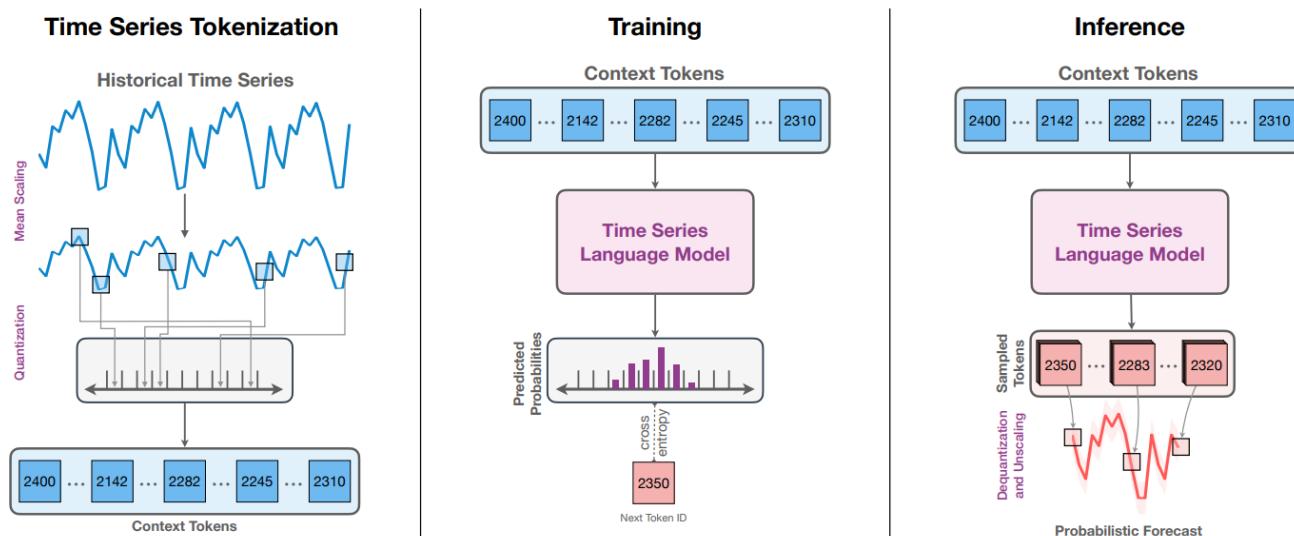
Table 3: Few-shot learning on 10% training data. We use the same protocol and notations as in Tab. 1.

Methods	TIME-LLM		GPT4TS		DLinear		PatchTST		TimesNet		FEDformer		Autoformer		Stationary		ETSformer		LightTS		Informer		Reformer		
Metric	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	
<i>ETTh1</i>	96	0.448	0.460	0.458	0.456	0.492	0.495	0.516	0.485	0.861	0.628	0.512	0.499	0.613	0.552	0.918	0.639	1.112	0.806	1.298	0.838	1.179	0.792	1.184	0.790
	192	0.484	0.483	0.570	0.516	0.565	0.538	0.598	0.524	0.797	0.593	0.624	0.555	0.722	0.598	0.915	0.629	1.155	0.823	1.322	0.854	1.199	0.806	1.295	0.850
	336	0.589	0.540	0.608	0.535	0.721	0.622	0.657	0.550	0.941	0.648	0.691	0.574	0.750	0.619	0.939	0.644	1.179	0.832	1.347	0.870	1.202	0.811	1.294	0.854
	720	0.700	0.604	0.725	0.591	0.986	0.743	0.762	0.610	0.877	0.641	0.728	0.614	0.721	0.616	0.887	0.645	1.273	0.874	1.534	0.947	1.217	0.825	1.223	0.838
	Avg.	0.556	0.522	0.590	0.525	0.691	0.600	0.633	0.542	0.869	0.628	0.639	0.561	0.702	0.596	0.915	0.639	1.180	0.834	1.375	0.877	1.199	0.809	1.249	0.833
<i>ETTh2</i>	96	0.275	0.326	0.331	0.374	0.357	0.411	0.353	0.389	0.378	0.409	0.382	0.416	0.413	0.451	0.389	0.411	0.678	0.619	2.022	1.006	3.837	1.508	3.788	1.533
	192	0.374	0.373	0.402	0.411	0.569	0.519	0.403	0.414	0.490	0.467	0.478	0.474	0.474	0.477	0.473	0.455	0.785	0.666	2.329	1.104	3.856	1.513	3.552	1.483
	336	0.406	0.429	0.406	0.433	0.671	0.572	0.426	0.441	0.537	0.494	0.504	0.501	0.547	0.543	0.507	0.480	0.839	0.694	2.453	1.122	3.952	1.526	3.395	1.526
	720	0.427	0.449	0.449	0.464	0.824	0.648	0.477	0.480	0.510	0.491	0.499	0.509	0.516	0.523	0.477	0.472	1.273	0.874	3.816	1.407	3.842	1.503	3.205	1.401
	Avg.	0.370	0.394	0.397	0.421	0.605	0.538	0.415	0.431	0.479	0.465	0.466	0.475	0.488	0.499	0.462	0.455	0.894	0.713	2.655	1.160	3.872	1.513	3.485	1.486
<i>ETTm1</i>	96	0.346	0.388	0.390	0.404	0.352	0.392	0.410	0.419	0.583	0.501	0.578	0.518	0.774	0.614	0.761	0.568	0.911	0.688	0.921	0.682	1.162	0.785	1.442	0.847
	192	0.373	0.416	0.429	0.423	0.382	0.412	0.437	0.434	0.630	0.528	0.617	0.546	0.754	0.592	0.781	0.574	0.955	0.703	0.957	0.701	1.172	0.793	1.444	0.862
	336	0.413	0.426	0.469	0.439	0.419	0.434	0.476	0.454	0.725	0.568	0.998	0.775	0.869	0.677	0.803	0.587	0.991	0.719	0.998	0.716	1.227	0.908	1.450	0.866
	720	0.485	0.476	0.569	0.498	0.490	0.477	0.681	0.556	0.769	0.549	0.693	0.579	0.810	0.630	0.844	0.581	1.062	0.747	1.007	0.719	1.207	0.797	1.366	0.850
	Avg.	0.404	0.427	0.464	0.441	0.411	0.429	0.501	0.466	0.677	0.537	0.722	0.605	0.802	0.628	0.797	0.578	0.980	0.714	0.971	0.705	1.192	0.821	1.426	0.856
<i>ETTm2</i>	96	0.177	0.261	0.188	0.269	0.213	0.303	0.191	0.274	0.212	0.285	0.291	0.399	0.352	0.454	0.229	0.308	0.331	0.430	0.813	0.688	3.203	1.407	4.195	1.628
	192	0.241	0.314	0.251	0.309	0.278	0.345	0.252	0.317	0.270	0.323	0.307	0.379	0.694	0.691	0.291	0.343	0.400	0.464	1.008	0.768	3.112	1.387	4.042	1.601
	336	0.274	0.327	0.307	0.346	0.338	0.385	0.306	0.353	0.323	0.353	0.543	0.559	2.408	1.407	0.348	0.376	0.469	0.498	1.031	0.775	3.255	1.421	3.963	1.585
	720	0.417	0.390	0.426	0.417	0.436	0.440	0.433	0.427	0.474	0.449	0.712	0.614	1.913	1.166	0.461	0.438	0.589	0.557	1.096	0.791	3.909	1.543	3.711	1.532
	Avg.	0.277	0.323	0.293	0.335	0.316	0.368	0.296	0.343	0.320	0.353	0.463	0.488	1.342	0.930	0.332	0.366	0.447	0.487	0.987	0.756	3.370	1.440	3.978	1.587
1 st Count	20		3		2		0		0		0		0		0		0		0		0		0		

Ablation Study

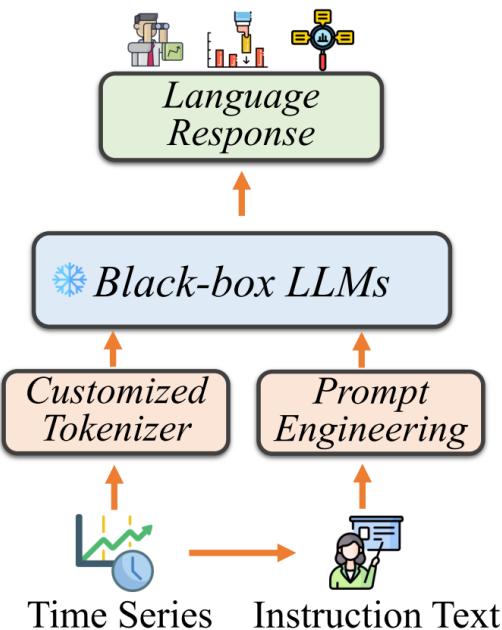
Variant	Long-term Forecasting				Few-shot Forecasting			
	ETTh1-96	ETTh1-192	ETTm1-96	ETThm1-192	ETTh1-96	ETTh1-192	ETTm1-96	ETThm1-192
A.1 Llama (Default ; 32)	0.362	0.398	0.272	0.310	0.448	0.484	0.346	0.373
A.2 Llama (8)	0.389	0.412	0.297	0.329	0.567	0.632	0.451	0.490
A.3 GPT-2 (12)	0.385	0.419	0.306	0.332	0.548	0.617	0.447	0.509
A.4 GPT-2 (6)	0.394	0.427	0.311	0.342	0.571	0.640	0.468	0.512
B.1 w/o Patch Reprogramming	0.410	0.412	0.310	0.342	0.498	0.570	0.445	0.487
B.2 w/o Prompt-as-Prefix	0.398	0.423	0.298	0.339	0.521	0.617	0.432	0.481
C.1 w/o Dataset Context	0.402	0.417	0.298	0.331	0.491	0.538	0.392	0.447
C.2 w/o Task Instruction	0.388	0.420	0.285	0.327	0.476	0.529	0.387	0.439
C.3 w/o Statistical Context	0.391	0.419	0.279	0.347	0.483	0.547	0.421	0.461

- A forecasting model based on pre-trained language models
 - **Core idea:** A novel tokenizer was designed to **project continuous values into a discrete vocabulary** to simulate language characteristics

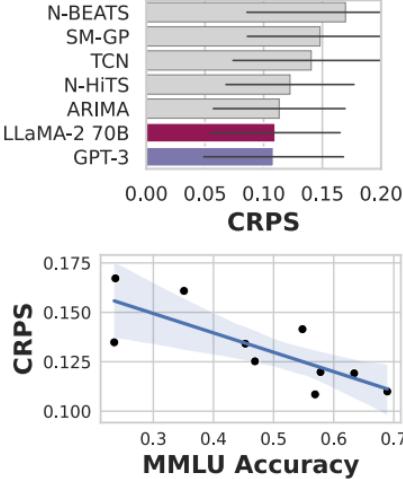
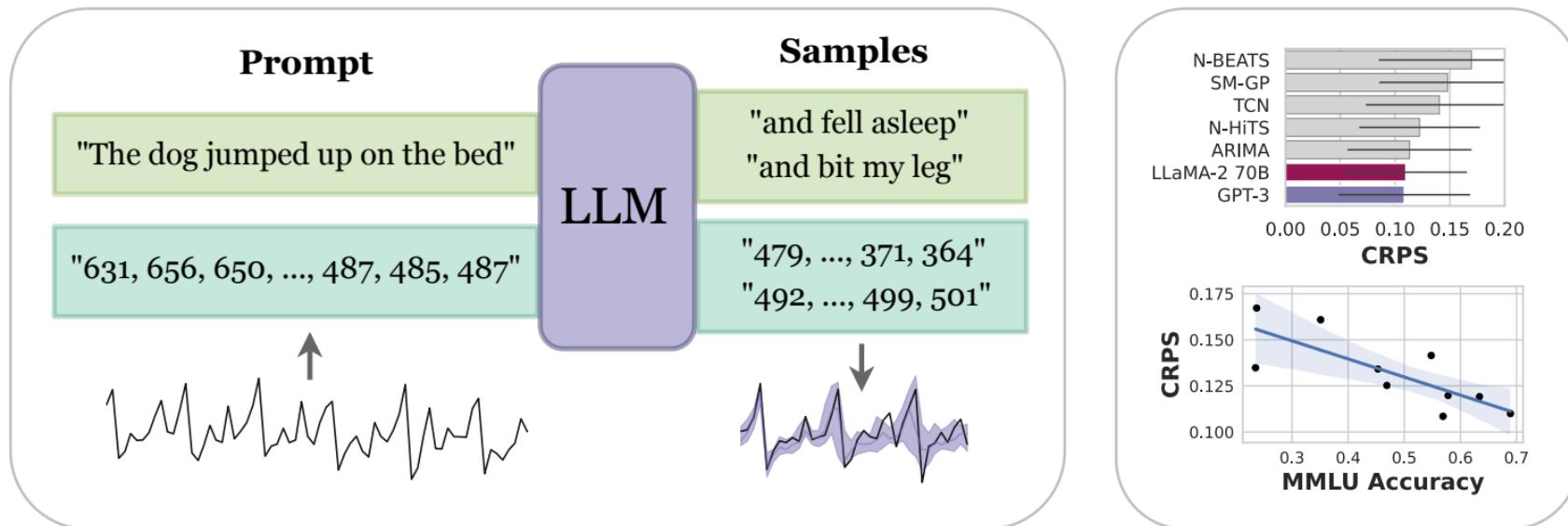


Non-Tuning-based LLM Predictors

- Non-tuning-based predictors, suitable for closed-source models, involve preprocessing ST data to fit LLM input spaces
 - Tokenizer
 - Prompt design
 - In-context learning
- Examples
 - LLMTIME for time series analysis
 - LLM-Mob for human mobility

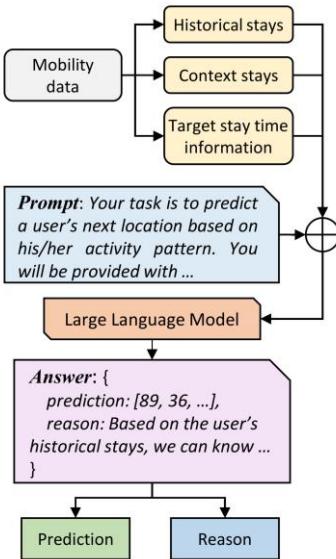
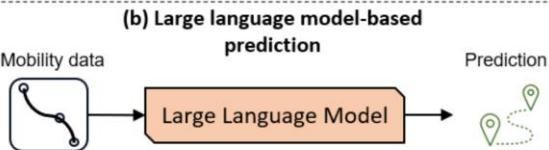
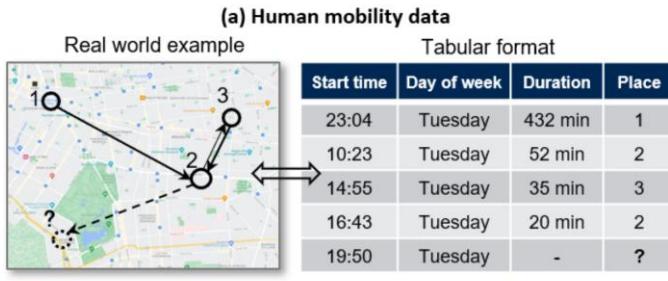


Example: LLMTTime



Example: LLM-Mob

- LLM-Mob leverages the language understanding and reasoning capabilities of LLMs for analyzing human mobility data



Instruction | Specify the task Your task is to predict a user's next location based on his/her activity pattern.

Data | Describe the data You will be provided with `<history>` which is a list containing this user's historical stays, then `<context>` which provide contextual information about where and when this user has been to recently. Stays in both `<history>` and `<context>` are in chronological order. Each stay takes on such form as `(start_time, day_of_week, duration, place_id)`. The detailed explanation of each element is as follows:
`start_time`: the start time of the stay in 12h clock format.
`day_of_week`: indicating the day of the week.
`duration`: an integer indicating the duration (in minute) of each stay. Note that this will be None in the `<target_stay>` introduced later.
`place_id`: an integer representing the unique place ID, which indicates where the stay is.
Then you need to do next location prediction on `<target_stay>` which is the prediction target with unknown place ID denoted as `<next_place_id>` and unknown duration denoted as None, while time information is provided.

Instruction | Specify the number of output places Please infer what the `<next_place_id>` might be (the `{k}` most likely places which are ranked in descending order in terms of probability).

Instruction | Guide the model to "think" Please consider the following aspects:
1. the activity pattern of this user that you learned from `<history>`, e.g., repeated visits to certain places during certain times;
2. the context stays in `<context>`, which provide more recent activities of this user;
3. the temporal information (i.e., `start_time` and `day_of_week`) of target stay, which is important because people's activity varies during different time (e.g., nighttime versus daytime) and on different days (e.g., weekday versus weekend).

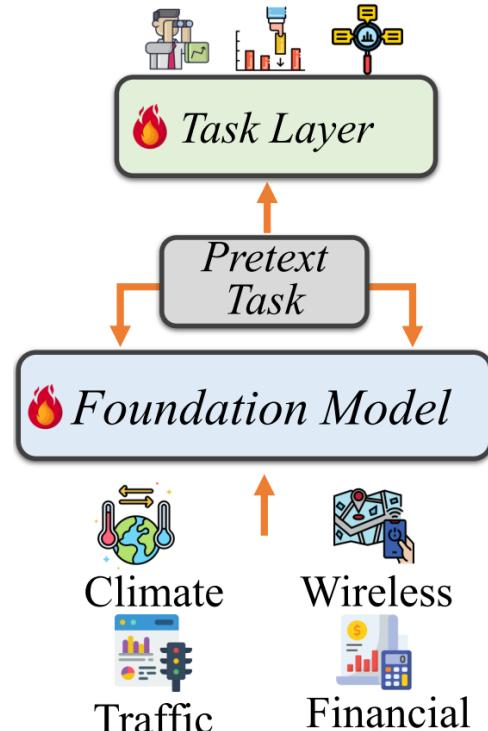
Instruction | Format the output and ask for explanations Please organize your answer in a JSON object containing following keys: "prediction" (the ID of the `{k}` most probable places in descending order of probability) and "reason" (a concise explanation that supports your prediction). Do not include line breaks in your output.

Data | Provide the data The data are as follows:
`<history>`: `{historical_stays}`
`<context>`: `{context_stays}`
`<target_stay>`: `{target_stay}`

Other LLM-as-Predictors

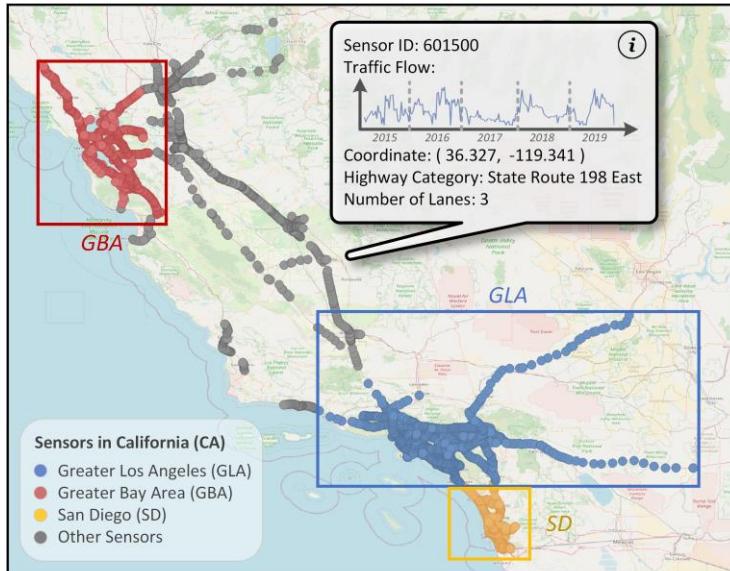
- Beyond the previously discussed methods, another significant approach in STDM involves building foundation models from scratch

A major challenge:
Large-scale datasets!



LargeST: A Large-Scale Traffic Dataset

- We crawled, processed, and released a large-scale traffic dataset
 - Scalability, Generalizability, Robustness, etc.

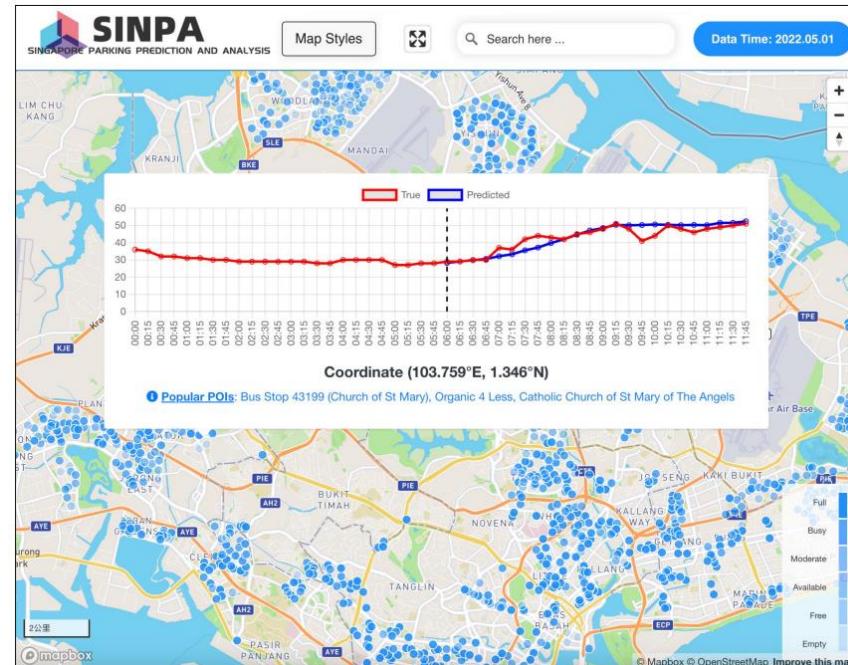


Dataset	Nodes	Edges	Degree	Meta	Time Range	Frames	Data Points
PeMSD7(M)	228	1,664	7.3	6	05/01/2012 – 06/30/2012	12,672	2.89M
PeMSD7(L)	1,026	14,534	14.2	0	05/01/2012 – 06/30/2012	12,672	13.00M
METR-LA	207	1,515	7.3	3	03/01/2012 – 06/27/2012	34,272	7.09M
PEMS-BAY	325	2,369	7.3	3	01/01/2017 – 06/30/2017	52,116	16.94M
PEMS03	358	546	1.5	1	09/01/2018 – 11/30/2018	26,208	9.38M
PEMS04	307	338	1.1	0	01/01/2018 – 02/28/2018	16,992	5.22M
PEMS07	883	865	1.0	0	05/01/2017 – 08/06/2017	28,224	24.92M
PEMS08	170	276	1.6	0	07/01/2016 – 08/31/2016	17,856	3.04M
CA	8,600	201,363	23.4	9	01/01/2017 – 12/31/2021	525,888	4.52B
GLA	3,834	98,703	25.7	9	01/01/2017 – 12/31/2021	525,888	2.02B
GBA	2,352	61,246	26.0	9	01/01/2017 – 12/31/2021	525,888	1.24B
SD	716	17,319	24.2	9	01/01/2017 – 12/31/2021	525,888	0.38B

SINPA: A Large-Scale Carpark Dataset

- We crawled, processed, and released a large-scale parking dataset

Data	Attributes	Values
Parking Availability	Time Spans	2020/07/01 - 2021/06/30
	Time Granularity	15 minutes
	# Parking lots	1,687
	# Samples	14,600
	Missing Rate	1.59%
Meteorology	Temperature (mean)	27.72
	Humidity (mean)	81.18
	Windspeed (mean)	4.62
Time-related	Time of Day	24
	Day of the Week	7
	Holiday	2
Geolocation	# Pln_Area Categories	36
Utilization Type	# Categories	10
Road Networks	# Segments	15,291



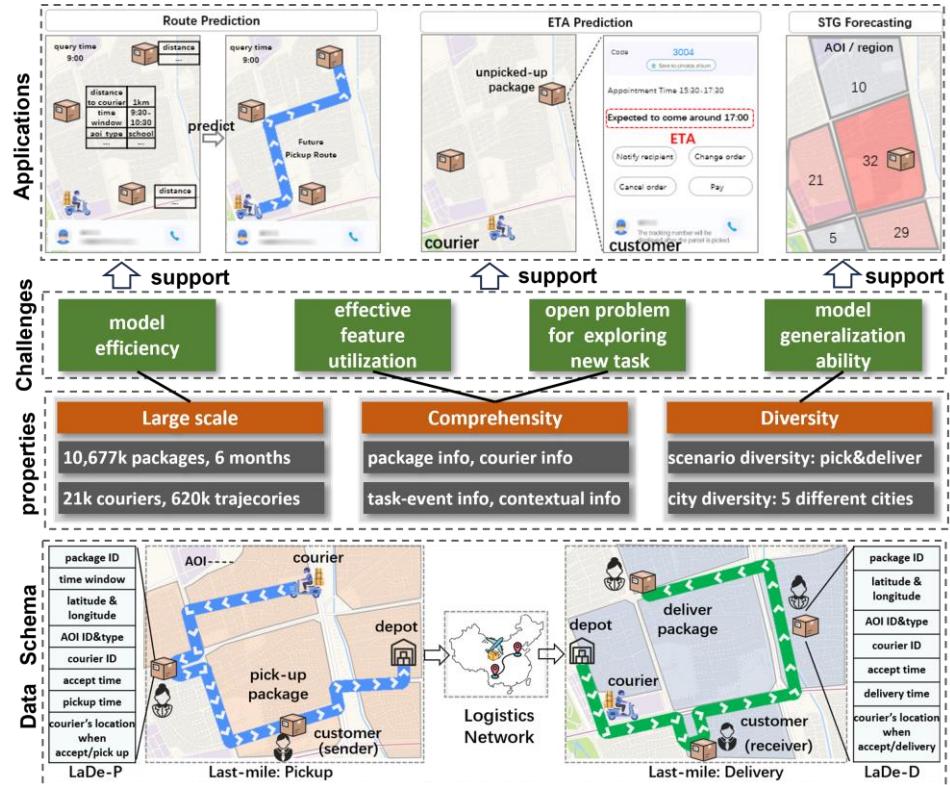
LaDe: The First Last-Mile Delivery Dataset

- We released **The First Last-Mile Delivery Dataset from Industry**
 - Large scale
 - Comprehensivity
 - Diversity

CAI
NIAO 菜鸟

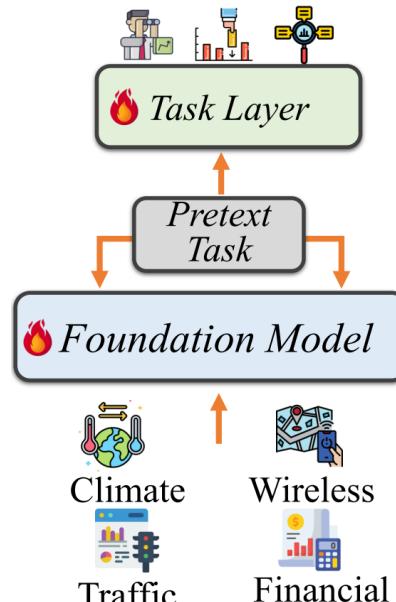
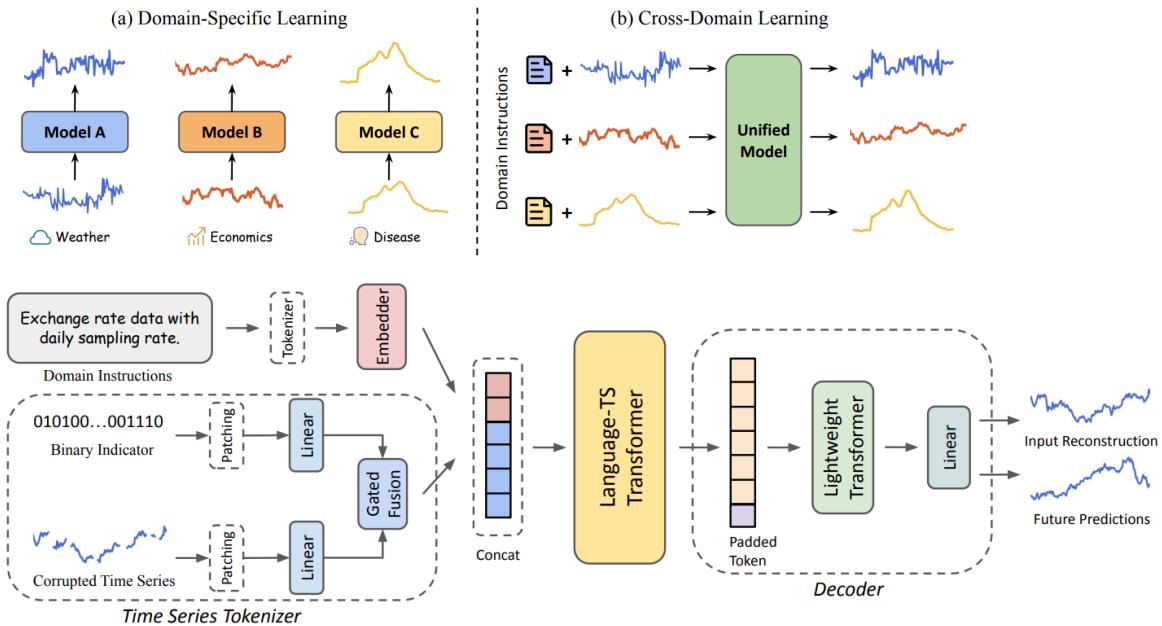


香港科技大学(广州)
THE HONG KONG
UNIVERSITY OF SCIENCE AND
TECHNOLOGY (GUANGZHOU)



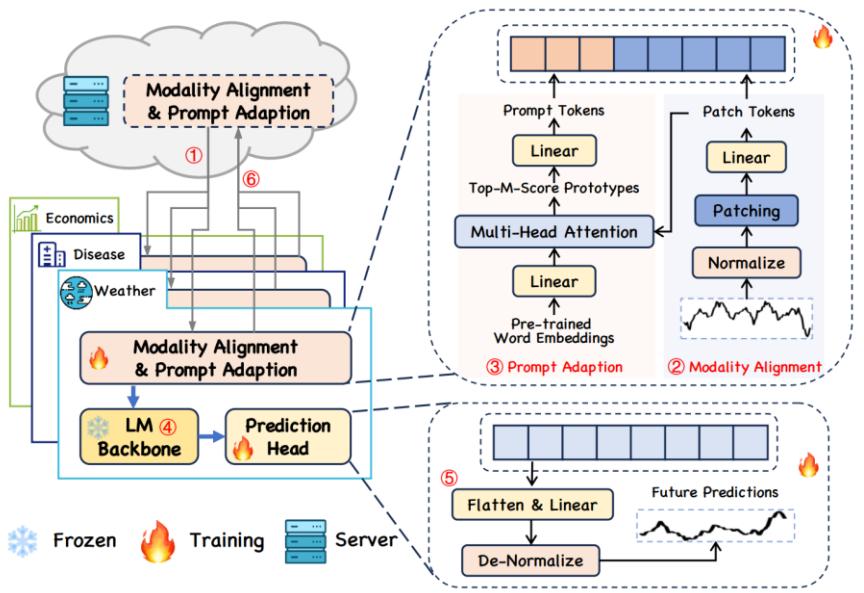
UniTime: Building Time Series Foundation Models

- The prerequisite of training a **Foundation Model for time series** is **training a model on cross-domain time series all at once**

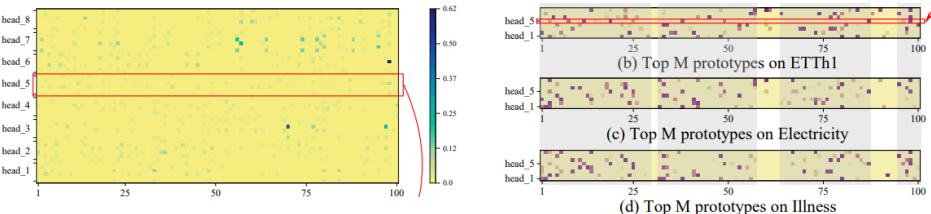


Time-FFM: Federated TS Learning

- What if the input data come from difference sources?

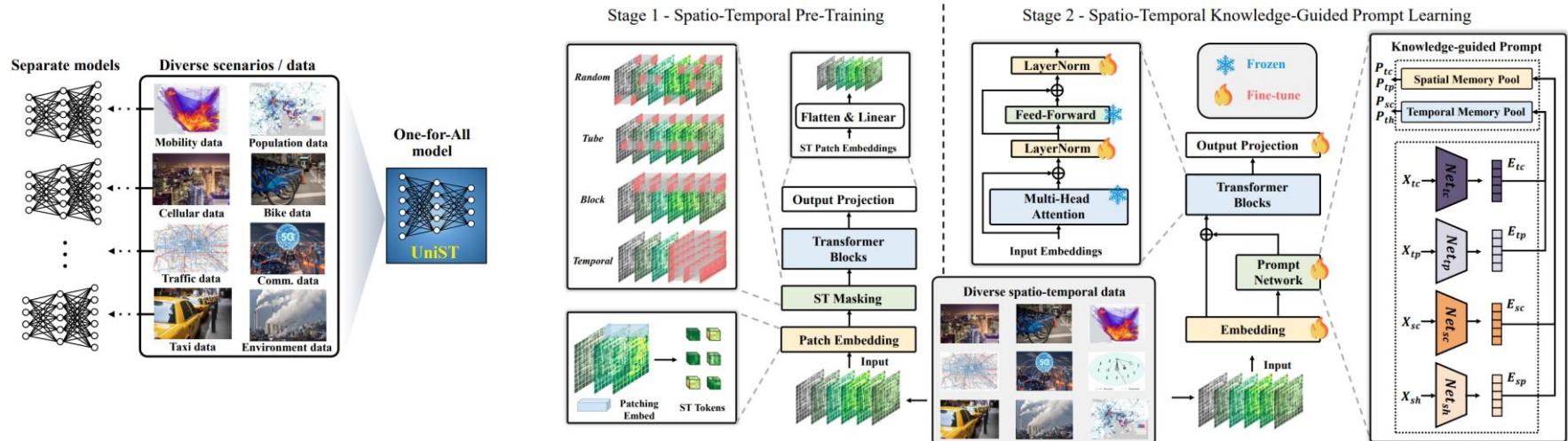


Type	TY1						TY2						TY3											
Method	TIME-FFM	FedIT	FedAdapter ^H	FedAdapter ^P	UniTime	GPT4TS	PatchTST	TimesNet	DLinear	FEDformer	Autoformer	Informer	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE		
ETTH1	0.442	0.434	0.481	0.461	0.488	0.467	0.503	0.479	0.442	0.448	0.502	0.461	0.472	0.451	0.458	0.450	0.456	0.452	0.440	0.460	0.496	0.487		
ETTH2	0.382	0.406	0.374	0.396	0.373	0.398	0.380	0.403	0.386	0.406	0.398	0.416	0.414	0.427	0.559	0.515	0.437	0.449	0.450	0.459	4.431	1.729		
ETTm1	0.399	0.402	0.644	0.517	0.643	0.511	0.640	0.518	0.385	0.399	0.551	0.483	0.971	0.629	0.388	0.406	0.403	0.407	0.448	0.452	0.588	0.517	0.961	0.734
ETTm2	0.286	0.332	0.297	0.341	0.295	0.340	0.298	0.342	0.293	0.334	0.321	0.356	0.340	0.373	0.291	0.322	0.350	0.401	0.305	0.349	0.327	0.371	1.410	0.810
Electricity	0.216	0.299	0.390	0.478	0.408	0.489	0.334	0.420	0.216	0.305	0.251	0.338	0.221	0.311	0.193	0.295	0.212	0.300	0.214	0.327	0.227	0.338	0.311	0.397
Weather	0.270	0.288	0.282	0.310	0.282	0.308	0.287	0.303	0.253	0.276	0.291	0.309	0.304	0.323	0.259	0.287	0.265	0.317	0.309	0.360	0.338	0.382	0.634	0.548
Exchange	0.338	0.391	0.389	0.423	0.382	0.419	0.380	0.417	0.364	0.404	0.421	0.446	0.411	0.444	0.416	0.443	0.354	0.414	0.519	0.500	0.613	0.539	0.550	0.998
IL1	2.107	0.924	4.423	1.448	5.247	1.621	5.251	1.601	2.137	0.929	3.678	1.372	4.210	1.480	2.139	0.931	2.616	1.090	2.847	1.144	3.006	1.161	5.137	1.544
Average	0.555	0.434	0.910	0.547	1.015	0.569	1.009	0.561	0.559	0.437	0.800	0.521	0.916	0.553	0.569	0.445	0.652	0.487	0.690	0.505	0.756	0.532	1.934	0.944
1 st Count	8	1	1	1	0	3	0	0	4	0	1	0	0	0	1	0	0	0	0	0	0	0		



UniST: A Spatio-Temporal Foundation Model

- Integrate **ST correlations** into UniTime while designing spatio-temporal prompts to enhance **out-of-domain generalization**



MOIRAI: a Time Series Foundation Model

- An encoder-only Transformer for probabilistic time series forecasting
 - Support **multi-frequency/variable TS tasks**; providing the **LOTSA** dataset

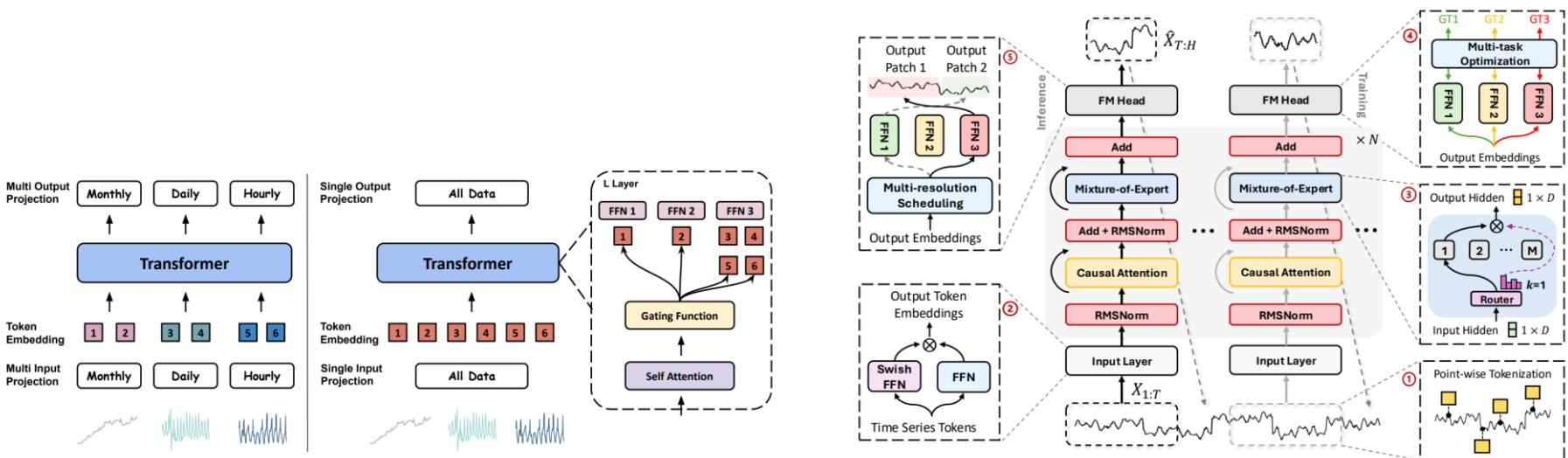
Table 2. Key statistics of LOTSA by domain.

	Energy	Transport	Climate	CloudOps	Web	Sales	Nature	Econ/Fin	Healthcare
# Datasets	30	23	6	3	3	6	5	23	6
# Obs. %	16,358,600,896 59.17%	4,900,453,419 17.73%	4,188,011,890 15.15%	1,518,268,292 5.49%	428,082,373 1.55%	197,984,339 0.72%	28,547,647 0.09%	24,919,596 0.10%	1,594,281 0.01%



MOIRAI-MoE & Time-MoE: Extra Large TSFM

- Utilizes the largest parameter size (**Billion-Scale**) TS foundation model, demonstrating outstanding zero-shot prediction performance, and achieves good results when fine-tuned on in-domain data.

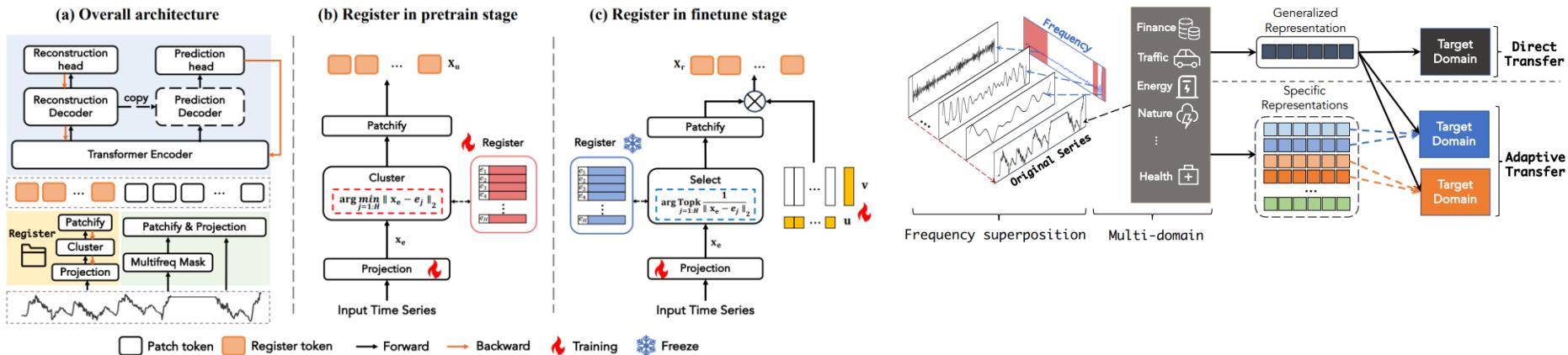


X. Liu et al., [MOIRAI-MOE: EMPOWERING TIME SERIES FOUNDATION MODELS WITH SPARSE MIXTURE OF EXPERTS](#). arXiv 2024.

X. Shi et al., [TIME-MOE: BILLION-SCALE TIME SERIES FOUNDATION MODELS WITH MIXTURE OF EXPERTS](#). arXiv 2024.

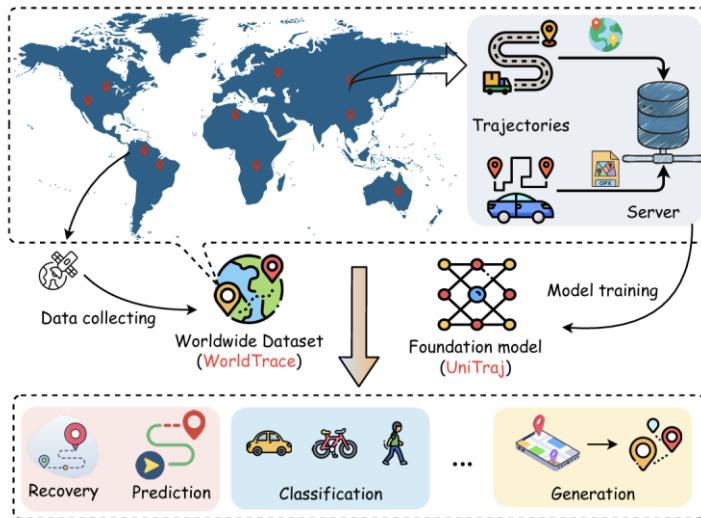
ROSE: A “Small” TS Foundation Model

- Based on the idea of frequency domain decomposition + register matching, a smaller-scale temporal foundation model has been developed.
 - It utilizes only 7.4M parameters and completes testing on the ETTh dataset within 0.65 seconds.



UniTraj: A Trajectory Foundation Model

- The **first** trajectory foundation model across the world!



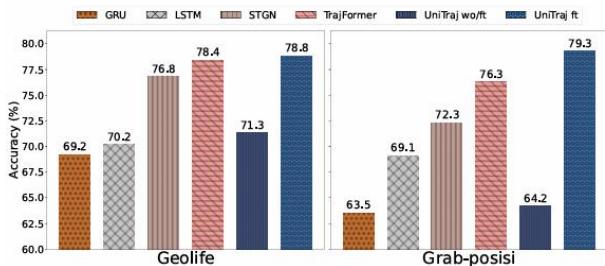
Methods	WorldTrace		Chengdu		Xi'an		GeoLife		Grab-Posisi		Porto	
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
Linear	427.68	516.15	205.74	258.52	176.49	220.87	196.85	249.76	507.41	617.28	396.61	482.39
DHTR	220.35	302.47	75.19	98.68	62.85	83.43	80.04	108.25	351.20	415.16	194.37	232.59
Transformer	130.82	147.62	55.23	62.85	45.85	51.96	94.68	113.77	136.58	163.29	104.36	126.96
DeepMove	51.16	62.29	29.32	39.02	27.31	35.67	86.38	107.78	126.93	168.07	136.66	174.96
TrajBERT	58.13	70.14	26.48	33.83	19.45	25.13	34.53	43.24	112.68	136.24	78.77	99.23
TrajFM	47.64	58.92	19.10	25.09	18.86	24.13	59.34	64.24	107.64	130.69	71.15	92.96
UniTraj (zero-shot)	10.22	13.56	11.98	20.94	8.93	13.83	37.21	63.89	114.07	167.01	78.28	100.14
Improvement(%)	[78.35]	[76.49]	[37.38]	[16.54]	[50.85]	[42.69]	[17.76]	[147.46]	[15.97]	[27.79]	[16.02]	[17.72]
UniTraj (fine-tune)	6.94	9.67	6.92	10.41	6.50	9.93	23.23	34.70	48.95	69.23	60.18	79.76
Improvement(%)	[78.43]	[78.59]	[76.37]	[78.51]	[76.54]	[78.85]	[32.73]	[119.75]	[74.52]	[74.03]	[71.42]	[71.20]

Recovery

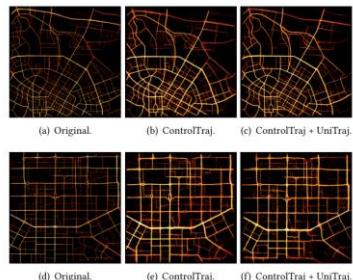
Prediction

Methods	WorldTrace		Chengdu		GeoLife	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
Linear	153.12	159.65	156.85	164.58	189.02	201.34
DHTR	146.48	151.63	123.47	129.73	180.32	187.59
Transformer	114.25	117.07	67.38	70.86	165.02	170.84
DeepMove	55.69	58.67	36.31	39.10	116.46	123.20
BERT	80.57	86.36	64.73	68.92	113.68	121.18
TrajFM	75.45	81.32	77.82	80.48	121.94	128.16
UniTraj (zero-shot)	49.85	55.02	42.75	45.93	108.35	133.60
Improvement(%)	[10.49]	[76.22]	[117.74]	[117.46]	[14.69]	[110.25]
UniTraj (fine-tune)	30.10	34.46	28.74	32.44	90.97	102.88
Improvement(%)	[45.95]	[74.17]	[126.74]	[117.03]	[119.98]	[115.10]

Classification



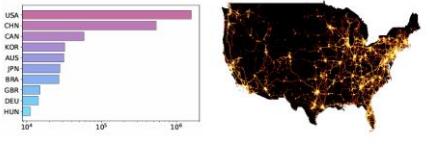
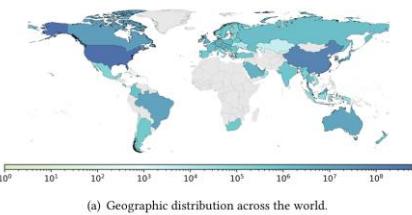
Generation



UniTraj: A Trajectory Foundation Model

Data level:

- ✓ **十亿级轨迹数据:** 构建十亿级的高质量轨迹数据集WorldTrace
- ✓ **高质量清洗规则:** 缓解设备异构和潜在过时等数据质量问题
- ✓ **统一标准化格式:** 来自OSM的原始数据以XML格式提供GPX多源信息



Model level:

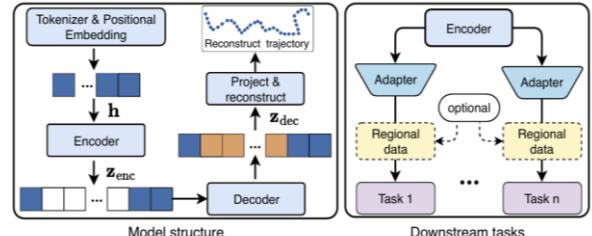
- ✓ **轨迹分词器:** 应对轨迹长度不同、时空组件的异质性以及捕捉跨时间动态依赖性的需要
- ✓ **编码器-解码器:** 使用定制Transformer块的堆栈构建的，结合RoPE驱动的自注意机制来捕获轨迹依赖关系

Algorithm 1 Ramer–Douglas–Peucker (RDP) Algorithm

```
1: function RDP( $\tau$ ,  $s$ ,  $e$ ,  $\epsilon$ )
2:   Initialize max distance  $d_{\max} \leftarrow 0$ 
3:   Initialize index  $k \leftarrow -1$ 
4:   for  $i = s + 1$  to  $e - 1$  do
5:     Calculate the distance from  $p_i$  to  $\overline{p_s p_e}$ :  $d_i$ 
6:     if  $d_i > d_{\max}$  then
7:       Update max distance  $d_{\max} \leftarrow d_i$ 
8:       Update index  $k \leftarrow i$ 
9:     end if
10:    end for
11:    if  $d_{\max} > \epsilon$  then
12:       $\tau_{\text{left}} \leftarrow \text{RDP}(\tau, s, k, \epsilon)$ 
13:       $\tau_{\text{right}} \leftarrow \text{RDP}(\tau, k, e, \epsilon)$ 
14:      return  $\{p_k\} \cup \tau_{\text{left}} \cup \tau_{\text{right}}$ 
15:    else
16:      return  $\{p_s, p_e\}$ 
17:    end if
18:  end function
```

Architecture level:

- ✓ **重新采样策略:** 旨在管理不同的采样间隔并增强模型对不同数据质量的适应能力
- ✓ **关键点掩码策略:** 设计一种RDP算法来识别这些关键点，提升去噪训练效率
- ✓ **轻量微调策略:** 可选的灵活微调层



Our Position

- Our standpoint is that LLMs can serve as the central hub for understanding and advancing STDM in three principal ways
 - **LLM-as-Enhancers**: augmenting ST data and existing approaches with enhanced external knowledge and analytical prowess
 - **LLM-as-Predictors**: utilizing their extensive internal knowledge and emerging reasoning abilities to benefit a range of downstream tasks, e.g., forecasting
 - **LLM-as-Agents**: transcending conventional roles to actively engage in and transform spatio-temporal data mining

Background of LLM-as-Agent

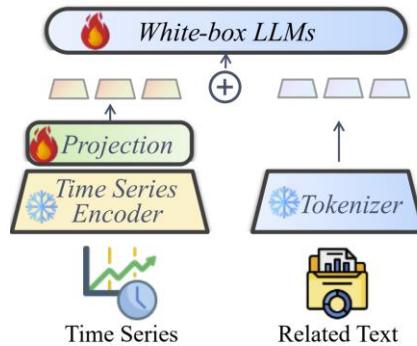
- **Tuning-based LLM-as-Predictors** in STDM utilize LLMs as robust model checkpoints, attempting to adjust certain parameters for specific domain applications.
 - However, this approach often **sacrifices the interactive capabilities of LLMs** and may not fully exploit the benefits offered by LLMs, such as in-context learning or chain-of-thought.
- **Non-tuning-based LLM-as-Predictors**, integrating ST data into textual formats or developing specialized tokenizers
 - Facing limitations due to LLMs' primary training on linguistic data, hindering their comprehension of complex ST knowledge and patterns not easily captured in language



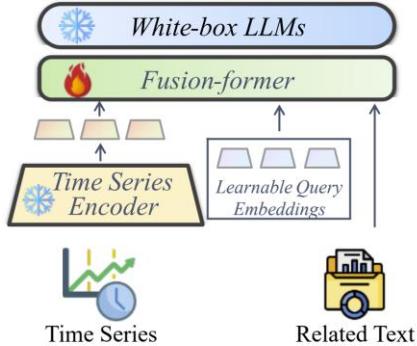
A new promising paradigm rises:
LLM-as-Agents!

LLM-as-Agent for Time Series Analysis

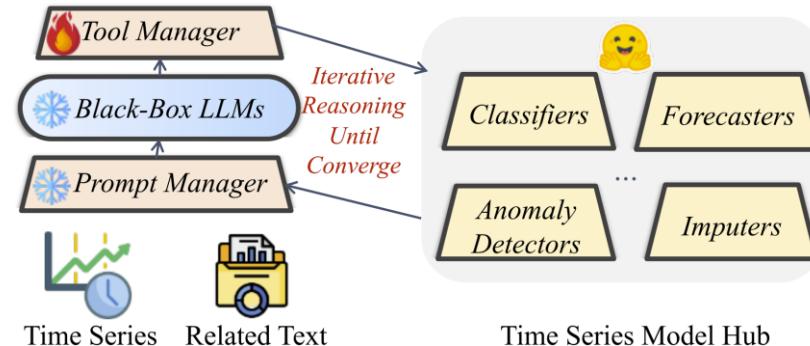
- Different directions for incorporating time series knowledge to LLMs



(a) Aligning



(b) Fusion



(c) Using External Tools

LLM-as-Agent for Time Series Analysis

- We empirically verify that LLM can serve as Effective Analytical Agent

Data format description:

The Human Activity Recognition database was built from the recordings of 30 study participants performing activities of daily living (ADL) while carrying a waist-mounted smartphone with embedded inertial sensors. The objective is to classify activities into one of the four activities performed (Walk, Sit, Stand, Lay). For each record in the dataset the following is provided:

- 1.Triaxial acceleration from the accelerometer (total acceleration) and the estimated body acceleration.
- 2.Triaxial Angular velocity from the gyroscope.

Few shot data instances:

Here are some classification examples:

```
tBodyAcc-mean()-X tBodyAcc-mean()-Y tBodyAcc-mean()-Z angle(X,gravityMean) angle(Y,gravityMean) angle(Z,gravityMean) Activity
0.257178 -0.02329 -0.01465 -0.72001 0.276801 -0.05798 STANDING
0.277235 -0.02568 -0.11843 -0.8159 0.166483 -0.09444 SITTING
0.300905 -0.02361 -0.09689 0.774053 -0.47774 -0.50714 LAYING
```

Task description:

Now we have the following data instances, please justify their Activity:

```
0.269066 -0.02769 -0.11018 -0.6805 0.302289 -0.06727
0.278291 -0.01454 -0.10524 -0.81653 0.170525 -0.09102
0.272059 -0.02127 -0.10064 0.767363 -0.4718 -0.51501
```



Certainly, based on a general understanding of the patterns in the provided Human Activity Recognition dataset, here are hypothetical guesses for the activities corresponding to the given instances:

- 1.The activity for the first instance (0.269066, -0.02769, -0.11018, -0.6805, 0.302289, -0.06727) might be **Walk**.
- 2.The activity for the second instance (0.278291, -0.01454, -0.10524, -0.81653, 0.170525, -0.09102) could be **Sit**.
- 3.The activity for the third instance (0.272059, -0.02127, -0.10064, 0.767363, -0.4718, -0.51501) may be **Lay**.



Correct answer of instances 2, 3 !

LLM-as-Agent for Time Series Analysis

- LLM agent can provide **interpretability** and **truthfulness**

Please tell me the reason.



It's important to note that these are speculative guesses based on general patterns observed in accelerometer and gyroscope data for common human activities. The reasoning behind these guesses is influenced by typical characteristics associated with certain activities:

Instance 1 The relatively consistent acceleration values along with angular velocity may suggest a pattern associated with walking. **Walking often involves rhythmic and repetitive motion.**

Instance 2 The lower acceleration values and certain angular velocity characteristics might resemble the patterns seen during sitting. **Sitting typically involves less movement compared to other activities.**

Instance 3 The specific combination of acceleration and angular velocity features could resemble the patterns observed during lying down or laying. **Laying down is associated with lower acceleration and distinct angular velocity patterns.**



Interpretability!

Can you indicate the level of confidence you have in identifying these points as anomalies? Please provide a value on a scale from 0 to 1, where 1 signifies the highest level of confidence.



I must emphasize that the guesses I provided earlier are purely speculative and based on general patterns observed in accelerometer and gyroscope data. Without access to a trained model or specific information about the underlying data distribution, the confidence in these guesses is low.

If I were to assign a confidence level on a scale from 0 to 1, where 1 signifies the highest confidence, it would be approximately 0.3. This low confidence level reflects the speculative nature of the guesses and the lack of a precise understanding of the data distribution and model specifics. For accurate predictions, a trained model with associated confidence scores would be necessary.



Truthfulness!

Limitations of LLM Agent for Time Series

- Difficulty in Understanding Complex Patterns
- Bias and Task Preferences
- **Hallucination**

Data format description:

The Electric Transformer Temperature (ETT) serves as a vital indicator for long-term electric power management. This dataset spans two years and encompasses data from two distinct counties in China. To delve into the intricacies of Long Sequence Time-Series Forecasting (LSTF) problems, various subsets have been curated: {ETTh1, ETTh2} for 1-hour intervals and ETThm1 for 15-minute intervals. Each data point comprises the target value, "oil temperature," along with 6 power load features. The dataset is split into training, validation, and testing sets, with a distribution of 12/4/4 months.

Task description:

Now, I would like to provide you with some instances from the dataset. Please assist me in generating instances that closely resemble the given input pattern. The instances are as follows:

Few shot data instances:

date, HUFL, HULL, MUFL, MULL, LUFL, LULL, OT
2016-07-01 00:00:00.5,827000141143799,2.009000062942505,1.5989999771118164,0.4620000123977661,4.203000068664552,1.340000033786009,30.5310001373291
2016-07-01 01:00:00.5,692999839782715,2.075999975204468,1.4919999837875366,0.425999990463257,1.42000198364259,1.371000051498413,27.78700065612793
2016-07-01 00:00:00.5,827000141143799,2.009000062942505,1.5989999771118164,0.4620000123977661,4.203000068664552,1.340000033786009,30.5310001373291
2016-07-01 01:00:00.5,692999839782715,2.075999975204468,1.4919999837875366,0.425999990463257,1.42000198364259,1.371000051498413,27.78700065612793
2016-07-01 02:00:00.5,1570000648498535,1.741000056266785,1.2790000438690186,0.35499998927116394,3.776999950408936,1.218000054359436,27.78700065612793
2016-07-01 03:00:00.5,090000152878915,1.9420000314712524,1.2790000438690186,0.3910000026226044,3.806999921798706,1.2790000438690186,25.04400062561035
2016-07-01 04:00:00.5,357999801635742,1.9420000314712524,1.4919999837875366,0.4620000123977661,3.868000030517578,1.2790000438690186,21.947999954223643
2016-07-01 05:00:00.5,625999927520752,1.42999874664307,1.5279999971389768,0.532999992370655,4.051000118255615,1.371000051498413,21.173999786376953



Certainly, here are instances from the dataset that closely resemble the given input pattern:

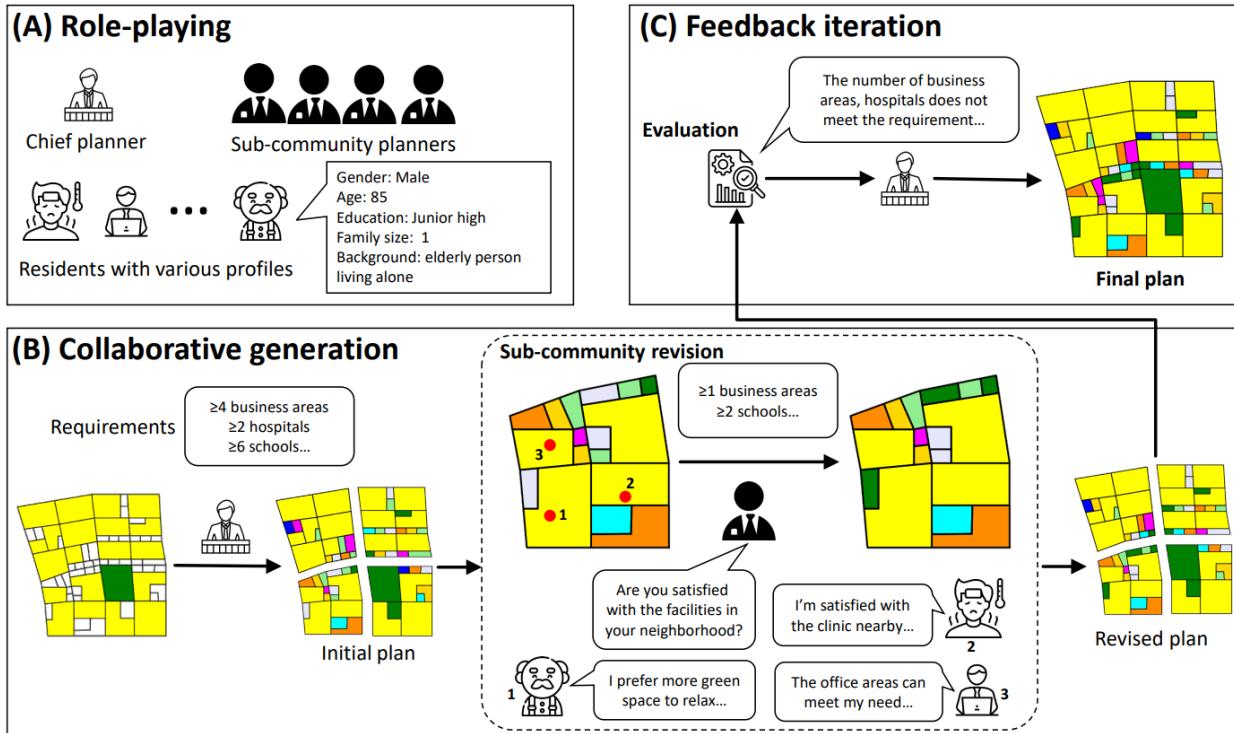
2016-07-01 00:00:05.692999839782715,2.075999975204468,1.4919999837875366,0.425999990463257,1.42000198364259,1.371000051498413,27.78700065612793
2016-07-01 02:00:00.5,1570000648498535,1.741000056266785,1.2790000438690186,0.35499998927116394,3.776999950408936,1.218000054359436,27.78700065612793
2016-07-01 03:00:00.5,090000152878915,1.9420000314712524,1.2790000438690186,0.3910000026226044,3.806999921798706,1.2790000438690186,25.04400062561035
2016-07-01 04:00:00.5,357999801635742,1.9420000314712524,1.4919999837875366,0.4620000123977661,3.868000030517578,1.2790000438690186,21.947999954223643

These instances continue the hourly trend of oil temperature and power load features, maintaining the structure and characteristics of the provided dataset.

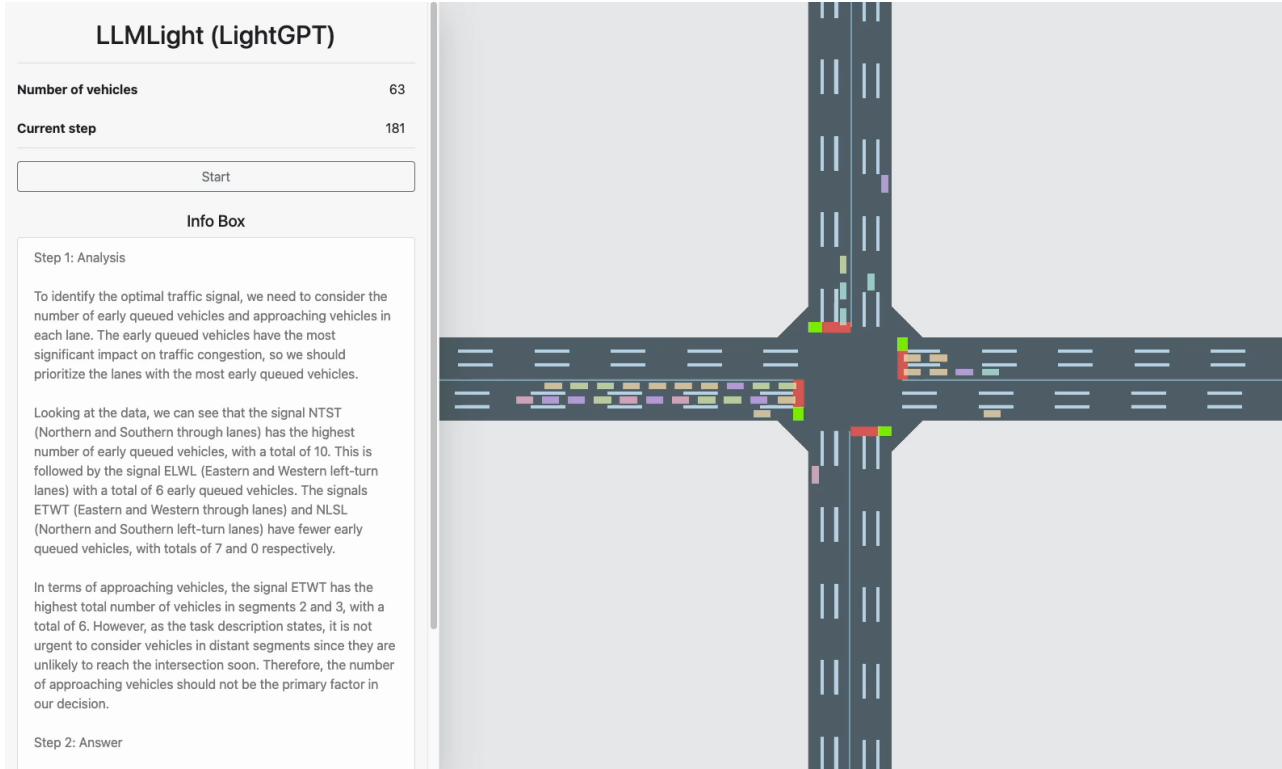


Hallucination!

LLM Agents for Urban Planning

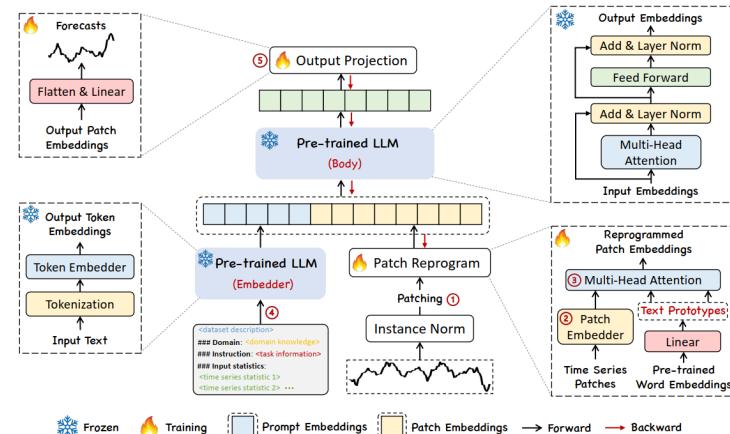
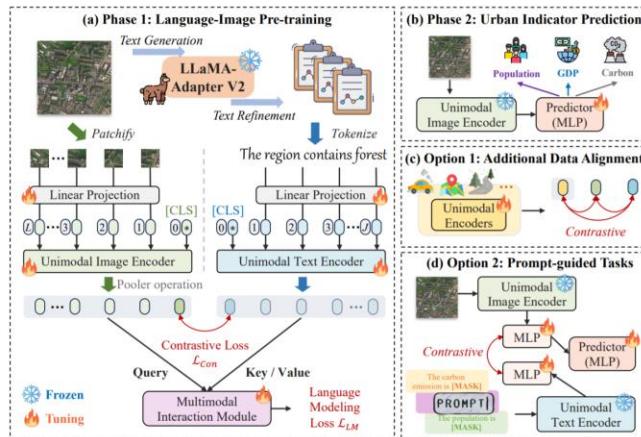


LLM Agents for Traffic Light Control



Summary

- When spatio-temporal data meet LLMs
 - Categories: LLM-as-Enhancer, LLM-as-Predictor, LLM-as-Agent
 - We introduce two examples that leverage LLMs for spatio-temporal data mining
 - UrbanCLIP for learning urban region profiling
 - Time-LLM and UniTime for time series analysis



Important Note

- Last course (project presentation) on 2 Dec
- Submit system report & code by **9 Dec @ 23:59**
- Random draw

12	2 Dec	L12: Summary and Future Trends	✓	* Project presentation * Submit Systems Report & Codes (by 9 Dec @ 23:59)
----	-------	--------------------------------	---	---

Final Presentation Instruction

- Final Presentation and Demo – general
 - Cover key essence of work
 - PPT presentation to cover the usual what (what problems), why (literature review part); how (your design and innovation), and why (innovations and justifications); plus results and analysis
 - Demo: show the key innovative parts of work; to highlight main features of system
- Final Presentation and Demo to the Class
 - To present within 15 mins
 - QA: 5 mins

Presented Papers

UniTime: A Language-Empowered Unified Model for Cross-Domain Time Series Forecasting, https://org/doipdf/10.1145/3589633	WWW	2024	HKUST(GZ)	Jiaxi Hu
UrbanGPT: Spatio-Temporal Large Language Models atio-temporal-large-lan	SIGKDD	2024	The University of Hong Kong	Zhixiong Wang
Mobility-LLM: Learning Visiting Intentions and Travel Preference from Human Mobility Data ips.cc/virtual/2024/poster	NeurIPS	2024	Beijing Jiaotong university	Qiongyan Wang
UniST: A Prompt-Empowered Universal Model for Urban Spatio-Temporal Prediction https://n.org/doipdf/10.1145/36375	KDD	2024	Tsinghua University	Yongkai GAO

Q&A



Thanks!

CITY  ND



Tencent



CAI
NIAO 菜鸟