Time-LLM: Time Series Forecasting by Reprogramming Large Language Models

Ming Jin*[1], Shiyu Wang*[2], Lintao Ma[2], Zhixuan Chu[2], James Y. Zhang[2], Xiaoming Shi[2],

Pin-Yu Chen[3], Yuxuan Liang[4], Yuan-Fang Li[1], Shirui Pan[5] , Qingsong Wen[6]

[1] Monash University
[2] Ant Group
[3] IBM Research
[4] HKUST (Guangzhou)
[5] Griffith University
[6] Squirrel AI

Paper

GitHub

ICLR

Talk on MLLM

April 6th, 2024

Outline

- Introduction
- Background

Part 1

- Time-LLM: Motivation
- Time-LLM: Architecture
- Time-LLM: Experiments
- Time-LLM: Summary

Part 2

- Other Related Works
- Prospects

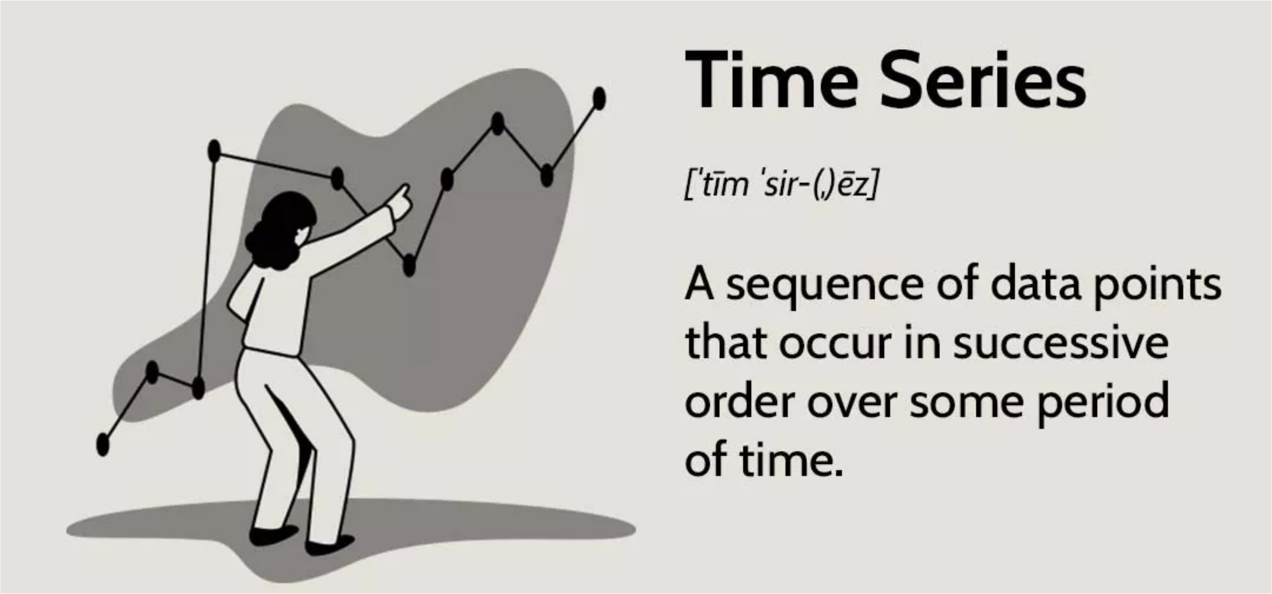
Part 3

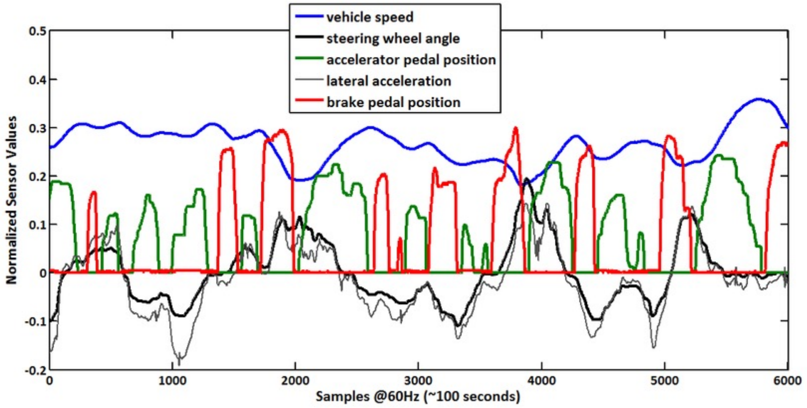
Part 1. Introduction & Background

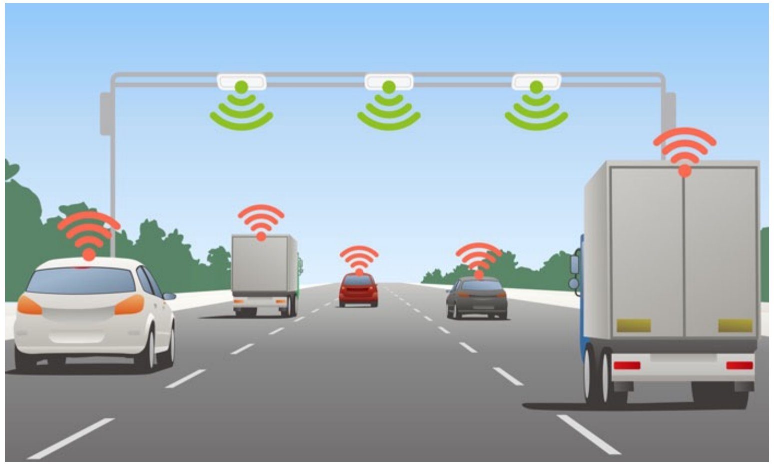
- Time series and language modeling
- Multimodal large language models
- Large language models for time series data
- Model reprogramming

Introduction

- What are time series?





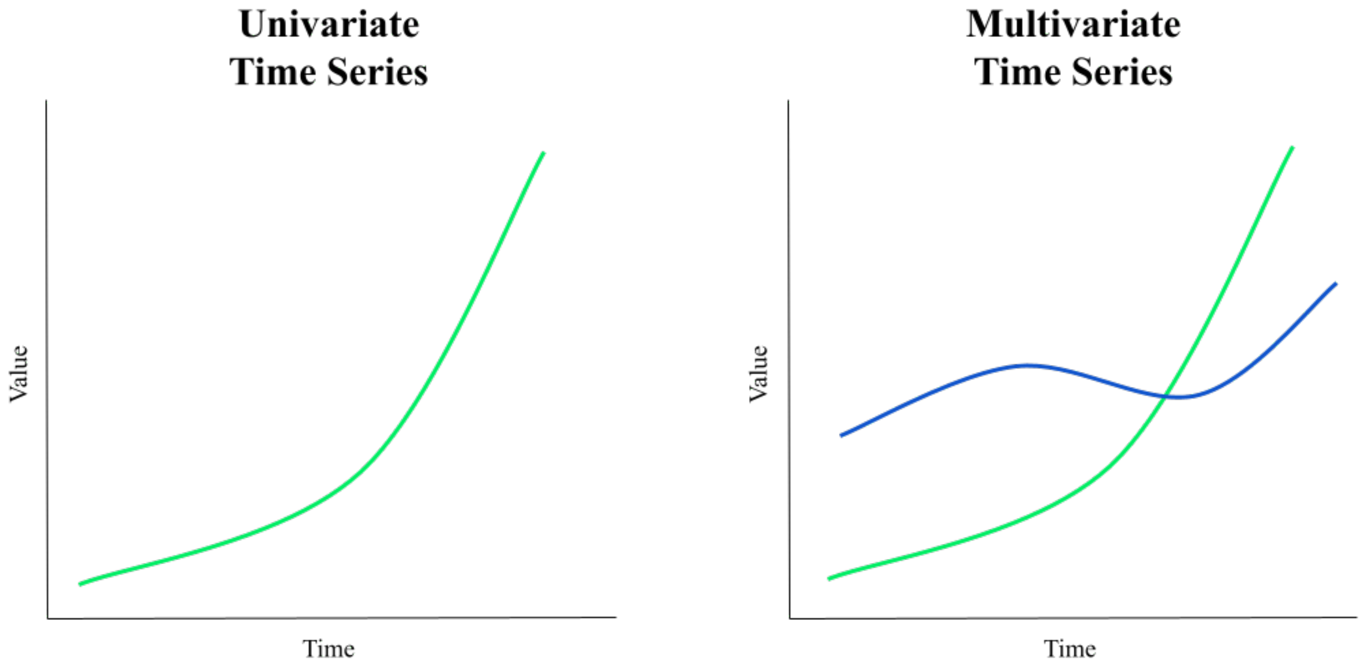


https://www.investopedia.com/terms/t/timeseries.asp

Enev, M., Takakuwa, A., Koscher, K., & Kohno, T. (2016). Automobile Driver Fingerprinting. Proc. Priv. Enhancing Technol., 2016(1), 34-50.

Introduction

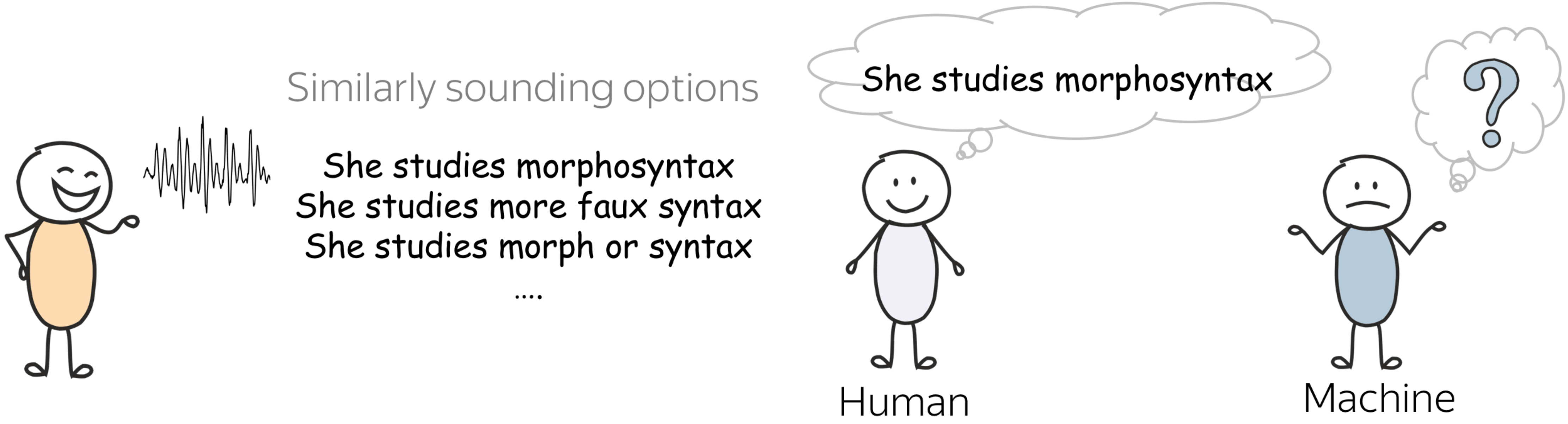
- What are time series?



https://www.mongodb.com/basics/time-series-data-analysis

Introduction

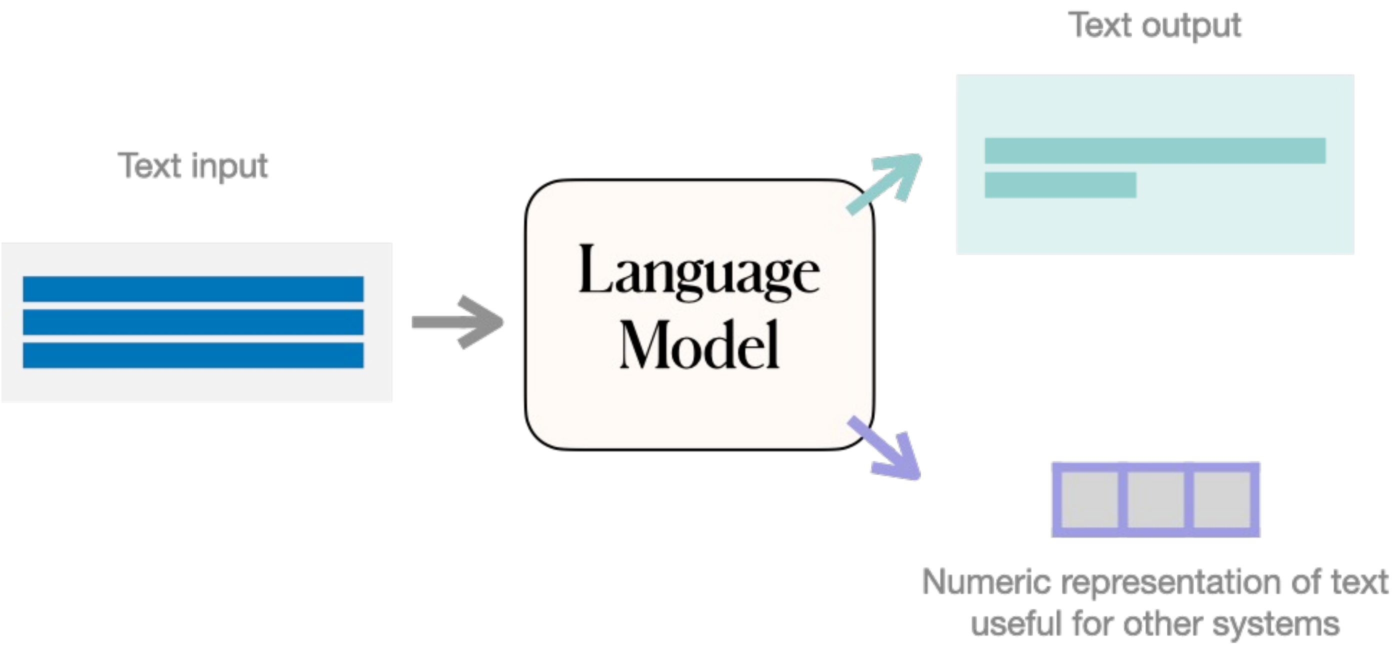
- What is language modeling?



https://lena-voita.github.io/nlp_course/language_modeling.html

Introduction

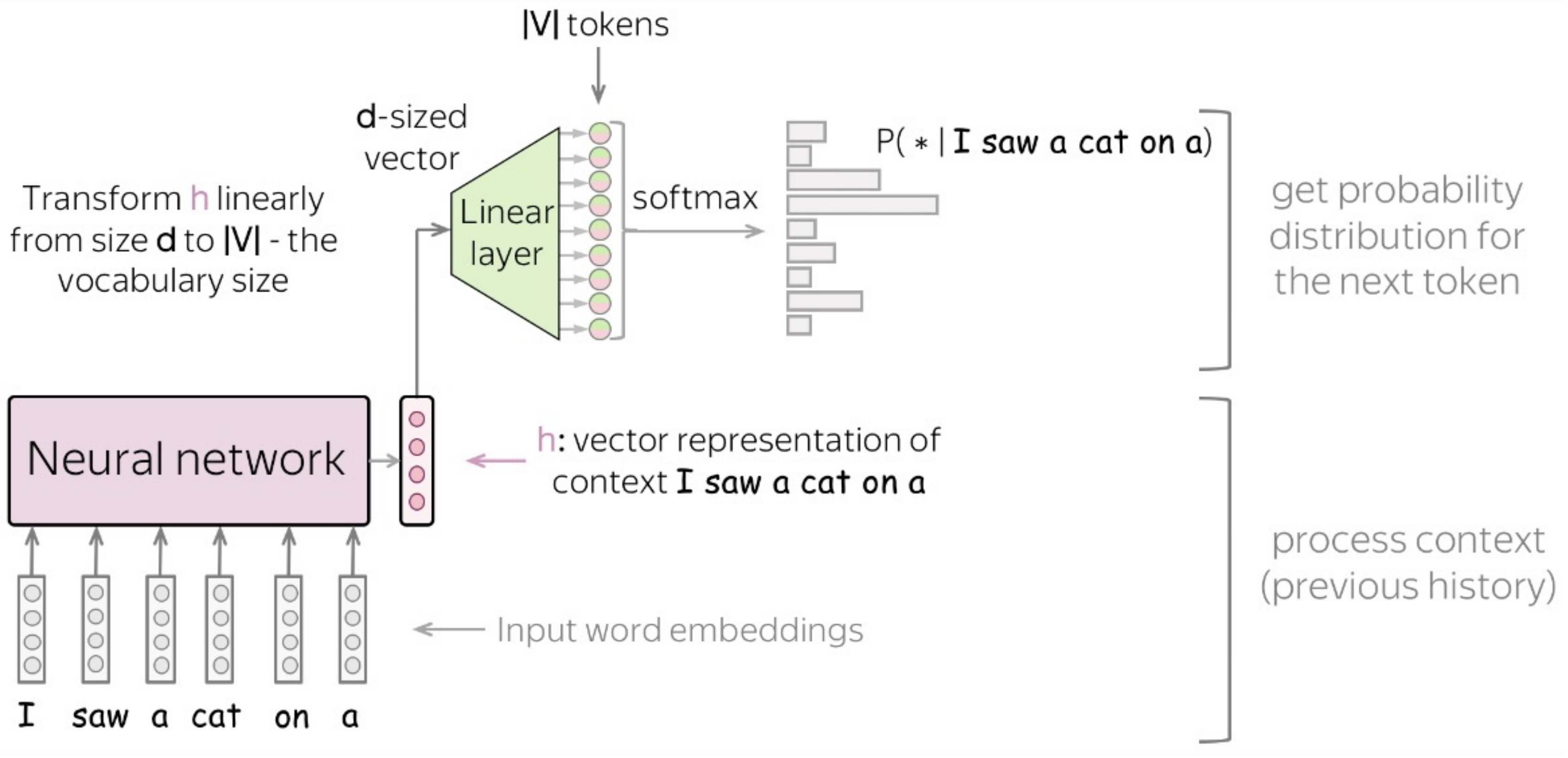
- What is language modeling?



https://lena-voita.github.io/nlp_course/language_modeling.html

Introduction

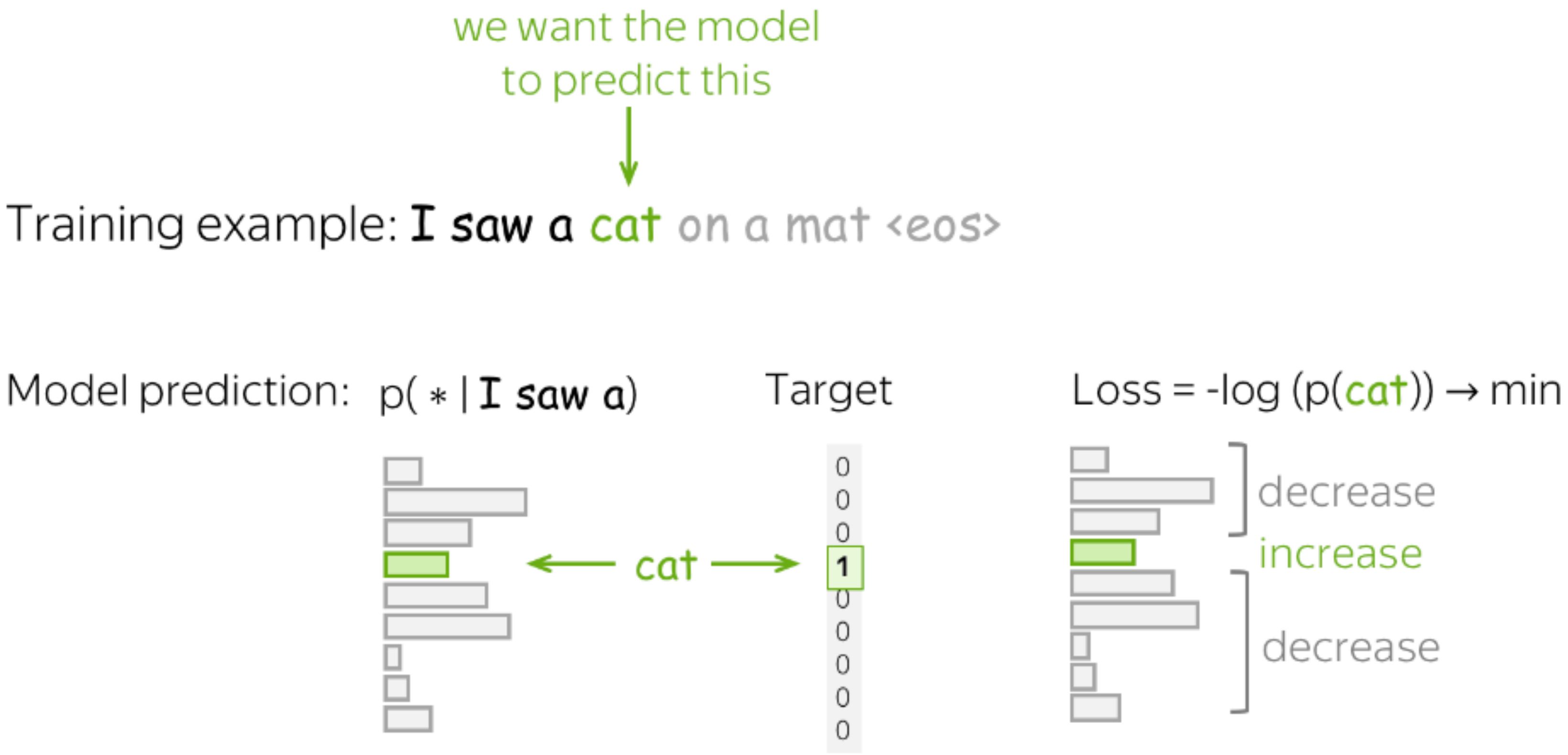
- What is language modeling?



https://lena-voita.github.io/nlp_course/language_modeling.html

Introduction

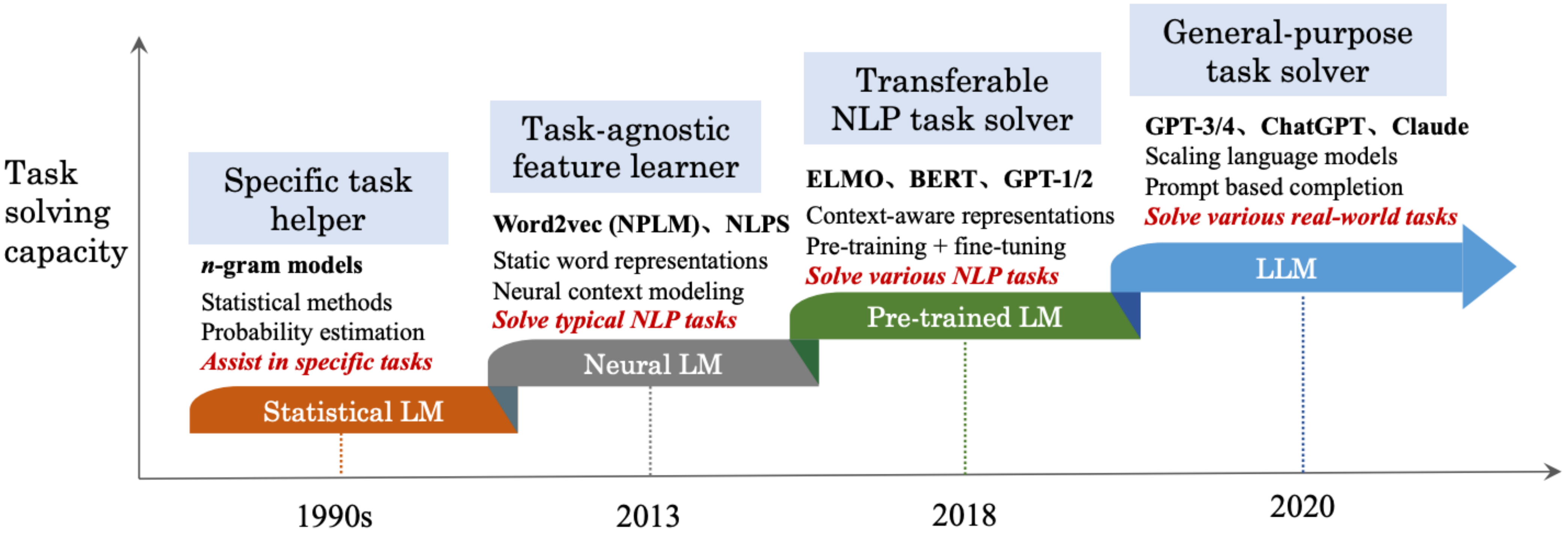
- What is language modeling?



https://lena-voita.github.io/nlp_course/language_modeling.html

Introduction

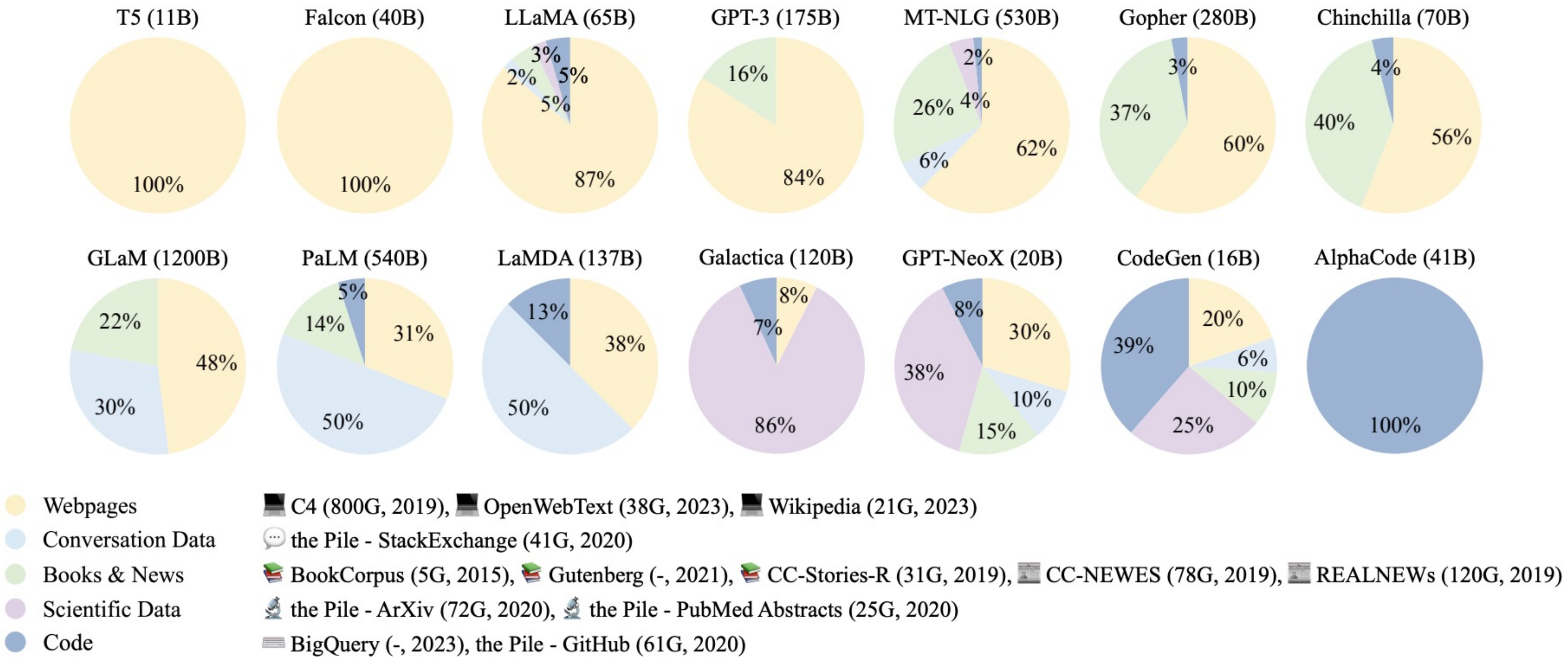
- What are large language models?



Zhao, W. X., Zhou, K., Li, J., Tang, T., Wang, X., Hou, Y., ... & Wen, J. R. (2023). A survey of large language models. arXiv preprint arXiv:2303.18223.

Introduction

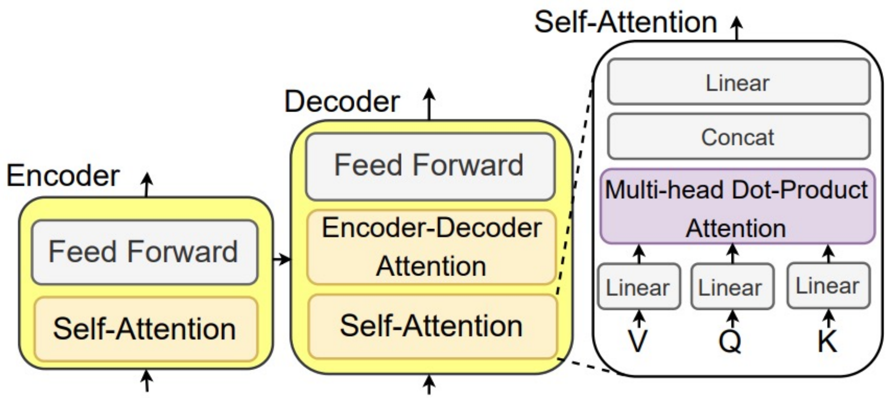
- What are large language models?

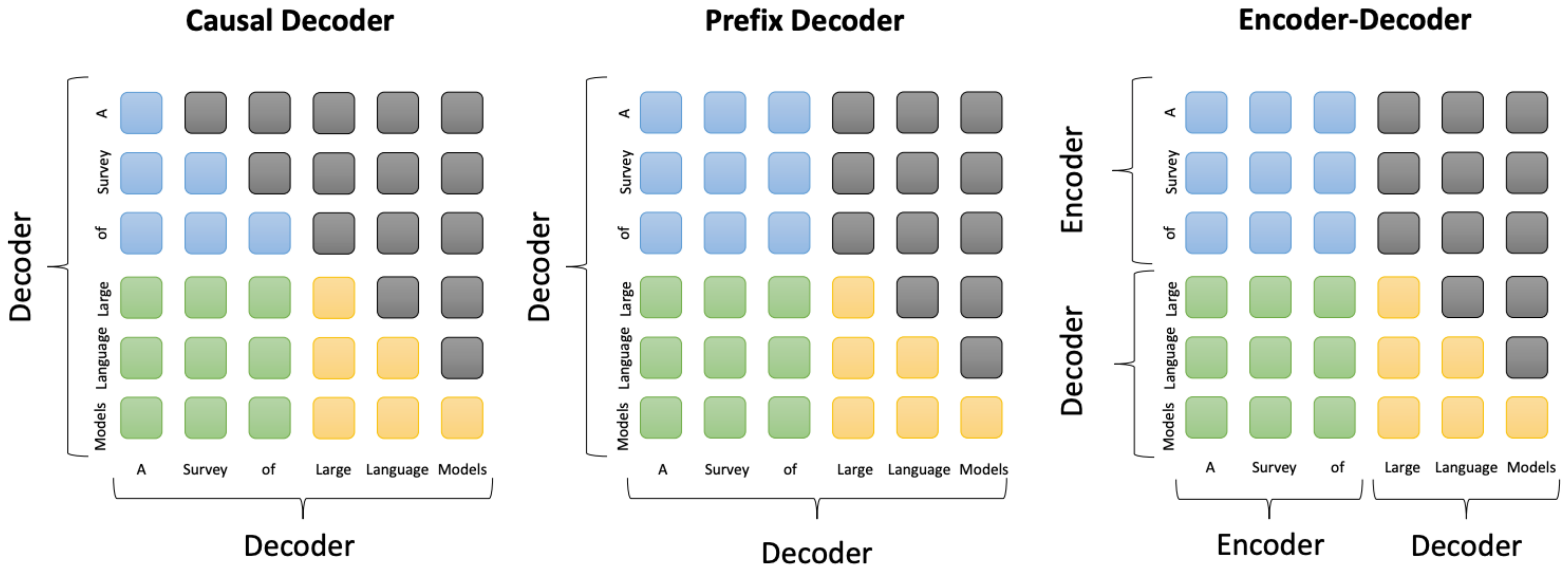


Zhao, W. X., Zhou, K., Li, J., Tang, T., Wang, X., Hou, Y., ... & Wen, J. R. (2023). A survey of large language models. arXiv preprint arXiv:2303.18223.

Introduction

• What are large language models?



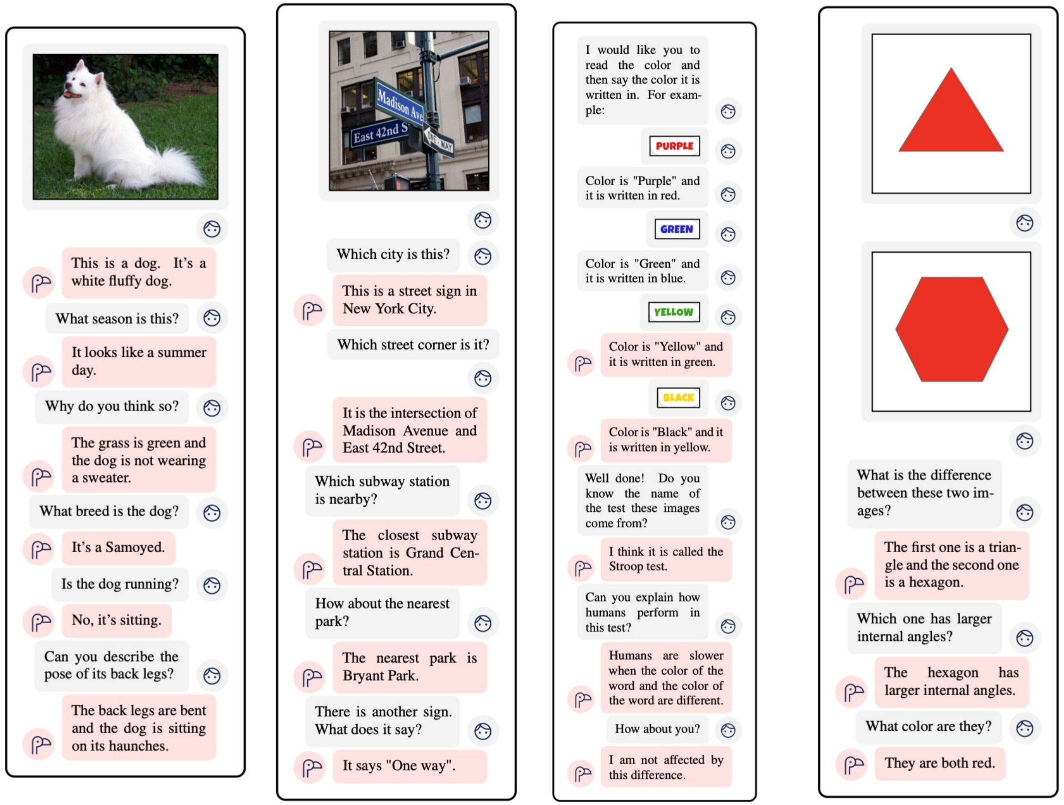


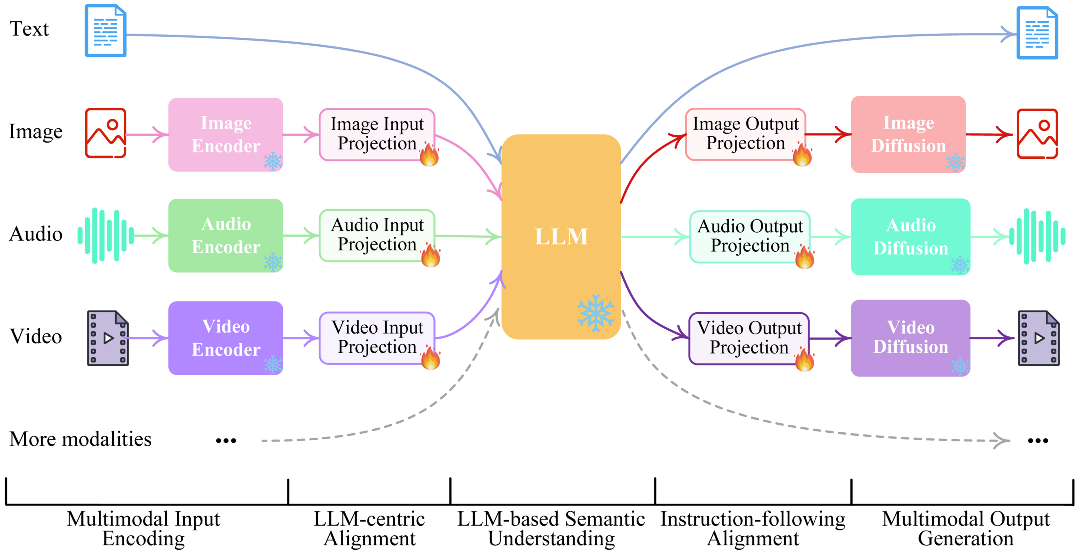
Zhao, W. X., Zhou, K., Li, J., Tang, T., Wang, X., Hou, Y., ... & Wen, J. R. (2023). A survey of large language models. arXiv preprint arXiv:2303.18223.

Pan, S., Luo, L., Wang, Y., Chen, C., Wang, J., & Wu, X. (2023). Unifying Large Language Models and Knowledge Graphs: A Roadmap. *arXiv preprint arXiv:2306.08302*.

Introduction

- Multimodal large language models





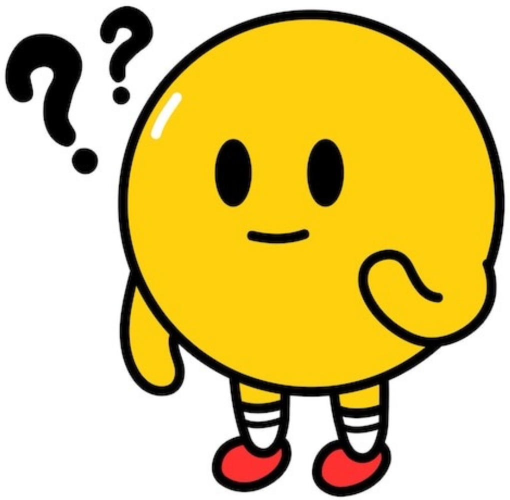
	Encoder		Input Projection		LLM		Output Projection		Diffusion	
	Name	Param	Name	Param	Name	Param	Name	Param	Name	Param
Text	—	—	—	—			—	—	—	—
Image					Vicuna [9]	7B	Transformer	31M	SD [43]	1.3B
Audio	ImageBind [15]	1.2B	Linear	4M	(LoRA	33M)	Transformer	31M	AudioLDM [34]	975M
Video							Transformer	32M	Zeroscope [5]	1.8B

https://next-gpt.github.io/

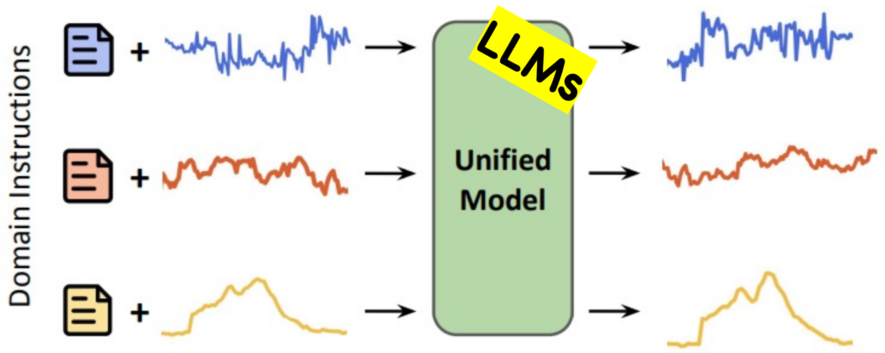
https://huyenchip.com/2023/10/10/multimodal.html

Introduction

- Multimodal large language models



How time series analysis benefits from the recent advances of LLMs?

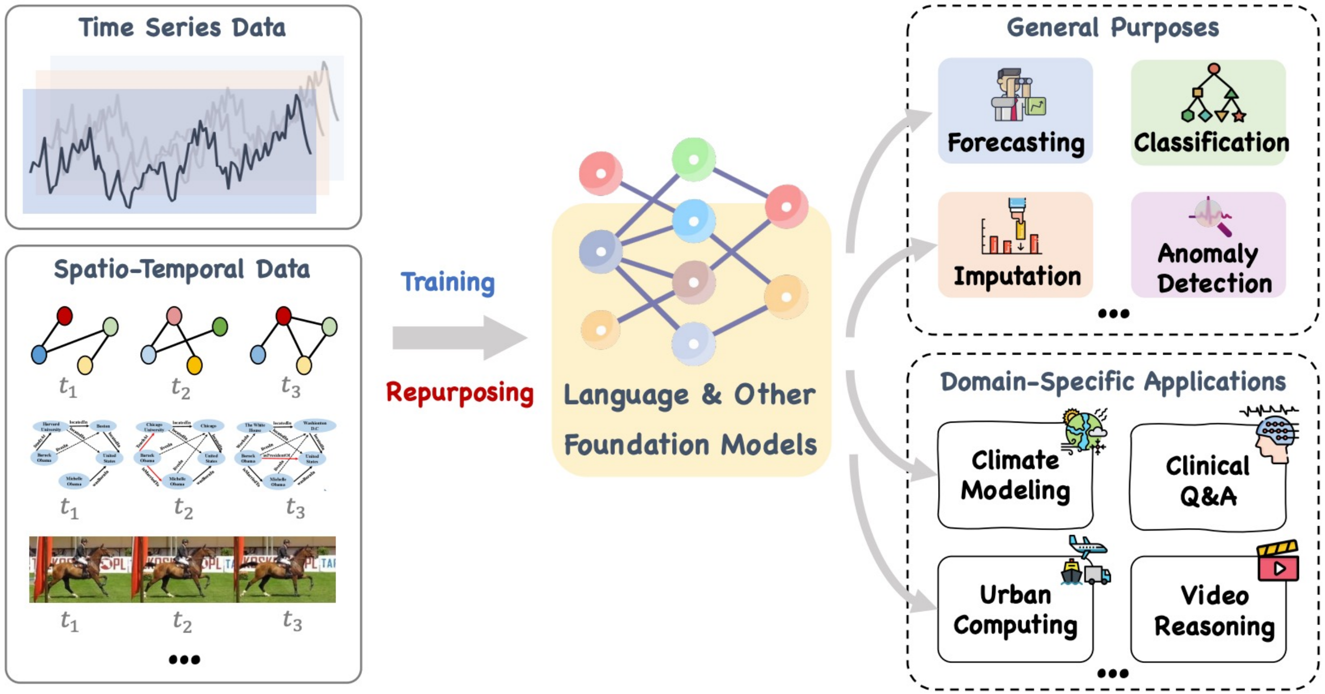


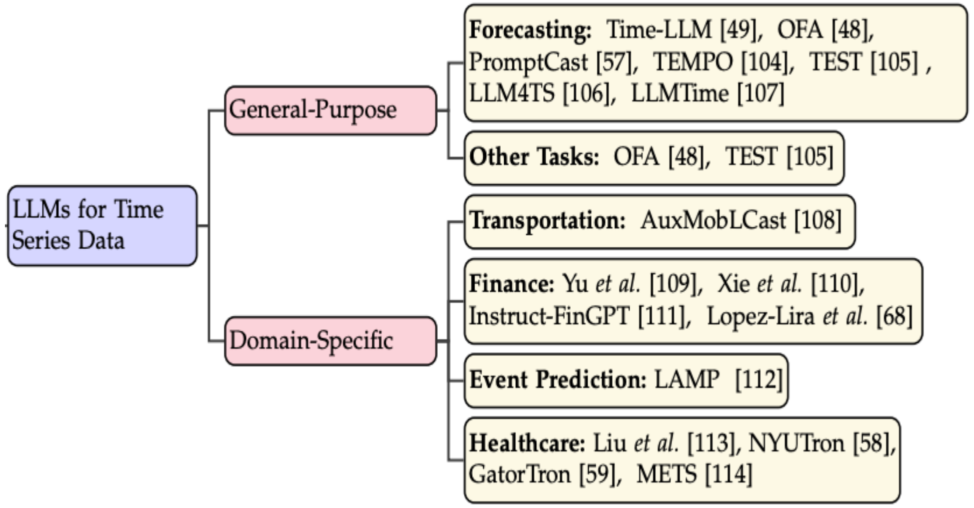
Example of TS forecasting

https://arxiv.org/pdf/2310.09751.pdf

Introduction

- Multimodal large language models

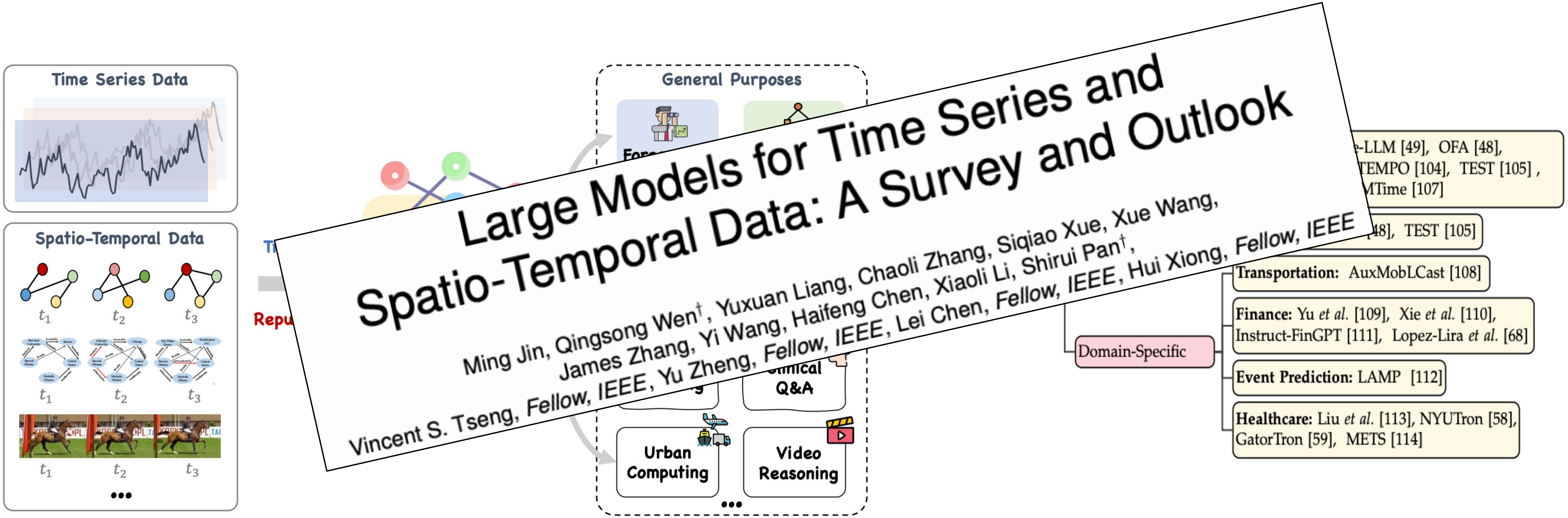




Jin, M., Wen, Q., Liang, Y., Zhang, C., Xue, S., Wang, X., ... & Xiong, H. (2023). Large models for time series and spatio-temporal data: A survey and outlook. arXiv preprint arXiv:2310.10196.

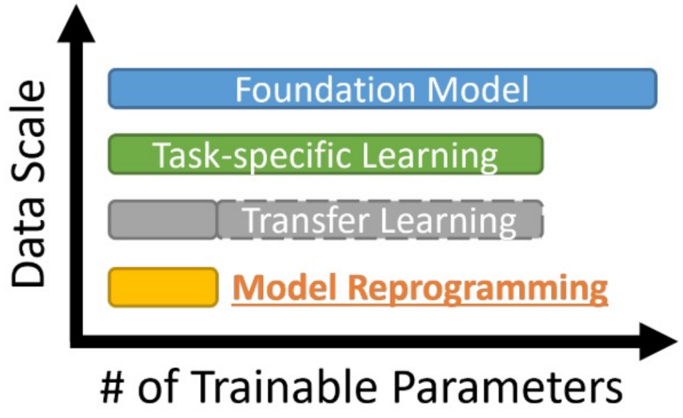
Introduction

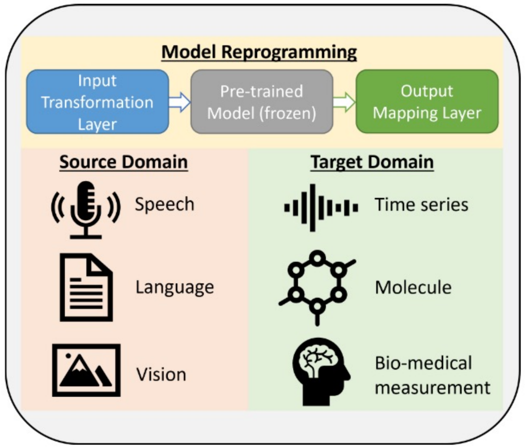
- Multimodal large language models



Jin, M., Wen, Q., Liang, Y., Zhang, C., Xue, S., Wang, X., ... & Xiong, H. (2023). Large models for time series and spatio-temporal data: A survey and outlook. arXiv preprint arXiv:2310.10196.

Background



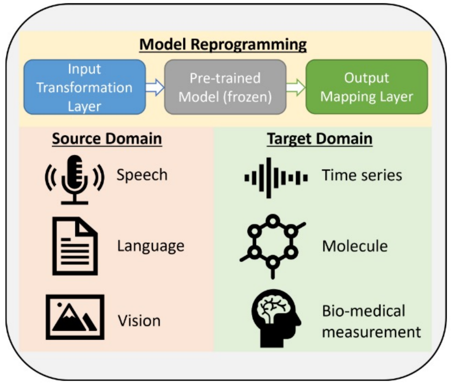


- **Task-Specific Learning**: Training a specific ML model from the scratch by minimizing the task-specific loss
- **Transfer Learning**: A common practice for in-domain knowledge transfer. One notable limitation is that in some target domains there may lack adequate pre-trained models from similar domains for effective finetuning

  *** The scale can be different depending on which layers to finetune**
- **Foundation Model**: It features task-agnostic pre-training (often on large-scale datasets) and efficient finetuning to downstream tasks
- **Model Reprogramming**: Only requires training the inserted input transformation and output mapping layers while keeping the source pre-trained model intact for target tasks

Chen, P. Y. (2022). Model reprogramming: Resource-efficient cross-domain machine learning. *arXiv preprint arXiv:2202.10629*.

Background



An example

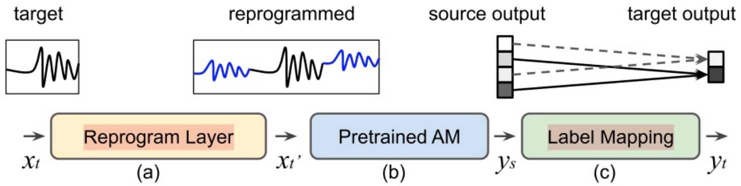


Figure 1. Schematic illustration of the proposed Voice2Series (V2S) framework: (a) trainable reprogram layer; (b) pre-trained acoustic model (AM); (c) source-target label mapping function.

Reference	Source domain	Source model	Target domain	Highlights
[Elsayed *et al.*, 2019]	General image	ImageNet	CIFAR-10/MNIST/counting	first work; mediocre accuracy
[Neekhara *et al.*, 2019]	Text	LSTM/CNN	Character/Word level tasks	context-based vocabulary mapping
[Tsai *et al.*, 2020]	General image	ImageNet/API	Bio-medical measurement/image	black-box reprogramming; new SOTA
[Vinod *et al.*, 2020]	Text	BERT/LSTM	Biochemical sequence	vocabulary embedding mapping
[Kloberdanz *et al.*, 2021]	General image	ImageNet	Caltech 101/256 (reduced)	trainable input & output layers
[Lee *et al.*, 2020; Dinh *et al.*, 2022]	Image/Spectrogram	GAN	Image/Spectrogram	reprogram GAN to conditional GAN
[Randazzo *et al.*, 2021]	MNIST/lizard pattern	Neural CA	MNIST/Lizard pattern	stable out-of-training configurations
[Hambardzumyan *et al.*, 2021]	Text	BERT & variants	GLUE/SuperGLUE	trainable tokens and data efficiency
[Yang *et al.*, 2021]	Speech	VGGish	Univariate time series	new/same SOTA on 19/30 datasets
[Yen *et al.*, 2021]	Speech	Acoustic model	Low-resource speech	new SOTA; reprogramming+finetuning
[Chen *et al.*, 2021]	General image	ImageNet	Financial transaction	overlay image and transaction feature
[Neekhara *et al.*, 2022]	General image	ViT/Imagenet	Sequence	text sentences and DNA sequences

Table 2: Summary of model reprogramming use cases. LSTM means long short-term memory, CNN means convolutional neural network, API means application programming interface, and SOTA means state of the art. BERT stands for bidirectional encoder representations from transformers. GLUE stands for the general language understanding evaluation benchmark. GAN stands for generative adversarial network. CA stands for cellular automata. ViT stands for vision transformer. We also maintain a list of model reprogramming studies at https://github.com/IBM/model-reprogramming.

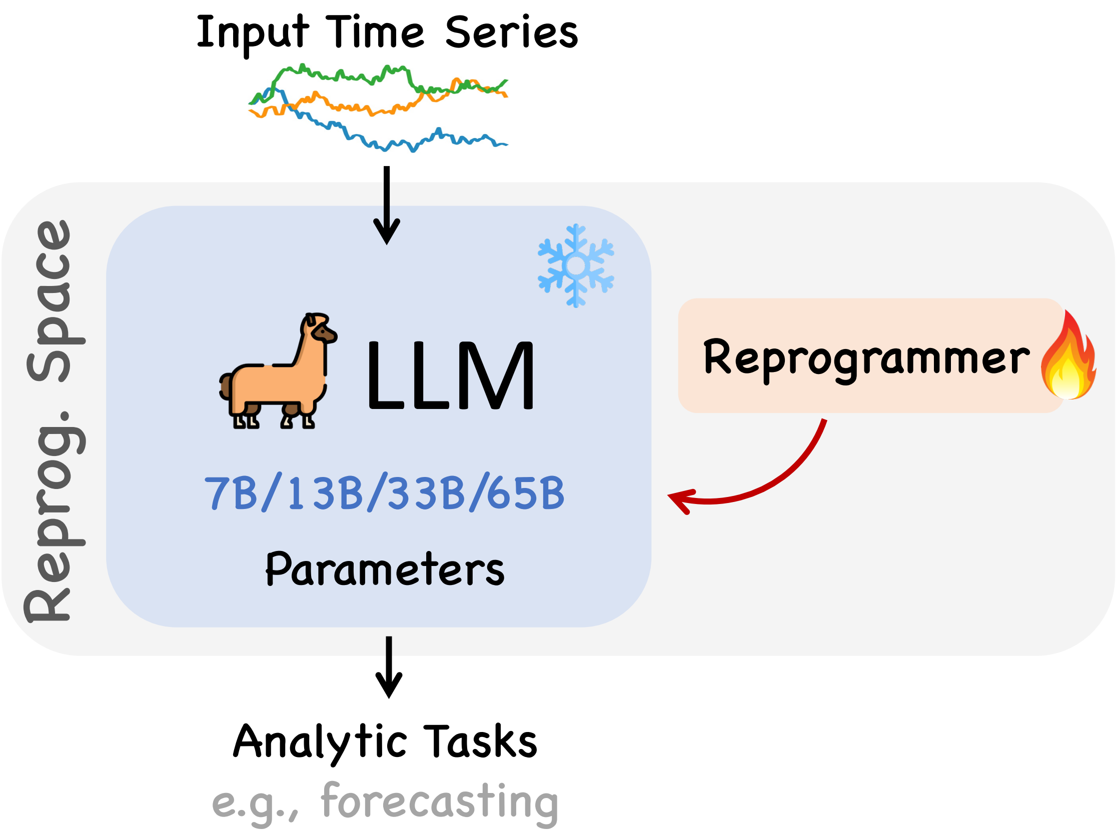
Chen, P. Y. (2022). Model reprogramming: Resource-efficient cross-domain machine learning. *arXiv preprint arXiv:2202.10629*.

Part 2. Time-LLM

- Motivation (Conceptual designs)
- Model architecture & Highlights
- Our main results

Motivation

- Reprogramming makes LLMs **instantly ready** for time series tasks



We keep pretrained LLMs intact and **only fine-tune reprogrammer** to achieve certain alignments

Reprogramming ≈ Adaptation + Alignment

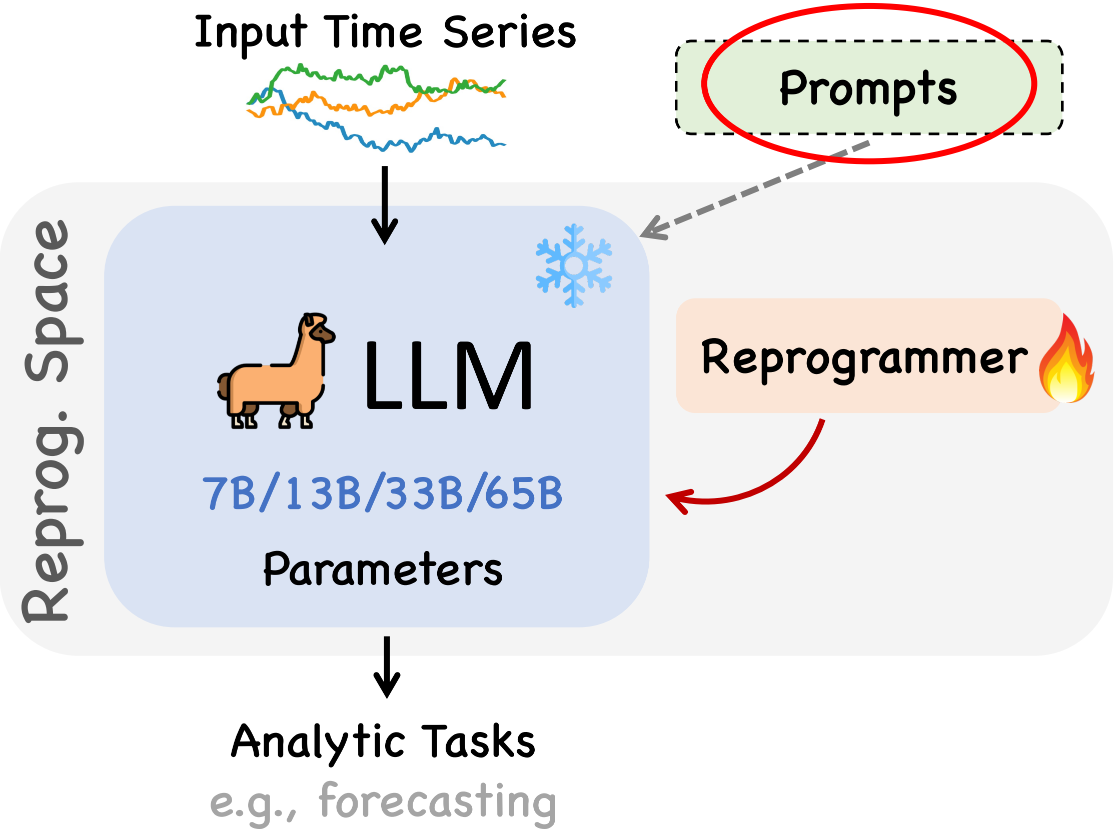
Adaptation makes LLMs to understand how to process the input time series data → Breaking domain isolation and enabling knowledge sharing

Alignment further eliminates domain boundary to facilitate knowledge acquiring

https://arxiv.org/pdf/2310.09751.pdf

Motivation

- Reprogramming makes LLMs **more powerful** for time series tasks



We keep pretrained LLMs intact and **only fine-tune reprogrammer** to achieve certain alignments

Reprogramming ≈ Adaptation + Alignment

Adaptation makes LLMs to understand how to process the input time series data → Breaking domain isolation and enabling knowledge sharing

Alignment further eliminates domain boundary to facilitate knowledge acquiring

https://arxiv.org/pdf/2310.09751.pdf

Motivation

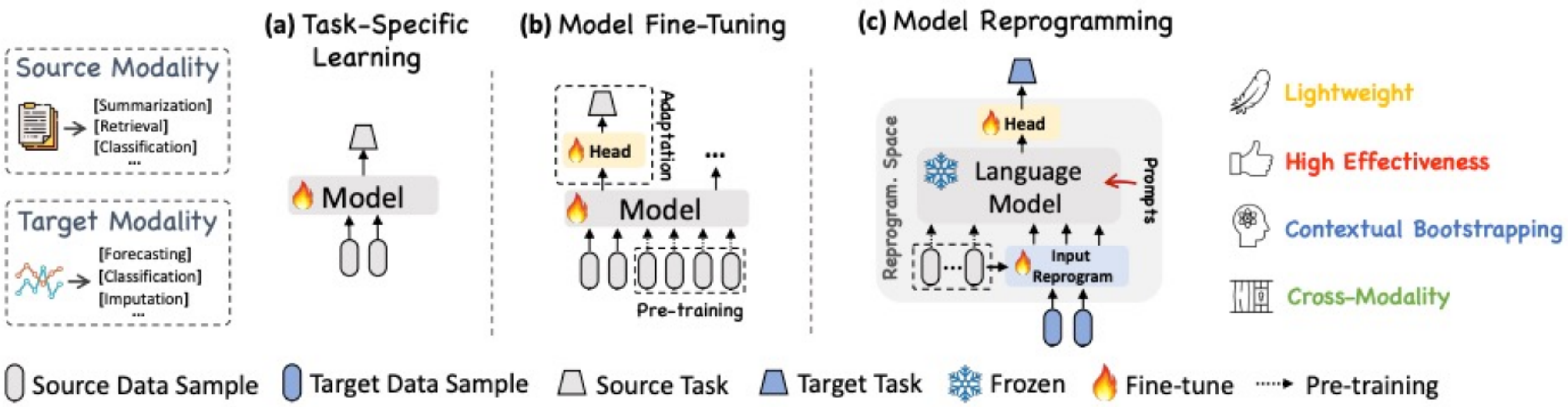
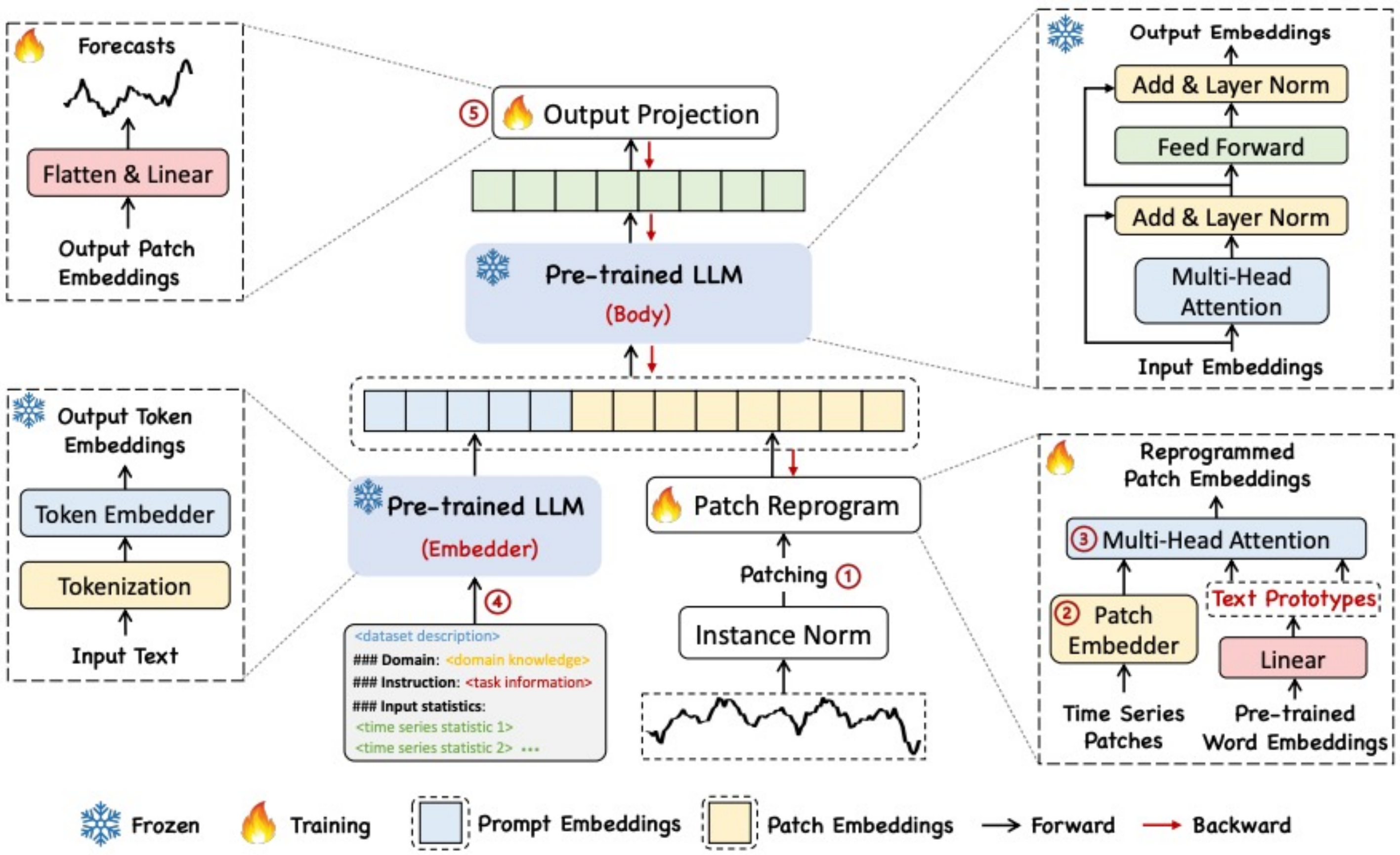


Figure: Schematic illustration of reprogramming LLMs in comparison of **(a)** task-specific learning and **(b)** model fine-tuning

- **Task-specific learning:** Most time series forecasting models are crafted for specific tasks and domains (e.g., traffic prediction), and trained end-to-end on small-scale data.
- **In-modality adaptation:** A typical example is the time series pre-trained models (TSPTMs)
- **Cross-modality adaptation:** Transferring the knowledge from powerful pre-trained source foundation models to perform target tasks via model fine-tuning or reprogramming

Architecture



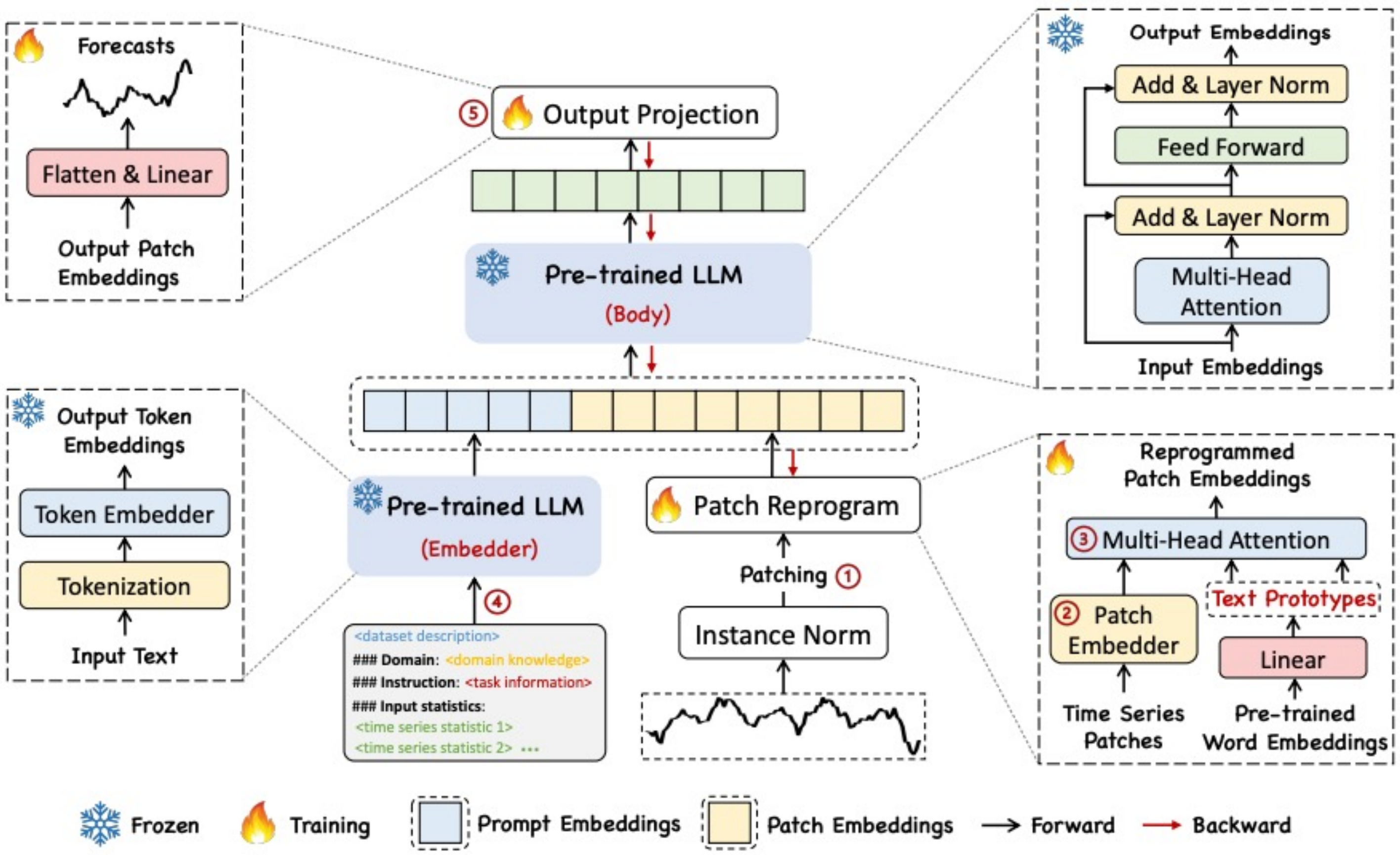
TL;DR Domain expert knowledge & Task instructions + Reprogrammed input time series = Significantly better forecasts

Unlocking the LLM's ability for time series

Cross-modal Adaptation: ① ② ⑤

Cross-modal Alignment: ③ ④

Architecture



TL;DR Domain expert knowledge & Task instructions + Reprogrammed input time series = Significantly better forecasts

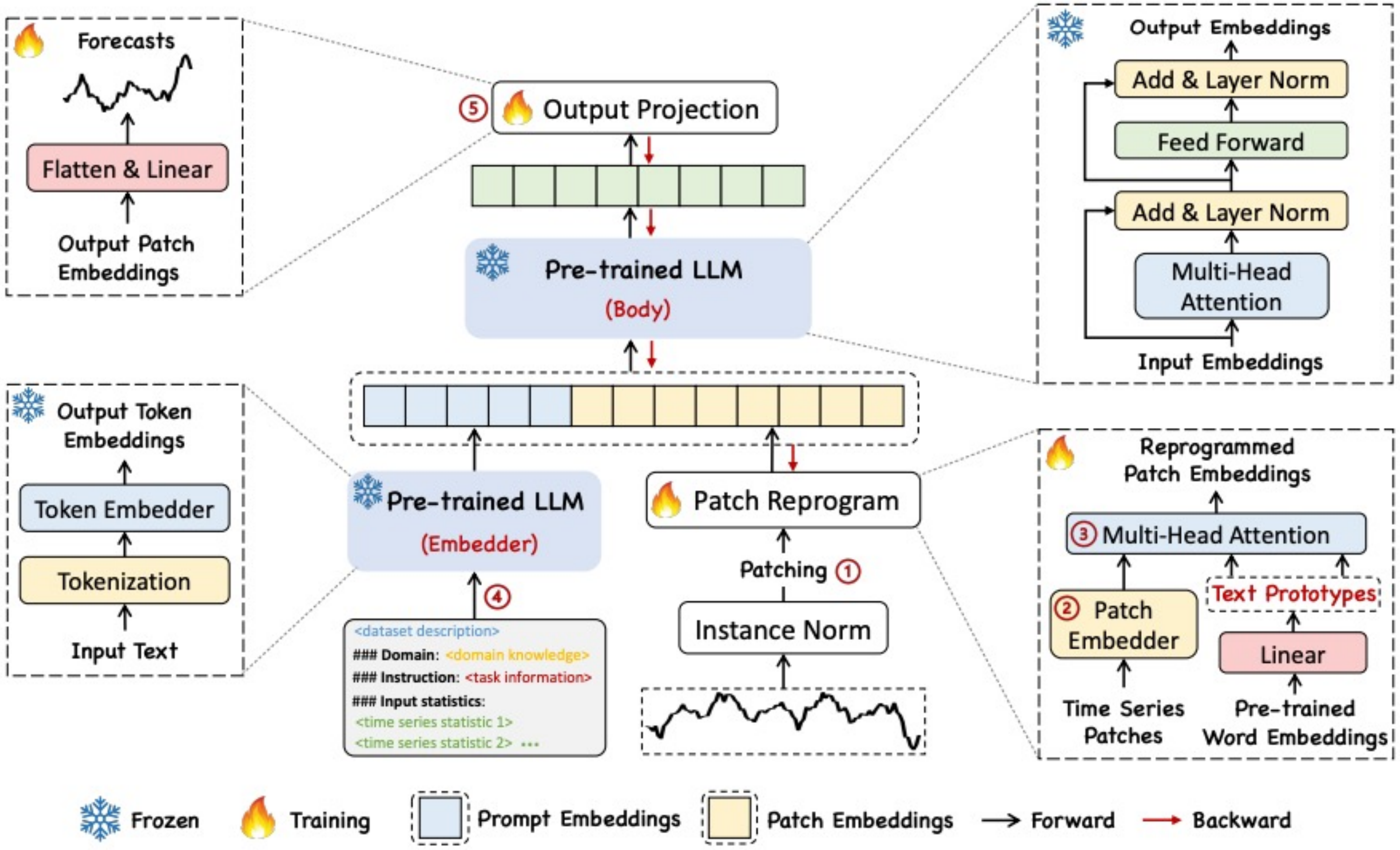
Unlocking the LLM's ability for time series

Cross-modal Adaptation: ① ② ⑤

Cross-modal Alignment: ③ ④

- **Patch Reprogramming:** we reprogram TS patch embeddings into the source data representation space to align the modalities of time series and natural language to activate the backbone's time series understanding and reasoning capabilities.

Architecture



TL;DR Domain expert knowledge & Task instructions + Reprogrammed input time series = Significantly better forecasts

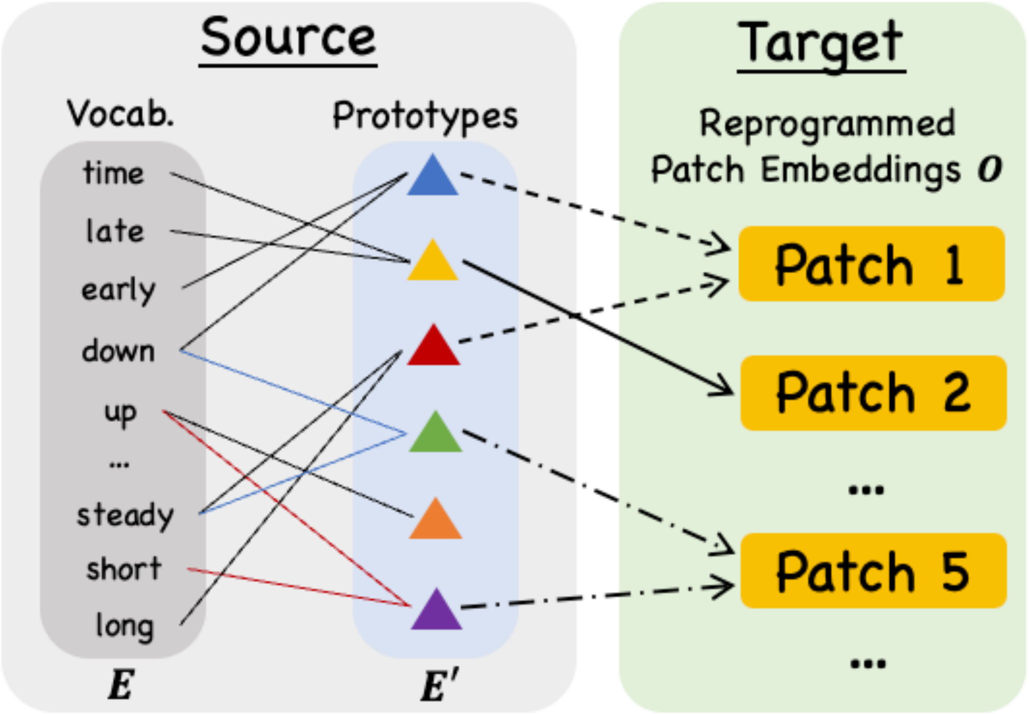
Unlocking the LLM's ability for time series

Cross-modal Adaptation: 1 2 5

Cross-modal Alignment: 3 4

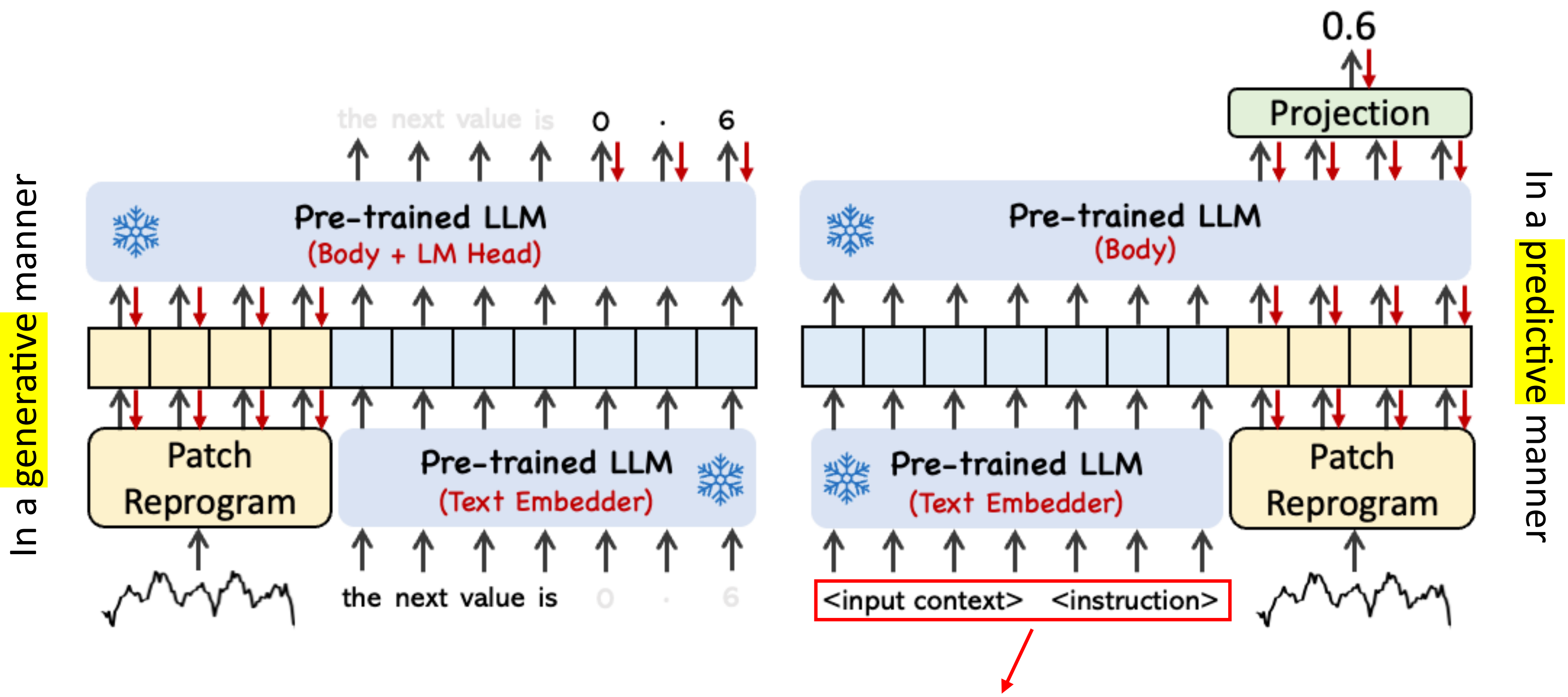
- **Prompt-as-Prefix:** natural language-based prompts (e.g., domain knowledge & task instructions) can act as prefixes to enrich the input context and guide the transformation of reprogrammed TS patches

Architecture



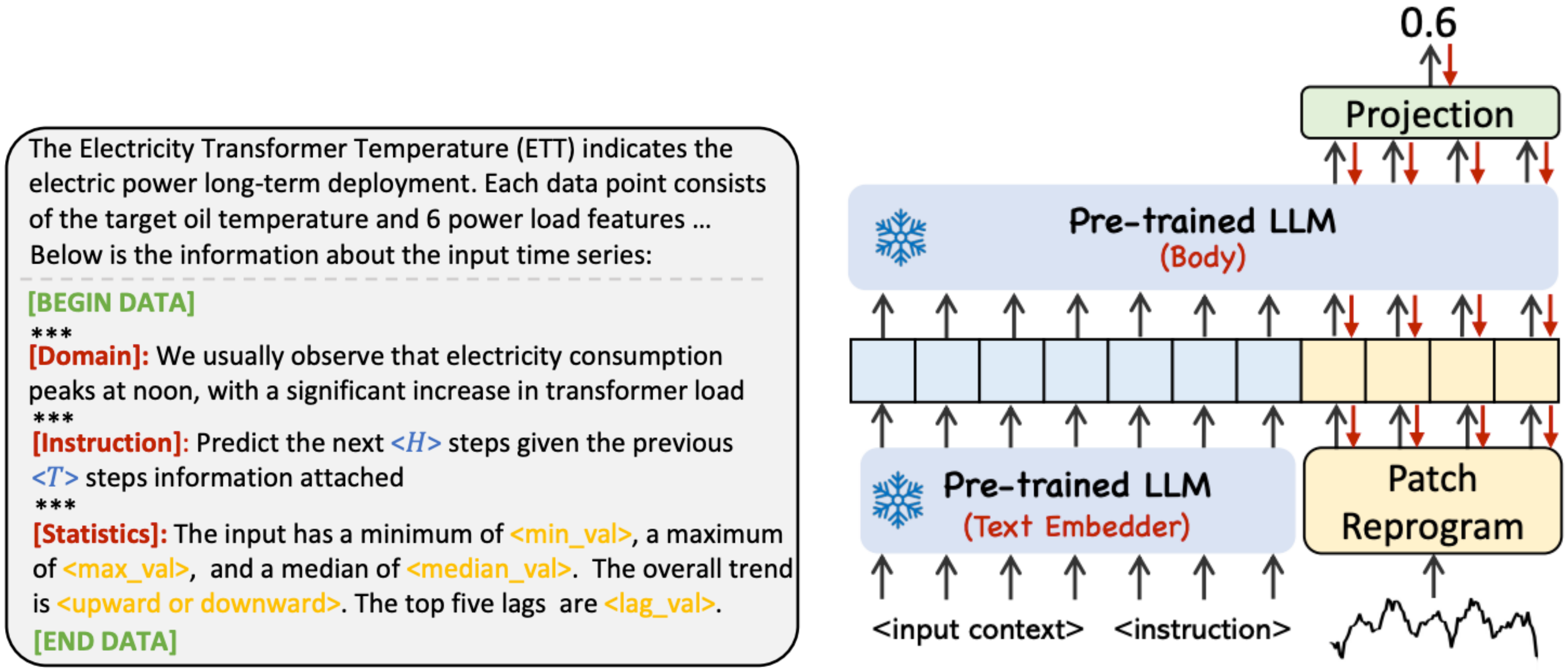
- **Patch reprogramming:** Text prototypes learn connecting language cues, e.g., “short up” (red lines) and “steady down” (blue lines), which are then combined to represent the local patch information (e.g., “short up then down steadily” for characterizing Patch 5)

Architecture



- **Prompt-as-Prefix** is proposed to enrich the input context and guide the transformation of reprogrammed time series patches
- **Prompt-as-Prefix** is more desired in time series forecasting compared to **Patch-as-Prefix**

Architecture



- In this prompt template, < > and < > are task-specific configurations and calculated input statistics
- In practice, there are **much more possibilities** in bringing time series and the related textual contexts (that are prompts) together

Main Results

Table 1: Long-term forecasting results. All results are averaged from four different forecasting horizons: $H \in \{24, 36, 48, 60\}$ for ILI and $\{96, 192, 336, 720\}$ for the others. A lower value indicates better performance. **Red**: the best, Blue: the second best. Our full results are in Appendix D.

Methods	TIME-LLM (**Ours**)		GPT4TS (2023a)		DLinear (2023)		PatchTST (2023)		TimesNet (2023)		FEDformer (2022)		Autoformer (2021)		Stationary (2022)		ETSformer (2022)		LightTS (2022a)		Informer (2021)		Reformer (2020)	
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
$ETTh1$	**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
$ETTh2$	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
$ETTm1$	**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
$ETTm2$	**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
$Weather$	**0.225**	**0.257**	0.237	0.270	0.248	0.300	**0.225**	0.264	0.259	0.287	0.309	0.360	0.338	0.382	0.288	0.314	0.271	0.334	0.261	0.312	0.634	0.548	0.803	0.656
ECL	**0.158**	**0.252**	0.167	0.263	0.166	0.263	0.161	**0.252**	0.192	0.295	0.214	0.327	0.227	0.338	0.193	0.296	0.208	0.323	0.229	0.329	0.311	0.397	0.338	0.422
$Traffic$	**0.388**	0.264	0.414	0.294	0.433	0.295	0.390	**0.263**	0.620	0.336	0.610	0.376	0.628	0.379	0.624	0.340	0.621	0.396	0.622	0.392	0.764	0.416	0.741	0.422
ILI	**1.435**	0.801	1.925	0.903	2.169	1.041	1.443	**0.797**	2.139	0.931	2.847	1.144	3.006	1.161	2.077	0.914	2.497	1.004	7.382	2.003	5.137	1.544	4.724	1.445
1st Count	**7**		0		0		5		0		0		0		0		0		0		0		0	

- We note average performance gains of **12%** and **20%** over GPT4TS (OFA) and TimesNet, respectively
- When compared with the SOTA task-specific Transformer model PatchTST, by reprogramming the smallest Llama, Time-LLM realizes an average MSE reduction of **1.4%**
- Relative to the other models, e.g., DLinear, our improvements are also pronounced, exceeding **12%**

Main Results

Table 2: Short-term time series forecasting results on M4. The forecasting horizons are in [6, 48] and the three rows provided are weighted averaged from all datasets under different sampling intervals. A lower value indicates better performance. **Red**: the best, Blue: the second best. More results are in Appendix D.

Methods		TIME-LLM (**Ours**)	GPT4TS (2023a)	TimesNet (2023)	PatchTST (2023)	N-HiTS (2023b)	N-BEATS (2020)	ETSformer (2022)	LightTS (2022a)	DLinear (2023)	FEDformer (2022)	Stationary (2022)	Autoformer (2021)	Informer (2021)	Reformer (2020)
Average	SMAPE	**11.983**	12.69	12.88	12.059	12.035	12.25	14.718	13.525	13.639	13.16	12.780	12.909	14.086	18.200
	MASE	**1.595**	1.808	1.836	1.623	1.625	1.698	2.408	2.111	2.095	1.775	1.756	1.771	2.718	4.223
	OWA	**0.859**	0.94	0.955	0.869	0.869	0.896	1.172	1.051	1.051	0.949	0.930	0.939	1.230	1.775

- Time-LLM consistently surpasses all baselines, outperforming GPT4TS (OFA) by **8.7%**
- Time-LLM remains competitive even when compared with the SOTA model, N-HiTS, w.r.t. MASE and OWA

Main Results

Table 3: Few-shot learning on 10% training data. We use the same protocol in Tab. 1. All results are averaged from four different forecasting horizons: $H \in \{96, 192, 336, 720\}$. Our full results are in Appendix E.

Methods	TIME-LLM (**Ours**)		GPT4TS (2023a)		DLinear (2023)		PatchTST (2023)		TimesNet (2023)		FEDformer (2022)		Autoformer (2021)		Stationary (2022)		ETSformer (2022)		LightTS (2022a)		Informer (2021)		Reformer (2020)	
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
ETTh1	**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
ETTh2	**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
ETTm1	**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
ETTm2	**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
Weather	**0.234**	**0.273**	0.238	0.275	0.241	0.283	0.242	0.279	0.279	0.301	0.284	0.324	0.300	0.342	0.318	0.323	0.318	0.360	0.289	0.322	0.597	0.495	0.546	0.469
ECL	**0.175**	0.270	0.176	**0.269**	0.180	0.280	0.180	0.273	0.323	0.392	0.346	0.427	0.431	0.478	0.444	0.480	0.660	0.617	0.441	0.489	1.195	0.891	0.965	0.768
Traffic	**0.429**	0.306	0.440	0.310	0.447	0.313	0.430	**0.305**	0.951	0.535	0.663	0.425	0.749	0.446	1.453	0.815	1.914	0.936	1.248	0.684	1.534	0.811	1.551	0.821
1st Count	**8**		1		0		1		0		0		0		0		0		0		0		0	

- In the realm of 10% few-shot learning, our methodology realizes a **5%** MSE reduction in comparison to GPT4TS (OFA) , without necessitating any fine-tuning on the LLM. In relation to recent SOTA models such as PatchTST, DLinear, and TimesNet, our average enhancements surpass **8%**, **12%**, and **33%** w.r.t. MSE

Main Results

Table 4: Few-shot learning on 5% training data. We use the same protocol in Tab. 1. All results are averaged from four different forecasting horizons: $H \in \{96, 192, 336, 720\}$. Our full results are in Appendix E.

Methods	TIME-LLM (**Ours**)		GPT4TS (2023a)		DLinear (2023)		PatchTST (2023)		TimesNet (2023)		FEDformer (2022)		Autoformer (2021)		Stationary (2022)		ETSformer (2022)		LightTS (2022a)		Informer (2021)		Reformer (2020)	
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
ETTh1	**0.627**	**0.543**	0.681	0.560	0.750	0.611	0.694	0.569	0.925	0.647	0.658	0.562	0.722	0.598	0.943	0.646	1.189	0.839	1.451	0.903	1.225	0.817	1.241	0.835
ETTh2	**0.382**	**0.418**	0.400	0.433	0.694	0.577	0.827	0.615	0.439	0.448	0.463	0.454	0.441	0.457	0.470	0.489	0.809	0.681	3.206	1.268	3.922	1.653	3.527	1.472
ETTm1	0.425	0.434	0.472	0.450	**0.400**	**0.417**	0.526	0.476	0.717	0.561	0.730	0.592	0.796	0.620	0.857	0.598	1.125	0.782	1.123	0.765	1.163	0.791	1.264	0.826
ETTm2	**0.274**	**0.323**	0.308	0.346	0.399	0.426	0.314	0.352	0.344	0.372	0.381	0.404	0.388	0.433	0.341	0.372	0.534	0.547	1.415	0.871	3.658	1.489	3.581	1.487
Weather	**0.260**	0.309	0.263	**0.301**	0.263	0.308	0.269	0.303	0.298	0.318	0.309	0.353	0.310	0.353	0.327	0.328	0.333	0.371	0.305	0.345	0.584	0.527	0.447	0.453
ECL	0.179	**0.268**	**0.178**	0.273	0.176	0.275	0.181	0.277	0.402	0.453	0.266	0.353	0.346	0.404	0.627	0.603	0.800	0.685	0.878	0.725	1.281	0.929	1.289	0.904
Traffic	0.423	0.298	0.434	0.305	0.450	0.317	**0.418**	**0.296**	0.867	0.493	0.676	0.423	0.833	0.502	1.526	0.839	1.859	0.927	1.557	0.795	1.591	0.832	1.618	0.851
1^{st}Count	**5**		2		1		1		0		0		0		0		0		0		0		0	

- Analogous trends are discernible in the 5% few-shot learning scenarios, where our average advancement over GPT4TS exceeds **5%**. When compared with PatchTST, DLinear, and TimesNet, TIME-LLM manifests a striking average improvement of over **20%**

Main Results

Table 5: Zero-shot learning results. **Red**: the best, Blue: the second best. Appendix E shows our detailed results.

Methods	TIME-LLM (**Ours**)		GPT4TS (2023a)		LLMTime (2023)		DLinear (2023)		PatchTST (2023)		TimesNet (2023)	
Metric	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
$ETTh1 \rightarrow ETTh2$	**0.353**	**0.387**	0.406	0.422	0.992	0.708	0.493	0.488	0.380	0.405	0.421	0.431
$ETTh1 \rightarrow ETTm2$	**0.273**	**0.340**	0.325	0.363	1.867	0.869	0.415	0.452	0.314	0.360	0.327	0.361
$ETTh2 \rightarrow ETTh1$	**0.479**	**0.474**	0.757	0.578	1.961	0.981	0.703	0.574	0.565	0.513	0.865	0.621
$ETTh2 \rightarrow ETTm2$	**0.272**	**0.341**	0.335	0.370	1.867	0.869	0.328	0.386	0.325	0.365	0.342	0.376
$ETTm1 \rightarrow ETTh2$	**0.381**	**0.412**	0.433	0.439	0.992	0.708	0.464	0.475	0.439	0.438	0.457	0.454
$ETTm1 \rightarrow ETTm2$	**0.268**	**0.320**	0.313	0.348	1.867	0.869	0.335	0.389	0.296	0.334	0.322	0.354
$ETTm2 \rightarrow ETTh2$	**0.354**	**0.400**	0.435	0.443	0.992	0.708	0.455	0.471	0.409	0.425	0.435	0.443
$ETTm2 \rightarrow ETTm1$	**0.414**	**0.438**	0.769	0.567	1.933	0.984	0.649	0.537	0.568	0.492	0.769	0.567

- Time-LLM consistently outperforms the most competitive baselines by a large margin, over **14.2%** w.r.t. the second-best in MSE reduction.
- Considering the few-shot results, we observe that reprogramming an LLM tends to yield significantly better results in data scarcity scenarios

Main Results

Table 6: Ablations on ETTh1 and ETTm1 in predicting 96 and 192 steps ahead (MSE reported). **Red**: the best.

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

- **Language model variants:** The scaling law retains after the LLM reprogramming. We adopt Llama-7B by default and it indeed surpasses its 1/4 capacity variant (A.2) by 14.5%. Also, an average MSE reduction of 14,7% is observed over GPT-2 (A.3), which slightly outperforms its 1/2 capacity variant (A.4).

- **Cross-modality alignment: (1)** we find that the alignment is crucial (see B.1 and B.2); **(2)** domain knowledge and task instructions are both valuable (C.1-C.3) and can be integrated via Prompt-as-Prefix (PaP)

Main Results

Table 7: Efficiency analysis of TIME-LLM on ETTh1 in forecasting different steps ahead.

Length	ETTh1-96			ETTh1-192			ETTh1-336			ETTh1-512		
Metric	Param. (M)	Mem. (MiB)	Speed(s/iter)	Param. (M)	Mem. (MiB)	Speed(s/iter)	Param. (M)	Mem. (MiB)	Speed(s/iter)	Param. (M)	Mem.(MiB)	Speed(s/iter)
D.1 LLama (32)	3404.53	32136	0.517	3404.57	33762	0.582	3404.62	37988	0.632	3404.69	39004	0.697
D.2 LLama (8)	975.83	11370	0.184	975.87	12392	0.192	975.92	13188	0.203	976.11	13616	0.217
D.3 w/o LLM	6.39	3678	0.046	6.42	3812	0.087	6.48	3960	0.093	6.55	4176	0.129

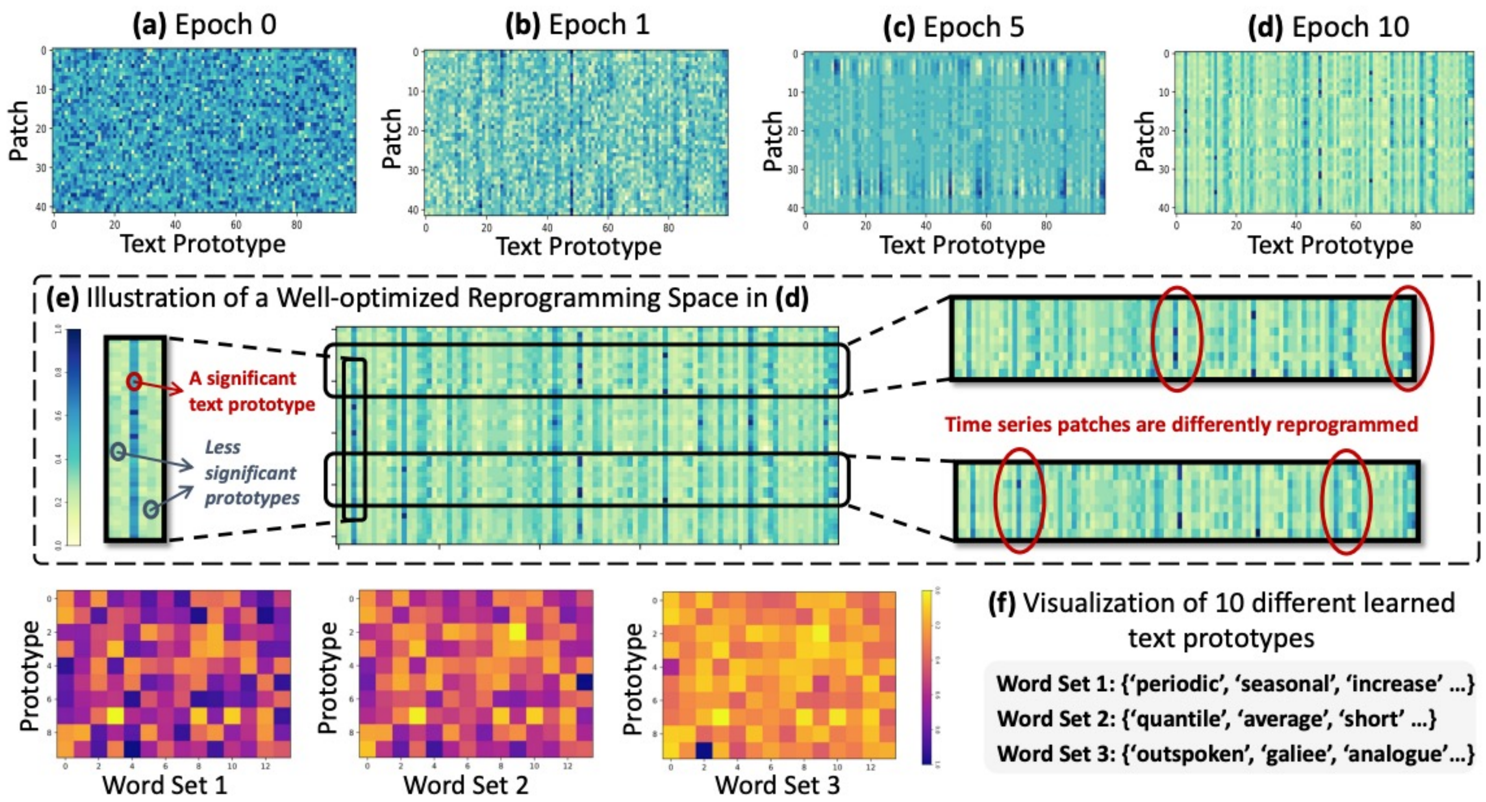
Table 17: Efficiency comparison between model reprogramming and parameter-efficient fine-tuning (PEFT) with QLoRA (Dettmers et al., 2023) on ETTh1 dataset in forecasting two different steps ahead.

Length		ETTh1-96			ETTh1-336		
Metric		Trainable Param. (M)	Mem. (MiB)	Speed(s/iter)	Trainable Param. (M)	Mem. (MiB)	Speed(s/iter)
Llama (8)	QLoRA	12.60	14767	0.237	12.69	15982	0.335
	Reprogram	5.62	11370	0.184	5.71	13188	0.203
Llama (32)	QLoRA	50.29	45226	0.697	50.37	49374	0.732
	Reprogram	6.39	32136	0.517	6.48	37988	0.632

- **Reprogramming efficiency: (1)** our reprogramming network is lightweight in activating the LLM's ability for time series forecasting (see D.3 -- i.e., fewer than 6.6M trainable parameters; only around 0.2% of the parameters in Llama-7B) **(2)** this is favorable even compared to parameter-efficient fine-tuning (PEFT; Tab. 17)

Main Results

- The top 4 subplots visualize the optimization of reprogramming space from (a) randomly-initialized to (d) well-optimized



- **Reprogramming interpretation:** Here we provide a showcase on ETTh1 of reprogramming 48 TS patches with 100 text prototypes

Observations

We find only a small set of prototypes (columns) participated in reprogramming the input patches (rows), see subplot (e)

Also, TS patches undergo different representations through varying combinations of prototypes

Interpretations

Text prototypes learn to summarize language cues, and a select few are highly relevant for representing information in local TS patches, which we visualize by randomly selecting 10 in subplot (f)

TS patches usually have different underlying semantics, necessitating different prototypes to represent

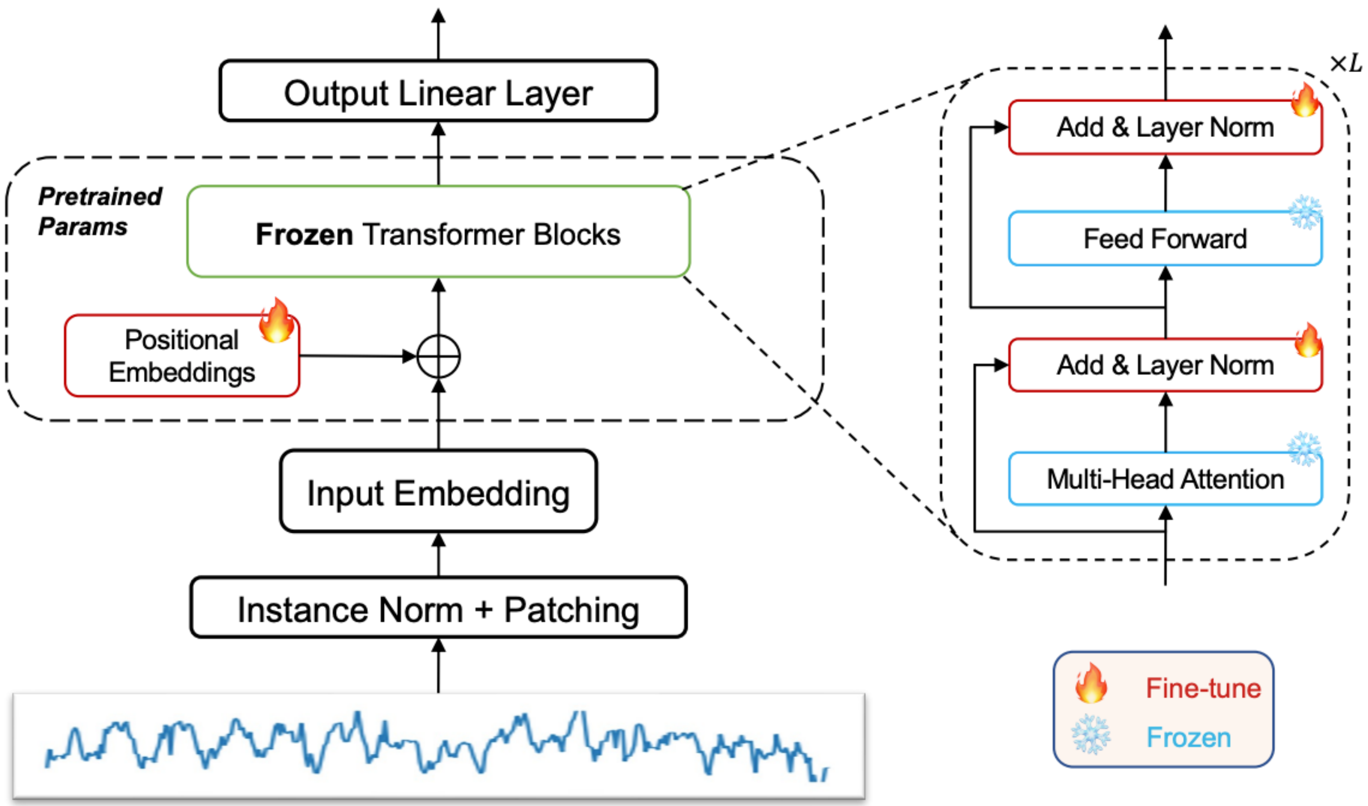
Time-LLM: Summary

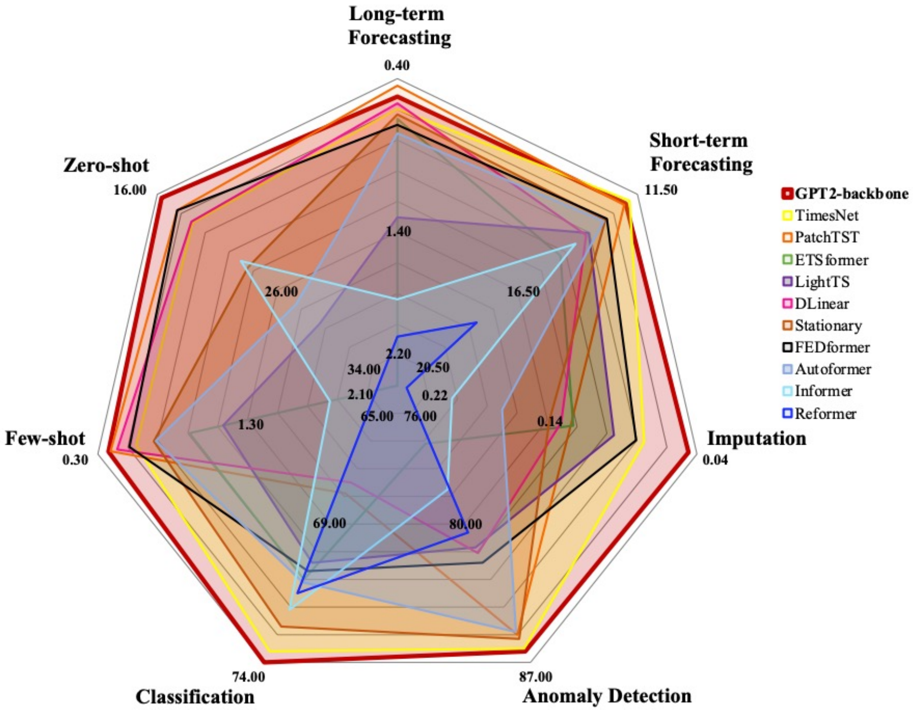
- Time-LLM shows promise in adapting frozen LLMs for time series forecasting by reprogramming time series data into natural language representation space more natural for LLMs and providing natural language guidance via Prompt-as-Prefix to augment reasoning
- Our evaluations demonstrate the adapted LLMs can significantly outperform many specialized expert models, indicating their potential as effective time series machines
- We provide a novel insight that time series forecasting can be cast as yet another "language" task that can be tackled by an off-the-shelf LLM to simply achieve or match SOTA performance
- We are the first to achieve "multimodal augmented time series forecasting" – We can even do more with the Prompt-as-Prefix!

Part 3. Related Work & Prospects

- Other related works
- What’s next?

Related Work: GPT4TS (OFA)





Zhou, T., Niu, P., Wang, X., Sun, L., & Jin, R. (2023). One Fits All: Power General Time Series Analysis by Pretrained LM. arXiv preprint arXiv:2302.11939.

Related Work: LLMTime

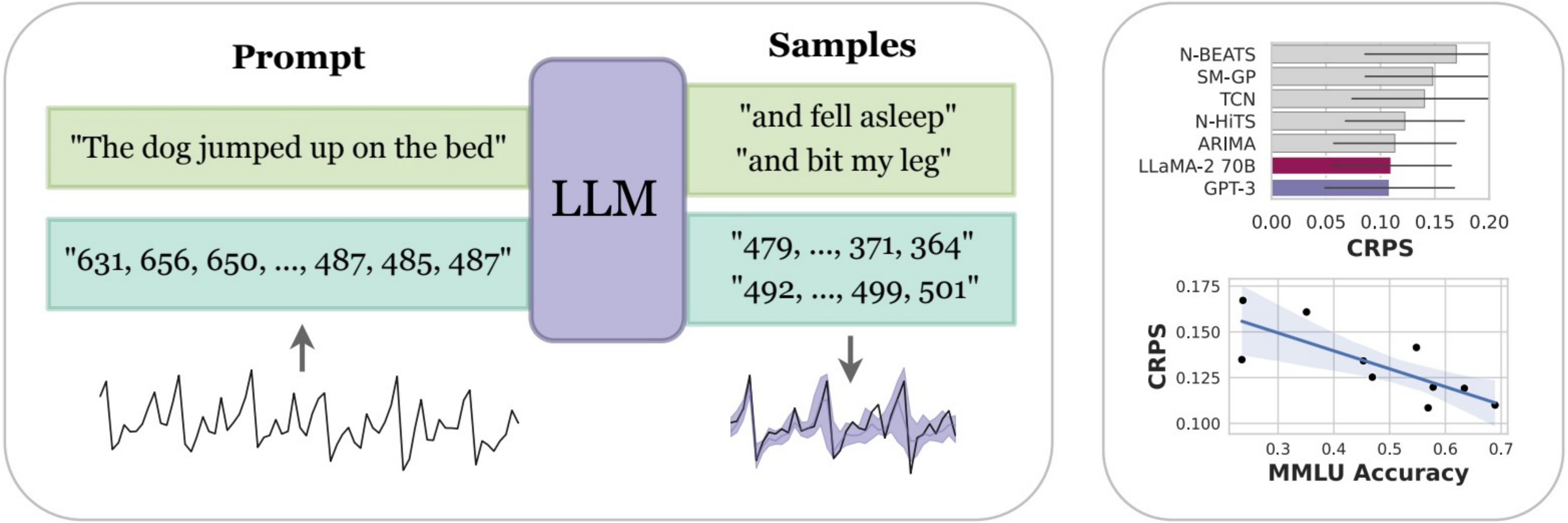


Figure 1: We propose **LLMTime**, a method for time series forecasting with large language models (LLMs) by encoding numbers as text and sampling possible extrapolations as text completions. LLMTime can outperform many popular time series methods without any training on the target dataset (i.e. zero-shot). The performance of LLMTime also scales with the power of the underlying base model. Notably, models that undergo alignment (e.g. RLHF) do not follow the scaling trend. For example, GPT-4 demonstrates inferior performance to GPT-3 (Section 6).

Gruver, N., Finzi, M. A., Qiu, S., & Wilson, A. G. (2023, November). Large Language Models Are Zero-Shot Time Series Forecasters. In Thirty-seventh Conference on Neural Information Processing Systems.

Related Work: LLMTime

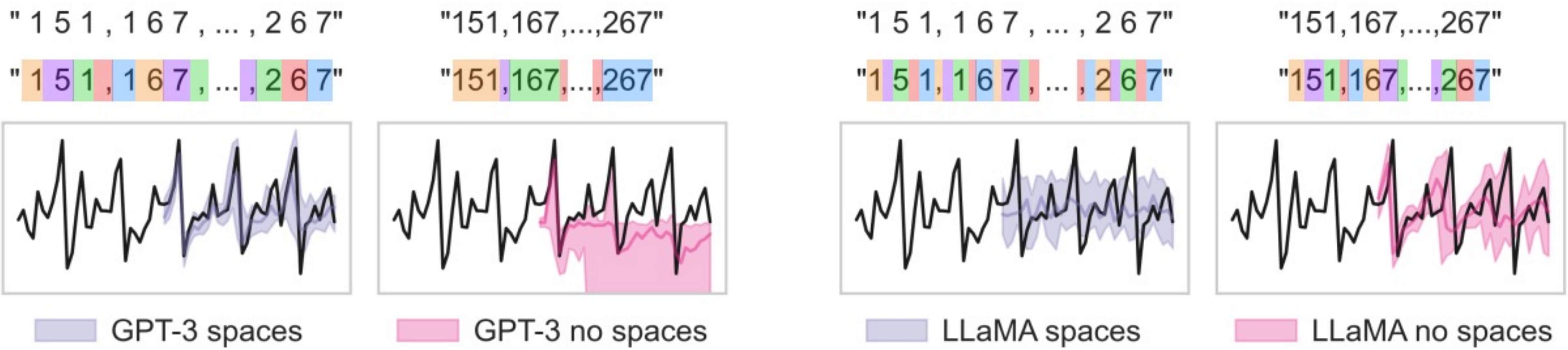


Figure 2: Careful tokenization is important for good forecasting with LLMs. Using the Australian Wine dataset from Darts [23], with values [151, 167, ..., 267], we show the tokenization used by GPT-3 [9] and LLaMA-2 [44] and the corresponding effect on forecasting performance. Added spaces allow GPT-3 to create one token per digit, leading to good performance. LLaMA-2, on the other hand, tokenizes digits individually, and adding spaces hurts performance.

Gruver, N., Finzi, M. A., Qiu, S., & Wilson, A. G. (2023, November). Large Language Models Are Zero-Shot Time Series Forecasters. In Thirty-seventh Conference on Neural Information Processing Systems.

Related Work: LLMTime

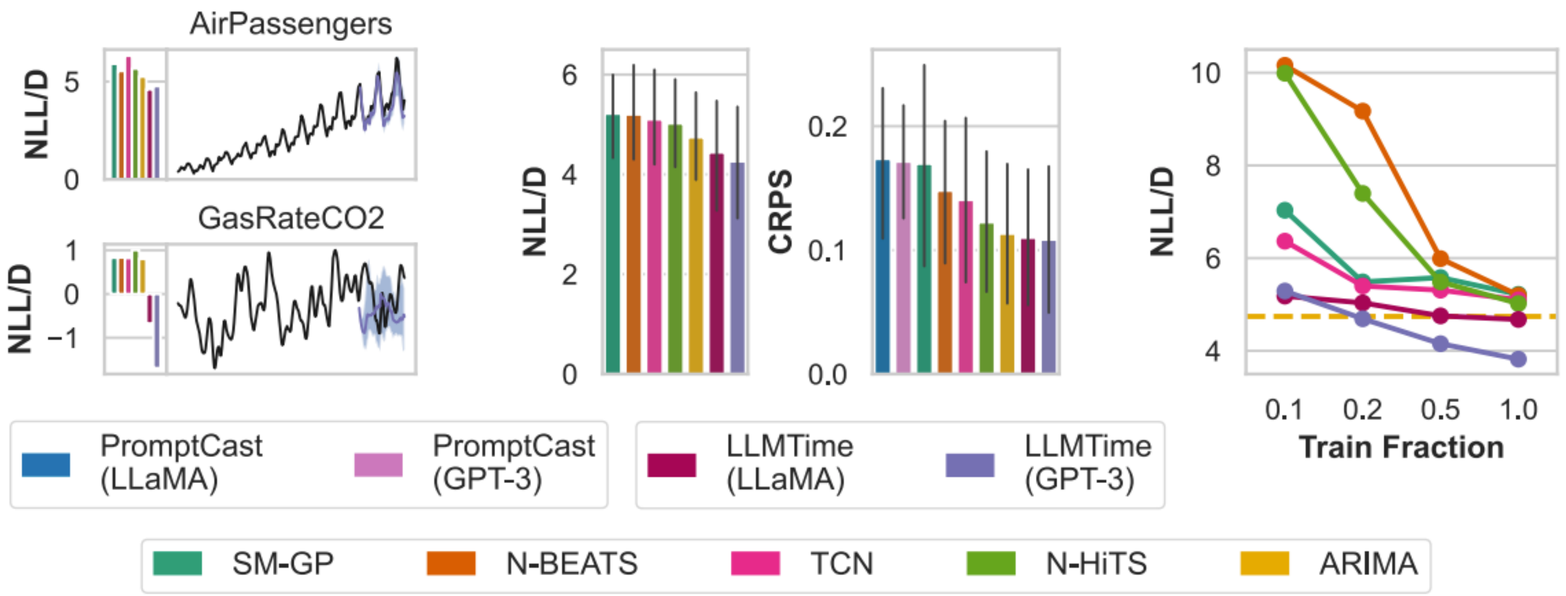
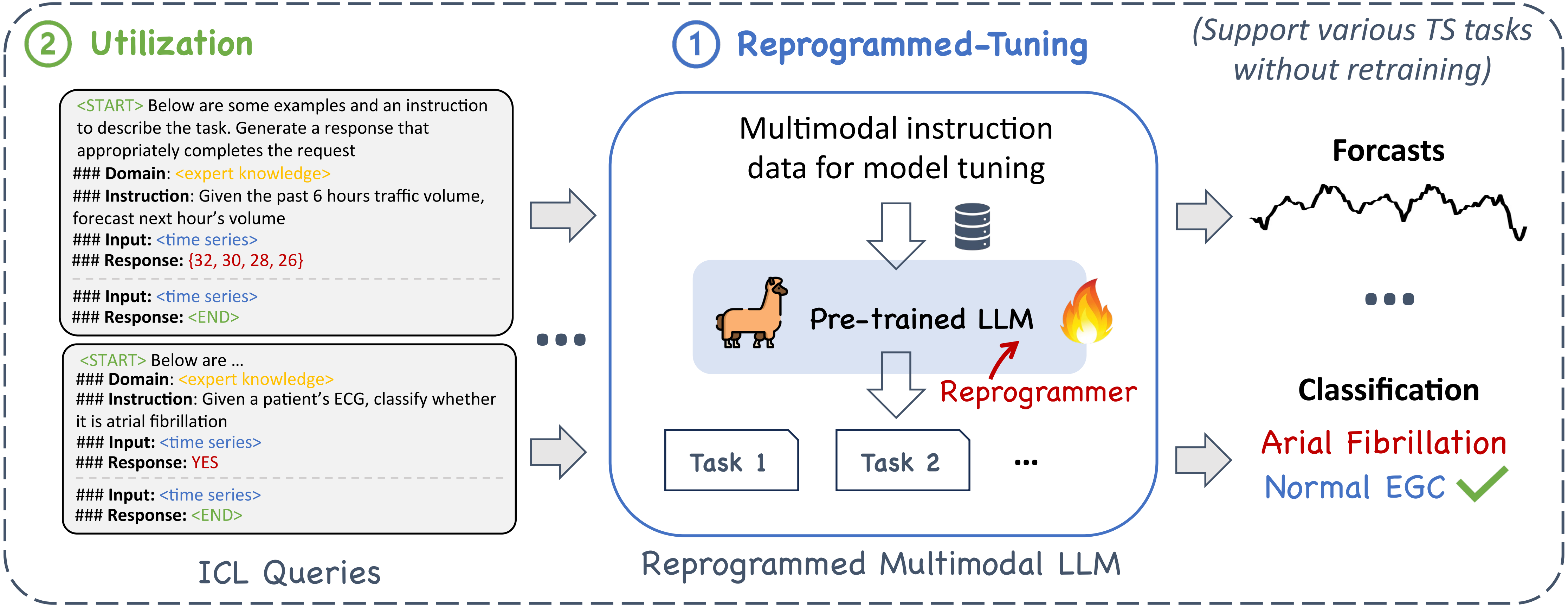


Figure 5: Extended experiments on the Darts datasets. (**left**): Example probabilistic forecasts with baseline negative log likelihood per dimension (NLL/D). LLMs easily extrapolate trends (e.g. AirPassengers) and reproduce local patterns when data is noisy (e.g. GasRateCO2). (**center**): When using probabilistic metrics like NLL and CRPS, LLMTIME outperforms all baselines, including PromptCast [50], a competing LLM method. Error bars show standard errors over datasets with Darts. (**right**): LLMTIME is much more sample efficient than competing methods. While the performance of other methods degrades rapidly when we restrict them to a fraction of the original training set, LLMTIME can assign high likelihood with only a few examples.

Gruver, N., Finzi, M. A., Qiu, S., & Wilson, A. G. (2023, November). Large Language Models Are Zero-Shot Time Series Forecasters. In Thirty-seventh Conference on Neural Information Processing Systems.

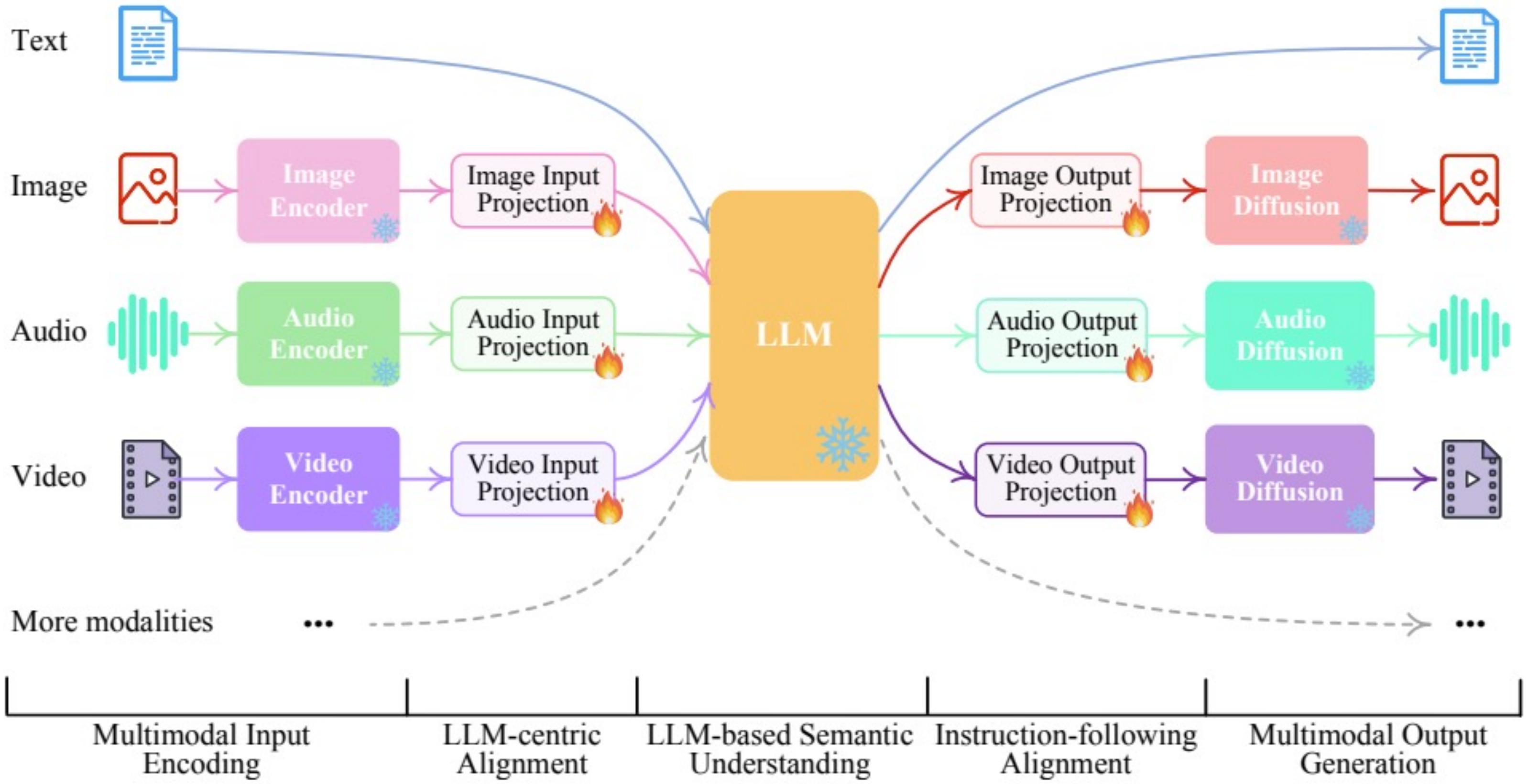
What’s Next?



Although we have witnessed great success of pre-trained models in NLP and CV, limited progress has been made for powerful general time series analysis…

Q: Can we just simply prompting a reprogrammed LLM to perform various general time series analytical tasks?

Any-to-Any Multimodal LLM



- By Connecting LLM with multimodal adapters and diffusion decoders, it is possible to achieve universal multimodal understanding and any-to-any modality input and output

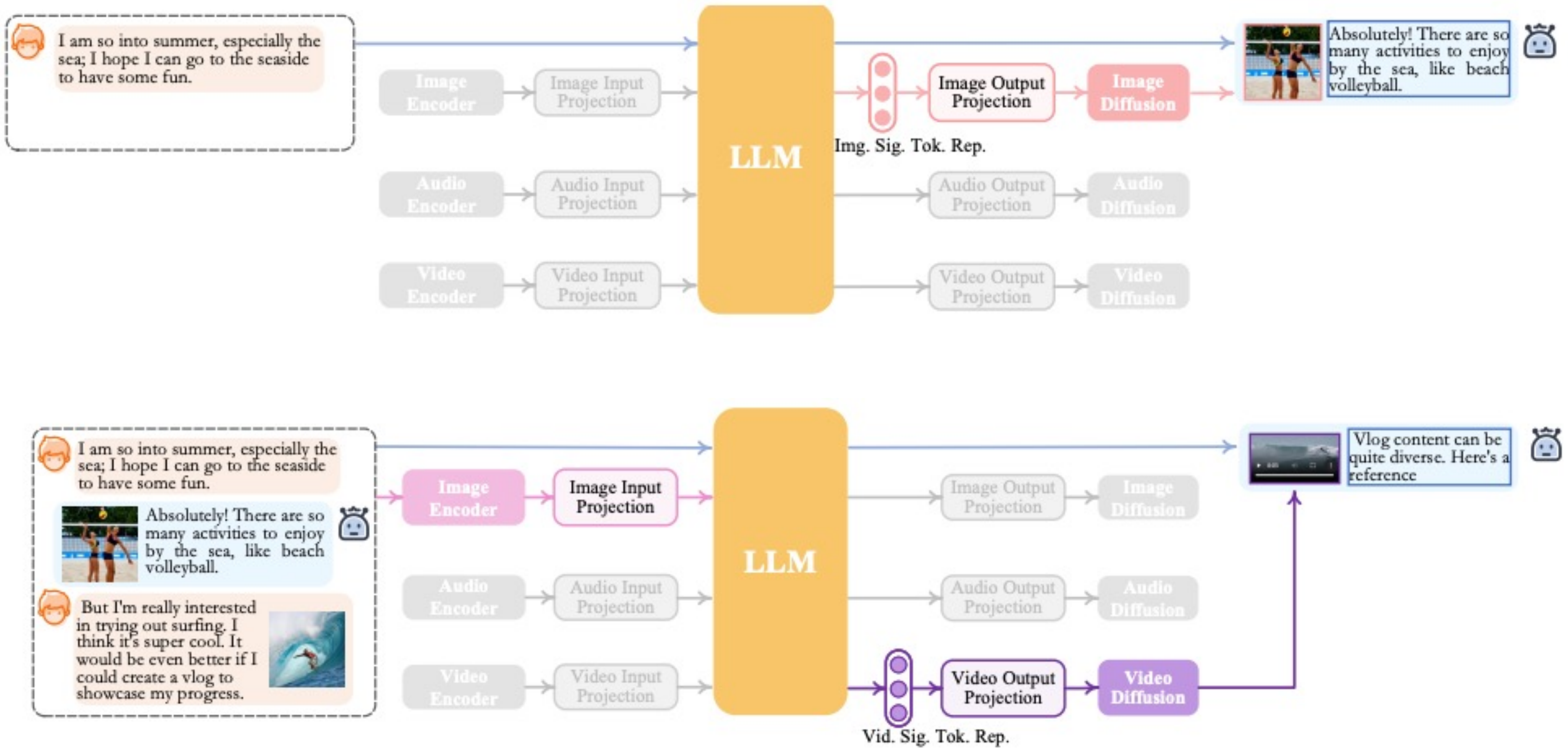
- This idea can be further explored on time series data

Case 1. Input a historical time series and some conditions, generate the corresponding forecasts

Case 2. Input a historical time series and then classify it with the reasons

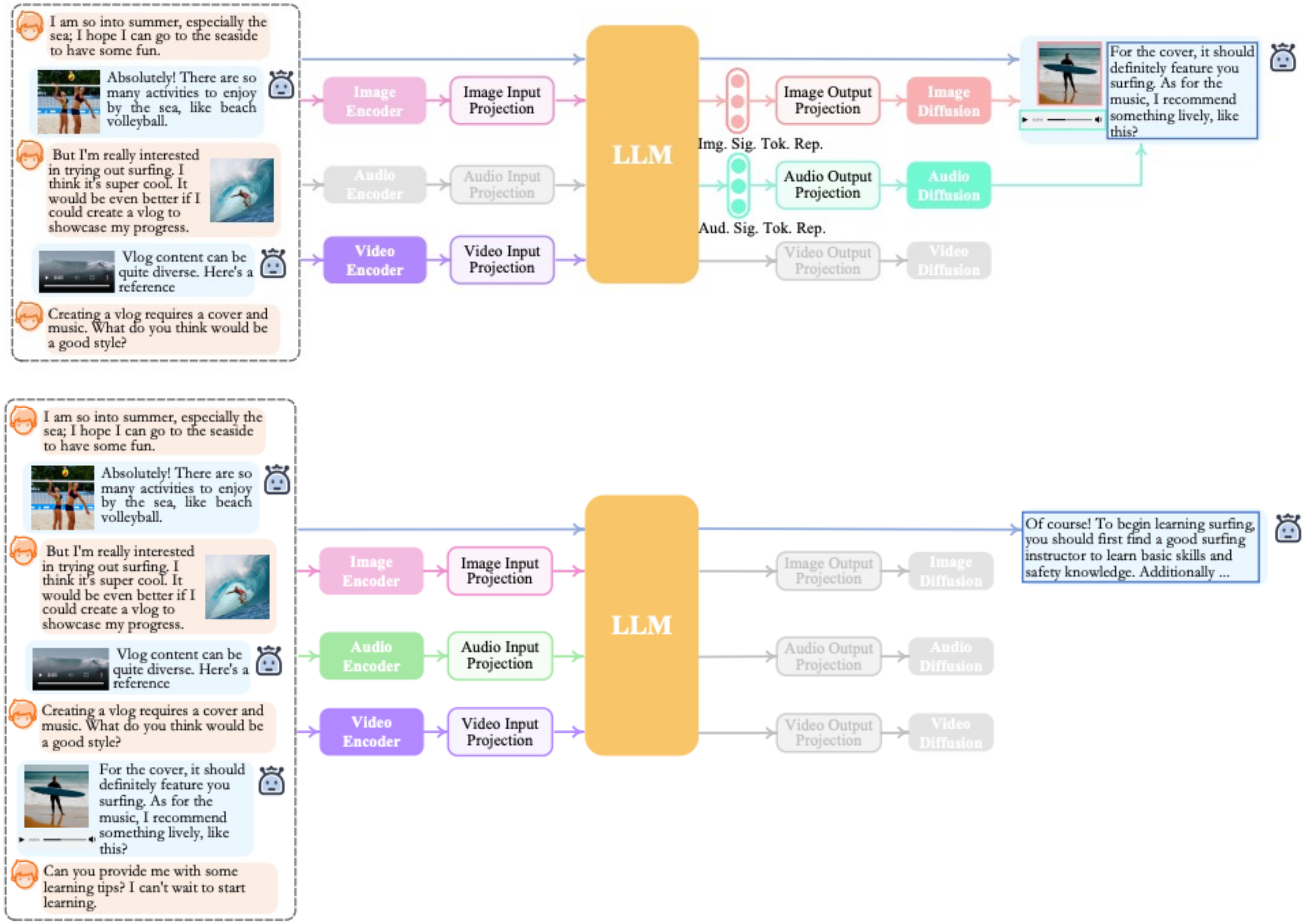
Wu, S., Fei, H., Qu, L., Ji, W., & Chua, T. S. (2023). NExT-GPT: Any-to-Any Multimodal LLM. arXiv preprint arXiv:2309.05519.

Any-to-Any Multimodal LLM



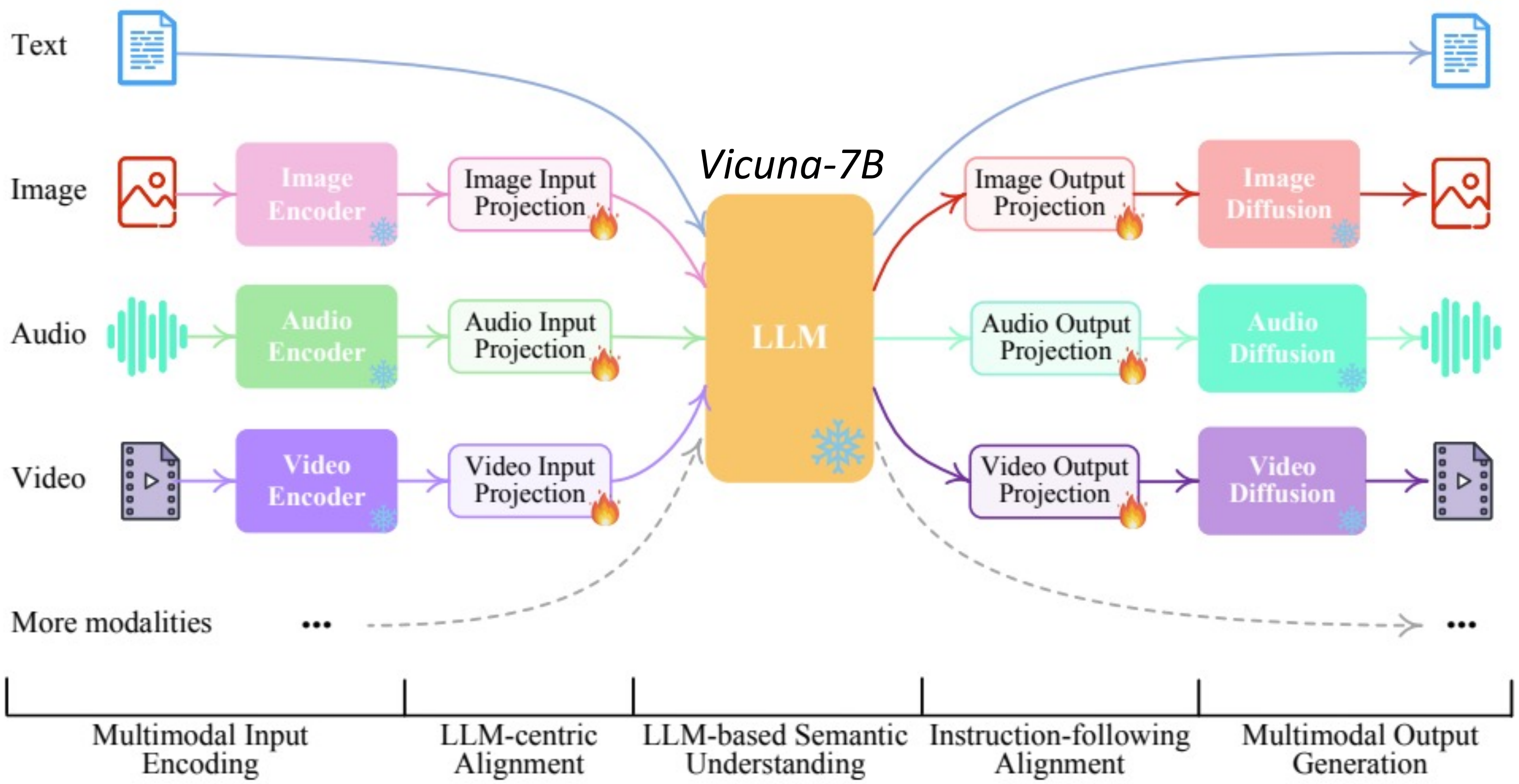
Wu, S., Fei, H., Qu, L., Ji, W., & Chua, T. S. (2023). NExT-GPT: Any-to-Any Multimodal LLM. arXiv preprint arXiv:2309.05519.

Any-to-Any Multimodal LLM



Wu, S., Fei, H., Qu, L., Ji, W., & Chua, T. S. (2023). NExT-GPT: Any-to-Any Multimodal LLM. arXiv preprint arXiv:2309.05519.

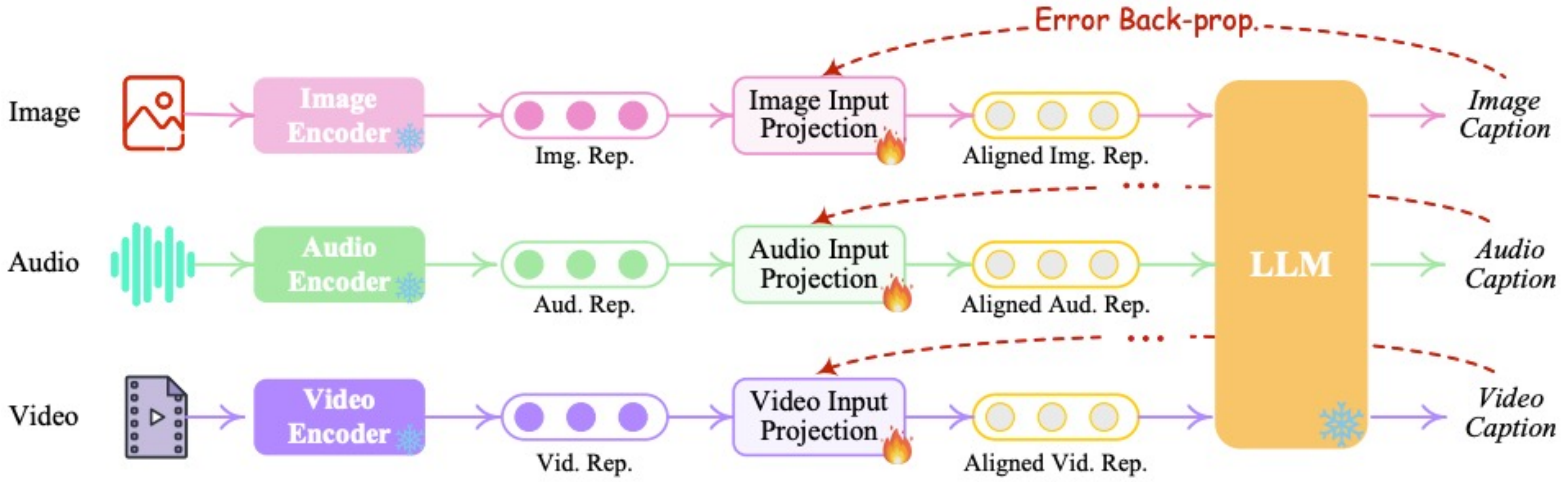
Any-to-Any Multimodal LLM



- **Two different projections**
- **Two different alignments**
- **An overall instruction tuning**

Wu, S., Fei, H., Qu, L., Ji, W., & Chua, T. S. (2023). NExT-GPT: Any-to-Any Multimodal LLM. arXiv preprint arXiv:2309.05519.

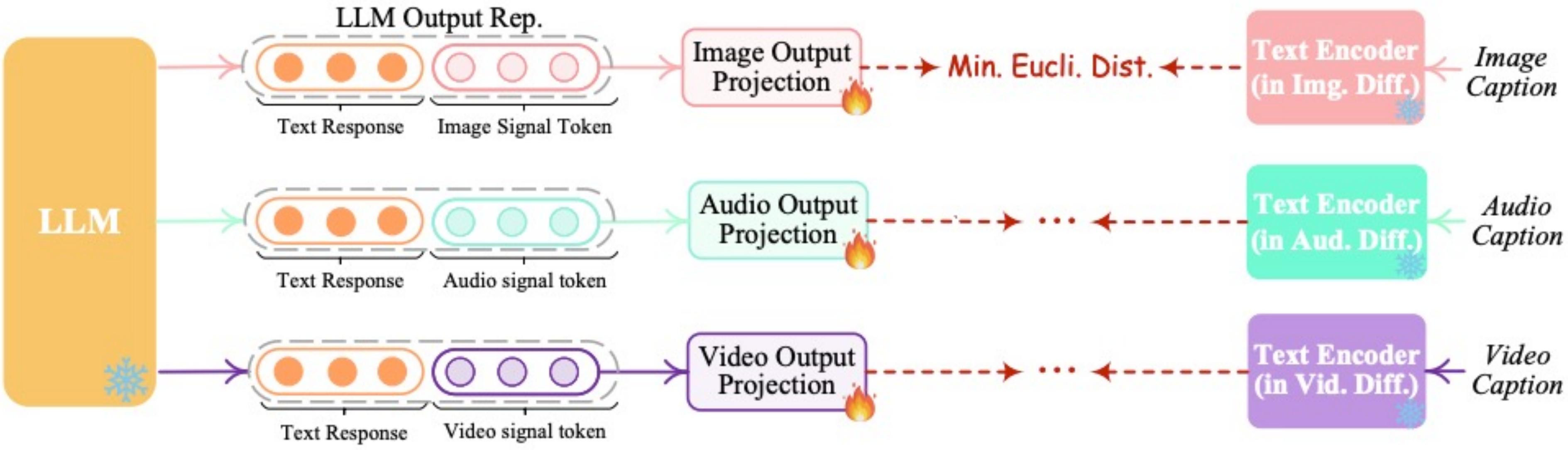
Any-to-Any Multimodal LLM



(a) Encoding-side LLM-centric Alignment

Wu, S., Fei, H., Qu, L., Ji, W., & Chua, T. S. (2023). NExT-GPT: Any-to-Any Multimodal LLM. arXiv preprint arXiv:2309.05519.

Any-to-Any Multimodal LLM



(b) Decoding-side Instruction-following Alignment

Wu, S., Fei, H., Qu, L., Ji, W., & Chua, T. S. (2023). NExT-GPT: Any-to-Any Multimodal LLM. arXiv preprint arXiv:2309.05519.

Any-to-Any Multimodal LLM

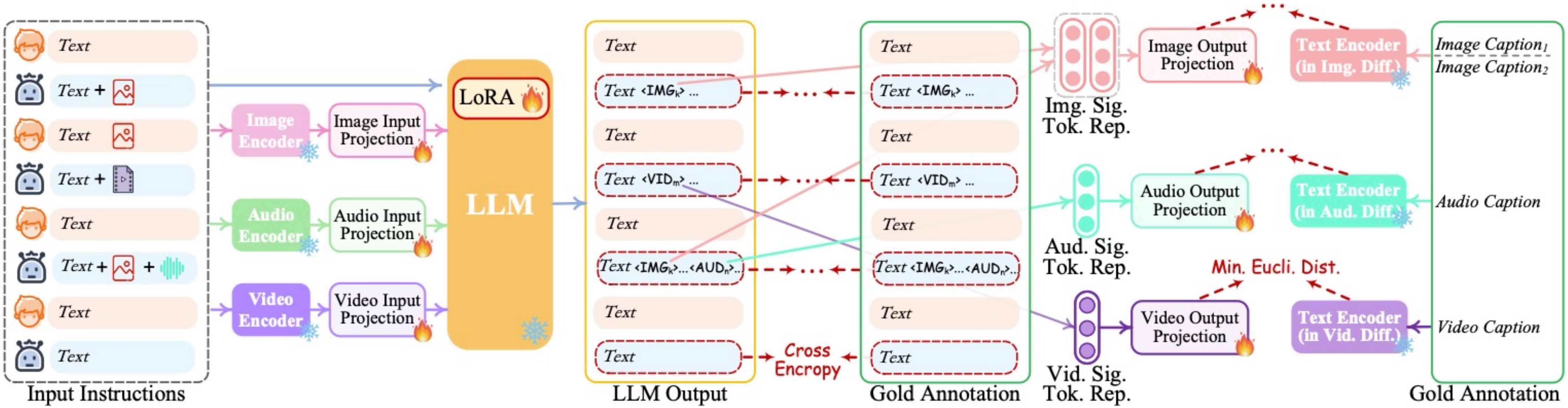
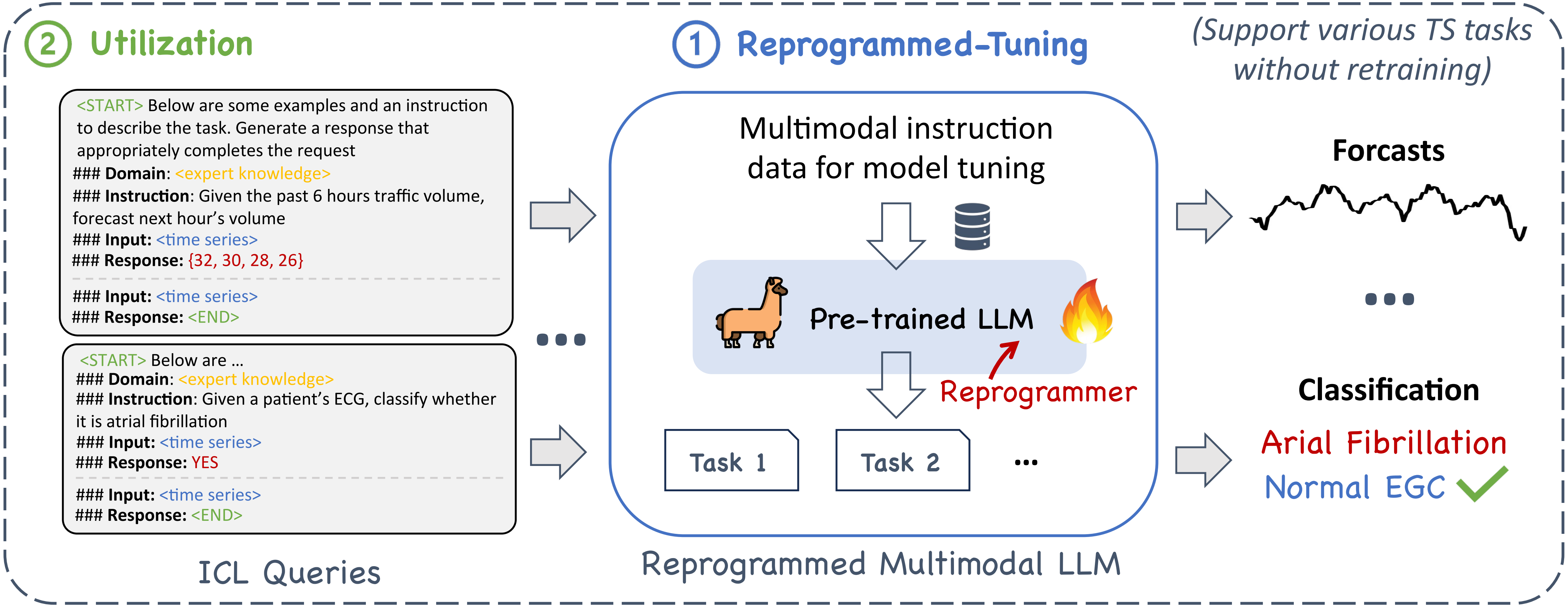


Figure 4: Illustration of modality-switching instruction tuning.

Wu, S., Fei, H., Qu, L., Ji, W., & Chua, T. S. (2023). NExT-GPT: Any-to-Any Multimodal LLM. arXiv preprint arXiv:2309.05519.

What's Next?



Although we have witnessed great success of pre-trained models in NLP and CV, limited progress has been made for powerful general time series analysis...

Q: Can we just simply prompting a reprogrammed LLM to perform various general time series analytical tasks?

Published as a conference paper at ICLR 2024

TIME-LLM: TIME SERIES FORECASTING BY REPROGRAMMING LARGE LANGUAGE MODELS

Ming Jin[1]*, Shiyu Wang[2]*, Lintao Ma[2], Zhixuan Chu[2], James Y. Zhang[2], Xiaoming Shi[2], Pin-Yu Chen[3], Yuxuan Liang[6], Yuan-Fang Li[1], Shirui Pan[4]†, Qingsong Wen[5]†
[1]Monash University [2]Ant Group [3]IBM Research [4]Griffith University [5]Alibaba Group
[6]The Hong Kong University of Science and Technology (Guangzhou)
{ming.jin, yuanfang.li}@monash.edu, pin-yu.chen@ibm.com
yuxliang@outlook.com, s.pan@griffith.edu.au, qingsongedu@gmail.com
{weiming.wsy,lintao.mlt,chuzhixuan.czx,james.z,peter.sxm}@antgroup.com

Thank you

Paper: https://arxiv.org/abs/2310.01728

Code: https://github.com/KimMeen/Time-LLM

Unwatch 11 | Fork 87 | Star 532

(ICLR'24) Time-LLM: Time Series Forecasting by Reprogramming Large Language Models

last commit last monday | Stars 532 | Forks 87 | PRs Welcome

[Paper Page] [Paper Explained] [中文解读1] [中文解读2] [中文解读3] [中文解读4]