USC Viterbi
School of Engineering

Big Data, AI and Transportation Planning Applications
University of Washington, Seattle, WA

A New Era Dawns: AI for New Generation Transportation System

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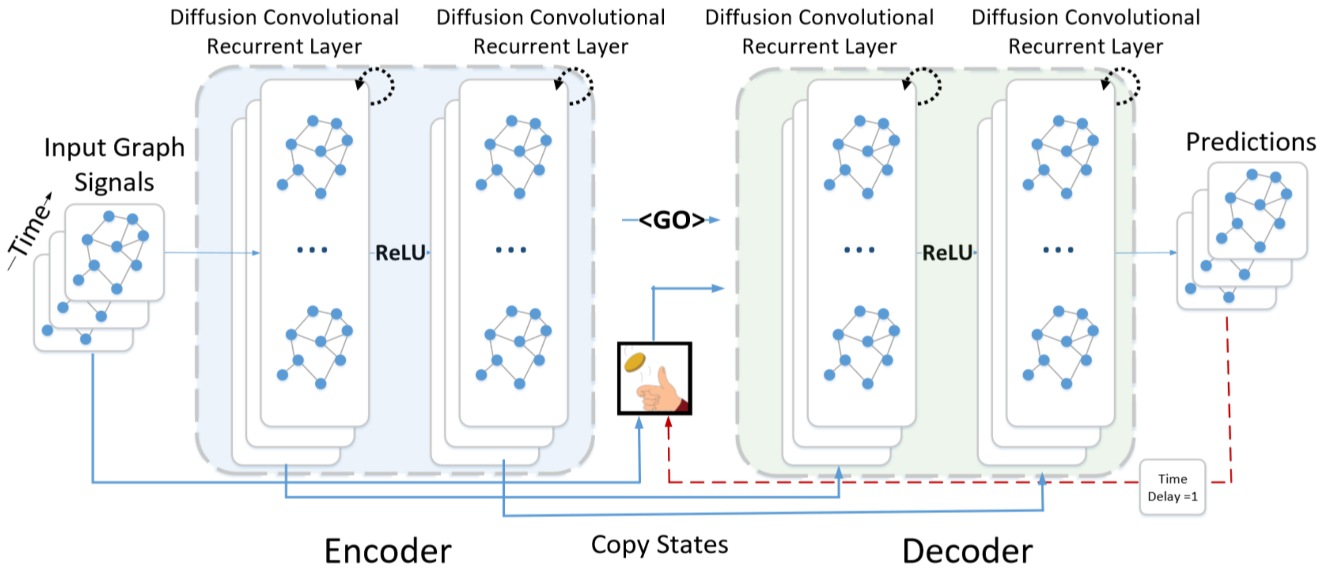
AI for Smart Transportation

Big data makes AI possible for transportation.

Example 1: Traffic Forecasting

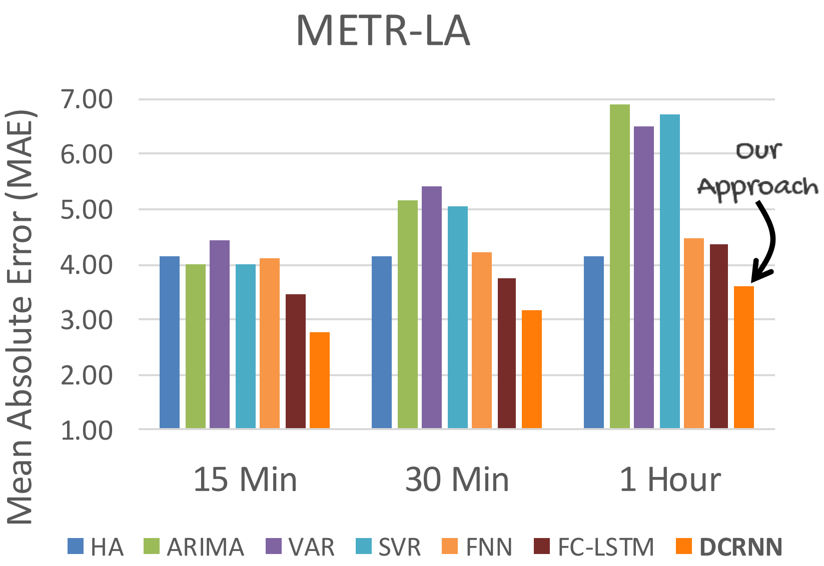
Li et al, Diffusion Convolutional Recurrent Neural Network: Data-driven Traffic Forecasting. ICLR 2018.

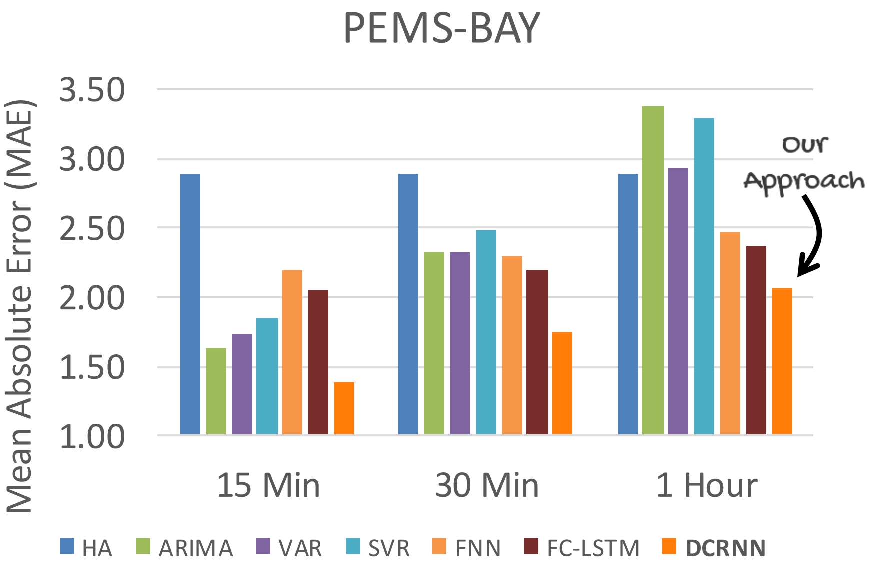


- Model spatial dependency with proposed ***diffusion convolution on graph***
- Model temporal dependency with ***augmented recurrent neural network***

Experiment Results

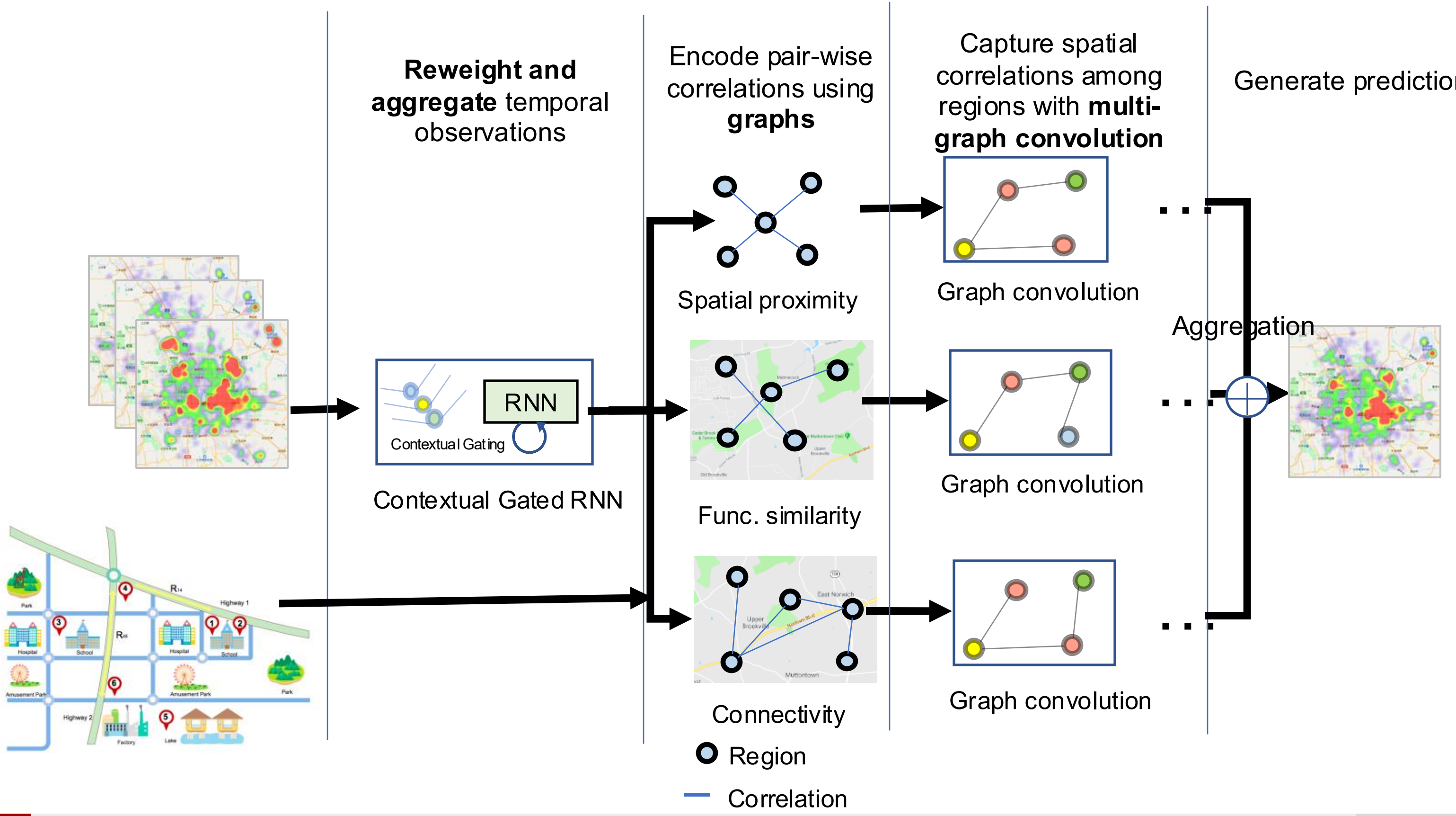
DCRNN achieves the ***best performance*** for all forecasting horizons for both datasets





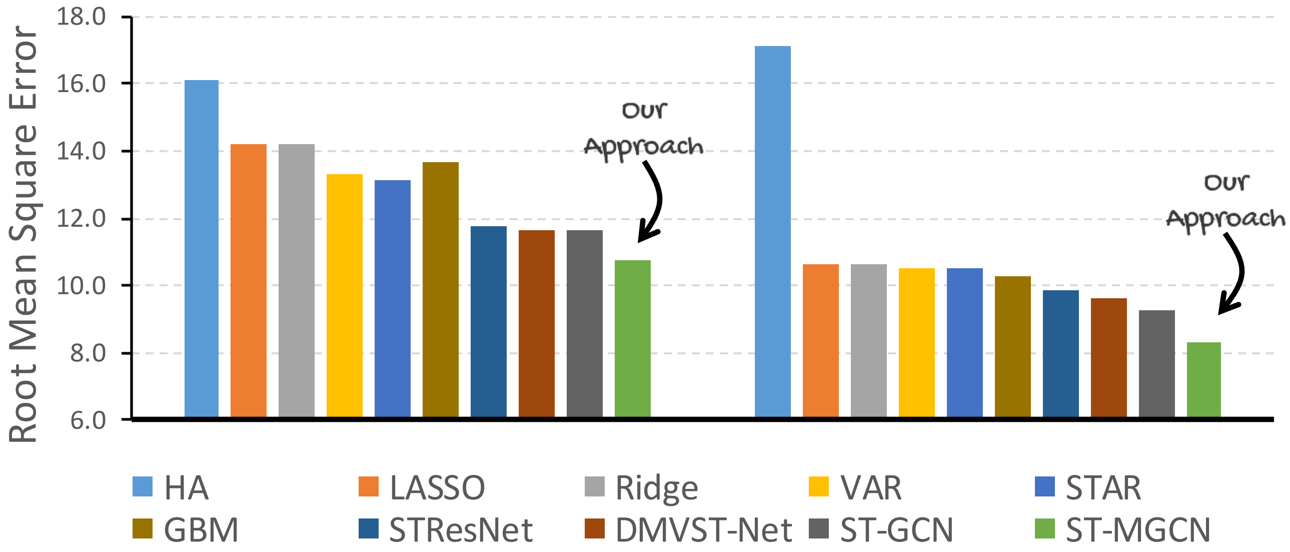
Example 2: Demand Forecasting

Geng et al, Spatiotemporal Multi-Graph Convolution for Ride-hailing Demand Forecasting, AAAI 2019



Experiment Results

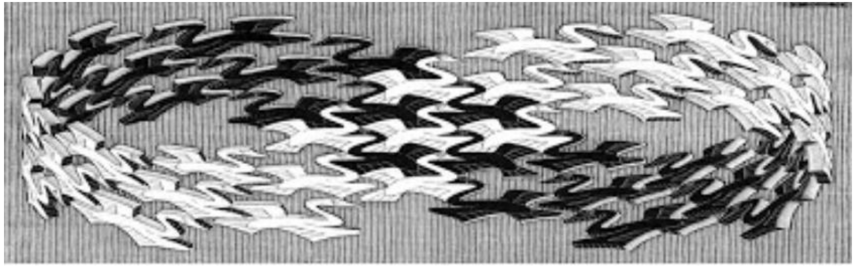
ST-MGCN achieves the **best performance** on both datasets (10+% improvement*)



Fundamental AI – Pushing the Frontier of AI

Grand challenge 1:

Qualitative description of dynamic systems from streaming data – Beyond common-sense physics

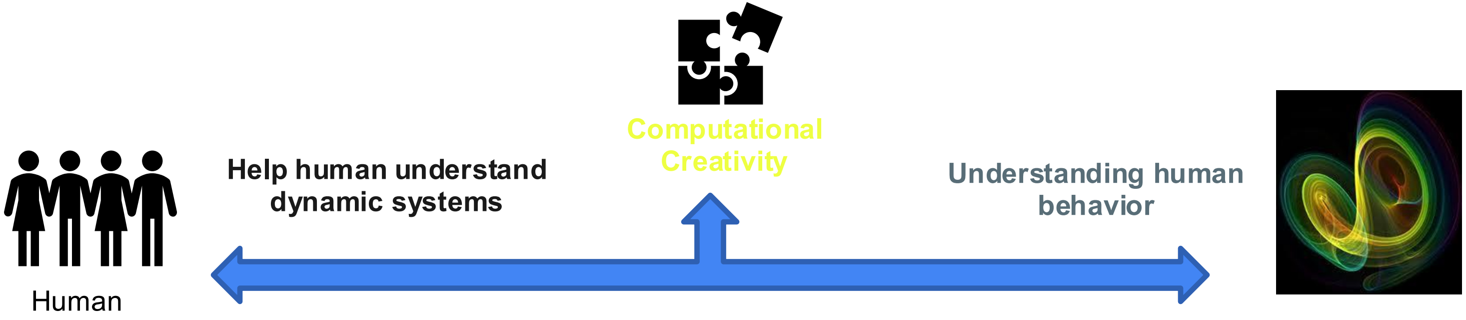


Proposed fundamental AI work contributing to the solution:

- Multi-resolution AI, non-stationary AI and physics-informed AI

Grand challenge 2

Democratizing High-dimensional real-time dynamic systems for human cognitive understanding and operation



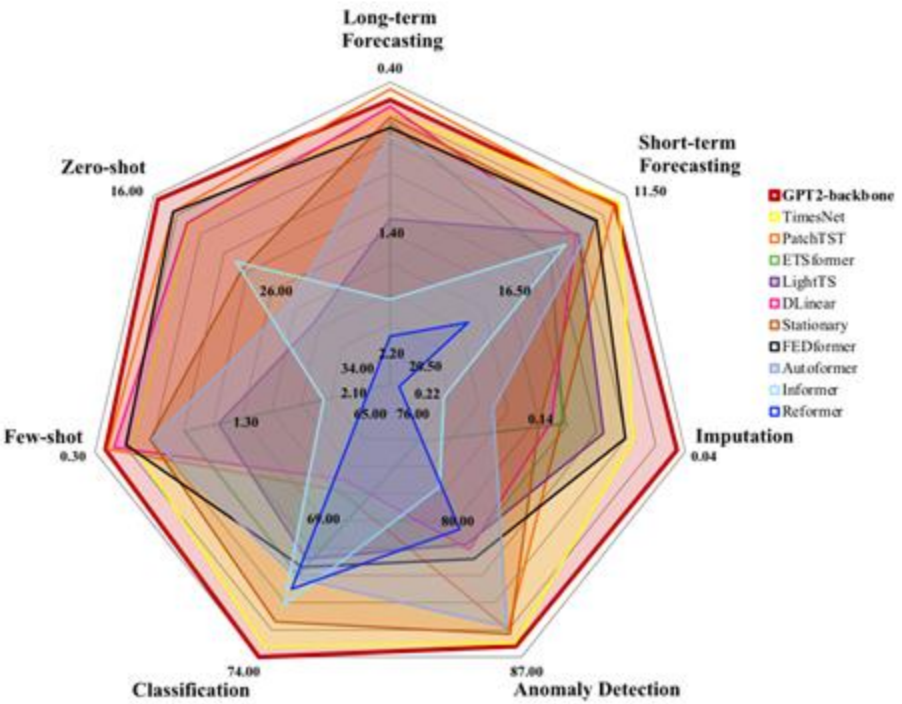
Proposed fundamental AI work contributing to the solution:

- Human-centered AI, interpretable AI, distributed/federated AI, data-efficient AI

Foundation Models for Spatiotemporal Data

Blueprint of Designing Foundation Models

- Representation for sequential input:
  - Patch (PatchTST, GPT2)
  - 2DConv (TimesNet)
  - Position Embedding (**former)
  - …
- Backbone models:
  - Linear (DLinear, NLinear)
  - Transformers (**former)
  - Timesblock (TimesNet)
  - LLM (LLM4TS)
  - …
- Challenges:
  - Separated training for different tasks
  - Distribution shift
  - Lack of textual information

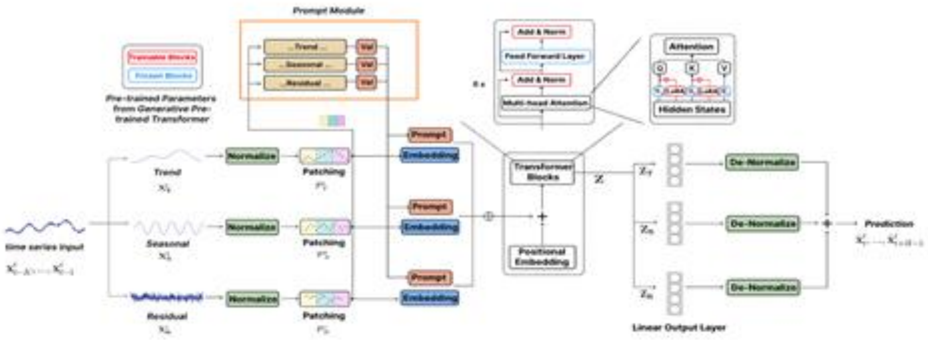


The performance of foundation models via LLM4TS [Chang, 2023]

TEMPO: Prompt-based Generative Pre-trained Transformer [ICLR 2024]

Towards Foundational Model – Zero-Shot Setting:

- Assumptions:
  - No access to target dataset during training
  - Relying on learned representations from pre-training on diverse time series data
- Key Challenges:
  - Capturing intrinsic attributes of time series, such as trend and seasonality
  - Generalizing to new datasets with varying characteristics and horizons
  - Natural incorporation of contextual text information



Code and Benchmarking Results

GIFT-Eval: A Benchmark for General Time Series Forecasting Model Evaluation

Time series forecasting is becoming increasingly important across various domains, thus having high-quality, diverse benchmarks are crucial for fair evaluation across model families.

[Image: apinan / Adobe Stock]

T	model	MASE	CRPS	Rank
◆	TEMPO_ensemble (code)	0.773	0.434	8.351
●	timesfm_2_0_500m (code)	0.680	0.465	7.794
●	TabPFN-TS	0.748	0.48	7.701
●	chronos_bolt_base (code)	0.725	0.485	7.773
●	chronos_bolt_small (code)	0.738	0.487	8.423
◆	TTM-R2-Finetuned (code)	0.679	0.492	9.351
◆	PatchTST	0.762	0.496	9.464
●	Moirai_large (code)	0.785	0.506	9.588
◆	TFT	0.822	0.511	10.835
●	Moirai_base (code)	0.809	0.515	9.639
●	Chronos_large (code)	0.781	0.547	13.526
●	Moirai_small (code)	0.849	0.549	12.629

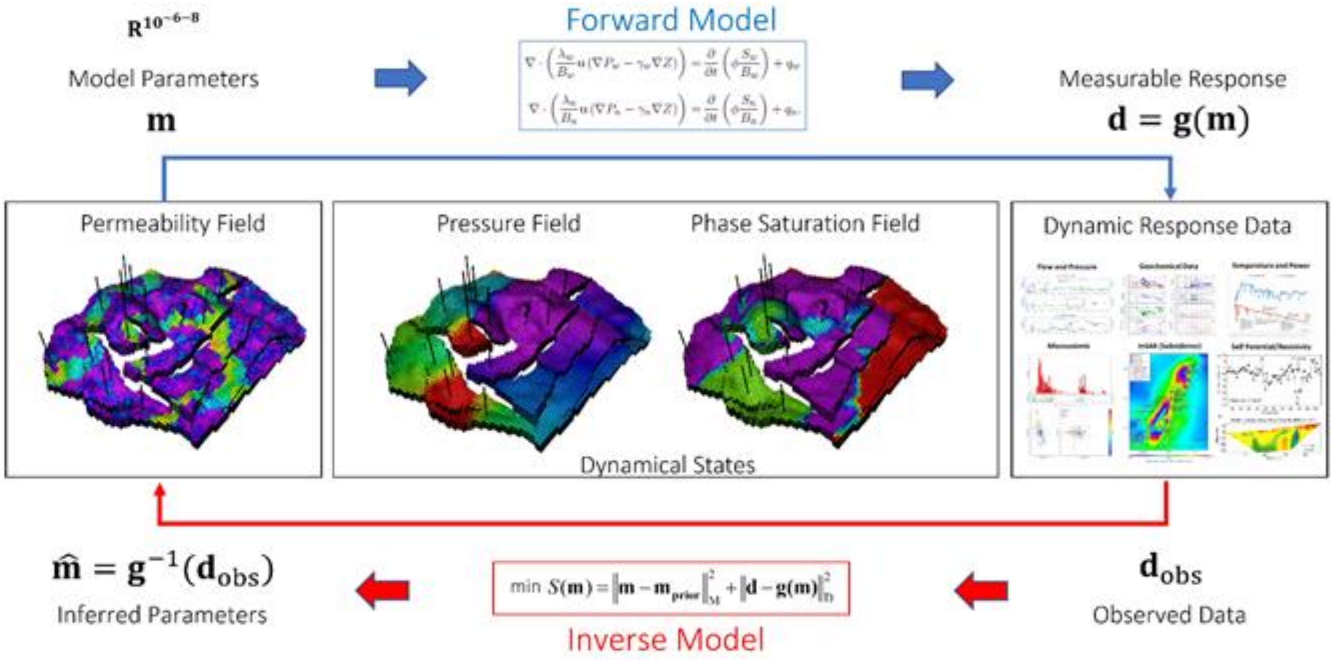
TEMPO – Cao et al, ICLR 2024

GitHub

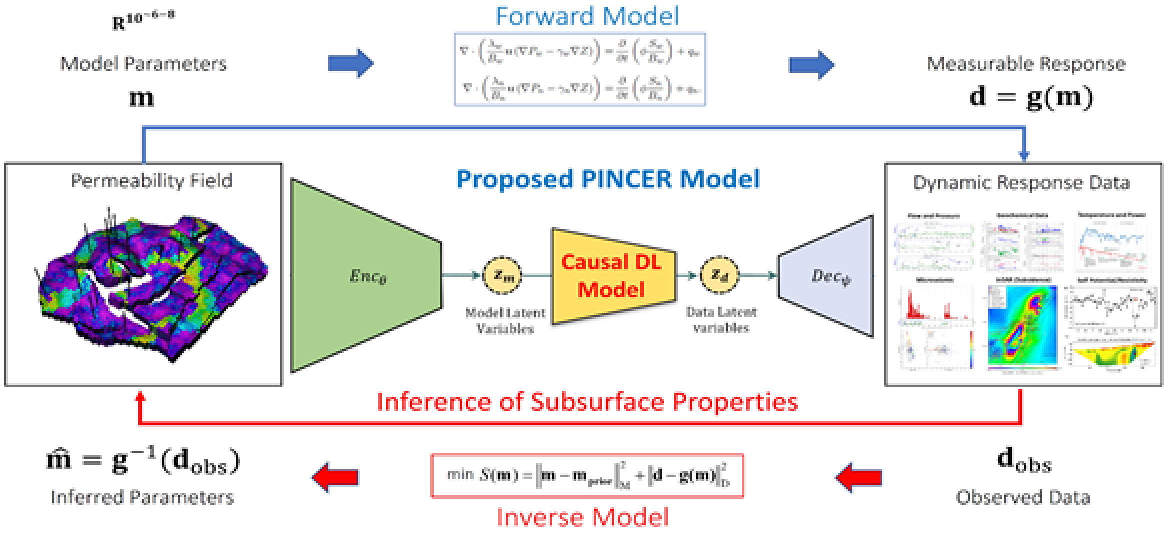
Hugging Face

Foundation Models for Dynamic Systems

- Traditional simulation models

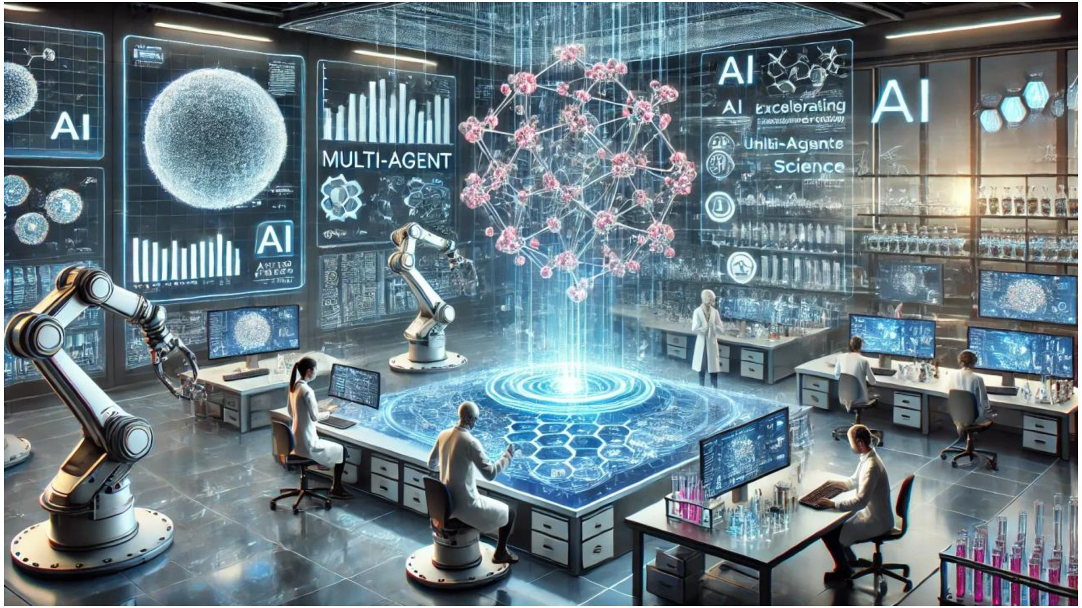


- Physics-informed AI Foundation Models (include physics / reduce data needs)
  - Novel physics-informed causal AI models tailored *for imaging, inference, and prediction* by processing and analyzing available *multi-physics monitoring data* in the field



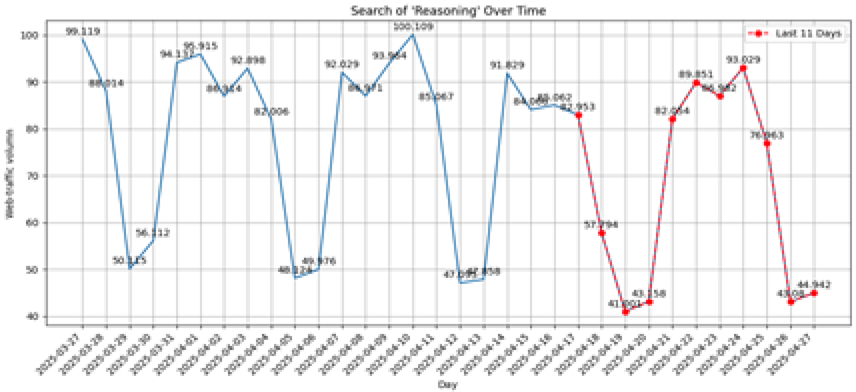
S. Griesemer, D. Cao, Z. Cui, C. Osorio, Y. Liu. Active Sequential Posterior Estimation for Sample-Efficient Simulation-Based Inference. NeurIPS 2024

Co-scientist and Agentic AI for Science



Can Large Language Model Understand Time Series?

Prompt: given the historical time series, please make predictions of the value in the next 11 days?



	ChatGPT o4-mini-high	ChatGPT 4o	Deepseek R1
2025-04-17	77.114	83.7	100.109
2025-04-18	76.949	82.9	85.067
2025-04-19	76.785	83.2	47.095
2025-04-20	76.621	84.1	47.858
2025-04-21	76.456	85.4	91.829
2025-04-22	76.292	87.1	84.066
2025-04-23	76.127	88.9	85.062
2025-04-24	75.963	89.7	100.109
2025-04-25	75.798	90.4	85.067
2025-04-26	75.634	91.6	47.095
2025-04-27	75.470	92.9	47.858

No seasonality

Aware seasonality, but choose to repeat

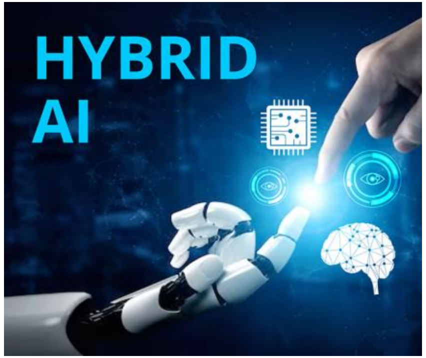
Limitations of LLM for Time Series

- Loss of Continuity and discretization error
  - Time series data relies on precise numerical relationships (e.g., 100.1 → 99.8 → 101.2). Tokenizers often discretize or bin these values, destroying the granularity needed to model trends, seasonality, or volatility.
- Embedding Mismatch
  - Token embeddings in LLMs prioritize semantic similarity (e.g., "cat" ≈ "kitten"), not numerical proximity. A value like 48.123 might be embedded far from 49.9768, even though they're adjacent in a time series.
- Temporal Structure Ignored
  - Time series require explicit modeling of order, lag effects, and local/global dependencies. Tokenizers treat data as unordered "bags of tokens," disrupting sequential coherence.

Timestamps	48.123; 49.9768; 92.02112
GPT-4o Token Split	48.123; 49.9768; 92.02112

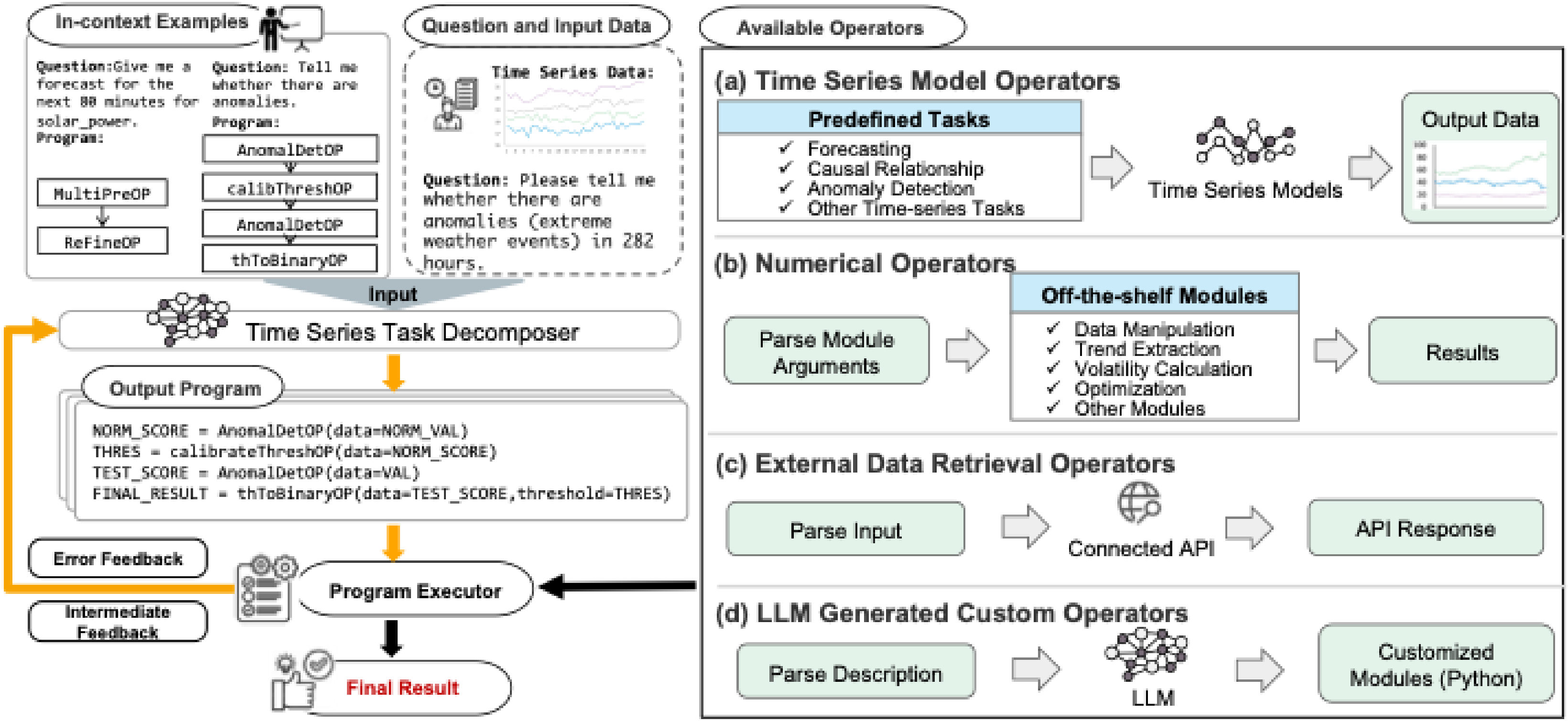
TS-Reasoner: A hybrid AI Solution [Ye et al, ArXiv 2024]

- LLM agent capable of compositional reasoning
  - Assembling **structured inference pipelines** that autonomously select external data, apply appropriate analytical tools
  - Refine predictions based **on task complexity, data availability, and domain knowledge or constraints.**
- Key tasks:
  - **Task understanding**
  - **Tool selection and composition**
  - **Execution and exception handling**



A more structured, hybrid approach that retains LLMs' reasoning strengths while ensuring accurate and efficient time series analysis

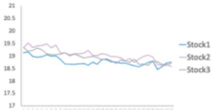
TS-Reasoner: A Hybrid Approach



Experiment Results: Basic Time Series Understanding Task

Stock Prediction

Data:



Question: I have the past 14 hours historical stock value data for some stocks that I'm interested in investing in. I want to predict the volatility of the stock price for the future 9 hours. Your goal is to make the most accurate prediction.

Program:

```
X0 = SinglePreOP(data=VAL, future_length=N)
FINAL_RESULT = VolDetOP(data=X0)
```

Output

```
final_result = [0.00471584 0.00944234 0.01529741]
```

Evaluation

```
evaluation result:  {'status': 1, 'mape': 0.6606216602825435, 'answer': array([0.00895906, 0.0623173 , 0.04498084])}
```

Causal Relationship

Data:

Question: I have historical Variable A, Variable B, Variable C data and want to get the causal relationship between each pair of the variables. I know that 16.66% of the variable pairs have relationship. Consider the potential influence of each variable on the others in this variable list: ['Variable A','Variable B','Variable C']. Please give me a causality matrix that indicates causal relationship.

Program:

```
X0 = GrangerCausalMatrixOP(data=VAL)
FINAL_RESULT = GetCausalRelationsOP(data=X0, relation_ratio=0.167)
```

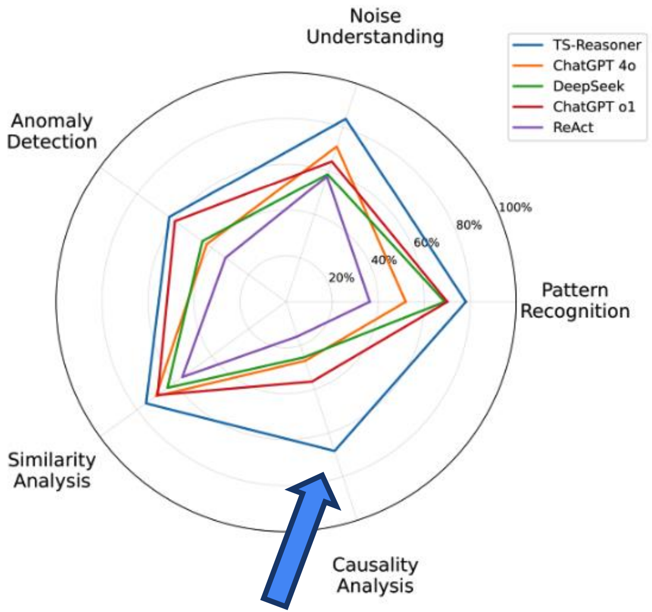
Output

```
final_result= [[0 0 0],[0 0 0],[0 1 0]]
```

Evaluation

```
evaluation result:  {'status': 1, 'accuracy': 1.0, 'ground_truth': [[0. 0. 0.], [0. 0. 0.], [0. 1. 0.]]}
```

TS-Reasoner consistently outperforms all baseline models across all dimensions

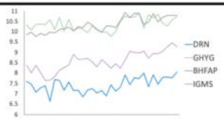


TS-Reasoner achieves an 87% improvement over the best-performing baseline.

Experiment Results: Constraint Injected Tasks

Investment Strategy Generation

Data:



Question: I have historical stock value data for some stocks that I'm interested in investing in with a budget of 14078 dollars. I want to make at least 1.31% profit. Please give me an investment strategy for the next 33 days. Consider the future trend and volatility of the stock, and answer the number of units to buy (units), the number of days to wait before buying (wait_days), and the number of day to hold after buying for each stock (hold_days).

Program:

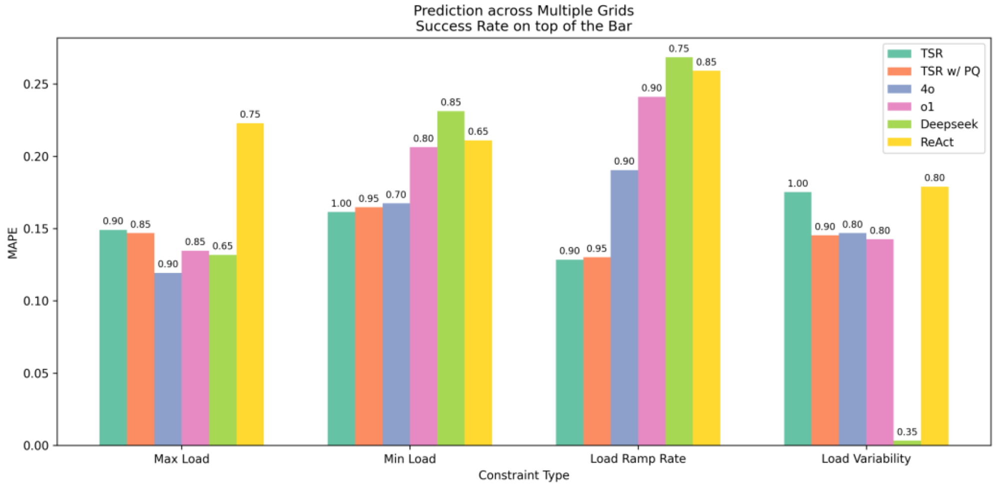
```
X0 = SinglePreOP(data=VAL, future_length=N)
OBJ = ObjGenOP(input=ObjDescription)
CON = ConGenOP(input=ConDescription)
FINAL_RESULT = OptOP(Objective=OBJ,Condiction=CON,data=X0)
```

Output

```
final_result = {'DRN': {'units': 536, 'wait_days': 17, 'hold_days': 7}, 'GHYG': {'units': 0, 'wait_days': 0, 'hold_days': 0}, 'BHFAP': {'units': 0, 'wait_days': 0, 'hold_days': 0}, 'IGMS': {'units': 0, 'wait_days': 0, 'hold_days': 0}}
```

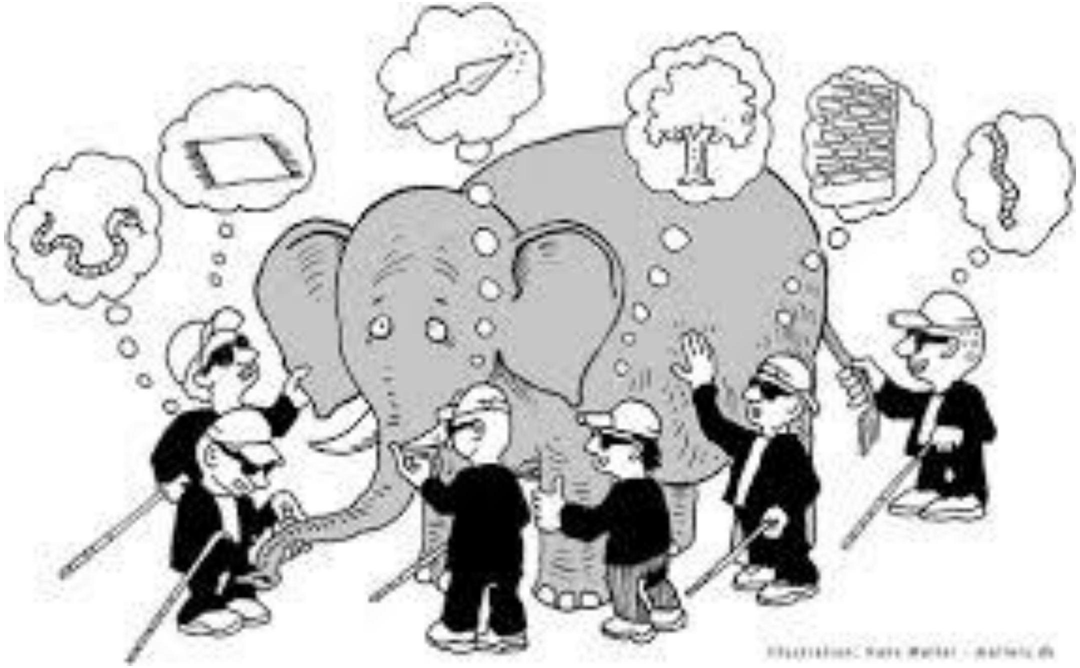
Evaluation

```
evaluation result: {'status': 1, 'total_return': 583.21}
```



Challenges and Opportunities

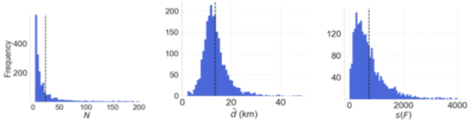
#1: High-quality data is limited in size and lacks diversity



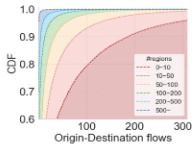
Large-scale Dataset including 3333 Urban Areas in the US and support modeling from network-level

Table 1: Comparison of the proposed dataset and other dataset utilized in existing works.

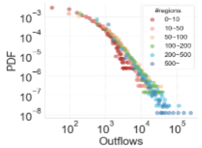
Dataset	#Area	Area Type	Cover Area (km^2)	Metropolitan	Town	Rural	Curated & Public
Karimi et al. (2020)	1	Central District	-	✓	✗	✗	✗
Pourebrahim et al. (2018; 2019)	1	Whole City	789	✓	✗	✗	✗
Liu et al. (2020)	1	Whole City	789	✓	✗	✗	✓
Yao et al. (2020)	1	Central District	900	✓	✗	✗	✗
Lenormand et al. (2015)	2	Whole City	15,755	✓	✗	✗	✗
Rong et al. (2023c;d;b)	8	Whole City	25,954	✓	✗	✗	✓
Simini et al. (2021)	2,911	National Gridding Coverage	686,983	✓	✓	✓	✗
Ours	3,333	Census Area Coverage	9,372,610	✓	✓	✓	✓



(a) #Regions (b) Distances. (c) Variance.




(a) Maricopa (b) Alameda (c) Contra Costa



Dataset and code

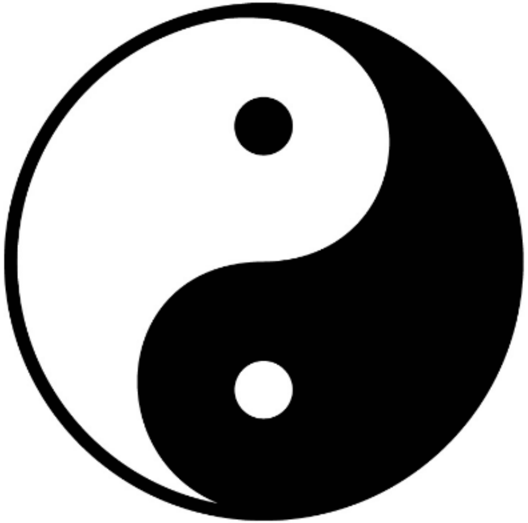
C. Rong, J. Ding, Y. Liu, Y. Li. A Large-scale Dataset and Benchmark for Commuting Origin-Destination Flow Generation. ICLR'2025.

2: A balanced model that captures both order and chaos is still in search

Known

Yang

Order
Masculinity
Day
The known
Authoritarianism
Fascism



Unknown

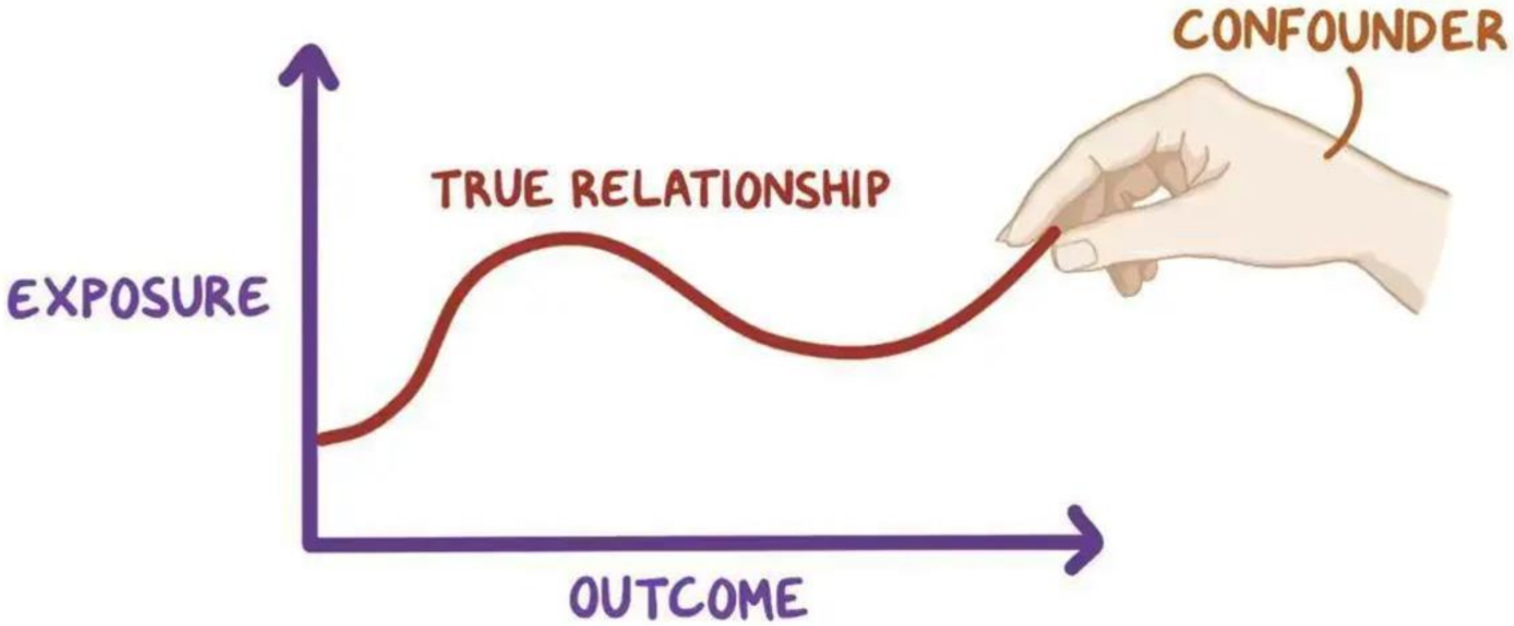
Yin

Chaos
Femininity
Night
The unknown
Decadence
Nihilism

Pursuit of Effective Models for Time Series

1. Are Transformers Effective for Time Series Forecasting? by Ailing Zeng, Muxi Chen, Lei Zhang, Qiang Xu (The Chinese University of Hong Kong, International Digital Economy Academy (IDEA), 2022) code 🔥🔥🔥🔥🔥
2. LLMs and foundational models for time series forecasting: They are not (yet) as good as you may hope by Christoph Bergmeir (2023) 🔥🔥🔥🔥🔥
3. Transformers Are What You Do Not Need by Valeriy Manokhin (2023) 🔥🔥🔥🔥🔥
4. Time Series Foundational Models: Their Role in Anomaly Detection and Prediction (2024) code
5. Deep Learning is What You Do Not Need by Valeriy Manokhin (2022) 🔥🔥🔥🔥🔥
6. Why do Transformers suck at Time Series Forecasting by Devansh (2023)
7. Frequency-domain MLPs are More Effective Learners in Time Series Forecasting by Kun Yi, Qi Zhang, Wei Fan, Shoujin Wang, Pengyang Wang, Hui He, Defu Lian, Ning An, Longbing Cao, Zhendong Niu (Bejing Institute of Technology, Tongji University, University of Oxford, Universuty of Technology Sydney, University of Macau, HeFei University of Technology, Macquarie University) (2023) 🔥🔥🔥🔥🔥
8. Forecasting CPI inflation under economic policy and geo-political uncertainties by Shovon Sengupta, Tanujit Chakraborty, Sunny Kumar Singh (Fidelity Investments, Sorbonne University, BITS Pilani Hyderabad). (2024) 🔥🔥🔥🔥🔥
9. Revisiting Long-term Time Series Forecasting: An Investigation on Linear Mapping by Zhe Li, Shiyi Qi, Yiduo Li, Zenglin Xu (Harbin Institute of Technology, Shenzhen, 2023) code
10. SCINet: Time Series Modeling and Forecasting with Sample Convolution and Interaction by Minhao Liu, Ailing Zeng, Muxi Chen, Zhijian Xu, Qiuxia Lai, Lingna Ma, Qiang Xu (The Chinese University of Hong Kong,2022) code

3: Causal modeling is essential in AI for science



Thank you !