Structured Intelligence - A Comprehensive Survey of Foundation Models and Research Outlook

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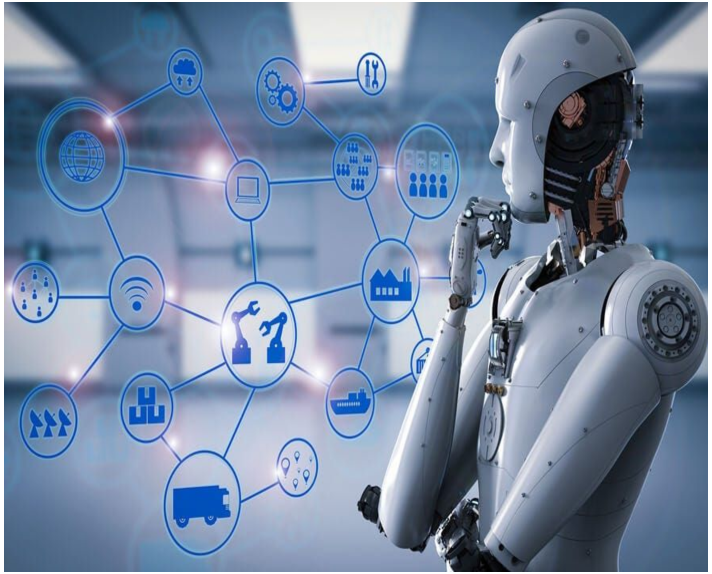


My Presentation is based on the following research paper:

A Survey of Time Series Foundation Models: Generalizing Time Series Representation with Large Language Model

By : JIEXIA YE, WEIQI ZHANG, KE YI, YONGZI YU, ZIYUE LI, JIA LI, FUGEE TSUNG

Research Paper Link: https://arxiv.org/pdf/2405.02358

Medium Article: https://medium.com/p/3d85ce6469b7/edit

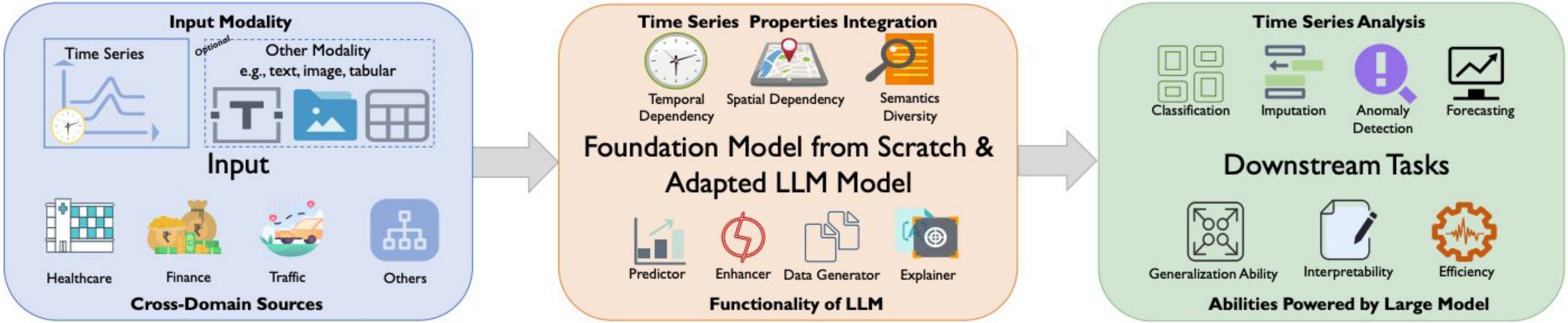
Other References:

https://github.com/start2020/Awesome-TimeSeries-LLM-FM

AGENDA OVERVIEW

- What are Foundation Models?
- 3E Framework & Research
- Time Series Tasks
- Pre Training Foundation Models
- Adaptation Paradigms
- Roles of LLMs in Time Series
- Improving Model Efficiency
- Making Models Explainable
- Foundation Models Across Domains
- Libraries, Datasets, Tools
- Limitations and Research Gap
- Conclusion

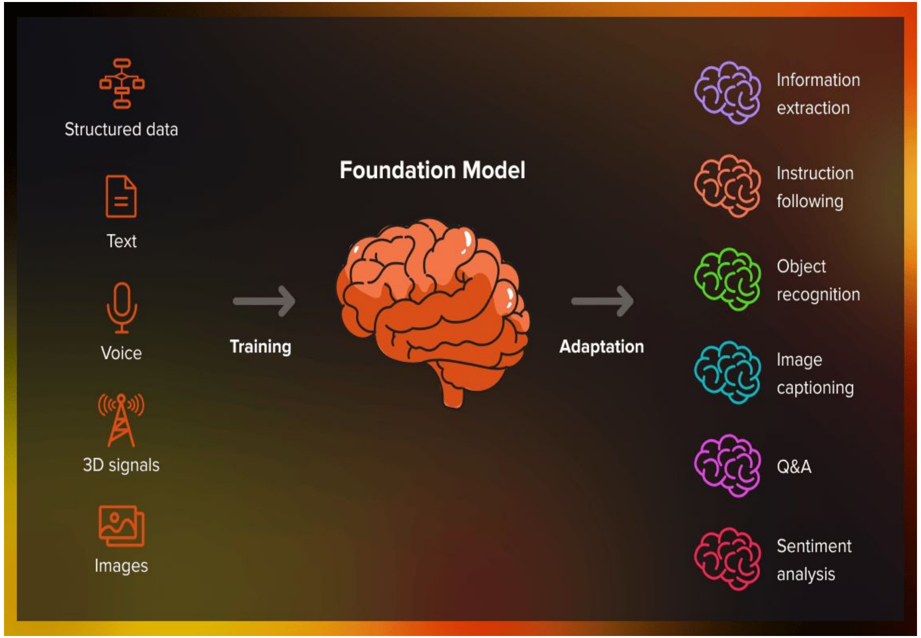
“Time waits for no one-except maybe foundation models”



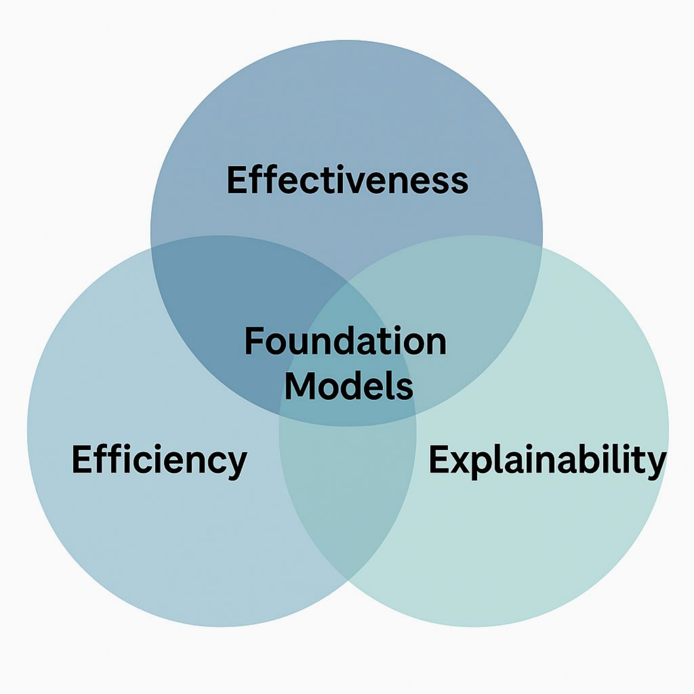
- Time series is everywhere: ECGs, stocks, sensors.
- Challenge: Extracting generalizable insights from it.
- Can foundation models match their success in NLP & vision?

What Are Foundation Models?

- Pretrain on massive data → fine-tune on tasks.
- Enable generalization, few-shot learning and zero-shot reasoning.
- Examples: GPT (text), CLIP (vision), DALL·E (multimodal).
- Have transformed fields like natural language processing and computer vision.



3E Framework & Research Questions



Framework:

- Effectiveness: Task performance.
- Efficiency: Computational cost.
- Explainability: Transparency of decisions.

Research Questions:

- Adapting foundation models effectively for time series.
- Efficient pretraining and fine-tuning methods.
- Enhancing explainability.
- Applications across domains.

Foundation Models and Time Series Tasks

Pretrain–then-finetune approach:

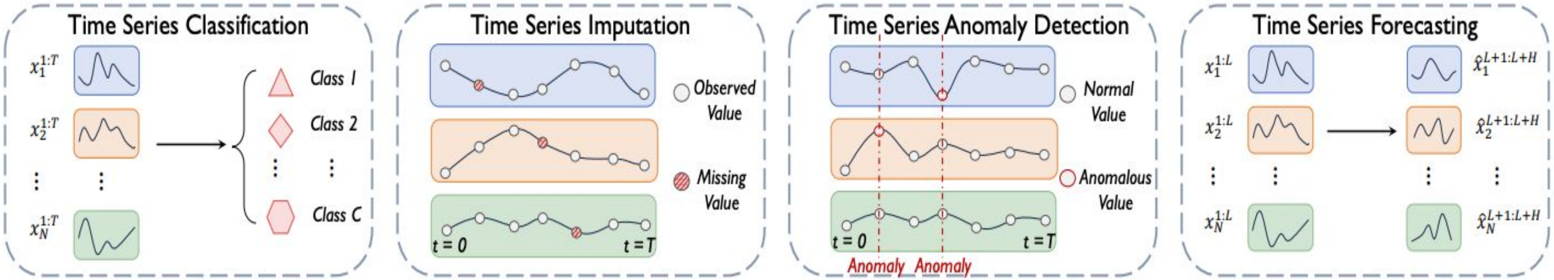
- Pretrained on large datasets → adapted to specific tasks
- Popular in NLP and vision (e.g., GPT, CLIP, DALL·E)
- Now extended to time series data

Time Series Tasks:

- Classification
- Forecasting
- Imputation
- Anomaly Detection

Unique Modeling Properties:

- Temporal Dependency
- Spatial Dependency
- Semantic Diversity



Pre-training Foundation Models

Approaches:

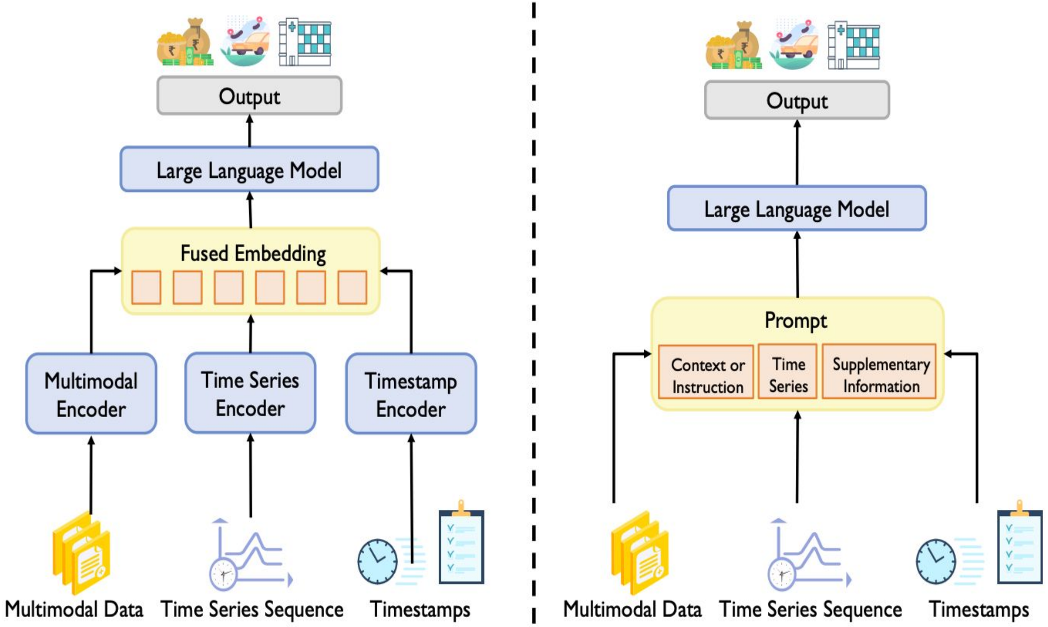
- Pre Training from scratch (Time GPT, TimesFM)
- Adapting LLMs via fine-tuning or prompting
- Goal: general-purpose, interpretable, multimodal models
- Both are complementary, not competing

Model	Parameter Size	Transformer Mode	Channel Setting	Task Type	Pre-trained Dataset	Data Size
ForecastPFN [45]	-	Encoder-only	Uni.	Fore.	Synthetic Data	-
TimeGPT [58]	-	Encoder-decoder	Uni.	Fore.	-	100 B time points
TimesFM [36]	225M	Decoder-only	Uni.	Fore.	Google Trends [2] Wiki Pageviews [4] Synthetic Data	101B time points
Lag-Llama [141]	-	Decoder-only	Uni.	Fore.	Monash [159]	0.3B time points
TimeCLR [195]	-	Encoder-only	Uni.	Class.	UCR [38]	-
GTT [54]	57M	Encoder-only	Multi.	Fore.	-	2.4B time points

Techniques & Models:

- Models: Time GPT, TimesFM, GTT, Lag-Llama
- Data Techniques: Jittering, patching, synthetic generation
- Architectures: Encoder-only, Decoder-only, Encoder-decoder
- Observed diversity in architectures and how they build temporal understanding.

Adaptation Paradigms



(a) Embedding Visible Large Language Models (b) Text Visible Large Language Models

- **Embedding-Visible:** Vectorized time series inputs.
  - Temporal Decomposition
  - Multivariate Patching
  - Semantic Alignment
  - Fine-tuning strategies
- **Text-Visible:** Time series converted into natural language prompts.
  - PromptCast and LLMF
  - LLM-Mob, TWSN
  - Timestamp, Cross-Sequence and Domain-specific context.

Roles of LLMs in Time Series

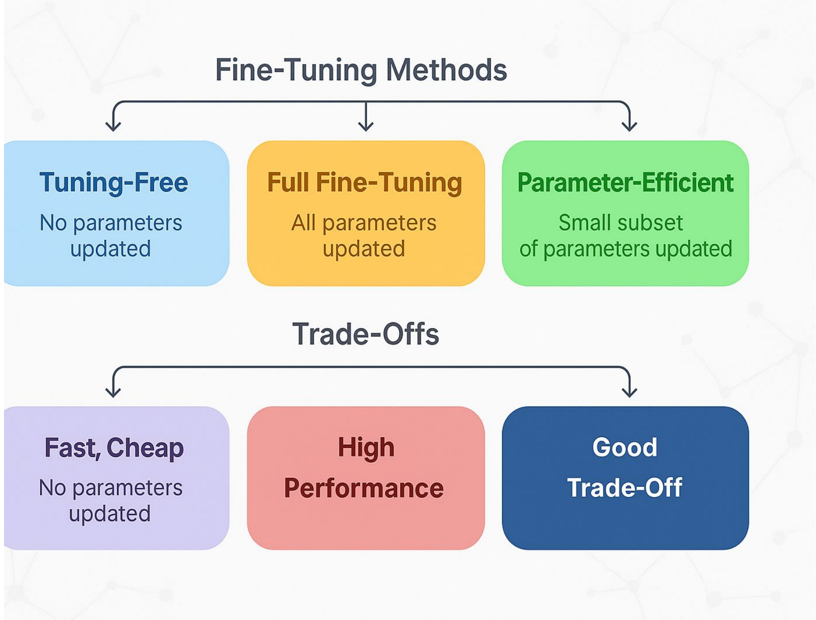
- Adapting LLMs for time series is a promising path, but it requires modality alignment, task-specific prompting, and careful architectural design
- **Applications**:
  - Forecasting
  - Classification
  - Anomaly detection
  - Imputation

Role	Description	Example Models
Predictor	Directly map time series to outputs	Time-LLM, UniTime
Enhancer	Provide auxiliary signals from text (e.g., news, reports)	METS, TEMPO
Generator	Create synthetic descriptions or context for input augmentation	TDML, CIGN
Explainer	Generate textual justifications or step-by-step reasoning	LLM-Mob, TWSN

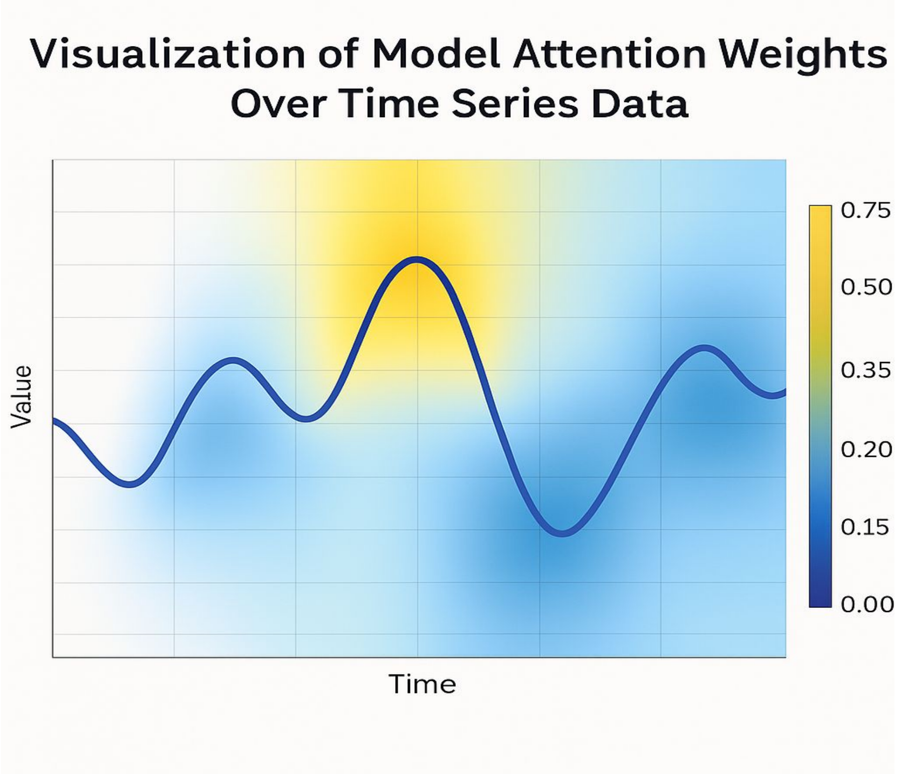
Improving Time Series Models Efficiency

Fine-Tuning Strategies:

- **Tuning-Free Prompting**: No parameter updates.
- **Full Fine-Tuning**: All model layers retrained.
- LoRA and prompt tuning offer promising results with lower costs
- **Parameter-Efficient Fine-Tuning (PEFT)**: Selective parameter updates (e.g., LoRA, adapters).
  - Adapters
  - Prompt Tuning
  - Prefix Tuning
  - LoRA



Making Foundation Models Explainable



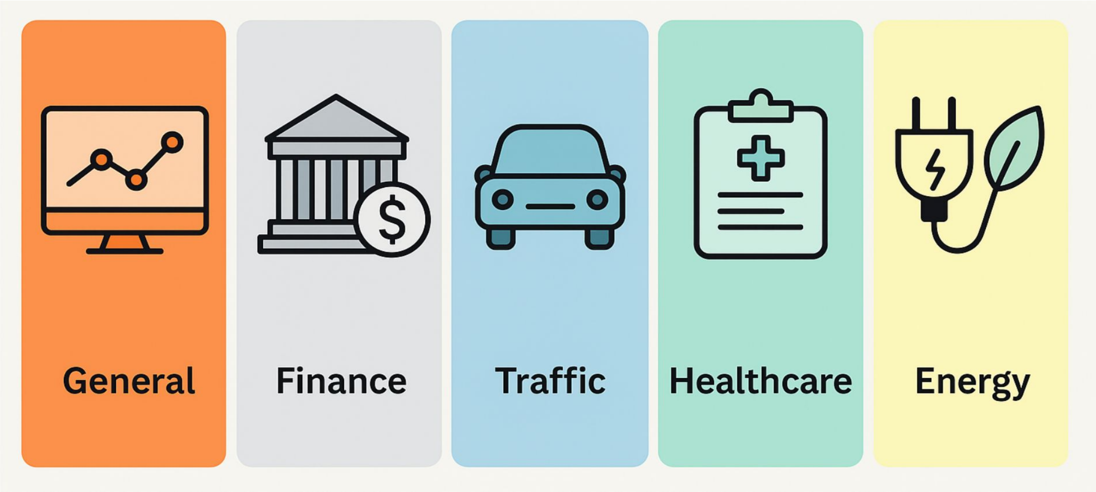
Explanation Types:

- Global Explanations: Overall model behavior.
- Local Explanations: Specific prediction justifications.

Techniques:

- Chain-of-Thought prompting.
- Attention visualization.

Foundation Models Across Domains



Foundation Models in Real-World Domains:

- **Finance**: Stock prediction using financial news.
- **Traffic**: Mobility forecasting and anomaly detection.
- **Healthcare**: ECG signal analysis guided by medical reports.
- **Energy**: Consumption forecasting with descriptive prompts.

Resources

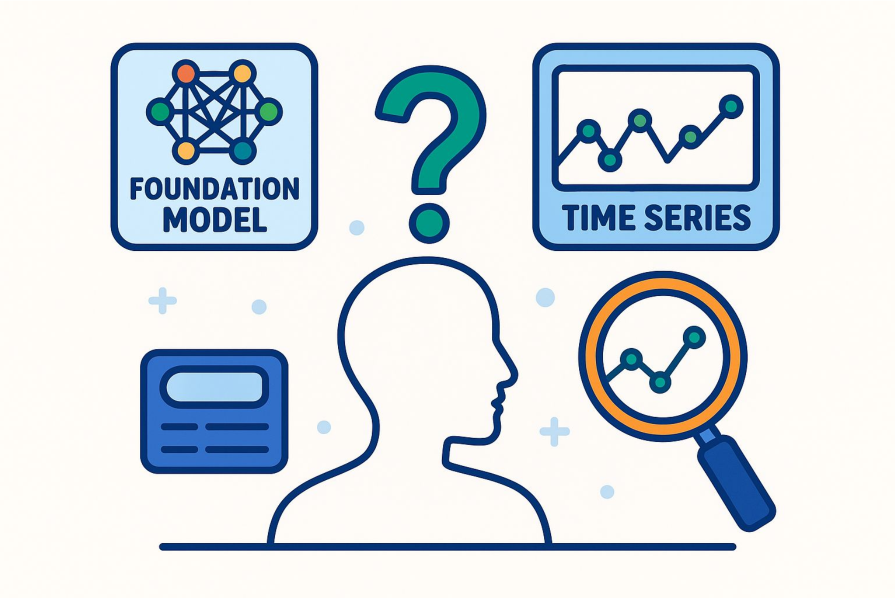
- **Datasets**: NASDAQ-100, PTB-XL, ETT, etc.
- **Libraries**: Darts, Prophet, Merlion, Time series analysis tools.
- **Frameworks**: LLM deployment platforms, Megatron, Hugging Face, DeepSpeed-MII
- These tools and datasets are essential to reproduce or extend the work.

Library	Tasks Supported	Type
Prophet	Forecasting	Statistical (Facebook)
GluonTS	Forecasting, Anomaly Detection	Deep Learning (Amazon)
Darts	Forecasting, Anomaly Detection	Hybrid (Unit8)
Merlion	Forecasting, Ensemble	Salesforce
Kats	Forecasting	Facebook

Tool	Key Use	Developer
Megatron	GPU optimization	Nvidia
ColossalAI	Distributed training	HPC-AI Tech
FairScale	Scalable PyTorch training	Meta
Pax	JAX-based training	Google
vLLM	Efficient inference (PagedAttention)	–
DeepSpeed-MII	Load balancing, quantization	Microsoft
text-generation-inference	Scalable deployment	HuggingFace

Limitations and Research Gap

- Lack of ImageNet-scale datasets for time series
- Poor alignment between time series and LLMs
- Limited explainability in embedding-visible setups
- Weak cross-domain generalization
- No standardized multi-task benchmark
- Underexplored multimodal combinations
- Evaluation metrics often lack depth
- Reproducibility issues due to closed-source models



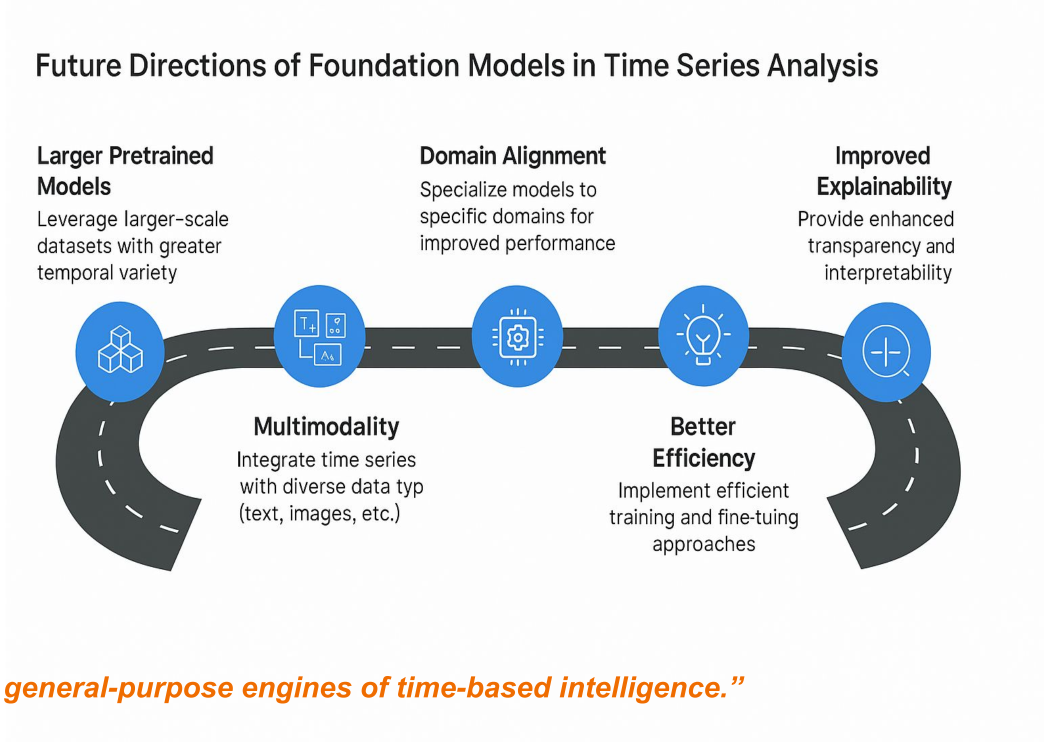
Conclusion

Summary:

- Foundation models are transforming time series analysis.
- The 3E framework provides a comprehensive evaluation approach.
- Real-world applications demonstrate the versatility of these models.

Future Outlook:

- Bridging the modality gap between time series and language.
- Developing unified, flexible, and interpretable solutions.



"Foundation models may become the general-purpose engines of time-based intelligence."

Thank You..!

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