AIOps Challenge | 2023 CCF国际AIOps挑战赛决赛
暨“大模型时代的AIOps”研讨会

Foundation Models for Time Series Analysis

Haixu Wu, School of Software, Tsinghua University

主办单位：中国计算机学会（CCF）、清华大学、中国建设银行股份有限公司、南开大学
承办单位：中国计算机学会互联网专委会、清华大学计算机科学与技术系、中国建设银行股份有限公司运营数据中心、南开大学软件学院、北京必示科技有限公司
赞助单位：华为技术有限公司、国网宁夏电力有限公司电力科学研究院、软通动力信息技术（集团）股份有限公司

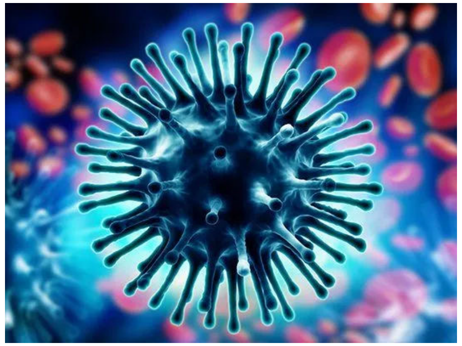
Time Series In Real World

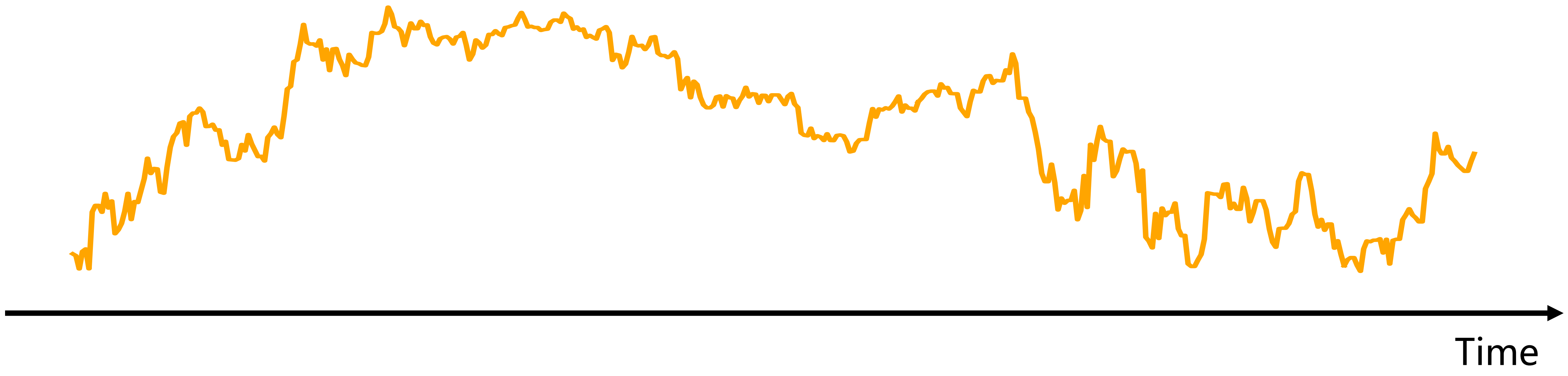

Energy
Consumption


Traffic
Flow

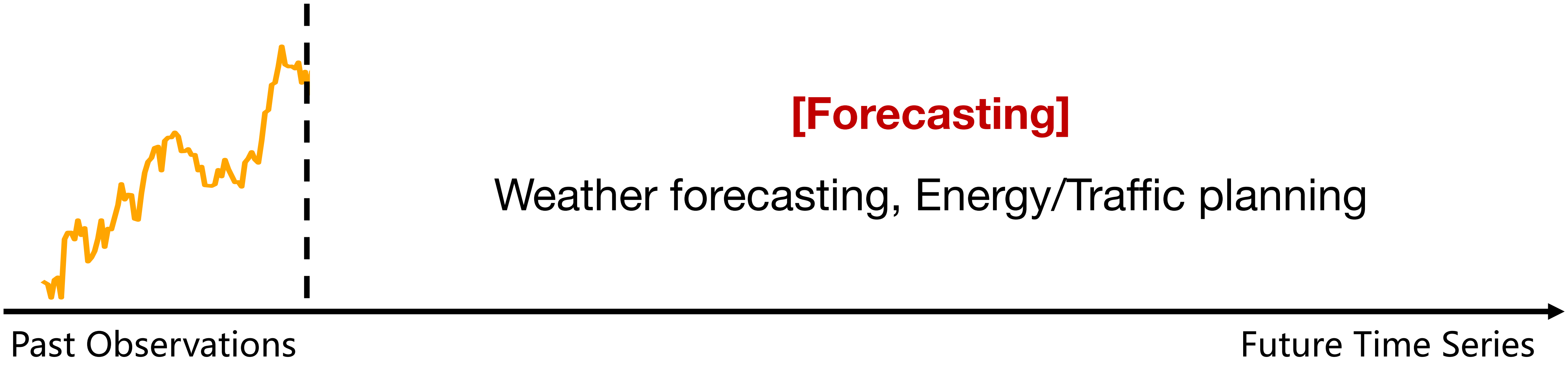
Economic
Changes


Weather
Variations

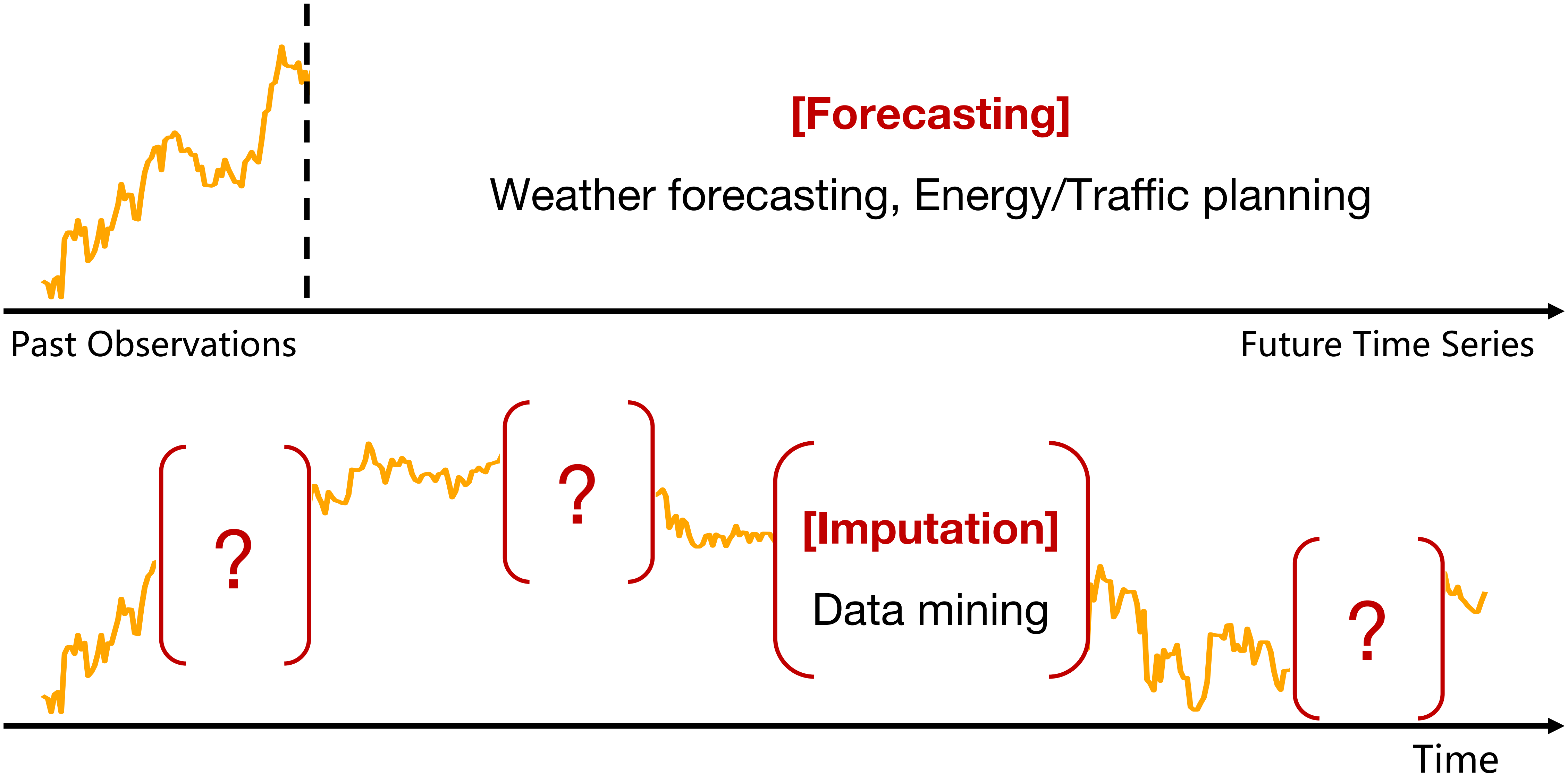

Disease
Propagation



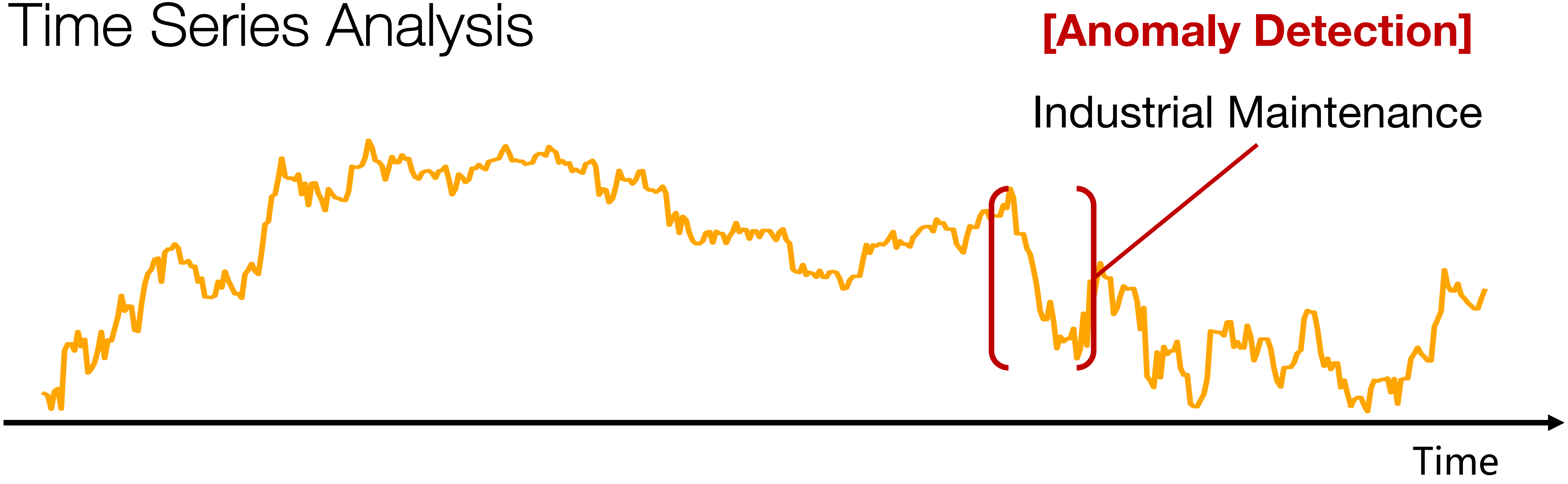
Time Series Analysis



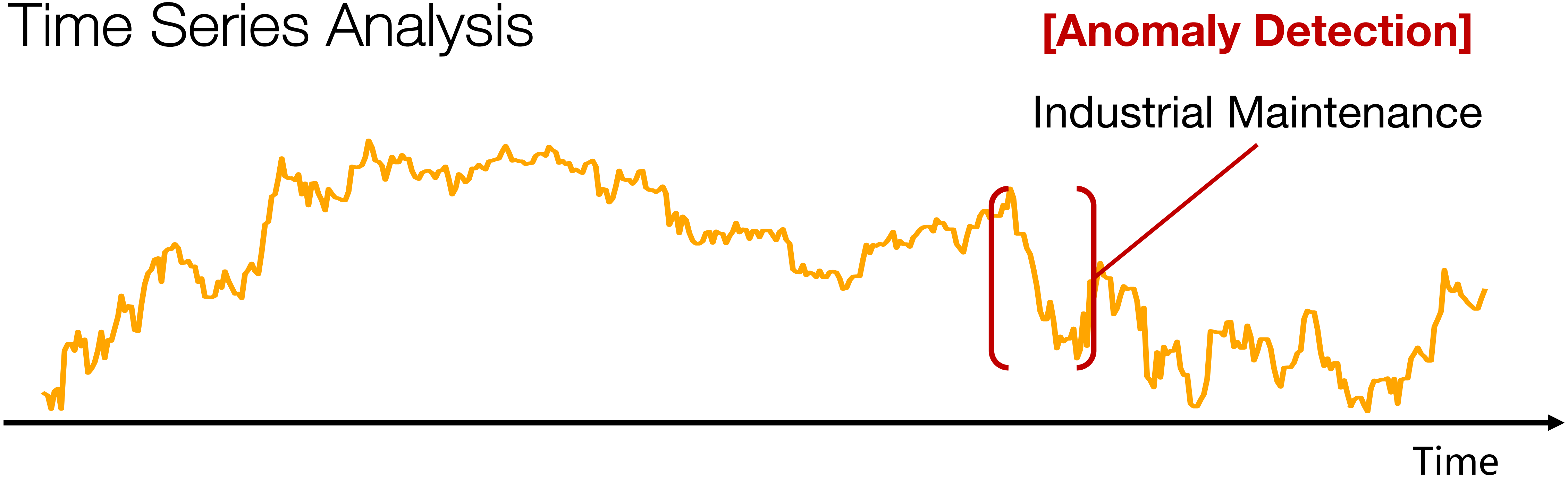
Time Series Analysis

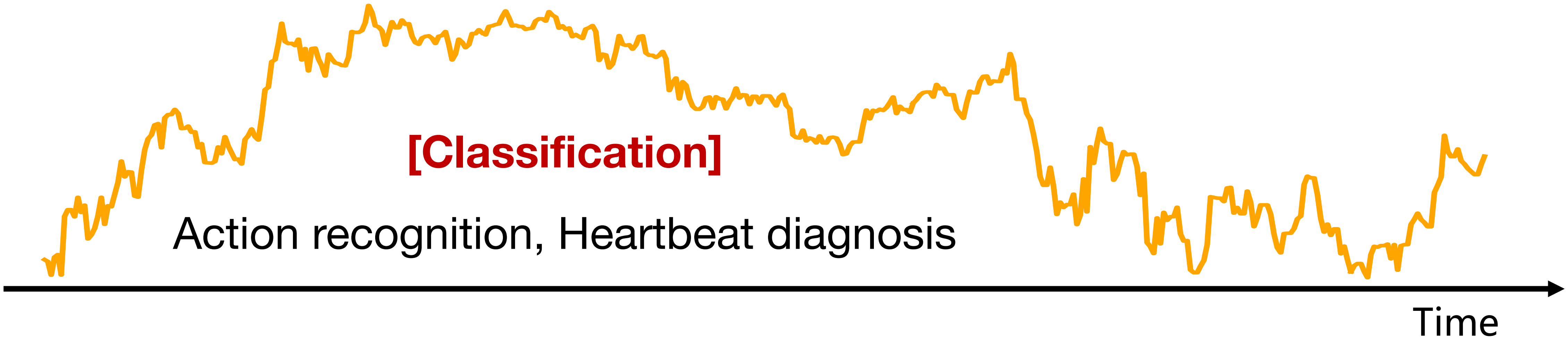


Time Series Analysis

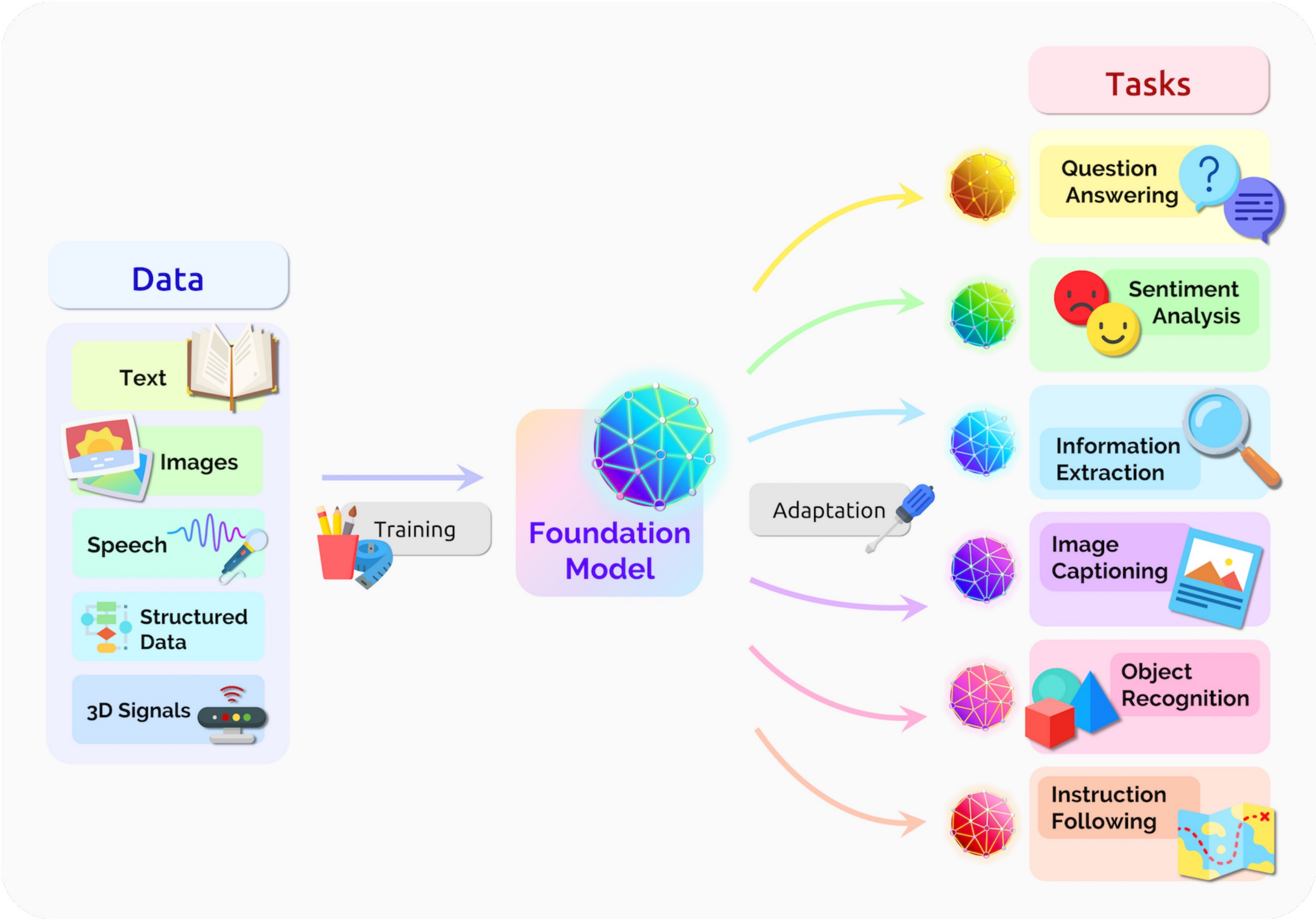


Time Series Analysis





In Pursing Foundation Models



[Data Universal]

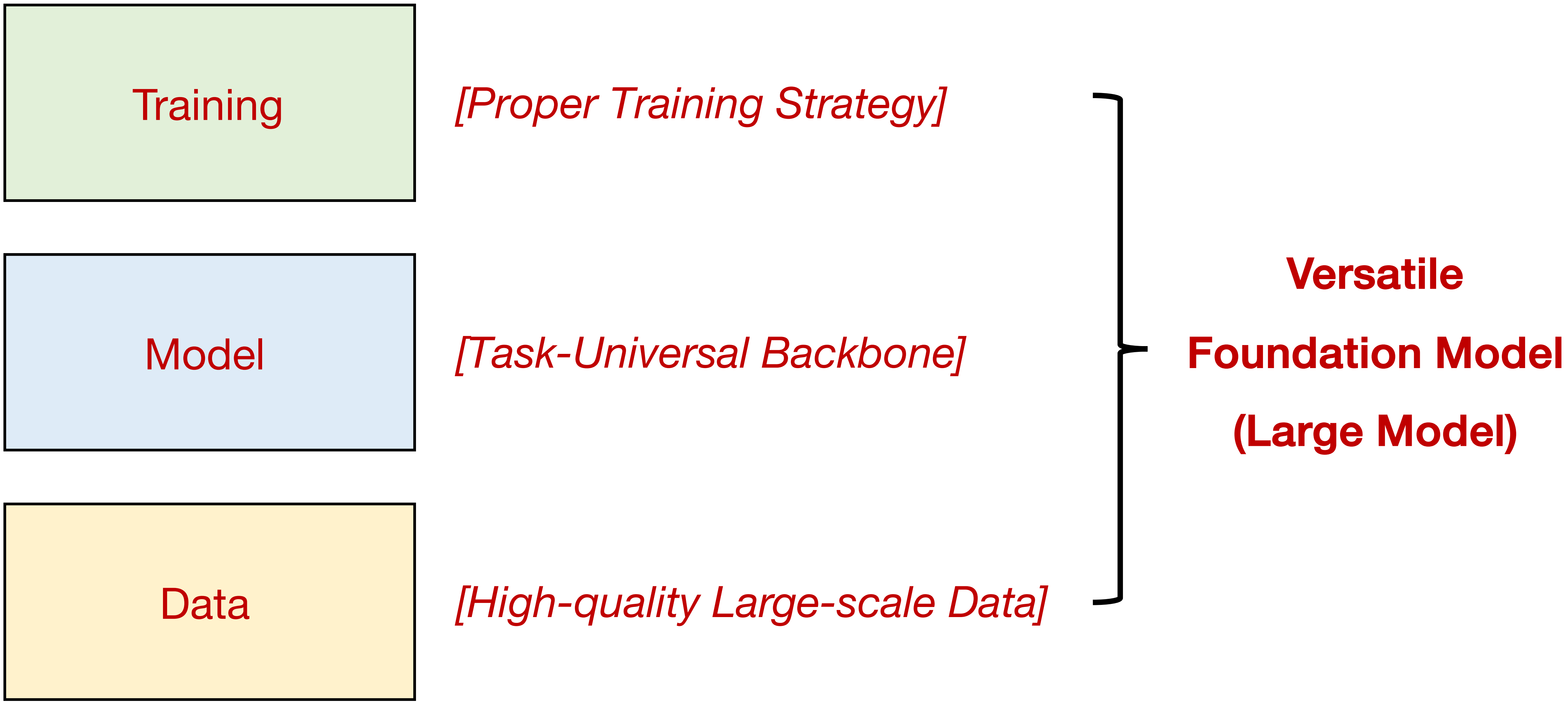
Learn from various modalities

[Task Universal]

Adapt to a wide range of downstream tasks

Bommasani et al. On the Opportunities and Risks of Foundation Models. *Arxiv 2021.*

In Pursing Foundation Models



37th Conference on Neural Information Processing Systems (NeurIPS 2023).

SimMTM: A Simple Pre-Training Framework for Masked Time-Series Modeling

Jiaxiang Dong[*], **Haixu Wu**[*], **Haoran Zhang, Li Zhang, Jianmin Wang, Mingsheng Long**[✉]
School of Software, BNRist, Tsinghua University, China
{djx20,whx20,z-hr20}@mails.tsinghua.edu.cn, {lizhang,jimwang,mingsheng}@tsinghua.edu.cn


Jiaxiang Dong


Haixu Wu

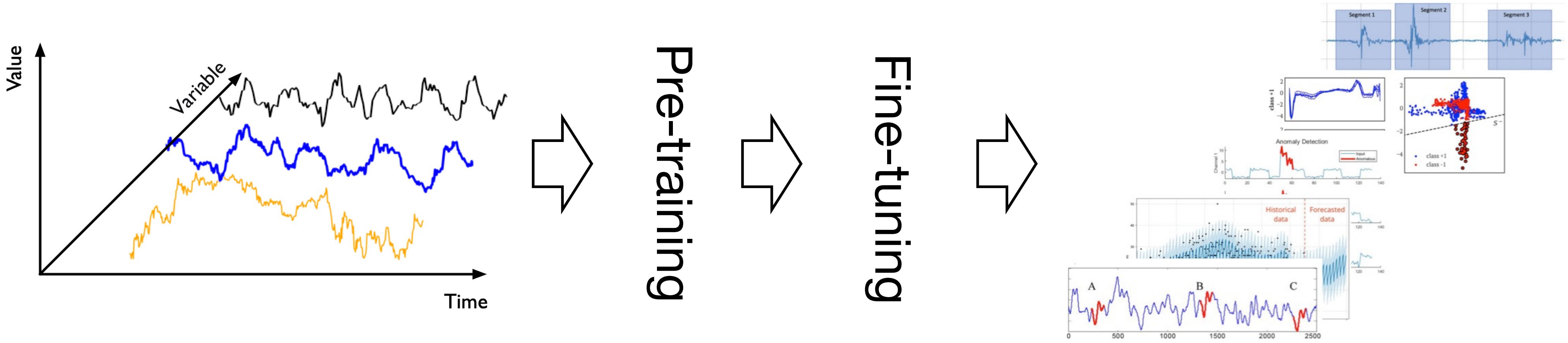

Haoran Zhang


Li Zhang


Jianmin Wang


Mingsheng Long

Time Series Pre-training



Large-scale time series data

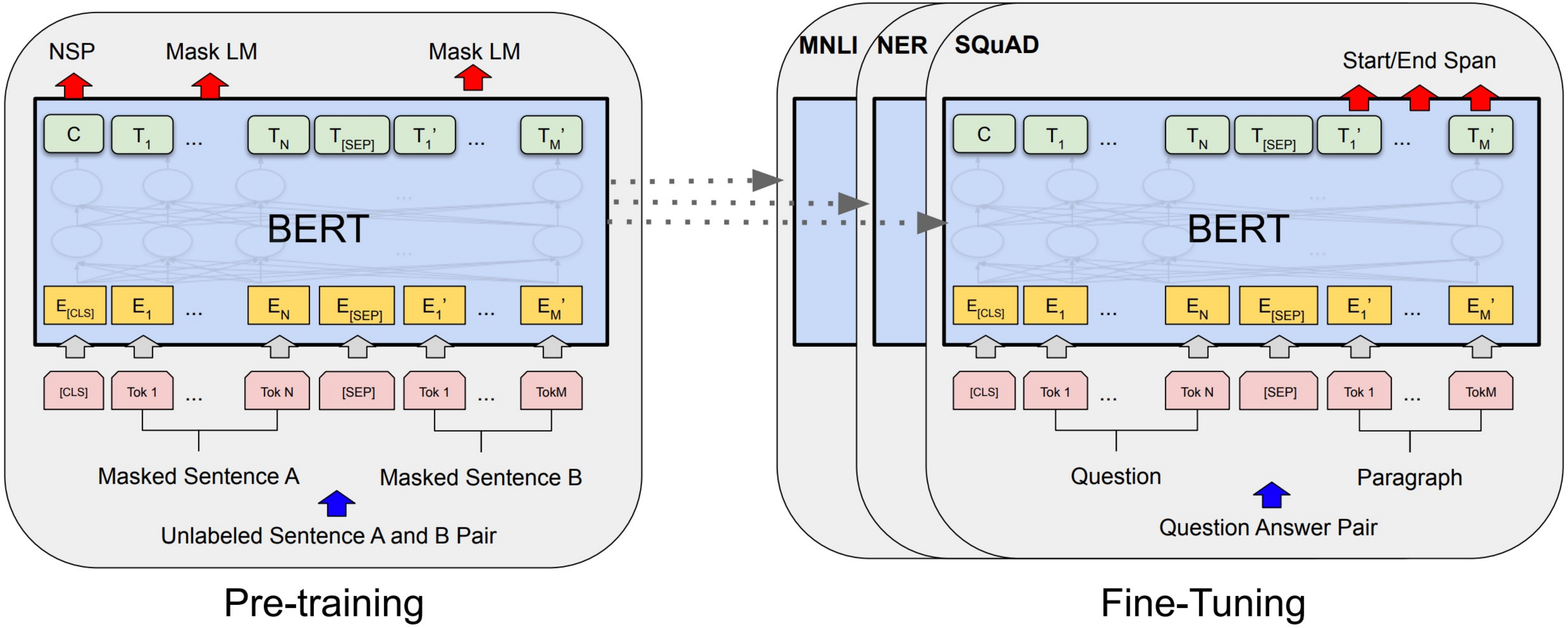
Diversified time series analysis tasks

① Use the model as the carrier of knowledge.

② Learn transferable temporal representations.

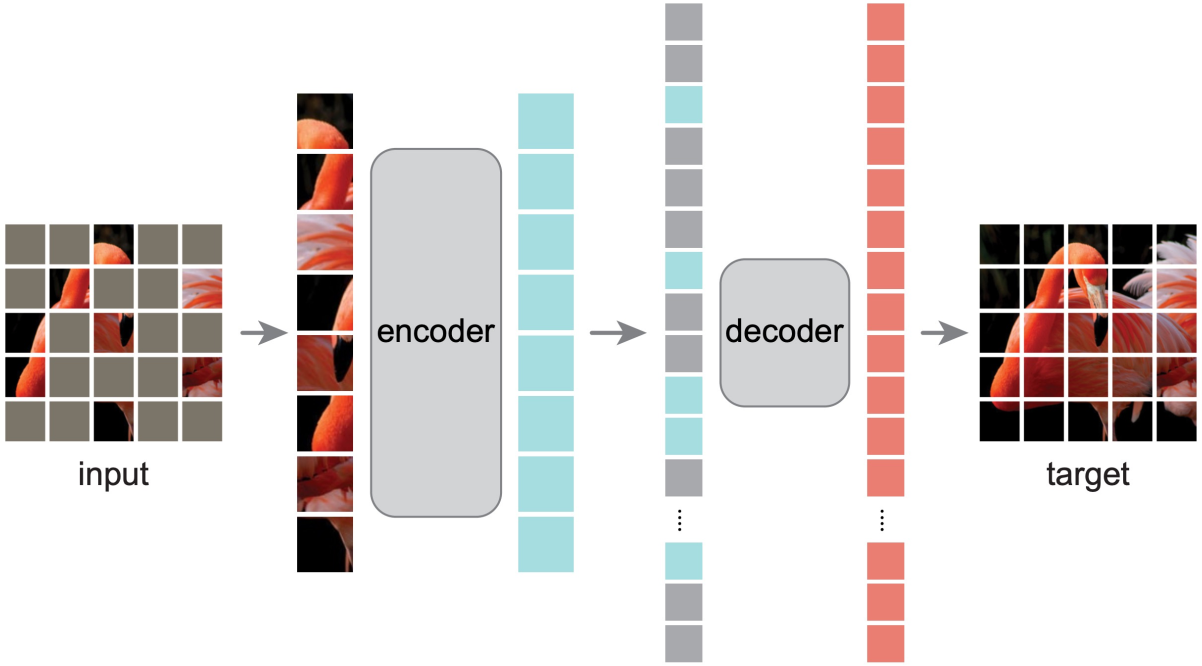
Masked Modeling in NLP

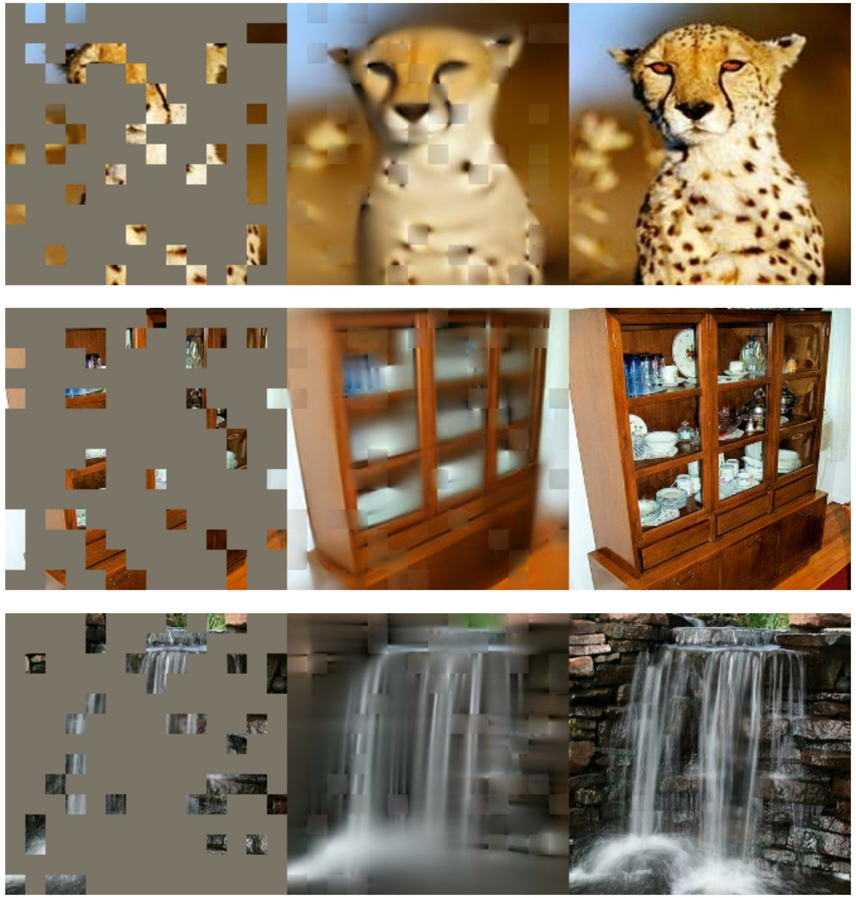
Random mask a portion of words.



Devlin et al. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *ACL 2019.*

Masked Modeling in CV

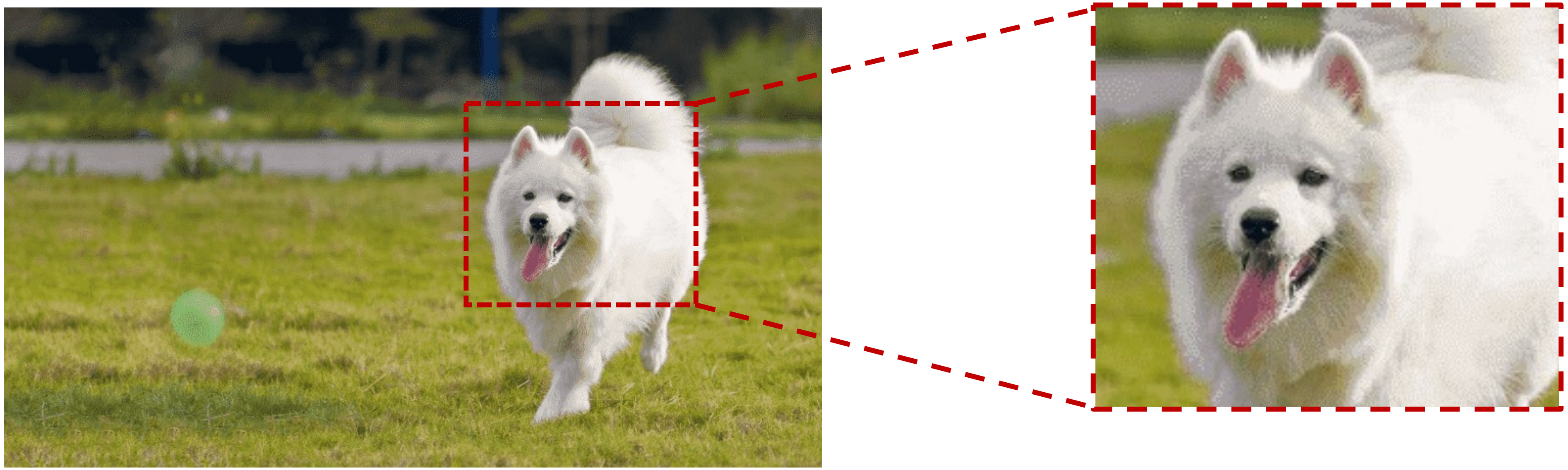




Random mask a portion of patches.

He et al. Masked Autoencoders Are Scalable Vision Learners. *CVPR 2022.*

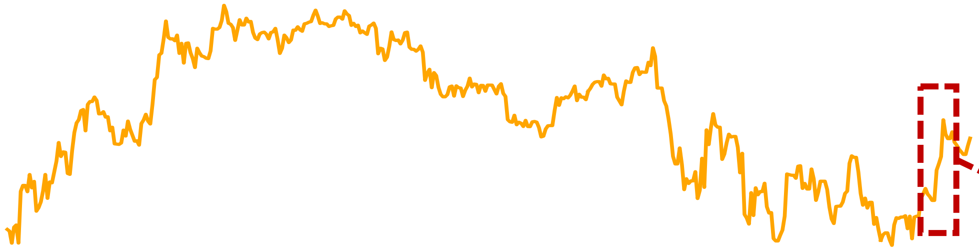
Differences among Image, Language, Time Series



TimesNet is for time series analysis.

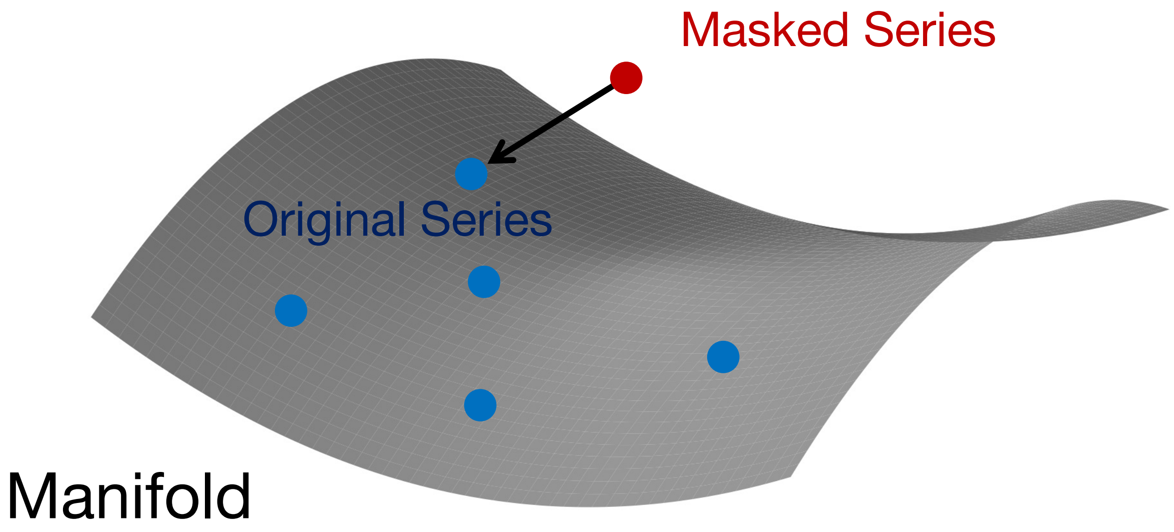
Analysis is the process of breaking a complex topic into smaller parts for a better understanding.

Wikipedia
The Free Encyclopedia

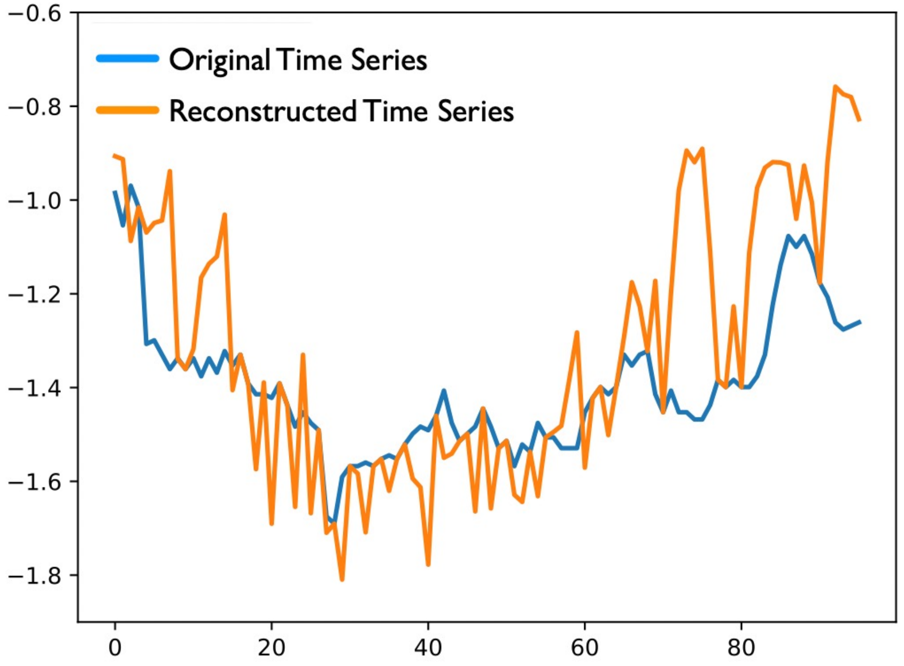


Each time point only saves some scalars.

Canonical Masked Modeling in Time Series



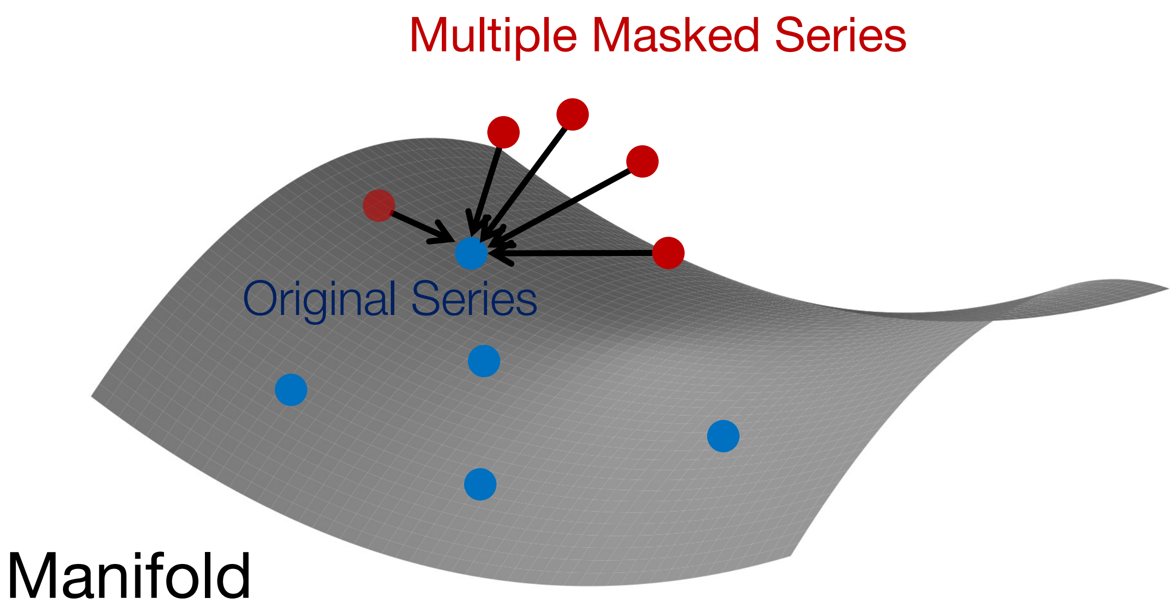
Hard to Reconstruct



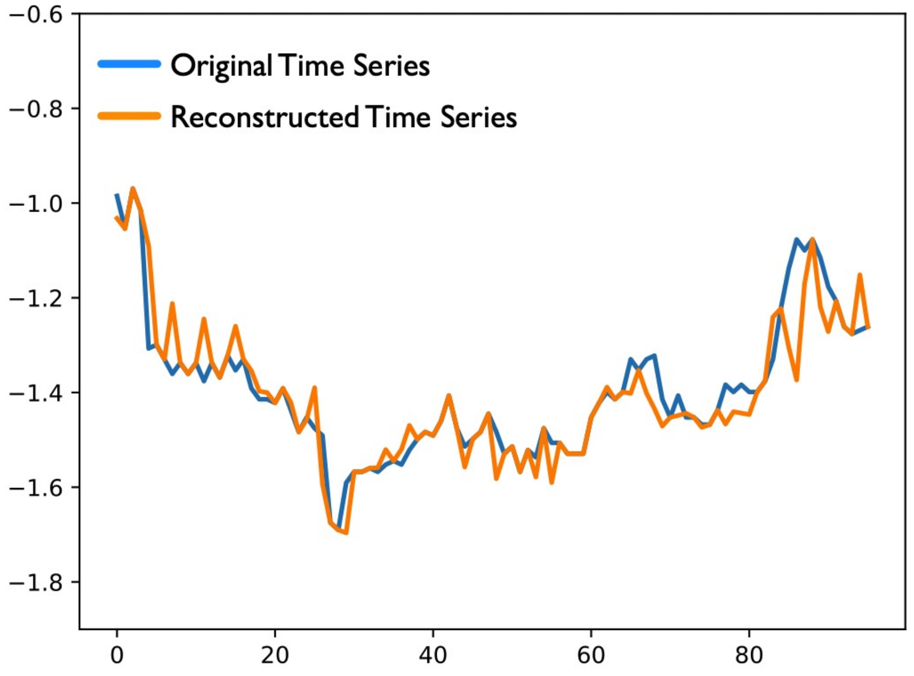
✓ Direct Reconstruction

Directly masking a portion of time points will seriously ruin the temporal variations of the original time series.

Multiple Masked Modeling



Benefit Masked Modeling

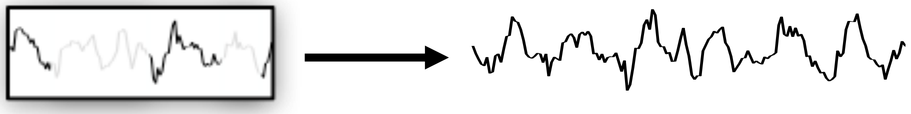


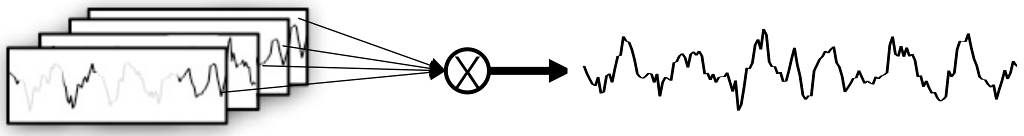
✓ Neighborhood Aggregation

Multiple randomly masked series will complement each other.

Neighborhood Aggregation Masked Modeling

Canonical **VS** **Neighborhood Aggregation**

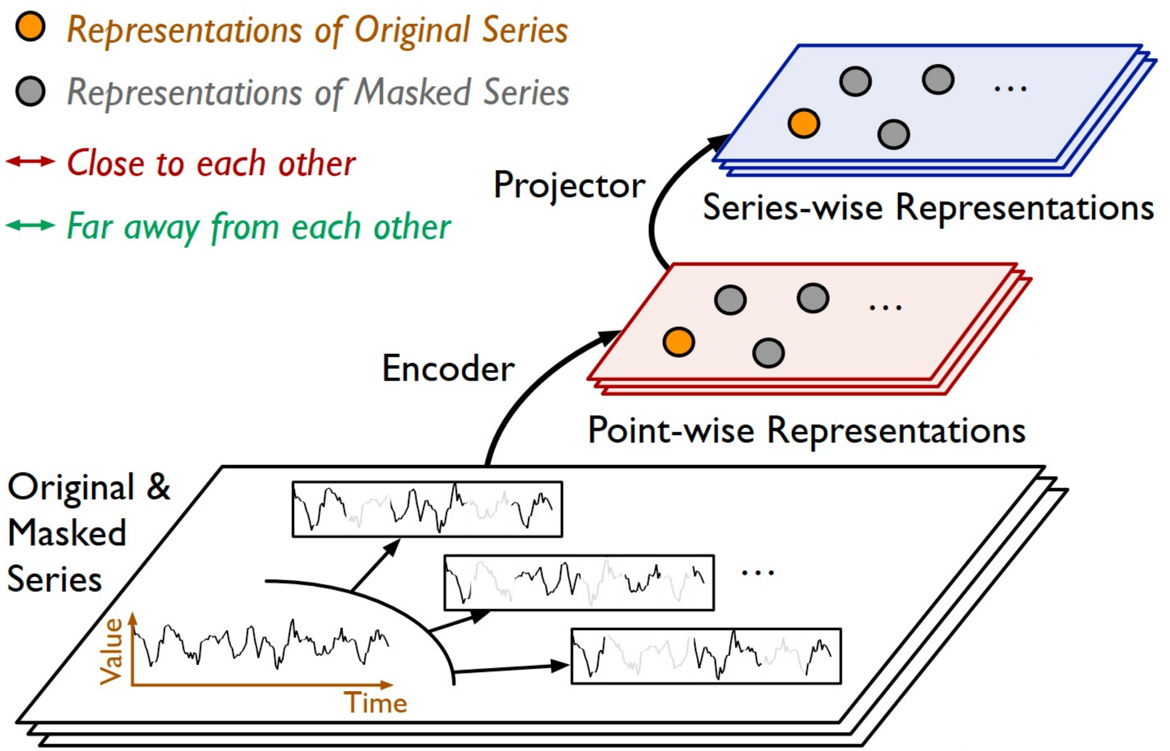




- ✗ Critical information destruction
- ✗ Mask ratio sensitive
- ✗ Reconstruction difficulty

- ✓ Multi-information perspective
- ✓ Information complementation
- ✓ Learnable aggregate weight

Overall design of SimMTM

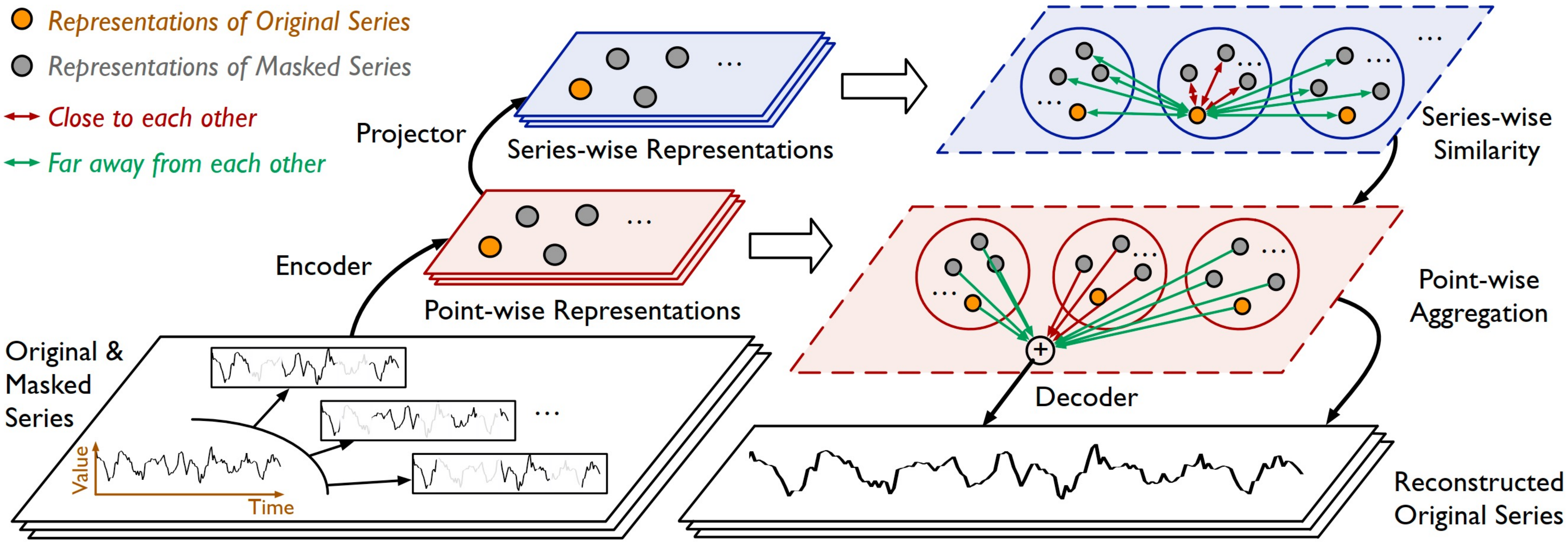


Generate original & masked series representations.

① Point-wise Representations

② Series-wise Representations

Overall design of SimMTM



① Series-wise Similarity ② Point-wise Aggregation

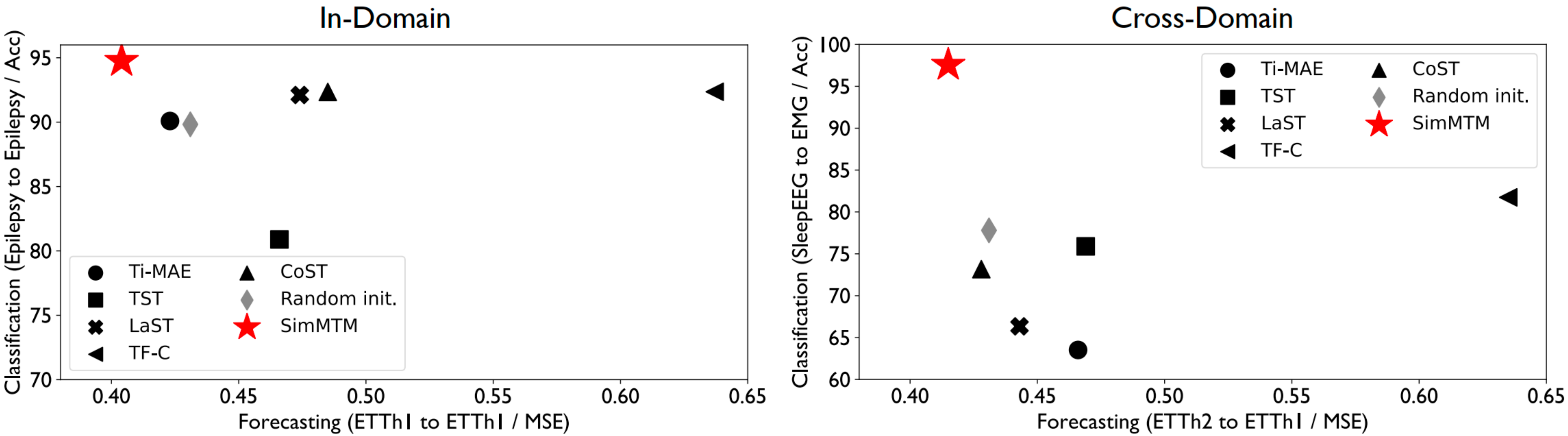
Multiple masked series complete each other and adaptive aggregate weight.

Experiment: Overall

Tasks	Datasets	Semantic
Forecasting	ETTh1,ETTh2	Electricity
	ETTm1,ETTm2	Electricity
	Weather	Weather
	Electricity	Electricity
	Traffic	Transportation
Classification	SleepEEG	EEG
	Epilepsy	EEG
	FD-B	Faulty Detection
	Gesture	Hand Movement
	EMG	Muscle Responses

- ✓ Two typical time series analysis tasks: **Forecasting and Classification.**
- ✓ Under multiple experiment settings: **In- and Cross domain**
- ✓ Compared to **6 advanced baselines in 12 databases.**

Experiment: Overall



SimMTM pretraining can benefit

both forecasting and classification tasks.

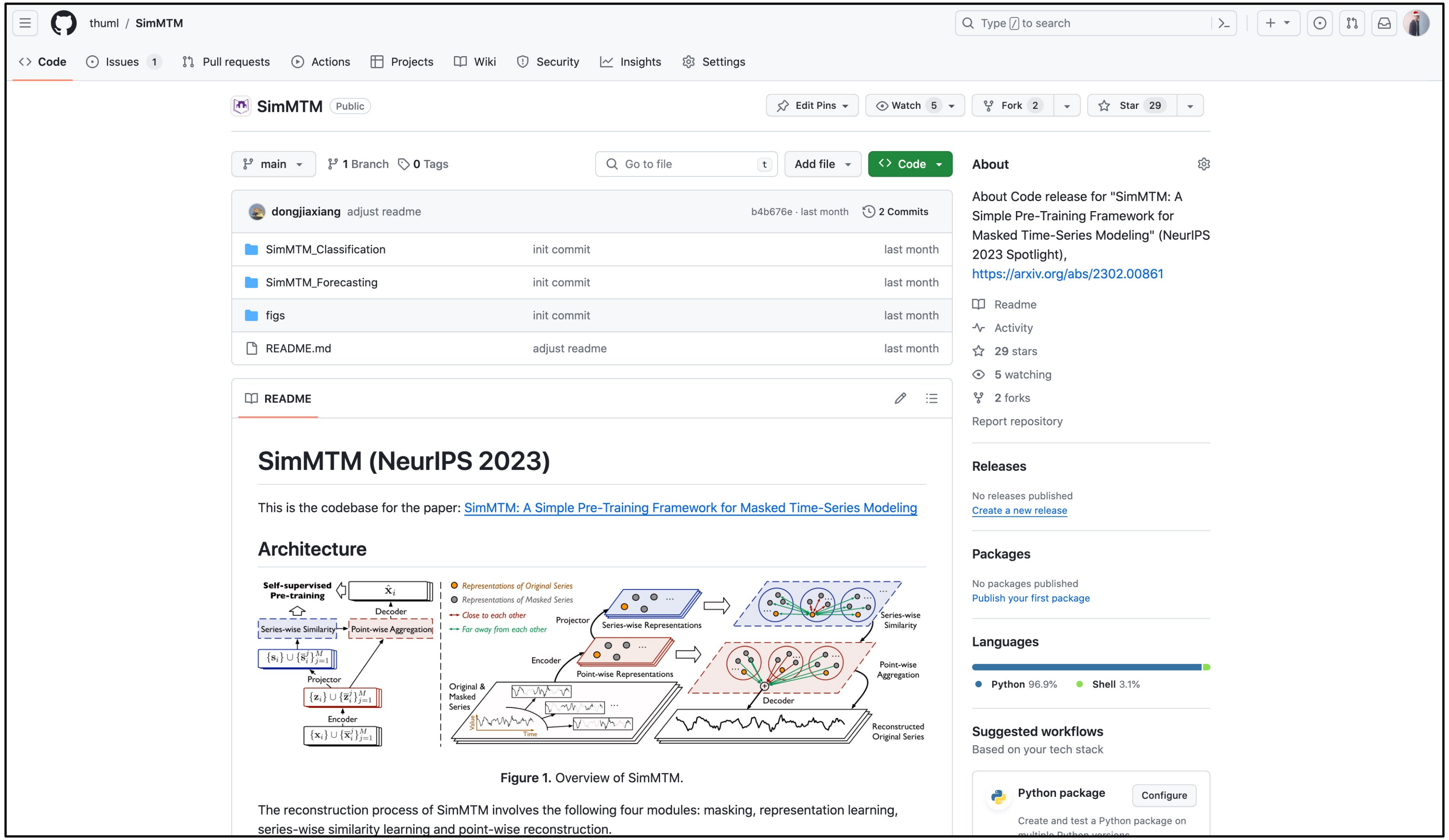
Model Generality on diverse base models

Dataset	ETTh1		ETTh2		ETTm1		ETTm2	
Model	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Transformer [39]	1.088	0.836	4.103	1.612	0.901	0.704	1.624	0.901
+ SimMTM	**0.927**	**0.761**	**3.498**	**1.487**	**0.809**	**0.663**	**1.322**	**0.808**
Autoformer [47]	0.573	0.573	0.550	0.559	0.615	0.528	0.324	0.368
+ SimMTM	**0.561**	**0.568**	**0.543**	**0.555**	**0.553**	**0.505**	**0.315**	**0.360**
NS Transformer [24]	0.570	0.537	0.526	0.516	0.481	0.456	0.306	0.347
+ SimMTM	**0.543**	**0.527**	**0.493**	**0.514**	**0.431**	**0.455**	**0.301**	**0.345**
PatchTST [26]	0.417	0.431	0.331	0.379	0.352	0.382	0.258	0.317
+ Sub-series Masking	0.430↓	0.445↓	0.355↓	0.394↓	**0.341**	0.379	0.258	0.318↓
+ SimMTM	**0.409**	**0.428**	**0.329**	0.379	0.348	**0.378**	**0.254**	**0.313**

SimMTM can consistently improve

the forecasting performance of **diverse base models.**

Open Source



Code is available at https://github.com/thuml/SimMTM

Published as a conference paper at ICLR 2023

TIMESNET: TEMPORAL 2D-VARIATION MODELING FOR GENERAL TIME SERIES ANALYSIS

Haixu Wu[*], Tengge Hu[*], Yong Liu[*], Hang Zhou, Jianmin Wang, Mingsheng Long[✉]
School of Software, BNRist, Tsinghua University, Beijing 100084, China
{whx20,liuyong21,htg21,h-zhou18}@mails.tsinghua.edu.cn
{jimwang,mingsheng}@tsinghua.edu.cn


Haixu Wu


Tengge Hu


Yong Liu


Hang Zhou

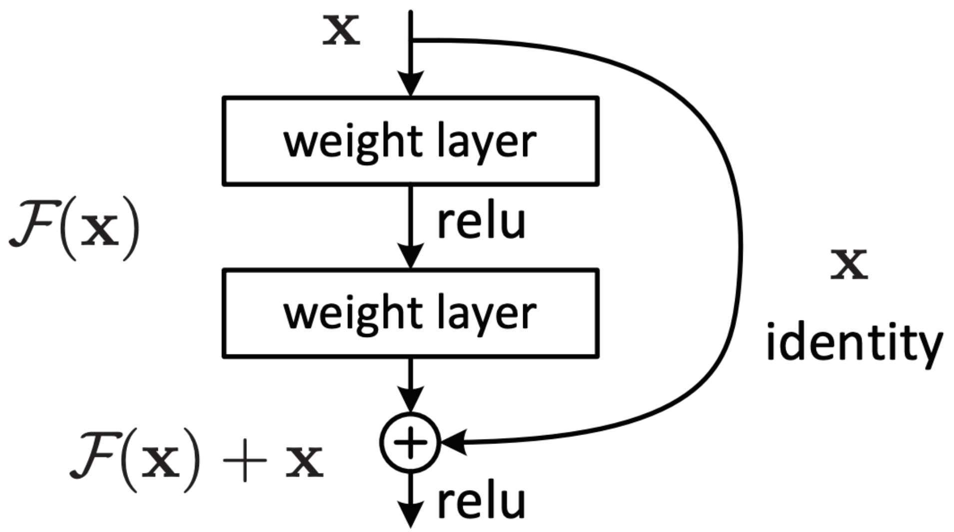

Jianmin Wang

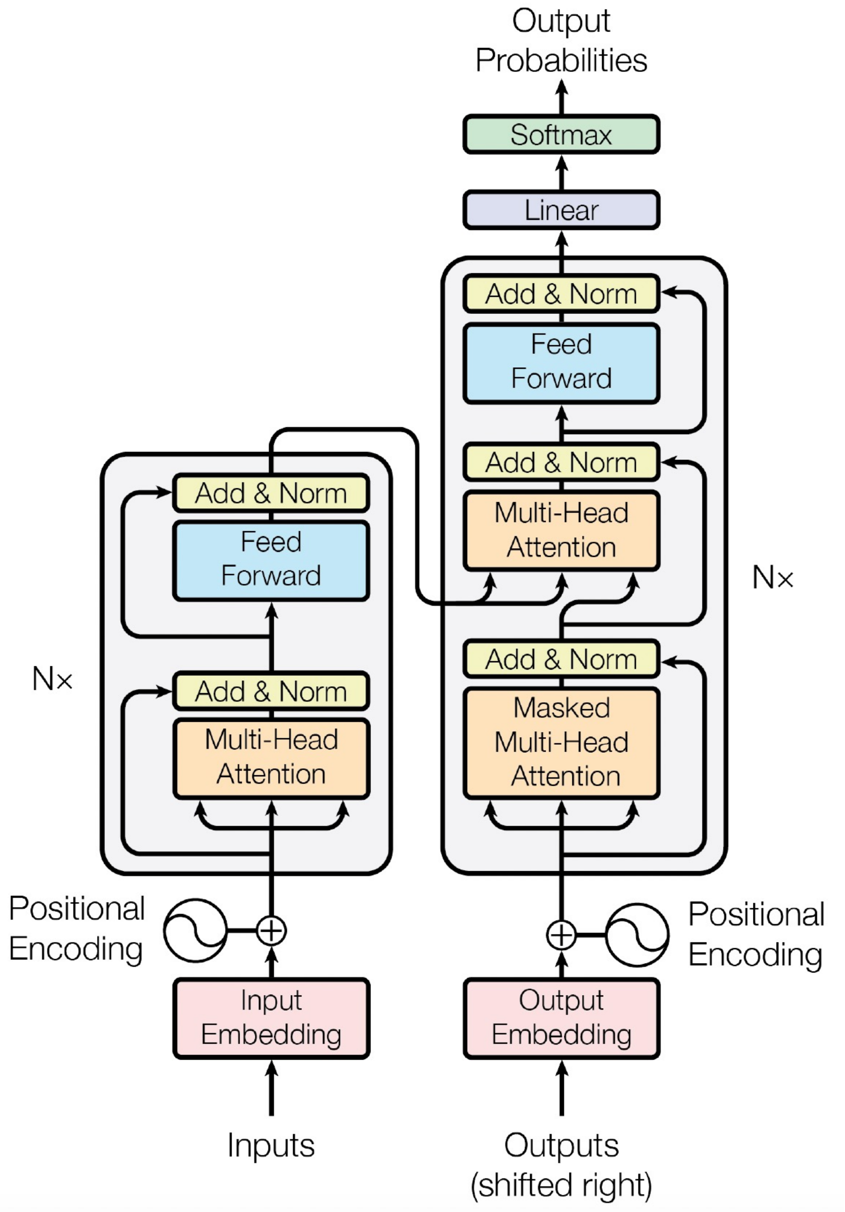

Mingsheng Long

Foundation Models in CV and NLP

Universal backbone with

task-specific heads for different tasks.



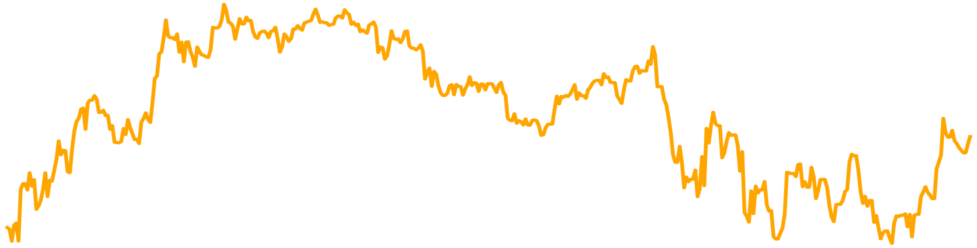


Classification, Object detection, Segmentation

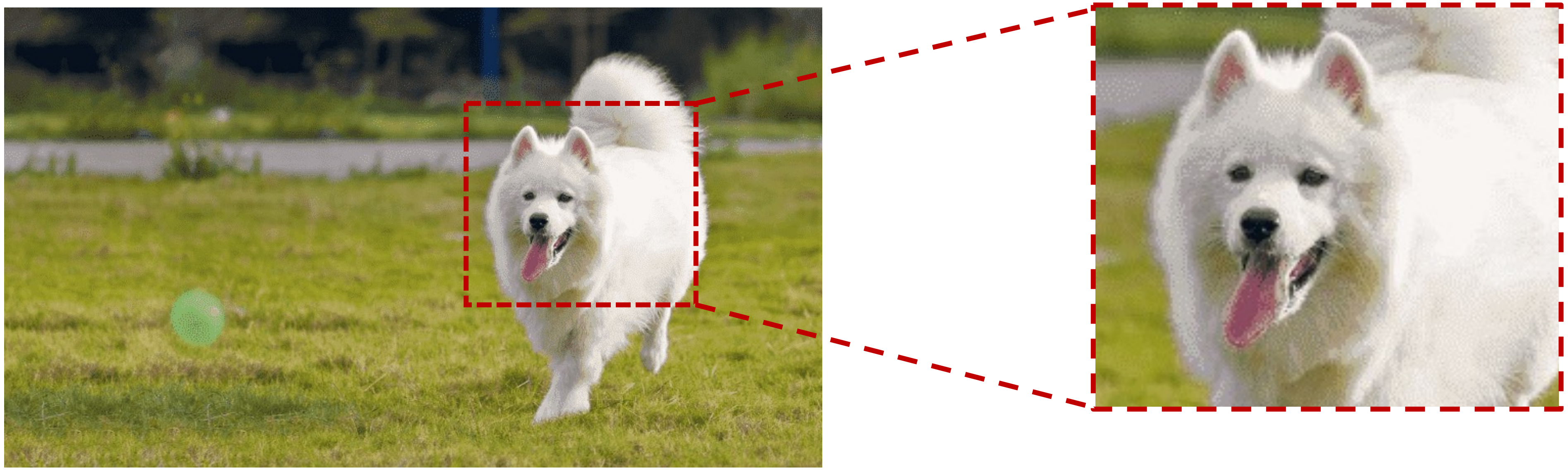
Classification, Generation

Differences among Image, Language, Time Series

TimesNet is for time series analysis.



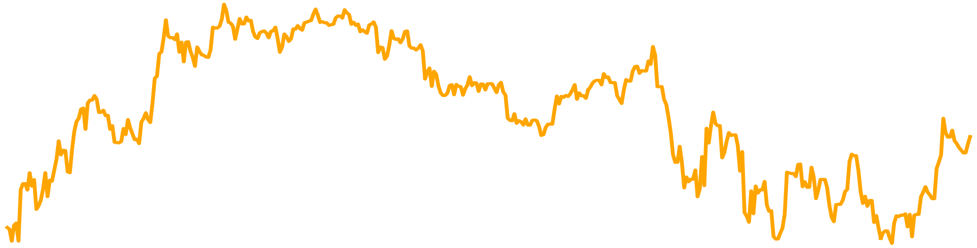
Differences among Image, Language, Time Series



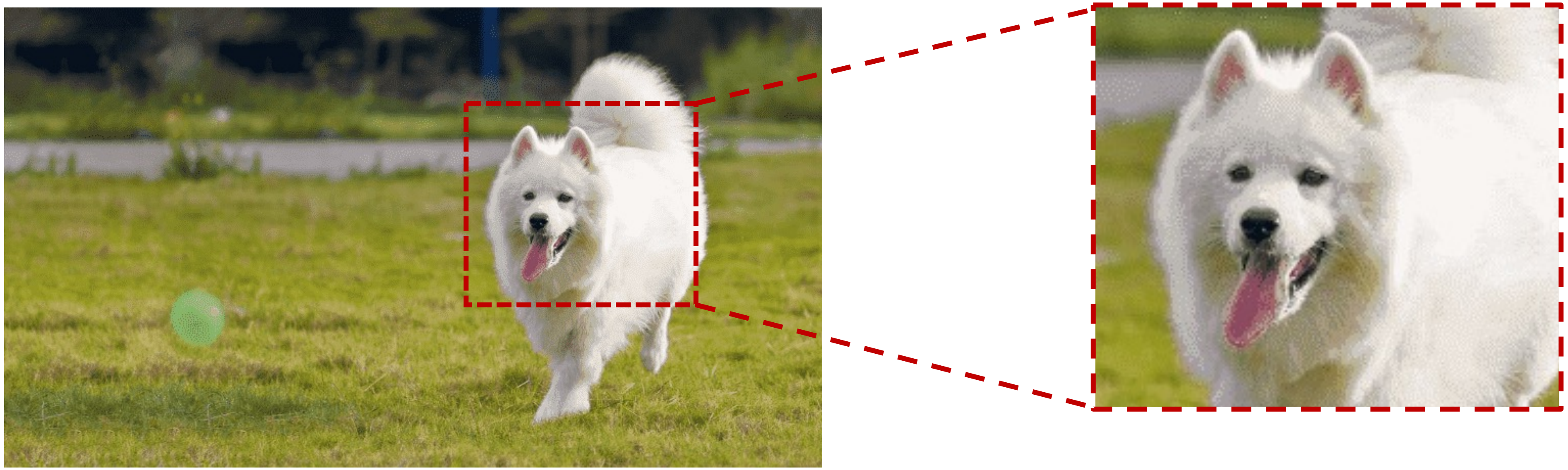
TimesNet is for time series analysis.

Analysis is the process of breaking a complex topic into smaller parts for a better understanding.

Wikipedia
The Free Encyclopedia

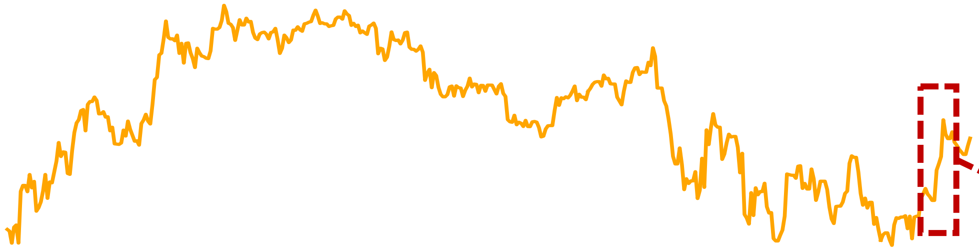


Differences among Image, Language, Time Series



TimesNet is for time series analysis.

Analysis is the process of breaking a complex topic into smaller parts for a better understanding.

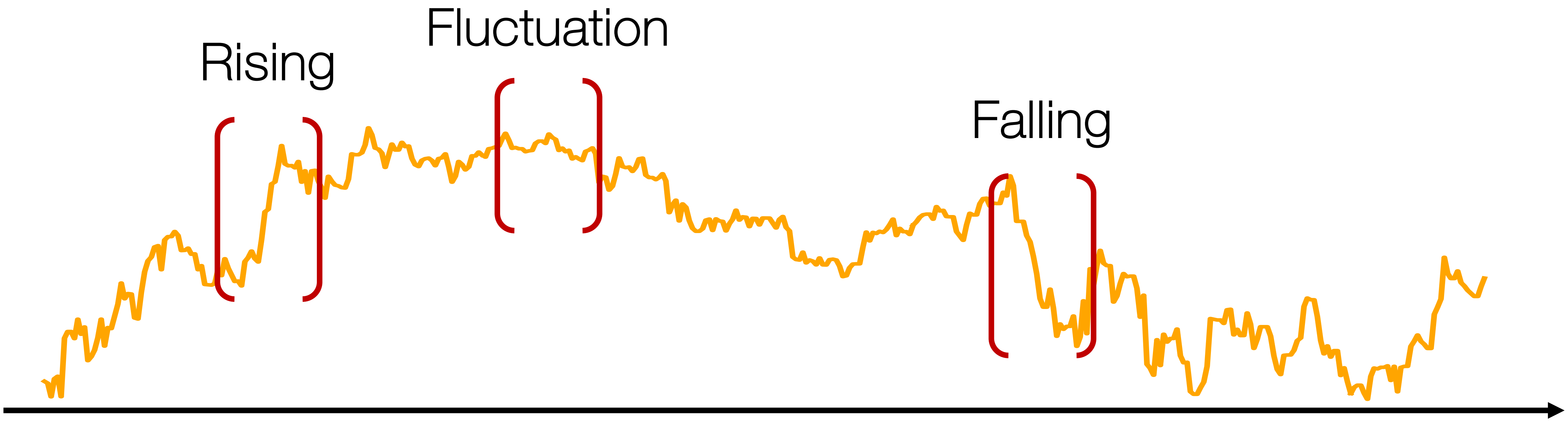


Each time point only saves some scalars.

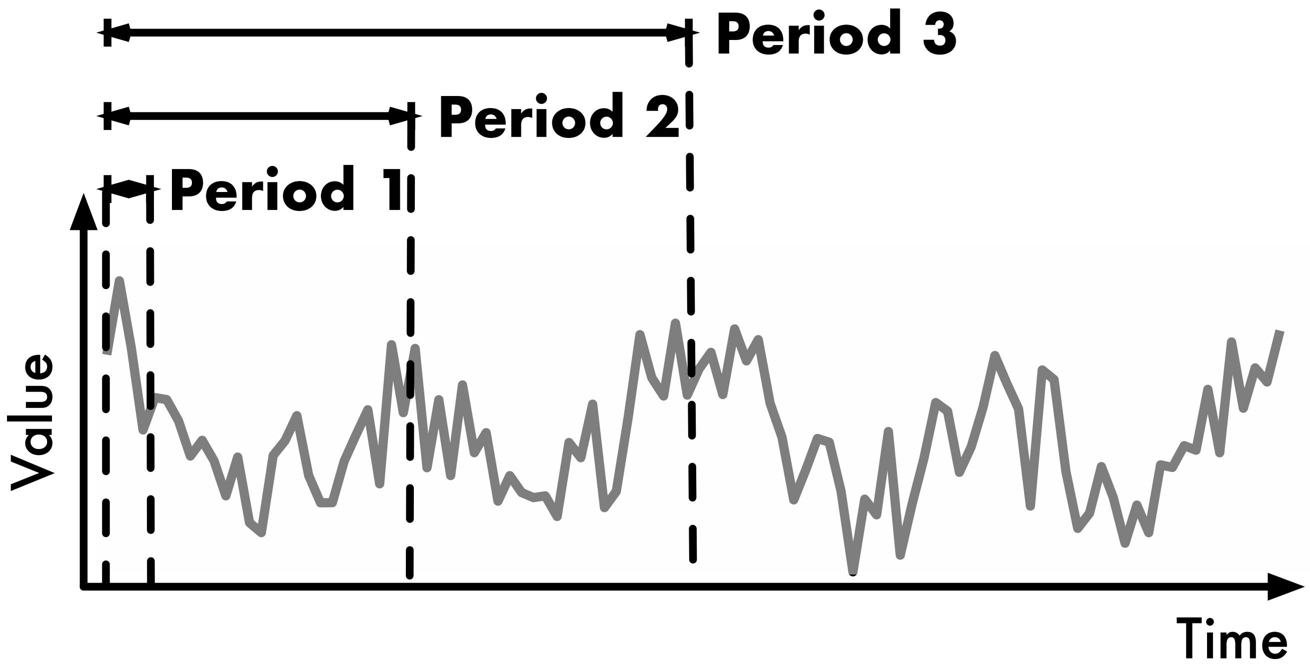
Temporal Variations of Time Series

More information of time series is in **temporal variations**,

such as continuity, periodicity, trend and etc.



Multi-periodicity View of Time Series

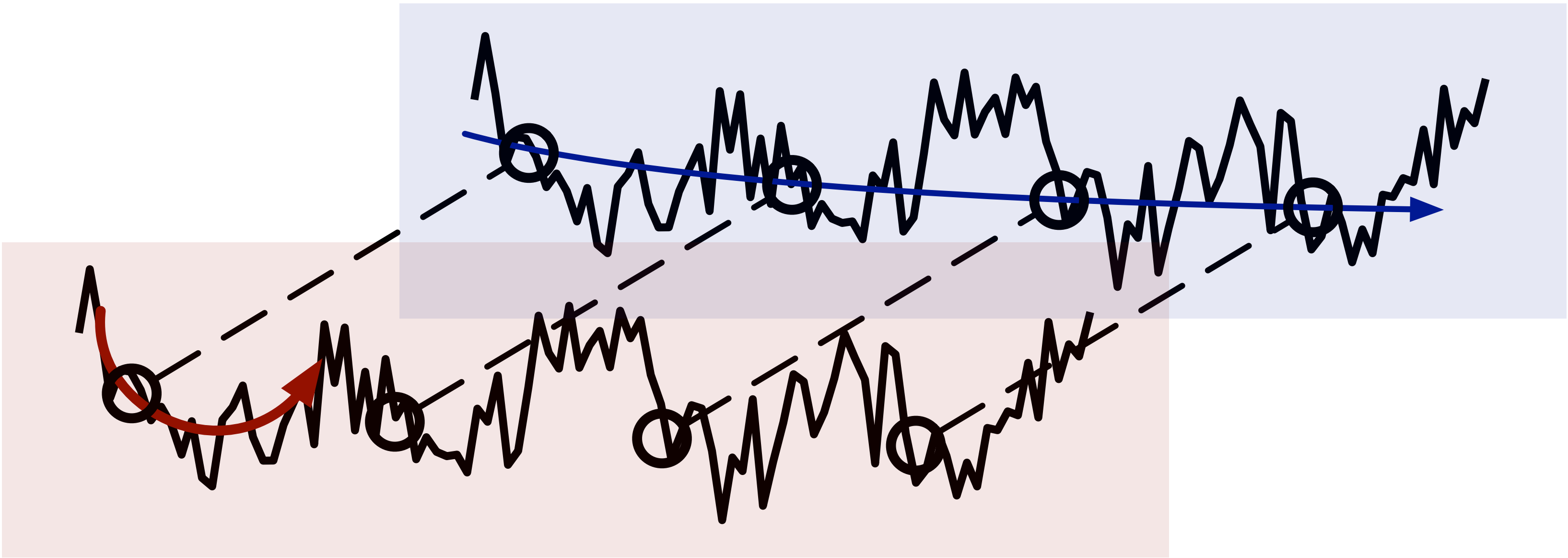


- ✓ Traffic: daily and weekly
- ✓ Weather: daily and yearly

Real-world time series usually present multi-periodicity.

Multiple periods overlap and interact with each other.

Intraperiod- and Interperiod-variations

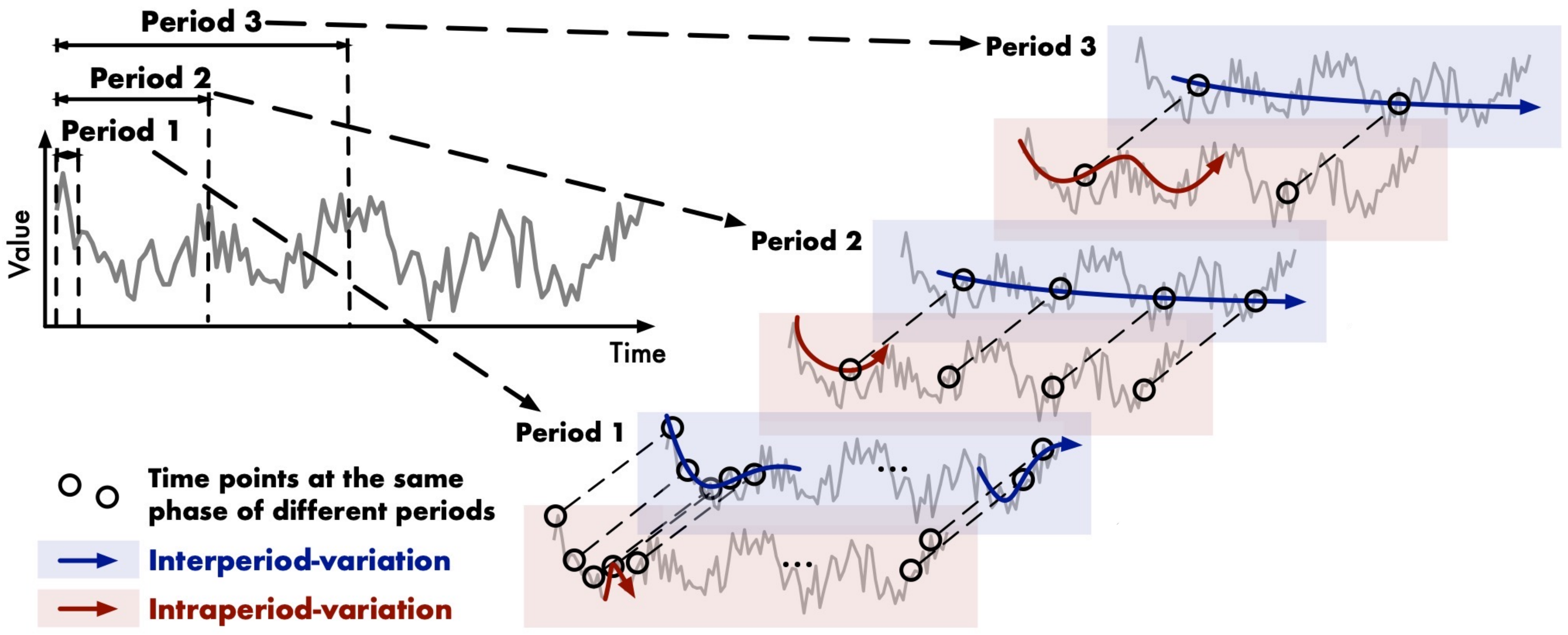


✓ **Intraperiod**: adjacent area, **short-term variations**

✓ **Interperiod**: same phase in adjacent periods, **long-term variations**

Non-periodic cases, the variations will be dominated by intraperiod-variations.

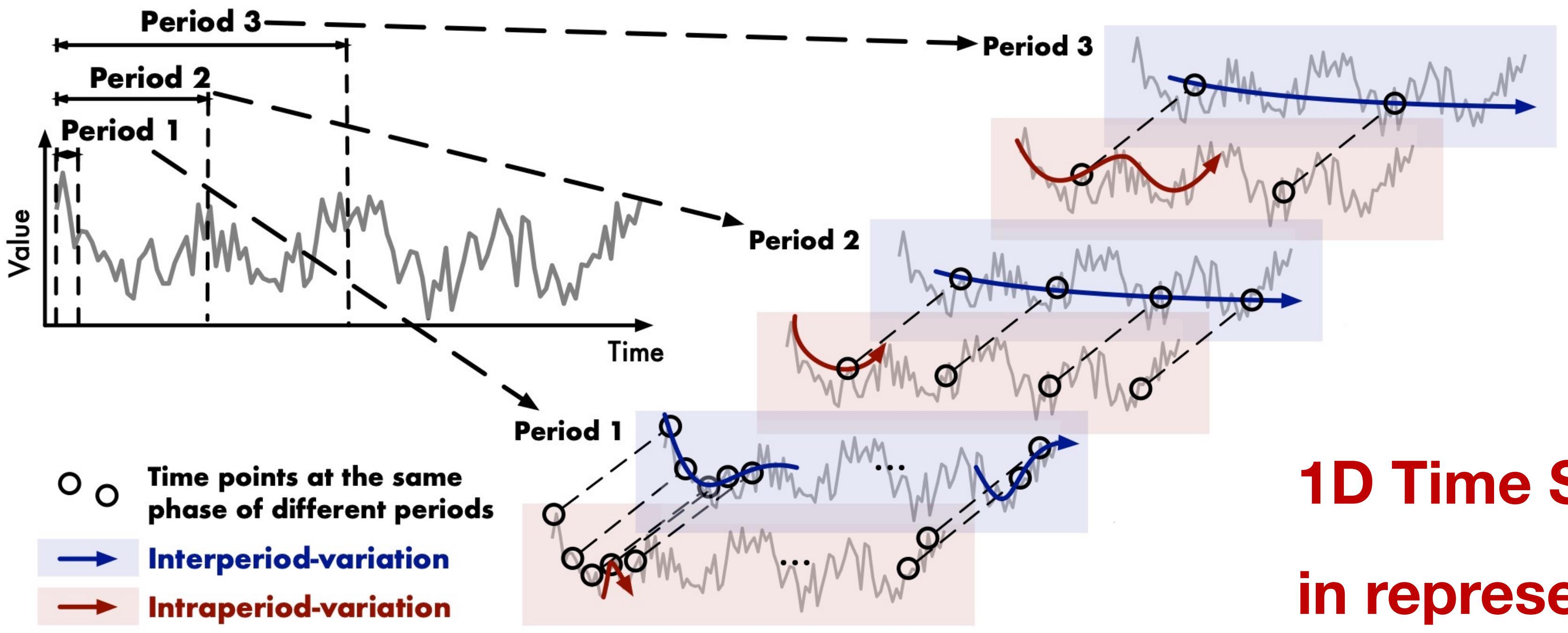
Overall design of TimesNet



① Multi-periodicity

A modular architecture to disentangle intricate temporal patterns

Overall design of TimesNet

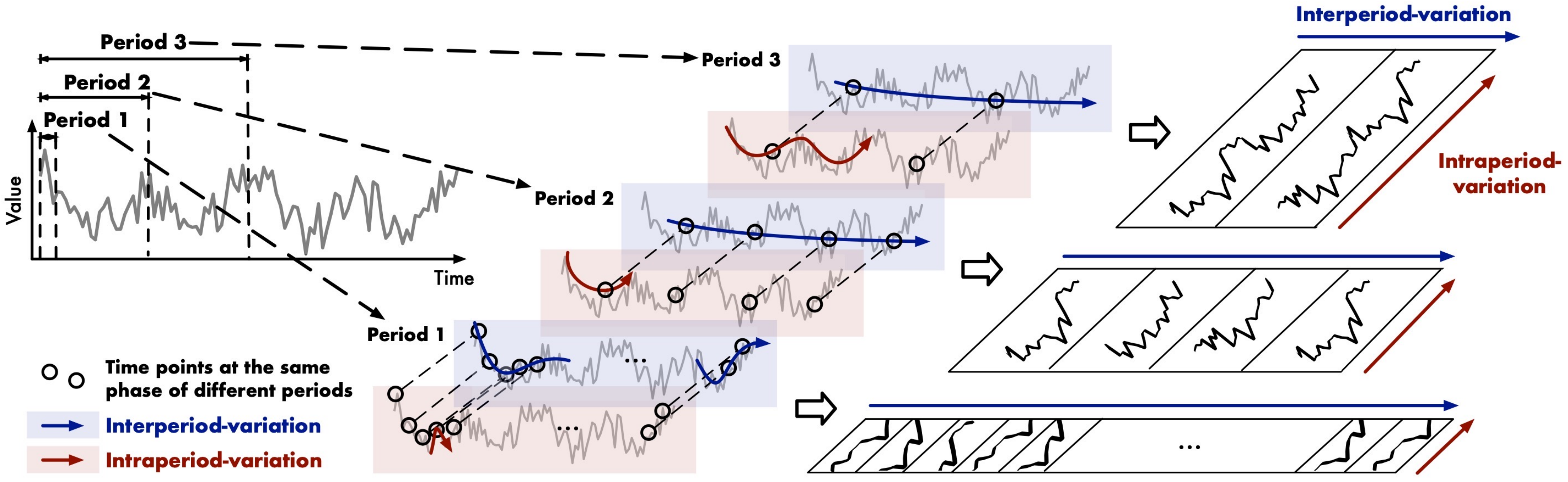


1D Time Series has limitations in representation capability.

① Multi-periodicity

A modular architecture to disentangle intricate temporal patterns

Overall design of TimesNet

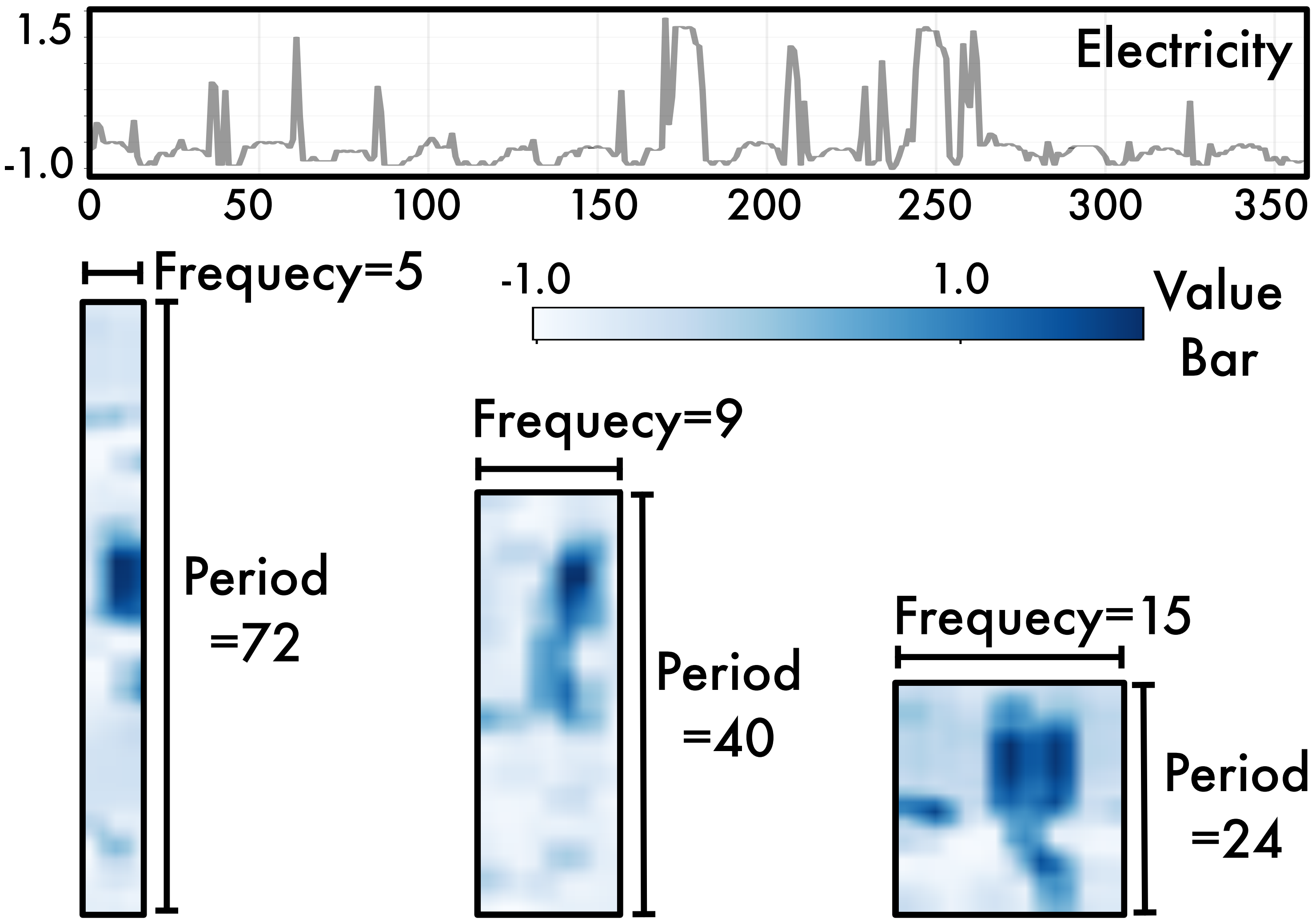


① Multi-periodicity ② Temporal 2D-variation

Unify intraperiod- and interperiod-variations in 2D space by reshape

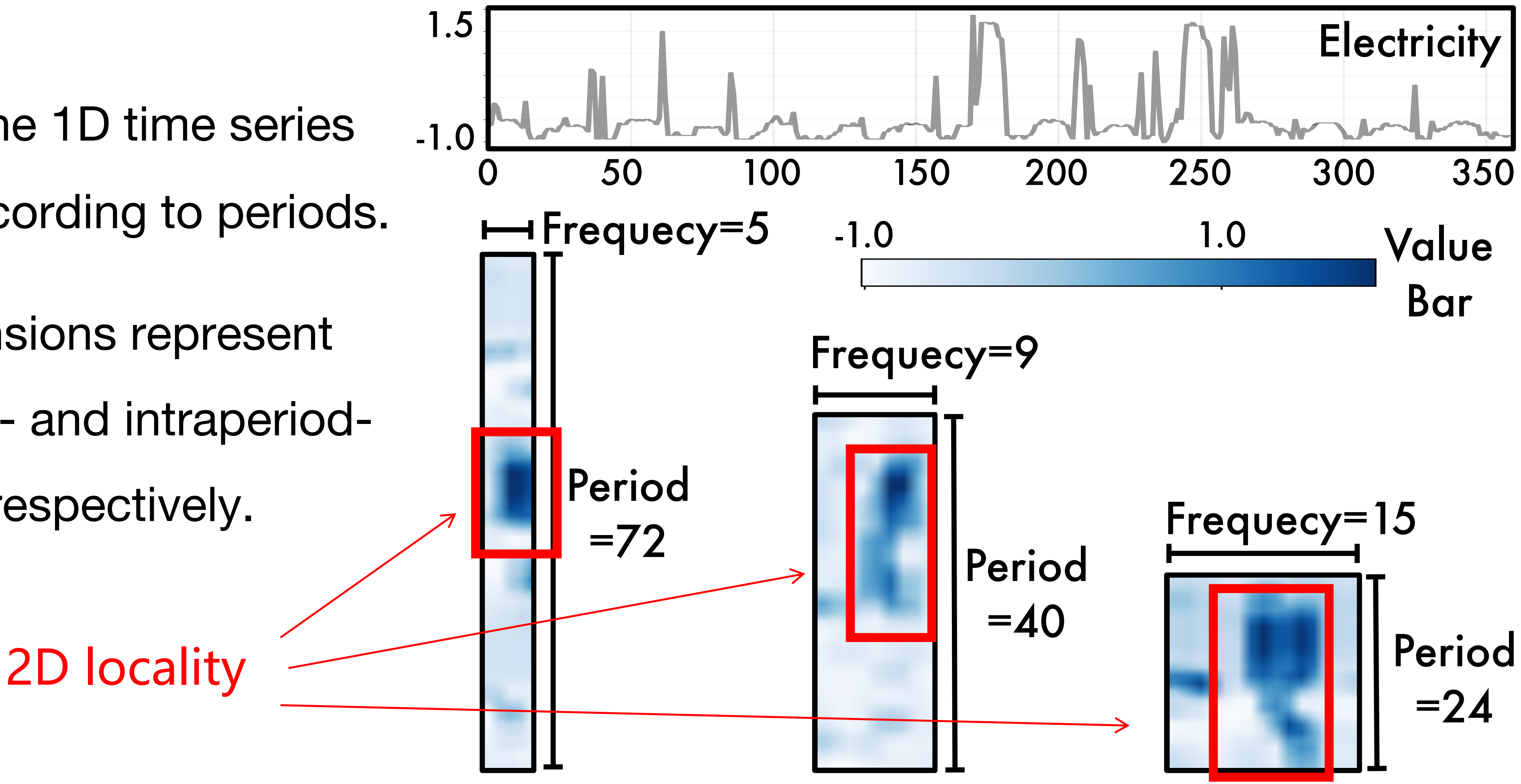
Temporal 2D-variation: A Case Study

- ✓ Reshape the 1D time series into 2D according to periods.
- ✓ Two dimensions represent interperiod- and intraperiod-variations respectively.

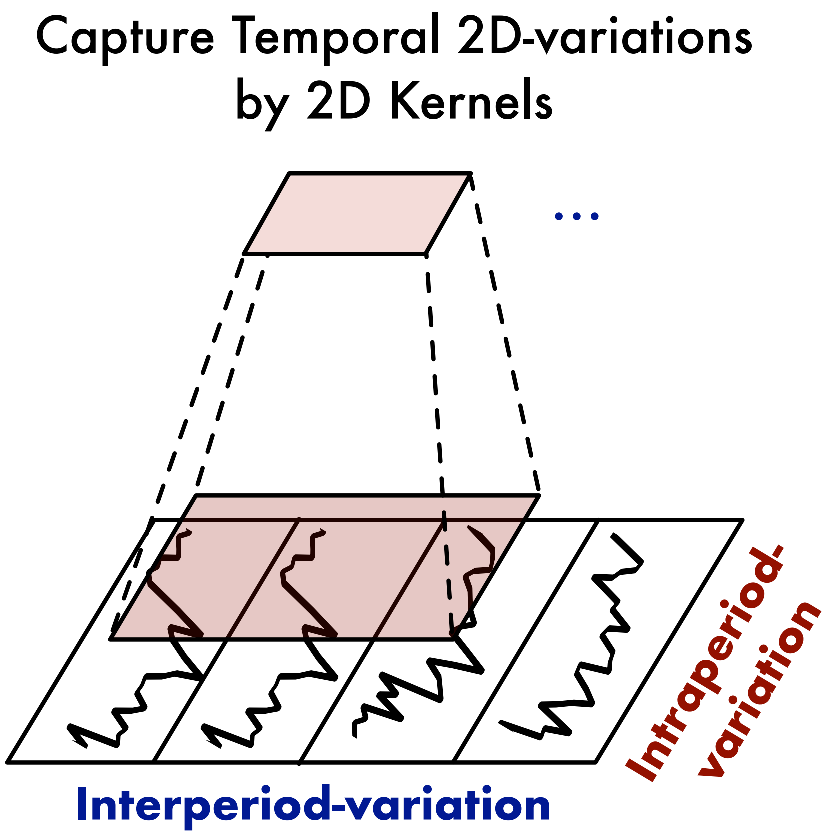


Temporal 2D-variation: A Case Study

- ✓ Reshape the 1D time series into 2D according to periods.
- ✓ Two dimensions represent interperiod- and intraperiod-variations respectively.



Temporal 2D-variation: A Case Study

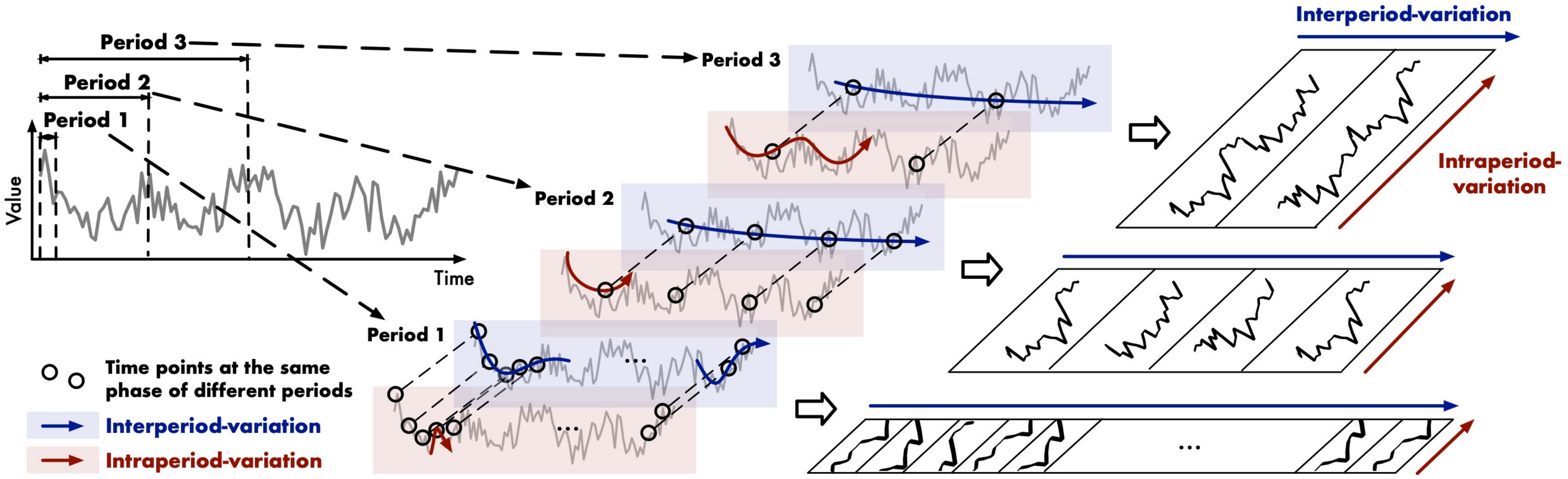


With temporal 2D-variations, we can

✓ Unify intraperiod- interperiod-variations

✓ Learn representations by 2D kernels

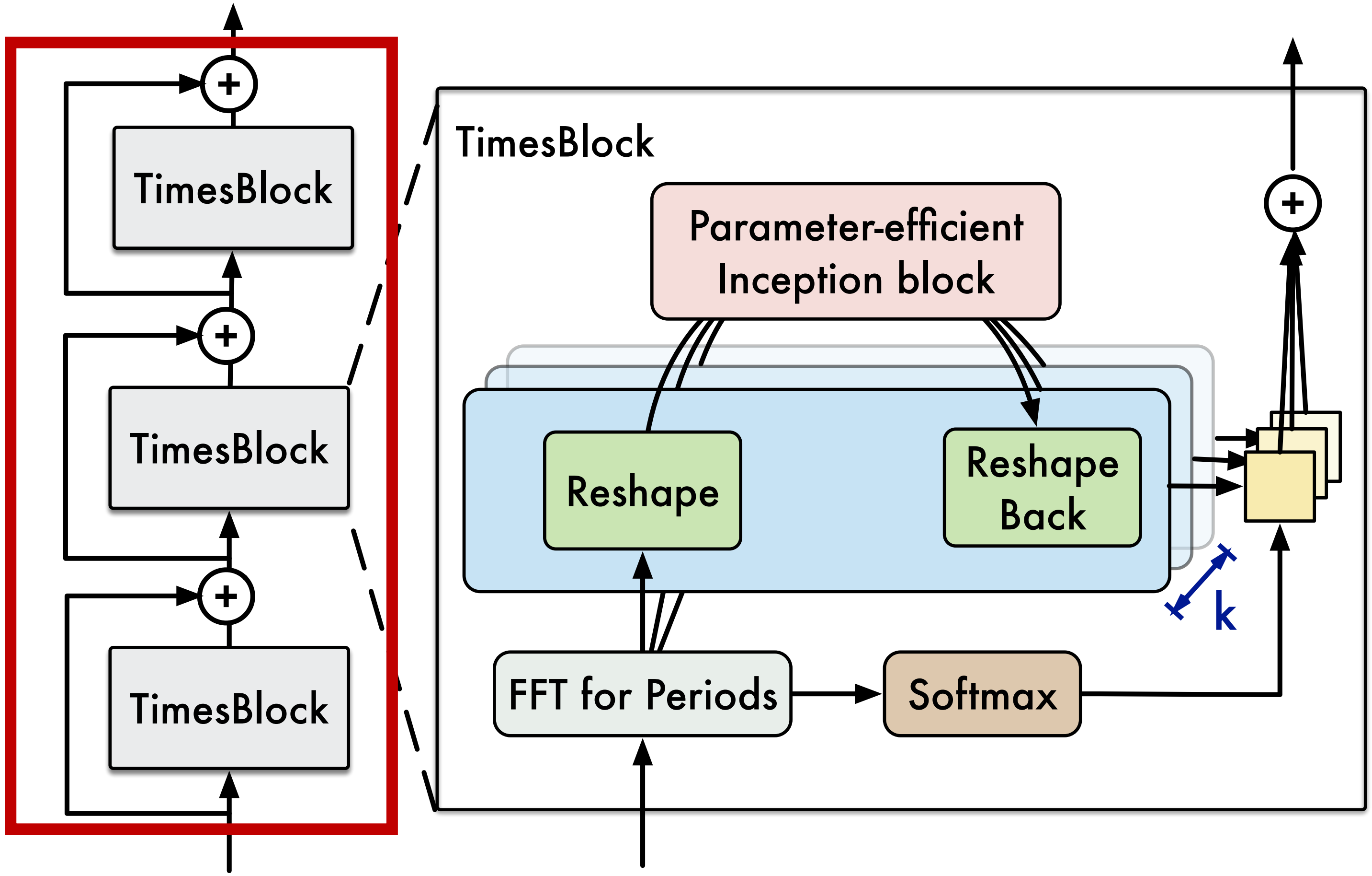
Overall design of TimesNet



① Multi-periodicity ② Temporal 2D-variation

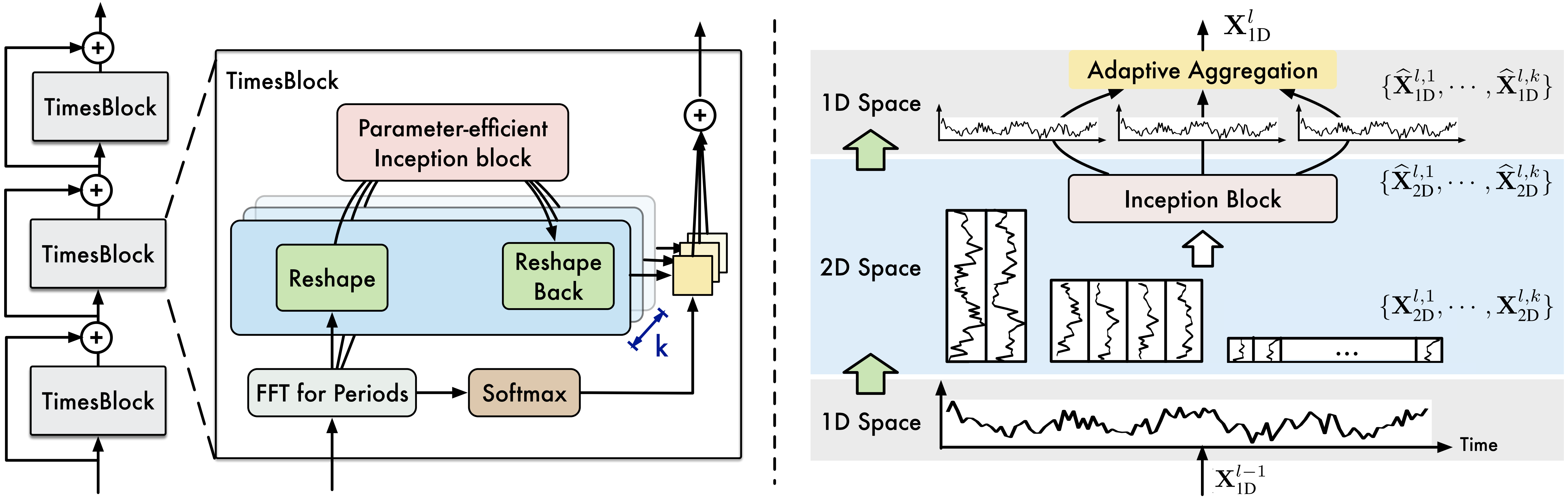
Unify intraperiod- and interperiod-variations in 2D

TimesNet



TimesNet consists of residual-connected **TimesBlocks**.

TimesBlock



TimesBlock learns representations in 2D space.

① 1D → 2D ② 2D representation learning ③ 2D → 1D

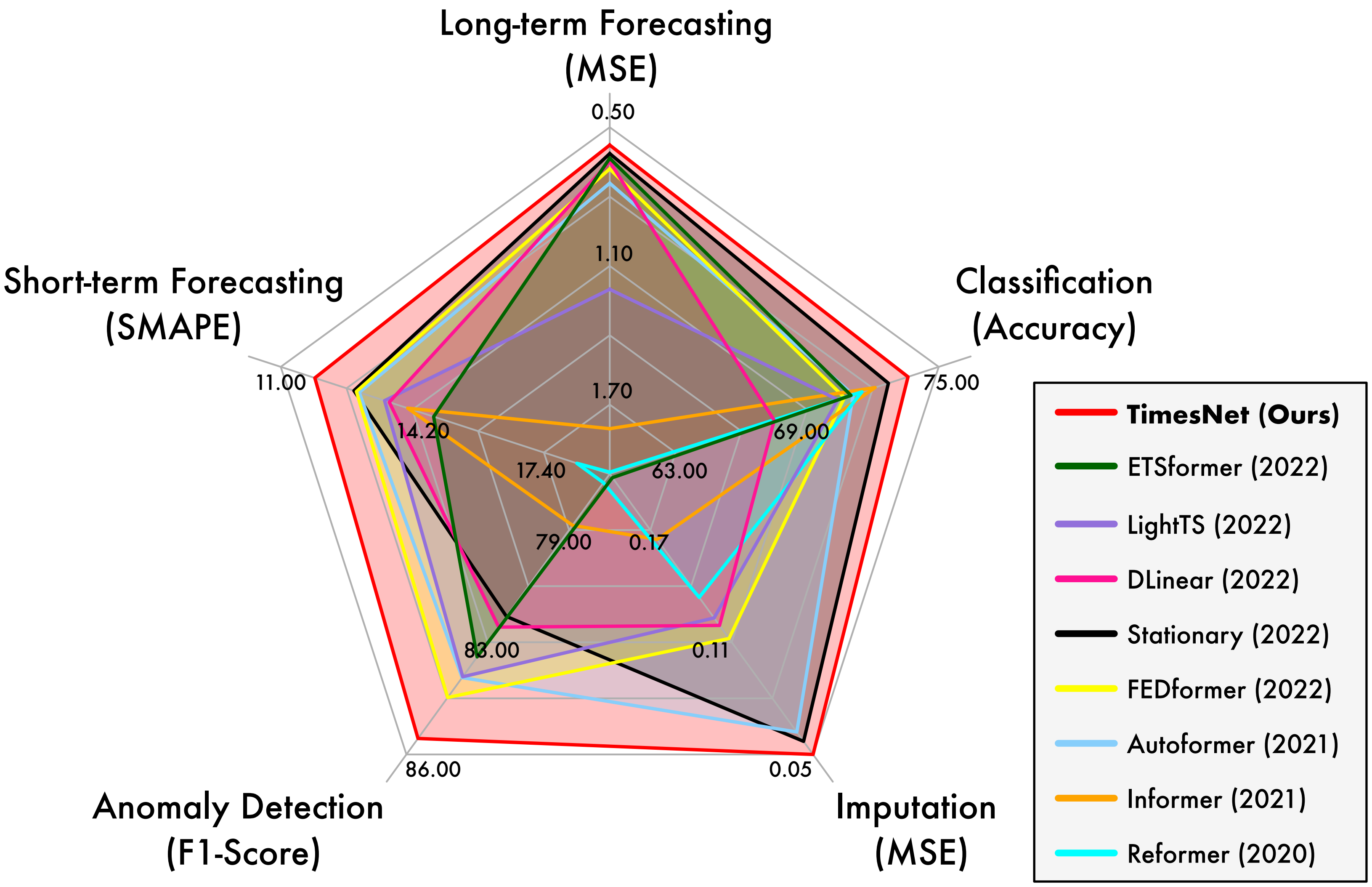
Experiment: Overall

Tasks	Benchmarks
Forecasting	**Long-term**: ETT (4 subsets), Electricity, Traffic, Weather, Exchange, ILI
	Short-term: M4 (6 subsets)
Imputation	ETT (4 subsets), Electricity, Weather
Classification	UEA (10 subsets)
Anomaly Detection	SMD, MSL, SMAP, SWaT, PSM

✓ Five mainstream time series analysis tasks.

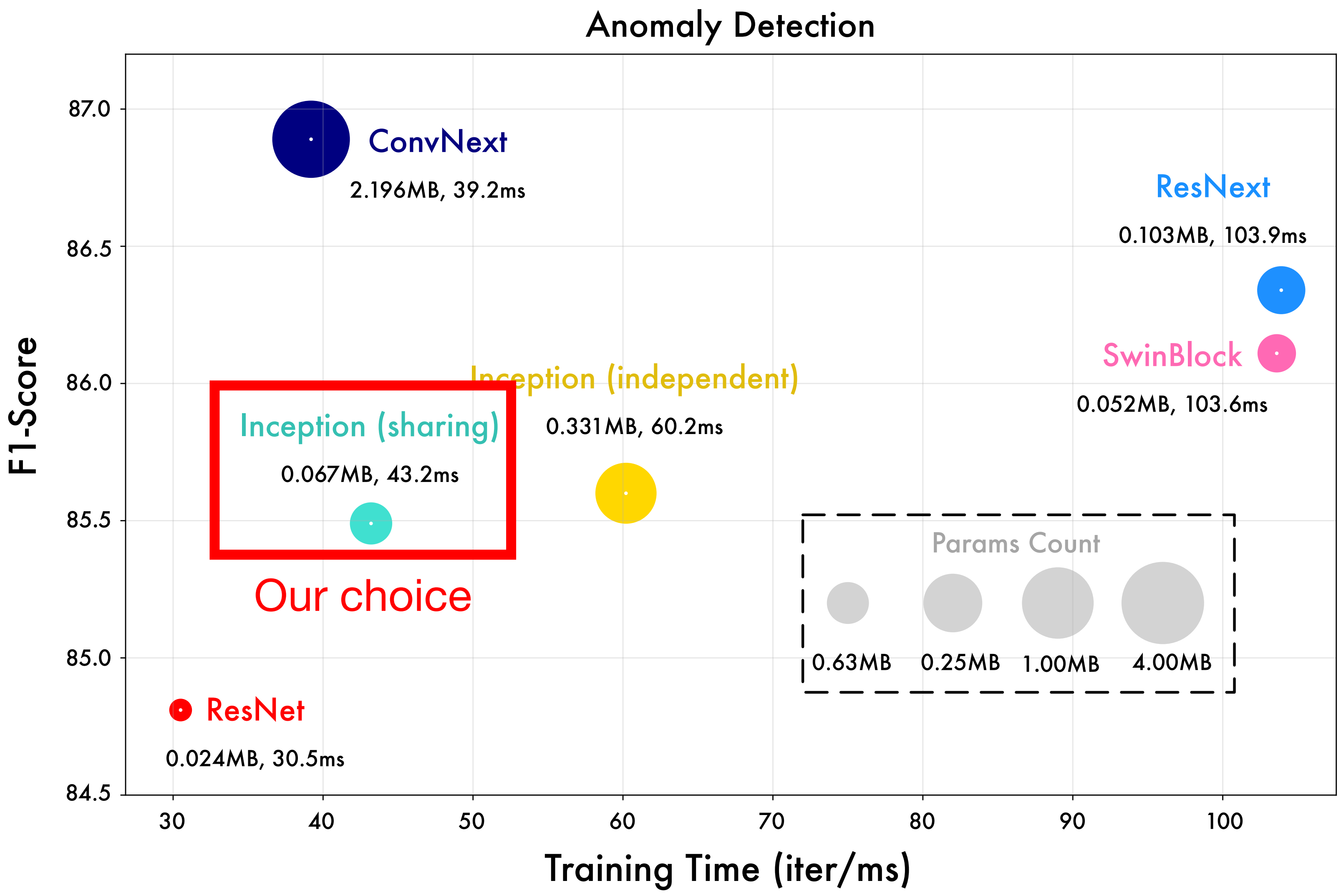
✓ 36 datasets, 81 settings, 20+ baselines

Experiment: Overall



TimesNet achieves state-of-the-art in all five tasks (2023/02)

Model Generality



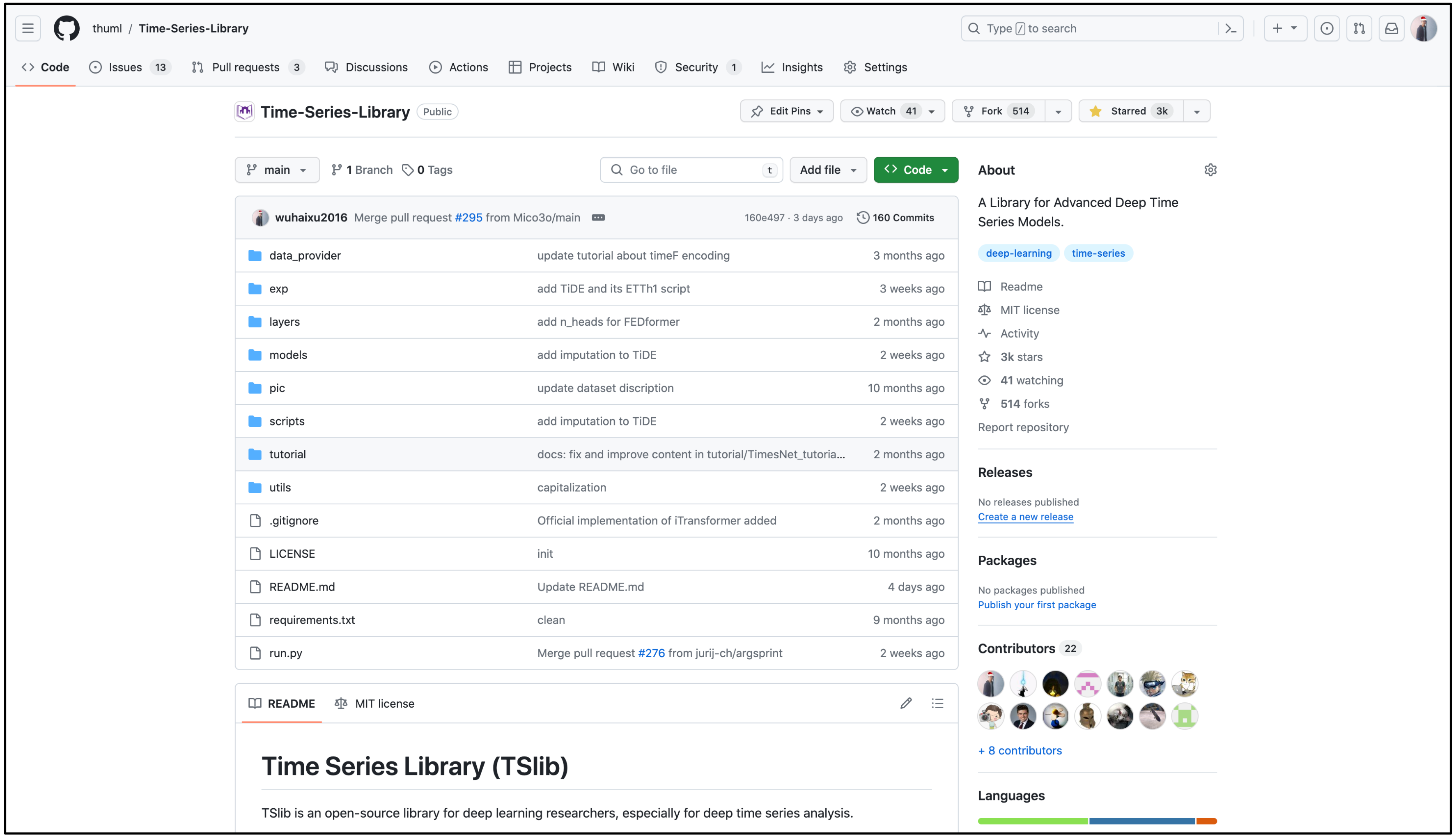
Better vision backbones,

Better performance 🏆

Bridge Time Series and

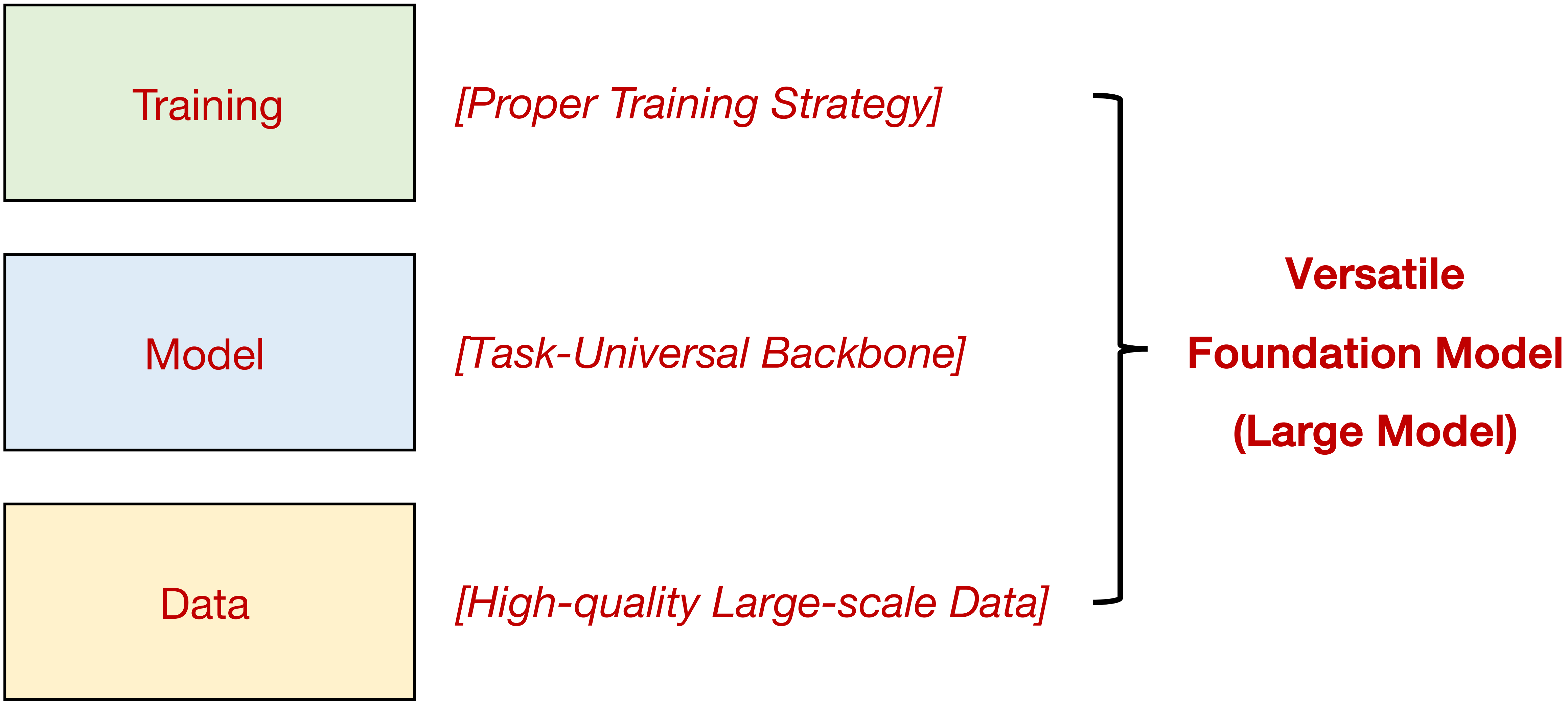
vision backbones 🏆

Time Series Library (TSlib)



Code is available at https://github.com/thuml/Time-Series-Library with 3000+ stars

Foundation Models for Time Series



AIOps Challenge

2023 CCF国际AIOps挑战赛决赛暨“大模型时代的AIOps”研讨会

THANKS