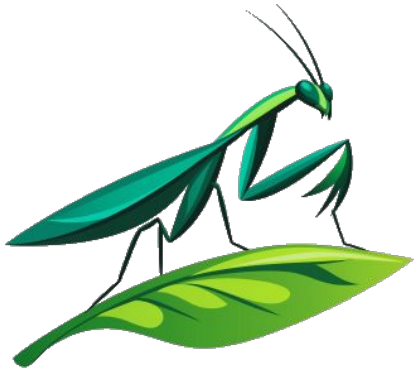


Mantis: Lightweight Foundation Model for Time Series Classification

Vasilii Feofanov

Collaborators: Songkang Wen, Shifeng Xie, Simon Roschmann, Marius Alonso, Romain Ilbert, Yessin Moakher, Théo Gnassounou, Youssef Attia El Hili, Ambroise Odonnat, Hongbo Guo, Malik Tiomoko, Quentin Bouniot, Zeynep Akata, Lujia Pan, Jianfeng Zhang, and Ievgen Redko

GitHub

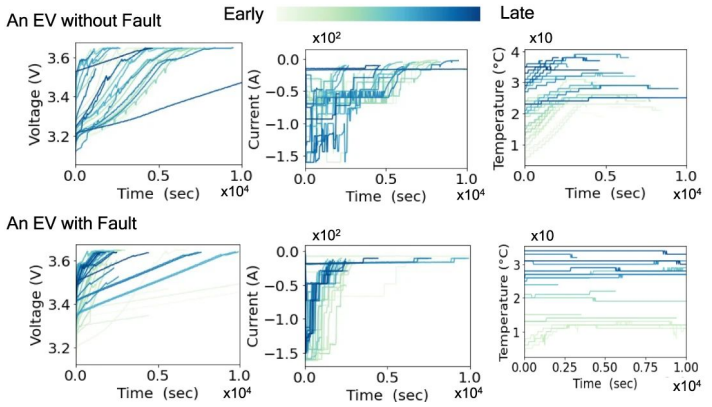
Paper

Scope

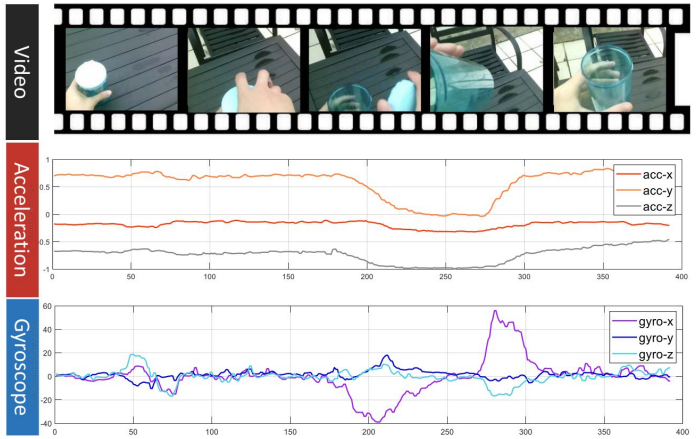
1. (Feofanov et al., 2025) Mantis: Lightweight calibrated foundation model for user-friendly time series classification.
2. (Feofanov et al., 2026) MantisV2: Closing the Zero-Shot Gap in Time Series Classification with Synthetic Data and Test-Time Strategies (*ICLR'26 TSALM workshop*).
3. (Xie et al., 2026) CauKer: classification time series foundation models can be pretrained on synthetic data only. (*ICLR'26 oral)*.
4. (Moakher et al., 2026) UTICA: Multi-Objective Self-Distillation Foundation Model Pretraining for Time Series Classification (*ICLR'26 TSALM workshop*).
5. (Odonnat et al., 2026) Layer by layer, module by module: Choose both for optimal OOD probing of ViT (*ICLR'26 CAO workshop*).
6. (Roschmann et al., 2025) Time Series Representations for Classification Lie Hidden in Pretrained Vision Transformers.
7. (Gnassounou et al., 2025) Leveraging Generic Time Series Foundation Models for EEG Classification.

Time Series Classification

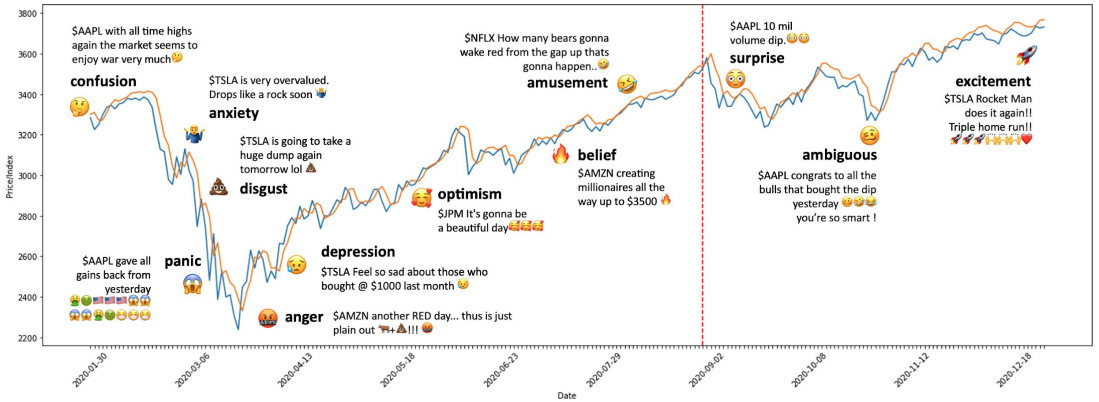
1. Cardiovascular Disease Diagnostic



2. Fault Detection of Electric Vehicle's Battery

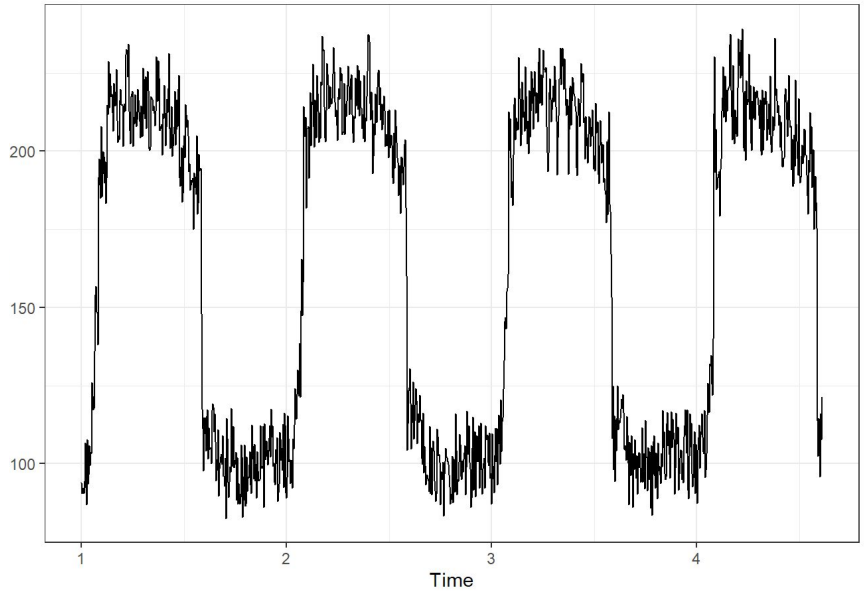


3. Human Activity Recognition



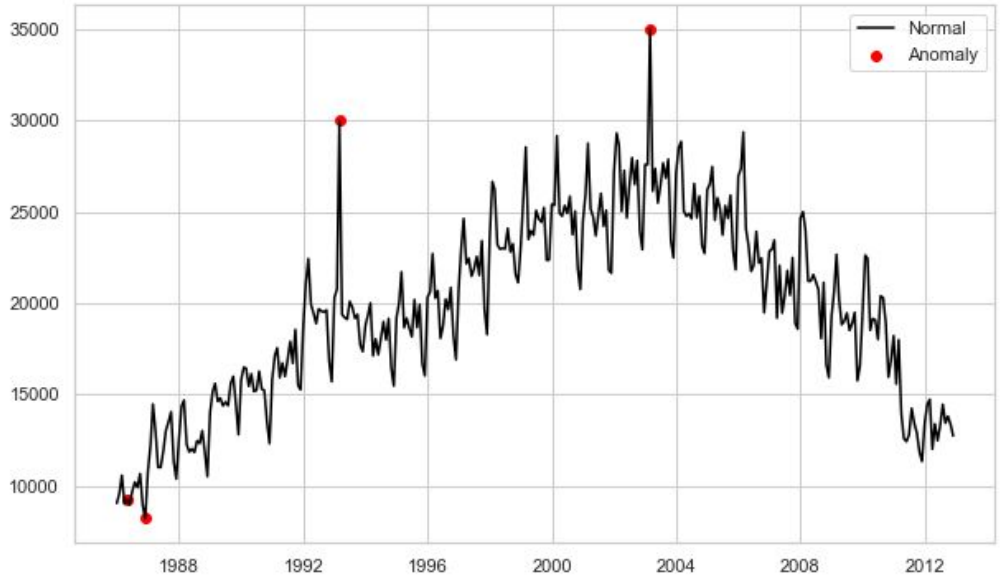
4. Finance: Prediction of Sentiment or Direction

Forecasting vs Classification



Forecasting: predict future patterns based on previously seen ones.

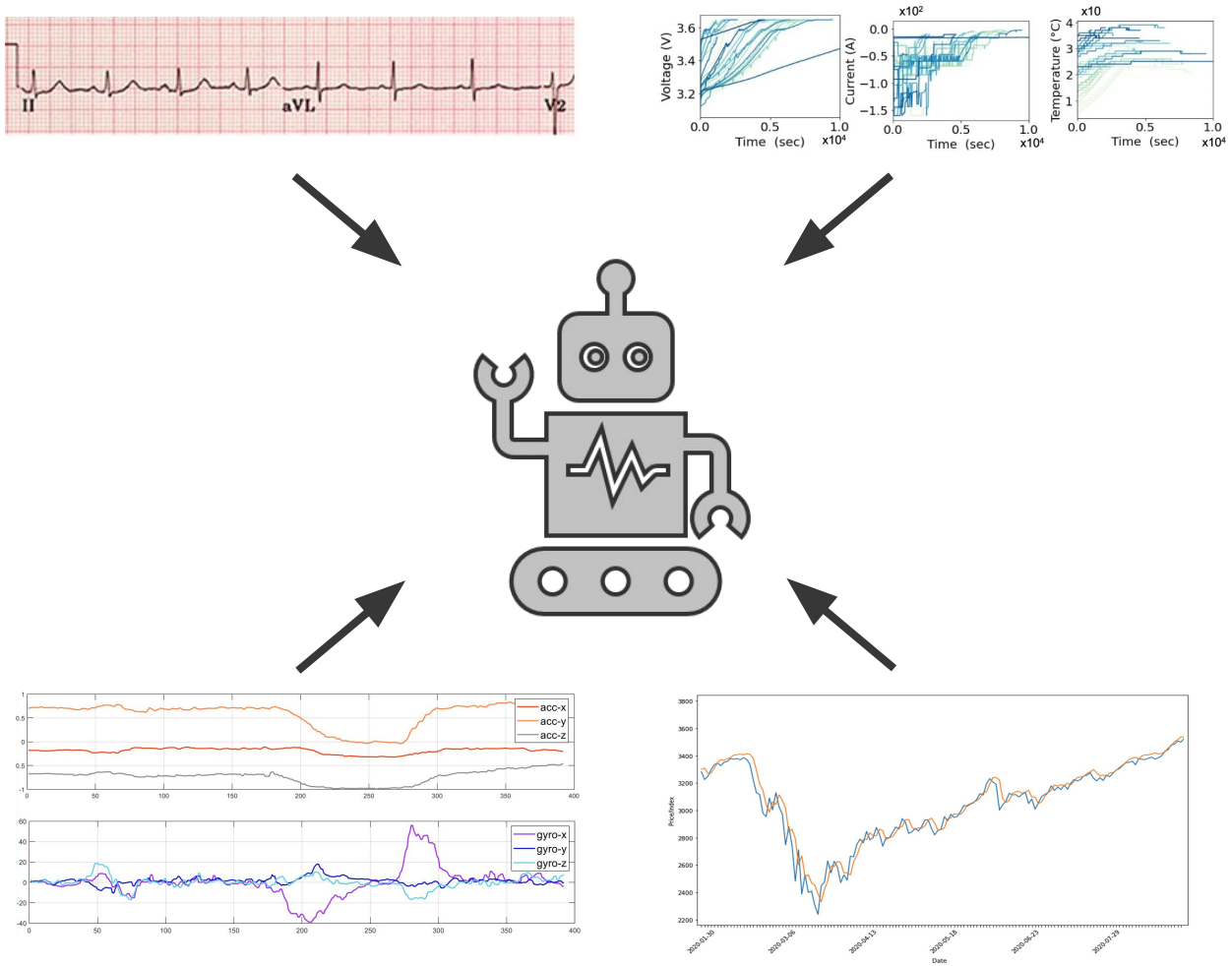
Jittering is often somewhat arbitrary => smoothing may be a good thing.



Classification: discriminate, detect anomalies.

Some spikes are a very important source of information!

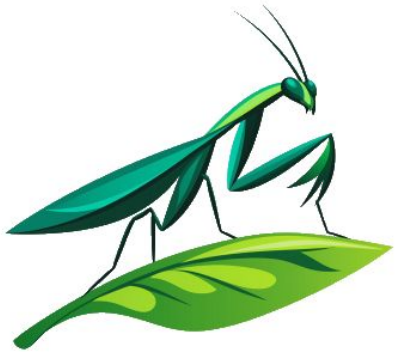
Time Series Foundation Model (TSFM)



The goal of a TSFM is to learn a projector using a large corpus of various datasets.

Advantages:

1. Versatility: one model for different problems.
2. Knowledge alignment with a new task.



Mantis: Framework

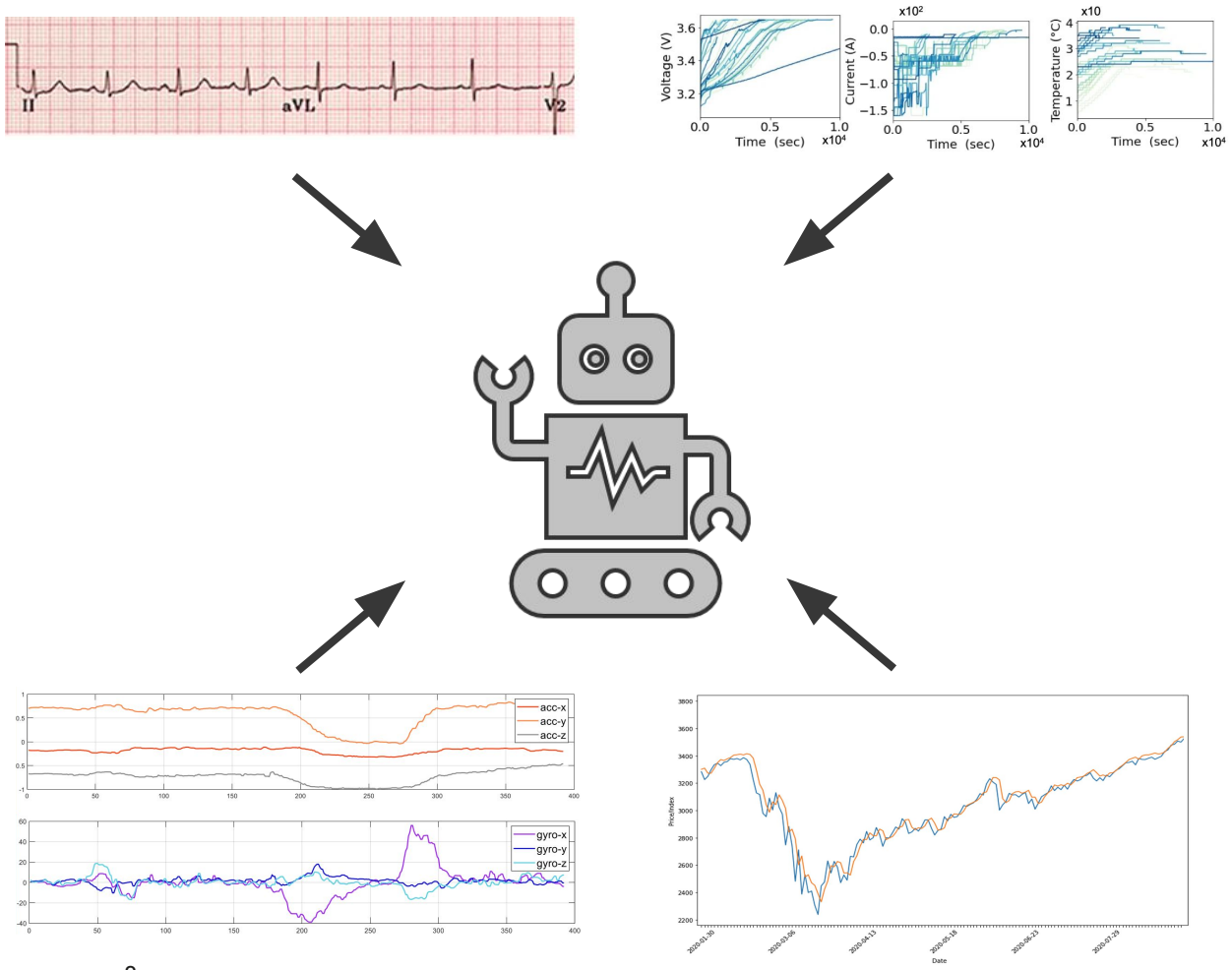
Available Models

	Mantis	Mantis+	MantisV2
Module	`MantisV1`	`MantisV1`	`MantisV2`
Checkpoint	`paris-noah/Mantis-8M`	`paris-noah/MantisPlus`	`paris-noah/MantisV2`

- **Mantis**: original version (8M params) pre-trained on a collection of real datasets.
- **Mantis+**: new checkpoint when pre-training on synthetic data.
- **MantisV2**: architecture refinement (4M params) + synthetic pre-training.

GitHub

Time Series Foundation Model (TSFM)



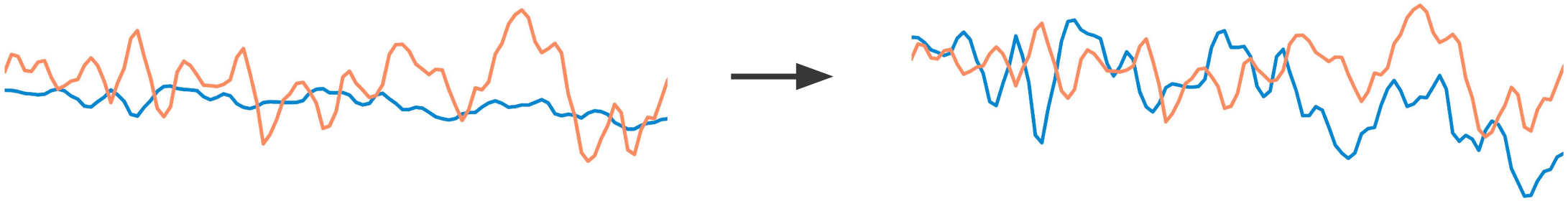
The goal of a TSFM is to learn a projector using a large corpus of various datasets.

Step 0: Data Preparation

a. Scale to same units.
b. Fix the context size.
c. Univariate dataset.

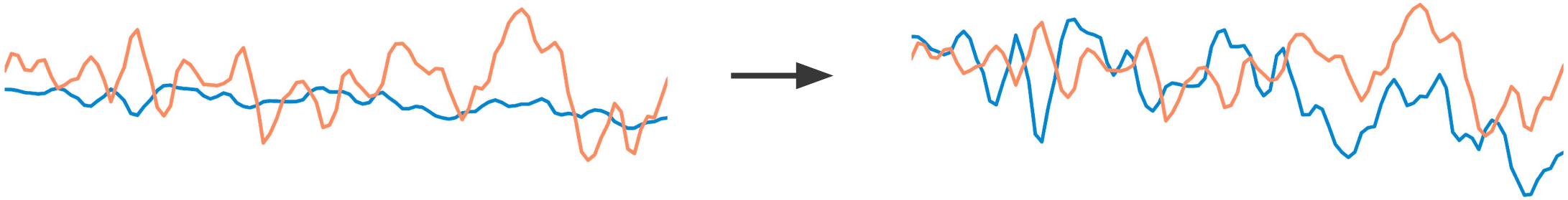
Pre-training Dataset Preparation

1. Instance-Wise Normalization

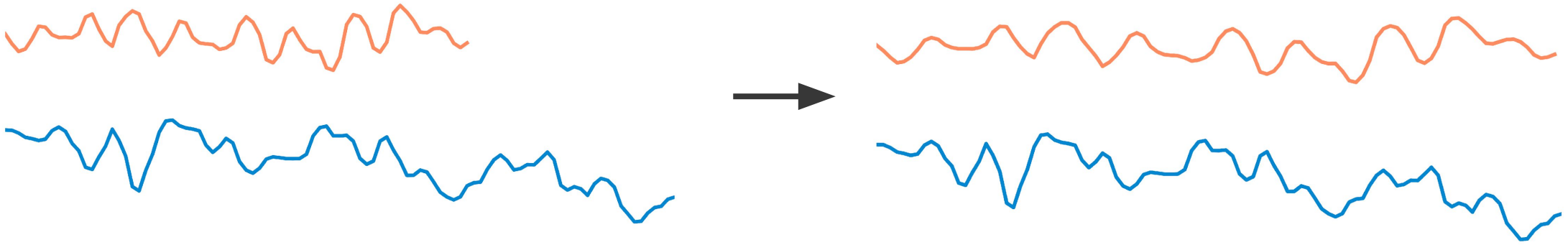


Pre-training Dataset Preparation

1. Instance-Wise Normalization

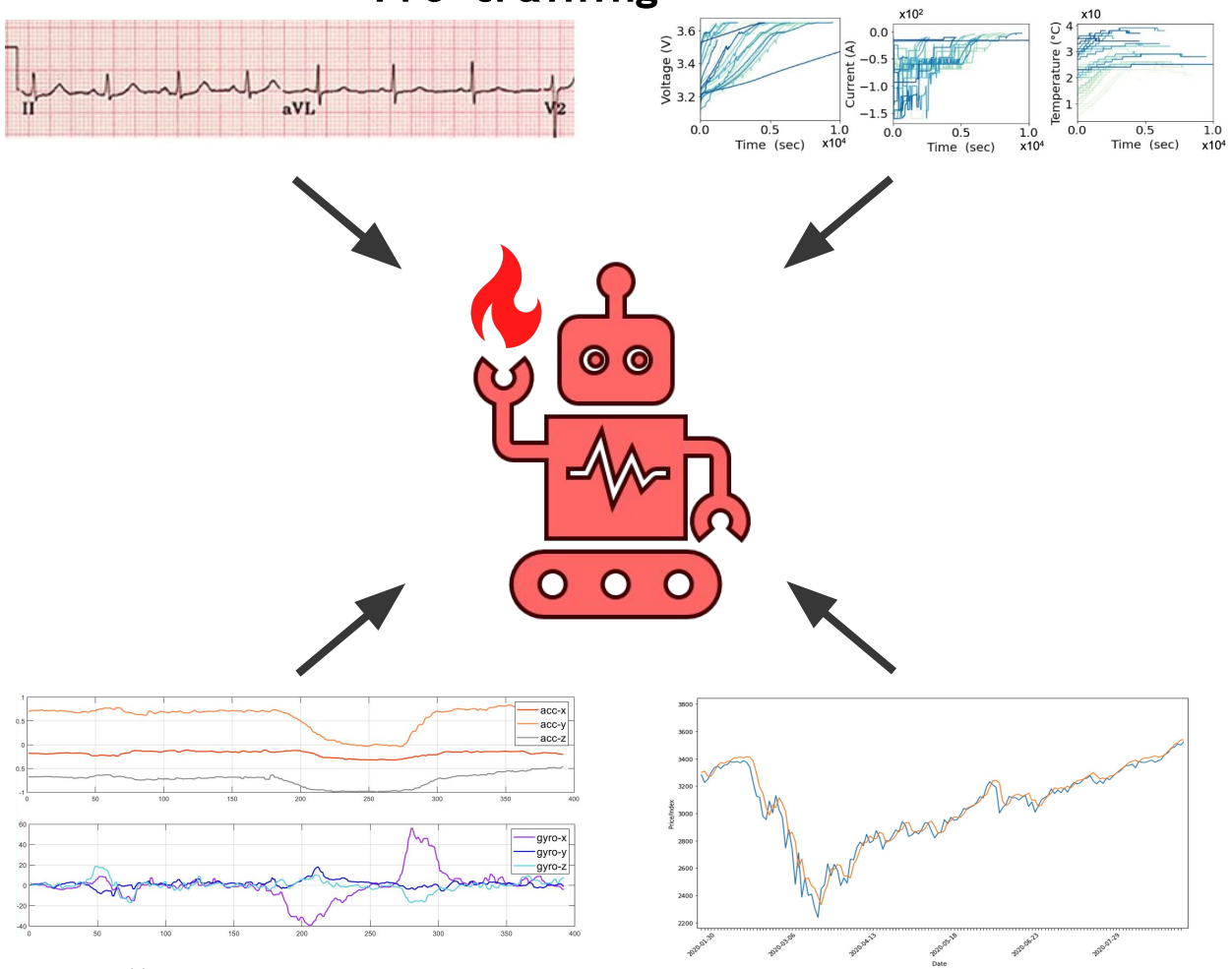


2. Resize by Interpolation



Time Series Foundation Model (TSFM)

Step 1:
Pre-training

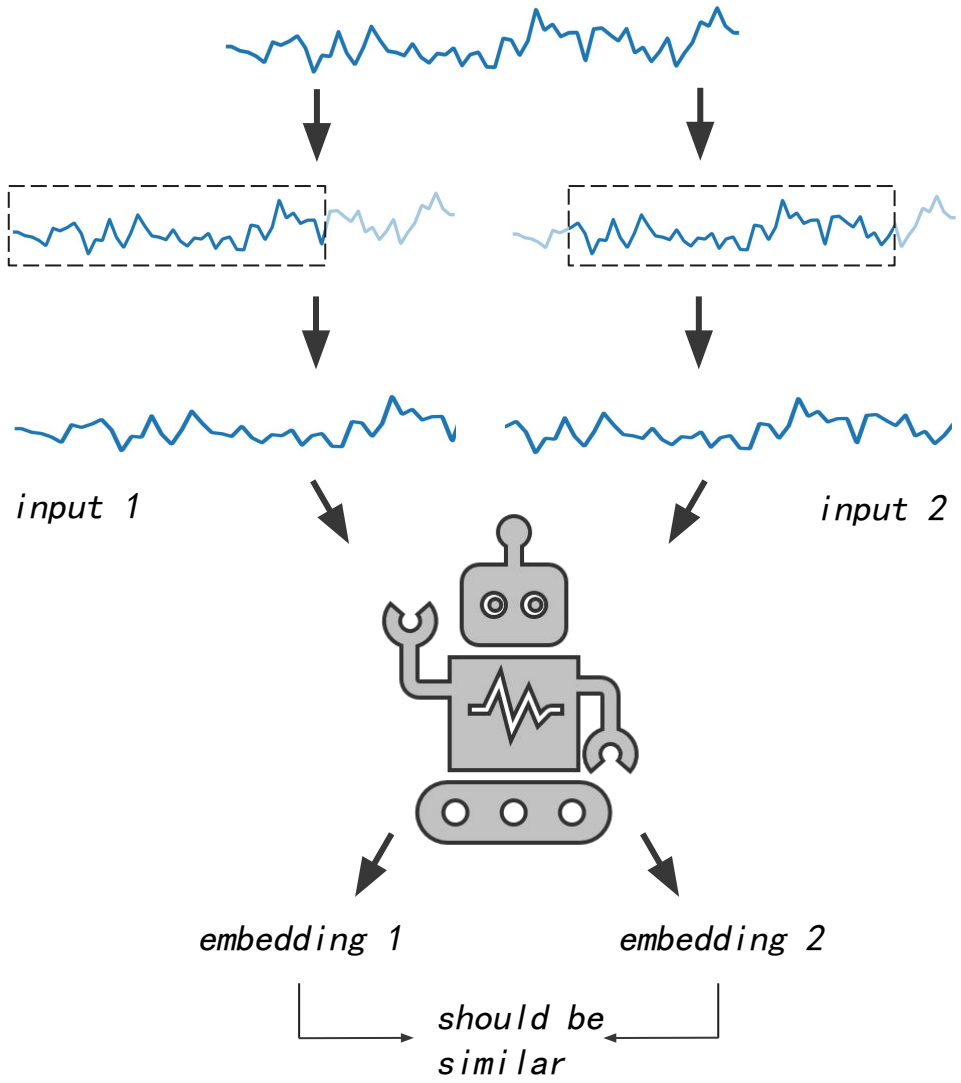


Pre-train a projector using one of the two options:

1. Unsupervised (self-supervised):
   a. Contrastive learning.
   b. Masked reconstruction.
   c. Self-distillation.

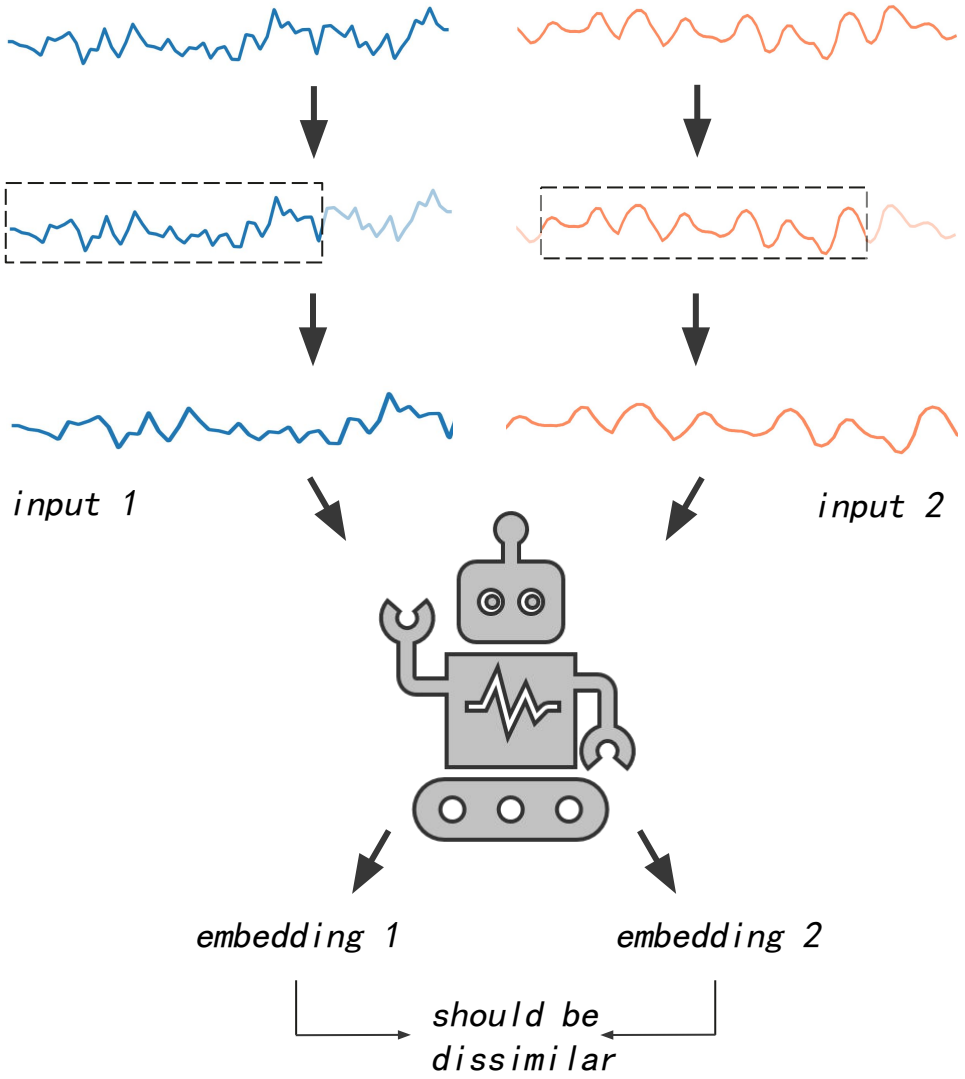
2. Supervised (multi-task).

Pre-training by Contrastive Learning



- Make positive pairs close to each other, negative pairs – far away from each other.
- Positive pair: 2 augmentations of the same time series.
- Augmentation: random-crop-resize.

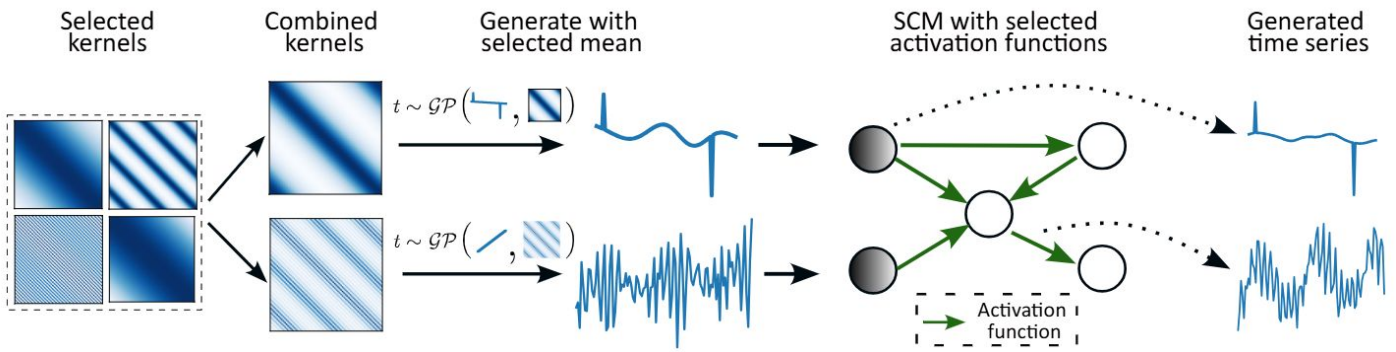
Pre-training by Contrastive Learning



- Make positive pairs close to each other, negative pairs – far away from each other.
- Positive pair: 2 augmentations of the same time series.
- Augmentation: random-crop-resize.
- Negative pair: different examples

Synthetic Pre-training Data

CauKer: synthetic data generation algorithm.



(1) *Priors*: multiple Gaussian processes with different mean functions and covariance kernels.

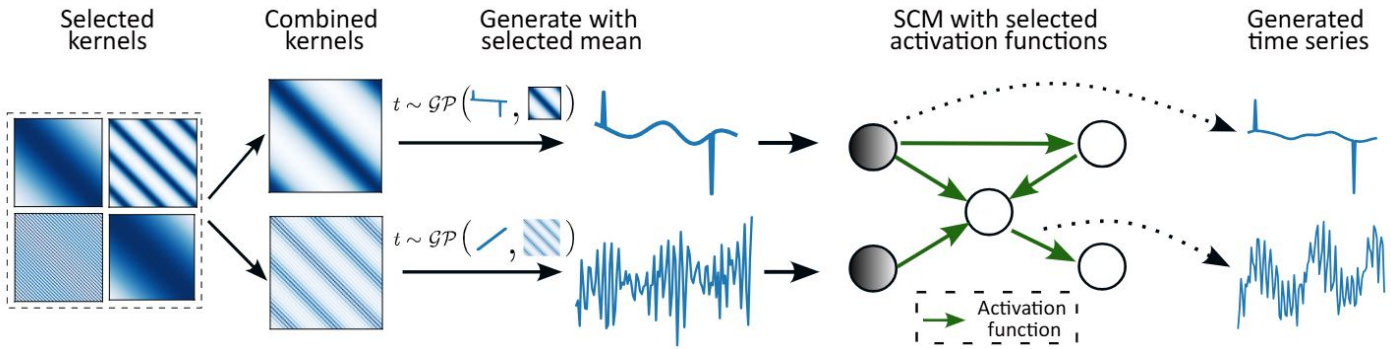
(2) *Causal graph*: priors are root nodes of a structural causal graph with a non-linear activation at each node.

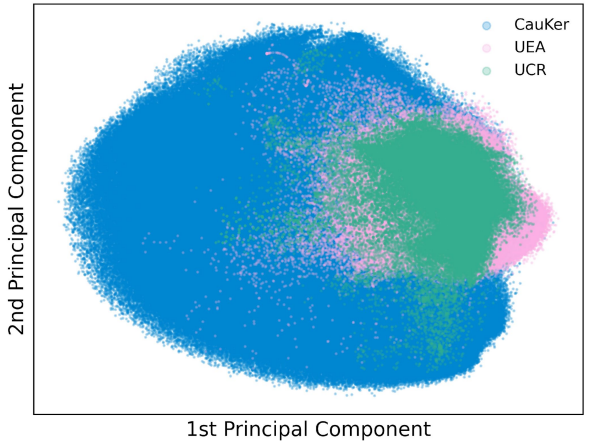
S. Xie et al. (2026). CauKer: classification time series foundation models can be pretrained on synthetic data only. (*ICLR'26 oral)*.

Synthetic Pre-training Data

CauKer: synthetic data generation algorithm that yields

- Large data diversity.
- Sample efficiency.
- Similar performance to real pre-training data.



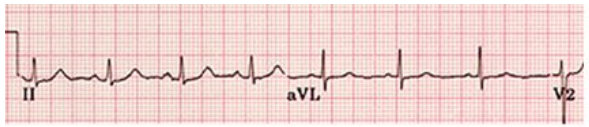


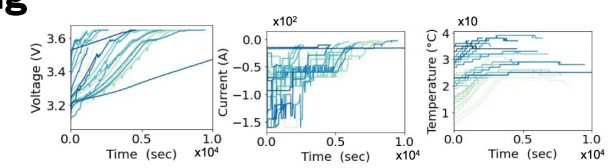
Pre-training Data	Nature	Size	UCR Included?	UCR acc. (%)
Anomaly	Real	38K	No	$0.7473_{\pm 0.0014}$
Subset of V1 Dataset	Real	100K	No	$0.7829_{\pm 0.0008}$
CauKer	Synth	100K	No	$78.81_{\pm 0.001}$
V1 Dataset	Real	1.89M	Yes	$79.21_{\pm 0.0012}$

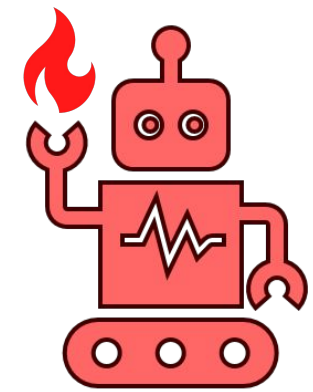
S. Xie et al. (2026). CauKer: classification time series foundation models can be pretrained on synthetic data only. (*ICLR'26 oral)*.

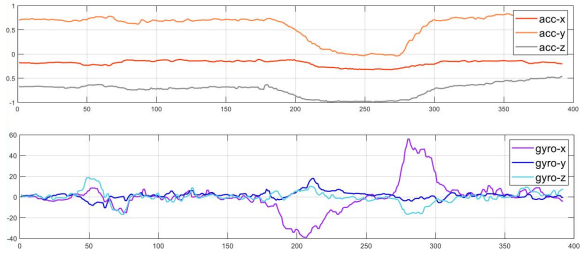
Time Series Foundation Model (TSFM)

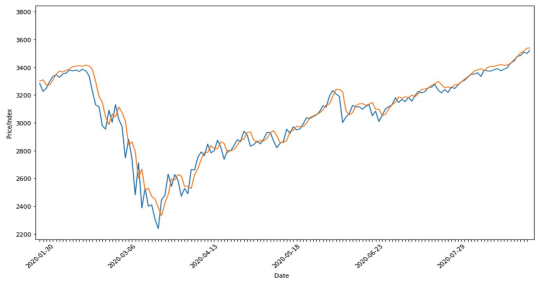
Step 1: Pre-training





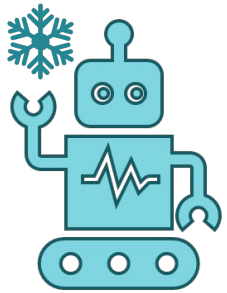






Step 2: Fitting to a New Task

Option 1:

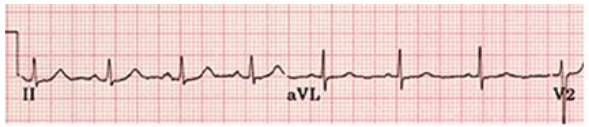


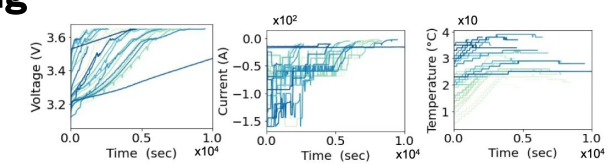
Random Forest

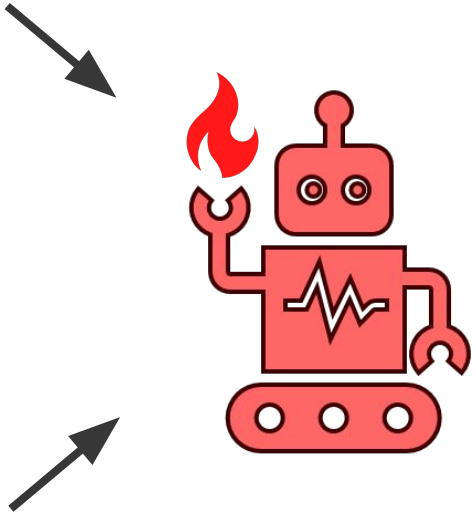
prediction

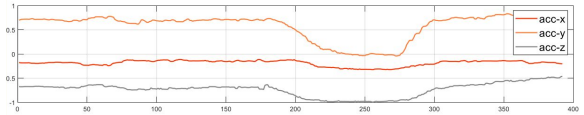
Time Series Foundation Model (TSFM)

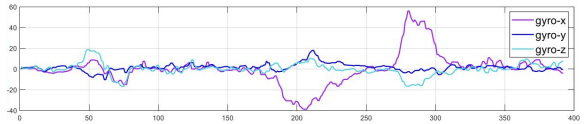
Step 1: Pre-training

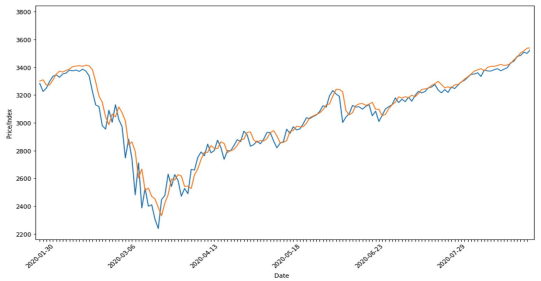






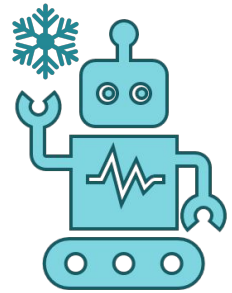






Step 2: Fine-tuning to New Task

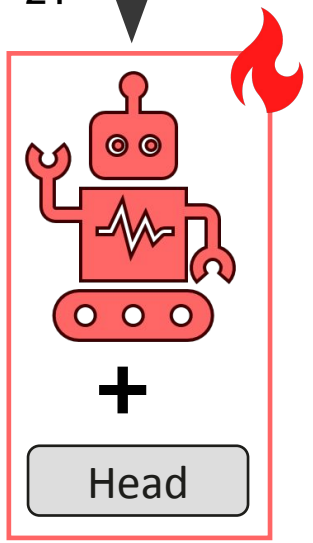
Option 1:



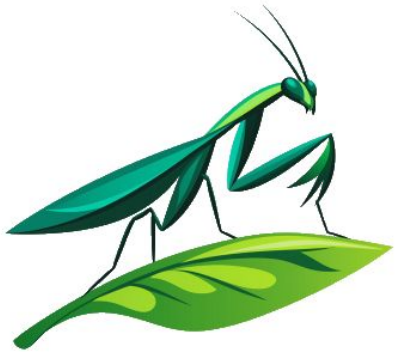
Random Forest

prediction

Option 2:

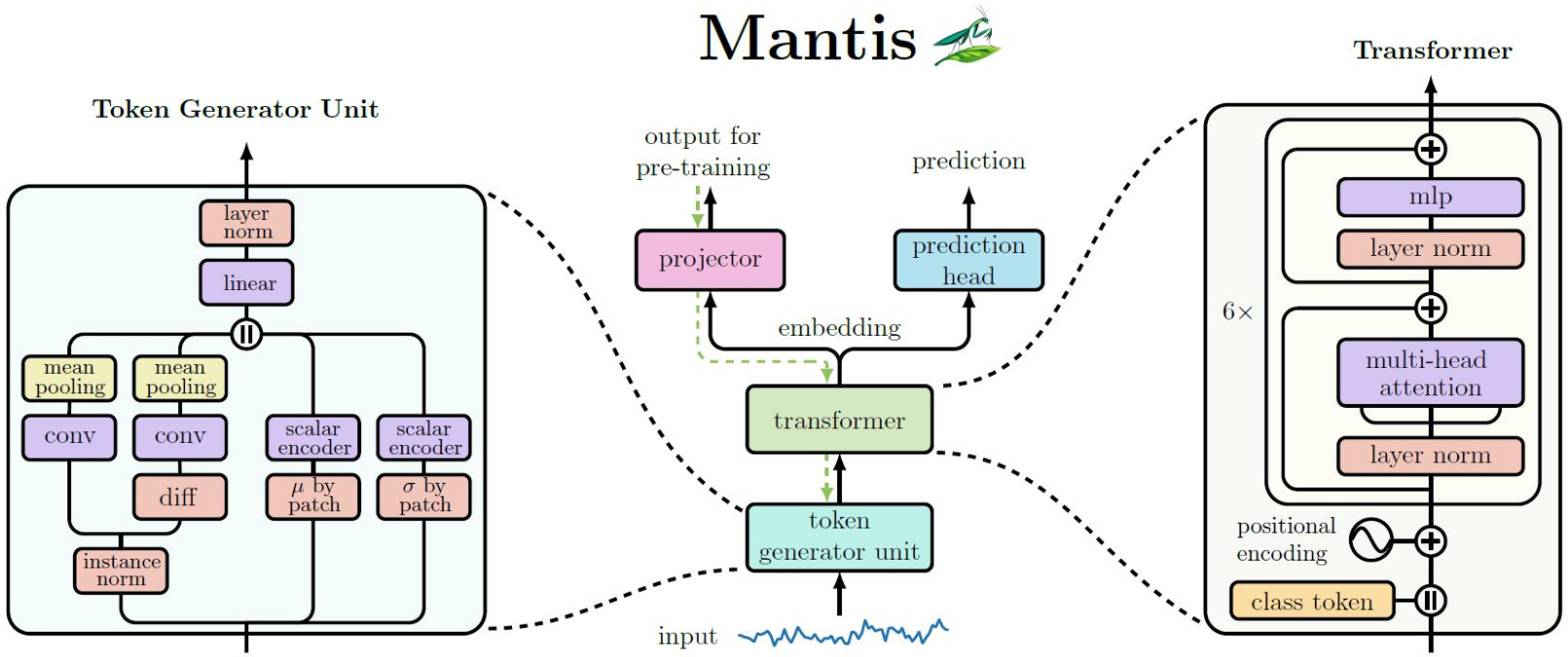


prediction



Mantis: Architecture

Architecture

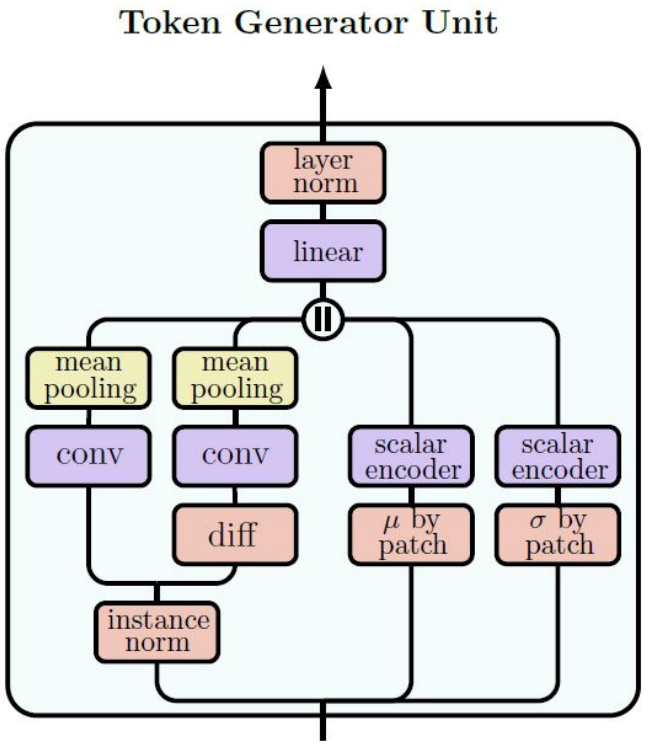


Tokenization is key to unlock the power of the transformer.

1. **Token Generator Unit:** converts time series into meaningful tokens.
2. **Transformer:** projects tokens to a new representation space.

Token Generator Unit

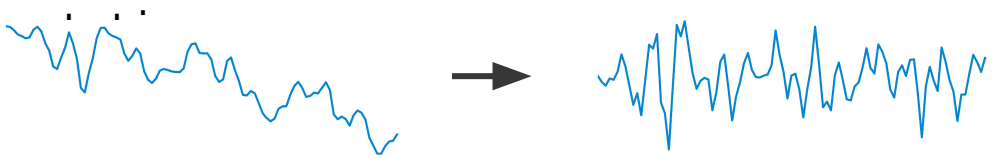
1. 32 x-patches:
   - norm x → conv → mean pooling.

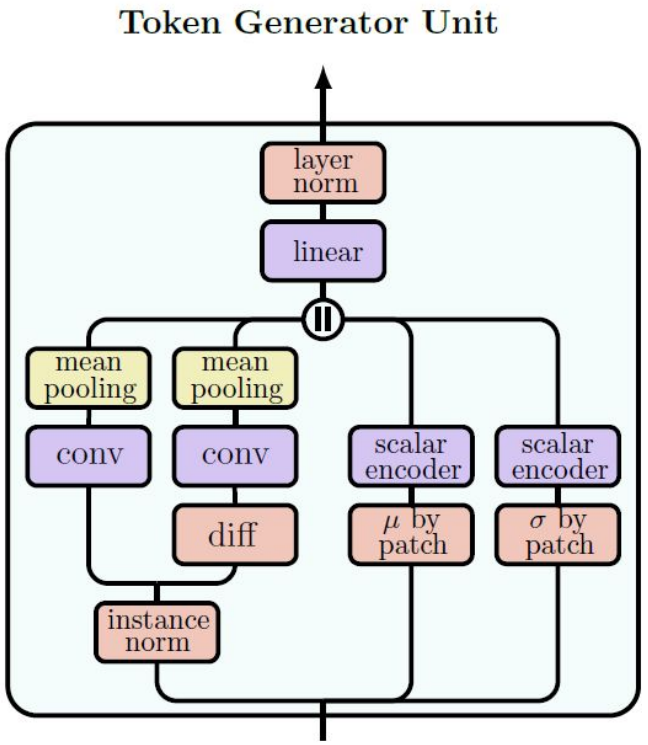


Token Generator Unit

1. 32 x-patches:
   - norm x → conv → mean pooling.

2. 32 diff-x-patches:
   - norm x → diff → conv → mean pooling.
   - diff: x[t]-x[t-1], makes time series

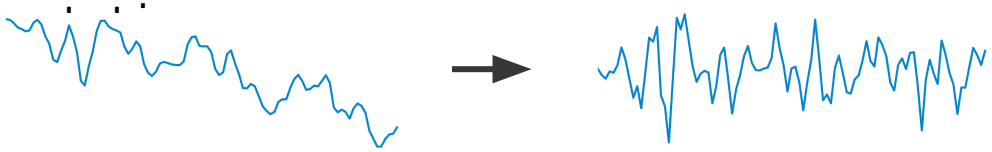




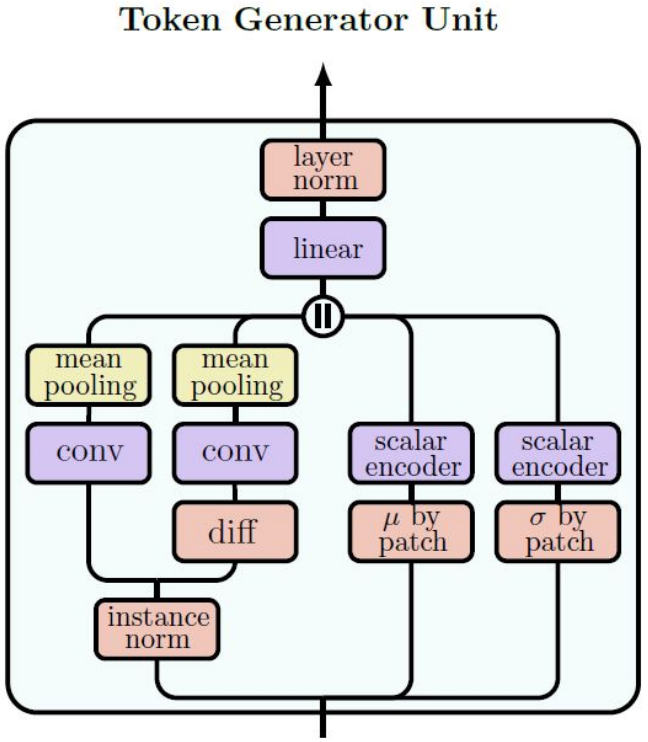
Token Generator Unit

1. 32 x-patches:
   - norm x → conv → mean pooling.

2. 32 diff-x-patches:
   - norm x → diff → conv → mean pooling.
   - diff: x[t]-x[t-1], makes time series
     . . .



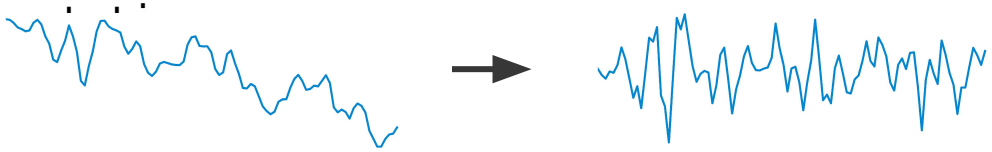
   - ablation study: diff improves performance.



Token Generator Unit

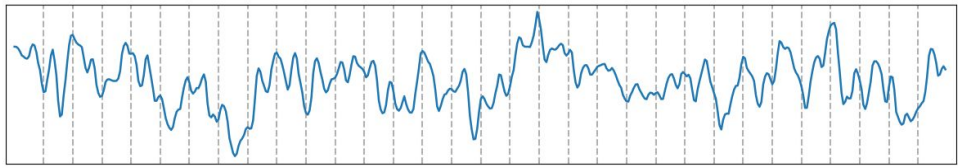
1. 32 x-patches:
   - norm x → conv → mean pooling.

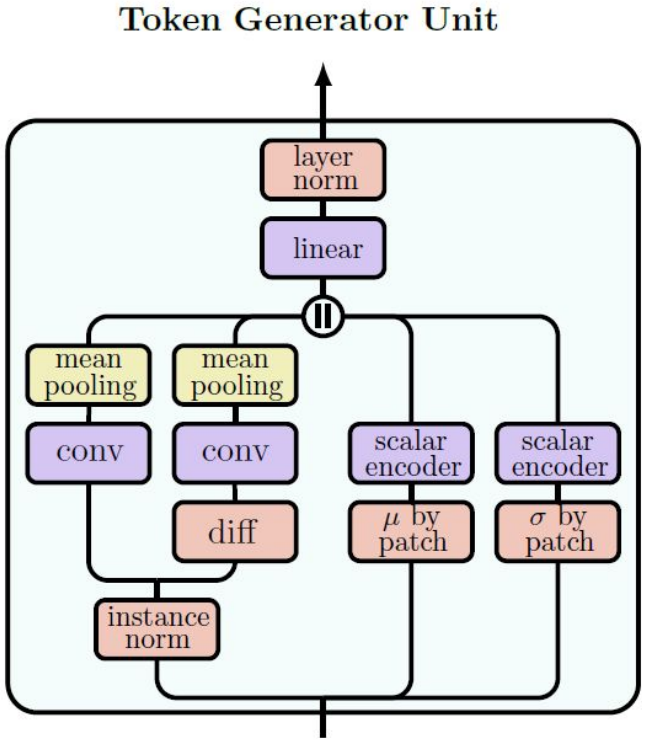
2. 32 diff-x-patches:
   - norm x → diff → conv → mean pooling.
   - diff: x[t]-x[t-1], makes time series
     . . .



   - ablation study: diff improves performance.

3. Scalar encoder (Lin et al., 2024):
   - split time series into 32 non-overlapping patches.
   - compute μ and σ for each patch.

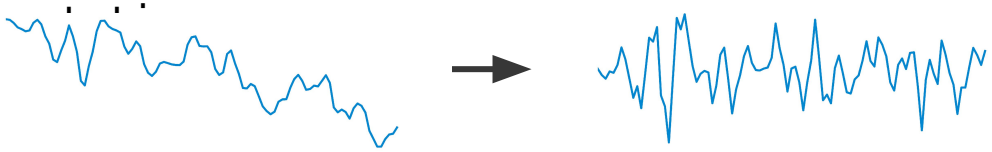




Token Generator Unit

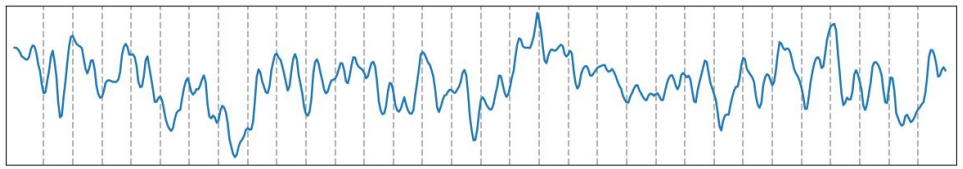
1. 32 x-patches:
   - norm x → conv → mean pooling.

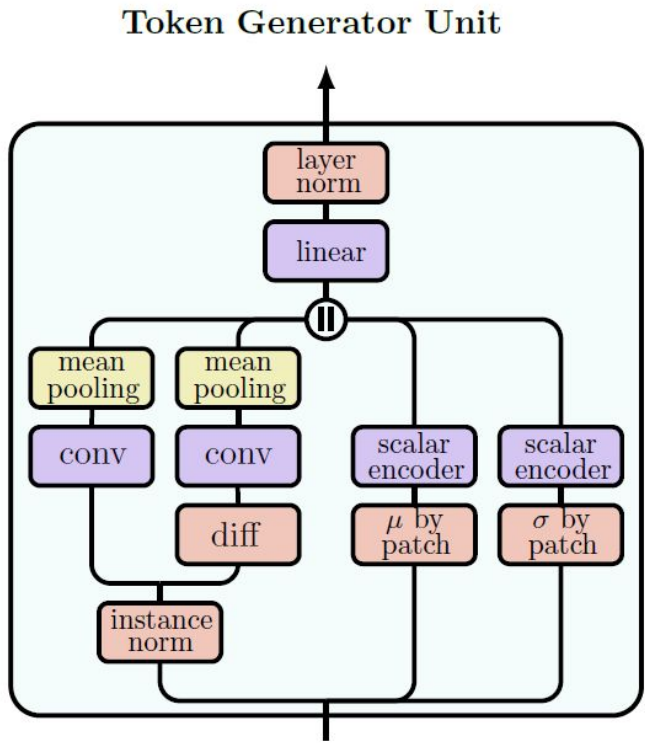
2. 32 diff-x-patches:
   - norm x → diff → conv → mean pooling.
   - diff: x[t]-x[t-1], makes time series
     . . .

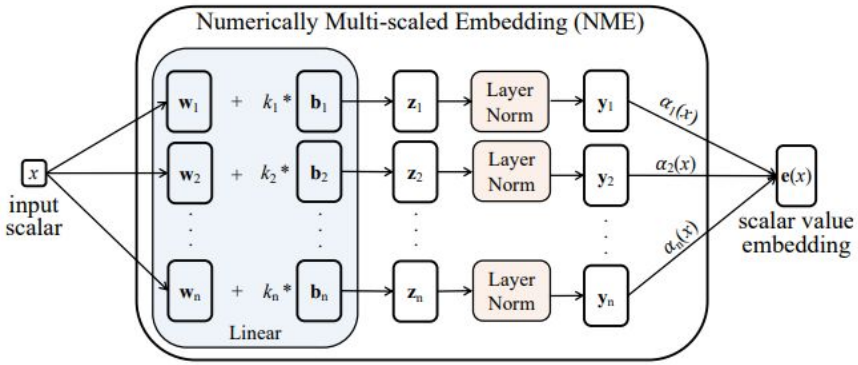


   - ablation study: diff improves performance.

3. Scalar encoder (Lin et al., 2024):
   - split time series into 32 non-overlapping patches.
   - compute μ and σ for each patch.
   - encode each scalar by a high-dimensional vector.

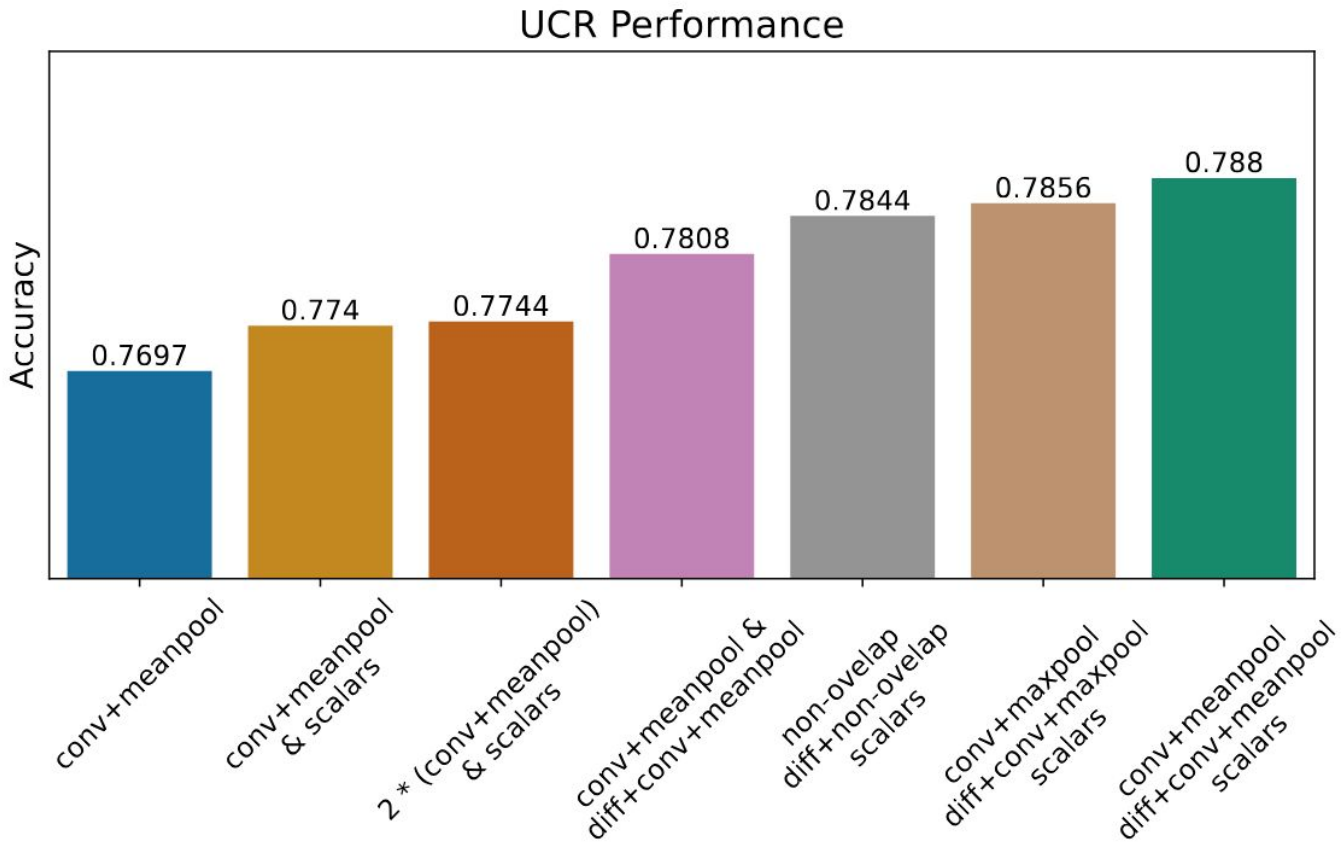


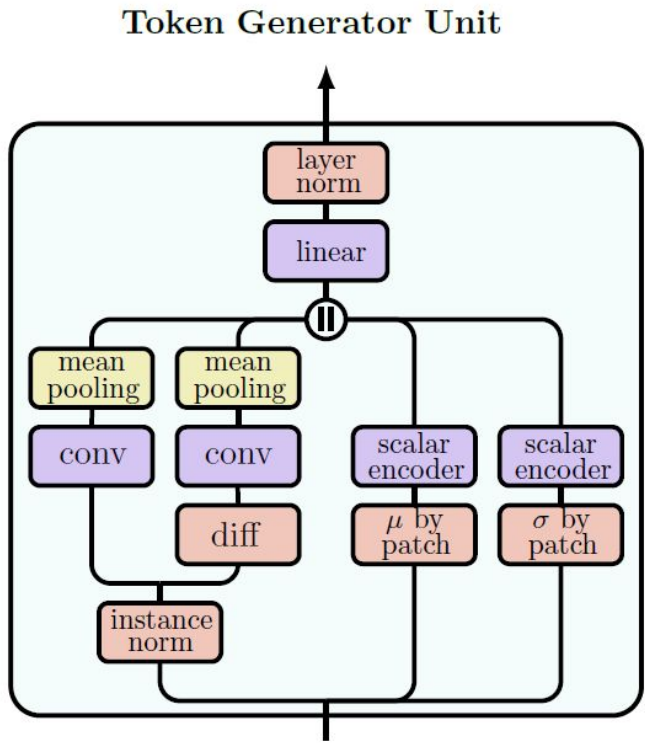




Token Generator Unit: Ablation Study

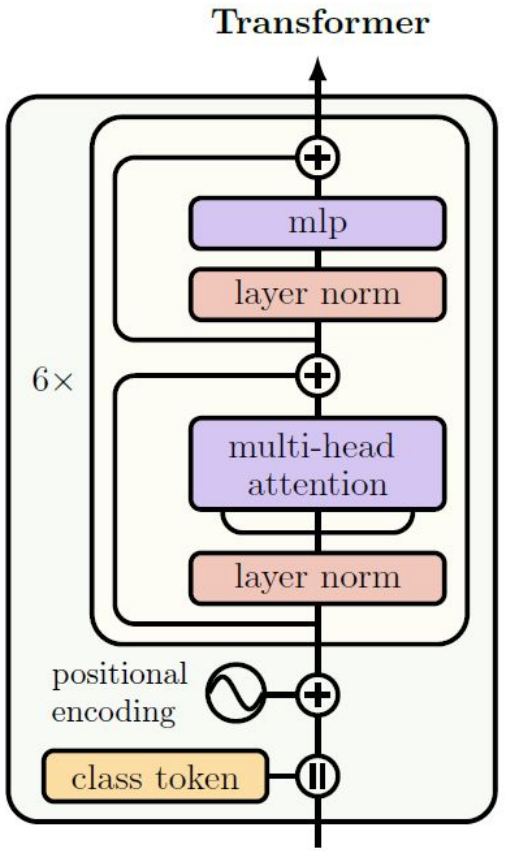
Ablation study validates the proposed scheme.





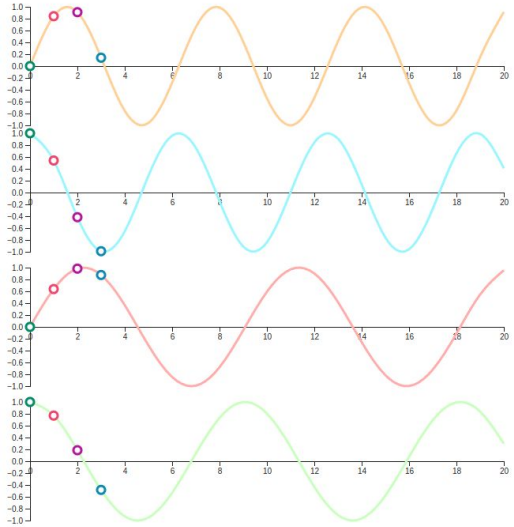
Transformer

1. Class token is appended to 32 input tokens:
   - learnable vector,
   - aggregates information from the entire input,
   - its embedding is the final output.



Transformer

2. Positional encoding:
   - incorporates the order of tokens,
   - encodes position into a high-dimensional vector.



$d_{model} = 50$

	p0	p1	p2	p3	
	0.000	0.841	0.909	0.141	i=0
	1.000	0.540	-0.416	-0.990	i=1
	0.000	0.638	0.983	0.875	i=2
	1.000	0.770	0.186	-0.484	i=3

Positional Encoding

$$PE_{(pos,2i)} = sin(\frac{pos}{10000^{2i/d_{model}}})$$

$$PE_{(pos,2i+1)} = cos(\frac{pos}{10000^{2i/d_{model}}})$$

Sinusoidal Positional Encoding

$$\boldsymbol{R}^d_{\Theta,m} = \begin{pmatrix} \cos m\theta_1 & -\sin m\theta_1 & 0 & 0 & \cdots & 0 & 0 \\ \sin m\theta_1 & \cos m\theta_1 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cos m\theta_2 & -\sin m\theta_2 & \cdots & 0 & 0 \\ 0 & 0 & \sin m\theta_2 & \cos m\theta_2 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & \cos m\theta_{d/2} & -\sin m\theta_{d/2} \\ 0 & 0 & 0 & 0 & \cdots & \sin m\theta_{d/2} & \cos m\theta_{d/2} \end{pmatrix}$$

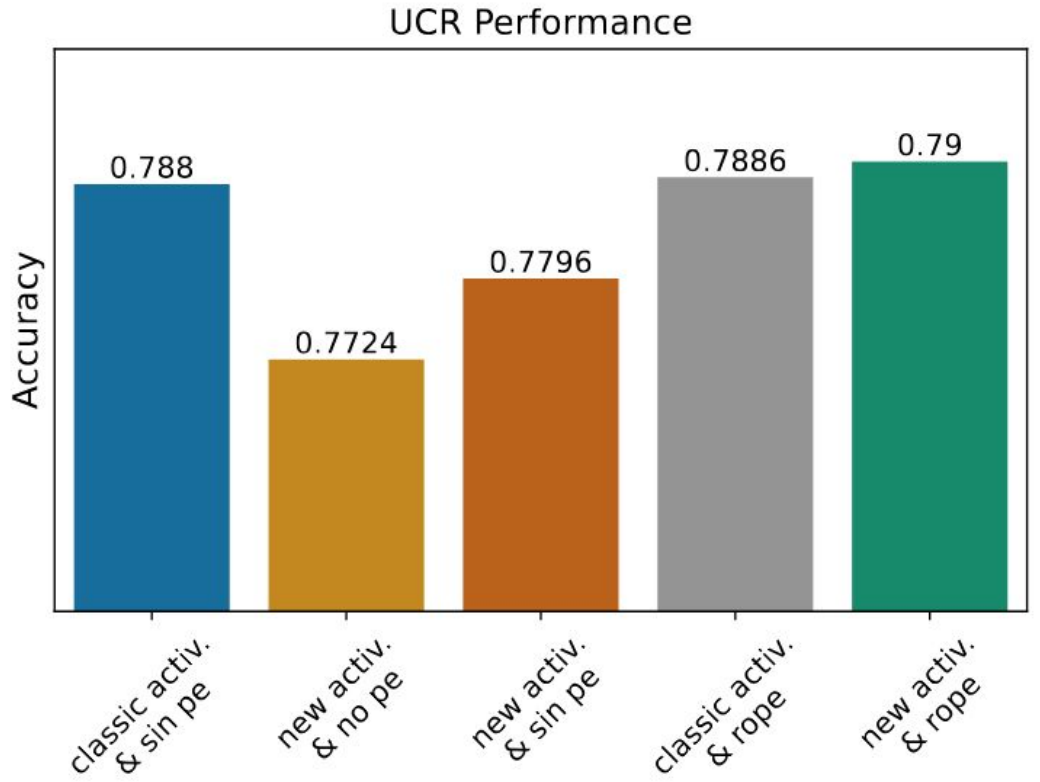
$$\boldsymbol{q}_m^\intercal \boldsymbol{k}_n = (\boldsymbol{R}^d_{\Theta,m}\boldsymbol{W}_q\boldsymbol{x}_m)^\intercal(\boldsymbol{R}^d_{\Theta,n}\boldsymbol{W}_k\boldsymbol{x}_n) = \boldsymbol{x}^\intercal\boldsymbol{W}_q R^d_{\Theta,n-m}\boldsymbol{W}_k\boldsymbol{x}_n$$

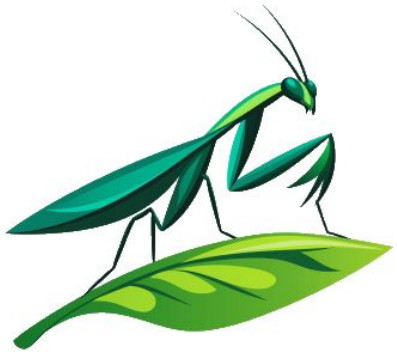
Rotary Positional Encoding

Transformer: Ablation Study

Some ablations:

- Normalization: LayerNorm vs RMSNorm
- Activation: GELU vs SwiGLU
- Sin PE vs ROPE



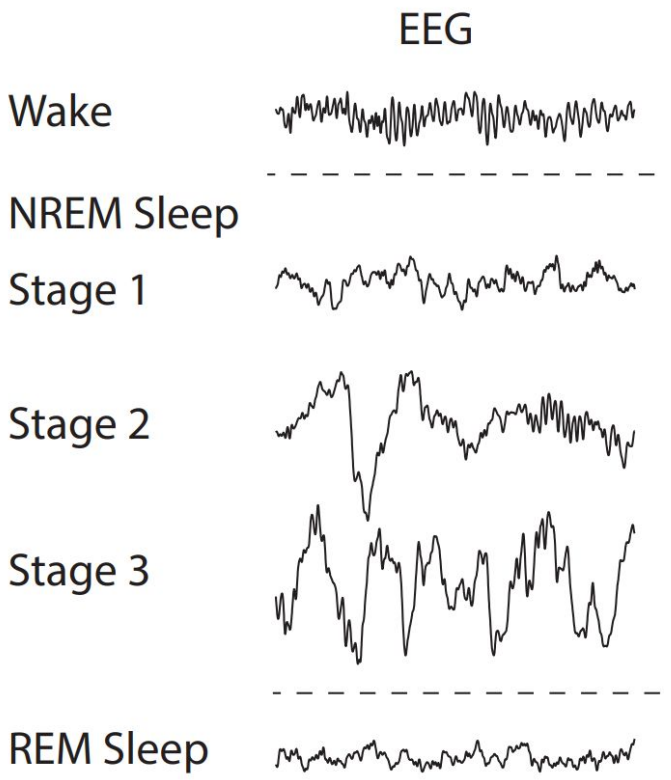


First Experimental Results

Application to EEG Sleep Staging

Dataset	EEGNet	CBraMod		Mantis		
		Random	EEG Pretrain	Random	Real Pretrain	Synth Pretrain
ABC	$67.94_{\pm 6.52}$	$70.61_{\pm 3.29}$	$74.90_{\pm 4.89}$	$72.82_{\pm 3.89}$	$75.50_{\pm 5.62}$	$\mathbf{75.74_{\pm 4.32}}$
CCSHS	$83.13_{\pm 0.10}$	$87.01_{\pm 0.27}$	$88.04_{\pm 0.59}$	$88.55_{\pm 0.39}$	$\mathbf{88.85_{\pm 0.48}}$	$88.80_{\pm 0.30}$
CFS	$78.60_{\pm 1.31}$	$83.48_{\pm 0.23}$	$84.30_{\pm 0.08}$	$84.96_{\pm 0.43}$	$\mathbf{85.35_{\pm 0.35}}$	$85.06_{\pm 0.75}$
CHAT	$78.91_{\pm 0.16}$	$84.11_{\pm 0.81}$	$85.01_{\pm 0.42}$	NaN	$\mathbf{85.94_{\pm 0.18}}$	$85.72_{\pm 0.29}$
HOMEPAP	$69.43_{\pm 0.08}$	$70.37_{\pm 1.90}$	$72.56_{\pm 2.35}$	$71.26_{\pm 1.93}$	$73.14_{\pm 2.09}$	$\mathbf{73.53_{\pm 2.00}}$
MASS	$79.85_{\pm 1.27}$	$77.40_{\pm 2.18}$	$81.12_{\pm 2.27}$	$79.06_{\pm 1.89}$	$\mathbf{84.09_{\pm 0.85}}$	$82.49_{\pm 1.22}$
PhysioNet	$75.73_{\pm 0.38}$	$77.19_{\pm 0.94}$	$78.97_{\pm 0.43}$	$77.98_{\pm 0.89}$	$\mathbf{79.82_{\pm 1.63}}$	$78.83_{\pm 1.60}$
SOF	$78.74_{\pm 1.81}$	$82.61_{\pm 0.35}$	$83.39_{\pm 0.67}$	$83.70_{\pm 1.01}$	$\mathbf{84.69_{\pm 0.73}}$	$84.31_{\pm 0.57}$

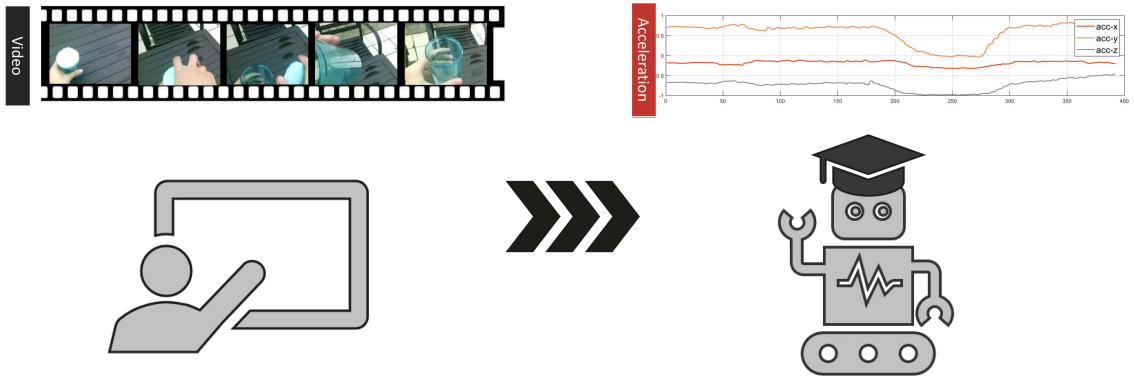
Mantis outperforms EEG foundation model on sleep stage prediction task!



T. Gnassounou et al. (2025). Leveraging Generic Time Series Foundation Models for EEG Classification. *arXiv:2510.27522*.

Application to HAR

- Mantis is a good student from a video teacher.
- Zero-shot after distillation matches the fine-tuning performance.

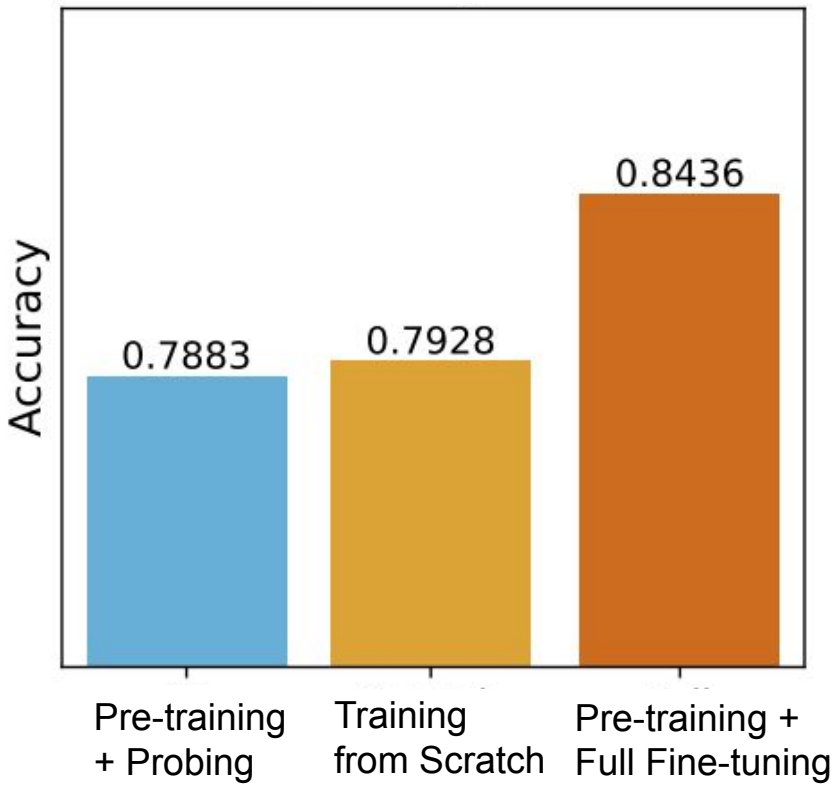


	Model	Ego4d			EgoExo4D			MMEA		
		acc@1	acc@3	acc@3	acc@1	acc@3	acc@3	acc@1	acc@3	acc@3
Zero-Shot	Moment-Small	39.70	64.47	75.32	68.14	93.55	98.43	83.66	95.52	97.42
	Mantis	47.49	71.63	81.24	76.47	96.98	99.21	90.96	98.56	99.39
	TSFormer→ Mantis	**59.13**	**78.79**	**85.65**	**84.92**	**98.28**	**99.59**	92.48	**99.01**	**99.77**
Fine-Tuned	Moment-Small	57.59	75.91	82.94	79.26	97.04	99.33	84.27	94.76	96.88
	Mantis	58.36	76.98	83.76	84.22	97.95	99.41	**93.01**	98.25	99.01

B. Chen et al. (2025). Comodo: Cross-modal video-to-imu distillation for efficient egocentric human activity recognition. *arXiv:2503.07259*.

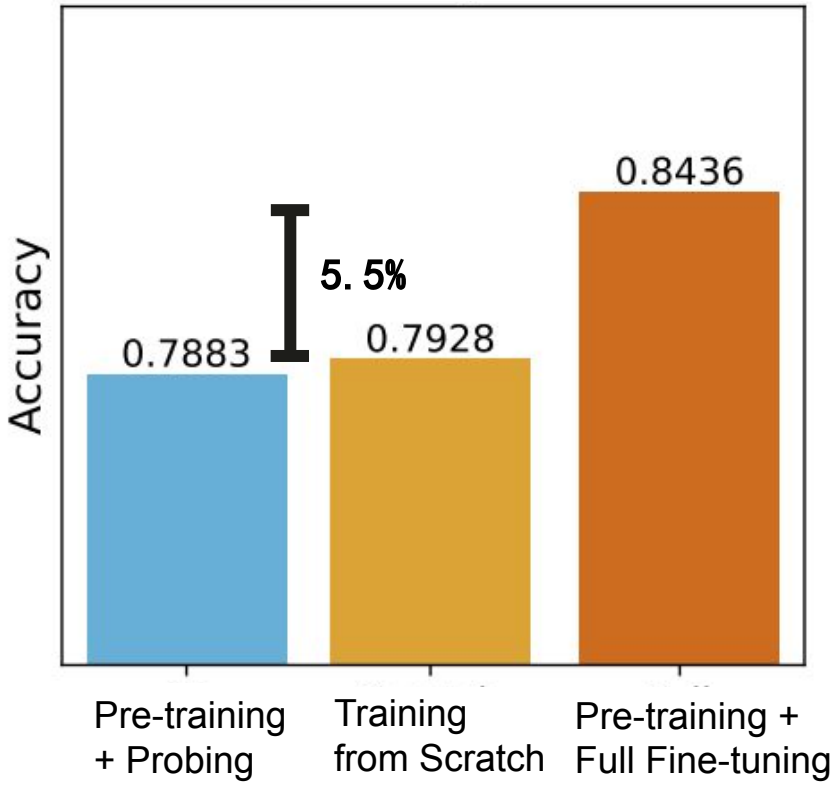
Influence of Pre-training and Fine-tuning

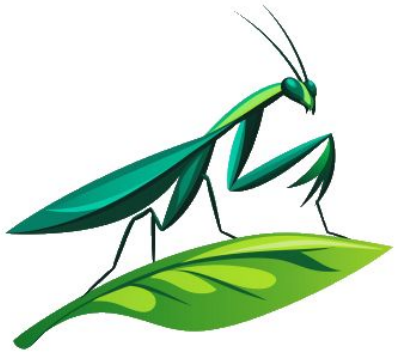
Best performance is achieved with pre-training + fine-tuning.



Influence of Pre-training and Fine-tuning

- **Issue:** A big gap in performance between frozen and fine-tuned Mantis.
- **Question:** Are we able to mitigate this gap?

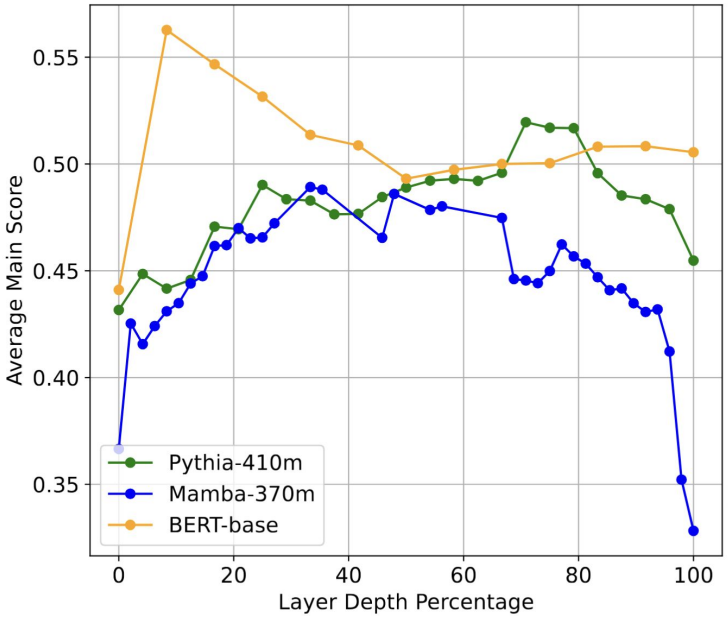




Leveraging Intermediate Layers

Strong Intermediate Representations

- Skean et al. (2025) showed that intermediate representations of LLMs may outperform the final one.

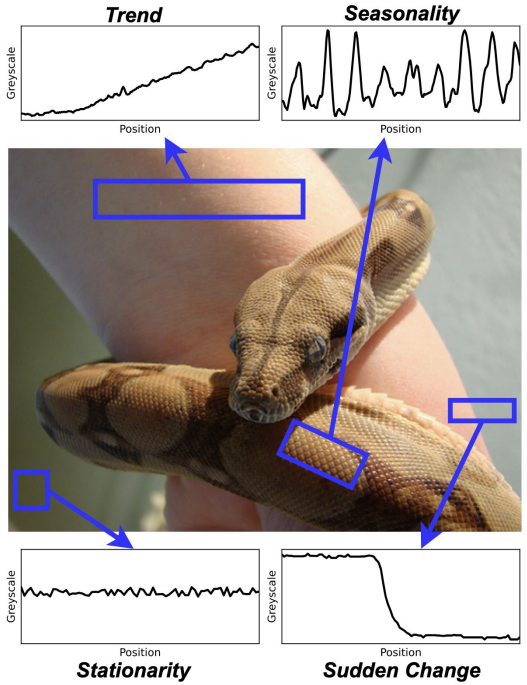


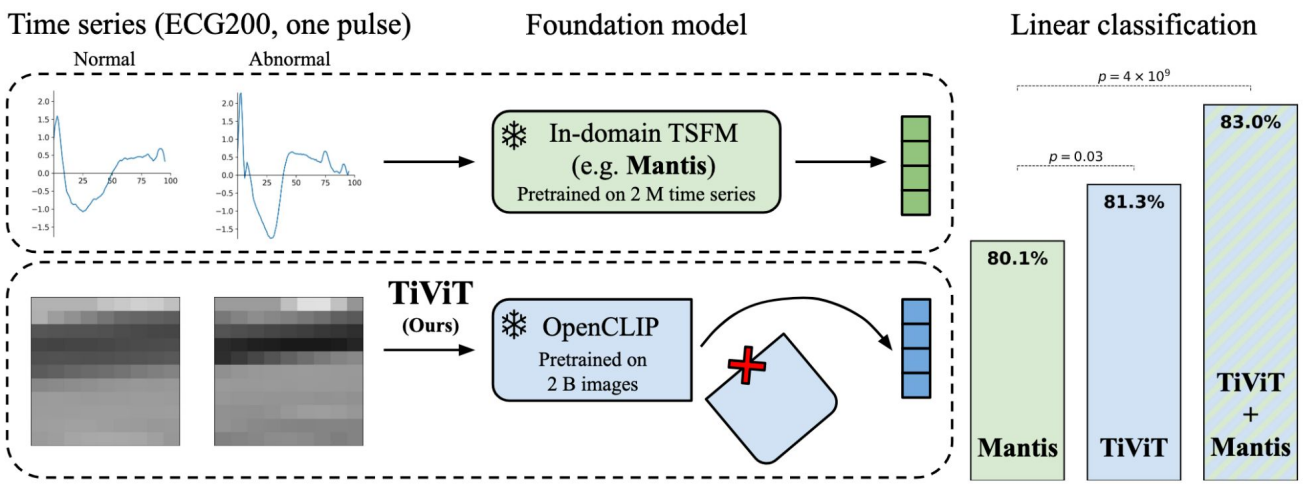
Performance of 32 embedding tasks from the Massive Text Embedding Benchmark (MTEB).

O. Skean et al. (2025). Layer by Layer: Uncovering Hidden Representations in Language Models.

Strong Intermediate Representations

- Skean et al. (2025) showed that intermediate representations of LLMs may outperform the final one.
- Roschmann et al. (2025) showed a cross-domain transfer: intermediate layers of pre-trained ViT are strong embeddings for time series classification!

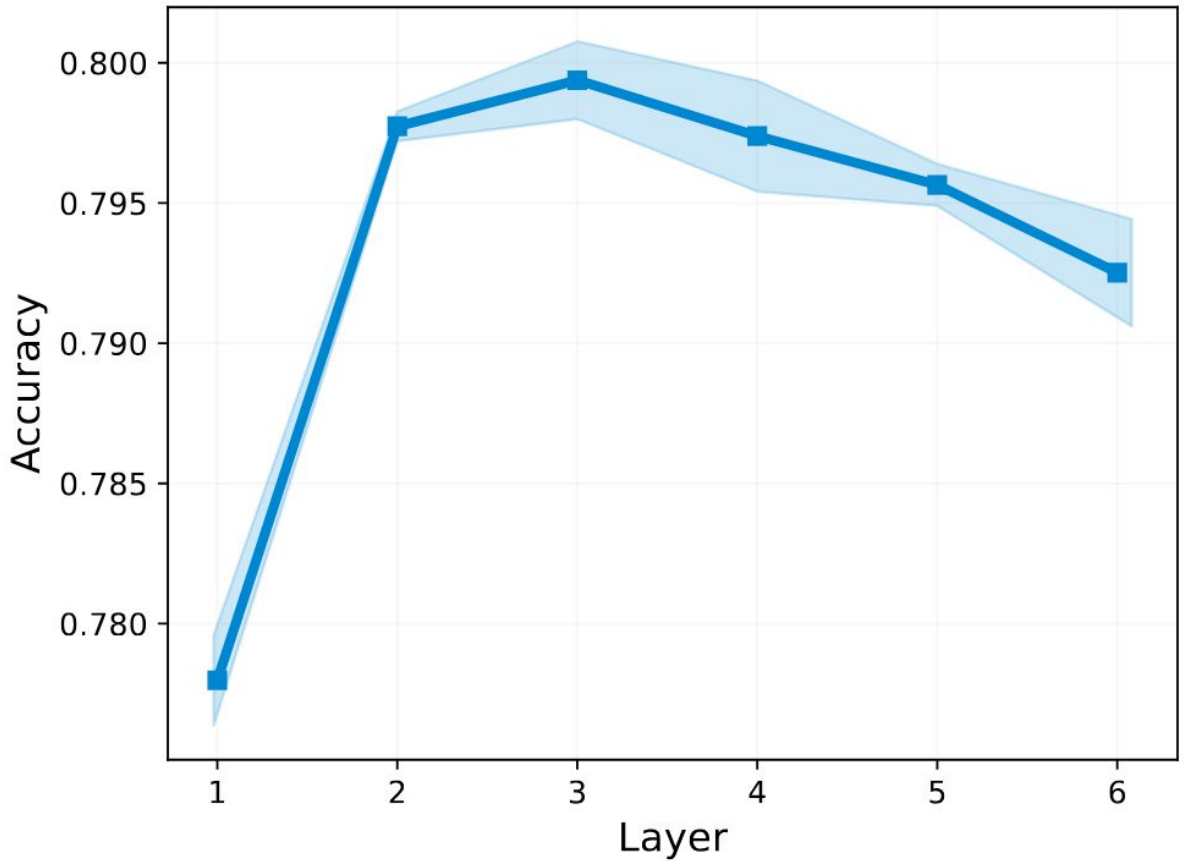




O. Skean et al. (2025). Layer by Layer: Uncovering Hidden Representations in Language Models.
M. Chen et al. (2025). VisionTS: Visual Masked Autoencoders Are Free-Lunch Zero-Shot Time Series Forecasters.
Roschmann et al. (2025). Time Series Representations for Classification Lie Hidden in Pretrained Vision Transformers.

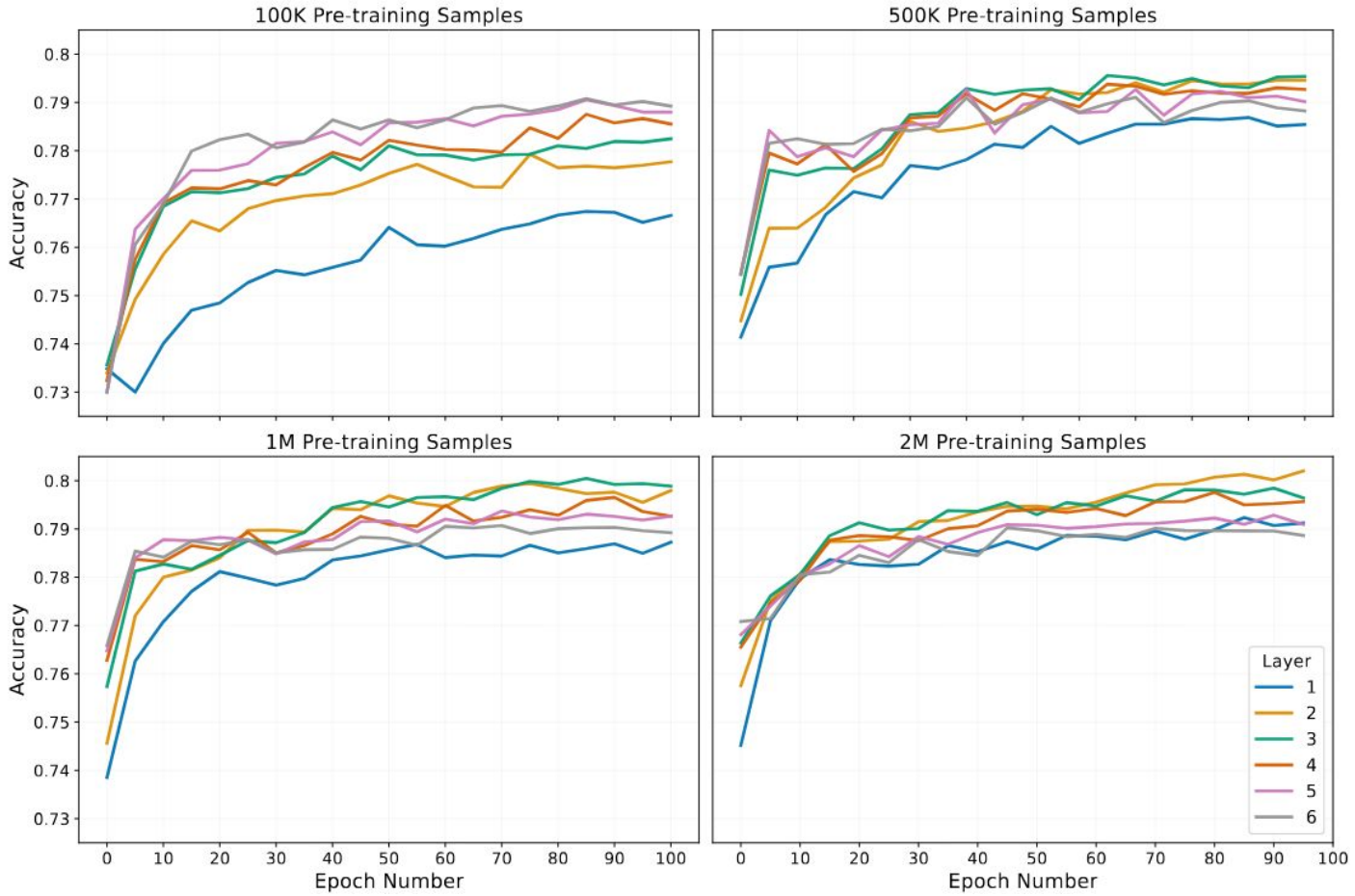
Layer by Layer for Mantis

Observation 1: Intermediate layers of transformers generalize better!



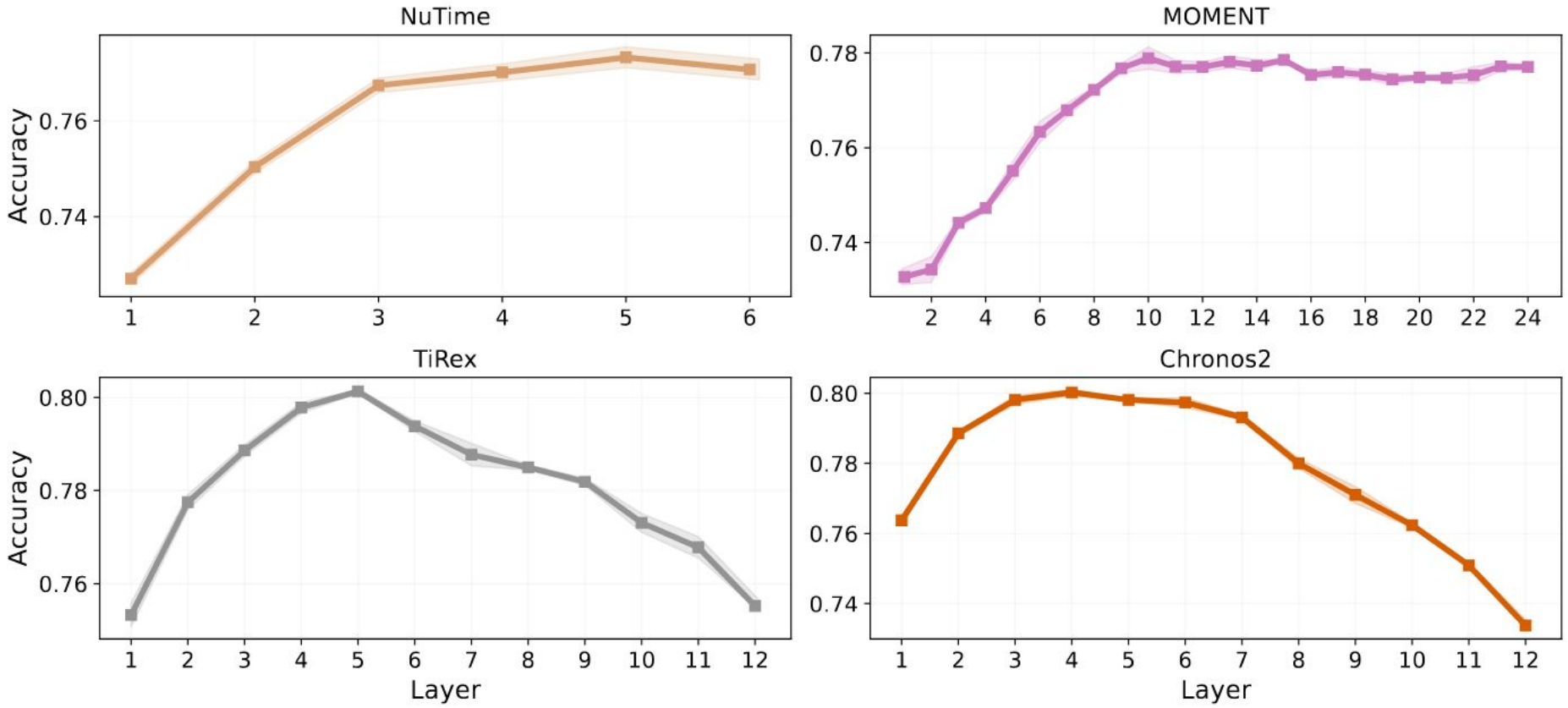
Layer by Layer, Epoch by Epoch

Observation 2: Intermediate layers unlock the scaling law!



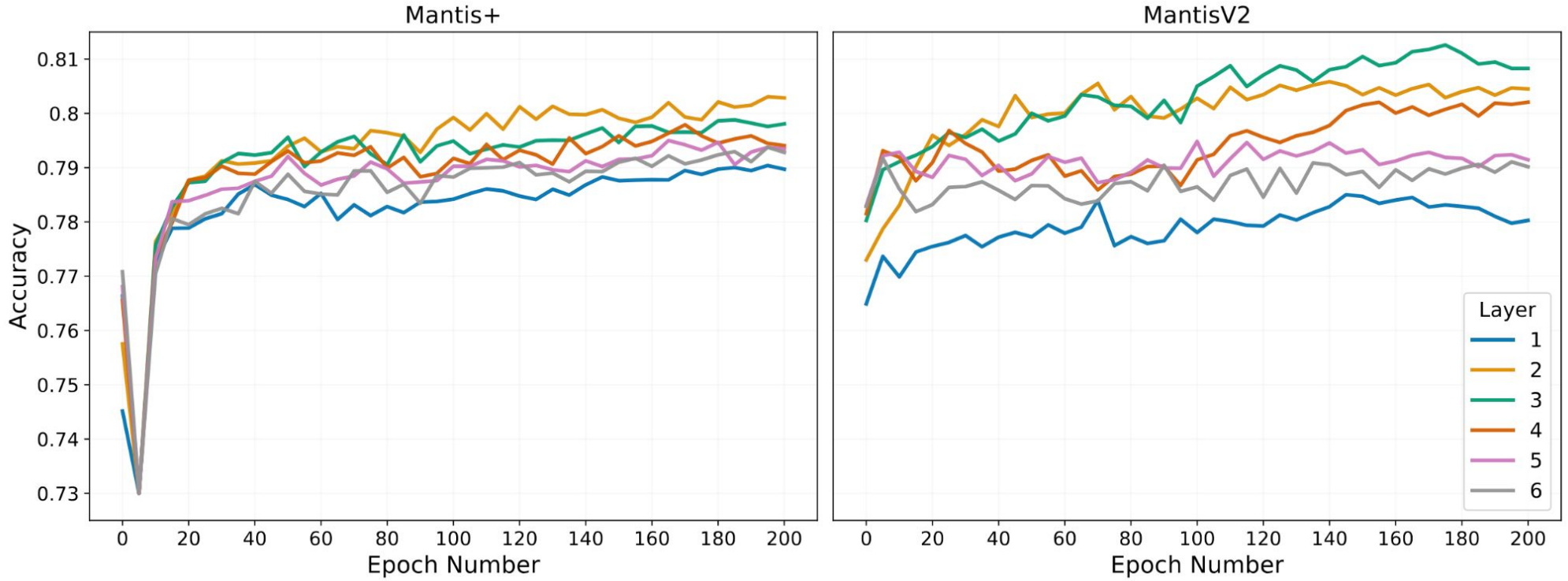
Layer by Layer for Other Methods

Observation 3: Intermediate layers make time series forecasting models relevant for time series classification.



Layer by Layer Epoch by Epoch

Final pre-training that gives Mantis+ and MantisV2.



Layer by Layer Module by Module

For image classification, Odonnat et al. (2026) showed that even better representations are found by looking after each module of a transformer layer!

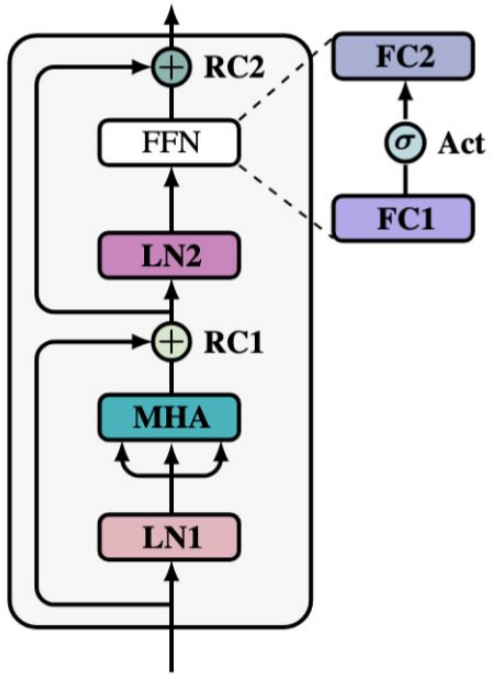


Figure 2: **Transformer block.**

Table 1: **Module by module.** For each module, we report the best linear probing accuracy over the layers. The best performance per dataset is in **bold** and the module with the highest win rate is in gray.

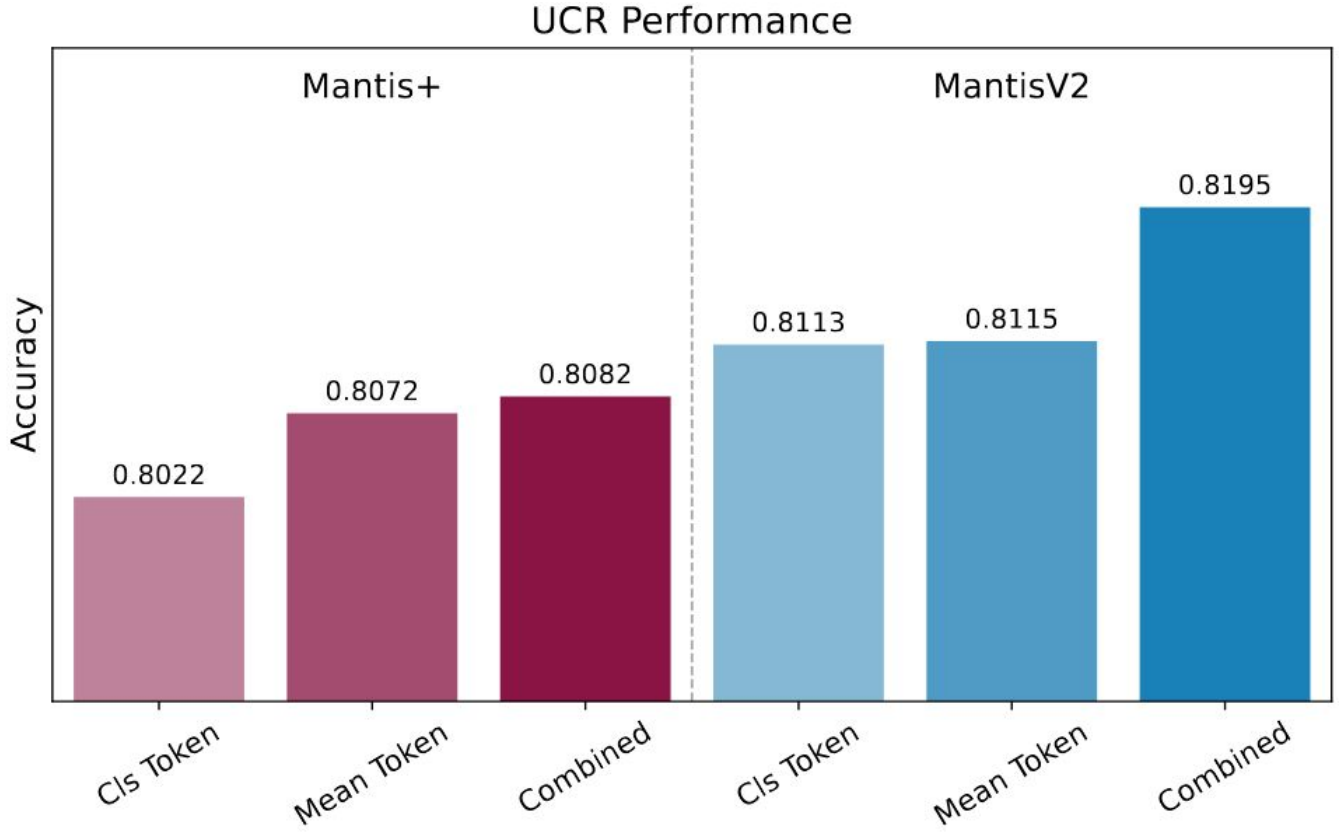
Dataset	LN1	MHA	RC1	LN2	FC1	Act	FC2	RC2
Cifar10	91.94	91.98	92.19	92.20	**92.28**	85.30	89.98	92.07
Cifar100	69.39	67.27	69.88	**69.97**	68.98	69.75	60.92	69.63
Contrast	78.05	74.55	78.30	79.05	78.15	**80.20**	70.85	77.95
Gaussian Noise	57.65	60.40	59.05	58.10	58.75	**61.85**	56.70	58.20
Motion Blur	66.85	64.30	68.50	67.75	66.80	**71.15**	60.90	67.75
Snow	67.30	66.15	68.10	67.30	67.35	**69.30**	61.50	67.70
Speckle Noise	59.75	61.85	60.25	59.95	59.90	**63.35**	58.00	59.80
Clipart	47.66	43.82	48.66	48.37	45.74	**49.34**	40.97	48.33
Sketch	32.36	30.95	33.32	33.07	31.11	**34.90**	28.45	32.99
Flowers102	96.58	96.34	96.58	**96.62**	96.44	91.64	95.23	**96.62**
Pet	88.36	88.33	89.48	**89.51**	88.47	83.46	85.80	89.18

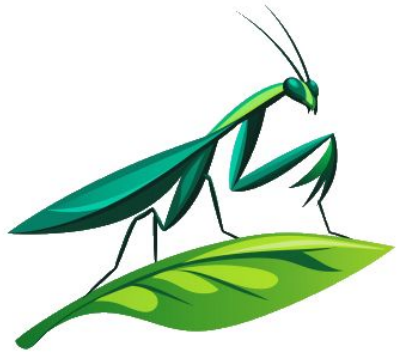
A. Odonnat et al. (2026). Layer by layer, module by module: Choose both for optimal OOD probing of ViT (*ICLR'26 CAO workshop*)

Output-Token Aggregation

Usually, a transformer encoder outputs classification token's embedding as the final one.

- Not optimal for intermediate layers.
- Concatenation of cls token and the mean of all other tokens improves performance.





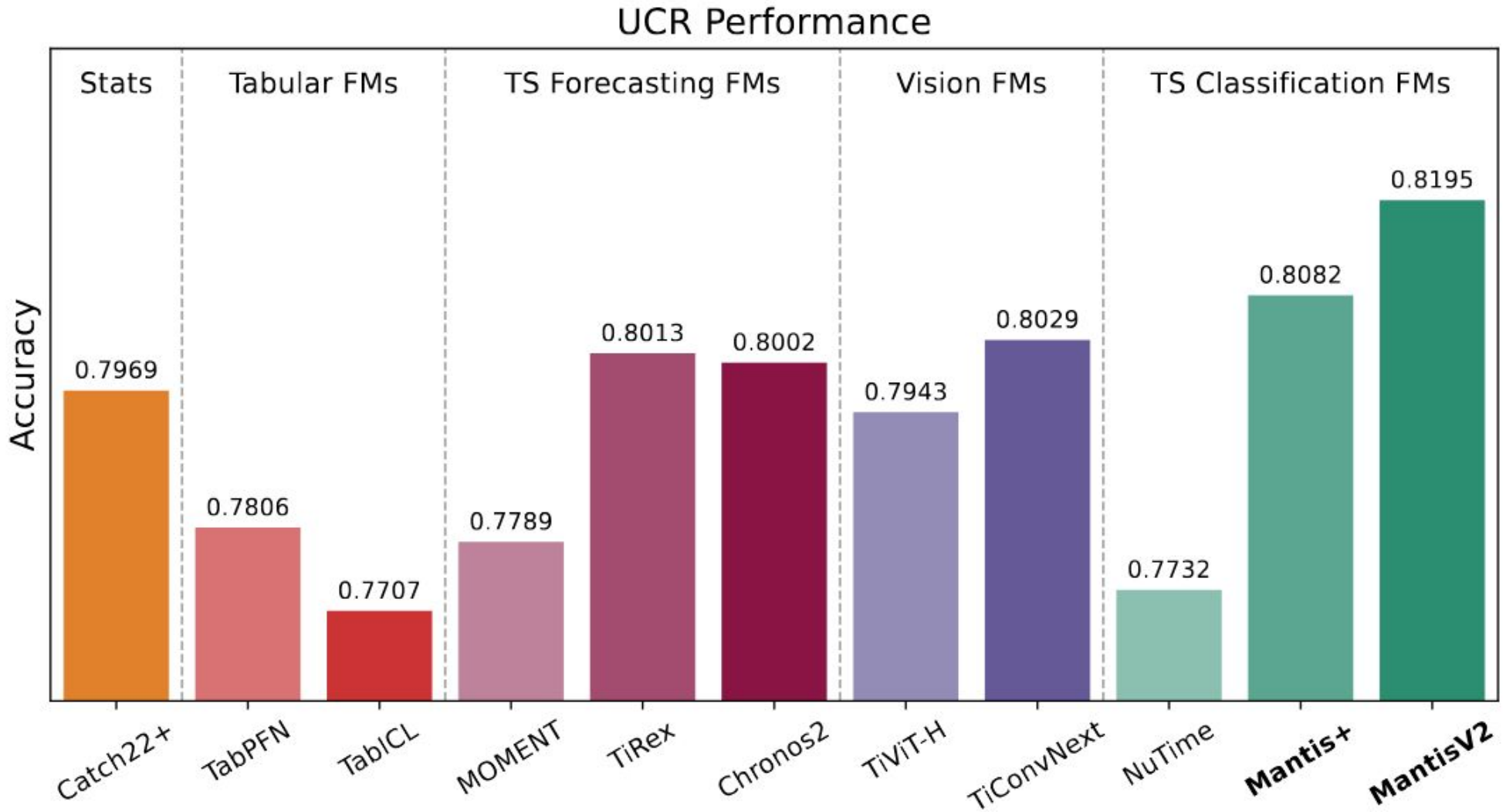
Main Experimental Results.

Baselines

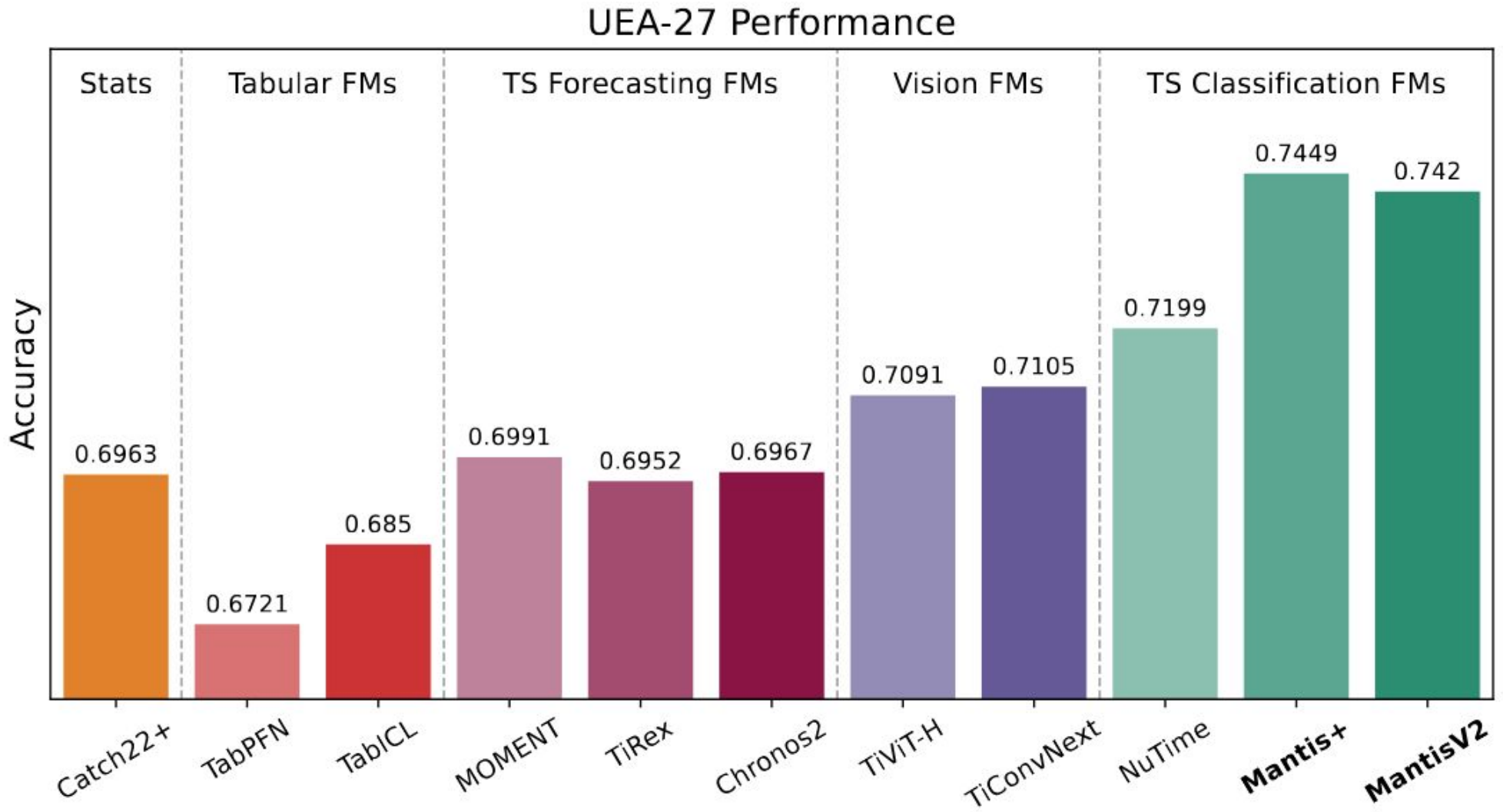
# of Params.	TabPFN	TabICL	MOMENT	TiRex	Chronos2	TiViT-H	TiConvNext	NuTime	Mantis+	MantisV2
Original	7.2M	27.1M	341.2M	35.3M	119.5M	630.8M	843.4M	2.4M	8.1M	4.2M
After Pruning	-	-	161.4M	16.5M	44M	276.6M	180.3M	2M	2.9M	2.2M

- **Catch22+**: Manually curated statistical features.
- 2 tabular FMs: **TabPFN** and **TabICL**.
- **MOMENT**: T5-based masked auto-encoder.
- 2 forecasting foundation models: **TiRex** and **Chronos2**.
- Adaptation of vision-based models to time series: **TiViT-H** and **TiConvNext**.
- **NuTime**: classification TSFM based on BYOL self-distillation.
- Our models: **Mantis+** and **MantisV2**.

UCR Performance (128 Univ. Datasets)



UEA Performance (27 Multivar. Datasets)



Performance on Human Activity Recognition Datasets

	Catch22+	TabPFN	TabICL	MOMENT	TiRex	Chronos2	TiViT-H	TiConvNext	NuTime	Mantis+	MantisV2
Ego4D	$0.4397_{\pm 0.002}$	NaN	NaN	$0.4068_{\pm 0.001}$	$0.5037_{\pm 0.001}$	$0.4742_{\pm 0.0}$	0.1912	0.1907	$0.5108_{\pm 0.0}$	$\mathbf{0.5273}_{\pm 0.0}$	$0.5258_{\pm 0.001}$
EMOPain	$0.8826_{\pm 0.006}$	0.7831	0.7831	$0.8469_{\pm 0.002}$	$0.7915_{\pm 0.003}$	$0.8075_{\pm 0.004}$	$0.83_{\pm 0.002}$	$0.8225_{\pm 0.003}$	$0.8901_{\pm 0.005}$	$\mathbf{0.8939}_{\pm 0.002}$	$0.8798_{\pm 0.009}$
HHAR-ID	$0.9738_{\pm 0.001}$	0.8938	0.9073	$0.9299_{\pm 0.0}$	$0.9481_{\pm 0.0}$	$0.9475_{\pm 0.002}$	$0.9338_{\pm 0.001}$	$0.9461_{\pm 0.001}$	$0.9808_{\pm 0.001}$	$0.9835_{\pm 0.001}$	$\mathbf{0.9845}_{\pm 0.001}$
HHAR-OOD	$0.4808_{\pm 0.008}$	0.5311	0.5441	$0.3081_{\pm 0.001}$	$0.5135_{\pm 0.014}$	$0.4174_{\pm 0.008}$	$0.3748_{\pm 0.007}$	$0.4031_{\pm 0.01}$	$0.56_{\pm 0.005}$	$0.5624_{\pm 0.016}$	$\mathbf{0.5822}_{\pm 0.005}$
MP8	$0.572_{\pm 0.008}$	0.6235	0.6185	$0.6392_{\pm 0.011}$	$0.5994_{\pm 0.016}$	$0.5966_{\pm 0.006}$	$0.6022_{\pm 0.009}$	$0.5966_{\pm 0.003}$	$0.6504_{\pm 0.008}$	$0.6403_{\pm 0.006}$	$\mathbf{0.6857}_{\pm 0.012}$
MP50	$0.3602_{\pm 0.016}$	0.5664	0.5042	$\mathbf{0.7434}_{\pm 0.017}$	$0.6644_{\pm 0.01}$	$0.6639_{\pm 0.007}$	$0.6908_{\pm 0.008}$	$0.6801_{\pm 0.008}$	$0.6913_{\pm 0.012}$	$0.7227_{\pm 0.008}$	$0.7345_{\pm 0.007}$
UCI-HAR	$0.8273_{\pm 0.003}$	0.809	0.8157	$0.8782_{\pm 0.001}$	$0.8744_{\pm 0.002}$	$0.8873_{\pm 0.002}$	$0.8936_{\pm 0.001}$	$0.8918_{\pm 0.001}$	$0.8842_{\pm 0.001}$	$0.8911_{\pm 0.0}$	$\mathbf{0.9013}_{\pm 0.002}$
Avg	0.6481	NaN	NaN	0.6789	0.6993	0.6849	0.6452	0.6473	0.7382	0.7459	**0.7562**
Avg UCR HAR	0.7564	0.7479	0.7285	0.7572	0.7687	0.7702	0.7726	0.772	0.756	0.7867	**0.8007**
Avg UEA HAR	0.8138	0.7591	0.764	0.8431	0.846	0.8492	0.8535	0.8488	0.8539	**0.8796**	0.8739

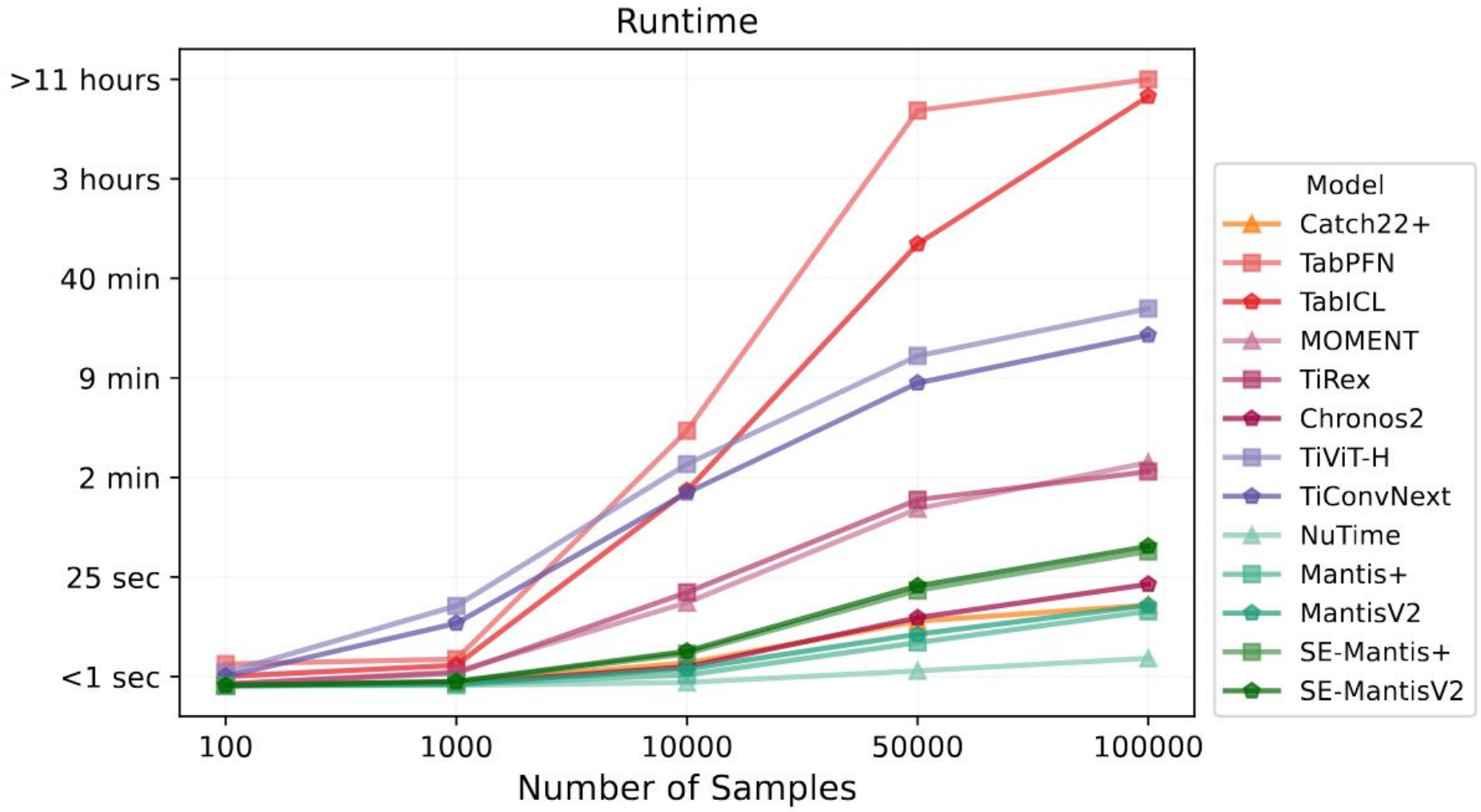
Lightweight models like MantisV2, Mantis+ and NuTime are the most appropriate ones for human activity recognition on device with highest performance and lowest complexity.

Performance on EEG Datasets

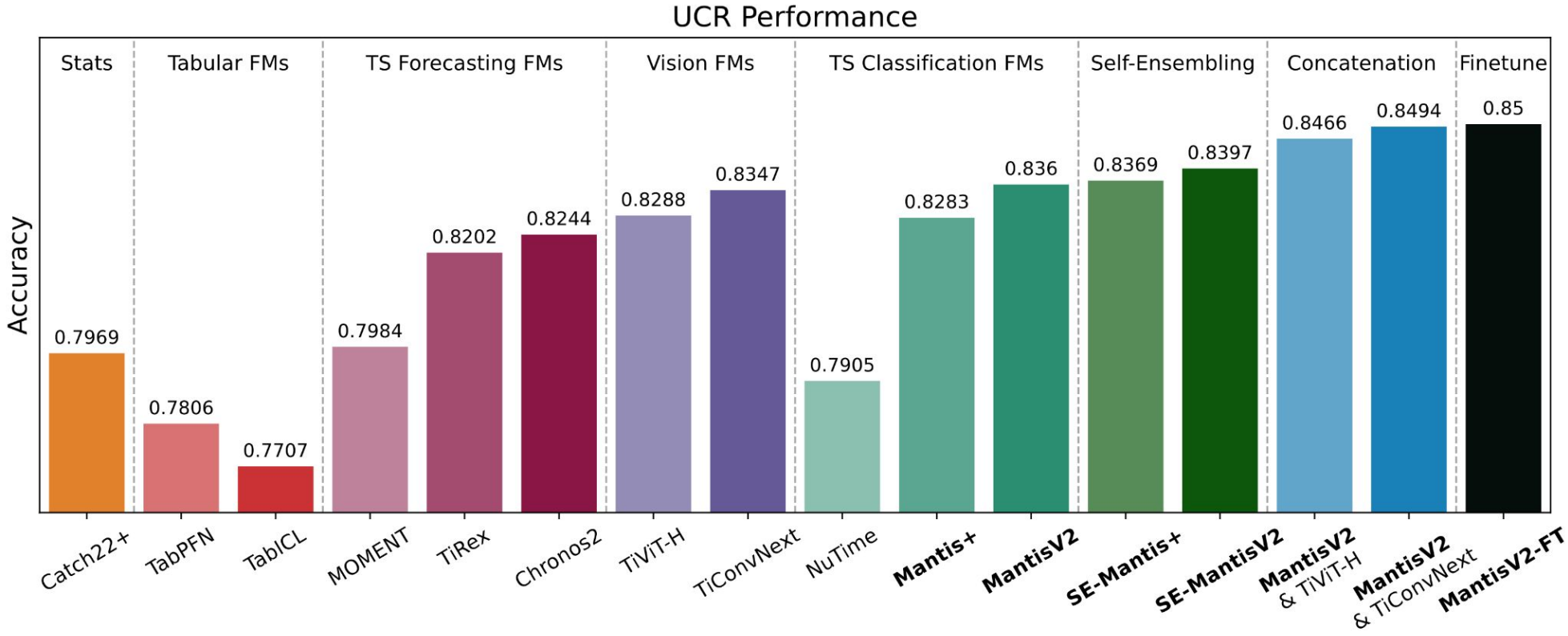
	Catch22+	TabPFN	TabICL	MOMENT	TiRex	Chronos2	TiViT-H	TiConvNext	NuTime	Mantis+	MantisV2
Blink	$0.9963_{\pm 0.001}$	0.9178	0.8978	$0.9674_{\pm 0.003}$	$\mathbf{0.997}_{\pm 0.001}$	$0.9733_{\pm 0.01}$	$0.9852_{\pm 0.006}$	$0.98_{\pm 0.002}$	$0.66_{\pm 0.006}$	$0.9778_{\pm 0.002}$	$0.9956_{\pm 0.002}$
CAP-ID	$0.751_{\pm 0.001}$	NaN	NaN	$0.7374_{\pm 0.002}$	$0.8104_{\pm 0.002}$	$0.8179_{\pm 0.001}$	$0.7983_{\pm 0.001}$	$0.8126_{\pm 0.001}$	$0.8044_{\pm 0.0}$	$\mathbf{0.8189}_{\pm 0.001}$	$0.8152_{\pm 0.001}$
CAP-OOD	$0.71_{\pm 0.003}$	NaN	NaN	$0.7408_{\pm 0.001}$	$0.7821_{\pm 0.001}$	$0.7857_{\pm 0.001}$	$0.7781_{\pm 0.001}$	$0.784_{\pm 0.001}$	$0.767_{\pm 0.002}$	$\mathbf{0.791}_{\pm 0.001}$	$0.7859_{\pm 0.0}$
Epilepsy-EEG	$0.9507_{\pm 0.002}$	0.9496	0.9447	$0.952_{\pm 0.001}$	$\mathbf{0.9614}_{\pm 0.001}$	$0.95_{\pm 0.001}$	$0.9548_{\pm 0.0}$	$0.9495_{\pm 0.001}$	$0.9234_{\pm 0.002}$	$0.9518_{\pm 0.001}$	$0.9558_{\pm 0.001}$
FingerMovements	$0.4967_{\pm 0.064}$	0.5	0.49	$0.53_{\pm 0.02}$	$0.52_{\pm 0.04}$	$0.5233_{\pm 0.021}$	$0.5367_{\pm 0.045}$	$0.5333_{\pm 0.059}$	$0.5267_{\pm 0.015}$	$0.51_{\pm 0.026}$	$\mathbf{0.55}_{\pm 0.01}$
PCL-ID	$0.5241_{\pm 0.003}$	NaN	NaN	$0.5431_{\pm 0.012}$	$0.5272_{\pm 0.011}$	$0.5308_{\pm 0.002}$	$0.5347_{\pm 0.007}$	$0.5385_{\pm 0.005}$	$0.5615_{\pm 0.003}$	$\mathbf{0.5764}_{\pm 0.006}$	$0.5716_{\pm 0.003}$
PCL-OOD	$0.5025_{\pm 0.004}$	NaN	NaN	$0.5129_{\pm 0.001}$	$0.4988_{\pm 0.001}$	$0.5072_{\pm 0.004}$	$0.5003_{\pm 0.005}$	$0.5132_{\pm 0.001}$	$0.5415_{\pm 0.004}$	$\mathbf{0.5427}_{\pm 0.002}$	$0.5311_{\pm 0.009}$
SEDFx-ID	$0.7574_{\pm 0.0}$	NaN	NaN	$0.7516_{\pm 0.001}$	$0.7904_{\pm 0.0}$	$0.8_{\pm 0.0}$	$0.7884_{\pm 0.001}$	$0.8008_{\pm 0.001}$	$0.7822_{\pm 0.001}$	$\mathbf{0.8066}_{\pm 0.0}$	$0.8_{\pm 0.0}$
SEDFx-OOD	$0.7142_{\pm 0.001}$	NaN	NaN	$0.7244_{\pm 0.001}$	$0.7714_{\pm 0.0}$	$\mathbf{0.7758}_{\pm 0.0}$	$0.7709_{\pm 0.0}$	$0.7755_{\pm 0.001}$	$0.741_{\pm 0.0}$	$0.7731_{\pm 0.0}$	$0.7636_{\pm 0.0}$
SelfRegulationSCP1	$0.7702_{\pm 0.007}$	**0.8942**	0.8874	$0.7747_{\pm 0.006}$	$0.7884_{\pm 0.012}$	$0.785_{\pm 0.003}$	$0.7986_{\pm 0.007}$	$0.7929_{\pm 0.01}$	$0.7952_{\pm 0.003}$	$0.7736_{\pm 0.005}$	$0.8134_{\pm 0.009}$
SelfRegulationSCP2	$0.4926_{\pm 0.031}$	0.4778	0.5056	$0.4907_{\pm 0.023}$	$0.4963_{\pm 0.049}$	$0.5167_{\pm 0.006}$	$0.4907_{\pm 0.033}$	$0.5056_{\pm 0.011}$	$0.5074_{\pm 0.018}$	$\mathbf{0.5611}_{\pm 0.02}$	$0.5167_{\pm 0.006}$
Avg	0.6969	NaN	NaN	0.7023	0.7221	0.7242	0.7215	0.726	0.6919	0.7348	**0.7363**

- Big datasets => Tabular FMs do not pass the scale.
- Complex data, small performance difference between models.

Running Time

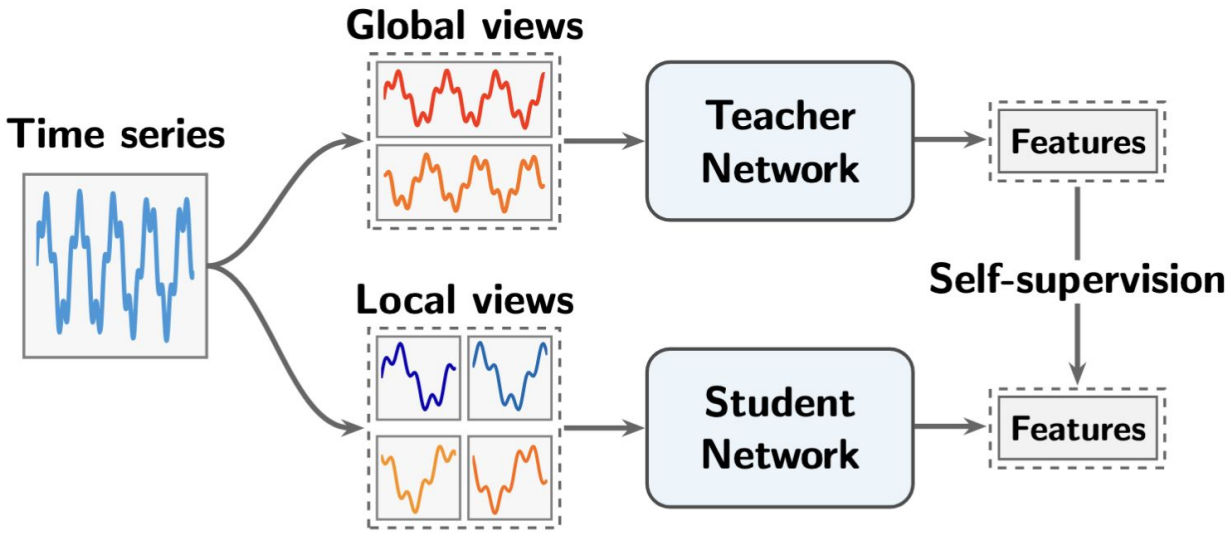


Reaching the Fine-tuning Performance



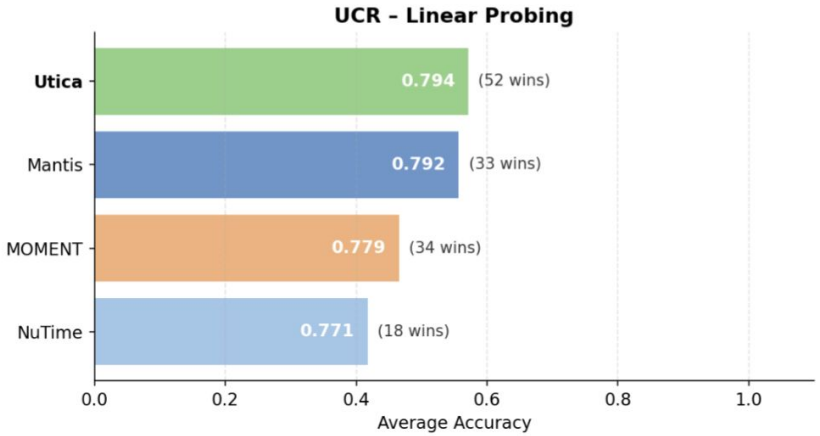
- Linear probing fails: use Standard Scaler or Batch Normalization!
- Self-Ensembling: interpolate the input to different lengths.
- Cross-Model Embedding Fusion: some models are complementary to each other.

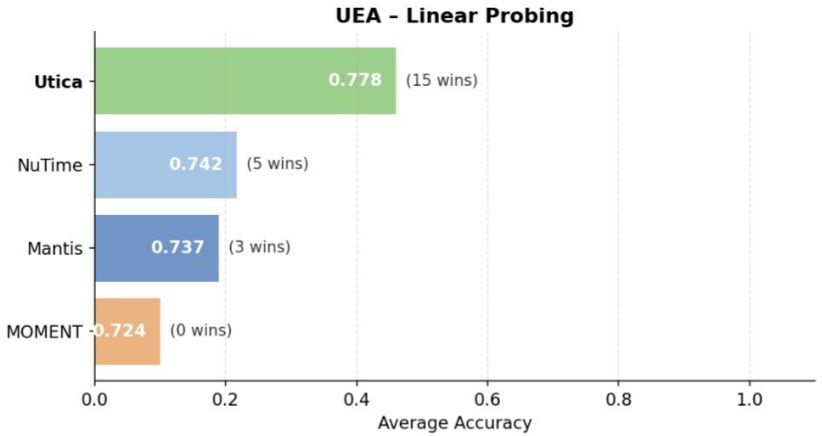
More Ideas: Self-distillation Loss



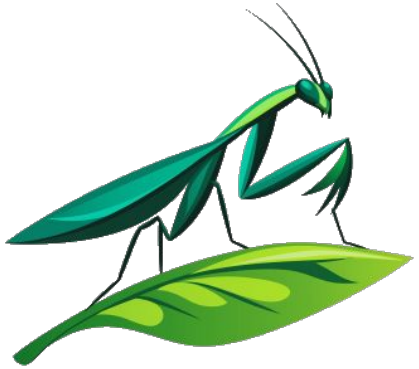
- Teacher and Student are identical encoders:

- DINO V2 Self-distillation Loss is a composition of:
  - DINO loss: local and global views give similar embeddings.
  - iBOT loss: masked and global views give similar embeddings.
  - KoLeo regularizer: prevent feature collapse.





Moakher et al. (2026) UTICA: Multi-Objective Self-Distillation Foundation Model Pretraining for Time Series Classification (*ICLR'26 TSALM workshop*).



Thank you for your attention!

GitHub

Paper