TimeEmb: A Lightweight Static-Dynamic Disentanglement Framework for Time Series Forecasting

Mingyuan Xia*[1], Chunxu Zhang*[1], Zijian Zhang†[1], Hao Miao[2], Qidong Liu[3],

Yuanshao Zhu[4], Bo Yang[1]

1. Jilin University
2. The Hong Kong Polytechnic University
3. Xi'an Jiaotong University
4. City University of Hong Kong

Outline

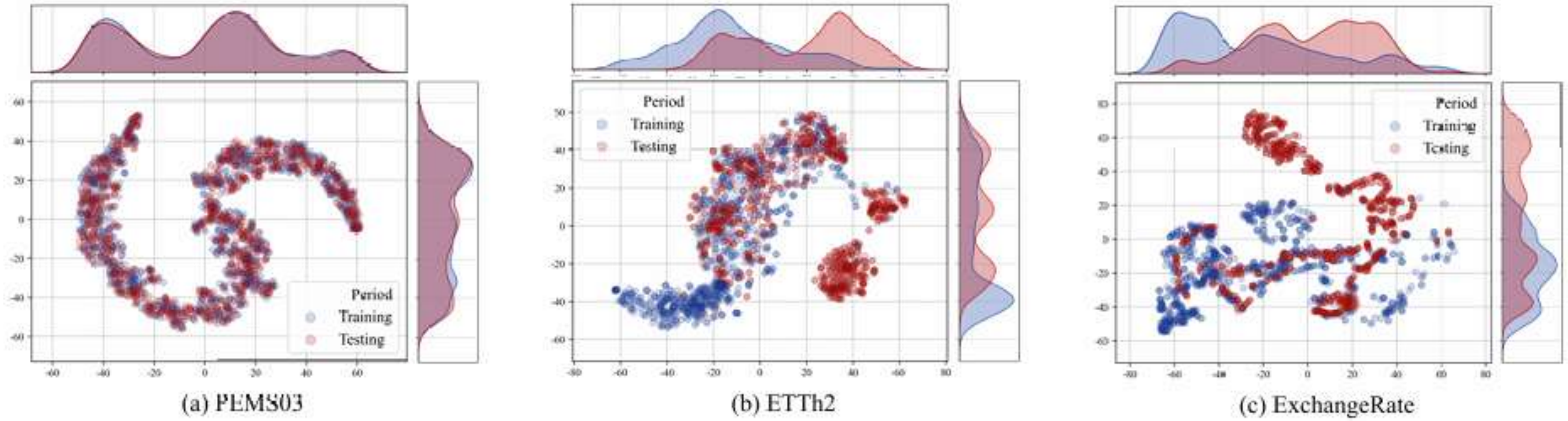
- Introduction
  - Research Background
  - Motivation
- Framework
- Experiments
- Conclusion

Introduction

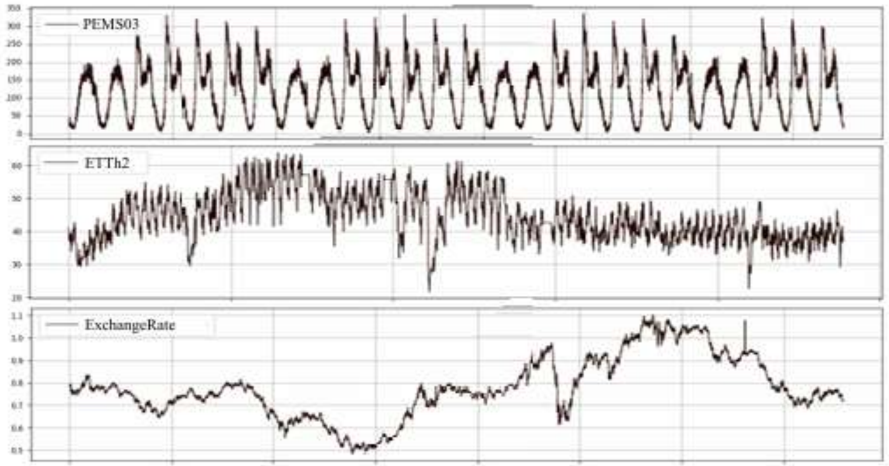
- Temporal non-stationarity challenges stable forecasting
- Time series can be decomposed into two complementary parts
- Existing methods conflate static and dynamic factors
- Goal: disentangle time-invariant and time-varying patterns for robustness

Research Background

- Temporal non-stationarity challenges stable forecasting



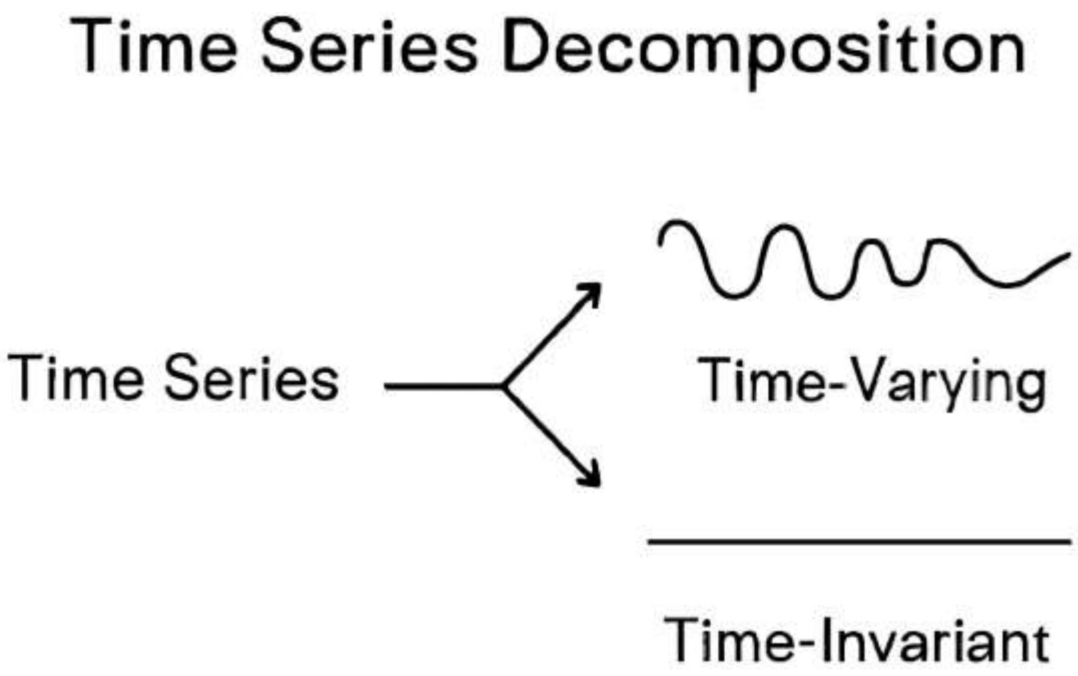
Visualization of data distribution based on t-SNE and kernel density estimation



Distinct temporal patterns in multiple MTS datasets

Research Background

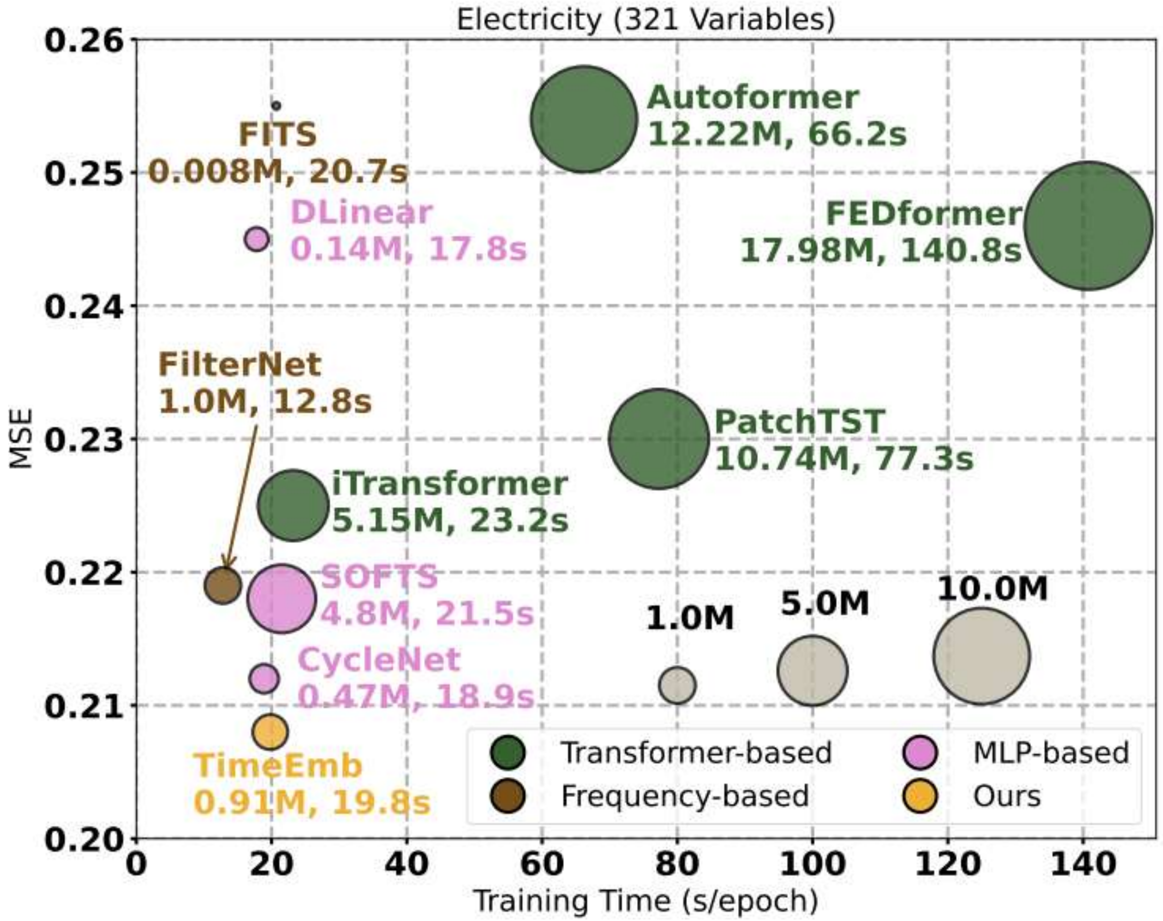
- Every time series can be decomposed into two complementary parts:
  - A **time-invariant** component that reflects long-term stable patterns, and
  - A **time-varying** component that represents short-term dynamics and fluctuations



Motivation

- Existing methods mix static and dynamic components:
  - **Decomposition methods** like DLinear rely on local statistical information but miss global patterns
  - **Transformer-based models** like iTransformer treat the entire sequence as one, confusing short-term noise with long-term trends
  - **Frequency-based methods** like FilterNet filter signals, but can't flexibly handle both static and dynamic factors

Motivation



- Our TimeEmb separates these components, preserving long-term patterns while capturing short-term changes, improving accuracy with high efficiency

Outline

- Introduction
- Framework
  - Overview
  - Domain Transformation
  - Static Component via Embedding Bank
  - Dynamic Component via Frequency Filtering
  - Prediction Layer and Optimization Objective
- Experiments
- Conclusion

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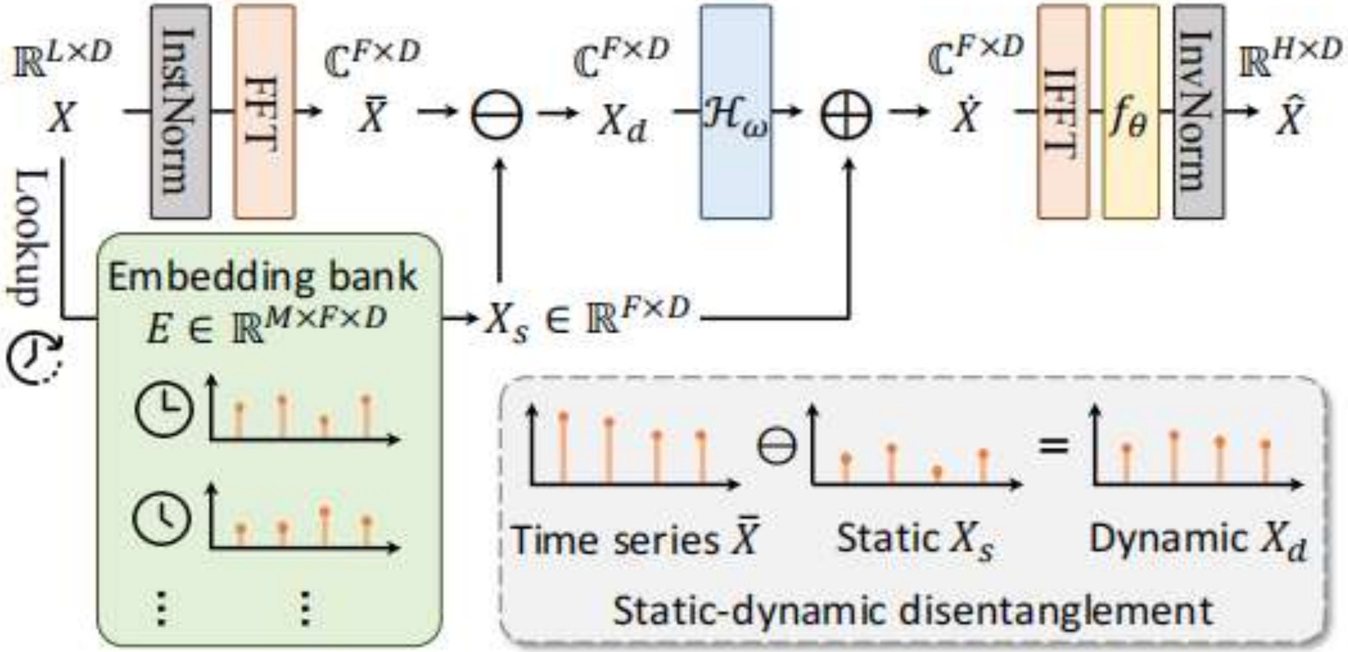
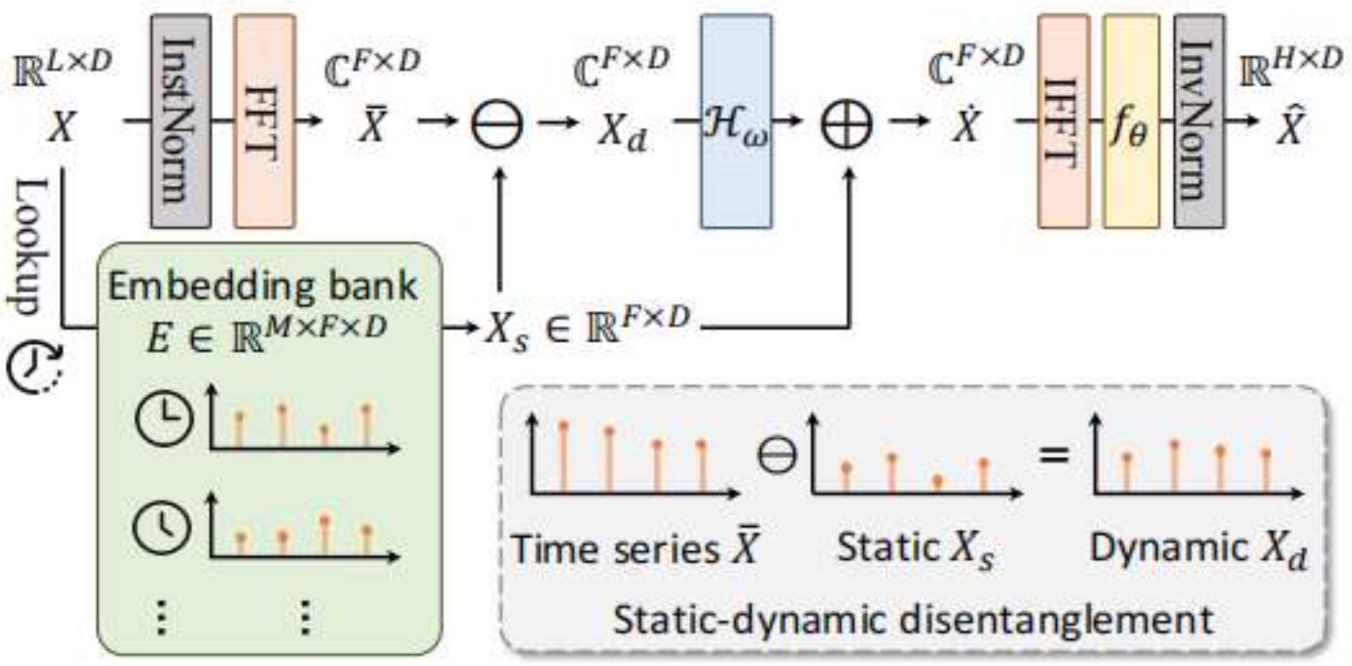
Overview



$\mathbb{R}^{L\times D}$
X
InstNorm
FFT
$\mathbb{C}^{F\times D}$
$\bar{X}$
$\mathbb{C}^{F\times D}$
X_d
$\mathcal{H}_\omega$
$\mathbb{C}^{F\times D}$
$\dot{X}$
IFFT
f_θ
InvNorm
$\mathbb{R}^{H\times D}$
$\hat{X}$
Lookup
Embedding bank
$E \in \mathbb{R}^{M\times F\times D}$
$X_s \in \mathbb{R}^{F\times D}$
Time series $\bar{X}$
Static X_s
Dynamic X_d
Static-dynamic disentanglement

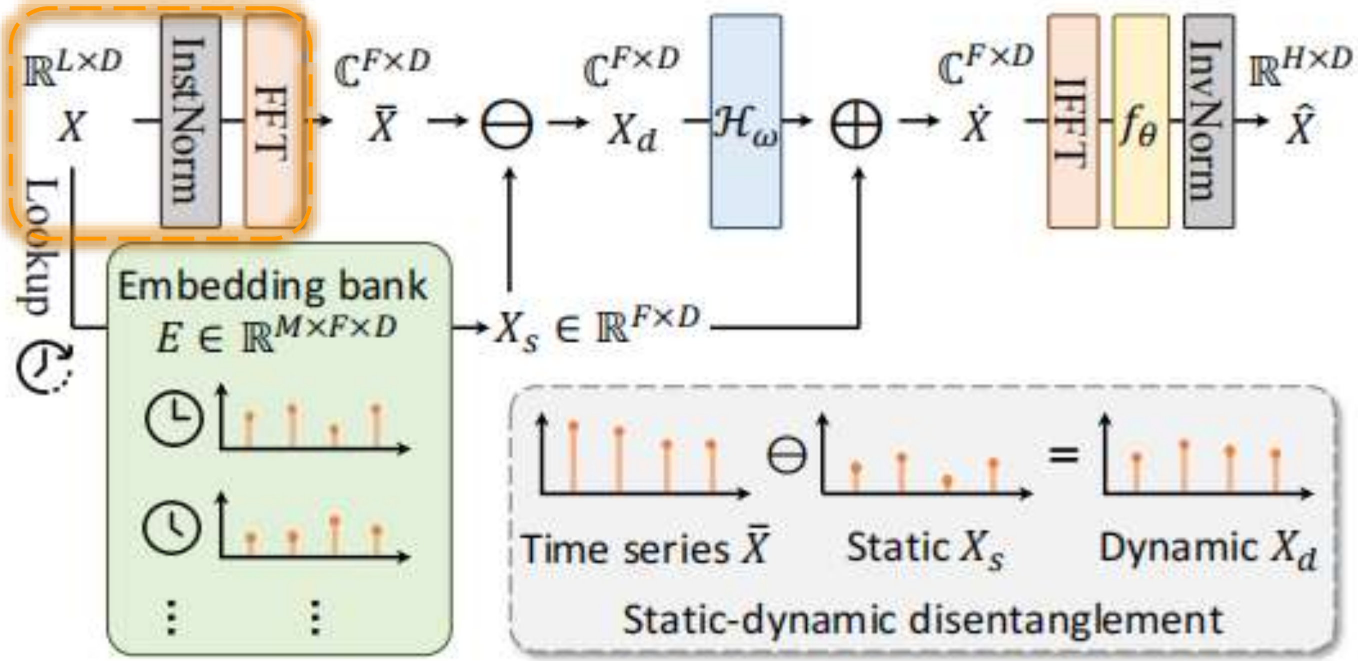
Overview



Benefits of Frequency Representation

- ✓ Reveal the underlying periodic structures hidden in time domain
- ✓ Provide a clearer perspective for disentanglement
- ✓ Explicitly separate periodic patterns and dynamic noise

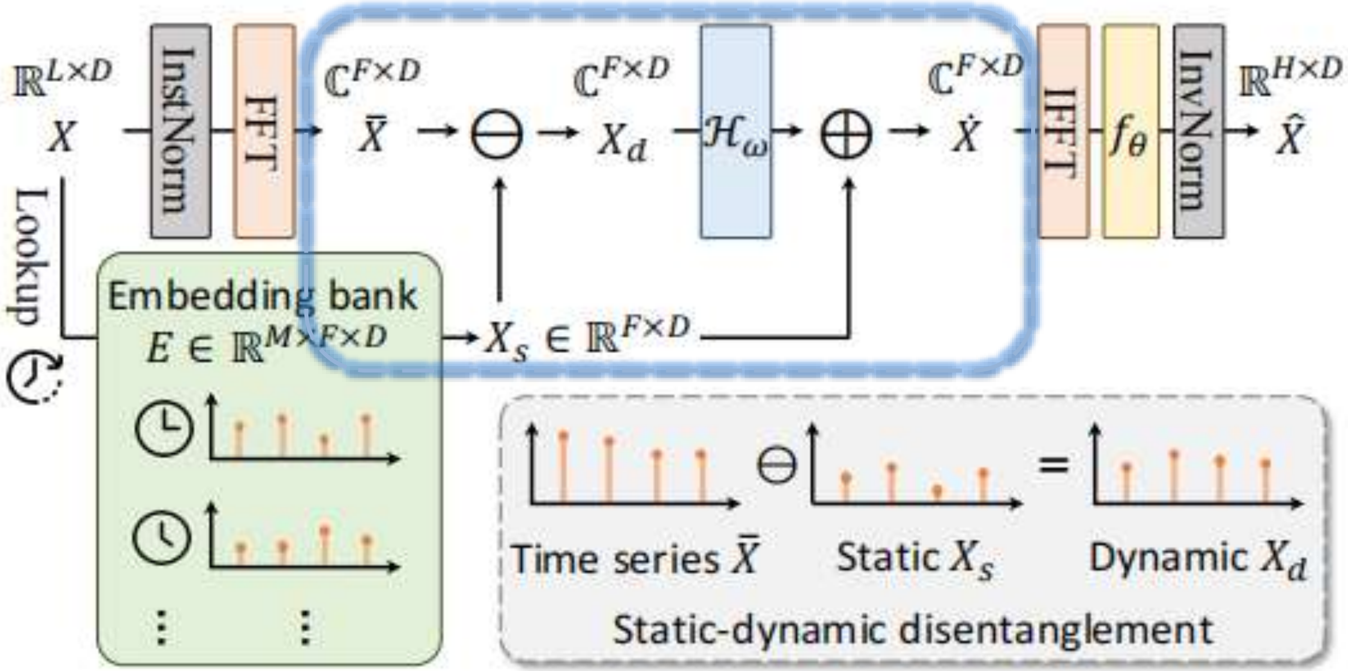
Overview



Domain Transformation Layer

- ✓ Tranform X to frequecy domain $\bar{X}$ via Fast Fourier Transform (FFT)

Overview



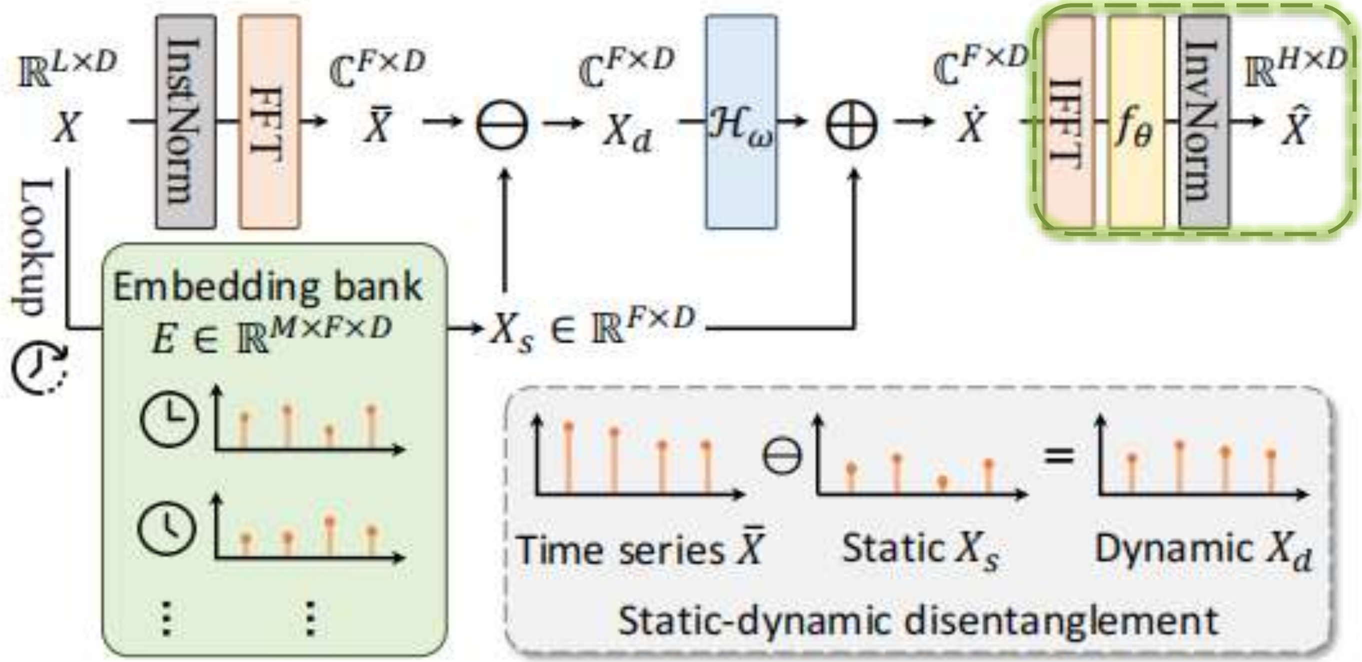
Domain Transformation Layer

- ✓ Tranform X to frequecy domain $\bar{X}$ via Fast Fourier Transform (FFT)

Static-dynamic Disentanglement Layer

- ✓ Introduce a learnable embedding bank to retrieve the static component
- ✓ Process the dynamic component via frequency filtering

Overview



Domain Transformation Layer

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Static-dynamic Disentanglement Layer

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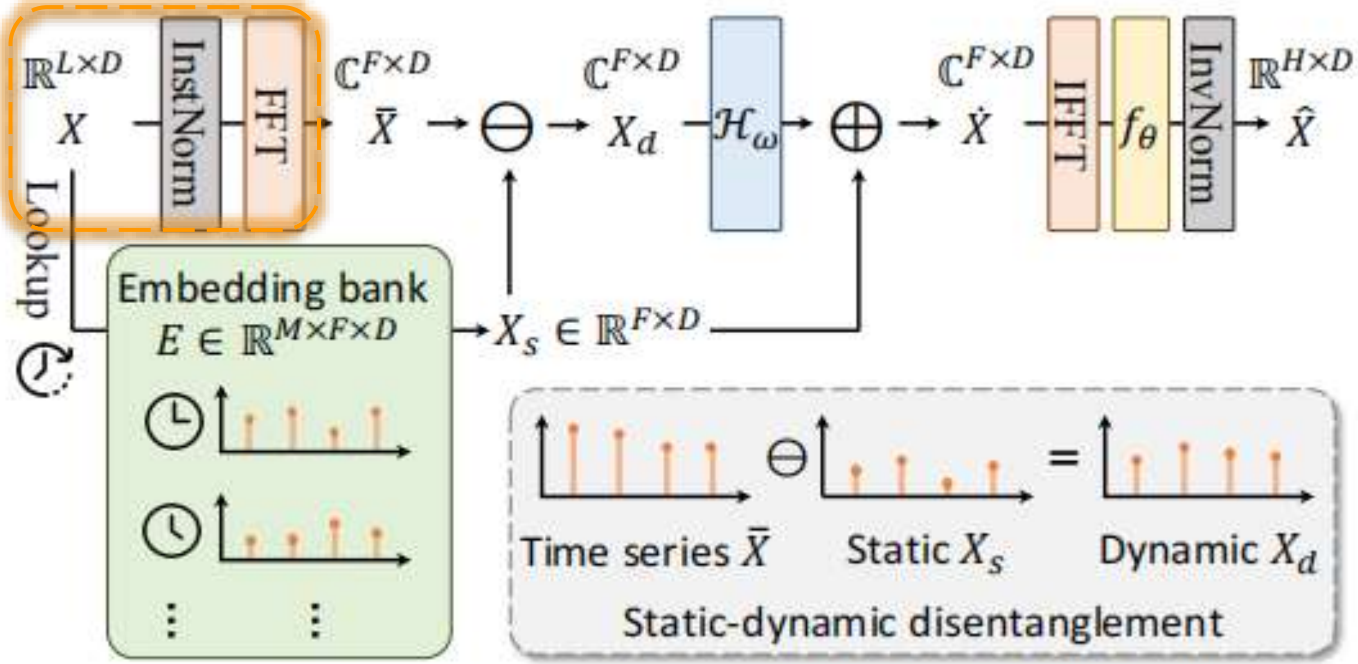
Prediction Layer

- ✓ Generate the final prediction

Domain Transformation Layer



① Domain Transformation

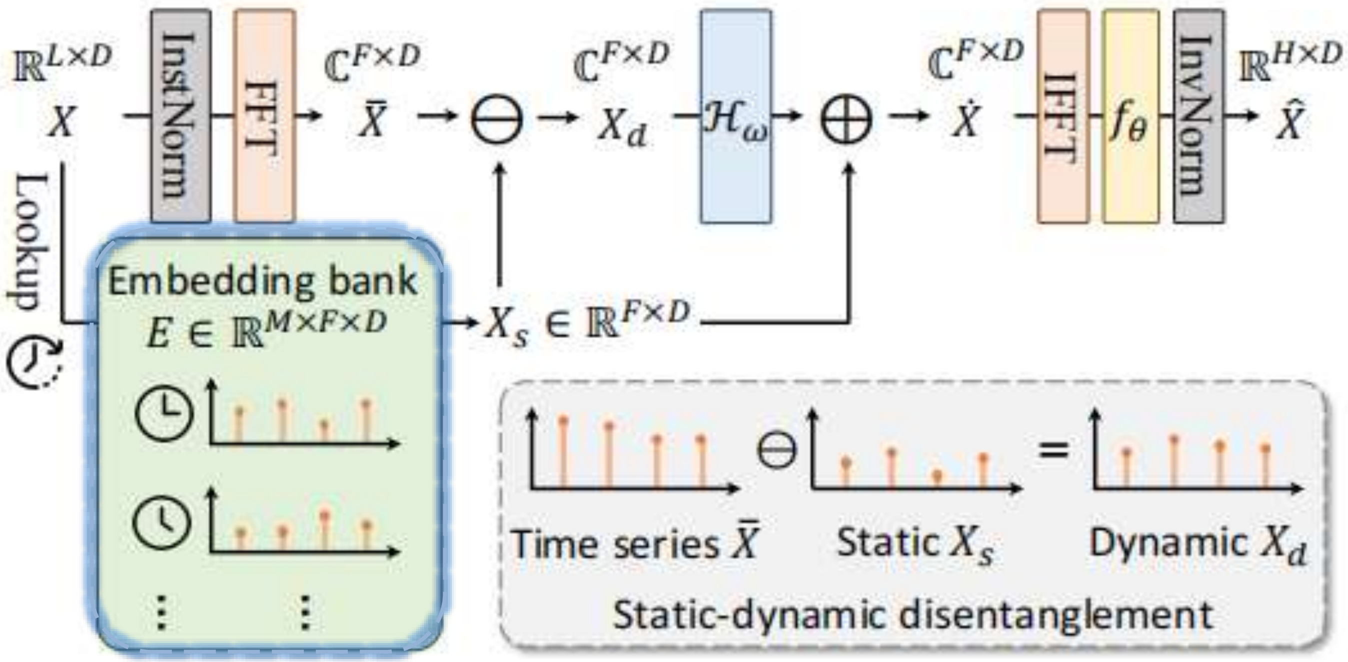
Transfer the time series from time domain to frequency domain:

$F = \lfloor L / 2 \rfloor + 1$

$$\overline{\boldsymbol{X}}[k] = \sum_{n=0}^{L-1} \boldsymbol{X}[n] e^{-\boxed{j} 2\pi kn/L}, \quad k = 0, 1, \ldots, \boxed{F} - 1,$$

imaginary unit

Static-dynamic Disentanglement Layer



② Static Component via Embedding Bank

Retrieve the corresponding embedding:

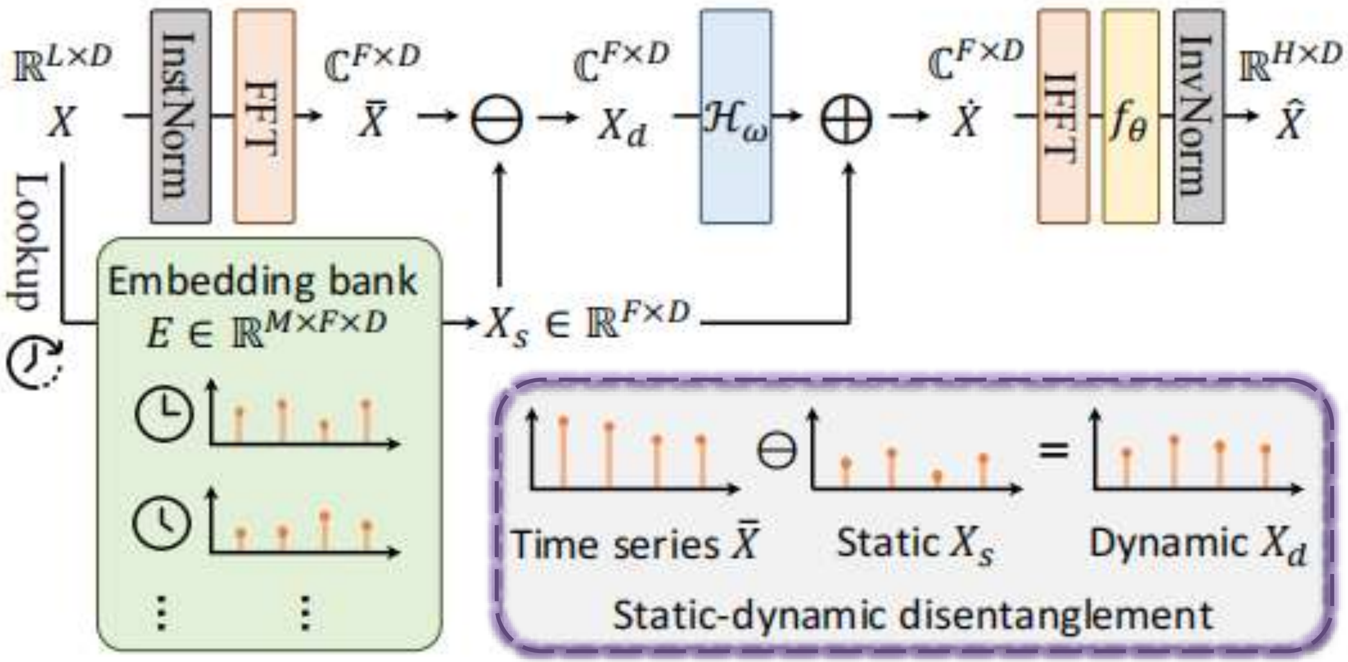
$$\boldsymbol{X}_s = \boldsymbol{E}[\boxed{t_{last}} \bmod \boxed{M}]$$

time index of X   size of Emb bank

Each embedding in E corresponds to a specific time slot

This bank captures persistent global patterns that are consistent across the entire dataset

Static-dynamic Disentanglement Layer



② Static Component via Embedding Bank

Separate the embedding X_s from time series $\bar{X}$:

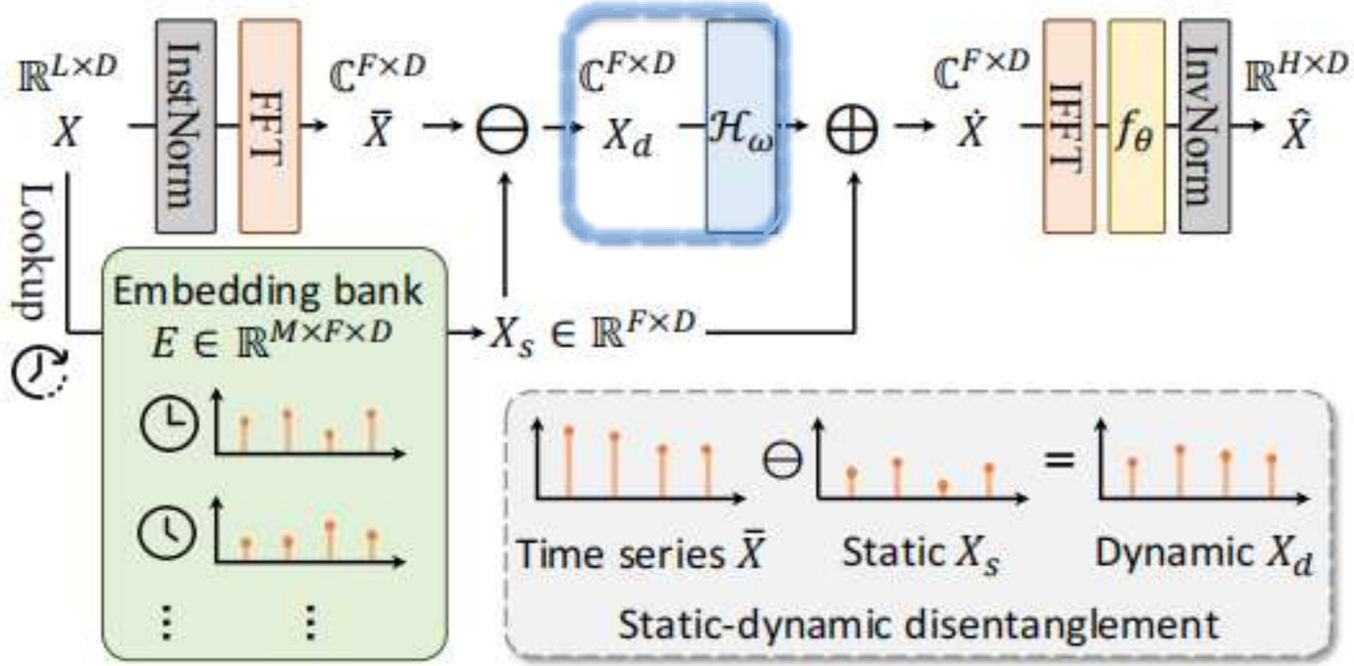
$$\boldsymbol{X}_d = \overline{\boldsymbol{X}} - \boldsymbol{X}_s.$$

Disentangle the time-varying and time-invariant components

Enable explicit modeling of both stable and changing patterns

Static-dynamic Disentanglement Layer

③ Dynamic Component via Freq Filtering



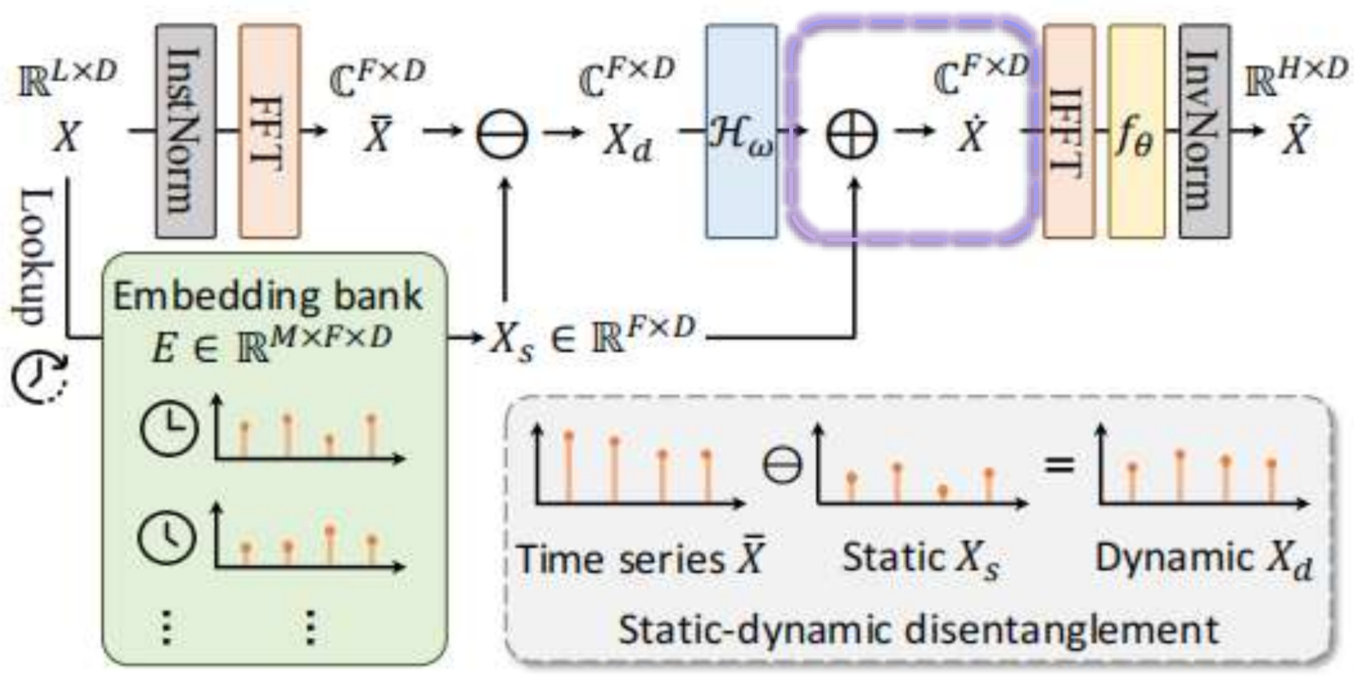
Reweight different frequency bands to adapt to distribution shifts:

$$\mathcal{H}_{\boldsymbol{\omega}}(\boldsymbol{X}_d)[k] = \boldsymbol{X}_d[k] \odot \boxed{\boldsymbol{\omega}}[k]$$

modulation vector

Provide practical flexibility for modeling diverse temporal dynamics

Static-dynamic Disentanglement Layer

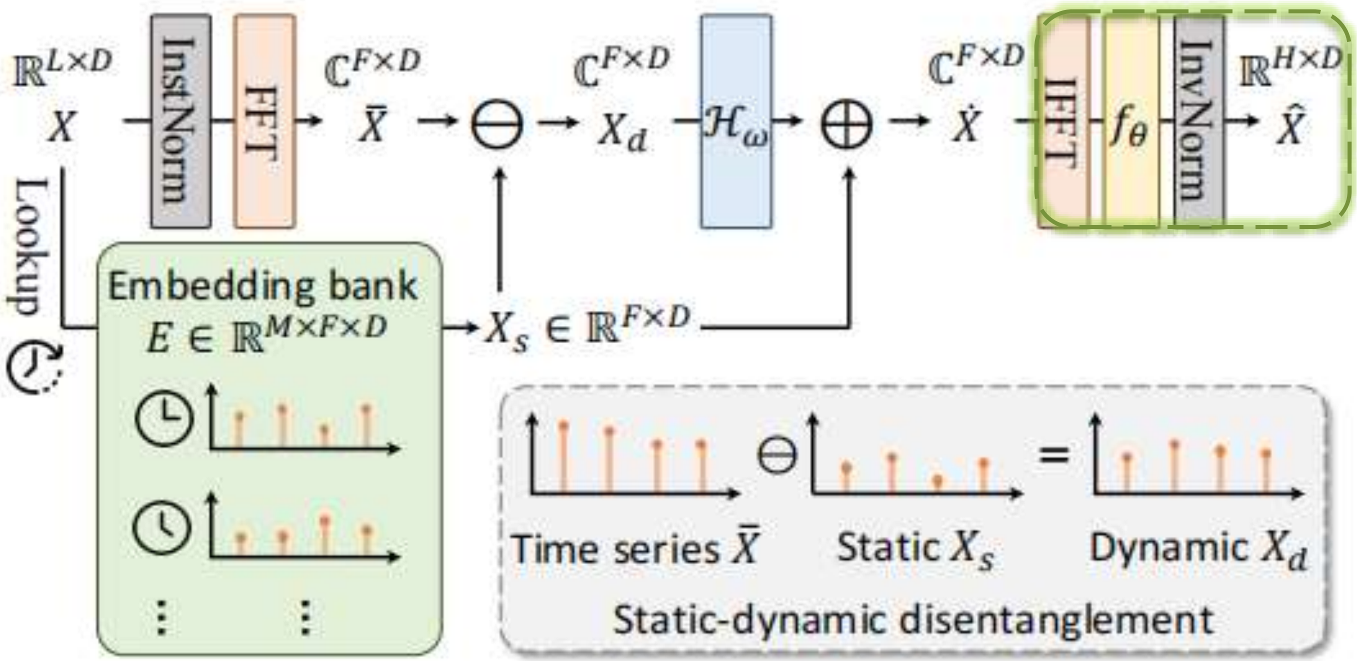


④ Reconstruct the Full Representation

Add back the static component X_s:

$$\dot{\boldsymbol{X}} = \mathcal{H}_\omega(\boldsymbol{X}_d) + \boldsymbol{X}_s$$

Prediction Layer



⑤ The Projection Layer

$$f_{\theta}(\boldsymbol{X}) = \boldsymbol{W}_2(\mathrm{ReLU}(\boldsymbol{W}_1\boldsymbol{X} + \boldsymbol{b}_1)) + \boldsymbol{b}_2$$

Generate the final prediction:

$$\widehat{\boldsymbol{X}} = \boxed{\mathrm{InvNorm}}(f_{\theta}(\boxed{\mathrm{IFFT}}(\dot{\boldsymbol{X}})))$$

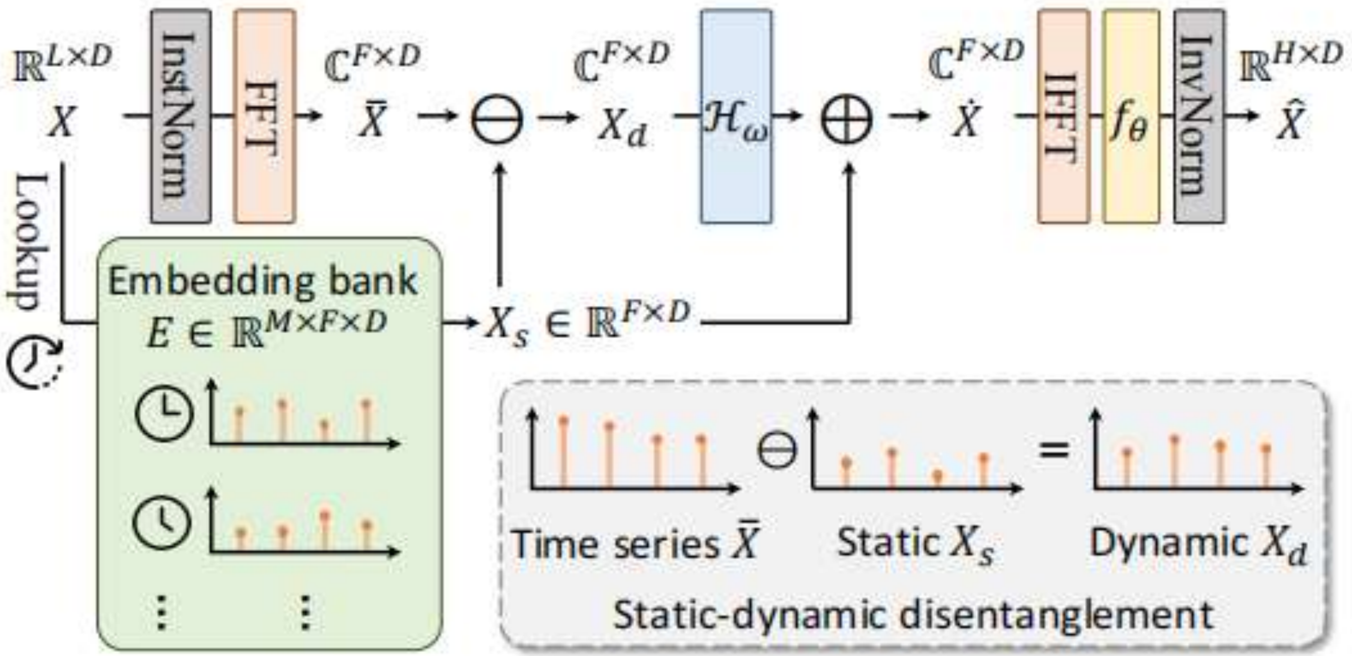
Inverse Instance Normalization

Inverse Fast Fourier Transformation

⑥ Objective Function

$$\mathcal{L}(\widehat{\boldsymbol{X}}, \boldsymbol{Y}) = \alpha \mathrm{MAE}(\mathrm{FFT}(\widehat{\boldsymbol{X}}), \mathrm{FFT}(\boldsymbol{Y})) + (1-\alpha)\mathrm{MSE}(\widehat{\boldsymbol{X}}, \boldsymbol{Y})$$

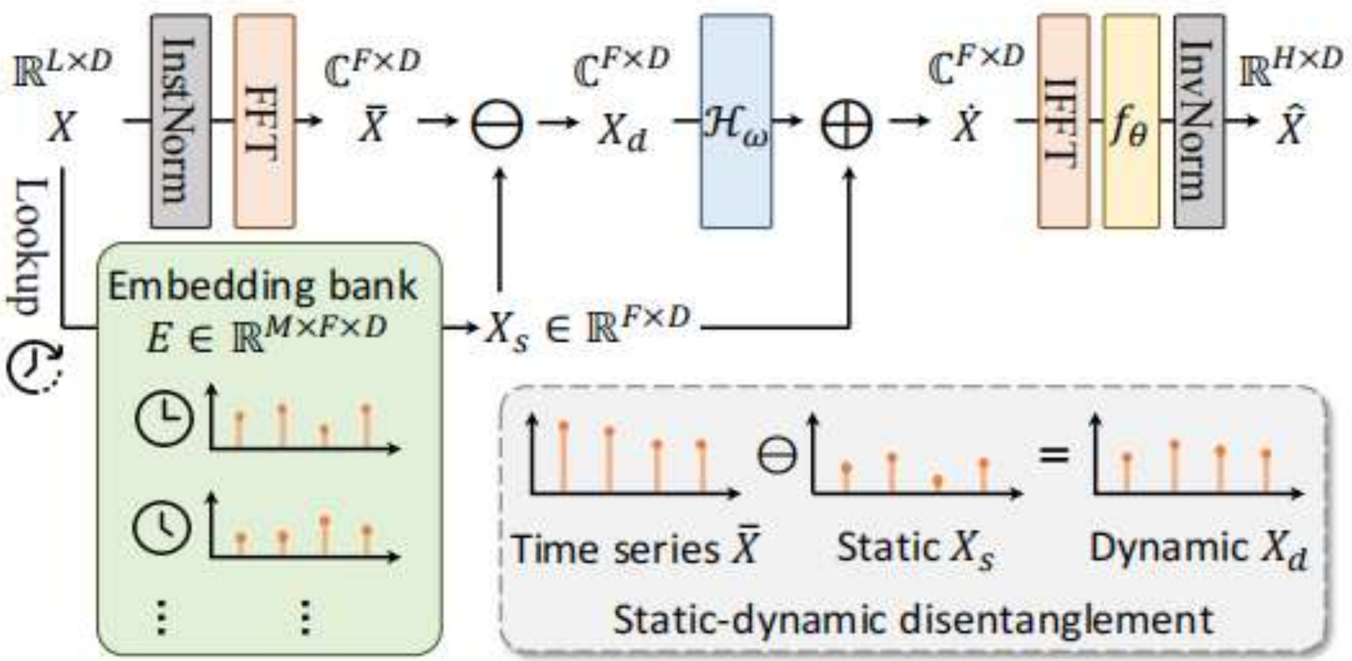
Pipeline



Embedding Bank

- ✓ Learns global, time-invariant patterns across the dataset
- ✓ No predefined cycles or assumptions
- ✓ Captures stable temporal structures flexibly

Pipeline



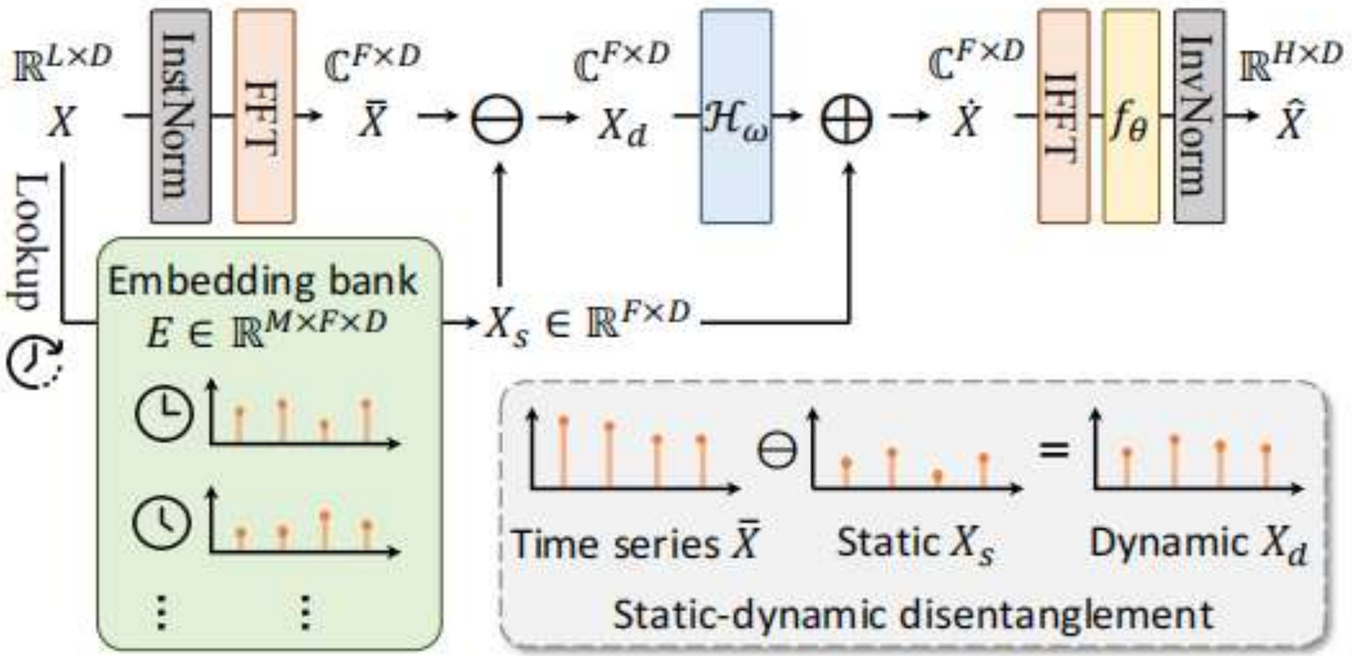
Frequency Filtering

✓ Adaptive reweighting of frequency components

✓ Models dynamic variations effectively

✓ Complements static embedding for robust forecasting

Pipeline



Framework Summary

- ✓ A frequency-domain disentanglement framework
- ✓ Separately models static and dynamic components
- ✓ Achieves robust, efficient, and interpretable forecasting

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- Introduction
- Framework
- Experiments
  - Experimental Settings
  - Overall Performance
  - Compatibility Analysis
  - Visualization
  - Ablation Study
  - Hyper-Parameter Analysis
- Conclusion

Experimental Settings

Dataset

- ETTs: ETTh1, ETTh2, ETTm1, ETTm2
- Electricity
- Weather
- Traffic

Datasets	ETTh1	ETTh2	ETTm1	ETTm2	Electricity	Weather	Traffic
Channels	7	7	7	7	321	21	862
Timesteps	17420	17420	69680	69680	26304	52696	17544
Frequency	Hourly	Hourly	15min	15min	Hourly	10min	Hourly
Domain	Electricity	Electricity	Electricity	Electricity	Electricity	Weather	Traffic

Experimental Settings

Baselines

- Frequency-based models:
  - FreTS(NeurIPS 2023), FilterNet(NeurIPS 2024), FITS(ICLR 2024)
- MLP-based models:
  - DLinear(AAAI 2023), CycleNet(NeurIPS 2024)
- Transformer-based Models:
  - PatchTST(ICLR 2023), iTransformer(ICLR 2024), Fredformer(KDD 2024)

Overall Performance

Model		TimeEmb (ours)		CycleNet 2024		Fredformer 2024		FilterNet 2024		iTransformer 2024		PatchTST 2023		FITS 2024		FreTS 2023		DLinear 2023	
Metric		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	96	**0.366±0.001**	**0.387±0.001**	0.378	0.391	0.373	0.392	0.375	0.394	0.386	0.405	0.394	0.406	0.386	0.396	0.395	0.407	0.386	0.400
	192	**0.417±0.001**	**0.416±0.001**	0.426	0.419	0.433	0.420	0.436	0.422	0.441	0.436	0.440	0.435	0.436	0.423	0.448	0.440	0.437	0.432
	336	**0.457±0.001**	**0.436±0.001**	0.464	0.439	0.470	0.437	0.476	0.443	0.487	0.458	0.491	0.462	0.478	0.444	0.499	0.472	0.481	0.459
	720	**0.459±0.002**	0.460±0.001	0.461	0.460	0.467	**0.456**	0.474	0.469	0.503	0.491	0.487	0.479	0.502	0.495	0.558	0.532	0.519	0.516
	avg	**0.425±0.001**	**0.425±0.001**	0.432	0.427	0.435	0.426	0.440	0.432	0.454	0.447	0.453	0.446	0.451	0.440	0.475	0.463	0.456	0.452
ETTh2	96	**0.277±0.001**	**0.328±0.001**	0.285	0.335	0.293	0.342	0.292	0.343	0.297	0.349	0.288	0.340	0.295	0.350	0.309	0.364	0.333	0.387
	192	**0.356±0.001**	**0.379±0.001**	0.373	0.391	0.371	0.389	0.369	0.395	0.380	0.400	0.376	0.395	0.381	0.396	0.395	0.425	0.477	0.476
	336	0.400±0.002	**0.417±0.001**	0.421	0.433	**0.382**	**0.409**	0.420	0.432	0.428	0.432	0.440	0.451	0.426	0.438	0.462	0.467	0.594	0.541
	720	**0.416±0.001**	0.437±0.002	0.453	0.458	**0.415**	**0.434**	0.430	0.446	0.427	0.445	0.436	0.453	0.431	0.446	0.721	0.604	0.831	0.657
	avg	**0.362±0.001**	**0.390±0.001**	0.383	0.404	0.365	0.393	0.378	0.404	0.383	0.407	0.385	0.410	0.383	0.408	0.472	0.465	0.559	0.515
ETTm1	96	**0.304±0.001**	**0.343±0.001**	0.319	0.360	0.326	0.361	0.318	0.358	0.334	0.368	0.329	0.365	0.355	0.375	0.335	0.372	0.345	0.372
	192	**0.354±0.001**	**0.373±0.001**	0.360	0.381	0.363	0.380	0.364	0.383	0.377	0.391	0.380	0.394	0.392	0.393	0.388	0.401	0.380	0.389
	336	**0.379±0.001**	**0.393±0.001**	0.389	0.403	0.395	0.403	0.396	0.406	0.426	0.420	0.400	0.410	0.424	0.414	0.421	0.426	0.413	0.413
	720	**0.435±0.001**	**0.428±0.001**	0.447	0.441	0.453	0.438	0.456	0.444	0.491	0.459	0.475	0.453	0.487	0.449	0.486	0.465	0.474	0.453
	avg	**0.368±0.001**	**0.384±0.001**	0.379	0.396	0.384	0.395	0.384	0.398	0.407	0.410	0.396	0.406	0.415	0.408	0.408	0.416	0.403	0.407
ETTm2	96	**0.163±0.001**	**0.242±0.001**	**0.163**	0.246	0.177	0.259	0.174	0.257	0.180	0.264	0.184	0.264	0.183	0.266	0.189	0.277	0.193	0.292
	192	**0.226±0.001**	**0.285±0.001**	0.229	0.290	0.243	0.301	0.240	0.300	0.250	0.309	0.246	0.306	0.247	0.305	0.258	0.326	0.284	0.362
	336	0.286±0.001	**0.324±0.001**	**0.284**	0.327	0.302	0.340	0.297	0.339	0.311	0.348	0.308	0.346	0.307	0.342	0.343	0.390	0.369	0.427
	720	**0.383±0.001**	**0.381±0.001**	0.389	0.391	0.397	0.396	0.392	0.393	0.412	0.407	0.409	0.402	0.407	0.399	0.495	0.480	0.554	0.522
	avg	**0.265±0.001**	**0.308±0.001**	0.266	0.314	0.279	0.324	0.276	0.322	0.288	0.332	0.287	0.330	0.286	0.328	0.321	0.368	0.350	0.401
Weather	96	**0.150±0.001**	**0.190±0.001**	0.158	0.203	0.163	0.207	0.162	0.207	0.174	0.214	0.176	0.217	0.166	0.213	0.174	0.208	0.196	0.255
	192	**0.200±0.001**	**0.238±0.001**	0.207	0.247	0.211	0.251	0.210	0.250	0.221	0.254	0.221	0.256	0.213	0.254	0.219	0.250	0.237	0.296
	336	**0.259±0.001**	**0.282±0.001**	0.262	0.289	0.267	0.292	0.265	0.290	0.278	0.296	0.275	0.296	0.269	0.294	0.273	0.290	0.283	0.335
	720	0.339±0.001	0.336±0.001	0.344	0.344	0.343	0.341	0.342	0.340	0.358	0.347	0.352	0.346	0.346	0.343	**0.334**	**0.332**	0.345	0.381
	avg	**0.237±0.001**	**0.262±0.001**	0.243	0.271	0.246	0.272	0.245	0.272	0.258	0.278	0.256	0.279	0.249	0.276	0.250	0.270	0.265	0.317
Electricity	96	**0.136±0.001**	0.231±0.001	**0.136**	**0.229**	0.147	0.241	0.147	0.245	0.148	0.240	0.164	0.251	0.200	0.278	0.176	0.258	0.197	0.282
	192	0.153±0.001	0.246±0.001	**0.152**	**0.244**	0.165	0.258	0.160	0.250	0.162	0.253	0.173	0.262	0.200	0.280	0.175	0.262	0.196	0.285
	336	**0.170±0.001**	**0.264±0.001**	**0.170**	**0.264**	0.177	0.273	0.173	0.267	0.178	0.269	0.190	0.279	0.214	0.295	0.185	0.278	0.209	0.301
	720	**0.208±0.001**	**0.297±0.001**	0.212	0.299	0.213	0.304	0.210	0.309	0.225	0.317	0.230	0.313	0.255	0.327	0.220	0.315	0.245	0.333
	avg	**0.167±0.001**	0.260±0.001	0.168	**0.259**	0.175	0.269	0.173	0.268	0.178	0.270	0.189	0.276	0.217	0.295	0.189	0.278	0.212	0.300
Traffic	96	0.432±0.002	0.279±0.001	0.458	0.296	0.406	0.277	0.430	0.294	**0.395**	**0.268**	0.427	0.272	0.651	0.391	0.593	0.378	0.650	0.396
	192	0.442±0.001	0.289±0.001	0.457	0.294	0.426	0.290	0.452	0.307	**0.417**	**0.276**	0.454	0.289	0.602	0.363	0.595	0.377	0.598	0.370
	336	0.456±0.002	0.295±0.002	0.470	0.299	**0.432**	**0.281**	0.470	0.316	0.433	0.283	0.450	0.282	0.609	0.366	0.609	0.385	0.605	0.373
	720	0.487±0.003	0.311±0.001	0.502	0.314	**0.463**	**0.300**	0.498	0.323	0.467	0.302	0.484	0.301	0.647	0.385	0.673	0.418	0.645	0.394
	avg	0.454±0.002	0.293±0.001	0.472	0.301	0.431	0.287	0.463	0.310	**0.428**	**0.282**	0.454	0.286	0.627	0.376	0.618	0.390	0.625	0.383

TimeEmb consistently outperforms strong baselines across diverse datasets

Overall Performance

Model		TimeEmb (ours)		CycleNet 2024		Fredformer 2024		FilterNet 2024		iTransformer 2024		PatchTST 2023		FITS 2024		FreTS 2023		DLinear 2023	
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	336	0.400±0.002	0.417±0.001	0.421	0.433	0.382	0.409	0.420	0.432	0.428	0.432	0.440	0.451	0.426	0.438	0.462	0.467	0.594	0.541
	720	0.416±0.001	0.437±0.002	0.453	0.458	0.415	0.434	0.430	0.446	0.427	0.445	0.436	0.453	0.431	0.446	0.721	0.604	0.831	0.657
	avg	0.362±0.001	0.390±0.001	0.383	0.404	0.365	0.393	0.378	0.404	0.383	0.407	0.385	0.410	0.383	0.408	0.472	0.465	0.559	0.515
ETTm1	96	0.304±0.001	0.343±0.001	0.319	0.360	0.326	0.361	0.318	0.358	0.334	0.368	0.329	0.365	0.355	0.375	0.335	0.372	0.345	0.372
	192	0.354±0.001	0.373±0.001	0.360	0.381	0.363	0.380	0.364	0.383	0.377	0.391	0.380	0.394	0.392	0.393	0.388	0.401	0.380	0.389
	336	0.379±0.001	0.393±0.001	0.389	0.403	0.395	0.403	0.396	0.406	0.426	0.420	0.400	0.410	0.424	0.414	0.421	0.426	0.413	0.413
	720	0.435±0.001	0.428±0.001	0.447	0.441	0.453	0.438	0.456	0.444	0.491	0.459	0.475	0.453	0.487	0.449	0.486	0.465	0.474	0.453
	avg	0.368±0.001	0.384±0.001	0.379	0.396	0.384	0.395	0.384	0.398	0.407	0.410	0.396	0.406	0.415	0.408	0.408	0.416	0.403	0.407
ETTm2	96	0.163±0.001	0.242±0.001	0.163	0.246	0.177	0.259	0.174	0.257	0.180	0.264	0.184	0.264	0.183	0.266	0.189	0.277	0.193	0.292
	192	0.226±0.001	0.285±0.001	0.229	0.290	0.243	0.301	0.240	0.300	0.250	0.309	0.246	0.306	0.247	0.305	0.258	0.326	0.284	0.362
	336	0.286±0.001	0.324±0.001	0.284	0.327	0.302	0.340	0.297	0.339	0.311	0.348	0.308	0.346	0.307	0.342	0.343	0.390	0.369	0.427
	720	0.383±0.001	0.381±0.001	0.389	0.391	0.397	0.396	0.392	0.393	0.412	0.407	0.409	0.402	0.407	0.399	0.495	0.480	0.554	0.522
	avg	0.265±0.001	0.308±0.001	0.266	0.314	0.279	0.324	0.276	0.322	0.288	0.332	0.287	0.330	0.286	0.328	0.321	0.368	0.350	0.401
Weather	96	0.150±0.001	0.190±0.001	0.158	0.203	0.163	0.207	0.162	0.207	0.174	0.214	0.176	0.217	0.166	0.213	0.174	0.208	0.196	0.255
	192	0.200±0.001	0.238±0.001	0.207	0.247	0.211	0.251	0.210	0.250	0.221	0.254	0.221	0.256	0.213	0.254	0.219	0.250	0.237	0.296
	336	0.259±0.001	0.282±0.001	0.262	0.289	0.267	0.292	0.265	0.290	0.278	0.296	0.275	0.296	0.269	0.294	0.273	0.290	0.283	0.335
	720	0.339±0.001	0.336±0.001	0.344	0.344	0.343	0.341	0.342	0.340	0.358	0.347	0.352	0.346	0.346	0.343	0.334	0.332	0.345	0.381
	avg	0.237±0.001	0.262±0.001	0.243	0.271	0.246	0.272	0.245	0.272	0.258	0.278	0.256	0.279	0.249	0.276	0.250	0.270	0.265	0.317
Electricity	96	0.136±0.001	0.231±0.001	0.136	0.229	0.147	0.241	0.147	0.245	0.148	0.240	0.164	0.251	0.200	0.278	0.176	0.258	0.197	0.282
	192	0.153±0.001	0.246±0.001	0.152	0.244	0.165	0.258	0.160	0.250	0.162	0.253	0.173	0.262	0.200	0.280	0.175	0.262	0.196	0.285
	336	0.170±0.001	0.264±0.001	0.170	0.264	0.177	0.273	0.173	0.267	0.178	0.269	0.190	0.279	0.214	0.295	0.185	0.278	0.209	0.301
	720	0.208±0.001	0.297±0.001	0.212	0.299	0.213	0.304	0.210	0.309	0.225	0.317	0.230	0.313	0.255	0.327	0.220	0.315	0.245	0.333
	avg	0.167±0.001	0.260±0.001	0.168	0.259	0.175	0.269	0.173	0.268	0.178	0.270	0.189	0.276	0.217	0.295	0.189	0.278	0.212	0.300
Traffic	96	0.432±0.002	0.279±0.001	0.458	0.296	0.406	0.277	0.430	0.294	0.395	0.268	0.427	0.272	0.651	0.391	0.593	0.378	0.650	0.396
	192	0.442±0.001	0.289±0.001	0.457	0.294	0.426	0.290	0.452	0.307	0.417	0.276	0.454	0.289	0.602	0.363	0.595	0.377	0.598	0.370
	336	0.456±0.002	0.295±0.002	0.470	0.299	0.432	0.281	0.470	0.316	0.433	0.283	0.450	0.282	0.609	0.366	0.609	0.385	0.605	0.373
	720	0.487±0.003	0.311±0.001	0.502	0.314	0.463	0.300	0.498	0.323	0.467	0.302	0.484	0.301	0.647	0.385	0.673	0.418	0.645	0.394
	avg	0.454±0.002	0.293±0.001	0.472	0.301	0.431	0.287	0.463	0.310	0.428	0.282	0.454	0.286	0.627	0.376	0.618	0.390	0.625	0.383

TimeEmb surpasses disentanglement-based baselines by offering more expressive and flexible decomposition

Overall Performance

Model		TimeEmb (ours)		CycleNet 2024		Fredformer 2024		FilterNet 2024		iTransformer 2024		PatchTST 2023		FITS 2024		FreTS 2023		DLinear 2023	
Metric		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	96	**0.366**±0.001	**0.387**±0.001	0.378	0.391	0.373	0.392	0.375	0.394	0.386	0.405	0.394	0.406	0.386	0.396	0.395	0.407	0.386	0.400
	192	**0.417**±0.001	**0.416**±0.001	0.426	0.419	0.433	0.420	0.436	0.422	0.441	0.436	0.440	0.435	0.436	0.423	0.448	0.440	0.437	0.432
	336	**0.457**±0.001	**0.436**±0.001	0.464	0.439	0.470	0.437	0.476	0.443	0.487	0.458	0.491	0.462	0.478	0.444	0.499	0.472	0.481	0.459
	720	**0.459**±0.002	0.460±0.001	0.461	0.460	0.467	**0.456**	0.474	0.469	0.503	0.491	0.487	0.479	0.502	0.495	0.558	0.532	0.519	0.516
	avg	**0.425**±0.001	**0.425**±0.001	0.432	0.427	0.435	0.426	0.440	0.432	0.454	0.447	0.453	0.446	0.451	0.440	0.475	0.463	0.456	0.452
ETTh2	96	**0.277**±0.001	**0.328**±0.001	0.285	0.335	0.293	0.342	0.292	0.343	0.297	0.349	0.288	0.340	0.295	0.350	0.309	0.364	0.333	0.387
	192	**0.356**±0.001	**0.379**±0.001	0.373	0.391	0.371	0.389	0.369	0.395	0.380	0.400	0.376	0.395	0.381	0.396	0.395	0.425	0.477	0.476
	336	0.400±0.002	0.417±0.001	0.421	0.433	**0.382**	**0.409**	0.420	0.432	0.428	0.432	0.440	0.451	0.426	0.438	0.462	0.467	0.594	0.541
	720	**0.416**±0.001	0.437±0.002	0.453	0.458	**0.415**	**0.434**	0.430	0.446	0.427	0.445	0.436	0.453	0.431	0.446	0.721	0.604	0.831	0.657
	avg	**0.362**±0.001	**0.390**±0.001	0.383	0.404	0.365	0.393	0.378	0.404	0.383	0.407	0.385	0.410	0.383	0.408	0.472	0.465	0.559	0.515
ETTm1	96	**0.304**±0.001	**0.343**±0.001	0.319	0.360	0.326	0.361	0.318	0.358	0.334	0.368	0.329	0.365	0.355	0.375	0.335	0.372	0.345	0.372
	192	**0.354**±0.001	**0.373**±0.001	0.360	0.381	0.363	0.380	0.364	0.383	0.377	0.391	0.380	0.394	0.392	0.393	0.388	0.401	0.380	0.389
	336	**0.379**±0.001	**0.393**±0.001	0.389	0.403	0.395	0.403	0.396	0.406	0.426	0.420	0.400	0.410	0.424	0.414	0.421	0.426	0.413	0.413
	720	**0.435**±0.001	**0.428**±0.001	0.447	0.441	0.453	0.438	0.456	0.444	0.491	0.459	0.475	0.453	0.487	0.449	0.486	0.465	0.474	0.453
	avg	**0.368**±0.001	**0.384**±0.001	0.379	0.396	0.384	0.395	0.384	0.398	0.407	0.410	0.396	0.406	0.415	0.408	0.408	0.416	0.403	0.407
ETTm2	96	**0.163**±0.001	**0.242**±0.001	**0.163**	0.246	0.177	0.259	0.174	0.257	0.180	0.264	0.184	0.264	0.183	0.266	0.189	0.277	0.193	0.292
	192	**0.226**±0.001	**0.285**±0.001	0.229	0.290	0.243	0.301	0.240	0.300	0.250	0.309	0.246	0.306	0.247	0.305	0.258	0.326	0.284	0.362
	336	0.286±0.001	**0.324**±0.001	**0.284**	0.327	0.302	0.340	0.297	0.339	0.311	0.348	0.308	0.346	0.307	0.342	0.343	0.390	0.369	0.427
	720	**0.383**±0.001	**0.381**±0.001	0.389	0.391	0.397	0.396	0.392	0.393	0.412	0.407	0.409	0.402	0.407	0.399	0.495	0.480	0.554	0.522
	avg	**0.265**±0.001	**0.308**±0.001	0.266	0.314	0.279	0.324	0.276	0.322	0.288	0.332	0.287	0.330	0.286	0.328	0.321	0.368	0.350	0.401
Weather	96	**0.150**±0.001	**0.190**±0.001	0.158	0.203	0.163	0.207	0.162	0.207	0.174	0.214	0.176	0.217	0.166	0.213	0.174	0.208	0.196	0.255
	192	**0.200**±0.001	**0.238**±0.001	0.207	0.247	0.211	0.251	0.210	0.250	0.221	0.254	0.221	0.256	0.213	0.254	0.219	0.250	0.237	0.296
	336	**0.259**±0.001	**0.282**±0.001	0.262	0.289	0.267	0.292	0.265	0.290	0.278	0.296	0.275	0.296	0.269	0.294	0.273	0.290	0.283	0.335
	720	0.339±0.001	0.336±0.001	0.344	0.344	0.343	0.341	0.342	0.340	0.358	0.347	0.352	0.346	0.346	0.343	**0.334**	**0.332**	0.345	0.381
	avg	**0.237**±0.001	**0.262**±0.001	0.243	0.271	0.246	0.272	0.245	0.272	0.258	0.278	0.256	0.279	0.249	0.276	0.250	0.270	0.265	0.317
Electricity	96	**0.136**±0.001	0.231±0.001	**0.136**	**0.229**	0.147	0.241	0.147	0.245	0.148	0.240	0.164	0.251	0.200	0.278	0.176	0.258	0.197	0.282
	192	0.153±0.001	0.246±0.001	**0.152**	**0.244**	0.165	0.258	0.160	0.250	0.162	0.253	0.173	0.262	0.200	0.280	0.175	0.262	0.196	0.285
	336	**0.170**±0.001	**0.264**±0.001	**0.170**	**0.264**	0.177	0.273	0.173	0.267	0.178	0.269	0.190	0.279	0.214	0.295	0.185	0.278	0.209	0.301
	720	**0.208**±0.001	**0.297**±0.001	0.212	0.299	0.213	0.304	0.210	0.309	0.225	0.317	0.230	0.313	0.255	0.327	0.220	0.315	0.245	0.333
	avg	**0.167**±0.001	0.260±0.001	0.168	**0.259**	0.175	0.269	0.173	0.268	0.178	0.270	0.189	0.276	0.217	0.295	0.189	0.278	0.212	0.300
Traffic	96	0.432±0.002	0.279±0.001	0.458	0.296	0.406	0.277	0.430	0.294	**0.395**	**0.268**	0.427	0.272	0.651	0.391	0.593	0.378	0.650	0.396
	192	0.442±0.001	0.289±0.001	0.457	0.294	0.426	0.290	0.452	0.307	**0.417**	**0.276**	0.454	0.289	0.602	0.363	0.595	0.377	0.598	0.370
	336	0.456±0.002	0.295±0.002	0.470	0.299	**0.432**	**0.281**	0.470	0.316	0.433	0.283	0.450	0.282	0.609	0.366	0.609	0.385	0.605	0.373
	720	0.487±0.003	0.311±0.001	0.502	0.314	**0.463**	**0.300**	0.498	0.323	0.467	0.302	0.484	0.301	0.647	0.385	0.673	0.418	0.645	0.394
	avg	0.454±0.002	0.293±0.001	0.472	0.301	0.431	0.287	0.463	0.310	**0.428**	**0.282**	0.454	0.286	0.627	0.376	0.618	0.390	0.625	0.383

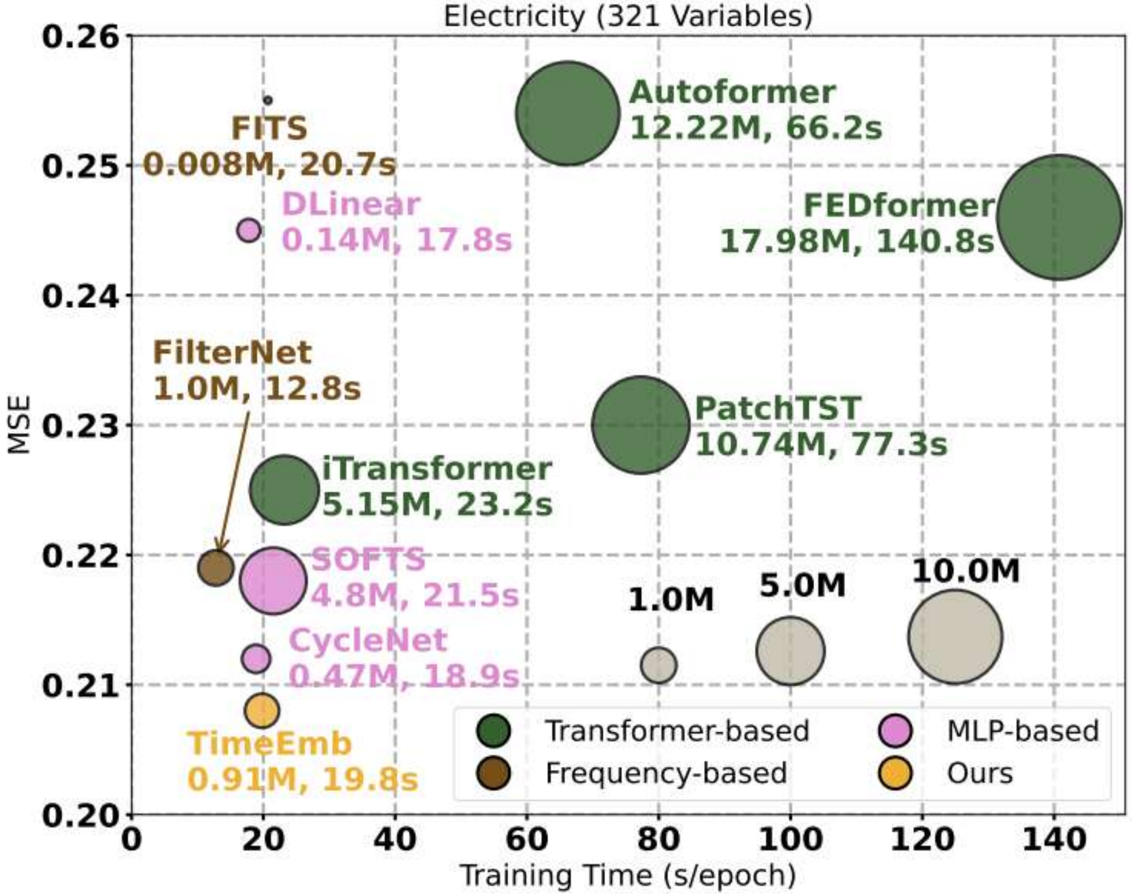
TimeEmb outperforms frequency-domain models by jointly modeling invariant and dynamic components

Overall Performance

Model		TimeEmb (ours)		CycleNet 2024		Fredformer 2024		FilterNet 2024		iTransformer 2024		PatchTST 2023		FITS 2024		FreTS 2023		DLinear 2023	
Metric		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	96	**0.366**±0.001	**0.387**±0.001	0.378	0.391	0.373	0.392	0.375	0.394	0.386	0.405	0.394	0.406	0.386	0.396	0.395	0.407	0.386	0.400
	192	**0.417**±0.001	**0.416**±0.001	0.426	0.419	0.433	0.420	0.436	0.422	0.441	0.436	0.440	0.435	0.436	0.423	0.448	0.440	0.437	0.432
	336	**0.457**±0.001	**0.436**±0.001	0.464	0.439	0.470	0.437	0.476	0.443	0.487	0.458	0.491	0.462	0.478	0.444	0.499	0.472	0.481	0.459
	720	**0.459**±0.002	0.460±0.001	0.461	0.460	0.467	**0.456**	0.474	0.469	0.503	0.491	0.487	0.479	0.502	0.495	0.558	0.532	0.519	0.516
	avg	**0.425**±0.001	**0.425**±0.001	0.432	0.427	0.435	0.426	0.440	0.432	0.454	0.447	0.453	0.446	0.451	0.440	0.475	0.463	0.456	0.452
ETTh2	96	**0.277**±0.001	**0.328**±0.001	0.285	0.335	0.293	0.342	0.292	0.343	0.297	0.349	0.288	0.340	0.295	0.350	0.309	0.364	0.333	0.387
	192	**0.356**±0.001	**0.379**±0.001	0.373	0.391	0.371	0.389	0.369	0.395	0.380	0.400	0.376	0.395	0.381	0.396	0.395	0.425	0.477	0.476
	336	0.400±0.002	0.417±0.001	0.421	0.433	**0.382**	**0.409**	0.420	0.432	0.428	0.432	0.440	0.451	0.426	0.438	0.462	0.467	0.594	0.541
	720	**0.416**±0.001	0.437±0.002	0.453	0.458	**0.415**	**0.434**	0.430	0.446	0.427	0.445	0.436	0.453	0.431	0.446	0.721	0.604	0.831	0.657
	avg	**0.362**±0.001	**0.390**±0.001	0.383	0.404	0.365	0.393	0.378	0.404	0.383	0.407	0.385	0.410	0.383	0.408	0.472	0.465	0.559	0.515
ETTm1	96	**0.304**±0.001	**0.343**±0.001	0.319	0.360	0.326	0.361	0.318	0.358	0.334	0.368	0.329	0.365	0.355	0.375	0.335	0.372	0.345	0.372
	192	**0.354**±0.001	**0.373**±0.001	0.360	0.381	0.363	0.380	0.364	0.383	0.377	0.391	0.380	0.394	0.392	0.393	0.388	0.401	0.380	0.389
	336	**0.379**±0.001	**0.393**±0.001	0.389	0.403	0.395	0.403	0.396	0.406	0.426	0.420	0.400	0.410	0.424	0.414	0.421	0.426	0.413	0.413
	720	**0.435**±0.001	**0.428**±0.001	0.447	0.441	0.453	0.438	0.456	0.444	0.491	0.459	0.475	0.453	0.487	0.449	0.486	0.465	0.474	0.453
	avg	**0.368**±0.001	**0.384**±0.001	0.379	0.396	0.384	0.395	0.384	0.398	0.407	0.410	0.396	0.406	0.415	0.408	0.408	0.416	0.403	0.407
ETTm2	96	**0.163**±0.001	**0.242**±0.001	**0.163**	0.246	0.177	0.259	0.174	0.257	0.180	0.264	0.184	0.264	0.183	0.266	0.189	0.277	0.193	0.292
	192	**0.226**±0.001	**0.285**±0.001	0.229	0.290	0.243	0.301	0.240	0.300	0.250	0.309	0.246	0.306	0.247	0.305	0.258	0.326	0.284	0.362
	336	0.286±0.001	**0.324**±0.001	**0.284**	0.327	0.302	0.340	0.297	0.339	0.311	0.348	0.308	0.346	0.307	0.342	0.343	0.390	0.369	0.427
	720	**0.383**±0.001	**0.381**±0.001	0.389	0.391	0.397	0.396	0.392	0.393	0.412	0.407	0.409	0.402	0.407	0.399	0.495	0.480	0.554	0.522
	avg	**0.265**±0.001	**0.308**±0.001	0.266	0.314	0.279	0.324	0.276	0.322	0.288	0.332	0.287	0.330	0.286	0.328	0.321	0.368	0.350	0.401
Weather	96	**0.150**±0.001	**0.190**±0.001	0.158	0.203	0.163	0.207	0.162	0.207	0.174	0.214	0.176	0.217	0.166	0.213	0.174	0.208	0.196	0.255
	192	**0.200**±0.001	**0.238**±0.001	0.207	0.247	0.211	0.251	0.210	0.250	0.221	0.254	0.221	0.256	0.213	0.254	0.219	0.250	0.237	0.296
	336	**0.259**±0.001	**0.282**±0.001	0.262	0.289	0.267	0.292	0.265	0.290	0.278	0.296	0.275	0.296	0.269	0.294	0.273	0.290	0.283	0.335
	720	0.339±0.001	0.336±0.001	0.344	0.344	0.343	0.341	0.342	0.340	0.358	0.347	0.352	0.346	0.346	0.343	**0.334**	**0.332**	0.345	0.381
	avg	**0.237**±0.001	**0.262**±0.001	0.243	0.271	0.246	0.272	0.245	0.272	0.258	0.278	0.256	0.279	0.249	0.276	0.250	0.270	0.265	0.317
Electricity	96	**0.136**±0.001	0.231±0.001	**0.136**	**0.229**	0.147	0.241	0.147	0.245	0.148	0.240	0.164	0.251	0.200	0.278	0.176	0.258	0.197	0.282
	192	0.153±0.001	0.246±0.001	**0.152**	**0.244**	0.165	0.258	0.160	0.250	0.162	0.253	0.173	0.262	0.200	0.280	0.175	0.262	0.196	0.285
	336	**0.170**±0.001	**0.264**±0.001	**0.170**	**0.264**	0.177	0.273	0.173	0.267	0.178	0.269	0.190	0.279	0.214	0.295	0.185	0.278	0.209	0.301
	720	**0.208**±0.001	**0.297**±0.001	0.212	0.299	0.213	0.304	0.210	0.309	0.225	0.317	0.230	0.313	0.255	0.327	0.220	0.315	0.245	0.333
	avg	**0.167**±0.001	0.260±0.001	0.168	**0.259**	0.175	0.269	0.173	0.268	0.178	0.270	0.189	0.276	0.217	0.295	0.189	0.278	0.212	0.300
Traffic	96	0.432±0.002	0.279±0.001	0.458	0.296	0.406	0.277	0.430	0.294	**0.395**	**0.268**	0.427	0.272	0.651	0.391	0.593	0.378	0.650	0.396
	192	0.442±0.001	0.289±0.001	0.457	0.294	0.426	0.290	0.452	0.307	**0.417**	**0.276**	0.454	0.289	0.602	0.363	0.595	0.377	0.598	0.370
	336	0.456±0.002	0.295±0.002	0.470	0.299	**0.432**	**0.281**	0.470	0.316	0.433	0.283	0.450	0.282	0.609	0.366	0.609	0.385	0.605	0.373
	720	0.487±0.003	0.311±0.001	0.502	0.314	**0.463**	**0.300**	0.498	0.323	0.467	0.302	0.484	0.301	0.647	0.385	0.673	0.418	0.645	0.394
	avg	0.454±0.002	0.293±0.001	0.472	0.301	0.431	0.287	0.463	0.310	**0.428**	**0.282**	0.454	0.286	0.627	0.376	0.618	0.390	0.625	0.383

On the Traffic dataset, TimeEmb underperforms Transformer-based models due to its lack of explicit variable correlation modeling, but it still surpasses other types of models

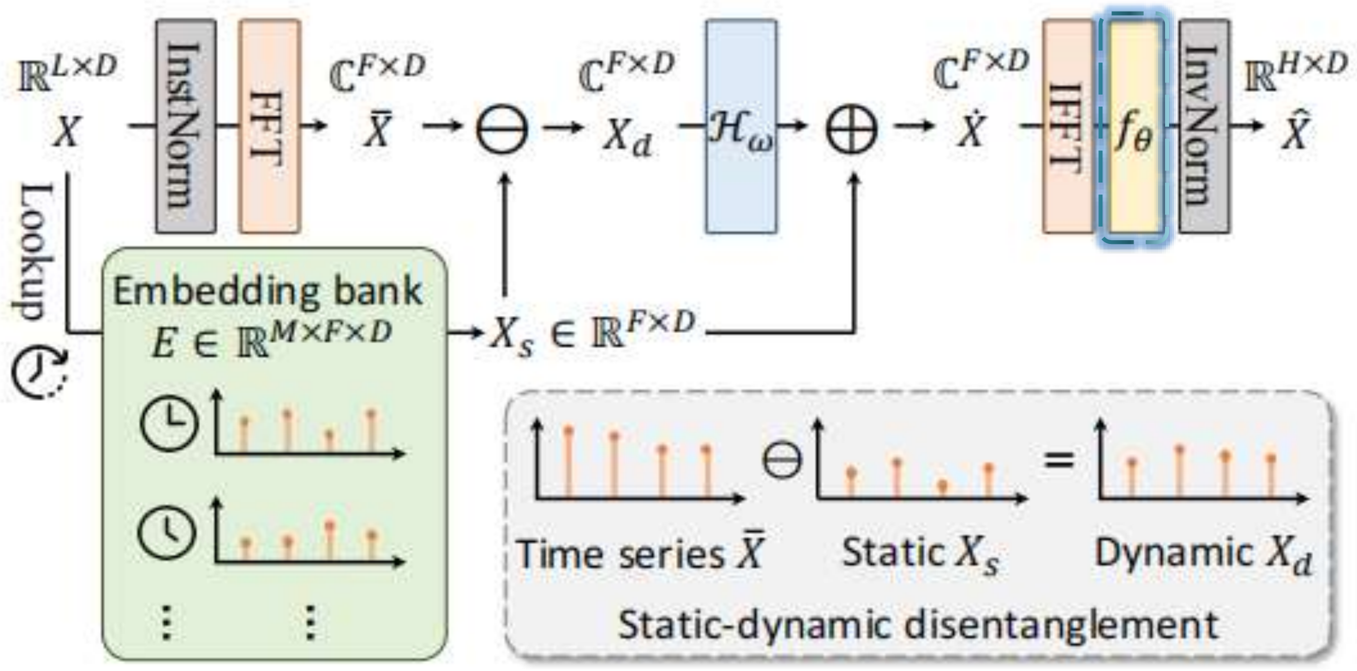
Efficiency Performance



Moreover, TimeEmb achieves the best performance–efficiency trade-off:

it uses only 0.9M parameters, over *5× fewer* than heavy Transformer-based models like iTransformer or FEDformer

Compatibility Analysis



Assess TimeEmb's Compatibility

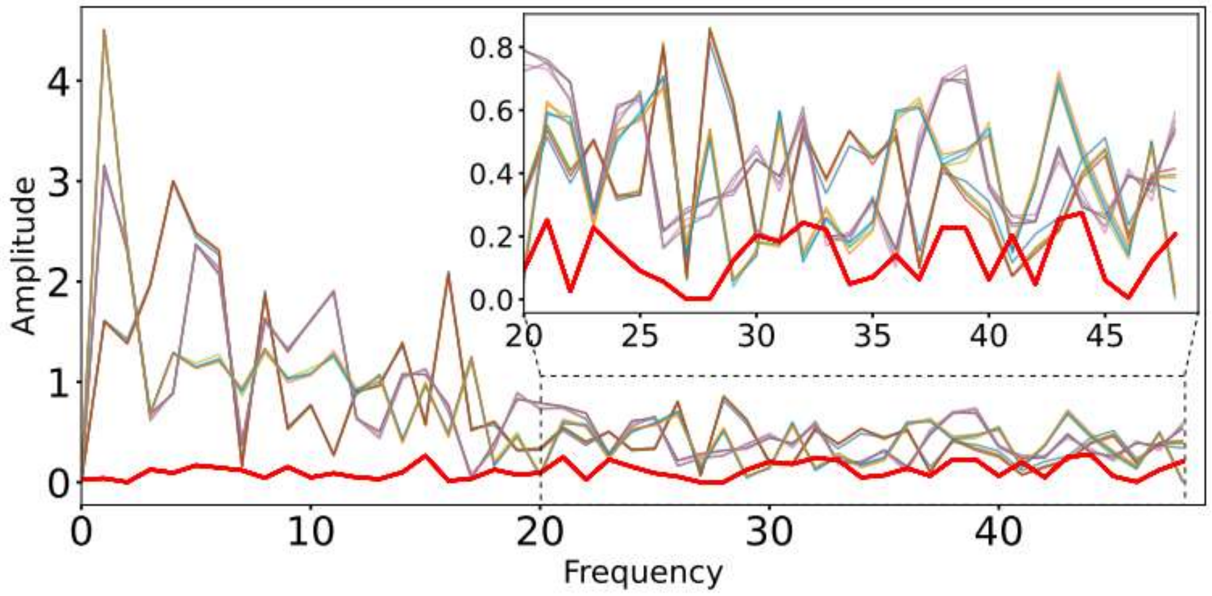
- ✓ Integrate TimeEmb as a plug-in module into existing models including DLinear, MLP, and iTransformer
- ✓ Replace the backbone prediction layer f_θ with the alternative model

Compatibility Analysis

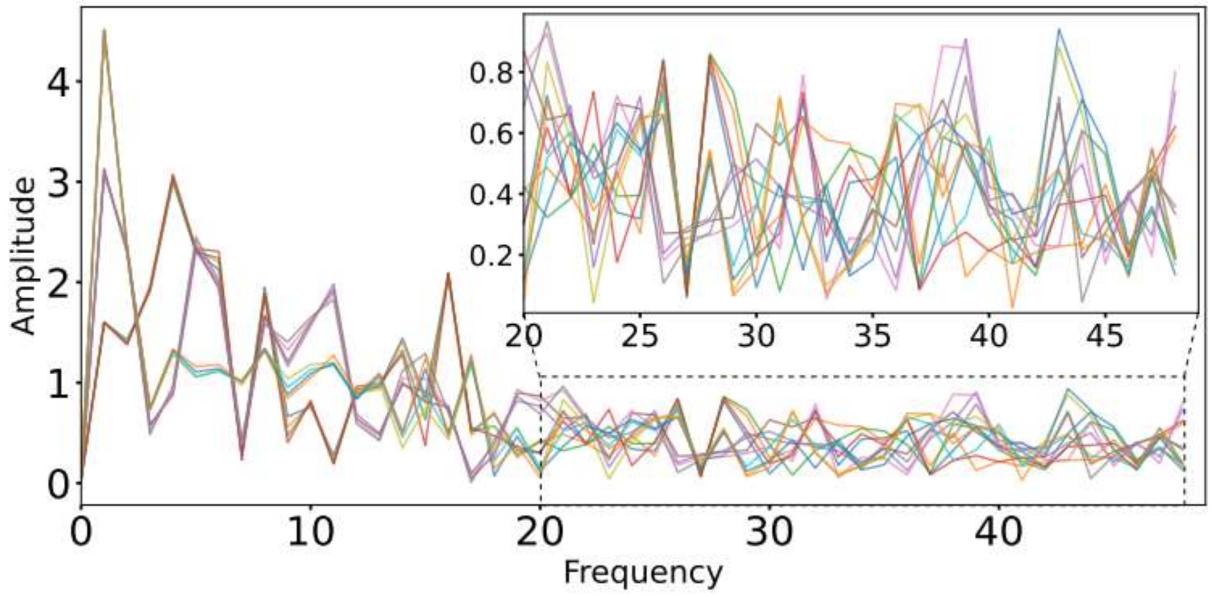
Dataset	Electricity								Weather							
Horizon	96		192		336		720		96		192		336		720	
Metric	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Linear	0.196	0.279	0.195	0.282	0.208	0.298	0.243	0.330	0.197	0.256	0.238	0.295	0.285	0.335	**0.346**	0.381
+ our model	**0.173**	**0.270**	**0.179**	**0.274**	**0.193**	**0.288**	**0.233**	**0.320**	**0.170**	**0.218**	**0.222**	**0.260**	**0.275**	**0.298**	0.349	**0.345**
Impr.	+11.7%	+3.2%	+8.2%	+2.8%	+7.2%	+3.4%	+4.1%	+3.0%	+13.7%	+14.8%	+6.7%	+11.9%	+3.5%	+11.0%	-0.9%	+9.4%
MLP	0.177	0.265	0.183	0.271	0.197	0.287	0.234	0.320	0.180	0.234	0.223	0.274	0.268	0.309	**0.342**	0.370
+ our model	**0.137**	**0.234**	**0.155**	**0.250**	**0.172**	**0.267**	**0.211**	**0.303**	**0.154**	**0.197**	**0.203**	**0.243**	**0.263**	**0.288**	0.344	**0.344**
Impr.	+22.6%	+11.7%	+15.3%	+7.7%	+12.7%	+7.0%	+9.8%	+5.3%	+14.4%	+15.8%	+9.0%	+11.3%	+1.9%	+6.8%	-0.6%	+7.0%
DLinear	0.195	0.278	0.194	0.281	0.207	0.297	0.243	0.330	0.195	0.254	0.237	0.295	0.281	0.329	0.347	0.385
+ our model	**0.171**	**0.271**	**0.181**	**0.281**	**0.190**	**0.291**	**0.223**	**0.321**	**0.168**	**0.230**	**0.216**	**0.277**	**0.264**	**0.316**	**0.333**	**0.370**
Impr.	+12.3%	+2.5%	+6.7%	+0.0%	+8.2%	+2.0%	+8.2%	+2.7%	+13.8%	+9.4%	+8.9%	+6.1%	+6.0%	+4.0%	+4.0%	+3.9%
iTransformer	0.153	0.245	0.166	**0.256**	0.182	**0.274**	0.218	0.306	0.181	0.222	0.226	0.260	0.284	0.302	0.360	0.352
+ our model	**0.142**	**0.242**	**0.163**	0.260	**0.175**	0.275	**0.203**	**0.299**	**0.162**	**0.208**	**0.210**	**0.251**	**0.269**	**0.296**	**0.346**	**0.344**
Impr.	+7.2%	+1.2%	+1.8%	-1.6%	+3.8%	-0.4%	+6.9%	+2.3%	+10.5%	+6.3%	+7.1%	+3.5%	+5.3%	+2.0%	+3.9%	+2.3%

→ The results show consistent improvements across all backbones with negligible computational cost, proving its broad compatibility and ease of integration

Visualization



(a) Time series $\overline{\boldsymbol{X}}$ spectrum (colorful lines) and time-invariant embedding $\boldsymbol{X}_s$ spectrum (bold red line)

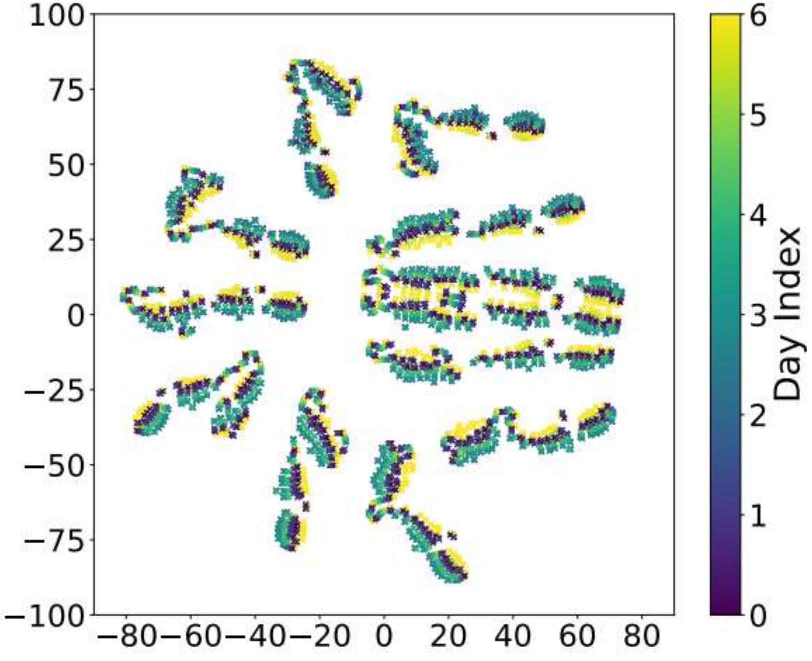


(b) Time-varying component $\boldsymbol{X}_d$ spectrum

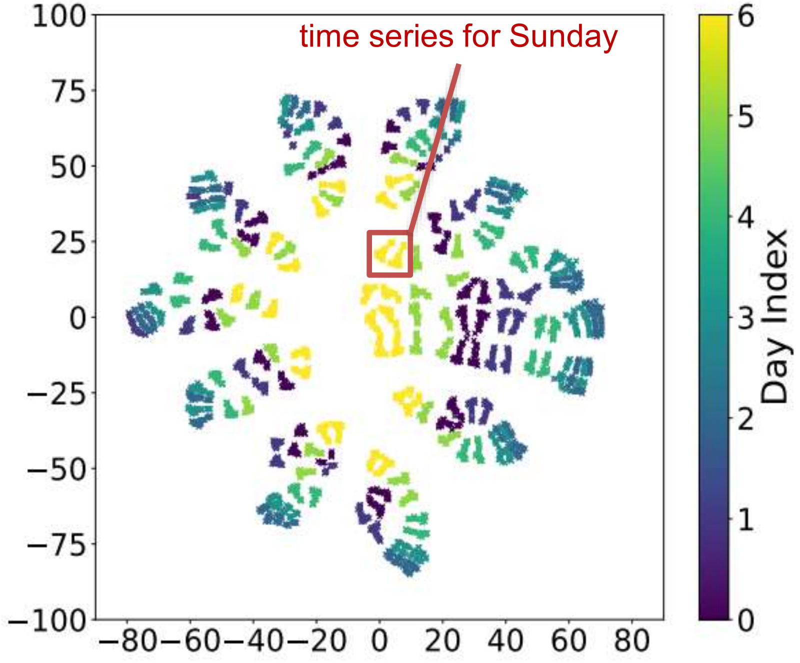
The embedding captures the shared low-frequency structure across days, while the time-varying component shows distinct high-frequency fluctuations

→ TimeEmb effectively separates global stable patterns from local dynamic variations

Visualization



Before Disentanglement



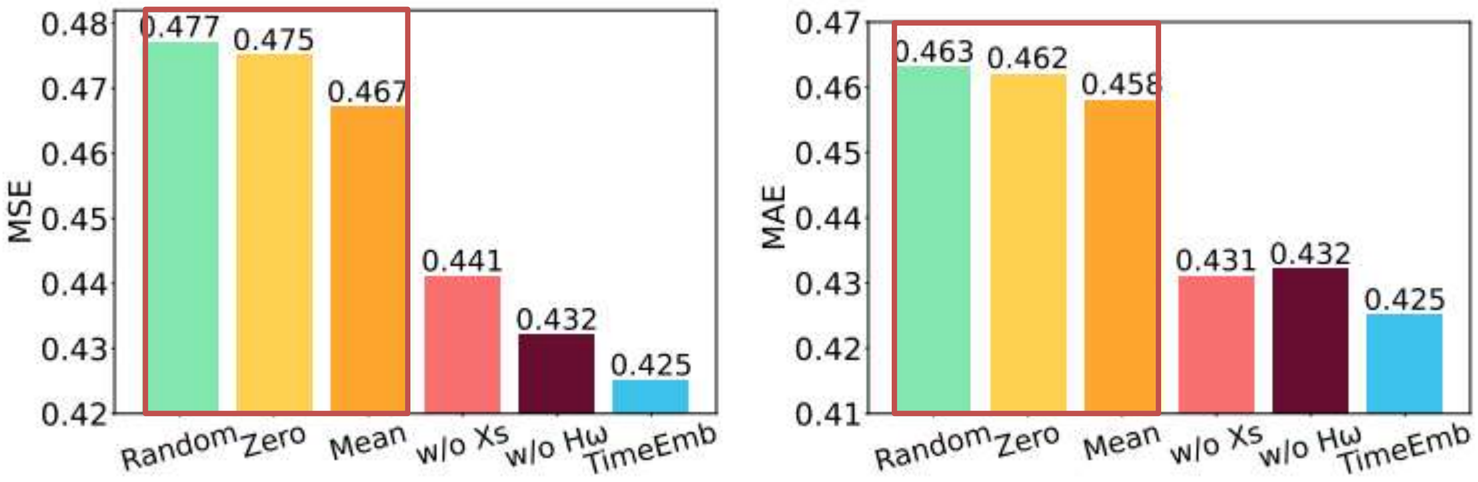
After Disentanglement

Before disentanglement, samples from different weekdays are mixed together; after disentanglement, they form clearer, separated clusters

→ Removing the invariant component enhances discriminability and verifies successful static-dynamic separation

Ablation Study

- Initialize emb bank randomly
- Fix emb bank to zero
- Fix emb bank to mean value
- w/o embedding bank
- w/o frequency filter

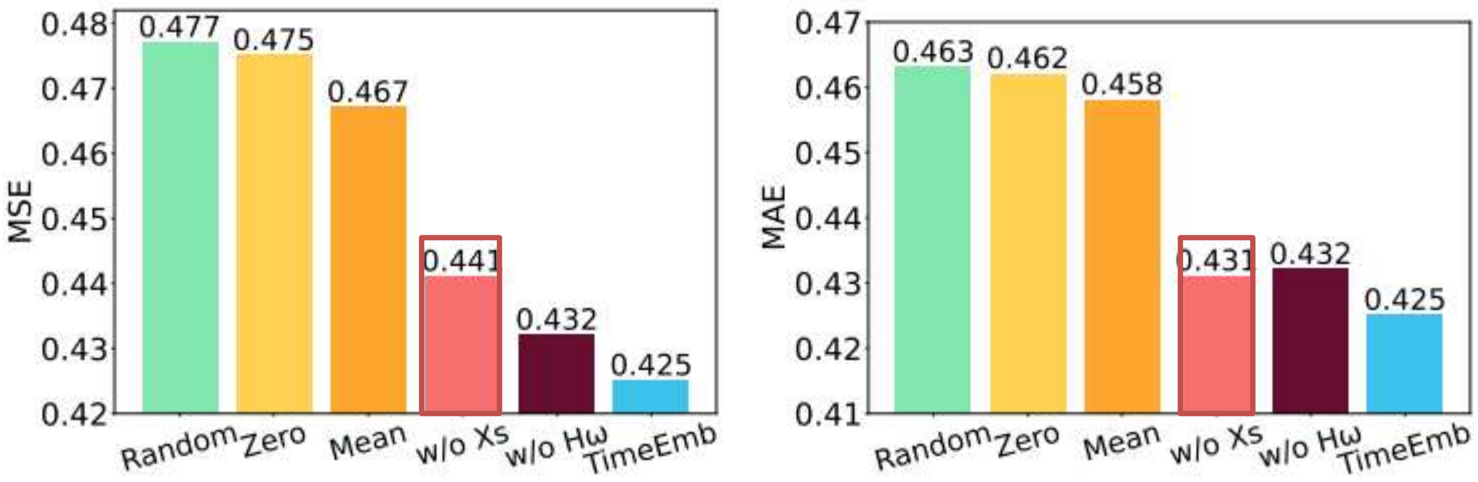


→ Performance is highly sensitive to the embedding bank design

→ Perturb the embedding bank (random / zero / mean) leads to performance drops

Ablation Study

- Initialize emb bank randomly
- Fix emb bank to zero
- Fix emb bank to mean value
- w/o embedding bank
- w/o frequency filter

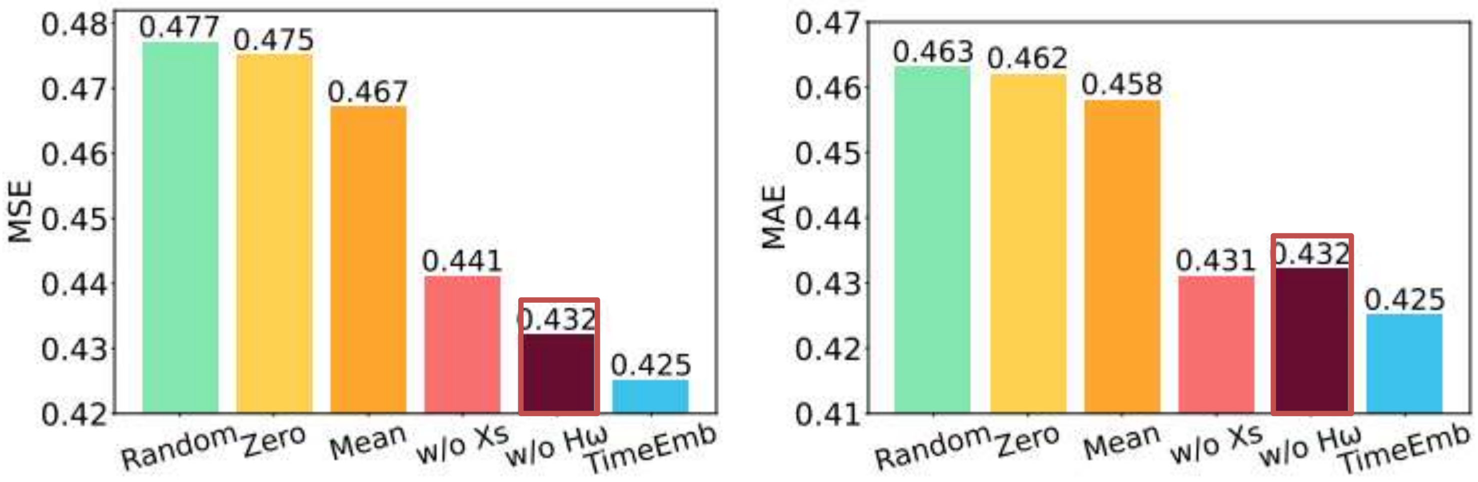


Removing the embedding bank significantly degrades performance

→ The model loses its ability to capture long-term stable patterns, confirming that static representations are essential for robust forecasting

Ablation Study

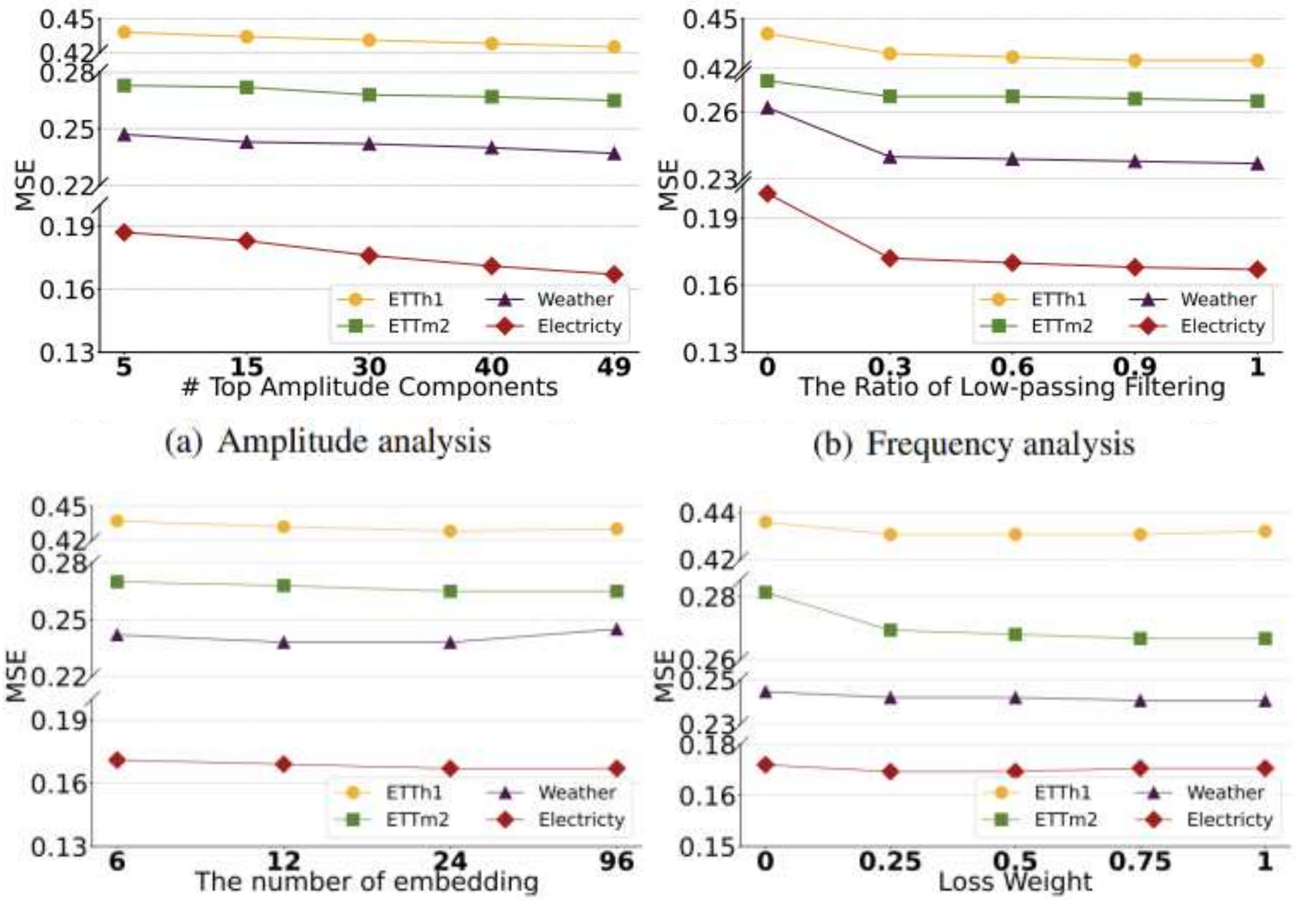
- Initialize emb bank randomly
- Fix emb bank to zero
- Fix emb bank to mean value
- w/o embedding bank
- w/o frequency filter



Removing the frequency filter also causes clear performance drops

→ The model struggles to adapt to short-term dynamics, proving the filter's importance in modeling temporal variability

Hyper - parameters Analysis



(a) Amplitude analysis

(b) Frequency analysis

(c) Results of different embedding lengths

(d) Results of different loss weight

→ TimeEmb remains robust across a wide range of values, indicating strong stability and generalizability.

Outline

- Introduction
- Framework
- Experiments
- Conclusion

Conclusion

We propose a new perspective for handling non-stationary time series —

by disentangling static and dynamic components in the frequency domain.

- Through a learnable embedding bank and a frequency filter, TimeEmb effectively models long-term invariance and short-term fluctuations.
- It achieves state-of-the-art performance, lightweight efficiency, and high interpretability.
- Moreover, TimeEmb can seamlessly enhance existing models, making it a practical, plug-and-play solution for real-world forecasting tasks.

Thanks!

Email: xiamy2322@mails.jlu.edu.cn
zhangzijian@jlu.edu.cn