CATCH: Channel-Aware Multivariate Time Series Anomaly Detection via Frequency Patching

华东师范大学 EAST CHINA NORMAL UNIVERSITY

香港科技大学(广州) THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY (GUANGZHOU)

Xingjian Wu[1], Xiangfei Qiu[1], Zhengyu Li[1], Yihang Wang[1], Jilin Hu[1], Chenjuan Guo[1], Hui Xiong[2], Bin Yang[1*]

{xjwu,xfqiu,lizhengyu,yhwang}@stu.ecnu.edu.cn, {jlhu,cjguo,byang}@dase.ecnu.edu.cn, xionghui@ust.hk

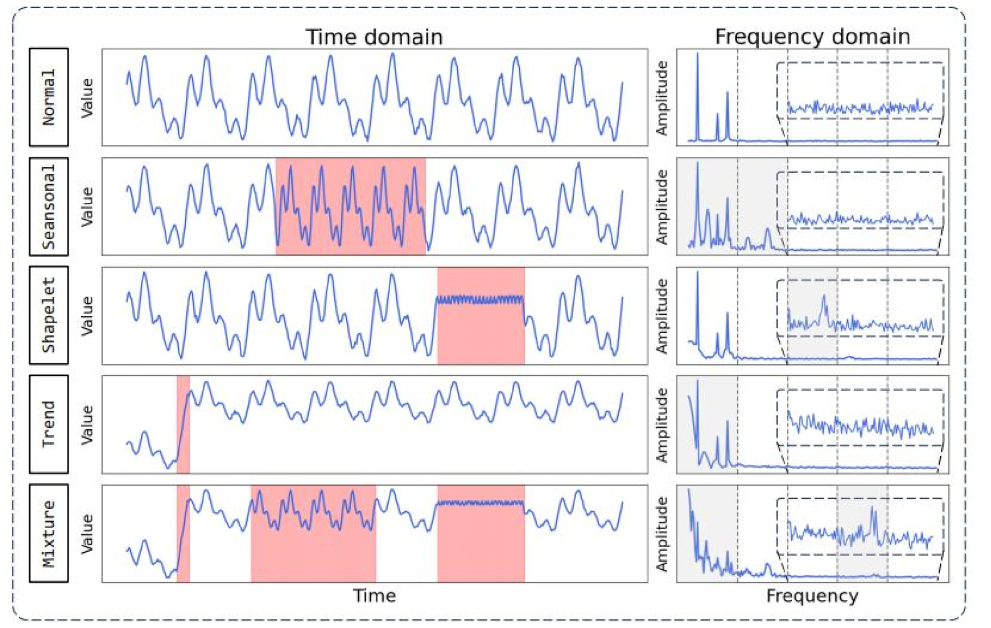
[1]East China Normal University [2]The Hong Kong University of Science and Technology (Guangzhou)

ICLR

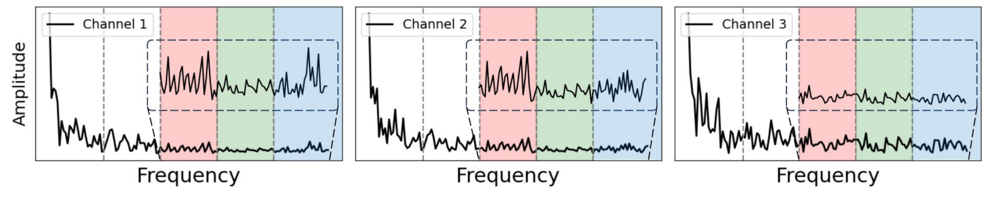
code paper

Introduction

Reconstruction-based Anomaly Detection methods achieve promising performance but still suffer from heterogeneous subsequence anomalies and varying channel correlations in Multivariate Time Series Anomaly Detection tasks.



(a) Different subsequence anomalies



(b) Varying Channel Correlations

(a) Shows a normal time series and its variations after being injected seasonal, shapelet, trend and mixture subsequence anomalies, reflecting the distinct affections due to the heterogeneity of subsequence anomalies. This calls for fine-grained modeling in each frequency band to precisely reconstruct the normal patterns.

(b) Shows the frequency bands of a multivariate time series with three channels, exhibiting varying correlations across different frequency bands, which is hard to be modeled by Channel Independent or Channel Dependent strategies. This calls for flexibly adapting the distinct channel interrelationships in different frequency bands.

Contribution

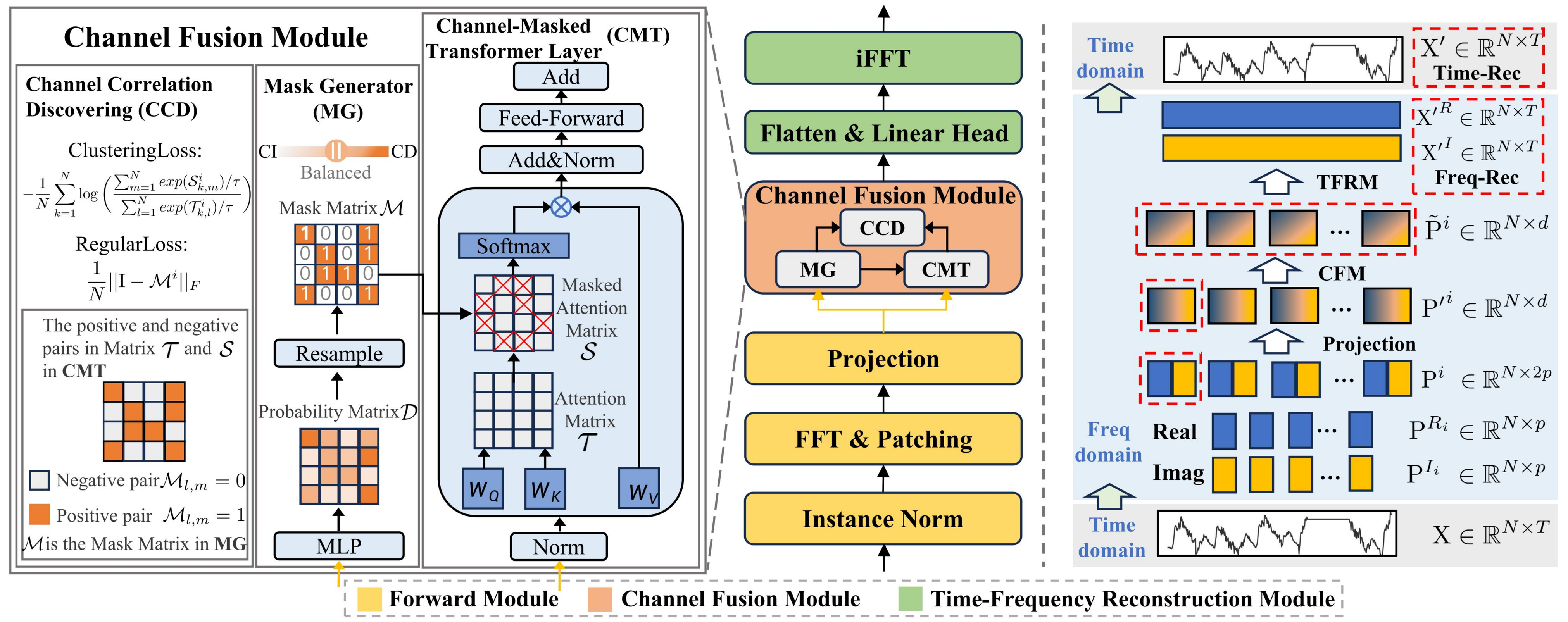
- We propose a general framework called **CATCH**, which enables simultaneous detection of heterogeneous point and subsequence anomalies via frequency patch learning. The framework enhances subsequence anomaly detection through frequency-domain patching and integrates fine-grained adaptive channel correlations across frequency bands.
- We design the Channel Fusion Module to fully utilize the fine-grained channel correlations. Driven by a bi-level multi-objective optimization algorithm, the Channel Fusion Module is able to iteratively discover appropriate channel correlations and facilitate the isolation of irrelevant channels and the clustering of relevant channels, which provides both the capacity and robustness.
- We conduct extensive experiments on 22 multivariate datasets. The results show that CATCH outperforms state-of-the-art baselines.

My **WeChat**:

Table 1: Comparison of existing frequency-based TSAD methods

Property	Mmultivariate time serie anomaly detection	Time-frequency granularity alignment	Handle high-frequency information	Capture channel correlations
SR-CNN	✗	✗	✗	✗
PFT	✗	✗	✗	✗
TFAD	✓	✗	✗	✗
Dual-TF	✓	✓	✗	✗
CATCH	✓	✓	✓	✓

CATCH Framework



Forward Module

We utilize FFT to transform time series into orthogonal trigonometric signals in the frequency domain and apply the frequency patching operation to create fine-grained frequency patches.

Channel Fusion Module

Mask Generator (MG): By generating a binary mask matrix, it can perceive the association of each frequency band's channels, and isolates the negative impacts of irrelevant channels.

$$\mathcal{D}^i = \sigma(\mathrm{Linear}(\mathrm{P}'^i)), \mathcal{M}^i = \mathrm{Resample}(\mathcal{D}^i)$$

Channel-Masked Transformer Layer (CMT): After the binary mask is generated by the Mask Generator, fine-grained channel correlations are further captured using Masked Transformer layers. The gradient is kept through calculation in the attentional mechanism:

$$\mathrm{Q}^i = \mathrm{P}^{*i} \cdot \mathrm{W}^Q, \mathrm{K}^i = \mathrm{P}^{*i} \cdot \mathrm{W}^K, \mathrm{V}^i = \mathrm{P}^{*i} \cdot \mathrm{W}^V,$$

$$\mathcal{T}^i = \mathrm{Q}^i \cdot (\mathrm{K}^i)^T, \mathcal{S}^i = \mathcal{T}^i \odot \mathcal{M}^i + (1 - \mathcal{M}^i) \odot (-\infty),$$

$$\mathrm{MaskedScores}^i = \mathcal{S}^i / \sqrt{d}, \tilde{\mathrm{P}}^i = \mathrm{Softmax}(\mathrm{MaskedScores}^i) \cdot \mathrm{V}^i$$

Channel Correlation Discovering (CCD): ClusteringLoss is proposed by assuming that the channel correlation generated by the Mask Generator is locally optimal, where relevant and irrelevant channels are determined. This encourages the attention mechanism to aggregate relevant channels. RegularLoss is used to limit the number of relevant channels, preventing the Mask Generator from outputting a constant '1' matrix.

$$\mathrm{ClusteringLoss} = -\frac{1}{N}\sum_{k=1}^{N}\log\left(\frac{\sum_{m=1}^{N} exp(\mathcal{S}^i_{k,m})/\tau}{\sum_{l=1}^{N} exp(\mathcal{T}^i_{k,l})/\tau}\right), \quad \mathrm{RegularLoss} = \frac{1}{N}||\mathrm{I} - \mathcal{M}^i||_F$$

Time-Frequency Reconstruction Module

After extracting the fine-grained channel correlations in each frequency band, the time series is reconstructed in both the frequency and time domain to detect heterogeneous anomalies.

$$\mathrm{RecLoss}^{time} = ||\mathrm{X} - \mathrm{X}'||_F^2, \mathrm{RecLoss}^{freq} = ||\mathrm{X}^R - \mathrm{X}'^R||_1 + ||\mathrm{X}^I - \mathrm{X}'^I||_1$$

Experiments

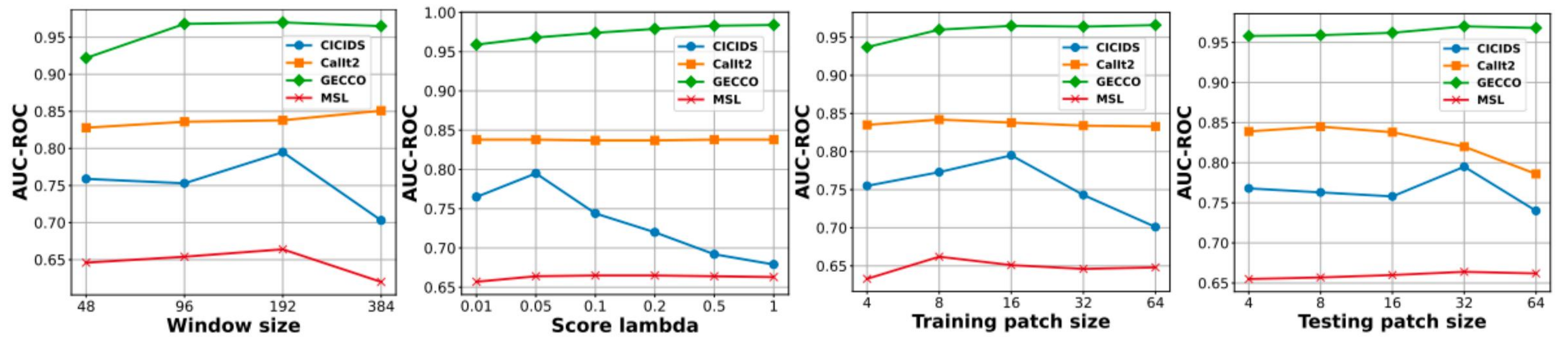
Main Results

Table 2: Average A-R (AUC-ROC) and aff-F (Affiliated-F1)

Dataset	Metric	CATCH	Modern	iTrans	DualTF	ATrans	DC	TsNet	Patch	DLin	NLin	AE	Ocsvm	IF	PCA	HBOS	TFAD
CICIDS	Aff-F	**0.787**	0.654	0.708	0.692	0.560	0.664	0.657	0.660	0.669	0.669	0.243	0.693	0.604	0.619	0.542	0.579
	A-R	**0.795**	0.697	0.692	0.603	0.528	0.638	0.732	0.716	0.751	0.691	0.629	0.537	0.787	0.601	0.760	0.504
CalIt2	Aff-F	**0.835**	0.780	0.812	0.751	0.729	0.697	0.794	0.793	0.793	0.757	0.587	0.783	0.402	0.768	0.756	0.744
	A-R	**0.838**	0.676	0.791	0.574	0.533	0.527	0.771	0.808	0.752	0.695	0.767	0.804	0.775	0.790	0.798	0.504
Credit	Aff-F	**0.750**	0.744	0.713	0.663	0.650	0.632	0.744	0.746	0.738	0.742	0.561	0.714	0.634	0.710	0.695	0.600
	A-R	**0.958**	0.957	0.934	0.703	0.552	0.504	0.957	0.957	0.954	0.948	0.909	0.953	0.860	0.871	0.951	0.500
GECCO	Aff-F	**0.908**	0.893	0.839	0.701	0.782	0.687	0.894	0.906	0.893	0.882	0.823	0.666	0.424	0.785	0.708	0.627
	A-R	**0.970**	0.952	0.795	0.714	0.516	0.555	0.954	0.949	0.947	0.936	0.769	0.804	0.619	0.711	0.557	0.499
Genesis	Aff-F	**0.896**	0.833	0.891	0.810	0.856	0.776	0.864	0.856	0.856	0.829	0.854	0.677	0.788	0.814	0.721	0.535
	A-R	**0.974**	0.676	0.690	0.937	0.947	0.659	0.913	0.685	0.696	0.755	0.931	0.733	0.549	0.815	0.897	0.497
MSL	Aff-F	**0.740**	0.726	0.710	0.588	0.692	0.694	0.734	0.724	0.725	0.723	0.625	0.641	0.584	0.678	0.680	0.665
	A-R	**0.664**	0.633	0.611	0.576	0.508	0.507	0.613	0.637	0.624	0.592	0.562	0.524	0.524	0.552	0.574	0.500
NYC	Aff-F	**0.994**	0.769	0.684	0.708	0.853	0.862	0.794	0.776	0.828	0.819	0.689	0.667	0.648	0.680	0.675	0.689
	A-R	**0.816**	0.466	0.640	0.633	0.671	0.549	0.791	0.709	0.768	0.671	0.504	0.456	0.475	0.666	0.446	0.502
PSM	Aff-F	**0.859**	0.825	0.854	0.725	0.710	0.682	0.842	0.831	0.831	0.843	0.707	0.531	0.620	0.702	0.658	0.628
	A-R	**0.652**	0.593	0.592	0.600	0.514	0.501	0.592	0.586	0.580	0.585	0.650	0.619	0.542	0.648	0.620	0.500
SMD	Aff-F	**0.847**	0.840	0.827	0.679	0.724	0.675	0.831	0.845	0.841	0.844	0.439	0.742	0.626	0.738	0.629	0.660
	A-R	**0.811**	0.722	0.745	0.631	0.508	0.502	0.727	0.736	0.728	0.738	0.774	0.602	0.664	0.679	0.626	0.500
ASD	Aff-F	**0.804**	0.782	0.780	0.605	0.674	0.702	0.800	0.777	0.782	0.766	0.731	0.617	0.781	0.656	0.669	0.630
	A-R	**0.824**	0.692	0.759	0.579	0.506	0.520	0.805	0.760	0.739	0.690	0.704	0.588	0.618	0.656	0.603	0.502
Contextual	Aff-F	**0.823**	0.619	0.802	0.635	0.601	0.597	0.666	0.766	0.780	0.700	0.755	0.696	0.679	0.475	0.481	0.569
	A-R	**0.910**	0.562	0.905	0.598	0.546	0.525	0.908	0.854	0.700	0.530	0.896	0.711	0.821	0.538	0.464	0.504
Global	Aff-F	**0.949**	0.748	0.922	0.649	0.656	0.567	0.910	0.940	0.928	0.808	0.919	0.849	0.912	0.704	0.528	0.566
	A-R	**0.997**	0.873	0.976	0.595	0.564	0.514	0.989	0.992	0.979	0.675	0.996	0.996	0.938	0.758	0.608	0.500
Seasonal	Aff-F	**0.997**	0.681	0.992	0.776	0.788	0.859	0.992	0.989	0.993	0.951	0.927	0.805	0.938	0.637	0.673	0.686
	A-R	**0.998**	0.512	0.946	0.701	0.584	0.644	0.958	0.922	0.823	0.623	0.949	0.829	0.918	0.437	0.516	0.502
Shapelet	Aff-F	**0.985**	0.675	0.961	0.692	0.699	0.737	0.941	0.933	0.961	0.759	0.871	0.771	0.887	0.683	0.640	0.684
	A-R	**0.970**	0.522	0.864	0.573	0.519	0.597	0.877	0.818	0.684	0.563	0.865	0.655	0.748	0.517	0.337	0.503
Trend	Aff-F	**0.916**	0.734	0.901	0.677	0.584	0.765	0.897	0.888	0.721	0.830	0.699	0.691	0.914	0.693	0.669	0.642
	A-R	**0.892**	0.612	0.847	0.524	0.500	0.569	0.858	0.835	0.671	0.642	0.482	0.471	0.878	0.484	0.468	0.502
Mixture	Aff-F	**0.892**	0.856	0.862	0.652	0.641	0.709	0.863	0.879	0.727	0.839	0.673	0.676	0.881	0.676	0.667	0.710
	A-R	**0.931**	0.763	0.854	0.570	0.522	0.516	0.861	0.863	0.767	0.749	0.493	0.475	0.911	0.517	0.531	0.501

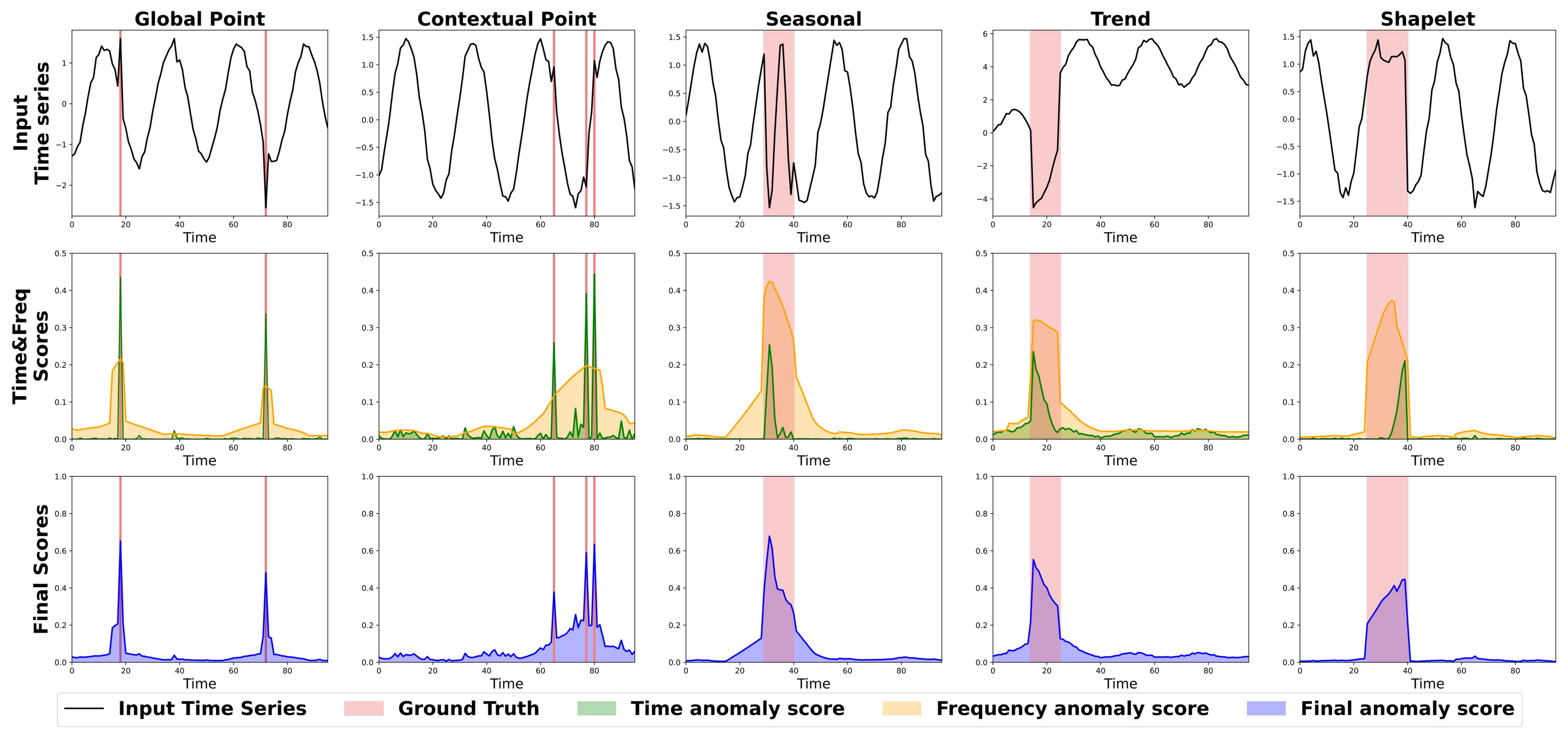
- CATCH consistly achieves state-of-the-art performance on 10 real-world datasets and 12 synthetic datasets.
- Resources: https://github.com/decisionintelligence/catch

Parameter Sensitivity



(a) Window size (b) Score lambda (c) Training patch size (d) Testing patch size

Visualization



- CATCH shows outstanding performance in detecting both the point and subsequence anomalies.