Deep Learning for Time Series Anomaly Detection : A Survey

Zahra Zamanzadeh Darban, Geoffrey I. Webb, Shirui Pan, Charu Aggarwal, and Mahsa Salehi. 2024.
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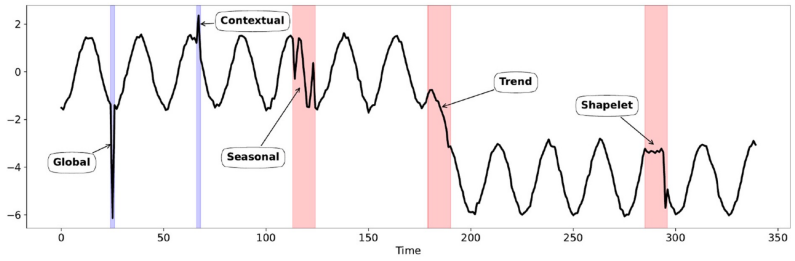
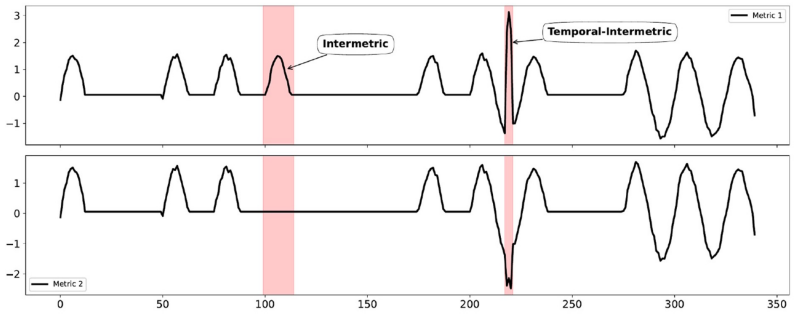
Time Series Anomaly Detection

- **Time Series**
  - A series of data points indexed sequentially over time
- **Time Series Anomaly Detection**
  - Identifying patterns or events in time-ordered data that deviate significantly from expected behavior or norms



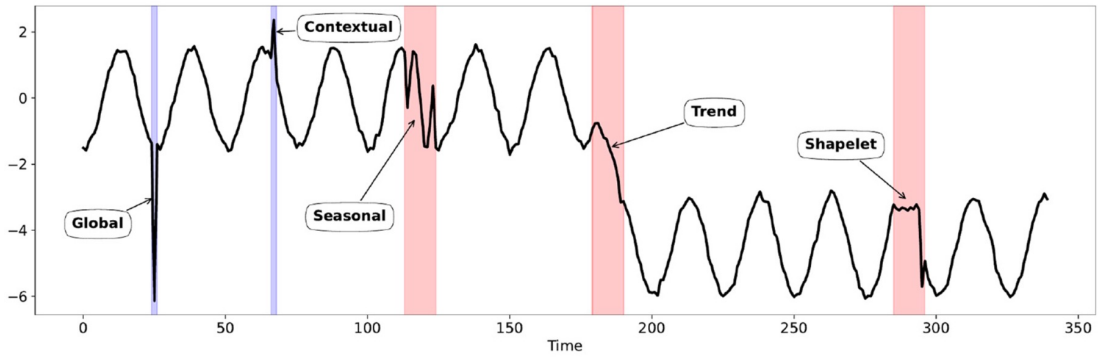
Univariate Time Series



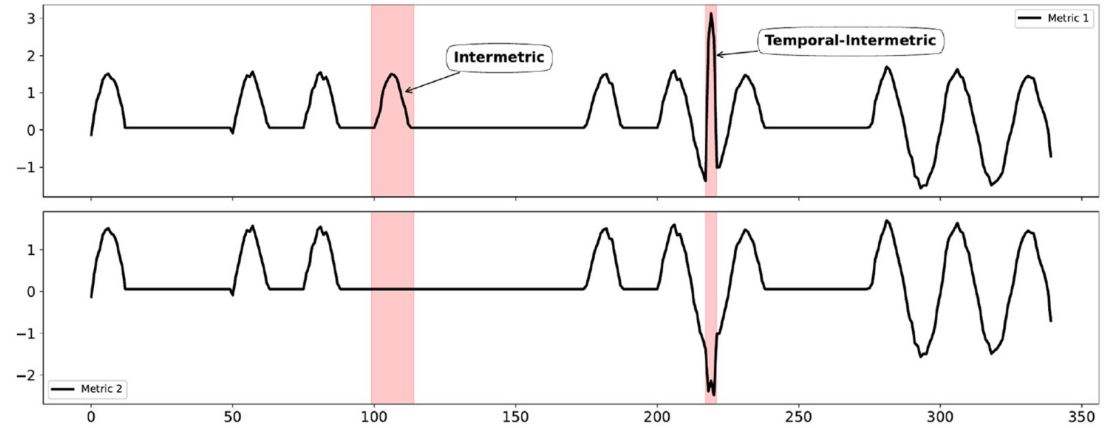
Multivariate Time Series

Anomalies in Time Series

- **Temporal(Time-wise)**

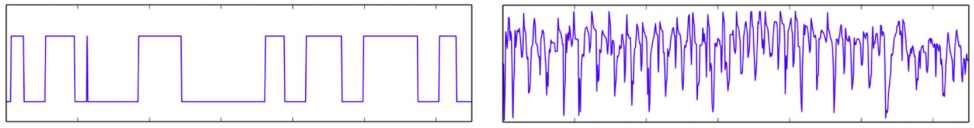


- **Spatial(Intermetric, Input-Tag, Feature-wise)**



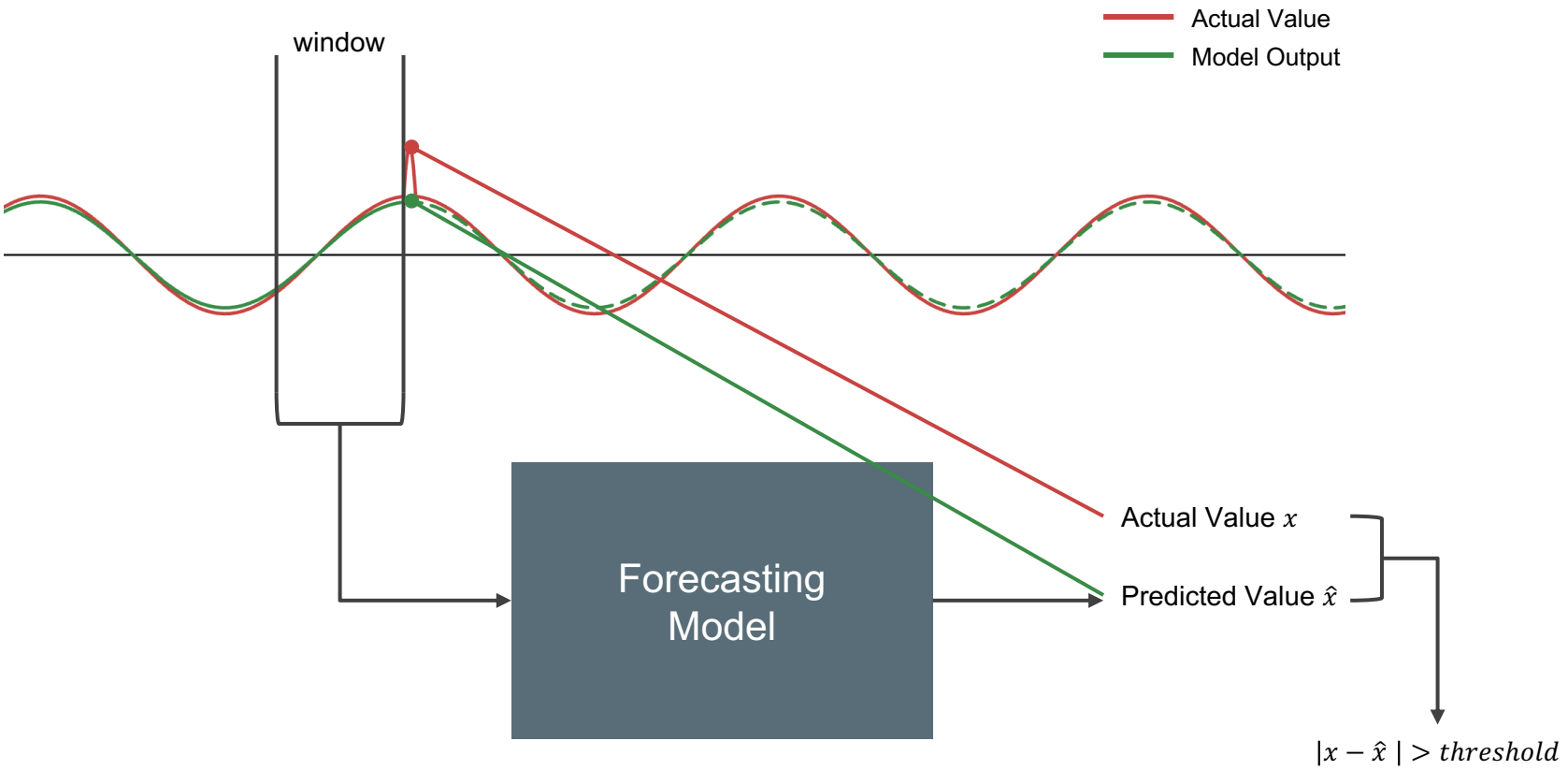
TSAD Methods: Main Approaches

- **Forecasting-based Models**
  - To **predict** a **future point** or subsequence **based on** a point or a **recent window**
- **Reconstruction-based Models**
  - To **reconstruct input** data
- **Representation-based Models**
  - To **learn** rich **representation** of time series data
- **Hybrid Models**
  - Forecasting || Reconstruction || Representation

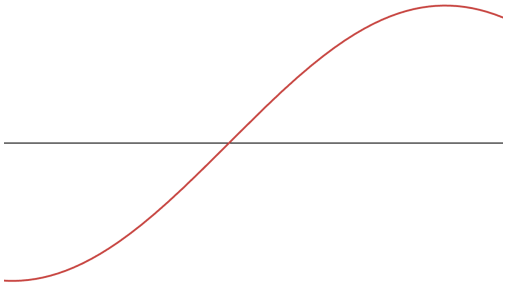


(a) Predictable (b) Unpredictable

TSAD Methods: Main Approaches

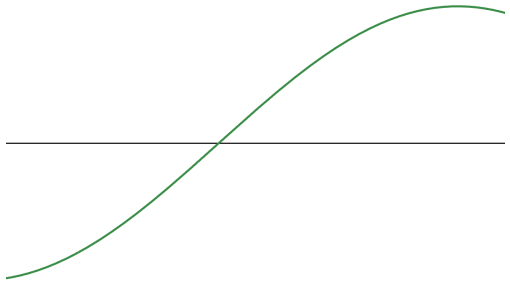


TSAD Methods: Main Approaches

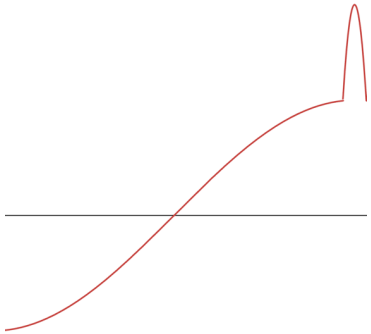


Window

Reconstruction Model



Reconstructed Window



Window

Reconstruction Model

Reconstructed Window

TSAD Methods: Aspects of the Models – 1

- **Temporal(Time) / Spatial(Feature)**
- **Learning Schemes**
  - Supervised: Normal, Anomaly label in train data
  - **Semi-Supervised: Normal label in train data**
  - Unsupervised: No label
  - Self-Supervised: Without explicit label, generate own supervisory signal
- **Input**
  - Point or **Subsequences(windows)**
  - **Representation** or Raw
- **Interpretability**
  - Identifying the dimension or feature that has the greatest impact on an anomaly

TSAD Methods: Aspects of the Models – 2

- **Point / Subsequence Anomaly**
  - Unusual point
  - Subsequence-level abnormality
- **Stochasticity**
  - To handle uncertainties in the inputs
  - ↔ Deterministic
- **Incremental**
  - Updates its knowledge with new data while preserving what it has learned from previous data

TSAD Methods: Forecasting

A[1]	MA[2]		Model		Year	T/S[3]	Su/Un[4]	Input[5]	Int[6]	P/S[7]	Stc[8]	Inc[9]	US[10]
Forecasting	RNN (3.2.1)	474	LSTM-PRED [66]	HASE	2017	T	Un	W	✓	–			
		1449	LSTM-NDT [92]	KDD	2018	T	Un	W	✓	Subseq			
		146	LGMAD [49]		2019	T	Semi	P		Point			✓
		297	THOC [156]	NeurIps	2020	T	Self	W		Subseq			✓
		61	AD-LTI [183]	TKDE	2020	T	Un	P		Point (frame)			
	CNN (3.2.2)	665	DeepAnt [135]	IEEE Access	2018	T	Un	W		Point + Subseq			
		201	TCN-ms [78]	JPCS	2019	T	Semi	W		Subseq			✓
		780	TimesNet [181]	ICLR	2023	T	Un	W		–			✓
	GNN (3.2.3)	922	GDN [45]	AAAI	2021	S	Un	W	✓	–			
		376	GTA* [34]	IEEE IoT Journal	2021	ST	Semi	–		–			
		92	GANF [40]	ICLR	2022	ST	Un	W					
	HTM (3.2.4)	53	RADM [48]	Sensors, MDPI	2018	T	Un	W		–			
	Transformer (3.2.5)	552	SAND [160]	AAAI	2018	T	Semi	W		–			
		376	GTA* [34]	IEEE IoT Journal	2021	ST	Semi	–		–			

TSAD Methods: Reconstruction

A[1]	MA[2]		Model		Year	T/S[3]	Su/Un[4]	Input[5]	Int[6]	P/S[7]	Stc[8]	Inc[9]	US[10]
Reconstruction	AE (3.3.1)	1461	AE/DAE [150]	MLSDA	2014	T	Semi	P		Point			
		2123	DAGMM [203]	ICLR	2018	S	Un	P		Point	✓		
		894	MSCRED [192]	AAAI	2019	ST	Un	W	✓	Subseq			
		837	USAD [10]	KDD	2020	T	Un	W		Point			
		58	APAE [70]	IJCAI	2020	T	Un	W		–			
		213	RANSynCoders [1]	KDD	2021	ST	Un	P	✓	Point		✓	
		59	CAE-Ensemble [22]	VLDB	2021	T	Un	W		Subseq			
		76	AMSL [198]	TKDE	2022	T	Self	W		–			
		11	ContextDA [106]	SIAM SDM	2023	T	Un	W		Point + Subseq			
	VAE (3.3.2)	115	STORN [159]	ICLR	2016	ST	Un	P		Point	✓		
		185	GGM-VAE [74]	PMLR	2018	T	Un	W		Subseq	✓		
		897	LSTM-VAE [143]	IEEE Robotics	2018	T	Semi	P		–	✓		
		1247	OmniAnomaly [163]	KDD	2019	T	Un	W	✓	Point + Subseq	✓		
		49	VELC [191]		2019	T	Un	–		–	✓		
		173	SISVAE [112]	TNNLS	2020	T	Un	W		Point	✓		✓
		166	VAE-GAN [138]	Sensors, MDPI	2020	T	Semi	W		Point	✓		✓
		98	TopoMAD [79]	TNNLS	2020	ST	Un	W		Subseq	✓		
		45	PAD [30]	Neural Computing	2021	T	Un	W		Subseq	✓		✓
		63	InterFusion [117]	KDD	2021	ST	Un	W	✓	Subseq	✓		
		82	MT-RVAE* [177]	Measurement	2022	ST	Un	W		–	✓		
		37	RDSMM [113]	TKDE	2022	T	Un	W		Point + Subseq	✓		✓
	GAN (3.3.3)	1142	MAD-GAN [111]	ICANN	2019	ST	Un	W		Subseq			
		286	BeatGAN [200]	IJCAI	2019	T	Un	W		Subseq			✓
		96	DAEMON [33]	ICDE	2021	T	Un	W	✓	Subseq			
		51	FGANomaly [54]	TKDE	2021	T	Un	W		Point + Subseq			
		84	DCT-GAN* [114]	TKDE	2021	T	Un	W		–			✓
	Transformer (3.3.4)	527	Anomaly Transformer [185]	ICLR	2021	T	Un	W		Subseq			
		84	DCT-GAN* [114]	TKDE	2021	T	Un	W		–			✓
		497	TranAD [171]	VLDB	2022	T	Un	W	✓	Subseq			✓
		82	MT-RVAE* [177]	Measurement	2022	ST	Un	W		–			
		4	Dual-TF [136]	WWW	2024	T	Un	W		Point + Subseq			✓

TSAD Methods: Representation, Hybrid

A[1]	MA[2]		Model		Year	T/S[3]	Su/Un[4]	Input[5]	Int[6]	P/S[7]	Stc[8]	Inc[9]	US[10]
Representation	Transformer (3.4.1)		TS2Vec [190]	549 AAAI	2022	T	Self	P		Point			✓
	CNN (3.4.2)	253	TF-C [196]	Neurlps	2022	T	Self	W		–			✓
		93	DCdetector [187]	KDD	2023	ST	Self	W		Point + Subseq			✓
		6	CARLA [42]	Pattern Recognition	2023	ST	Self	W		Point + Subseq			✓
		2	DACAD [43]		2024	ST	Self	W		Point + Subseq			
Hybrid	AE (3.5.1)	205	CAE-M [197]	TKDE	2021	ST	Un	W		Subseq			
		78	NSIBF* [60]	KDD	2021	T	Un	W		Subseq			
	RNN (3.5.2)	156	TAnoGAN [13]	IEEE SSCI	2020	T	Un	W		Subseq			
		78	NSIBF* [60]	KDD	2021	T	Un	W		Subseq			
	GNN (3.5.3)	567	MTAD-GAT [199]	ICDM	2020	ST	Self	W	✓	Subseq			
		76	FuSAGNet [76]	KDD	2022	ST	Semi	W		Subseq			

Public Dataset: Multivariate

Dataset/Benchmark	Real/Synth	MTS/UTS[1]	# Samples[2]	# Entities[3]	# Dim[4]	Domain
MSL [92]	Real	MTS	132,046	27	55	Aerospace
NAB-realAdExchange [5]	Real	MTS	9,616	3	2	Business
NAB-realAWSCloudwatch [5]	Real	MTS	67,644	1	17	Server machines monitoring
NASA Shuttle Valve Data [62]	Real	MTS	49,097	1	9	Aerospace
OPPORTUNITY [55]	Real	MTS	869,376	24	133	Computer networks
Pooled Server Metrics (PSM) [1]	Real	MTS	132,480	1	24	Server machines monitoring
PUMP [154]	Real	MTS	220,302	1	44	Industrial control systems
SMAP [92]	Real	MTS	562,800	55	25	Environmental management
SMD [115]	Real	MTS	1,416,825	28	38	Server machines monitoring
SWAN-SF [9]	Real	MTS	355,330	5	51	Astronomical studies
SWaT [129]	Real	MTS	946,719	1	51	Industrial control systems
WADI [7]	Real	MTS	957,372	1	127	Industrial control systems

Public Dataset: Univariate

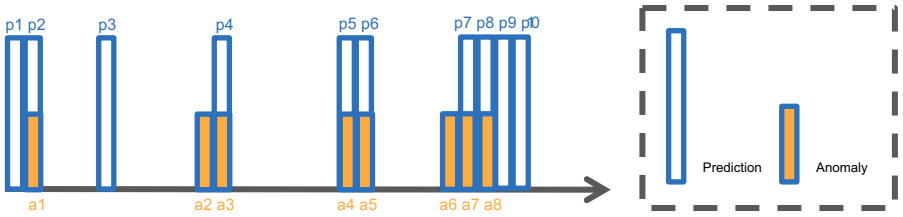
Dataset/Benchmark	Real/Synth	MTS/UTS[1]	# Samples[2]	# Entities[3]	# Dim[4]	Domain
NYC Bike [123]	Real	MTS/UTS	+25M	NA	NA	Urban events management
NYC Taxi [166]	Real	MTS/UTS	+200M	NA	NA	Urban events management
UCR [44]	Real/Synth	MTS/UTS	NA	NA	NA	Multiple domains
Dodgers Loop Sensor Dataset [55]	Real	UTS	50,400	1	1	Urban events management
KPI AIOPS [25]	Real	UTS	5,922,913	58	1	Business
MGAB [170]	Synth	UTS	100,000	10	1	Medical and health
MIT-BIH-LTDB [67]	Real	UTS	67,944,954	7	1	Medical and health
NAB-artificialNoAnomaly [5]	Synth	UTS	20,165	5	1	–
NAB-artificialWithAnomaly [5]	Synth	UTS	24,192	6	1	–
NAB-realKnownCause [5]	Real	UTS	69,568	7	1	Multiple domains
NAB-realTraffic [5]	Real	UTS	15,662	7	1	Urban events management
NAB-realTweets [5]	Real	UTS	158,511	10	1	Business
NeurIPS-TS [107]	Synth	UTS	NA	1	1	–
NormA [18]	Real/Synth	UTS	1,756,524	21	1	Multiple domains
Power Demand Dataset [44]	Real	UTS	35,040	1	1	Industrial control systems
SensoreScope [12]	Real	UTS	621,874	23	1	Internet of things (IoT)
Space Shuttle Dataset [44]	Real	UTS	15,000	15	1	Aerospace
Yahoo [93]	Real/Synth	UTS	572,966	367	1	Multiple domains

Evaluation Metrics

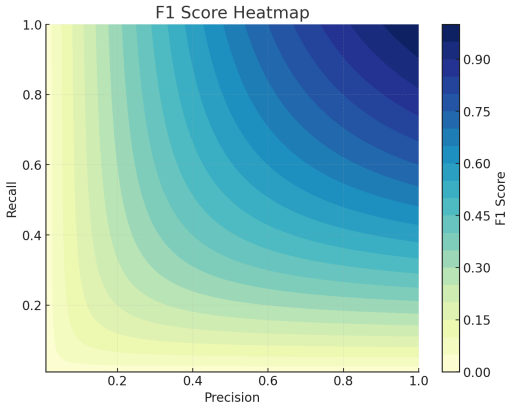
Definitions and Formulas		
Metric	**Definition**	**Formula***
Precision	The proportion of true positive results among all positive results predicted by the model. In time series anomaly detection, it indicates the accuracy of the detected anomalies.	$\text{Precision} = \frac{TP}{TP+FP}$
Recall	The proportion of true positive results among all actual positive cases. It measures the model's ability to detect all actual anomalies.	$\text{Recall} = \frac{TP}{TP+FN}$
F1 Score	The harmonic mean of precision and recall, providing a balance between the two metrics. It is useful when both precision and recall are important.	$\text{F1} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision}+\text{Recall}}$
F1$_{PA}$ Score	**F1$_{PA}$ score** is an F1 score that utilises a segment-based evaluation technique named point adjustment (PA), which at least one point within that segment is detected as abnormal [184]. This method can overestimate the performance of TSAD models (as mentioned in [42]).	$\text{F1}_{\text{PA}} = 2 \cdot \frac{\text{Precision}_{\text{PA}} \cdot \text{Recall}_{\text{PA}}}{\text{Precision}_{\text{PA}}+\text{Recall}_{\text{PA}}}$
PA%K	**F1$_{PA}$** is mitigated by employing a **PA%K** protocol [152] by focusing on segments of data w. A segment is correctly detected as anomalous if at least $K\%$ of its points are TP (TP_w).	$Accuracy_w = \begin{cases} 1 & \text{if } \frac{TP_w}{\lvert w \rvert} \geq \frac{K}{100} \\ 0 & \text{otherwise} \end{cases}$
AU-PR	Area Under Precision-Recall Curve is a performance measurement for classification problems at various thresholds (t). It is particularly useful for imbalanced datasets.	$\text{AU-PR} = \int_0^1 \text{Precision}(t) \frac{d(\text{Recall}(t))}{dt} \, dt$
AU-ROC	Area Under Receiver Operating Characteristic Curve represents the ability of the model to distinguish between classes based on different thresholds (t). A higher AU-ROC indicates better model performance.	$\text{AU-ROC} = \int_0^1 \text{Recall}(t) \frac{d(\text{FPR}(t))}{dt} \, dt$
MTTD	Mean Time to Detect is the average time taken to detect an anomaly at time T_{detect} after it occurs in time T_{true}. This metric evaluates the model's responsiveness.	$\text{MTTD} = \frac{1}{n} \sum_{i=1}^{n} (T_{\text{detect}} - T_{\text{true}})$
Affiliation	The affiliation metric assesses the degree of overlap between the detected anomalies (D) and the actual anomalies (A). It is designed to provide a more nuanced evaluation by considering both the precision and recall of the detected anomalies.	$\text{Affiliation} = \frac{\lvert D \cap A \rvert}{\lvert D \cup A \rvert}$
VUS	The Volume Under the Surface quantifies the volume between the true anomaly signal y and the predicted one, $\hat{y}$, over time. It captures both the temporal and amplitude differences between the two signals, providing a holistic measure of the detection performance.	$\text{VUS} = \int_0^T \lvert y_t - \hat{y}_t \rvert \, dt$

Evaluation Metrics: Conventional

- **Precision**
  - $\frac{True\ Positives}{True\ Positives + False\ Positives} = \frac{Correct\ Predictions}{Total\ Predictions}$
- **Recall**
  - $\frac{True\ Positives}{True\ Positives + False\ Negatives} = \frac{Detected\ Anomalies}{Total\ Anomalies}$
- **F1 Score**
  - $2 \times \frac{Precision \times Recall}{Precision + Recall}$
  - Evaluates the balance between precision and recall

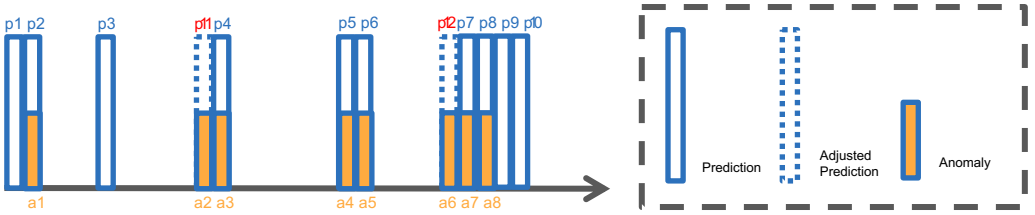


Precision = 0.6, Recall = 0.75, F1 Score = 0.667



Evaluation Metrics: Point Adjust

- **Point Adjust Precision & Recall**
  - Continuous anomalies are considered as a single anomaly segment
  - If even one point within an anomaly segment is detected, the entire segment is considered as detected
- **Point Adjust Precision**
  - $\frac{Correct\ Predictions}{Total\ Predictions}$ $(Predictions = Predictions + Adjusted\ Predictions)$
- **Point Adjust Recall**
  - $\frac{Detected\ Anomalies}{Total\ Anomalies}$

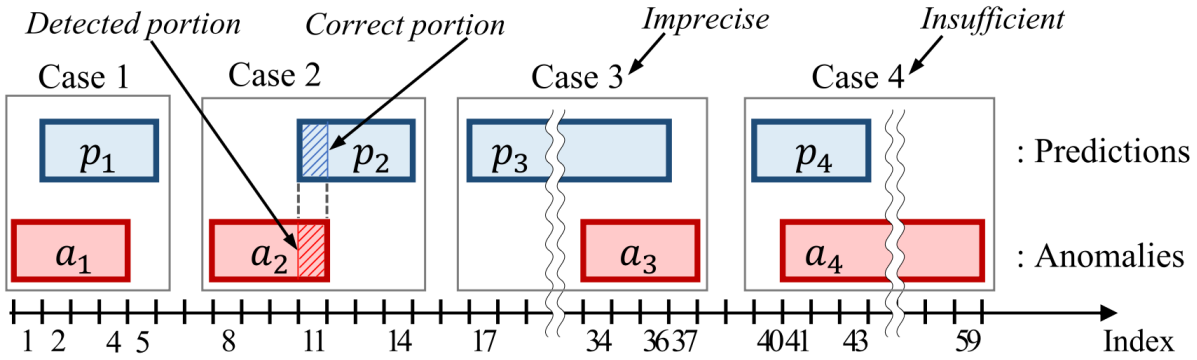


truth	0	0	1	1	1	0	0	1	1	1
score	0.6	0.4	0.3	0.7	0.6	0.5	0.2	0.3	0.4	0.3
point-wise alert	1	0	0	1	1	1	0	0	0	0
adjusted alert	1	0	1	1	1	1	0	0	0	0

PA Precision = 0.75, PA Recall = 1
F1 Score = 0.857

Evaluation Metrics: eTaPR

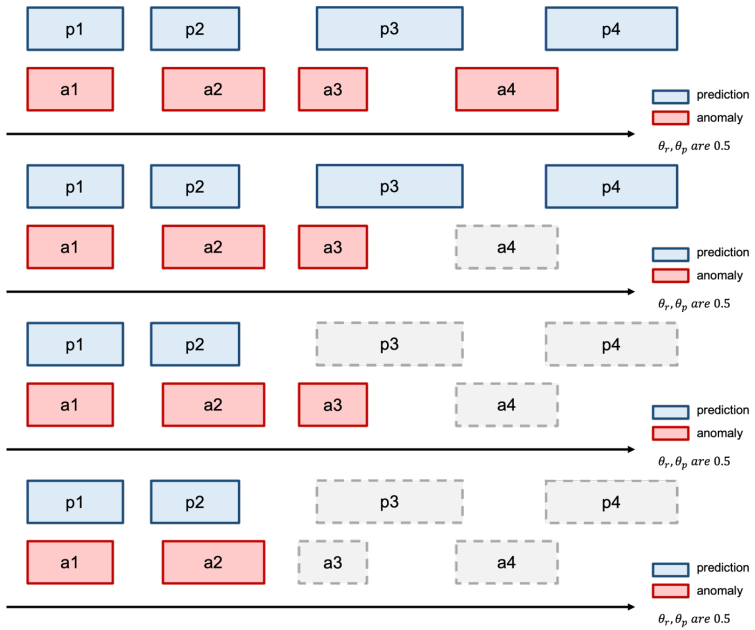
- **Enhanced Time-series Aware Precision & Recall (eTaPR)**
  - Imprecise or insufficient cases are not suitable for expert scenarios
  - Using cross-referencing, imprecise predictions and insufficiently detected anomalies are not scored
  - A weighting scheme is applied to penalize lengthy incorrect predictions



Evaluation Metrics: eTaPR

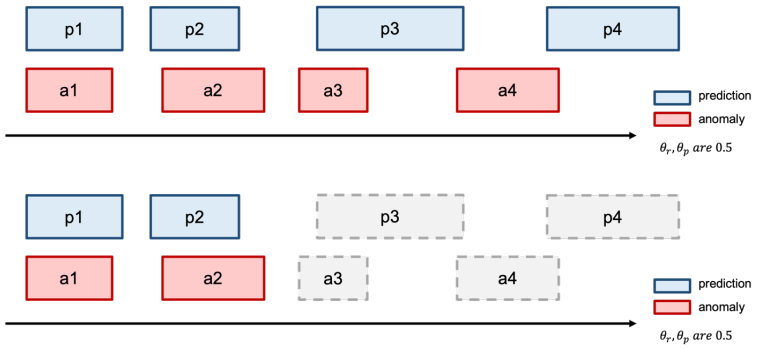
- **Cross referencing**
  - Refine cases of insufficiency or inaccuracy by cross-referencing between A^d and P^c
  - $A^d = \left\{a \mid a \in A \; and \; \frac{\sum_{p \in P^c} |a \cap p|}{|a|} \geq \theta_r\right\}$
  - $P^c = \left\{p \mid p \in P \; and \; \frac{\sum_{a \in A^d} |a \cap p|}{|p|} \geq \theta_p\right\}$
  - P $\rightarrow \boldsymbol{A^d(1)}$, $\boldsymbol{A^d(1) \rightarrow P^c(1)}$
  - $\boldsymbol{P^c(1) \rightarrow A^d(2)}$, $\boldsymbol{A^d(2) \rightarrow P^c(2)}$, $\boldsymbol{P^c(2) \rightarrow A^d(3)}$ …

    until $\boldsymbol{P^c(i) = P^c(i-1)}$ and $\boldsymbol{A^d(i) = A^d(i-1)}$



Evaluation Metrics: eTaPR

- **Enhanced Time-series Aware Precision**
  - $eTaP = \sum_{p \in P} \left(\frac{s^d(p) + s^d(p) \times s^p(p)}{2} \right) \times w_p$
  - $s^d(p) = \begin{cases} 1, & if\ p \in P^c \\ 0, & otherwise \end{cases}$ $s^p(p) = \frac{\sum_{a \in A^d} |a \cap p|}{|p|}$ $w_p = \frac{\sqrt{|p|}}{\sum_{q \in P} |q|}$ weighting scheme
- **Enhanced Time-series Aware Recall**
  - $eTaR = \frac{1}{|A|} \sum_{a \in A} \left(\frac{s^d(a) + s^d(a) \times s^p(a)}{2} \right)$
  - $s^d(a) = \begin{cases} 1, & if\ a \in A^d \\ 0, & otherwise \end{cases}$ $s^p(a) = \frac{\sum_{p \in P^c} |a \cap p|}{|a|}$



Challenges

- **Non-Stationary Data**
  - Incremental learning
- **Multivariate Time Series**
  - High dimensional time series (Many input tags)
- **Unlabeled Data**
  - Unsupervised, Semi-supervised, Self-supervised
  - Minimize false positive rate, Improve recall
- **Noise in the input data**
- **Interpretability**
- **Periodic Outlier Detection**
  - Appear at regular intervals but are rare compared to other patterns in the dataset
  - Not noise

Thank you