# ASTER: Latent Pseudo-Anomaly Generation for Unsupervised Time-Series Anomaly Detection

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SNT

# Presentation Outline

1. Context & Objectives
2. Time-Series Anomaly Detection
3. Positioning
4. Proposed Method
5. Discussion

# Section Outline

# Autonomous Recognition of Foreign Assets

***Respond to growing concerns emerging from the exploitation of Earth orbit***

1. **Threatening Objects & Payloads**
   - Debris, unexpected assets, antennas, lasers...
2. **Threatening Behaviour**
   - Orientation, change in orbit, speed, relative position...

This research was funded by the Luxembourg National Research Fund (FNR), grant reference DEFENCE22/17813724/AUREA.

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# Problem Formulation

*Data challenges*

- Rarity
- Intractability
- Evolutive
- Subtlety

→

***Normality*** *as a starting point*

- More accessible
- Better known
- Less subject to changes

***Unsupervised Anomaly Detection***

*Designing a robust methodology without access to anomalies*

[4] Chandola, Banerjee, and Kumar, ***Anomaly detection: A survey*** (CSUR 2009)
[21] Salehi et al., ***A Unified Survey on Anomaly, Novelty, Open-Set, and Out-of-Distribution Detection: Solutions and Future Challenges*** (TMLR 2022)
[23] Tuli, Casale, and Jennings, ***TranAD: Deep Transformer Networks for Anomaly Detection in Multivariate Time Series Data*** (VLDB 2022)

# Problem Formulation: Settings

## Observations Through Time

- Objects position and orientation
- Objects speed and direction
- ...
- *(Objects visual characteristics)*

***Multivariate Time-Series Anomaly Detection***

# Section Outline



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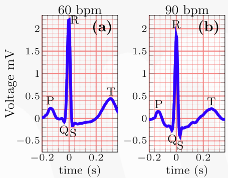
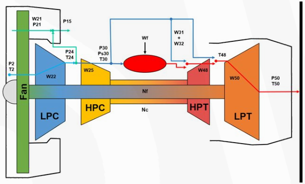
# Datasets for TSAD




Medical [3]


IoT [10]




Industry [6]

Finance [19]

**Time-Series Anomaly Detection**

- Existence of specialised benchmarks
- Sensor readings at different time

→ Predominance of industrial data for benchmark purposes



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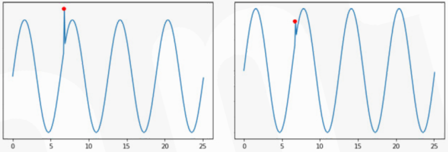
# Datasets for TSAD: Generic Benchmarks

- Pooled Server Metrics (**PSM**) [1], **PUMP** [8], Secure Water Treatment (**SWaT**) [16], Controlled Anomalies Time Series (**CATSv2**) [9].

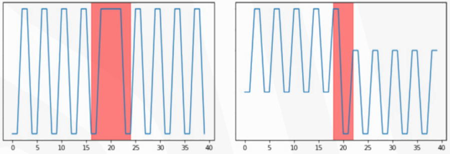
| | A | B | C | D | E | G | R | AJ | AZ | BA |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | | | | | | | | | |
| 2 | Timestamp | FIT101 | LIT101 | MV101 | P101 | AIT201 | DPIT3 | AIT50 | P603 | Normal/Attack |
| 3 | 28/12/2015 10:00:00 AM | 2.427057 | 522.8467 | 2 | 2 | 262.0161 | 19.7 | 7.9 | 1 | Normal |
| 4 | 28/12/2015 10:00:01 AM | 2.446274 | 522.886 | 2 | 2 | 262.0161 | 19.7 | 7.9 | 1 | Normal |
| 5 | 28/12/2015 10:00:02 AM | 2.489191 | 522.8467 | 2 | 2 | 262.0161 | 19.7 | 7.9 | 1 | Normal |
| 6 | 28/12/2015 10:00:03 AM | 2.53435 | 522.9645 | 2 | 2 | 262.0161 | 19.7 | 7.9 | 1 | Normal |
| 7 | 28/12/2015 10:00:04 AM | 2.56926 | 523.4748 | 2 | 2 | 262.0161 | 19.7 | 7.9 | 1 | Normal |
| 8 | 28/12/2015 10:00:05 AM | 2.609294 | 523.8673 | 2 | 2 | 262.0161 | 19.7 | 7.9 | 1 | Normal |
| 9 | 28/12/2015 10:00:06 AM | 2.637158 | 524.1028 | 2 | 2 | 262.0161 | 19.7 | 7.9 | 1 | Normal |
| 10 | 28/12/2015 10:00:07 AM | 2.652211 | 524.2206 | 2 | 2 | 262.0161 | 19.7 | 7.9 | 1 | Normal |
| 11 | 28/12/2015 10:00:08 AM | 2.655735 | 524.4954 | 2 | 2 | 262.0161 | 19.7 | 7.9 | 1 | Normal |
| 12 | 28/12/2015 10:00:09 AM | 2.64997 | 524.0636 | 2 | 2 | 262.0161 | 19.7 | 7.9 | 1 | Normal |

SWaT: Example

# Detecting Anomalies Through Time




(a) Global outlier (b) Contextual outlier




(d) Seasonal outlier (e) Trend outlier

- A single observation is not enough to detect abnormality
- The values are **dependant on the previous observations**
- Anomalies can depend on when a value is observed
- A succession of events, themselves normal, can be an abnormality

[17] Mejri et al., ***Unsupervised anomaly detection in time-series: An extensive evaluation and analysis of state-of-the-art methods*** (Exp. Syst. Appl. 2024)



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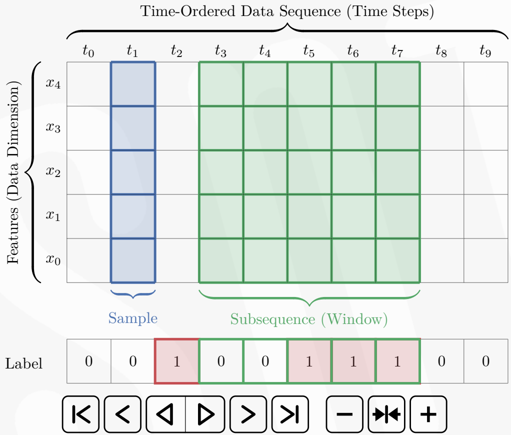
# Data Processing




- Models are trained using **subsequences** of the data
- Each subsequence is analysed and predicted normal or abnormal
- Performance is measured *w.r.t.* the subsequence labels

$$s_t = \mathfrak{f}([\mathbf{x}_{t-L+1}, \ldots, \mathbf{x}_t])$$

$\mathfrak{f}$ - Model $\mathbf{x}$ - Time-series $\mathbf{x}_t$ - Current time-step
$s_t$ - Anomaly score $L$ - Window size

# Section Outline



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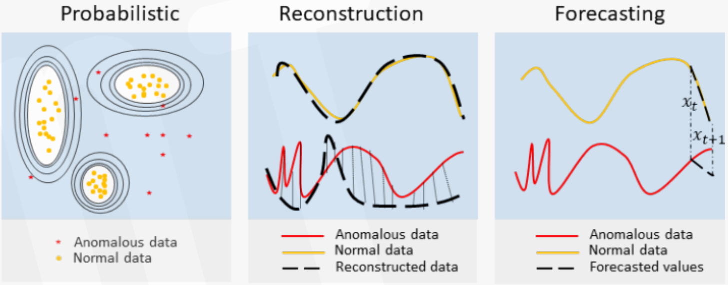
# Existing Approaches



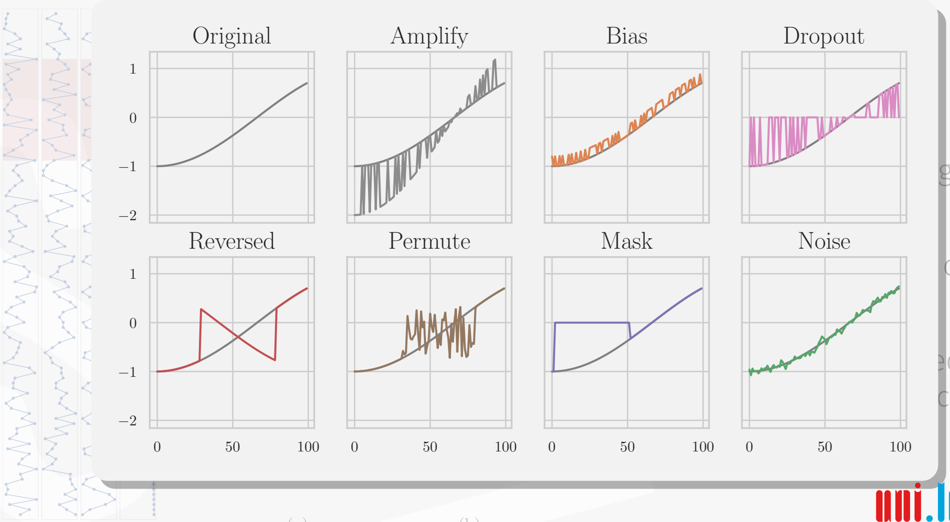

Source [17]

- Reconstruction [15], forecasting [7], clustering [22], statistics [24, 2]...

→ ***Pseudo-Anomaly Generation***

[15] Lin et al., ***Anomaly Detection for Time Series Using VAE-LSTM Hybrid Model*** (ICASSP 2020)
[7] Deng and Hooi, ***Graph Neural Network-Based Anomaly Detection in Multivariate Time Series*** (AAAI 2021)
[22] Shen, Li, and Kwok, ***Timeseries Anomaly Detection using Temporal Hierarchical One-Class Network*** (NeurIPS 2020)
[2] Baptista et al., ***Deformation-Based Abnormal Motion Detection using 3D Skeletons*** (IPTA 2018)

# Addressing Existing Limitations



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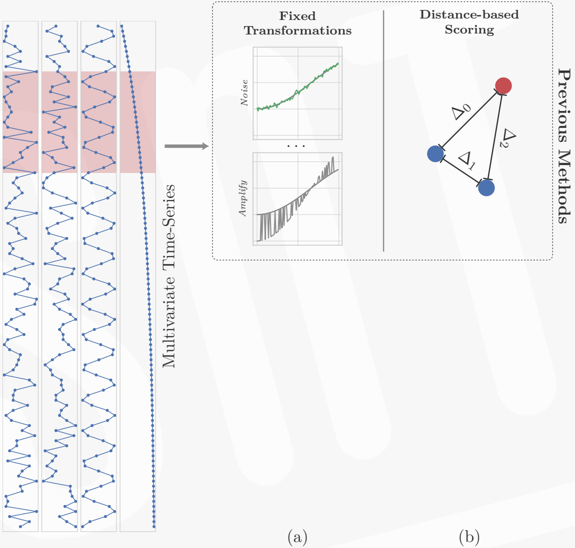


- Limited flexibility
- Requires manual design and expert tuning
- Requires domain and data expertise
- Performance correlated to datasets characteristics

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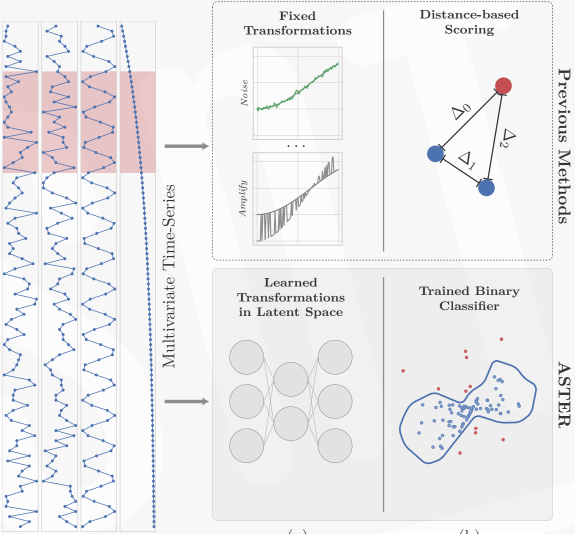


(a) (b)

- **Adaptability**
  → *Learned transformations, decision boundary–**in latent space***
- **Non-triviality**
  → *Adversarially optimised generation*
- **Diversity**
  → *Stochastic modelling*



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# Leveraging Latent Space

## Motivations

- Expressive, data-agnostic representations
- Powerful backbone, lightweight specialised head
- Multi-task and **multimodal** flexibility

***Using pre-trained LLMs to capture complex temporal dependencies [11, 14, 13]***

- Addressing data scarcity and heterogeneity, weak pre-trained models [5]
- Utilise abundant data and studies in NLP
- Leverage the rapid growth on LLM research

---

[14] Liang et al., ***Foundation Models for Time Series Analysis: A Tutorial and Survey*** (SIGKDD 2024)
[5] Chang et al., ***LLM4TS: Aligning Pre-Trained LLMs as Data-Efficient Time-Series Forecasters*** (TIST 2025)
[11] Gruver et al., ***Large Language Models Are Zero-Shot Time Series Forecasters*** (NeurIPS 2023)
[13] Jiang et al., ***Empowering Time Series Analysis with Large Language Models: A Survey*** (IJCAI 2024)

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# Anomaly Synthesis through Transformer-based Embedding Representation


$$\mathfrak{L}_{\text{CE}} = -\left[y_t \log(\bar{s}_t) + (1 - y_t)\log(1 - \bar{s}_t)\right]$$

# Anomaly Synthesis through Transformer-based Embedding Representation




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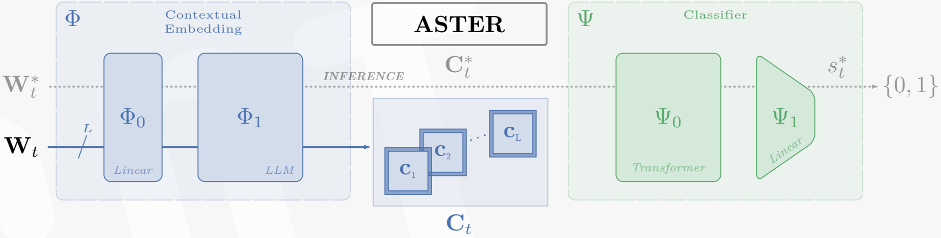
# Anomaly Synthesis through Transformer-based Embedding Representation



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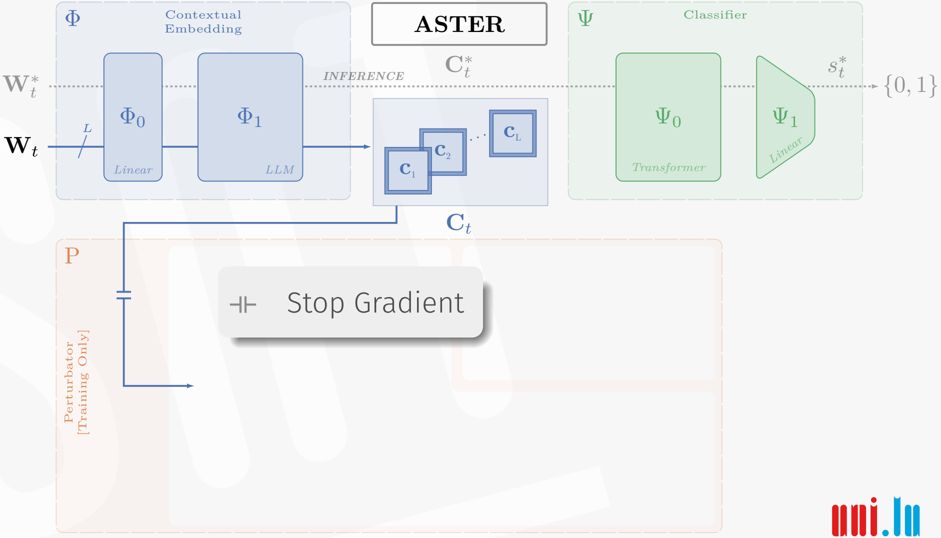

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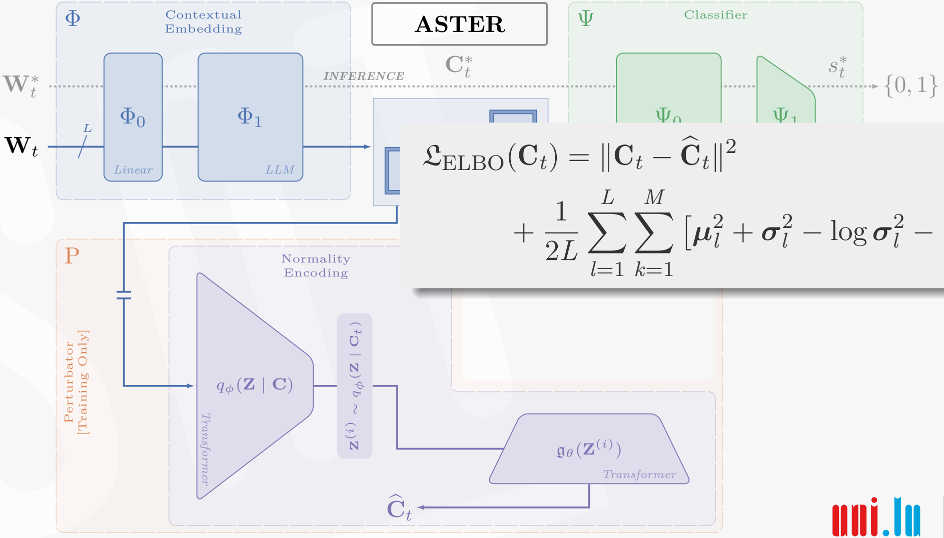


$$\mathfrak{L}_{\text{ELBO}}(\mathbf{C}_t) = \|\mathbf{C}_t - \widehat{\mathbf{C}}_t\|^2 + \frac{1}{2L} \sum_{l=1}^{L} \sum_{k=1}^{M} \left[\boldsymbol{\mu}_l^2 + \boldsymbol{\sigma}_l^2 - \log \boldsymbol{\sigma}_l^2 - 1\right]_k$$

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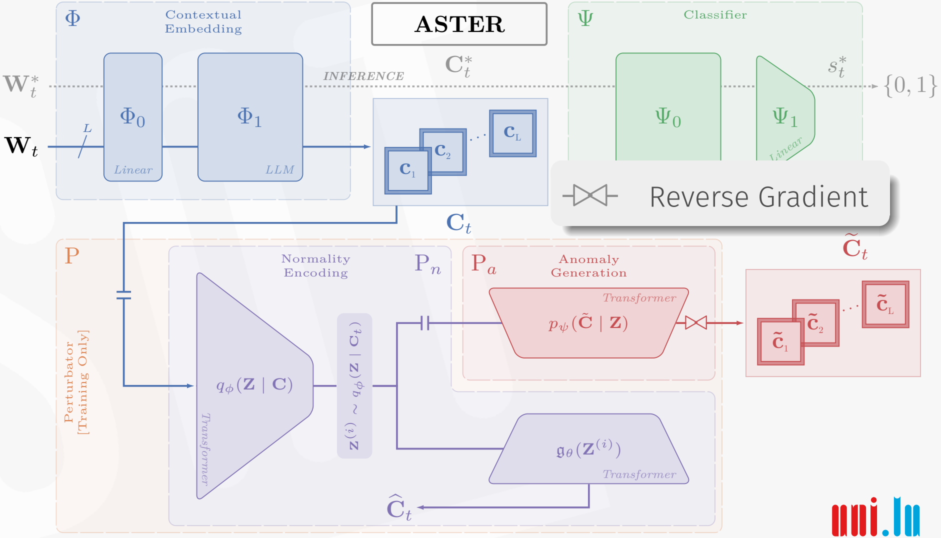

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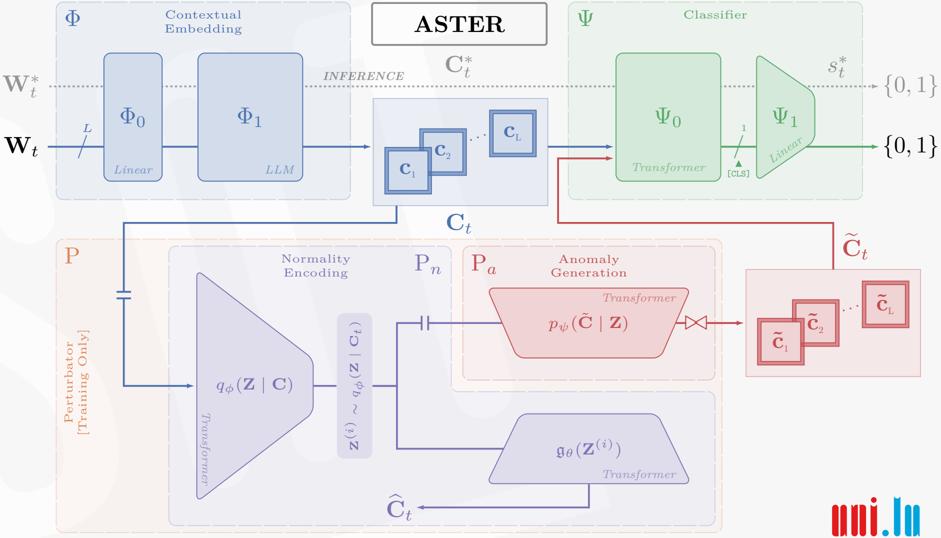




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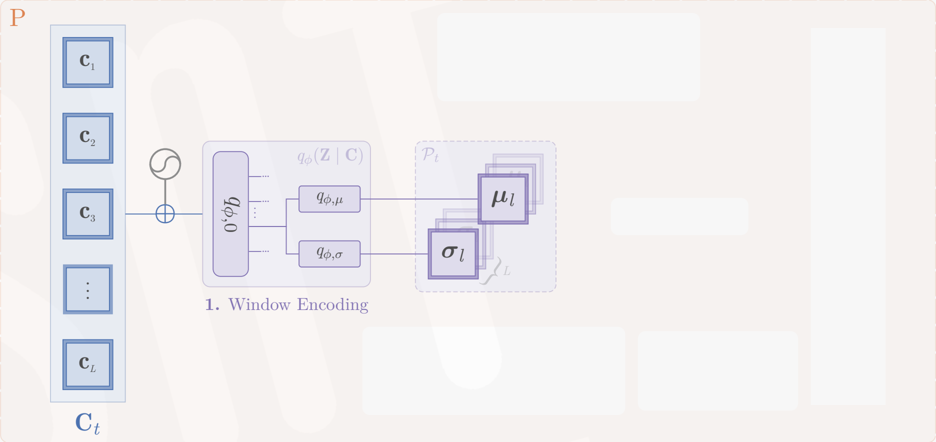

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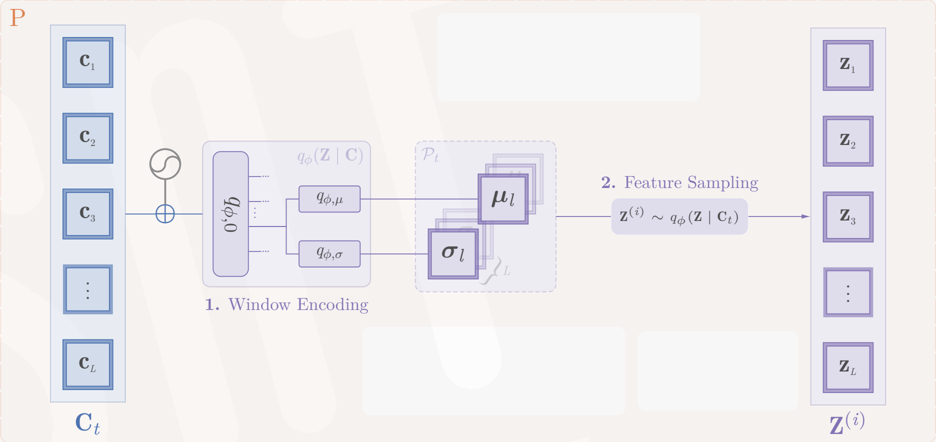

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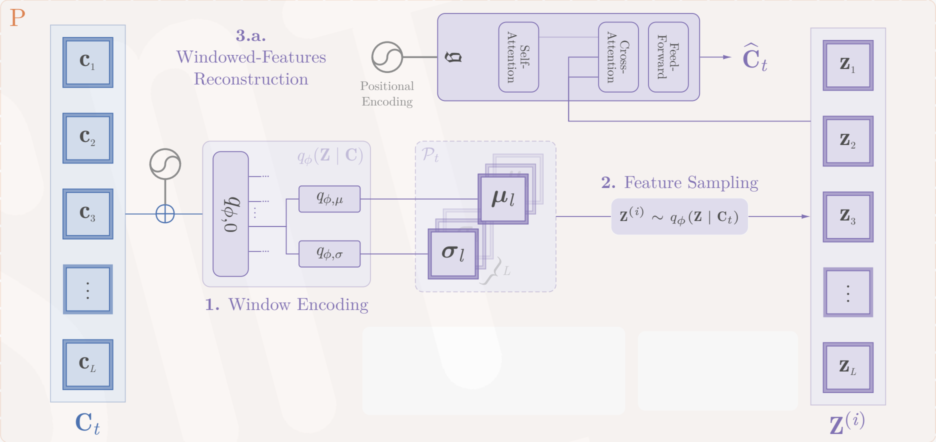




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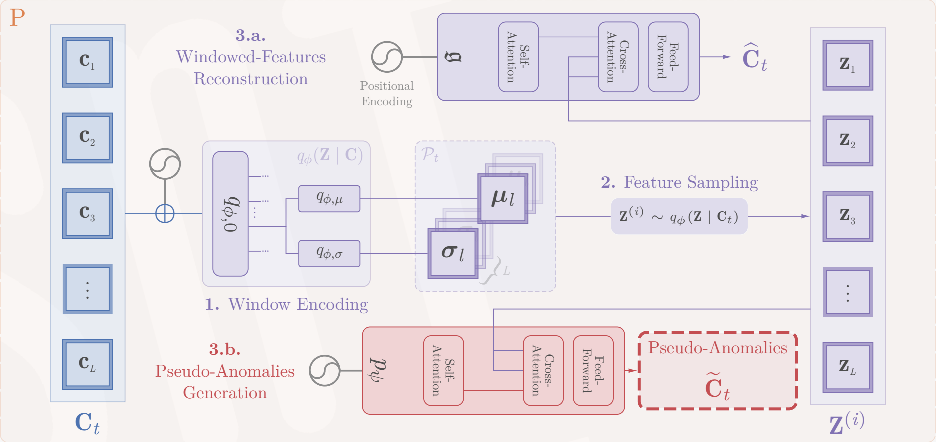

# Results – TAB Codebase [20]

| Data | Metrics | Deep Learning | | | Pre-trained Models | | | | LLM-based | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | DAGMM | TsNet | TranAD | Timer | TimesFM | Moment | Chronos | GPT4TS | UniTime | CALF | LLMMixer | **ASTER** |
| PSM | $F_1$ | 0.007 | 0.088 | 0.403 | 0.143 | 0.082 | 0.117 | 0.131 | 0.089 | 0.097 | 0.102 | 0.186 | **0.512** |
| | AUROC | 0.637 | 0.592 | 0.631 | 0.556 | - | 0.545 | 0.565 | 0.580 | 0.579 | 0.589 | 0.593 | **0.697** |
| | AUPR | 0.416 | 0.391 | 0.388 | 0.359 | - | 0.332 | 0.370 | 0.376 | 0.377 | 0.370 | 0.385 | **0.501** |
| | VUS-ROC | 0.608 | 0.593 | 0.566 | 0.541 | - | 0.540 | 0.547 | 0.576 | 0.579 | 0.587 | 0.579 | **0.631** |
| | VUS-PR | 0.404 | 0.395 | 0.431 | 0.350 | - | 0.329 | 0.362 | 0.374 | 0.377 | 0.374 | 0.383 | **0.452** |
| PUMP | $F_1$ | 0.174 | 0.017 | 0.454 | 0.129 | 0.037 | 0.140 | 0.102 | 0.014 | 0.020 | 0.017 | 0.081 | **0.458** |
| | AUROC | 0.447 | 0.485 | 0.800 | 0.529 | 0.409 | 0.485 | 0.469 | 0.414 | 0.549 | 0.566 | 0.398 | **0.839** |
| | AUPR | 0.163 | 0.121 | 0.110 | 0.139 | 0.117 | 0.129 | 0.108 | 0.101 | 0.129 | 0.130 | 0.104 | **0.254** |
| | VUS-ROC | 0.504 | 0.630 | 0.792 | 0.712 | 0.568 | 0.669 | 0.576 | 0.551 | 0.690 | 0.665 | 0.545 | **0.833** |
| | VUS-PR | 0.235 | 0.219 | 0.243 | 0.260 | 0.203 | 0.240 | 0.175 | 0.177 | 0.224 | 0.204 | 0.181 | **0.290** |
| SWAT | $F_1$ | 0.073 | 0.077 | 0.321 | 0.144 | 0.099 | 0.132 | 0.613 | 0.034 | 0.063 | 0.075 | 0.098 | **0.695** |
| | AUROC | 0.290 | 0.288 | 0.818 | 0.286 | 0.242 | 0.263 | 0.803 | 0.224 | 0.234 | - | 0.240 | **0.823** |
| | AUPR | 0.082 | 0.107 | **0.729** | 0.119 | 0.086 | 0.109 | 0.410 | 0.081 | 0.082 | - | 0.086 | 0.542 |
| | VUS-ROC | 0.328 | 0.392 | 0.699 | 0.399 | 0.344 | 0.370 | **0.814** | 0.322 | 0.335 | - | 0.342 | 0.757 |
| | VUS-PR | 0.250 | 0.169 | **0.520** | 0.172 | 0.121 | 0.161 | 0.449 | 0.112 | 0.115 | - | 0.120 | 0.506 |
| CATSv2 | $F_1$ | 0.088 | **0.262** | 0.126 | - | 0.129 | 0.060 | 0.120 | 0.089 | - | 0.138 | 0.081 | 0.172 |
| | AUROC | 0.619 | **0.712** | 0.604 | 0.541 | 0.633 | - | 0.624 | 0.601 | 0.334 | 0.616 | 0.617 | 0.665 |
| | AUPR | 0.090 | **0.261** | 0.129 | 0.112 | 0.109 | - | 0.103 | 0.094 | 0.039 | 0.133 | 0.085 | 0.106 |
| | VUS-ROC | 0.667 | **0.772** | 0.625 | 0.584 | 0.705 | - | 0.705 | 0.676 | 0.373 | 0.689 | 0.689 | 0.709 |
| | VUS-PR | **0.314** | 0.265 | 0.130 | 0.132 | 0.125 | - | 0.112 | 0.107 | 0.058 | 0.145 | 0.099 | 0.110 |

[20] Qiu et al., ***TAB: Unified Benchmarking of Time Series Anomaly Detection Methods*** (VLDB 2025)



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# Ablation Studies

LLM and fine-tuning

| LLM | Fine Tuning | PSM | | | PUMP | | |
|---|---|---|---|---|---|---|---|
| | | $F_1$ | AUROC | AUPR | $F_1$ | AUROC | AUPR |
| ✗ | ✗ | 0.479 | 0.669 | 0.447 | 0.021 | 0.460 | 0.087 |
| GPT-2 | ✗ | 0.354 | 0.496 | 0.389 | 0.370 | 0.802 | 0.199 |
| GPT-2 | ✓ | 0.361 | 0.499 | 0.417 | 0.265 | 0.707 | 0.146 |
| GPT-2 | ✓(LoRA) | 0.512 | 0.697 | 0.501 | 0.458 | 0.839 | 0.254 |

Classifier architectures

| Classifier | PSM | | | PUMP | | |
|---|---|---|---|---|---|---|
| | $F_1$ | AUROC | AUPR | $F_1$ | AUROC | AUPR |
| Transformer | 0.512 | 0.697 | 0.501 | 0.458 | 0.839 | 0.254 |
| MLP-based | 0.497 | 0.724 | 0.471 | 0.016 | 0.307 | 0.069 |

→ Frozen LLM has a mitigated impact (dataset disparity)

→ Fine-tuning brings value and stability

→ The Transformer architecture is well suited for classification

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# Ablation studies

## Window Size

| Window Size | PSM | | | PUMP | | |
|---|---|---|---|---|---|---|
| | $F_1$ | AUROC | AUPR | $F_1$ | AUROC | AUPR |
| 4 | 0.512 | 0.697 | 0.501 | 0.458 | 0.839 | 0.254 |
| 8 | 0.456 | 0.644 | 0.387 | 0.399 | 0.774 | 0.185 |
| 16 | 0.450 | 0.639 | 0.387 | 0.429 | 0.777 | 0.189 |
| 32 | 0.461 | 0.656 | 0.419 | 0.433 | 0.785 | 0.191 |
| 64 | 0.475 | 0.681 | 0.487 | 0.441 | 0.828 | 0.224 |

## Algorithm complexity

| Method | Window Size | Time (s) | | | Memory (MB) |
|---|---|---|---|---|---|
| | | Train | Validation | Test | |
| ASTER | 4 | 209 | 15 | 51 | 2572 |
| | 8 | 336 | 25 | 86 | 3523 |
| | 16 | 588 | 45 | 152 | 5364 |
| | 32 | 1083 | 83 | 285 | 8845 |
| | 64 | 2074 | 160 | 545 | 16145 |
| TimesNet | 100 | 274 | 22 | 98 | 951 |
| GPT4TS | 100 | 997 | 80 | 369 | 9370 |

→ Best results achieved with the smallest window

→ Competitive training time and memory footprint

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# Conclusion & Limitations

## Contributions

- Proposed a pseudo-anomaly-driven framework for TSAD
- Introduced a novel integration of LLM, VAE and Transformer architectures
- Conducted evaluations under fair experimental settings

## Limitations

- Good performance on only a subset of datasets
- The framework is heavier than regular TSAD models
- Sensitivity to model initialisation
- Limited diversity in generated pseudo-anomalies

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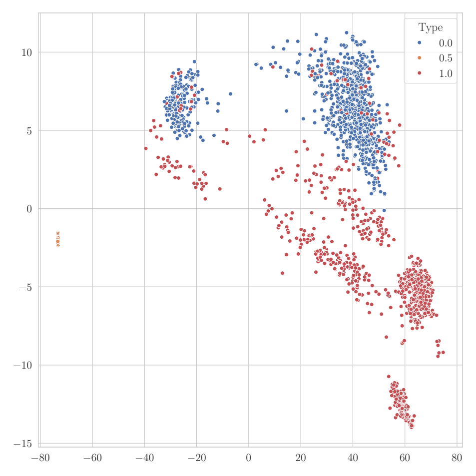


## Limitations

- Good performar
- The framework i
- Sensitivity to mc
- Limited diversity



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# Future Work

## Further evaluations

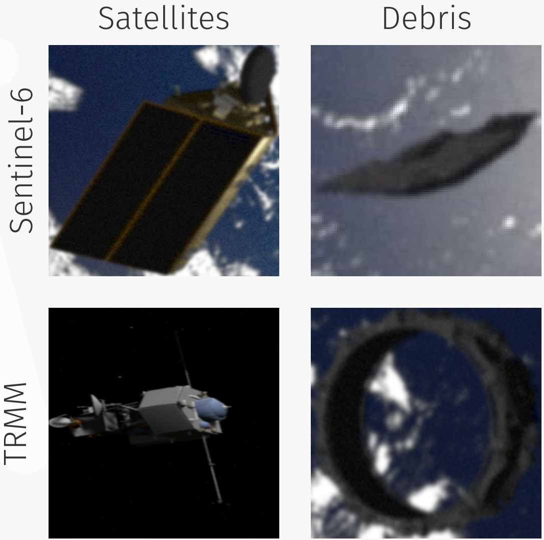
- Multimodal space datasets (leveraging LLMs multimodality)
- Different LLMs (newer, smaller...)
- Exploring latent space interpretability

## Algorithm improvements

- Constraints on the anomaly generation
- Sampling with temporal knowledge
- Zero-shot feature extraction

## Completing Work: Debris Detection

**Removing Geometric Bias in One-Class Anomaly Detection with Adaptive Feature Perturbation** (WACV 2025) [12]




[18] Musallam et al., ***Spacecraft Recognition Leveraging Knowledge of Space Environment: Simulator, Dataset, Competition Design and Analysis*** (ICIPC 2021)

6.

# References

[1] **Ahmed Abdulaal, Zhuanghua Liu, and Tomer Lancewicki.** **"Practical approach to asynchronous multivariate time series anomaly detection and localization".** In: *SIGKDD*. 2021.

[2] **Renato Baptista et al.** **"Deformation-Based Abnormal Motion Detection using 3D Skeletons".** In: *IPTA*. IEEE, 2018, pp. 1–6.

[3] **Diego Carrera et al.** **"Online anomaly detection for long-term ECG monitoring using wearable devices".** In: *Pattern Recognit.* 88 (2019), pp. 482–492. DOI: `10.1016/J.PATCOG.2018.11.019`.

[4] **Varun Chandola, Arindam Banerjee, and Vipin Kumar.** **"Anomaly detection: A survey".** In: *ACM Computing Surveys* 41 (2009), 15:1–15:58.

[5] **Ching Chang et al.** **"LLM4TS: Aligning Pre-Trained LLMs as Data-Efficient Time-Series Forecasters".** In: *TIST* (2025).

[6] **Manuel Arias Chao et al.** **"Aircraft Engine Run-to-Failure Dataset under Real Flight Conditions for Prognostics and Diagnostics".** In: *Data* 6.1 (2021), p. 5. DOI: `10.3390/DATA6010005`.

UNIVERSITÉ DU LUXEMBOURG

[7] **Ailin Deng and Bryan Hooi. "Graph Neural Network-Based Anomaly Detection in Multivariate Time Series".** In: *AAAI*. AAAI Press, 2021, pp. 4027–4035.

[8] **Cheng Feng and Pengwei Tian. "Time series anomaly detection for cyber-physical systems via neural system identification and bayesian filtering".** In: *SIGKDD*. 2021.

[9] **P. Fleith. *Controlled Anomalies Time Series (CATS) Dataset*.** Technical Report. Darmstadt, Germany: Solenix Engineering GmbH, 2023.

[10] **Sebastian Garcia, Agustin Parmisano, and Maria Jose Erquiaga. *IoT-23: A labeled dataset with malicious and benign IoT network traffic*.** Version 1.0.0. Zenodo, May 2021. DOI: `10.5281/zenodo.4743746`.

[11] **Nate Gruver et al. "Large Language Models Are Zero-Shot Time Series Forecasters".** In: *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 - 16, 2023*. Ed. by Alice Oh et al. 2023.

[12] **Romain Hermary et al. "Removing Geometric Bias in One-Class Anomaly Detection with Adaptive Feature Perturbation".** In: *IEEE Winter Conference on Applications of Computer Vision, WACV 2025, Tucson, AZ, USA, February 28-March 4, 2025*. IEEE, 2025.

UNIVERSITÉ DU LUXEMBOURG

[13] **Yushan Jiang et al. "Empowering Time Series Analysis with Large Language Models: A Survey".** In: *Proceedings of the Thirty-Third International Joint Conference on Artificial Intelligence, IJCAI-24*. Ed. by Kate Larson. Survey Track. International Joint Conferences on Artificial Intelligence Organization, Aug. 2024, pp. 8095–8103. DOI: `10.24963/ijcai.2024/895`.

[14] **Yuxuan Liang et al. "Foundation Models for Time Series Analysis: A Tutorial and Survey".** In: *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, KDD 2024, Barcelona, Spain, August 25-29, 2024*. Ed. by Ricardo Baeza-Yates and Francesco Bonchi. ACM, 2024, pp. 6555–6565.

[15] **Shuyu Lin et al. "Anomaly Detection for Time Series Using VAE-LSTM Hybrid Model".** In: *ICASSP*. IEEE, 2020, pp. 4322–4326.

[16] **Aditya P. Mathur and Nils Ole Tippenhauer. "SWaT: a water treatment testbed for research and training on ICS security".** In: *CySWATER@CPSWeek*. IEEE Computer Society, 2016, pp. 31–36.


UNIVERSITÉ DU LUXEMBOURG

[17] **Nesryne Mejri et al. "Unsupervised anomaly detection in time-series: An extensive evaluation and analysis of state-of-the-art methods".** In: *Expert Syst. Appl.* 256 (2024), p. 124922. DOI: 10.1016/J.ESWA.2024.124922.

[18] **Mohamed Adel Musallam et al. "Spacecraft Recognition Leveraging Knowledge of Space Environment: Simulator, Dataset, Competition Design and Analysis".** In: *2021 IEEE International Conference on Image Processing Challenges (ICIPC)* (2021), pp. 11–15.

[19] **Andrea Dal Pozzolo et al. "Calibrating Probability with Undersampling for Unbalanced Classification".** In: *SSCI*. IEEE, 2015, pp. 159–166.

[20] **Xiangfei Qiu et al. "TAB: Unified Benchmarking of Time Series Anomaly Detection Methods".** In: *VLDB*. 2025.

[21] **Mohammadreza Salehi et al. "A Unified Survey on Anomaly, Novelty, Open-Set, and Out-of-Distribution Detection: Solutions and Future Challenges".** In: *Transactions on Machine Learning Research* 2022 (2022).

[22] **Lifeng Shen, Zhuocong Li, and James T. Kwok. "Timeseries Anomaly Detection using Temporal Hierarchical One-Class Network".** In: *NeurIPS*. 2020.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SnT

[23] **Shreshth Tuli, Giuliano Casale, and Nicholas R. Jennings.** **"TranAD: Deep Transformer Networks for Anomaly Detection in Multivariate Time Series Data".** In: *Very Large Data Base Endowment Inc.* 15 (2022), pp. 1201–1214.

[24] **H. Zare Moayedi and M.A. Masnadi-Shirazi.** **"Arima model for network traffic prediction and anomaly detection".** In: *ISCIT*. Vol. 4. 2008, pp. 1–6.

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# ASTER: Latent Pseudo-Anomaly Generation for Unsupervised Time-Series Anomaly Detection

arXiv

Code

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