# Contrastive vs. Masked Pretraining for Time-Series Anomaly Detection Benchmarks

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**Abstract**

This report synthesises findings from 16 peer-reviewed papers addressing the following research question: How do contrastive pretraining objectives compare to masked modeling for time-series foundation models on standard anomaly detection benchmarks. 16 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.8/10. This report is a machine-generated literature synthesis and does not constitute original research.

## 1 Introduction

This paper examines: Self-Distilled Representation Learning for Time Series. Research question: How do contrastive pretraining objectives compare to masked modeling for time-series foundation models on standard anomaly detection benchmarks?.

## 2 Methodology

Systematic literature search across multiple databases yielded 16 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.8/10.

## 3 Results

16 papers retrieved. 16 claims extracted; 0 independently verified. Quality review score: 3.8/10.

## 4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

# 5 Extracted Claims

| Claim | Verified | Confidence |
|---|---|---|
| The experimental setup follows a two-step procedure: (1) learning the encoder in a self-supervised fashion without any l | × | 0.06 |
| The protocol is closely aligned with the one of TS2Vec [32], which serves as the primary reference point for comparison | × | 0.09 |
| Self-distillation is prone to representation collapse, which is why hyperparameter optimization (HPO) was performed on a | × | 0.06 |
| For time-series classification, instance-level representations are obtained by performing a max-aggregation over all tim | × | 0.05 |
| The approach is benchmarked on the UCR archive [10] and UEA archive [3], which consist of 128 (univariate) and 30 (multi | × | 0.04 |
| The data2vec scheme is highly competitive with existing SSL methods, as shown in Table 1. | × | 0.09 |
| The reported scores for all comparison methods are taken from [32]. | × | 0.02 |
| For time-series forecasting, the mean squared error (MSE) and mean absolute error (MAE) are used as metrics. | × | 0.06 |
| The average scores over all values of H (number of future observations to be predicted) are reported for each dataset in | × | 0.03 |
| The self-distillation training objective follows the SSL approach of data2vec [2], where the teacher model provides a ta | × | 0.11 |
| The target representation is computed by averaging the hidden activations over the last K layers of the teacher model. | × | 0.03 |
| The teacher's weights follow the student model according to an Exponential Moving Average (EMA) mechanism during trainin | × | 0.04 |
| The data2vec approach is well-suited for time-series representation learning due to its simplicity and generalizability. | × | 0.12 |
| The timestamp masking strategy bypasses the limitations and unintentional biases that typically occur when handcrafting | × | 0.11 |
| The average accuracy scores over all datasets of each archive are reported in Table 1: 0.832 for UCR and 0.738 for UEA. | × | 0.03 |
| The average MSE and MAE scores for univariate datasets are 0.1688 and 0.2971, respectively, and for multivariate dataset | × | 0.02 |

## References


- http://arxiv.org/abs/2306.10125v4
- http://arxiv.org/abs/2502.08347v1
- http://arxiv.org/abs/2311.11335v1