Using Deep Learning for anomaly detection in the Virgo Advanced interferometer

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Introduction

- The VIRGO gravitational wave detector continuously generates an immense amount of data containing important information about the status of the system. All this information could be used not only to optimize the system's performance but also to provide real-time alerts for any anomalies. These anomalies could indeed affect both the detector's tuning activities and the quality of the strain signal used for gravitational wave search.
- The search for anomalies in time series data has become a highly active research field, particularly focusing on methodologies that can be applied "online," meaning while the data is being acquired. This direction of research is motivated by two fundamental aspects:
  - Transfer of Knowledge: researchers aim to transfer the expertise gained from many years of both online and offline analyses to develop real-time applications.
  - Real-Time Assistance: there is a desire to create applications that can provide practical assistance in the control room of the VIRGO detector, offering prompt guidance when needed.

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Anomalies

- What do we mean by anomaly? An old, very general definition reads: 'An observation which deviates so much from other observations as to arouse suspicions that it was generated by a different mechanism'. Given a time sequence of multidimensional data, coming from multiple channels sampled simultaneously, the first categorization criterion used in the literature is based on the temporal duration of the anomaly. We, therefore, have:
    - 'point anomaly' if the deviation from other observations concerns only a single sample.
    - 'sub-sequence anomaly' if it affects only a part of the sequence.
    - 'time-series anomaly' if it pertains to the entire sequence.

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ML-Based Approaches

- Anomaly detection can be performed in three different ways: supervised, semi-supervised, and unsupervised. The main challenge with supervised methods is the limited availability of "labeled" time sequences. Besides being time-consuming and resource-intensive, the number and variety of labeled anomalies would still be inadequate. Semi-supervised and unsupervised procedures are, therefore, more attractive alternatives.
- In both semi-supervised and unsupervised methodologies, the goal is to create a data-driven representation of the system and identify "model-based" anomalies. Currently, the most prevalent semi-supervised and unsupervised methodologies can be grouped into four main categories: predictive models, reconstructive models, generative models, and transformer models.

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Online Anomaly Detection

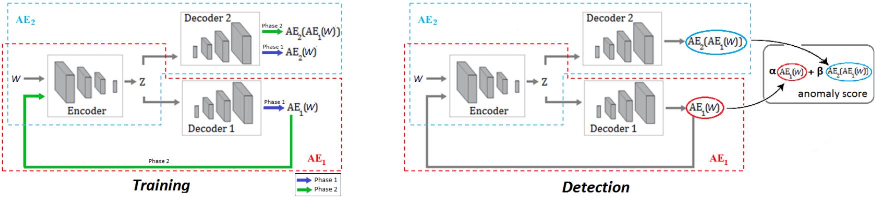
- The online anomaly detection process identifies anomalies in data as they arrive in real-time. The only information available at any given moment consists of the observed data up to that point. This excludes the use of methods that require the entire data sequence to make a decision. This real-time process is, in fact, a subset of online detection because the computation time must necessarily be less than or equal to the rate at which data arrives.

Models

- We tested different models with different parameters on Virgo Superattenuator data.
- Narrow focus. (1hr train data, only data concerning upper part of a few Superattenuators)
- Models chosen represent current state of the art for online multivariate timeseries Anomaly detection: TranAD (Transformer for Anomaly Detection) and USAD (UnSupervised Anomaly Detection)
- We did various test on data from O3b, the most recent period during which the interferometer was in science mode.
- Normalization method, model hyperparamters,training time, channels for each model ...

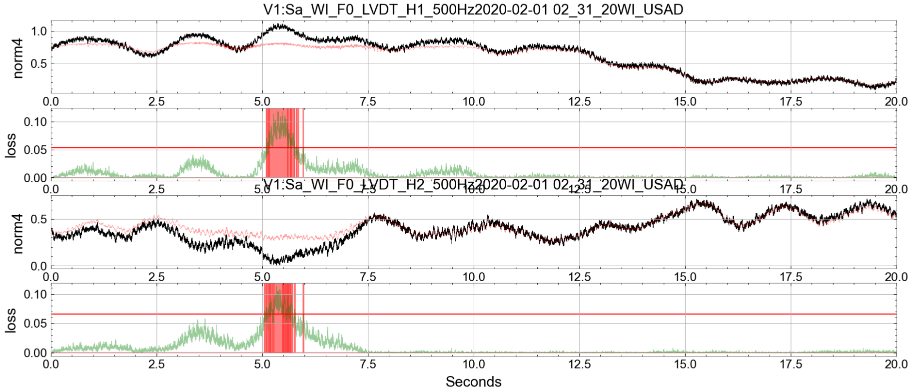
USAD

- Unsupervided anomaly detection: simple model
- Basic idea : input reconstruction trought an encoder decoder scheme. Anomalies found trough reconstruction error
- Main features : Adversarial training between 2 decoders. One decoder aims at reconstructing the input while the other fools the encoder

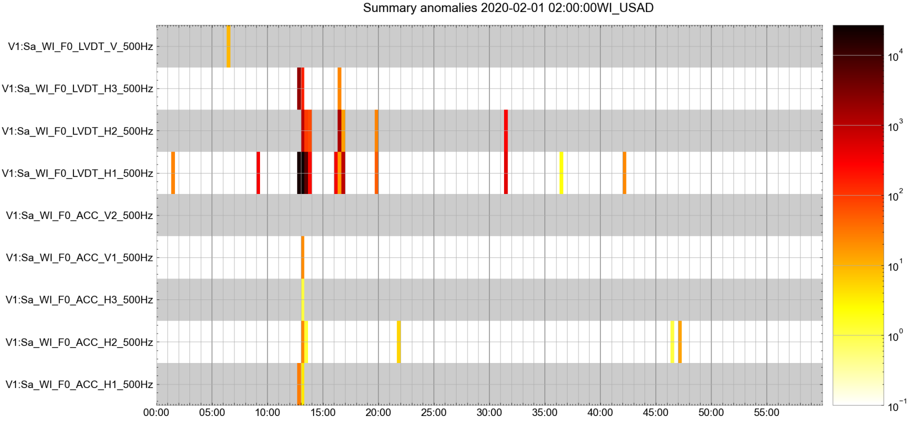


Credit: *https://dl.acm.org/doi/10.1145/3394486.3403392*

Example, single SA (WI)

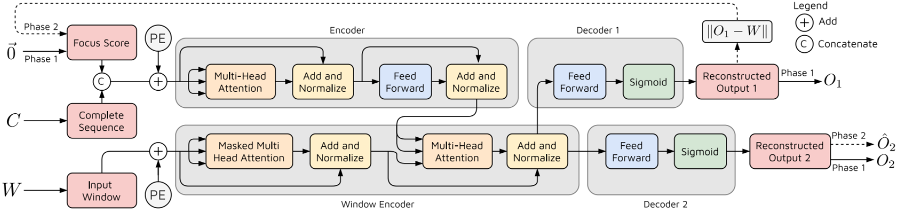


Example, single SA (WI)



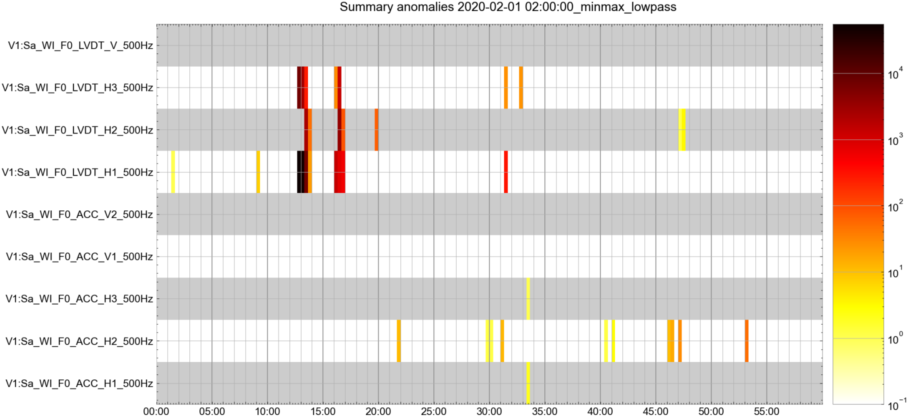
TranAD

- TranAD for now is the best performing one.
- Basic idea : input reconstruction trought an encoder decoder scheme. Anomalies found trough reconstruction error
- Main features : Focus score and 2 phase adversarial training

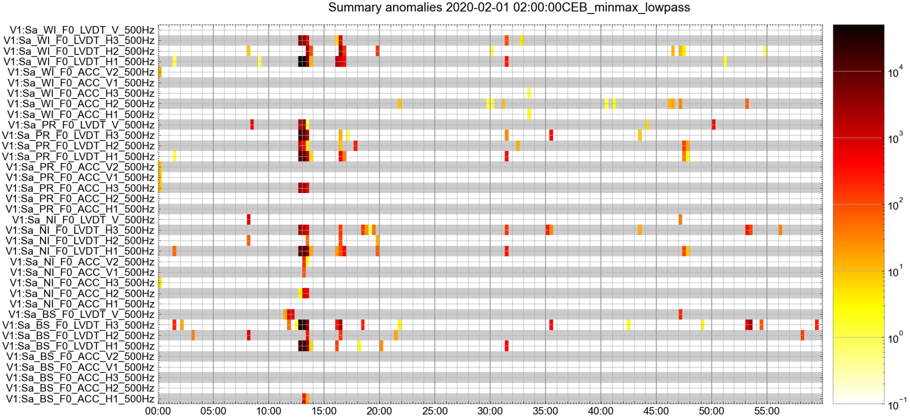


Credit: ***https://arxiv.org/abs/2201.07284***

Results, single SA (WI)



Results, Multiple SAS (NI,WI,BS,PR)



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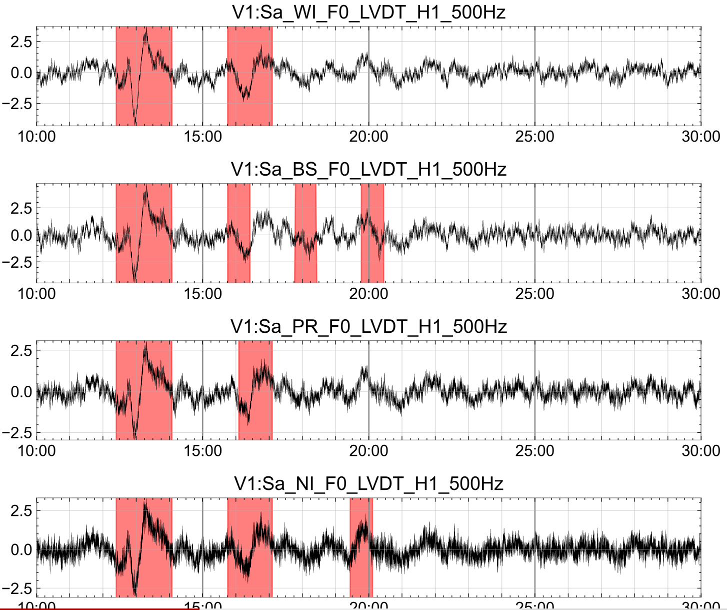

Comparison

- Tran AD results much faster than USAD, for 20 seconds of SAT f0 data TranAD process it in 0.9 seconds while USAD takes 6 seconds
- possible imporvements in USAD by vectorizing code better
- Number of anomalies similar over 2 hours of inference (53 VS 50) with big anomalies overlapping but disagreeing over small anomalies (29 in common)
- USAD seems to find more anomalies in the LVDTS and more false alarms in the ACC