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1 INTRODUCTION

Unsupervised time series anomaly detection is a challenging task. The models not only need to learn informative representations from complicated temporal dynamics under an unsupervised setting, but also have to obtain a distinguishable criterion on rare anomalous time points from plenty of normal time points.

A classic family of unsupervised time series anomaly detection methods includes the *density-estimation* and *clustering-based methods*. Density-estimation methods detect anomalies through locating data points in the low probability density area while clustering-based methods calculate anomaly scores as the distance to the cluster centroid.

With the recent advent of deep learning, deep *reconstruction-based* and *autoregression-based* methods have gained much attention. Both methods aim to learn the point-wise representations of the multivariate time series and are self-supervised through either a reconstruction objective or an autoregression objective.

2 TIMESERIES ANOMALY DETECTION USING TEMPORAL HIERARCHICAL ONE-CLASS NETWORK [1]

This paper was accepted at NIPS 2020. In this paper, the authors propose THOC, a deep *clustering-based* method for unsupervised time series anomaly detection. They leverage a dilated recurrent neural network (RNN) with skip connections to efficiently extract multi-scale temporal features from the time series. Instead of using only the lowest resolution features obtained at the top layer of the dilated RNN, THOC fuses features from all intermediate layers together by a differentiable hierarchical clustering mechanism. At each resolution, normal behaviors are represented by multiple hyperspheres.

3 ANOMALY TRANSFORMER: TIME SERIES ANOMALY DETECTION WITH ASSOCIATION DISCREPANCY [2]

This paper was accepted at ICLR 2022. In this paper, the authors proposes a new *association-based* anomaly detection criterion for time series and a corresponding Anomaly Transformer model. They observe that due to the rarity of anomalies and the dominance of normal patterns, it is harder for anomalies to build strong associations with the whole series and should thus focus more on the adjacent time points. Therefore, they leverages a Transformer to learn the global association among time points and a learnable Gaussian kernel to obtain the local association among time points. Finally, they utilize a minimax strategy to optimize the discrepancy between the local and global association.

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REFERENCES

[1] L. Shen, Z. Li, and J. Kwok. Timeseries anomaly detection using temporal hierarchical one-class network. *Advances in Neural Information Processing Systems*, 33:13016–13026, 2020.

[2] J. Xu, H. Wu, J. Wang, and M. Long. Anomaly transformer: Time series anomaly detection with association discrepancy. *arXiv preprint arXiv:2110.02642*, 2021.