

Post-doc 2026 or 2027
Deep anomaly detection in time series

Keywords

Anomaly detection; Deep Learning; Optimal transport; Signal processing; Change point detection; Online Learning

Description

Anomaly detection is a challenge in itself. The capacity to detect anomalies is a major ingredient of safe and trustworthy AI systems across major application areas. Anomaly detection is unsupervised by nature, since abnormal events are rare, varied, and cumbersome to collect. Conventional methods can be roughly grouped into three interconnected categories: discriminative decision boundaries using one-class classification, reconstruction models that test any new sample by measuring its reconstruction error on a manifold or with prototypes, and probabilistic models based on density or level-set estimation. The major deep anomaly detection methods fall within these categories, redefined in a latent space generated by deep representation learning, such as deep one-class, autoencoders, generative adversarial networks, and self-supervised learning [1, 2].

The challenge is higher for anomaly detection in time series (i.e., temporal data), and it is even harder when it comes to online detection, namely in the context of streaming data [3, 4, 5]. When dealing with time series, temporal continuity is central to defining the “normality”, and thus to identifying and detecting anomalies. Time series may have specific characteristics such as seasonality, periodicity/cycles, trend, concept drift, recurrent concept drift, cyclo-stationarity, and non-stationarity, as well as modalities at multiple temporal scales.

This post-doc fellowship aims to provide novel advances in anomaly detection in time series, mainly focusing on the even harder online detection, namely in the context of streaming data. For this purpose, the post-doc fellow may address one of the two online detection formalisms, which arise depending on whether the anomaly is short-term or persistent:

- Point anomaly detection, namely, one seeks to detect whether each new sample is an anomaly. Anomalies may not be restricted to isolated samples, but can also form a group or sequence of points (often called collective anomalies).
- Change point detection (also denoted concept drift), namely, one seeks to identify, as early as possible, whether the recent samples have deviated significantly from the historical ones. Investigated tools for comparing before/after distributions can be from change point detection literature or from recent advances in optimal transport.

This post-doc fellowship is an integral part of the global project ODD (Online Deep anomaly Detection). Led by the LITIS Lab, the ODD project brings together several PhD students and post-doc fellows, as well as several permanent researchers from the Machine Learning group of the LITIS Lab. This project tackles a wide spectrum of signal scenarios to demonstrate the versatility of the proposed methods. The post-doc fellow will have the possibility to tackle signals in environmental science (including a startup collaboration), signals in industrial processes (including industrial and international collaborations), and medical signals/images (including a novel startup collaboration).

Profile of the candidate

We are seeking a highly motivated candidate for a postdoctoral position, with a PhD in applied mathematics, machine learning, advanced statistics, computational mathematics, computer science, AI or related fields. The candidate must have solid technical skills in deep learning and advanced optimization, with experience in Python and the common Machine Learning libraries.

Interested candidates are invited to apply with their CV and contact references by email to paul.honeine@univ-rouen.fr.

Host Lab: LITIS Lab, Rouen Normandy

Starting date: when available in 2026 or 2027 (flexible).

Duration: 12 months

References

- [1] Ruff, L., Kauffmann, J. R., Vandermeulen, R. A., Montavon, G., Samek, W., Kloft, M., ... & Müller, K. R. (2021). A unifying review of deep and shallow anomaly detection. *Proceedings of the IEEE*, 109(5), 756-795.
- [2] Pang, G., Shen, C., Cao, L., & Hengel, A. V. D. (2021). Deep learning for anomaly detection: A review. *ACM computing surveys (CSUR)*, 54(2), 1-38.
- [3] Boniol, P., Liu, Q., Huang, M., Palpanas, T., & Paparrizos, J. (2024). Dive into time-series anomaly detection: A decade review. *arXiv preprint arXiv:2412.20512*.
- [4] Jia, X., Xun, P., Peng, W., Zhao, B., Li, H., & Shen, C. (2025). Deep anomaly detection for time series: A survey. *Computer Science Review*, 58, 100787.
- [5] Zamanzadeh Darban, Z., Webb, G. I., Pan, S., Aggarwal, C., & Salehi, M. (2024). Deep learning for time series anomaly detection: A survey. *ACM Computing Surveys*, 57(1), 1-42.