

Towards Reproducible, Automated, and Scalable Anomaly Detection

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Anomaly detection (AD), often termed outlier detection, is a key machine learning (ML) task, aiming to identify uncommon yet crucial patterns in data. With the increasing complexity of the modern world, the applications of AD span wide—from NASA’s spacecraft monitoring to early patient prioritization at University of Pittsburgh Medical Center. Technology giants like Google and Amazon also leverage AD for service disruption identification. Here, I will traverse my AD works with promising new directions, particularly emphasizing *reproducible benchmarks* (Part 1), *automated algorithms* (Part 2), and *scalable systems* (Part 3).

Part I: Reproducible Benchmarks. The efficacy and characteristics of AD algorithms remain understudied due to ad-hoc evaluations on small datasets, resulting in questionable advancements and conclusions. In my recent works, I conducted extensive AD analyses on various data types—tabular (ADBench (Han et al. 2022)), time-series (Lai et al. 2021), graph data (BOND (Liu et al. 2022)), and deep AD (ADGym (Jiang et al. 2023)). In ADBench, we performed a comprehensive benchmark on 57 datasets using 30 detection algorithms, encompassing various settings, and totaling 98,436 experiments. Our statistical analysis revealed that *no unsupervised AD method stands out statistically*. These benchmarks offer critical insights into AD, guiding the development of optimized algorithms. I will briefly introduce two of my recent AD benchmarks, specifically for tabular and graph data: ADBench (Han et al. 2022) and BOND (Liu et al. 2022). They identify two key challenges/needs in AD research: (1) automatic AD model selection for underlying applications (covered in Part 2), and (2) fast and scalable AD systems (covered in Part 3).

Part II: Automated Algorithms. Despite the large number of existing AD algorithms, the pressing question arises: *how do we automatically determine the optimal detector for various applications?* Given the absence of ground truth in unsupervised AD, this challenge is important, where random model selection may yield inadequate accuracy for crucial tasks. In this part, I will introduce our progress in automating AD model selection and composition. Our spotlight will be on MetaOD (Zhao, Rossi, and Akoglu 2021) and ADGym (Jiang et al. 2023)—marking both the advent and the latest innovations. The key of discussion will center around meta-

learning—leveraging insights from similar historical datasets for fast model selection and more automated ML tasks.

Part III: Scalable Detection Systems. From a system perspective, applying AD algorithms in real-world scenarios with large, high-dimensional data remains challenging. I have designed scalable ML systems (MLSys) for various AD types to mitigate this, integrating distributed learning, approximation, and more. I will first cover the important Python Outlier Detection (PyOD) (Zhao, Nasrullah, and Li 2019). It stands out for its comprehensive nature, housing 50+ methods, and unparalleled efficiency, with advanced techniques such as JIT optimization. Our main focus, however, will be on demonstrating TOD (Zhao, Chen, and Jia 2022), the pioneering GPU system accommodating a broad spectrum of AD algorithms. TOD can abstract complex AD algorithms into simple tensor operations for multi-GPU computation, offering an $11\times$ speed improvement to PyOD. **Future Directions.** We will discuss promising directions including the design principles for effective benchmarks, fully automated AD pipelines from hardware to models, and an open AD ecosystem to unify data modalities and usage.

References

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