




nonconform: Conformal Anomaly Detection (Python)

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Summary

The Python package nonconform provides statistically principled uncertainty quantification for unsupervised anomaly detection. It implements methods from conformal anomaly detection (Bates et al., 2023; Jin & Candès, 2023; Laxhammar & Falkman, 2010) based on the principles of one-class classification (Petsche & Gluck, 1994). The ability to quantify uncertainty is a fundamental requirement for AI systems in safety-critical domains, where reliable decision-making is essential.

Based on the underlying principles of conformal inference (Lei & Wasserman, 2013; Papadopoulos et al., 2002; Vovk et al., 2005), nonconform converts raw anomaly scores from an underlying detection model into statistically valid p -values. This is achieved by calibrating the model on a hold-out set of normal data; the p -value for a new test instance is then calculated as the relative rank of its anomaly score compared to the scores from the calibration set. By framing anomaly detection as a series of statistical hypothesis tests, these p -values allow for the systematic control of the False Discovery Rate (FDR) (Bates et al., 2023; Benjamini & Hochberg, 1995) at a pre-defined significance level (e.g., $\alpha \leq 0.1$). The library integrates with the popular pyod library (Chen et al., 2024; Zhao et al., 2019), making it easy to apply these conformal techniques to a wide range of anomaly detection models.

Statement of Need

A primary challenge in anomaly detection is setting an appropriate anomaly threshold, which directly impacts the false positive rate. In high-stakes domains such as fraud detection, medical diagnostics, and industrial quality control, controlling the proportion of false positives is crucial, as frequent false alarms can lead to *alert fatigue* and render a system impractical. The nonconform package addresses this by replacing raw anomaly scores with p -values, which enables formal FDR control. This makes the conformal methods *threshold-free*, as decision thresholds are a direct result of respective statistical procedures.

$$FDR = \frac{\text{Efforts Wasted on False Alarms}}{\text{Total Efforts}}$$

(Benjamini et al., 2009)

Moreover, conformal methods are *non-parametric* and *model-agnostic*, making them compatible with any model that produces consistent anomaly scores. The nonconform package provides a range of strategies for creating the calibration set from training data, even in low-data regimes (Hennhofer & Preisach, 2024). With the gathered calibration set, the package can compute standard conformal p -values or modified *weighted* conformal p -values (Jin & Candès, 2023) for test data. Weighted p -values are particularly useful when the statistical assumption of exchangeability is weakened by covariate shift between calibration and test data. By providing these tools, nonconform enables researchers and practitioners to build anomaly detectors whose outputs are statistically controlled to cap the FDR at a desired nominal level.

The core assumption for the methods in nonconform is that the data is exchangeable, meaning the joint probability distribution is invariant to the order of observations. This makes the methods suitable for many cross-sectional data analysis tasks but not for time-series data where temporal ordering is informative.

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