

¹ nonconform: Conformal Anomaly Detection (Python)

² Oliver Hennhöfer  ¹

³ 1 Intelligent Systems Research Group, Karlsruhe University of Applied Sciences, Karlsruhe, Germany

DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

Software

- ⁴ [Review](#) 
- ⁵ [Repository](#) 
- ⁶ [Archive](#) 

Editor: [Open Journals](#) 

Reviewers:

- ⁷ [@openjournals](#)

Submitted: 01 January 1970

Published: unpublished

License

Authors of papers retain copyright and release the work under a ¹⁴ Creative Commons Attribution 4.0 International License ([CC BY 4.0](#)).¹⁵

⁴ Summary

⁵ Quantifying uncertainty is fundamental for AI systems in safety-critical, high-cost-of-error domains, as reliable decision-making depends on it. The Python package `nonconform` offers ⁶ statistically principled uncertainty quantification for semi-supervised anomaly detection based ⁷ on one-class classification (Tax, 2001). It implements methods from conformal anomaly ⁸ detection (Bates et al., 2023; Jin & Candès, 2025; Laxhammar & Falkman, 2010), grounded in ⁹ conformal inference (Lei & Wasserman, 2013; Papadopoulos et al., 2002; Vovk et al., 2005).¹⁰

¹¹ The package `nonconform` calibrates anomaly detection models to produce statistically valid ¹² *p*-values from raw anomaly scores. Conformal calibration uses a hold-out set $\mathcal{D}_{\text{calib}}$ of size n ¹³ containing normal instances, while the model is trained on a separate normal dataset. For a ¹⁴ new observation X_{n+1} with anomaly score $\hat{s}(X_{n+1})$, the *p*-value is computed by comparing ¹⁵ this score to the empirical distribution of calibration scores $\hat{s}(X_i)$ for $i \in \mathcal{D}_{\text{calib}}$. The conformal ¹⁶ *p*-value $\hat{u}(X_{n+1})$ is calculated by ranking the new score among the calibration scores augmented ¹⁷ by the test score itself (Bates et al., 2023; Liang et al., 2024):¹⁸

$$\hat{u}(X_{n+1}) = \frac{1 + |\{i \in \mathcal{D}_{\text{calib}} : \hat{s}(X_i) \leq \hat{s}(X_{n+1})\}|}{n + 1}.$$

¹⁹ By framing anomaly detection as a sequence of statistical hypothesis tests, these *p*-values ²⁰ enable systematic control of the *marginal* (average) false discovery rate (FDR) (Benjamini & Hochberg, 1995). For standard exchangeable data, conformal *p*-values satisfy the PRDS ²¹ property, allowing the use of the Benjamini-Hochberg procedure (Bates et al., 2023). The ²² library integrates seamlessly with the widely used `pyod` library (Chen et al., 2025; Zhao et al., ²³ 2019), extending conformal techniques to a broad range of anomaly detection models.²⁴

²⁴ Statement of Need

²⁵ A major challenge in anomaly detection lies in setting an appropriate anomaly threshold, as ²⁶ it directly influences the false positive rate. In high-stakes domains such as fraud detection, ²⁷ medical diagnostics, and industrial quality control, excessive false alarms can lead to *alarm fatigue* and render systems impractical.²⁸

²⁹ The package `nonconform` mitigates this issue by replacing raw anomaly scores with *p*-values, ³⁰ enabling formal control of the FDR. Consequently, conformal methods become effectively ³¹ *threshold-free*, since anomaly thresholds are implicitly determined by underlying statistical ³² procedures.³³

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

³³ (Benjamini et al., 2009)

34 Conformal methods are *nonparametric* and *model-agnostic*, applying to any model that
35 produces consistent anomaly scores on arbitrarily distributed data. Their key requirement is
36 the assumption of *exchangeability* between calibration and test data, ensuring the validity of
37 resulting conformal *p*-values.
38 Exchangeability only requires that the joint data distribution is invariant under permutations,
39 making it more general—and less restrictive—than the independent and identically distributed
40 (*i.i.d.*) assumption common in classical machine learning.
41 To operationalize this assumption, nonconform constructs calibration sets from training data
42 using several strategies, including approaches for low-data regimes (Hennhofer & Preisach,
43 2024) that do not require a dedicated hold-out set. Based on these calibration sets, the
44 package computes *standard* or *weighted* conformal *p*-values (Jin & Candès, 2025), which
45 address scenarios of covariate shift where the assumption of exchangeability is violated. Under
46 covariate shift, specialized weighted selection procedures are required to maintain FDR control
47 (Jin & Candès, 2025). These tools enable practitioners to build anomaly detectors whose
48 outputs are statistically controlled to maintain the FDR at a chosen nominal level.
49 Overall, reliance on exchangeability makes these methods well-suited to cross-sectional data
50 but less appropriate for time series applications, where temporal ordering conveys essential
51 information.

52 Acknowledgements

53 This work was conducted in part under the research projects *Biflex Industrie* (Grant no.
54 01MV23020A) funded by the *German Federal Ministry of Economic Affairs and Climate Action*.

55 References

- 56 Bates, S., Candès, E., Lei, L., Romano, Y., & Sesia, M. (2023). Testing for outliers with
57 conformal p-values. *The Annals of Statistics*, 51(1). <https://doi.org/10.1214/22-aos2244>
- 58 Benjamini, Y., Heller, R., & Yekutieli, D. (2009). Selective inference in complex research.
59 *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering*
60 *Sciences*, 367(1906), 4255–4271. <https://doi.org/10.1098/rsta.2009.0127>
- 61 Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and
62 powerful approach to multiple testing. *Journal of the Royal Statistical Society: Series B*
63 (*Methodological*), 57(1), 289–300. <https://doi.org/10.1111/j.2517-6161.1995.tb02031.x>
- 64 Chen, S., Qian, Z., Siu, W., Hu, X., Li, J., Li, S., Qin, Y., Yang, T., Xiao, Z., Ye, W., Zhang,
65 Y., Dong, Y., & Zhao, Y. (2025). PyOD 2: A python library for outlier detection with
66 LLM-powered model selection. *Companion Proceedings of the ACM on Web Conference*
67 2025, 2807–2810. <https://doi.org/10.1145/3701716.3715196>
- 68 Hennhofer, O., & Preisach, C. (2024). Leave-One-Out-, Bootstrap- and Cross-Conformal
69 Anomaly Detectors . *2024 IEEE International Conference on Knowledge Graph (ICKG)*,
70 110–119. <https://doi.org/10.1109/ICKG63256.2024.00022>
- 71 Jin, Y., & Candès, E. J. (2025). Model-free selective inference under covariate shift via weighted
72 conformal p-values. *Biometrika*, asaf066. <https://doi.org/10.1093/biomet/asaf066>
- 73 Laxhammar, R., & Falkman, G. (2010). Conformal prediction for distribution-independent
74 anomaly detection in streaming vessel data. *Proceedings of the First International Workshop*
75 *on Novel Data Stream Pattern Mining Techniques*, 47–55. <https://doi.org/10.1145/1833280.1833287>
- 77 Lei, J., & Wasserman, L. (2013). Distribution-free prediction bands for non-parametric
78 regression. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 76(1),

- 79 71–96. <https://doi.org/10.1111/rssb.12021>
- 80 Liang, Z., Sesia, M., & Sun, W. (2024). Integrative conformal p-values for out-of-distribution
81 testing with labelled outliers. *Journal of the Royal Statistical Society Series B: Statistical
82 Methodology*, 86(3), 671–693. <https://doi.org/10.1093/jrsssb/qkad138>
- 83 Papadopoulos, H., Proedrou, K., Vovk, V., & Gammerman, A. (2002). Inductive confidence
84 machines for regression. In *Machine learning: ECML 2002* (pp. 345–356). Springer Berlin
85 Heidelberg. https://doi.org/10.1007/3-540-36755-1_29
- 86 Tax, D. (2001). *One-class classification; concept-learning in the absence of counter-examples*
87 [Dissertation (TU Delft)]. Delft University of Technology. ISBN: 90-75691-05-X
- 88 Vovk, V., Gammerman, A., & Shafer, G. (2005). *Algorithmic learning in a random world*.
89 Springer. <https://doi.org/10.1007/b106715>
- 90 Zhao, Y., Nasrullah, Z., & Li, Z. (2019). PyOD: A python toolbox for scalable outlier detection.
91 <https://doi.org/10.48550/ARXIV.1901.01588>