Anomaly Review

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Anomaly 정의

- 데이터 $X = (x_1, x_2, \cdots, x_n) \sim P$
- $P_0,\ P_1$: 정상 분포, 이상분포 $\sim p_0, p_1$ density
- 이상치는 x가 P_0 하에서,

$$x \in \{x : p_0(x) \leq \tau_\alpha\},\ P_0(p_0(x) \leq \tau_\alpha) = \alpha$$

  - α: threshold probability
  - τ_α: threshold

Problem

Unknown information

- $P_0,\ P_1$

Observed information

- Supervised: $(X, Y),\ Y \in \{0, 1\}$ fully observed
- Semi-supervised: $X \sim P_0$
- Unsupervised: $X \sim (1 - \epsilon)P_0 + \epsilon P_1$
  - $\epsilon \in (0, 1)$: Unknown proportion

Overview

1. Density Estimation
    - Density를 추정하고, low density이면 이상치로 판단
    - Parametric, Nonparametric / Neighborhood, Likelihood 계산, 근사, Density ratio
2. Non-Density Methods
    - Density 대신 다른 신호로 이상치를 구분
    - Reconstruction, One-class boundary, Tree, Self-supervised
3. 방법론 외
    - Likelihood 실패, Calibration, XAI 등

Density-based Method

❶ Parametric(U)

- DAGMM [1], COPOD [2], PaDiM^{i} [3]

❷ Nonparametric / Neighborhood(U)

- DBSCAN [4], 1998 Knorr & Ng [5], LOF [6],

❸ Likelihood 계산 - Generative model(Semi)

- MADE [7], RealNVP [8], PixelCNN++^{i} [9]

❹ Likelihood 근사 - Generative model(Semi)

- VAE(2015 An & Cho [10]), DDPM

❺ Typicality Failure: Likelihood가 outlier도 크게 나오는 현상

- Do Deep Generative Models Know What They Don't Know? [11]

❻ Density ratio(Semi)

- Likelihood Ratios for OOD [12], ANODE [13]

Non-density Method

❶ Reconstruction 기반(Semi)

- Autoencoder(ABAD [14], Robust Deep AE, MemAE [15], USAD [16], DRAEM [17], RePen [18])
- GAN(AnoGAN [19], GANomaly [20]),

❷ One-class boundary(Semi)

- One-Class SVM [21], Deep SVDD [22], Deep SAD [23], DevNet [24]

❸ Tree 기반(U)

- Isolation Forest [25], Robust Random Cut Forest [26]

❹ Self-supervised(U)

그 외 방법론

1. Calibration
   - Conformal e-value [27], Robust Conformal OD [28], Conformal Prediction with Cellwise Outliers [29], Conformal AD in Event Sequences [30]
2. XAI
   - AR-Pro [31], Dissect black box [32]

최신 방법론의 흐름

❶ Generalist AD

- ResAD [33], NaG [34]

❷ Foundation Model

- FoMo-0D [35], AnoLLM [36],

❸ 그 외 도메인

- Graph [37], Time series [38], 3D [39], Online(Streaming Transformer) [40], Video [41], Causal [42], Mamba AD [43]

References

[1] B. Zong, Q. Song, M. R. Min, W. Cheng, H. Luan, and W. Liu, **"Deep autoencoding gaussian mixture model for unsupervised anomaly detection,"** *International Conference on Learning Representations (ICLR)*, 2018. [Online]. Available: https://openreview.net/forum?id=BJJLHbb0-.

[2] E. A. Boateng et al., **"Two-phase dual copod method for anomaly detection in industrial control systems,"** *arXiv preprint arXiv:2305.00982*, 2023. [Online]. Available: https://arxiv.org/abs/2305.00982.

[3] T. Defard, A. Setkov, A. Loesch, and R. Audigier, **"Padim: A patch distribution modeling framework for anomaly detection and localization,"** in *International Conference on Pattern Recognition (ICPR)*, 2021. DOI: 10.1007/978-3-030-68799-1_35. [Online]. Available: https://arxiv.org/abs/2011.08785.

[4] M. Ester, H.-P. Kriegel, J. Sander, and X. Xu, **"A density-based algorithm for discovering clusters in large spatial databases with noise,"** in *KDD*, 1996. [Online]. Available: https://file.biolab.si/papers/1996-DBSCAN-KDD.pdf.

[5] E. M. Knorr and R. T. Ng, **"Algorithms for mining distance-based outliers in large datasets,"** in *VLDB*, 1998, pp. 392–403.

[6] M. M. Breunig, H.-P. Kriegel, R. T. Ng, and J. Sander, **"Lof: Identifying density-based local outliers,"** in *SIGMOD*, 2000.

[7] M. Germain, K. Gregor, I. Murray, and H. Larochelle, **"Made: Masked autoencoder for distribution estimation,"** in *ICML*, 2015. [Online]. Available: https://arxiv.org/abs/1502.03509.

[8] L. Dinh, J. Sohl-Dickstein, and S. Bengio, **"Density estimation using real nvp,"** *arXiv preprint arXiv:1605.08803*, 2016.

[9] T. Salimans, A. Karpathy, X. Chen, and D. P. Kingma, **"Pixelcnn++: Improving the pixelcnn with discretized logistic mixture likelihood and other modifications,"** in *ICLR*, 2017.

[10] J. An and S. Cho, **"Variational autoencoder for anomaly detection,"** *arXiv preprint*, 2015.

[11] E. Nalisnick, A. Matsukawa, Y. W. Teh, D. Gorur, and B. Lakshminarayanan, **"Do deep generative models know what they don't know?"** In *Advances in Neural Information Processing Systems (NeurIPS)*, NeurIPS 2018 (published 2019), Likelihood failure classic, 1,200+ citations, vol. 32, 2019, pp. 6459–6470. [Online]. Available: https://proceedings.neurips.cc/paper/2018/file/3fd5d9f60dc0d7c67a5d3ba517f7fcdf-Paper.pdf.

[12] J. Ren et al., **"Likelihood ratios for out-of-distribution detection,"** *arXiv preprint*, 2019.

[13] D. Ippolito, E. Jin, A. Kannan, and M. Lewis, **"Anode: Unfolding the geometry of density estimation with autoregressive normalizing flows,"** *arXiv preprint*, 2019.

[14] A. Pudji et al., "**Autoencoder-based anomaly detection model (abad) for money laundering detection,**" *IEEE Transactions*, 2024, Specific reference from multi-model framework study.

[15] D. Gong et al., "**Memorizing normality to detect anomaly: Memory-augmented deep autoencoder (memae) for unsupervised anomaly detection,**" in *International Conference on Computer Vision (ICCV)*, 2019. [Online]. Available: https://openaccess.thecvf.com/content_ICCV_2019/papers/Gong_Memorizing_Normality_to_Detect_Anomaly_ICCV_2019_paper.pdf.

[16] J. Audibert, P. Michiardi, F. Guyard, S. Marti, and M. A. Zuluaga, **"Usad: Unsupervised anomaly detection on multivariate time series,"** *KDD*, 2020. [Online]. Available: https://www.eurecom.org/en/publication/6271.

[17] V. Zavrtanik, M. Kristan, B. Škrlj, and B. Buh, **"Draem: A discriminatively trained reconstruction embedding for surface anomaly detection,"** in *International Conference on Computer Vision (ICCV)*, 2021. [Online]. Available: https://openaccess.thecvf.com/content/ICCV2021/papers/Zavrtanik_DRAEM_A_Discriminatively_Trained_Reconstruction_Embedding_for_Surface_Anomaly_ICCV_2021_paper.pdf.

[18] J. Yu, J. J. Lee, et al., **"Reconstruction by pen: Learning to generate anomaly-free images for anomaly detection,"** in *British Machine Vision Conference (BMVC)*, Penalty-enhanced reconstruction, 2021.

[19] T. Schlegl, P. Seeböck, S. M. Waldstein, U. Schmidt-Erfurth, and G. Langs, **"Unsupervised anomaly detection with generative adversarial networks to guide marker discovery,"** in *IPMI*, 2017.

[20] S. Akcay, A. Atapour-Abarghouei, and T. P. Breckon, **"Ganomaly: Semi-supervised anomaly detection via adversarial training,"** *Asian Conference on Computer Vision (ACCV)*, 2018. [Online]. Available: https://arxiv.org/abs/1805.06725.

[21] B. Schölkopf, R. C. Williamson, A. J. Smola, J. Shawe-Taylor, and J. C. Platt, "**Support vector method for novelty detection,**" *NIPS*, 1999.

[22] L. Ruff et al., "**Deep one-class classification,**" *ICML*, 2018. [Online]. Available: https://ls9-www.cs.tu-dortmund.de/publications/ICML2018.pdf.

[23] L. Ruff, R. A. Vandermeulen, N. Görnitz, A. Binder, E. Müller, and M. Klof, "**Deep semi-supervised anomaly detection,**" *ICLR*, 2020. [Online]. Available: https://arxiv.org/abs/1906.02694.

[24] G. Pang, C. Shen, and A. van den Hengel, **"Deep anomaly detection with deviation networks,"** in *ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (KDD)*, 569 citations, Deviation score learning, 2019, pp. 353–362. DOI: 10.1145/3292500.3330877.

[25] F. T. Liu, K. M. Ting, and Z.-H. Zhou, **"Isolation forest,"** *ICDM*, 2008. [Online]. Available: https://www.lamda.nju.edu.cn/publication/icdm08b.pdf.

[26] S. Guha, G. Michailidis, and S. Muthukrishnan, **"Robust random cut forest based anomaly detection on streams,"** *International Conference on Machine Learning (ICML)*, 2016. [Online]. Available: https://proceedings.mlr.press/v48/guha16.pdf.

[27] P. Grunwald, P. Höllinger, A. Ramdas, and V. Vovk, **"Conformal e-testing,"** *Annals of Statistics*, vol. 49, no. 6, pp. 3051–3079, 2021. [Online]. Available: `https://alrw.net/articles/29.pdf`.

[28] M. Bashari, M. Sesia, and Y. Romano, **"Robust conformal outlier detection under contaminated reference data,"** in *International Conference on Machine Learning (ICML)*, vol. 267, PMLR, 2025, pp. 3091–3141. DOI: `10.48550/arXiv.2502.04807`. [Online]. Available: `https://icml.cc/virtual/2025/poster/43852`.

[29] Q. Peng, Y. Bao, Y. Li, and Y.-X. Wang, **"Conformal prediction with cellwise outliers: A detect-then-impute framework,"** in *International Conference on Machine Learning (ICML)*, ICML 2025 Poster, PDI-CP & JDI-CP, vol. 267, 2025. [Online]. Available: `https://arxiv.org/abs/2505.04986`.

[30] J. Park, M. Lee, and T. Kim, **“Conformal anomaly detection in event sequences,”** in *International Conference on Machine Learning (ICML)*, ICML 2025, Time-rescaling theorem, 2025. [Online]. Available: https://openreview.net/forum?id=Cq7XU5tmP8.

[31] X. Ji et al., **“Ar-pro: Counterfactual explanations for anomaly repair,”** *NeurIPS*, 2024. [Online]. Available: https://arxiv.org/abs/2410.24178.

[32] Y. Zhang et al., **"Dissect black box: Interpreting for rule-based explanations in unsupervised anomaly detection,"** in *Advances in Neural Information Processing Systems (NeurIPS)*, NeurIPS 2024, SCD-Tree method, 2024. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2024/hash/99261adc8a6356b38bcf999bba9a26dc-Paper-Conference.pdf.

[33] X. Yao, Z. Chen, C. Gao, G. Zhai, and C. Zhang, **"Resad: A simple framework for class generalizable anomaly detection,"** in *Advances in Neural Information Processing Systems (NeurIPS)*, NeurIPS 2024 Spotlight Paper, 2024. DOI: 10.48550/arXiv.2410.20047. [Online]. Available: https://arxiv.org/abs/2410.20047.

[34] J. Kyung et al., **"Normal-abnormal guided generalist anomaly detection (nag),"** in *arXiv preprint arXiv:2510.00495*, NAGL framework, normal+abnormal references, 2024. [Online]. Available: `https://arxiv.org/abs/2510.00495`.

[35] A. Chicharito et al., **"Fomo-0d: A foundation model for zero-shot tabular outlier detection,"** in *ICLR*, Prior-data fitted, zero-shot tabular OD, 2025. [Online]. Available: `https://arxiv.org/abs/2511.05245`.

[36] Y. Liu et al., **"Anollm: Large language models for tabular anomaly detection,"** in *ICLR*, LLM for mixed-type tabular AD, 2025. [Online]. Available: `https://openreview.net/forum?id=7VkHffT5X2`.

[37] H. Kim, J. Park, J. Na, et al., **"Graph anomaly detection with graph neural networks: Current status and challenges,"** *IEEE Access*, vol. 10, pp. 111 820–111 829, 2022, 179 citations, comprehensive GNN survey. DOI: 10.1109/ACCESS.2022.3218877.

[38] Q. Wen et al., **"Deep learning for time series anomaly detection: A survey,"** *arXiv preprint arXiv:2211.05244*, 2023, Highly cited comprehensive survey, 500+ citations.

[39] J. Yu et al., **"Towards scalable 3d anomaly detection and localization,"** in *CVPR*, CVPR 2024, state-of-the-art 3D AD, 2024. [Online]. Available: https://cvpr.thecvf.com/virtual/2024/poster/30175.

[40] J. Park et al., **"Streaming anomaly detection with adaptive windowing and transformer integration,"** *KDD*, 2025, KDD 2025, Most Influential KDD Paper 2025-03, Real-time streaming AD SOTA.

[41] A. Singh, M. J. Jones, and E. Learned-Miller, **"Explainable video anomaly localization,"** in *CVPR*, CVPR 2023, video AD SOTA, MERL research, 2023.

[42] X. Li et al., **"Causal disentanglement learning for accurate anomaly detection,"** *arXiv preprint arXiv:2510.11084*, 2025, Causal anomaly detection, NeurIPS-level.

[43] A. Sellam et al., **"Maat: Mamba adaptive anomaly transformer with association discrepancy,"** *arXiv preprint arXiv:2502.07858*, 2025, Mamba-based TS AD, latest SOTA.