Finding Clarity in Chaos: Leveraging Noisy Labels for Superior Anomaly Detection

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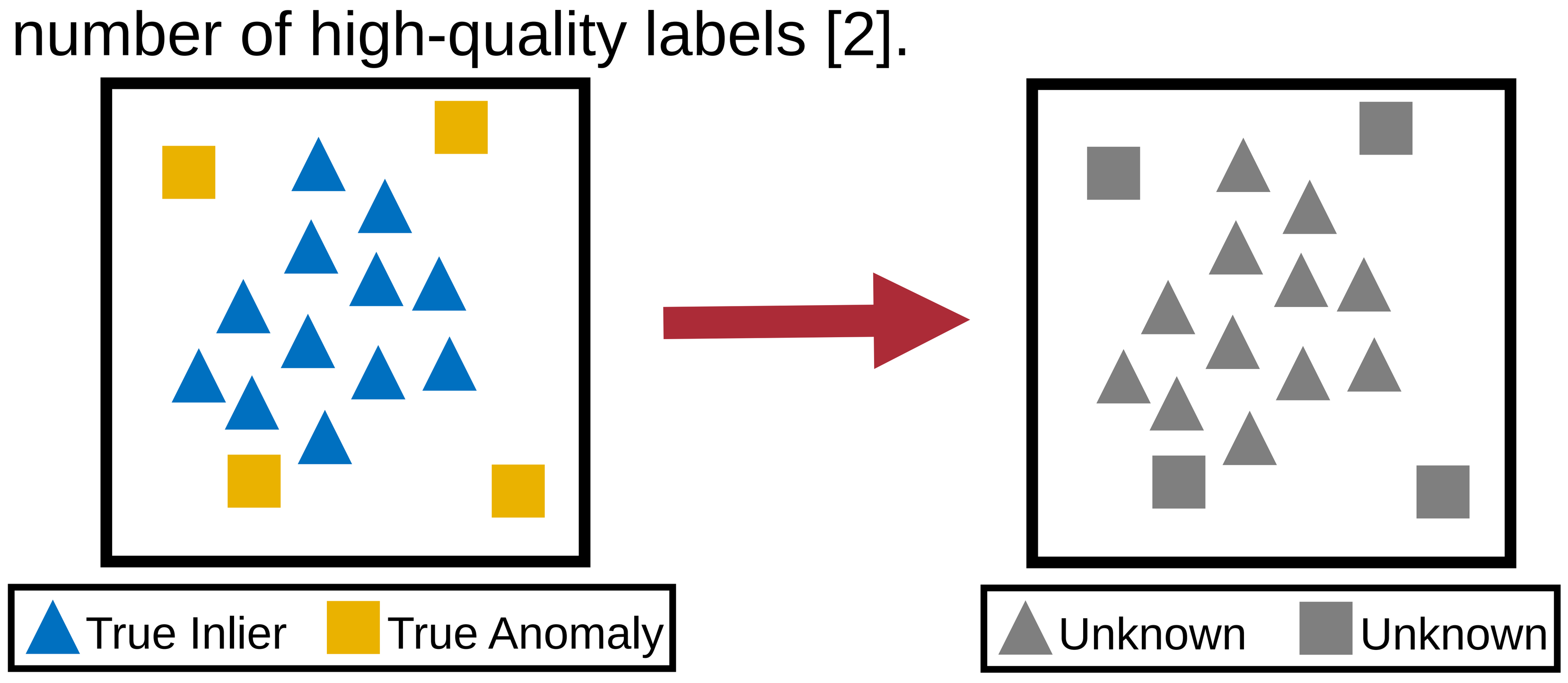
Based on the paper “Agree to Disagree: Robust Anomaly Detection with Noisy Labels” [1] accepted at SIGMOD 2025.

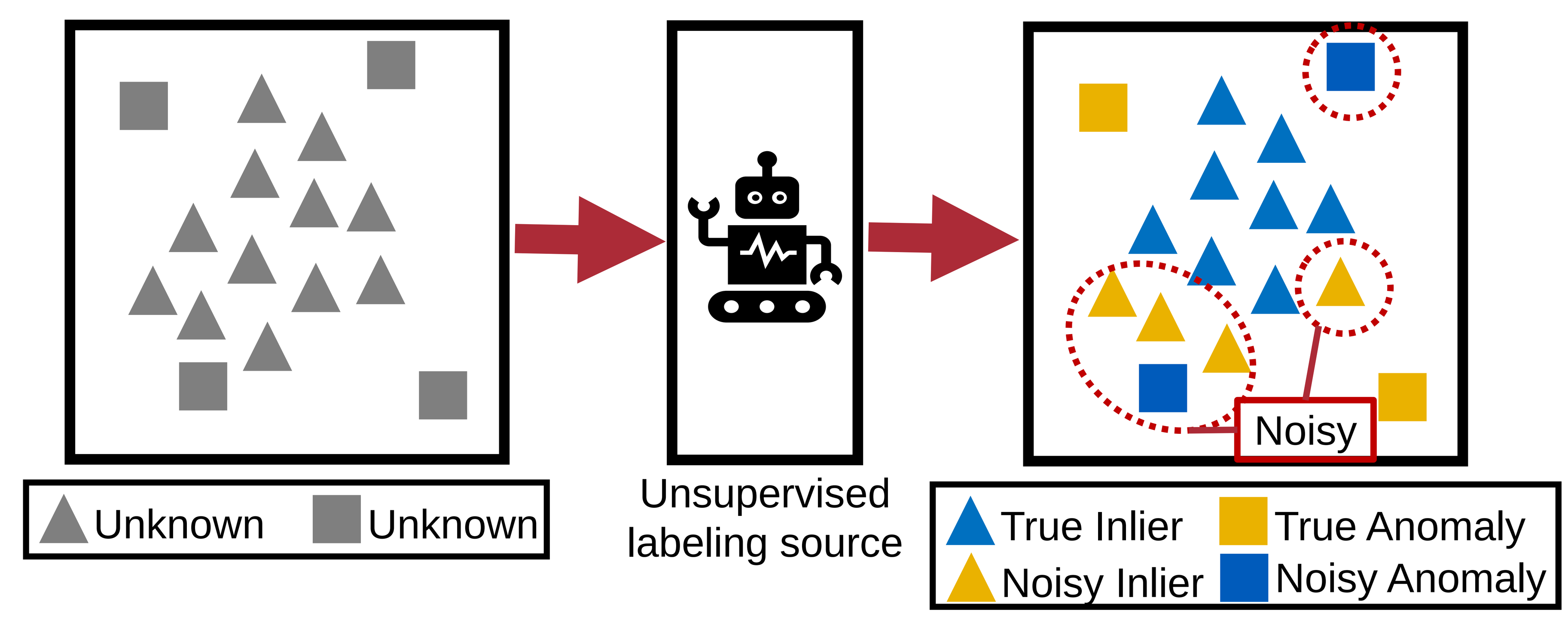
Background: Anomaly detection aims to identify objects that significantly differ from the expected behavior. Anomaly detection is critical for tasks such as detecting cybersecurity attacks, financial fraud, and life-threatening health conditions. [2]

1 Motivation

Since anomalies are rare, it is difficult to acquire large number of high-quality labels [2].

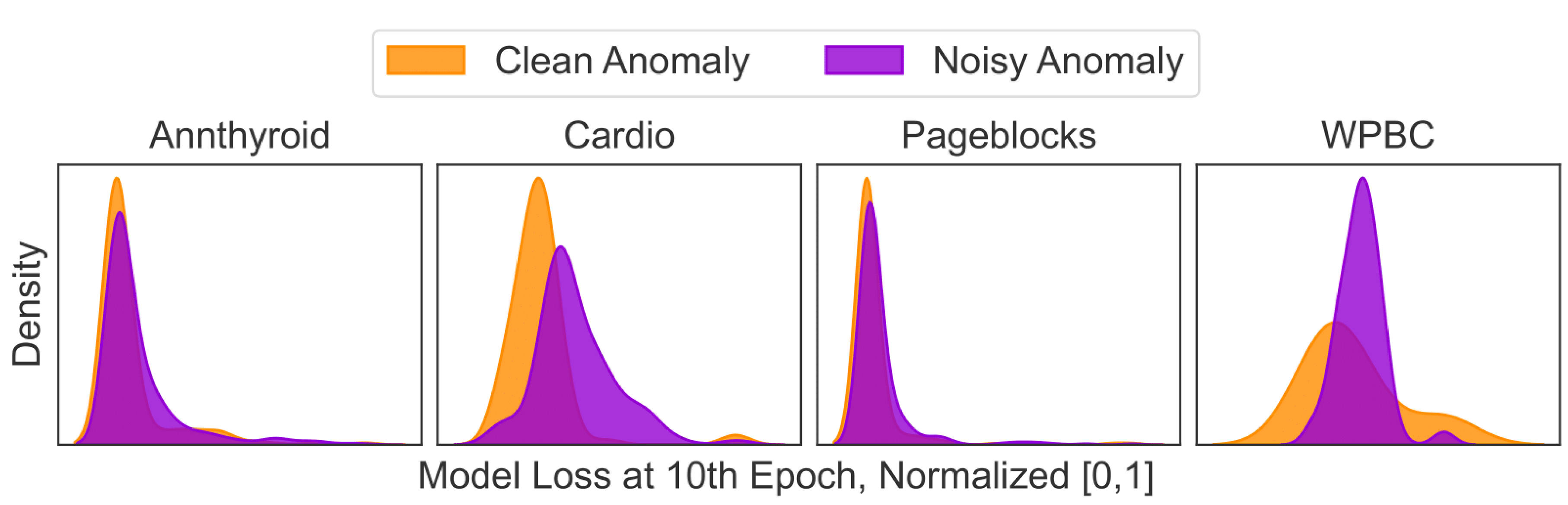


We can cheaply generate pseudo-labels.

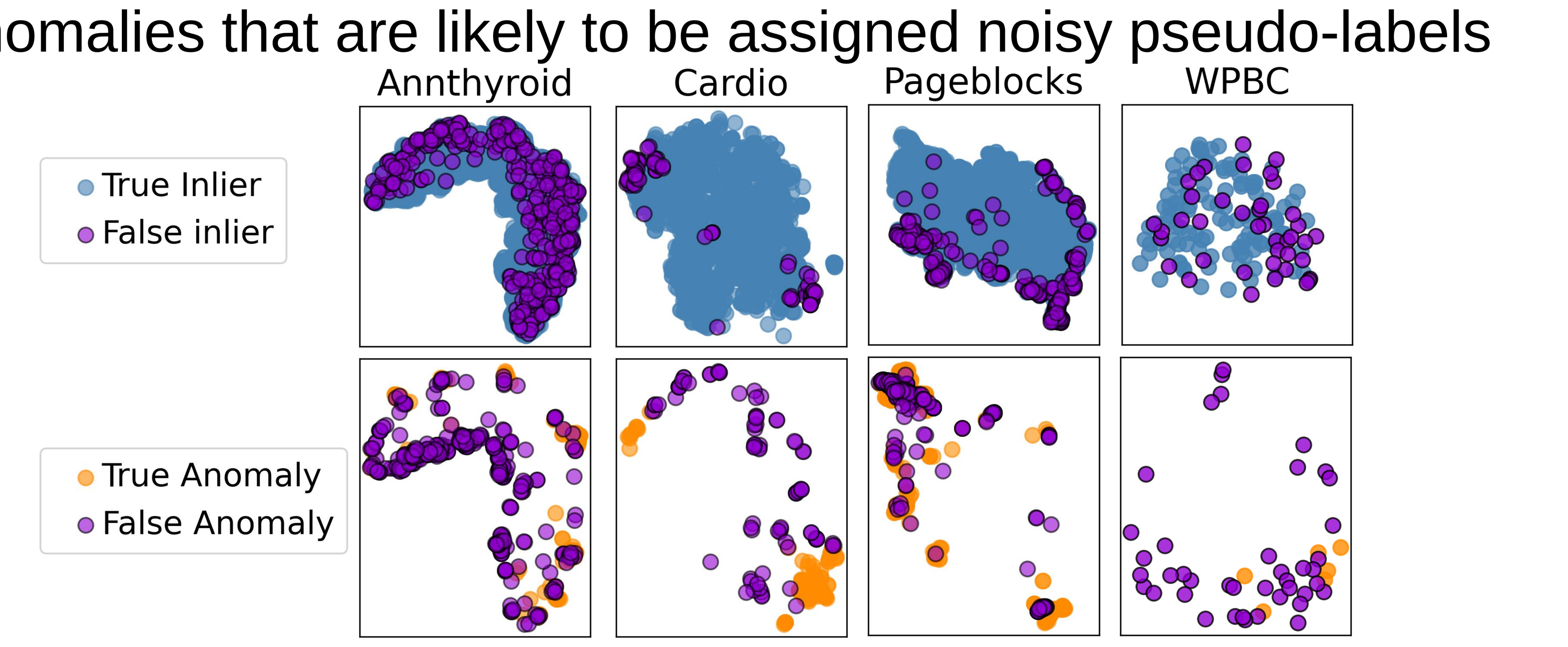


2 Challenges: Learning from Noisy Labels for Anomaly Detection

Challenge 1: The scarcity of anomalies invalidates common clean sample selection metrics (such as loss [3]).

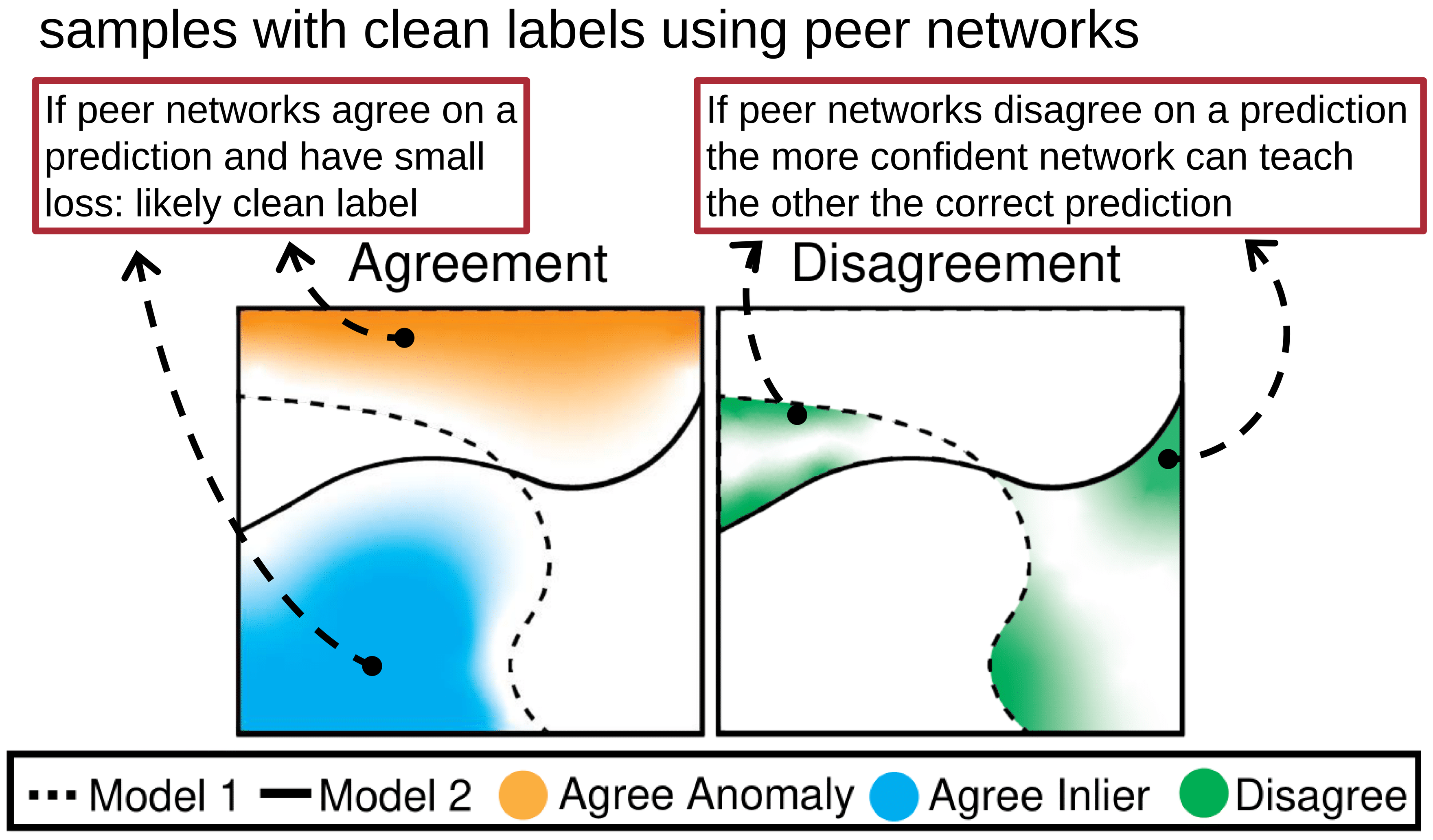


Challenge 2: The diversity of anomalies leads to many *marginal* anomalies that are likely to be assigned noisy pseudo-labels

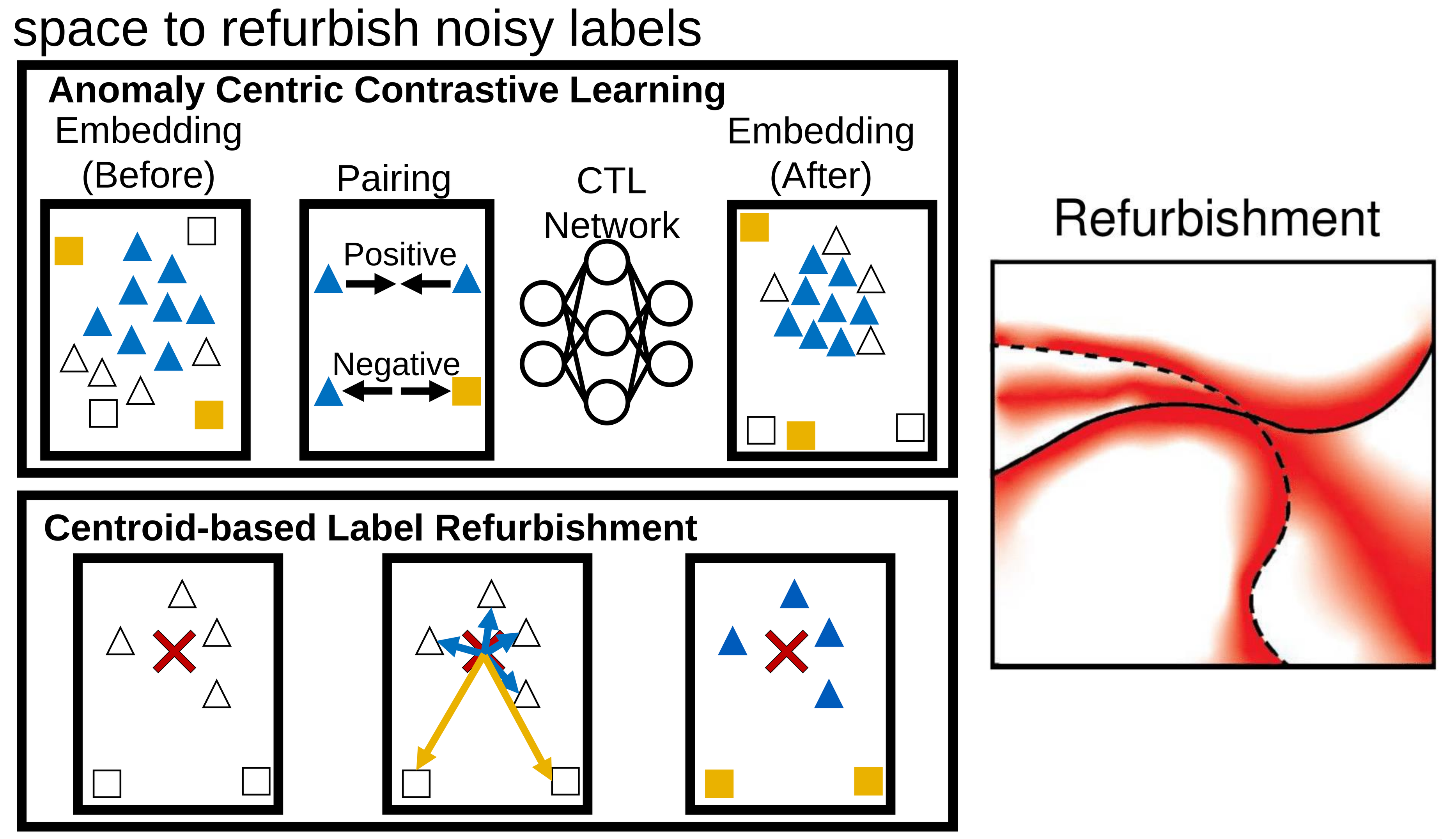


3 Solutions

Solution 1: Select a diverse set of easy and marginal samples with clean labels using peer networks

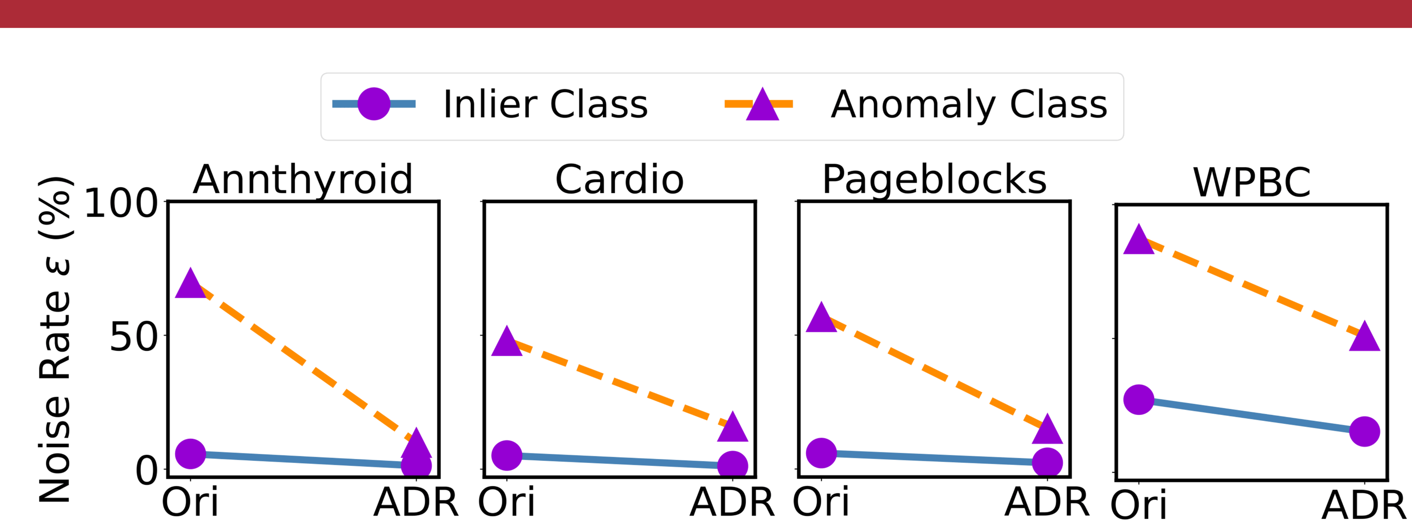


Solution 2: Learn a contrastive anomaly-aware embedding space to refurbish noisy labels



4 Experiments

Method	Datasets (F-1 score)			
	Annthyroid	Cardio	Pageblocks	WPBC
IF (Base)	0.34_{01}	0.54_{02}	0.44_{01}	0.17_{02}
AutoOD [4]	0.48_{04}	0.12_{04}	0.49_{06}	0.32_{03}
UADB [5]	0.39_{02}	0.61_{04}	0.25_{18}	0.17_{02}
UNITY (ours)	$\underline{0.78_{00}}$	$\mathbf{0.65_{09}}$	$\mathbf{0.63_{01}}$	$\mathbf{0.36_{02}}$



1. Unity outperforms SOTA LNL-AD Methods
2. Unity significantly decreases the noise rate

References

[1] D. Hofmann, et al. *Agree to Disagree: Robust Anomaly Detection with Noisy Labels.* SIGMOD 2025
[2] S. Han et al. *ADBench: Anomaly Detection Benchmark.* NeurIPS. 2022.
[3] H. Song, et al. Learning From Noisy Labels With Deep Neural Networks: A Survey. TNNLS 2023
[4] L. Cao et al. AutoOD: Automatic Outlier Detection. SIGMOD. 2023.
[5] H. Ye et al. UADB: Unsupervised Anomaly Detection Booster. ICDE. 2023.

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