

KU LEUVEN



DTAI

DECLARATIVE LANGUAGES &
ARTIFICIAL INTELLIGENCE

fwo



HELSINGIN YLIOPISTO
HELSINGFORS UNIVERSITET
UNIVERSITY OF HELSINKI



University of
Stuttgart

Estimating the Contamination Factor's Distribution in Unsupervised Anomaly Detection

Lorenzo Perini, Paul Bürkner, Arto Klami

lorenzo.perini@kuleuven.be

paul-christian.buerkner@simtech.uni-stuttgart.de

arto.klami@helsinki.fi

<https://people.cs.kuleuven.be/~lorenzo.perini/>



@LorenzoPerini95

Anomaly Detection is the Task of Detecting the Instances that Deviate from a Normal Behaviour

Fraudulent transactions



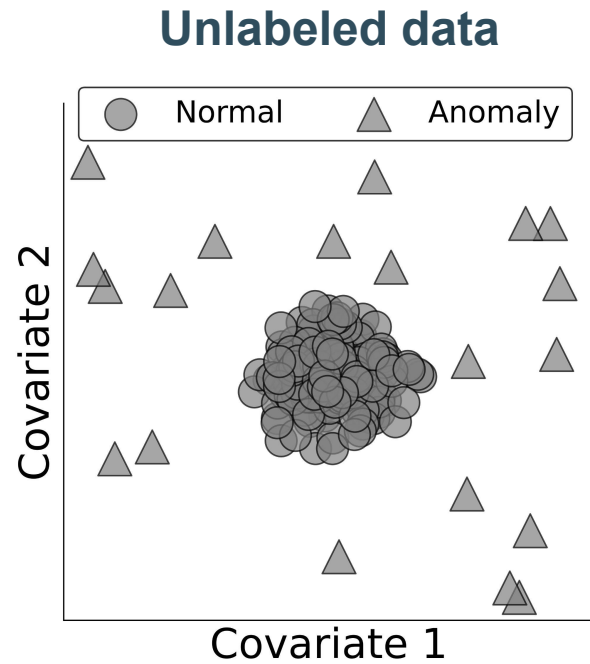
Machine breakdowns



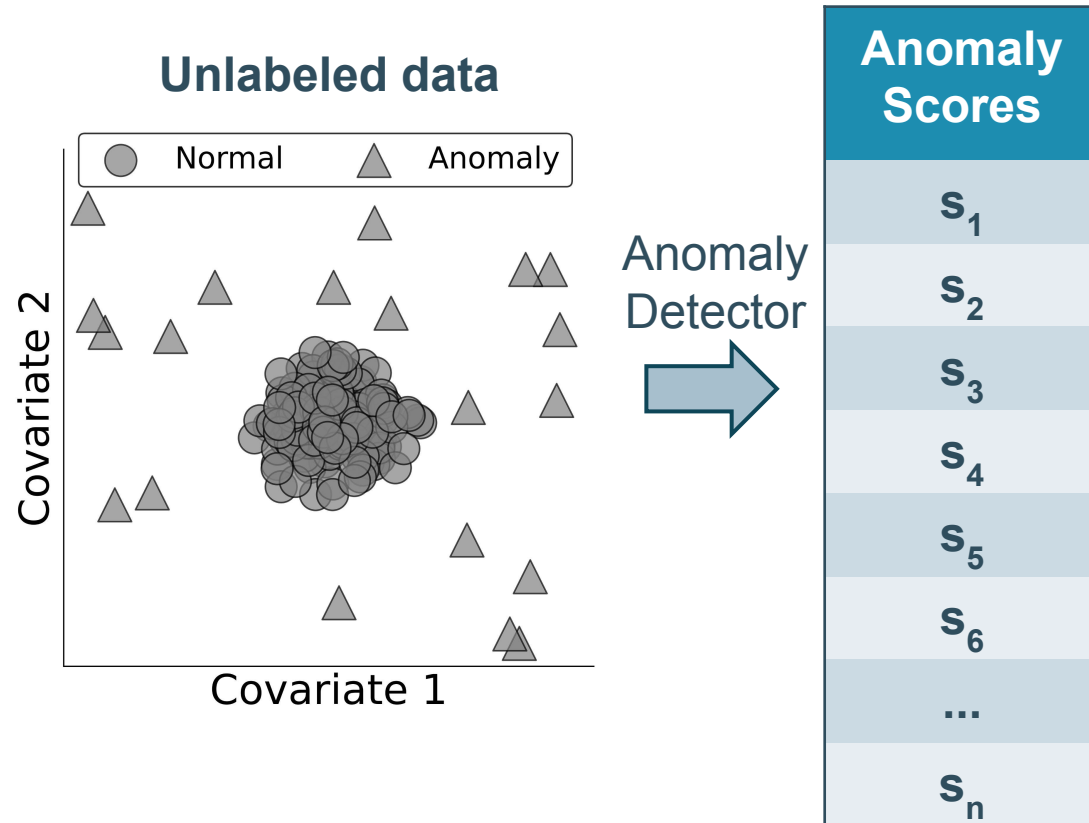
Cyberattacks



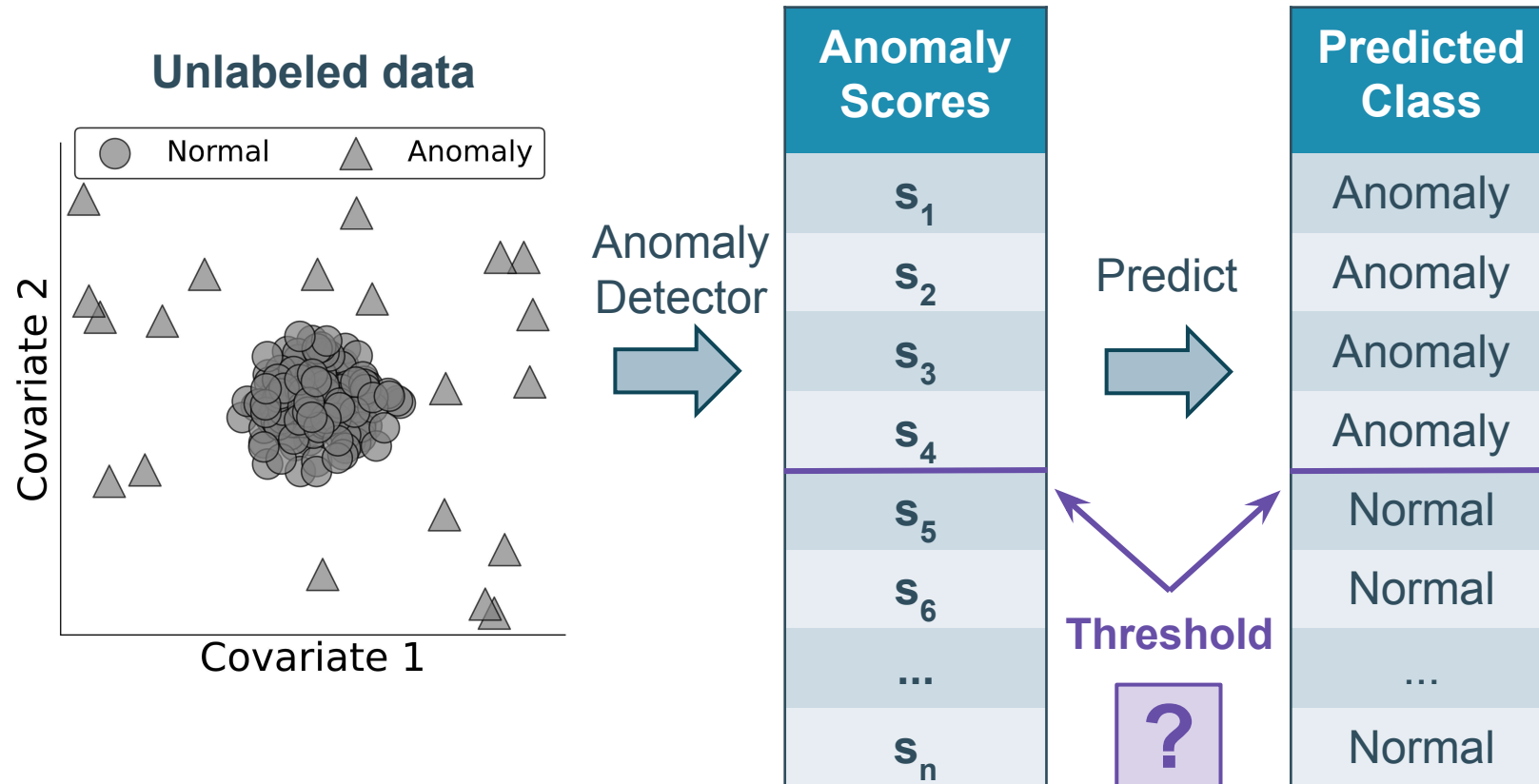
Because Labels Are Hard to Collect, Anomaly Detection Is Usually Tackled from an Unsupervised Perspective



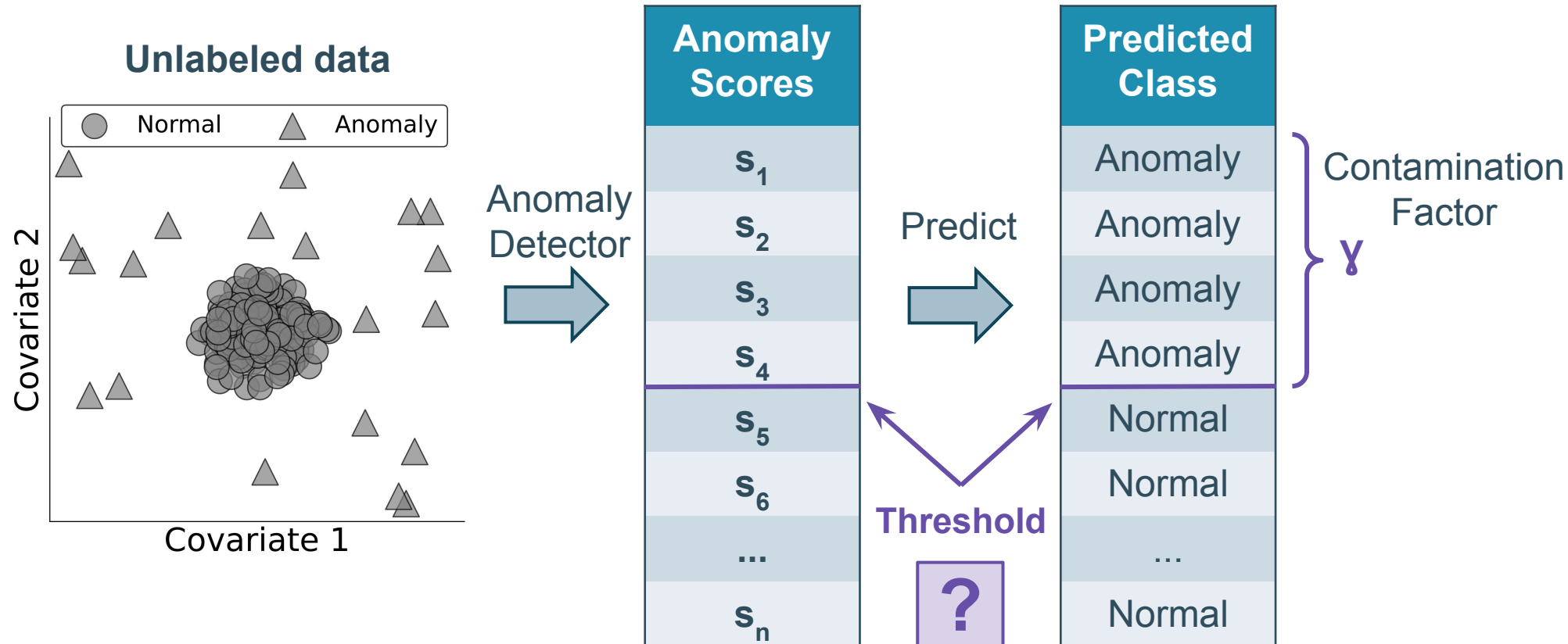
Unsupervised Anomaly Detectors Exploit Data-Driven Intuitions to Assign Anomaly Scores



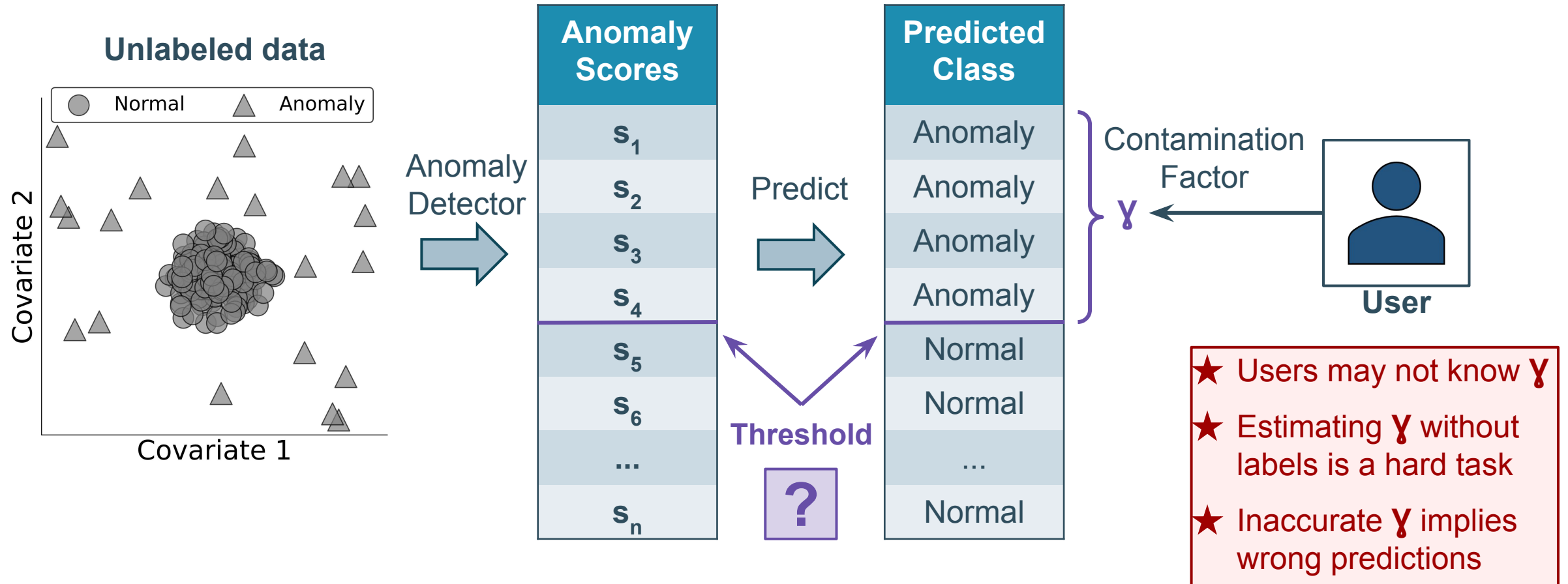
Transforming the Anomaly Scores into Hard Predictions Requires Setting a Decision Threshold



One Can Set the Threshold Using the Contamination Factor, i.e. the Proportion of Anomalies in the Data



Setting a Correct Contamination Factor is Essential to Get Accurate Predictions

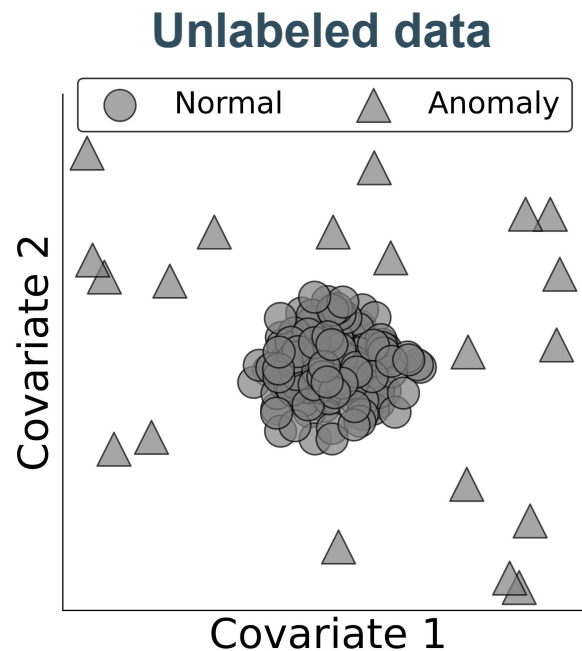


How Can We Estimate the Contamination Factor in an Unsupervised Setting?

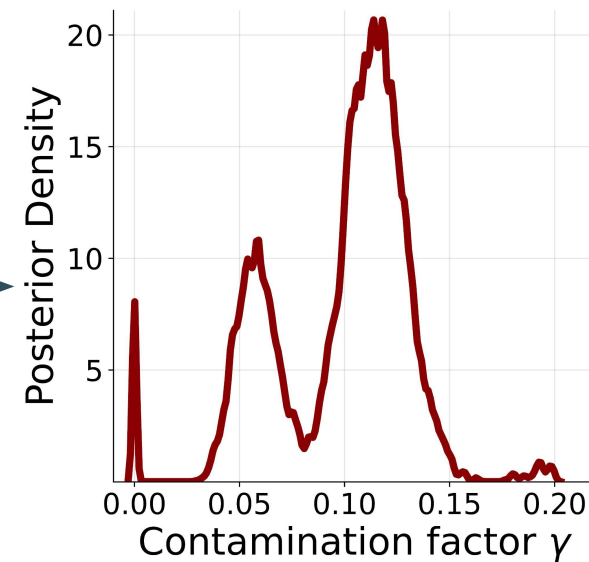
We Assume a Bayesian Perspective and Propose to Estimate the Contamination Factor's Distribution

Task

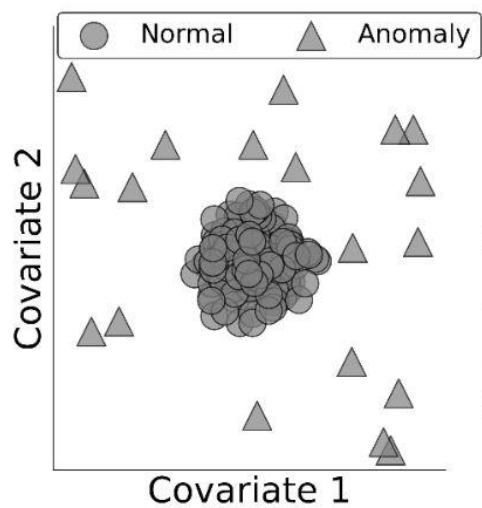
Given:



Estimate:



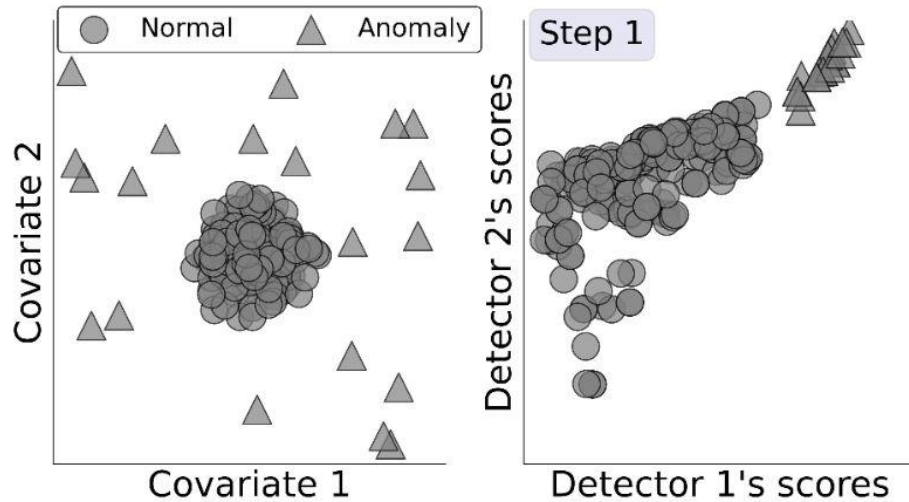
Our Method γ GMM Estimates γ 's Posterior in Four Steps



Unlabeled Data

Because Anomalies May Not Follow Patterns, We Map the Data into an M-dimensional Anomaly Score Space

Step 1

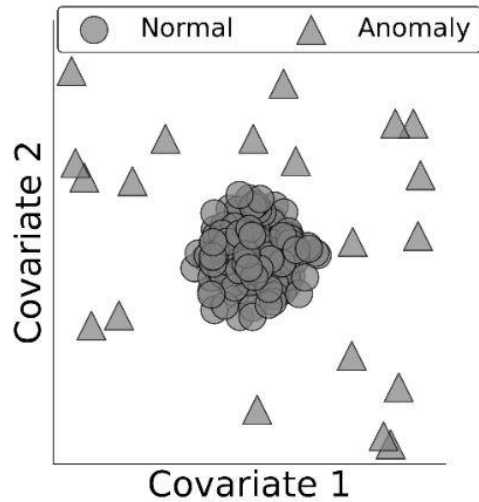


Unlabeled Data

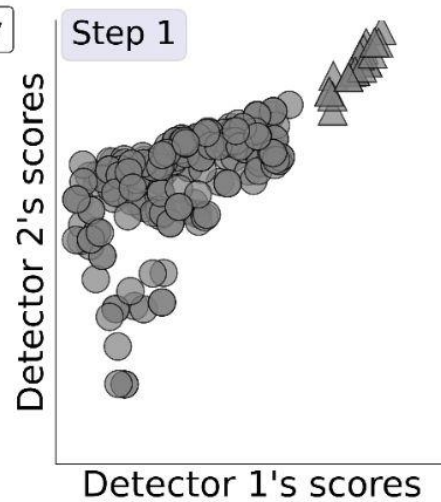
1. Compute the anomaly scores using M unsupervised detectors

Linking Contamination and Data using a DPGMM: the Components' Mass Reflect the Contamination

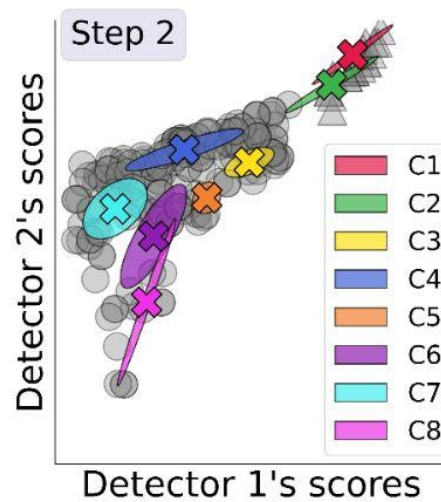
Step 2



Unlabeled Data



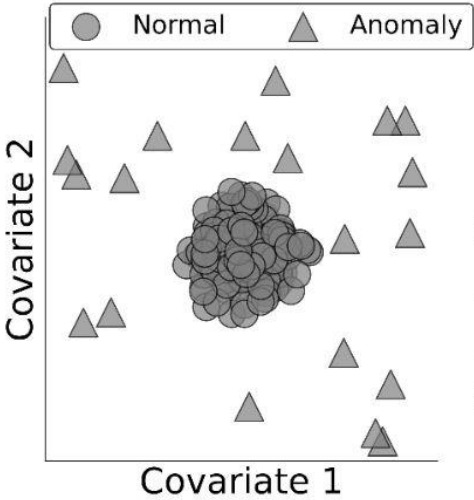
1. Compute the anomaly scores using M unsupervised detectors



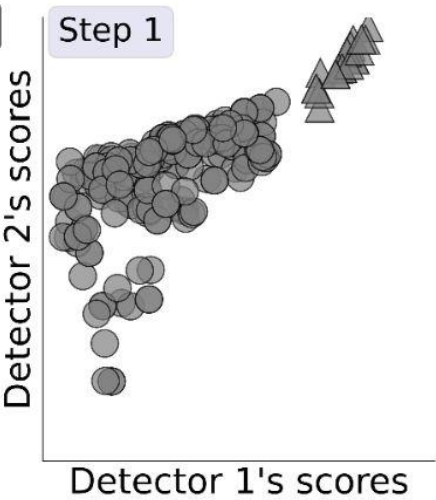
2. Model the family of scores as a DPGMM (using V.I.)

Because We Do Not Know Which Component Is Anomalous, We Estimate Their (Joint) Probability

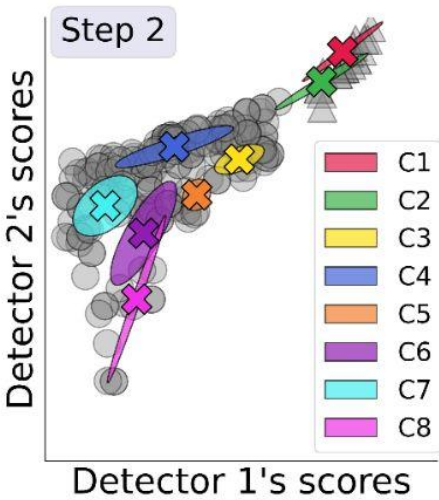
Step 3



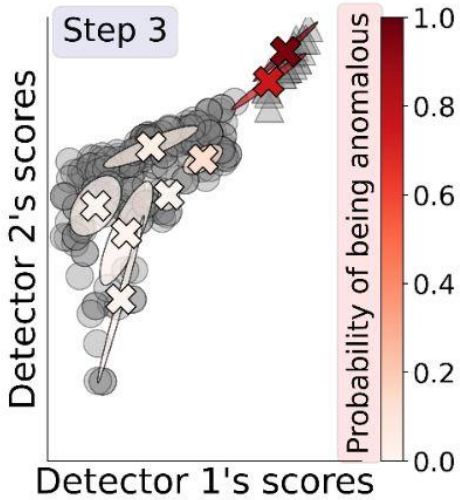
Unlabeled Data



1. Compute the anomaly scores using M unsupervised detectors



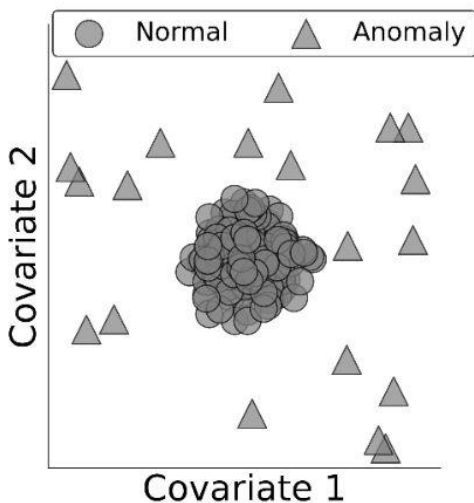
2. Model the family of scores as a DPGMM (using V.I.)



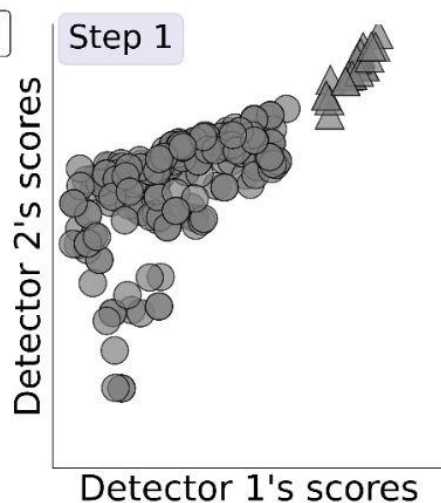
3. Compute the components' probability of being anomalous

We Derive the Posterior by Combining Step 3's Probabilities with Step 2 Components' Posterior

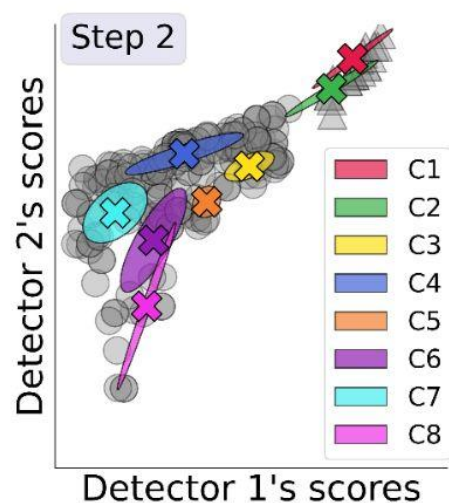
Step 4



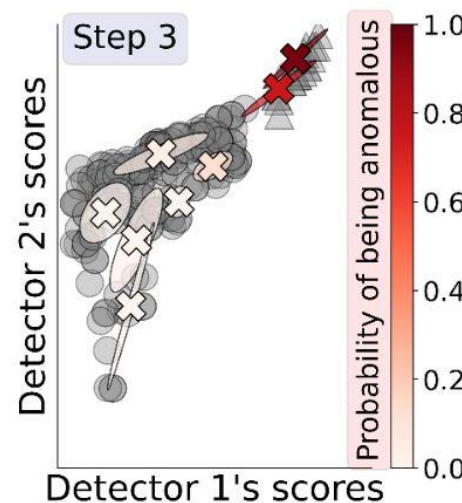
Unlabeled Data



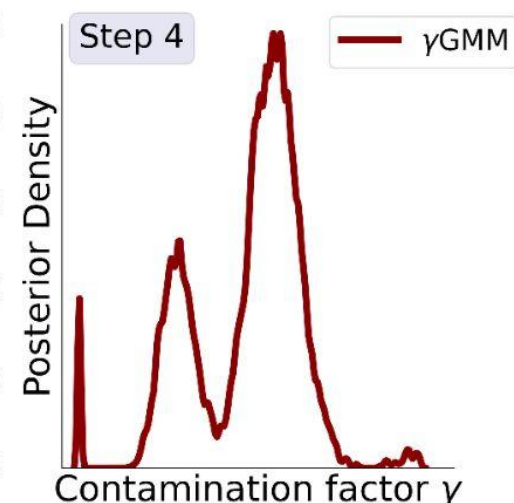
1. Compute the anomaly scores using M unsupervised detectors



2. Model the family of scores as a DPGMM (using V.I.)



3. Compute the components' probability of being anomalous



4. Derive γ 's posterior distribution

$$p(\gamma) = \sum_{k=1}^K \mathbb{P}(\text{exact } c_1, \dots, c_k) \mathcal{B}(a_k, b_k)$$

How Does γ GMM Compare to Existing Approaches?

Estimating the Contamination Factor's Distribution in Unsupervised Anomaly Detection

For further details:

- ★ Check out the [paper online](#)
- ★ Reach out to us via [email](#)

Lorenzo Perini, Paul Bürkner, Arto Klami

lorenzo.perini@kuleuven.be

paul-christian.buerkner@simtech.uni-stuttgart.de

arto.klami@helsinki.fi

<https://people.cs.kuleuven.be/~lorenzo.perini/>

 @LorenzoPerini95