

Coincident Learning for Beam-Based Radio Frequency (RF) Station Fault Identification Using Phase Information at SLAC Linac Coherent Light Source

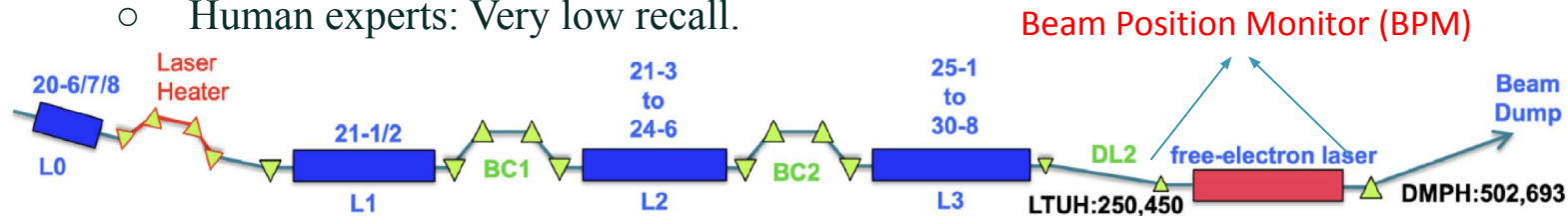
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Unsupervised Anomaly Detection in SLAC

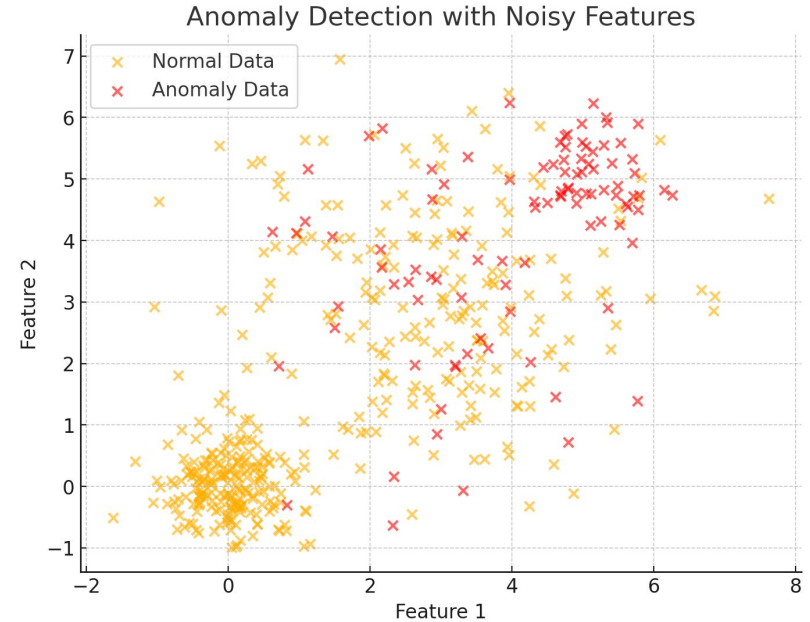
- LCLS experiences unplanned downtime and unexpected behavior, reducing beam stability and introducing noise sources that can interfere with user data analysis.
- The goal here is to identify faulty RF stations (in blue regions) that also degrades the beam quality measured by BPM (near the red region). RF stations directly impact beam energy and represent a significant source of failure.
- Limitations of existing non-AI solutions underscore the need for an automated, unsupervised AI method (we don't have labels):
 - Thresholding & status bits: High false positive rate.
 - Human experts: Very low recall.



Layout of the LCLS showing the location of RF stations. Specifically, L0, L1, L2, L3 in the figure are the locations of the RF stations. For example, 20-6 is a RF station. Beam Position Monitor (BPM) is used to measure the overall quality of the system.

Limitation of Existing AI solutions

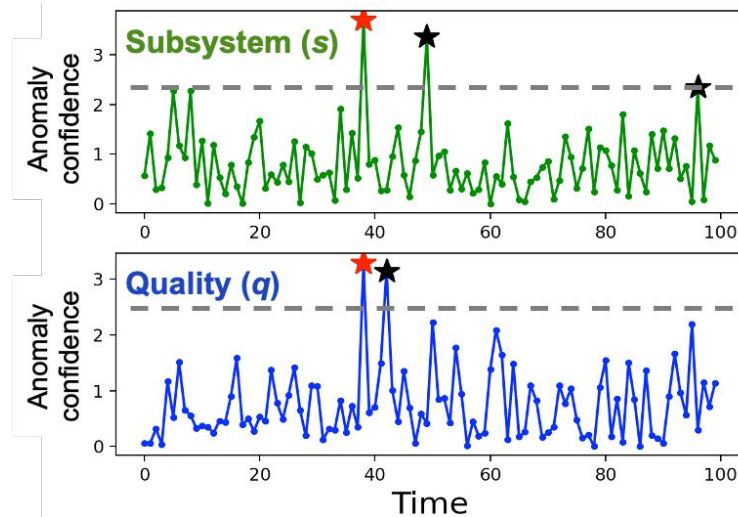
- Existing Unsupervised Anomaly Detection may break down in the following situations:
 - Very noisy features
 - High-dimensional setting
 - Training set is contaminated with anomalous samples



Anomaly detection can become very difficult in the presence of noisy features.

Coincident Anomaly Detection (CoAD)

Consider two algorithms making decisions on two streams of data.



- **Red** stars = consistent
black stars = inconsistent
- More **red** = higher recall;
less **black** = higher precision

FP rate = product of black star rates

TP rate = red star rate - FP rate

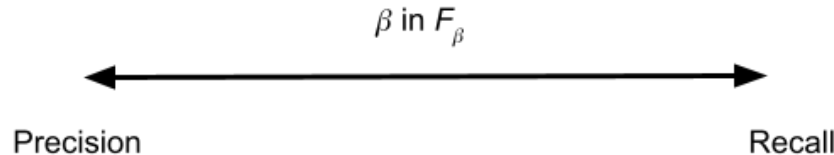
→ Unsupervised precision/recall

Self-Consistency Metrics

$$\text{Max Cov}(p_1, p_2) \longrightarrow \text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

$$\text{Max Corr}(p_1, p_2) \longrightarrow \text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

$$\text{Max } \widehat{F}_\beta(p_1, p_2) \longrightarrow F_\beta = (1 + \beta^2) \cdot \frac{\text{Precision} \times \text{Recall}}{\beta^2 \cdot \text{Precision} + \text{Recall}}$$



As β increases, F_β converges to Recall. As β decreases, F_β converges to Precision.

Two-Stages Method

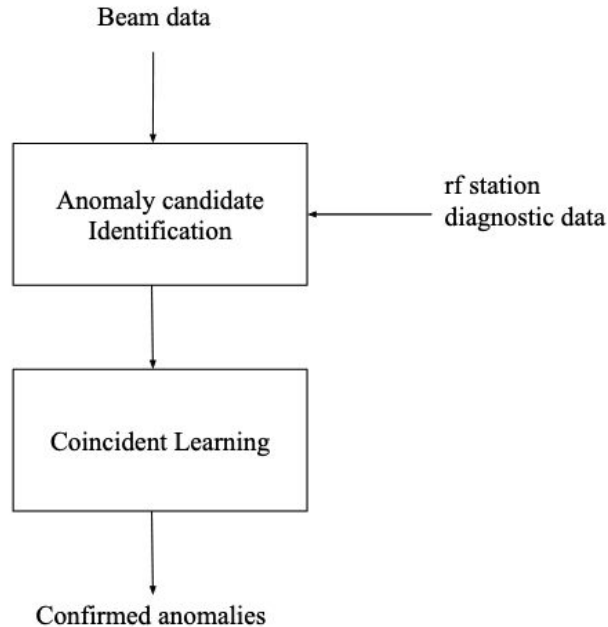


Illustration of two-stage rf station anomaly detection method.

1. The anomaly candidate identification step increases the concentration of the anomalies in the dataset.
 - a. Compute rolling median-based anomaly score from beam data to select candidate time window.
 - b. Pair beam data with diagnostic data from most anomalous RF station.
2. Coincident learning automatically detect anomalies and optimal thresholds.

Algorithm Performance

		AUCPR	Best f_1
Traditional	CCA-1D	0.382	0.464
	CCA-2D	0.437	0.491
	IForest	0.413	0.426
	OCSVM	0.631	0.649
Deep Learning	DGHL	0.824	0.76
	OmniAnomaly	0.463	0.527
	CoAD	0.93	0.851

Comparison of different anomaly detection methods on phase-based diagnostic data. CCA-1D and CCA-2D represent the linear variants of COAD. On the other hand, IForest, OCSM, DGHL, and OmniAnomaly are designed specifically for single-stream data. The scores reported for those methods are the higher scores from either stack & score and score & stack.

Previous work: Improvement of CoAD (Amplitude) over existing non-AI solutions

100x more anomalies vs. manual recording

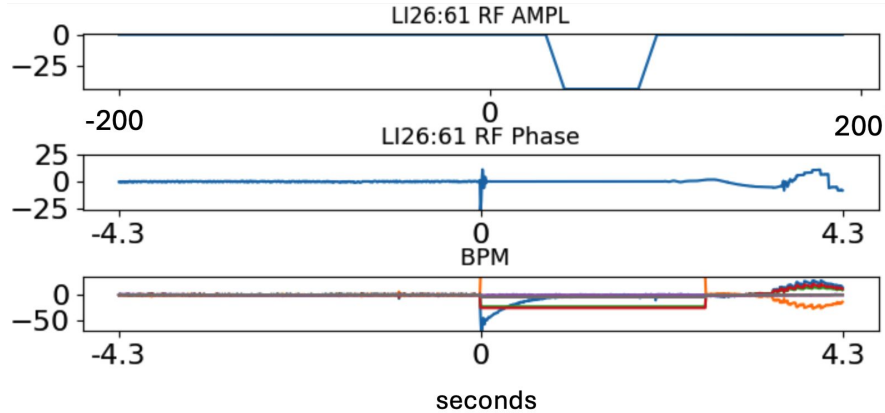
	Precision	Recall (events)
Manual recording by operator	NA	6
Status bit	0.31	385
Coincident Detection (Amplitude)	0.88	504

30% more anomalies vs. status bit

6x fewer false positives vs. status bit

Previous CoAD result using Amplitude by Ryan over the period Nov. 2 to Dec 10, 2020. This work was lead by Ryan Humble.

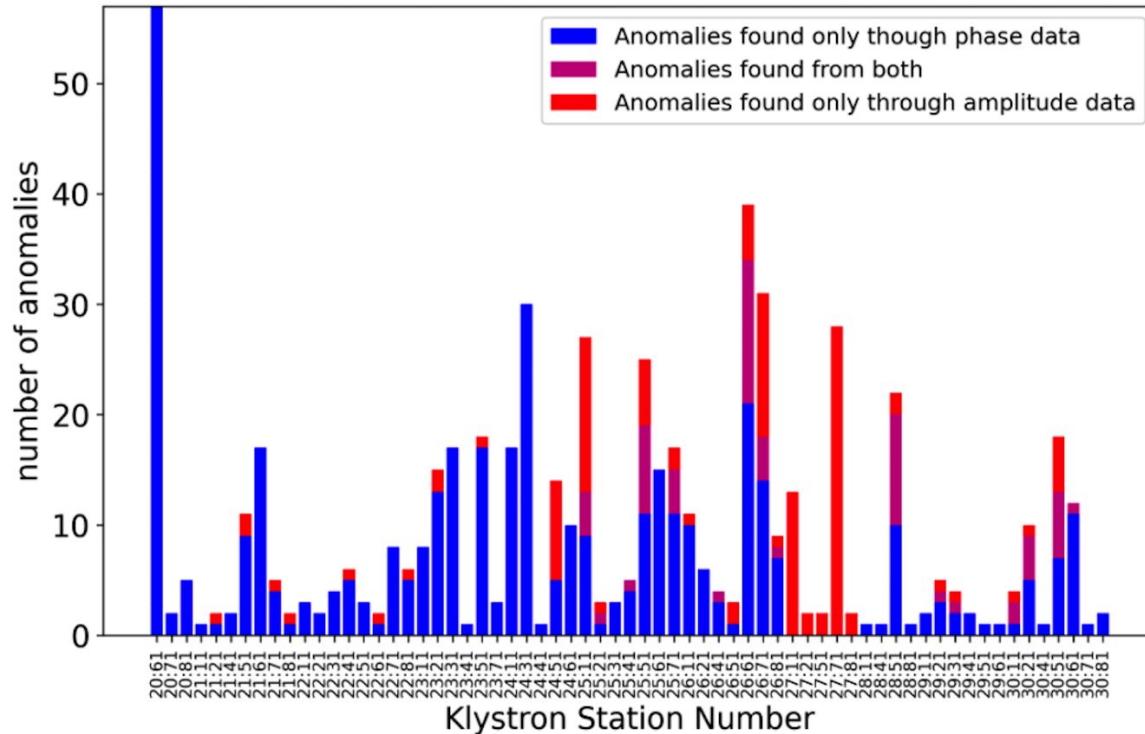
Improve CoAD with Phase Data



- Improvements made using phase data:
 - 120 Hz and synchronous → potential for better recall.
 - The complexity of the RF phase data could reveal signatures of underlying root cause.
 - Interpreting CoAD model with Shapley value.

	Previous	Current
Data Streams	Amplitude (s) BPM (q)	Phase (s) BPM (q)
Sampling Rate	s (~0.2 Hz) q (120 Hz)	s (120 Hz) q (120 Hz)
Synchronicity	s lags behind q for 5 seconds	s and q are synchronous

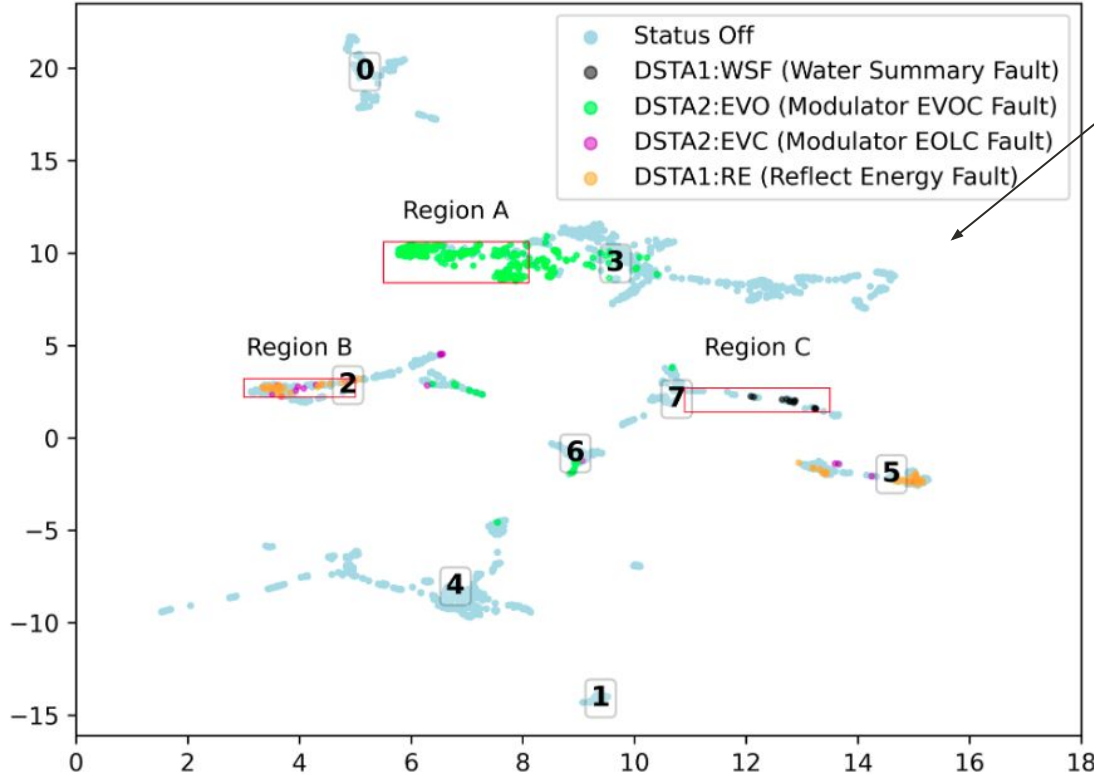
Anomalies Detected: RF Amplitude vs RF Phase



3x gain in recall using RF Phase Data

Anomalies found with CoAD from Jan. 19 to Jan. 31, 2024. Injector (sector 20) faults ONLY found by phase data. Phase data not available in Sector 27 due to software fault in archiver.

Clustering of Anomalies



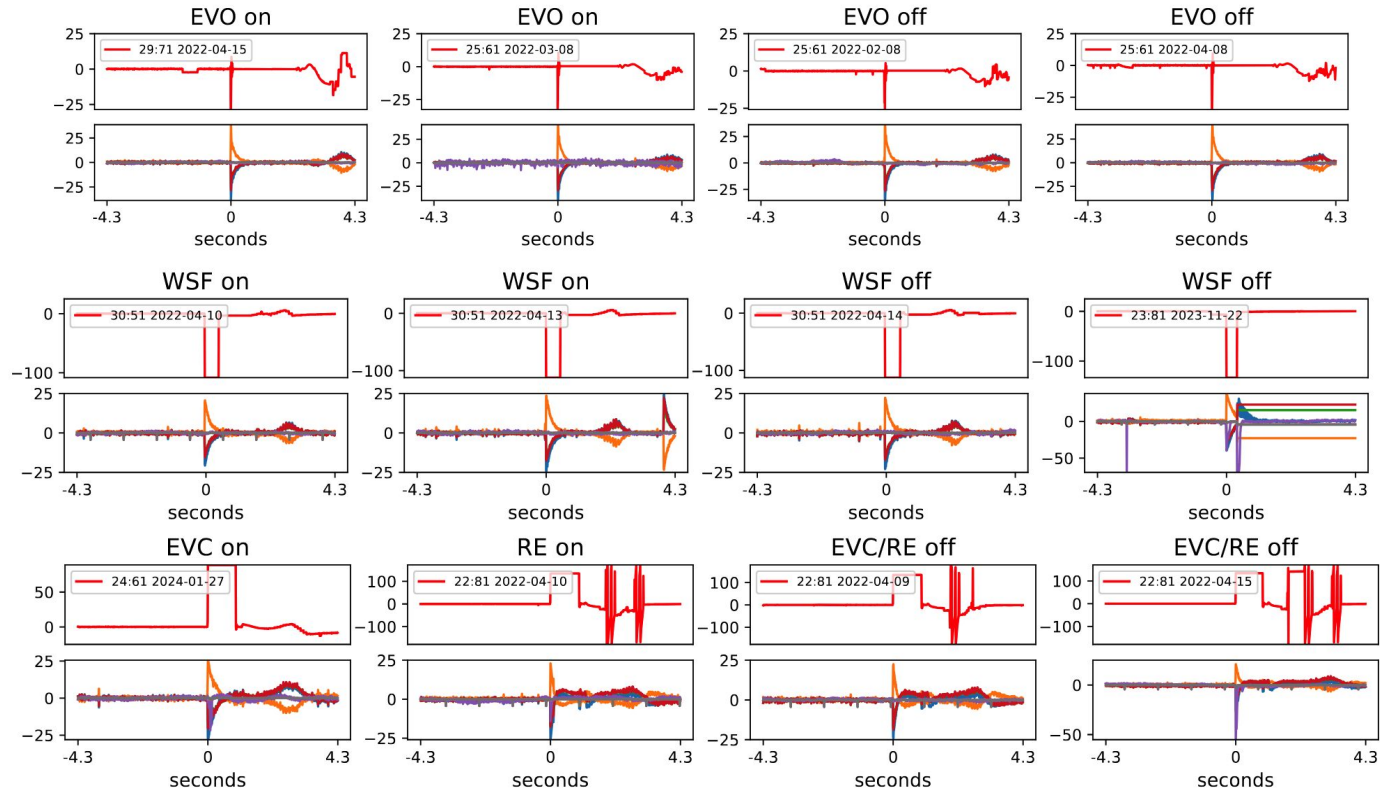
After UMAP dimensionality reduction, anomalies in the phase signals naturally cluster into distinct groups.

Different cluster corresponding to different root causes

Status bits: reveal the underlying causes of a hardware problem. Not used due to poor precision.

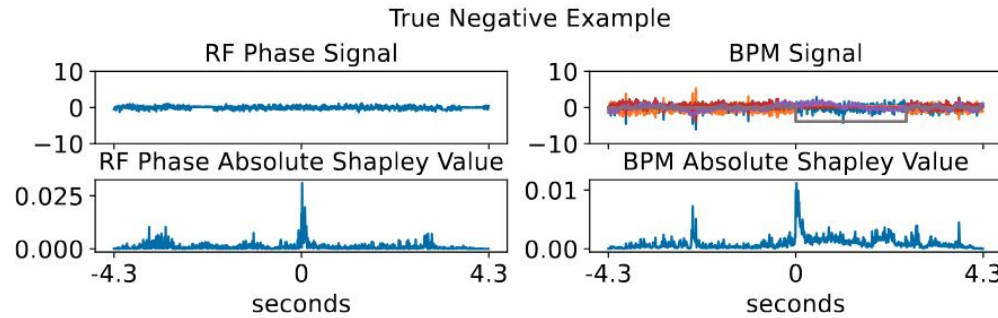
- **DSTA1:WSF** – Cooling water flow switch fault detected
- **DSTA2:EVO** – Excessive current in klystron pulse (Electrode Voltage Overcurrent)
- **STA2:EVC** – High reverse voltage causes overcurrent (End of Line Clipper)
- **DSTA1:RE** – Excessive energy reflected back to klystron.

Physical Signature of Anomalies

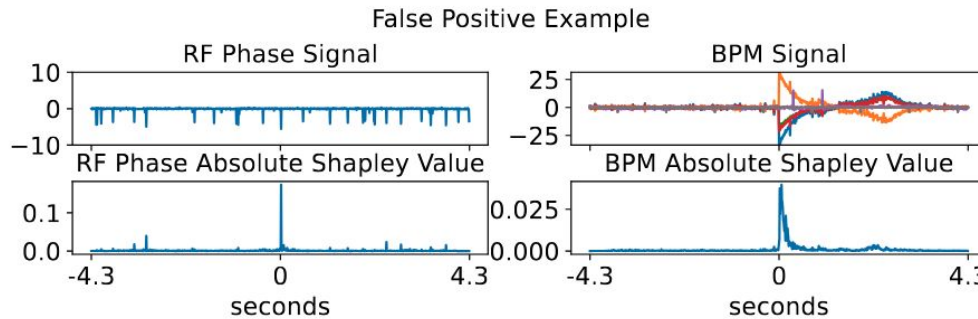


Details of the phase signals associated with different faulty bits. Different status bits are associated with distinctive features in the RF phase.

Shapley Value Interpretation



Shapley value help us understand *how* the model makes decisions.



Shapley value help us understand *Why* the model makes mistakes.

The Shapley value assigns a fair portion of the total contribution to each participant based on their individual inputs. In the true negative example, the absolute Shapley value is highest at the center, indicating that the model focuses on the middle of the window when making decisions. The false positive example indicates that the model disregards broader statistical properties instead concentrates solely on the central region.

Conclusion

- CoAD is state-of-art for full-unsupervised, multi-modal anomaly detection.
- Reasons why phase is advantageous (over amplitude):
 - high-frequency, synchronous as BPM data
 - 3x more anomalies detected
 - root-cause analysis
- Next Steps:
 - Jitter station detection
 - Generalize CoAD using Graph Neural Network
- Special thanks for all the helps from Ryan Humble, Zhe Zhang, William Coloco, Ben Morris, David A. Steele, Franz-Josef Decker, Finn O'Shea, Eric Darve, and Daniel Ratner.

Thank You

\widehat{F}_β Metric

$$\widehat{F}_\beta \stackrel{\text{def}}{=} \frac{(1 + \beta^2)(J - D)}{J + \alpha\beta^2} \leq F_\beta = (1 + \beta^2) \frac{PR}{R + \beta^2 P} = \frac{(1 + \beta^2)(J - P_{\text{FP}})}{J + \alpha\beta^2}$$

We define J as the fraction of Joint Event: $J = \mu_{12} = \mathbb{E}(f_1 f_2)$

P is precision; R is recall; D is the estimated fraction of false positive.

$$D \stackrel{\text{def}}{=} \frac{\mu_1 - \mu_{12}}{1 - \mu_2} \frac{\mu_2 - \mu_{12}}{1 - \mu_1}, \quad \mu_i : \text{mean of } f_i$$

Humble, Ryan, et al. "Coincident learning for unsupervised anomaly detection of scientific instruments."

Hyperparameter β^*

Maximize

$$\hat{F}_{\beta}^* = \frac{\mu_{12} - \mu_1\mu_2}{\mu_{12} + (\beta^*)^2} \frac{1 - \mu_{12}}{(1 - \mu_1)(1 - \mu_2)}$$

μ_i : mean of f_i

μ_{12} : mean of $f_1 f_2$

- Small β^* : this maximizes the precision; this is analogous to maximizing the correlation between f_1 and f_2 .
- Large β^* : this maximizes the recall; this is analogous to maximizing the covariance of f_1 and f_2 .