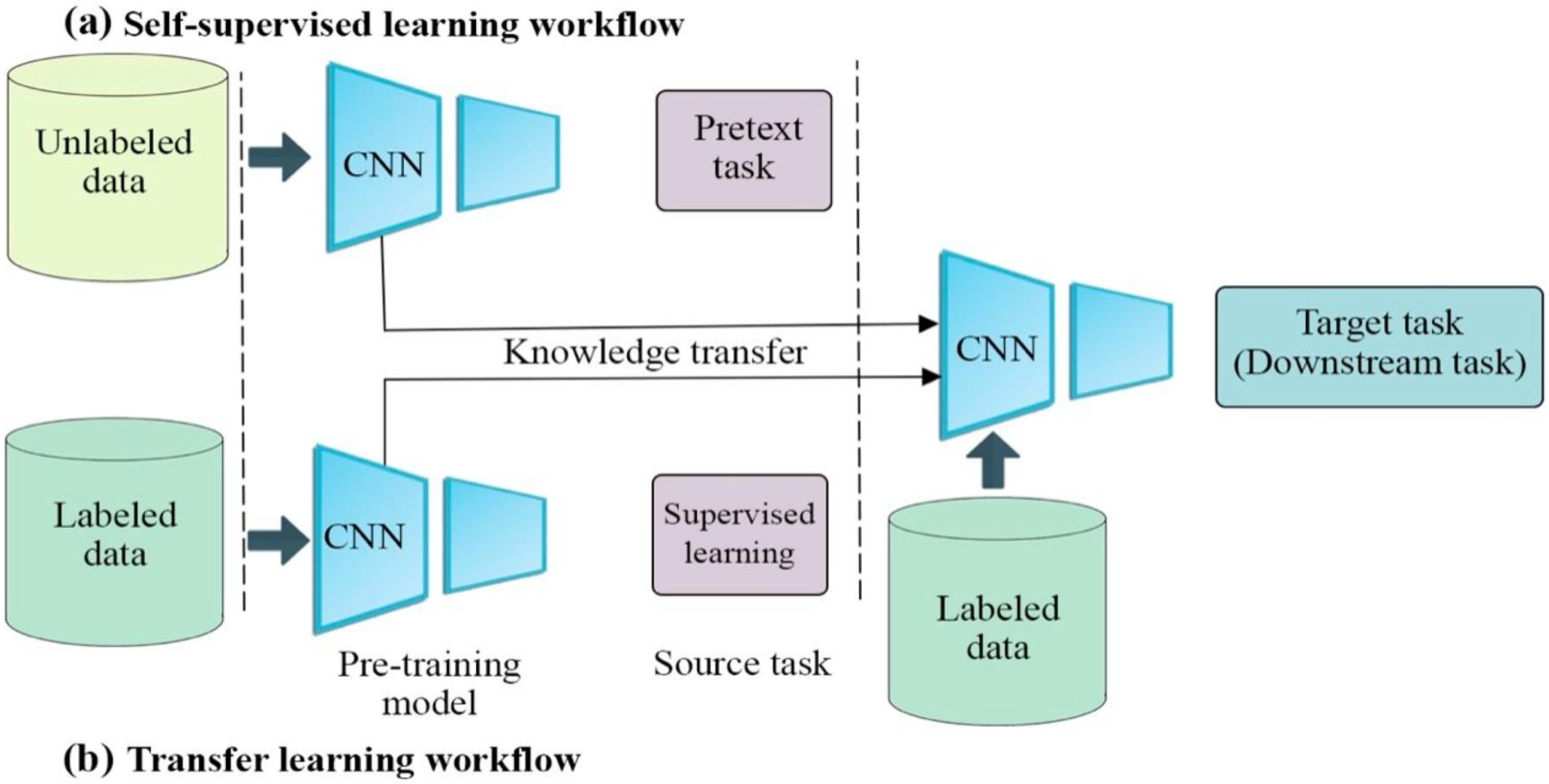
A self-supervised learning approach for reliable anomaly detection in rotating machinery

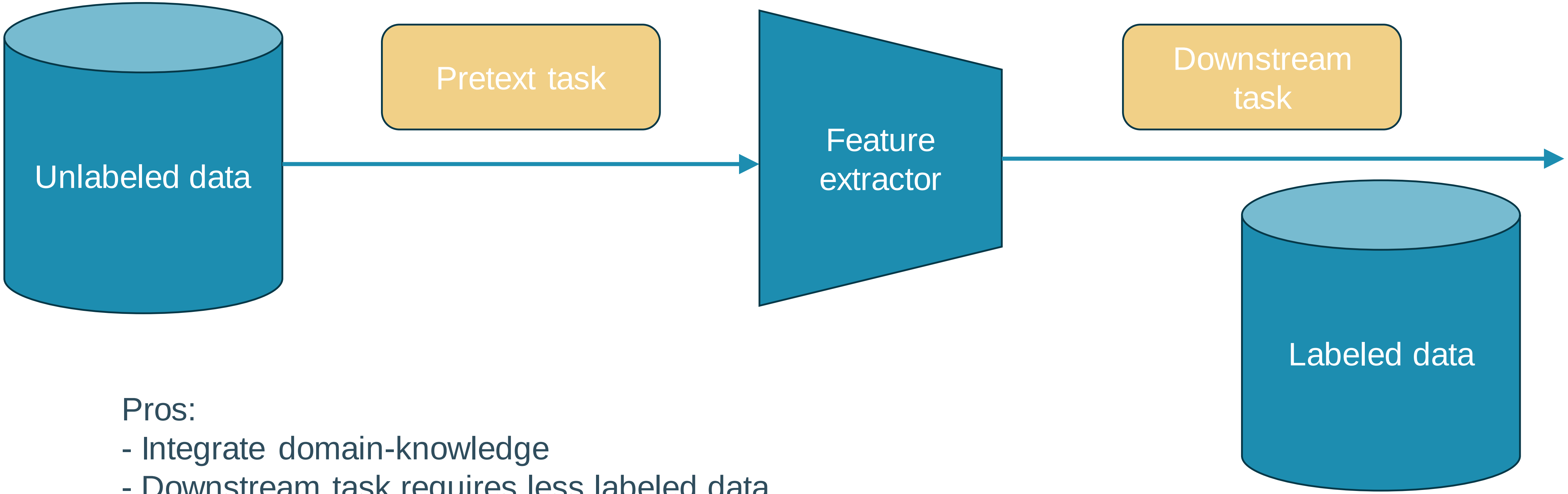
Outline

- Introduction to self-supervised learning
- Cycle consistency learning
- Methodology
- Results
- Conclusion

Knowledge transfer

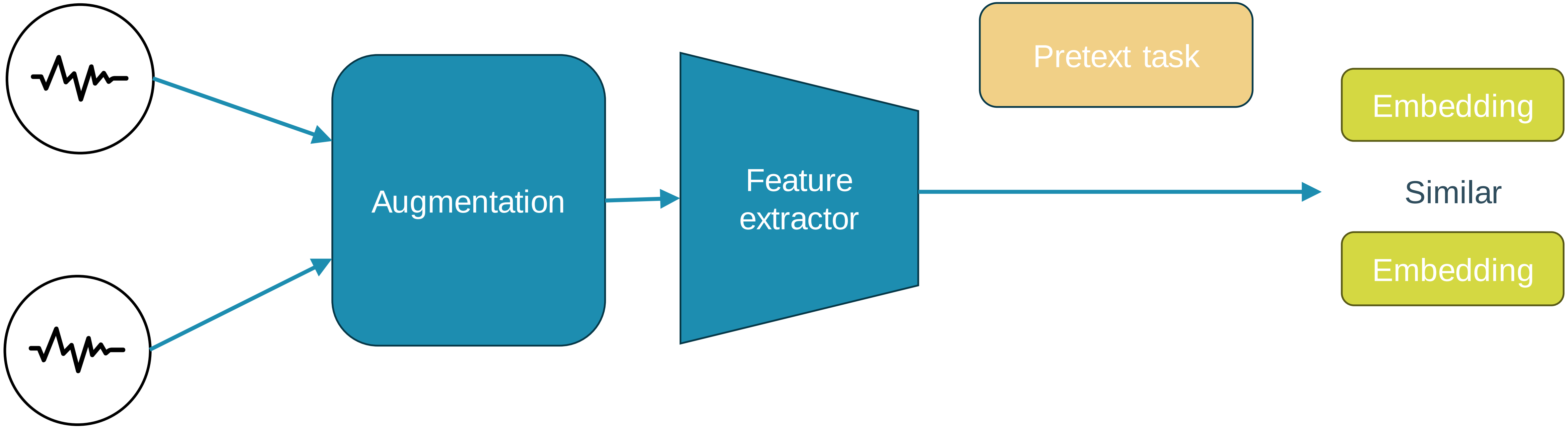


Self-supervised learning

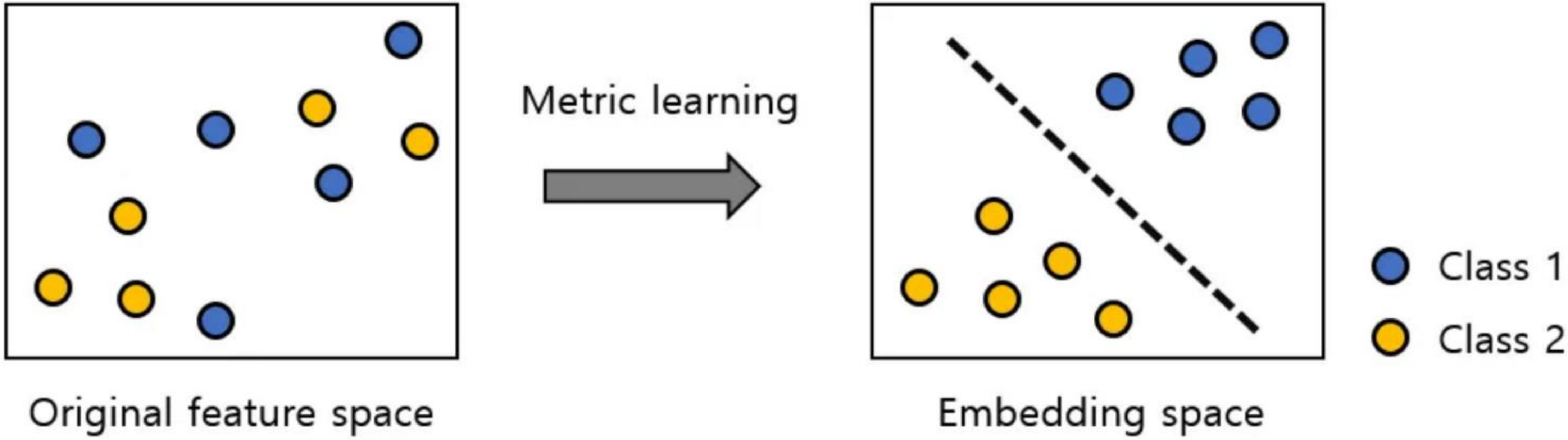


Pros:
- Integrate domain-knowledge
- Downstream task requires less labeled data

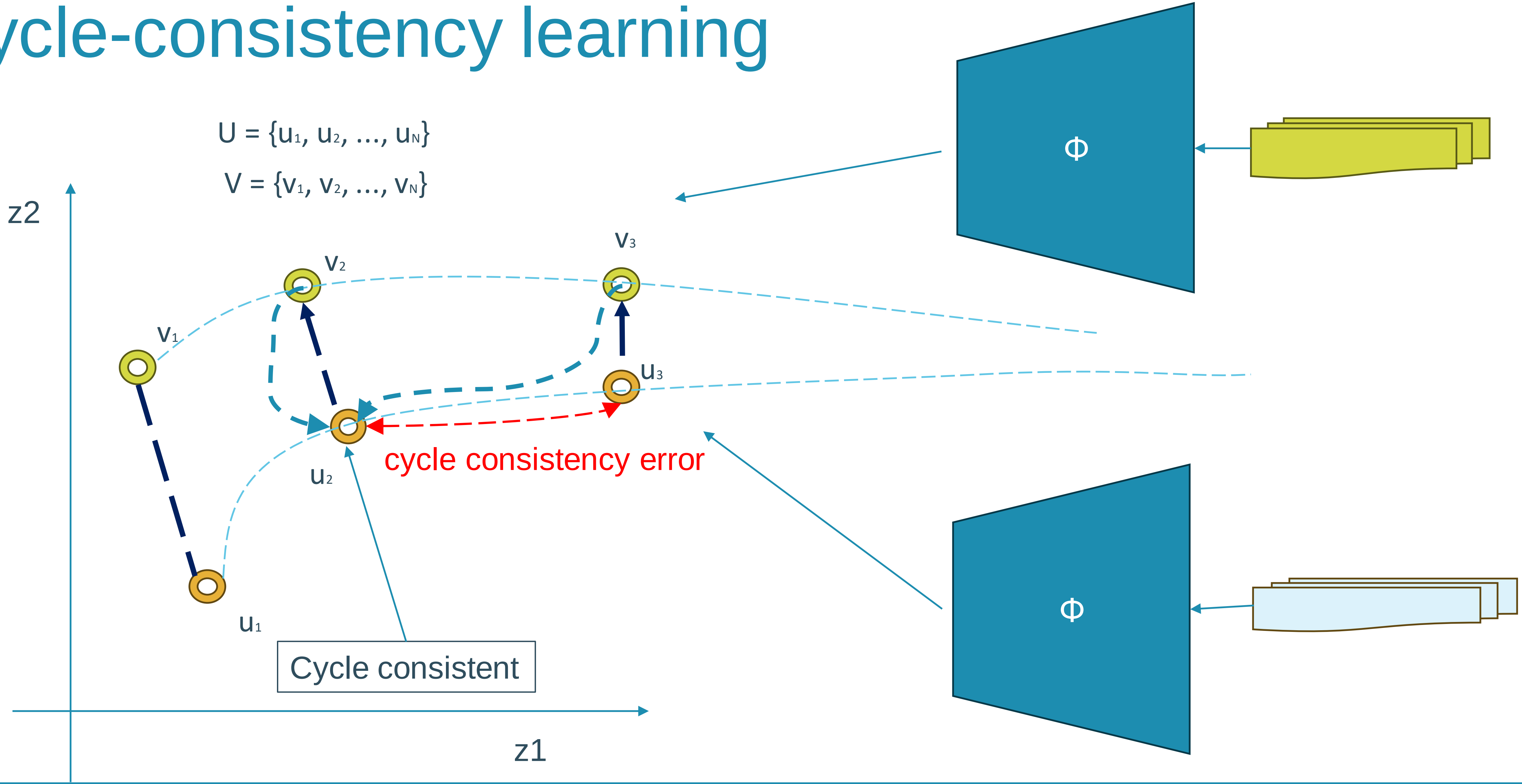
Invariance-based SSL



Deep metric learning



Cycle-consistency learning



Classification loss for cycle-consistency learning

Soft nearest neighbour of u_i in V

$$\tilde{v} = \sum_{j}^{M} \alpha_j v_j, \quad where \quad \alpha_j = \frac{e^{-||u_i - v_j||^2}}{\sum_k^M e^{-||u_i - v_k||^2}}$$

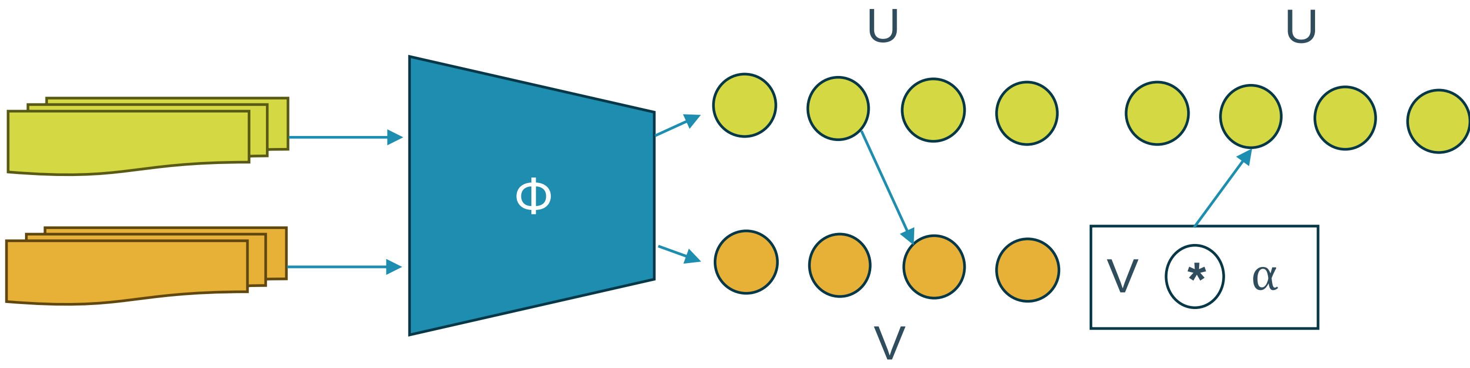
logits

$$x_k = -||\tilde{v} - u_k||^2$$

predictions

$$\hat{y} = softmax(x)$$

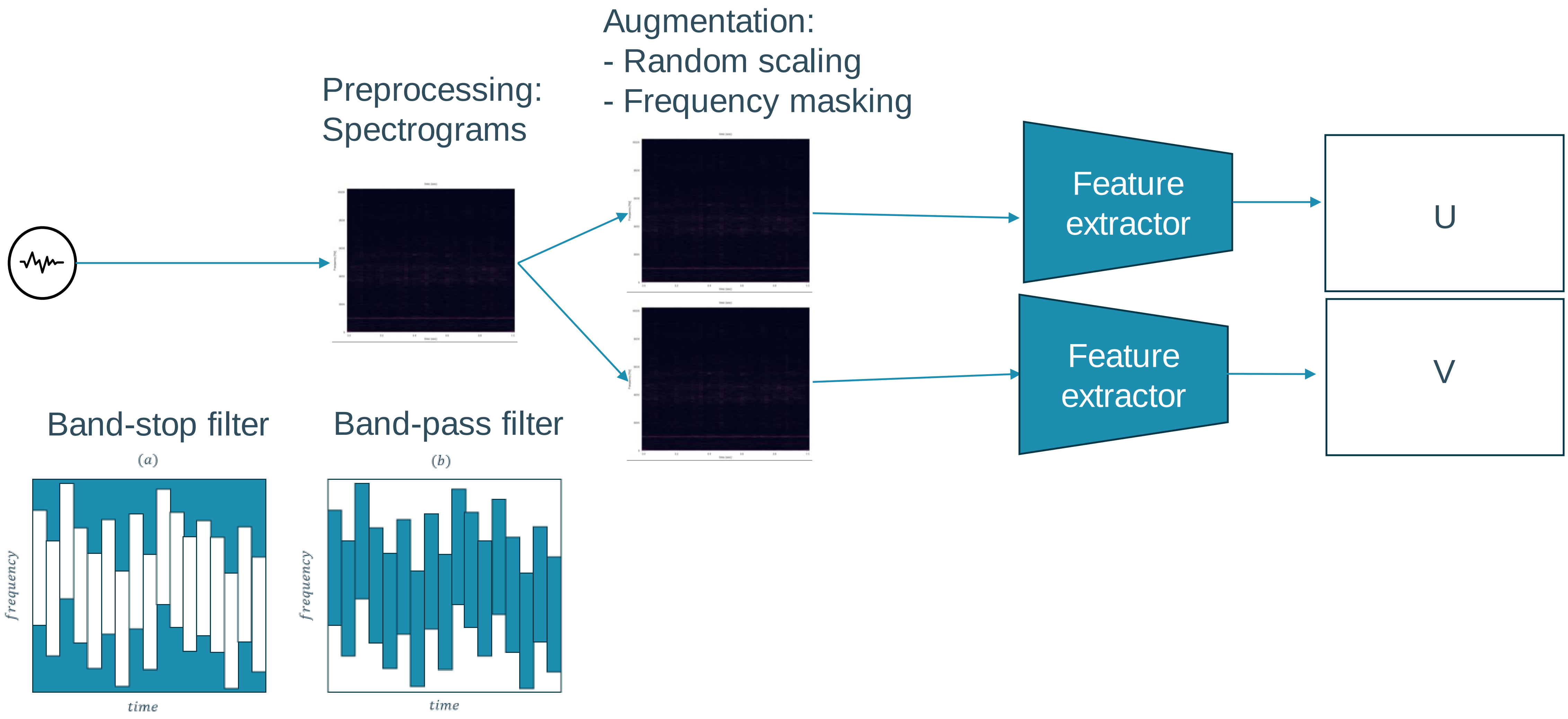
Nearest neighbour of $\tilde{v}$ in U



Cross entropy loss

$$L_{cbc} = -\sum_{j}^{N} y_j \log(\hat{y}_j)$$

Data pre-processing and augmentation



Threshold computation

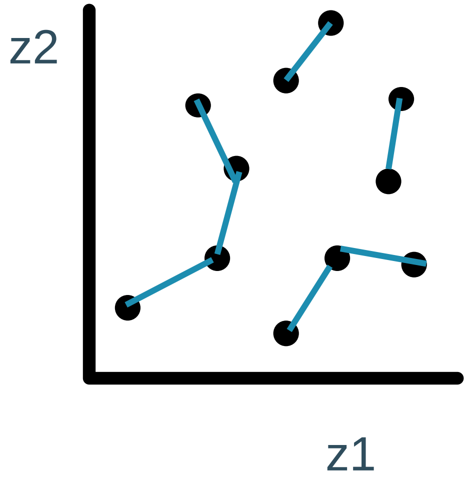
mean

$$\mu = (1/n)\sum_{i=1}^{n} \min_{j\neq i} |\varphi(\boldsymbol{xtrain_i}, \mathcal{W}) - \varphi(\boldsymbol{xtrain_j}, \mathcal{W})|$$

Standard deviation

$$\sigma = \sqrt{1/(n-1)\sum_{i=1}^{n} (\min_{j\neq i} |\varphi(\boldsymbol{xtrain_i}, \mathcal{W}) - \varphi(\boldsymbol{xtrain_j}, \mathcal{W})| - \mu)^2}$$

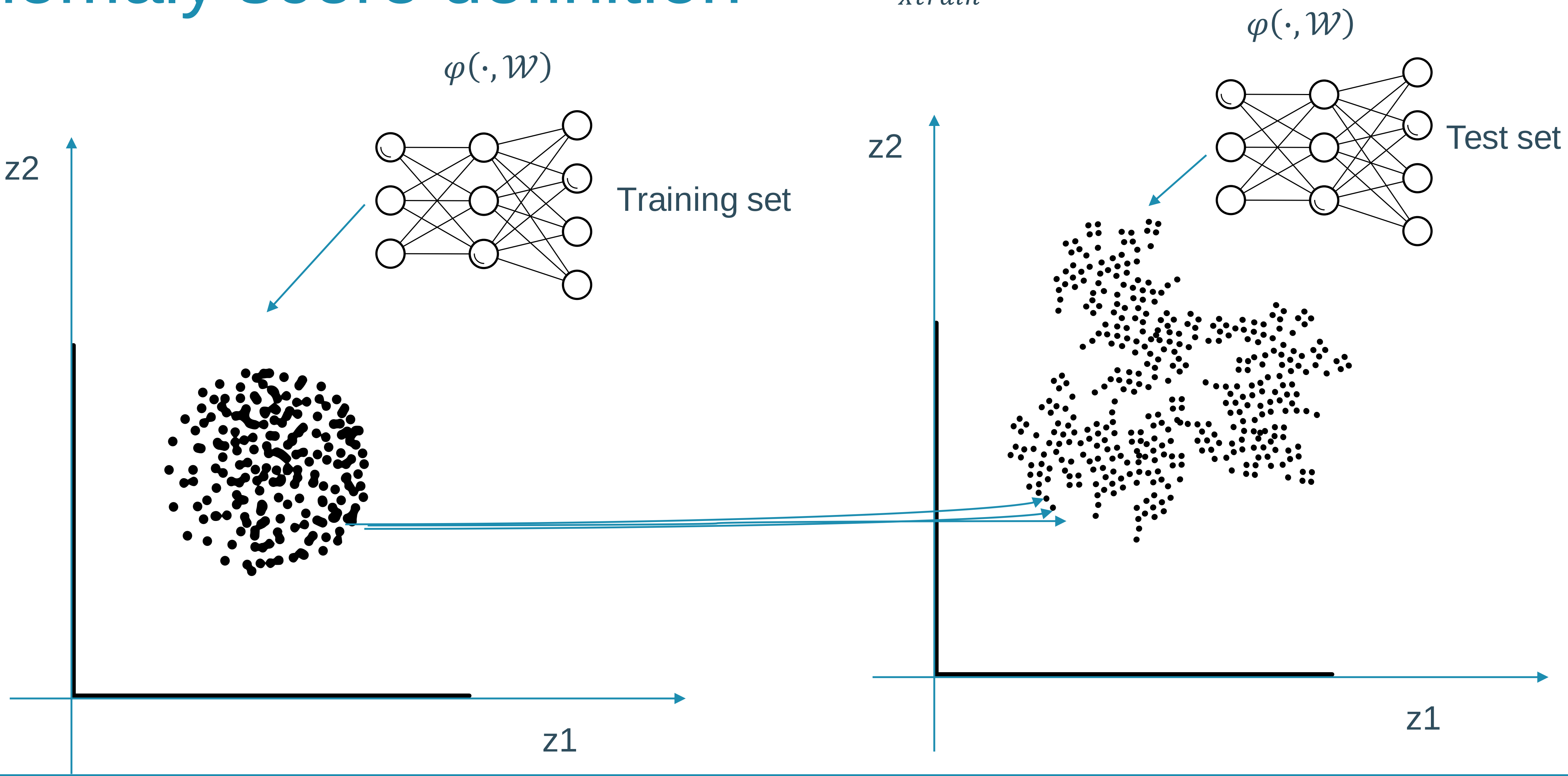
Threshold = μ + 3 σ



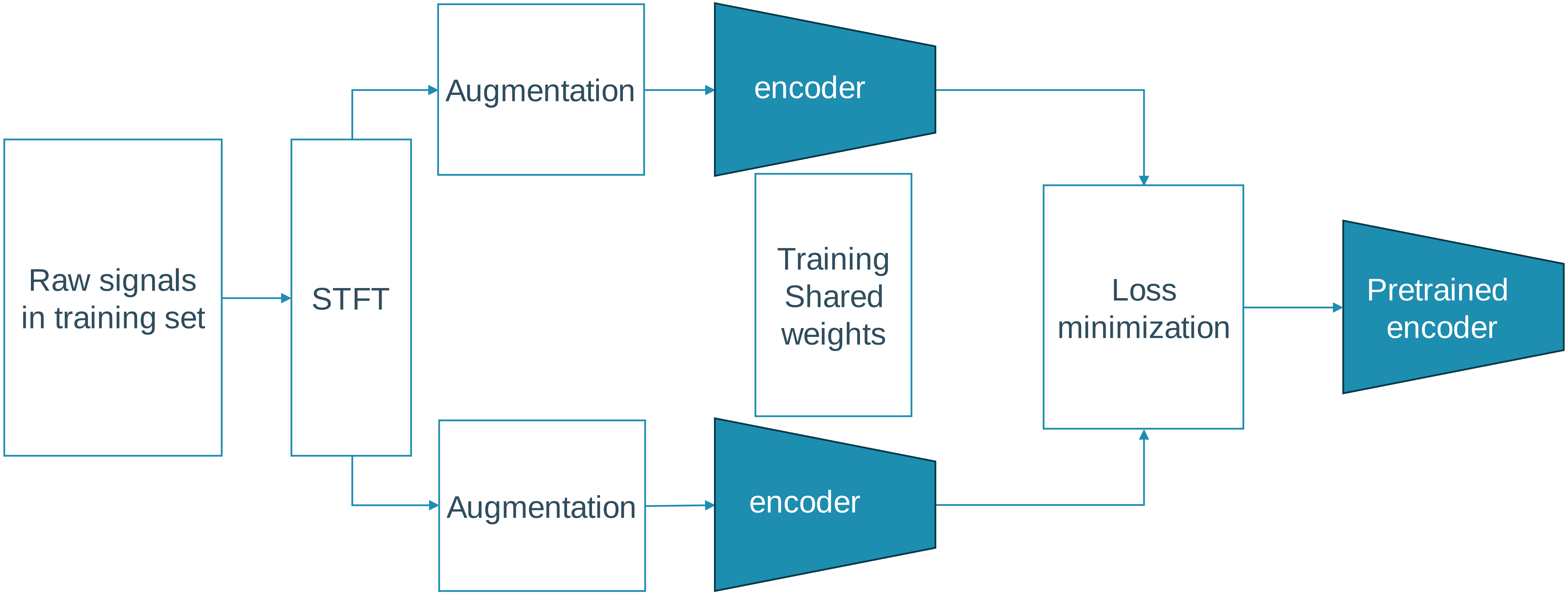
For each embedding in the training set, the distance from the closest embedding in the training set is selected, in analogy with the selection of the closest embedding in the training set for each embedding in the test set.

Anomaly score definition

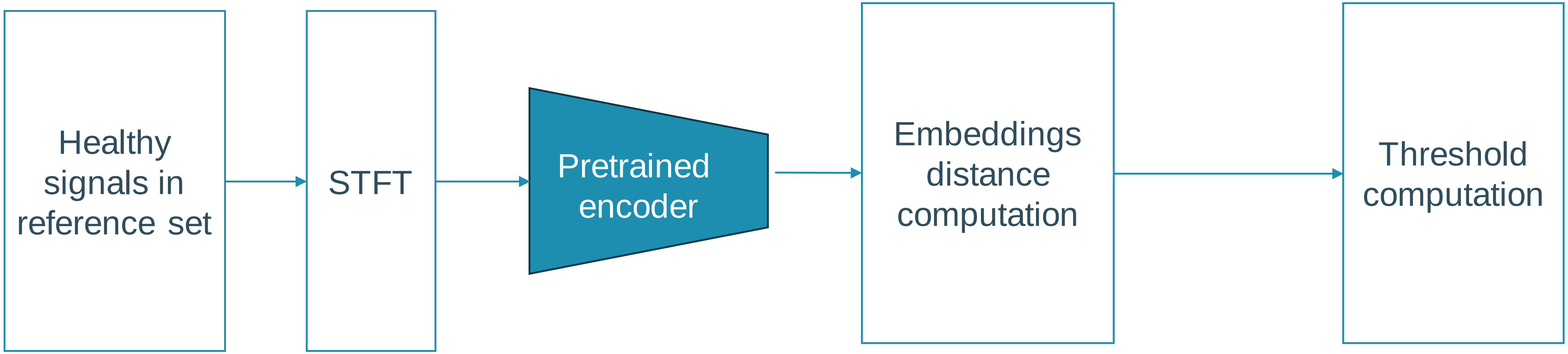
$$An_{i=}\min_{Xtrain}|\varphi(\boldsymbol{x}train,\mathcal{W})-\varphi(\boldsymbol{x}test_{\boldsymbol{i}},\mathcal{W})|$$



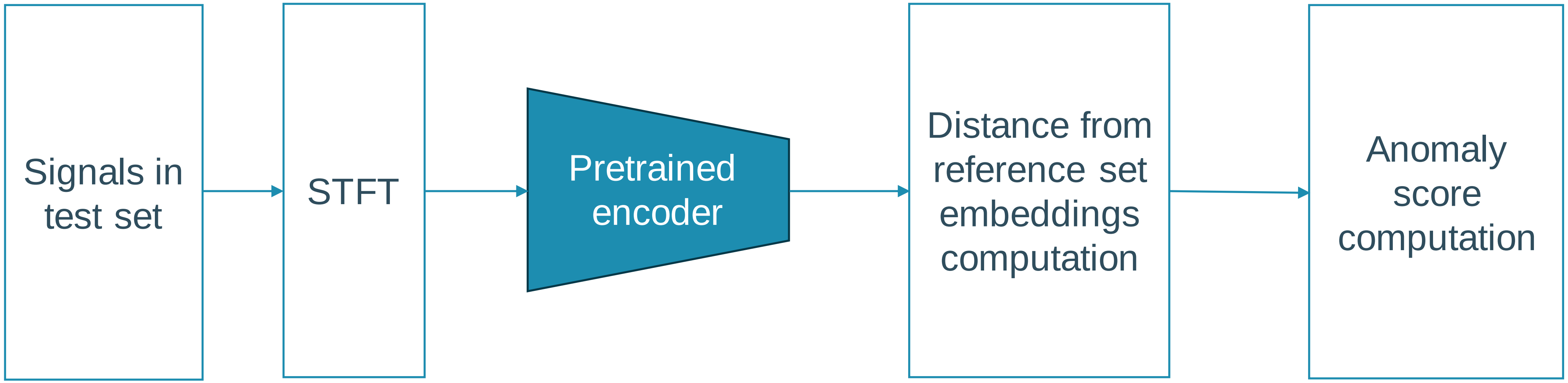
Training procedure



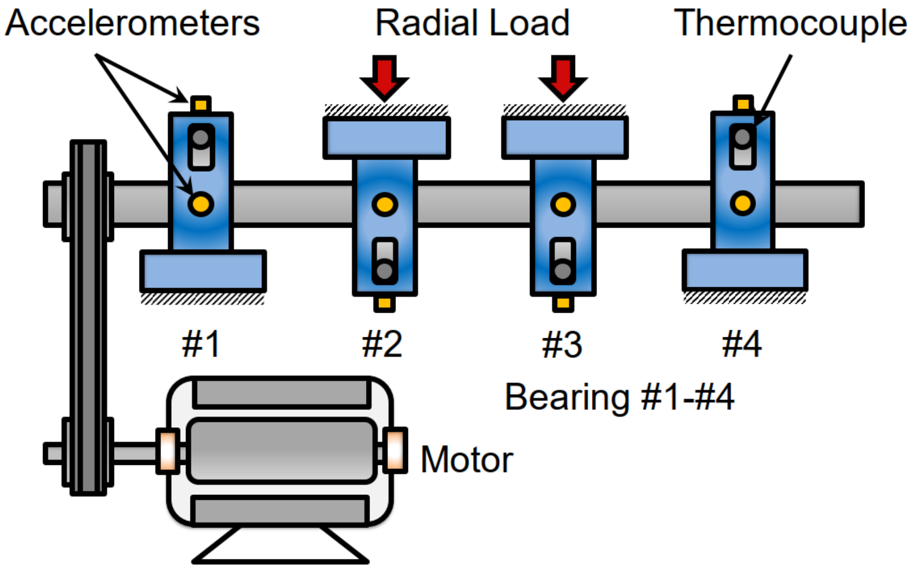
Threshold computation



Anomaly scores computation



IMS dataset



Run-to-failure experiment:
Test stopped when the accumulation of debris on a magnetic plug exceeded a certain level.
Fixed speed and load.

	# samples	#channels	#bearing failing	#failure type
Test 1	2187	8	3,4	Inner race, roller element
Test 2	984	4	1	Outer race
Test 3	6324	4	3	Outer race

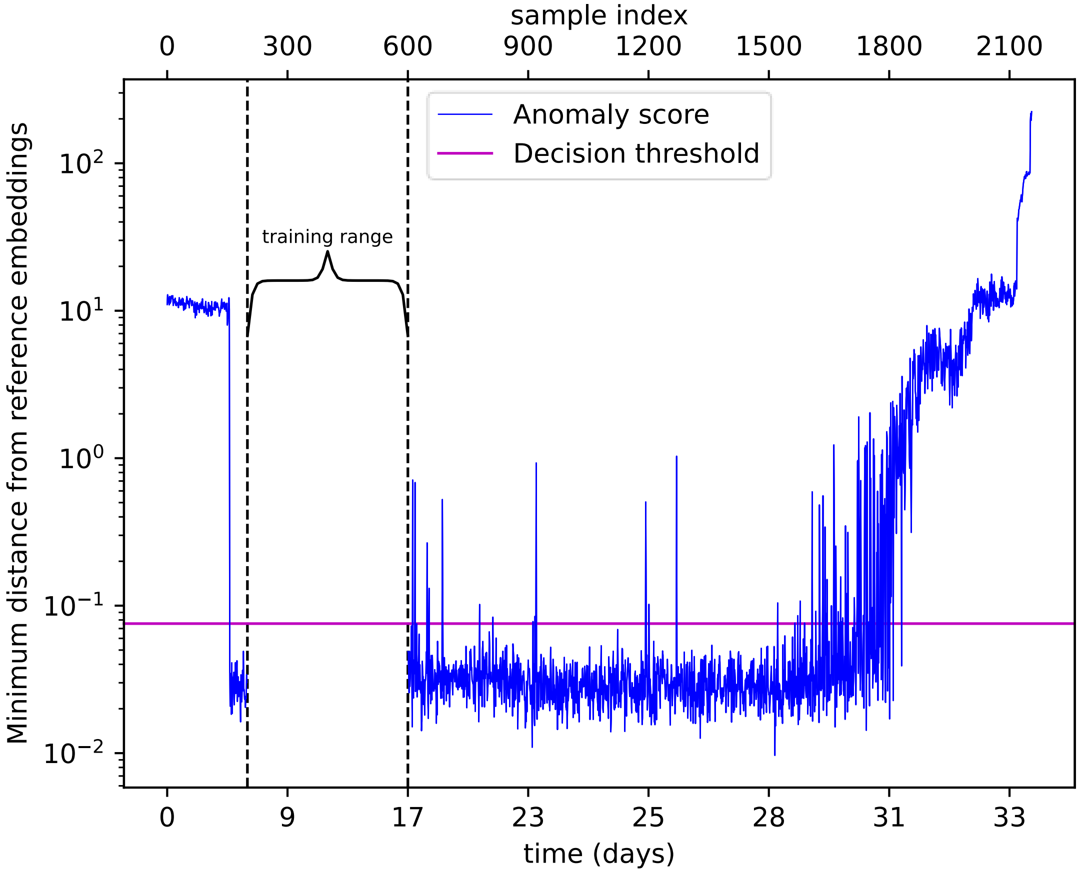
Fault recognition strategy

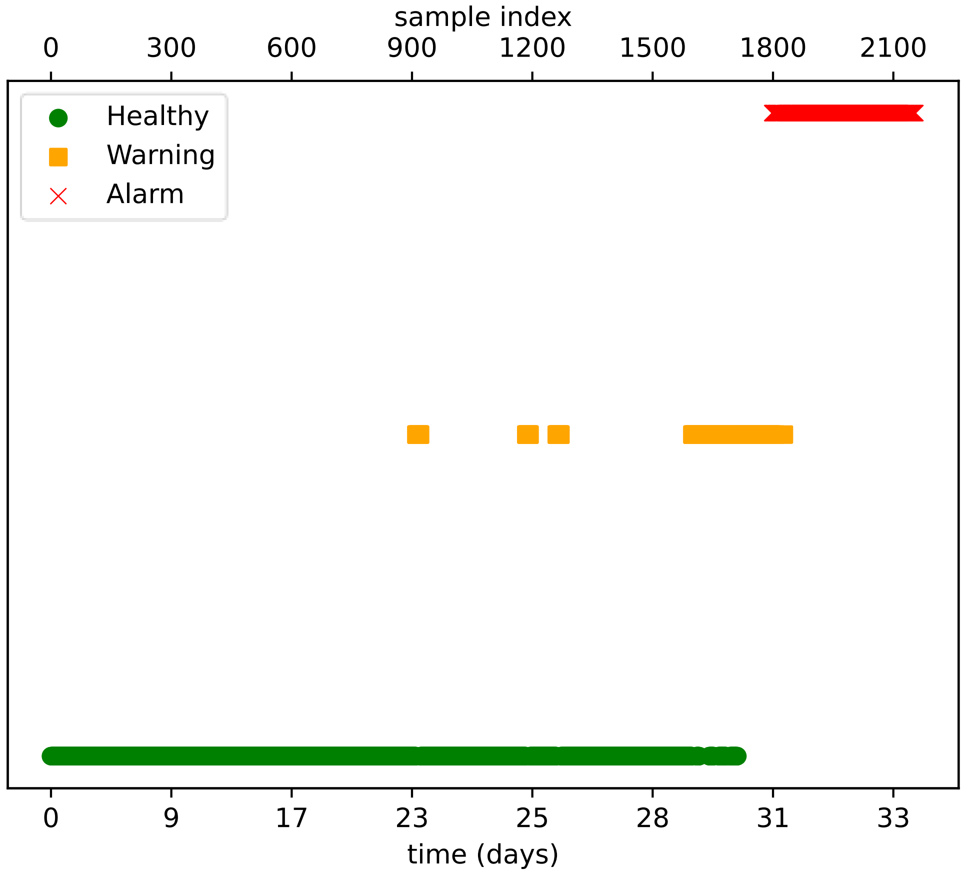
A moving window on the time history of the computed anomaly scores is considered

(1) 50% or more of the distances in the window are above the threshold.
(2) 50% or more of the distances in the window continuously pass the threshold.
(3) The average distance of the data in the window is equal or greater than the threshold.

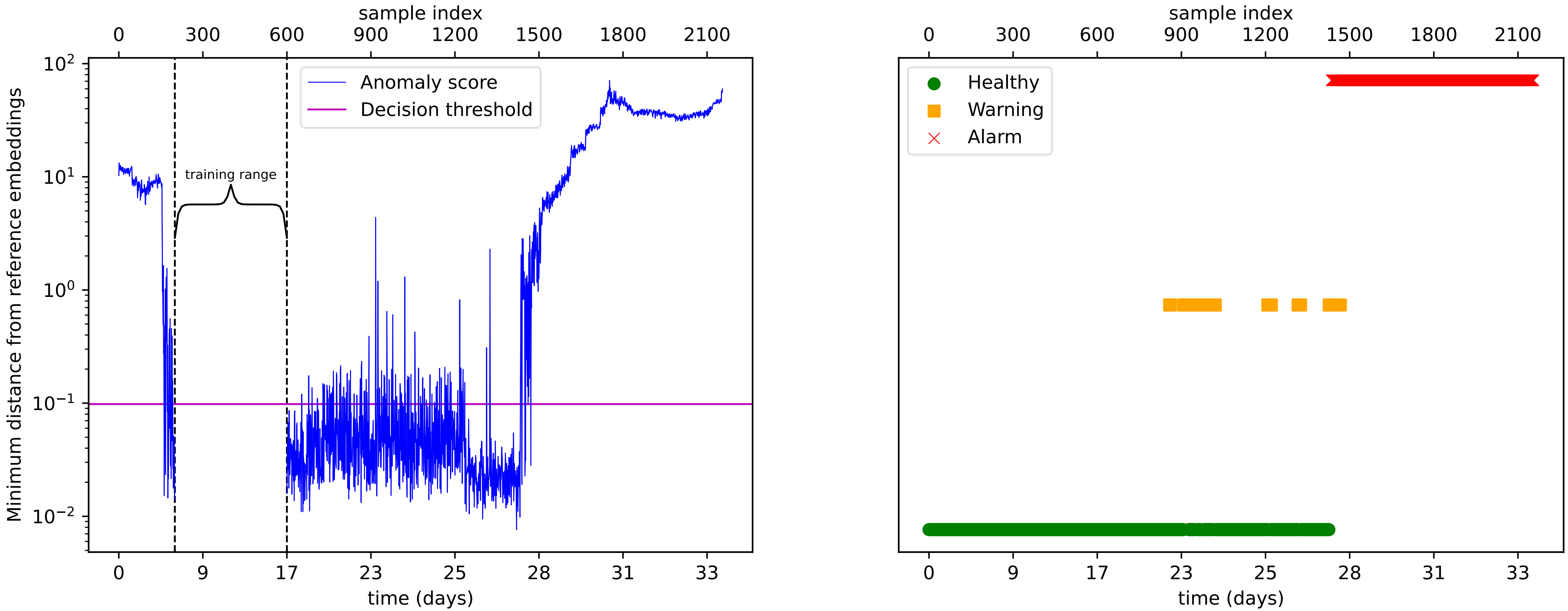
If all conditions are satisfied → Fault status ✖
If one or two conditions are satisfied → Alarm status
If one or two of the conditions is satisfied → Healthy status

Sensor level results bearing 3 dataset 1

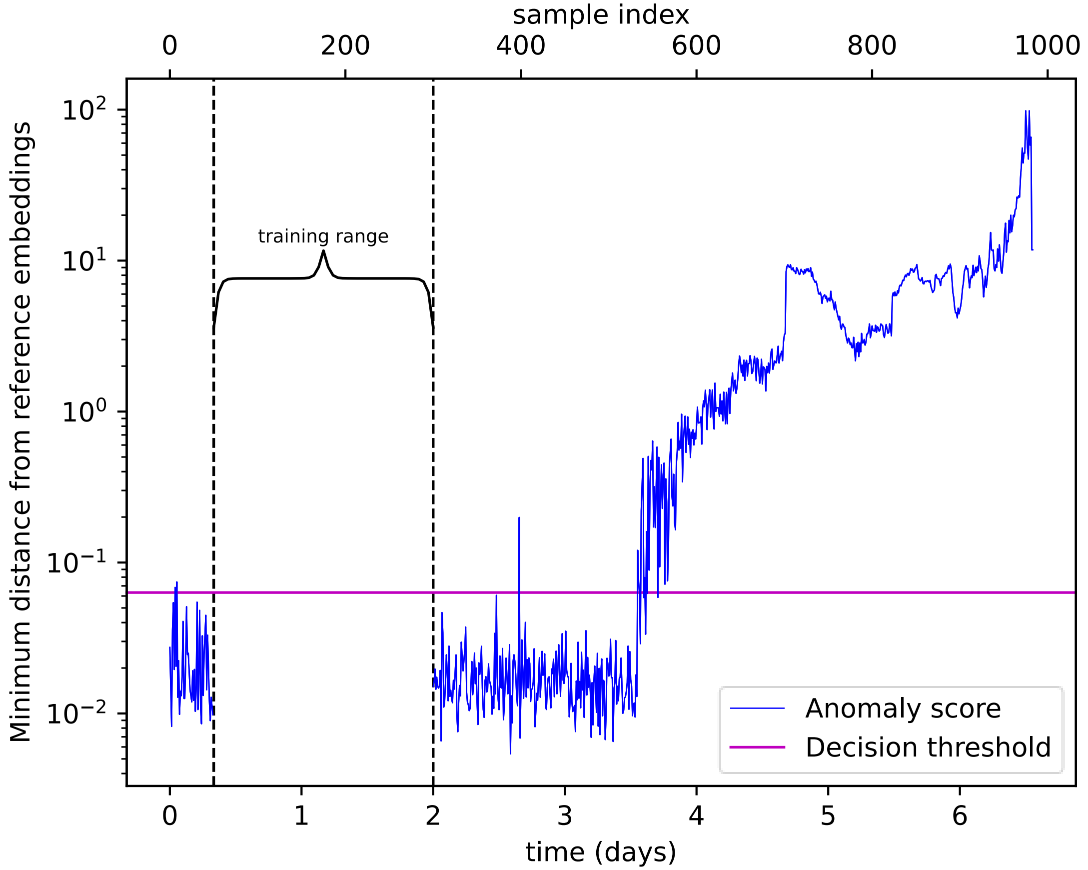


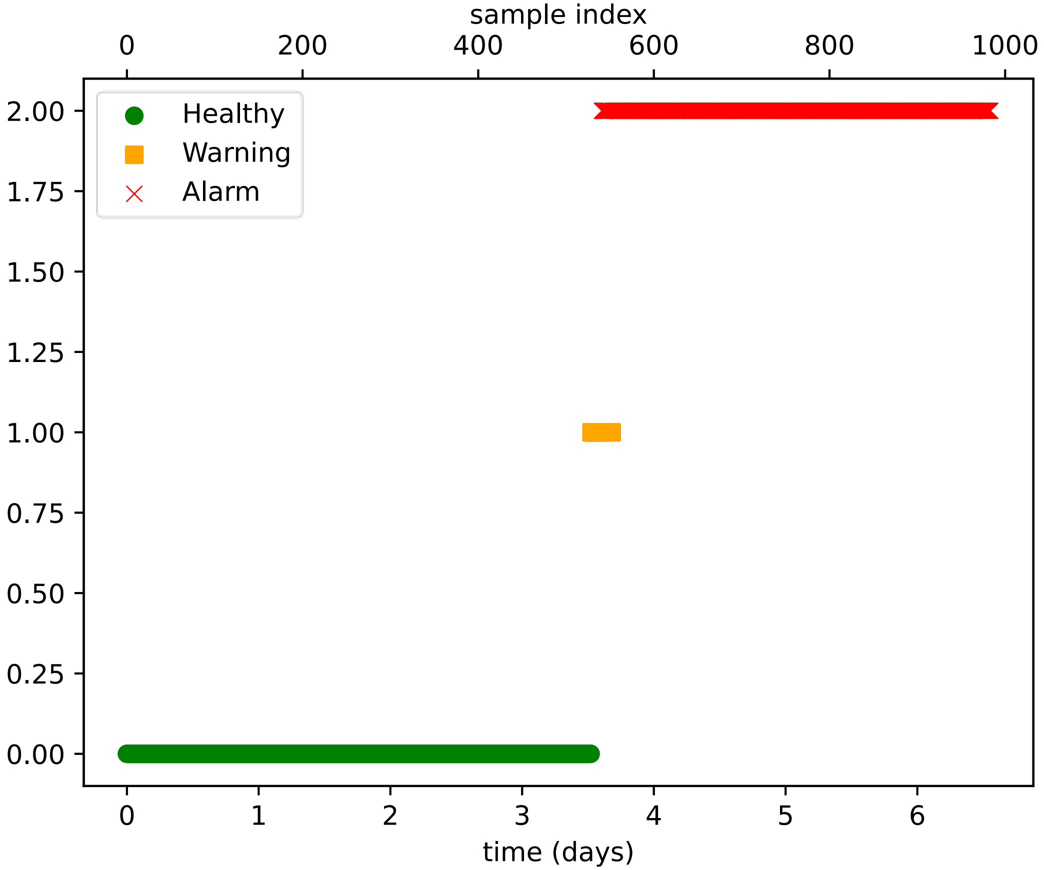


Sensor level results bearing 4 dataset 1

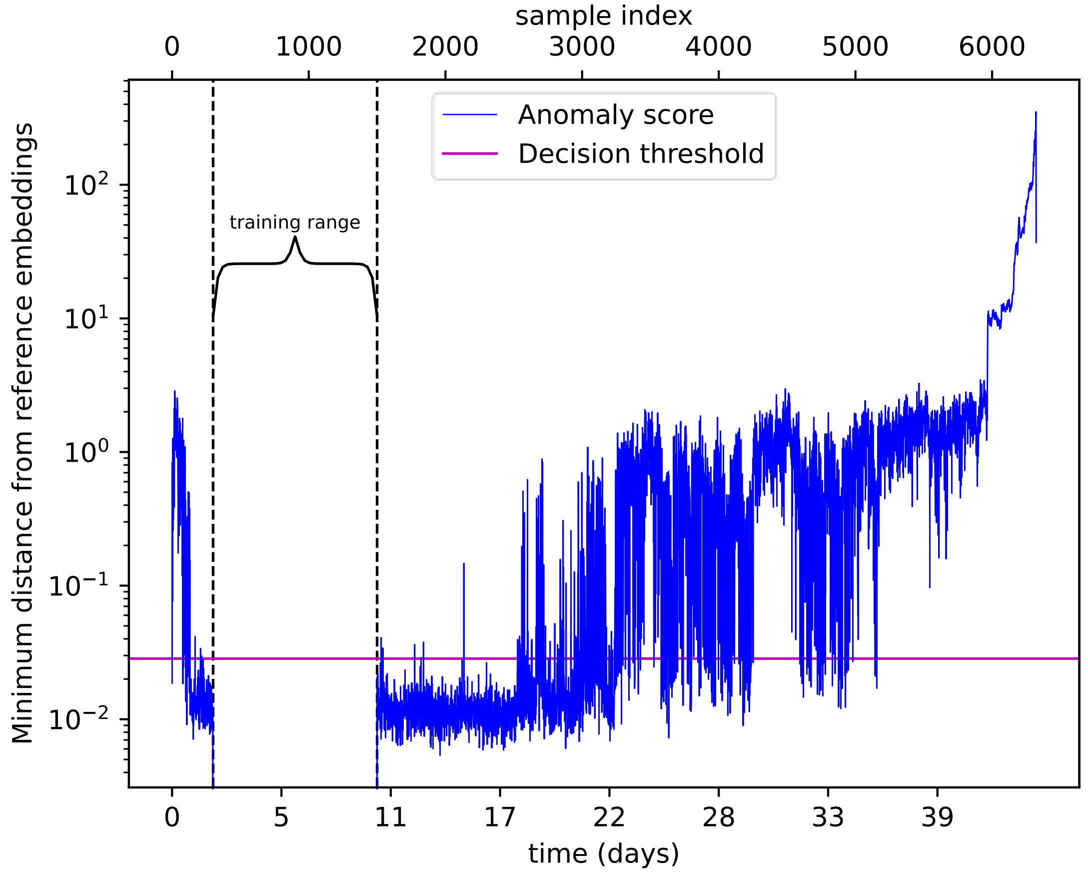


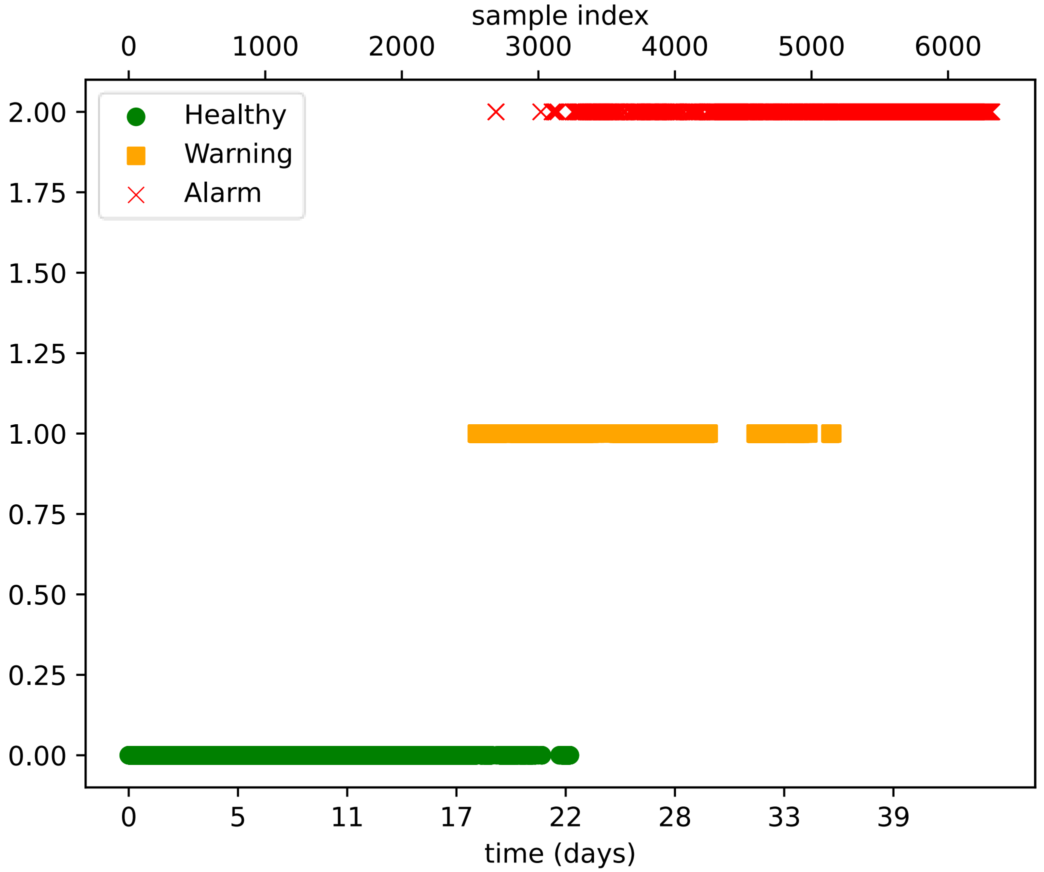
Sensor level results bearing 1 dataset 2



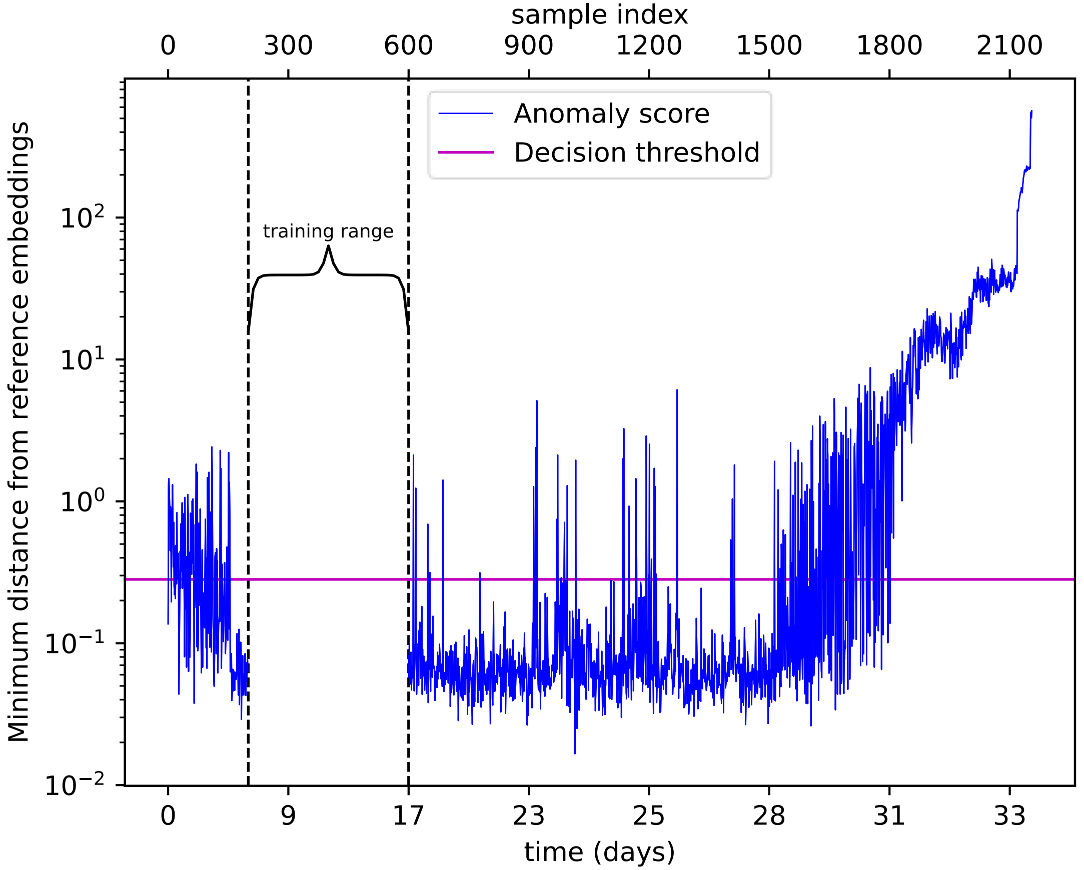


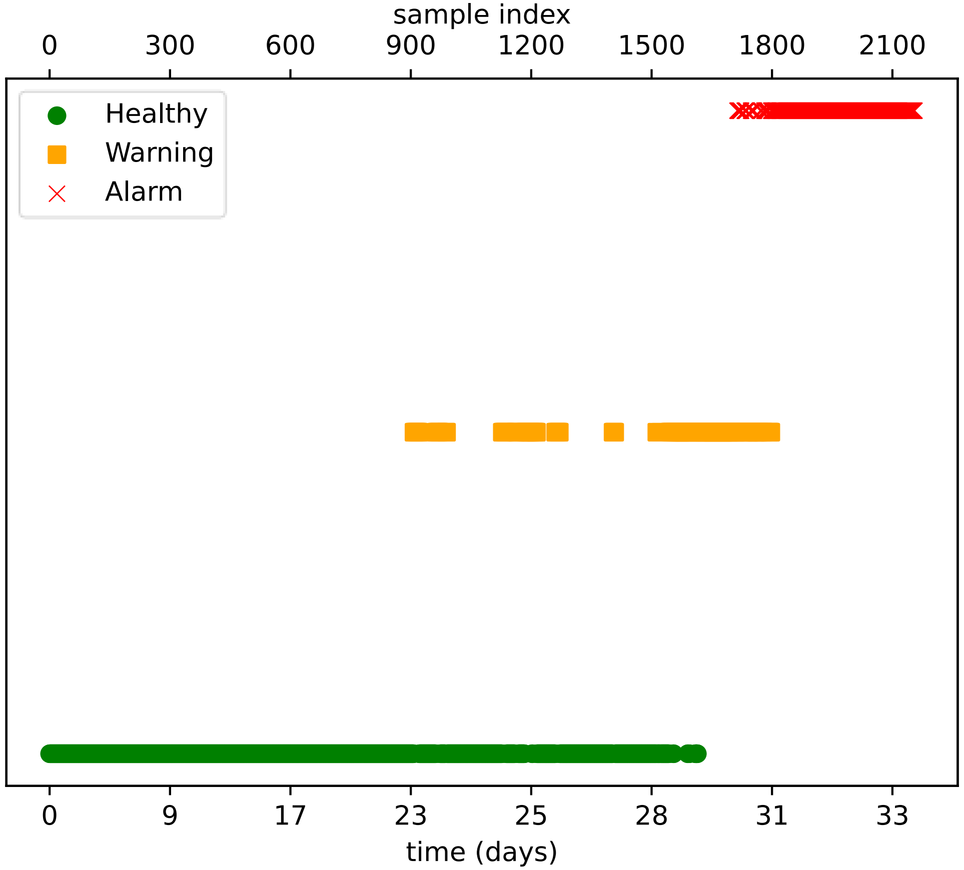
Sensor level results bearing 3 dataset 3





Machine level results bearing 3 dataset 1





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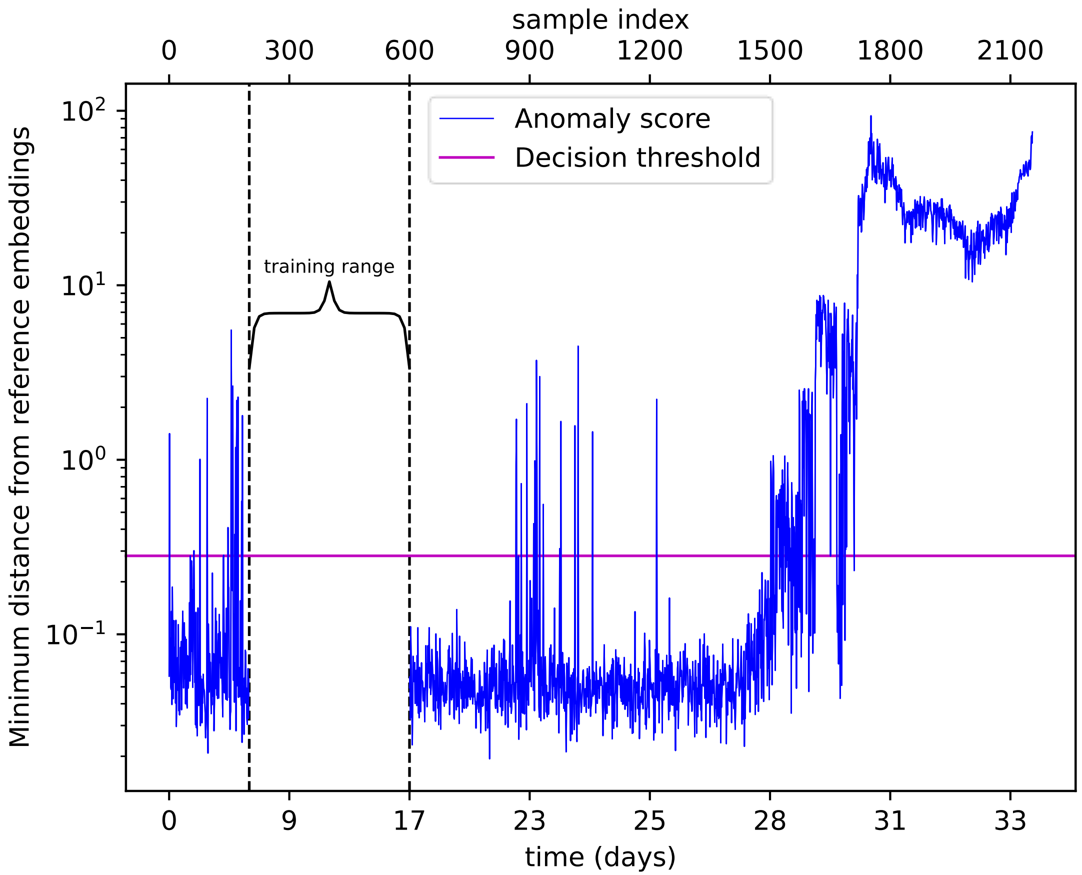
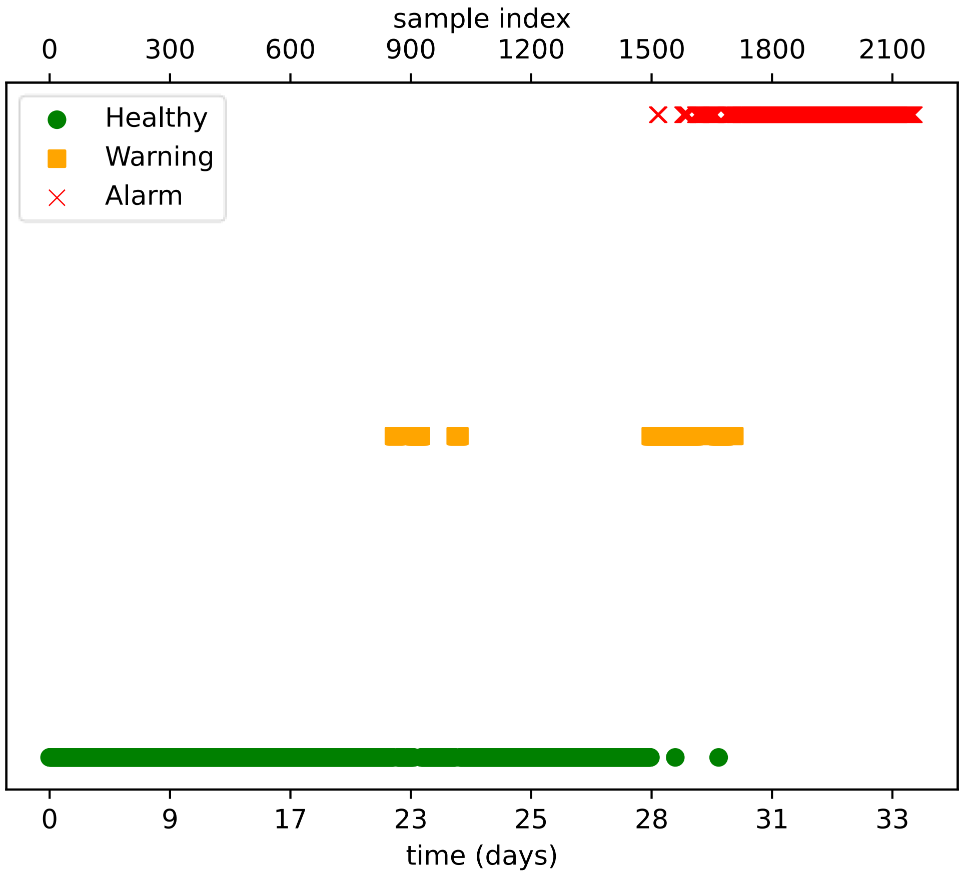
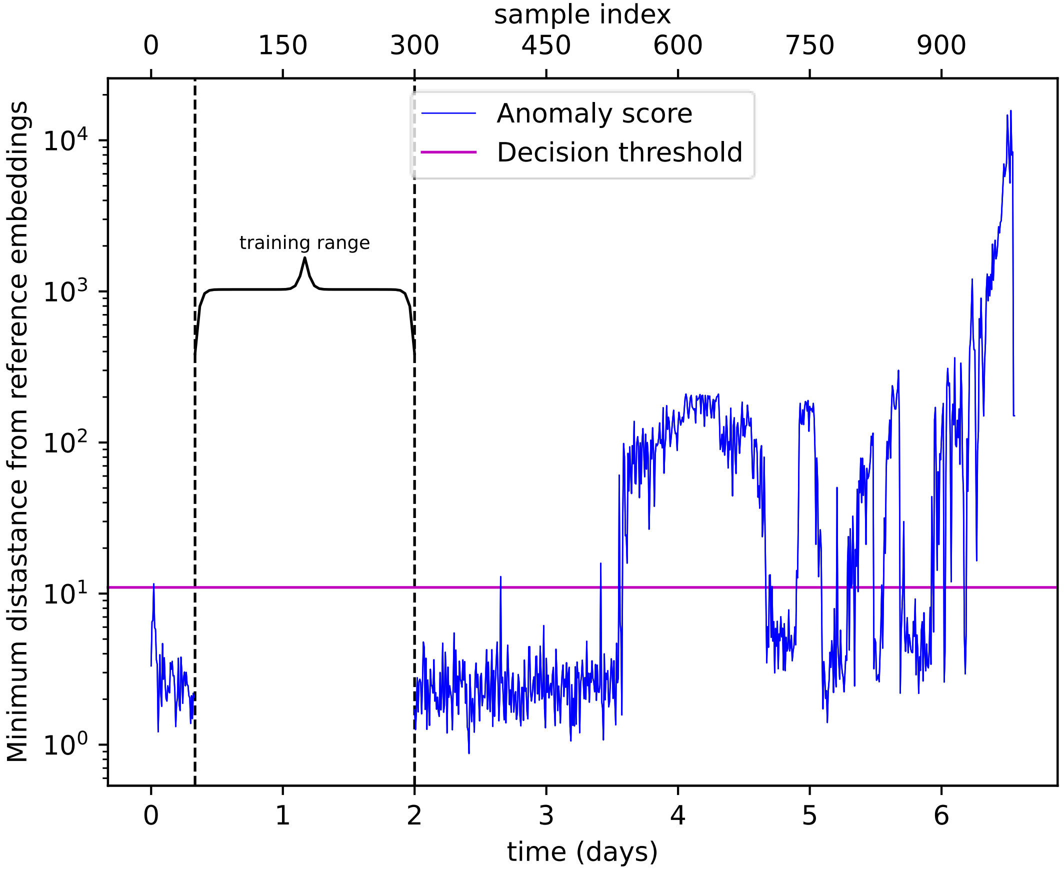
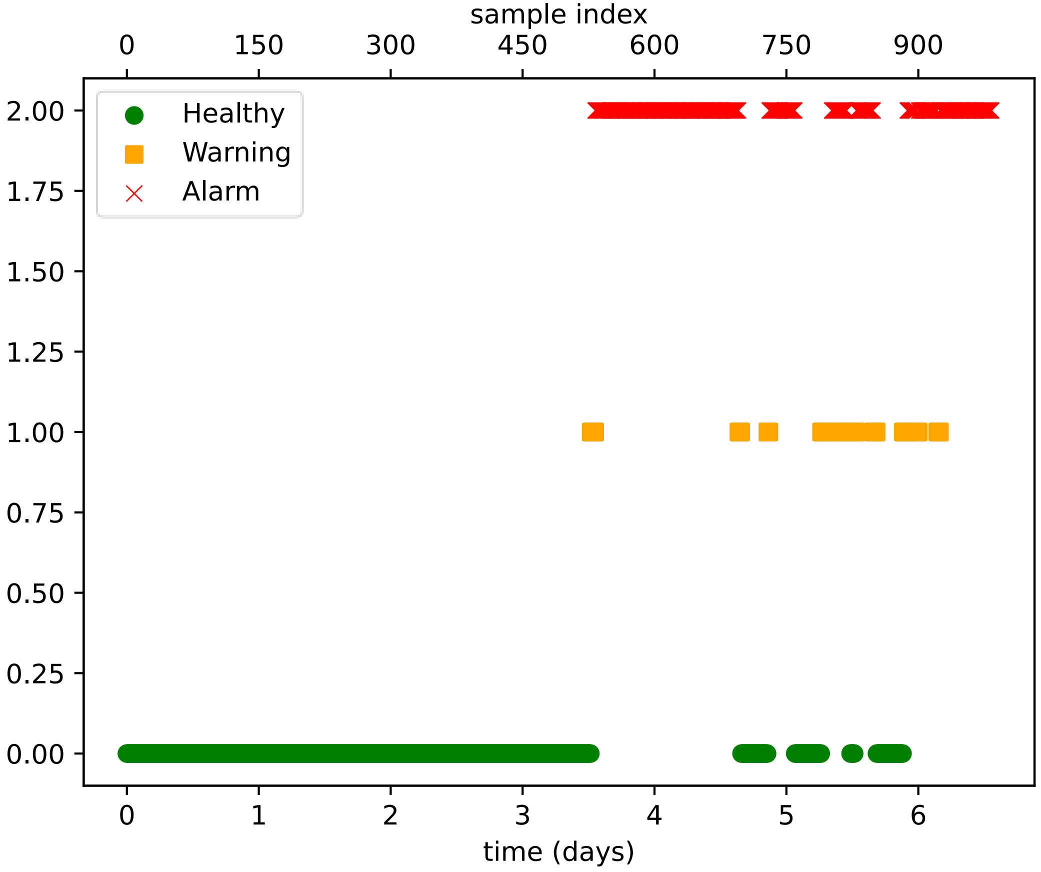


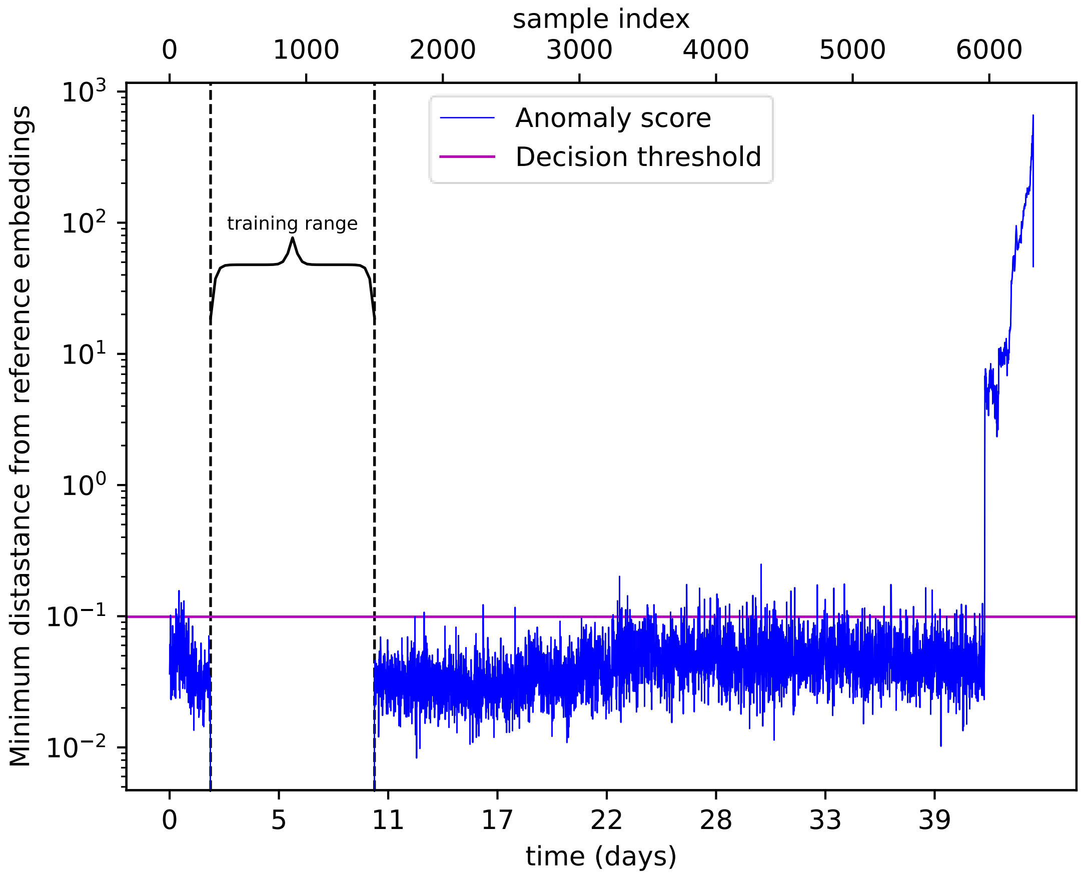


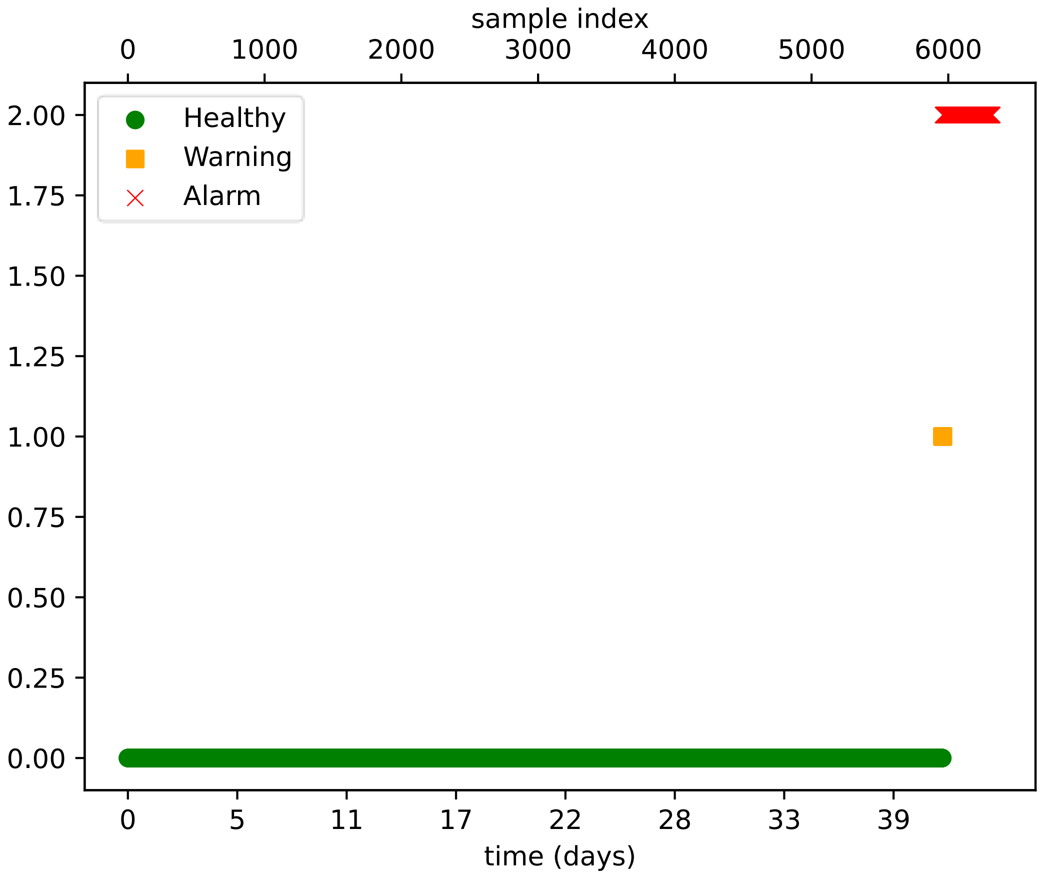
Machine level results bearing 1 dataset 2





Machine level results bearing 3 dataset 3





Conclusion

- In this study, a new methodology for early fault detection from vibration signals has been proposed
- A distance metric is enforced with a cycle consistency loss optimization during training
- The results show that the methodology can be applied on a limited amount of training data and that allows easily comparison between vibration signal to measure (dis)similarity

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