ETH zürich

Intelligent Maintenance Systems

Contrastive Feature Learning for Fault Detection and Diagnostics

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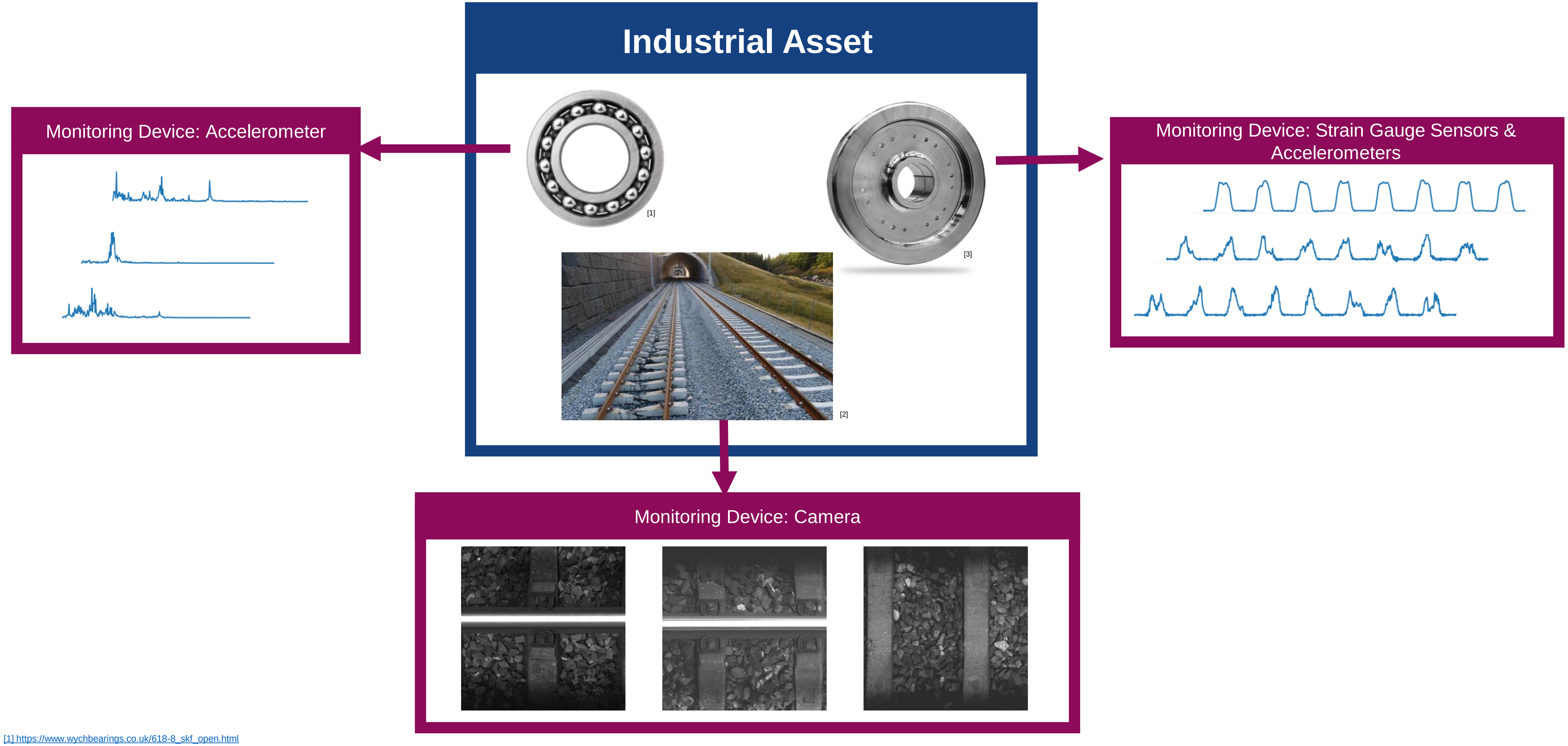
Condition Monitoring Data



[1] https://www.wychbearings.co.uk/618-8_skf_open.html
[2] https://www.emag.com/workpieces/railway-wheel.html
[3] https://skandbaunews.e-ls.de/2017/09/29/gleisbau-26-500-neu-eingebaute-schwellen-zerstoert/

Factors of Variations in Condition Monitoring Data

Distinguishing these factors can be difficult

Controlable Factors	Uncontrolable Factors	Health Factors
Operating Conditions, New Components, …	Environmental Factors, …	Fault Types, Fault Severities, …

Different loads

Different loads, velocities

Ambient Temperature

Lighting, Background

Faults are rare

Fault data not available

Often the available dataset is not representative!

Data-driven fault detection and diagnostics model fail!

Objective

Objective 1:

Invariance to any fluctuation caused by «other» factors

Controlable Factors

Operating Conditions, …

Uncontrolable Factors

Environmental Factors, …

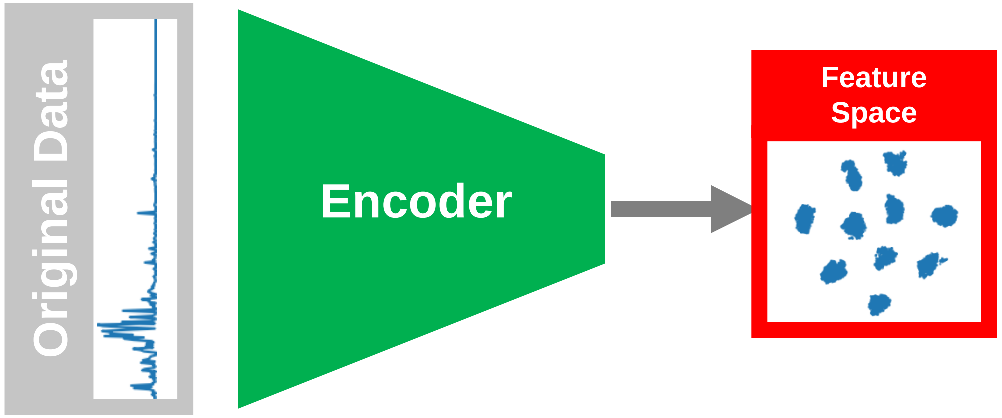
Objective 2:

Sensitivity to Faults

Health Factors

Fault Types & Severities, …

Feature Learning



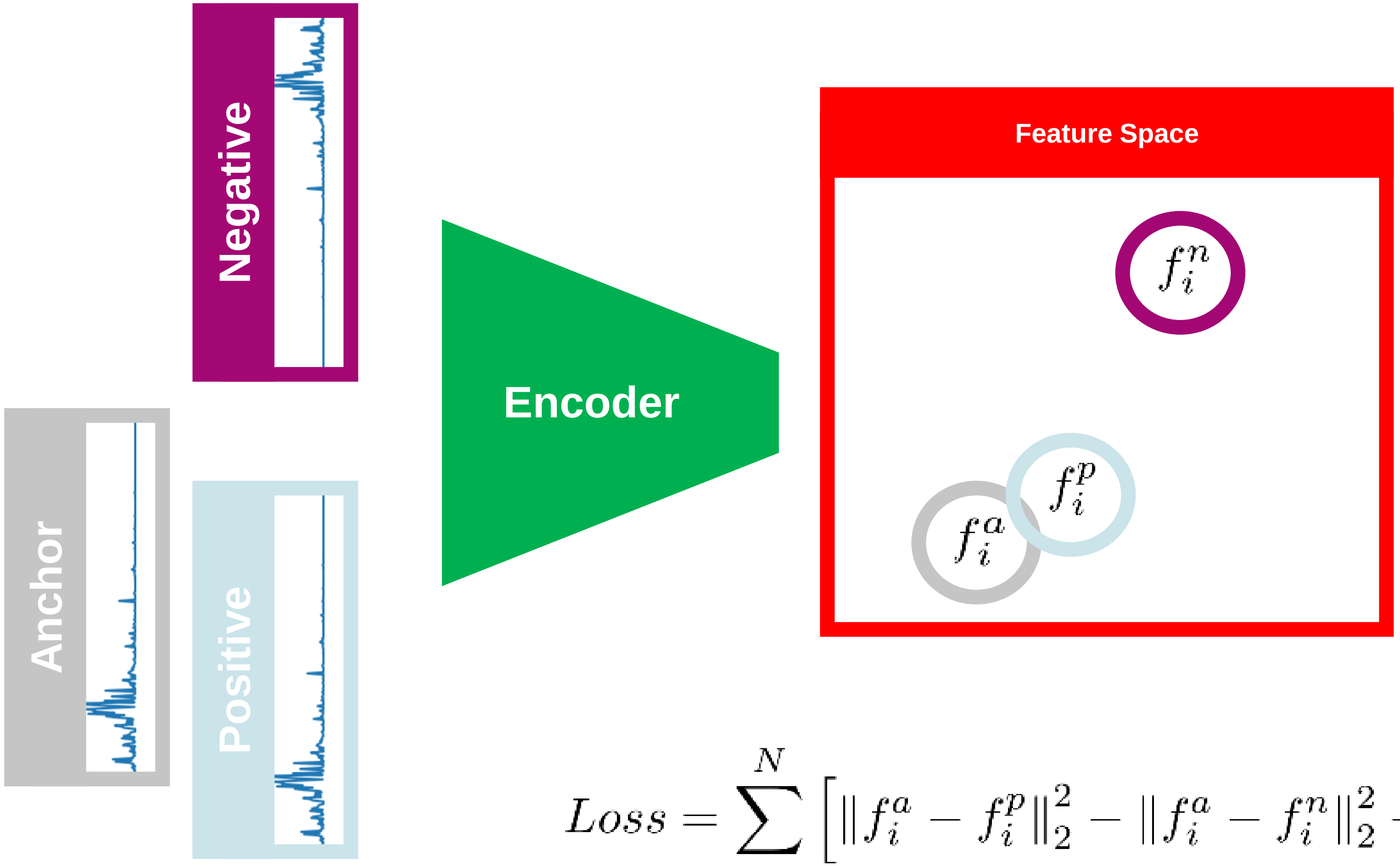
Objective 1:

Model invariant to "other" factors

Objective 2:

Model sensitive to faults

Contrastive Feature Learning – Triplet Loss



Objective 1:

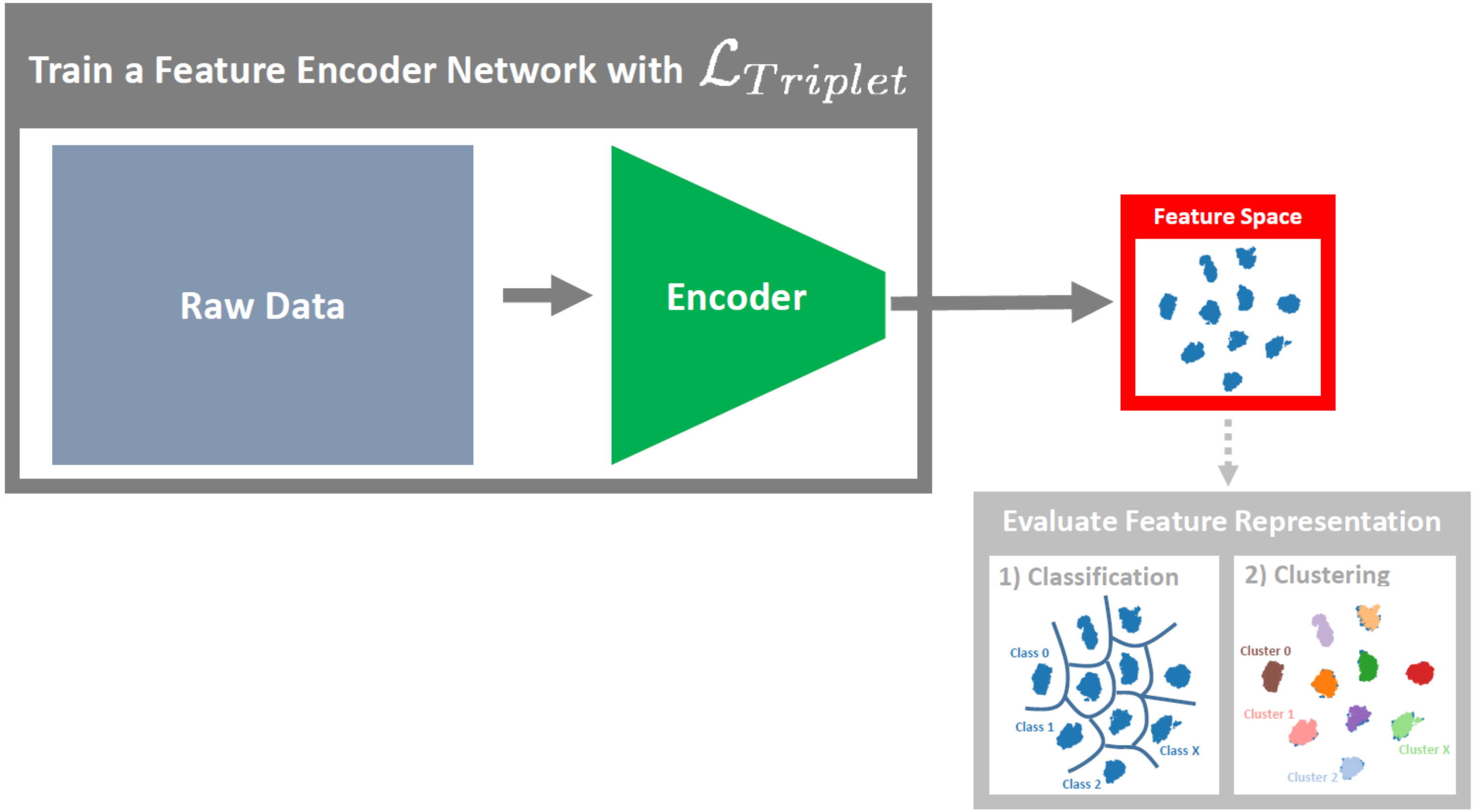
Model invariant to "other" factors

Objective 2:

Model sensitive to faults

$$Loss = \sum_{i=1}^{N} \left[\| f_i^a - f_i^p \|_2^2 - \| f_i^a - f_i^n \|_2^2 + \alpha \right]_+$$

Methodology



Objective 1:

Model invariant to "other" factors

Objective 2:

Model sensitive to faults

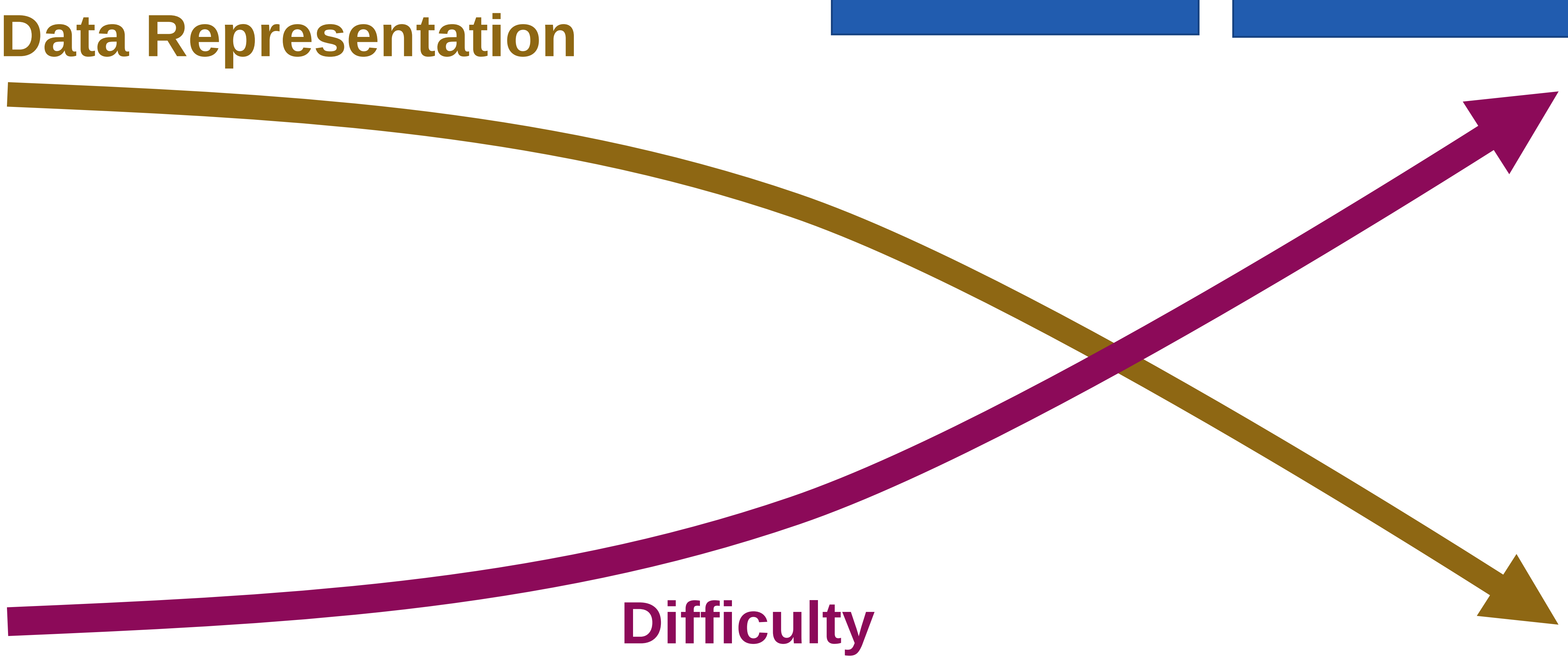
Applications

Objective 1:

Model invariant to “other” factors

Objective 2:

Model sensitive to faults



Applications

Objective 1:

Model invariant to "other" factors

Objective 2:

Model sensitive to faults

Sufficient data from «other» factors

All Fault Data Available

Limited data from «other» factors

Limited fault data

Limited data from «other» factors

No Faults Data

Difficulty

Applications

Objective 1:

Model invariant to “other” factors

Objective 2:

Model sensitive to faults

Classification

Sufficient data from «other» factors

All Fault Data Available

Limited data from «other» factors

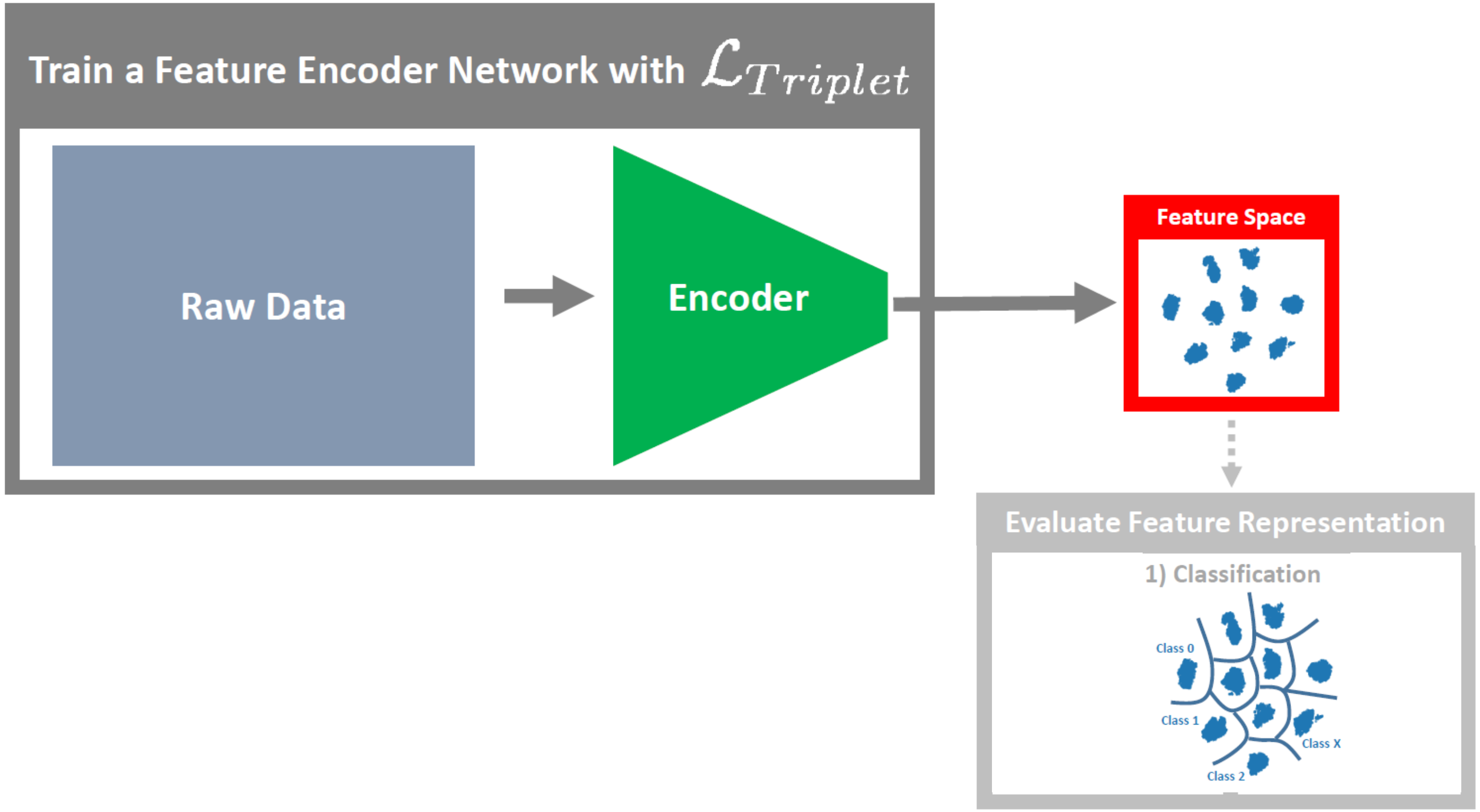
Limited fault data

Limited data from «other» factors

No Faults Data

Difficulty

Application 1: Defect Type Classification of Sleepers



Objective 1:

Model invariant to "other" factors

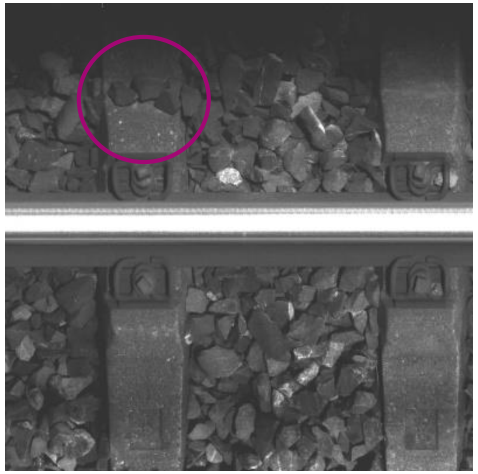
Objective 2:

Model sensitive to known faults

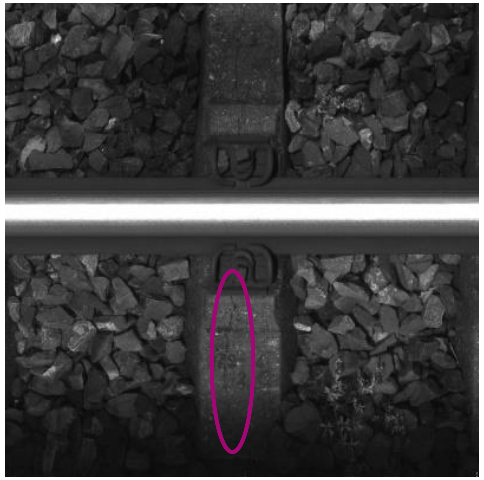
Scenario:

All fault types known

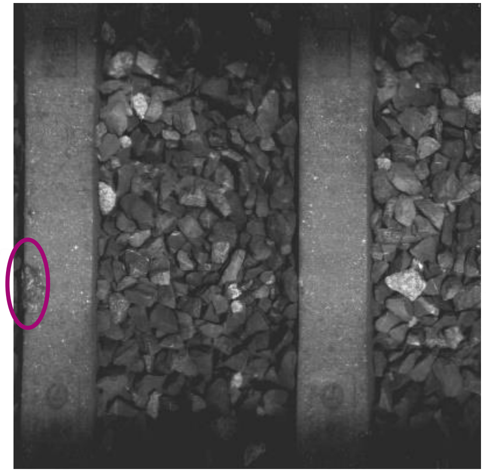
Application 1: Defect Type Classification of Sleepers



Healthy



Cracks



Spalling

Objective 1:

Model invariant to "other" factors

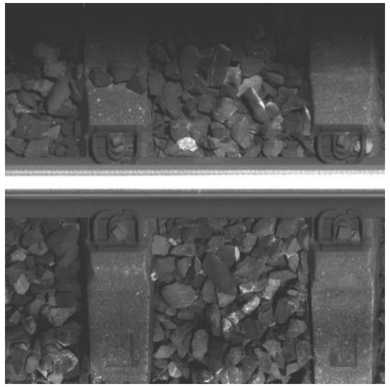
Objective 2:

Model sensitive to known faults

Scenario:

All fault types known

Results Application 1: Defect Type Classification of Sleepers



	Classification $\mathbb{T}$ acc
CLE	**81%**
TE	**94%**

+ 13% accuracy gain

Applications

Objective 1:

Model invariant to “other” factors

Objective 2:

Model sensitive to faults

Sufficient data from «other» factors

All Fault Data Available

Classification & Detection

Limited data from «other» factors

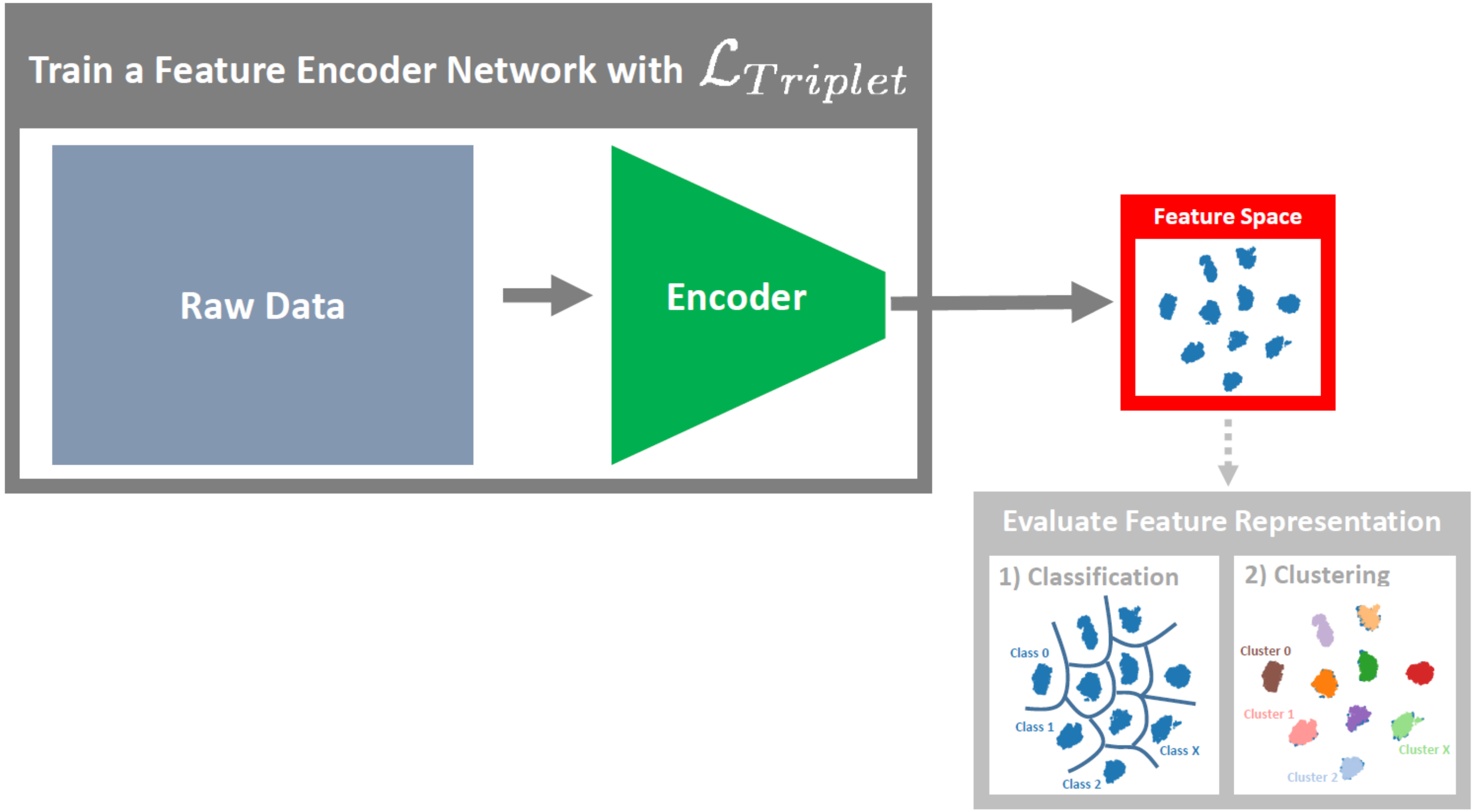
Limited fault data

Limited data from «other» factors

No Faults Data

Difficulty

Methodology



SVM

OPTICS

Objective 1:

Model invariant to "other" factors

Objective 2:

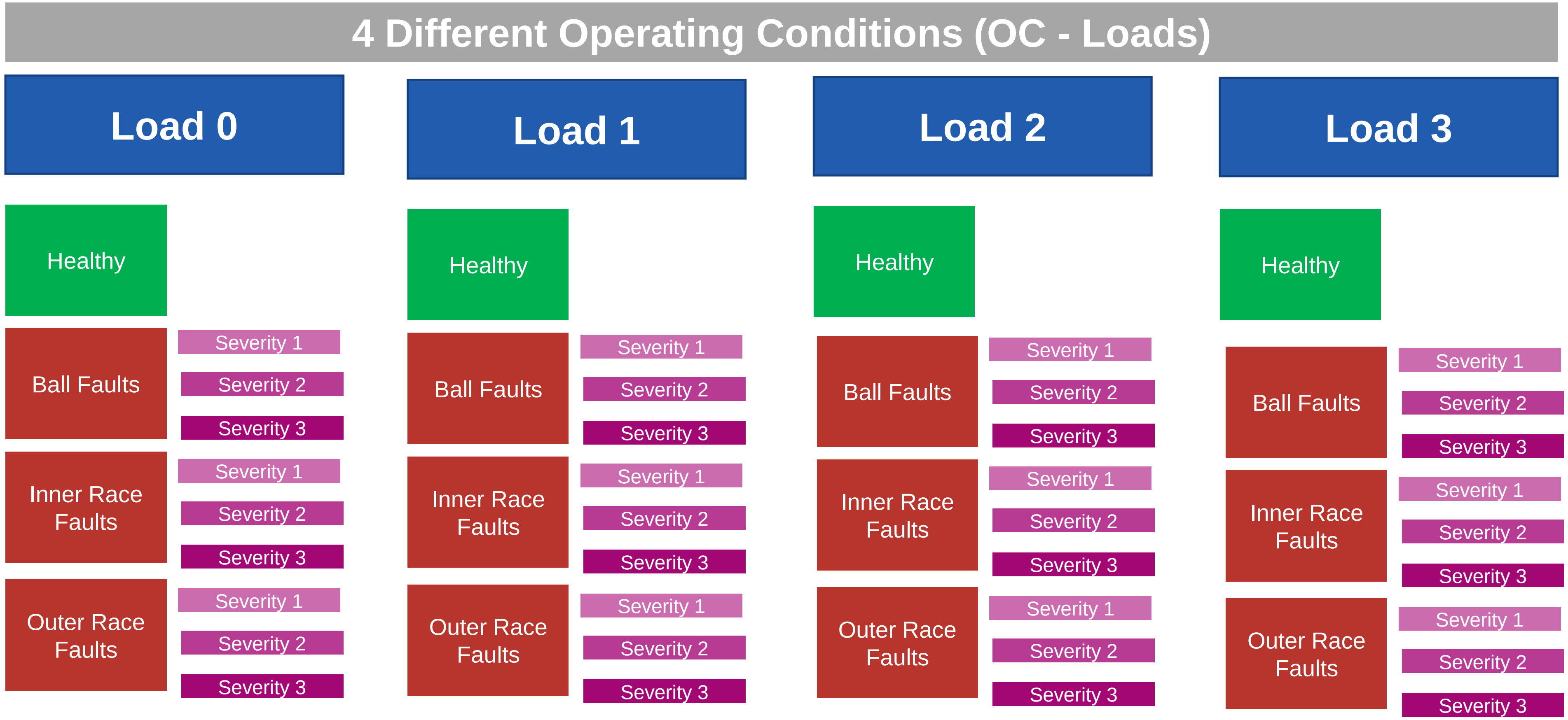
Model sensitive to known and novel faults

Scenario:

Limited data from «other» factors

Limited fault data

Experiments Conducted on CWRU Dataset (Bearing)



Case Studies

Objective 1:

Model invariant to “other” factors

Case Study 1:

Train Models on a subset of the OC

Load 0 **Load 2** **Load 3**

Load 0 **Load 2** **Load 3**

Load 1

Evaluate Models on
- Known OC
- Novel OC

Objective 2:

Model sensitive to known and novel faults

Case Study 2:

Train Models on a subset of the faults

Evaluate Models on
- Known Faults
- Novel Faults

Case Study 1: Classification and Clustering Results on Various Operating Conditions

Objective 1:

Model invariant to "other" factors

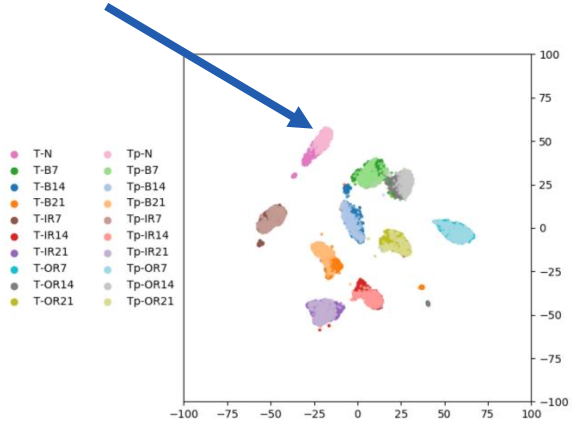
Case Study 1:

Train Models on a subset of the OC

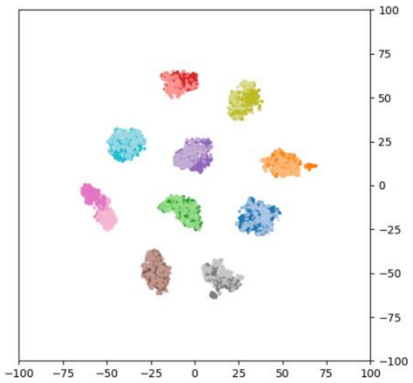
Evaluate Models on
- Known OC
- Novel OC

Softer Color represent data recorded under «novel» OC

Compact Class Clusters in the Triplet Encoder feature space despite changing OC



Classifier Encoder (CLE)



Triplet Encoder (TE)

TSNE Plots of the Different Feature Spaces

Case Study 1: Classification and Clustering Results on Various Operating Conditions

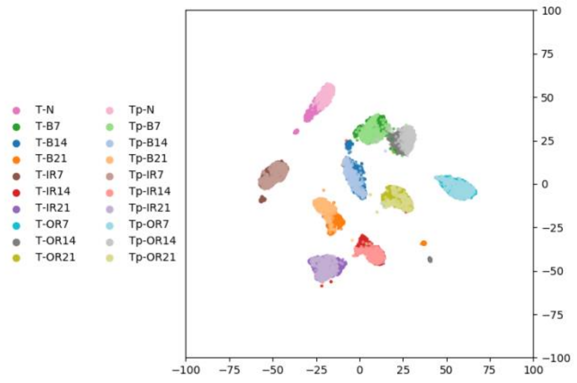
Objective 1:

Model invariant to "other" factors

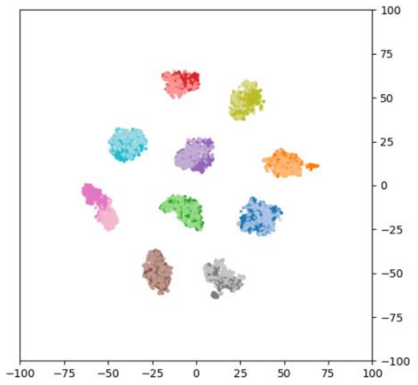
Case Study 1:

Train Models on a subset of the OC

Evaluate Models on
- Known OC
- Novel OC



Classifier Encoder (CLE)



Triplet Encoder (TE)

TSNE Plots of the Different Feature Spaces

Known OC

Novel OC

	Classification		Clustering—OPTICS	
	$\mathbb{T}$	$\mathbb{T}_p$	$\mathbb{T}$	$\mathbb{T} \cup \mathbb{T}_p$
	acc	acc	AMI	AMI
CLE	**100%**	99%	14%	23%
TE	**100%**	**100%**	**98%**	**97%**

Classification and Clustering Results

Case Study 2: Classification and Clustering Results with Novel Faults

Objective 2:

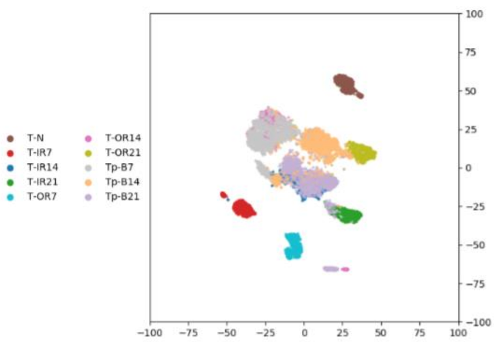
Model sensitive to known and novel faults

Case Study 2:

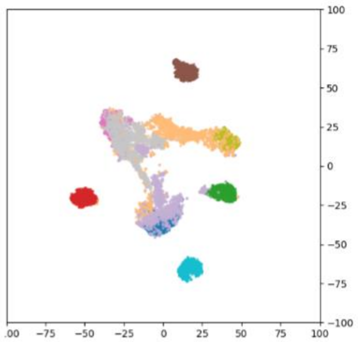
Train Models on a subset of the faults

Evaluate Models on
- Known Faults
- Novel Faults

94% of the detected outliers novel faults



Classifier Encoder (CLE)



Triplet Encoder (TE)

TSNE Plots of the Clustered Feature Spaces

Case Study 2: Classification and Clustering Results with Novel Faults

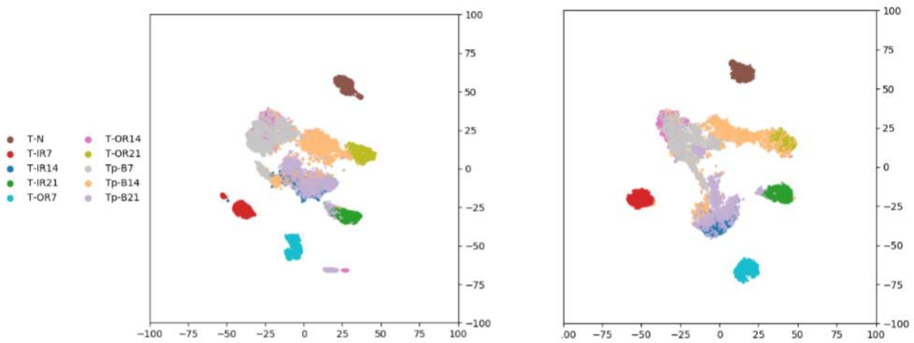
Objective 2:

Model sensitive to known and novel faults

Case Study 2:

Train Models on a subset of the faults

Evaluate Models on
- Known Faults
- Novel Faults



Classifier Encoder (CLE)

Triplet Encoder (TE)

TSNE Plots of the Clustered Feature Spaces

Known Faults

Novel Faults

	Classification		Clustering—OPTICS	
	$\mathbb{T}$	$\mathbb{T}_p$	$\mathbb{T}$	$\mathbb{T} \cup \mathbb{T}_p$
	acc	**acc**	**AMI**	**AMI**
CLE	**100%**	0%	7%	7%
TE	**100%**	0%	**96%**	**73%**

Classification and Clustering Results

Summary & Outlook

Objective 1:

Model invariant to “other” factors

Objective 2:

Model sensitive to faults

Anomaly Detection

Sufficient data from «other» factors

All Fault Data Available

Limited data from «other» factors

Limited fault data

Limited data from «other» factors

No Faults Data

Difficulty

Thank you!