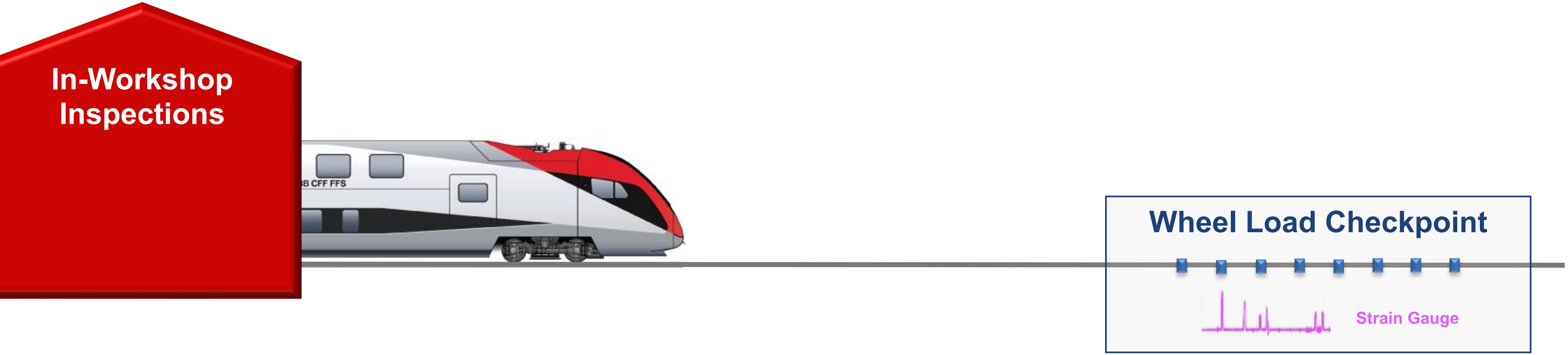
Chair of Intelligent Maintenance Systems

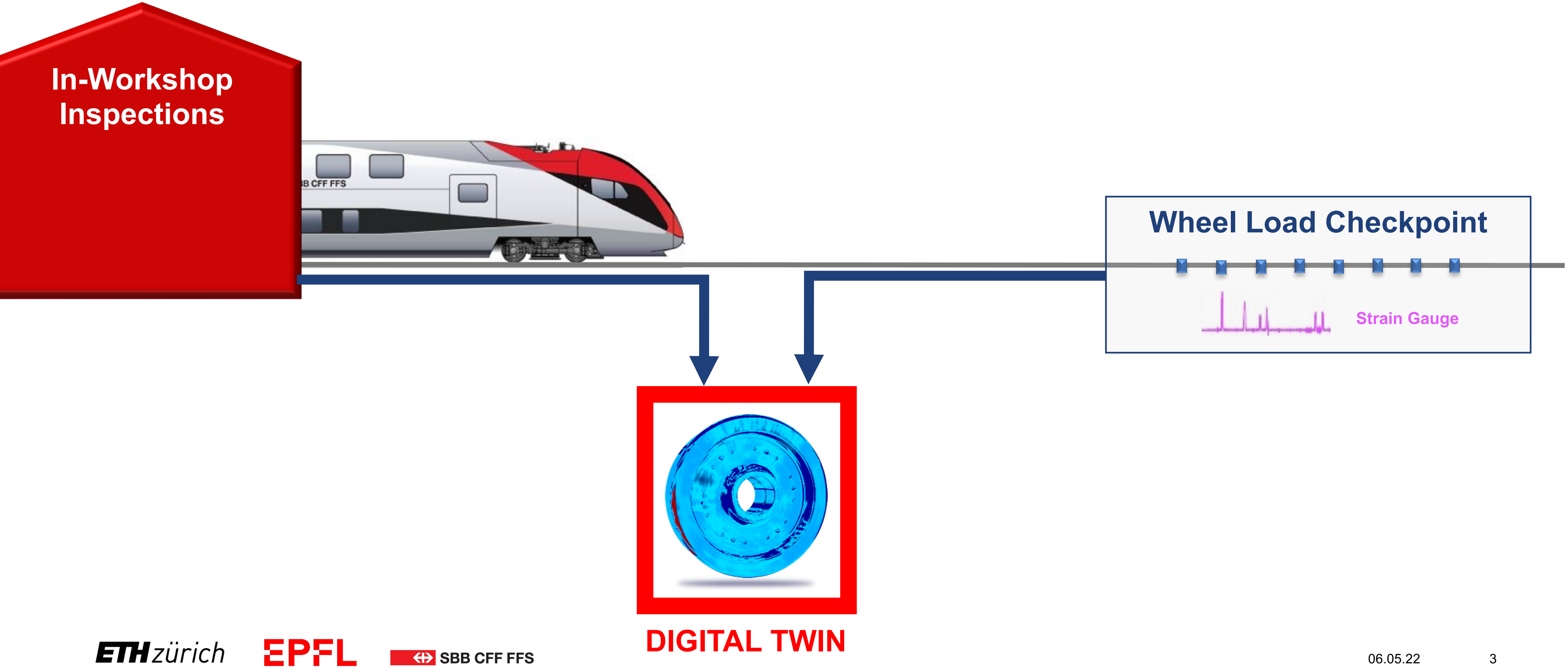
Towards a Data-driven Operational Digital Twin for Railway Wheels

Katharina Rombach, Dr. Gabriel Michau, Prof. Olga Fink

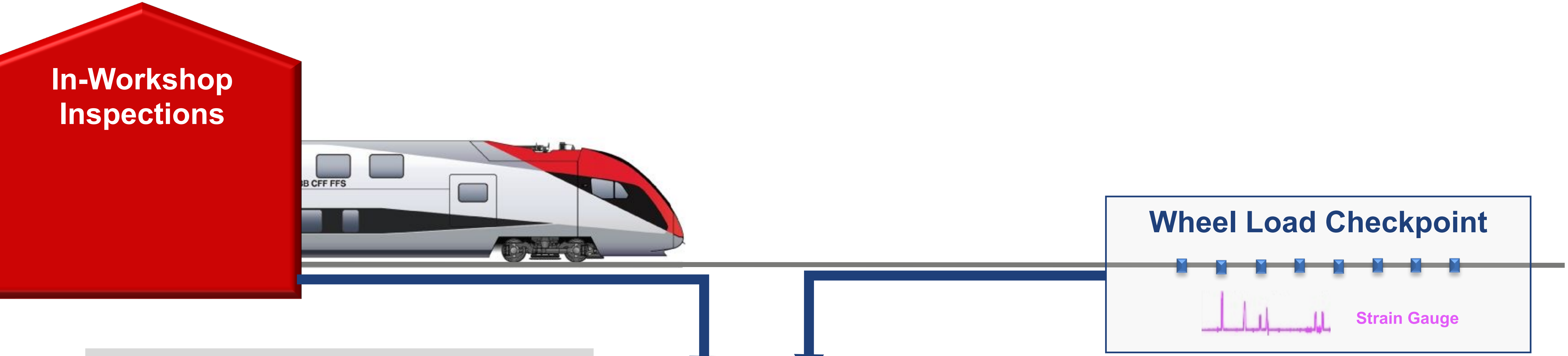
Wayside Monitoring of Railway Wheels

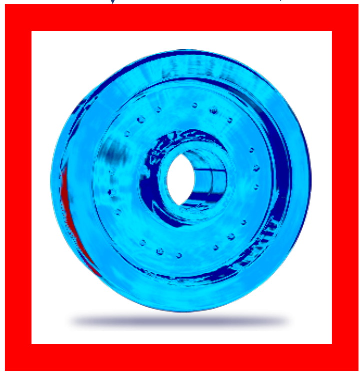


Wayside Monitoring Data to a Data-driven Digital Twin



Wayside Monitoring Data to a Data-driven Digital Twin





DIGITAL TWIN

Requires algorithms for

- **Fault Detection**
- **Fault Diagnostic**
- **Fault Evolution Prediction**

Challenges for Data-driven Solutions

Requires algorithms for

- **Fault Detection**
- **Fault Diagnostic**
- **Fault Evolution Prediction**

Health Factors

Fault Types, Fault Severities,
…

Faults are rare

Fault data not available

Challenges for data-driven solutions

Requires algorithms for

- **Fault Detection**
- **Fault Diagnostic**
- **Fault Evolution Prediction**

Different Factors of Variations in the Data

Health Factors

Fault Types, Fault Severities, …

Controlable Factors

Operating Conditions, New Components, …

Uncontrolable Factors

Environmental Factors, …

Faults are rare

Fault data not available

Different loads, velocities

Ambient Temperature

Challenges for data-driven solutions

Requires algorithms for

- **Fault Detection**
- **Fault Diagnostic**
- **Fault Evolution Prediction**

Distinguishing these factors can be difficult

Health Factors

Fault Types, Fault Severities, …

Controlable Factors

Operating Conditions, New Components, …

Uncontrolable Factors

Environmental Factors, …

Faults are rare

Fault data not available

Different loads, velocities

Ambient Temperature

Often the available dataset is not representative!

Data-driven fault detection and diagnostics model fail!

Objective

Objective 1:

Sensitivity to Faults

Health Factors

Fault Types & Severities, …

Objective 2:

Invariance to any fluctuation caused by «other» factors

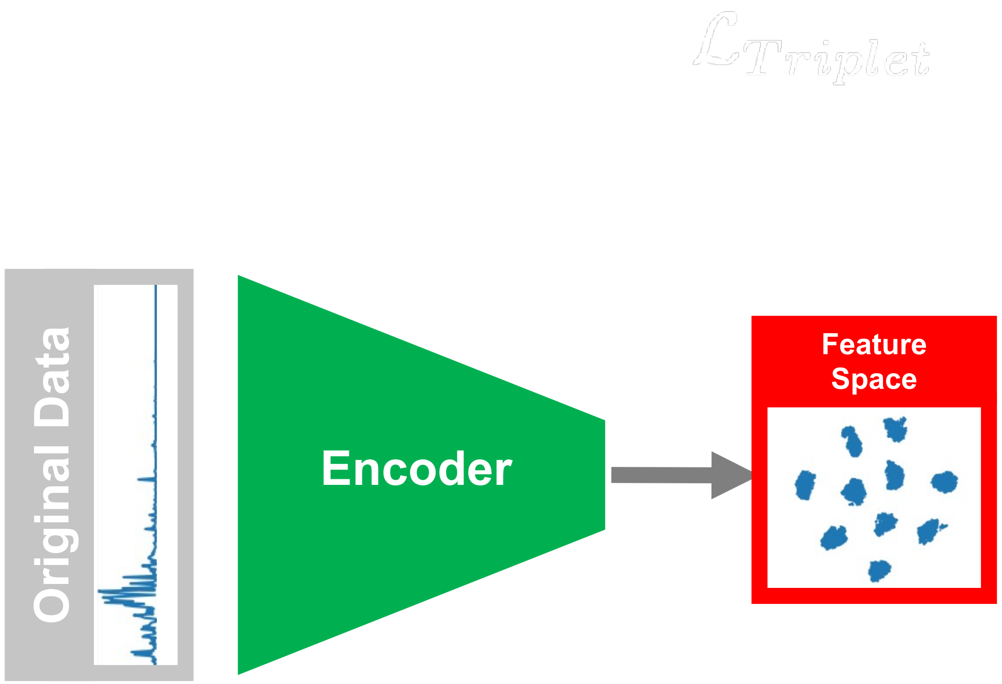
Controlable Factors

Operating Conditions, …

Uncontrolable Factors

Environmental Factors, …

Learn a Suitable Feature Representation



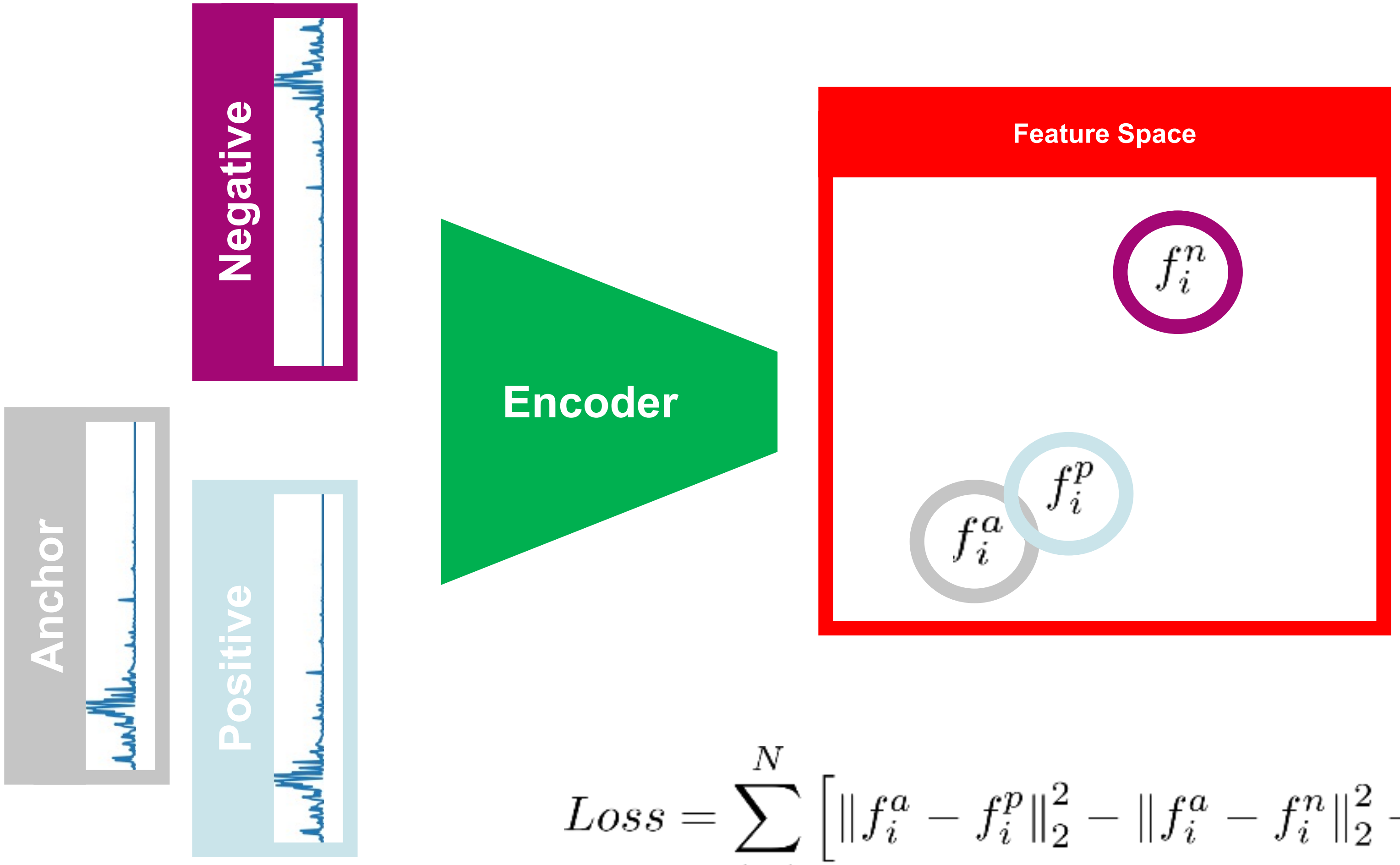
Objective 1:

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

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

Schroff, Florian, Dmitry Kalenichenko, and James Philbin. "Facenet: A unified embedding for face recognition and clustering." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2015.

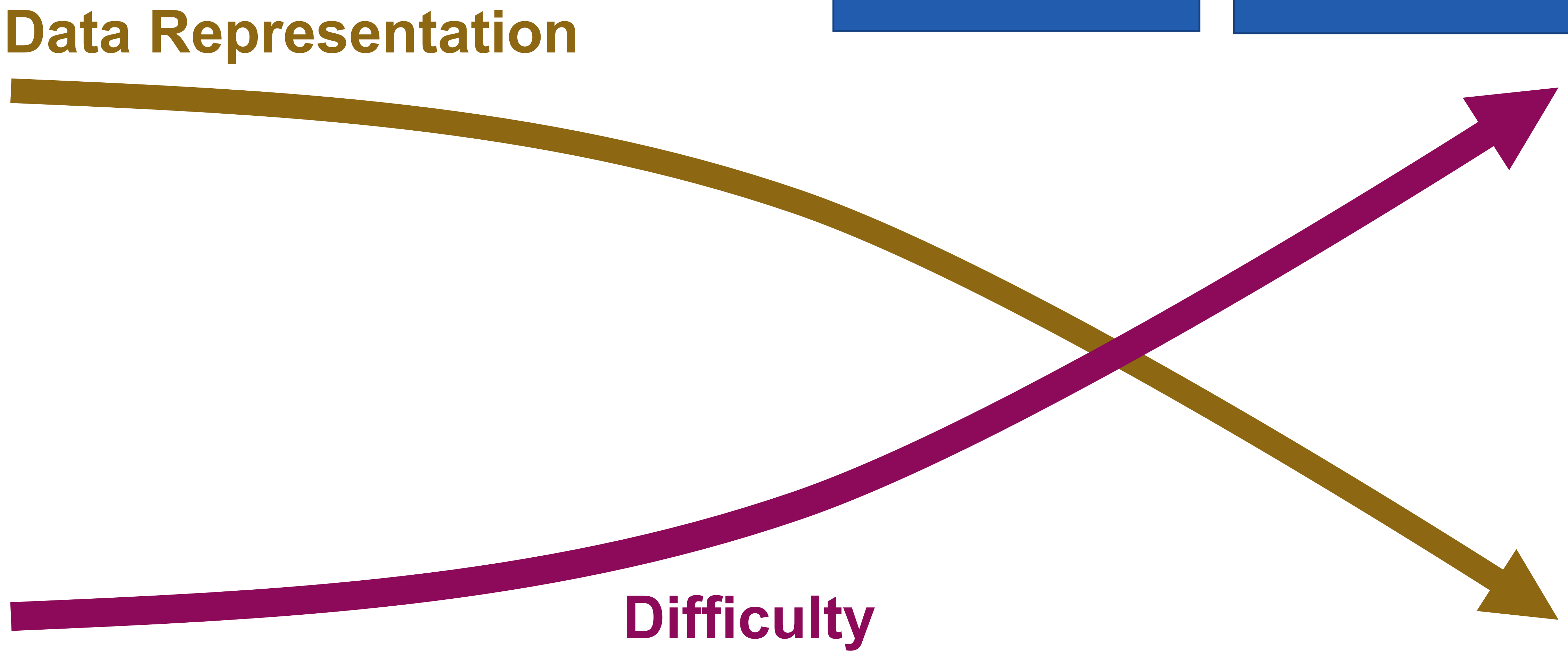
Challenge Contrastive Feature Learning

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

Sufficient data from «other» factors

All Fault Data Available

Classification & Detection

Limited data from «other» factors

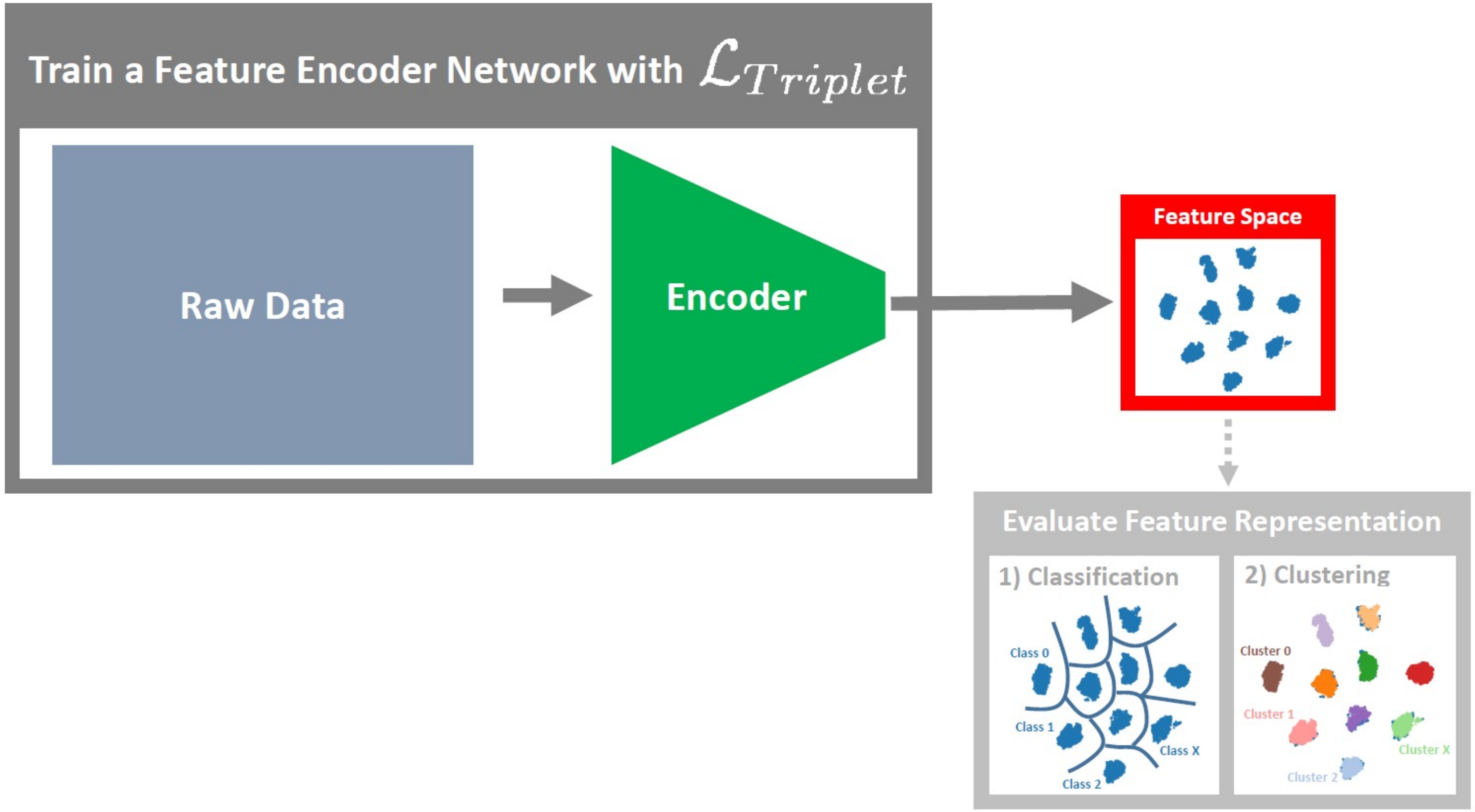
Limited fault data

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

Application on a bearing dataset (CWRU dataset)

Objective 1:

Model invariant to “other” factors

Case Study 1:

Train Models on a subset of the operating conditions (OC)

OC 0 | OC 2 | OC 3

OC 0 | OC 2 | OC 3 | OC 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

ETH zürich EPFL SBB CFF FFS

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

Objective 1:

Model invariant to “other” factors

Case Study 1:

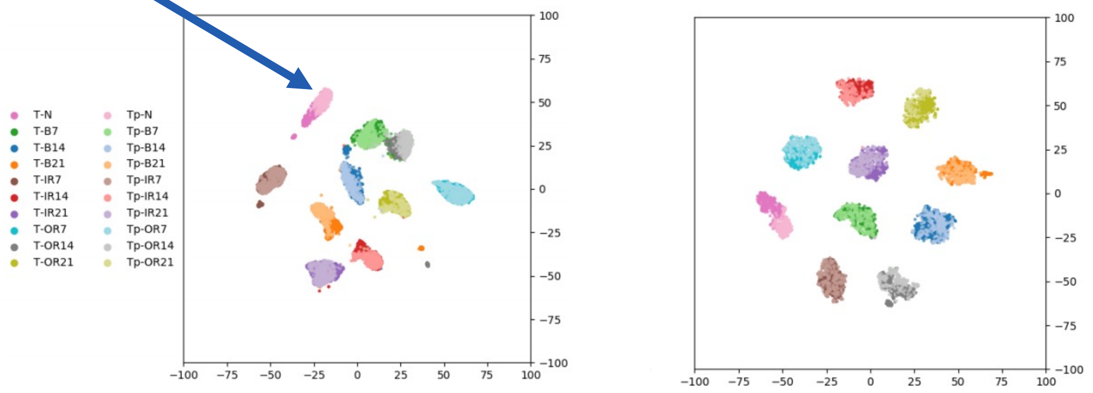
Train Models on a subset of the OC

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

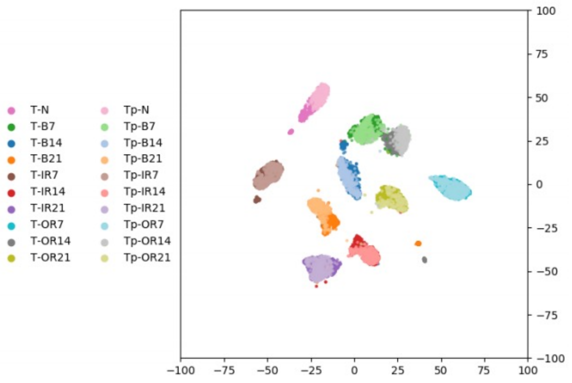
Objective 1:

Model invariant to “other” factors

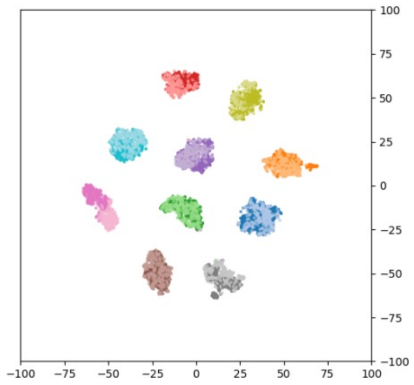
Case Study 1:

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

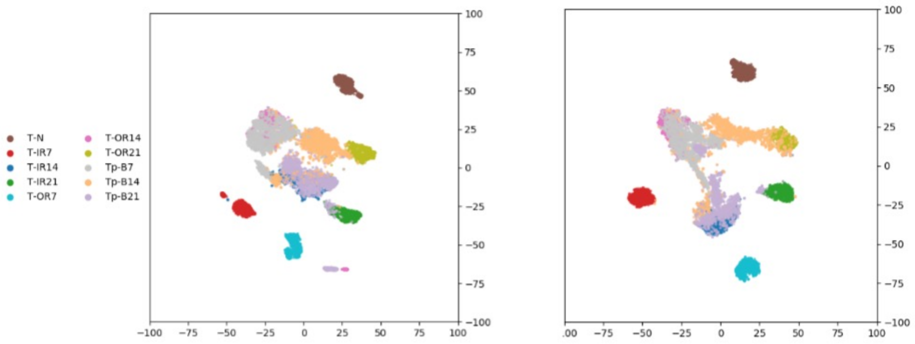
Case Study 2:

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

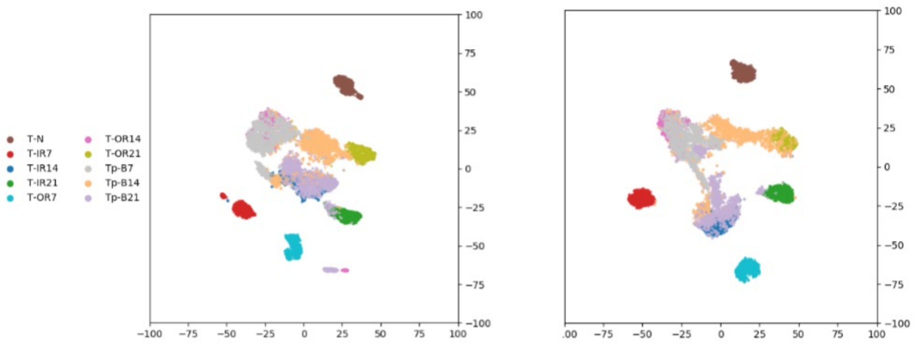
Objective 2:

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

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

Anomaly Detection

Limited data from «other» factors

No Faults Data

Difficulty

Applications

Objective 1:

Model invariant to "other" factors

Objective 2:

Model sensitive to faults

Anomaly Detection

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All Fault Data Available

Limited data from «other» factors

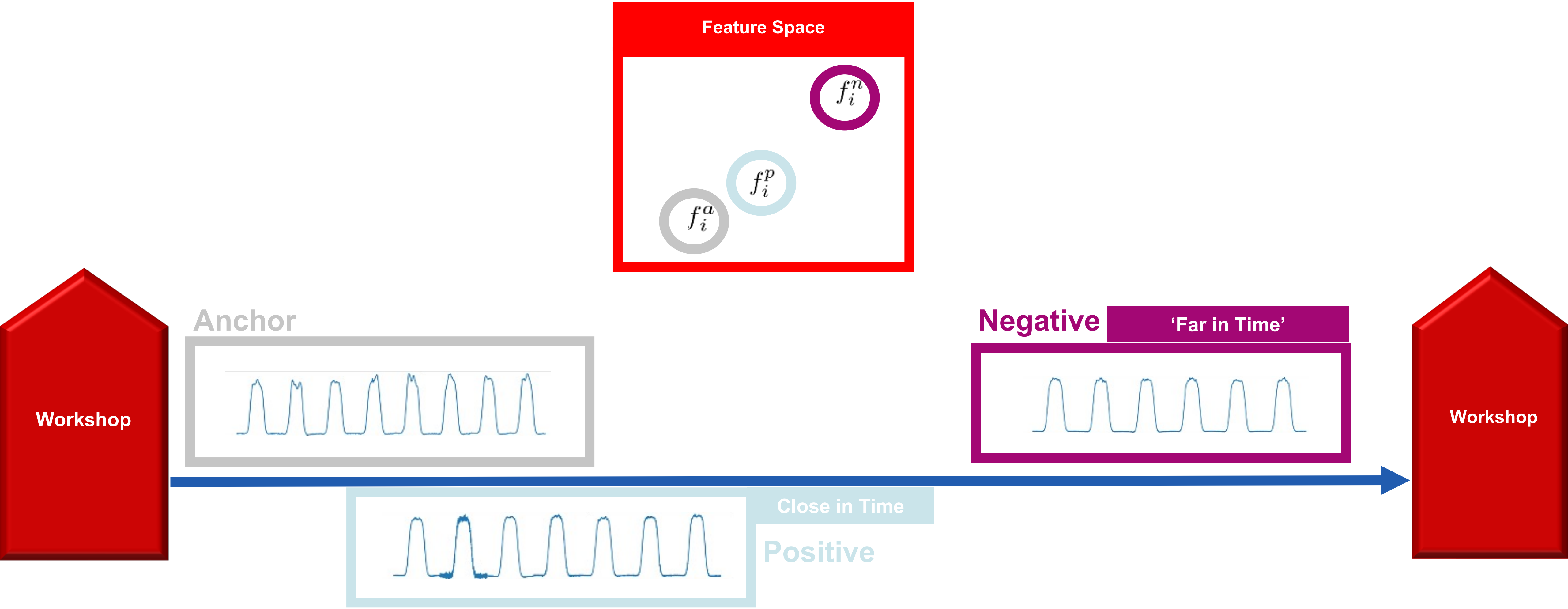
Limited fault data

Limited data from «other» factors

No Faults Data

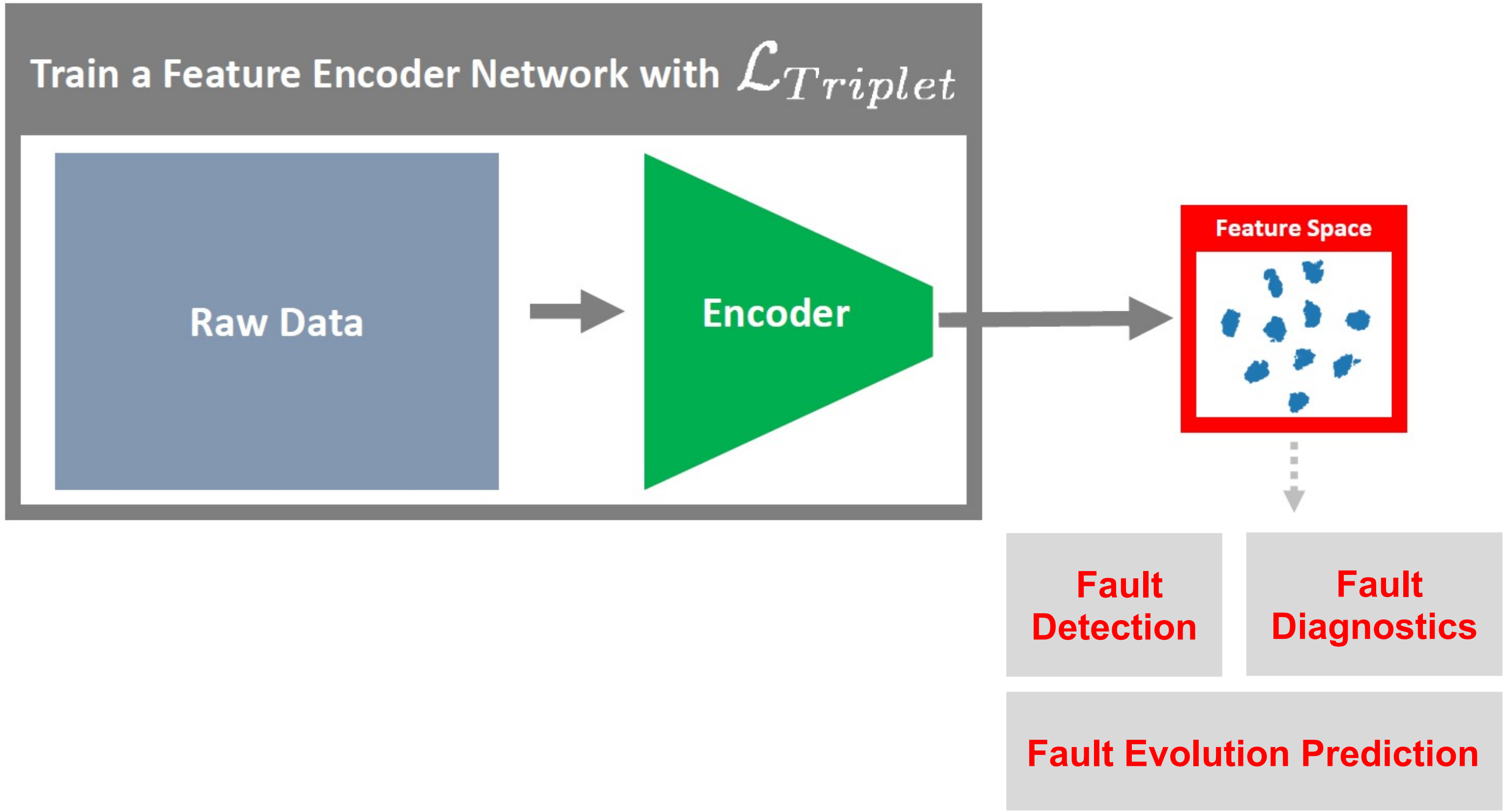
Difficulty

Unsupervised Contrastive Learning in Time



Franceschi, Jean-Yves, Aymeric Dieuleveut, and Martin Jaggi. "Unsupervised scalable representation learning for multivariate time series." Advances in neural information processing systems 32 (2019).

Methodology



Objective 1:

Model invariant to "other" factors

Objective 2:

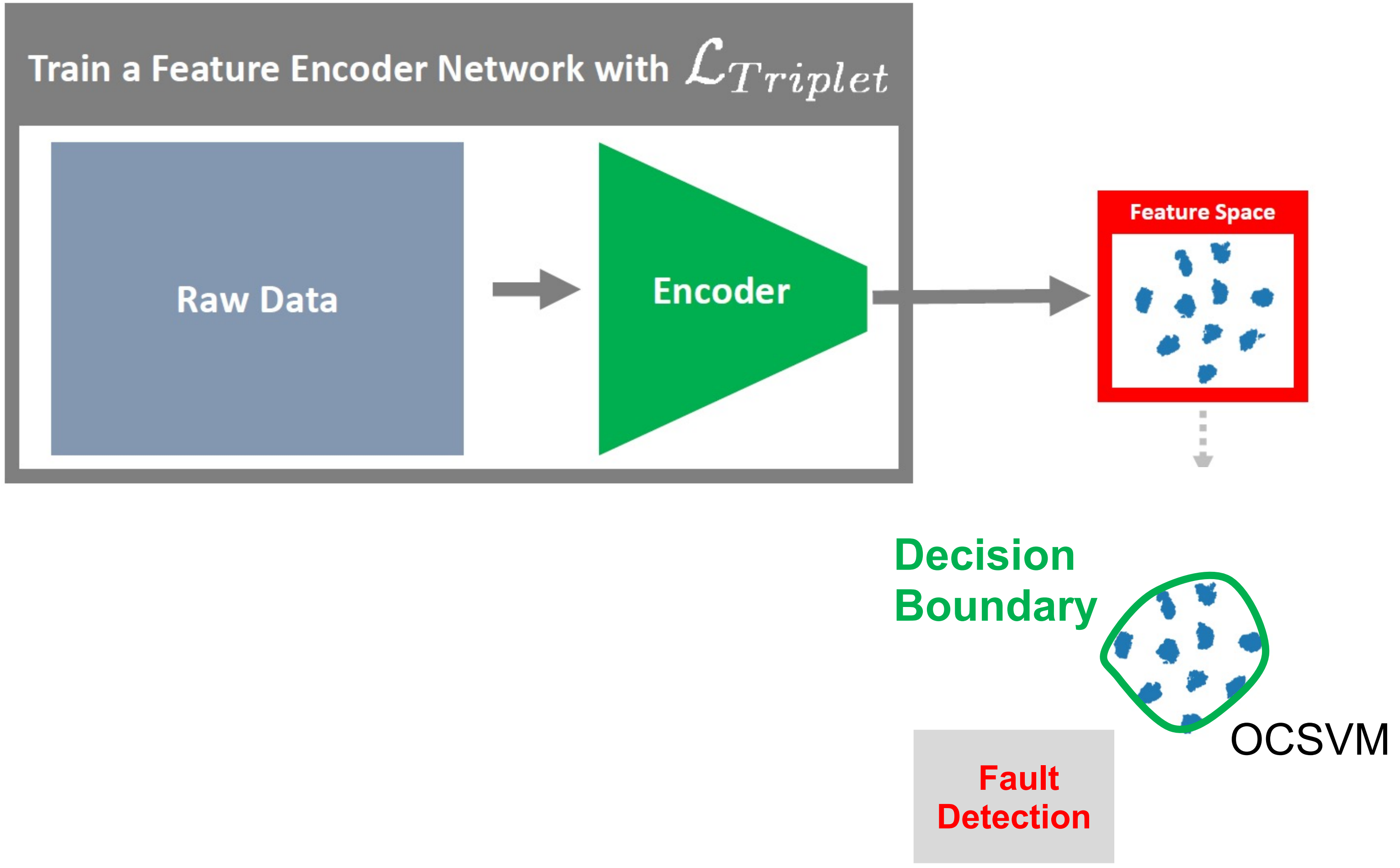
Model sensitive to known and novel faults

Scenario:

Limited data from «other» factors

NO fault data

Methodology



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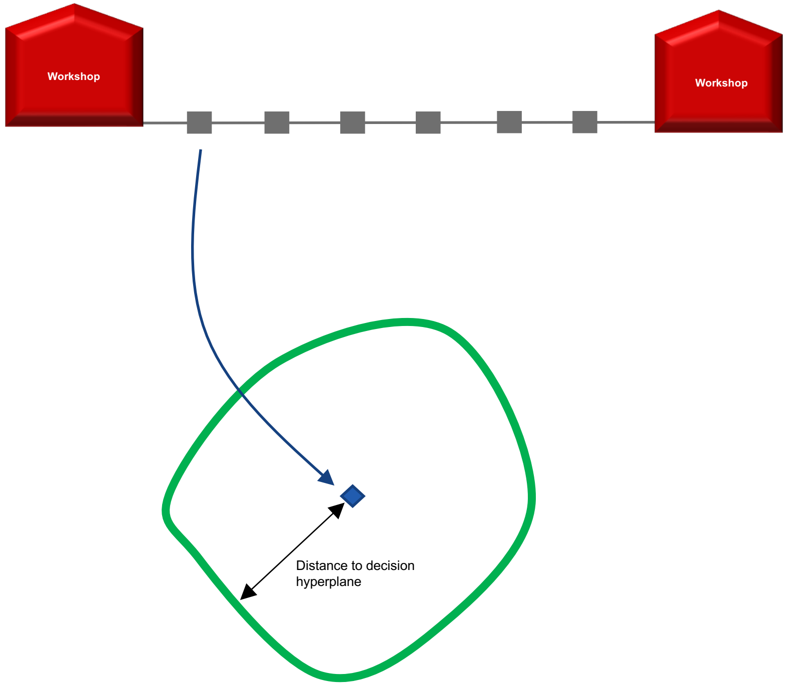
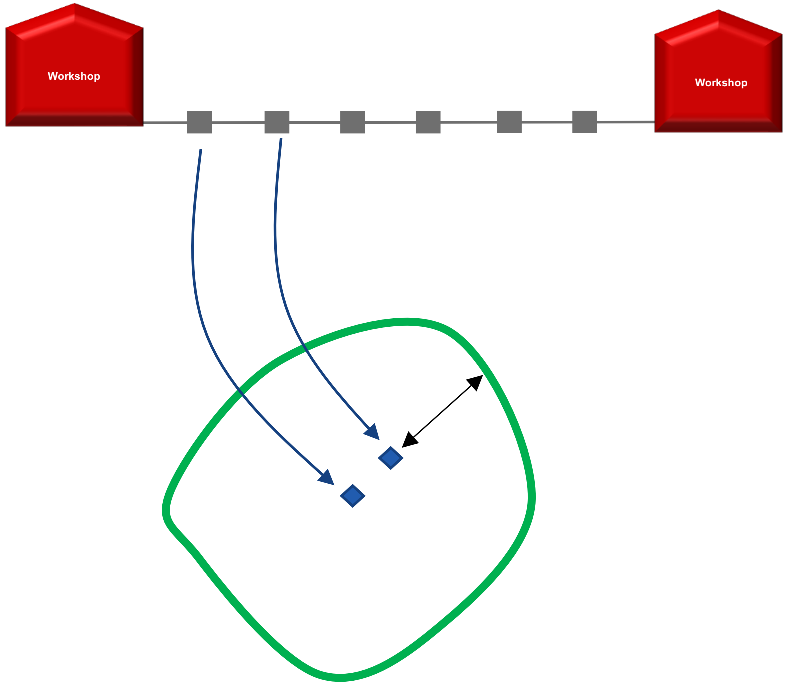
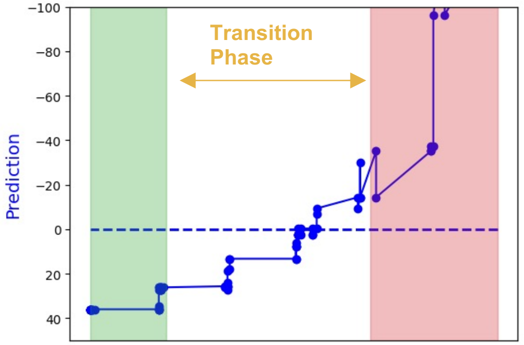
Visualization Median

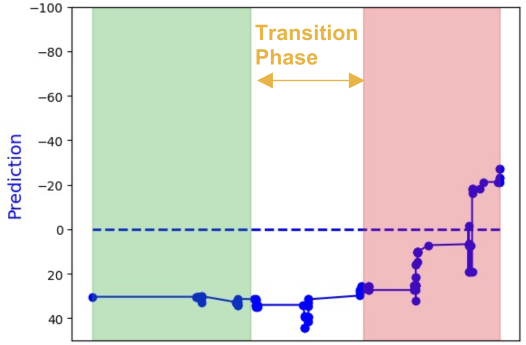


Visualization Median

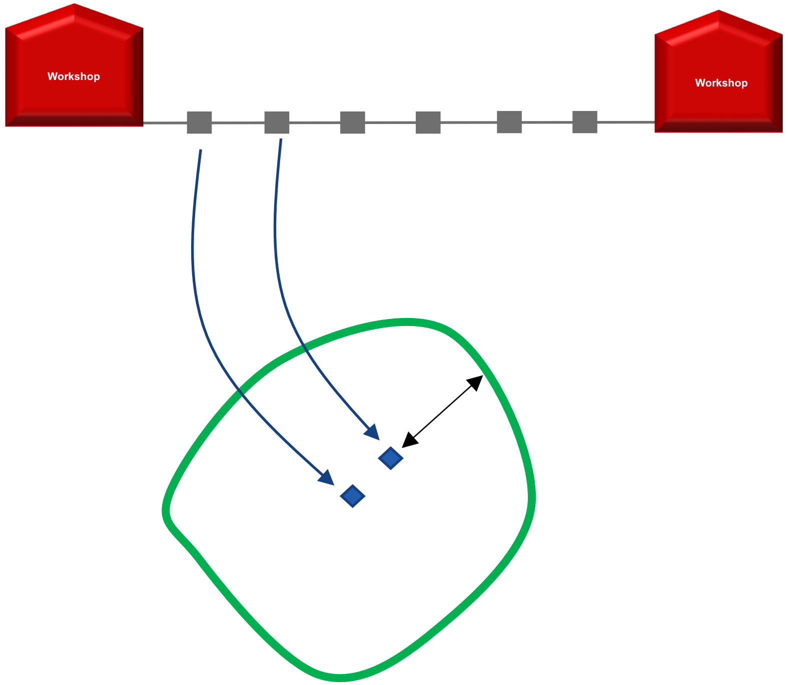


Fault Trajectories

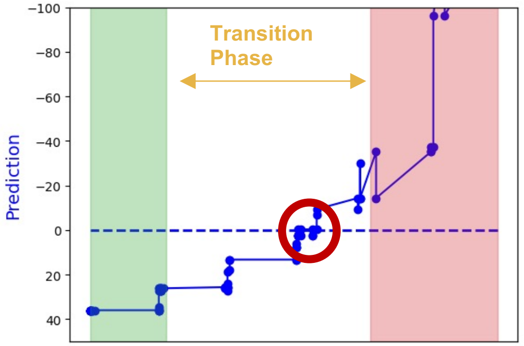


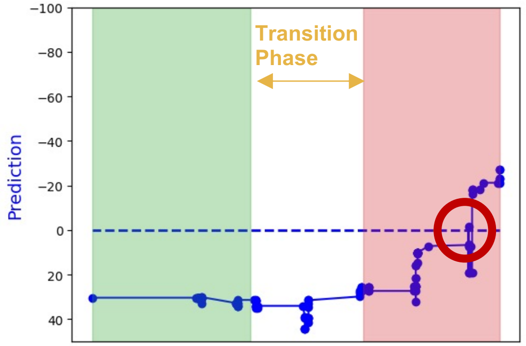


Visualization Median

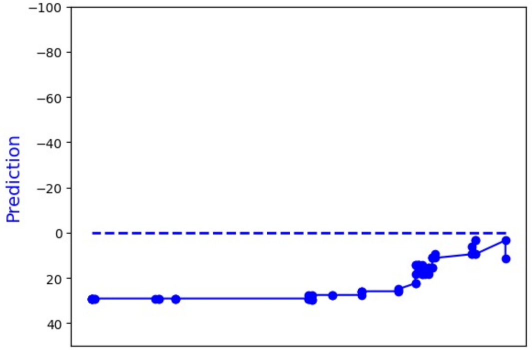


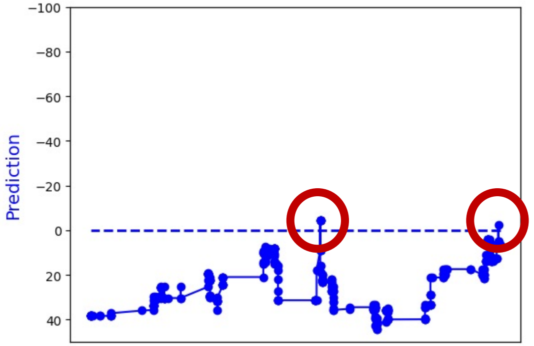
Fault Trajectories



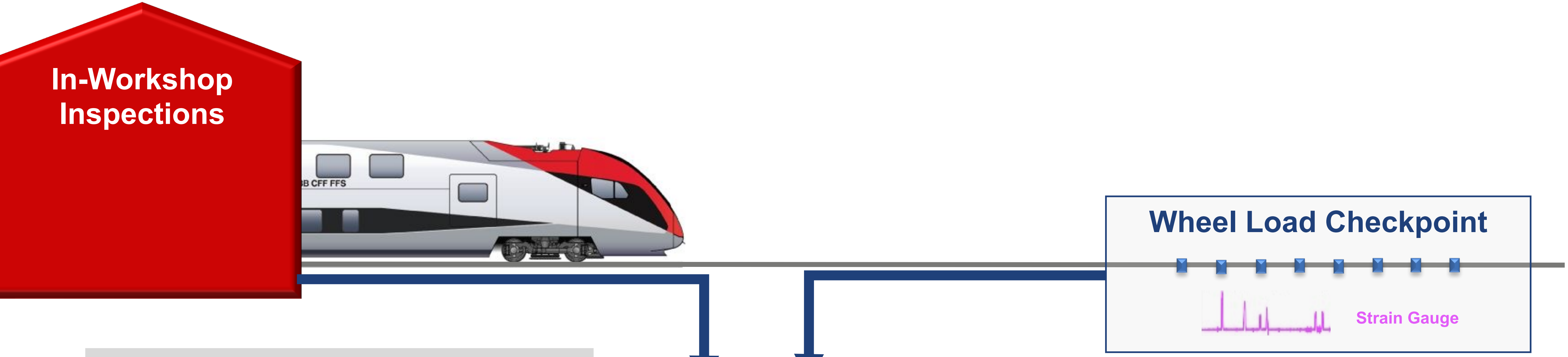


Healthy Trajectories



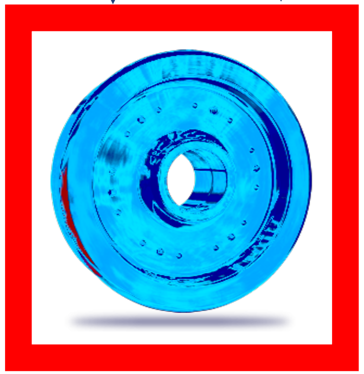


Wayside Monitoring Data to a Data-driven Digital Twin



Requires algorithms for

- **Fault Detection**
- **Fault Diagnostic**
- **Fault Evolution Prediction**



DIGITAL TWIN

Thank you!

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

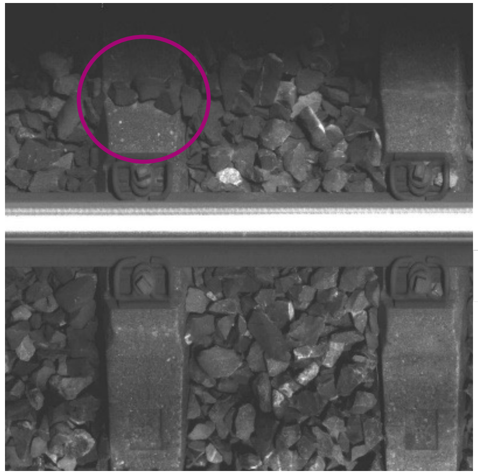
Limited fault data

Limited data from «other» factors

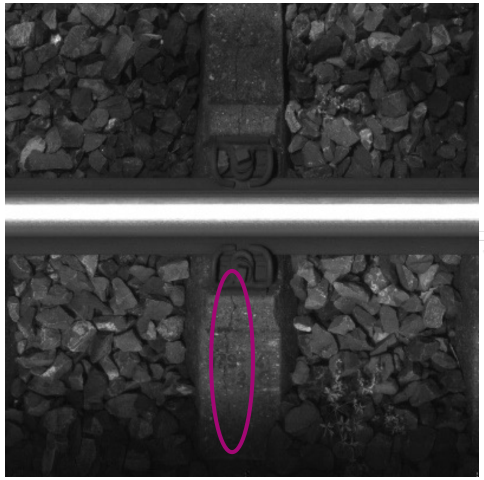
No Faults Data

Difficulty

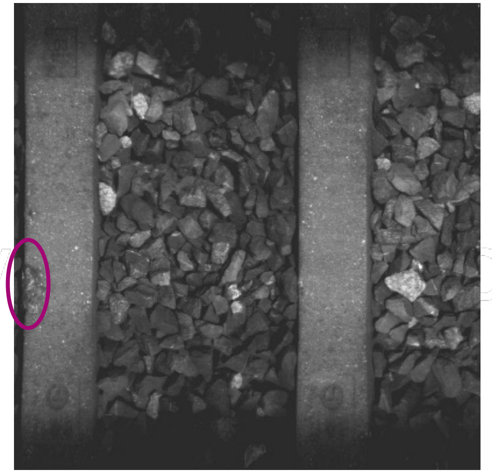
Application 1: Defect Type Classification of Sleepers



Healthy



Cracks



Spalling

Objective 1:

Model invariant to “other” factors

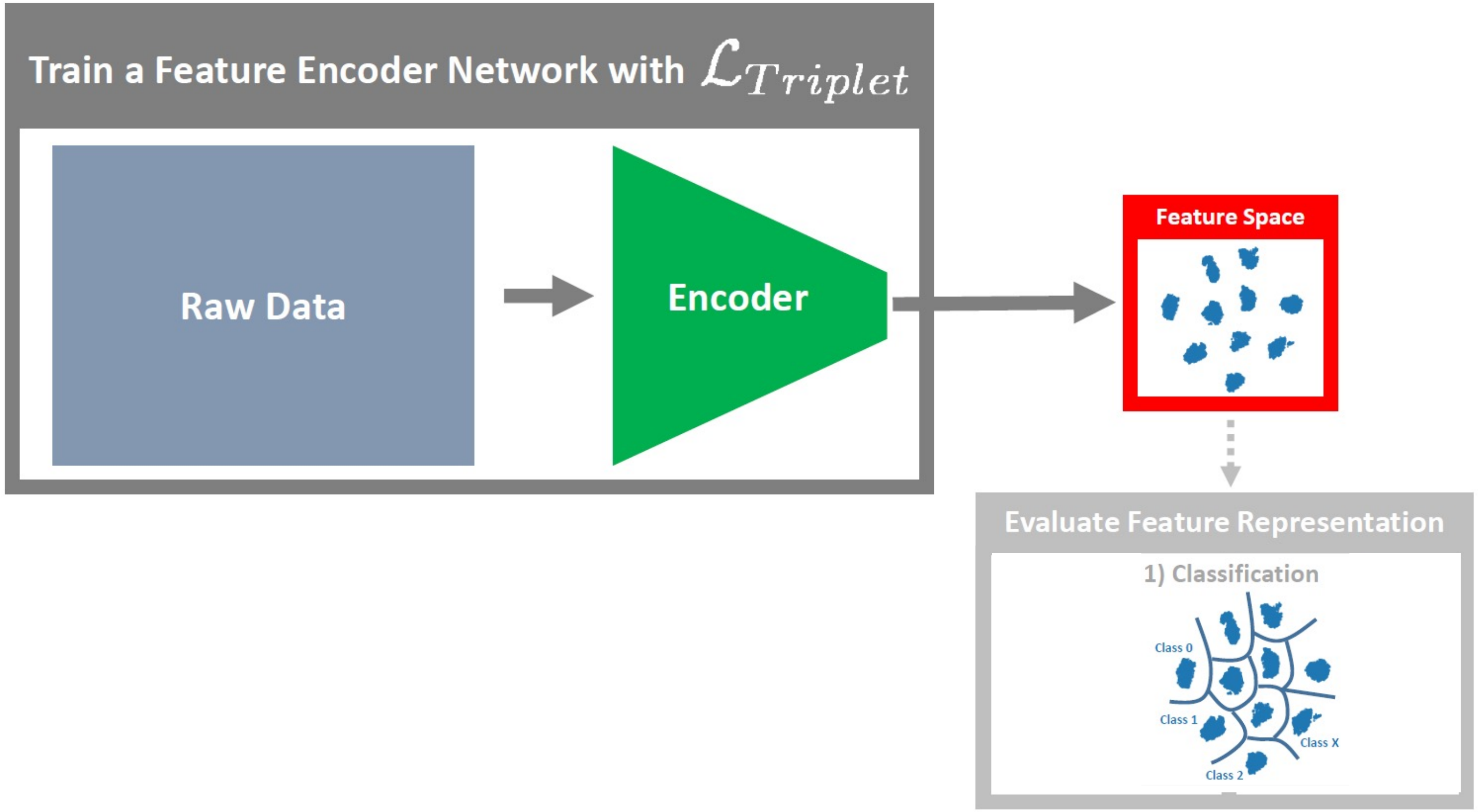
Objective 2:

Model sensitive to known faults

Scenario:

All fault types known

Application 1: Defect Type Classification of Sleepers



Objective 1:

Model invariant to "other" factors

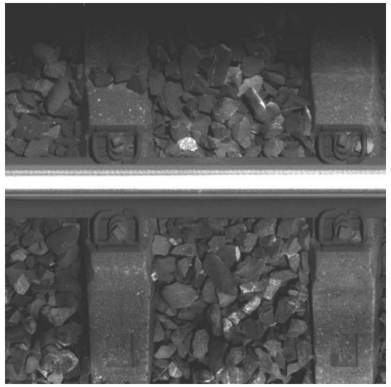
Objective 2:

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