eXplainable Predictive Maintenance

Halmstad University & Inesc Tec & Jagiellonian University & IMT Lille-Douai
Scientific Background

• Integrate explanations into AI solutions in Predictive Maintenance

• PM effectiveness depends less on the accuracy of alarms from AI...
  o than on the relevancy of actions operators perform based on these alarms
  o today, AI does not really support experts in making “smart” maintenance decisions based on the deviations that the black-box model detects

• Repair plan requires complex reasoning and planning processes
  o involving many actors and balancing different priorities
  o not realistic to be automated, with too much context to consider
Key Challenges

• Develop several different types of explanations, e.g.,
  - visual analytics, prototypical examples, deductive argumentative systems
  - in four domains: electric vehicles, metro trains, steel plants, wind farms

• Demonstrate benefits of explanations for AI decisions
  - identify component/part of the process where the problem has occurred
  - understand the severity and future consequences of detected deviations
  - choose optimal repair from several alternatives based on different priorities
  - understand the reasons why the problem has occurred in the first place, as a way to improve system design for the future
Partners

(coordinator)

- Halmstad University, Center for Applied Intelligent Systems Research
  - CAISR research focuses on weakly-supervised machine learning
  - “aware” intelligent systems & semi-automatic knowledge creation
- Inesc Tec, Laboratory of Artificial Intelligence and Decision Support
  - LIAAD works on modelling non-stationary data that evolve over time
  - require ability of handling regime shifts in the process generating data
- Jagiellonian University, Human-Centred AI Laboratory
  - researchers from engineering, law, psychology, games, physics
  - integration of human expert-based decision making with the AI operation
- IMT Lille-Douai
  - define a strategy for the design of predictive maintenance actions
  - optimize maintenance costs, logistic inventory and environmental conditions
Organised Events

Summer School on Data-Driven Predictive Maintenance for Industry 4.0

70+ attendees

DSAA 2021
06. October - 09. October

Special Sessions

- GeoData - EnGeData: Environmental and Geo-Spatial Data Analytics
- PraXai - Practical applications of explainable artificial intelligence methods
- Tensor - Tensor Analytics for Emerging Applications
- XPM - XPdM 2021 - Data-Driven Predictive Maintenance for Industry 4.0

Website: https://sites.google.com/g.upto.port/dppdm2021/home
Starts: 10-07-2021 10:00 - 11:00
### Introduction to Predictive Maintenance

**States of the equipment**
- Normal/Healthy is acceptable/desired state, while Fault is an unpermitted deviation from the acceptable operating condition
- Failure is permanent inability of a system to perform its function; Failure Mode is cause of failure or one way a system can fail
- Component Degradation or Wear is change in condition over time, and Health Indicators are quantifiable characteristics of it
- Anomaly or Outlier is a deviation from the majority (or norm)

**Analysis & Approach**
- Fault Detection is determination of whether a fault is present in the system
- Fault Isolation is determination of the kind, location and time of fault occurrence (typically follows fault detection)
  - Root Cause Analysis is the process of discovering the underlying original causes of problems
- Fault Identification is determination of the size and time-variant behaviour of a fault (typically follows fault isolation)
- Fault Diagnosis is an overall terms combining fault isolation and fault identification
- Prognosis is determination of whether a fault (or failure) is imminent and forecasting future behaviour of the system
  - Failure Prediction is forecasting whether failure(s) will occur within a predefined future time frame
  - RUL Prediction is forecasting the time left until the equipment no longer functions correctly
  - Survival Analysis is estimating expected duration of time until an event occurs (reliability analysis, event history analysis)

**Maintenance Paradigm**
- Reactive Maintenance is performing maintenance after the equipment breakdown happens
- Preventive Maintenance are maintenance actions performed based on predetermined time intervals or age of the equipment
- Predictive Maintenance is maintenance being adaptively scheduled based on continuously monitored condition
- Prescriptive Maintenance aims to predict required maintenance measures, or a course of actions based on current condition
Incremental Learning and Anomaly Explanation

<table>
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<tr>
<th>Bus 369</th>
<th>Mode</th>
<th>#FP</th>
<th>#TP</th>
<th>#FN</th>
<th>Precision (%)</th>
<th>Recall (%)</th>
<th>F1 score (%)</th>
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<td>16</td>
<td>1</td>
<td>84</td>
<td>94</td>
<td>89</td>
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Explainable Anomaly Detection for Asset Degradation

- Slab is passed through a roughing mill where its thickness is reduced to about 30 mm.
- Transfer bar is passed through six rolling stands to reach final thickness (1.8 – 25.0 mm).
- Steel is cooled in the lamina cooling section.
- At end steel is wound up to form a coil.

Table 5. The obtained hyperparameters form HRM data set.

<table>
<thead>
<tr>
<th>Hyperparameter</th>
<th>AE</th>
<th>VAE</th>
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<td>Activation</td>
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<td>Batch size</td>
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<td>Epochs</td>
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<td>Quantile threshold</td>
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<td>Beta max</td>
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<tr>
<td>Epochs Beta</td>
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Table 6. Confusion matrices for HRM data set.

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<tr>
<th></th>
<th>AE</th>
<th>VAE</th>
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Graph showing SHAP values and their impact on model output.
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XPM

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