Machine Learning in Industry: What and SWOT?

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Content

• Machine Learning: what is it and how does it work?

• Machine Learning: what opportunities?

• Machine Learning: what classes of problems does it address?

• Machine Learning: what methods?

• Machine Learning: what applications in industry?

• Machine Learning: some practical results?

• SWOT Analysis
Content

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• Machine Learning: some practical results?

• SWOT Analysis
Machine Learning: what is it and how does it work?

Industrial System Physical Model
System of equations which describes the physical processes of the industrial equipment

Detailed expert knowledge

Output = $f(\text{Input})$

Input

Current ($I$)
Voltage ($V$)
Magnetic Field ($B$)
Temperature ($T$)

Output

Torque

Torque = $f(I,V,B,T)$

Complex systems (aircraft, train, power plant, etc.) and variable conditions

Difficult to develop a physical model (too complex, too expensive)
Machine Learning: what is it and how does it work?

Data-Driven approaches which automatically learn relationships among data

Output = \( f \) (Input) \( \rightarrow \) \( f \) is unknown

Machine learning model of the motor

Machine Learning learns and numerically approximates the function \( f \)

\[
\text{Torque} = \tilde{f} (I, V, B, T) \rightarrow \tilde{f} \text{ approximates } f
\]
Machine Learning Framework

**TRAINING:**
Input and Output data are fed to the algorithm, which tries to approximate and generalize their relationship by minimizing the error between its own outcome and the training output.
**Machine Learning Framework**

- **TRAINING**
  Input and Output data are fed to the algorithm which tries to approximate and generalize their relationship by minimizing the error between its own outcome and the training output.

- **USE**
  Input is fed to the algorithm which approximates the corresponding expected output by using:

\[
\text{Output} = \bar{f}(\text{Input})
\]

\[
\text{New Input} = (I,V,B,T)
\]

\[
\text{Algorithm Output} = \bar{f}(\text{New Input})
\]

\[
\text{Torque} = (I,V,B,T)
\]
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• SWOT Analysis
Machine Learning: the solution to several tasks

- Heart Attack Early Detection

Current Recording

Normal Signature

Danger Detection Alert
Machine Learning: what opportunities?

- Heart Attack Early Detection
- Customer Profiling

Profile A: The young
Profile B: The trouble maker
Profile C: The musician
Profile D: The old
Machine Learning: the solution to several tasks

- Heart Attack Early Detection
- Customer Profiling
- Financial Forecasting
Machine Learning: the solution to several tasks

- Heart Attack Early Detection
- Customer Profiling
- Financial Forecasting
- (Game) Strategy Optimization

“GO” Chinese Game
Much trickier than chess

Google AI “AlphaGO”

Beat the GO World Champion

Not computationally possible to simulate all the possible scenarios (differently from chess…)

Much trickier than chess
Machine Learning: what classes of problems does it address?

Content

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• **Machine Learning: what classes of problems does it address?**

• Machine Learning: what methods?

• Machine Learning: what applications in industry?

• Machine Learning: some practical results

• SWOT Analysis
Machine Learning: the solution to several problems

- (Anomalous) Pattern Recognition
Machine Learning: what classes of problems does it address?

- (Anomalous) Pattern Recognition
- Data Classification
Machine Learning: what classes of problems does it address?

- (Anomalous) Pattern Recognition
- Data Classification
- Data Regression
Machine Learning: the solution to several problems

- (Anomalous) Pattern Recognition
- Data Classification
- Data Regression
- Data Trend Prediction
Machine Learning: what classes of problems does it address?

- (Anomalous) Pattern Recognition
- Data Classification
- Data Regression
- Data Trend Prediction
- Optimization

Maintenance Model → Max Availability → Max Revenues

- Repair
- Replace
- No intervention
Content

• Machine Learning: what is it and how does it work?

• Machine Learning: what opportunities?

• Machine Learning: what classes of problems does it address?

• **Machine Learning: what methods?**

• Machine Learning: what applications in industry?

• Machine Learning: some practical results

• SWOT Analysis
Machine Learning: the solution to several problems

- (Anomalous) Pattern Recognition
  - Neural Network (ANN)
  - Self-Organizing Maps (SOM)
  - Support Vector Machine (SVM)
Machine Learning: the solution to several problems

- **Data Classification**
  - Neural Network (ANN)
  - Self-Organizing Maps (SOM)
  - Support Vector Machine (SVM)
  - Spectral Clustering
  - Relevance Vector Machine (RVM)
Machine Learning: the solution to several problems

- **Data Regression**
  - Neural Network (ANN)
  - Recurrent Neural Network (RNN)
  - Reservoir Computing (RC)
  - Support Vector Machine (SVM)

\[
\bar{x}_t = \begin{bmatrix} x_t^1 \\ x_t^2 \\ \vdots \\ x_t^N \end{bmatrix} \quad \rightarrow \quad y^t = \tilde{f}(\bar{x}_t)
\]
Machine Learning: what methods?

- **Data Trend Prediction**
  - Recurrent Neural Network (RNN)
  - Reservoir Computing (RC)
  - Support Vector Machine (SVM)

\[
\bar{x}_t = \begin{bmatrix} x_1^t \\ x_2^t \\ \vdots \\ x_N^t \end{bmatrix} \quad \rightarrow \quad f_k(\bar{x}_t) = y^{t+k}
\]
Machine Learning: the solution to several problems

- Optimization
  - Reinforcement Learning (RL)

Reinforcement Learning

Input
- System Model
- Constraints
- Goals

Output
- Optimal decision making to achieve the desired goals
Machine Learning: what applications in industry?

Content

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• Machine Learning: what applications in industry?

• Machine Learning: some practical results

• SWOT Analysis
Machine Learning: the solution to several industrial needs

- Fault Detection

Monitored Signals:
- $x_1$ vs. $t$
- $x_2$ vs. $t$
- $x_3$ vs. $t$

OK
Healthy

KO
Abnormal
Machine Learning: the solution to several industrial needs

- Fault Detection
- Fault Diagnostics
Machine Learning: what applications in industry?

- Fault Detection
- Fault Diagnostics
- Degradation Assessment
Machine Learning: the solution to several industrial needs

- Fault Detection
- Fault Diagnostics
- Degradation Assessment
- Failure Prediction

Predictive Maintenance

Monitored Signals:

$x_1(t)$

$x_2(t)$

$x_3(t)$

RUL

Time (hours)
Machine Learning: the solution to several industrial needs

- Fault Detection
- Fault Diagnostics
- Degradation Assessment
- Failure Prediction
- Maintenance Strategy Optimization

Business Goals
- Maximize Revenues
- Environmental Safety

Maintenance KPIs
- Maximum Plant Availability
- Minimum Maintenance Costs

Monitored Signals

Optimized maintenance strategy for achieving the desired goals
Content

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• Machine Learning: what applications in industry?

• Machine Learning: some practical results

• SWOT Analysis
Machine Learning: some practical results

- Turbine Fault Detection

Monitored Signals

- $x_1$ vs. t
- $x_2$ vs. t
- $x_3$ vs. t

- OK: Healthy
- KO: Abnormal
Historical signal measurements in healthy condition

Monitored signals
(current time)

\[ s_1(t) \]

\[ x_1^{obs} \]
\[ x_2^{obs} \]
\[ x_n^{obs} \]

Machine Learning model of healthy component

Signal reconstructions (expected values of the current signal measurements in healthy condition)

\[ \hat{x}_1^{nc} \]
\[ \hat{x}_2^{nc} \]
\[ \hat{x}_n^{nc} \]

Difference

\[ \hat{s}_1 = s_1 - \hat{x}_1^{nc} \]

RESULT

Early detection of the turbine incipient degradation

Detection Decision

KO
Machine Learning: some practical results

- Turbine Fault Detection
- Train Wheel Defect Detection
Machine Learning: some practical results

Sensors of Vertical Force permanently installed on the railway

Healthy Wheel

Defected Wheel
Detection of Sensor Failure in a Nuclear Power Plant

Available data
• (Big) data from OKG Nuclear Power Plant (Sweden):
• 752 sensors
• 1 year of data sampled every 10 min

Adopted Method
Ensemble of Auto Associative Kernel Regression models

EMPIRICAL MODEL OF PLANT BEHAVIOR IN NORMAL OPERATION

Signal reconstructions ≠ Real measurements

Difference between signals implies a sensor failure
Advantages

- **Early** identification of sensors failures such as freeze, noise, spikes, bias, drift, quantization
- **Robust** to multiple sensor failures
- **Reduction of sensor calibration costs**
- **Increase of plant availability** (no production interruption due to sensor failures)
Compressor – Fault Detection
Compressor

Sensor Validation Tool

Are the sensors healthy?

Sensor 1
Sensor 2
Sensor N

Fault Detection Tool

Is the compressor healthy?

Normal Condition
Abnormal Condition
(Incipient System Degradation)
Sensor validation - Method

Monitored signals (current time)

\[
x_1^{obs} \\
x_2^{obs} \\
\vdots \\
x_N^{obs}
\]

Reconstruction Model 1 = PCA
Reconstruction Model 2 = PCA
Reconstruction Model \( M \) = PCA

\[
\hat{x}_1^{nc} \\
\hat{x}_2^{nc} \\
\vdots \\
\hat{x}_N^{nc}
\]

Signal reconstructions (expected values of the measurements in healthy condition)

Difference

Residuals

Sensor Fault Detector

Z-Test

Sensor OK

Sensor KO
Fault Detection Method

- **METHOD**: Principal Component Analysis (PCA) + Z-Test

- **Monitored signals** (current time)
  - $x_1$

- **Model of component healthy behavior**
  - $x_1^{obs}$
  - $x_2^{obs}$
  - $x_N^{obs}$

- **Signal reconstructions** (expected values of the measurements in healthy condition)
  - $\hat{x}_1^{nc}$
  - $\hat{x}_2^{nc}$
  - $\hat{x}_N^{nc}$

- **Difference**

- **Signals RMSR**
  \[
  RMSR_t = \sum_{s=1}^{S} \left( r_t^s \right)^2 
  \]

- **Compressor Fault Detector**
  - **Z-Test**

- **OK (Normal Condition)**
- **Abnormal Condition (Incipient Failure)**
Compressor: Results

Activity: Development of a Fault Detection Tool

Outcome

RESULTS

- No False Alarms (FP=0%)
- No Missed Alarm: Robust Detection of the compressor degradation before failure (TP=100%)
- Prompt Failure Detection (Average Detection Delay=124.5 min)

ADDED VALUE

- Allows Condition-based Maintenance
  - No system catastrophic failure
  - Possibility of scheduling the maintenance at the end of the production cycle
  - Enable less expensive and faster maintenance intervention
  - Reduce system unavailability due to degradation
  - The methodology can be applied to other systems
Machine Learning: some practical results

- Turbine Fault Detection
- Train Wheel Defect Detection
- Packaging Machine Fault Diagnostics

Monitored Signals

- $x_1$ vs. $t$
- $x_2$ vs. $t$
- $x_3$ vs. $t$

Fault Class A
Fault Class B
Fault Class C
EDF - Unsupervised fault diagnostics method for nuclear power plant diagnostics

Available data
- 5 signals (operational conditions) + 7 signals (turbine behaviour)
- 149 shut-down transients from a nuclear power plant
- Types of anomalies are unknown

Adopted method
- Spectral Clustering + Unsupervised Fuzzy C-means (FCM) + consensus clustering

Obtained results

Advantages
- Grouping together the transients caused by the same malfunctioning
- Help to experts to identify the specific root causes of a group of transients
- Prediction of the failure evolution of any new turbine and support to maintenance decisions
Machine Learning: some practical results

- Turbine Fault Detection
- Train Wheel Defect Detection
- Train Braking System Fault Detection
- Packaging Machine Fault Diagnostics
- Packaging Machine Degradation Assessment
Machine Learning: some practical results

- Turbine Fault Detection
- Train Wheel Defect Detection
- Train Braking System Fault Detection
- Packaging Machine Fault Diagnostics
- Packaging Machine Degradation Assessment
- Electric Vehicle: Motor Degradation Assessment
Machine Learning: some practical results

**RESULT**
Assessment of electric motor (PMSM) demagnetization level

**Motor Currents**
Different Operating Conditions

Real Degradation: 50% Nominal Flux

<table>
<thead>
<tr>
<th>Flux Linkage</th>
<th>Assignment Confidence</th>
</tr>
</thead>
<tbody>
<tr>
<td>20%</td>
<td>0.00</td>
</tr>
<tr>
<td>50%</td>
<td>0.80</td>
</tr>
<tr>
<td>80%</td>
<td>0.40</td>
</tr>
<tr>
<td>100%</td>
<td>0.00</td>
</tr>
</tbody>
</table>
Machine Learning: some practical results

- Turbine Fault Detection
- Train Wheel Defect Detection
- Train Braking System Fault Detection
- Packaging Machine Fault Diagnostics
- Packaging Machine Degradation Assessment
- Electric Vehicle: Motor Degradation Assessment
- Electric Vehicle: Inverter Degradation Assessment

Monitored Signals

\[ x_1(t), x_2(t), x_3(t) \]
Machine Learning: some practical results

Inverter Monitored Signals
Different Operating Conditions

RESULT
Degradation Assessment of the inverter of the electric vehicle
Machine Learning: some practical results

- Turbine Fault Detection
- Train Wheel Defect Detection
- Train Braking System Fault Detection
- Packaging Machine Fault Diagnostics
- Packaging Machine Degradation Assessment
- Electric Vehicle: Motor Degradation Assessment
- Electric Vehicle: Inverter Degradation Assessment

- Turbine Failure Prediction

Monitored Signals

![Graph showing monitored signals and turbine failure prediction](image)
Machine Learning: some practical results

Monitored Signals

Decreasing RUL

Healthy
Partially Degraded
Severely Degraded

Real RUL
Predicted RUL
Confidence interval

Time (hours)
RUL

Energy Production Prediction

![Diagram showing the process of energy production prediction]

- Weather forecasting data
- Prediction model
- Energy production

\[ W \hat{F} \quad \hat{P} \]
Method: ensemble of ANN

Data repository: historical input ($WF$)-output ($P$) patterns

Bagging

ANN 1

$P_1 = \sigma_{h} h \cdot w_1(t) \cdot b_1(t)$

ANN 2

$P_2 = \sigma_{h} h \cdot w_2(t) \cdot b_2(t)$

...  

ANN $H$

$P_H = \sigma_{h} h \cdot w_H(t) \cdot b_H(t)$

Local Fusion (LF)

$\hat{P}_{LF} = \frac{\sum_{h=1}^{H} w^h \cdot (\hat{P}^h - b^h)}{\sum_{h=1}^{H} w^h}$
Results

\[ p_{g_{MAE}}(\%) = \left( \frac{MAE_{ensemble} - MAE_{baseline}}{MAE_{baseline}} \right) \times 100 \]
Machine Learning: some practical results

- Turbine Fault Detection
- Train Wheel Defect Detection
- Train Braking System Fault Detection
- Packaging Machine Fault Diagnostics
- Packaging Machine Degradation Assessment
- Electric Vehicle: Motor Degradation Assessment
- Electric Vehicle: Inverter Degradation Assessment
- Turbine Failure Prediction
- Turbine Fleet Part Flow Optimization

Business Goals
- Maximize Revenues
- Environmental Safety

Maintenance KPIs
- Maximum Plant Availability
- Minimum Maintenance Costs

Monitored Signals

Optimized maintenance strategy for achieving the desired goals
Machine Learning: some practical results

Turbine Parts Warehouse State

Turbine Fleet States

OPTIMAL DECISION MAKING
Maintenance Intervention Scheduling for Achieving the Business Goals

- Repair
- Replace
- No intervention

Business Goals to Achieve

[Image of a brain with gears and a bag of euros]
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• Machine Learning: some practical results

• SWOT Analysis
### Machine Learning: SWOT Analysis

#### Helpful
- **To achieving the objective**

#### Harmful
- **To achieving the objective**

### Internal

#### STRENGTHS
- Great generalization capabilities
- Advanced data processing
- Great level of automation
- Powerful speculation
- Decision making improvement

#### WEAKNESSES
- Informative data needed
- Possible overfitting (no generalization)
- Computational efforts needed
- Black-box modeling

### External

#### OPPORTUNITIES
- IoT industrial revolution: huge amount of collectable data
- Integration in the IT infrastructure
- Continuous model improvement
- Continuous business improvement
- Business efficiency increase

#### THREATS
- Drop of expertise knowledge (due to too much extensive machine learning use)
- Not possible to fully understand its functioning (black-box): wrong decision based on wrong machine learning application
- Reduction of jobs (extensive work automation)
Machine Learning: frontiers in methods

- Extreme Learning Machines (ELM)
- Deep Neural Networks (DNN)
- Convolutionary Neural Networks (CNN)
- Generative Adversarial Networks (GAN)
- Optimal Transport and Cumulative Distribution Transform (OT-CDT)
Machine Learning: frontiers in methods

- Extreme Learning Machines (ELM)

Output = $f$ (Input) → $f$ is unknown

- Randomly generated
- Analytically calculated

Input:
- Current (I)
- Voltage (V)
- Magnetic Field (B)
- Temperature (T)

Torque

Very fast training
Improved accuracy

Monitoring in Non-stationary Environment
**Machine Learning: frontiers in methods**

- Extreme Learning Machines (ELM)
- Deep Neural Networks (DNN)

**DNN**

- Very complex input-output model
- Able to manage a very large number of input signals
- Monitoring of complex systems
- No hand-crafted feature selection/extraction

- Stacked Autoencoders

- Classification/regression layer
Machine Learning: frontiers in methods

- Extreme Learning Machines (ELM)
- Deep Neural Networks (DNN)
- Convolutionary Neural Networks

Input = Image
Output = class/regression

Fault Detection
Fault Diagnostics
Degradation Assessment

scalogram
Machine Learning: frontiers in methods

- Extreme Learning Machines (ELM)
- Deep Neural Networks (DNN)
- Convolutionary Neural Networks
- Generative Adversarial Networks

Adversarial training of two networks:

- **Generator G**: tries to produce real samples
- **Discriminator D**: tries to distinguish a sample comes from the true or not

Unsupervised Anomaly Detection

Capability of managing:
- data of different sources (e.g. signals, images, videos)
- complex input-output mappings
Machine Learning: frontiers in methods

- Extreme Learning Machines (ELM)
- Deep Neural Networks (DNN)
- Convolutionary Neural Networks
- Generative Adversarial Networks
- Optimal Transport (OT) and Cumulative Distribution Transform (CDT)

Transfer from one distribution to another with min cost and a smooth path (‘geodesic’)

Capture time variant characteristics

Accurate classification after projection

Fault Detection
Fault Diagnostics
Machine Learning: frontiers in applications

- Resilience and Vulnerability Analysis of Complex Technical Infrastructures:
  - Functional Dependence Identification
  - Critical Component Identification
Motivation of the work: Complex Technical Infrastructures

Complex technical Infrastructures (CTI) Characteristics:

- large-scale systems
- 10,000+ components
- Hierarchical architectures
- Technologies of various domains
Motivation of the work: Complex Technical Infrastructures

Complex technical Infrastructures (CTI)
Complex Technical Infrastructures: What’s the problem?

Complex technical Infrastructures (CTI)

- Functional Dependencies (FD)
- Critical Components

Important to know because of:
- Risk Reduction in Operations
- CTI Monitoring & Control
- Maintenance
- Design Retrofit/Updating
- …
Traditional Methods for FD and Critical Component Identification

• Functional Analysis

• Logic Decomposition

• Dynamic reliability block diagrams

• Petri nets

Importance Measures
• Birnbaum
• Risk Achievement Worth
• Fussel-Vesely
• …
CTIs grow and change in time
- New/updated components/connections

Intricate interactions among components of different systems
- Physical, functional, spatial, data, operator etc.

Unclear Functional logic
- Hidden functional dependencies and interconnections

What to do?

Traditional methods cannot be applied
Complex Technical Infrastructures: Opportunities

Alarm Messages

Operational Data collected from sensors
Machine Learning: frontiers in applications

- Resilience and Vulnerability Analysis of Complex Technical Infrastructure:

1. Database of alarms

2. Operational Data

- $y_1(t)$
  - $N \gg 1$ signals (e.g. $10^4$)

Functional Dependences

Critical Components
1) Association Rules Extraction for the Identification of Dependent Abnormal Behaviours in Complex Technical Infrastructure

**Politecnico di Milano**, Department of Energy Laboratory of Signal and Risk Analysis (LASAR)

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Enrico ZIO

**CERN**  
EN-ARP-PPM Section  
Ugo GENTILE  
Luigi SERIO

10.04.2018
Complex Technical Infrastructures:

- **Objective:** Identification of Dependent Abnormal Behaviours in Complex Technical Infrastructure
- **Methodology:** Multiple Constraints Targeted Association Rules Mining [MCT-ARM]
2) A Feature Selection-Based Approach for the Identification of Critical Components in Complex Technical Infrastructures: Application to the CERN Large Hadron Collider

Politecnico di Milano, Department of Energy Laboratory of Signal and Risk Analysis (LASAR)

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Luigi SERIO

10.04.2018
Identification of the critical components

= 

Feature selection problem

\[ y = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ \vdots \\ y_N \end{bmatrix} \]

\[ y^* = \begin{bmatrix} y_4 \\ y_{31} \\ y_{54} \\ \vdots \\ y_{N-3} \end{bmatrix} \]

\[ x_{CTI} = \begin{cases} 1 & \text{failed} \\ 0 & \text{safe} \end{cases} \]
Case study

CERN LHC electrical network

Electrical disturbances

5,000+ components (transformers, distribution switchboards,...) in 8 Sectors

10,000+ signals (power, current,...)

Objective: Identification of the critical components

Possible preventive dumping of LHC beams

\[ x_{\text{CTI}} = \begin{cases} 
1 & \text{dumped} \\
0 & \text{not dumped} 
\end{cases} \]

The data and images related to CERN which are shown in this work are confidential and property of CERN (Copyright © CERN).
**Year 2016:** 3723 electrical disturbances

3675 without dump ($x_{CTI} = 0$)

48 with dump ($x_{CTI} = 1$)

For each electrical disturbance:

<table>
<thead>
<tr>
<th>$x_{CTI}$</th>
<th>Line</th>
<th>Signal (Feature)</th>
<th>Value</th>
<th>Component</th>
<th>Sector</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>66kV</td>
<td>$y_1$</td>
<td>$y_{144}$</td>
<td>$C_{120}$</td>
<td>2E</td>
</tr>
<tr>
<td>18 kV</td>
<td>145</td>
<td>$y_{145}$</td>
<td>$C_{121}$</td>
<td>1E</td>
<td></td>
</tr>
<tr>
<td></td>
<td>5822</td>
<td>$y_{5822}$</td>
<td>$C_{5500}$</td>
<td>8E</td>
<td></td>
</tr>
</tbody>
</table>

For Year 2016:

- 3723 electrical disturbances
- 3675 without dump ($x_{CTI} = 0$)
- 48 with dump ($x_{CTI} = 1$)
Results

22 selected features

EMD101_SLASH_5E_EA_DASH
EMD101_SLASH_7E_EA+
EMD101_SLASH_7E_PM10_STAR
...
EMD302_SLASH_1E_PM10_STAR

19 critical components

1E_201
1E_203
1E_208
...
8E_205

- 19 identified components: all powered by the 18 kV power distribution level
- 18 kV power distribution level = most sensitive to perturbations coming from the 400 kV level.
- CERN is progressively upgrading the power converter units with new generation four-quadrant switch-mode units less sensitive to electrical disturbances.
- Work results + engineering considerations → the upgrade will start with components powered at the 18 kV level.

<table>
<thead>
<tr>
<th>Computational time</th>
<th>1 week *</th>
</tr>
</thead>
<tbody>
<tr>
<td>* 20 processors, 2.4 GHz clock rate, 130 GB memory</td>
<td></td>
</tr>
</tbody>
</table>

Performance evaluation
False alarm rate = 7.3%
Missed alarm rate = 25.0%
Machine Learning CERN-POLIMI:…

WORK IN PROGRESS:

- Artificial Neural Networks and statistical tests for anticipating sensor failures in CERN Collimators instrumentation
- Development of a method for the identification of the signals responsible of anomalies
- Advanced Deep Learning techniques for defect detection and diagnostics from images in CERN Large Hadron Collider components and systems