POLITECNICO DI MILANO | MINES ParisTech | PSL

Trustworthy Complex and Intelligent Systems Webinar Series

Prognostics and Health Management for Condition-based and Predictive Maintenance: A Look In and a Look Out

With

Enrico Zio
CRC MINES ParisTech

Tuesday, 8 June 2021
16:00 – 17:00 CET
Free Online Zoom Webinar

Register via Zoom:

https://us02web.zoom.us/meeting/register/tZYlcuCoqjotHdx5gVCnm7gi1_w7RFuM1fRw

A number of methods of Prognostics and Health Management

Outline

1 Prognostics and Health Management (PHM)

2 PHM, a look in: Theory

3 PHM, a look in: Practice

4 PHM, a look out: Practice

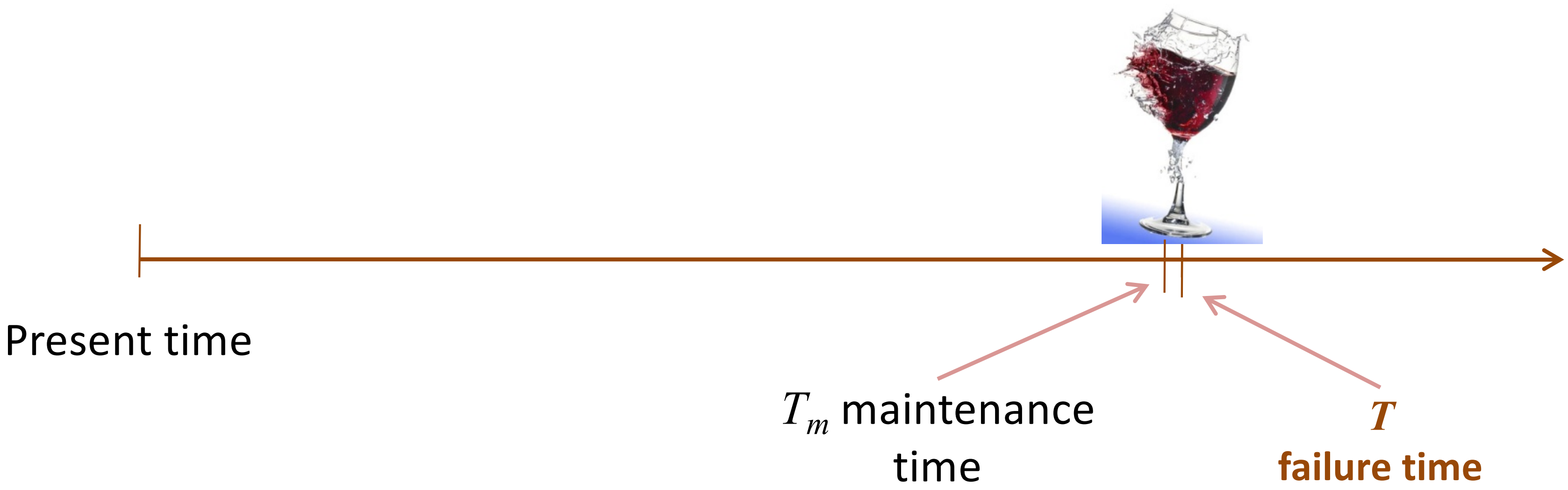
5 PHM, a look out: Theory

6 Conclusions

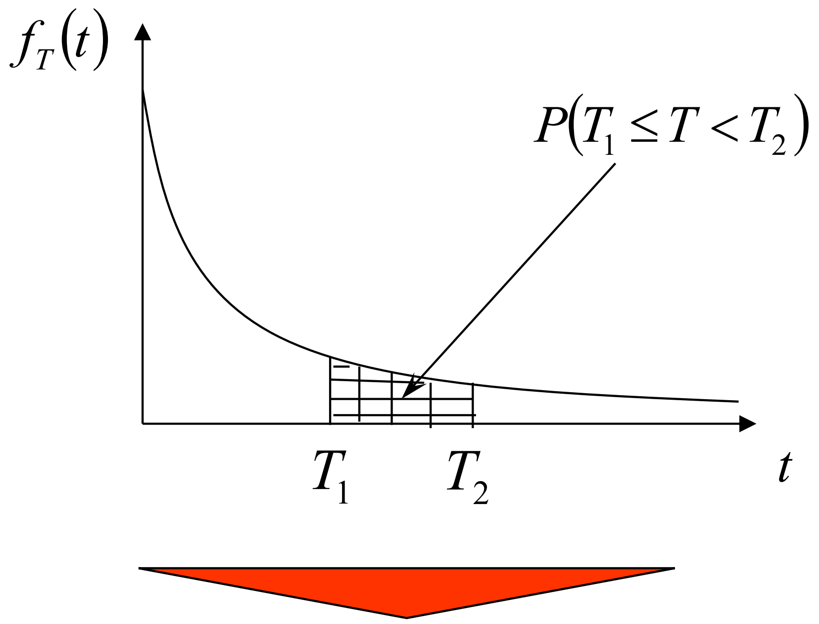
Ideal Maintenance: When?

$$T_m = T - dt$$

- Component's life fully exploited
- Unavailability due to maintenance actions are avoided

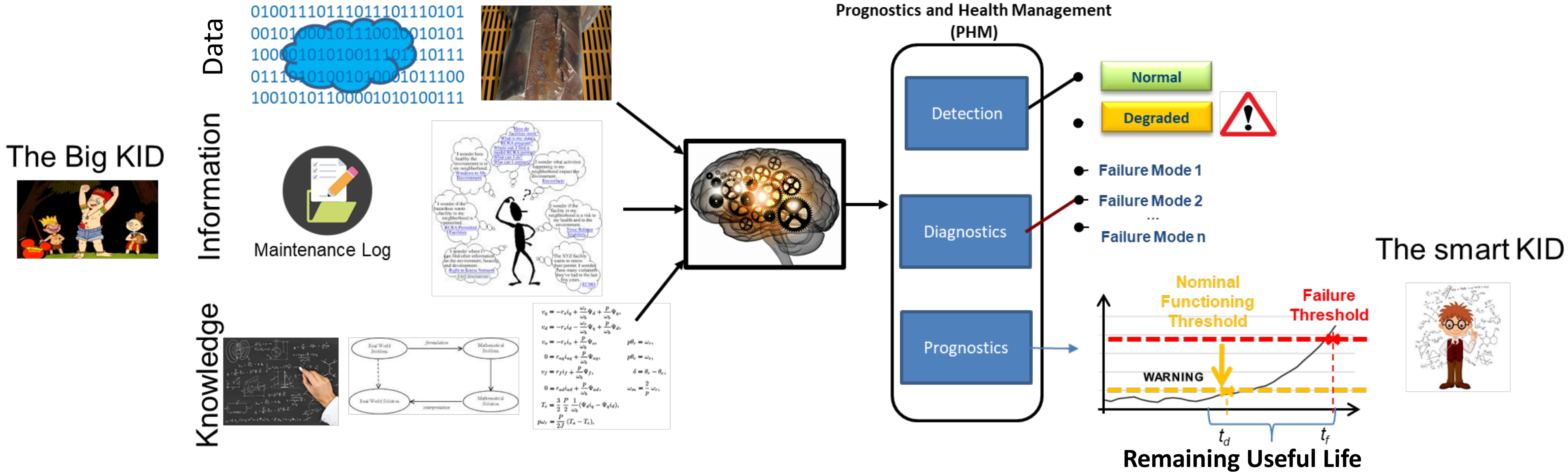


- The failure time is uncertain

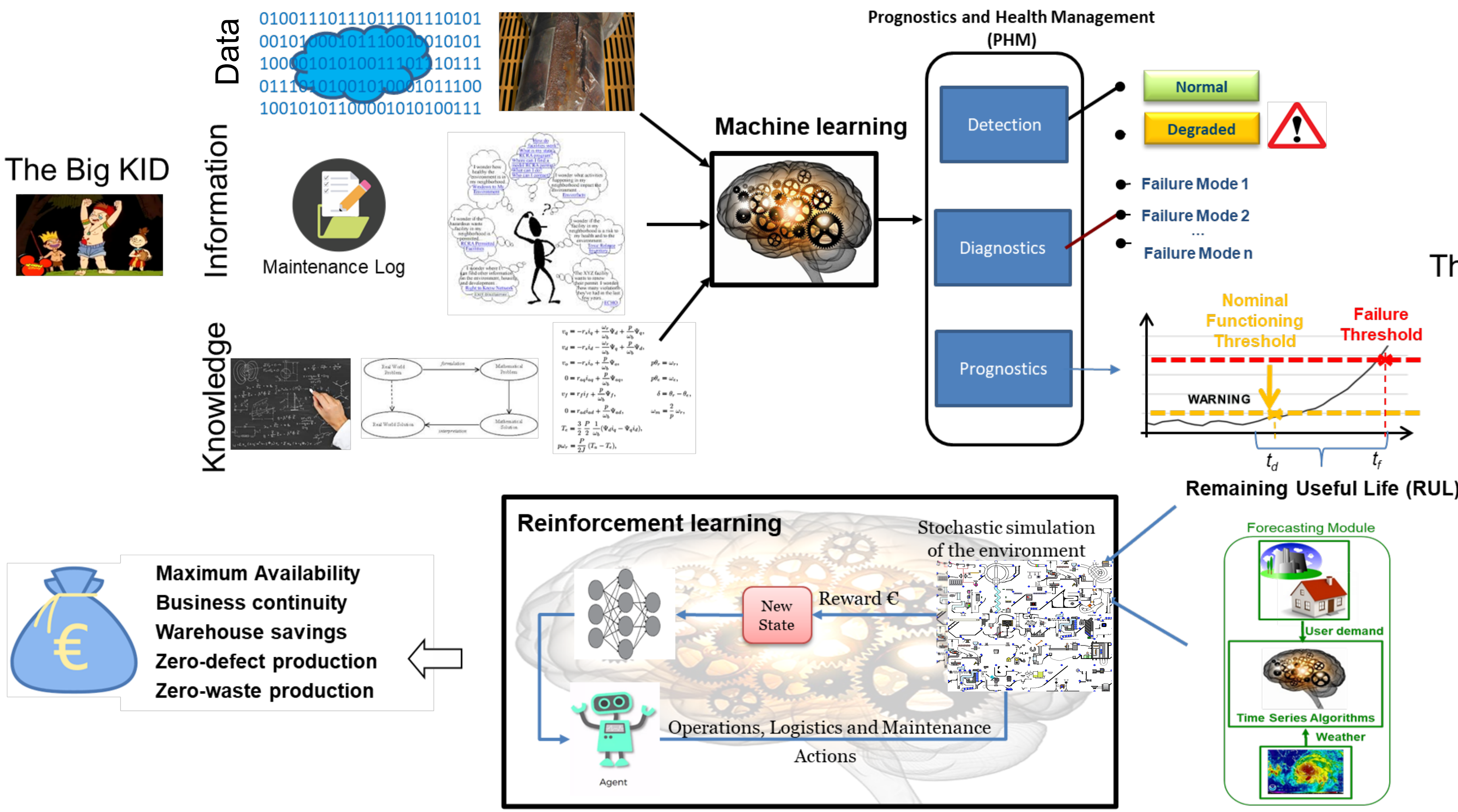


- When to perform maintenance: non-trivial decision

Prognostics and Health Management (PHM)



PHM for what?



…at the right time…

"…doing the right thing…"

Outline

1 Prognostics and Health Management (PHM)

2 PHM, a look in: Theory

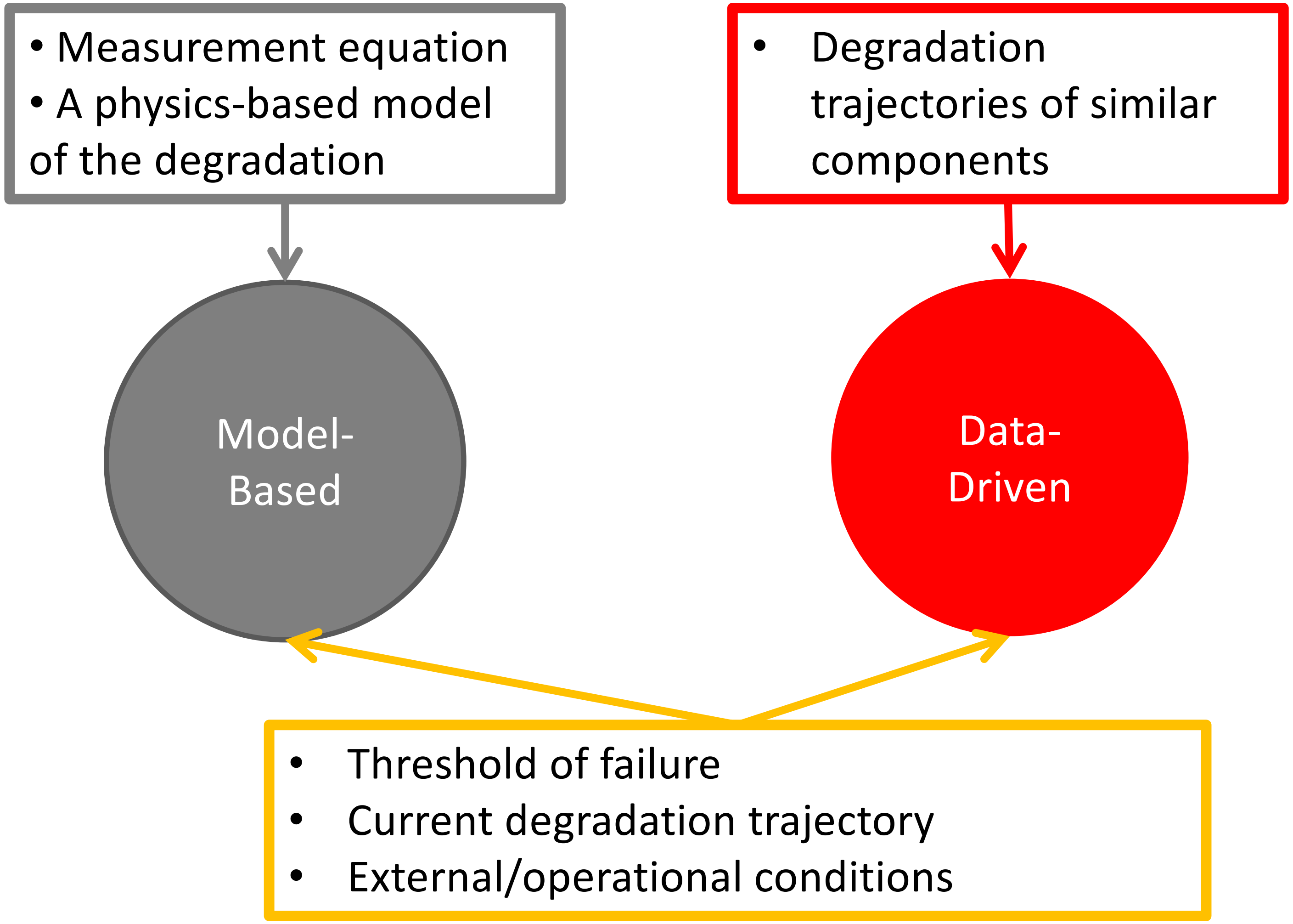
3 PHM, a look in: Practice

4 PHM, a look out: Practice

5 PHM, a look out: Theory

6 Conclusions

PHM approaches



PHM approaches

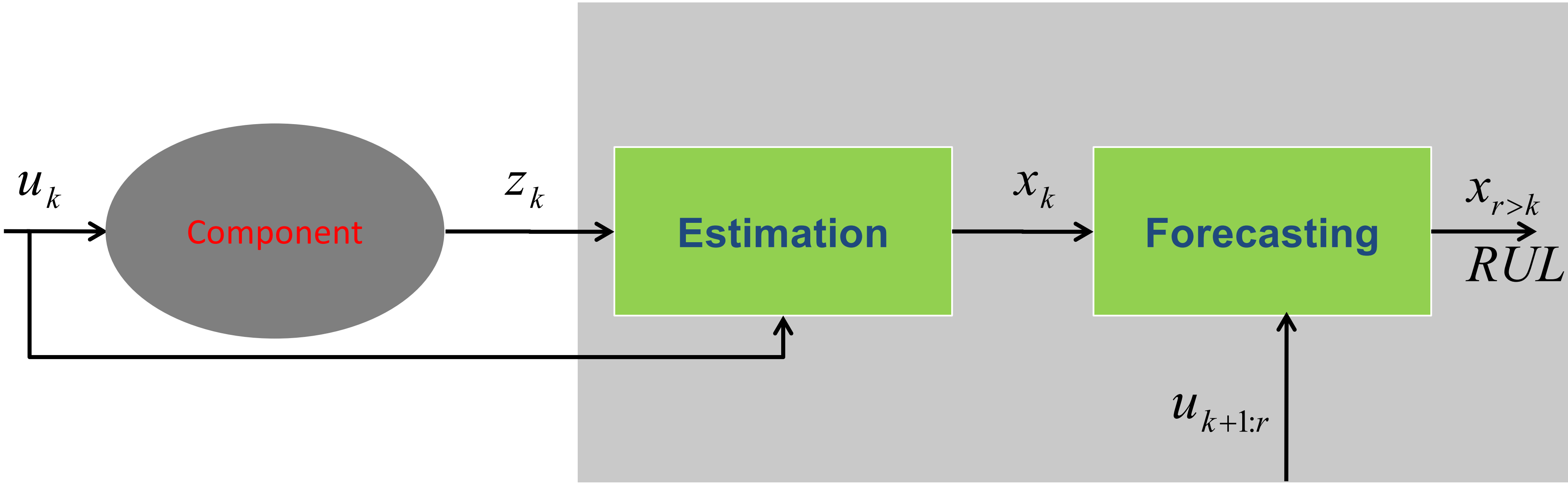
Model-Based

- Kalman filtering
- Extended kalman filtering
- Particle filtering
- …

Data- Driven

- k-nearest neighbor
- Bayesian classifier
- Support vector machine
- Artificial neural network
- Deep learning
- …

Model-based prognostics: the methodology



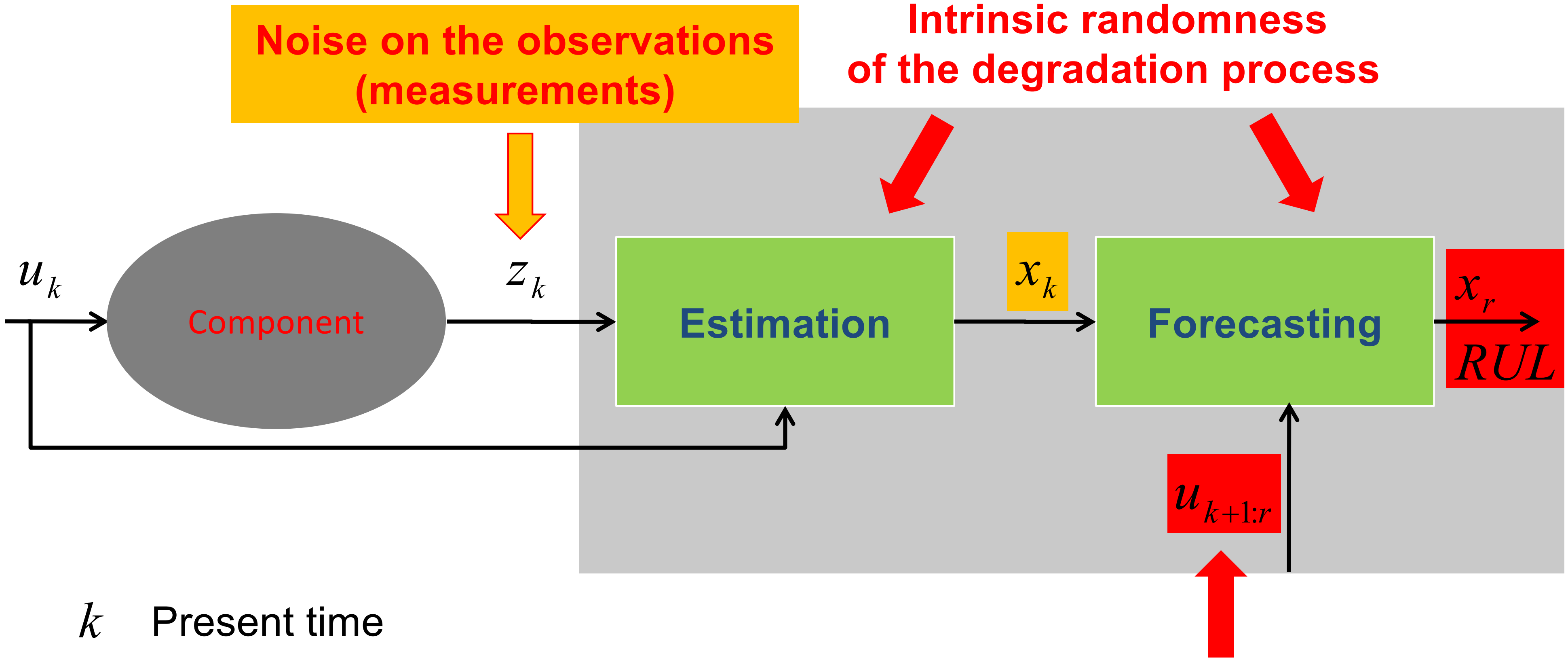
k Present time

u External/operating conditions

z Observations

x Degradation state

Main sources of uncertainty



k Present time

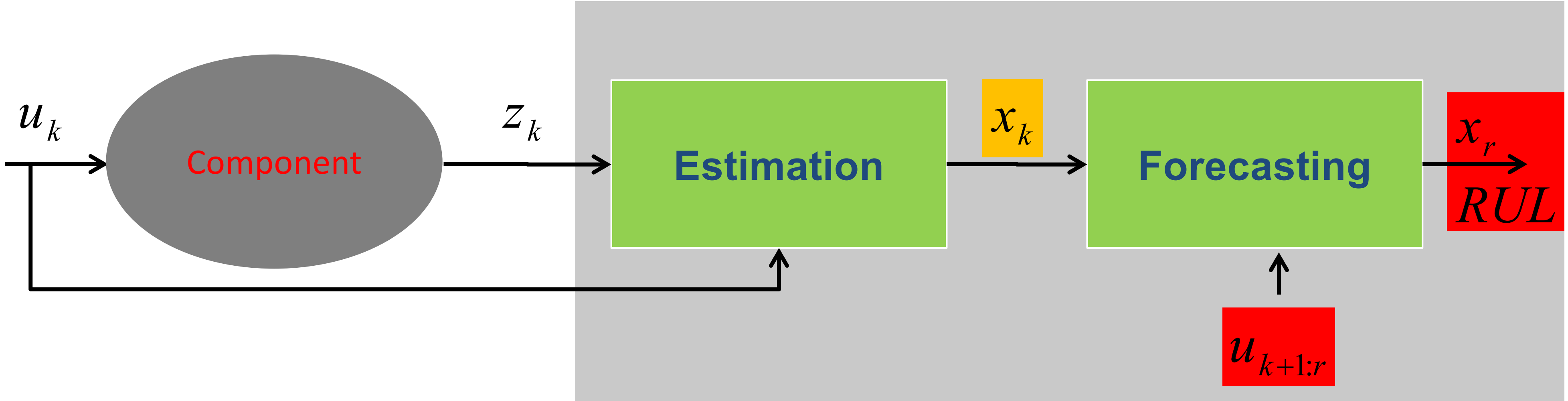
u External/operating conditions

z Observations

x Degradation state

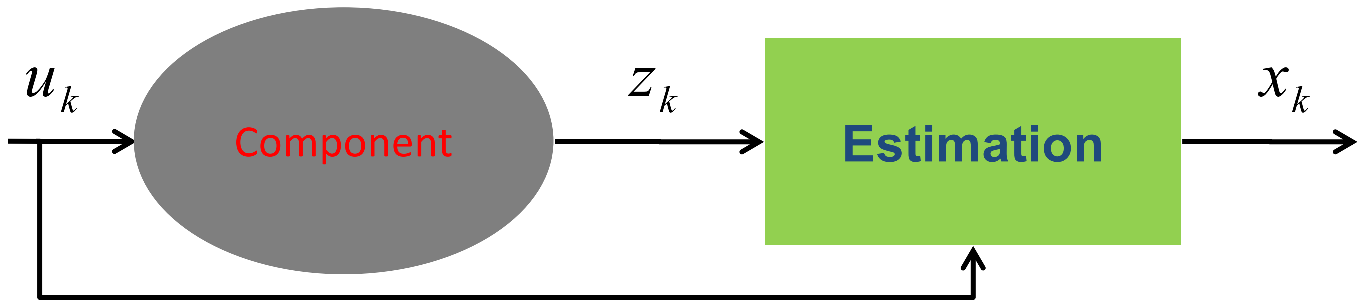
Future external/operating conditions are uncertain

Prognostics=Filtering + Forecasting



1. The filtering problem: to estimate the degradation state, x_k , at the present time
2. The forecasting problem:
   - to predict the degradation state, x_r, at a future time *r*
   - to predict the component RUL

Filtering



- Physical model of the degradation process
  - x = **hidden** degradation state
  - ω = random **process noise**
  - f = physical model of the degradation process (non-linear dynamic law)
  - k = time step index

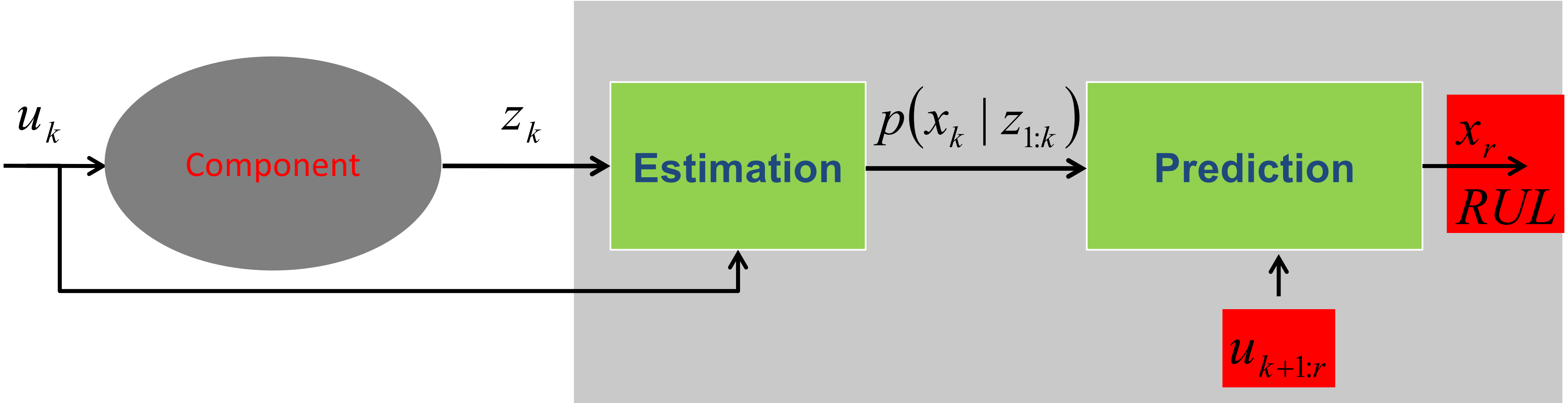
$$x_k = f_k(x_{k-1}, \omega_{k-1})$$

Time-discrete, hidden Markov process

- Measurement equation:
  - υ = random **measurement noise**
  - h = non-linear measurement equation

$$z_k = h(x_k, v_k)$$

Forecasting



Information Available:

- Estimate of the pdf of the state at the current time $p(x_k \mid z_{1:k})$
- Future (random) distribution of the operational/external conditions: $p_r(u_r, \omega_r)$
- Physical model of the degradation process $x_k = f_k(x_{k-1}, \omega_{k-1})$

- Estimate $p(x_r \mid z_{1:k})$
- Estimate RUL

PHM approaches

Model-Based

- Kalman filtering
- Extended kalman filtering
- Particle filtering
- …

Data- Driven

- k-nearest neighbor
- Bayesian classifier
- Support vector machine
- Artificial neural network
- Deep learning
- …

Data-driven PHM: the methodology

- **Model training**

t Time

x A set of features related to degradation of some identical or similar equipment

RUL Remaining Useful Life

- **Use the trained model for RUL prediction**

k Present Time

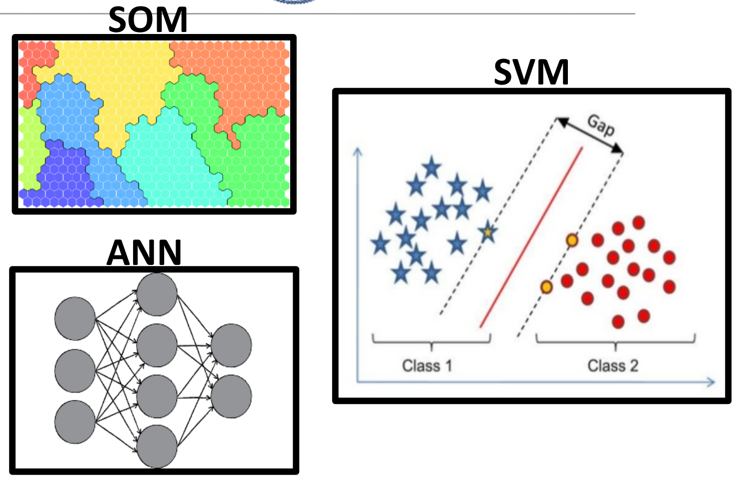
x^{new} A set of features of the current equipment

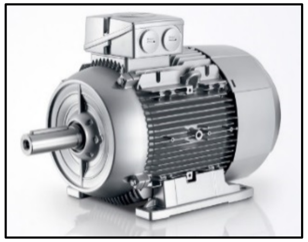
RUL^{new} RUL of the current equipment

Data-driven PHM

➢ Data-Driven PHM: Fault Detection

❑ (Anomalous) Pattern Recognition





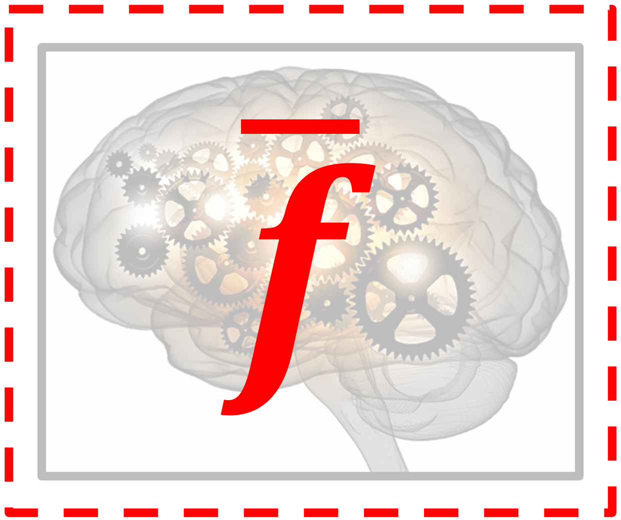
Input

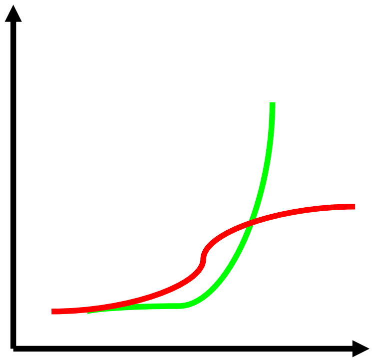
Current (I) →

Voltage (V) →

Magnetic Field (B) →

Temperature (T) →





→

Output

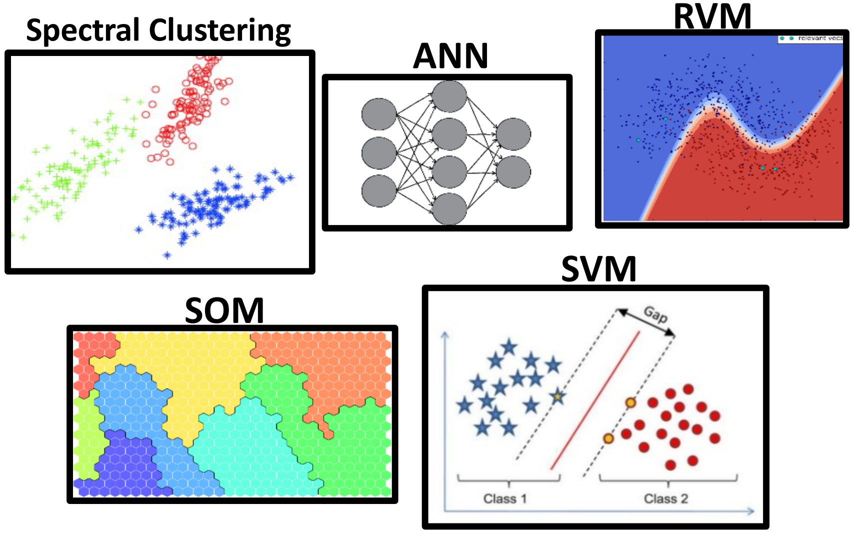
KO

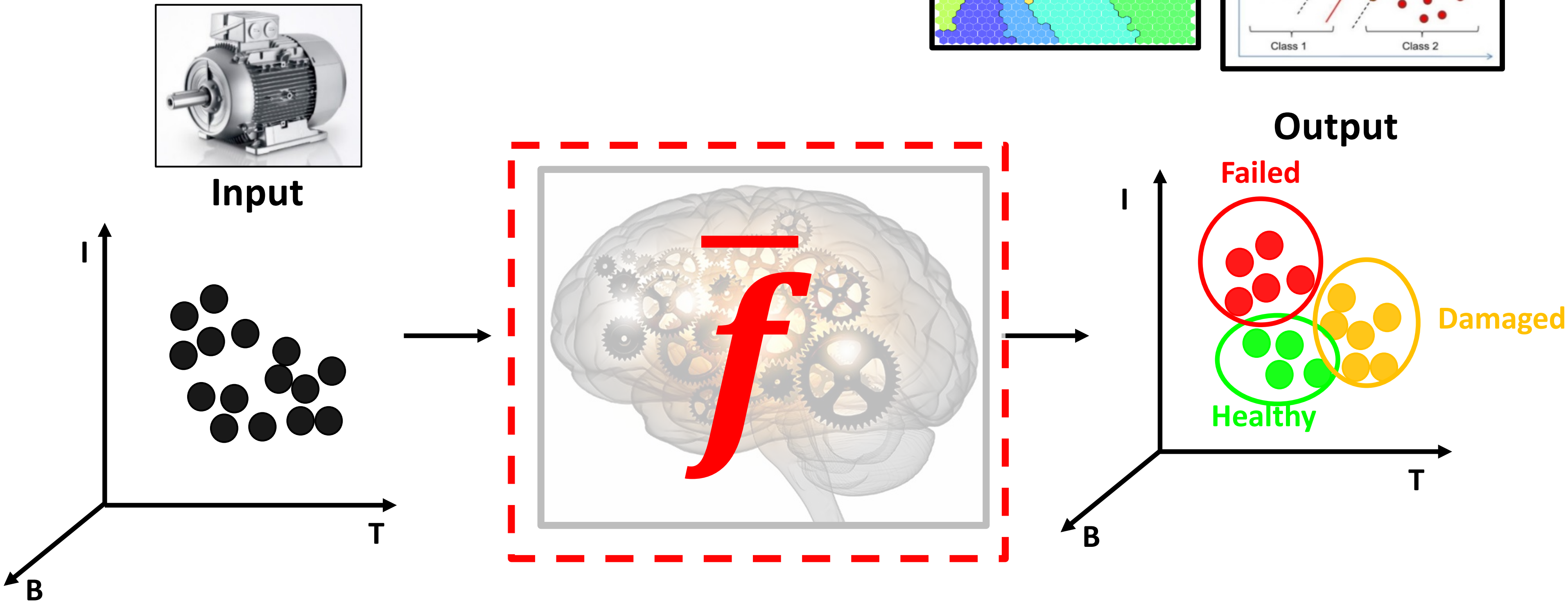
OK

ALERT

Data-driven PHM: Fault Diagnostics

- (Anomalous) Pattern Recognition
- **Data Classification**





Data-driven PHM

➢ Data-driven PHM: Virtual Sensors

- ❑ (Anomalous) Pattern Recognition
- ❑ Data Classification
- ❑ **Data Regression**

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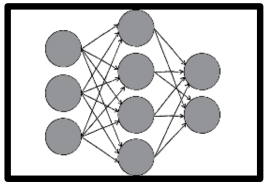
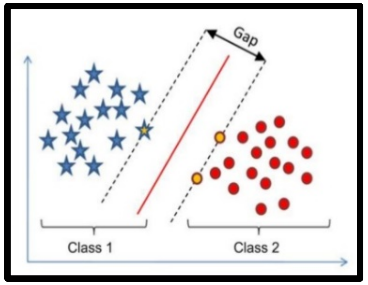
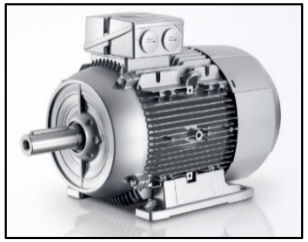


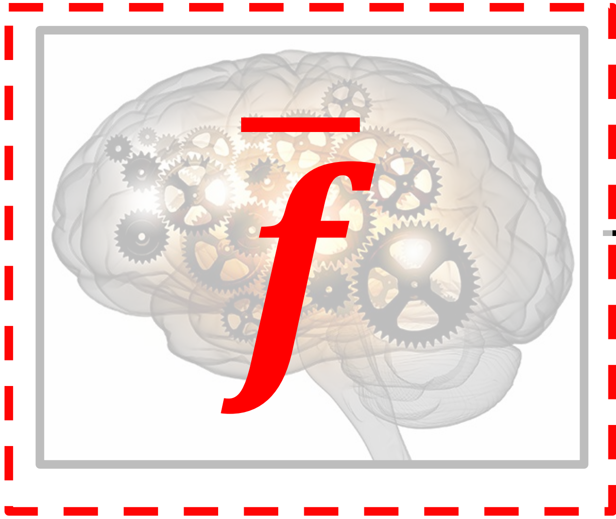
SVM



Input



$$\begin{bmatrix} I_t \\ B_t \\ V_t \\ T_t \end{bmatrix} \rightarrow$$



Output

$$\rightarrow \overline{Torque}_t$$

➢ Data-driven PHM: Failure Prognostics (RUL Prediction)

- ❑ (Anomalous) Pattern Recognition
- ❑ Data Classification
- ❑ Data Regression
- ❑ **Data Prediction**

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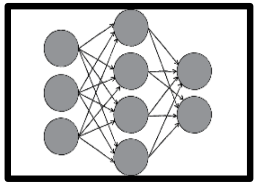
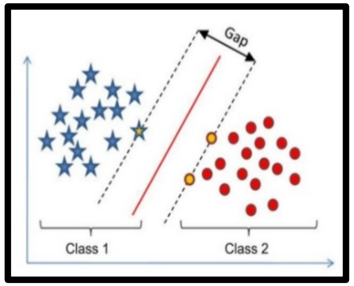
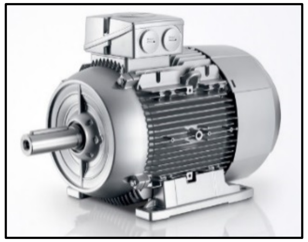


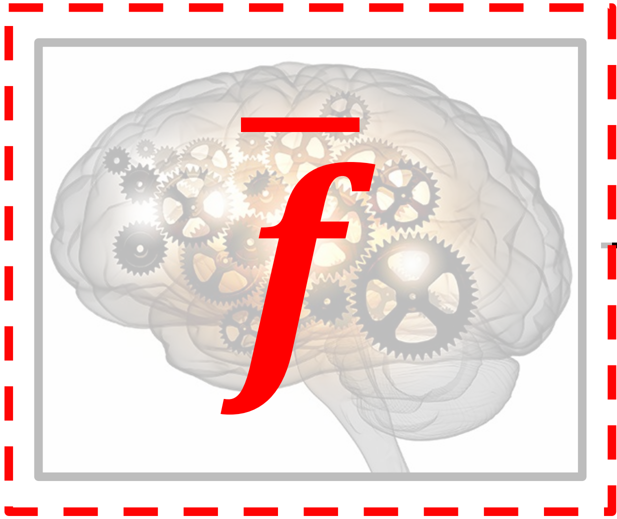
SVM





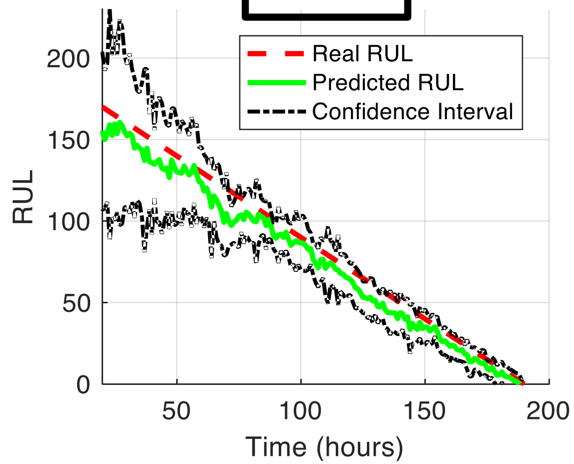
Input

$$\begin{bmatrix} I_t \\ B_t \\ V_t \\ T_t \end{bmatrix}$$



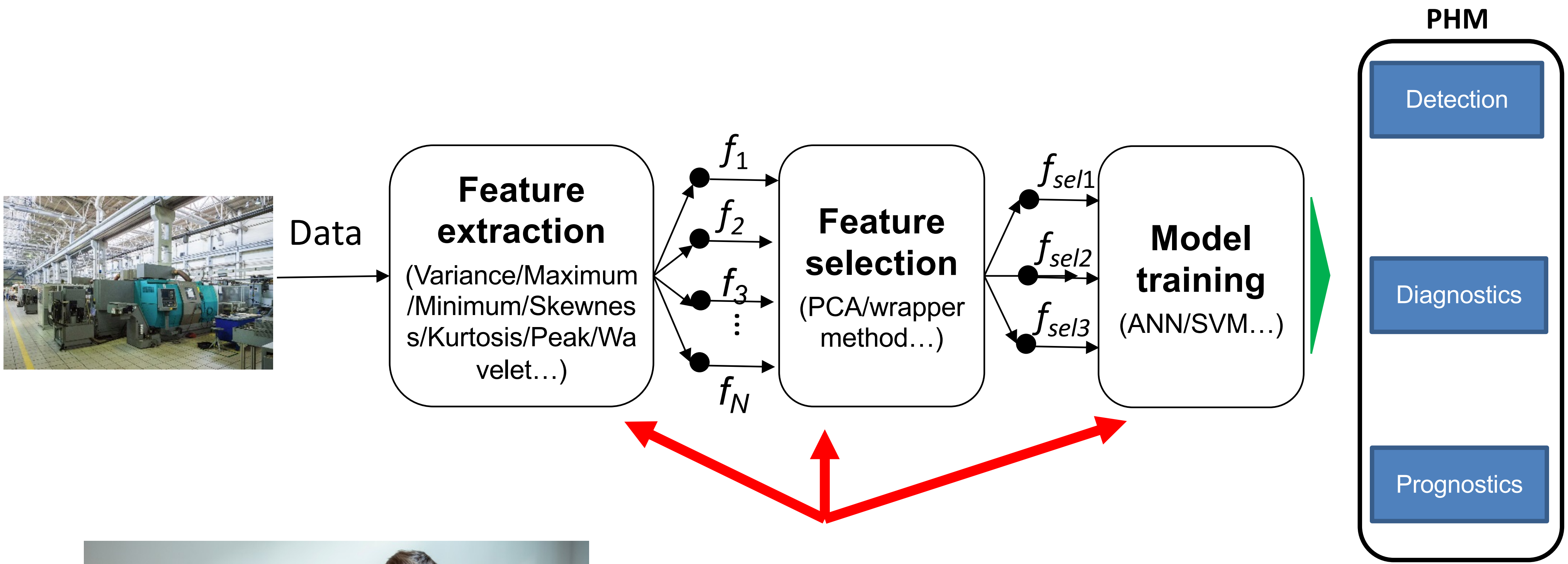
Output

$$RUL_t$$



Outline

Data-driven PHM in practice

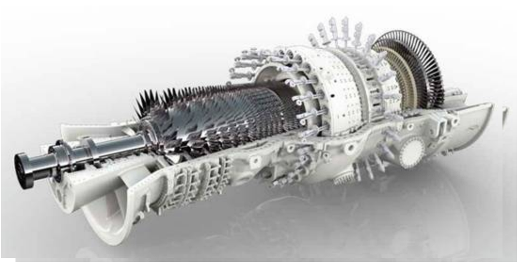


Expert intervention

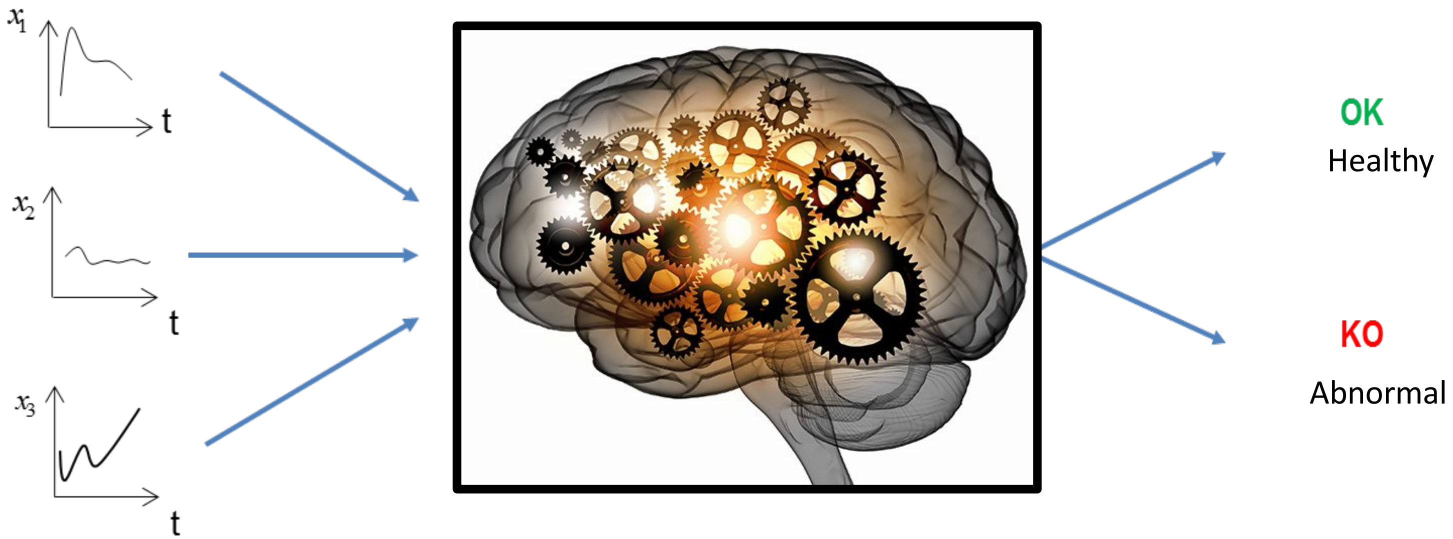
- **Feature extraction:** Hand-crafted feature design
- **Feature selection:** By trial and errors, expert experience, time consuming filter/ wrapper feature selection algorithms
- **Model training**

➢ Data-Driven PHM practical results: Fault Detection

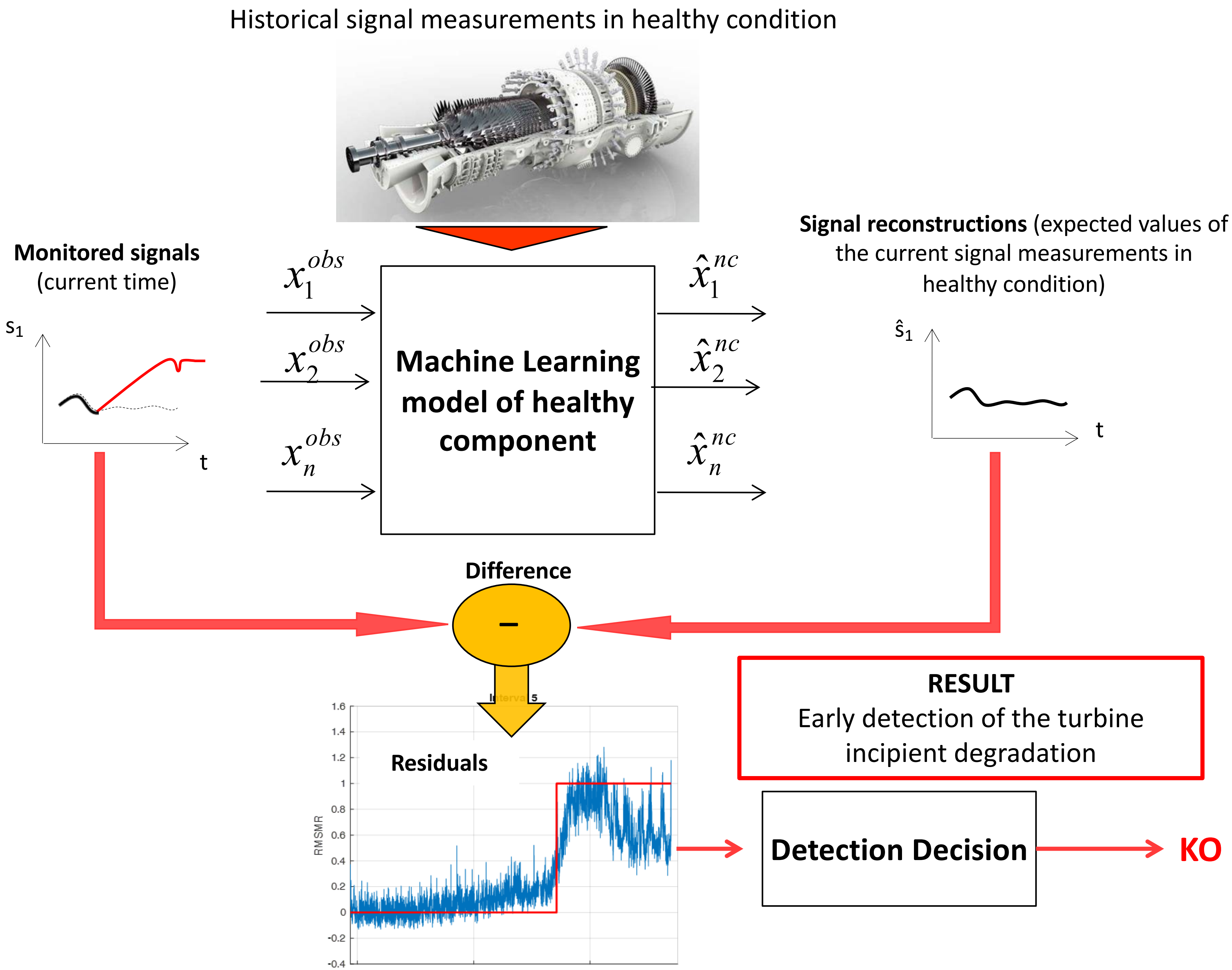
❑ **Turbine Fault Detection**



Monitored Signals



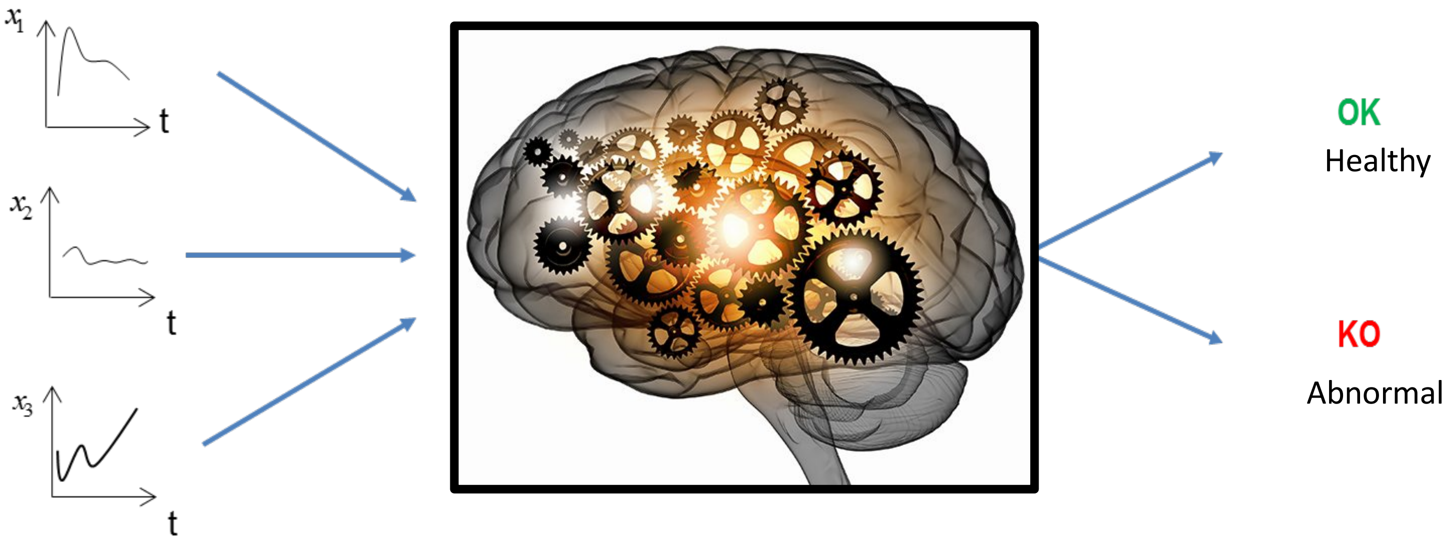
Data-driven PHM in practice



Data-driven PHM practical results: Fault Detection

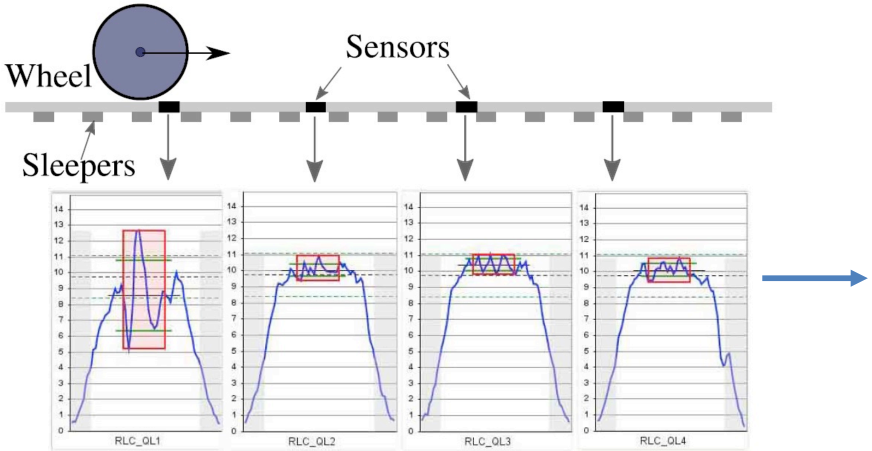
- Turbine Fault Detection
- **Train Wheel Defect Detection**

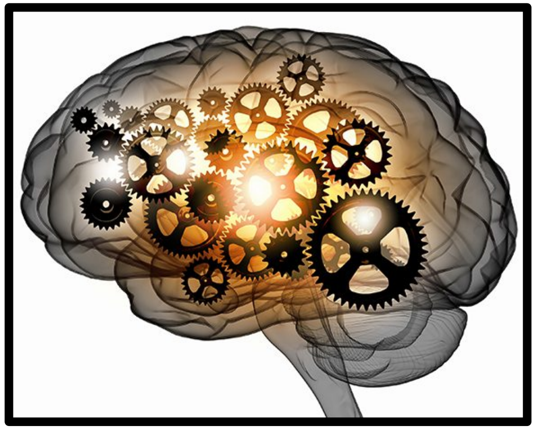
Monitored Signals

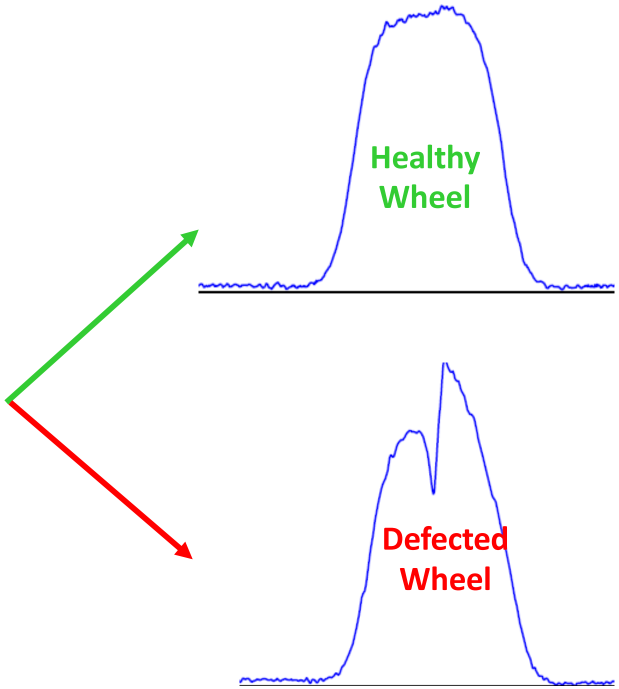


Data-driven PHM in practice

Sensors of Vertical Force permanently installed on the railway

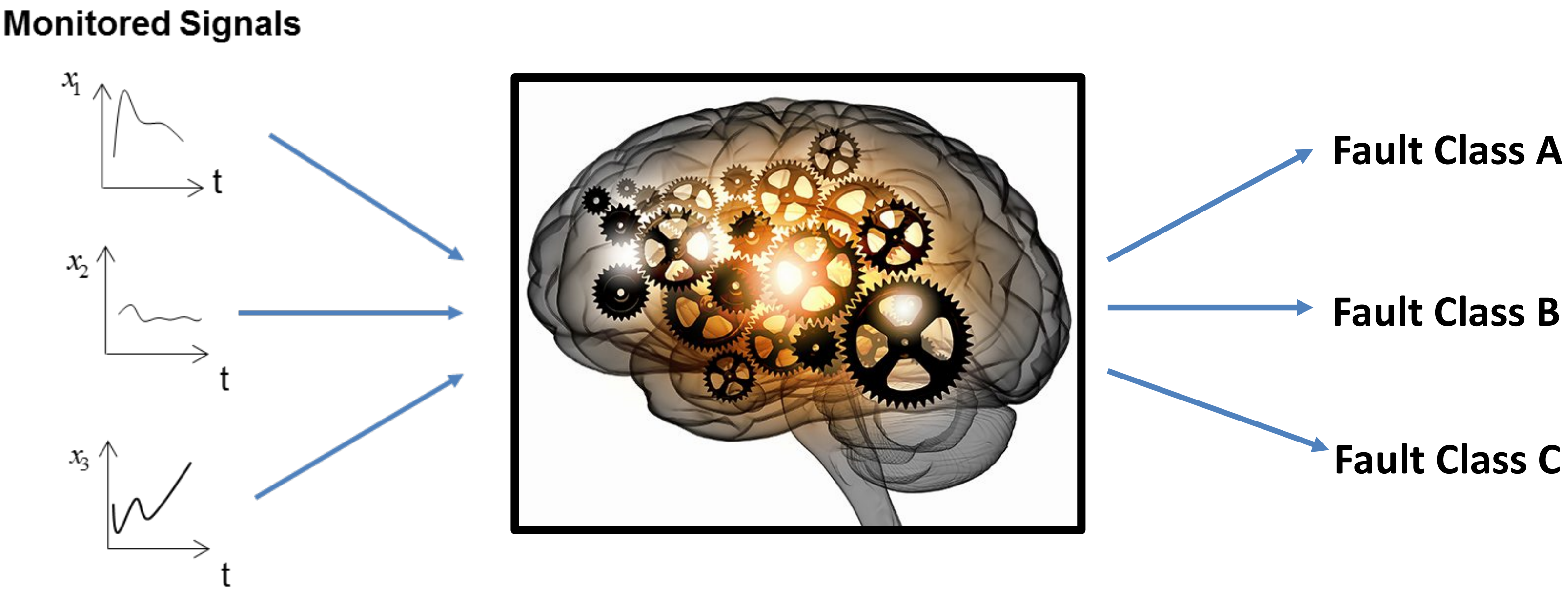






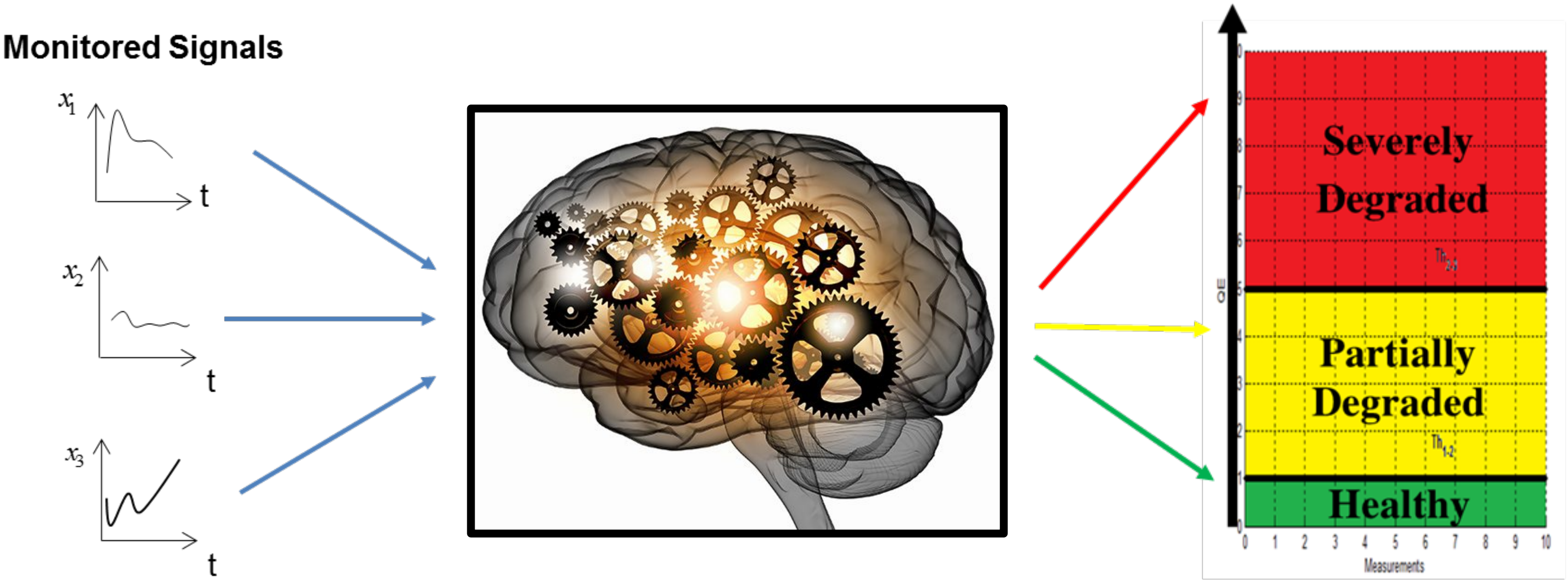
Data-driven PHM practical results: Fault Diagnostics

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



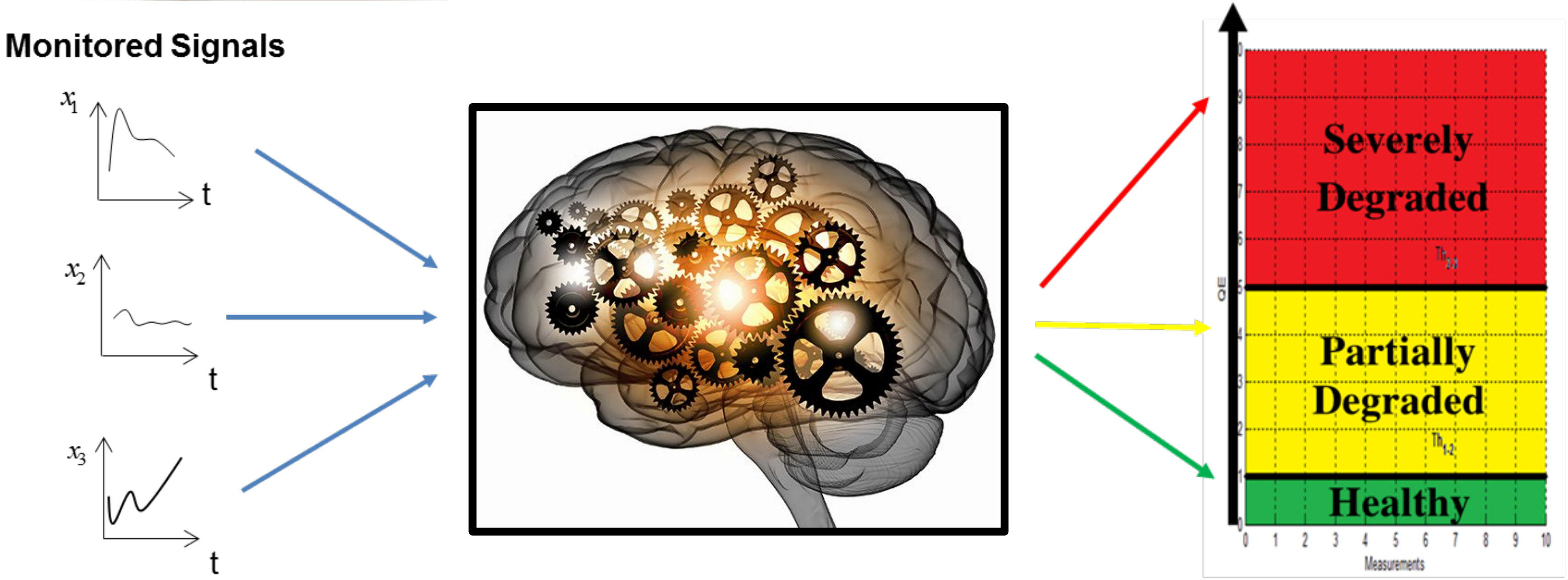
Data-driven PHM practical results: Fault Diagnostics

- Turbine Fault Detection
- Train Wheel Defect Detection
- Train Braking System Fault Detection
- Packaging Machine Fault Diagnostics
- **Packaging Machine Degradation Assessment**



Data-driven PHM practical results: Fault Diagnostics

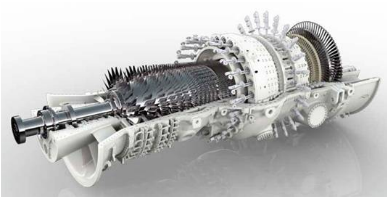
- Turbine Fault Detection
- Train Wheel Defect Detection
- Train Braking System Fault Detection
- Packaging Machine Fault Diagnostics
- Packaging Machine Degradation Assessment
- **Electric Vehicle: Motor Degradation Assessment**



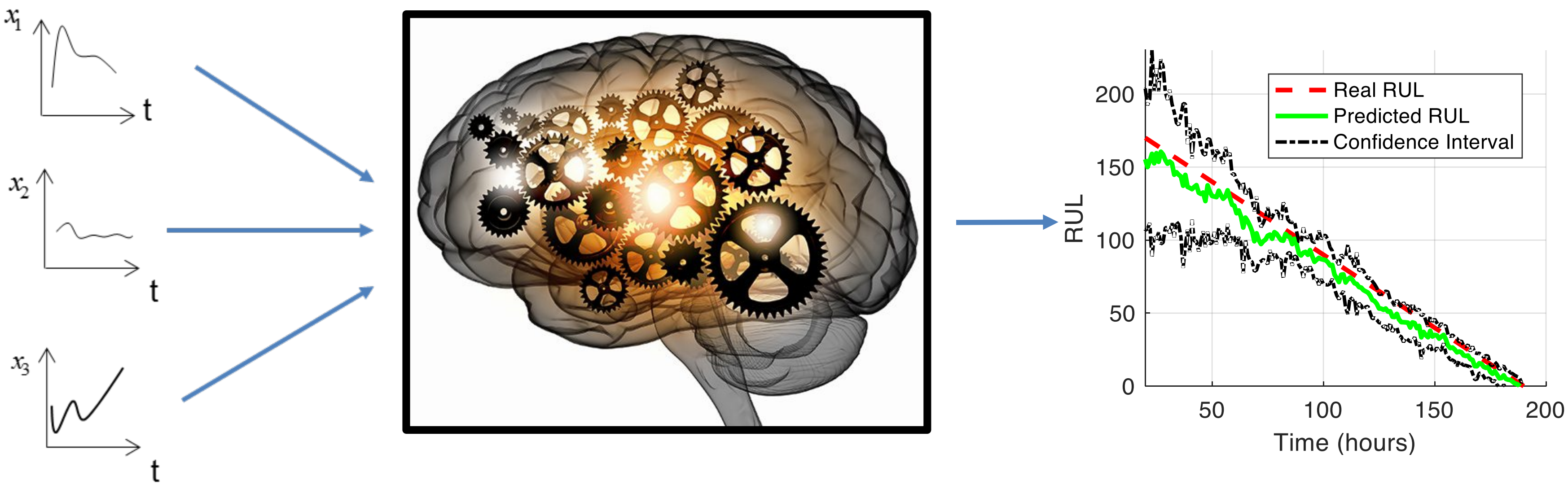
➢ Data-driven PHM practical results: Failure Prognostics

- ❑ 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



Outline

Data-driven PHM:Challenges

- ❑ Real data anomalies
- ❑ Changing environment
- ❑ Intelligible models
- ❑ Secure models

Challenges to IoT-Enabled Predictive Maintenance for Industry 4.0

Michele Compare, Piero Baraldi, and Enrico Zio, *Senior Member, IEEE*

***Abstract*—The Industry 4.0 paradigm is boosting the relevance of predictive maintenance (PdM) for manufacturing and production industries. PdM strongly relies on Internet of Things (IoT), which digitalizes the physical actions allowing human-to-human, human-to-machine, and machine-to-machine connections for intelligent perception. Several issues still need to be addressed for reaching the maturity stage for the widespread application of PdM. To do this, IoT needs to be empowered with data science capabilities, to reach the ultimate objective of digitalization, which is supporting decision making to optimally act on the physical systems. In this article, we present a comprehensive outlook of the current PdM issues, with the final aim of providing a deeper understanding of the limitations and strengths, challenges and opportunities of this dynamic maintenance paradigm. This is done through extensive research and analysis of the scientific and technical literature. On this basis, this article outlines some main research issues to be addressed for the successful development and deployment of IoT-enabled PdM in industry.**

***Index Terms*—Industry 4.0, Internet of Things (IoT), predictive maintenance (PdM).**

I. Introduction

INDUSTRY 4.0, the fourth industrial revolution [1]–[3], aims at creating smart factories, equipped with disruptive technologies, such as advanced robotics, 3-D printing, high computing power and connectivity, etc., which are integrated with analytical and cognitive technologies that enable machine-to-machine (M2M) and machine-to-human (M2H) communication. The smart factory provides the opportunity of offering new services and products to customers, with efficiency, standards of quality, and reliability higher than before. These allow expanding the value chain by generating new business models that create value for customers and revenue for manufacturing companies [4].

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M. Compare is with the Department of Energy, Politecnico di Milano, 20146 Milan, Italy, and also with Aramis s.r.l., 20124 Milan, Italy (e-mail: michele.compare@polimi.it).

P. Baraldi is with the Department of Energy, Politecnico di Milano, 20146 Milan, Italy (e-mail: piero.baraldi@polimi.it).

E. Zio is with the Department of Energy, Politecnico di Milano, 20146 Milan, Italy, and with Aramis s.r.l., 20124 Milan, Italy, also with the Department of Nuclear Engineering, College of Engineering, Kyung Hee University, Seoul, South Korea, and also with MINES ParisTech, PSL Research University, CRC, Sophia Antipolis, France (e-mail: enrico.zio@polimi.it).

Digital Object Identifier 10.1109/JIOT.2019.2957029

One of the opportunities (among others) most spoken of in Industry 4.0 is predictive maintenance (PdM), which makes use of condition monitoring data to detect anomalies (i.e., recognize deviations from normal operating conditions) in production processes, manufacturing equipment and products, and diagnose (i.e., characterize the occurring abnormal state) and prognose (i.e., predict the future evolution of the abnormal state up to failure). The set of detection, diagnostic, and prognostic tasks is often referred to as prognostics and health management (PHM) [7]–[11]. The capability of performing these tasks with sufficient accuracy provides the opportunity of setting efficient, just-in-time, and just-right maintenance strategies: in other words, providing the right part to the right place at the right time. This opportunity is big because doing this would maximize the production profits and minimize all costs and losses, including asset ones [12].

Boosted by the intuitive and appealing potential of PdM, the industry is making significant investments for equipping itself with the elements necessary for deploying PdM. For example, the investments by the Italian industry in research and development and innovation for Industry 4.0 increased by 15% in 2017, a significant part of which allocated to PdM [16], and similar investments are reported in other countries (e.g., [17]). This situation has sparked the birth of a large number of PdM specialized companies, commercial softwares, dedicated journals and conferences, etc.

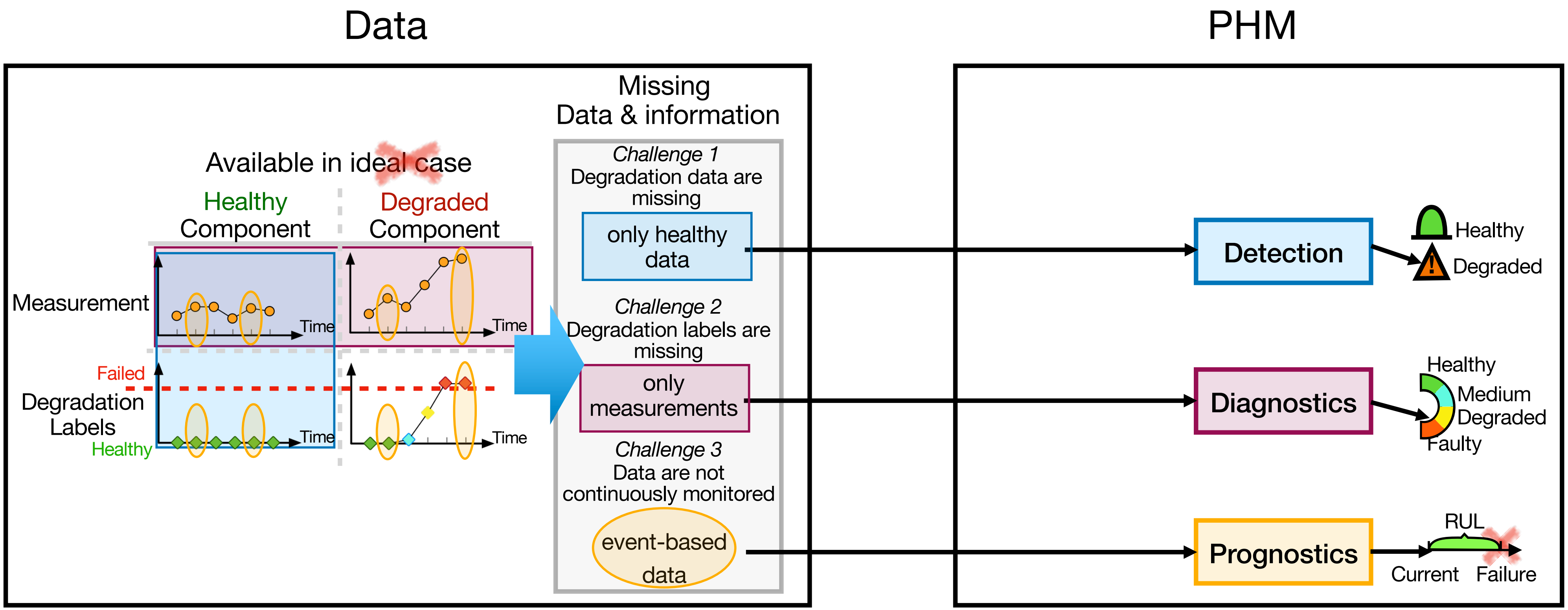
The Internet of Things (IoT) is a main pillar of PdM [5], [6], as it allows translating physical actions from machines into digital signals used for PdM. Namely, IoT continuously streams data from sensors, such as temperature, vibration, etc., and from other sources, such as a machine programmable logic controller (PLC), manufacturing execution system (MES) terminals, computerized maintenance management systems (CMMSs) [13]–[15], or even an enterprise resource planning (ERP) system. These pieces of information provide the basis for setting PdM approaches.

Up to now, the focus of the effort made has been mainly on the development of hardware (i.e., IoT, smart meters, etc. [5], [6], [18], [19]) and software (e.g., PHM tools, platforms for IoT interconnection and clouding, etc. [20]–[22]) for tracking the health state of monitored components. On the other hand, the industrial-scale deployment of PdM involves many other aspects and impacts various sectors of the workplace involved in maintenance (i.e., workers can use smart systems, maintenance engineers can analyze big data for the maintenance process), logistics (spare parts and warehouse management can be driven by the PHM results), occupational health, safety

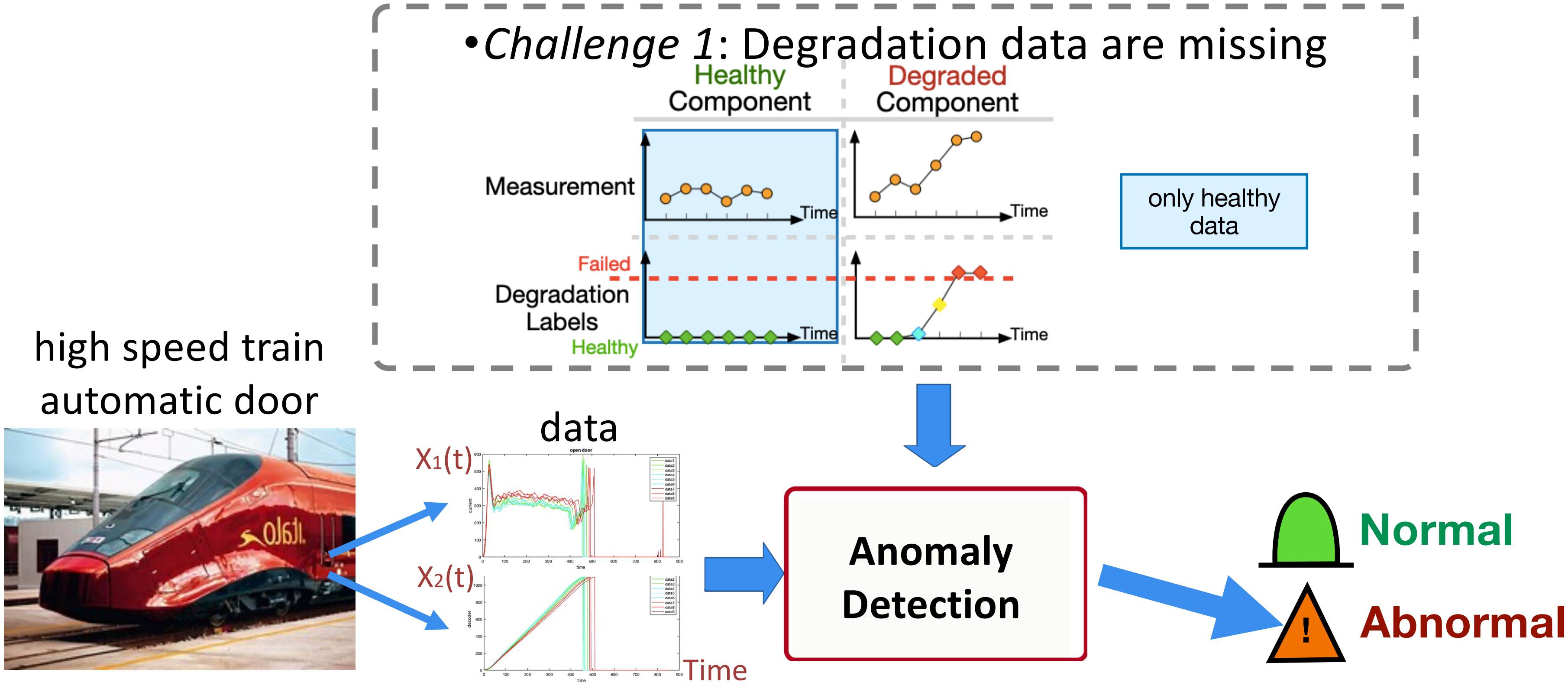
Data-driven methods: Challenges

- Real data anomalies
- Changing environment
- Intelligible models
- Secure models

Three challenges from data anomalies in PHM



Challenge 1: Degradation data are missing
Practical problem of relevance

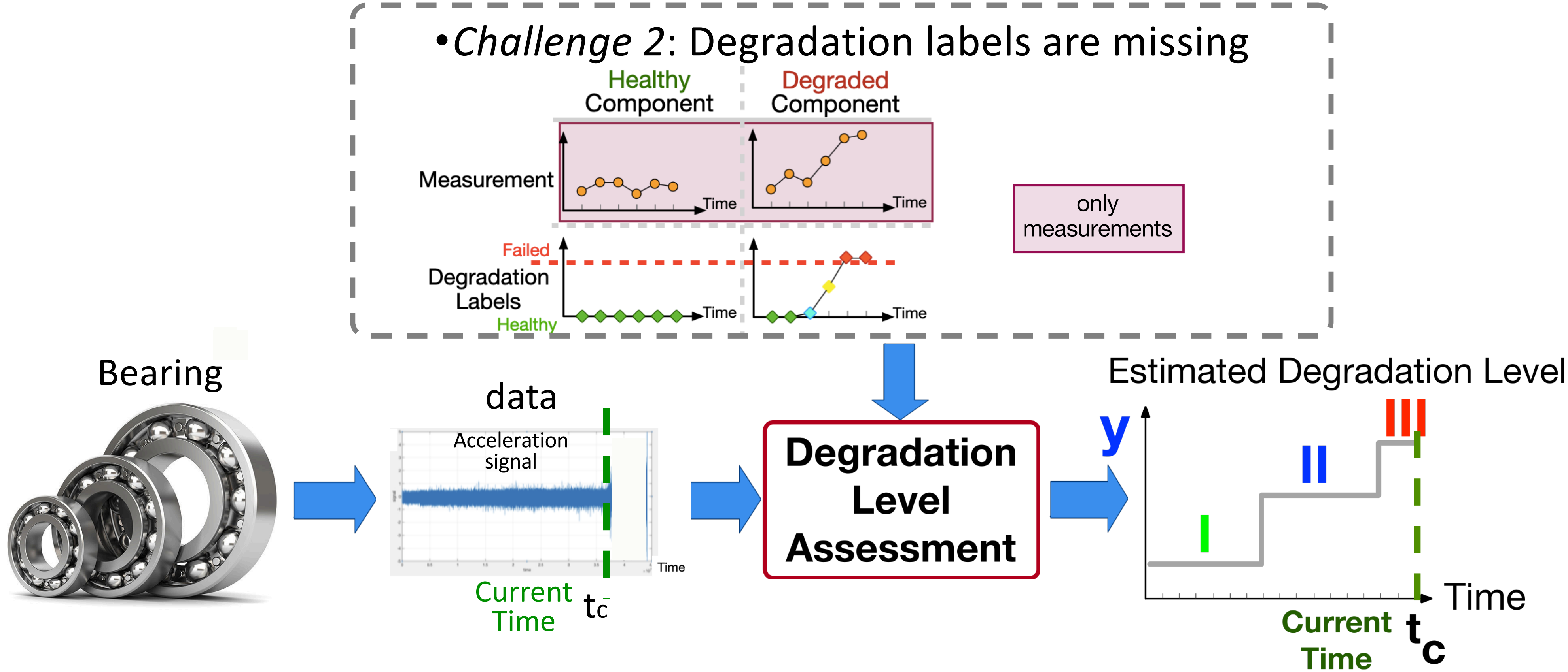


➢ Mathematical problem

Assume the availability of N_{normal} normal components, the generic $N_f \times L$ measurement matrix $\boldsymbol{X}^r, r = 1, \dots, N_{normal}$ is obtained by monitoring N_f degradation–related features during operation of L time steps.

The objective is to identify whether test component is normal/abnormal, given measurement $\boldsymbol{X}^{test}$.

Challenge 2: Degradation labels are missing
Practical problem of relevance



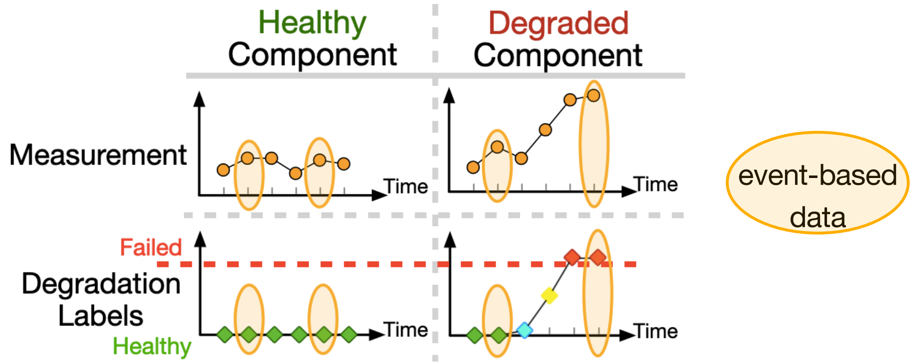
➢ Mathematical problem

Assume the availability of R run−to−failure equipment trajectories, each measures S degradation−related signals up to failure. The generic r−th trajectory is represented by $S \times N_r$ matrix $\boldsymbol{P}^r$ whose entry $p_{s,i}^{r}$ represents the value of signal $s, s = 1, \ldots, S,$ taken at time $t_i, i = 1, \ldots, N_r$.

We assume that all equipment have the same number of degradation levels, given historical measurement of test equipment $p_{1:S,1:i}^{test}$, the objective is to estimate its degradation level at the present time t_i, denoted by d_i^{test}.

Challenge 3: Data are not continuously monitored
Practical problem of relevance

- Challenge: Event-based measurements



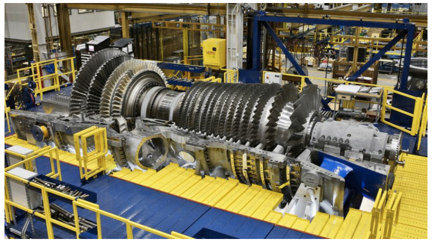
- Signal is measured when event occur !
- Irregular time steps

$\Delta t_1 \neq \Delta t_2$

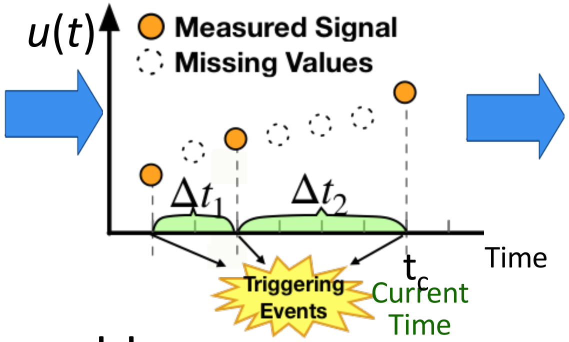
- Large number of missing values

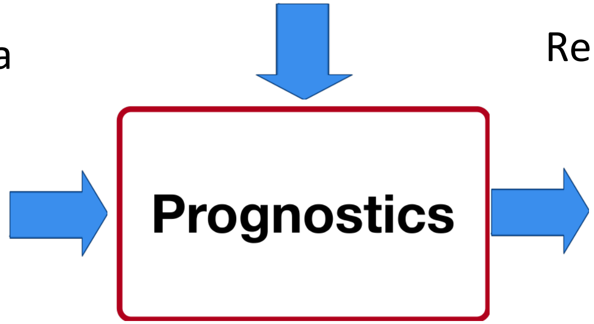
No. Missing Values > No. Measured Values

Turbine SlideBearing

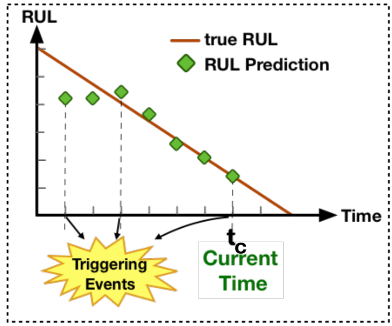


Event-based data





Remaining Useful Life Prediction



➢ Mathematical problem

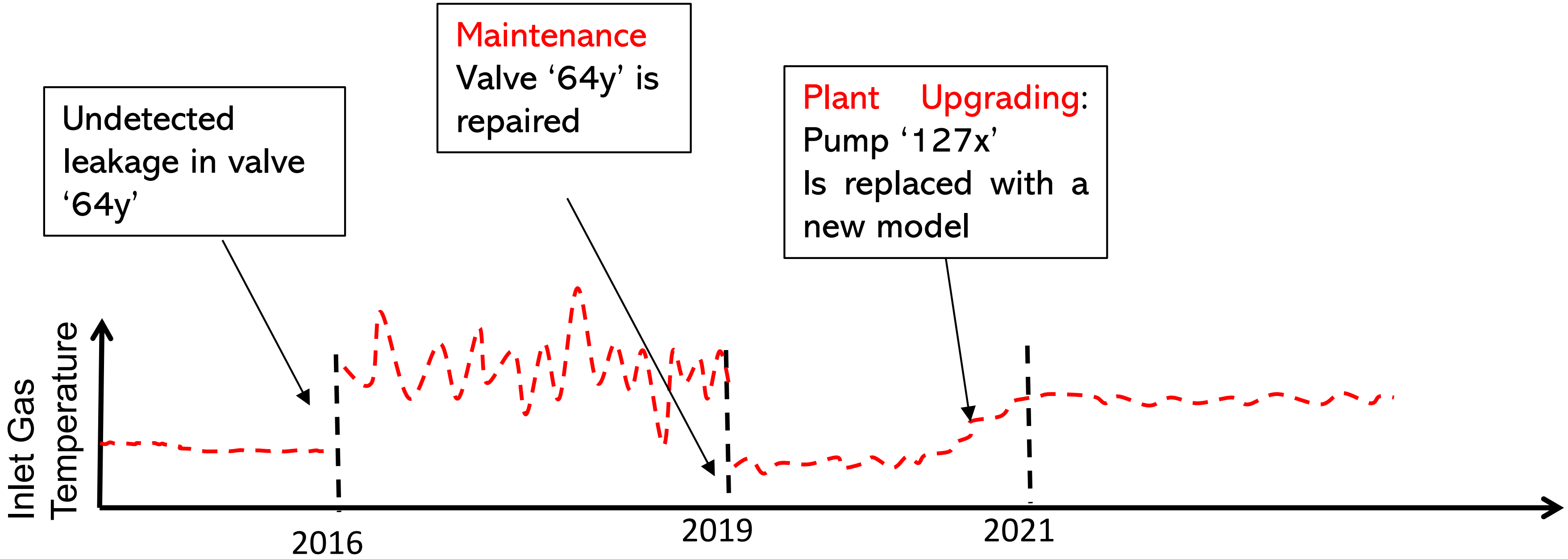
This work assumes the availability of the measurements of P signals collected in correspondence of the occurrence of events during R run−to−failure degradation trajectories. The measurement vector of the generic r−th trajectory is denoted by $\mathbf{z}^r(\tau_j^r), \tau_j^r$ is the time of occurrence of the j−th event of the r−th trajectory, $j = 1, \ldots, n^r$, and n^r is the number of events in r−th trajectory.

The objective is to predict RUL of equipment at time $t, R\widehat{U}L(t)$, on the basis of the signal measurements $\mathbf{z}^{test}(\tau_j)$ collected in correspondence of the occurred events.

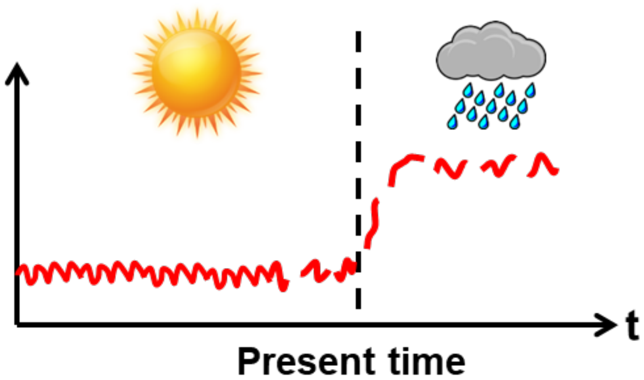
Data-driven methods: Challenges

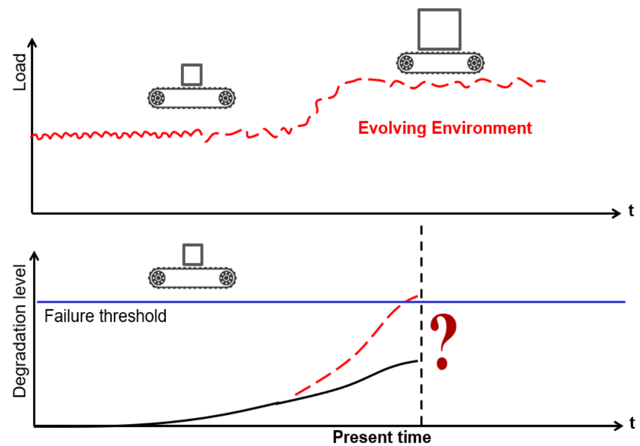
- Real data anomalies
- Changing environment
- Intelligible models
- Secure models

Changing environment



Non-stationary Environment





Data-driven methods: Challenges

- Real data anomalies
- Changing environment
- Intelligible models
- Secure models

electronics

MDPI

Review

Machine Learning Interpretability: A Survey on Methods and Metrics

Diogo V. Carvalho [1,2,*], Eduardo M. Pereira [1] and Jaime S. Cardoso [2,3]

1 Deloitte Portugal, Manuel Bandeira Street, 43, 4150-479 Porto, Portugal
2 Faculty of Engineering, University of Porto, Dr. Roberto Frias Street, 4200-465 Porto, Portugal
3 INESC TEC, Dr. Roberto Frias Street, 4200-465 Porto, Portugal
* Correspondence: diocarvalho@deloitte.pt

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check for updates

Abstract: Machine learning systems are becoming increasingly ubiquitous. These systems's adoption has been expanding, accelerating the shift towards a more algorithmic society, meaning that algorithmically informed decisions have greater potential for significant social impact. However, most of these accurate decision support systems remain complex black boxes, meaning their internal logic and inner workings are hidden to the user and even experts cannot fully understand the rationale behind their predictions. Moreover, new regulations and highly regulated domains have made the audit and verifiability of decisions mandatory, increasing the demand for the ability to question, understand, and trust machine learning systems, for which interpretability is indispensable. The research community has recognized this interpretability problem and focused on developing both interpretable models and explanation methods over the past few years. However, the emergence of these methods shows there is no consensus on how to assess the explanation quality. Which are the most suitable metrics to assess the quality of an explanation? The aim of this article is to provide a review of the current state of the research field on machine learning interpretability while focusing on the societal impact and on the developed methods and metrics. Furthermore, a complete literature review is presented in order to identify future directions of work on this field.

Keywords: machine learning; interpretability; explainability; XAI

1. Introduction

The ubiquity of machine learning systems is unquestionable: These are becoming increasingly present in different domains and becoming increasingly capable of different tasks. Regarding the presence of machine learning in the contemporary society, this evolution has accentuated the need and importance of machine learning interpretability, which only in the last half-decade has started gaining some traction as a research field. Nevertheless, when in comparison with the focus on developing machine learning techniques and models themselves as well as the focus on achieving better performance metrics, interpretable machine learning research is still a relatively small subset of the whole machine learning research.

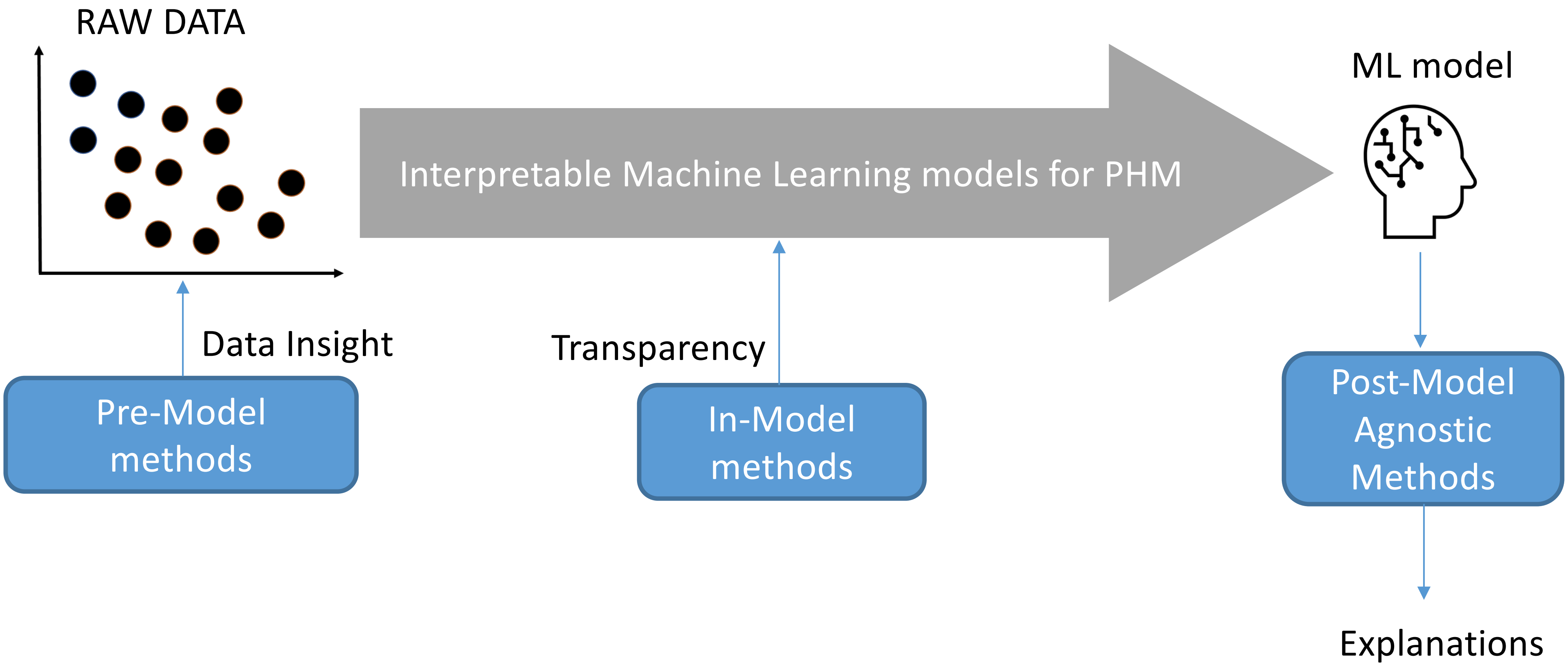
Given the importance of interpretability in machine learning, this means there is a clear need to increase the focus on this research field in order to increase progress and converge scientific knowledge. This article aims to be a step forward in that direction by gathering all the relevant details on the research field of machine learning interpretability. Despite being a survey, this article takes a stand on how important interpretability is for our society and our future and on the importance of the sciences involved coming together and producing further and sustained knowledge on this field. The aim is to thoroughly describe the relevance of the field as well as to piece together the existing scientific literature in order to encourage and facilitate future research on this field while encapsulating the

Better Understanding

An **interpretable** ML model can also lead to:

- **Better understanding** of the phenomena analyzed with the ML algorithm
- **Extracting knowledge** from ML patterns
- **Discovering i**nteractions among inputs
- Extrapolation (small) for **gaining knowledge** on unexplored scenarios
- **Quantifying reliability** of predictions/classifications

Phases of building a ML model



Flowchart interpretability in PHM

Raw data
- Signals
- Texts
- Images

Remove Outliers
- Box Plot
- Bag Plot

Missing data
- Recons-truction

Normalize data
- Distort-ion

Features Extraction
- Auto-encoders
- PCA

Features Selection
- Interpret features

ML model Training
- ANN
- SVM

ML model validation
- Simulations
- Case study

Interpretable Machine Learning models for PHM

- Fault Detection
- Fault Diagnostic
- Fault Prognostic

Pre-Model methods → Data Insight
- EDA: Exploratory Data Analysis
- Visualization tools (e.g. scatterplot of pairs of input)

In-Model methods → Transparency

Constraints:
- Monotonicity
- Linearity
- Causal Relations
- Physical Constraints

Post-Model Agnostic Methods

Local
- LIME, SHAPLEY

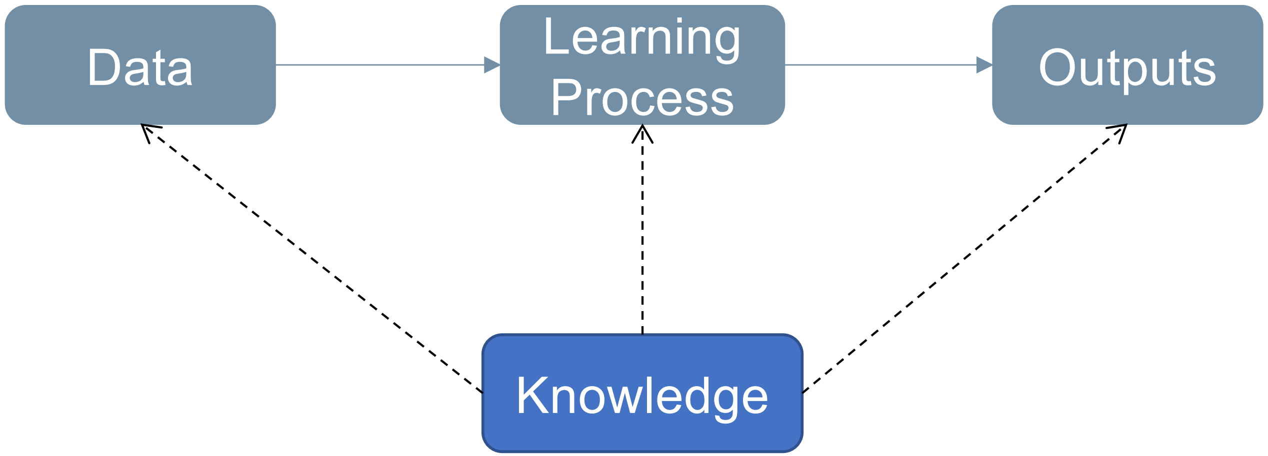
Global
- PDP, ALE,ICE

Explanations:
- Feature Summary and data points
- Graphical Representation

Physics-Induced ML

- Physics-Induced Machine Learning

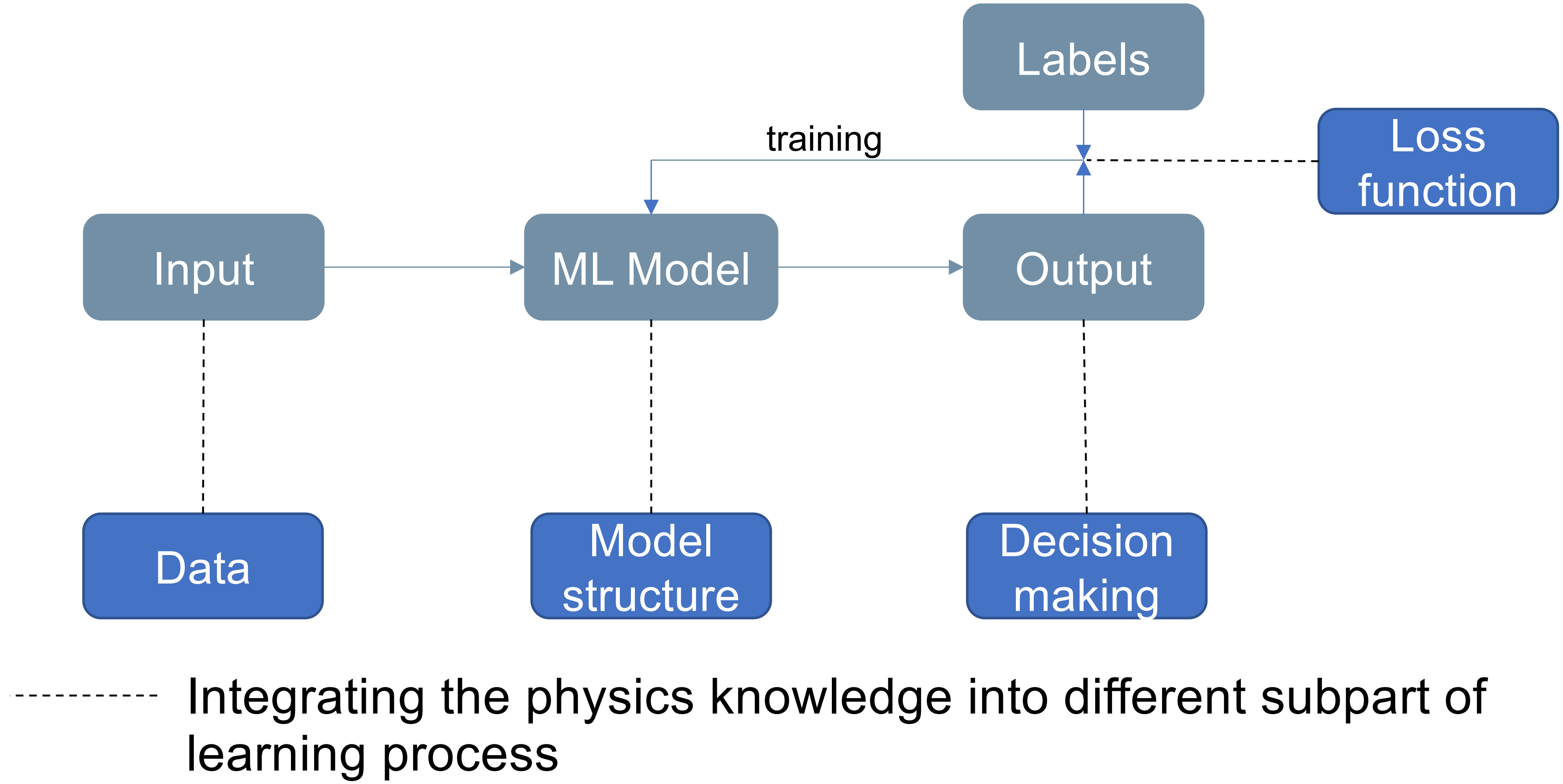
Physics-Induced ML focuses on incorporating domain knowledge into the learning process of ML model in a synergistic manner.



It also has different names like Physics-Informed ML, Theory-Guided ML, Physics-Guided ML and so on

Physics-Induced ML

- Specifically, classify the physics-induced methods based on ML application process



Integrating the physics knowledge into different subpart of learning process

Data-driven methods: Challenges

- Real data anomalies
- Changing environment
- Intelligible models
- Secure models

Failure Modes in Machine Learning

Ram Shankar Siva Kumar*, David O'Brien#, Kendra Albert^, Salome Viljoen#, Jeffrey Snover*

ram.shankar@microsoft.com; jsnover@microsoft.com
*Microsoft

dobrien@cyber.harvard.edu; sviljoen@cyber.harvard.edu
#Berkman Klein Center for Internet and Society at Harvard University

kalbert@law.harvard.edu
^Harvard Law School

Introduction & Background

In the last two years, more than 200 papers have been written on how machine learning (ML) can fail because of adversarial attacks on the algorithms and data; this number balloons if we were to incorporate papers covering non-adversarial failure modes. The spate of papers has made it difficult for ML practitioners, let alone engineers, lawyers, and policymakers, to keep up with the attacks against and defenses of ML systems. However, as these systems become more pervasive, the need to understand how they fail, whether by the hand of an adversary or due to the inherent design of a system, will only become more pressing. The purpose of this document is to jointly tabulate both of these failure modes in a single place.

- *Intentional failures* where the failure is caused by an active adversary attempting to subvert the system to attain her goals – either to misclassify the result, infer private training data, or to steal the underlying algorithm.
- *Unintentional failures* where the failure is because an ML system produces a formally correct but completely unsafe outcome

We would like to point out that there are other taxonomies and frameworks that individually highlight intentional failure modes[1,2] and unintentional failure modes.[3,4] Our classification brings the two separate failure modes together in one place and addresses the following needs:

1) The need to equip software developers, security incident responders, lawyers, and policy makers with a common vernacular to talk about this problem. After developing the initial version of the taxonomy last year, we worked with security and ML teams across Microsoft, 23 external partners, standards organization, and governments to understand how stakeholders would use our framework. Based on this usability study and stakeholder feedback, we iterated on the framework.
   Result: When presented with an ML failure mode, we frequently observed that software developers and lawyers mentally mapped the ML failure modes to traditional software attacks like data exfiltration. So, throughout the paper, we attempt to highlight how machine learning failure modes are meaningfully different from traditional software failures from a technology and policy perspective.
2) The need for a common platform for engineers to build on top of and to integrate into their existing software development and security practices. Broadly, we wanted the taxonomy to be more than an educational tool – we want it to effectuate tangible engineering outcomes.

[1] Li, Guofu, et al. "Security Matters: A Survey on Adversarial Machine Learning." *arXiv preprint arXiv:1810.07339* (2018).
[2] Chakraborty, Anirban, et al. "Adversarial attacks and defences: A survey." *arXiv preprint arXiv:1810.00069* (2018).
[3] Ortega, Pedro, and Vishal Maini. "Building safe artificial intelligence: specification, robustness, and assurance." *DeepMind Safety Research Blog* (2018).
[4] Amodei, Dario, et al. "Concrete problems in AI safety." *arXiv preprint arXiv:1606.06565* (2016).

Threat Modeling AI/ML Systems and Dependencies

By Andrew Marshall, Jugal Parikh, Emre Kiciman and Ram Shankar Siva Kumar
Special Thanks to Raul Rojas and the AETHER Security Engineering Workstream
November 2019

Outline

1 Prognostics and Health Management (PHM)

2 PHM, a look in: Theory

3 PHM, a look in: Practice

4 PHM, a look out: Practice

5 PHM, a look out: Theory

6 Conclusions

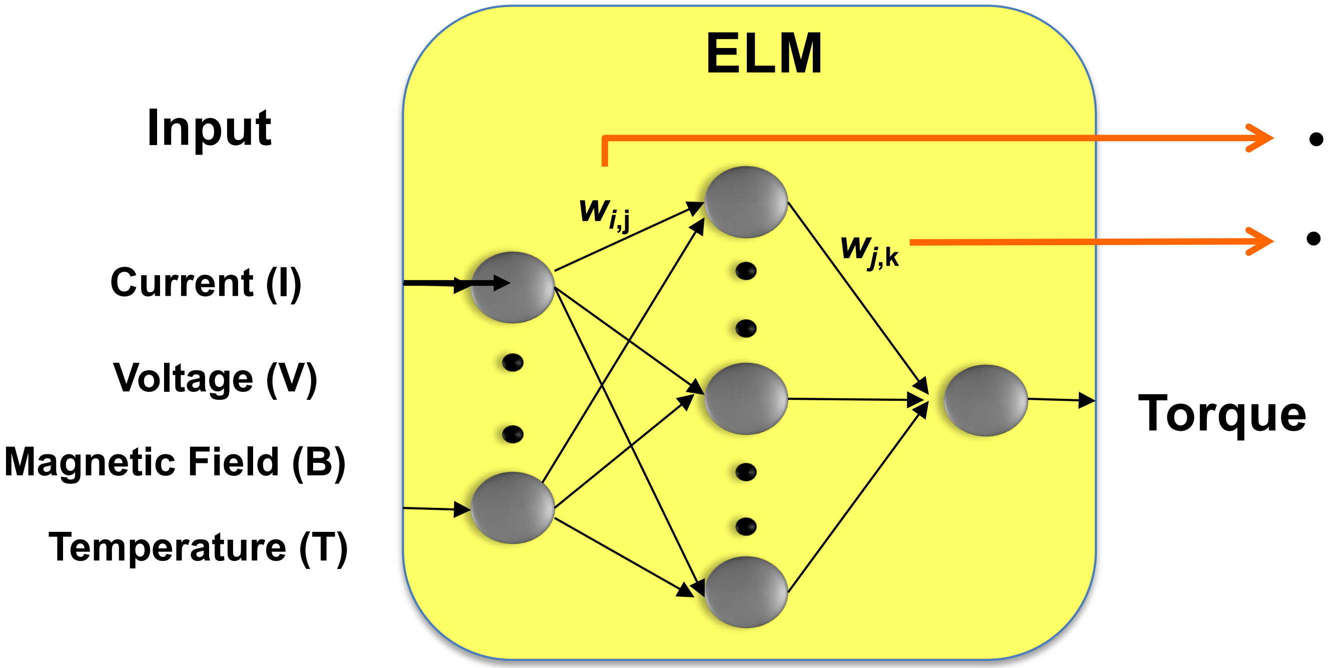
Data-driven methods: frontiers

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

➢ Data-driven methods: frontiers

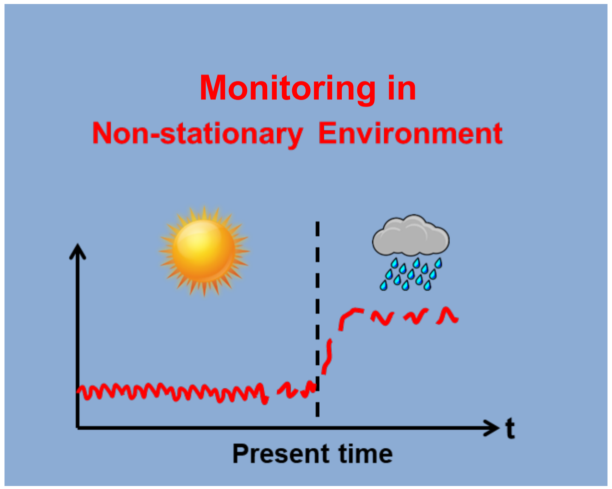
- ❑ Extreme Learning Machines (ELM)

Output= *f* (Input) → ***f* is unknown**

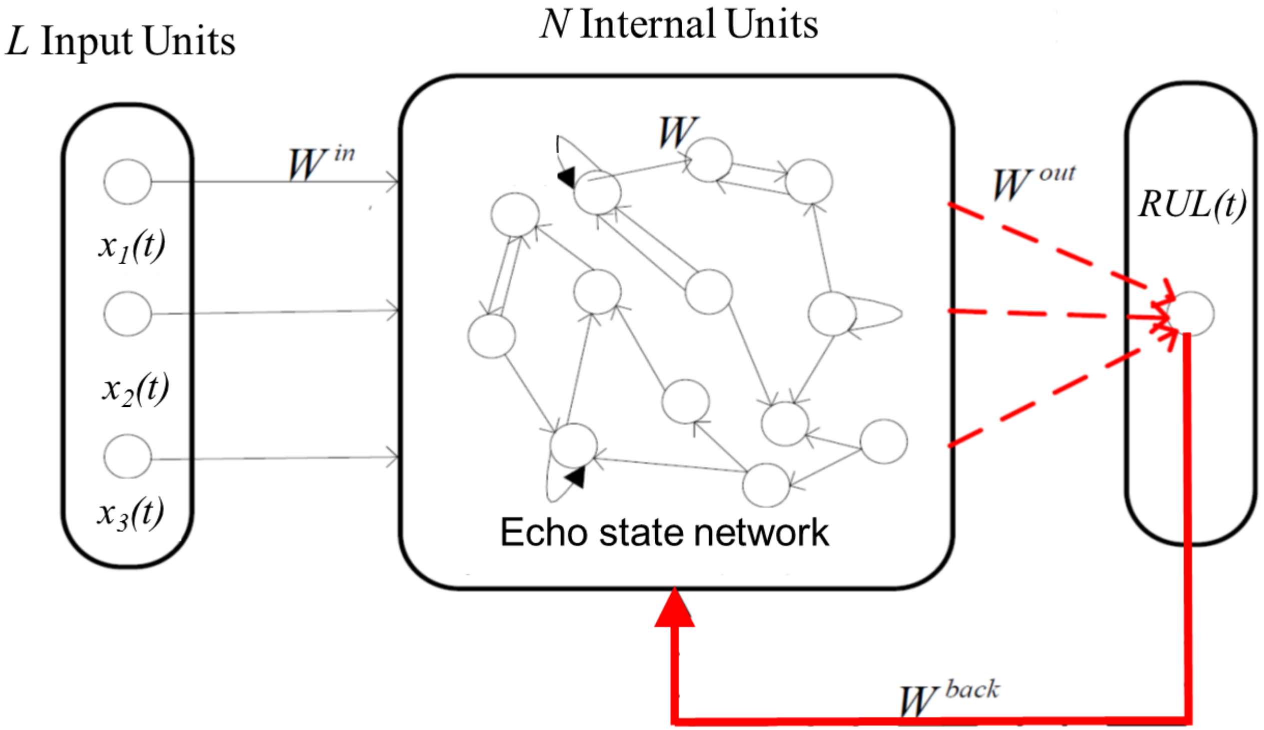


- **Randomly generated**
- **Analytically calculated**

Very fast training
Improved accuracy



Recurrent ELM: Echo state network (ESN) (Reservoir computing)



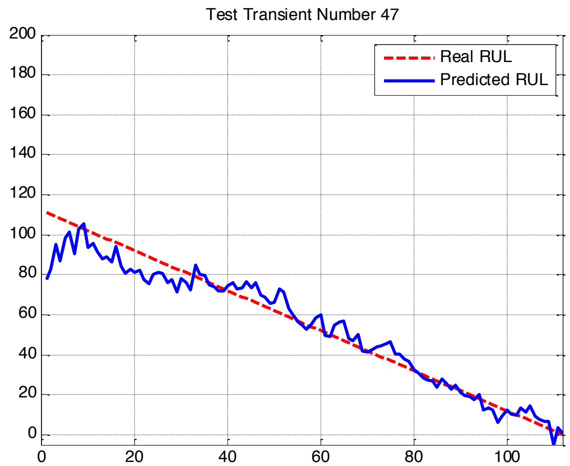
Advantages

- Non linear modeling
- Memory Property
- Intrinsic dynamic characteristics

*M. Rigamonti, P. Baraldi, E. Zio, I. Roychoudhury, K. Goebel, S. Poll, *Echo State Network for Remaining Useful Life Prediction of a Turbofan Engine*, PHM 2016, Bilbao

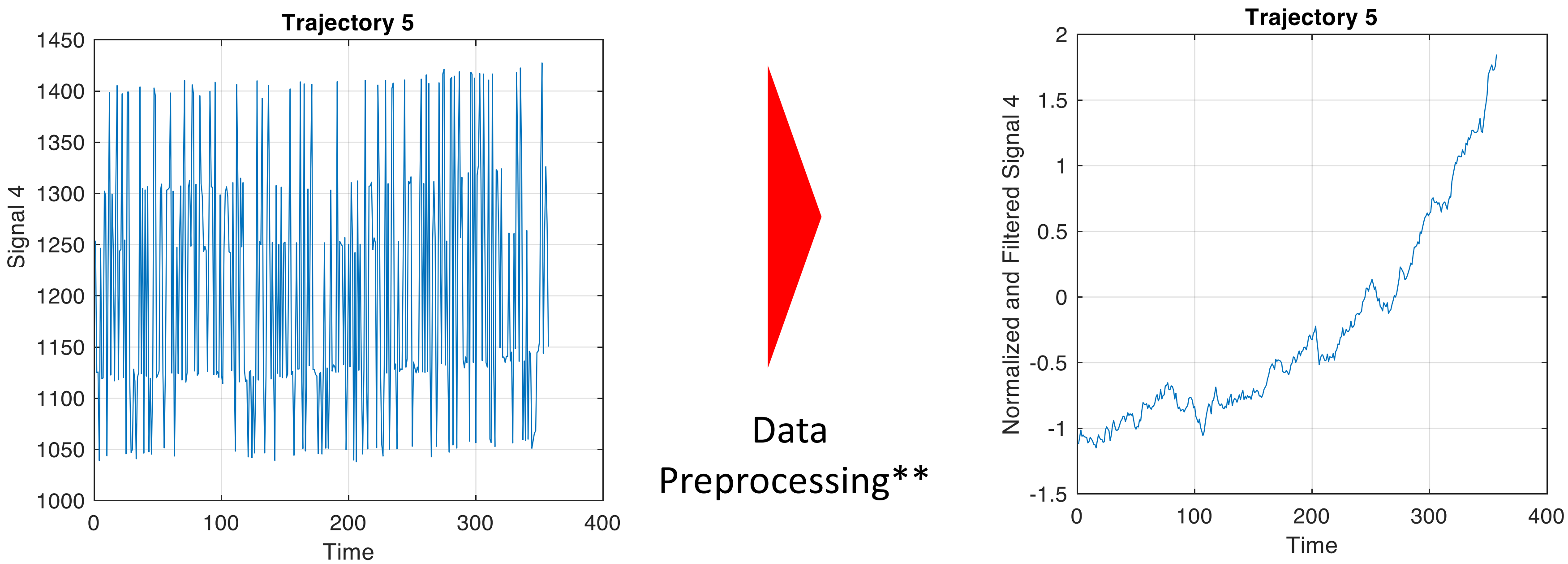
Prognostics of turbofan engines

Echo-State Network



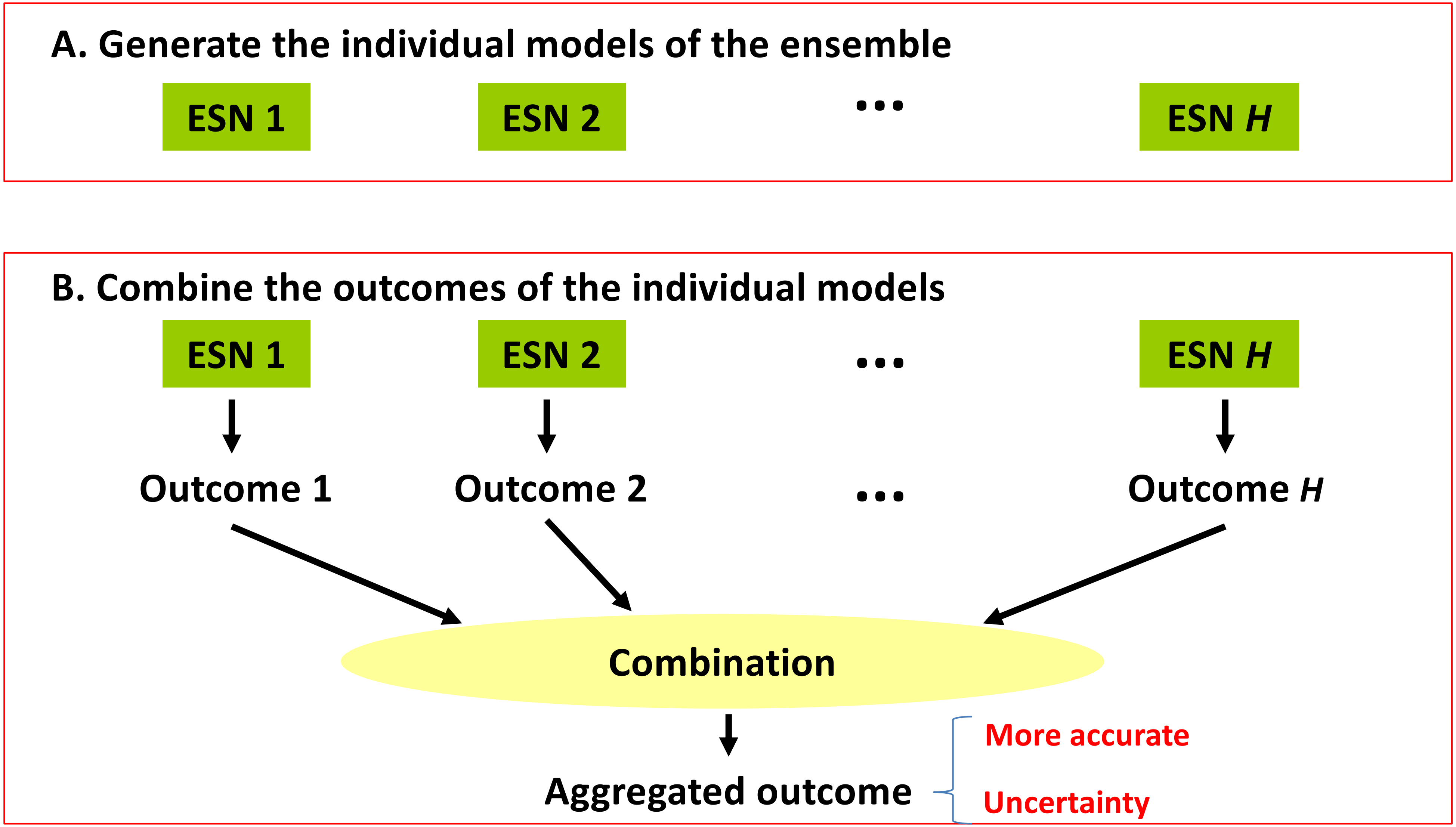
Available data

- The C-MAPPS dataset*
  - 260 run-to-failure trajectories
  - 21 measured signals + 3 signals representative of the operating conditions
  - 6 different operating conditions



* A. Saxena, K. Goebel, D. Simon, N. Eklund, *Damage propagation modeling for aircraft engine run-to-failure simulation*, PHM2008
**M. Rigamonti, P. Baraldi, E. Zio, I. Roychoudhury, K. Goebel, S. Poll, *Echo State Network for Remaining Useful Life Prediction of a Turbofan Engine*, PHM 2016, Bilbao

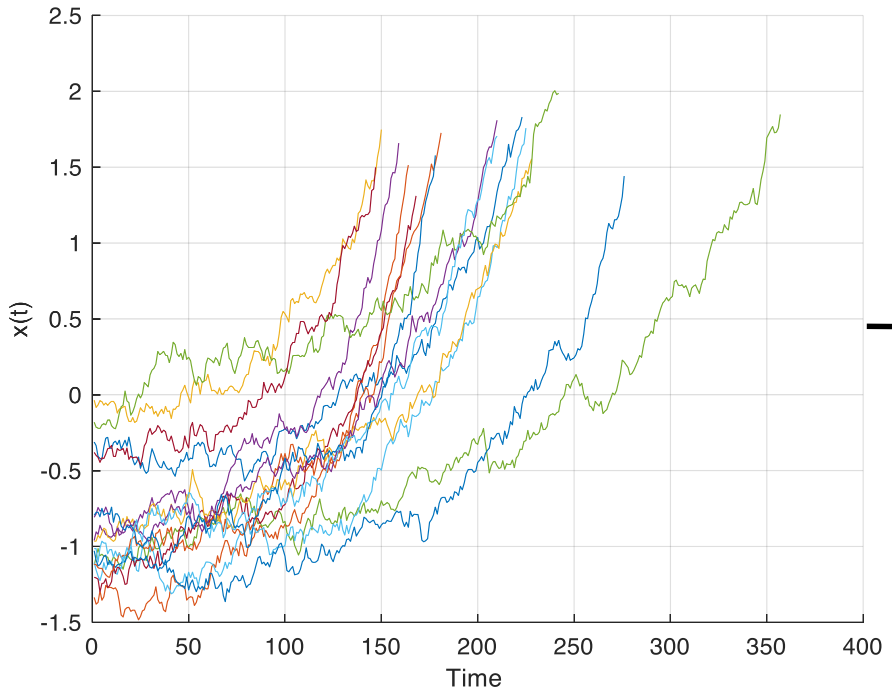
Ensemble of ESNs

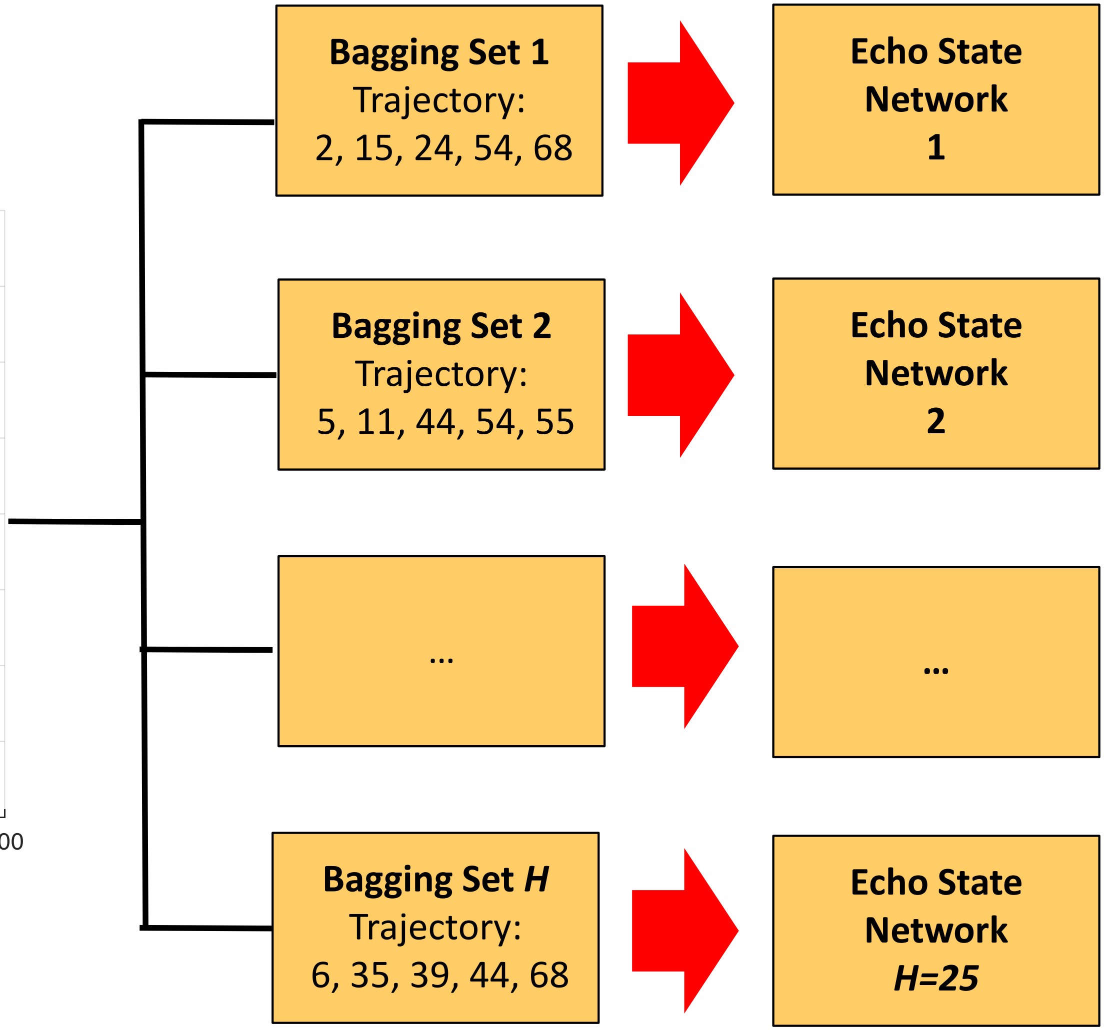


Generate the individual ESNs of ensemble

- Bagging

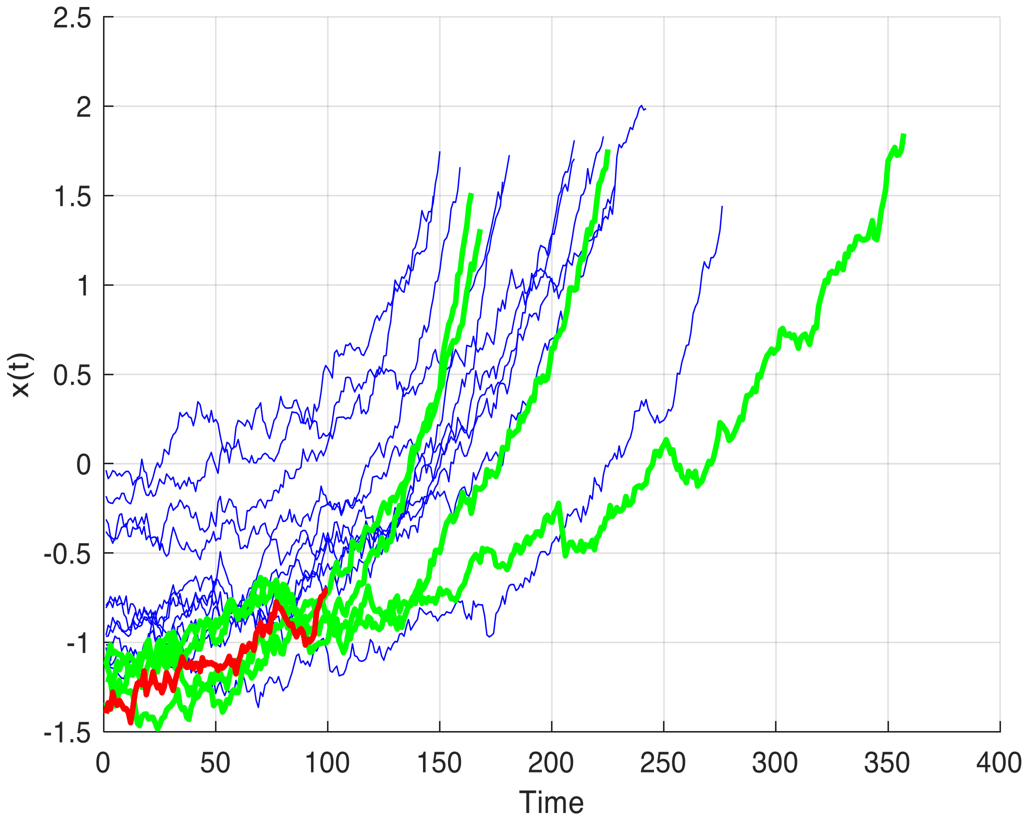
70 run-to-failure training trajectories





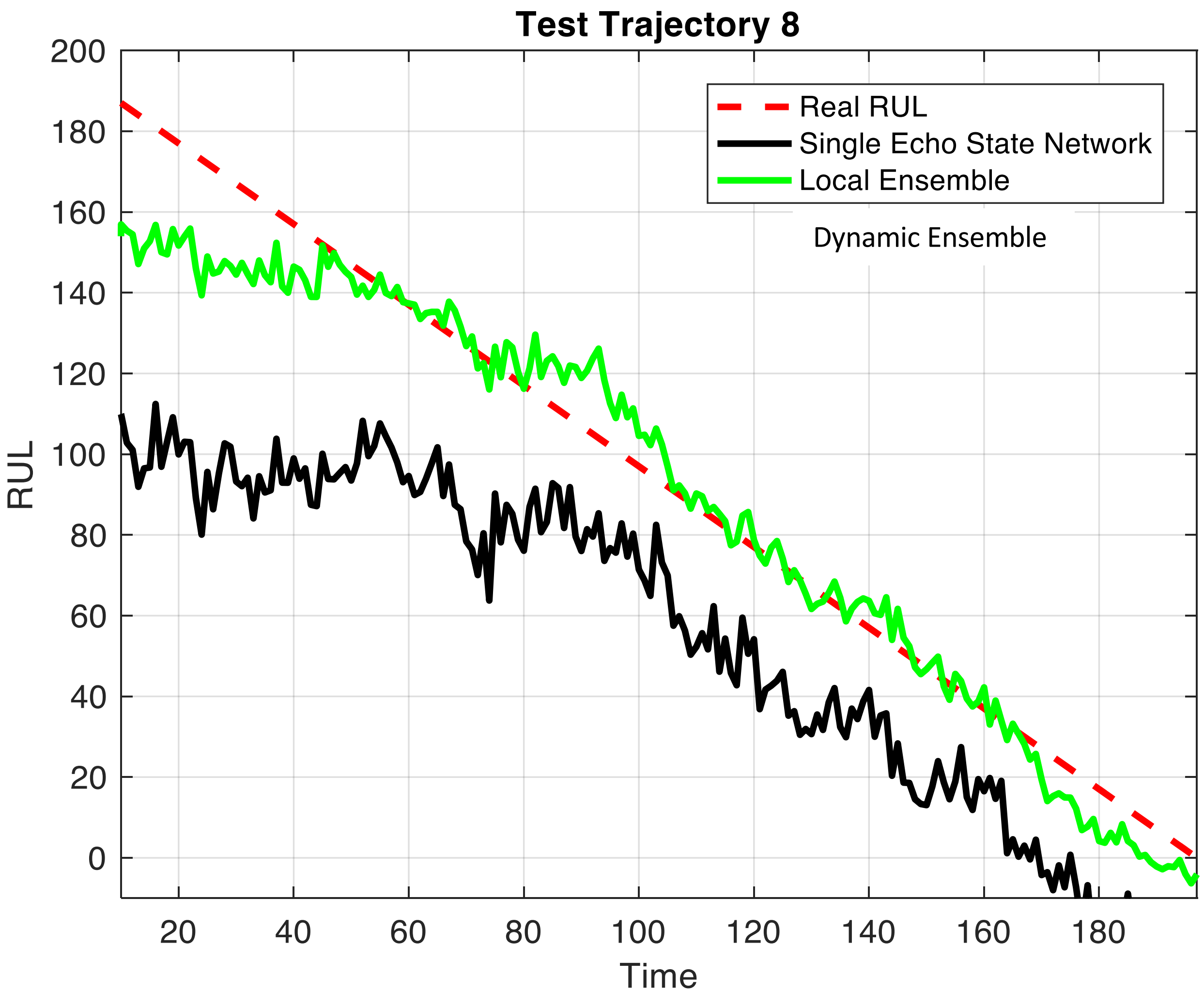
Combine the outputs of individual ESNs

- dynamic approach



- **Identify the *K* trajectories of the validation set most similar to the test trajectory**

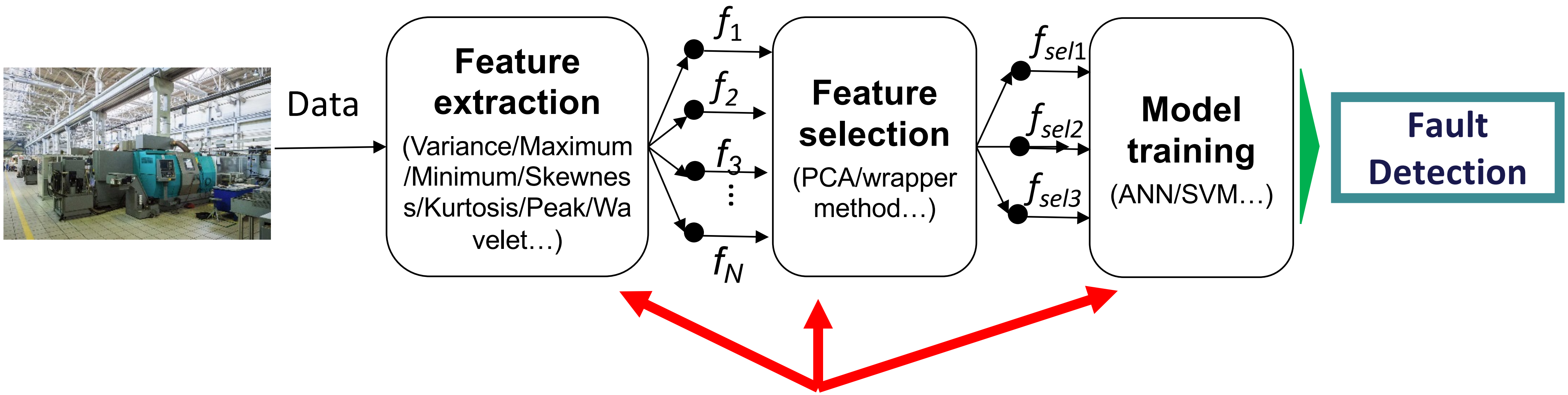
- Example: a trajectory



Data-driven methods: frontiers

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

Traditional data-driven methods



Expert intervention

- **Feature extraction:** Hand-crafted feature design
- **Feature selection:** By trial and errors, expert experience, time consuming filter/ wrapper feature selection algorithms
- **Model training**

Deep learning

Data

Deep learning

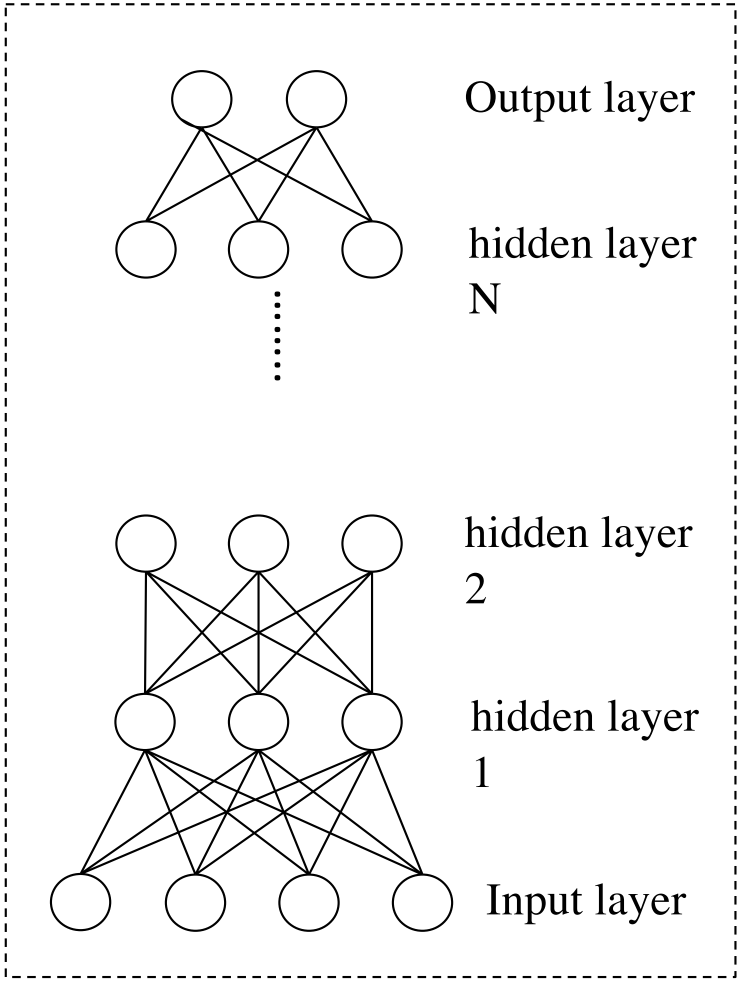
(**Deep neural network**/ Deep belief network/ Convolutional neural network/ Recurrent neural network…)

Fault Detection

No expert intervention !

Deep Neural Network

- DNNs have deep architectures containing multiple hidden layers and each hidden layer conducts a non-linear transformation from the previous layer to the next one.

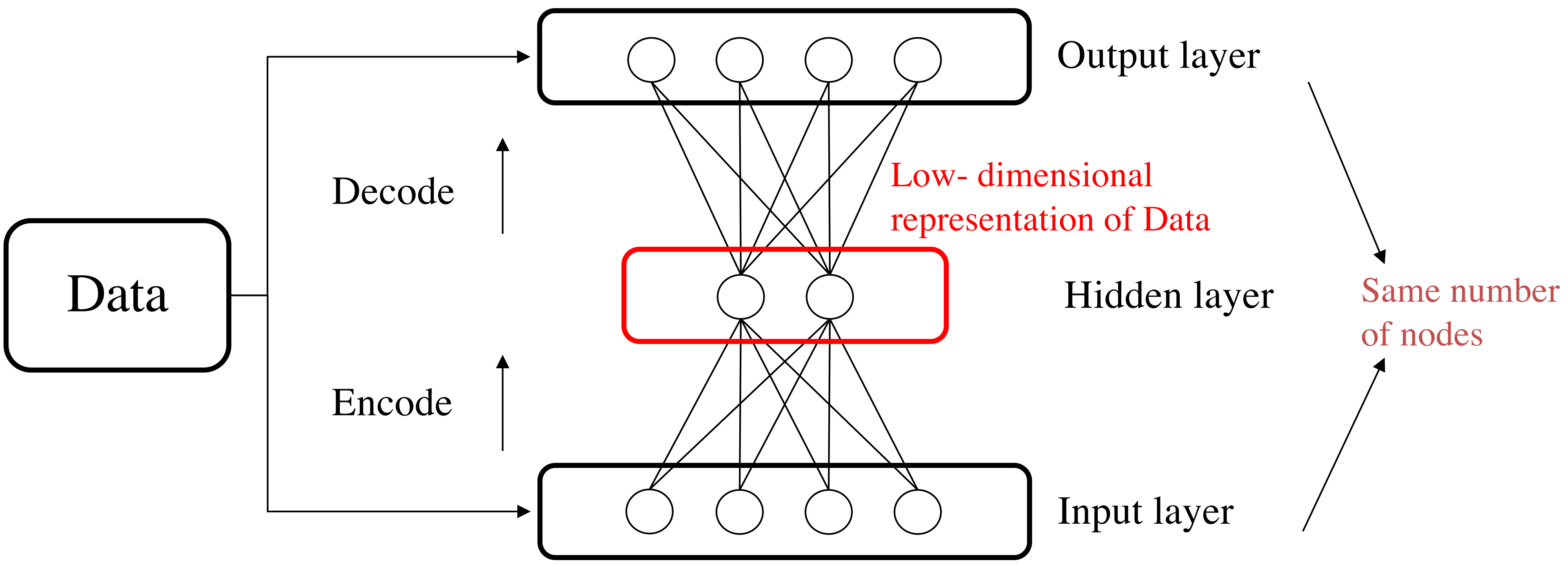


Training:

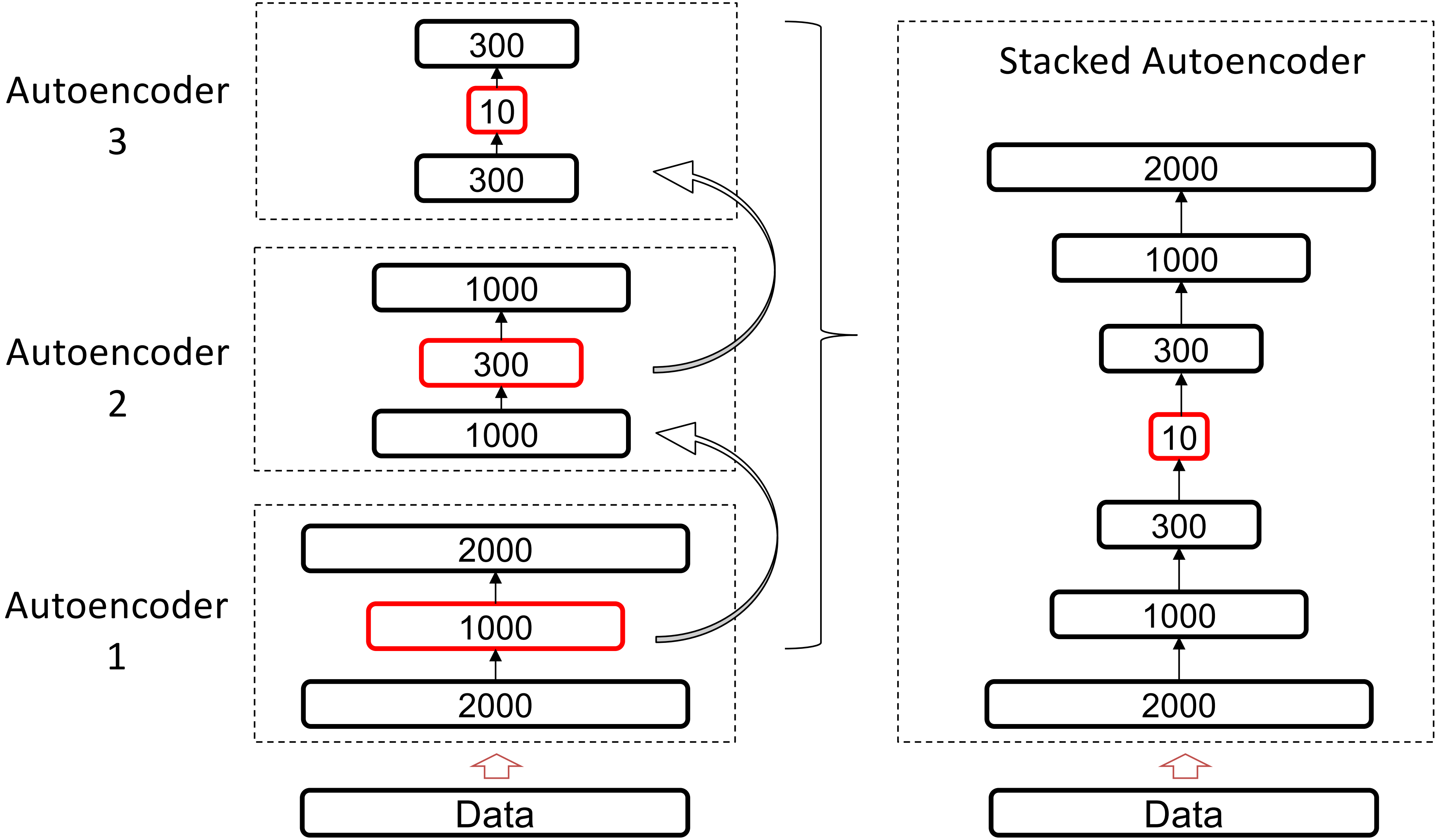
- Pre-train the DNN layer by layer with unsupervised techniques, such as Autoencoder.
- Further fine-tune the DNNs with BackPropagation (BP) algorithms for classification

Autoencoder

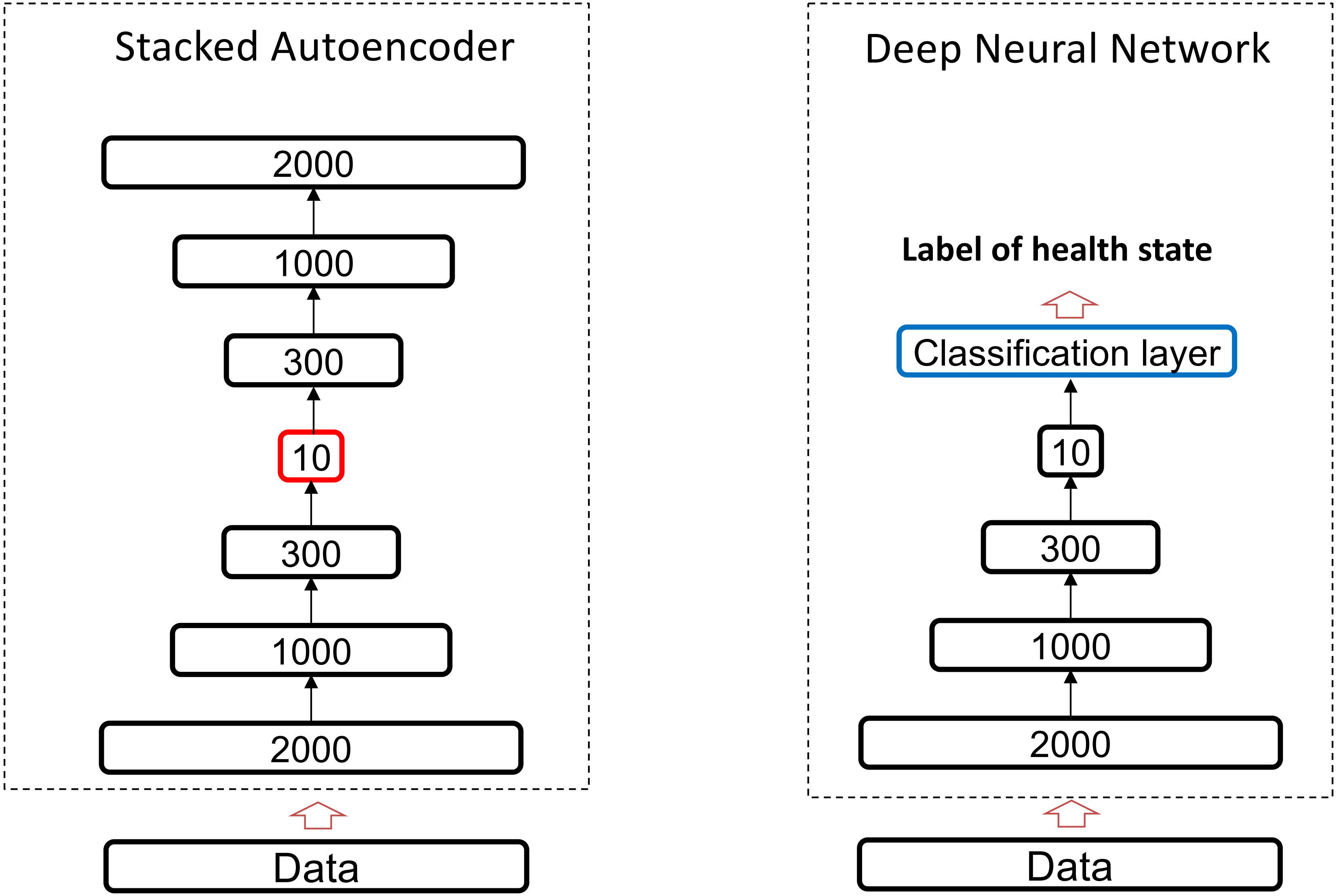
- Autoencoder is a kind of artificial neural network (autoassociative neural network)
- Special point: the output layer has the same number of nodes as the input layer
- Autoencoder is an unsupervised approach because the target is the input itself. The aim of an autoencoder is to learn a representation (encoding) for a set of data.



Stacked Autoencoder



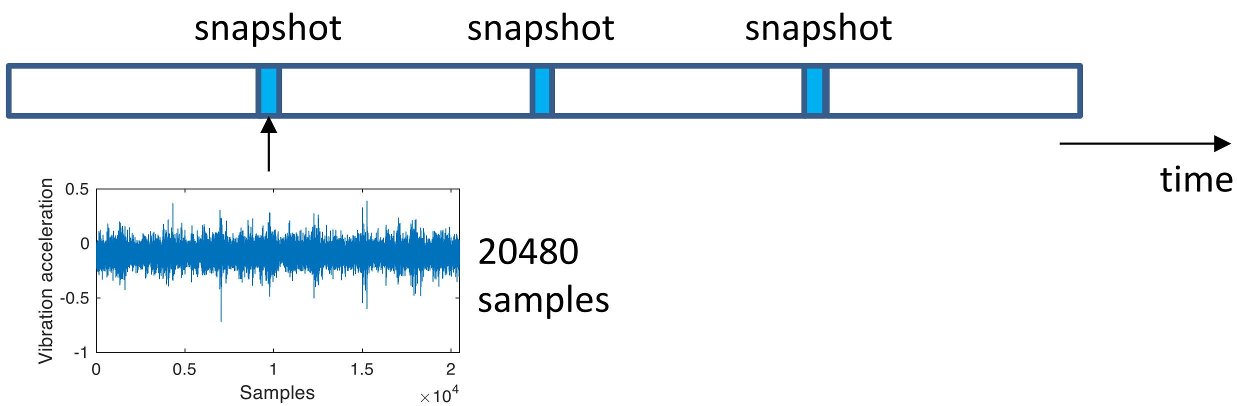
Build the Deep Neural Network



Fault detection of bearing: Available data

➢ Monitoring data of a bearing [1]

- During the run-to-failure process, the vibration acceleration signal is acquired with a snapshot of 20,480 samples collected every 10 min.



➢ Label of the health state of snapshots

Onset of failure: 1617 [1], 2027 [2]

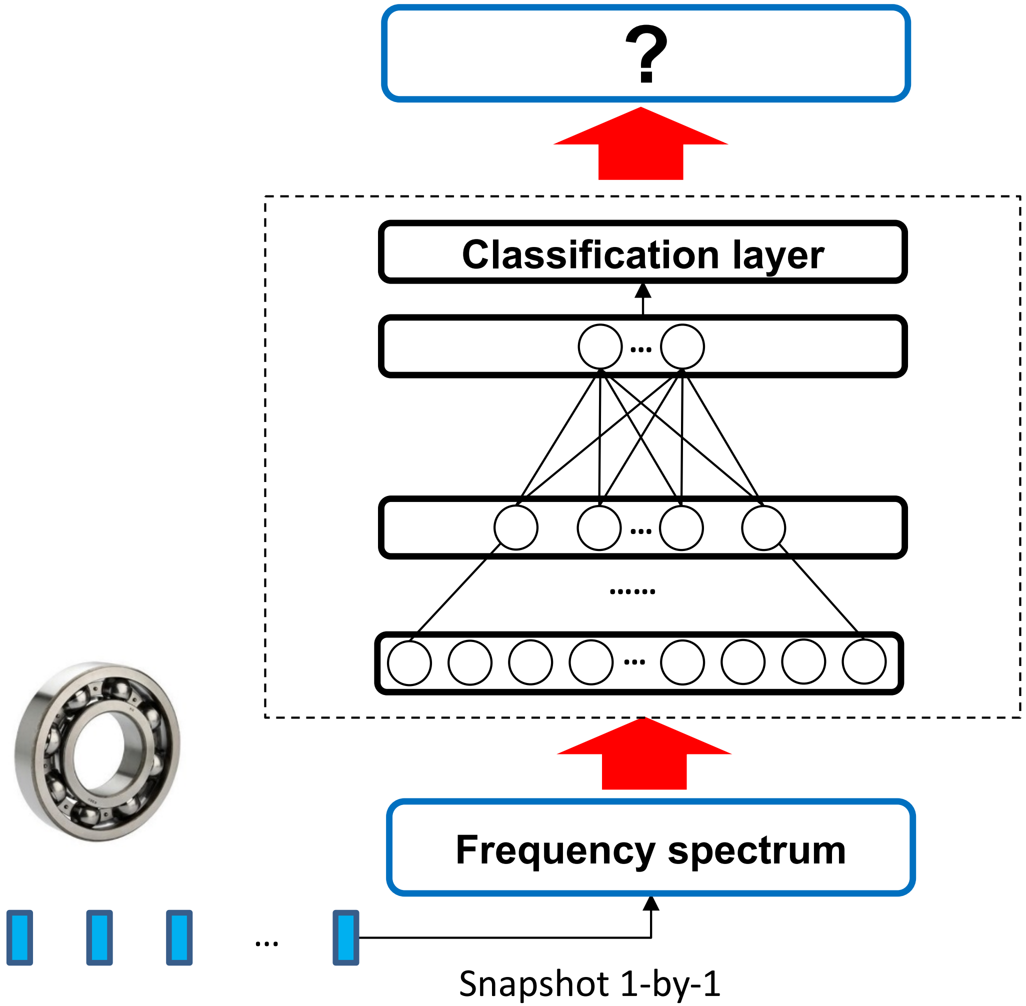
Snapshot	Label	Health State
1~1616	0	Healthy
1617~2027	0.5	Possibly Failed
2028~2156	1	Failed

[1] Qiu, H., J. Lee, J. Lin, and G. Yu, *Wavelet filter-based weak signature detection method and its application on rolling element bearing prognostics.* Journal of sound and vibration, 2006. 289(4): p. 1066-1090.

[2] Hasani, R.M., G. Wang, and R. Grosu, *An Automated Auto-encoder Correlation-based Health-Monitoring and Prognostic Method for Machine Bearings.* arXiv preprint arXiv:1703.06272, 2017.

Objective

- Detect the failure onset of another ideal bearing (test bearing)



Result of Fault Detection

- For comparison, the true label of the test bearing is obtained with respect to [1-3]

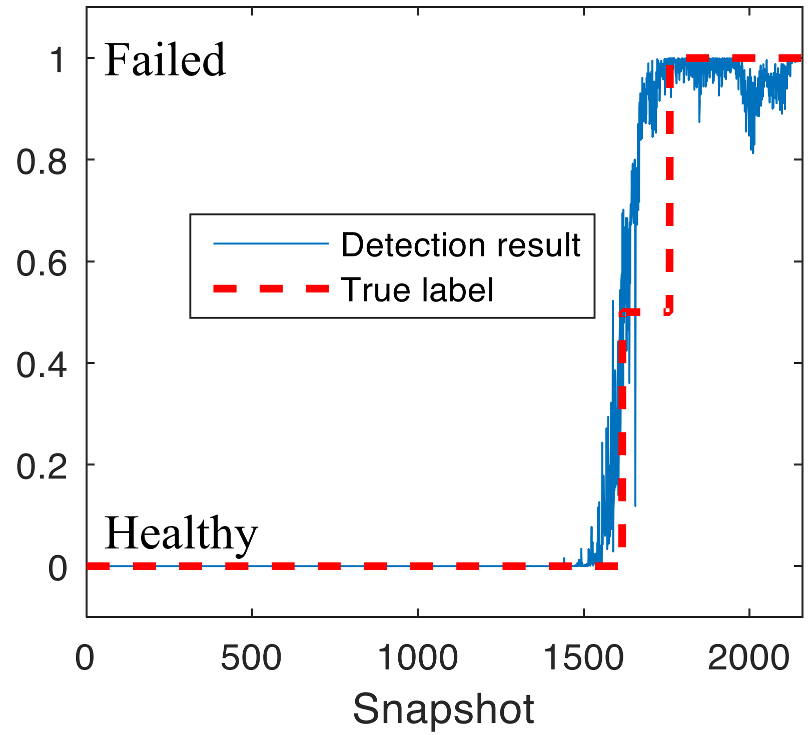
Snapshot	Label	Health State
1~1616	0	Healthy
1617~1760	0.5	Possibly Failed
1761~2156	1	Failed

[1] Qiu, H., J. Lee, J. Lin, and G. Yu, *Wavelet filter-based weak signature detection method and its application on rolling element bearing prognostics.* Journal of sound and vibration, 2006. **289**(4): p. 1066-1090.

[2] Hasani, R.M., G. Wang, and R. Grosu, *An Automated Auto-encoder Correlation-based Health-Monitoring and Prognostic Method for Machine Bearings.* arXiv preprint arXiv:1703.06272, 2017.

[3] Yu, J., *Health condition monitoring of machines based on hidden Markov model and contribution analysis.* IEEE Transactions on Instrumentation and Measurement, 2012. **61**(8): p. 2200-2211.

- Result



The onset is identified at snapshot 1680 with threshold *Th*=0.5, which lies in the possibly failed range [1617, 1760]

Data-driven methods: frontiers

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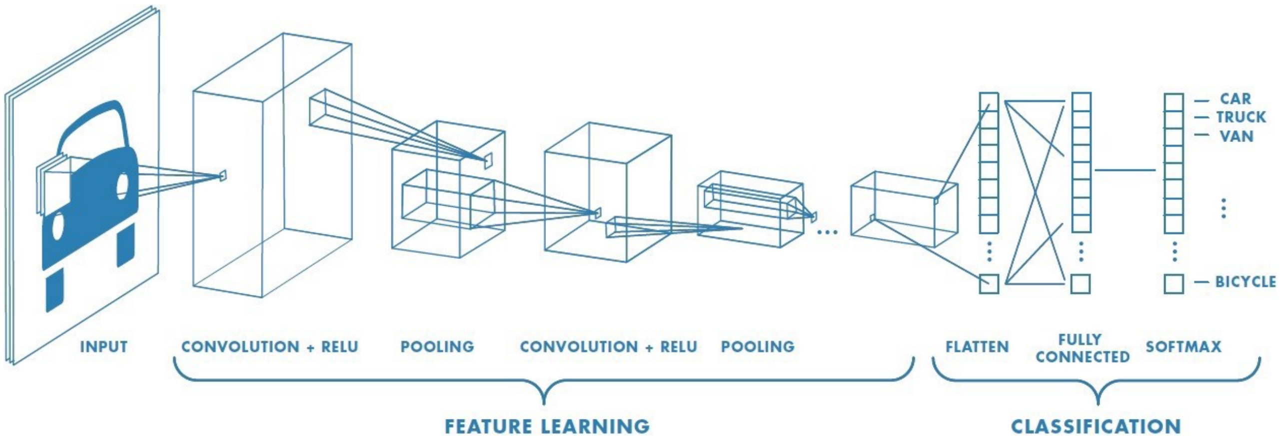
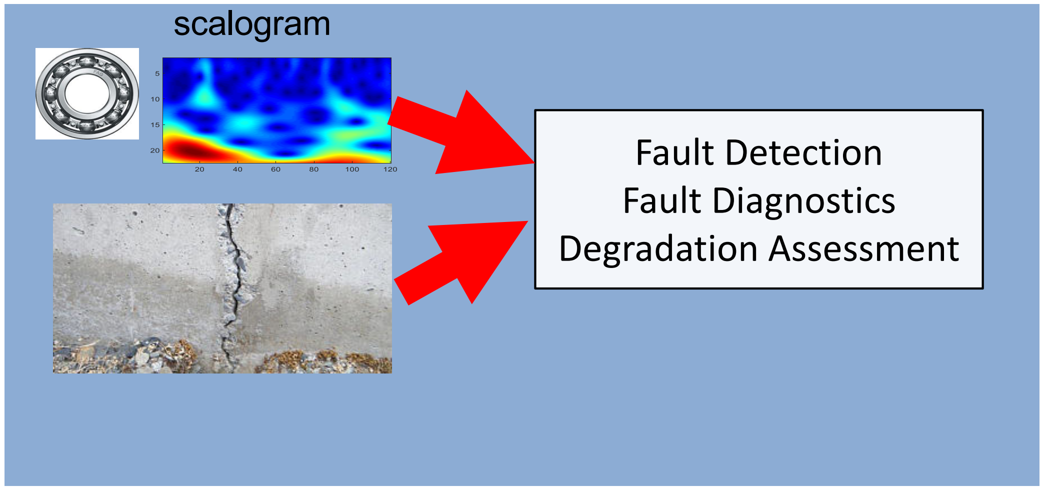
- Generative Adversarial Networks (GAN)
- Optimal Transport and Cumulative Distribution Transform (OT-CDT)

➢ Machine Learning: frontiers in methods

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



Input = Image
Output = class/regression



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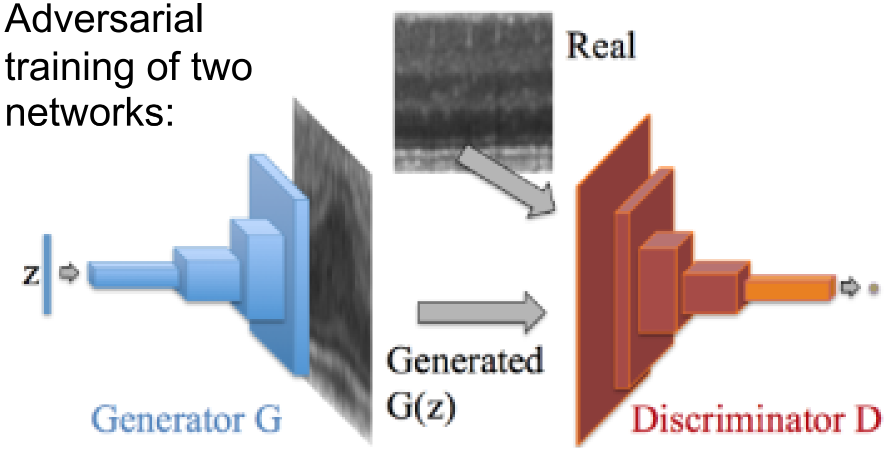
➢ Machine Learning: frontiers in methods

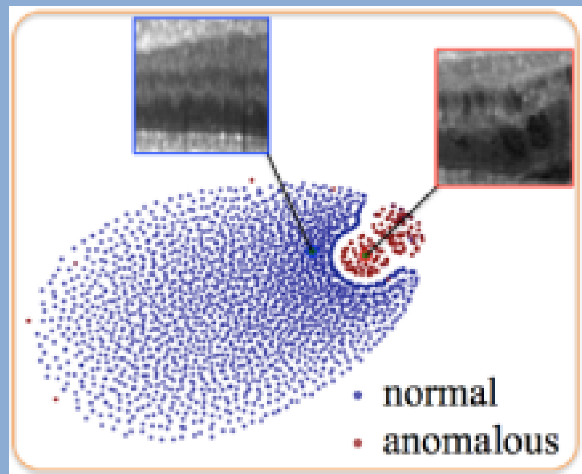
- ❑ Extreme Learning Machines (ELM)
- ❑ Deep Neural Networks (DNN)
- ❑ Convolution Neural Networks
- ❑ Generative Adversarial Networks

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

Data-driven methods: frontiers

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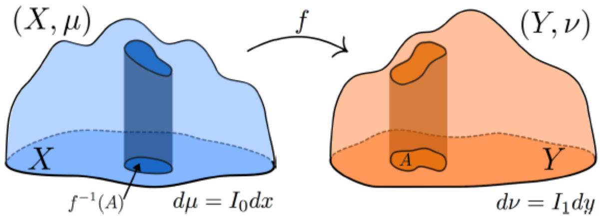
Machine Learning: frontiers in methods

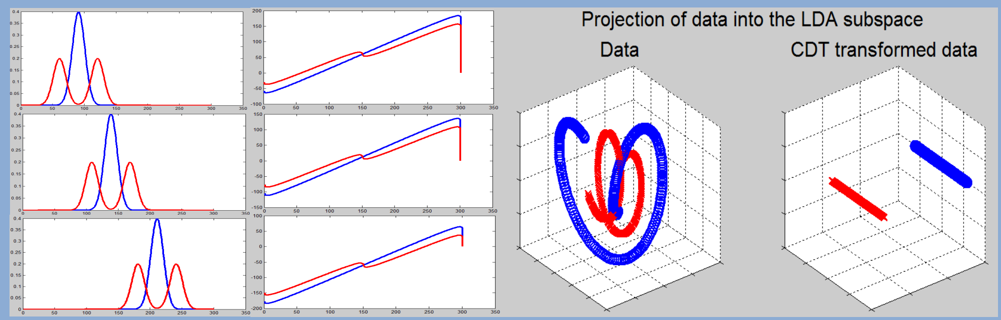
- Extreme Learning Machines (ELM)
- Deep Neural Networks (DNN)
- Convolution Neural Networks
- Generative Adversarial Networks
- Optimal Transport (OT) and Cumulative Distribution Transform (CDT)



$$\int_{f^{-1}(A)} I_0(x)dx = \int_A I_1(y)dy$$

$$M(\mu, \nu) = \inf_{f \in MP} \int_X c(x, f(x)) I_0(x)dx$$

- 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

Unsupervised Domain Adaptation (UDA)

For the problem of fault diagnosis:

- Source-domain data D_S: $\{(\boldsymbol{x}_S^i, y_S^i)\}_{i=1}^{N_S}$, $\boldsymbol{x}_S^i = matrix\ of\ measured\ signal\ values$

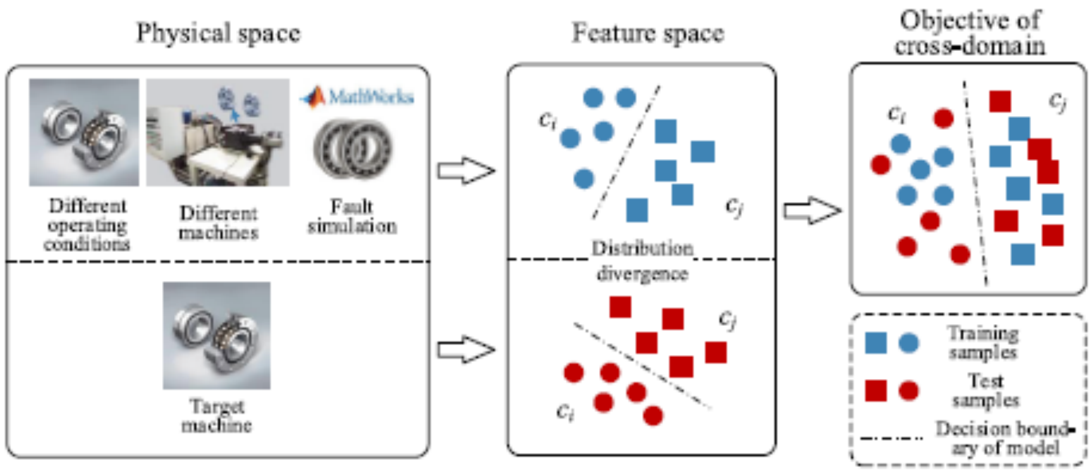
  $y_S^i \in \mathcal{Y}_S = \{C_0, C_1, \cdots, C_k\}$, *k-class health conditions*

- Target-domain data D_T: $\{(\boldsymbol{x}_T^i\ )\}_{i=1}^{N_T}$, unlabeled.

- Label space $\mathcal{Y}_S = \mathcal{Y}_T$, but marginal distribution $P(X_S) \neq P(X_T)$

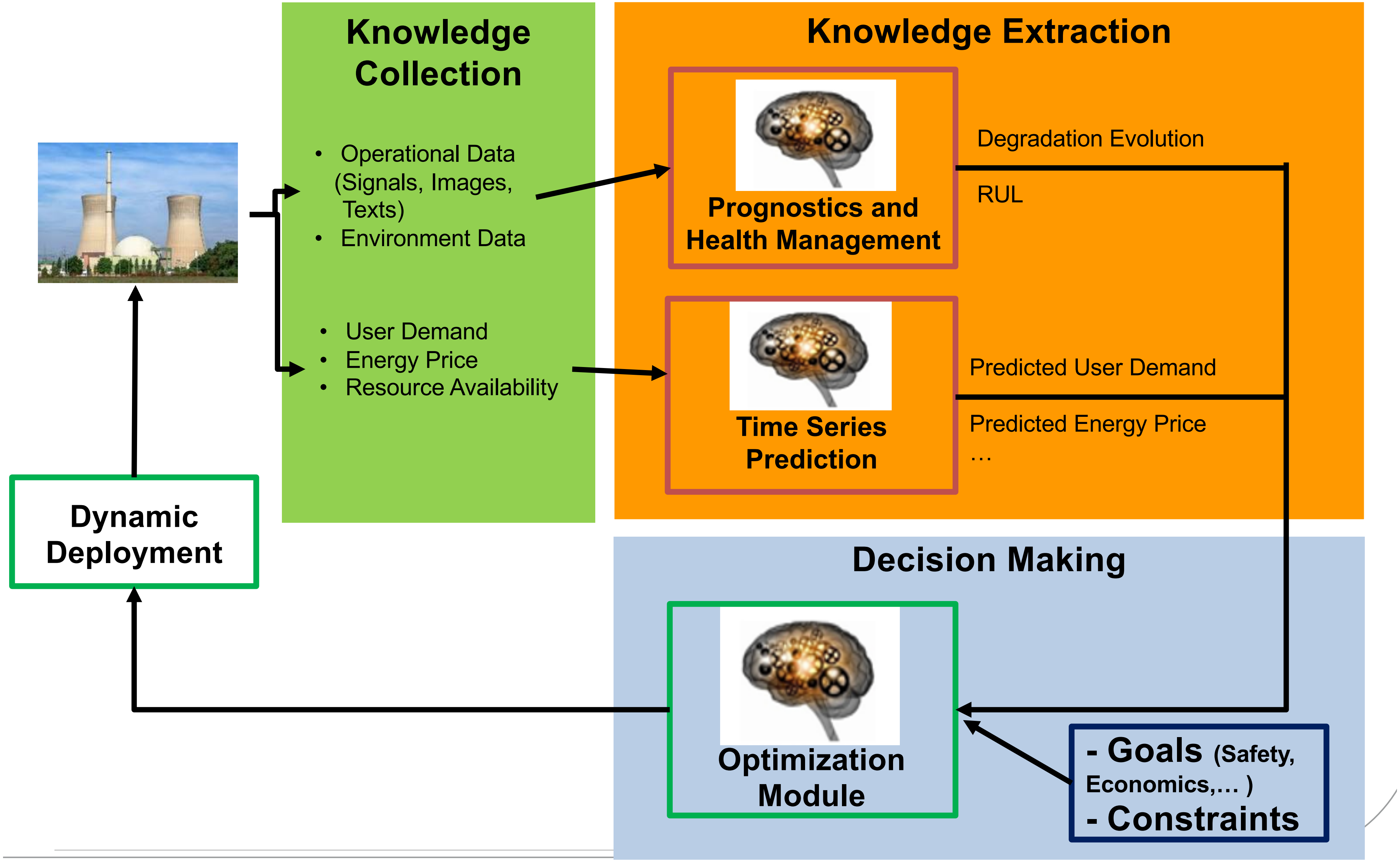
➢ ***Aim***: to learn a cross-domain fault diagnosis model η for D_T through leveraging the knowledge from D_S, i.e. $y_T^i \approx \eta(\boldsymbol{x}_T^i)$, with low target risk R_{D_T}:

$$R_{D_T}(\eta) = \Pr_{(x_T^i, y_T^i)\sim D_T} \left(\eta(\boldsymbol{x}_T^i) \neq y_T^i\right)$$



Outline

Conclusions



Contact Information

Enrico Zio

Tel: (+39) 02 23996340

E-mail:

enrico.zio@mines-paristech.fr

enrico.zio@polimi.it