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SurferLab


Artificial intelligence tools in transportation

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l'Europe
S'engage
en
Nord Pas de Calais - Picardie
avec le FEDER



UMR CNRS 8201 Laboratoire en intelligence distribuée pour les systèmes de transport

Outline

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1. Background and motivation
2. Artificial intelligence
3. Machine learning
4. Case studies
 - Unsupervised learning illustration
 - Supervised learning illustration
5. Conclusion and perspectives



Background and motivation

- **Transportation systems** are very complex (door, HVAC,
- Big data context



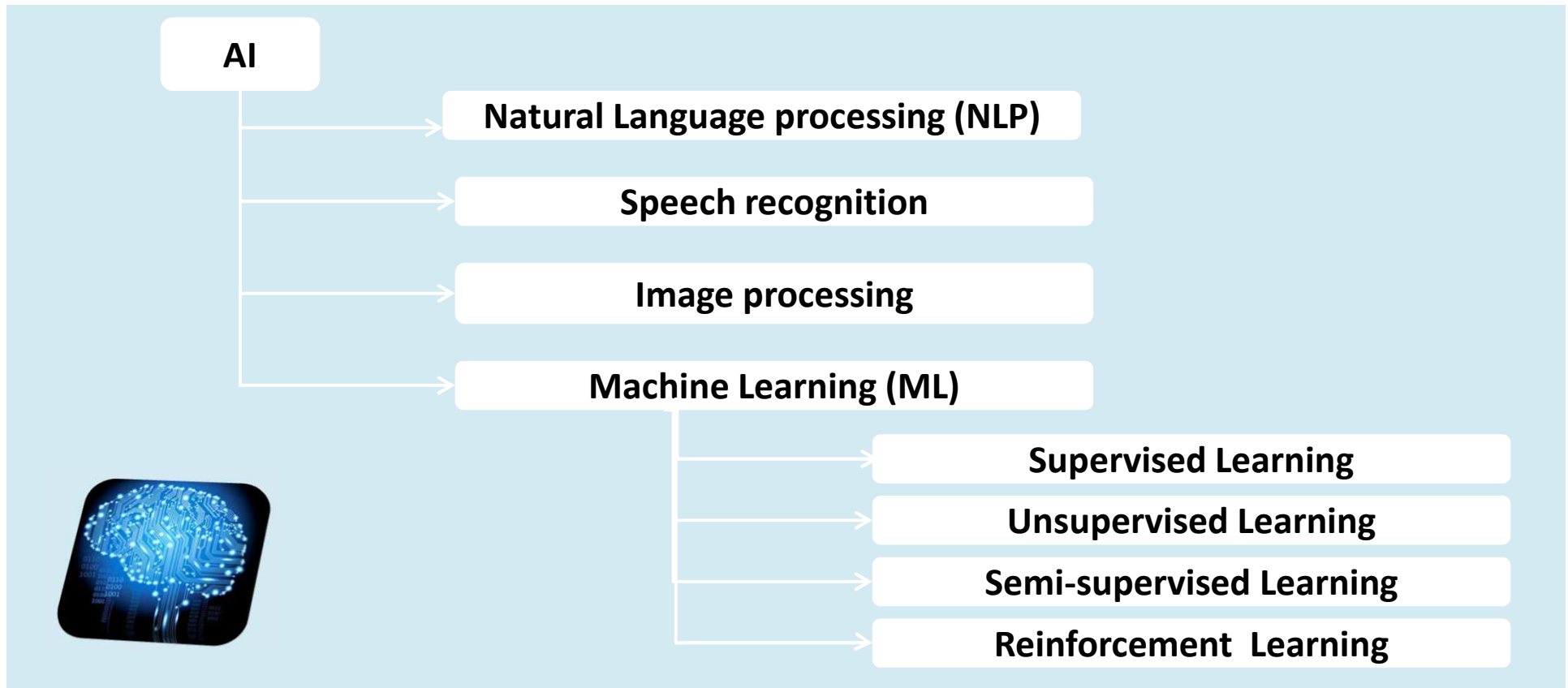
- **Artificial Intelligence (AI)** : is the ability of the machine to reproduce human tasks.

- It is based on the exploitation of the potential of the Data to :

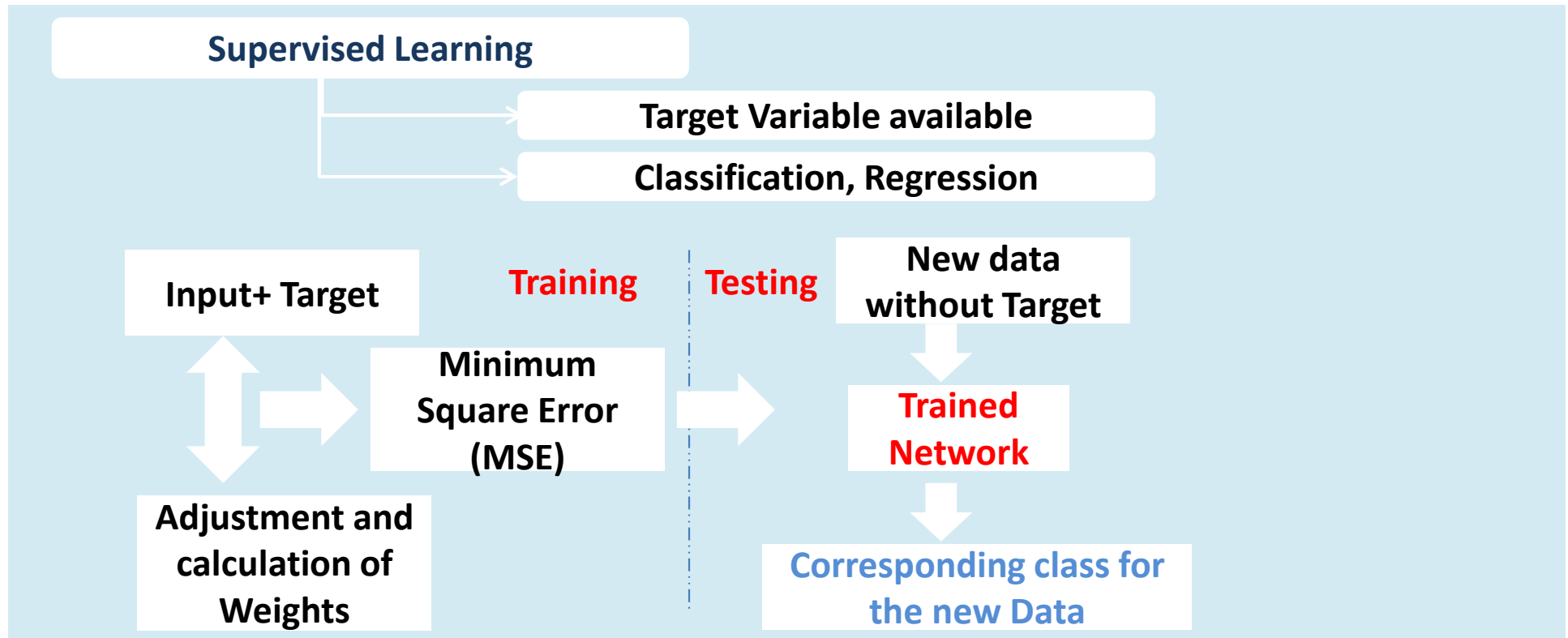
- Learn
- Adapt
- Be autonomous.



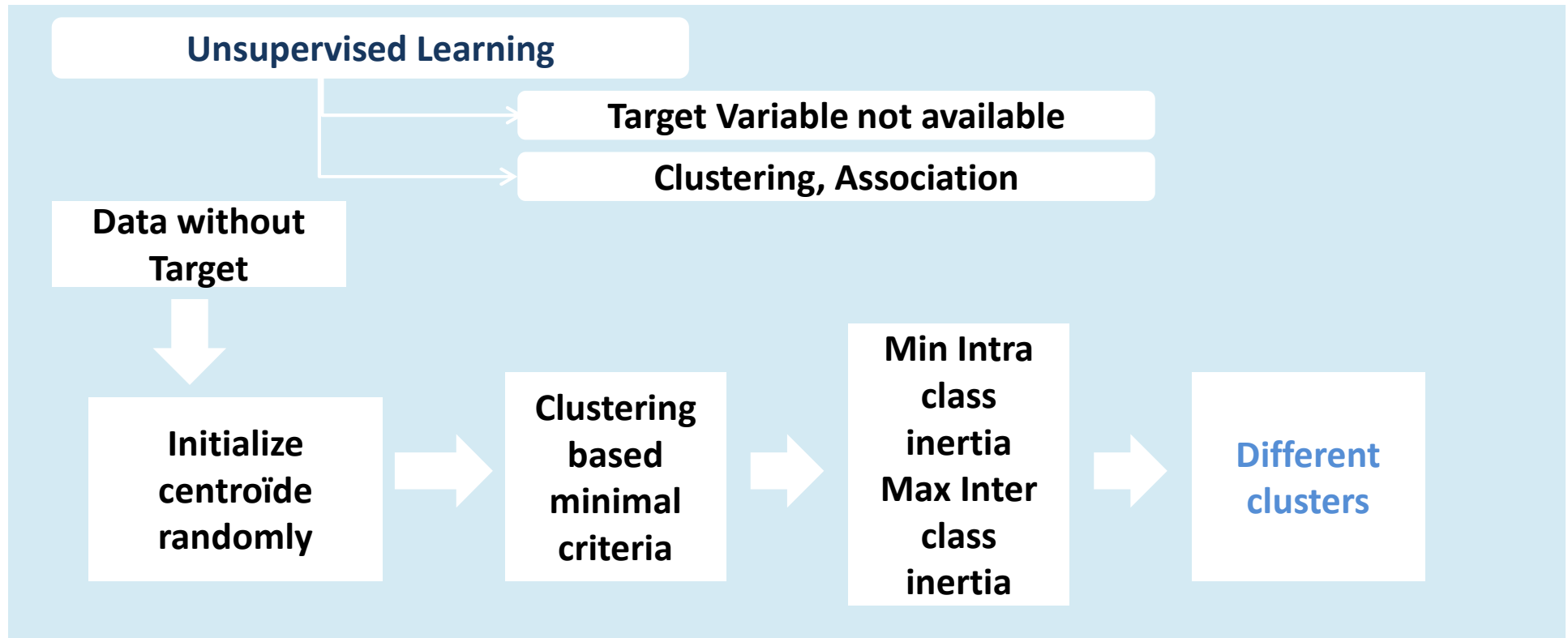
Artificial Intelligence



Machine Learning



Machine Learning



Case studies

- Creating machine learning models capable of:
 - Predicting certain targeted faults in a door system (classification)
 - Distinguishing different root causes for the same types of faults (clustering)



Unsupervised learning

Root cause identification model

- Assumption:
 - The door event patterns (current, position, tension, etc...) from the occurrences of the same type of fault are not completely the same

- Hypothesis:
 - The slight differences among the door event patterns when the same fault occurs might tell something on the root cause of the fault



Unsupervised learning

Clustering for root cause identification

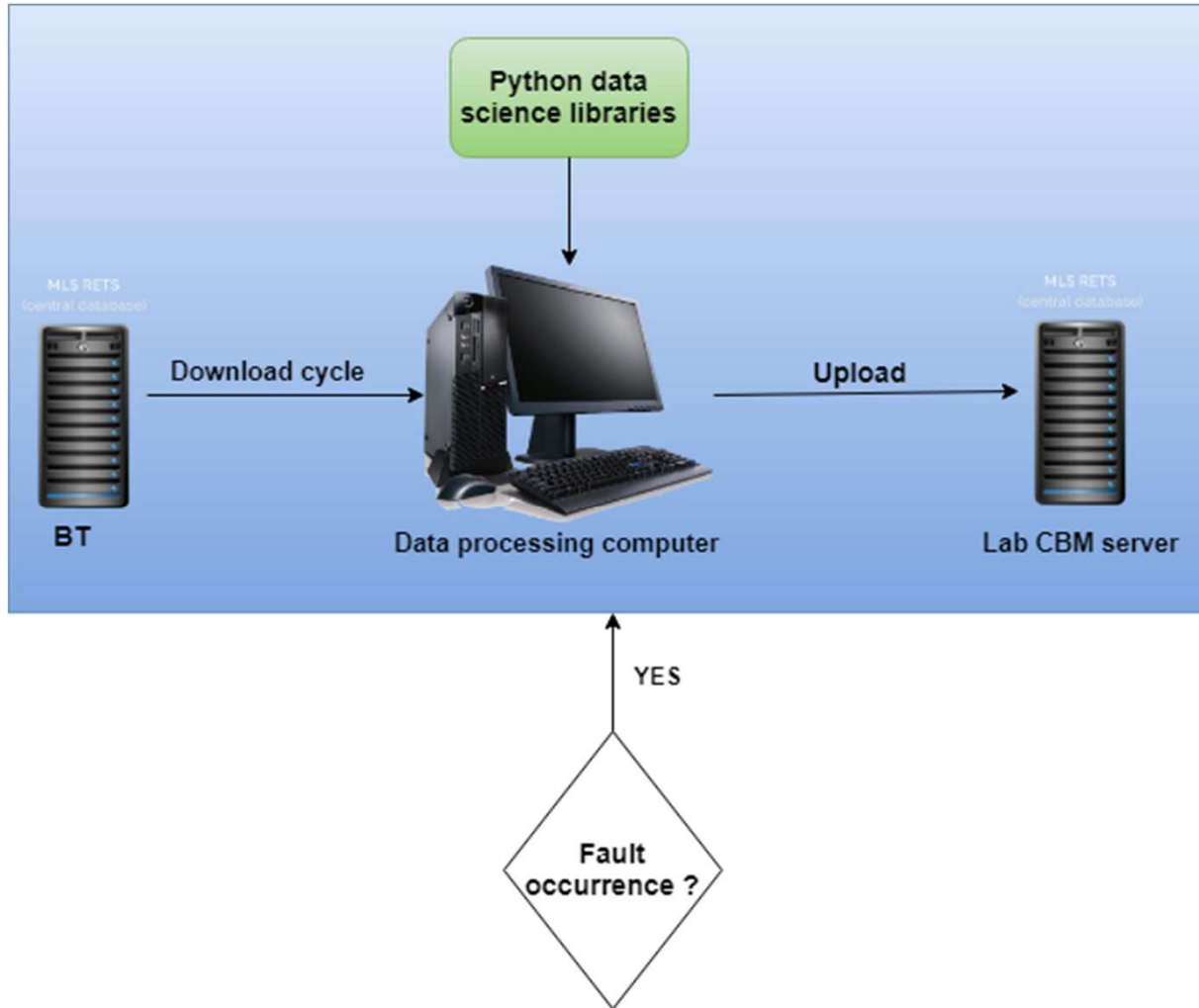
- K-means clustering should:
 - From the occurrences of the same fault, be able to distinguish the occurrences from different causes

- Targeted fault: Obstacle detection
 - F_Obstruc_CS – For closed cycle
 - F_Obstruc_OS – For open cycle

- Data collection:
 - The file with event patterns is collected whenever there is a presence of the obstacle detection fault code

Unsupervised learning

Clustering for root cause identification



Unsupervised learning

Clustering for root cause identification

Index	Courant_Valeur_DCU_	Tension_Valeur_DCU_	Position_Top_	Bp_Ext_I17	Bp_Int_I16	Cle_Ext_I11	Dever_O02	rnal_digital_input	_the_LAN_control	FCC_1_I22	FCC_1_I27	FCC_1_I32	FCC_2_I23	FCC
2018-11-06-18...	nan	nan	nan	0	0	0	0	1	1	1	1	0	1	1
2018-11-06-18...	nan	nan	nan	0	1	0	1	1	1	1	1	0	1	1
2018-11-06-18...	nan	nan	nan	0	1	0	1	1	1	1	1	0	1	1
2018-11-06-18...	-0.50303	0	1	0	1	0	1	1	1	1	1	0	1	1

...



Unsupervised learning

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Clustering for root cause identification

- From the clustering results:
 - Each fault occurrence is associated with a cluster
 - Once the root cause of the fault is identified, the cluster is labelled
 - In the future, the root cause of the fault can be automatically identified as the occurrence will be clustered automatically,



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Supervised learning

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Predictive model

- Assumption:
 - Door event patterns (current, position, tension, etc...) before the faults are highly different from the event patterns during healthy functioning

- Hypothesis:
 - Before the fault happens, there will be symptoms on the event patterns some time before that fault. If these symptoms could be captured then prediction on the fault is possible



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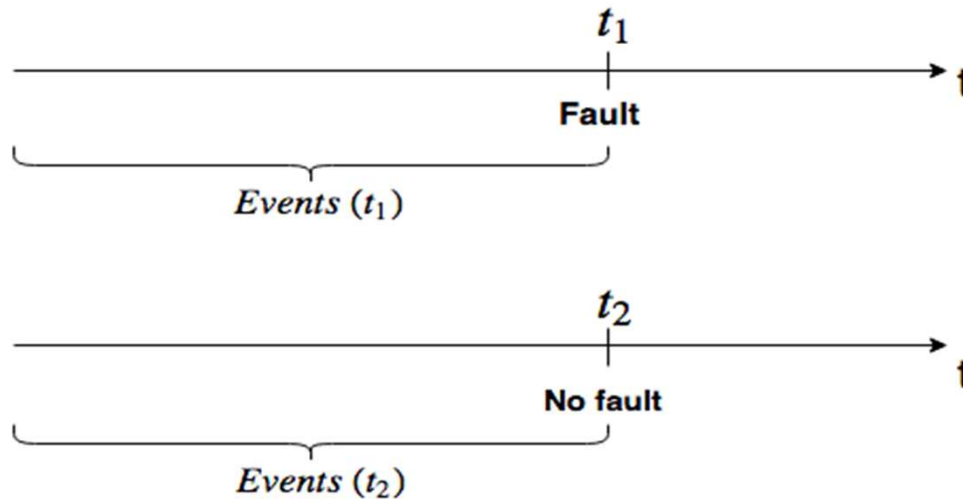


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Supervised learning

Predictive model



$Events(t_1) \neq Events(t_2)$

- We need to distinguish these two events from each other – Classification problem

Supervised learning

Classification problem

- RNN classifier should:
 - Tell if a fault is about to happen when fed with current and historical data

- Door faults targeted:
 - Code 72 - marche - F_SwitchLimit_PMR
 - Code 2 - porte - F_Limit_DC_Fail

- Collected data:
 - 15 cycles of event patterns are collected before the occurrences of the targeted faults
 - 15 cycles of event patterns are collected during normal/healthy functioning

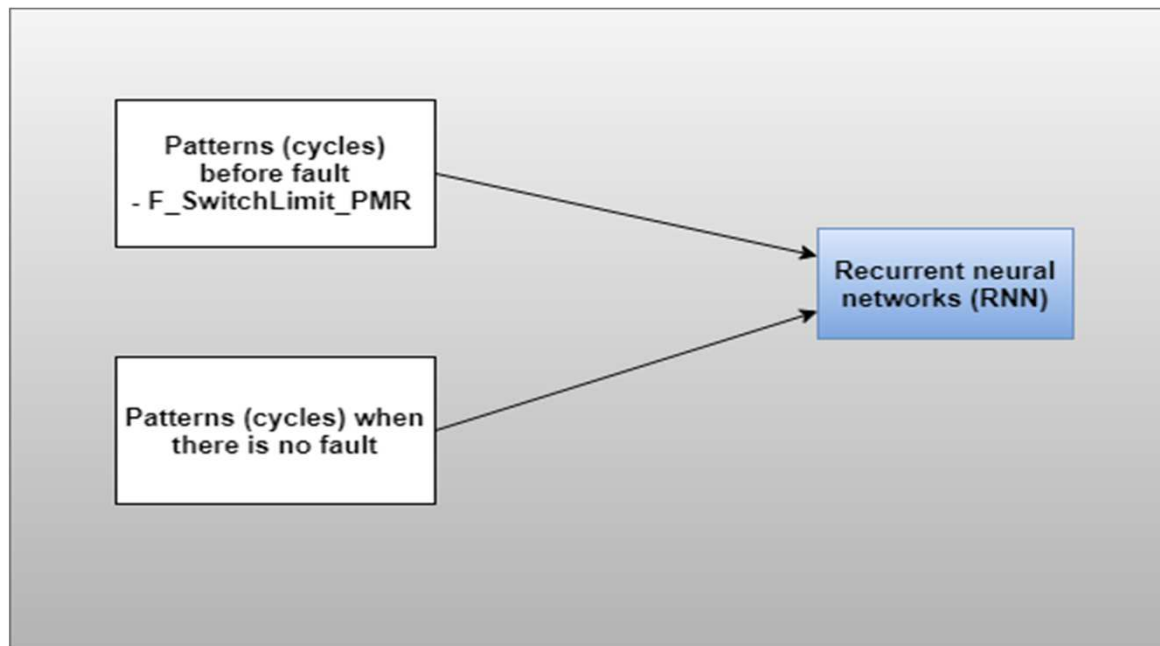
Supervised learning

Classification problem - CBM server

- The CBM server used to store the collected data has a classification database with three tables:
 - Table 1 -> Corresponds to the data mined before Code 72 - marche - F_SwitchLimit_PMR faults
 - Table 2 -> Corresponds to the data mined before Code 2 - porte - F_Limit_DC_Fail
 - Table 3 -> corresponds to the data which is mined during normal/healthy conditions (i.e. Absence of the targeted faults)

Supervised learning

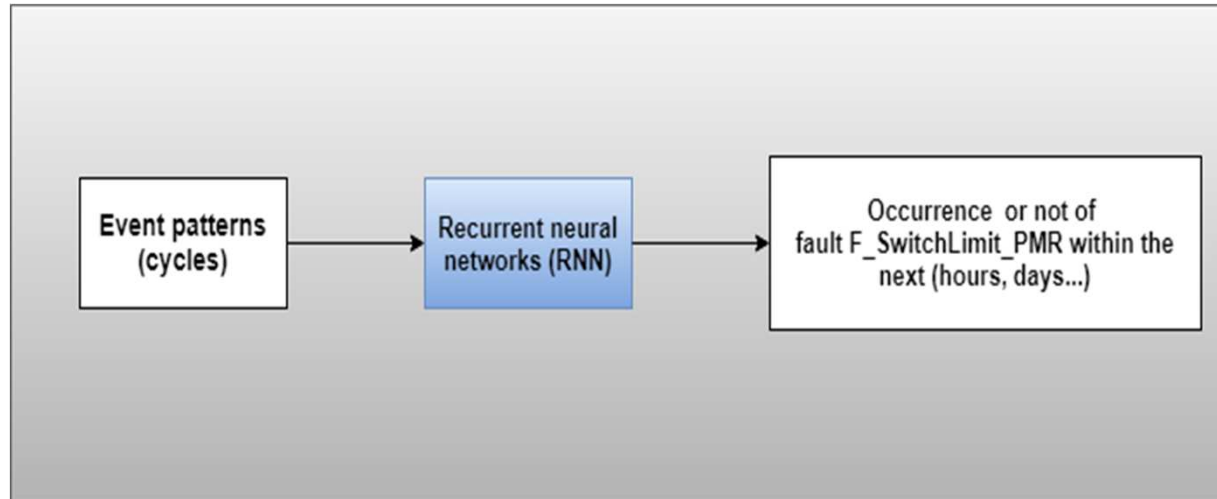
Classification problem - Training phase



- The data from the tables are fed into an RNN model in order to train it

Supervised learning

Classification problem - Validation



- After the model has been trained, it is fed with event patterns (preferably as they happen – real time) then the model should be able to tell if a fault will likely happen or not in the near future

Conclusion

- Machining learning techniques:
 - Clustering – Root cause identification
 - Classification – Fault prediction

- Perspectives:
 - Testing other unsupervised methods
 - Parameters configuration in RNN

References



- [1] Draa, I. C., Nouiri, M., Niar, S., & Bekrar, A. (2016). Device Context Classification for Mobile Power Consumption Reduction. In 2016 Euromicro Conference on Digital System Design (DSD) (pp. 682-685). IEEE.
- [2] Grabot, B. (2018). Rule mining in maintenance: Analyzing large knowledge bases. Computers & Industrial Engineering.
- [3] Mbuli, J., Trentesaux, D., Clarhaut, J., & Branger, G. (2017). Decision support in condition-based maintenance of a fleet of cyber-physical systems: a fuzzy logic approach. In 2017 Intelligent Systems Conference (IntelliSys) (pp. 82-89). IEEE.
- [4] Mbuli, J., Trentesaux, D., & Dailly, T. (2018). Specifying a condition-based maintenance decision support system of a fleet of cyber-physical systems. In International Workshop on Service Orientation in Holonic and Multi-Agent Manufacturing (pp. 285-294). Springer, Cham.