From Predictive Maintenance to Machine Learning

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Schedule

1. General introduction
   Now.
2. Case study
   This morning.
3. Presentations and discussion
   Beginning of the afternoon.
4. The Data Scientist point of view
   The rest of the afternoon.

Course goals

By the end of the class, you should be able to :

- explain the workflow of data analysis for Predictive Maintenance problems ;
- know the main bottlenecks and challenges of data-driven approaches to Maintenance ;
- link the Predictive Maintenance problems to their formal Machine Learning counterparts ;
- know the main categories of Machine Learning algorithms and which formal problem they solve ;
- know the name of some key methods in Machine Learning ;
- know the existence of sciki-learn and its API.

Course material

`https://github.com/erachelson/PredMaintenanceClass`

Case study

In small groups. Several cases of failure analysis.

- Turbo-fan engine
- Air conditioning systems (HVAC)
- Truck air compressor
- Pneumatic valve
- IOT deployment and railroad use-cases.
- Bearings

Your task :

- Prepare a synthesis of your case study (tell the story !).
- Highlight in particular :
  - nature of data (scalar, booleans, time series, images, text . . .) ;
  - properties of data (volume, cleanliness, dimensionnality . . .) ;
  - nature of the automated task (visualisation, anomaly detection, RUL prediction . . .) ;
  - name of the Machine Learning (and related) methods used ;
  - open challenges, bottlenecks.

Presentations and discussion

Along the presentations, let's fill the table below, to build a common understanding of :

- the nature of predictive maintenance data
- the different tasks to automate
- the difficulties

Use case	Type of data	Properties of data	Task to automate	Difficulties	Comments

The Data Scientist perspective

Identified needs

We would like to build automated tools for the following tasks :

- Visualize system state
- Identify anomalies
- Predict Remaining Useful Life (RUL) / Time To Failure (TTF)
- Predict failure occurrence or probability at a given horizon

Traditionaly, all this is based on user expertise.
Let's take a data-driven approach.

Data analysis workflow for Predictive Maintenance

1. Collect

- Sensors deployment
- Historical data collection
- Integrated storage and retrieval issues

Data analysis workflow for Predictive Maintenance

1. Collect
2. Analyse

- data cleaning
- feature selection / engineering
- algorithm selection
- parameters tuning

Data analysis workflow for Predictive Maintenance

1. Collect
2. Analyse
3. Predict

- Deploy solution in your operational process
- Make things usable

Data analysis workflow for Predictive Maintenance

1. Collect
2. Analyse
3. Predict
4. React

- Improve your maintenance decisions

Data analysis workflow for Predictive Maintenance

1. Collect
2. Analyse
3. Predict
4. React

Need to automate as many steps as possible in this workflow

$\rightarrow$ data-driven approaches

$\rightarrow$ Machine Learning for step 2 (and 3)

A word on data quality

- amount of data : data is often scarce
- noise, errors, missing data, outdated data : reliability
- high-dimensional data
- class imbalance
- heterogeneous data (scalars, booleans, time series, images, text, . . .)

All these will influence your choice of Machine Learning solutions

Machines that learn ?

Let's try to give a general definition.

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Machine learning is a field of computer science that gives computer systems the ability to "learn" (i.e. progressively improve performance on a specific task) with data, without being explicitly programmed.

ML examples

Examples

ML tasks

Software :

- Many free libraries : scikit-learn, tensorflow, caffe, ...
- Commercial embedded solutions (more or less specialized) : Matlab, IBM, emaint, Microsoft, ...

Evaluation

Evaluating ML methods ?

- Regression : RMSE, margin . . .
- Classification : Misclass rate, TP, FP, cross entropy, ROC. . .
- Clustering : similarity scores

Relating PM and ML

Let’s finish with a focus on a practical use-case