MS SPAPS

Machine learning for space application - BE

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Note about data

This BE contains non sensitive data.

All data provided are comming from a toy case provided in pedagogical purpose.

Plan

1. What is ML ? Recap on practical elements

2. Focus on deep learning: a popular method in the industry

3. ML methods for space: revue of methods and applications

4. Data scientist toolbox: how to run a perfect study

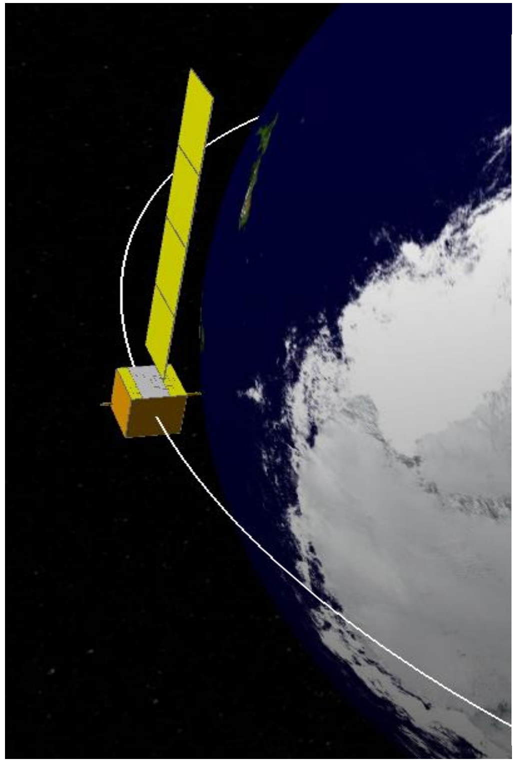
5. [FACULTATIVE]: Complex deep learning

6. Application: realistic space use case (BE)
    - Context
    - Data
    - Workflow

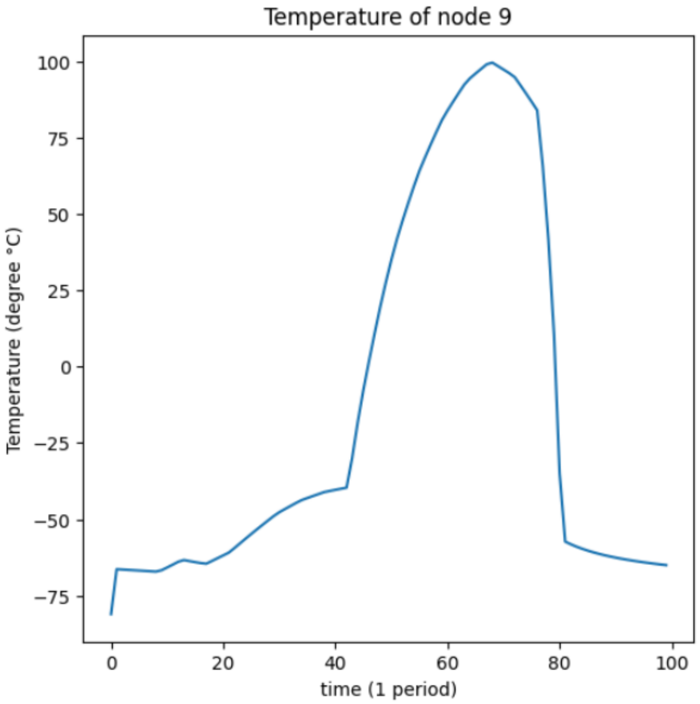
1. Context

Context

Some order of magnitude



*At 800km altitude, 1 period is less than **2 hours (orbit)**.*



*Expected temperature of a fictive panel node throughout 1 period (1 Revolution around the Earth) varies between **-75 and 100 °C***

- Space systems are subjected to a harsh environment (**radiation**, **large temperature variations**, **no convection**)

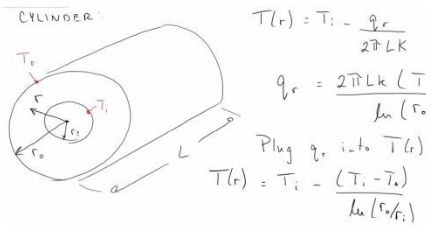
Having accurate thermal models is vital to **monitor** the satellite and make sure that every component will be within **operational temperatures boundaries** for mission success

Context

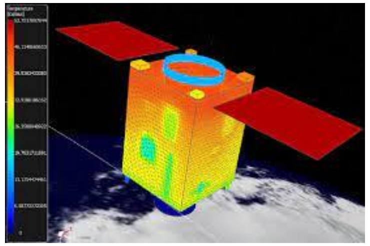
Life cycle of a thermal model

Satellite Life cycle

Conceptual Design



Detailed Design



Thermal model

"Dimensioning": *Check if spacecraft will correctly do the mission based on Worst case modelling scenarios.*

Assembly Integration Test (AIT)

Calibrated Thermal Model

"Correlation": *Compare test measures vs worst case scenarios. And calibrate the Thermal model*

Operations

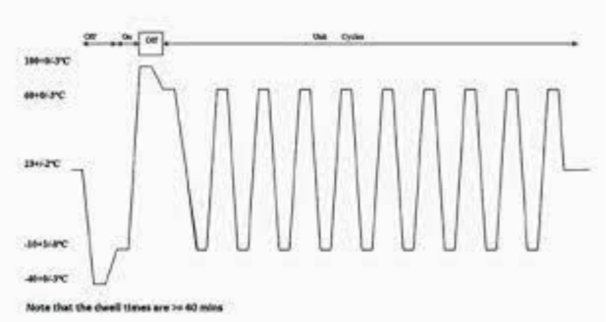
Correlated Thermal simulator

Monitoring: *Train the operators and prepare operations (manoeuvres, …) with simulators.*

Context

Calibration of thermal model via TVAC (Thermal Vacuum Chamber) measures

A thermal vacuum chamber



TVAC Thermal cycle

1. **Cycles of T° in a « represnetative » environment (Thermal Vacuum Chamber)**
2. **Measures of T° on the satellite (test measures)**

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Context

Model « correlation »

4. Calibration of the thermal model: modify some parameters (dissipation levels, coeffiscient of heat transfert)

Manual model tweaking

Thermal model

Dissipations

Heat rejection coeff

TMM

T° predicted

ΔT

3. Comparison with Thermal model predictions

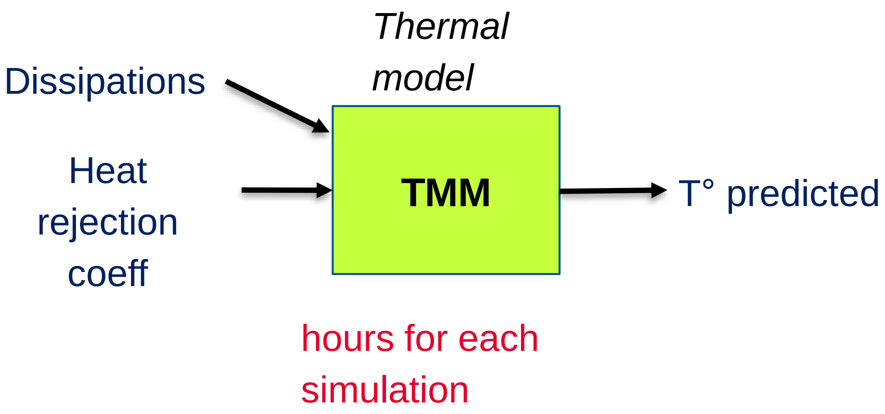
Tests

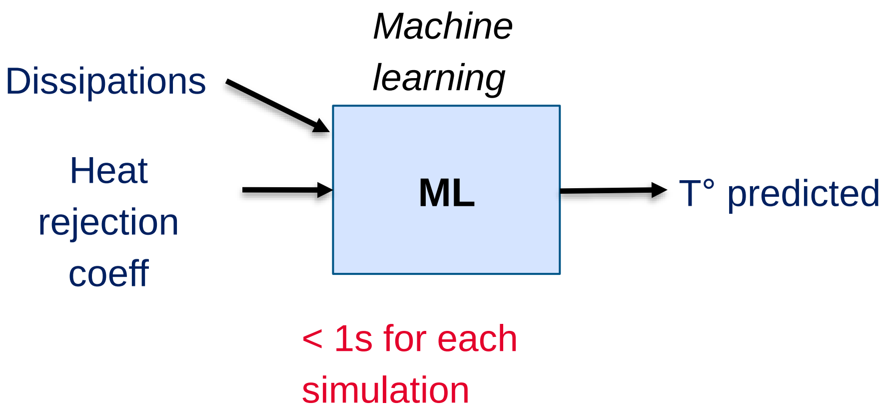
T° measured

Context

Challenge

Purpose of the BE: *surrogate model* of a thermal model: an AI model to drastically reduce the computing time





Challenge:

1. *Precision:* < 1°
2. *Computing time:* < 1 second for one orbit simulated

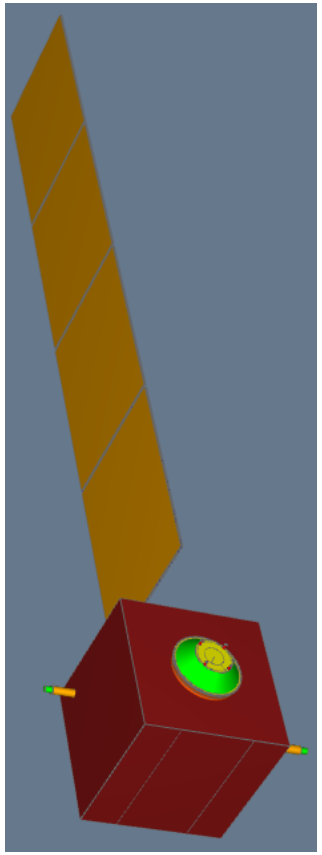
2. Data

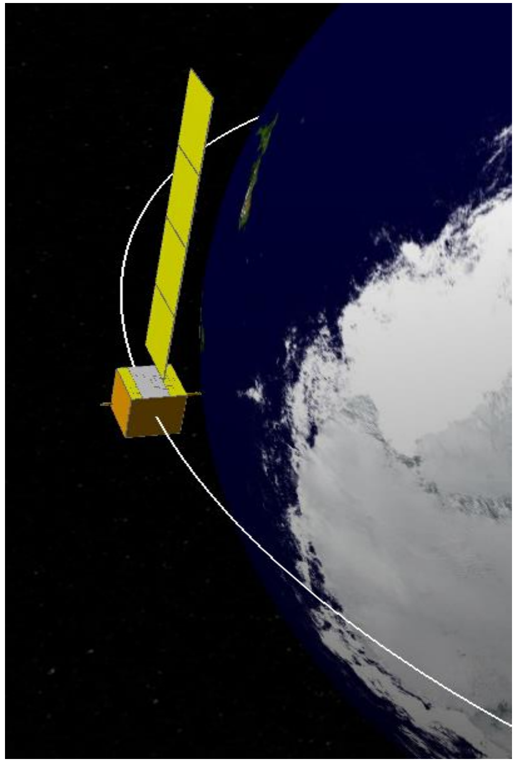
Data

Model used

Train Sat

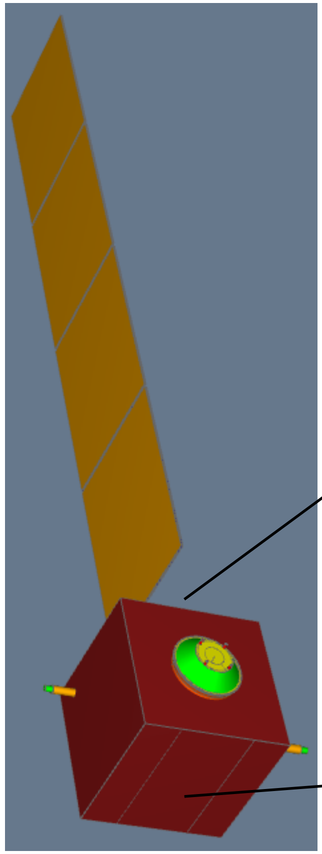
- Observation satellite (low orbit)
- 45 thermal nodes
- Multiple equipements



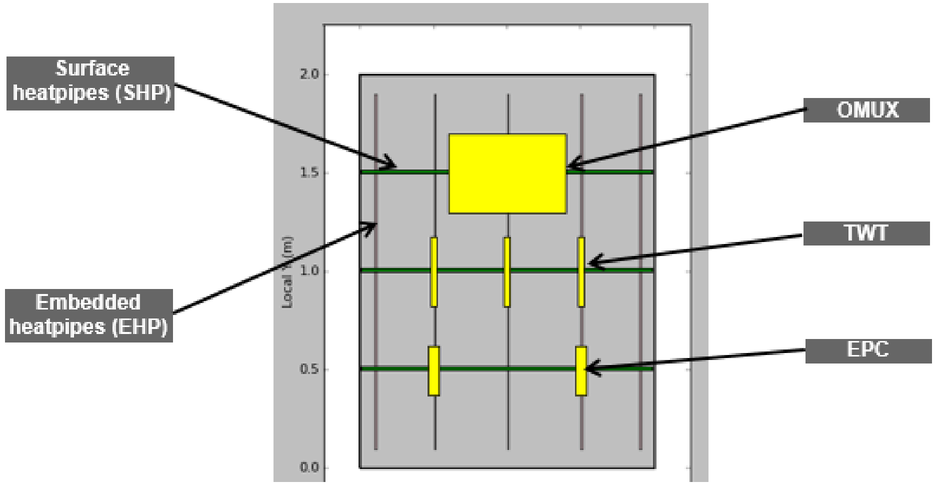


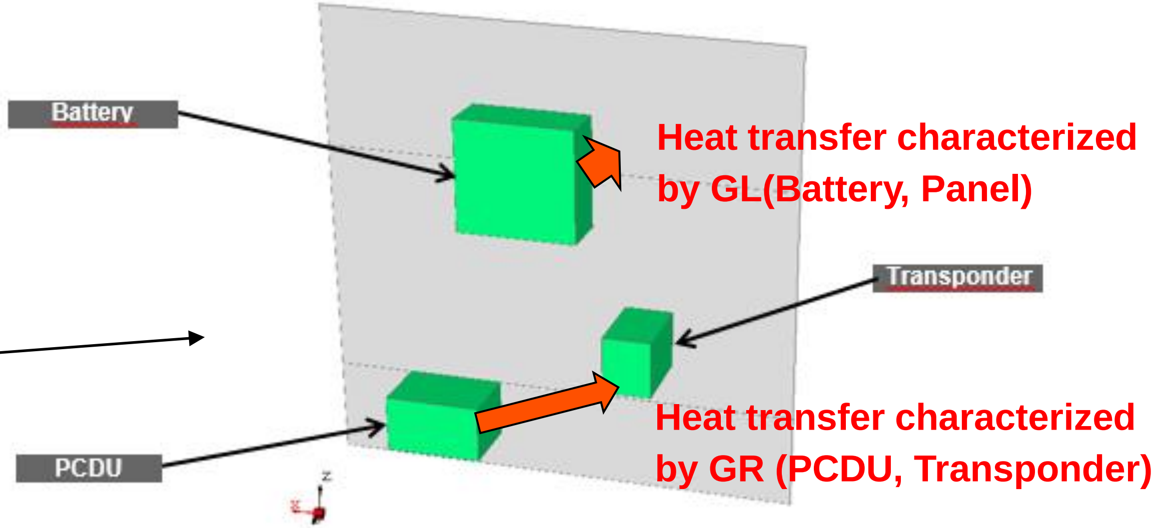
Data

Model used



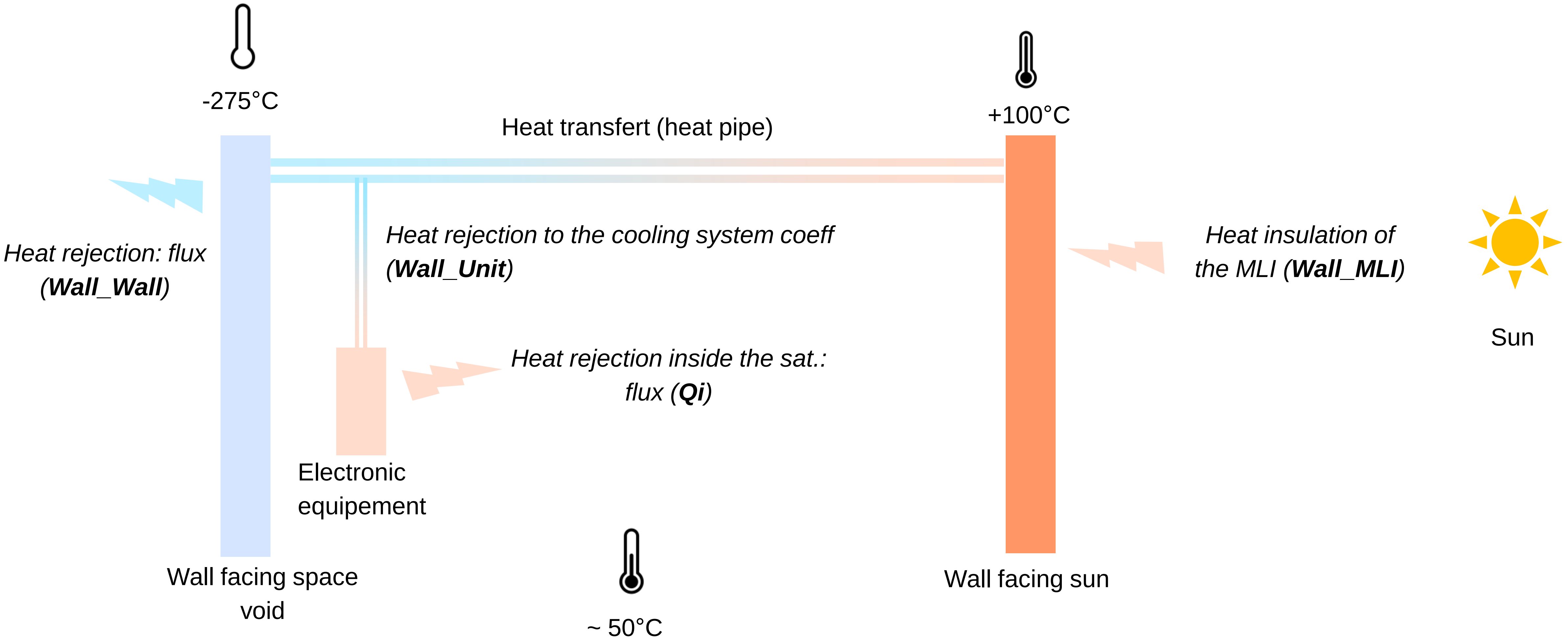
Inside the satellite





Data

Some thermal elements



Data

Dataset

12 TMM Input:

- 6 dissipation parameters: in [0.1, 2]
  - *QI_BATTERY*: dissipation of the battery
  - *QI EPC*: dissipation of the EPC: Electronic Power Converter
  - *QI_OMUX:* dissipation of the OMUX: Output Multiplexer
  - *QI_PCDU*: dissipation of the PCDU (Power Conditioning and Distribution Unit)
  - *QI_TRANSPONDER*: dissipation of the transponder
  - *QI_TWT*: Dissipation of the Travelling Wave Tube (repeater)
- 3 coupling parameters: in [0.1 ; 5]
  - *Wall_MLI*: Coefficient of heat insulation of the MLI (Multi Layer Insulation)
  - *Wall_Units*: Coefficient of heat transfert between the equipements and the wall
  - *Wall_Wall*: : Coefficient of rejection of heat between the wall and space (measure efficiency of the heat pipes).

TMM Output: 45 Temepratures (one per node).

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Data

Generation of the data

<u>12 parameters defined :</u>

- 9 QI_PASTA_Parameters:
  - PASTA_QI_BATTERY
  - PASTA_QI_EPC_i (i = 1 or 2)
  - PASTA_QI_OMUX
  - PASTA_QI_PCDU
  - PASTA_QI_TRANSPONDER
  - PASTA_QI_TWT_i (i = 1, 2 or 3)
- 3 Sub_System_Coupling_PASTA Parameters:
  - PASTA_Wall_MLI
  - PASTA_Wall_Units
  - PASTA_Wall_Wall

<u>Allowables</u>

QI_PASTA_Parameters: [0,1; 2]

Sub_System_Coupling_PASTA Parameters: [0,1; 5]

<u>Design of Experiment:</u>

- 2000 Simulations have been launched
- These 2000 samples corresponds to various set of parameters

- NB: A Latin Hypercube Sampling have been used
- NB: PASTA is the software used to launch the simulations

3. Workflow

Recap

Formalize your problem

Useful questions

What goes in ?

1. Kind of data ? (image, tables, …)
2. Amount of **useful** data (identify useless data)
3. Estimation of time to get the data
4. Estimation of time to pre-process the data (clean, …)

In a data science study, there is ~80% of time spent to get the correct data (extract, clean, pre-process…) and 20% to build and train a model.

$\longrightarrow$ My ML model $\longrightarrow$

What is the best class of model to solve the problem ?

1. Quantity of data
2. Type of data (homogeneous, heterogeneous)
3. Type of problem (supervised / unsupervised)

A literature review is always necessary

What goes out ?

1. What is the thing to predict ? *(ageing, forecast, …)*
2. What is the better way to represent them ? *(difference with an average value, hourly/daily/monthly average value, …)*

Personal advise: avoid the study based on the sentence "I have a lot of data, what could you do with AI ?"

Recap

Formalize your problem

Useful questions

What goes in ?

1. Kind of data ? (tables)
2. Amount of **useful** data (No useless data)
3. ~~Estimation of time to get the data~~ (you are lucky !)
4. Estimation of time to pre-process the data (Not the purpose of this BE)

→ My ML model →

What goes out ?

1. What is the thing to predict ?
   T° of the nodes
2. What is the better way to represent them ? *Scaling.*

What is the best class of model to solve the problem ?

1. Quantity of data (2000 runs)
2. Type of data (homogeneous, ~~heterogeneous~~)
3. Type of problem (supervised / ~~unsupervised~~)

	PASTA_QI_BATTERY	PASTA_Wall_Units	PASTA_QI_EPC_2
0	1.870325	1.184125	0.777825
1	1.971025	2.855025	1.344025
2	0.843375	0.936675	0.419675

Input data: parameters

	0	1	2	3
0	0.585262	0.249293	0.472491	-83.528588
1	-14.613094	-14.685090	-14.615978	-89.434313
2	-2.143549	-2.334472	-2.289555	-69.535581

Output data : T°

Full workflow of a data science study

Recap

Steps

1. ~~Generate the dataset~~
    - ~~DoE / Latin Hypercube Sampling (LHS)~~
2. Choose the cost function
3. Choose a reference
    - *Linear regression*
4. Benchmark ML models
    - Find ML models to test in the litterature
5. Optimize hyper-parameters

Challenge

Purpose of the BE

1. **Build a benchmark workflow**
   - *Goal:* Ease the ML model testing

2. **Find the best surrogate model**
   - *Criterion:*
     - *MAE:* Lowest Average (absolute) error
     - *STD:* Lowest standard deviation (dispersion of the errors)
     - *Max absolute error:* Lowest maximal error

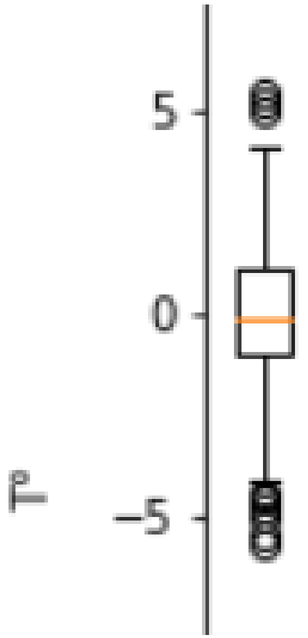

Illustration: boxplot of error ML_prediction – T° to predict (2000 simulations)

Challenge

Purpose of the BE

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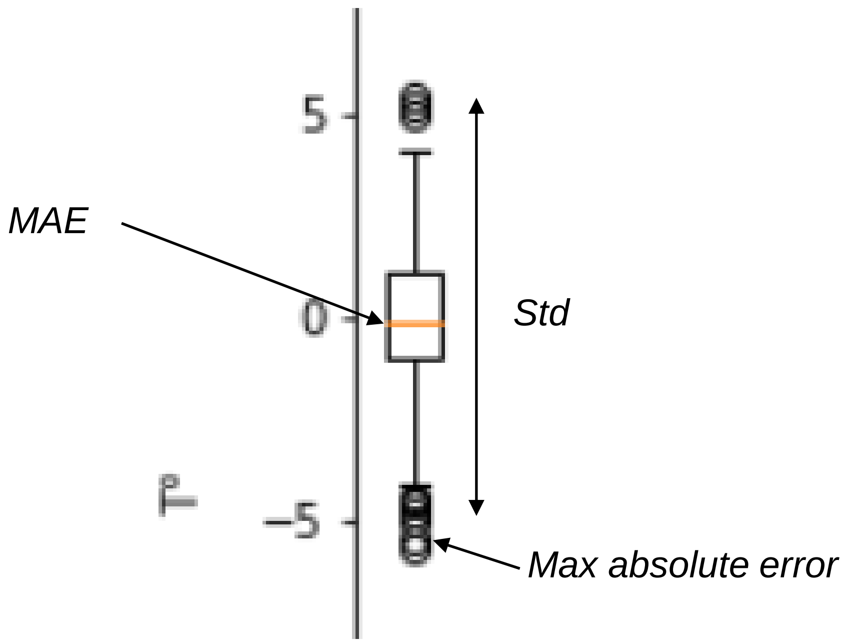

Illustration: boxplot of error
ML_prediction – T° to predict
(2000 simulations)

Access to the BE

Git clone
https://github.com/TheJulesGithub/SPAPS_BE_ML_for_space_application.git

Annex

Heat equation

For a given thermal node i, **in stationary:**

External fluxes | Node i dissipation | Radiative couplings | Conductive couplings

$$P_{ext} = -\boxed{P_{int,i}} + \sum_{j=1}^{n} \boxed{R_{i,j}} \sigma\left(T_i^4 - T_j^4\right) + \sum_{j=1}^{n} \boxed{C_{i,j}} (T_i - T_j)$$

Correlation Parameters: QI_i | GR(i, j) | GL(i, j)

Source : Heat Balance Equation