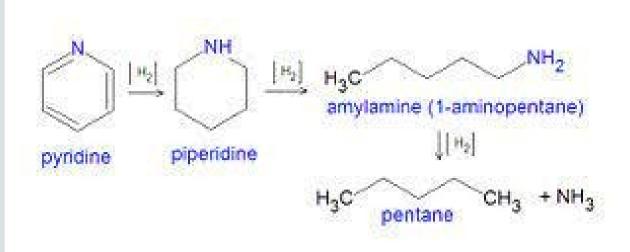
Institut Mines-Télécom

Estimation of a catalyst lifespan through machine-learning



Examples of <u>organic nitrogen</u> <u>compounds</u> to be catalytically removed with hydrogen.

1. Introduction

- **Context:** catalytic hydrodenitrification of crude oil distillates.
- ► Aging of the catalyst: increase of the necessary reaction temperature until 450 °C is reached \rightarrow replacement of the catalyst.
- Goal: predict the evolution of a catalytic reactor's temperature based on data from similar reactors (machine learning).

2. Pre-processing

Partners

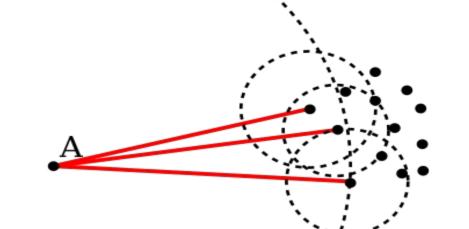


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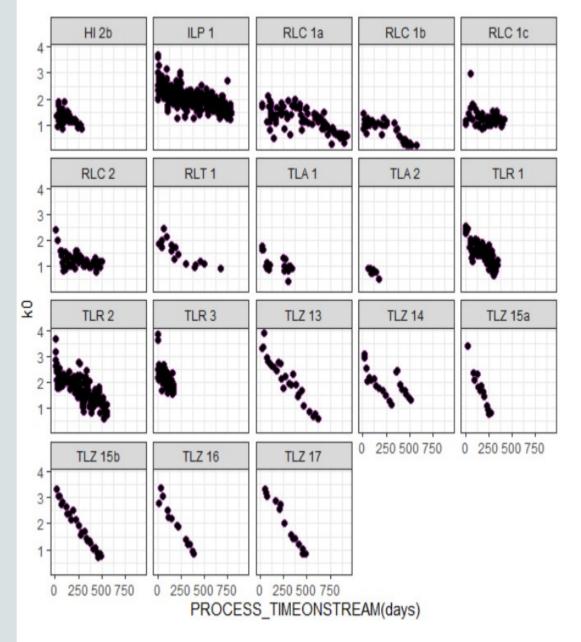
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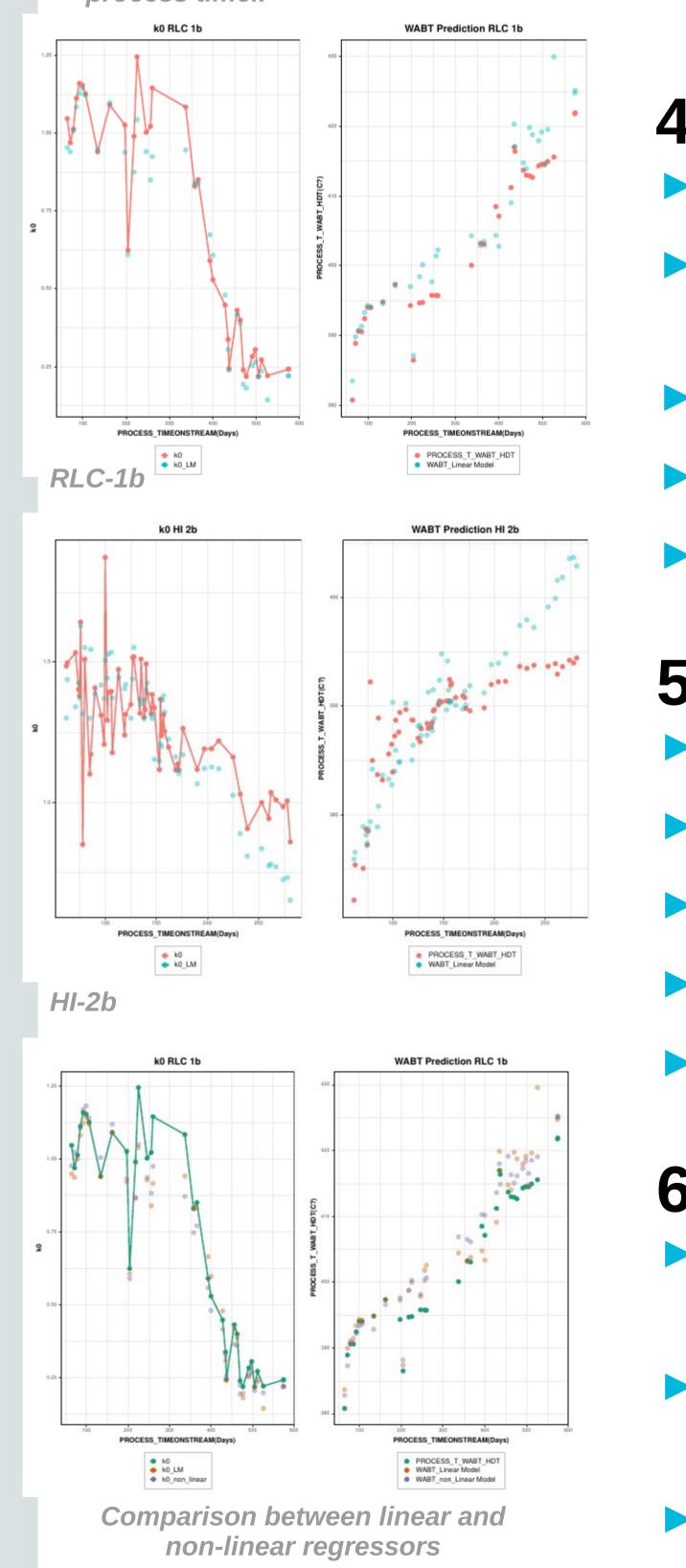
Basic idea of LOF: comparing the local density of a point with the densities of its neighbors. A has a much lower density than its neighbors.



Experimental profiles of k0 for different catalysts as a function of process time..

- Variable selection : 12 most relevant variables selected based on expert knowledge: t, p, p(H₂)_{out}, q_{feed}, q_{outlet}, reflux - ratio, p(N)_{out}, p(S)_{in}, p(resines), p(N)_{in}, density_{in}, p_{H₂, in}
- Missing values: removal of physically aberrant and missing values.
- **Computation of cumulative variables :** $CUMSUM = \sum_{i=1}^{n-1} \frac{h_i}{2} (X_{i+1} + X_i)$.
- Identification and removal of outliers: use of the local outlier factor (LOF).
- Remaining data: 23 cycles and 1885 time points.
- **3. Methodology Chemical kinetic model:** $\frac{dC_N}{dt} = \frac{-k_0 \cdot exp\left(-\frac{E_a}{R}\left(\frac{1}{T} - \frac{1}{T_0}\right)\right)\left(\frac{ppH_2}{ppH_{2,ref}}\right)^m \cdot C_N^n}{(1 + A_0 \cdot Res_0)\left(1 + C_0\frac{C_{N,0}}{C_{S,0}}\right)}$
- **Prediction** of the catalyst efficiency represented by k_0 .
- **Computation** of the experimental k_0 from the temperature measurements and computation of the predicted *T* from the predicted value of k_0 .
- **Design mode**: we suppose that we know the profiles of all other variables than T and use them to predict $k_0(t)$ and in turn T(t) at a given time t.
- ▶ Multiple linear model: based on 10 regressors, we seek to predict $log(k_0)$.
- **Cross-validation:** the evolution of T(t) for a cycle is predicted based on all

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other cycles.

I. Results	Mean RMSE	4.847
Global metrics:	Standard deviation Median	$1.774 \\ 4.27$

- Satisfying average prediction error: -> the average prediction error for T is 4.8 °C.
- Some cycles such as RLC-1b are well predicted from the beginning to the end.
- For others such as HI-2b there is a systematic gap towards the end.
- Linear relationships are not enough to fully grasp the system's behavior!

5. Addition of non-linear terms

- Addition of non-linear terms to the regressors : X^2 , log(X), \sqrt{X} , $\frac{1}{X}$, XY
- We now want to select the 10 best regressors out of 552 potential regressors.
- Doing an <u>exhaustive</u> search would be computationally prohibitive.
- Use of an <u>adaptive random search</u> to find a good combination of regressors.

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rics	Linear model	Non-linear model
n RMSE	4.847	4.186
dard deviation	1.774	1.817
lian	4.27	3.541

6. Conclusion and outlook

- While multiple linear regression is conceptually very simple, a reasonable agreement was reached.
- To better grasp the non-linear relationship, methods like neural networks and support vector regression could prove quite fruitful.
- It is also important to make sure that the machine learning method does not deliver unphysical predictions.
- Introduction of weights depending on the proximity of the cycle to the cycle to be predicted.
- ▶ What if mode: regression model based on both the other cycles and the beginning of the cycle \rightarrow creation of a digital twin.