

Contexte

- Automated selection & parametrization of machine learning algorithms.
- Guided Hyperparameters optimization.
- Optimal performance of ML models for a given classification task.
- Explainability of the recommended models.
- Application to the Industry 4.0.
- Empirical study on manufacturing data for validation and usability purposes.

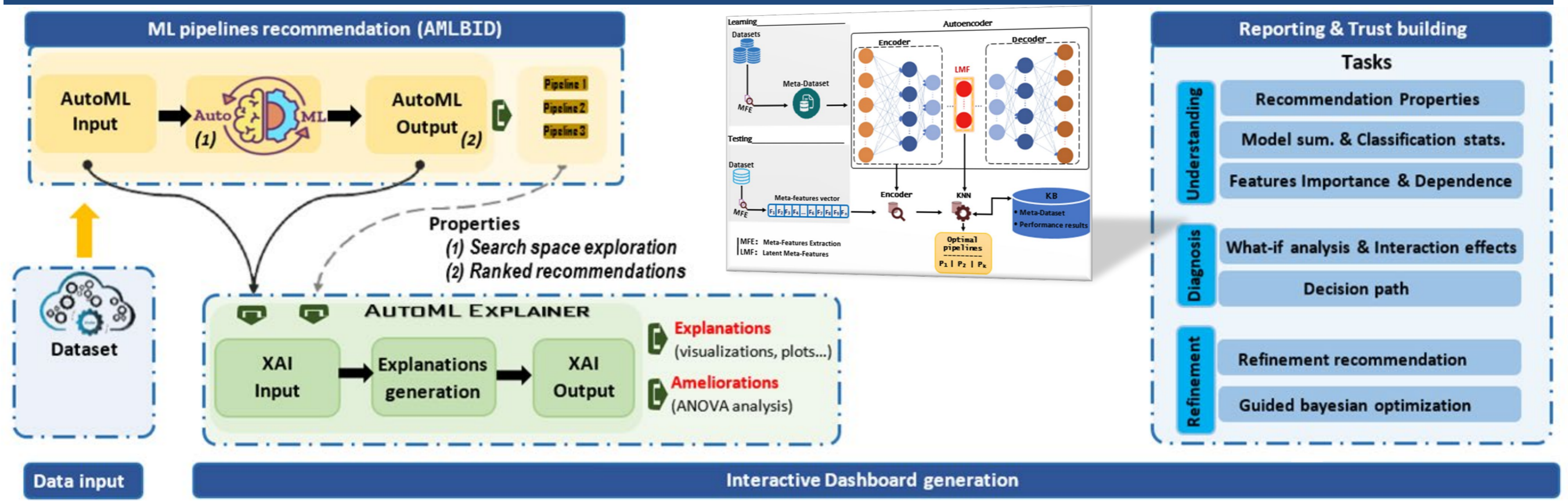
Key concepts

Automated Machine Learning (AutoML) Auto ML is often used to help domain experts, who typically have limited ML expertise, in order to generate and build high quality models to better meet their specific business needs.

Meta-learning refers to the algorithms that are concerned with their own learning process as well as learning across a series of related prediction tasks.

Explainable AutoML (XAutoML) provide a set of tools and frameworks to better understand and interpret the predictions of a machine-learning model.

Proposed assistance system



Recommender module

Suggested configurations

Recommendation 1: RandomForestClassifier Expected accuracy: 0.97917 [Export Pipeline](#)

Recommendation 2: GradientBoostingClassifier Expected accuracy: 0.97826 [Export Pipeline](#)

Gradient Boosting Classifier

Class sklearn.ensemble.GradientBoostingClassifier

Recommended model configuration

Hyperparameter	Value
n_estimators	50
min_impurity_decrease	0.0
max_features	sqrt
learning_rate	1.0
loss	deviance
random_state	324089

Explainer module

What-If Analysis

Select Observation: 1218

Prediction: label 0 (32.9%), label 1 (0.0%), label 2 (67.1%)

Contributions Table

Reason	Effect
Average of population	95.49%
T4U = 7	-24.56%
T4 = 69	-1.84%

Decision Path

Select Observation: 1218

Decision path visualization showing individual prediction process.

AMLBD package

AMLBD is a self-explainable AutoML system in the form of a Python-package. The system proposes a transparent and justified analysis to discover the most suitable model for optimal performance among multiple ML models. It attempts to automate the process of the algorithms selection, the tuning of hyperparameters, and traceability in supervised ML.

```

1 from AMLBD.recommender import AMLBD_Recommender
2 from AMLBD.explainer import AMLBD_Explainer
3 from AMLBD.loader import *
4
5 #Load dataset
6 Data, X_train, Y_train, X_test, Y_test = load_data("Dataset.csv")
7
8 #Generate the optimal configurations
9 model, config = AMLBD_Recommender.recommend(Data,
10                                             metric="Accuracy",
11                                             mode="Recommender_Explainer")
12 model.fit(X_train, Y_train)
13
14 #Generate the interactive explanatory dash
15 Explainer = AMLBD_Explainer.explain(model, config,
16                                     X_test, Y_test)
17 Explainer.dash()
    
```

Results

- Garouani, M., Ahmad, A., Bouneffa, et al. Using meta-learning for automated algorithms selection and configuration: an experimental framework for big industrial data. *Journal of Big Data* 9, 57 (2022). <https://doi.org/10.1186/s40537-022-00612-4>
- Garouani, M., Ahmad, A., Bouneffa, M, et al. Towards big industrial data mining through explainable automated machine learning. *The International Journal of Advanced Manufacturing Technology* (2022). <https://doi.org/10.1007/s00170-022-08761-9>
- Garouani, M., Ahmad, A., Bouneffa, M., et al. AMLBD: An Automated Machine Learning tool for Big Industrial Data. *SoftwareX* (2021) 100919, <https://doi.org/10.1016/j.softx.2021.100919>
- Scan the QR Code to explore all results and publications



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