

A Hands-on Tutorial on Time Series Imputation with ImputeGAP

Quentin Nater & Mourad Khayati

Hands-on Tutorial @KDD'25, Toronto (Canada)

<https://imputegap-tutorials.github.io/KDD-2025>

<https://imputegap.readthedocs.io>
v1.1.1 with support of LLMs

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Schedule

- ▶ Section 1: Introduction and Overview (20 min)
- ▶ Section 2: ImputeGAP Features (10 min)
- ▶ Section 3: Imputation Pipeline Synthesis (60 min)
- ▶ Break (15 min)
- ▶ Section 4: Downstream Analysis (20 min)
- ▶ Section 5: Imputation Explainability (20 min)
- ▶ Section 6: Library Extension (20 min)

Presenters

► Mourad Khayati

- ▶ Ph.D. from University of Zürich
- ▶ Senior Lecturer at the University of Fribourg (Switzerland)
- ▶ Time series analytics, data cleaning, missing data imputation, Time Series Database Systems
- ▶ KDD 2025 Outstanding Reviewer Award, VLDB 2020 Best Experiments and Analysis Paper Award



► Quentin Nater

- ▶ PhD student at the University of Fribourg (Switzerland) since 01/2025
- ▶ Web of Things, missing data imputation, multimodal learning
- ▶ Fantasy writer



Current Section

Introduction and Overview

Introduction to ImputeGAP

Imputation Pipeline Synthesis

Downstream Imputation Analysis

Explainable Imputation

Library Extension

Data with Missing Values

- ▶ Technical glitches or downtime in data collection systems.
- ▶ Combining data from multiple sources can yield missing entries.
- ▶ Some stocks trade infrequently, so price updates may be missing on certain days.
- ▶ During preprocessing, some data might be excluded if it is not worth being retained.
- ▶ Data can be withheld due to privacy or proprietary concerns.
- ▶ Organizations might not record all the statistical data.
- ▶ Participants in a survey do not answer all the questions.

Missing Values in Time Series

- ▶ Transmission and hardware problems often occur:
 - ▶ Device failure
 - ▶ calibration drift
 - ▶ Intermittent connectivity
 - ▶ Power outages
 - ▶ External interference

Missingness in Public Repositories

- ▶ Intel-Berkeley Research Lab dataset is missing about 40% (source: A Pipelined Framework for Online Cleaning of Sensor Data Streams, Berkeley technical report, 2005).
- ▶ The UCI repository contains datasets with up to 20% missing data (source: A Survey on Missing Data in Machine Learning, J. Big Data, 2021).
- ▶ MIMIC Clinical Database has up to 80% missing observations (source: Recurrent Neural Networks for Multivariate Time Series with Missing Values, Scientific Reports, 2018).
- ▶ Up to 49% data loss in wearable monitoring (source: Data Quality Evaluation in Wearable Monitoring, Scientific Reports, 2022).

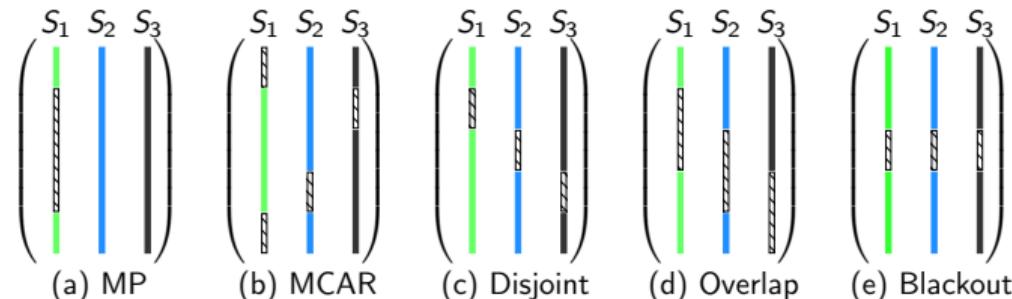
Why Imputation?

- ▶ Data management systems and models assume that the data is complete.
- ▶ Ignoring missing values has a detrimental impact on time series tasks:
 - ▶ ↓ 97% AVG F1 in classification
 - ▶ ↓ 55% AVG RMSE in forecasting
- ▶ Time Series Database Systems (TSDBs)¹ have begun to incorporate native support for missing value imputation.

¹khelifati A., Khayati M., Difallah D., Dignös A., and Cudré-Mauroux P.: "TSM-Bench: Benchmarking Time Series Database Systems for Monitoring Applications", PVLDB'23

Imputation Caveats

- ▶ Compared to tabular data, time series imputation is challenging:
 - ▶ temporal dependency
 - ▶ high-variability data
 - ▶ blocks of consecutive values



Current Section

Introduction and Overview

Introduction to ImputeGAP

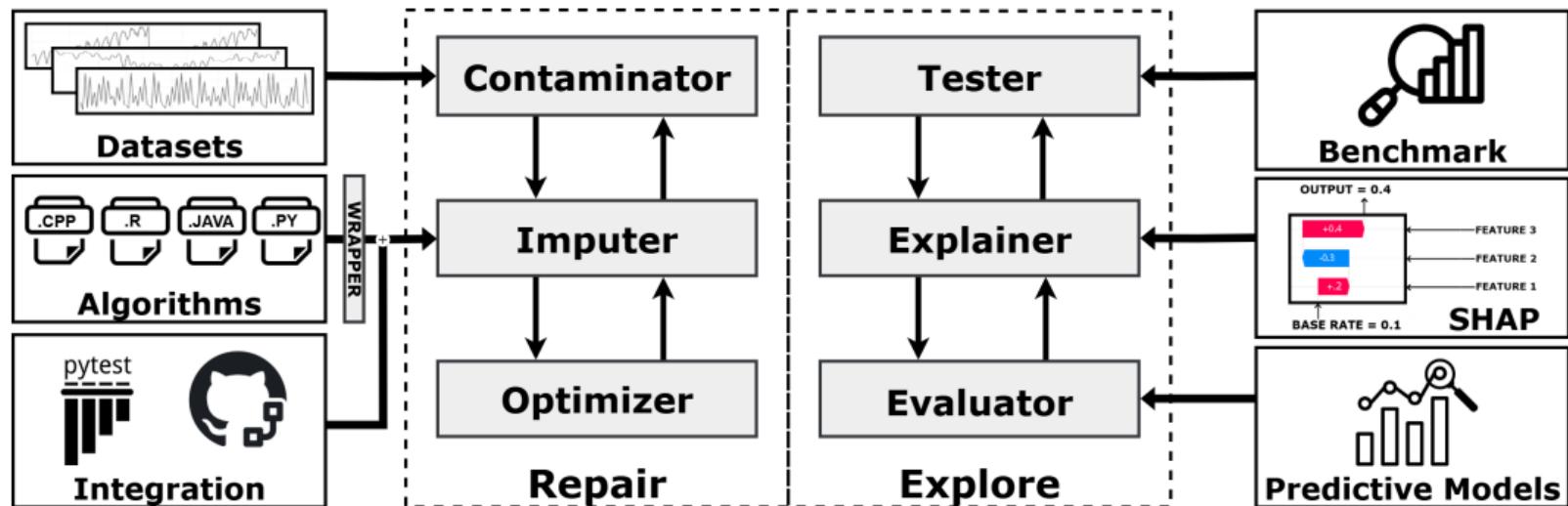
Imputation Pipeline Synthesis

Downstream Imputation Analysis

Explainable Imputation

Library Extension

Python Library

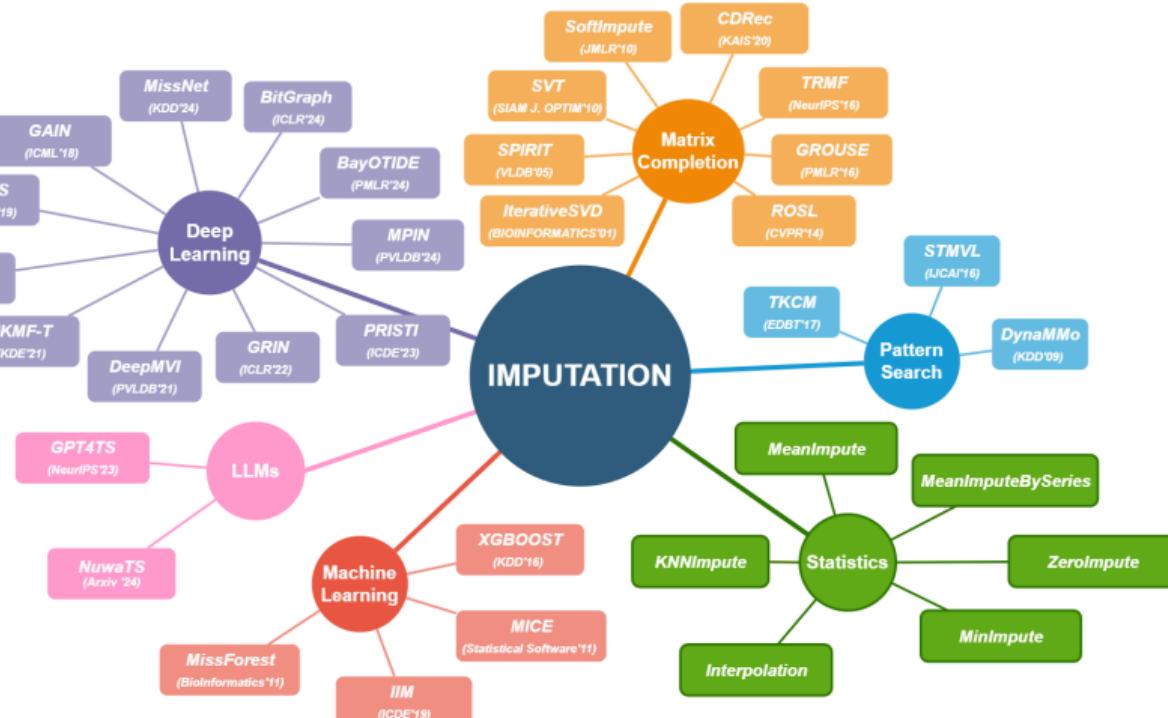


Comparison with Existing Libraries

- ▶ Other imputation libraries for time series imputation exist, e.g., PyPOTS, CleanTS, Amelia II, and sktime.
- ▶ Limited coverage of imputation algorithms, missingness patterns, and datasets.
- ▶ Limited benchmarking customization.
- ▶ Do not support the explainability of the results.
- ▶ Lack of downstream analysis.
- ▶ Lack of integration module.

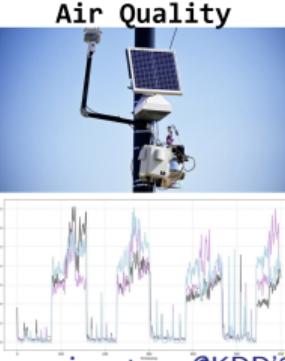
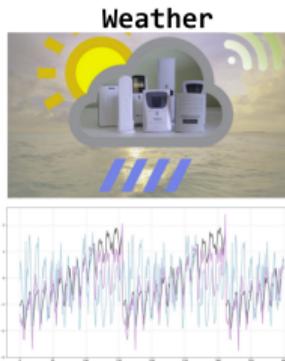
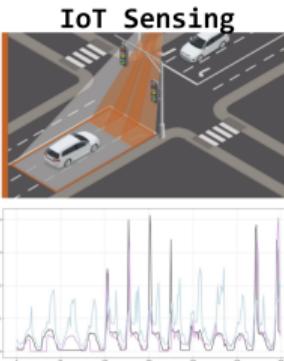
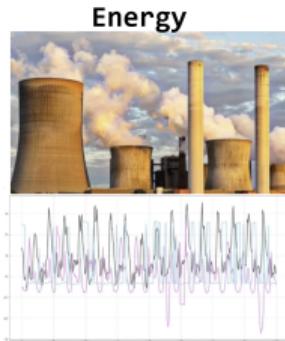
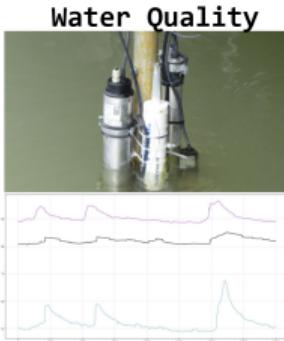
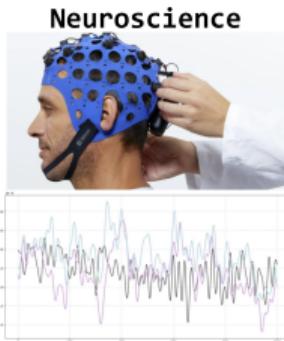
Available Algorithms

- ▶ 34 off-the-shelf imputation algorithms.
- ▶ Six families: Matrix Completion, ML, DL, Statistics, Pattern Search, and LLMs.



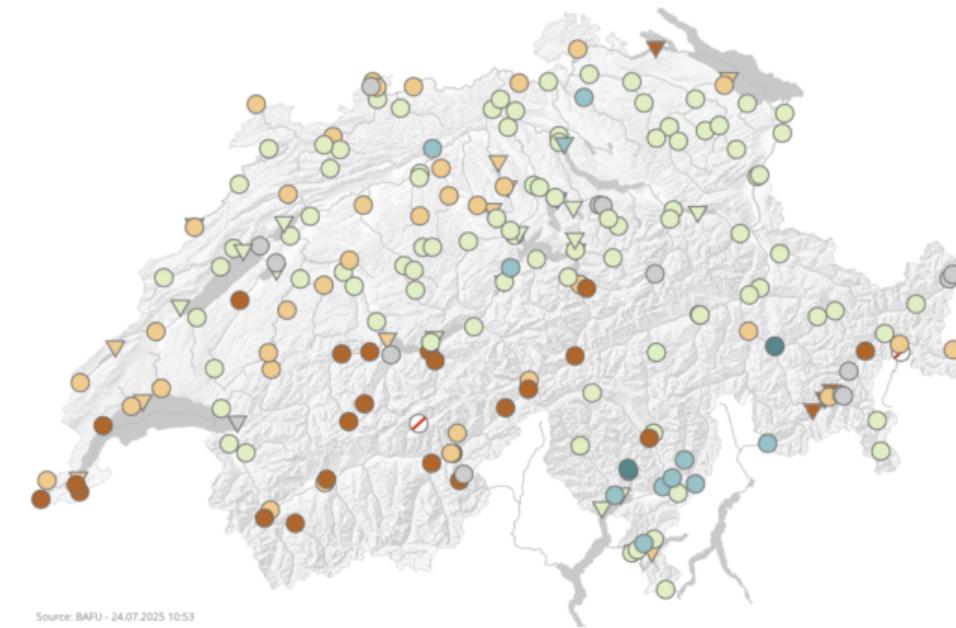
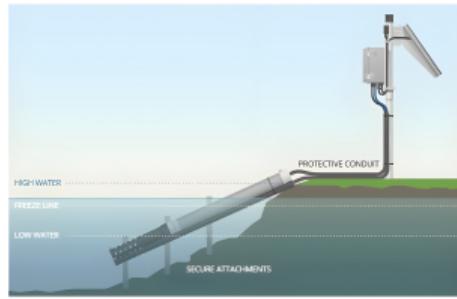
Available Datasets

- ▶ 17 ready-to-deploy time series datasets.
- ▶ 8 real-world applications.



Water Quality

- ▶ BAFU¹ deploys sensors to monitor the water quality in Swiss rivers.
- ▶ Multivariate time series: discharge, conductivity, oxygen level, temperature, pH values, etc.



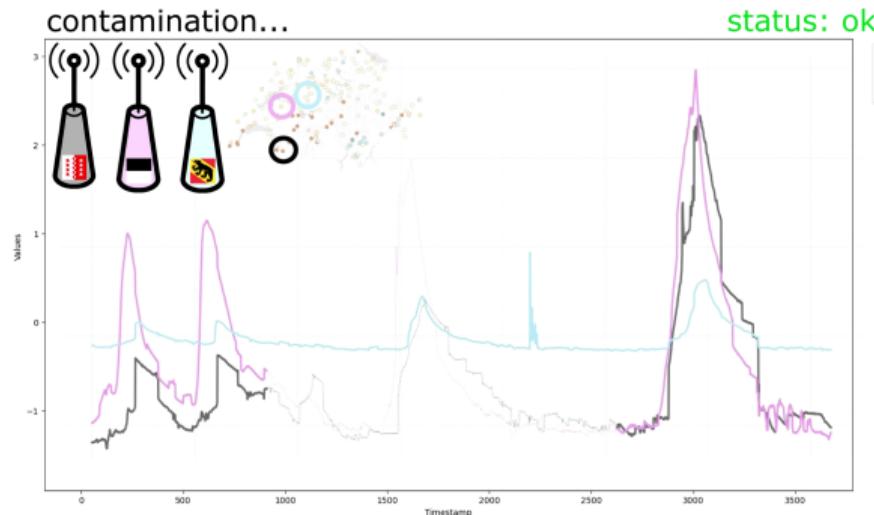
¹ Federal Office for the Environment in Switzerland

BAFU Dataset

- ▶ Monitoring of river levels across three regions, but the sensors suddenly stopped transmitting data.
- ▶ The missing data poses safety risks.



Viège (VS) - 21.06.2024



Current Section

Introduction and Overview

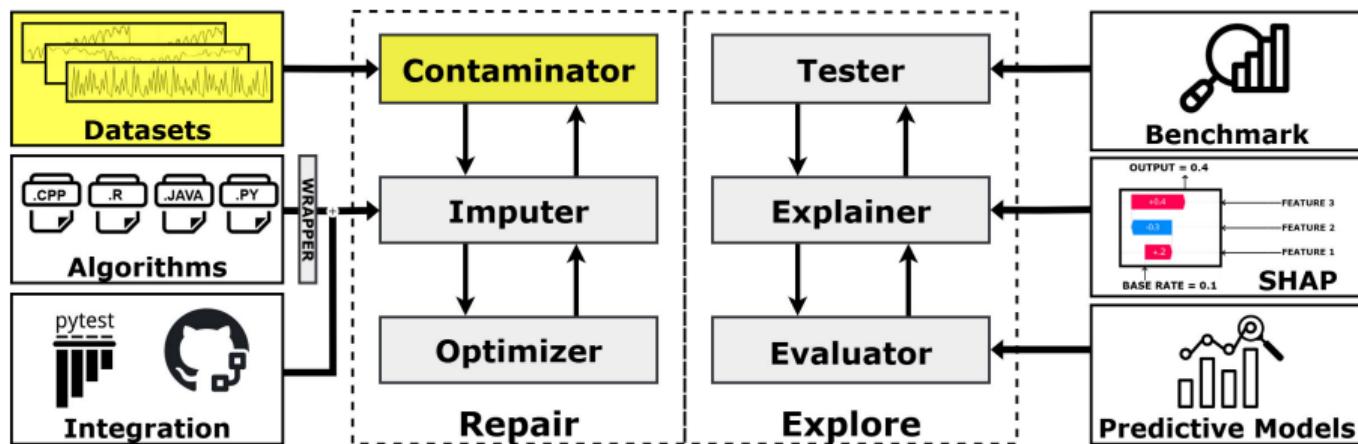
Introduction to ImputeGAP

Imputation Pipeline Synthesis

Downstream Imputation Analysis

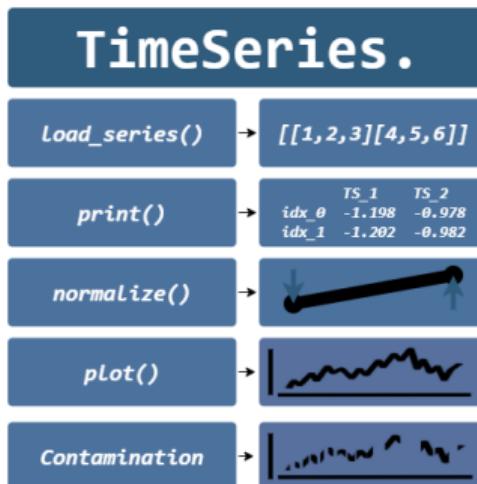
Explainable Imputation

Library Extension



One Object to Rule Them All

- ▶ A single object to manage the entire time series lifecycle, from loading to evaluation.



Note

- Input: `file`, `str`, `pathlib.Path`, `list`
- Output: `numpy.ndarray`
- Instance variable: `TimeSeries.data`

```
1 from imputegap.recovery.manager import TimeSeries  
2 ts = TimeSeries()
```

Data Loader

- ▶ Load time series data internally or from a file.

```
load_series(data, nbr_series=None, nbr_val=None, header=False, replace_nan=False,  
verbose=True) ↴
```

[source]

```
1 # load from built-in datasets  
2 ts.load_series(utils.search_path("eeg-alcohol"))  
3  
4 # load your dataset  
5 ts.load_series("../imputegap/datasets/kdd.txt"))  
6  
7 # load as a matrix  
8 ts.import_matrix([[1,2,3],[4,5,6]])  
9  
10 # print your ts  
11 ts.print(nbr_series=3, nbr_val=20)
```

TimeSeries.

Load_series()	→ <code>[[1,2,3][4,5,6]]</code>									
print()	→ <table><thead><tr><th></th><th>TS_1</th><th>TS_2</th></tr></thead><tbody><tr><td>idx_0</td><td>-1.198</td><td>-0.978</td></tr><tr><td>idx_1</td><td>-1.202</td><td>-0.982</td></tr></tbody></table>		TS_1	TS_2	idx_0	-1.198	-0.978	idx_1	-1.202	-0.982
	TS_1	TS_2								
idx_0	-1.198	-0.978								
idx_1	-1.202	-0.982								
normalize()	→									
plot()	→									
Contamination	→									

Note

Please ensure that your input data satisfies the following format:

- Columns are the series' values
- Column separator: empty space
- Row separator: newline
- Missing values are NaNs

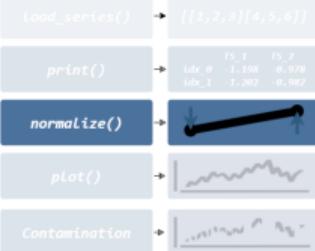
Adaptive Rescaling

- ▶ Normalize the time series data into a different scale.

```
normalize(normalizer='z_score', verbose=True) ↗
```

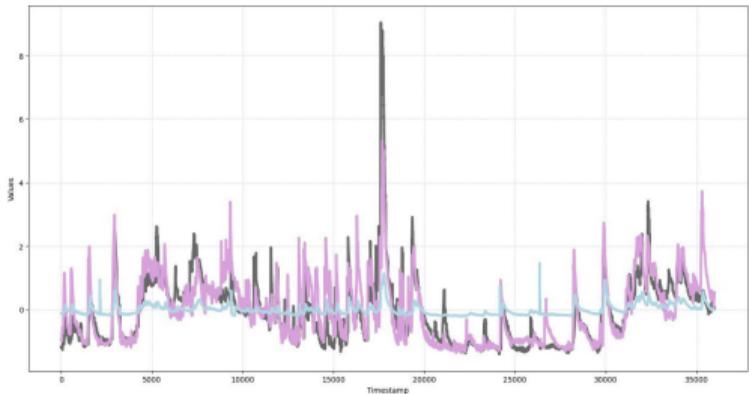
[source]

TimeSeries.



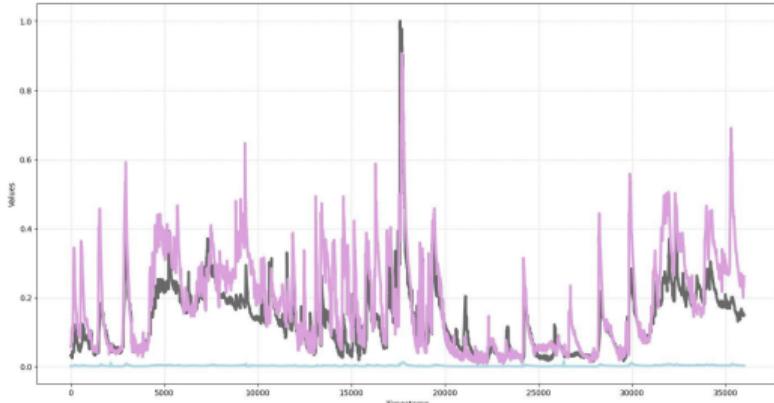
- ▶ Z-Score

```
1 ts.normalize(normalizer="z_score")
```



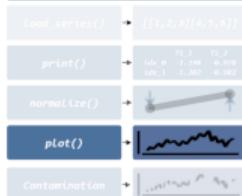
- ▶ Min-Max

```
1 ts.normalize(normalizer="min_max")
```



Plotting

TimeSeries.



- ▶ Plot the time series: original, contaminated, and reconstructed.

```
plot(input_data, incomp_data=None, recov_data=None, nbr_series=None, nbr_val=None,  
     series_range=None, subplot=False, size=(16, 8), algorithm=None,  
     save_path='./imputegap_assets', cont_rate=None, display=True, verbose=True) ↴ [source]
```

Parameters

`input_data : numpy.ndarray`
The original time series data without contamination.

`incomp_data : numpy.ndarray, optional`
The contaminated time series data.

`recov_data : numpy.ndarray, optional`
The imputed time series data.

`nbr_series : int, optional`

The maximum number of series to plot.

`nbr_val : int, optional`

The maximum number of values per series to plot.

`series_range : int, optional`

The index of a specific series to plot. If set, only this series will be plotted.

`subplot : bool, optional`

Print one time series by subplot or all in the same plot.

`size : tuple, optional`

Size of the plot in inches. Default is (16, 8).

`algorithm : str, optional`

Name of the algorithm used for imputation.

`save_path : str, optional`

Path to save the plot locally.

`cont_rate : str, optional`

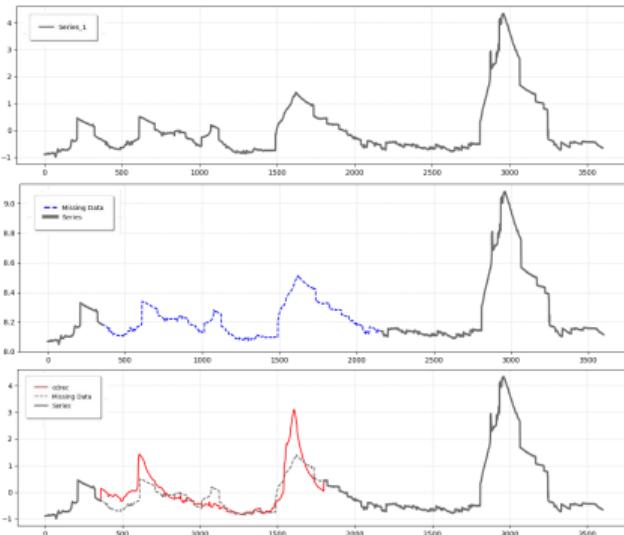
Percentage of contamination in each series to plot.

`display : bool, optional`

Whether to display the plot. Default is True.

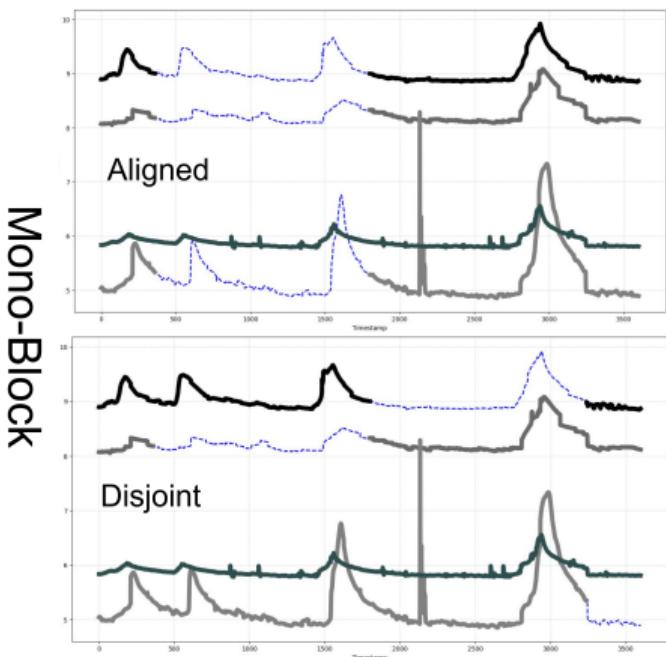
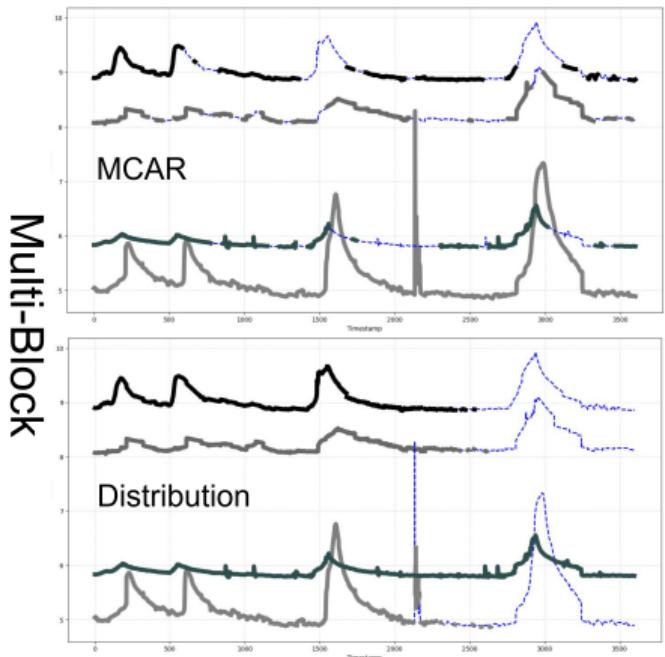
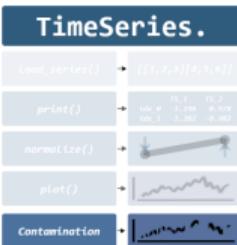
`verbose : bool, optional`

Whether to display the plot information. Default is True.



Missingness Patterns

- ▶ Simulate two groups of patterns: Multi-block and Mono-block.

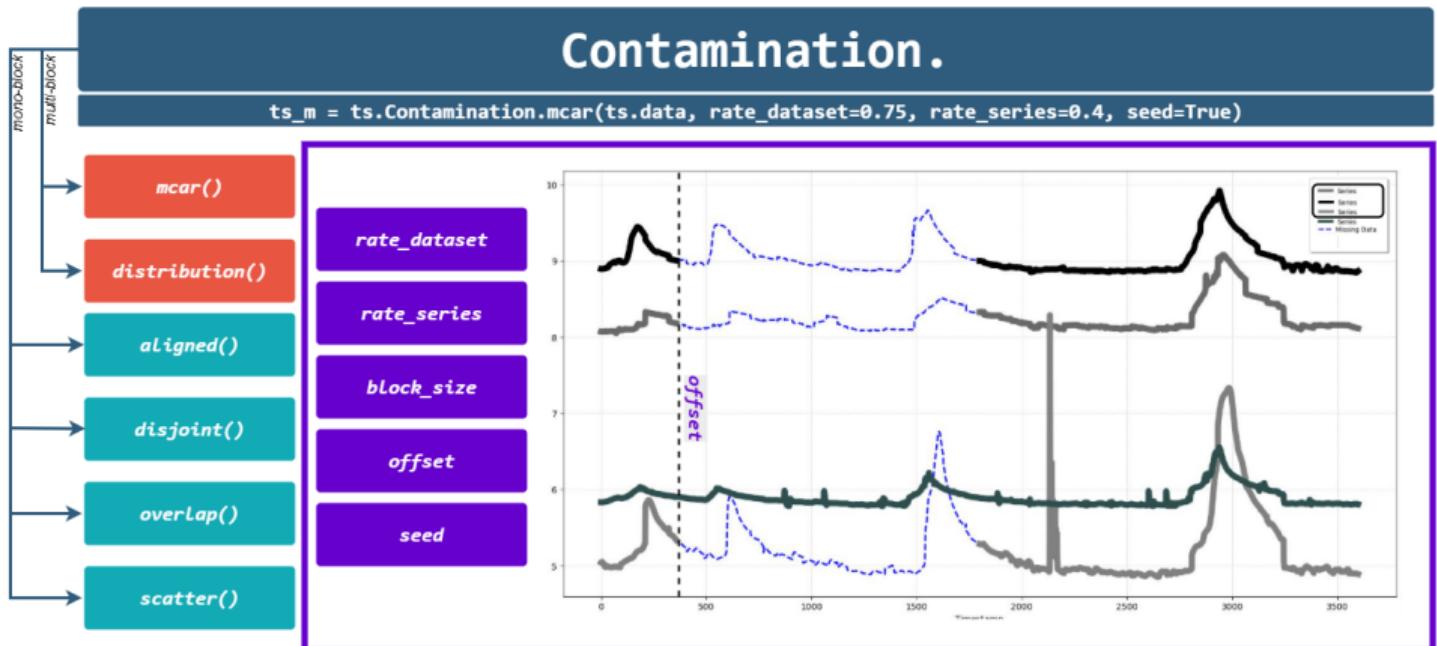


Pattern Customization

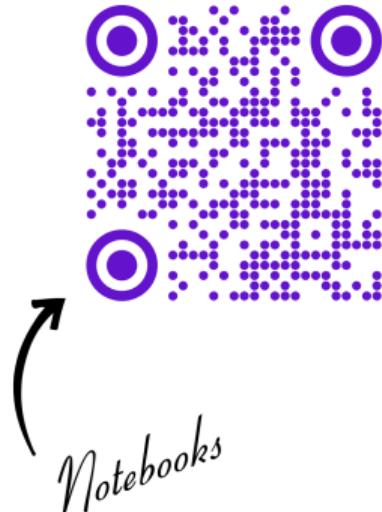
TimeSeries.

load_series()	$\rightarrow \{(1,2,3)(4,5,6)\}$
point()	$\rightarrow \{10, 11, 12, 13, 14, 15\}$
normalize()	\rightarrow
plot()	\rightarrow
Contamination	\rightarrow

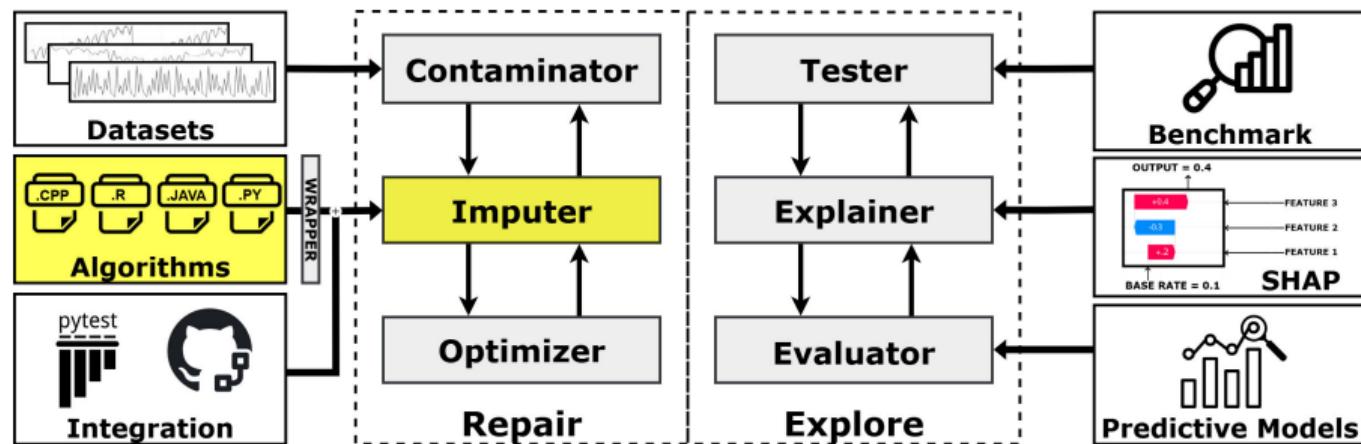
- ▶ The patterns can be used with default or customizable configurations.



Demo N°1 - Loading and Contamination



https://imputegap-tutorials.github.io/KDD-2025/html/slides_codes.html



Data Splitting Problem

- ▶ Using traditional ML splitting, NaN values might appear in the training set.
- ▶ The evaluation of Deep Learning techniques might yield data leakage.

	Training Set					Imputation
	s1	s2	s3	s4	s5	
s1	1.0	NaN	4.3	3.3	5.2	
s2	1.2	3.2	5.1	2.3	0.0	
s3	0.0	1.5	2.8	1.2	3.3	
s4	4.3	2.2	3.3	3.3	1.1	
s5	1.1	2.0	3.0	4.0	5.0	
s6	5.5	NaN	3.3	2.2	1.1	
s7	7.7	6.6	5.5	4.4	3.3	
s8	2.1	0.0	1.2	2.4	3.6	
s9	NaN	9.9	NaN	7.7	NaN	
s10	1.6	1.4	8.8	1.1	1.2	

Construction of Masks

s ₁	1.0	NaN	NaN	NaN	5.2
s ₂	1.2	3.2	5.1	2.3	0.0
s ₃	0.0	1.5	2.8	1.2	3.3
s ₄	4.3	2.2	3.3	3.3	1.1
s ₅	1.1	2.0	3.0	4.0	5.0
s ₆	5.5	NaN	3.3	2.2	1.1
s ₇	7.7	6.6	5.5	4.4	3.3
s ₈	2.1	0.0	1.2	2.4	3.6
s ₉	NaN	9.9	NaN	7.7	NaN
s ₁₀	1.6	1.4	8.8	1.1	1.2

- ▶ Control the overall proportion of missing values by artificially inserting missing entries.
- ▶ Create a training mask that excludes all missing values with complete time series.
- ▶ Create a testing mask for imputation, maintaining a consistent missing ratio across all DL models.

```
1 original_missing_ratio = get_missing_ratio(cont_data_matrix)
```

```
1 cont_data_matrix, new_mask = prepare_testing_set(cont_data_matrix, original_missing_ratio,
    block_selection=True, tr_ratio=0.8)
```

Data Leakage Prevention

s1	1.0	-99	-99	-99	5.2
s2	1.2	3.2	5.1	2.3	0.0
s3	0.0	1.5	2.8	1.2	3.3
s4	4.3	2.2	3.3	3.3	1.1
s5	1.1	2.0	3.0	4.0	5.0
s6	5.5	-99	3.3	2.2	1.1
s7	7.7	6.6	5.5	4.4	3.3
s8	2.1	0.0	1.2	2.4	3.6
s9	-99	9.9	-99	7.7	-99
s10	1.6	1.4	8.8	1.1	1.2

- ▶ Avoid data leakage by replacing all values that must be hidden from the model with large negative constants.
- ▶ The model will reveal potential data leakage during evaluation.

```
1 cont_data_matrix = prevent_leakage(cont_data_matrix, new_mask, nan_val=-99)
```

Final Masking

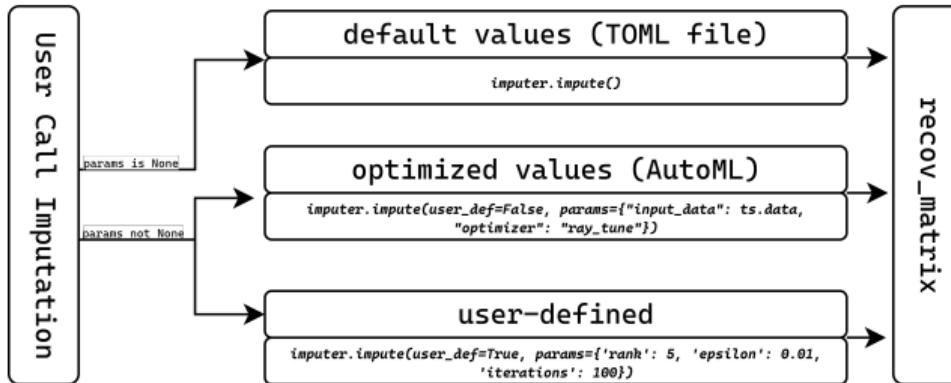
- ▶ Split the training set into internal training and testing subsets for the model.
- ▶ Artificially mask the internal testing set to evaluate model performance during training.

s1	1.0	-99	-99	-99	5.2	Imp
s2	1.2	3.2	5.1	2.3	0.0	Train
s3	0.0	1.5	2.8	1.2	3.3	
s4	4.3	2.2	3.3	3.3	1.1	
s5	1.1	2.0	3.0	4.0	5.0	
s6	5.5	-99	3.3	2.2	1.1	Imp
s7	7.7	6.6	5.5	4.4	3.3	Test
s8	2.1	0.0	1.2	2.4	3.6	
s9	-99	9.9	-99	7.7	-99	Imp
s10	1.6	1.4	8.8	1.1	1.2	Train

```
1 mask_test, mask_valid, nbr_nans = split_mask_bwt_test_valid(cont_data_matrix, test_rate=1, valid_rate  
=0, nan_val=-99, seed=42)  
2 mask_train = generate_random_mask(cont_data_matrix, mask_test, mask_valid, droprate=0.6, offset=0.1,  
seed=42)
```

Build Imputation

```
1 imputer = Imputation.MatrixCompletion.CDRec(ts_m)
2 imputer.impute()
```



```
1 def impute(self, user_def=True, params=None):
2     if params is not None:
3         rank, epsilon, iters = self._check_params(user_def, params)
4     else:
5         rank, epsilon, iters = utils.load_parameters(query="default", algorithm=self.algorithm)
6
7     self.recov_data = cdrec(incomp_data=self.incomp_data, rank=rank, iters=iters, epsilon=epsilon)
8
9     return self
```

Imputation Evaluation

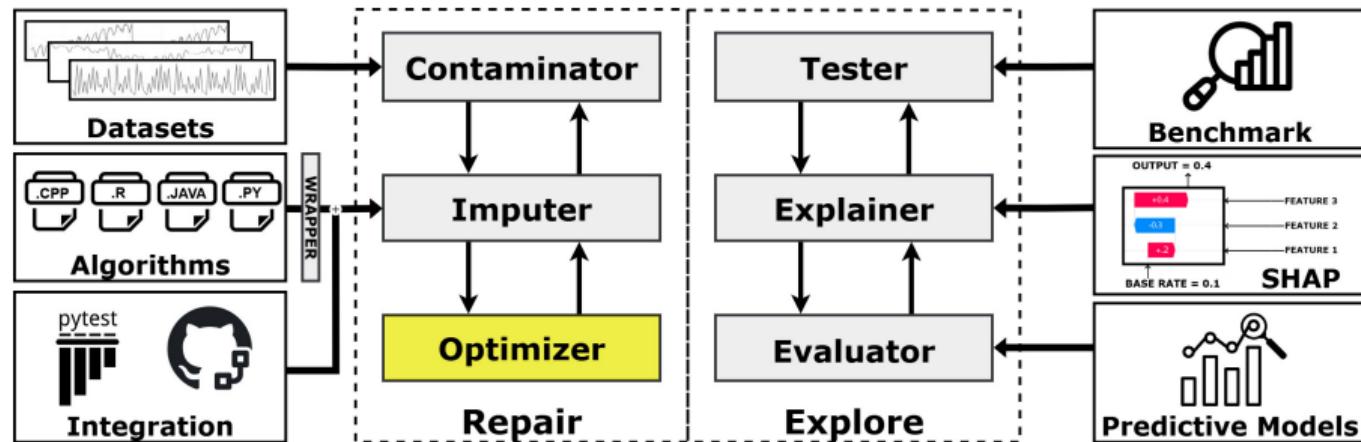
```
class imputegap.recovery.evaluation.Evaluation(input_data, recov_data, incomp_data,  
    algorithm='', verbose=True) .  
[source]
```

- ▶ Imputation scoring:

```
1 imputer.score(ts.data, imputer.recov_data)  
2 ts.print_results(imputer.metrics)
```

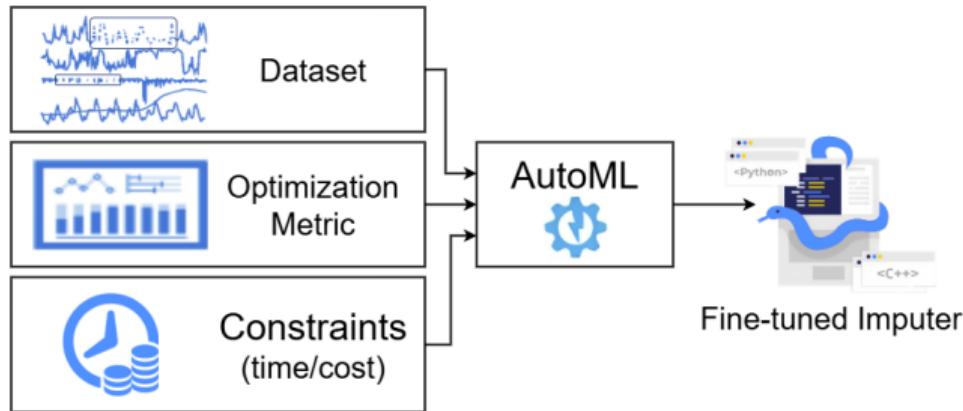
- ▶ Dictionary of metrics:

```
1 recov_vals = self.recov_data[np.isnan(self.incomp_data)]  
2 return {"RMSE": self.compute_rmse(), "MAE": self.compute_mae(), "MI": self.compute_mi(),  
         "CORRELATION": self.compute_correlation()}
```



Optimization Methods for Imputation

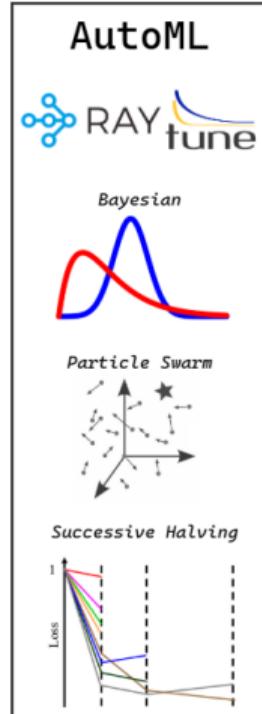
- ▶ Domain-specific imputation algorithms.
- ▶ Manually tuning and evaluating each parameter is time-consuming.



<https://medium.com/@haimantikamitra/azure-automated-ml-the-journey-from-zero-to-ai-hero-b37335d63af>

```
1 cdrec_imputer.impute(params={'rank': 5, 'epsilon': 0.01, 'iterations': 100}) # RMSE +0.1
2 cdrec_imputer.impute(params={'rank': 10, 'epsilon': 0.001, 'iterations': 50}) # RMSE +0.15
3 cdrec_imputer.impute(params={'rank': 7, 'epsilon': 0.1, 'iterations': 200}) # RMSE -0.1
```

Objective Function

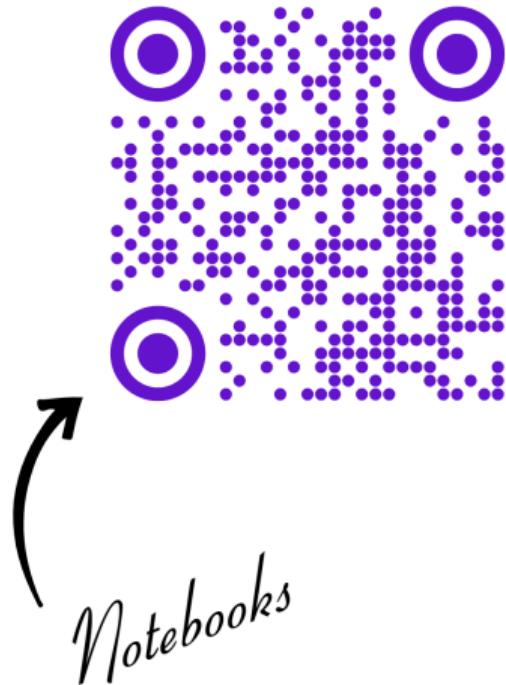


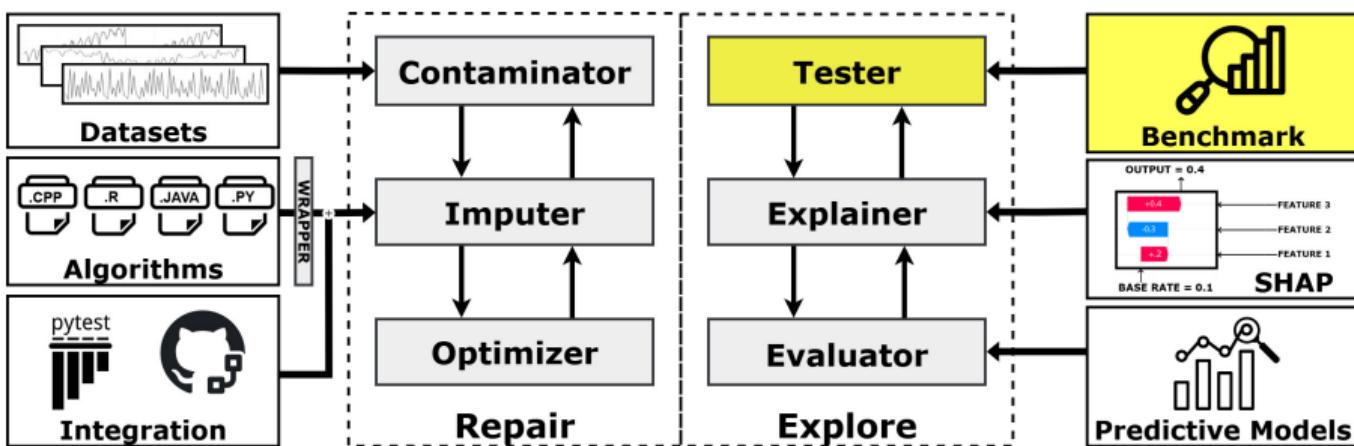
- ▶ The objective function is shared across all optimizers.
- ▶ Parameter ranges are defined for each algorithm.
- ▶ The wider the range, the more computationally expensive the search becomes.

```
1 RAYTUNE_PARAMS = {  
2     "cdrec": {  
3         "rank" : tune.grid_search([i for i in range(2,16,1)]),  
4         "eps" : tune.loguniform(1e-6, 1),  
5         "iters": tune.grid_search([i*50 for i in range(1,4)])  
6     }  
7 }
```

```
1 imputer.impute(user_def=False, params={"input_data": ts.data, "optimizer": "ray_tune"})
```

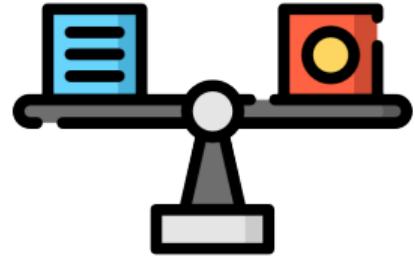
Demo N°2 - Imputation





Benchmarking

- ▶ “Fairness” is key in benchmarking:
 - ▶ Are the algorithms properly calibrated?
 - ▶ How different are the datasets and metrics?
 - ▶ Are the results generalizable?
 - ▶ No silver bullet imputation algorithm¹.
- ▶ Existing evaluation imputation frameworks:
 - ▶ lack of comprehensive end-to-end support
 - ▶ limited customization, transparency, and extensibility
 - ▶ benchmark failures due to heavy workloads



¹Khayati M., Lerner A., Tymchenko Z., and Cudré-Mauroux P.: “Mind the Gap: An Experimental Evaluation of Imputation of Missing Values Techniques in Time Series”, PVLDB’20 [Best Experiments and Analysis Award]

Workload Execution



18 datasets



7 missingness patterns



34 algorithms



5 optimizers



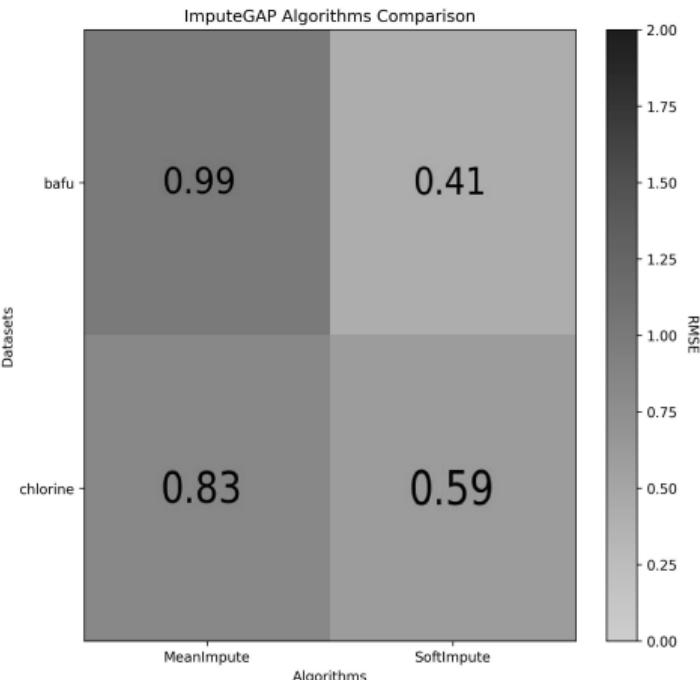
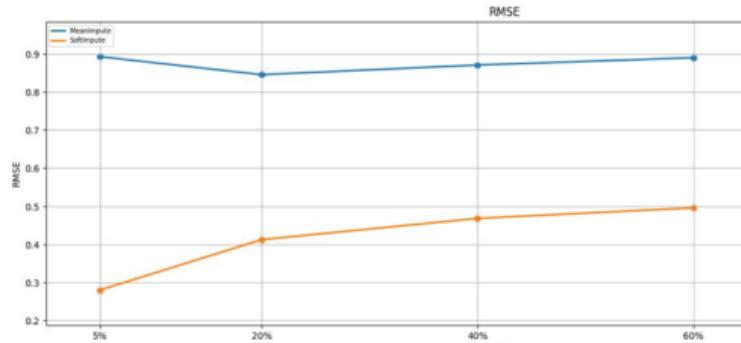
fully customizable
missing rate

- ▶ Over 100k possible combinations.
- ▶ On-demand materialization of results.
- ▶ GPU accelerators are used when available.
- ▶ The optimizer derives optimal parameters based on average runs.

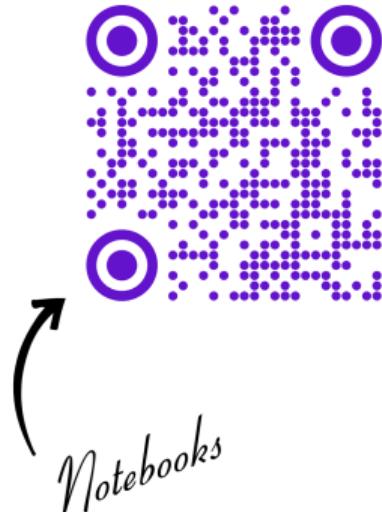
Benchmarking

- ▶ Fully-customizable evaluation (algorithms, datasets, metrics, patterns, rate, optimizer, etc.).
- ▶ Multi-resolution result visualization.

```
1 bench.eval(datasets=["bafu", "chlorine"],
2   patterns=["mcar", "aligned"],
3   algorithms=["MeanImpute", "SoftImpute"],
4   optimizers=["default_params"],
5   x_axis=[0.05,0.2,0.4,0.6],
6   metrics=["rmse", "runtime"])
```

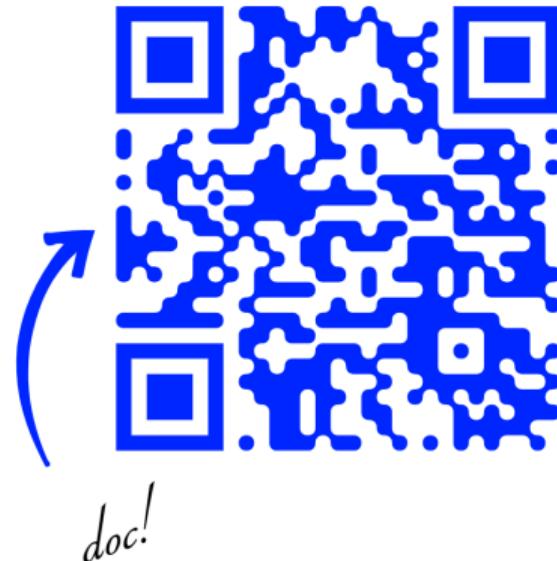
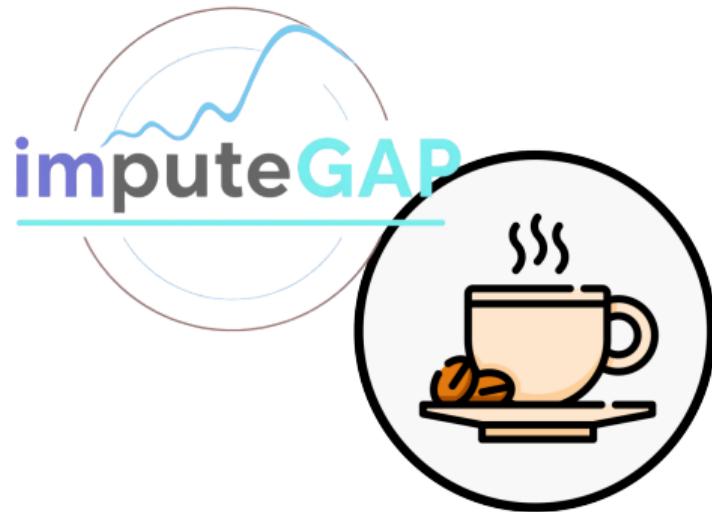


Demo N°3 - Benchmark



https://imputegap-tutorials.github.io/KDD-2025/html/slides_codes.html

Coffee Break



<https://imputegap.readthedocs.io/>

Current Section

Introduction and Overview

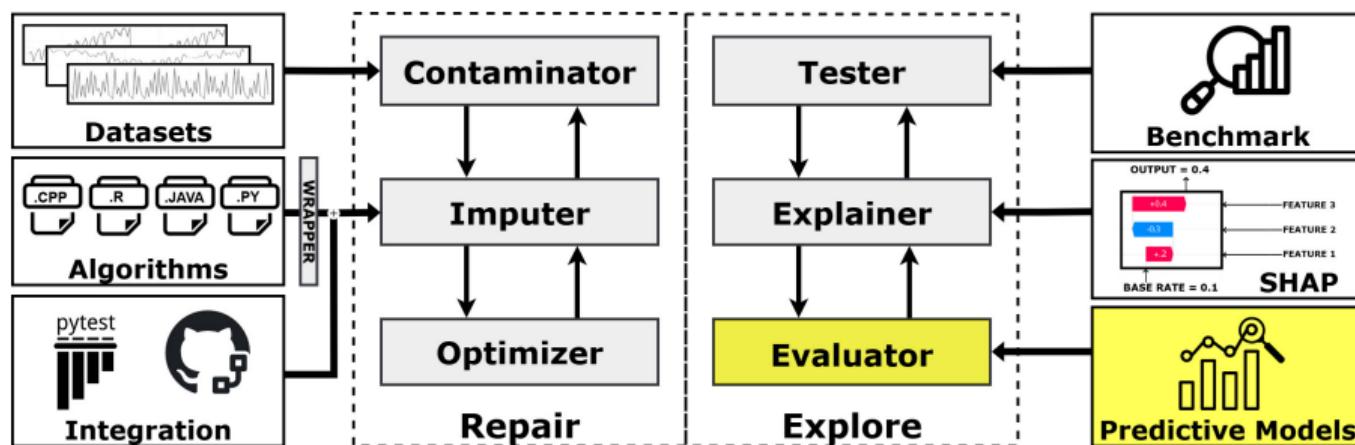
Introduction to ImputeGAP

Imputation Pipeline Synthesis

Downstream Imputation Analysis

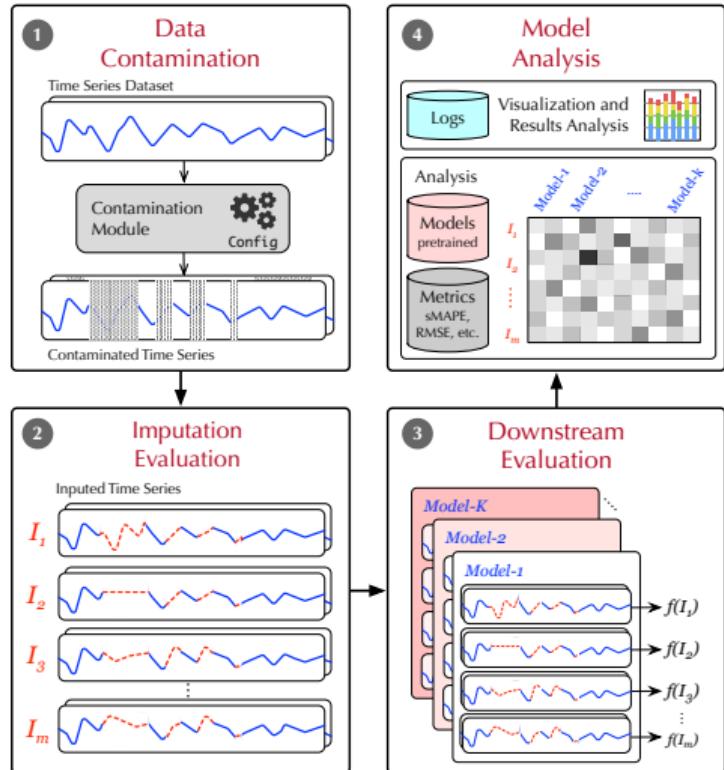
Explainable Imputation

Library Extension



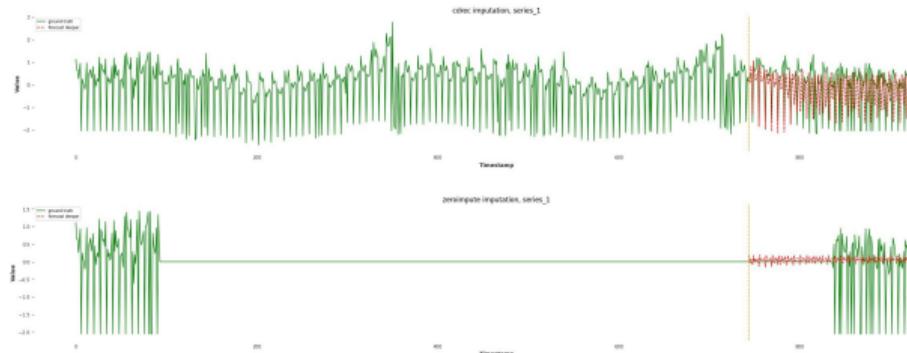
Imputation Impact on Downstream

- ▶ Are downstream and upstream gains proportional?
- ▶ Do upstream and downstream metrics align?
- ▶ Are downstream models comparable when fed with imputed data?
- ▶ Do downstream tasks behave differently w/t imputation?



Downstream Implementation

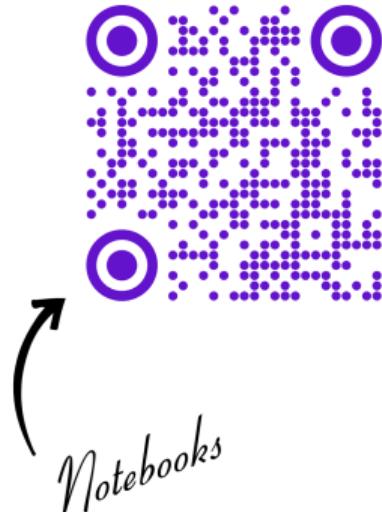
- ▶ Current version implements forecasting task (classification is under development)
- ▶ 16 parameterizable forecasters from sktime and darts APIs.



```
1 ImputeGAP downstream models for forecasting : ['arima', 'bats', 'croston', 'deepar', 'ets', 'exp-  
    smoothing', 'hw-add', 'lightgbm', 'lstm', 'naive', 'nbeats', 'prophet', 'sf-arima', 'theta', '  
    transformer', 'unobs', 'xgboost']
```

```
1 def downstream_analysis(self):  
2     task = self.downstream.get("task", "forecast")  
3     model = self.downstream.get("model", "lightgbm")  
4     baseline = self.downstream.get("baseline", "zero-impute")
```

Demo N°4 - Downstream Analysis



https://imputegap-tutorials.github.io/KDD-2025/html/slides_codes.html

Current Section

Introduction and Overview

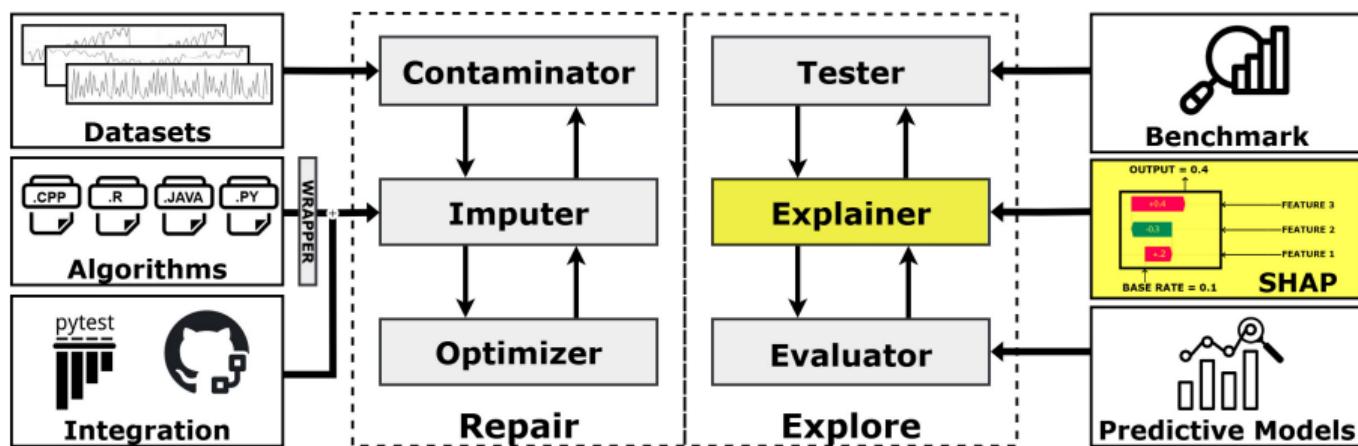
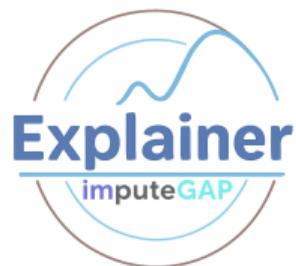
Introduction to ImputeGAP

Imputation Pipeline Synthesis

Downstream Imputation Analysis

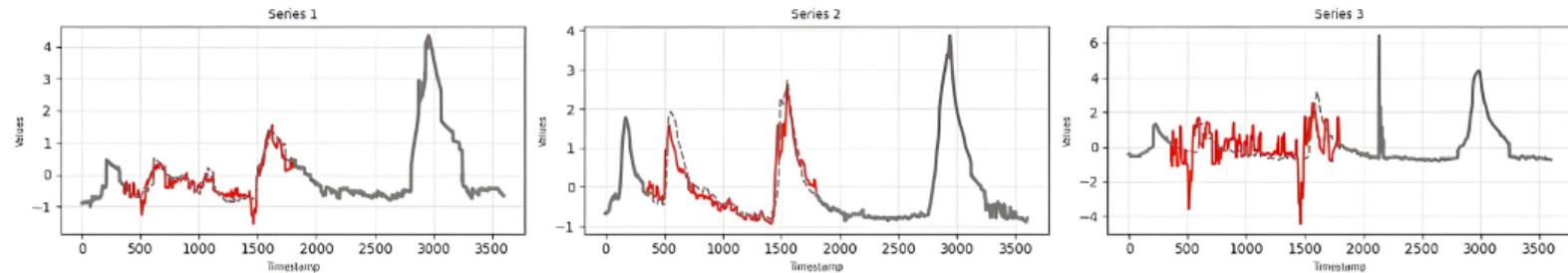
Explainable Imputation

Library Extension



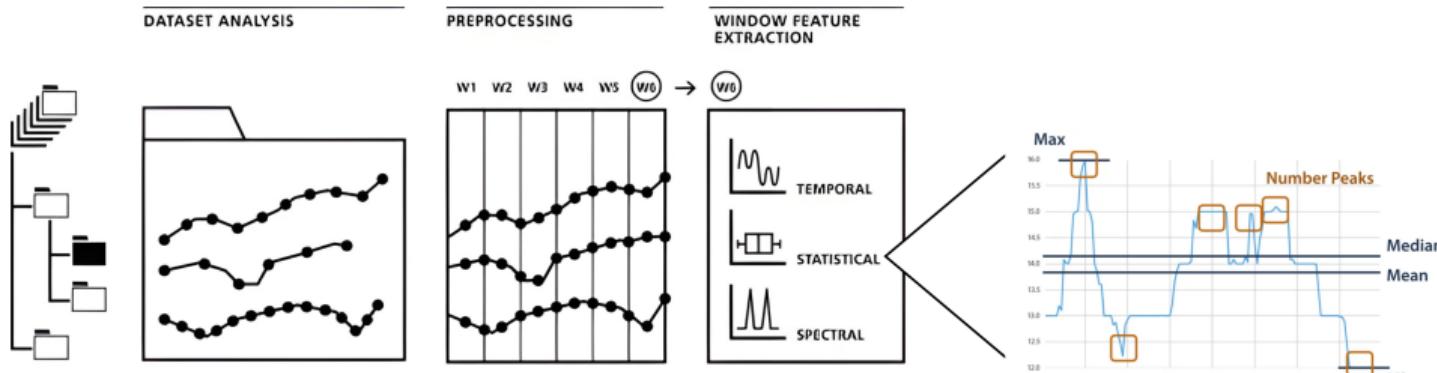
Imputation Fine-grained Analysis

- ▶ The evaluation metrics are useful, but can we interpret the imputation results?
- ▶ Is the performance of imputation algorithms consistent?
- ▶ Which factors contribute to it?



Time Series Characterization

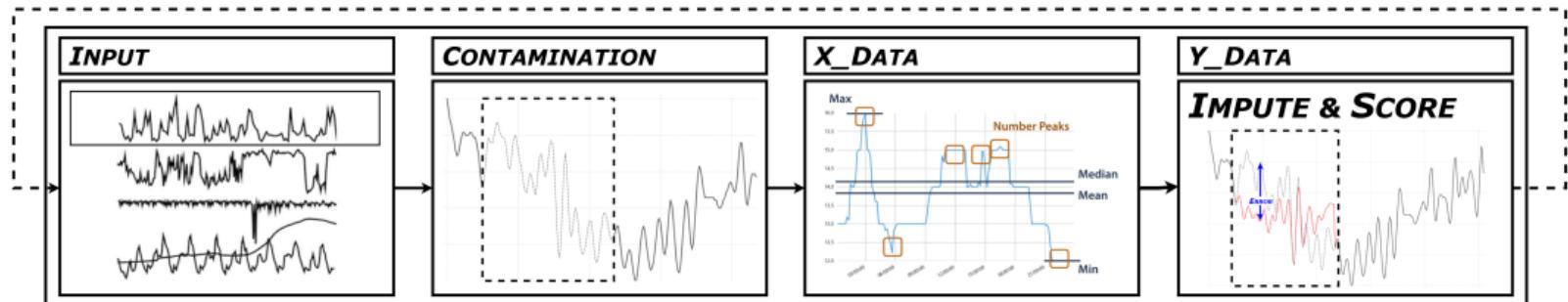
- ▶ Interpret imputation results and identify the factors influencing their quality.
- ▶ Using feature extractors, we assess imputation quality by analyzing feature-level characteristics of the contaminated data.



<https://medium.com/@thedatabeast/time-series-part-3-feature-engineering-bc283b9bf07>
<https://www.sciencedirect.com/science/article/pii/S2352711020300017>

Explainer Dataset

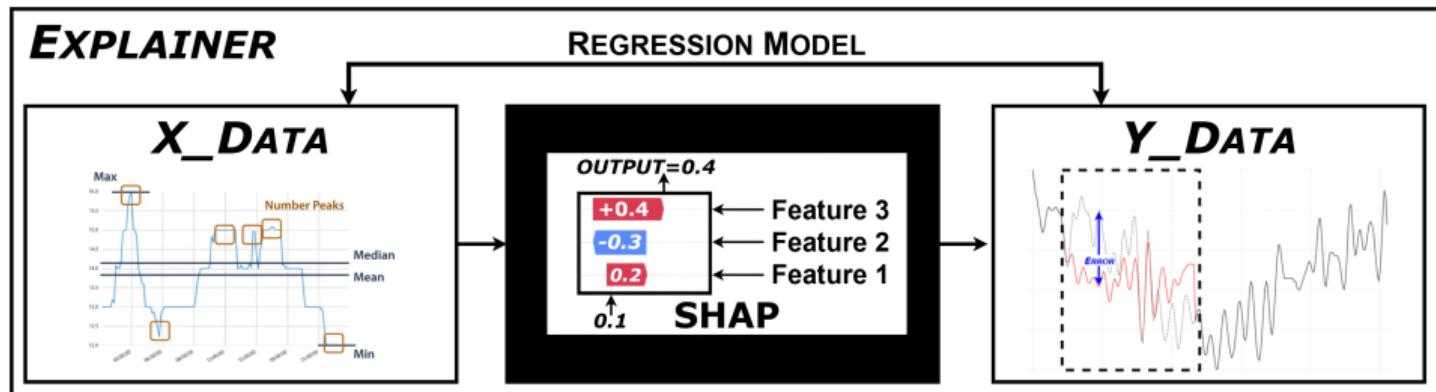
- ▶ Iterative process: extract features for each time series contamination.



```
1 for si in range(0, limit): # 1) series iterator
2     tmp = TimeSeries.import_matrix(data)
3     ts_m = utils.config_contamination(tmp, si, pattern="aligned", series_rate=0.6) # 2) contaminate si
4
5     extracted_features = self.extractor(ts_m, categories, features) # 3) extract features
6
7     imputer.impute(user_def=True, params=params) # 4) impute
8     imputer.score(input_data) # 4) score
9
10    x_data.append(extracted_features) # store data
11    y_data.append(imputer.metrics) # store labels
```

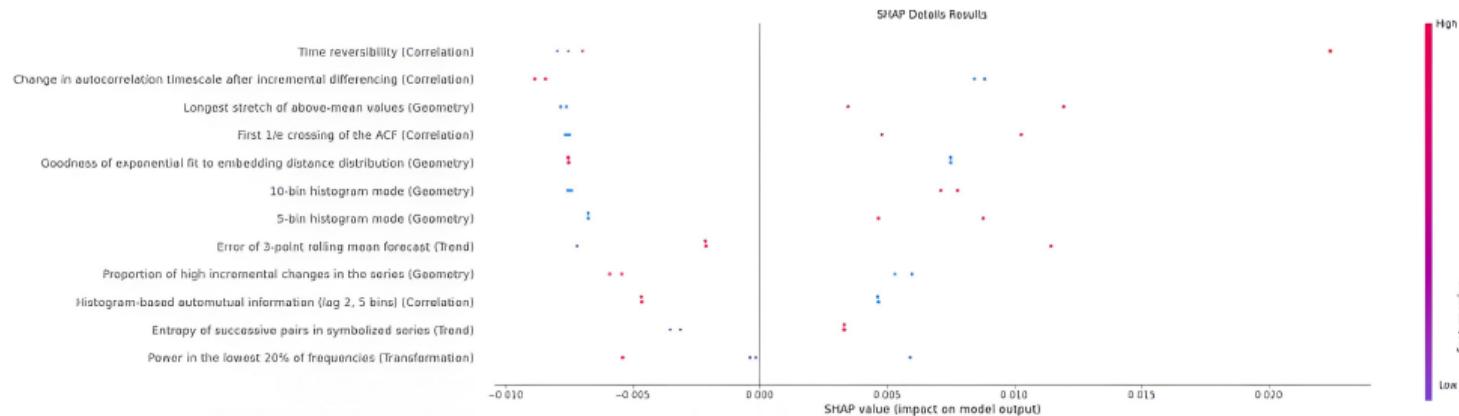
Regression Model

- ▶ We use SHAP to learn the relationship between feature values and the imputation score.
- ▶ We compute a weight that reflects the contribution to the input.



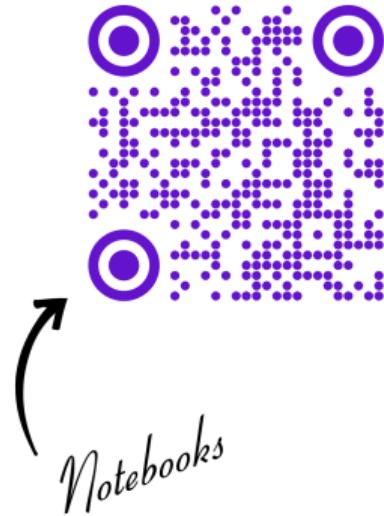
```
1 model = RandomForestRegressor()  
2 model.fit(x_train, y_train)  
3 exp = shap.KernelExplainer(model.predict, x_test)  
4 shval = exp.shap_values(x_test)
```

Feature Contribution



```
1 Feat:5 CDRec/Bafu score=13.21 Correlation Time reversibility
2 Feat:12 CDRec/Bafu score=10.17 Correlation Change of autocorrelation timescale after incr. diff
3 Feat:7 CDRec/Bafu score=9.07 Geometry Longest stretch of above-mean values
```

Demo N°5 - Explainer



https://imputegap-tutorials.github.io/KDD-2025/html/slides_codes.html

Current Section

Introduction and Overview

Introduction to ImputeGAP

Imputation Pipeline Synthesis

Downstream Imputation Analysis

Explainable Imputation

Library Extension

Integration

- ▶ ImputeGAP is fully extensible and customizable
- ▶ We provide a C++ wrapper that can be easily extended to other languages such as JAVA, MATLAB, or R.



add your dataset



add your missingness pattern



add your algorithm



add your optimizer

Integration Python

- ▶ Add your custom algorithm rationale.

your_llm.py

```
1 def your_llm(ts_m, par_1, par_2, tr_ratio, logs, verbose):
2     start_time = time.time()
3     recov_data = your_algo(ts_m, par_1, par_2, tr_ratio, logs, verbose)
4     end_time = time.time()
5     return recov_data
```

- ▶ Assign it to the appropriate algorithm family by creating a dedicated class.

imputation.py

```
1 class Imputation:
2     class LLMs:
3         class YourLLM(BaseImputer):
4             algorithm = "your_llm"
5             def impute(self, user_def=True, params=None, tr_ratio=0.9):
6                 from imputegap.algorithms.your_llm import your_llm
7
8                 self.recov_data = your_llm(ts_m=self.incomp_data, par_1, par_2, tr_ratio, self.logs,
9                                             self.verbose)
10
11             return self
```

Integration Toolbox

- ▶ Define default values the hyperparameters.

```
utils.py
```

```
1 config = toml.load(filepath)
2 if algorithm == "your_llm":
3     par_1 = int(config[algorithm]['par_1'])
4     par_2 = str(config[algorithm]['par_2'])
5     return (par_1, par_2)
```

```
default_values.toml
```

```
1 [your_algo]
2 par_1 = 42
3 par_2 = "val"
```

- ▶ Register the algorithm in the toolkit interface for easier access.

```
utils.py
```

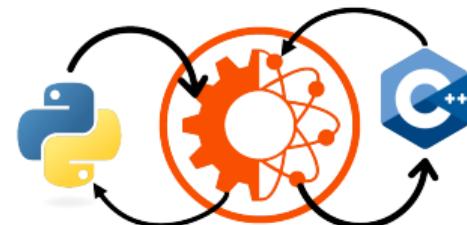
```
1 alg = algorithm.lower().replace('_', '').replace('-', '')
2
3 if alg == "your_algo":
4     imputer = Imputation.YourClass.YourAlgo(incomp_data)
5
6 return imputer
```

C++ Wrapper

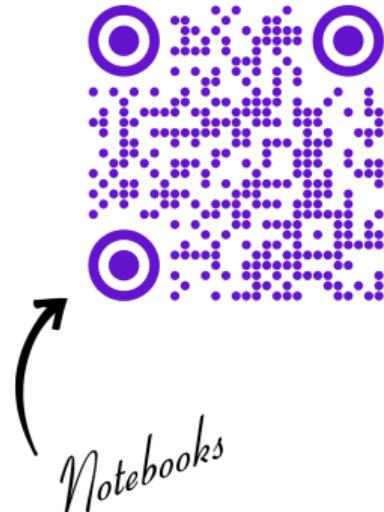
- ▶ The wrapper converts input and output variables between Python and C++.
- ▶ C++ code is compiled into shared objects (.so files)

```
1 shared_lib = utils.load_share_lib("lib_cdrec.so")
2 __ctype_matrix = utils.__marshal_as_native_column(__py_matrix);
3 shared_lib.cdrec_imputation(__ctype_matrix);
4
5 py_matrix = utils.__marshal_as_numpy_column(__ctype_matrix);
```

```
1 void
2 cdrec_imputation(double *matrixNative)
3 {
4     arma::mat input = marshal_as_arma(matrixNative, dimN, dimM);
5     Algorithms::CDMissingValueRecovery rmv(input);
6 }
```



Demo N°6 - Integration



https://imputegap-tutorials.github.io/KDD-2025/html/slides_codes.html

A Hands-on Tutorial on Time Series Imputation with ImputeGAP

Thank you!

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mourad.khayati@unifr.ch

Questions?



<https://imputegap.readthedocs.io>

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arXiv, 2025
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- [4] Mourad Khayati, Alberto Lerner, Zakhar Tymchenko, and Philippe Cudré-Mauroux
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- [6] Abdelouahab Khelifati, Mourad Khayati, Anton Dignös, Djellel Difallah and Philippe Cudré-Mauroux,
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Proc. of VLDB Endowment (PVLDB 2023), Vancouver, Canada.
- [7] Mourad Khayati, Ines Arous, Zakhar Tymchenko, and Philippe Cudré-Mauroux,
ORBITS: Online Recovery of Missing Values in Multiple Time Series.
Proc. of VLDB Endowment (PVLDB 2021), Copenhagen, Denmark.