# 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

August 4, 2025

UNIVERSITÉ DE FRIBOURG
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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)
- Section 4: Downstream Analysis (20 min)
- Break (15 min)
- Section 5: Imputation Explainability (20 min)
- Section 6: Library Extension (20 min)
- Q&A (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

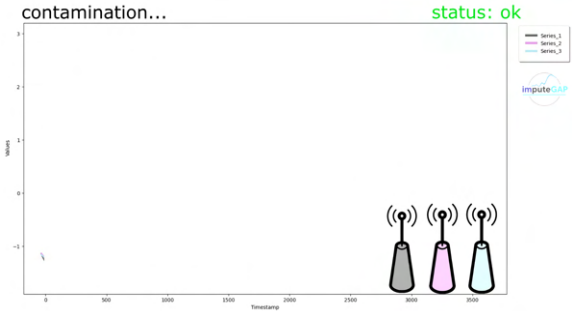
Library Extension

# Data with Missing Values

- Technical glitches or downtime in data collection systems yield incomplete data.
- Combining data from multiple sources can introduce 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
  - External interference
  - Power outages



# 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).

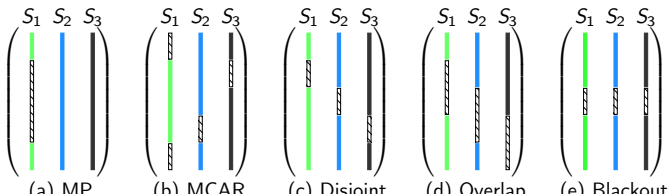
# Why Imputation?

- 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.

[1] khelifati 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

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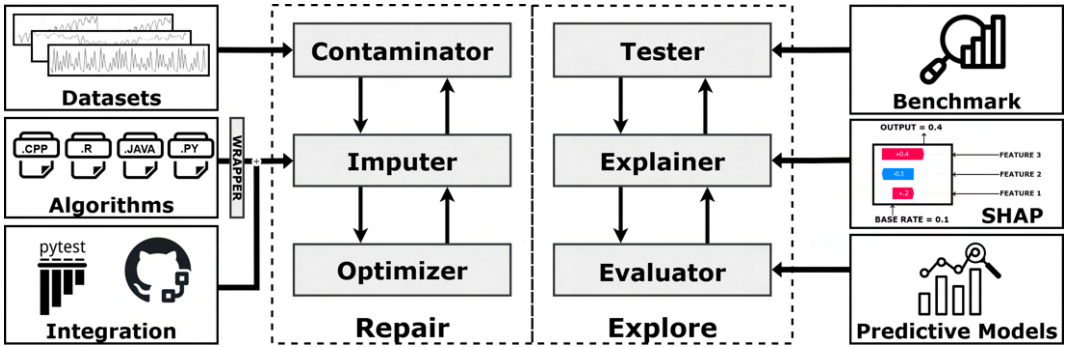
# Python Library

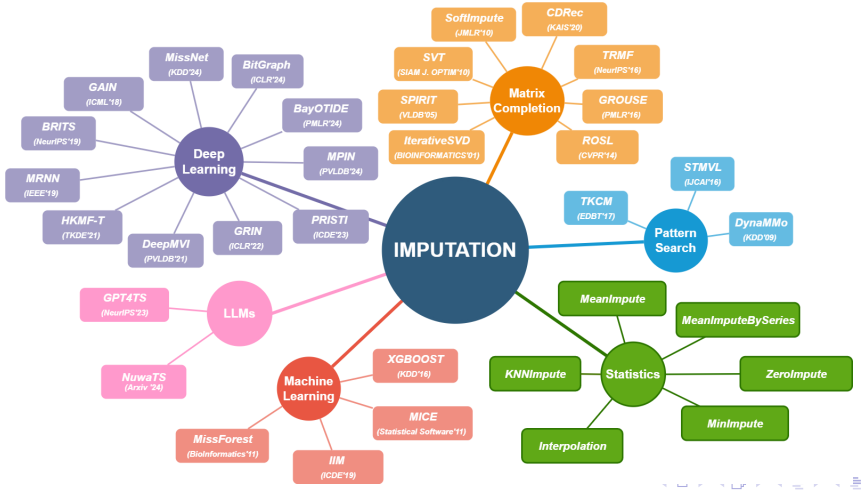


# Comparison with Existing Libraries

- 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.

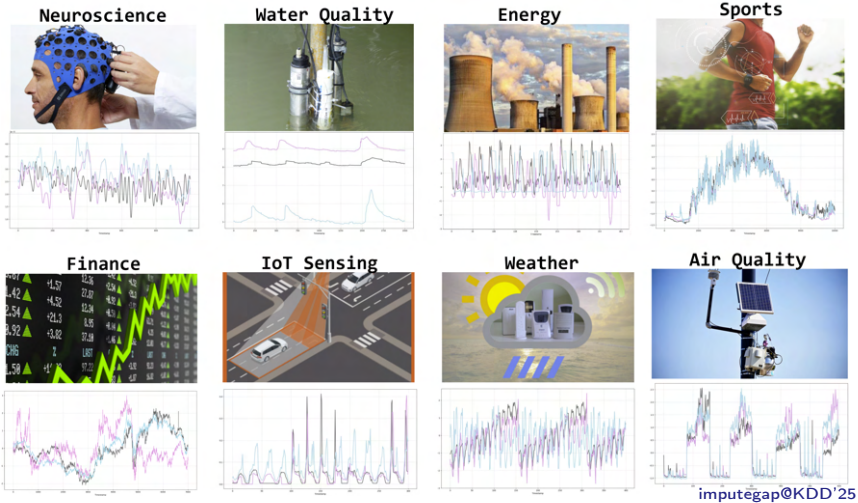
# Available Algorithms

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



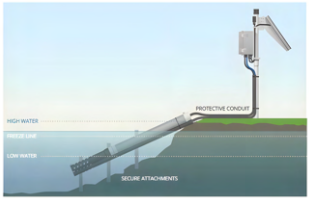
# Available Datasets

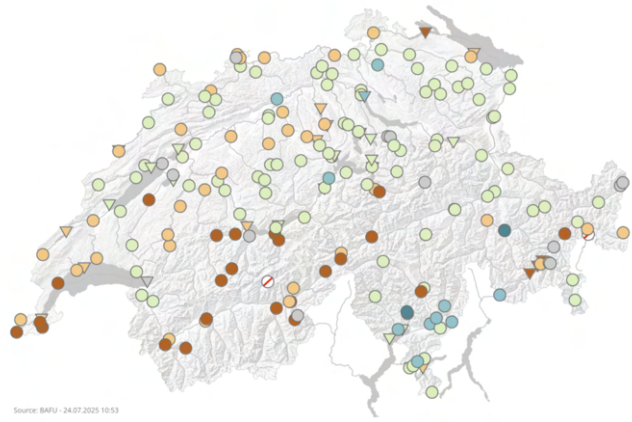
- 17 ready-to-deploy time series datasets.
- 8 real-world applications.



# Water Quality

- BAFU[1] deploys sensors to monitor the water quality in Swiss rivers.
- Multivariate time series: discharge, conductivity, oxygen level, temperature, pH values, etc.



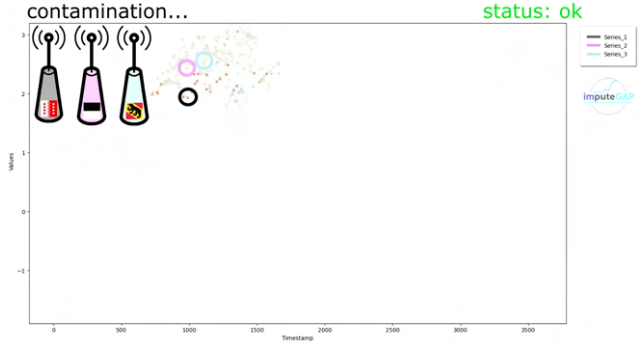



[1] Federal Office for the Environment in Switzerland

# 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

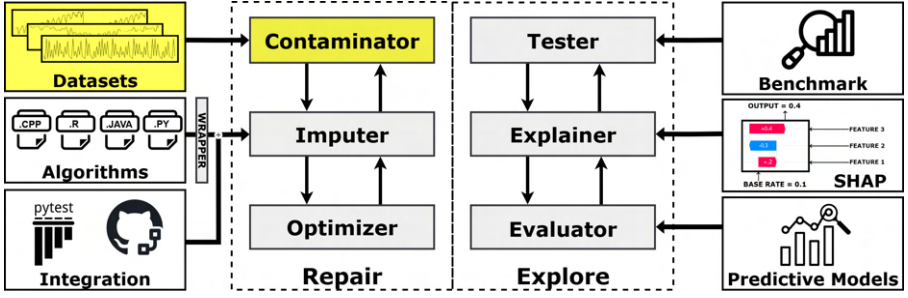
Imputation Pipeline Synthesis

Downstream Imputation Analysis

Explainable Imputation

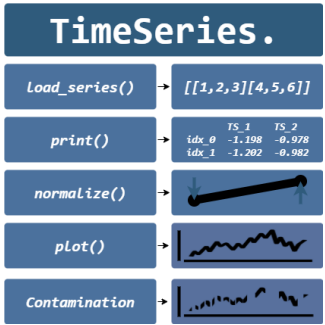
Library Extension

Manager
imputeGAP



# One Object to Rule Them All

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

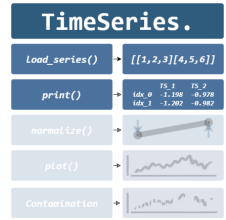



**Note**

- 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]
```

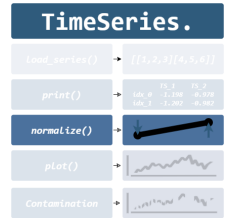
```
1  # load from built-in datasets
2  ts.load_series(utils.search_path("eeg-alcohol"))
3
4  # load your dataset
5  ts.load_series("../imputegap/datasets/kdd.txt"))
6
7  # load as a matrix
8  ts.import_matrix([[1,2,3],[4,5,6]])
9
10 # print your ts
11 ts.print(nbr_series=3, nbr_val=20)
```

**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

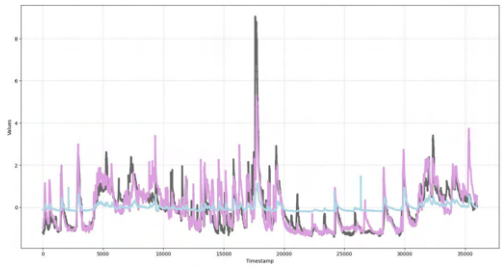



- Normalize the time series data into a different scale.

```
normalize(normalizer='z_score', verbose=True) ¶                    [source]
```

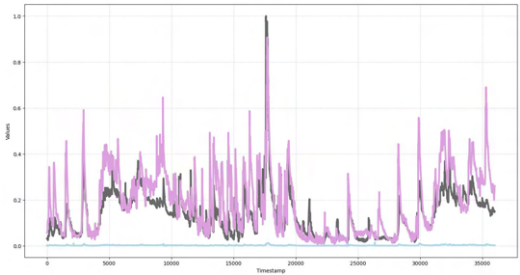
- Z-Score

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

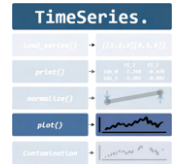



- Min-Max

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



# Plotting




- 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).

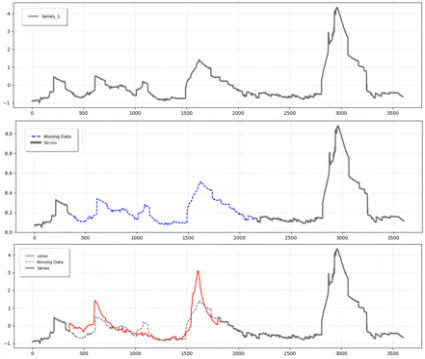
**algorithm : str, optional**
Name of the algorithm used for imputation.

**save_path : str, optional**
Path to save the plot locally.

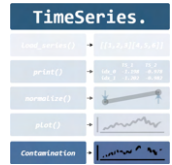
**cont_rate : str, optional**
Percentage of contamination in each series to plot.

**display : bool, optional**
Whether to display the plot. Default is True.

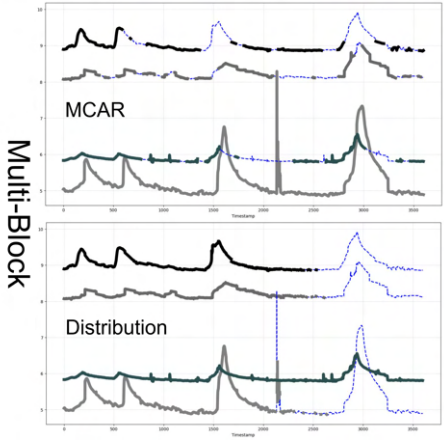
**verbose : bool, optional**
Whether to display the plot information. Default is True.

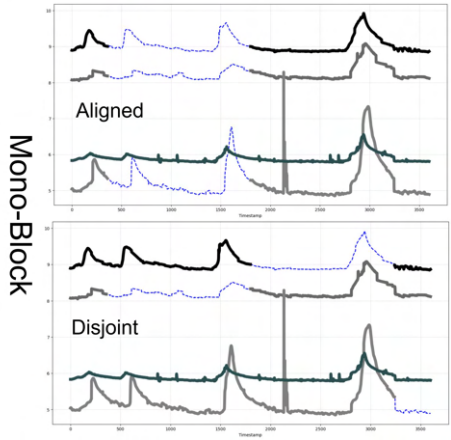


# Missingness Patterns

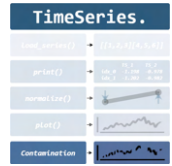



- Simulate two groups of patterns: Multi-block and Mono-block.

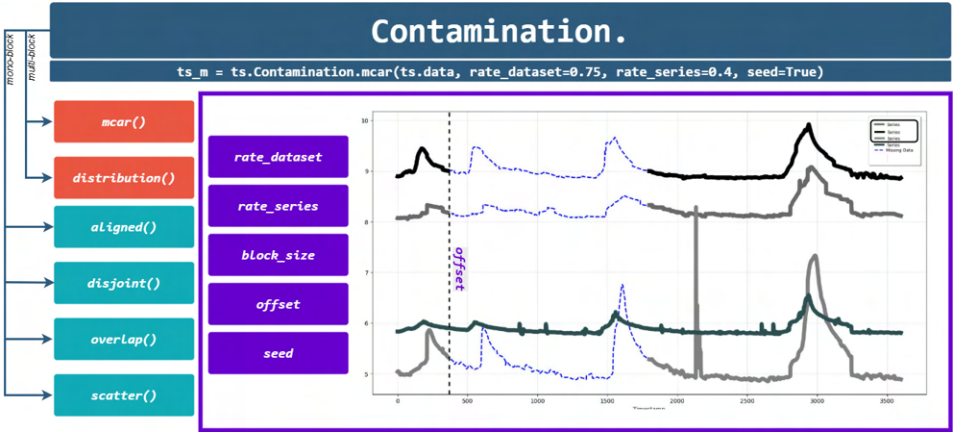


# Pattern Customization

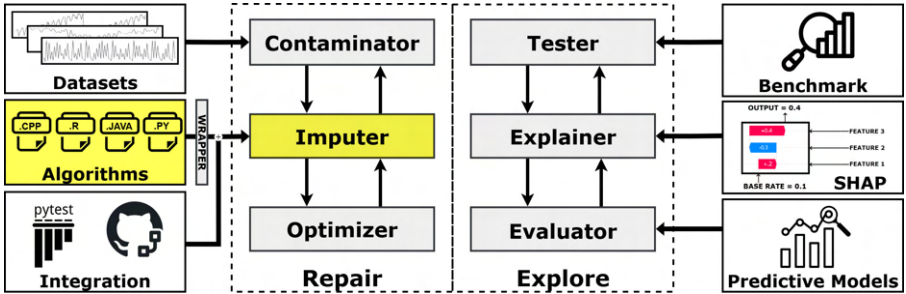



- The patterns can be used with default or customizable configurations.



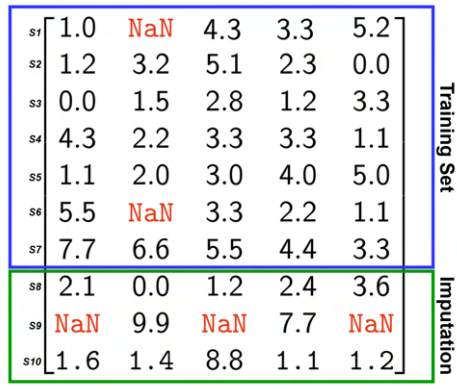
# Demo N°1 - Loading and Contamination

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


Datasets
.CPP
.R
.JAVA
.PY
Algorithms
WRAPPER
pytest
Integration
Contaminator
Imputer
Optimizer
Repair
Tester
Explainer
Evaluator
Explore
Benchmark
OUTPUT = 0.4
FEATURE 3
FEATURE 2
FEATURE 1
BASE RATE = 0.1
SHAP
Predictive Models

# 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.



# 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.

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

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

# Data Leakage Prevention

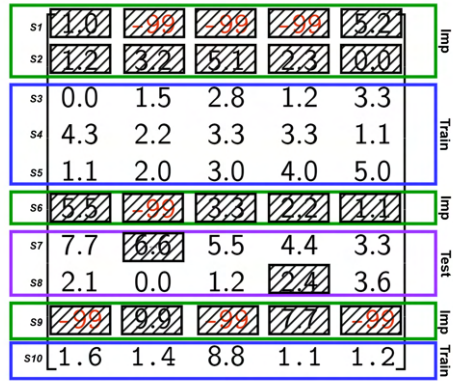
| | | | | | |
|---|---|---|---|---|---|
| s1 | 1.0 | -99 | -99 | -99 | 5.2 |
| s2 | 1.2 | 3.2 | 5.1 | 2.3 | 0.0 |
| s3 | 0.0 | 1.5 | 2.8 | 1.2 | 3.3 |
| s4 | 4.3 | 2.2 | 3.3 | 3.3 | 1.1 |
| s5 | 1.1 | 2.0 | 3.0 | 4.0 | 5.0 |
| s6 | 5.5 | -99 | 3.3 | 2.2 | 1.1 |
| s7 | 7.7 | 6.6 | 5.5 | 4.4 | 3.3 |
| 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

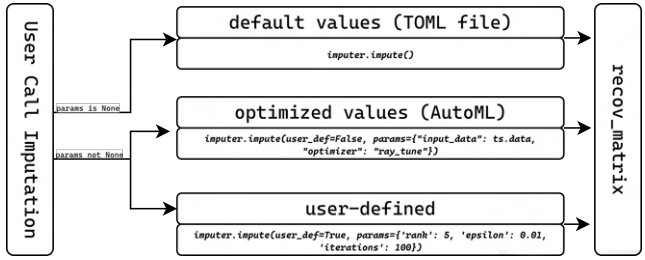
- Split the training set into internal training and testing subsets for the model.
- Artificially mask the internal testing set to evaluate model performance during training.




```
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)
mask_train = generate_random_mask(cont_data_matrix, mask_test, mask_valid, droprate=0.6, offset=0.1,
    seed=42)
```

# Build Imputation

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




```
def impute(self, user_def=True, params=None):
    if params is not None:
        rank, epsilon, iters = self._check_params(user_def, params)
    else:
        rank, epsilon, iters = utils.load_parameters(query="default", algorithm=self.algorithm)

    self.recov_data = cdrec(incomp_data=self.incomp_data, rank=rank, iters=iters, epsilon=epsilon)

    return self
```

# Imputation Evaluation

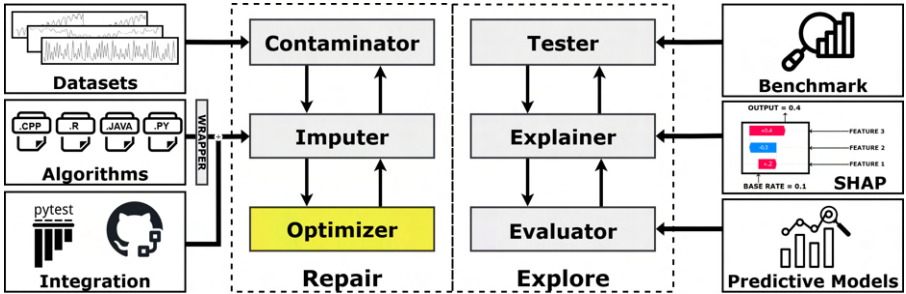
```
class imputegap.recovery.evaluation.Evaluation(input_data, recov_data, incomp_data,
    algorithm='', verbose=True) ¶                                              [source]
```

- Imputation scoring:

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

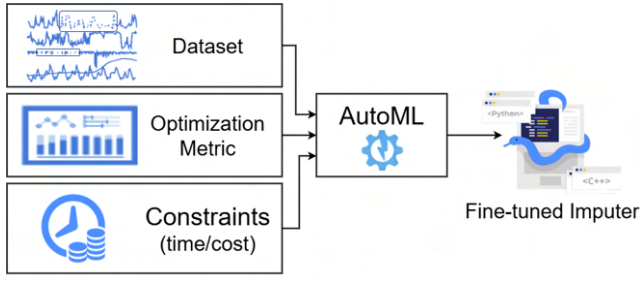
- Dictionary of metrics:

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


Datasets
.CPP
.R
.JAVA
.PY
Algorithms
WRAPPER
pytest
Integration
Contaminator
Imputer
Optimizer
Repair
Tester
Explainer
Evaluator
Explore
Benchmark
OUTPUT = 0.4
FEATURE 3
FEATURE 2
FEATURE 1
BASE RATE = 0.1
SHAP
Predictive Models

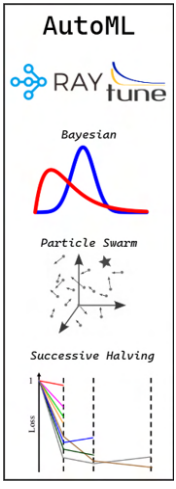
# Optimization Methods for Imputation

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




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

# Objective Function



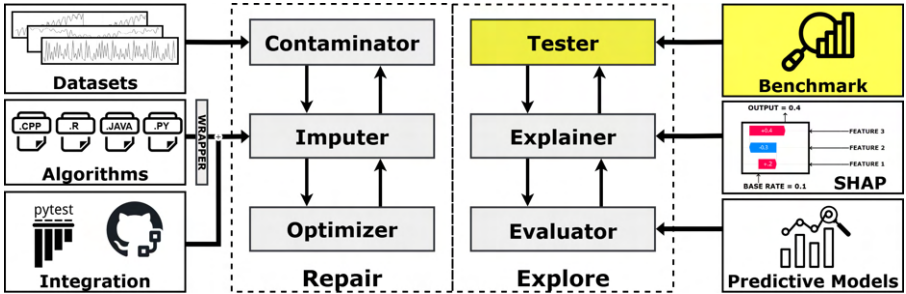

- The objective function is shared across all optimizers.
- Parameter ranges are defined for each algorithm.
- The wider the range, the more computationally expensive the search becomes.

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

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

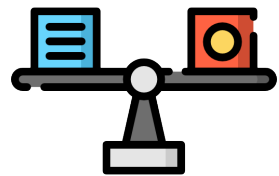
# Demo N°2 - Imputation

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


Datasets
.CPP
.R
.JAVA
.PY
Algorithms
WRAPPER
pytest
Integration
Contaminator
Imputer
Optimizer
Repair
Tester
Explainer
Evaluator
Explore
Benchmark
OUTPUT = 0.4
+0.4
-0.3
+0.2
FEATURE 3
FEATURE 2
FEATURE 1
BASE RATE = 0.1
SHAP
Predictive Models

# 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 algorithm[1].
- Existing evaluation imputation frameworks:
  - lack of comprehensive end-to-end support
  - limited customization, transparency, and extensibility
  - benchmark failures due to heavy workloads



[1] Khayati 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

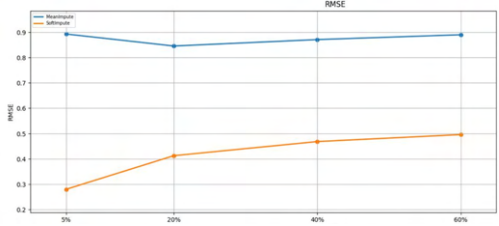
fully customizable missing rate

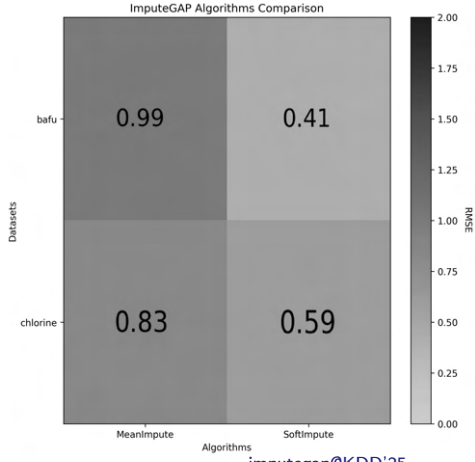
- Over 100k possible combinations.
- On-demand materialization of results.
- GPU accelerators are used when available.
- The optimizer derives optimal parameters based on average runs.

# Benchmarking

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

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

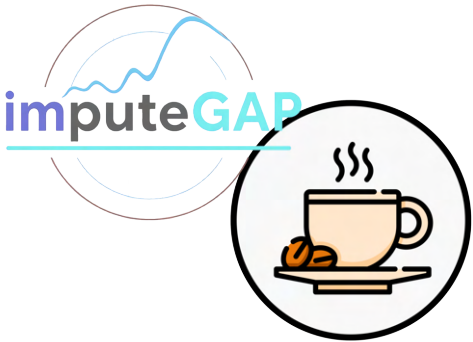


# Demo N°3 - Benchmark

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

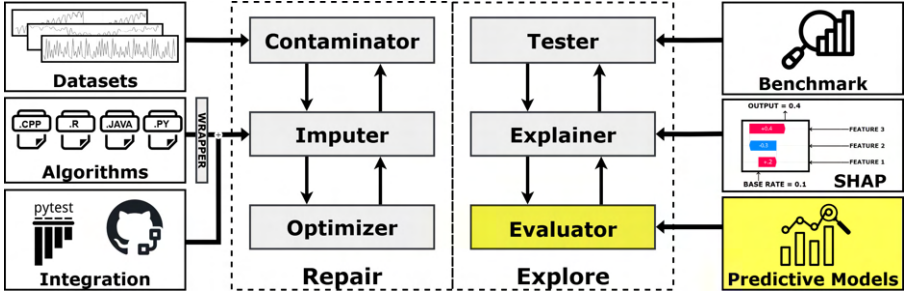
Imputation Pipeline Synthesis

Downstream Imputation Analysis

Explainable Imputation

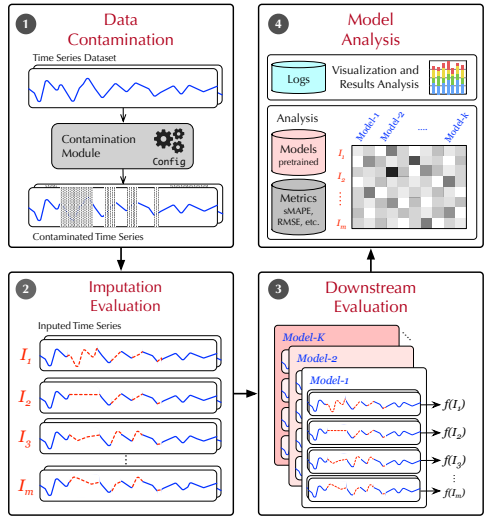
Library Extension

Downstream imputeGAP



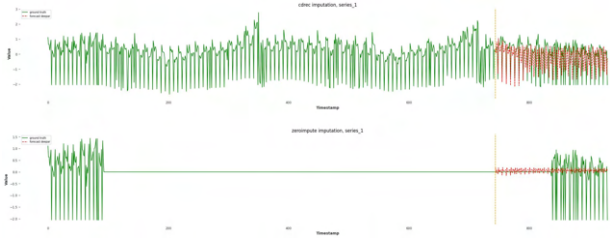
# Imputation Impact on Downstream

- 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 in under development)
- 16 parameterizable forecasters from sktime and darts APIs.




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

```
def downstream_analysis(self):
    task = self.downstream.get("task", "forecast")
    model = self.downstream.get("model", "lightgbm")
    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

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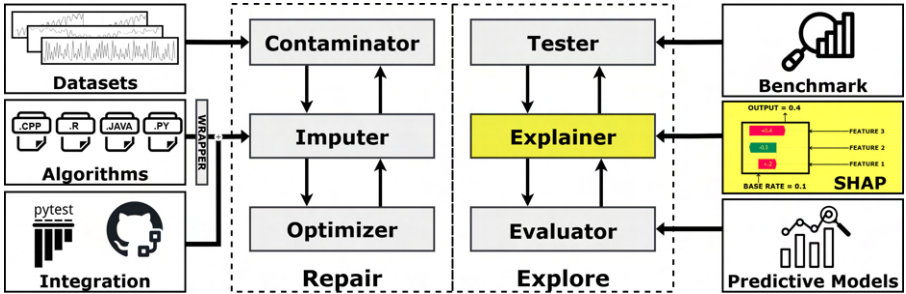
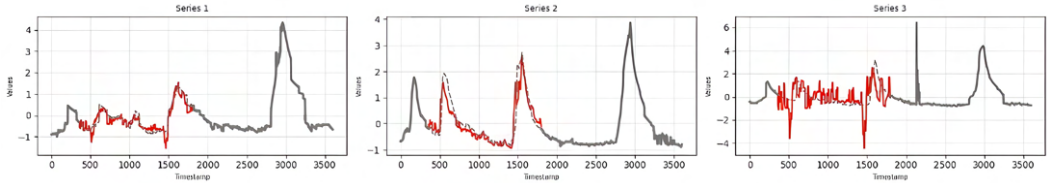
Explainer
imputeGAP



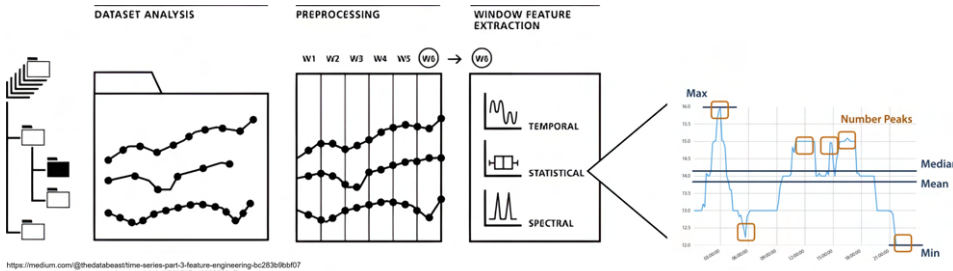
# Imputation Fine-grained Analysis

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



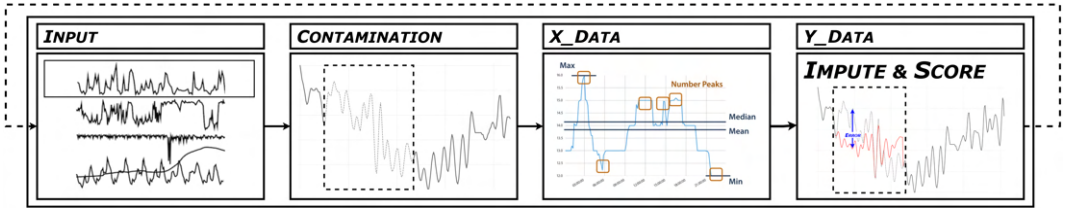
# Time Series Characterization

- 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.



# Explainer Dataset

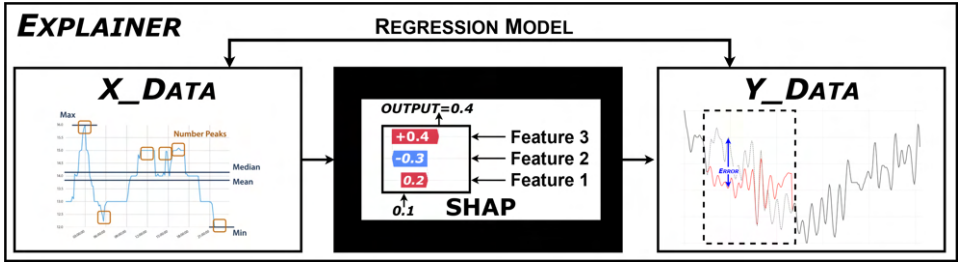
- Iterative process: extract features for each time series contamination.




```
for si in range(0, limit):  # 1) series iterator
    tmp = TimeSeries.import_matrix(data)
    ts_m = utils.config_contamination(tmp, si, pattern="aligned", series_rate=0.6) # 2) contaminate si

    extracted_features = self.extractor(ts_m, categories, features) # 3) extract features

    imputer.impute(user_def=True, params=params)  # 4) impute
    imputer.score(input_data)  # 4) score

    x_data.append(extracted_features)  # store data
    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.




```
model = RandomForestRegressor()
model.fit(x_train, y_train)
exp = shap.KernelExplainer(model.predict, x_test)
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

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# 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

```python
def your_llm(ts_m, par_1, par_2, tr_ratio, logs, verbose):
    start_time = time.time()
    recov_data = your_algo(ts_m, par_1, par_2, tr_ratio, logs, verbose)
    end_time = time.time()
    return recov_data
```

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

imputation.py

```python
class Imputation:
    class LLMs:
        class YourLLM(BaseImputer):
        algorithm = "your_llm"
        def impute(self, user_def=True, params=None, tr_ratio=0.9):
            from imputegap.algorithms.your_llm import your_llm

            self.recov_data = your_llm(ts_m=self.incomp_data, par_1, par_2, tr_ratio, self.logs,
                  self.verbose)

            return self
```

# Integration Toolbox

- Define default values the hyperparameters.

utils.py

```python
config = toml.load(filepath)
if algorithm == "your_llm":
    par_1 = int(config[algorithm]['par_1'])
    par_2 = str(config[algorithm]['par_2'])
    return (par_1, par_2)
```

default_values.toml

```toml
[your_algo]
par_1 = 42
par_2 = "val"
```

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

utils.py

```python
alg = algorithm.lower().replace('_', '').replace('-', '')

if alg == "your_algo":
        imputer = Imputation.YourClass.YourAlgo(incomp_data)

return imputer
```

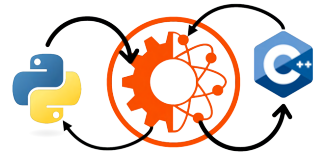
# C++ Wrapper

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

```
shared_lib = utils.load_share_lib("lib_cdrec.so")
__ctype_matrix = utils.__marshal_as_native_column(__py_matrix);
shared_lib.cdrec_imputation(__ctype_matrix);

py_matrix = utils.__marshal_as_numpy_column(__ctype_matrix);
```

```
void
cdrec_imputation(double *matrixNative)
{
    arma::mat input = marshal_as_arma(matrixNative, dimN, dimM);
    Algorithms::CDMissingValueRecovery rmv(input);
}
```



# 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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Questions?

https://imputegap.readthedocs.io

# References I


[1] Quentin Nater, Mourad Khayati, and Jacques Pasquier
*ImputeGAP: A Comprehensive Library for Time Series Imputation*.
arXiv, 2025

[2] Mourad Khayati, Guillaume Chaucun, Zakhar Tymchenko, and Philippe Cudré-Mauroux
*A-DARTS: Stable Model Selection for Data Repair in Time Series*.
Proc. of the 41st IEEE International Conference on Data Engineering (ICDE 2025), Hong Kong.

[3] Mourad Khayati, Quentin Nater, and Jacques Pasquier
*ImputeVIS: An Interactive Evaluator to Benchmark Imputation Techniques for Time Series Data*.
Proc. of VLDB Endowment (PVLDB 2024), Guangzhou, China.

[4] Mourad Khayati, Alberto Lerner, Zakhar Tymchenko, and Philippe Cudré-Mauroux
*Mind the Gap: An Experimental Evaluation of Imputation of Missing Values Techniques in Time Series*.
Proc. of VLDB Endowment (PVLDB 2020), Japan.

# References II


[5] Luca Althaus, Mourad Khayati, Abdelouahab Khelifati, Anton Dignös, Djellel Eddine Difallah, and Philippe Cudré-Mauroux
*SEER: An End-to-End Toolkit for Benchmarking Time Series Database Systems in Monitoring Applications*.
Proc. of VLDB Endowment (PVLDB 2024), Guangzhou, China.

[6] Abdelouahab Khelifati, Mourad Khayati, Anton Dignös, Djellel Difallah and Philippe Cudré-Mauroux,
*TSM-Bench Benchmarking Time Series Database Systems for Monitoring Applications*.
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.