Efficient AI with Rust Lab
Rapid Time Series Datasets Library
RWTH Aachen University

Group 1

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RWTH AACHEN UNIVERSITY

Overview

Goal

- Preprocessing of time series datasets

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- Python package implemented in Rust

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- Passing data by reference

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- Two types of datasets

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  - `ForecastingDataSet`

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Data Input Format

Input 3D numpy array:

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Row	Features
1	...
2	...
3	...
4	...
. . .	
n-1	...
n	...

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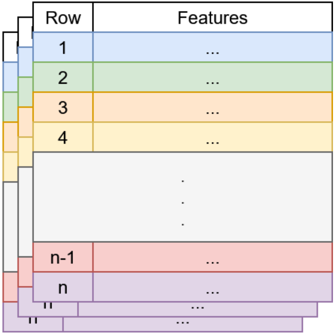

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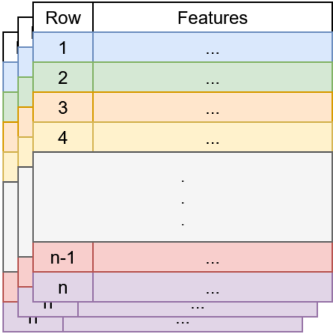

In practice

- Forecasting datasets:
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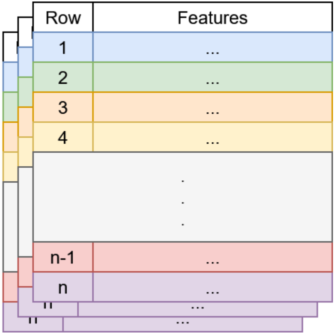

In practice

- Forecasting datasets:
    - One instance
- Classification datasets:
    - Multiple instances

Performance considerations

Copying

- Copying data is expensive

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Data-flow

Forecasting Dataset Data-Flow

Original Data
(NumPy Array)

Classification Dataset Data-Flow

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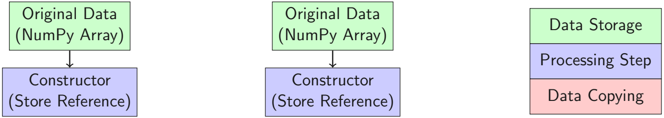
Data Storage
Processing Step
Data Copying

Data-flow

Forecasting Dataset Data-Flow **Classification Dataset Data-Flow**



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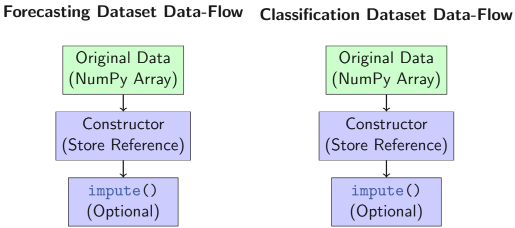

Forecasting Dataset Data-Flow
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impute() (Optional)
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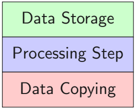

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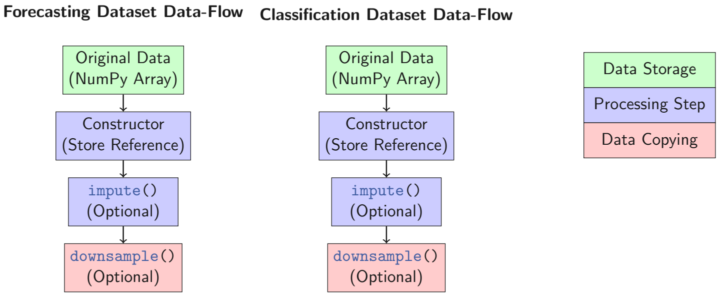
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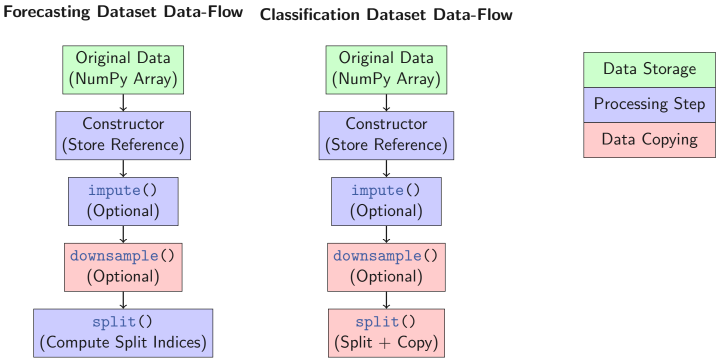
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split() (Split + Copy)
Data Storage
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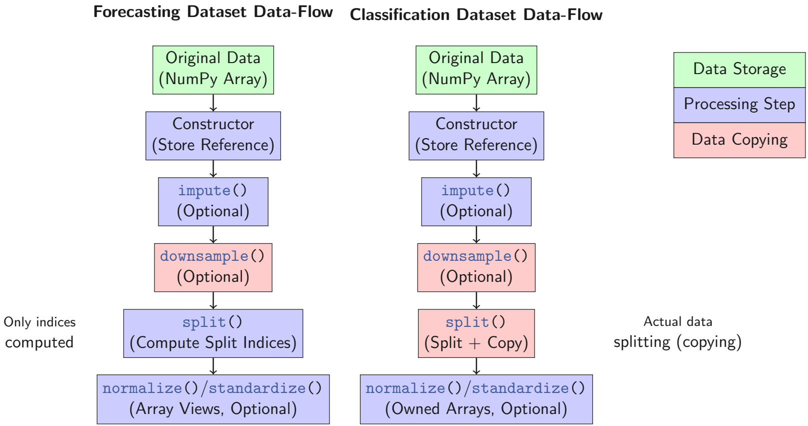
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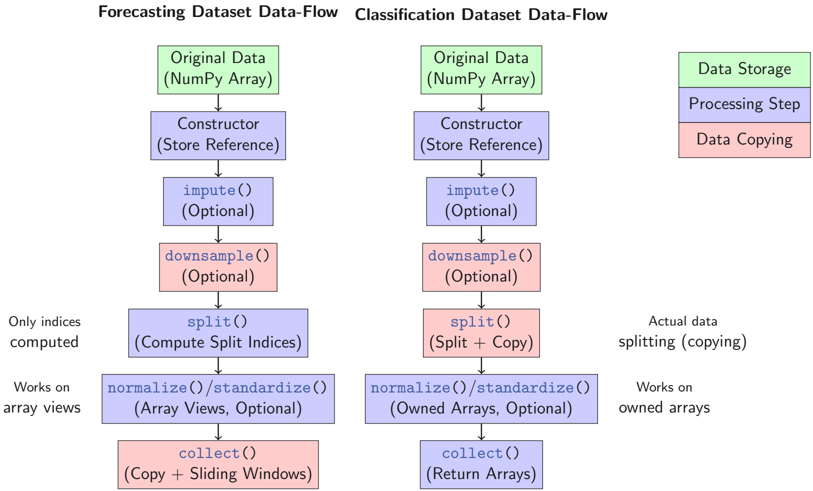
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Data Copying

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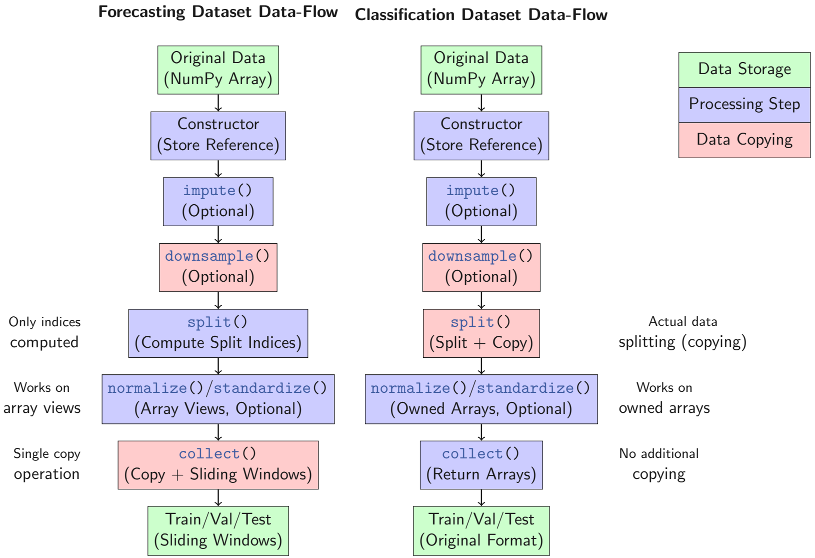

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Train/Val/Test (Sliding Windows)
Only indices computed
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Single copy operation
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Constructor (Store Reference)
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downsample() (Optional)
split() (Split + Copy)
normalize()/standardize() (Owned Arrays, Optional)
collect() (Return Arrays)
Train/Val/Test (Original Format)
Actual data splitting (copying)
Works on owned arrays
No additional copying
Data Storage
Processing Step
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Pipeline Design

ForecastingDataSet

```
# Create instance
fore = ForecastingDataSet(
  data, 0.7, 0.2, 0.1
)

# call the pipeline methods
fore.impute(
  ImputeStrategy.Median
)
fore.downsample(2)
fore.split()


fore.normalize()
fore.standardize()

# collect the results
fore_res = fore.collect(3, 1, 1)
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```

ClassificationDataSet

```
# create instance
clas = ClassificationDataSet(
  data, labels, 0.7, 0.2, 0.1
)

# call the pipeline methods
clas.impute(
  ImputeStrategy.Median
)
clas.downsample(2)
clas.split(
  SplittingStrategy.Random
)
clas.normalize()
clas.standardize()

# collect the results
clas_res = clas.collect()
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Downsampling I

Goal: Reduce the number of data points in a time series dataset.

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Example:

- Downsampling factor of 2: Every second data point is kept

Downsampling II

f1	f2	f3
1	2	1
3	4	6
5	6	11
7	8	16
9	10	21
11	12	26

f1	f2	f3
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Downsampling example with a factor of 2

Downsampling III

How it works:

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- Downsampling does not yield a contiguous data structure.

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How it works:

1. Validate the proportions of train, validation, and test sets.

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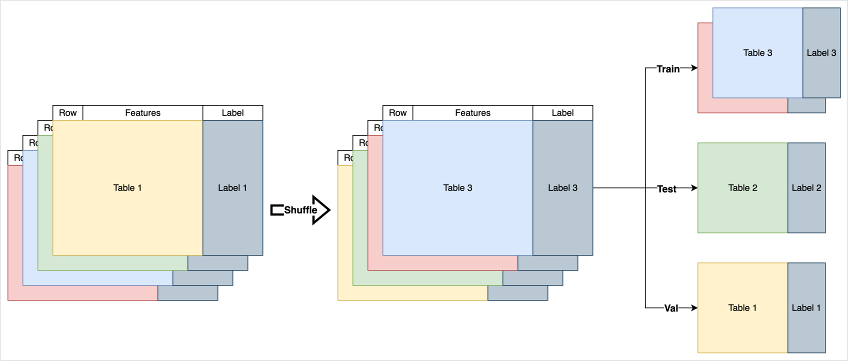
4. Split the instances into three sets.
5. Return the three sets as separate datasets.

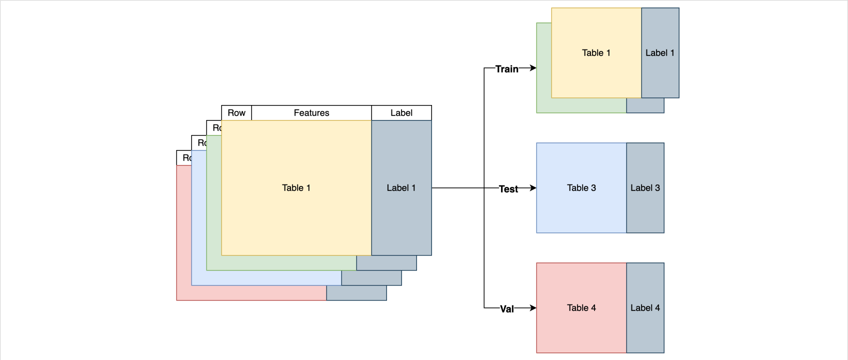
Splitting III (Random Split - Classification Data)



Random split example

Splitting IV (In-Order Split - Classification Data)

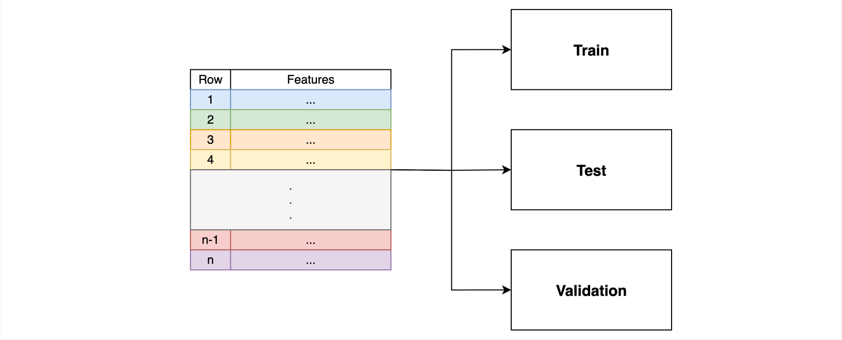
Works very similar to the random split, but it **doesn't shuffle** the dataset anymore.



In-Order split example

Splitting V (Temporal Split - Forecasting Data)

Similar to the in-order split, but this time we are dealing with forecasting data, which in most cases is only one instance and we split over **timesteps** and not instances anymore.



Temporal split example

Standardization

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- Apply the same mean and standard deviation to the **validation** and **test** sets.

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- Use the PyO3 testing framework to run the tests.

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Example: Testing the `impute()` method.

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- Since tests are not native Rust tests, we couldn't use the standard Rust coverage tools.
- We used the PyO3 testing framework to run the tests and check the coverage.
- The coverage is not as detailed as with the standard Rust testing framework, but it is sufficient for our needs.

Unit Tests III

How we calculated the coverage:

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Results:

- Number of all methods: 47

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- Counted the number of all methods.
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- Calculated the coverage as a percentage.

Results:

- Number of all methods: 47
- Number of methods called during tests: 40

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- Counted the number of all methods.
- Counted the number of methods that were called during the tests.
- Calculated the coverage as a percentage.

Results:

- Number of all methods: 47
- Number of methods called during tests: 40
- Coverage: 85.1%

Kilian's Part