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

Group 1

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Overview

Goal

- Preprocessing of time series datasets

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- Two types of datasets
    - `ForecastingDataSet`

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  - `normalize()`/ `standardize()`

Data Input Format

Input 3D numpy array:

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

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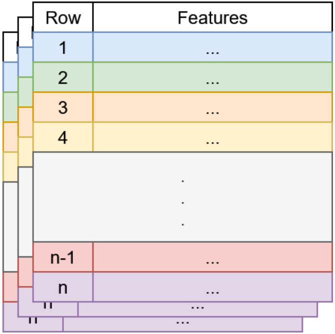

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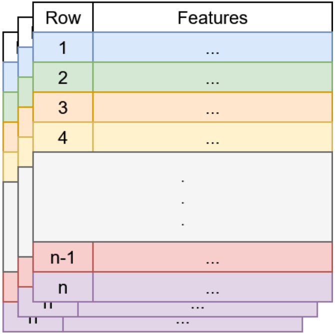

In practice

- Forecasting datasets:
  - One instance

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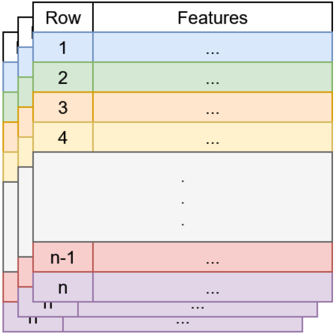

In practice

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

Performance considerations

Copying

- Copying data is expensive

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- For `ClassificationDataSet`:

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- For `ClassificationDataSet`:
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Data-flow

Forecasting Dataset Data-Flow

Original Data
(NumPy Array)

Classification Dataset Data-Flow

Original Data
(NumPy Array)

Data Storage

Processing Step

Data Copying

Data-flow

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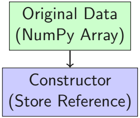
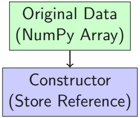
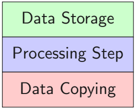
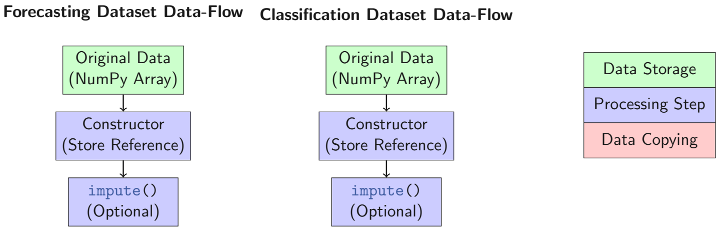


Classification Dataset Data-Flow





Data-flow


Forecasting Dataset Data-Flow
Original Data
(NumPy Array)
Constructor
(Store Reference)
impute()
(Optional)
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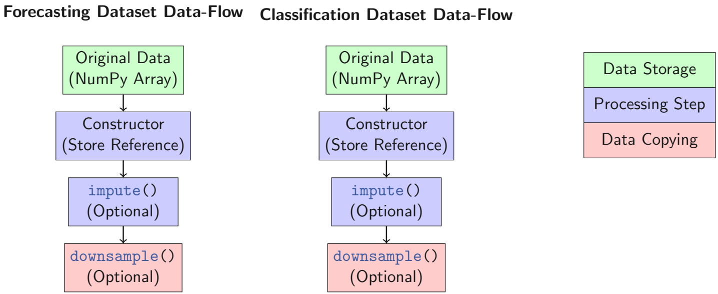
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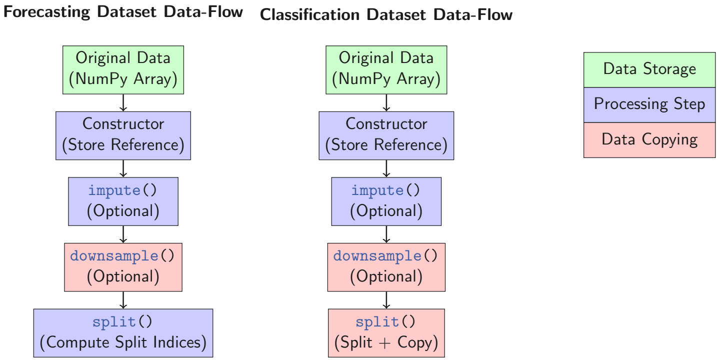
Forecasting Dataset Data-Flow
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split() (Split + Copy)
Data Storage
Processing Step
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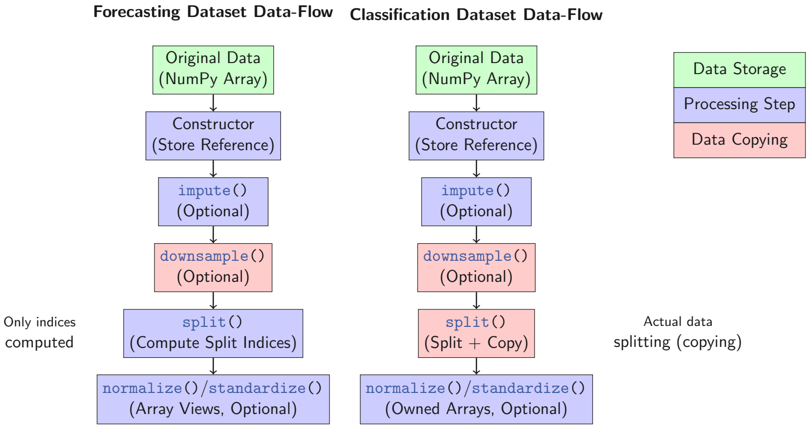

Forecasting Dataset Data-Flow
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Constructor (Store Reference)
impute() (Optional)
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normalize()/standardize() (Array Views, Optional)
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Constructor (Store Reference)
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split() (Split + Copy)
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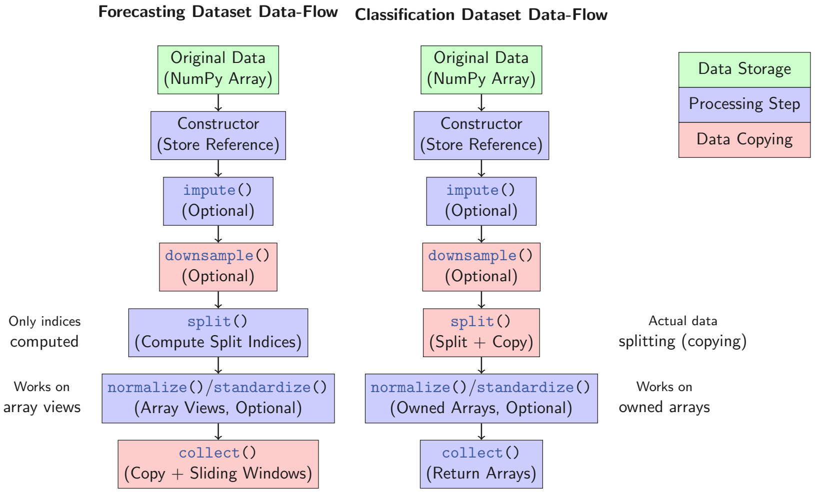
Actual data splitting (copying)
Data Storage
Processing Step
Data Copying

Data-flow


Forecasting Dataset Data-Flow
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split() (Compute Split Indices)
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collect() (Copy + Sliding Windows)
Only indices computed
Works on array views
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Constructor (Store Reference)
impute() (Optional)
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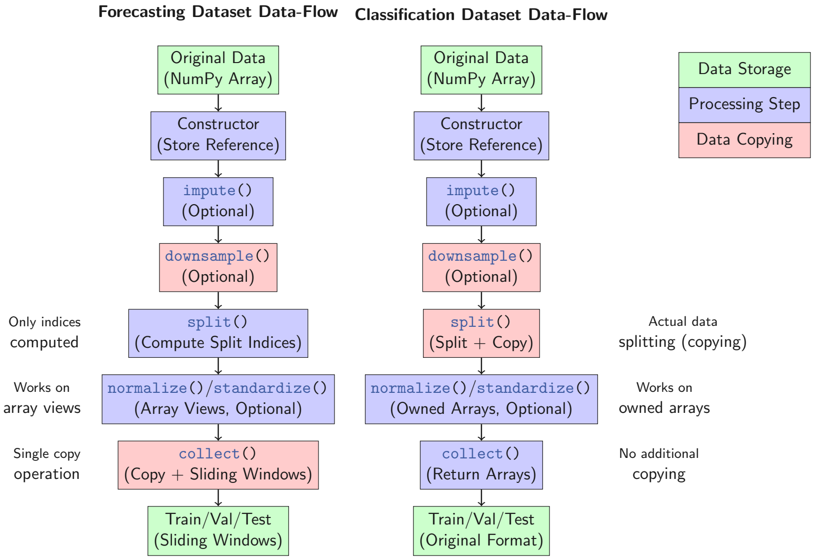
collect() (Return Arrays)
Actual data splitting (copying)
Works on owned arrays
Data Storage
Processing Step
Data Copying

Data-flow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downsample() (Optional)
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split() (Compute Split Indices)
Works on array views
normalize()/standardize() (Array Views, Optional)
Single copy operation
collect() (Copy + Sliding Windows)
Train/Val/Test (Sliding Windows)
Original Data (NumPy Array)
Constructor (Store Reference)
impute() (Optional)
downsample() (Optional)
split() (Split + Copy)
Actual data splitting (copying)
normalize()/standardize() (Owned Arrays, Optional)
Works on owned arrays
collect() (Return Arrays)
No additional copying
Train/Val/Test (Original Format)
Data Storage
Processing Step
Data Copying

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
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clas.downsample(2)
clas.split(
  SplittingStrategy.Random
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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 as shown in Figure 1

Downsampling II

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

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Downsampling example with a factor of 2

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How it works:

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Bottleneck of passing the data by reference:

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- Creating view only possible on contiguous data.
- Downsampling does not yield a contiguous data structure.

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Splitting II (Random Split - Classification Data)

How it works:

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

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How it works:

1. Validate the proportions of train, validation, and test sets.
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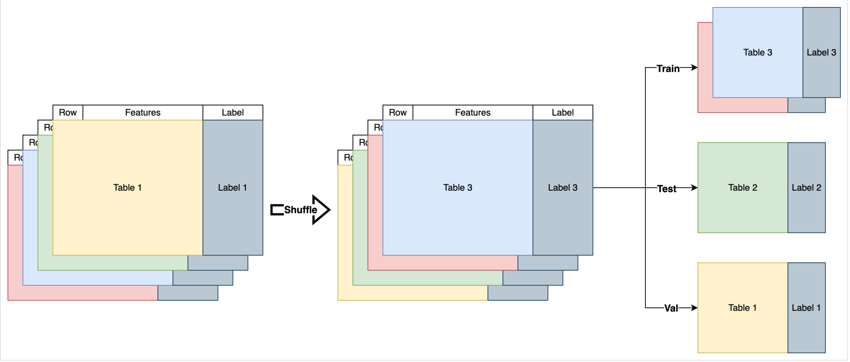
3. Compute the split offsets based on the proportions.
4. Split the instances into three sets.
5. Return the three sets as separate datasets.

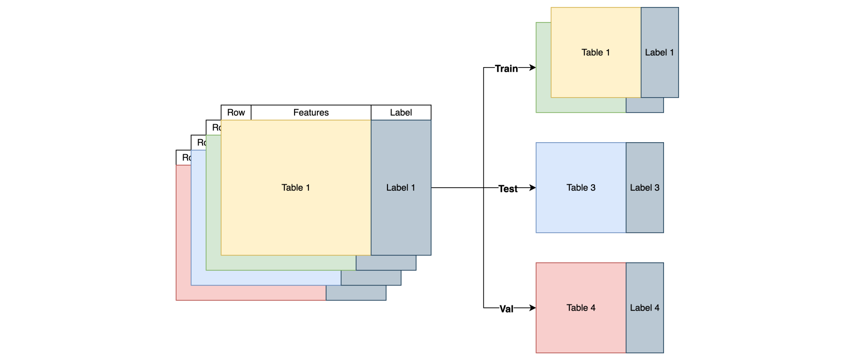
Splitting III (Random Split - Classification Data)



Random split example

Splitting IV (In-Order Split - Classification Data)

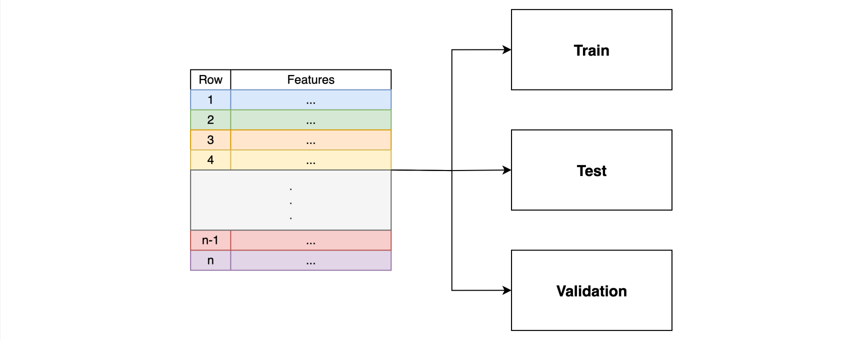
Works very similar to the random split, but it **doesn't shuffle** the dataset anymore.



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 **timestamps** and not isntances anymore.



Temporal split example

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Goal: Transform each feature in a time series dataset to have a mean of 0 and a standard deviation of 1.

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$$x' = \frac{x - \text{mean}}{\text{std}} \tag{1}$$

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

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- Apply the same min and max to the validation and test sets.

Kilian’s Part