# 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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  - `ForecastingDataSet`

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

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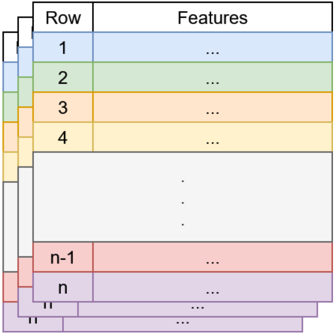

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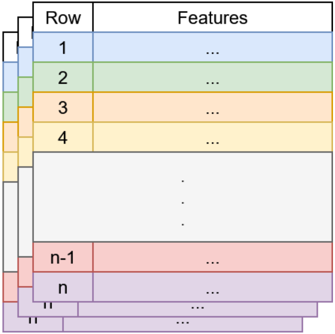


## In practice

- Forecasting datasets:

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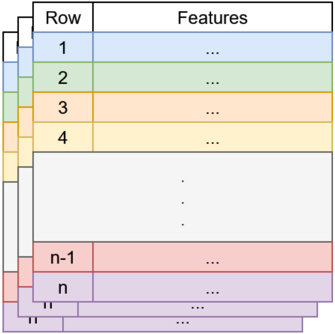

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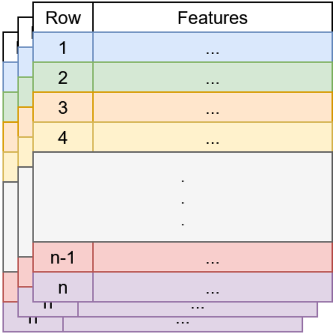


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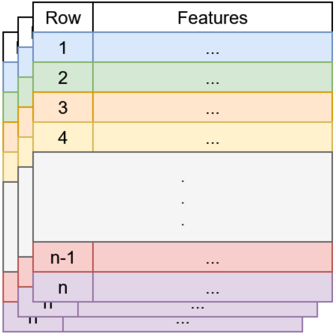


## In practice

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

# Performance considerations

## Copying

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# Data-flow

**Forecasting Dataset Data-Flow**

Original Data
(NumPy Array)

**Classification Dataset Data-Flow**

Original Data
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| |
|---|
| Data Storage |
| Processing Step |
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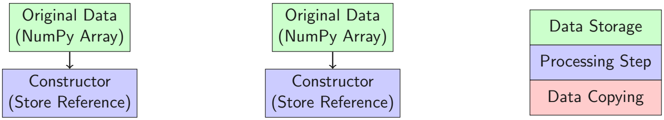

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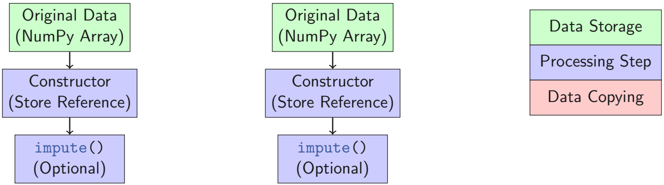

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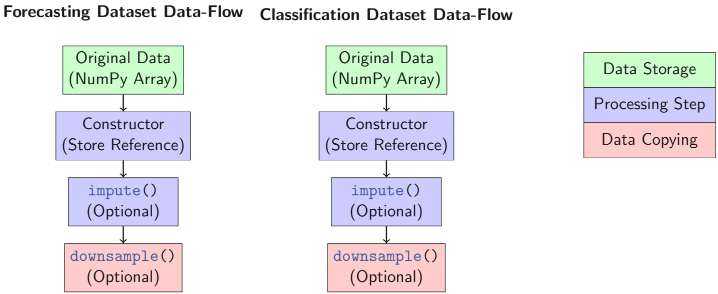
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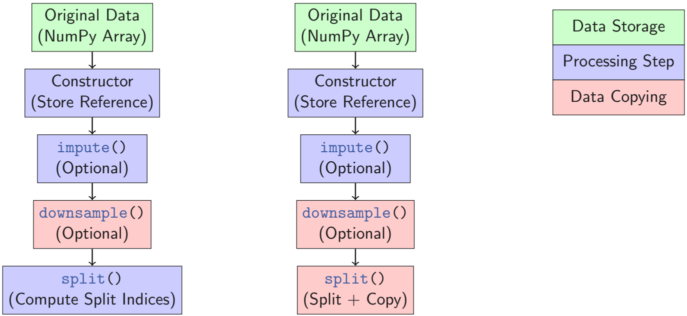

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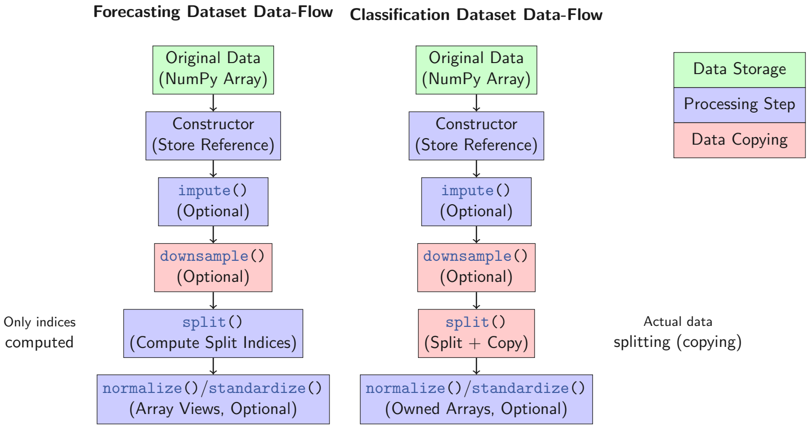
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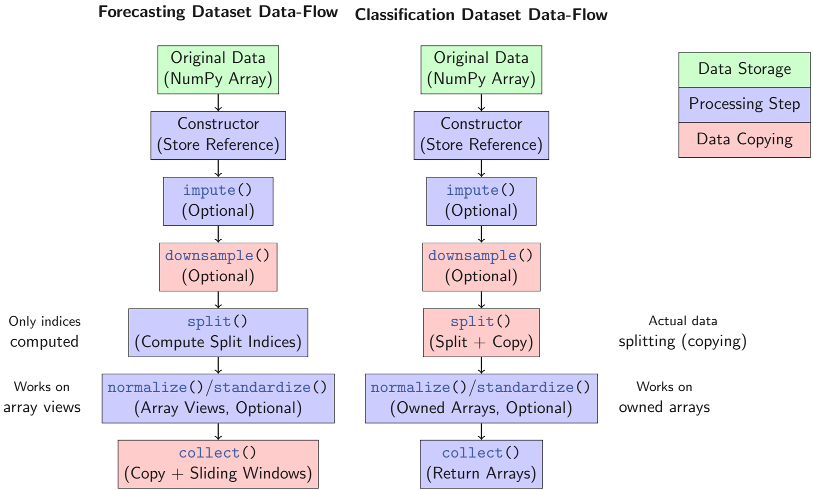

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Processing Step
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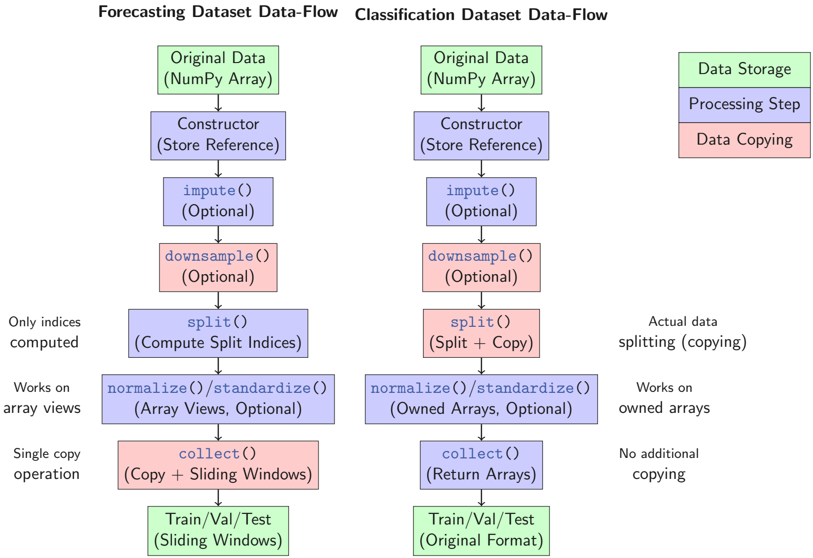

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Train/Val/Test (Sliding Windows)
Only indices computed
Works on array views
Single copy operation
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split() (Split + Copy)
normalize()/standardize() (Owned Arrays, Optional)
collect() (Return Arrays)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

```python
# 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
)
clas.normalize()
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# collect the results
clas_res = clas.collect()
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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 |

| f1 | f2 | f3 |
|---|---|---|
| 1 | 2 | 1 |
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Downsampling example with a factor of 2

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- It iterates over the dataset and keeps every n-th data point, where n is the downsampling factor.

### 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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### 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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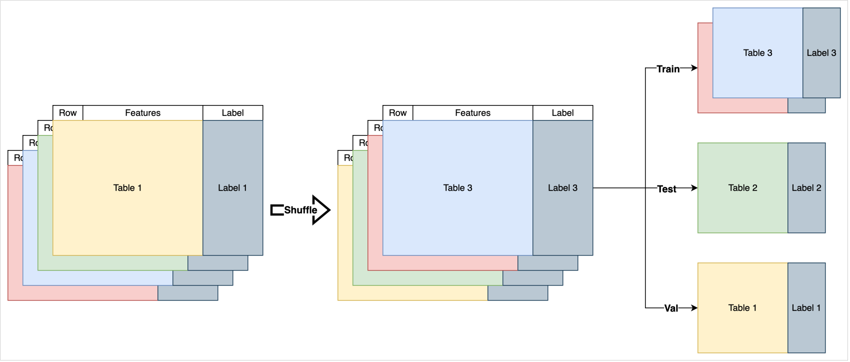
3. Compute the split offsets based on the proportions.
4. Split the instances into three sets.
5. Return the three sets as separate datasets.

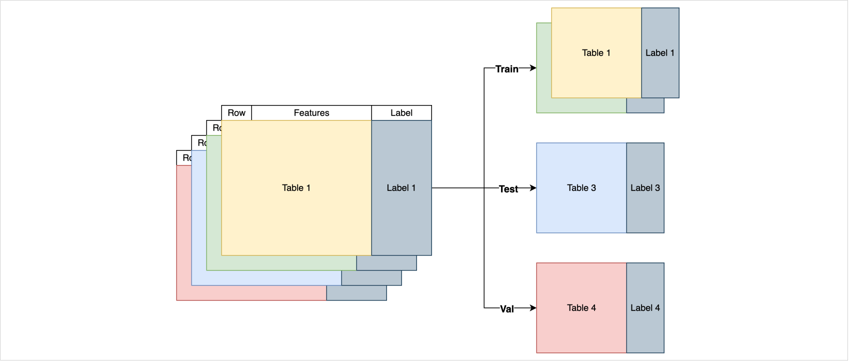
# Splitting III (Random Split - Classification Data)




Random split example

# Splitting IV (In-Order Split - Classification Data)

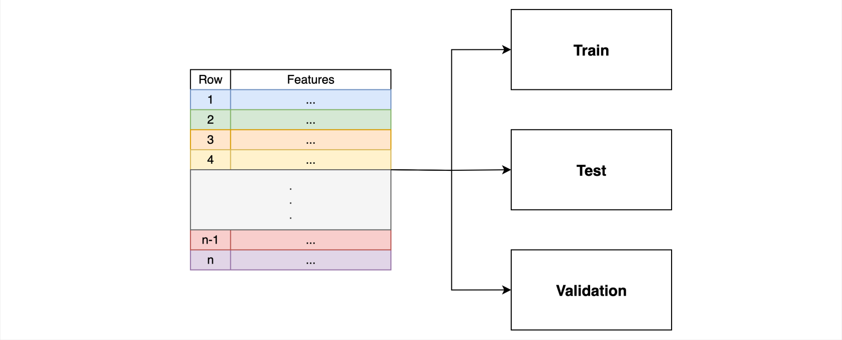
Works very similar to the random split, but it **doesn't shuffle** the dataset anymore.




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

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

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# Kilian's Part