Efficient AI with Rust Lab Rapid Time Series Datasets Library RWTH Aachen University Group 1

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Goal

Preprocessing of time series datasets

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Scope

Two types of datasets

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Input 3D numpy array:

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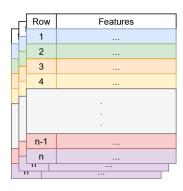
Row	Features
1	
2	
3	
4	
	•
n-1	
n	

Input 3D numpy array:

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Second dimension: Timesteps

▶ Third dimension: Features



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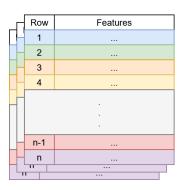
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Second dimension: Timesteps

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In practice

- Forecasting datasets:
 - One instance



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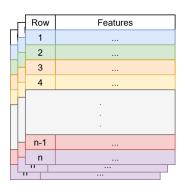
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In practice

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



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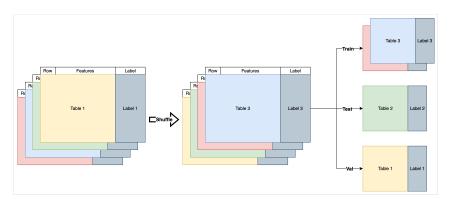
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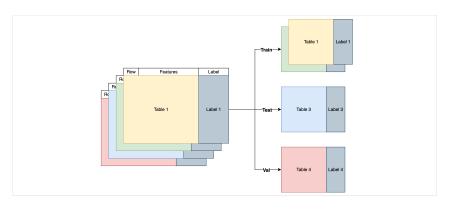
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- 5. Return the three sets as separate datasets.



Random split example

Splitting IV (In-Order Split - Classification Data)

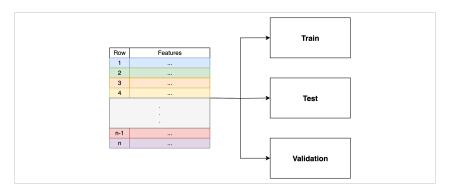
Works very similar to the random split, but it **doesn't shuffle** the dataset anymore.



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

Performance considerations

Copying

Copying data is expensive

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When to copy?

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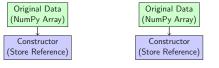
Forecasting Dataset Data-Flow Classification Dataset Data-Flow

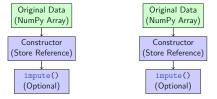
Original Data (NumPy Array) Original Data (NumPy Array)

Data Storage

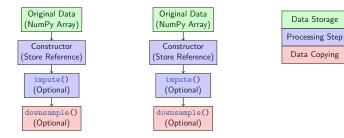
Processing Step

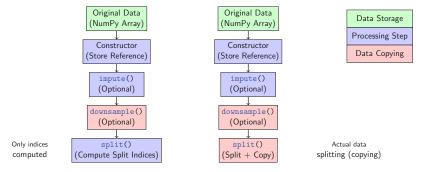
Data Copying

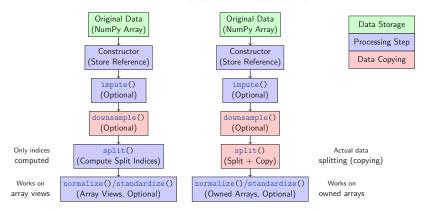


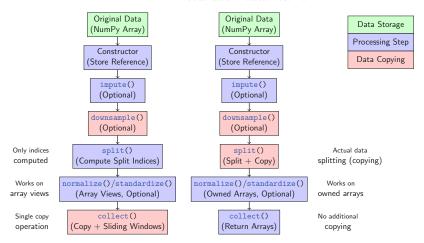


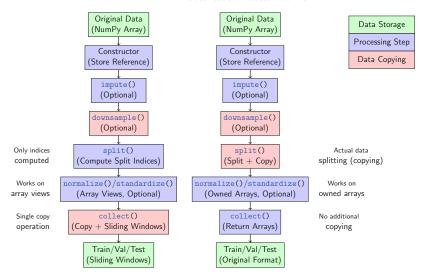












Pipeline Design

${\tt ForecastingDataSet}$

```
# 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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fore res = fore.collect(3, 1, 1) clas res = clas.collect()
```

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
```

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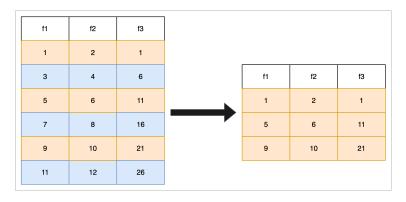
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Example:

Downsampling factor of 2: Every second data point is kept



Downsampling example with a factor of 2

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- Downsampling does not yield a contiguous data structure.

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- Compute the mean and standard deviation for each feature column in the **training** dataset.
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$$x' = \frac{x - \mathsf{mean}}{\mathsf{std}} \tag{1}$$

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- Use the PyO3 testing framework to run the tests.

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- ▶ 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.

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Results:

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

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► Compare vs. PyTorch TimeSeriesDataSet

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How:

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- Vary parameters

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How:

- Implmenent similar Module
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- Measure timings and memory use

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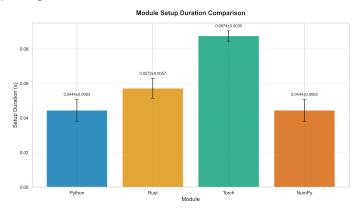
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- Setup or measurement error.

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Setup durations on GunPoint

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Explanation:

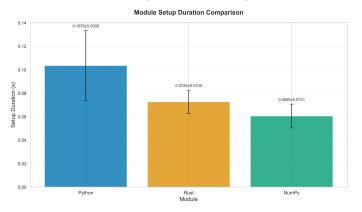
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Explanation:

- Numpy uses vectorized operations in C
- Torch overhead from Pandas

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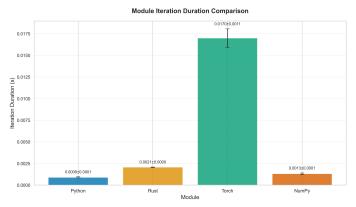
More processing benefits Rust and Numpy

▶ Goal: Measure total data retrieval

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▶ Motivation: Pytorch uses lazy compute

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Iteration durations on GunPoint

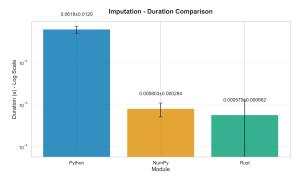
- ▶ **Goal:** Measure total data retrieval
- Motivation: Pytorch uses lazy compute

Explanation:

PyTorch slowest due to deferred preprocessing during retrieval

▶ **Goal:** Measure imputing in isolation

▶ Goal: Measure imputing in isolation



Imputing durations on GunPoint

▶ Goal: Measure imputing in isolation

Explanation:

Rust benefits from compiler

▶ Goal: Measure imputing in isolation

Explanation:

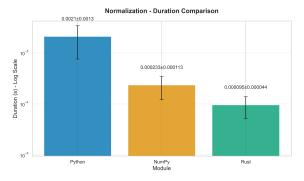
- Rust benefits from compiler
- NumPy benefits from partial vectorization

Normalization durations

▶ Goal: Measure normalization in isolation

Normalization durations

▶ Goal: Measure normalization in isolation



Normalization durations on GunPoint

Normalization durations

▶ Goal: Measure normalization in isolation

Explanation:

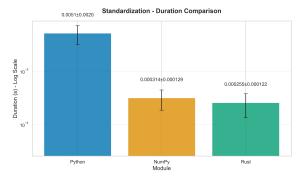
- ► Again:
- Rust benefits from compiler
- NumPy benefits from partial

Standardization durations

▶ Goal: Measure standardization in isolation

Standardization durations

▶ **Goal:** Measure standardization in isolation



Standardization durations on GunPoint

Standardization durations

▶ Goal: Measure standardization in isolation

Explanation:

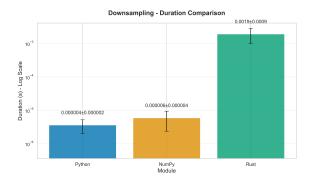
- Again:
- Rust benefits from compiler
- NumPy benefits from partial

Downsampling durations

▶ **Goal:** Measure downsampling in isolation

Downsampling durations

▶ **Goal:** Measure downsampling in isolation



Downsampling durations on GunPoint

Downsampling durations

▶ **Goal:** Measure downsampling in isolation

Explanation:

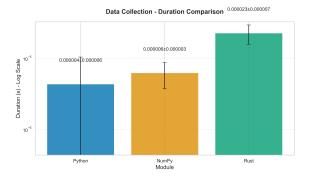
Rust slowest due to costly data copying

Data collection durations

▶ **Goal:** Measure data collection in isolation

Data collection durations

▶ Goal: Measure data collection in isolation



Data collection durations on GunPoint

Data collection durations

▶ Goal: Measure data collection in isolation

Explanation:

Rust slowest due to Python data transfer