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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  - `impute()`

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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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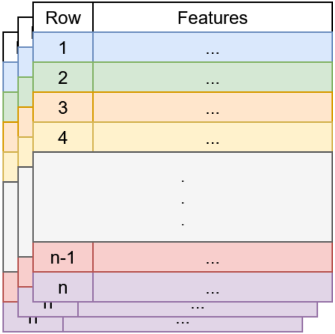

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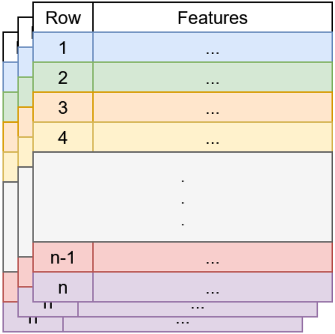
In practice

- Forecasting datasets:
  - One instance



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In practice

- Forecasting datasets:
  - One instance
- Classification datasets:
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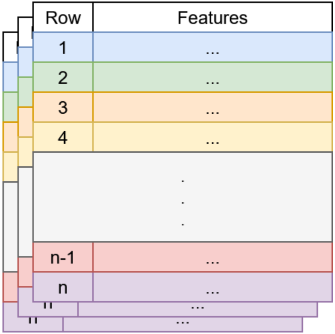

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Goal: Split a time series dataset into three parts: training, validation, and test.

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Splitting II (Random Split - Classification Data)

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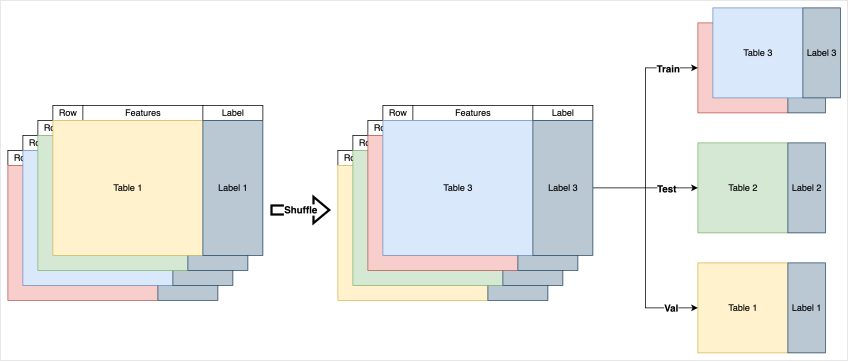
3. Compute the split offsets based on the proportions.
4. Split the instances into three sets.
5. Return the three sets as separate datasets.

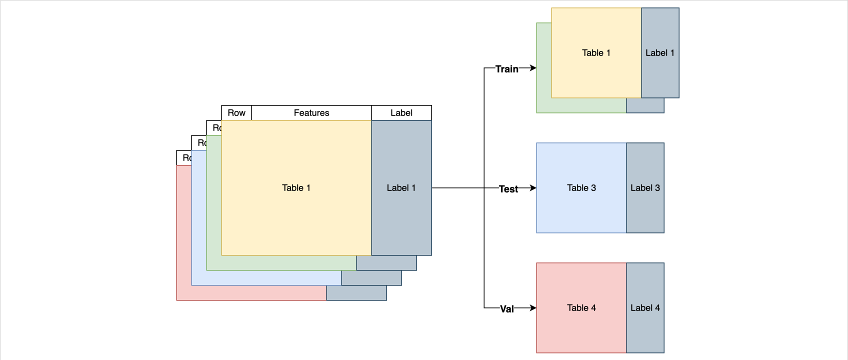
Splitting III (Random Split - Classification Data)



Random split example

Splitting IV (In-Order Split - Classification Data)

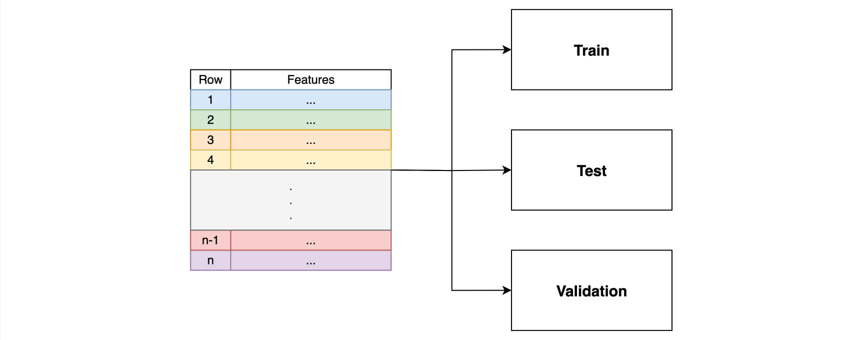
Works very similar to the random split, but it **doesn't shuffle** the dataset anymore.



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 **timesteps** and not instances anymore.



Temporal split example

Performance considerations

Copying

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- For `ForecastingDataSet`:
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  - Copying unavoidable

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- For `ForecastingDataSet`:
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  - Copying unavoidable
- For `ClassificationDataSet`:
  - Random splitting strategy offered

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Data-flow

Forecasting Dataset Data-Flow

Original Data
(NumPy Array)

Classification Dataset Data-Flow

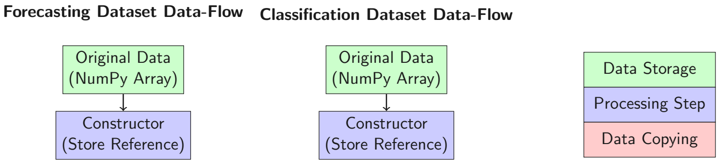
Original Data
(NumPy Array)

Data Storage

Processing Step

Data Copying

Data-flow


Forecasting Dataset Data-Flow
Original Data (NumPy Array)
Constructor (Store Reference)
Classification Dataset Data-Flow
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Data Storage
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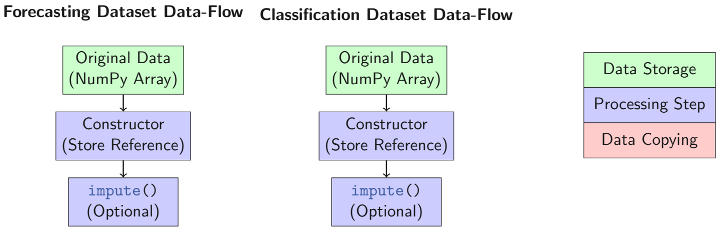
Forecasting Dataset Data-Flow
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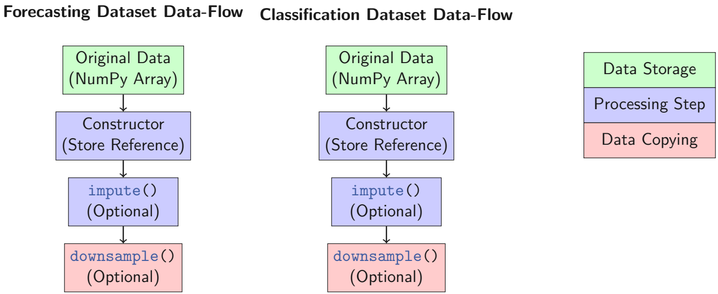
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(NumPy Array)
Constructor
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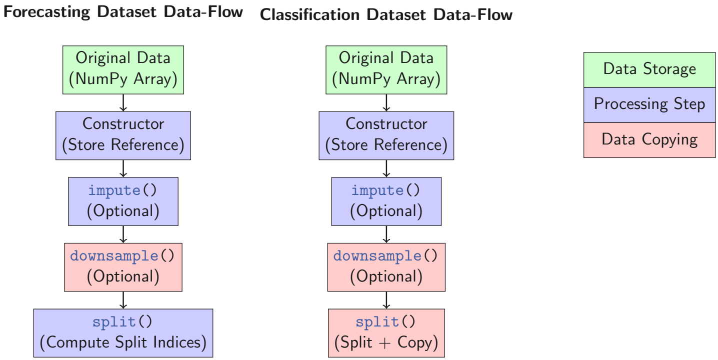

Forecasting Dataset Data-Flow
Original Data (NumPy Array)
Constructor (Store Reference)
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split() (Compute Split Indices)
Classification Dataset Data-Flow
Original Data (NumPy Array)
Constructor (Store Reference)
impute() (Optional)
downsample() (Optional)
split() (Split + Copy)
Data Storage
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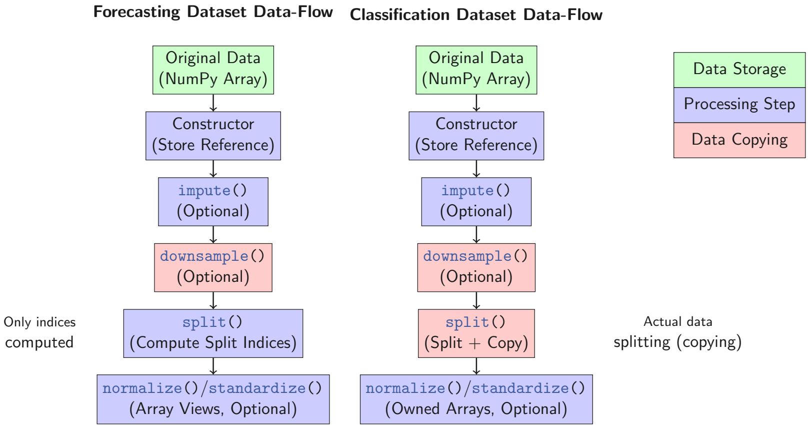
Data-flow


Forecasting Dataset Data-Flow
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Original Data (NumPy Array)
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split() (Compute Split Indices)
normalize()/standardize() (Array Views, Optional)
Only indices computed
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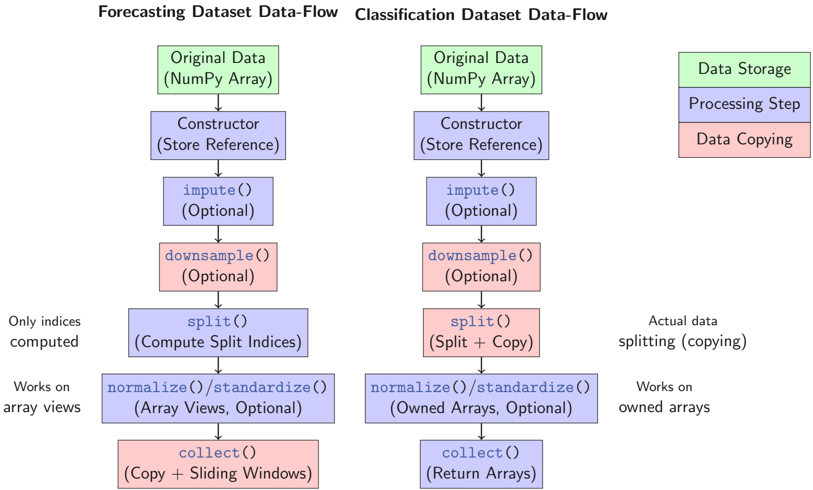
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(Return Arrays)
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Data Copying

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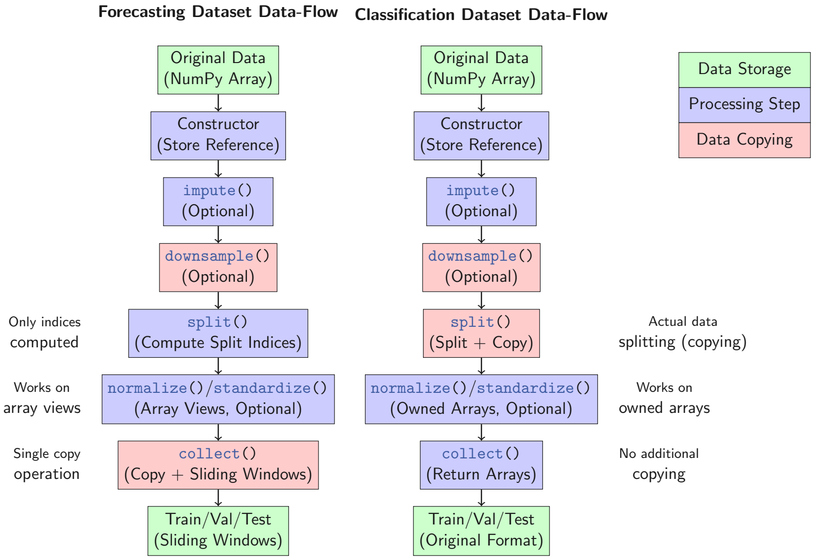
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Train/Val/Test (Sliding Windows)
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Constructor (Store Reference)
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collect() (Return Arrays)
Train/Val/Test (Original Format)
Data Storage
Processing Step
Data Copying
Only indices computed
Works on array views
Single copy operation
Actual data splitting (copying)
Works on owned arrays
No additional 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
)
clas.downsample(2)
clas.split(
  SplittingStrategy.Random
)
clas.normalize()
clas.standardize()

# collect the results
clas_res = clas.collect()
```

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:

- The downsampling function takes a time series dataset and a downsampling factor as input.

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

Standardization

Goal: Transform each feature in a time series dataset to have a **mean** of $\mathbf{0}$ and a **standard deviation** of $\mathbf{1}$.

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- Write unit tests in Rust that can be called from Python.
- Use the PyO3 testing framework to run the tests.

Unit Tests II

Example: Testing the `impute()` method.

How it works:

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- The unit tests cover most of the implemented methods.
- 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.

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How it works:

- Create a simpe numpy array with missing values.
- Call the `impute()` method with a specific strategy.
- Check if the missing values are filled correctly.

Coverage:

- The unit tests cover most of the implemented methods.
- 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:

- We used the PyO3 testing framework to run the tests.

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Results:

- Number of all methods: 47

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Results:

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

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- 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%

Benchmarking

Goal:

- Compare vs. PyTorch TimeSeriesDataSet

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- Additionally: Numpy and Python

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- Test on real data

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How:

- Implmenent similar Module
- Vary parameters
- Test on real data
- Measure timings and memory use

Measurements

Timing:

- Measure timing for each method

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- Measure timing for each method
- Works for Rust, Python and Numpy
- But Torch: Not so much
- Also: Torch input & output formatting

Peak Memory:

- Track memory use via Python
- Record peak use
- **But:** Measurements show the same value (312 MB)
- Setup or measurement error.

Total setup durations I

- **Goal:** Measure total setup over different paremeters

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- **Here:** Fixed stride, normalization, downsampling, imputing and splitting

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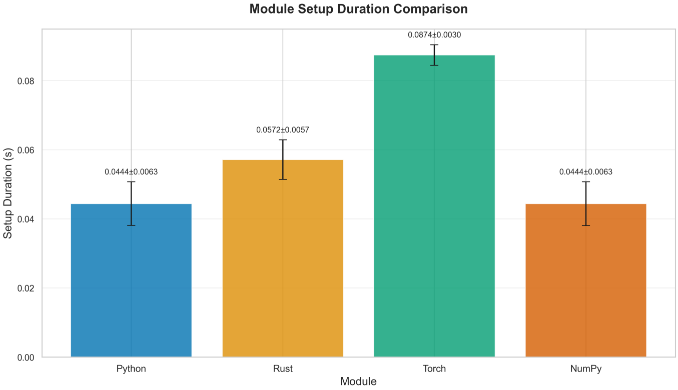

Setup durations on GunPoint

Total setup durations I

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Explanation:

- Numpy uses vectorized operations in C

Total setup durations I

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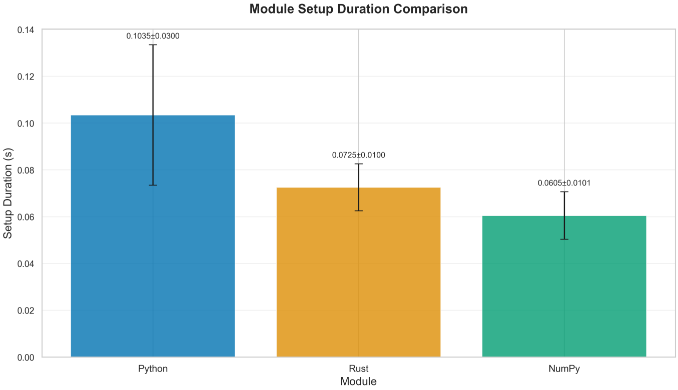
Explanation:

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

Total setup durations II

- **Goal:** Measure total setup over different paremeters



Setup durations on GunPoint

Total setup durations II

- **Goal:** Measure total setup over different paremeters

Explanation:

- More processing benefits Rust and Numpy

Total iteration durations

- **Goal:** Measure total data retrieval

Total iteration durations

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- **Motivation:** Pytorch uses lazy compute

Total iteration durations

- **Goal:** Measure total data retrieval
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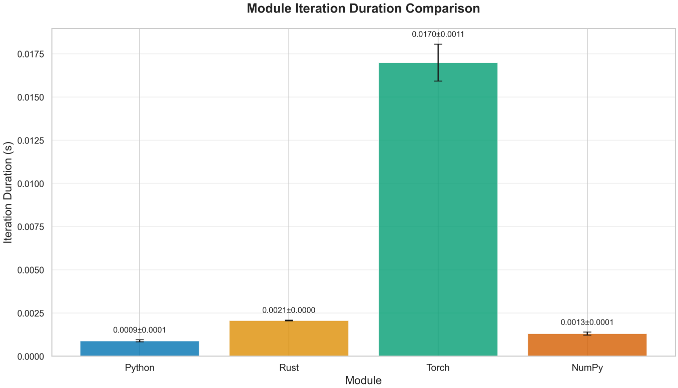


Iteration durations on GunPoint

Total iteration durations

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

Explanation:

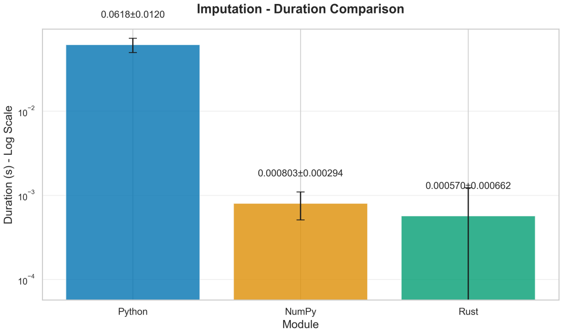
- PyTorch slowest due to deferred preprocessing during retrieval

Imputing durations

- **Goal:** Measure imputing in isolation

Imputing durations

- **Goal:** Measure imputing in isolation



Imputing durations on GunPoint

Imputing durations

- **Goal:** Measure imputing in isolation

Explanation:

- Rust benefits from compiler

Imputing durations

- **Goal:** Measure imputing in isolation

Explanation:

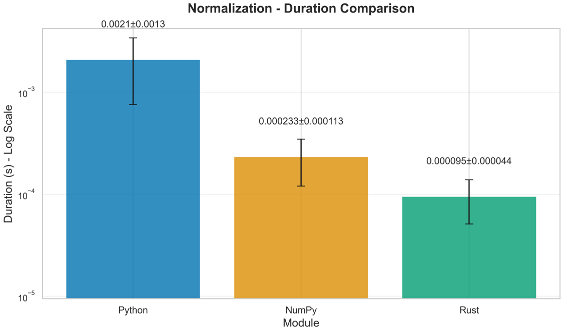
- Rust benefits from compiler
- NumPy benefits from partial vectorization

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

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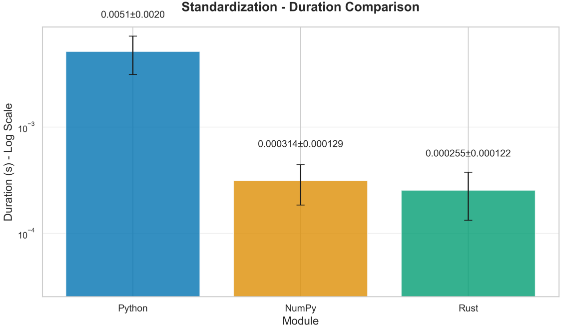


Standardization durations on GunPoint

Standardization durations

- **Goal:** Measure standardization in isolation

Explanation:

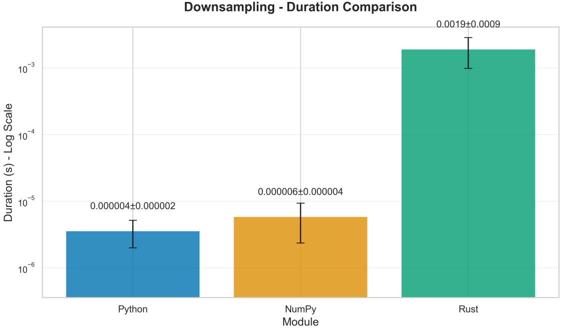
- **Again:**
- Rust benefits from compiler
- NumPy benefits from partial

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:

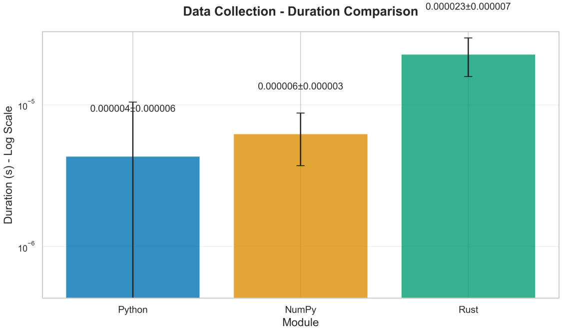
- Rust slowest due to costly data copying

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