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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Data Input Format

Input 3D numpy array:

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Row	Features
1	...
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4	...
. . .	
n-1	...
n	...

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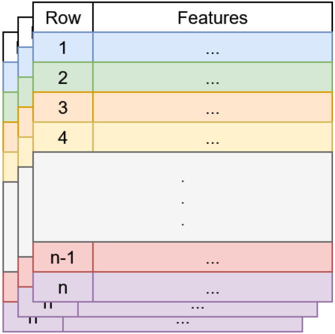

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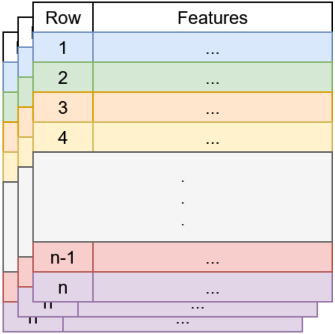

In practice

- Forecasting datasets:
  - One instance

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In practice

- Forecasting datasets:
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- Classification datasets:
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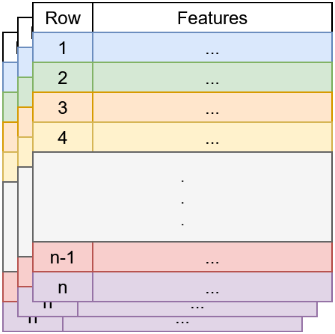

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Goal: Split a time series dataset into three parts: training, validation, and test.

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Splitting II (Random Split - Classification Data)

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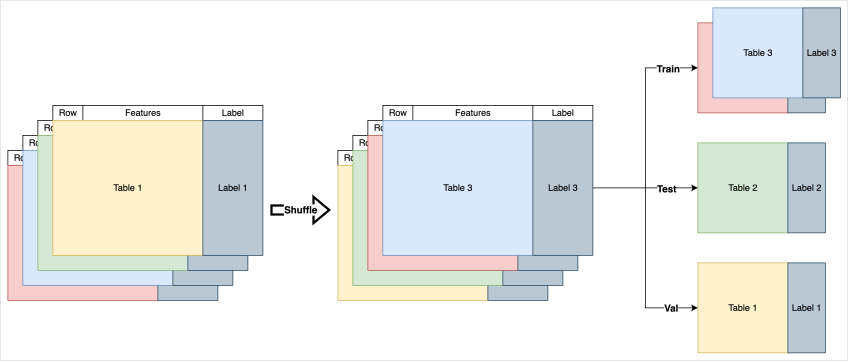
4. Split the instances into three sets.
5. Return the three sets as separate datasets.

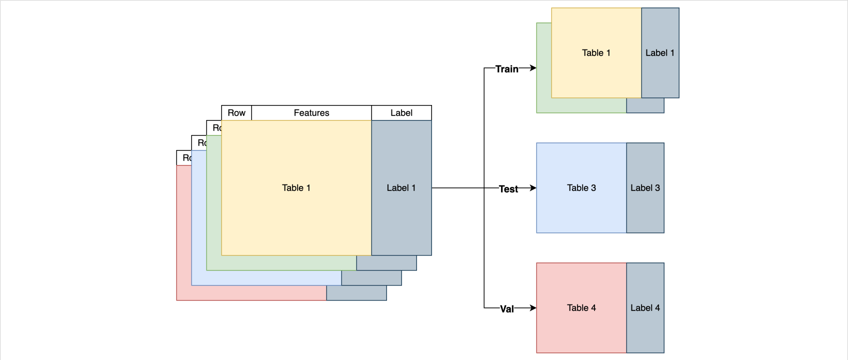
Splitting III (Random Split - Classification Data)



Random split example

Splitting IV (In-Order Split - Classification Data)

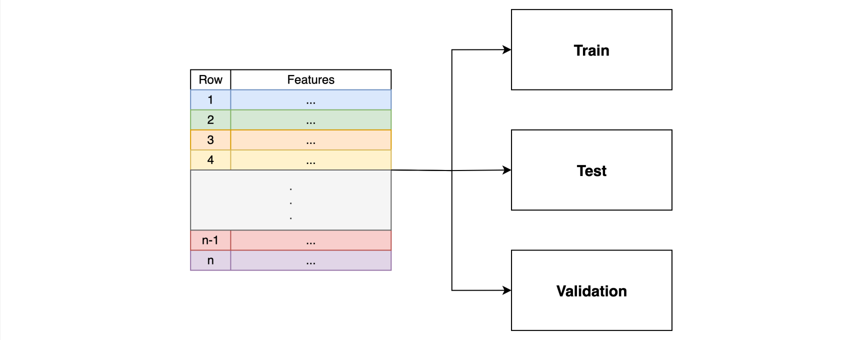
Works very similar to the random split, but it **doesn't shuffle** the dataset anymore.



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

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- For `ForecastingDataSet`:
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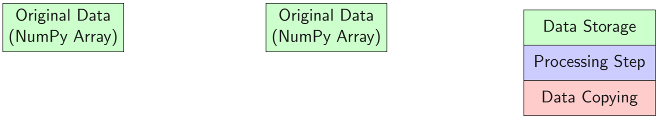
Data-flow

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



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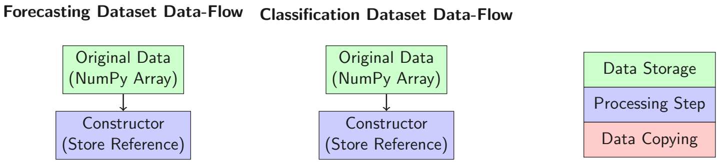
Forecasting Dataset Data-Flow
Original Data (NumPy Array)
Constructor (Store Reference)
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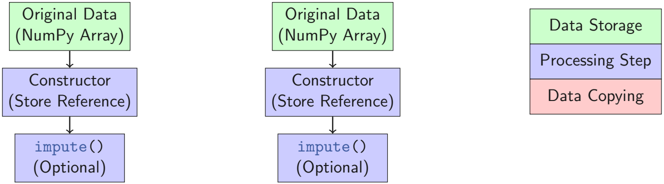

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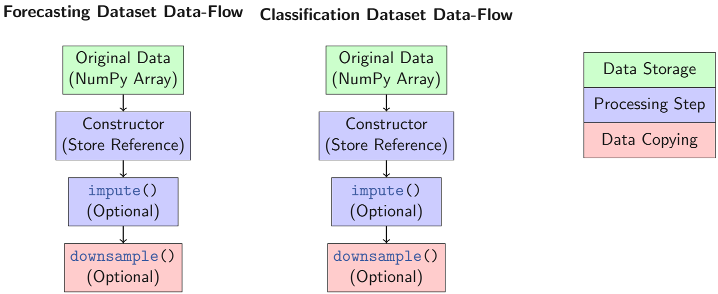
Forecasting Dataset Data-Flow
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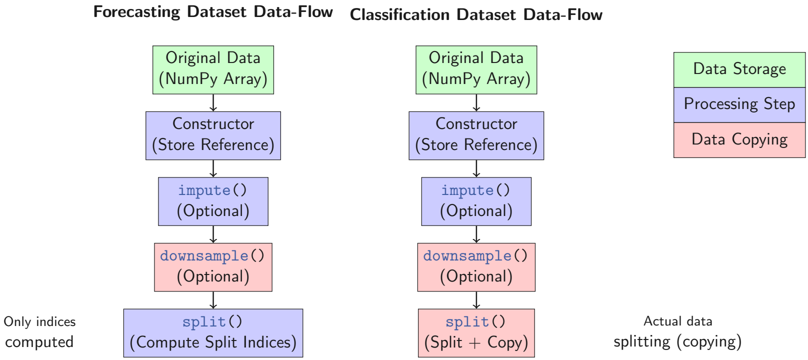

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Actual data splitting (copying)
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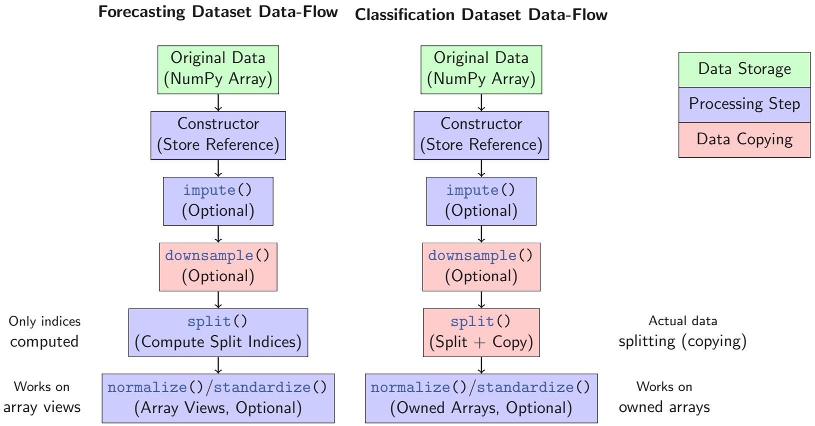
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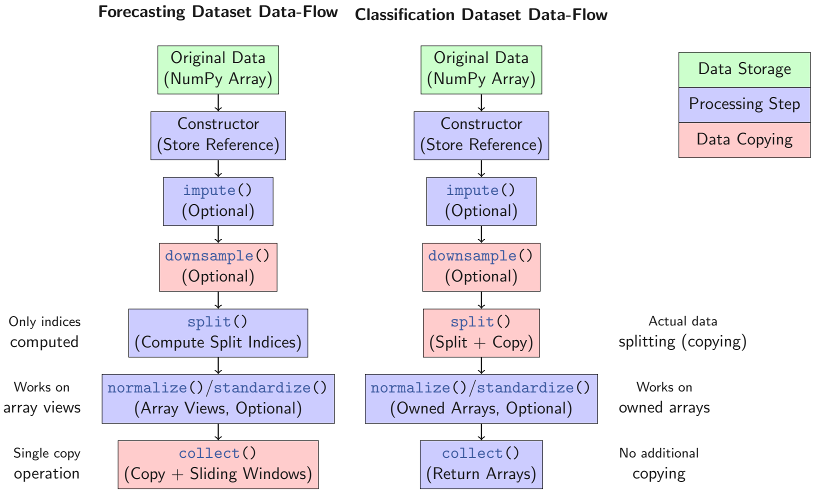
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Single copy operation
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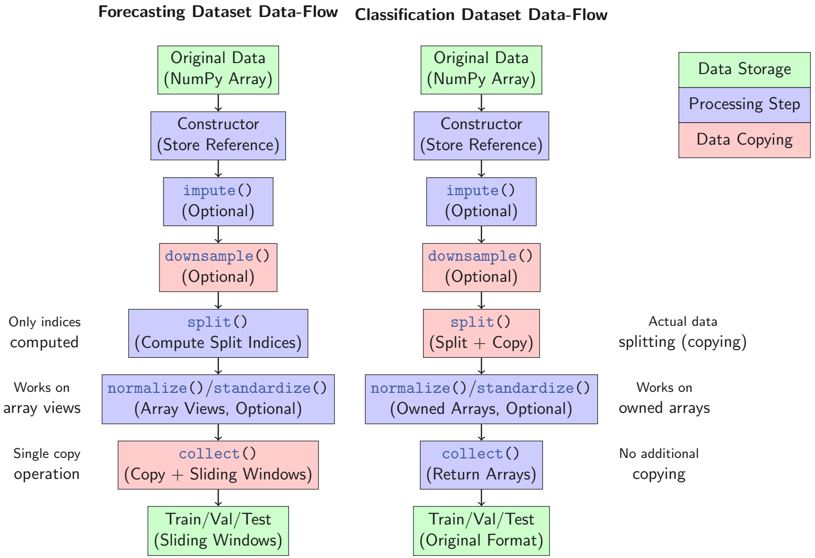
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Pipeline Design

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()
```

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

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Downsampling example with a factor of 2

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How it works:

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- Downsampling does not yield a continuos data structure.

Standardization

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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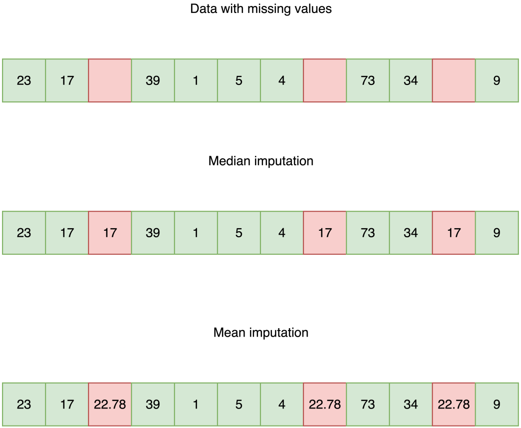

Median and Mean imputation methods applied to an array

Imputing III

Forward-Fill and Backward-Fill imputation methods applied to an array

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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.

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Coverage:

- The unit tests cover most of the implemented methods.

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- The coverage is not as detailed as with the standard Rust testing framework, but it is sufficient for our needs.

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How we calculated the coverage:

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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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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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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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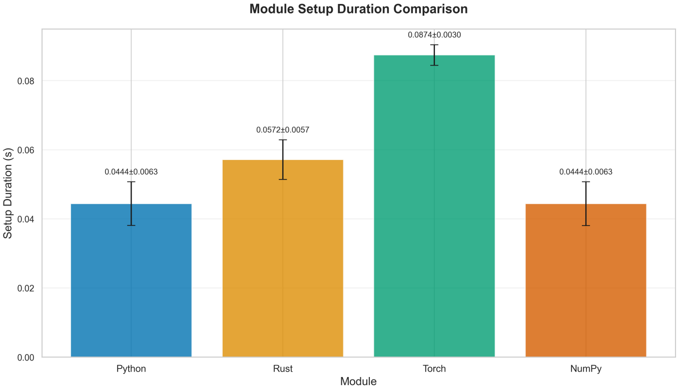

Setup durations on GunPoint

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Explanation:

- Numpy uses vectorized operations in C

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- Torch overhead from Pandas

Total setup durations II

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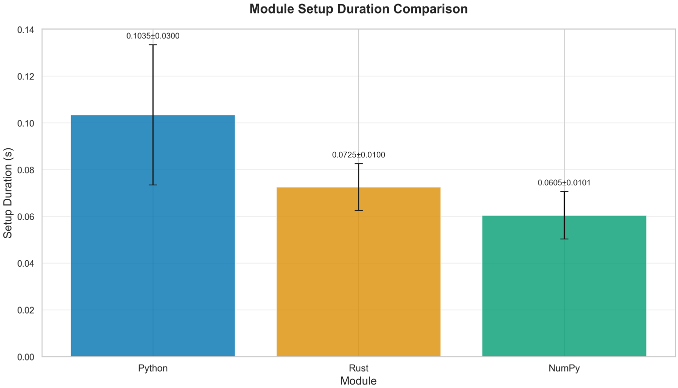

Setup durations on GunPoint

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

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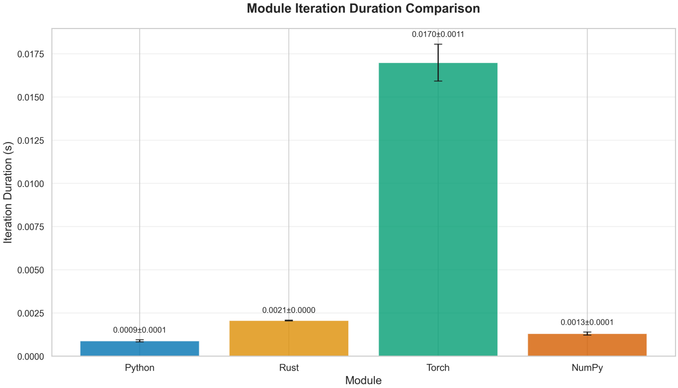


Iteration durations on GunPoint

Total iteration durations

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

Explanation:

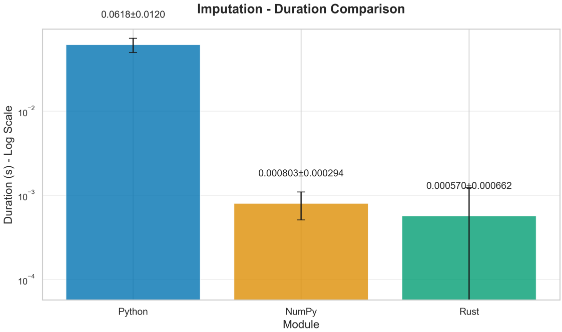
- PyTorch slowest due to deferred preprocessing during retrieval

Imputing durations

- **Goal:** Measure imputing in isolation

Imputing durations

- **Goal:** Measure imputing in isolation



Imputing durations on GunPoint

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- NumPy benefits from partial vectorization

Normalization durations

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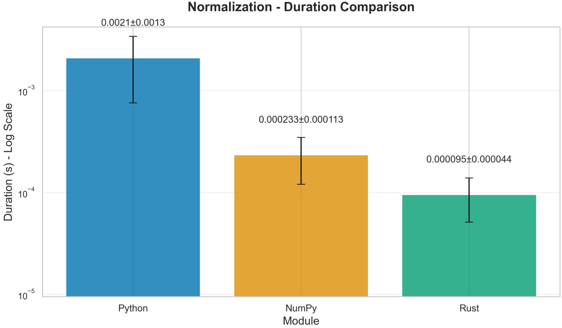

Normalization durations on GunPoint

Normalization durations

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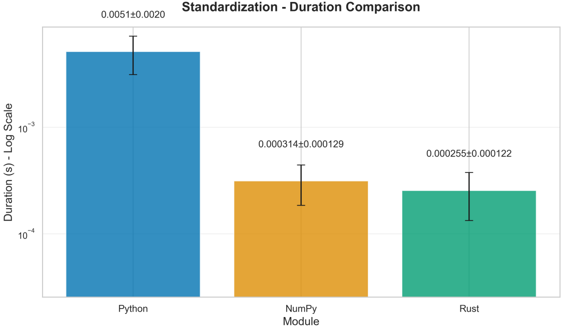

Standardization durations on GunPoint

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Downsampling durations

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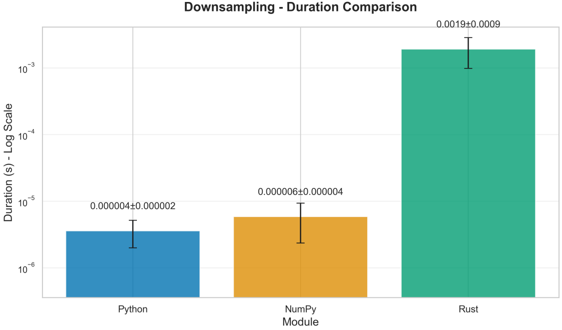

Downsampling durations on GunPoint

Downsampling durations

- **Goal:** Measure downsampling in isolation

Explanation:

- Rust slowest due to costly data copying

Data collection durations

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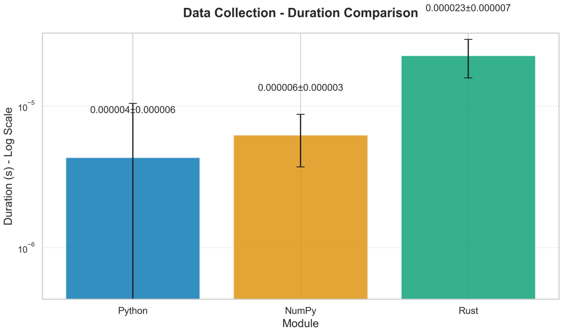
Data collection durations

- **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