# MOABB

## Benchmark your BCI algorithms on a rich collection of Motor Imagery, ERP, SSVEP and c-VEP datasets

Workshop 2: Designing Brain-Computer Interfaces, from theory to real-life scenarios

Pierre Guetschel
**Data-Driven NeuroTechnology Lab**, Radboud University, Donders Institute, Nijmegen, Netherlands
Currently affiliated with META, Paris, France

September 9 — $9^{th}$ Graz BCI Conference 2024

Radboud University Radboudumc

# MOABB

Mother Of All BCI Benchmarks (MOABB)

- Python library
- to compare/benchmark
- classification algorithms
- used for Brain-Computer Interfaces (BCI).

## Design Philosophy

Reproducible research in BCI built on a rich Python ecosystem to design FAIR benchmarks with the help of a community.

# Why Do We Need MOABB?

MOABB

**Reproducible research in BCI has a long way to go...**

- Unavailable code
- Exotic data format/data structure/language/toolboxes
- Preprocessed data (including errors)

**No comprehensive benchmark of BCI algorithms (until last year...)**
**Huge waste of time for everyone**

$\Rightarrow$ **MOABB aims to be the standard benchmark for any new paper**

- Comprehensive benchmark of popular BCI algorithms
- Extensive list of freely available EEG datasets
- Ranking algorithms with fair evaluations

# (Un)reproducible Research in BCI

MOABB

## Design Philosophy

Reproducible research in BCI built on a rich Python ecosystem to design FAIR benchmarks with the help of a community.

# Built on a rich ecosystem

## Design Philosophy

Reproducible research in BCI built on a rich Python ecosystem to design FAIR benchmarks with the help of a community.

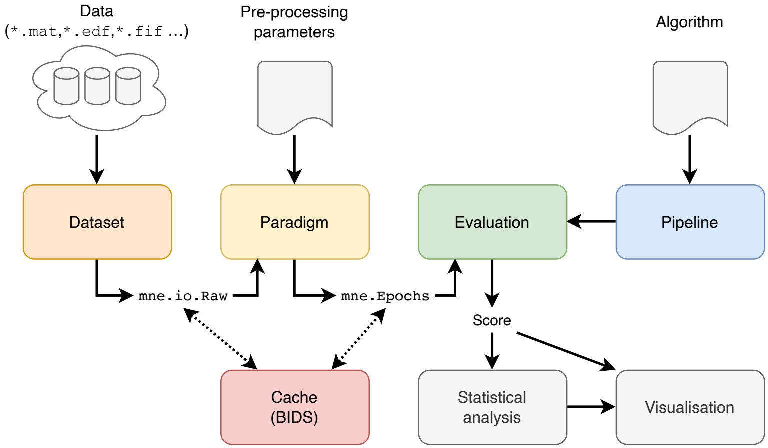
# Framework Architecture

MOABB

## Design Philosophy

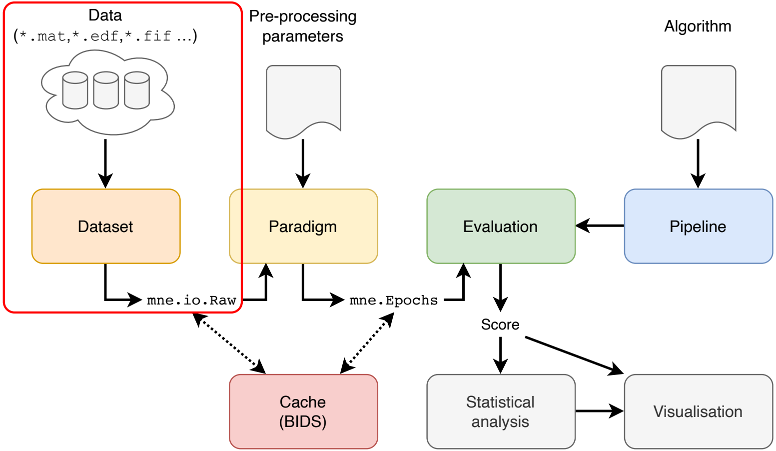
Reproducible research in BCI built on a rich Python ecosystem to design FAIR benchmarks with the help of a community.

# MOABB Architecture




⇒All the components of MOABB

# MOABB Architecture: Datasets




**Dataset**

- Stored locally, converted in MNE format
- Pick only subjects you need

# MOABB Architecture: Datasets

MOABB

**Dataset list**

- Wrapper around any data format (`.mat`, `.edf`, `.fif`, etc.);
- 18 Motor Imagery, 16 ERP, 7 SSVEP and 6 c-VEP datasets available;
- Only public datasets;
- Only un-processed datasets.

# MOABB Architecture: Datasets

MOABB

Dataset list

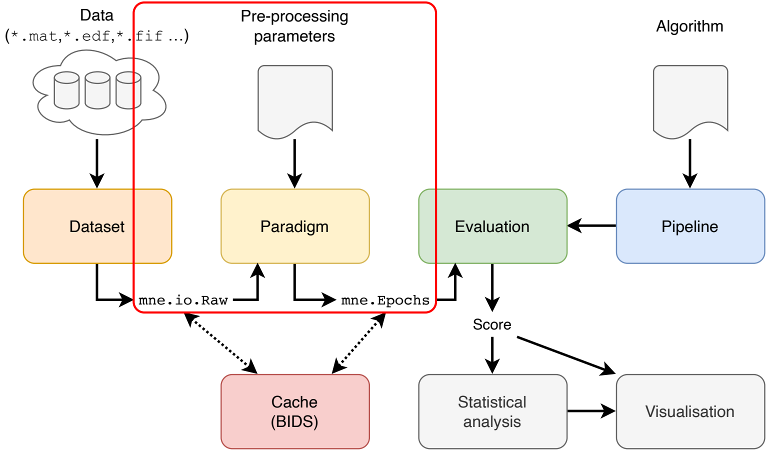
- Wrapper around any data format (.mat, .edf, .fif, etc.);
- 18 Motor Imagery, 16 ERP, 7 SSVEP and 6 c-VEP datasets available;
- Only public datasets;
- Only un-processed datasets.

```python
from moabb.datasets import BNCI2014_001
dataset = BNCI2014_001()
data = dataset.get_data(subjects=[1, 2])

data  # dict[int, dict[str, dict[str, mne.io.Raw]]]
```

Returns nested dictionary containing:

- subjects,
  - sessions of the subjects,
    - and runs within the sessions.

# MOABB Architecture: Paradigm




**Paradigm**

- Motor Imagery, P300, SSVEP, c-VEP
- Preprocessing

# MOABB Architecture: Paradigm

MOABB

```python
from moabb.paradigms import MotorImagery
paradigm = MotorImagery(fmin=1, channels=['C3', 'C4'])
X, labels, metadata = paradigm.get_data(dataset)

X           # numpy.ndarray
labels      # list[str]
metadata    # pandas.DataFrame
```

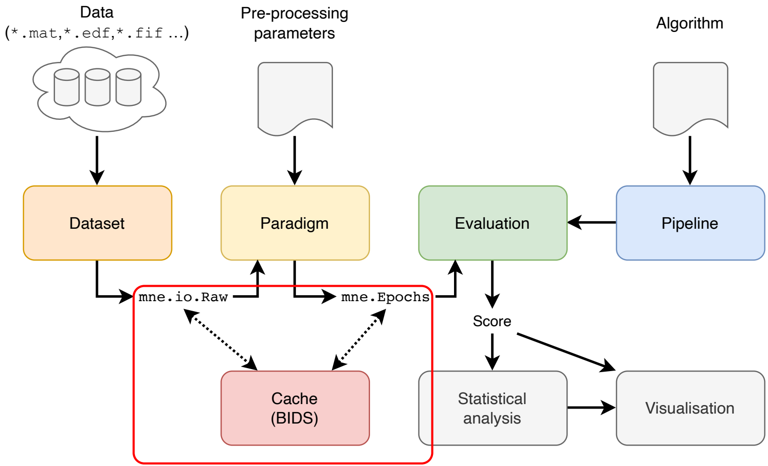
# MOABB Architecture: Paradigm

```
from moabb.paradigms import MotorImagery
paradigm = MotorImagery(fmin=1, channels=['C3', 'C4'])
X, labels, metadata = paradigm.get_data(dataset)

X          # numpy.ndarray
labels     # list[str]
metadata   # pandas.DataFrame
```

Alternatively, you can get MNE epochs:

```
epochs, _, _ = paradigm.get_data(dataset, return_epochs=True)

epochs     # mne.Epochs
```

# MOABB Architecture: Cache ★new★




**Cache**

- Disk cache: **raw** (`.edf`) or **pre-processed** (`_epo.fif` or `.npy`)
- In **BIDS** format for easy export.

# MOABB Architecture: Cache ★new★

MOABB

Time for one subject of Zhou2016

**Without cache** 3.8 seconds

**Raw** 1.4 seconds

```
data = dataset.get_data(
    cache_config={'save_raw': True, 'use': True})
```

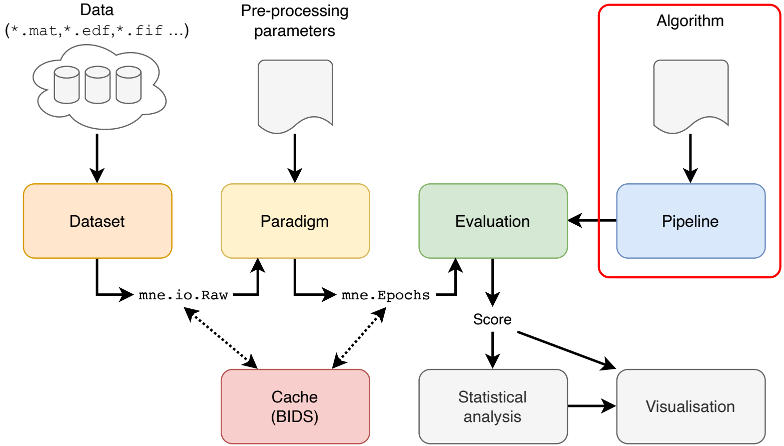
**Epochs** 0.8 seconds

```
epochs, _, _ = paradigm.get_data(
    dataset,
    return_epochs=True,
    cache_config={'save_epochs': True, 'use': True})
```

**Numpy array** 0.6 seconds

```
X, _, _ = paradigm.get_data(
    dataset,
    cache_config={'save_array': True, 'use': True})
```

# MOABB Architecture: Pipelines




**Pipelines**

- All steps required for obtaining a prediction
- Scikit-learn style

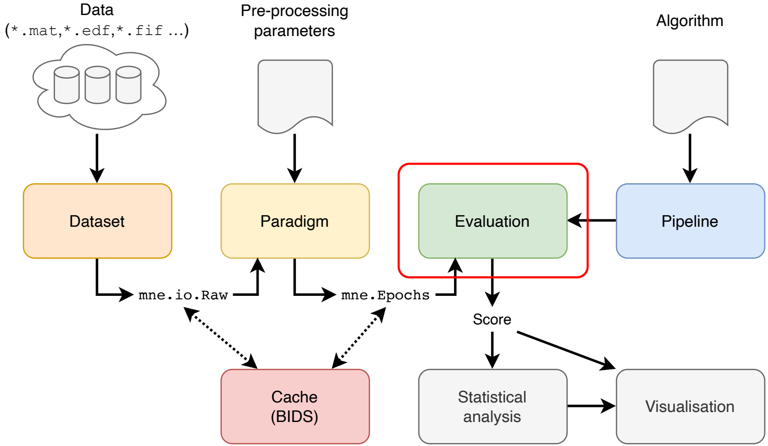
# MOABB Architecture: Pipelines

A Scikit-learn pipeline example:

```python
from moabb.pipelines.features import LogVariance
from sklearn.svm import SVC
from sklearn.pipeline import make_pipeline
classifier = make_pipeline(
    LogVariance(),  # step 1
    SVC(),          # step 2
)

classifier  # sklearn Pipeline
```

# MOABB Architecture: Evaluations

MOABB

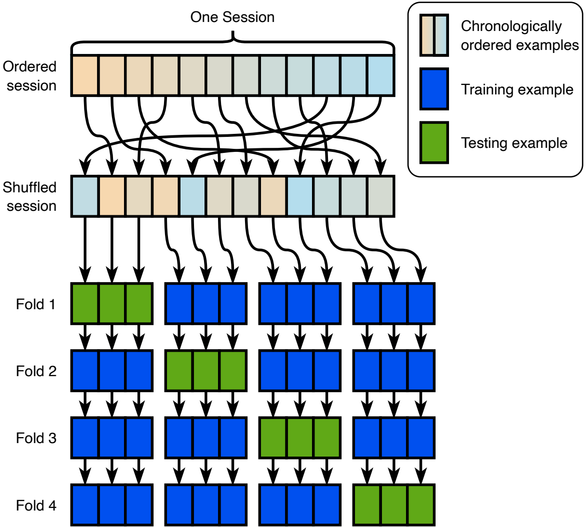



**Evaluations**

- Defines a scoring method (AUC, accuracy, ...)
- within or across session, across-subject, ...

# MOAABB Architecture: Evaluations – Within-Session

- Within-session,
- Shuffled,
- 5-folds cross-validation.

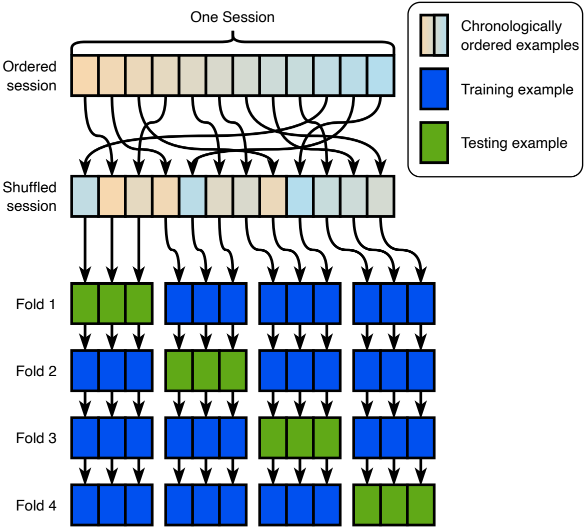


# MOABB Architecture: Evaluations – Within-Session

- Within-session,
- Shuffled,
- 5-folds cross-validation.

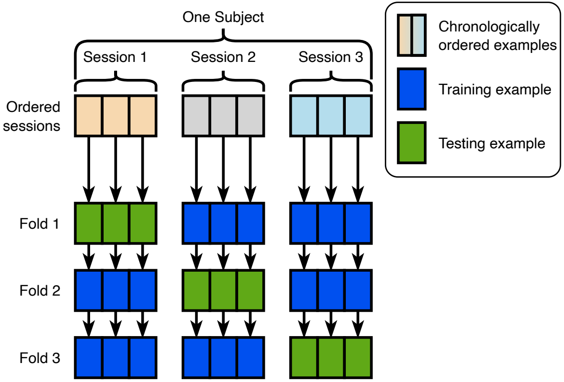
**Arriving soon:**

- Within-session,
- Pseudo-online evaluation,
- (respecting chronological aspect of data).



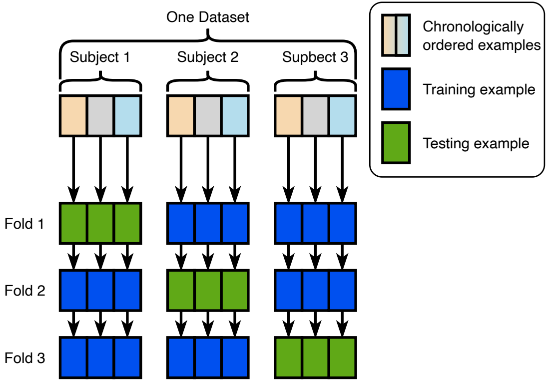
# MOABB Architecture: Evaluations – Cross-Session

- Within-subject,
- Leave-one-session-out cross-validation.



# MOAABB Architecture: Evaluations – Cross-Subject

- Within-dataset,
- Leave-one-subject-out cross-validation.



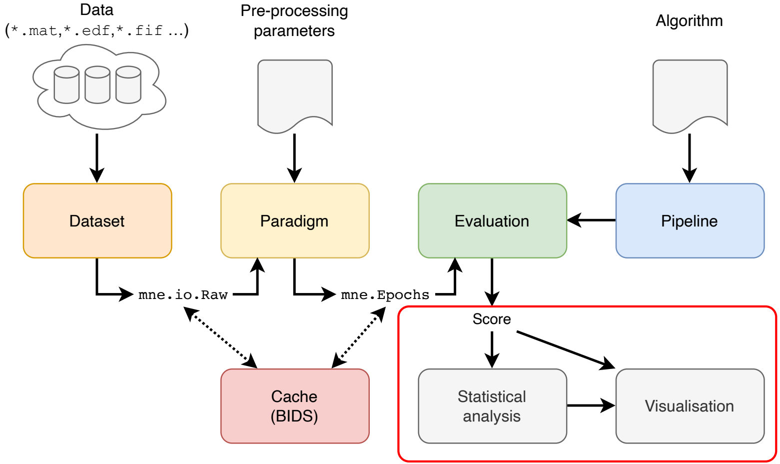
# MOABB Architecture: Evaluations

```python
from moabb.evaluations import WithinSessionEvaluation
evaluation = WithinSessionEvaluation(
    paradigm=paradigm, datasets=[dataset])
results = evaluation.process({'AM+SVM': classifier})

results  # pandas.DataFrame
```

Results are easy to save as `.csv`

```python
results.to_csv('my_results.csv')
```

# MOABB Architecture: Results

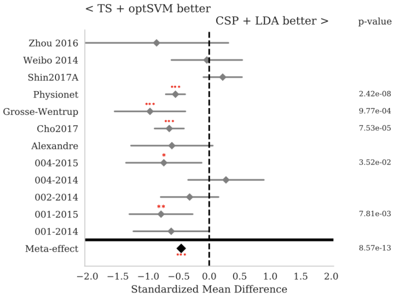


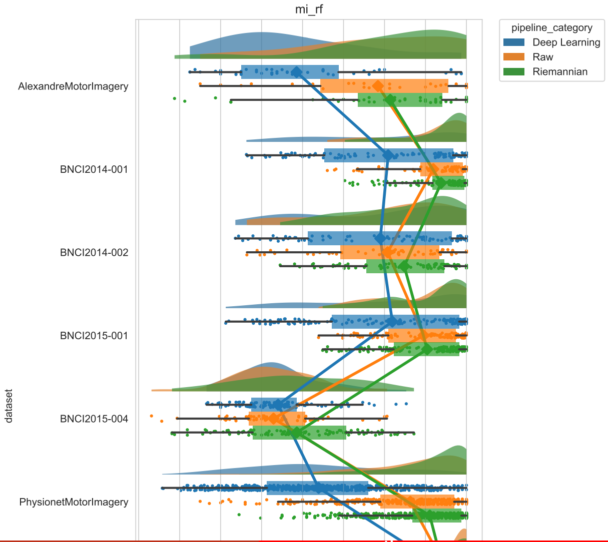

**Results**

- Statistics & visualization
- Results are store in a DataFrame

# Fair and Reproducible Benchmarks

1. Load multiple datasets
2. Apply pipelines
3. Run meta-analysis and plot



# Community of MOABB

MOABB

## Design Philosophy

Reproducible research in BCI built on a rich Python ecosystem to design FAIR benchmarks with the help of a community.

# An NTX Community Project

## Maintainers:

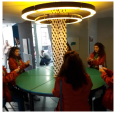
Sylvain Chevallier

Bruno Aristimunha

Igor Carrara

Pierre Guetschel

Sara Sedlar



Bruna Junqueira Lopes

Sébastien Velut

## Founders:

Alexandre Barachant

Vinay Jayaram

## Contributors:

# The largest BCI benchmark ★new★

## Already in pre-print

Chevalier et al. (2024). *"The largest EEG-based BCI reproducibility study for open science: the MOABB benchmark"*. `arXiv:2404.15319`

- We benchmarked 30 machine learning pipelines:
  - 13 Riemmanian,
  - 11 raw signal,
  - and 6 deep learning.
- On 36 public datasets:
  - 14 motor imagery,
  - 15 P300,
  - 7 SSVEP.

# How To Get Started or Contribute

**Getting-started tutorial**

Check the github and the documentation

- `https://github.com/NeuroTechX/moabb`
- `https://neurotechx.github.io/moabb/`

Discuss during Office Hours or on Gitter

- `https://github.com/NeuroTechX/moabb/issues/191`
- `https://gitter.im/moabb_dev/community`

Possible contributions:

- Add new datasets,
- Add working examples and use cases,
- Help on character-level decoding of ERP and c-VEP,
- ...

Thank you !