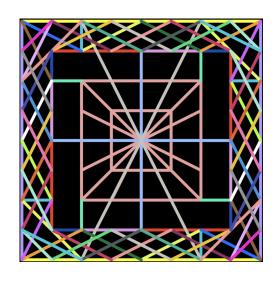
Accelerating scientific Python code with dispatching: Graphs and Arrays

- By Aditi Juneja and Sebastian Berg

Aditi Juneja (@Schefflera-Arboricola)

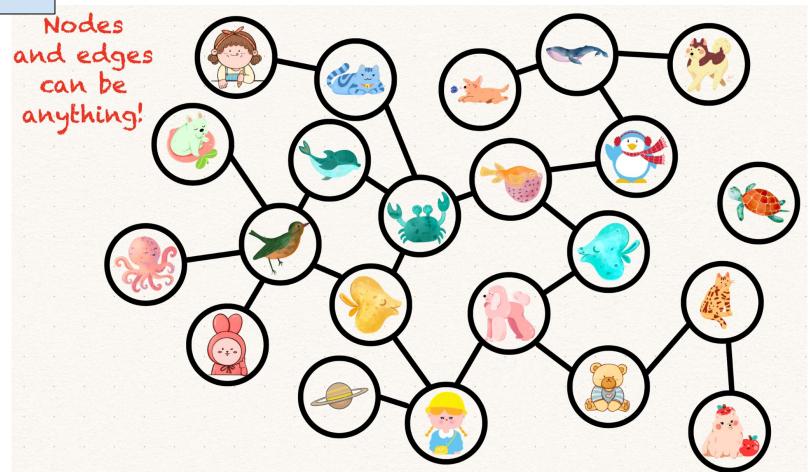
- **Grants/programs**: Google Summer of Code 2024, NumFOCUS's Small Development Grant (R3, 2024), CZI (NetworkX Internship)
- Open-source projects/contributions: nx-parallel, NetworkX (Core developer), scikit-image (dispatching), other small small contributions in various scientific Python projects!
- Communities and Volunteering roles: SciPy India (core-organiser), GSoC 2025 mentor (NetworkX), SciPy 2025 (proceedings paper reviewer), Scientific Python (maintainer dispatch team), IndiaFOSS 2025 ("FOSS in Science" devroom manager), PyDelhi (reviewer), PyData Global 2024 (reviewer), PyCon US 2025 (proposal mentor)



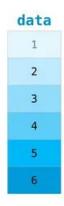
Find more about my work at https://github.com/Schefflera-Arboricola/blogs

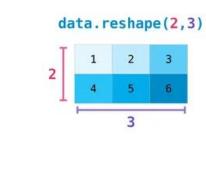
Accelerating scientific Python code with dispatching: Graphs and Arrays

Graphs

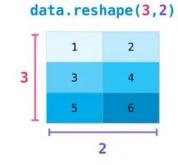


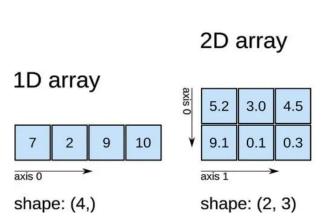
Arrays

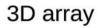


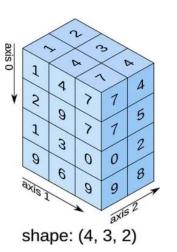


3









Dispatching??

Arriving Sunday





Apsara Dustless Chalks | 4x Longer Than Regular Chalks | Hypoallergenic Chalk for Safe Using | Non-dust Chalk for Clean Writing | Available in Vibrant Colors | Ideal for Schools Box of 100 Chalks.

Sold by: Cocoblu Retail

₹343.00

Track package

Request cancellation

Return or replace items

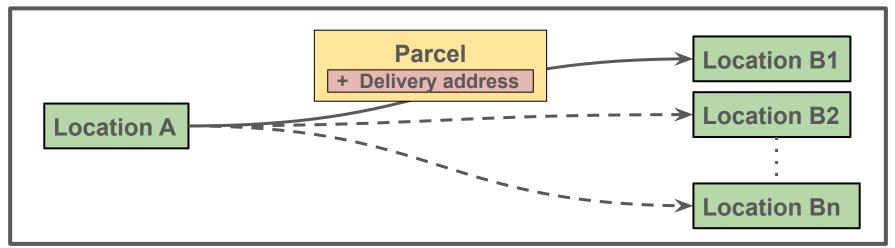
Share gift receipt

Leave seller feedback

Write a product review

Dispatching- in general





Dispatching – in programming

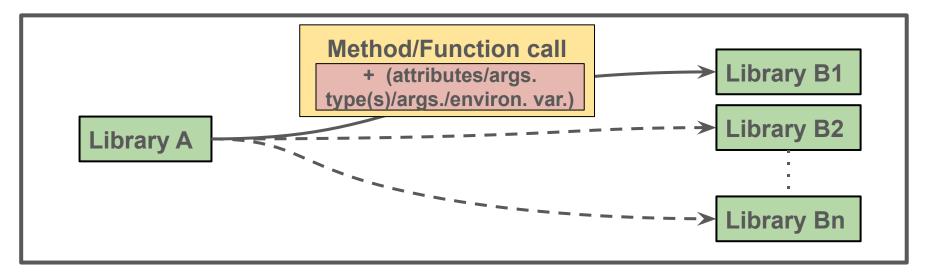
"In computer science, **dynamic dispatch** is the process of selecting which implementation of a polymorphic operation (method or function) to call at <u>run</u> <u>time.</u>"

Ref. https://en.wikipedia.org/wiki/Dynamic_dispatch

Dispatching – in programming

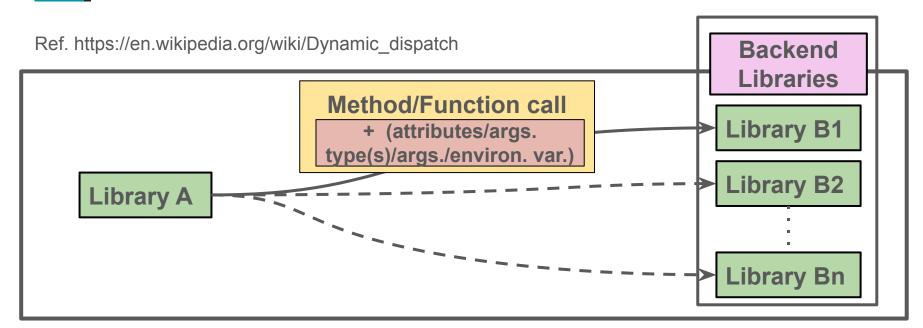
"In computer science, **dynamic dispatch** is the process of selecting which implementation of a polymorphic operation (method or function) to call at <u>run</u> <u>time.</u>"

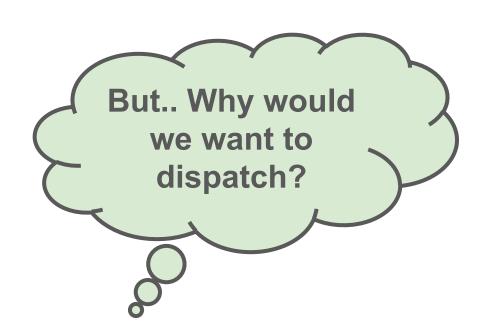
Ref. https://en.wikipedia.org/wiki/Dynamic_dispatch



Dispatching – in programming

"In computer science, **dynamic dispatch** is the process of selecting which implementation of a polymorphic operation (method or function) to call at <u>runtime</u>."







Improve Performance

Type Compatibility

Enable different workflows



And how do we do it?

Example

What does dispatching mean here?

```
library_A

def add(x, y, z):
    return x + y + z
```

Importing and Calling (hard-coded)

Importing and Calling (hard-coded)

library_A

```
def add(x, y, z, libB=None):
    if libB == "library B1":
        import library B1 as libB1
        z = float(z)
        return libB1.mod1.add(x, y, z)
    elif libB == "library B2" :
    else:
        return x + y + z
```

Importing and Calling (hard-coded)

Inside `library_A`

```
def add(x, y, z, libB=None):
    if libB == "library B1":
        import library B1 as libB1
        z = float(z)
        return libB1.mod1.add(x, y, z)
    elif libB == "library B2" :
    else:
        return x + y + z
```

Can we make this more general?

Steps involved

```
library A
                                                 Get `libB`
def add(x, y, z, libB=None):
                                                Import `libB`
     if libB == "library B1":
         import library B1 as libB1
         z = float(z)
                                                Convert args for `libB`
         return libB1.mod1.add(x, y, z)
     elif libB == "library B2" :
     . . .
                                                Find 'add' in 'libB' and call
     . . .
                                                it with converted args
     else:
         return x + y + z
```

Steps involved

... maybe we can delegate some of these steps to `libB`...

```
library A
                                                  Get 'libB'
def add(x, y, z, libB=None):
                                                  Import `libB`
     if libB == "library B1":
          import library B1 as libB1
          z = float(z)
                                                 Convert args for 'libB'
          return libB1.mod1.add(x, y, z)
     elif libB == "library B2" :
     . . .
                                                  Find 'add' in 'libB' and
     . . .
                                                  call it with converted
     else:
                                                  args
         return x + y + z
```

Step 4: Find 'add' in 'libB' and call it

Inside `library_A`

```
def add(x, y, z, libB=None):
    if libB == "library B1":
        import library B1 as libB1
        z = float(z)
        return libB1.mod1.add(x, y, z)
    elif libB == "library B2" :
    else:
        return x + y + z
```

Find 'add' in 'libB' and call it with converted args

Step 4: Find 'add' in 'libB' and call it

```
Inside `library_A`
```

```
def add(x, y, z, libB=None):
    if libB == "library B1":
        import library B1 as libB1
        z = float(z)
        all funcs = libB1. all funcs ()/
        libb1 add = all funcs.add
        return libb1 add(x, y, z)~
    elif libB == "library B2" :
    . . .
    else:
        return x + y + z
```

Get a namespace* of all the functions in `libB1`

Extract `add` from this namespace

Call the extracted 'add'

*Assumption: all functions in the namespace have unique names

Step 3: convert args for 'add' in 'libB'

```
Inside `library A`
 def add(x, y, z, libB=None):
     if libB == "library B1":
         import library B1 as libB1
                                             Convert args for 'libB'
         z = float(z)
         all funcs = libB1. all funcs ()
         libb1 add = all funcs.add
         return libb1 add(x, y, z)
     elif libB == "library B2" :
     else:
         return x + y + z
```

Step 3: convert args for 'add' in 'libB'

Inside `library_A`

```
def add(x, y, z, libB=None):
    if libB == "library B1":
        import library B1 as libB1
        x, y, z = libb1.convert args(add, <math>x, y, z)
        all funcs = libB1. all funcs ()
        libb1 add = all funcs.add
        return libb1 add(x, y, z)
    elif libB == "library B2" :
    else:
        return x + y + z
```

Convert function in `libB`

```
Inside `library A`
 def add(x, y, z, libB=None):
     if libB == "library B1":
                                                      Import `libB`
          import library B1 as libB1
         x, y, z = libb1.convert args(add, <math>x, y, z)
         all funcs = libB1. all funcs ()
         libb1 add = all funcs.add
          return libb1 add(x, y, z)
     elif libB == "library B2" :
     else:
         return x + y + z
```

```
Inside `library A`
                                                 Generalising importing
 def add(x, y, z, libB=None):
     lib = import (libB)_
     if libB == "library B1":
         x, y, z = lib.convert args(add, x, y, z)
         all funcs = lib. all funcs ()
         lib add = all funcs.add
         return lib add(x, y, z)
     elif libB == "library B2" :
     else:
         return x + y + z
```

```
Inside `library A`
                                                 Generalising importing
 def add(x, y, z, libB=None):
     lib = import (libB)_
     if libB == "library B1":
         x, y, z = lib.convert args(add, x, y, z)
                                                           Implication:
         all funcs = lib. all funcs_()
                                                           code inside
         lib add = all funcs.add
                                                           if-else also
         return lib add(x, y, z)
                                                           became
     elif libB == "library B2" :
                                                           generalised
     else:
         return x + y + z
```

Inside `library_A`

```
def add(x, y, z, libB=None):
    if libB != None:
        lib = import (libB)
        x, y, z = lib.convert args(add, x, y, z)
        all funcs = lib. all funcs ()
        lib add = all funcs.add
        return lib add(x, y, z)
   else:
        return x + y + z
```

Generalising importing

Getting rid of `if-else` conditions

Can we do something more here?

Inside `library_A`

```
def add(x, y, z, libB=None):
    if libB != None:
        lib = import (libB)
        x, y, z = lib.convert args(add, <math>x, y, z)
        all funcs = lib. all funcs ()
        lib add = all funcs.add
        return lib add(x, y, z)
    else:
        return x + y + z
```

Dispatching

Yes! Decorators. Generalising for all functions

Inside `library_A`

```
@_dispatchable
def add(x, y, z):
    return x + y + z
```

```
def dispatchable():
    @functools.wraps(func)
   def wrapper(*args, **kwargs):
        # check for libB kwarg in the function signature
        libB = kwarqs.get("libB")
       try:
           lib = import (libB)
            args = lib.convert args(func, *args, **kwargs)
            all funcs = lib. all funcs ()
           lib func = all funcs.func
            return lib func(args)
        except ImportError:
             return func(*args, **kwargs)
    return wrapper
```

*there are other ways of dispatching as well.

How is dispatching done in real projects?

Some projects we'll discuss:

- Graphs: **NetworkX**
- Arrays:
 - NumPy dispatching : __array_function__
 - Array API standards
 - Scikit-image

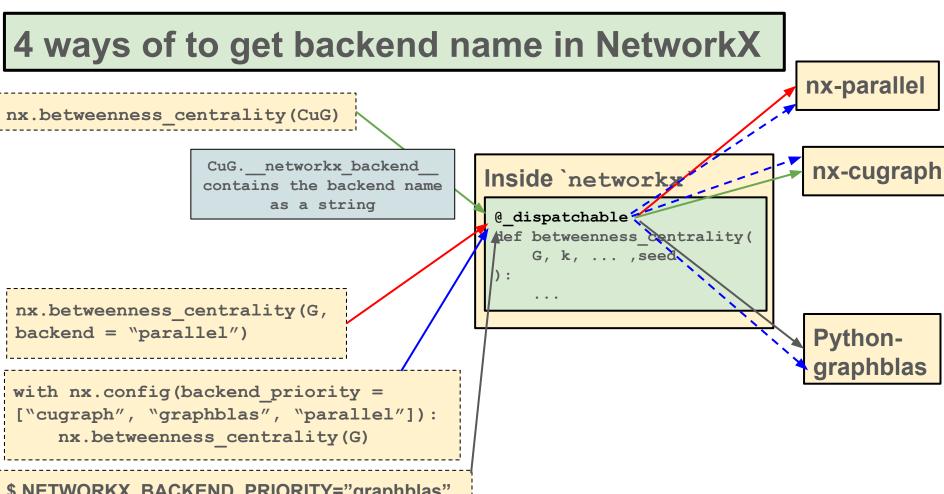
Dispatching in NetworkX for Graphs

What is NetworkX?

NetworkX is a network/graph analysis library

Demo

https://colab.research.google.com/drive/1n1oqMr BXdg7RSaM8eZpwM07utaEru9?usp=sharing



\$ NETWORKX_BACKEND_PRIORITY="graphblas" python nx_code.py

4 ways of to get backend name in NetworkX nx-parallel nx.betweenness centrality(CuG) CuG. networkx backend nx-cugraph Type-based Inside `networkx contains the backend name dispatching as a string @ dispatchable def betweenness centrality(G, k, ... , seed Name-based nx.betweenness centrality(G, dispatching backend = "parallel") Pythongraphblas with nx.config(backend priority = ["cugraph", "graphblas", "parallel"]): nx.betweenness centrality(G)

\$ NETWORKX_BACKEND_PRIORITY="graphblas" python nx_code.py

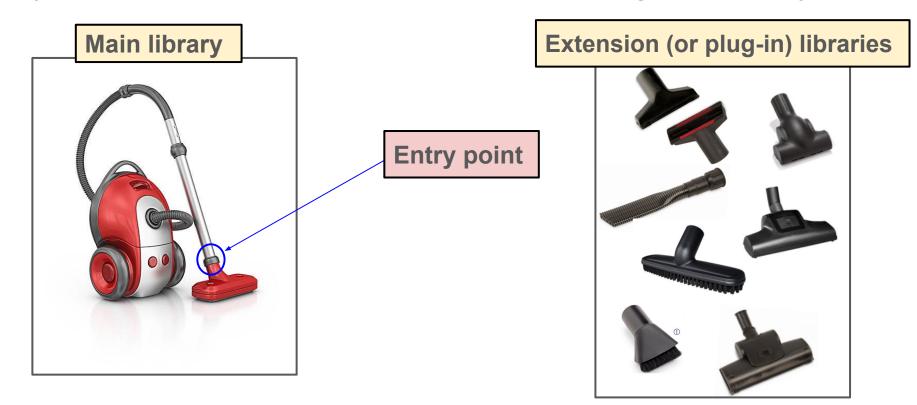
Getting the backend implementation

Python entry-points to get all the installed backends...

... and their metadata – supported functions and convert functions.

What are entry-points?

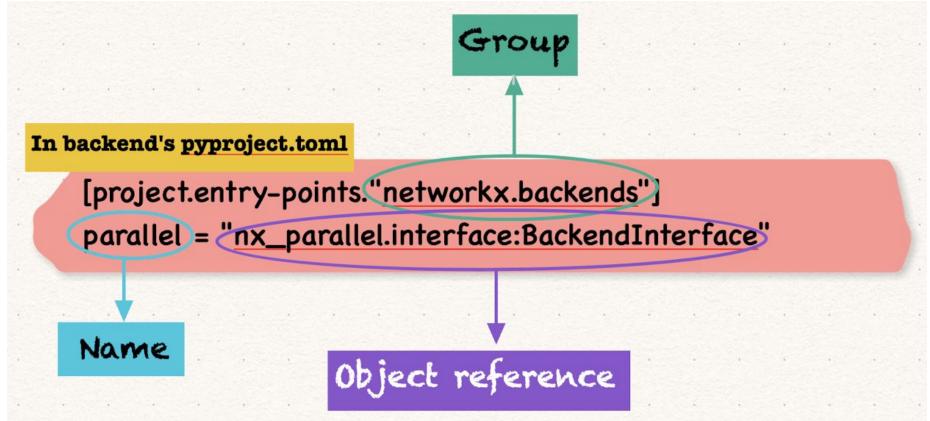
Entry-points are used to extend a functionality of a library.



Dispatching with entry-points is exploiting entry-points to the max-

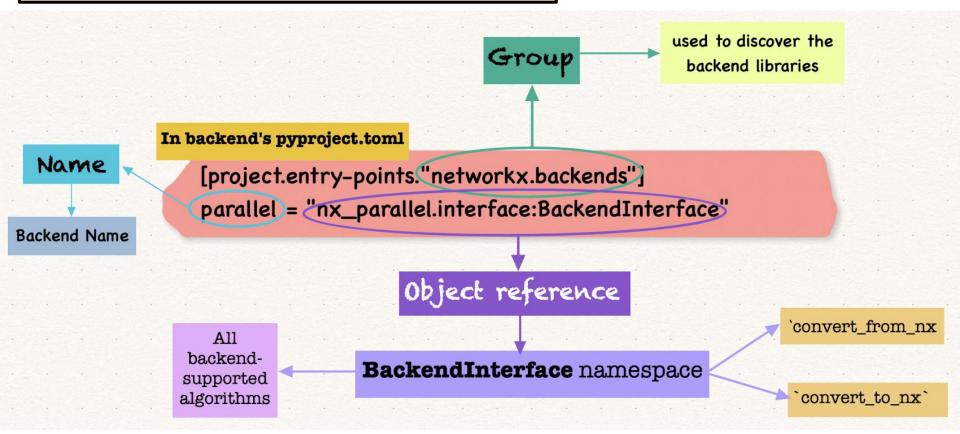
i.e. change the whole machinery inside the vacuum cleaner (main library's implementation)— and just keep the outside red UI-plastic-buttons frame (user-API).

Inside nx-parallel backend



ref. https://packaging.python.org/en/latest/specifications/entry-points/

Inside nx-parallel backend



ref. https://packaging.python.org/en/latest/specifications/entry-points/

In NetworkX

```
>>> from importlib.metadata import entry points
>>> entry points(group="networkx.backends")
    EntryPoint(
         name="parallel",
        value="nx parallel.interface: BackendInterface",
         group="networkx.backends",
    ) ,
    EntryPoint (
        name="cugraph",
        value="nx cugraph.interface: BackendInterface",
        group="networkx.backends",
```

Other features of NetworkX dispatching (if time permits)

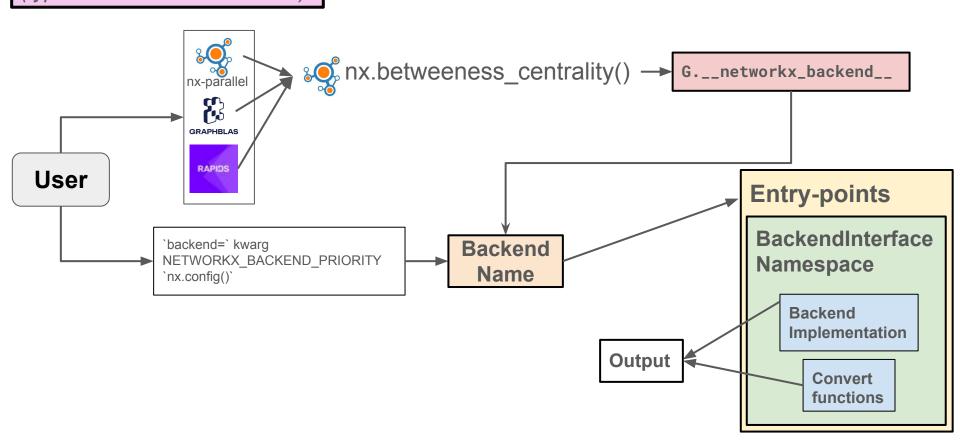
- can_run and should_run : quick checks by backend to optimise dispatching workflow
- Testing backend on NetworkX's test suite NETWORKX_TEST_BACKEND="parallel"
- Showing Backend docs in NetworkX docs (<u>see here</u>)
- Caching of converted graphs
- `.backends` attribute to get the set of all the installed backends that implement a particular function. For example:

```
>>> nx.betweenness_centrality.backends
{'parallel'}
```

- Specialised backend priority for algorithms, generators,.. etc.
- Logging
- Fallback

NetworkX

(type-based and name-based)

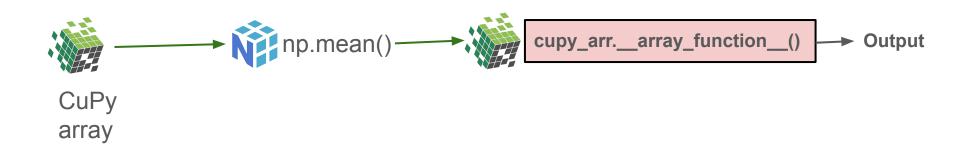


Dispatching in NumPy and for Arrays

Disclaimer: I'm not an expert in arrays or array dispatching. It is just a brief introduction!

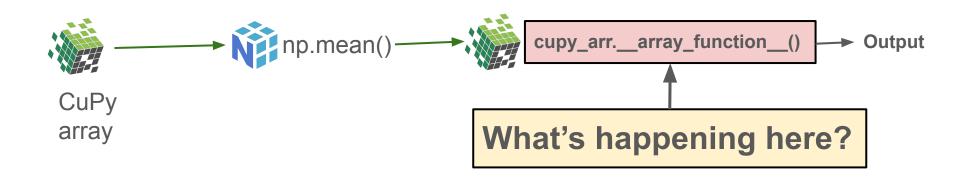
NumPy Dispatching

directly calls the apt. array library's implementation, corresponding to the function that's being called, if it exists.



NumPy Dispatching

directly calls the apt. array library's implementation, corresponding to the function that's being called, if it exists.



Inside the CuPy (simplified)

```
class ndarray:
  def __array_function__(self, func, types, *args, **kw):
      if not supported_function(func):
          return NotImplemented
      for t in types: # checking array types
          if not issubclass(t, (ndarray, numpy.ndarray)):
               return NotImplemented
      return cupy.func(*args, **kw)
```

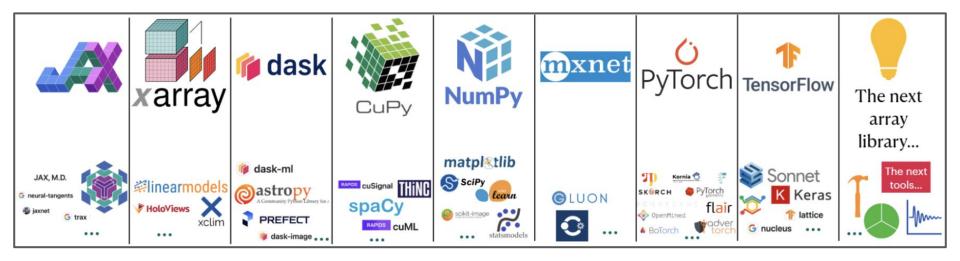
Some drawbacks...

No fallbacks!

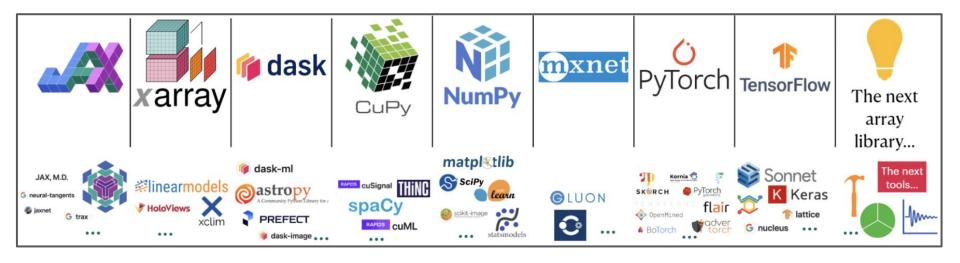
Not a nice API: NumPy returning CuPy arrays Other array libraries might have additional functionality on top of NumPy.

Array API Standards

Ecosystem of Array Libraries



Ecosystem of Array Libraries



Goal: Array agnostic functionality

Borrowed from Lucas Colley's EuroSciPy 2025 talk: https://lucascolley.github.io/talks/euroscipy-25-array-api/

Ecosystem of Array Libraries

Array (producer) libraries



Array consuming libraries

Borrowed from Aaron Meurer's SciPy 2023 talk: https://youtu.be/16rB-fosAWw?si=dzQ VUGW7h25AG4i

Array API Standards

- Standard API guidelines for array producer libraries, for e.g., function names, argument names, etc.
- `__array_namespace__` for array consuming libraries to easily use all the supported functions
- But, it is just a standardisation guidelines adopting it doesn't guarantee interoperability with all kinds of array libraries

How to adopt it?

Array consuming library

```
import numpy as np

def covariance(x, y):
    mean_x, mean_y = np.mean(x), np.mean(y)
    cov = np.mean((x - mean_x) * (y - mean_y))
    return cov
```

How to adopt it?

Array consuming library

```
def covariance(x, y):
    xp = x.__array_namespace__()

    mean_x, mean_y = xp.mean(x), xp.mean(y)
    cov = xp.mean((x - mean_x) * (y - mean_y))
    return cov
```

How to adopt it?

Array consuming library

```
def covariance(x, y):
    xp = array_api_compat.array_namespace(x, y)

    mean_x, mean_y = xp.mean(x), xp.mean(y)
    cov = xp.mean((x - mean_x) * (y - mean_y))
    return cov
```

*array-api-compat

Ref. https://github.com/data-apis/array-api-compat

Dispatching in scikit-image

Dispatching in scikit-image

- **Challenge**: Hard to adopt Array API standards (Cython-heavy array consuming library)— therefore using entry-points for dispatching.
- Goal: want it to look like type-based dispatching internally entry-point based dispatching.
- Current state: No array conversions in dispatching code! backend developers and users need to take care of the types. (<u>Read more</u>)

Possible Solution: https://github.com/scientific-python/spatch

Some more resources:

- SPEC 2: https://scientific-python.org/specs/spec-0002/
- spatch : https://github.com/scientific-python/spatch/
- Array API standards: https://data-apis.org/array-api/latest/
- NumPy's type-based dispatching
 - https://numpy.org/neps/nep-0037-array-module.html
 - https://numpy.org/neps/nep-0047-array-api-standard.html
- NetworkX
 - https://networkx.org/documentation/latest/reference/backends.html
 - https://networkx.org/documentation/latest/reference/configs.html
 - Dispatch meetings: https://scientific-python.org/calendars/networkx.ics
 - https://github.com/networkx/networkx/issues?g=is%3Aissue%20state%3Aopen%20label%3ADispatching
 - Scikit-image
 - https://scikit-image.org/docs/dev/development/dispatching.html
 - https://github.com/rapidsai/cucim/issues/829
 - Scikit-learn
 - https://scikit-learn.org/stable/modules/array_api.html
 - https://youtu.be/f42C1daBNrg?si=A9mZ2mZd2HzEhu8S
 - SciPy's Array API adoption
 - https://docs.scipy.org/doc/scipy/dev/api-dev/array api.html
 - https://youtu.be/16rB-fosAWw?si=ys -ZTnUKvO aZKu
 - DataFrame API standards
 - https://github.com/narwhals-dev/narwhals
 - https://data-apis.org/dataframe-api/draft/
 - Scientific Python discord(#dispatching thread): https://discord.com/invite/vur45CbwMz
- https://github.com/scikit-hep/ragged?tab=readme-ov-file https://github.com/Saransh-cpp/SwissPythonSummit25-GLASS-array-api