

python™

Parallel Computing in Python

PRACE Winter School 2017 @ Tel-Aviv/Israel

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All material is under



Few Words

- I'm a graduate student @ Geophysics, Tel-Aviv University
- Dealing with physics, geophysics & applied mathematics
- Parallel computing is essential in my work
- Participated in PRACE Summer of HPC 2013
- **Don't miss a chance to take part**
- Registration ends by 19/2
- **Apply here:**
 - <https://summerofhpc.prace-ri.eu/apply>
- You would enjoy it, and if not I'm here to complain...



Why Are We Here?

- Python is very popular, simple and intuitive
- Increasing use in many fields of research & industry
- Open-source and free
- Many toolboxes available in almost every field
 - NumPy/SciPy are prerequisite for scientists
 - Replacement for MATLAB/Mathematica (to some extent)
- Natural to ask if parallel computing can be simpler too
 - Indeed yes!
 - And also take advantage of existing C/Fortran code

(My) Audience Assumptions

- Some may know python
 - But not much of its multiprocessing capabilities
- Some may know parallel computing
 - But not quite familiar with python
- Working in Linux environments
 - Not mandatory but highly advised
- Knowing a descent programming language

(My) Workshop Goals

- Don't worry
- The workshop was designed for introductory purposes
- First basic theory, then practical hands-on session
- Hands-on will be in different levels (3 as usual)
 - **Basic** – for those who make their first steps
 - **Intermediate** – for those with moderate programming familiarity
 - **Advanced** – for those who are proficient in python

Agenda

- Introduction To Python
 - The Interpreter Concept
 - Scientific Computing
- Python <-> C Interoperability Overview
- Node-Level Parallel Processing
 - “**multiprocessing**” Module
- Cluster-Level Parallel Processing
 - IPython “**ipyparallel**” Package
 - MPI Support Using “**mpi4py**”

- Basic Python & NumPy/SciPy
- Motivation

INTRODUCTION

Python in High-Level

- Is a script based, interpreted language
- Very common in technology (websites etc.)
- Highly popular in recent years for many purposes

- Shares very intuitive syntax
- Still with advanced features (~OOP etc.)

- Two versions:
 - 2.7 – Providing legacy support and actively maintained
 - 3 – New features, new python, better target for it

- All our examples will work on both versions

Meet the Interpreter

- The interpreter is responsible for running our code
 - Either if it's interactive
 - Or running a script from a shell

- Issue the interpreter (Python 2) by running:

```
# python <optional_script_file>
```

- Or for Python 3:

```
# python3 <optional_script_file>
```

Meet the Interpreter (Cont.)

- A much nicer interpreter is “**idle**” or even “**idlespork**”
 - Remembers past statements
 - Auto statement completion
 - Code editing and running
- Some good IDE’s:
 - PyCharm (the best so far)
 - Microsoft Visual Studio Code (supports Linux & Mac as well!)

Python Syntax & Reference

- The web is full of perfect guides to python
- Including the main website: <http://www.python.org>
- You may consult for any issue

Scientific Computing

- An essential suite of packages for researchers:
 - **NumPy** (<http://www.numpy.org>)
 - **SciPy** (<http://www.scipy.org>)
 - **matplotlib** (<http://www.matplotlib.org>)
 - **SymPy** (Symbolic expressions, equations, integrals etc.)
- Can be used immediately after downloading and installing

Scientific Computing (Cont.)

- For those who consider migrating from MATLAB
- Most functions are available with similar names and semantics
- Support for Linear Algebra, Statistics, Optimization...
 - Just name it
- Again, the web is full of examples and great documentation
- Including full source code

Motivation (restated)

- Considering all that...
- We have state-of-the-art simulations
- Usually written to run on a single CPU core (serial)
- But this is not enough

- We would like to:
 1. Take advantage of all CPU cores
 2. Perhaps even utilize other computers as well
 3. Pass **NumPy** and python objects seamlessly
 4. Maintain simple & scalable code
 5. And much more (don't get greedy though)

“No Free Lunch” Theorem

- Parallel programming is not easy at all
- In fact it is the most complex task in programming
 - We will deal with task parallelization mostly
 - **Not** the usual “*OpenMP*” approach (*parallel for*)
- Python is a very high-level language
- Performance is sacrificed for faster coding
 - Don’t expect same performance as true C/C++/Fortran code
 - But writing and debugging it will be about 10x faster if not more
- We’ll see in a minute that python can interface native code
- So performance isn’t much sacrificed

- Python <-> C/Fortran Interoperability
- “ctypes” module

PYTHON <-> C

Motivation

- A significant amount of code is still written in C/Fortran
- Scientific code runs much faster in native code
 - Keep performance-critical code in C/Fortran
 - Manage the rest of simulation including I/O in python
- Pass NumPy/SciPy data structures to native code
 - But avoid data transfer overhead
- Keep elegant code
- All this can be accomplished using “**ctypes**” module

Fortran Disclaimer

- C and Fortran are very much alike
- We'll focus on C interoperability
- Although it can all be accomplished with Fortran as well

“ctypes” Module

- A standard built-in python module
- Provides python data types that match C:
 - Primitive types: `c_int`, `c_int16`, `c_float`, `c_size_t` ...
 - Define structures, unions, arrays, pointers
- Functions:
 - Call C functions (system, e.g. `printf`, and custom)
 - Access to Windows API (on Windows)
 - Pass python callbacks to C
- And much more

Immediate Benefits

- The calling code is pure python
- No CPython nightmare

- NumPy arrays are C allocated pointers
- Pass NumPy array to C transparently
- Minimal performance overhead

- A note to Fortran programmers:
 - Possible to allocate column-major NumPy arrays
 - Native processing in Fortran
 - No transposing etc.

Example

- Assume the following C function:

```
#include <stddef.h>
```

```
double sum_my_numbers(double* numbers, size_t N)
{
    double result = 0.0;
    size_t i;

    for (i = 0; i < N; i++)
        result += numbers[i];

    // Nasty, change one element.
    numbers[N/2] = - numbers[N/2];

    return result;
}
```

Example (Cont.)

- Let's save the function in *funcs.c*
- Compile it to SO (Unix **S**hared **O**bject, aka DLL):

```
# gcc -fPIC funcs.c -shared -o libfuncs.so
```
- Note that since the file has "**c**" extension the function is automatically exposed
- And given the actual name we chose (name mangling)
- With "**cpp**" files, must prefix the function with **extern "C"**
- Otherwise it will be cumbersome to load it in python

Example (Cont.)

- Now we want to call it from python...

```
from ctypes import CDLL, POINTER, c_double, c_size_t
import numpy as np
```

```
# Open the SO.
```

```
my_lib = CDLL('./libfuncs.so')
```

```
# Configure function parameters and return type.
```

```
my_lib.sum_my_numbers.argtypes = [POINTER(c_double), c_size_t]
```

```
my_lib.sum_my_numbers.restype = c_double
```

```
# Create a native array of 100 elements, fill with values and get pointer.
```

```
arr = np.linspace(5, 50, 100, dtype=np.double)
```

```
arr_ptr = arr.ctypes.data_as(POINTER(c_double))
```

```
# Call function and print result.
```

```
print(my_lib.sum_my_numbers(arr_ptr, len(arr)))
```

CDLL SO Handling in Linux

- **CDLL** cannot find custom SO files automatically
- Options:
 1. Specify exact path in **CDLL** creation
 2. Specify path in **LD_LIBRARY_PATH** prior to invoking python

Conclusion

- We've seen direct integration of NumPy and C
- **ctypes** is very mature and provides advanced features
- Consult online documentation for further topics

- Sometimes it might still be necessary to use CPython
 - (cases of interpreter lock "GIL" etc.)
- Hope you will not get to that point

- “multiprocessing” module

NODE-LEVEL PARALLEL COMPUTING

“multiprocessing” Module

- A standard built-in python module
- Provides **process** level parallelization (SPMD class)
- Simply distributing functions among CPU cores
- Includes many advanced constructs:
 - Synchronization
 - Message Passing
 - Shared memory
- **Important** technical caveat:
 - Can only be used with scripts that include a “main”
 - => Cannot be used from the interpreter ☹️

Example Task

- Let's write a function that computes the STD and VAR of randomly generated samples:
 - Accepts a number **N** as input (number of samples to generate)
 - Generates N random samples (of some distribution)
 - Computes the STD and VAR of the samples
 - Returns the results
- We'll write a script that loops over the function with different values of N

Sample Code

```
import numpy as np
from time import clock

def my_statistics(N):
    samples = np.random.randn(N)
    return (N, np.std(samples), np.var(samples))

if __name__ == '__main__':
    tic = clock()
    # Randomize about 1M samples in 10 iterations.
    for N in range(1000000, 1000010):
        print(my_statistics(N))
    toc = clock()
    print('Total runtime: %f s' % (toc - tic))
```

Parallelization with Pool

- **Pool** is a special class in the “**multiprocessing**” module

- Allocates a predetermined number of workers:

```
pool = Pool(6) # Create a pool of 6 workers
```

- Or dynamically by the number of CPU cores:

```
pool = Pool(cpu_count() - 1)
```

- Distributes function calls among the workers
- A result is returned per function call (if needed)

Example

- Most of the sample code remains the same

...

```
from multiprocessing import Pool, cpu_count
```

```
if __name__ == '__main__':
```

```
    tic = clock()
```

```
    # Create a list of arguments for distribution.
```

```
    args = [N for N in range(1000000, 1000010)]
```

```
    # Create a pool, leaving 1 core free for the OS.
```

```
    pool = Pool(cpu_count() - 1)
```

```
    # Run my_statistics in parallel, each worker receives single argument.
```

```
    print(pool.map(my_statistics, args))
```

```
    toc = clock()
```

```
    print('Total runtime: %f s' % (toc - tic))
```

Some Remarks

- Replacing the **for** loop with **Pool** was very simple
- A single **Pool** can be reused many times (**close** when finished)
- More advanced features we didn't review

- *map* passes a single call to each worker
- Causes overhead if the function finishes fast
- Pass additional "**chunksize**" to handle multiple calls per worker

- *map* blocks until all results arrive
- Use *map_async* to run computations in background
- Allows later blocking until results arrive

Some Remarks (Cont.)

- Each item in “**args**” should fully describe a function call
- But map can pass only a single argument

```
def my_func(args):  
    <rest_of_function_code>
```

- Solution 1:
 1. Pack arguments in a **tuple/list** before calling: (arg1, arg2,...)
 2. Unpack them inside the function: arg1 = args[0] etc.
- Solution 2:
 1. Pass arguments as **dictionary**: **dict**(arg1=value, arg2=value...)
 2. Unpacking is trivial: args['arg1'] etc.

Synchronization

- Sometimes a worker needs exclusive access to a resource
 - A file, DB or so
- All other workers must wait to get access too
- This can be accomplished by the **Lock** class
- The same **Lock** object must be passed to all workers
- Use lock *acquire* function to gain exclusive access
- Call *release* to let other workers lock in their turn

Message Passing

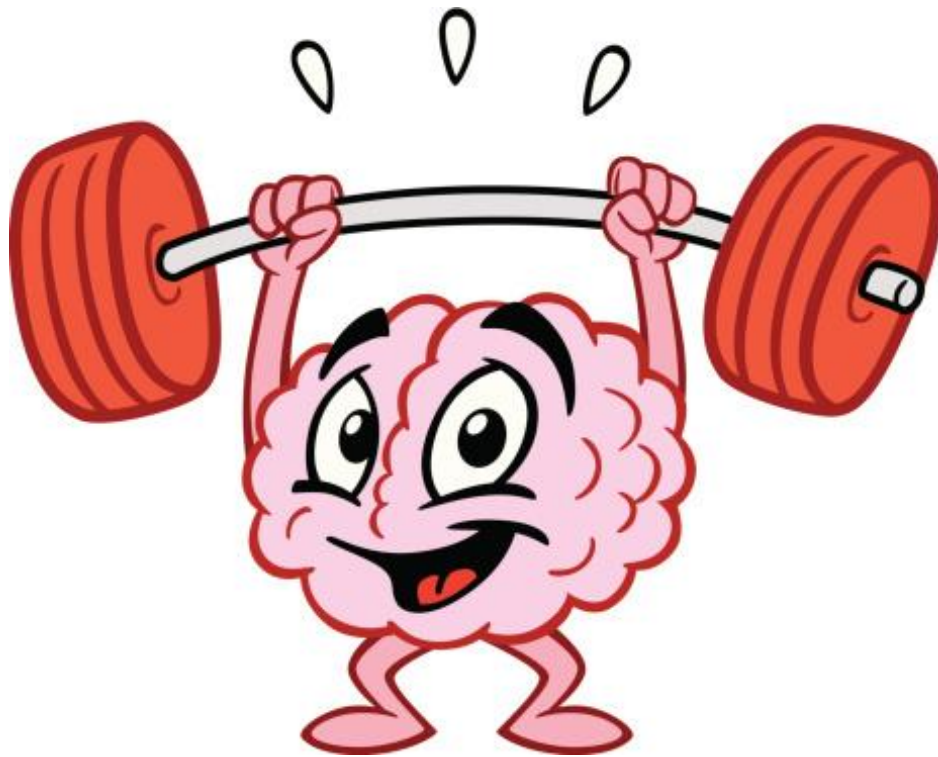
- It is possible to exchange synchronized messages and objects:
 - Between workers
 - Between the master and workers
- **Queue** class provides the simplest means to do so
- The sender calls ***put*** to place an object (message)
- The receiver calls ***get*** to get an object (message)
 - If queue is empty the call is blocking until a message arrives
- For those concerned, there are options for asynchronous and non-blocking messaging within this class

Short Summary

- “**multiprocessing**” provides advanced parallel constructs
- Very simple and intuitive to use
- We got a small taste of what it can offer
- There is more:
 - Shared memory with synchronization
 - More synchronization objects
 - Data passing using pipes
 - Distributing work on remote machines (through **Manager**)
 - ...

Hands-On Time

- 30-45 minutes of work



Exercise Benefit

- Registration to PRACE Summer of HPC 2017 requires to submit a simple code test
- You probably guessed it right
- **Computing $\pi(N)$ is a code test for SoHPC 2017**
- You are now ready to apply 😊
- But not during class
- And there is no requirement for parallel solutions!

A Numerical Note

- Floating point numbers are approximated in our computers
- Operations are usually not commutative or associative
 - Due to roundoff errors mostly
- Example 1:
 - $0.1 + 0.2 + 0.3 \neq 0.3 + 0.2 + 0.1$
- Example 2:
 - $(0.1 + 0.2) + 0.3 \neq 0.1 + (0.2 + 0.3)$
- Order of operations matters for deterministic values
- Especially true in a parallel world, where order is not guaranteed
- If possible, start summing from smaller values to larger ones

- IPython
- “mpi4py” module

CLUSTER-LEVEL PARALLEL COMPUTING

IPython

- Why another python? It's actually the same but better
 - I stands for interactive
 - Much more user friendly
 - Reminds Mathematica by Wolfram
 - Equipped with many useful packages (e.g. data visualization)
 - A backend for Jupyter (advanced GUI)
- Take a look here: <http://ipython.org>
- And for Jupyter: <http://jupyter.org>

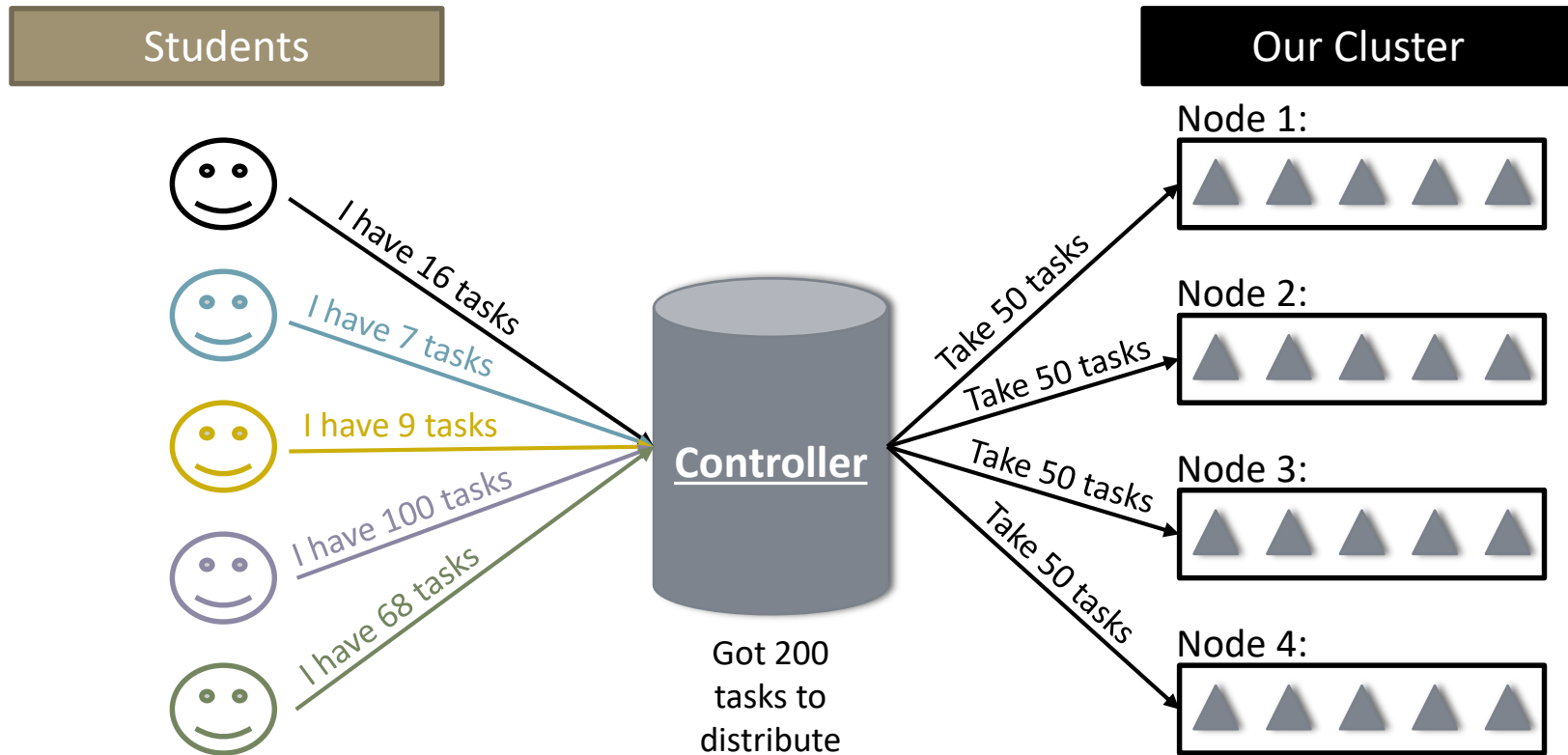
Parallel Processing in IPython

- The main package is **ipyparallel** (download separately)
- Advanced framework for parallel processing in python
- Can be **interactive!**
- Very intuitive parallelization constructs

- Built-in engine for node & cluster scale computations
- Supports many other cluster engines (LSF, SGE, Condor, MPI etc.)

- See: <https://ipyparallel.readthedocs.io>

ipyparallel Basic Concepts



Arrows are **bi-directional**, also returning results.

▲ = CPU Core
= Compute **engine**

Starting a Controller

- We are running on a single computer
- To start a controller with 4 compute engines:

```
# ipcluster start -n 4 &
```

- Or equivalently in separate commands:

```
# ipcontroller &
```

```
# ipengine &
```

```
# ipengine &
```

```
# ipengine &
```

```
# ipengine &
```

Starting a Controller (Cont.)

- It is possible to spawn engines on a cluster or remote computers (--ip and --url options)
- See online documentation for further configuration details

Connecting a Controller

- Let's connect to a controller and submit some work

- Start ipython:

```
# ipython
```

- Connect:

```
import ipyparallel as ipp  
c = ipp.Client()
```

Example

- Recall my_statistics function from **multiprocessing**:
`print(c[:].map_sync(my_statistics, args))`
- c[:] above means we target all connected engines
- Also called a **DirectView**:
 - We view all engines directly
 - No automatic load balancing
 - It is possible to have a **LoadBalancedView**
 - See online documentation

DirectView At Glance

- In previous slide we mentioned that `c[:]` is a **DirectView**

```
dview = c[:]
```

- It gives some very nice features

- Share data with engines:

```
dview['const1'] = 12.1
```

```
dview.push(dict(const1=12.1))
```

- Or get data from engines:

```
print(dview['const1'])
```

```
print(dview.pull('const1'))
```


DirectView At Glance (Cont.)

- Similar to MPI we can use scatter operations:

```
dview.scatter('const1', [i**2 for i in range(100)])
```

- And gather operations:

```
const1 = dview.gather('const1')
```

Synchronizing Imports

- **ipyparallel** doesn't know in advance which imports are used by functions
- Contrast to **multiprocessing**
- So before parallelizing functions remember to synchronize imports:

```
with dview.sync_imports():  
    import numpy as np
```

- This performs the necessary imports on all engines
- Or use the **@require** decorator with dependencies (preferred)

Synchronizing Imports (Cont.)

- Another elegant option is to embed imports within functions:

```
def my_parallel_function(some_params):
```

```
    import numpy as np
```

```
    <rest_of_function_code>
```

Hands-On Time

- 30-45 minutes of work



Back to MPI

- Until now we managed to simplify our life
- Starting with **multiprocessing** and then **ipyparallel**
- MPI is a low-level interface for parallel computing
- Standard, supported on Unix-like and Windows platforms
- A lecture given by Dr. Guy Tel-Zur few days ago
- Our goal is not to review MPI again
- Instead we'll see the MPI wrapper provided in Python

mpi4py

- A python module you have to install by request
- Preferably using pip (*# pip install mpi4py*)
- It provides access to almost all MPI 1/2/3 APIs in pythonic way
- Also in object-oriented way
- Allows passing NumPy/SciPy arrays between processes
- And also pure python objects! (if picklable, even custom ones)

- **ipyparallel** is also built on top of **mpi4py**

- See: <http://pythonhosted.org/mpi4py>

- Also: <https://mpi4py.readthedocs.io>



mpi4py (Cont.)

- A script runs as a standalone program (SPMD)
 - No interactive prompt
 - Similar to **multiprocessing**
-
- Use the usual *mpiexec* command to run a program in parallel:
`# mpiexec -n 4 python my_mpi4py_program.py`

mpi4py Example #1

```
from mpi4py import MPI

# Get communicator.
comm = MPI.COMM_WORLD

# Get process ID.
rank = comm.Get_rank()

if rank == 0:
    data = {'a': 'my-string', 'b': 3.14}
    print('Master, sending: ', data)
    comm.send(data, dest=1, tag=11)
elif rank == 1:
    data = comm.recv(source=0, tag=11)
    print('Worker, received: ', data)
```


Few Notes...

- No need to call the familiar ***MPI_Init!***
- Automatically called once MPI is imported from **mpi4py**

- No need to define “***main***”
- Implicit when importing **MPI**
- The script is encapsulated in a “***main***”

- We are passing a pure python dictionary

- No need to call the familiar ***MPI_Finalize!***
- Automatically called once the python process exits

mpi4py Example #2

```
from mpi4py import MPI
import numpy as np
```

```
comm = MPI.COMM_WORLD
rank = comm.Get_rank()
```

```
if rank == 0:
```

```
    data = np.arange(1000, dtype='d')
    comm.Send([data, MPI.DOUBLE], dest=1, tag=77)
```

```
elif rank == 1:
```

```
    data = np.empty(1000, dtype='d')
    comm.Recv([data, MPI.DOUBLE], source=0, tag=77)
```

mpi4py Example #3

```
from mpi4py import MPI
import numpy as np
```

```
comm = MPI.COMM_WORLD
rank = comm.Get_rank()
```

```
if rank == 0:
    data = np.arange(1000, dtype=np.float64)
    comm.Send(data, dest=1, tag=77)
```

```
elif rank == 1:
    data = np.empty(1000, dtype=np.float64)
    comm.Recv(data, source=0, tag=77)
```

Few Notes...

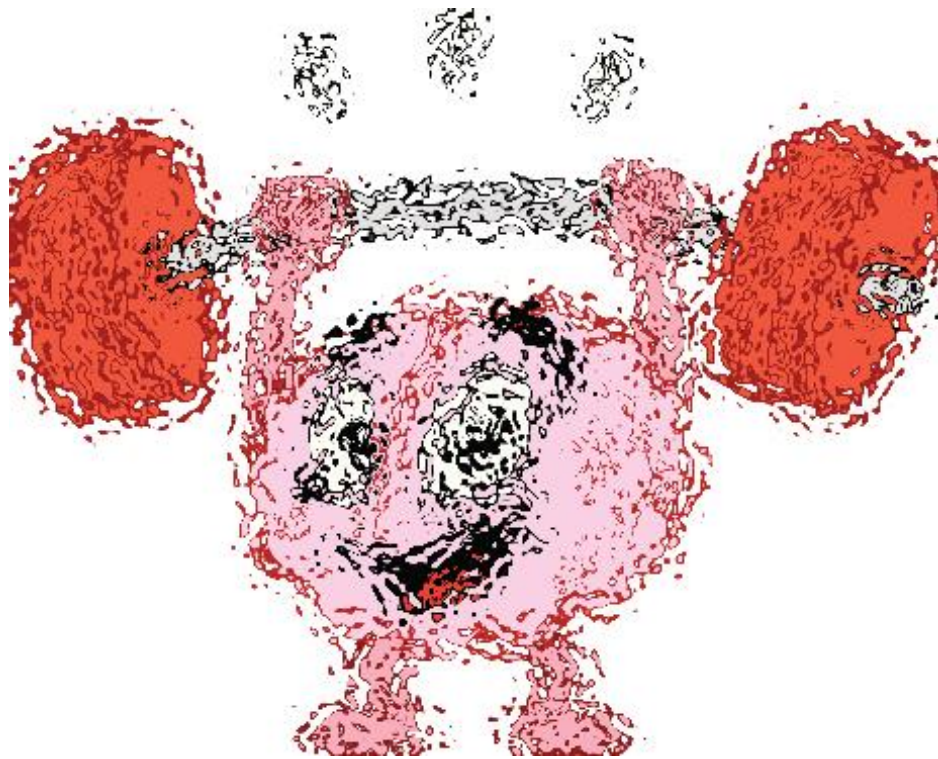
- Now we managed to pass NumPy arrays
- It can infer the underlying datatype explicitly (#2)
- Or implicitly (#3)

mpi4py Brief Reference

- The module provides support for almost all MPI functions
 - Communication (P2P, Collective, Map-Reduce, Scatter-Gather etc.)
 - Blocking and non-blocking communications
 - I/O
 - Dynamic process management (de-attaching workers)
- Communication functions have two variants:
 1. Buffer based methods – starting with uppercase (e.g. **Send**)
 - These are the familiar MPI functions
 2. Accept generic python objects – all lowercase (e.g. **send**)

Hands-On Time

- 30-45 minutes of work



Final Remarks

- Had an overview of parallel toolkits/modules in python
- Very useful, simplifying programming tasks
- See online resources for more information

- We covered about 10% of available features
- But a necessary fraction to get started

Hope you enjoyed it 😊

Go Parallel !