

Research Computing at Mines Workshop

Serial and Parallel Computing

October 2023

Presented by:

Nicholas A. Danes, PhD

Computational Scientist

Cyber Infrastructure & Advanced Research Computing (ITS)



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Recap of Day 1

- Overview of the world of Cyberinfrastructure & Research Computing
- HPC options for Mines Researchers
- Overview of skills needed to be a successful researcher on HPC
 - Linux/Bash
 - Slurm/Job Scheduler
 - Parallel Computing
 - Computational Notebook Practices
- Intro to Linux/Bash Lab
- Overview of Job Schedulers, SLURM and Python
- Intro to Slurm & Python Lab

Goals for Day 2

- Overview of Serial vs Parallel Computing
- A case study using a Python serial code (Lab)
- Parallel Programming Overview
 - Shared vs Distributed Memory
 - MPI
 - OpenMP
- Lab on using parallelized software: GROMACS

HPC Resource Usage

- How do we use them?
 - Most programs spawn 1 process (“task” in Slurm) and use one thread (“cpu” in Slurm)
 - On a desktop, some programs can see how many CPU cores you have and request that many threads for the process and use them
 - Examples: Some MATLAB functions, Games using DX12, Chrome/Firefox
 - Slurm does not know how your program will use the resources you give it
 - If you give it 12 cores (“cpus”) but program only works with 1 core, those 11 cores will idle and do nothing
 - To think about how to utilize HPC resources, we need to learn how **parallel programming/processing** is implemented.

Serial vs Parallel Computing

- When a program uses a single process (“task”) with 1 core (“cpu”), we say it is a **serial computing** program.
- When a program uses multiple cores, we say it is a **parallel computing** program.
- Before thinking about parallel computing, we need to focus on how well the program performs with serial computing.

Note: Optimization before Parallelization!

- *"Premature optimization is the root of all evil"* – Donald Knuth
- Often, writing your code to run as fast as possible (*within reason*) with a single core is necessary before thinking about parallelization.
- We will explore optimization with a simple Python code for a single core next!

How to profile Python code

- **cProfile**

- Gives you a breakdown of all functions' runtime in a code
- Multiple ways to use it:

- Call it in the command line:

```
$ python -m cProfile myscript.py
```

- Call it in another script:

```
import cProfile  
  
cProfile.run("mycode.main()")
```

- Other options: lineprofiler, timeit, pstats

References: <https://towardsdatascience.com/how-to-profile-your-code-in-python-e70c834fad89>
https://github.com/pyutils/line_profiler

A starting point for optimization: Writing an ODE solver

Consider the initial value problem of the form:

$$\begin{aligned}y'(t) &= f(t, y) \\ y(t_0) &= y_0\end{aligned}$$

which can numerically solved using Heun's Method:

$$\begin{aligned}\hat{y}^{[i+1]} &= y^{[i]} + h f(t^{[i]}, y^{[i]}) \\ y^{[i+1]} &= y^{[i]} + \frac{h}{2} \left(f(t^{[i]}, y^{[i]}) + f(t^{[i+1]}, \hat{y}^{[i+1]}) \right)\end{aligned}$$

Where h is the time step size, i is the time step index, and \hat{y} denotes the intermediate solution. Let's use this problem to see how to optimize writing scientific code for Python!

Lab #1: Serial Python Optimization

Copy the workshop materials using the following command:

```
cp /sw/BUILD/src/workshop/Workshop_Fall2023_day2.tar.gz ~/scratch
```

And untar it and go to the directory:

```
cd ~/scratch && tar -xf Workshop_Fall2023_day2.tar.gz  
cd Workshop_Fall2023/rk2_python && ls
```

Using Open OnDemand Interface

Go To: <https://wendian-ondemand.mines.edu>



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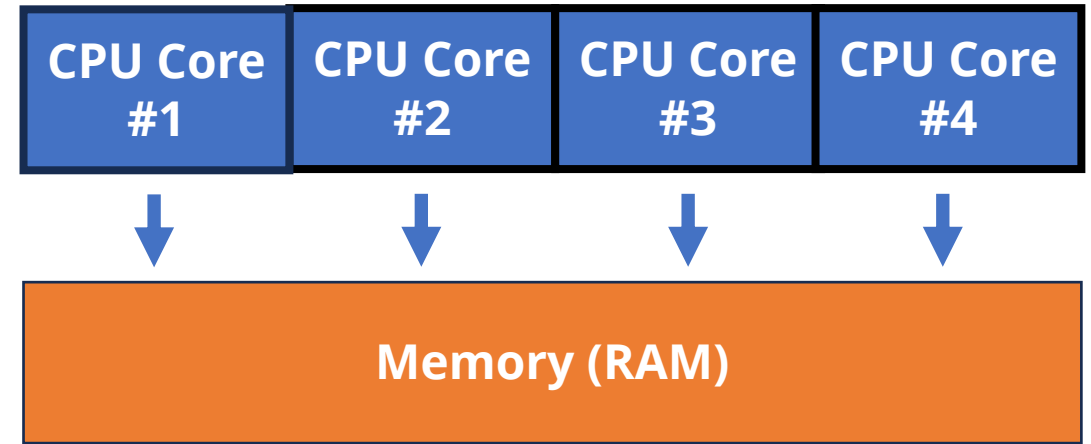
Lab #1 Summary: Profiling multiple versions of our ODE code

- Pure Python
 - **Surprisingly Performant!**
- NumPy only
 - Performs poorly due to lack of vectorization
- NumPy + Cython
 - <https://cython.org/>
 - Cython effectively allows one to write static-typed code in Python/"Cython", which is parsed into C and compiled into a Python module.

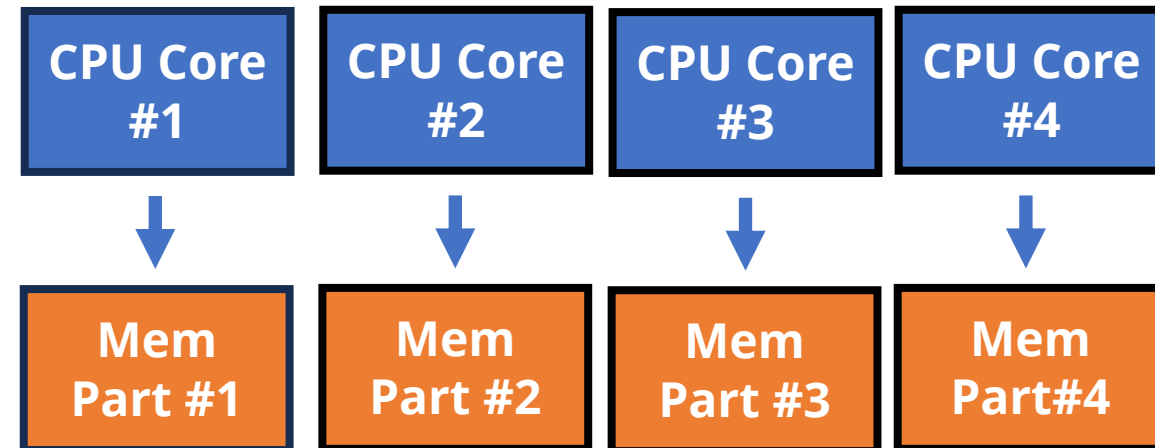
Parallel Programming

- Shared vs Distributed Memory Programming
 - Shared (e.g. OpenMP)
 - All CPU cores have access to the same pool of memory
 - Typically, all CPU cores are on the same CPU node
 - Ideal for multi-threaded loops
 - Distributed-memory program (e.g. MPI)
 - Each CPU core is given access to a specific pool of memory, which may or may not be shared
 - A “communicator” designates how each CPU core can talk to another CPU core
 - CPU cores do not have to live on the same CPU node

Shared Memory Parallelism: 1 task, 4 threads



Distributed Memory Parallelism: 4 tasks, 1 thread per task



Shared Memory Parallelism: OpenMP

- OpenMP is a portable, high-level API that is used to write multithreaded applications
 - It provides a set of directives that can be used to parallelize loops, regions of code, and entire functions.
 - Supported by a wide range of compilers and hardware platforms (e.g. C/C++, Fortran, Python, etc)
 - For loops typically a compiler directive is added before a loop to tell the compiler that OpenMP is being used:
 - *#pragma omp parallel*
 - The environment variable OMP_NUM_TASKS will tell the operating system how many OpenMP threads to use in the program.

A note on Python and the GIL: A constraint on shared memory programming

- Python Global Interpreter Lock (GIL)
 - A mechanism with Python which allows only one CPU thread to use the Python interpreter
 - The GIL addressed the problem of memory management for Python programs.
 - Releasing the GIL can cause memory leaks if not managed correctly.
- Solutions:
 - Use **multiprocessing** instead of **multithreading**
 - Each process gets its own Python interpreter and memory space
 - Module options: mpi4py, multiprocessing
 - Use a different interpreter
 - Use Cython to release the GIL to allow multithreading within subroutines

Reference: <https://realpython.com/python-gil/>

Distributed Memory Parallelism: MPI

- MPI stands for **m**essage-**p**assing **i**nterface, standard provided as a library for exchanging data (called messages) between objects.
- Different libraries have implemented the MPI standard:
 - OpenMPI
 - MPICH
 - Intel MPI
- Objects that can be used to send messages are separated by memory
 - Can be entire CPU nodes, or CPU cores, called *ranks*.
 - By breaking up by memory of each tasks, a rank can send messages theoretically anywhere as long as there is another layer of network communication
 - MPI most commonly uses Infiniband for node-to-node communication
 - Intra-node communication uses CPU architecture

Distributed Memory Parallelism: MPI

- It provides a set of functions for sending and receiving messages, as well as for synchronizing the execution of different processes. Common functions:
 - Send a message from one rank to another: `MPI_SEND`
 - Receive a message from a rank: `MPI_RECV`
 - Broadcast the same message to all ranks from a particular rank: `MPI_BCAST`
 - Take a message from multiple ranks to a single rank: `MPI_GATHER`
 - Block messages from continuing until all ranks have finished: `MPI_BARRIER`

Choosing between Shared vs Distributed Memory Parallelism

- Shared Memory Parallel is ideal for:
 - Single computer/node workloads
 - Speeding up for-loops
 - By splitting up the work across loop iterations
- Distributed Memory Parallel works best for
 - Large memory workloads that require multiple compute nodes
- Shared and distributed memory parallel programming can sometimes be combined
 - Called **hybrid** parallel programming
 - Combining MPI and OpenMP

Lab #2: Running Parallel Code: GROMACS

And exploration of SLURM commands

Summary of Slurm commands to monitor jobs

- `squeue` – View job queue
- `squeue $USER` – View job queue for your jobs
- `sacct -j <jobid>` – Get info on a particular job ID
- `sinfo` – Show info on nodes
- `scontrol show node <name>` – show info on a particular node

GPU: Further Accelerate computational workloads

- Use graphical processing units (GPUs)
 - NVIDIA
 - The CUDA library is by far the most popular GPU computing language
 - Provides an API to use NVIDIA CUDA codes
 - Popular CUDA uses:
 - AI/ML: PyTorch, Tensorflow
 - Molecular Dynamics: LAMMPS, GROMACS
 - Scientific Visualization: Paraview
 - OpenCL
 - Open source alternative to CUDA
 - Works on AMD, NVIDIA, and Intel GPUs
 - HIP (Heterogeneous-Compute Interface)
 - GPU acceleration library developed by AMD

Limitations to GPUs

- Hardware is more expensive and less widely available
- Programming for GPUs requires more setup
- Not all workloads can be easily ported to GPUs

Final Takeaways

- When developing your own scientific programs, get the serial case working as efficiently as possible (within time constraints)
 - Try different libraries, compiler options, etc.
 - Run benchmarks to compare setups
- When jumping to parallel programming
 - Understand the differences between shared and distributed memory parallel programming
 - Leverage established libraries to implement parallel programming methods
 - Use software with these libraries already in use (e.g. GROMACS)

Further Resources

Python Parallel Processing:

<https://wiki.python.org/moin/ParallelProcessing>

Parallel Programming with MPI for Python:

https://rabernat.github.io/research_computing/parallel-programming-with-mpi-for-python.html

Intro to F2Py:

https://www2.atmos.umd.edu/~dkleist/docs/pythonTraining/Slides/F2Py_SSSO.pdf

OpenMP: [Open MPI Open Source High Performance Computing \(open-mpi.org\)](http://open-mpi.org)

OpenMP: [Specifications – OpenMP](#)

NVIDIA CUDA Toolkit: [CUDA Toolkit - Free Tools and Training | NVIDIA Developer](#)