"My hypothesis is that we can solve [the software crisis in parallel computing], but only if we work from the algorithm down to the hardware — not the traditional hardware first mentality"

Tim Mattson, Principal Engineer at Intel, 1993

Lecture A.4: Application Parallelism

CS205: Computing Foundations for Computational Science
Dr. David Sondak
Spring Term 2021





Lectures developed by Ignacio M. Llorente

Before We Start

Where We Are

Computing Foundations for Computational and Data Science

How to use modern computing platforms in solving scientific problems

Intro: Large-Scale Computational and Data Science

- A. Parallel Processing Fundamentals
 - A.1. Parallel Processing Architectures
 - A.2. Large-scale Processing on the Cloud
 - A.3. Practical Aspects of Cloud Computing
 - A.4. Application Parallelism
 - A.5. Designing Parallel Programs
- **B.** Parallel Computing
- C. Parallel Data Processing

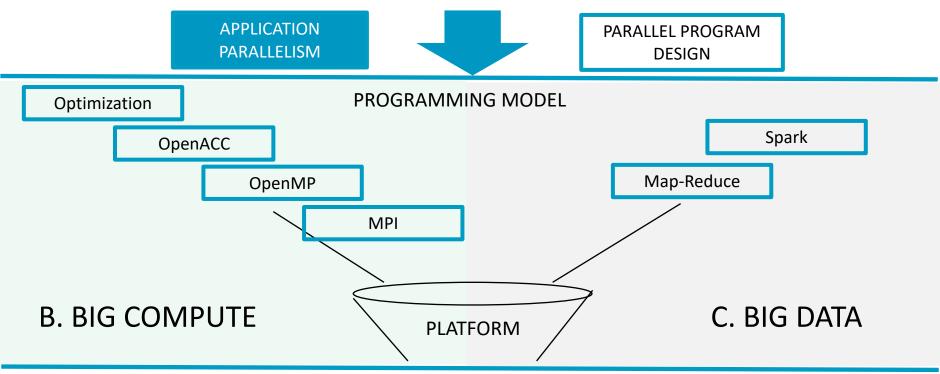
Wrap-Up: Advanced Topics





CS205: Contents

APPLICATION SOFTWARE















PARALLEL ARCHITECTURES



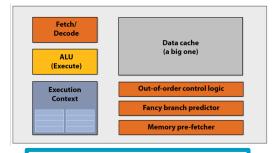




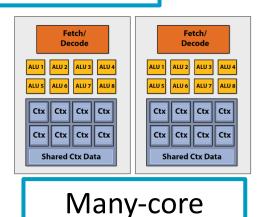
Context

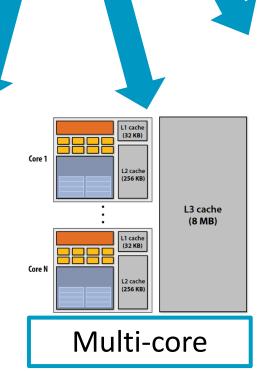
Application Parallelism

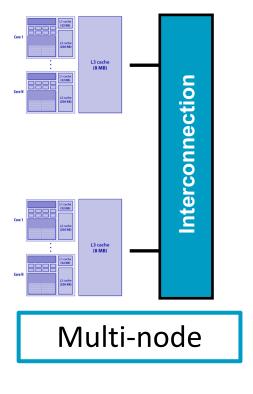
How to make effective use of existing parallelism at different levels?



ILP/Data











Roadmap

Application Parallelism

Types of Applications

Levels of Parallelism

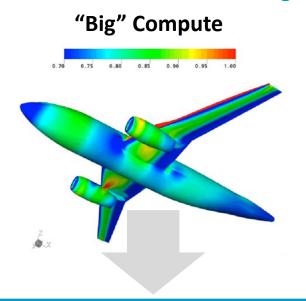
Types of Parallelism

Parallel Execution Models

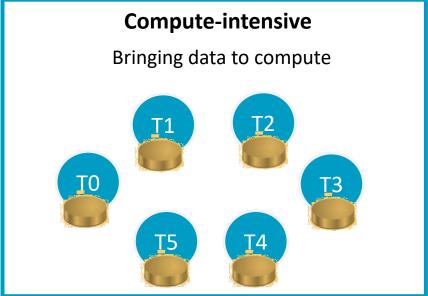


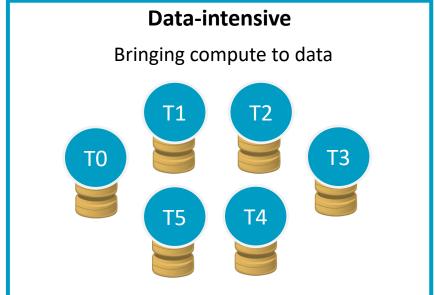


Big Compute vs Big Data









Compute-Intensive Applications

Paradigm Independent parallel tasks that are performed simultaneously to address a

particular part of the problem

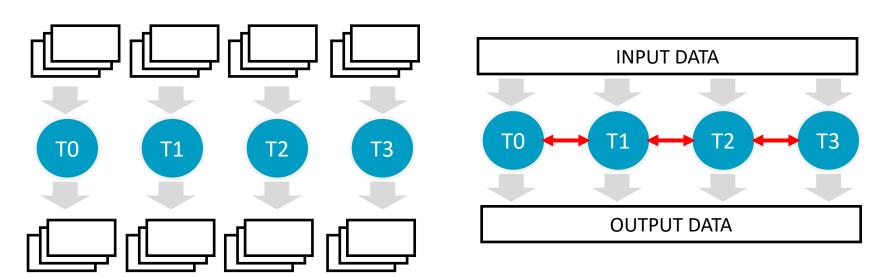
Challenge Decompose the application into tasks and define their communication and

synchronization

Bottleneck CPU/Network

Input data Gigabyte-scale to describe initial conditions

Programming Optimization, OpenACC, OpenMP and MPI





HPC (Capability)

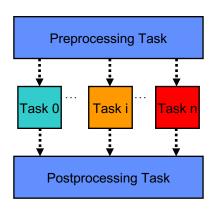




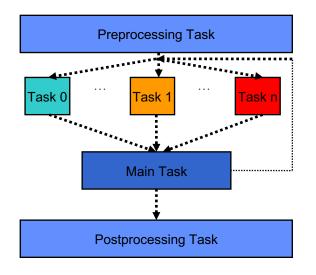
Compute-Intensive Applications

High Throughput Computing (Capacity)

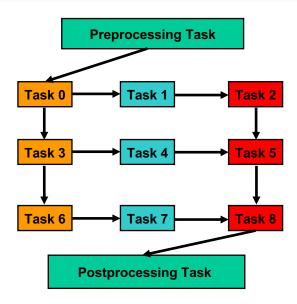
- Application consists of a very large number of independent tasks to explore design space
- Tasks could have dependencies, as in the case of workflows
- Optimize for throughput: number of tasks executed per time unit



Embarrassingly Parallel











Compute-Intensive Applications

HTC: Simplest Approach to Distributed Processing

- Visualization: Image rendering
- Bioinformatics: DNA sequence analysis
- Marketing: Analyze the purchase pattern of BestBuy customers in MA
- High Energy Physics: Generate 10⁶ CMS experiment events
- IT: Database queries
- Finance: Monte Carlo to value and analyze instruments, portfolios and investments
- Automotive: Mechanical forensics using Monte Carlo for Crash Analysis

• ...







Compute-Intensive Applications



Examples?

Number of Instances?

Size of each instance?

MTC: Many-task Computing

 MTC is reminiscent of HTC, but it differs in the emphasis of using many computing resources over short periods of time to accomplish many computational tasks

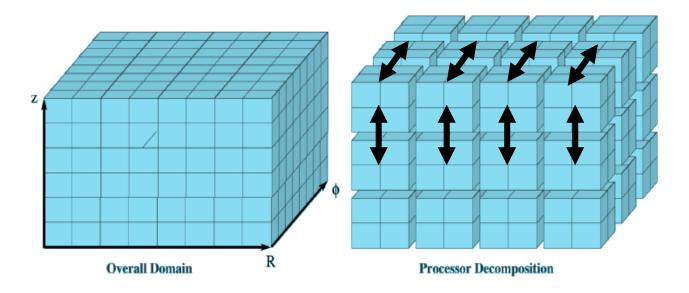




Compute-Intensive Applications

High Performance Computing (Capability)

- High-fidelity long-running large-scale computations
- Application consists of multiple parallel tasks that are performed simultaneously to address a particular part of the problem
- Tasks communicate and/or synchronize with each other
- Optimize for speed: number of floating point operations per time unit







Compute-Intensive Applications

HPC: Parallel Programming

Aeronautics: CFD simulation

• Earth Science: Simulation of weather and science

• ...







Compute-Intensive Applications



Examples?

Level of coupling?

Tightly-coupled vs. Loosely-coupled





Compute-Intensive Applications

нтс	HPC
Independent execution of multiple instances of the same application	Parallel execution of a single large application instance
Throughput (jobs per second)	Speed-up (execution time)
Straightforward implementation, it does not require parallel programming	Difficult and time-consuming implementation
Main challenge is to tune the job scheduler (LRMS) of the management platform	Main challenge is to tune the parallel implementation of the code
Requires fast storage access	Requires low latency, high bandwidth network (Tightly-coupled vs. Loosely-coupled)



HA (maintain readiness): Time-sensitive mission-critical applications that require HPC resources on-demand (NASA)



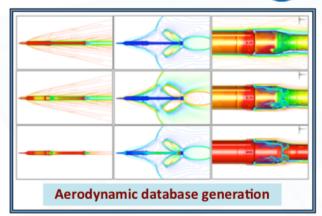


Compute-Intensive Applications

NASA's Diverse HPC Requirements

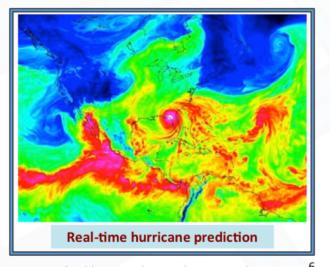


- 1) Engineering requires HPC resources that can process large ensembles of moderatescale computations to efficiently explore design space (high throughput / capacity)
- 2) Research requires HPC resources that can handle high-fidelity long-running large-scale computations to advance theoretical understanding (leadership / capability)





Time-sensitive mission-critical applications require HPC resources on demand (high availability / maintain readiness)



National Aeronautics and Space Administration

http://hpcuserforum.com/presentations/korea2013/Biswas-NASA%20HPC-UF-Seoul.pdf



Compute-Intensive Applications



What is more difficult to code, HPC or HTC?

What is the critical part for achieving performance in both profiles?

What type of architecture is more cost-effective in both cases?



Different Approaches

Centralized Coupled

- Network Links
- Administration
- Homogeneity

Decentralized Decoupled

MPP (Massive Parallel Processors)



Network Systems
Intranet/Internet







High Performance Computing

High Throughput Computing

Where to invest my budget?





Data-intensive Applications

Paradigm Same task is applied to large volumes of data

Challenge Partition the data into multiple segments and the subsequent combination

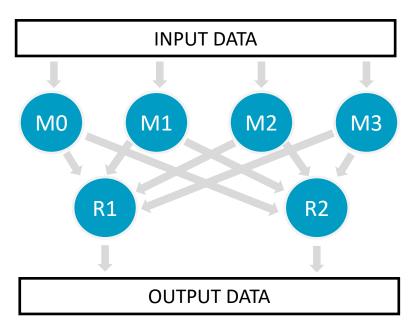
of the intermediate results in multiple stages

Bottleneck Storage

Input data Far beyond gigabyte-scale: datasets are commonly on the order of tens,

hundreds, or thousands of terabytes

Programming MapReduce, Spark







Data-intensive Applications

Science is Facing a Scalability to 'Big Data' Challenge.

- Scalability of applications
 - Data set is growing exponentially
 - Weather and Climate Modelling
 - Life sciences data driven bio genomics: Molecular data for species doubling every 18 months
 - Computational Neuroscience: 2 PetaBytes for 1mm³ in human connectome
 - Computational Cosmology
 - Computational Ecology
 - Modelling complexity is increasing
 - Ecology combined with data driven biology
- New data models: distributed arrays, trees, hash tables, dictionaries (key-value pairs)
- Resilience and failure of components is the norm with billions of threads on millions of processors



Data-Intensive Applications



Examples?

Big data?

Data Science vs. Big Data



From Bit to Application Parallelism

Coarse-grained

EXTERNAL

NTERNAL

Fine-grained

Application Level

•Independent applications within a system

Task Level

Interrelated tasks within an application

Procedure Level

Regions of code within a task

Loop Level

•Iterations within a loop

THREADS

Instruction Level

=> SUPERSCALAR

Instructions with an executable

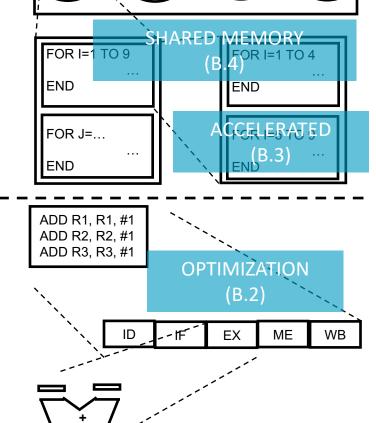
Instruction Phase Level => PIPELINING

Overlap execution of multiple instructions

Bit Level

=> ARITHMETIC UNIT

Processor word size



JOB MANAGER (LRMS)

DISTRIBUTED MEMORY

(B.5) P2





Dr. David Sondak

Granularity

Application Level	Very-coarse Grained > Tens of thousands of instructions Exploited by job managers (SLURM)
Task Level	Coarse Grained > Thousands of instructions Exploited by the programmer (MPI)
Procedure Level	Medium Grained > Thousand instructions Exploited by the programmer (OpenMP)
Loop Level	Fine Grained < 500 instructions Exploited by the programmer (OpenMP/OpenACC)
Instruction Level	Very-fine Grained < 20 instructions Exploited by the compiler and the CPU (-O3)

Towards a Hybrid Approach

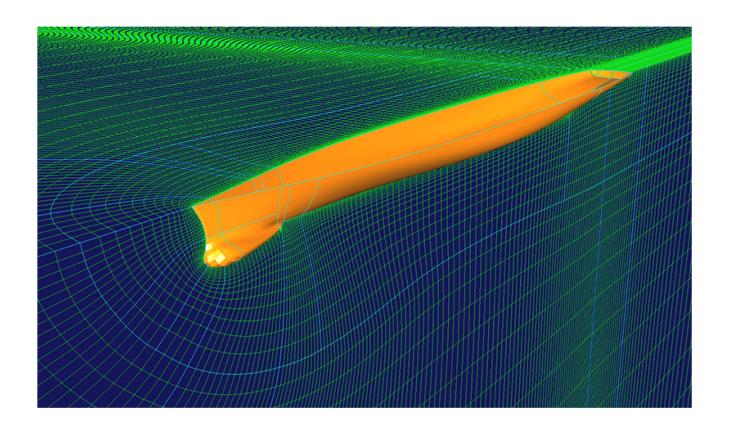
Coarse-Grained	Fine-Grained
Higher level parallelism: Domain decomposition in numerical simulation	Lower level parallelism: Loop decomposition
Does require knowledge about the application	Does not require knowledge about the algorithm or method implemented by the code
Development of a new parallel version of the application	Parallelization of an existing "sequential" code version
Higher scalability and, in principle, efficiency	Faster development
Distributed memory, multi-node, MPI-like	Shared memory, multi-core, OpenMP-like







Towards a Hybrid Approach



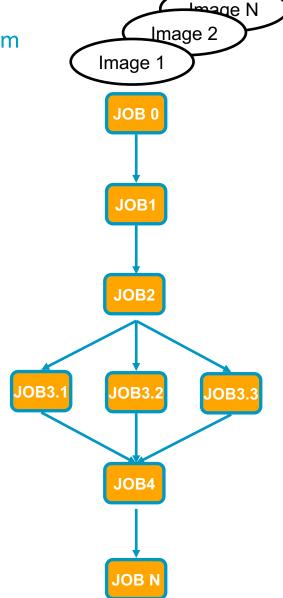
Evaluate the Application vs. Evaluate the Code

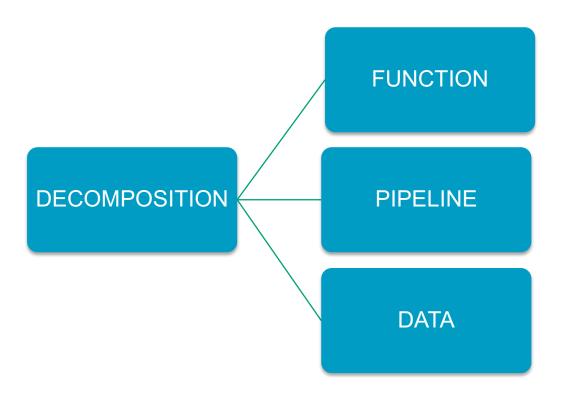
Develop a Parallel App vs. Parallelize a Code





Data, Function and Pipeline Parallelism



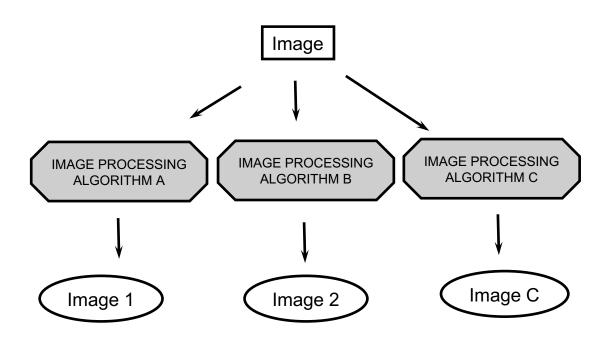


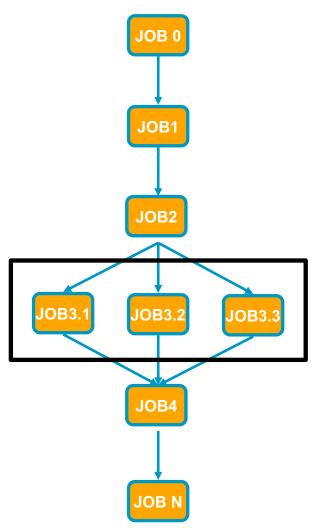


Function (Control) Parallelism

Different Jobs Running on the Same Data

- Several functions on the same data
- No dependencies between the tasks, so all can run in parallel





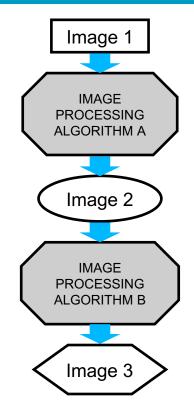


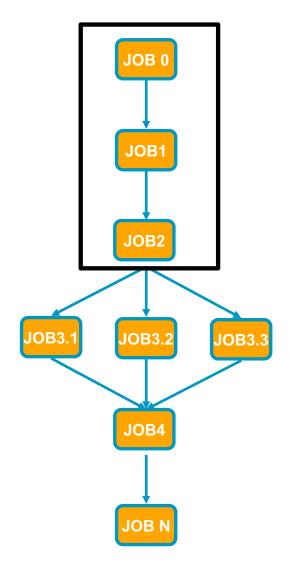


Pipeline Parallelism

Output of One Job is the Input to the Next

- Each task can run in parallel
- Throughput impacted by the longest-latency element in the pipeline





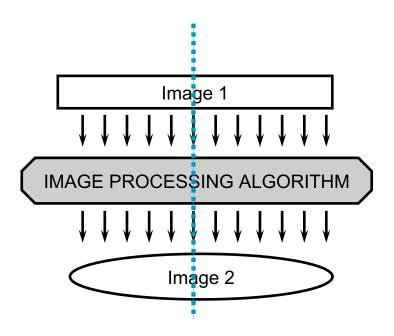


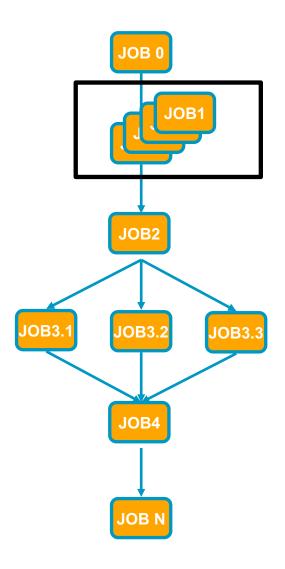


Data Parallelism

Same Job Run on Different Data in Parallel

- Data partitioning across nodes
- Could require communication between task instances





Tasks Decomposition for Data Parallelism

Dividing the work into multiple tasks

Often, there are many valid decompositions for a given computation

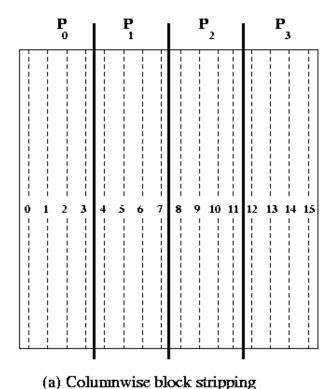
Static vs. Dynamic

- Static: Decide the decomposition at the beginning of the program computation
- Dynamic: Decide the decomposition dynamically, based on the input characteristics

Data Distribution May not Mean Load Balance

Balanced

Matrix addition



Unbalanced

Mandelbrot

```
for m = 0 ... 1023 do

for n = 0 ... 1023 do

c = x+yj

a = 0+0j

while ((k<1000) and (abs(a)<2)) do

a = a^2+c

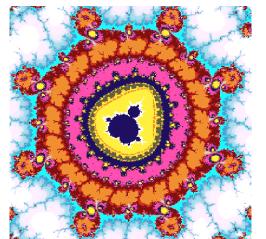
k = k+1

end

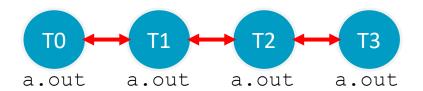
data(n,m) = k

end

end
```

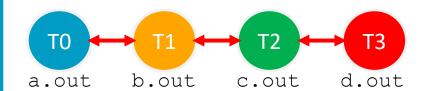


SPMD vs MPMD



Single Program – Multiple Data

- A single program executes on all tasks simultaneously, but at a single point in time, they may be executing the same or different instructions.
- Most common form of parallelism.
- Think of multiple processors running the same program at different points.



Multiple Program - Multiple Data

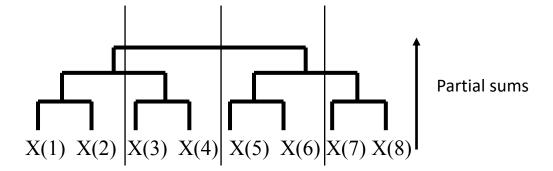
 Each task may be executing the same or different programs than other tasks



Parallel Algorithms

What Is it?

 A parallel algorithm is an algorithm that can be executed a piece at a time on many different processing devices, and then combined together again at the end to get the correct result.



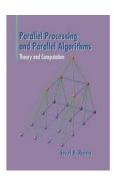
- Most of today's algorithms are sequential, that is, they specify a sequence of steps in which each step consists of a single operation
- Parallel algorithms usually exhibit a higher level parallelism at the cost of a higher number of operations

Parallel Algorithms

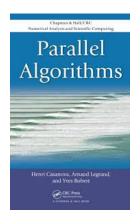


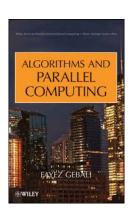
Examples of sequential algorithms?

Examples of parallel algorithms?











Next Steps

Lab session this week:

Help with HWA

I.7 (Part 1) Installation of MPI in a single node Linpack compilation (Performance Competition!)

Get ready for next lecture:

A.5. Designing Parallel Programs

Questions

Application Parallelism

