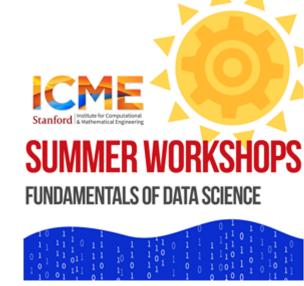


ICME Fundamentals of Data Science

Introduction to Parallel Computing

1) Algorithms	Lecture	9:00	10:10
	Problem solving and Q&A	10:10	10:20
	Break	10:20	10:30
2) Shared	Lecture	10:30	11:45
Memory	Problem solving and Q&A	11:45	12:00
	Lunch	12:00 pm	1:15
	Q&A	1:15	1:30
3) Distributed	Lecture	1:30	2:40
Memory	Problem solving and Q&A	2:40	2:50
	Break	2:50	3:00
4) Spark	Lecture	3:00	4:15
	Problem solving and Q&A	4:15	4:25
	Final Remarks	4:25	4:45



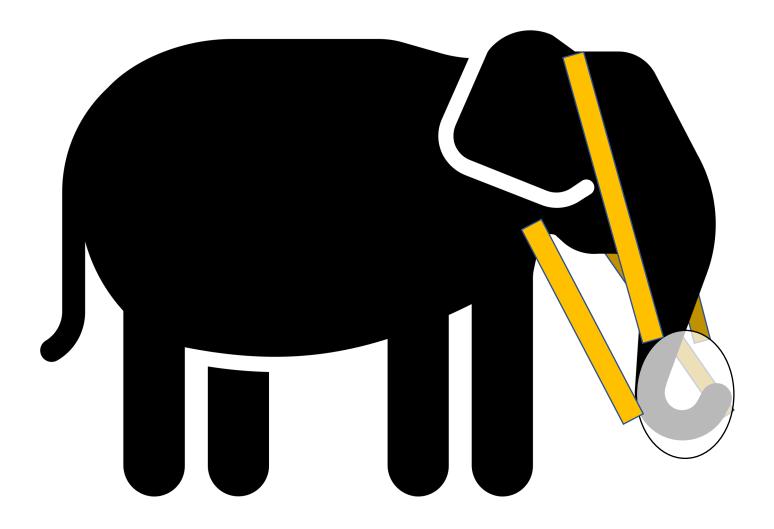


Introduction to High Performance Computing

ICME Summer Workshop : Fundamentals of Data Science Cindy C. Orozco Bohorquez

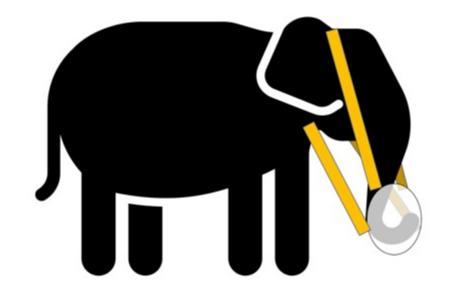


First, the elephant in the room...





First, the elephant in the room...



COVID-19 emergency

Synchronous vs. Asynchronous

Time Zones

Responsibilities and conditions at home

Thank you!

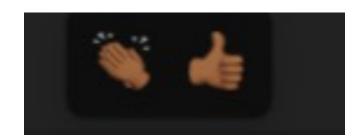
New experiment together



Zoom etiquette

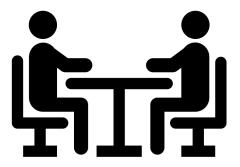


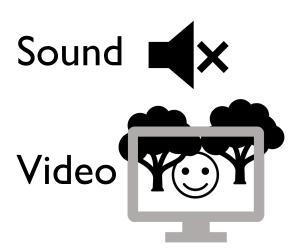
Zoom Reactions





Chat



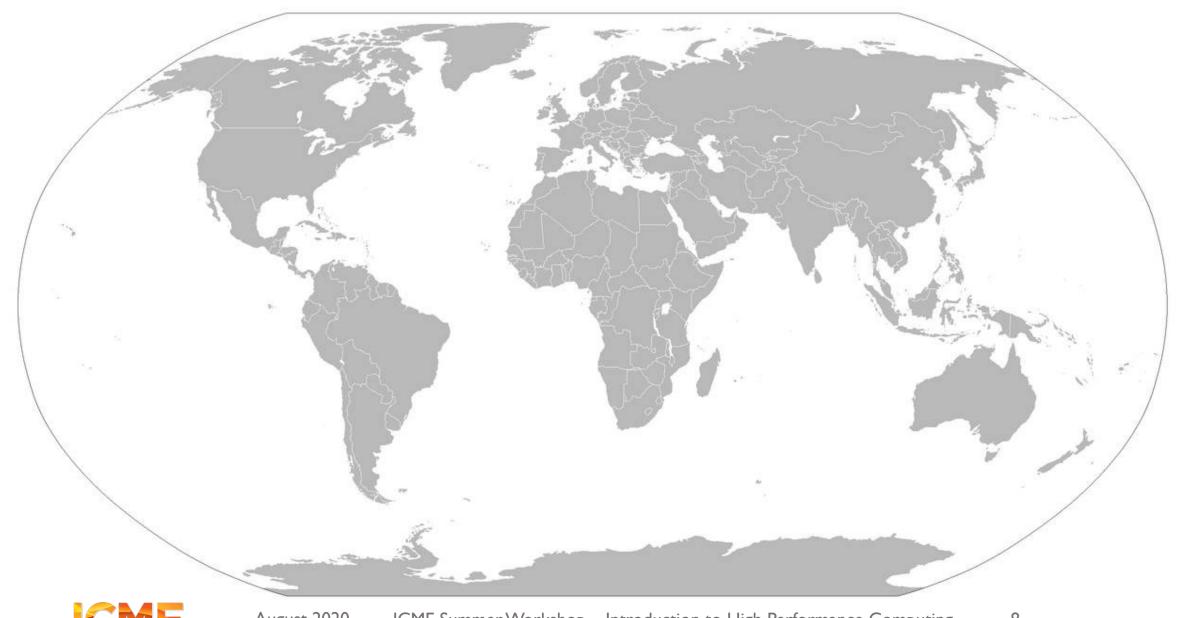




Getting to know each other



From where are you taking this workshop?



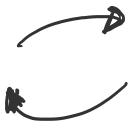
What is exciting about parallel computing?



A bit about me ...

- Cindy Orozco (orozcocc@stanford.edu)
- 6th year ICME PhD student

Numerical Analysis (Engineering Simulations)



Data Science (Learning from Data)











Our TA today... Rahul Sarkar

ICME Ph.D. Student
Current Research Interests:

- Inverse Problems
- Mathematical Analysis
- Quantum Computing

Contact: rsarkar at stanford dot edu

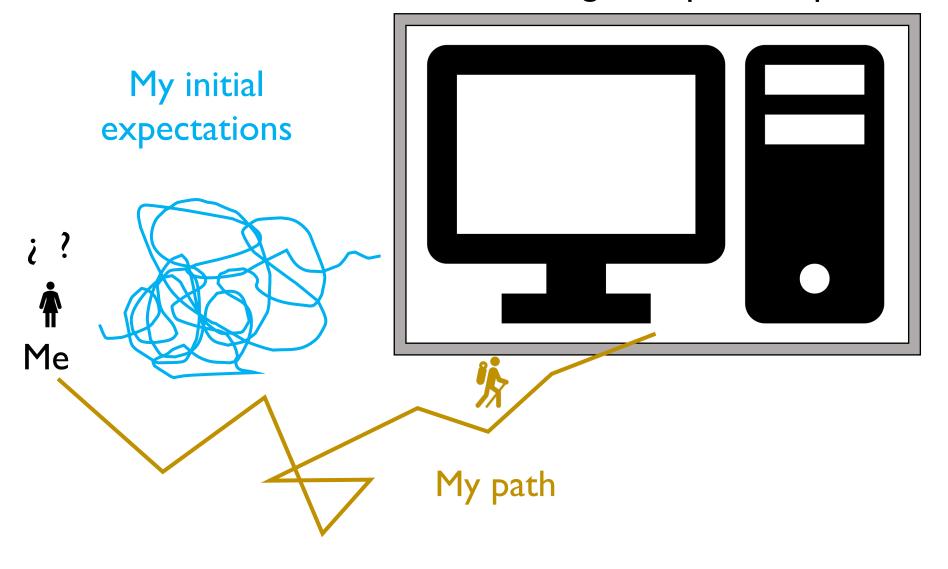
Website:

http://web.stanford.edu/~rsarkar/



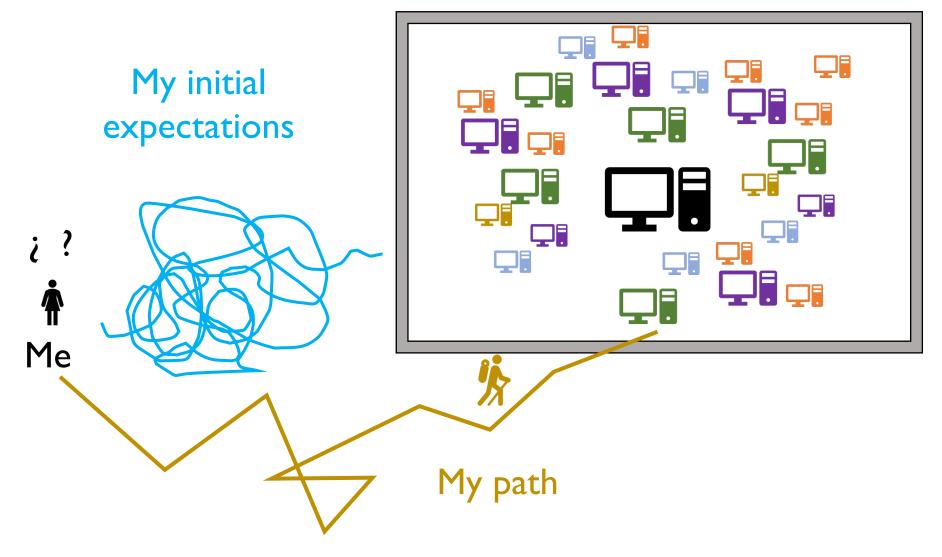


HPC = The largest super computer

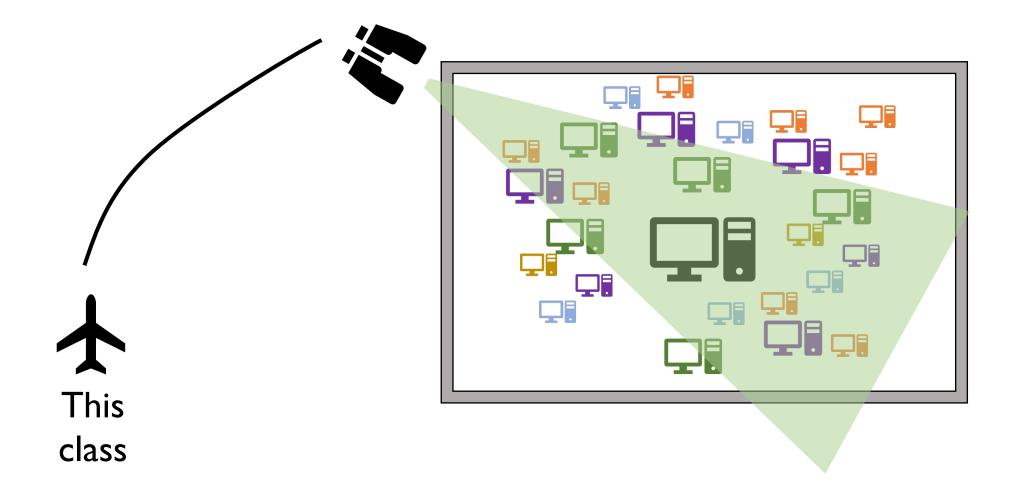




HPC = The largest super computer... not quite

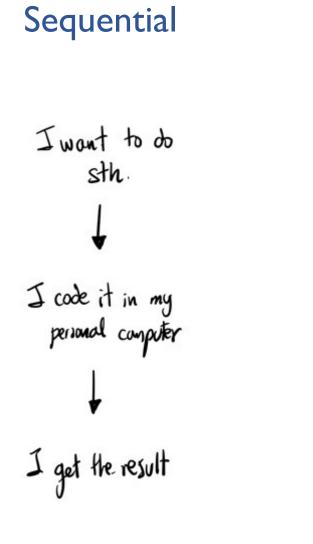




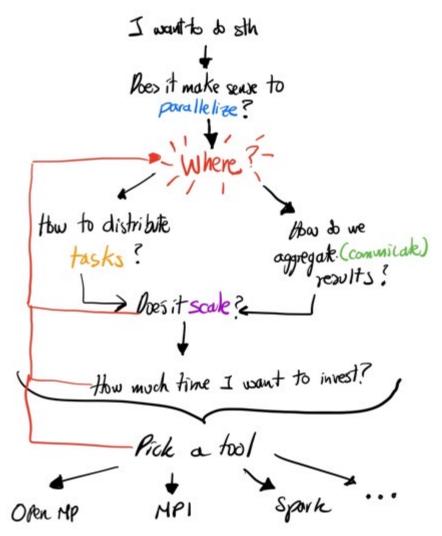




What to expect at the end of today?



Parallel





What to expect at the end of today?

Parallel programming is an art. It requires a masterful combination of hardware knowledge, parallelization types and existing tools.

I)How do we think to parallelize something?

Algorithms

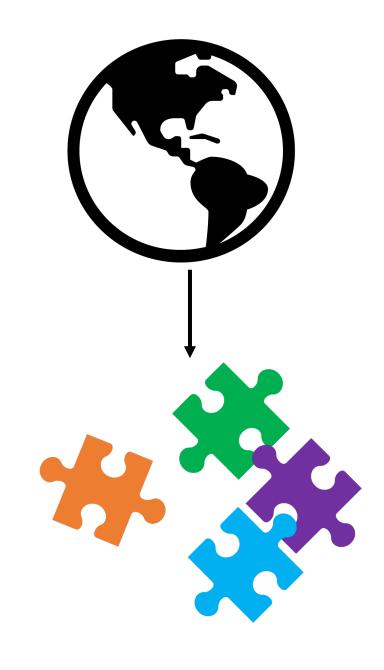
2) What do we do to parallelize something?

Computation vs Communication



1)Algorithms

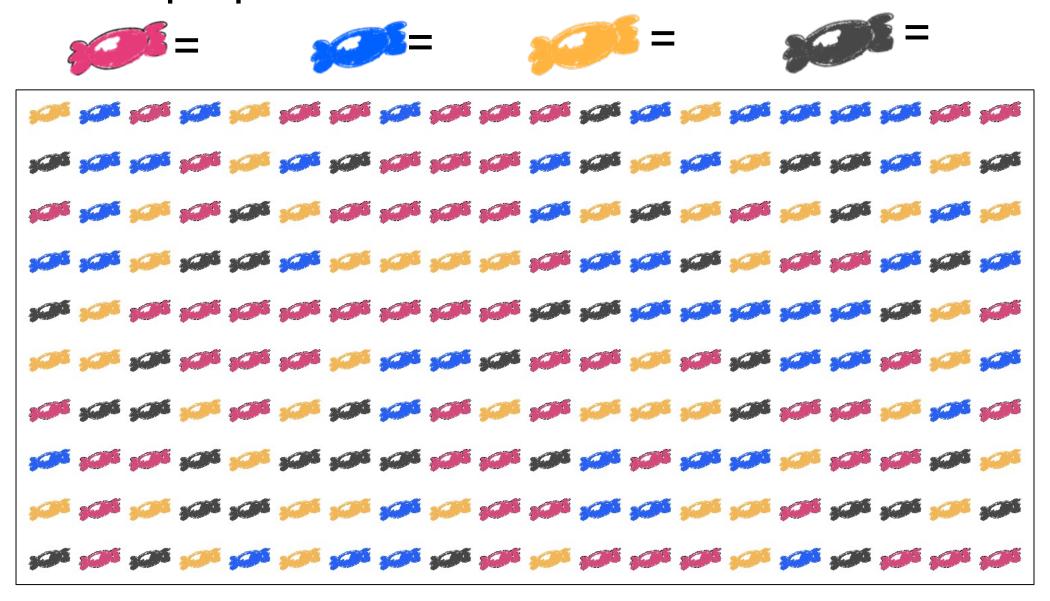
Looking for Parallelization





What do we need to parallelize?





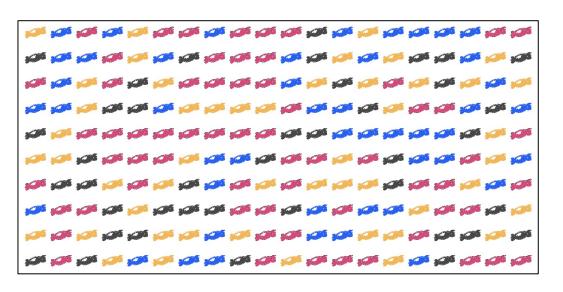












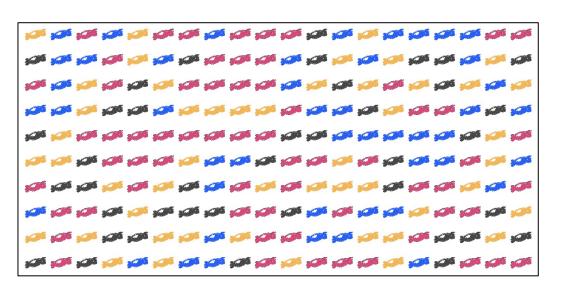












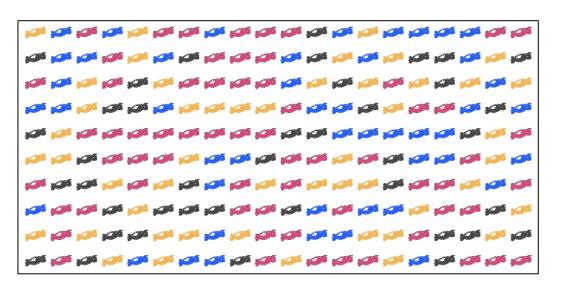








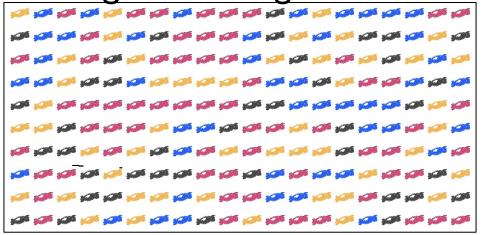




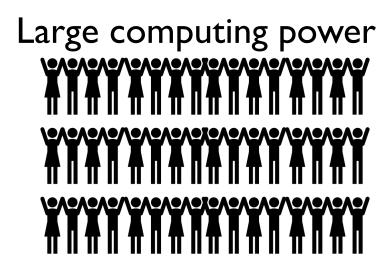


What do we need to parallelize?

Large data, Large # tasks

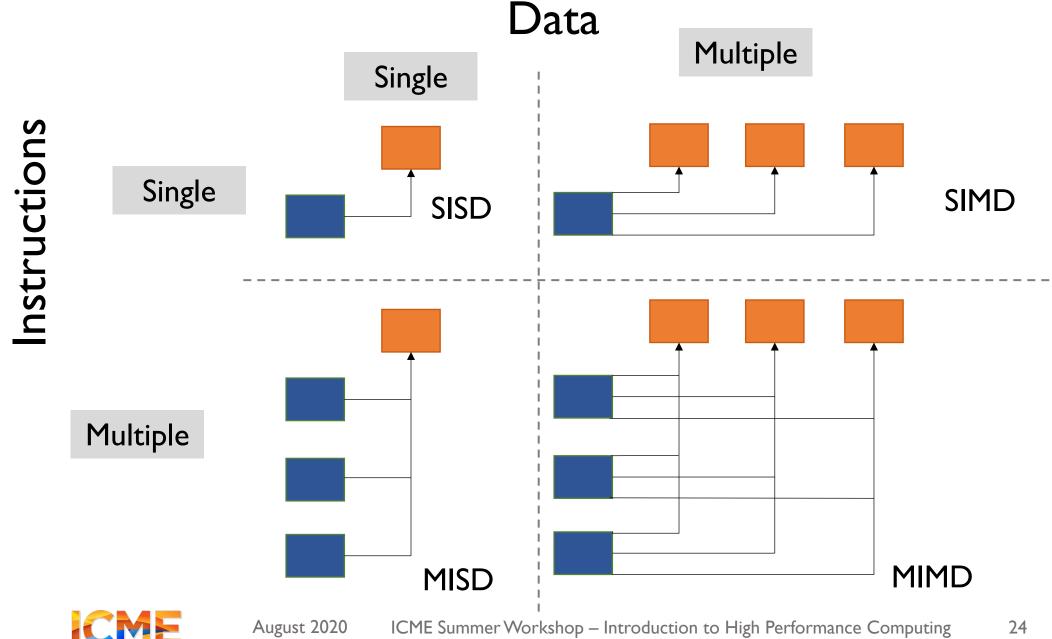








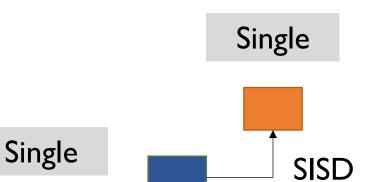
How does distributing Data and Tasks work?



How does distributing Data and Tasks work?

Data

Instructions







SIMD







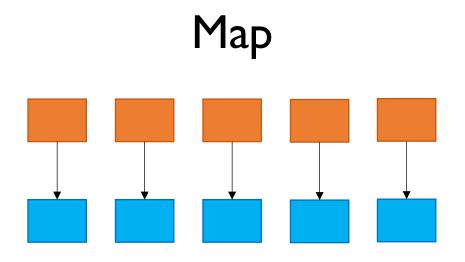
MIMD



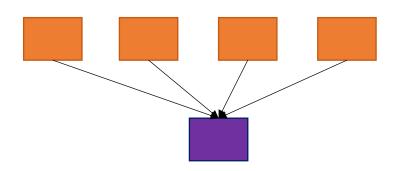
SIMD challenge: Distribute data (a.k.a. Data Parallelism)

Transform Data

Aggregate results

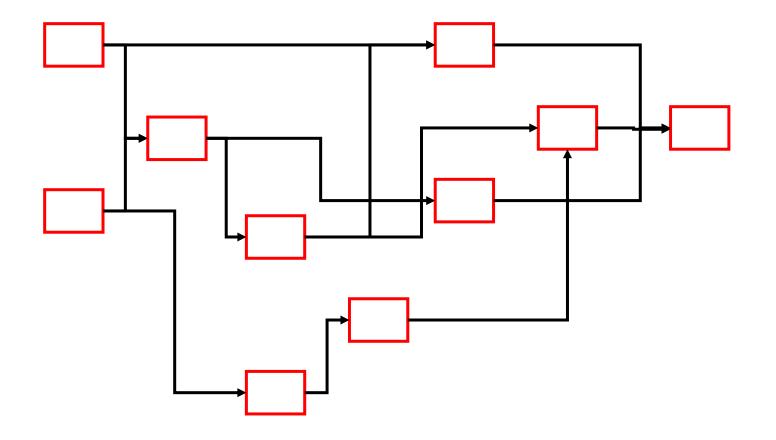






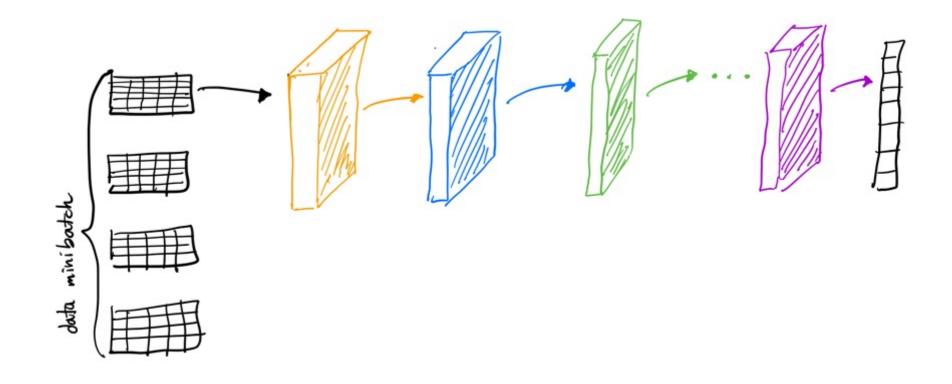


MISD challenge: Manage tasks dependencies (a.k.a. Task Parallelism)



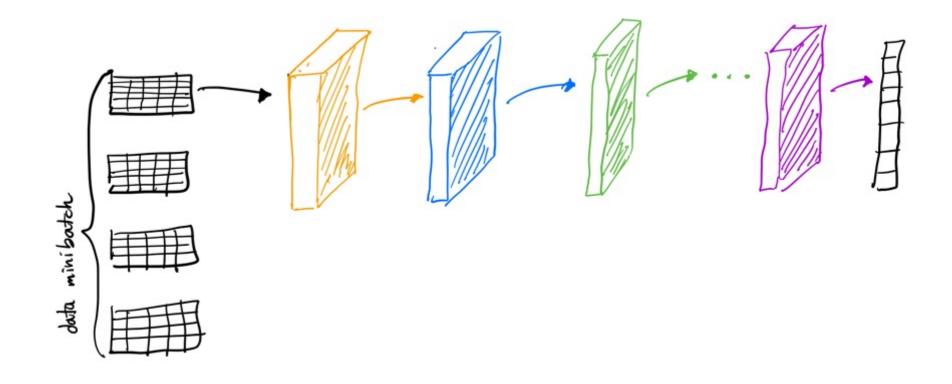


Example: Inference with Deep Neural Networks





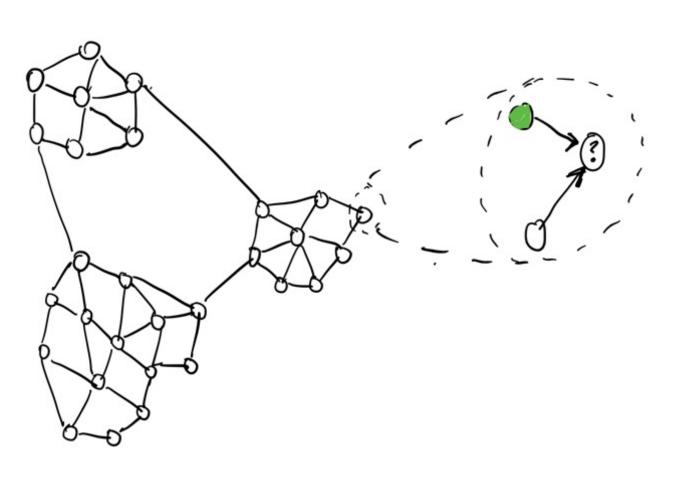
Example: Inference with Deep Neural Networks





Example: Neighbor effects in a sparse network

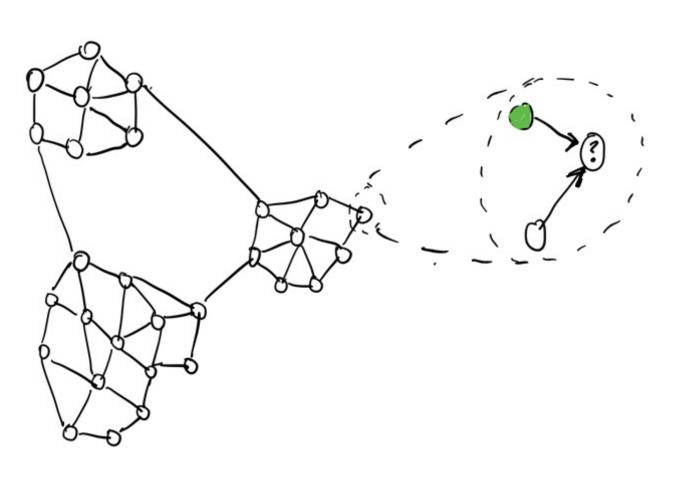
(a.k.a. sparse matrix-vector product)



Heat equation, Page rank, Contact tracing ...

Example: Neighbor effects in a sparse network

(a.k.a. sparse matrix-vector product)



Heat equation, Page rank, Contact tracing ...

Recap

✓ Parallelism = Large data/tasks + Large number of resources

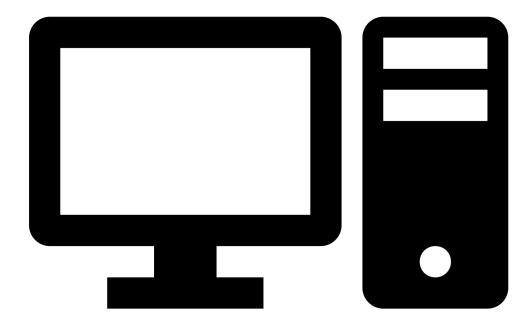
Data Parallelism

How to distribute, transform, and aggregate data?

Task Parallelism

How to distribute and execute tasks given data dependencies?

✓ Constrains: Problem based + Resources based: Memory & Communication



2) Architecture

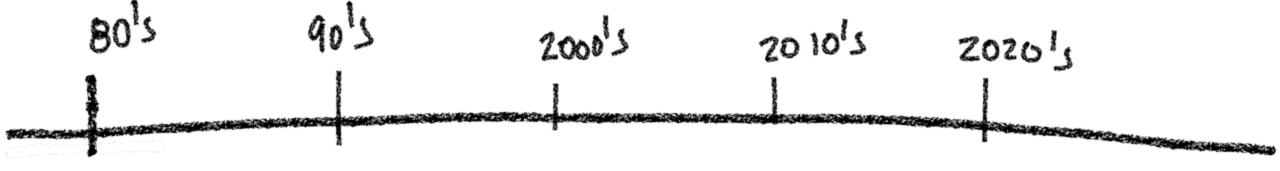
From the Chip to the Supercomputer

Inspired by: The Future of Scientific Computation by Bruce Hendrickson

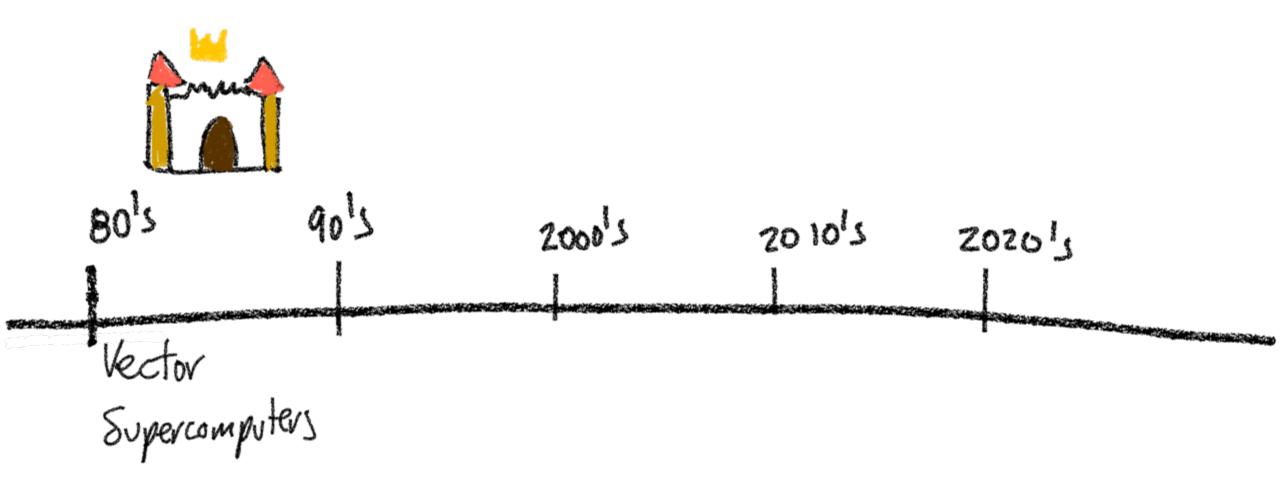


When you think about hardware for parallel computing, what comes to mind?

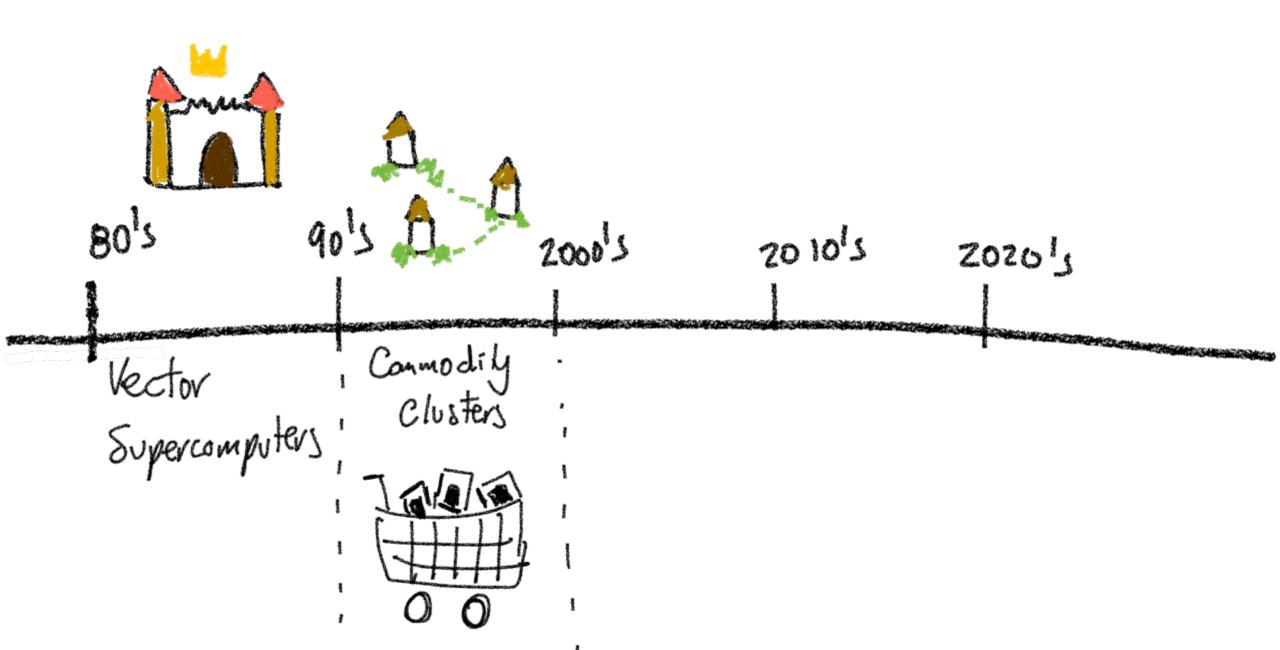




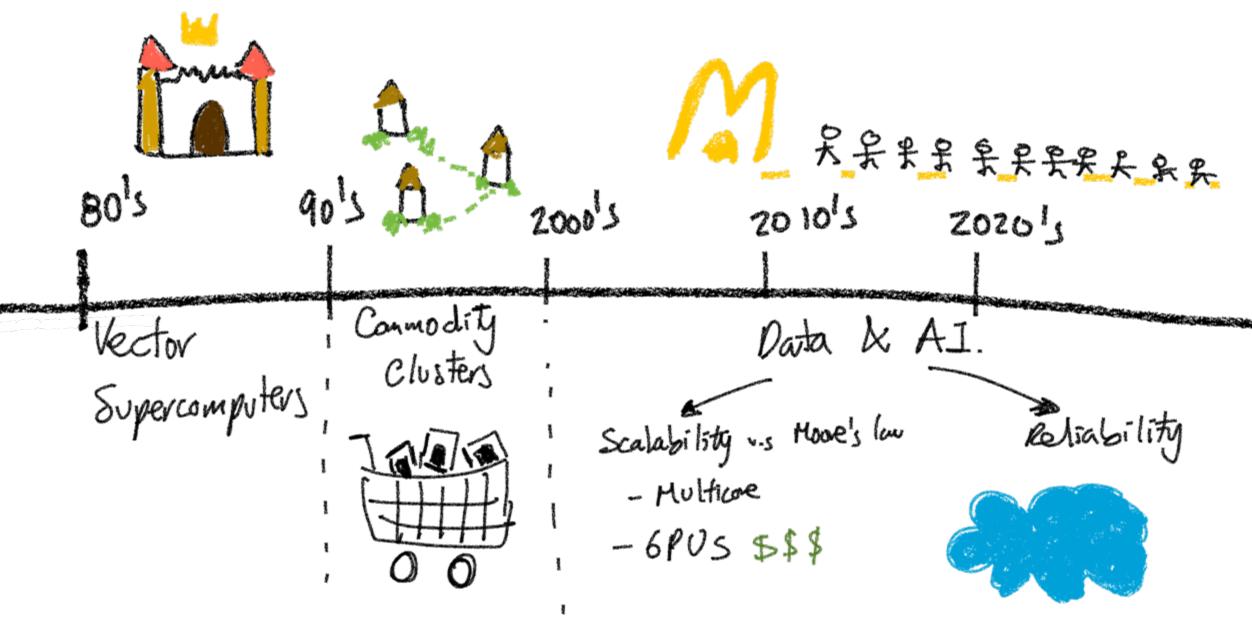












Reality of Scientific Computation today

Heterogenous

Continuous change

Local & In demand

Portability & Reliability



Reality of Scientific Computation today

Heterogenous

Continuous change

Local & In demand

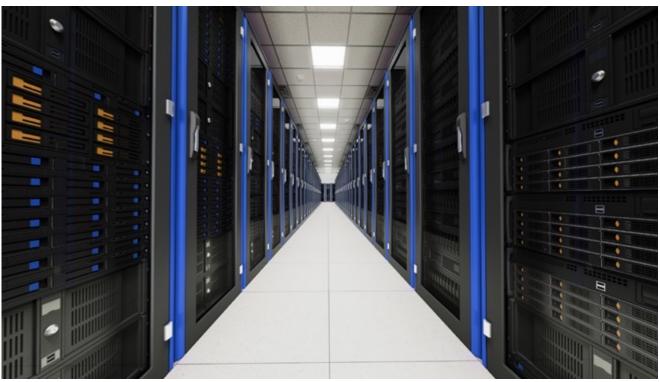
Portability & Reliability

Balanced communication is more challenging than ever!

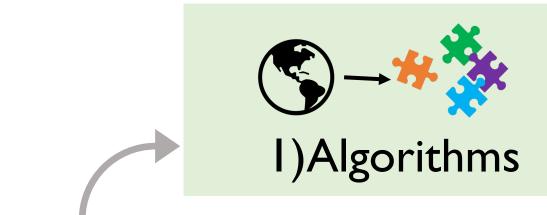


Communication decisions from Laptop to HPC cluster











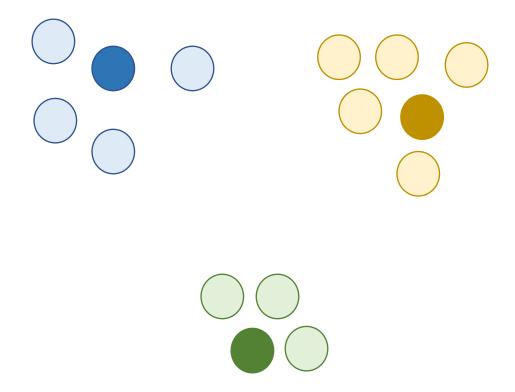
Solutions

- 3)Shared Memory OpenMP
- 4) Distributed Memory
- 5) Unified Engine Spark



HPC

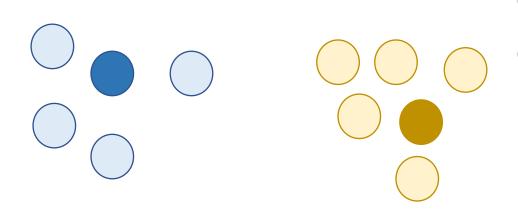
Exercise: K-means algorithm



Find prototypes and clusters that minimize

$$J = \sum_{l=1}^{L} \sum_{i \in C_l} d(x^{(i)}, \tilde{x}_l)$$

Exercise: K-means algorithm



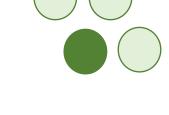


(I) Iterate until clusters do not change

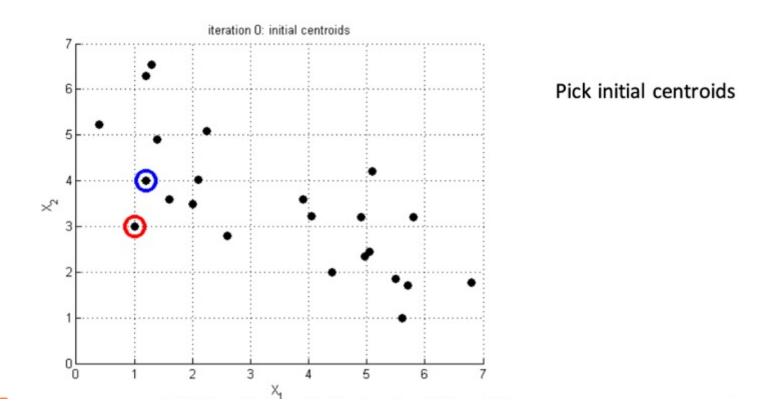
(a) Find best cluster for each point $x^{(i)}$ cluster $(x^i) = \underset{1,...,k}{\operatorname{argmin}} d(x^i, \tilde{x}_l)$

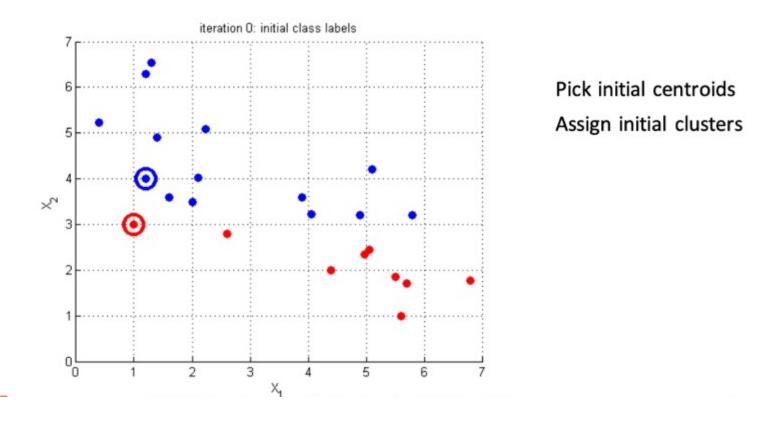
(b) Update centroid \tilde{x}_l for each cluster C_l

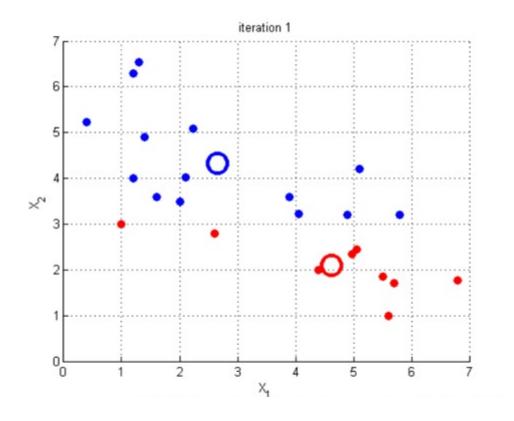
$$\tilde{x}_l = \frac{1}{|C_l|} \sum_{i \in C_l} x^i$$





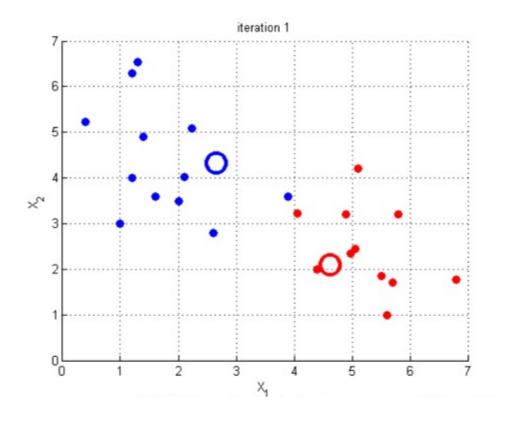






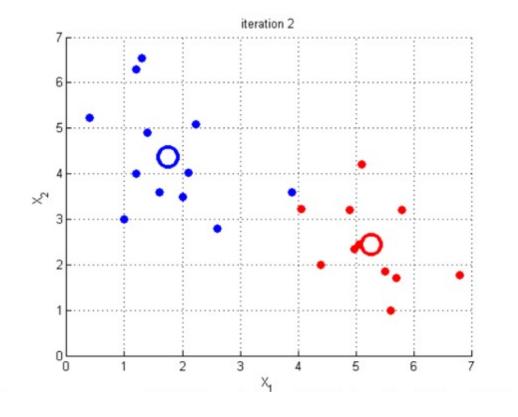
Pick initial centroids
Assign initial clusters
Update centroids

^{*} Simulation done by Karianne Bergen

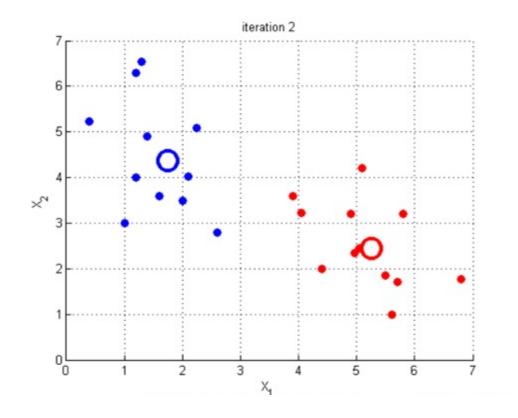


Pick initial centroids
Assign initial clusters
Update centroids
Reassign clusters

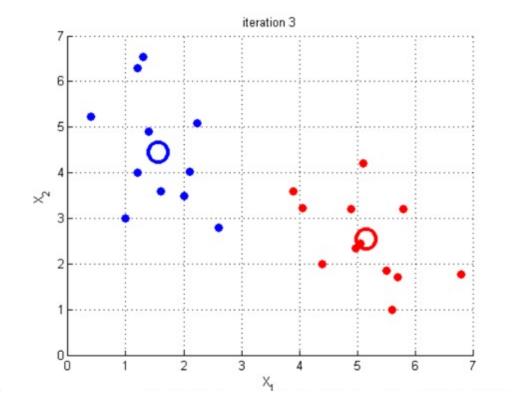
^{*} Simulation done by Karianne Bergen



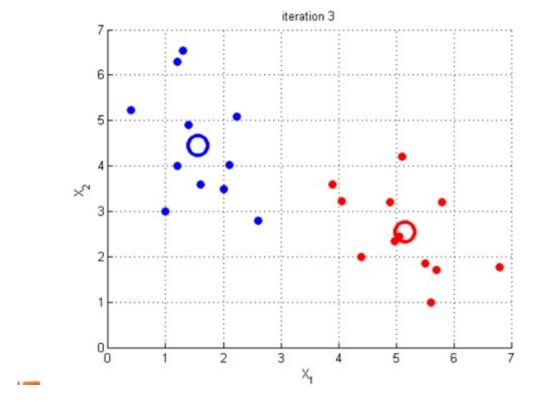
Pick initial centroids
Assign initial clusters
Update centroids
Reassign clusters
Update centroids



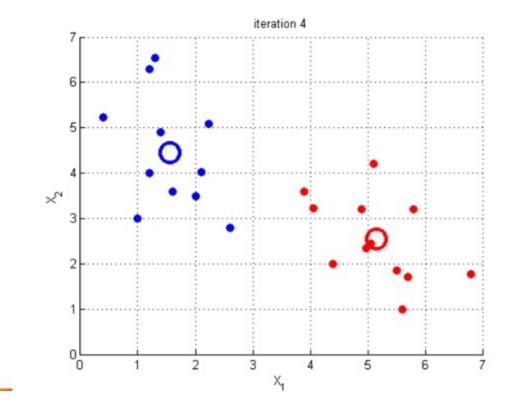
Pick initial centroids
Assign initial clusters
Update centroids
Reassign clusters
Update centroids
Reassign clusters



Pick initial centroids
Assign initial clusters
Update centroids
Reassign clusters
Update centroids
Reassign clusters
Update centroids
Update centroids



Pick initial centroids
Assign initial clusters
Update centroids
Reassign clusters
Update centroids
Reassign clusters
Update centroids
Reassign clusters
Update centroids
Reassign clusters



Pick initial centroids
Assign initial clusters
Update centroids
Reassign clusters
Update centroids
Reassign clusters
Update centroids
Reassign clusters
Update centroids
Converged

Exercise: K-means algorithm

To do:

- Identify regions of the algorithm that can be parallelizable
- 2. How would you divide the work in each parallelizable region?
- 3. What dependencies do you find?

Given a set of points $x^1, ..., x^n$

- (0) Initialize centroids $\tilde{x}_1, \dots, \tilde{x}_k$ at random
- (I) Iterate until clusters do not change
 - (a) Find best cluster for each point x^i cluster $(x^i) = \underset{1,...,k}{\operatorname{argmin}} d(x^i, \tilde{x}_l)$
 - (b) Update centroid \tilde{x}_l for each cluster C_l

$$\tilde{x}_l = \frac{1}{|C_l|} \sum_{i \in C_l} x$$