# Models of Computation for Massive Data 

Jeff M. Phillips

August 28, 2013

## Outline

Sequential:

- External Memory / (I/O)-Efficient
- Streaming

Parallel:

- PRAM and BSP
- MapReduce
- GP-GPU
- Distributed Computing



## RAM Model

RAM model (Von Neumann
Architecture):

- CPU and Memory
- CPU Operations ( $+,-, *, \ldots$ ) constant time
- Data stored as words, not bits.
- Read, Write take constant time.



## Today's Reality

What your computer actually looks like:

- 3+ layers of memory hierarchy.
- Small number of CPUs.

Many variations!


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## External Memory Model



- $N=$ size of problem instance
- $B=$ size of disk block
- $M=$ number of items that fits in Memory
- $T=$ number of items in output
- $1 / \mathrm{O}=$ block move between Memory and Disk


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Advanced Data Structures: Sorting, Searching

## Streaming Model



CPU makes "one pass" on data

- Ordered set $A=\left\langle a_{1}, a_{2}, \ldots, a_{m}\right\rangle$
- Each $a_{i} \in[n]$, size $\log n$
- Compute $f(A)$ or maintain $f\left(A_{i}\right)$ for $A_{i}=\left\langle a_{1}, a_{2}, \ldots, a_{i}\right\rangle$.
- Space restricted to $S=O($ poly $(\log m, \log n))$.
- Updates $O($ poly $(S))$ for each $a_{i}$.


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## PRAM

Many (p) processors. Access shared memory:

- EREW : Exclusive Read Exclusive Write
- CREW : Concurrent Read Exclusive Write
- CRCW : Concurrent Read Concurrent Write

Simple model, but has shortcomings...
...such as Synchronization.

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Advanced Algorithms

## Bulk Synchronous Parallel

Each Processor has its own Memory Parallelism Procedes in Rounds:

1. Compute: Each processor computes on its own Data: $w_{i}$.
2. Synchronize: Each processor sends messages to others:
$s_{i}=$ MessSize $\times$ CommCost.
3. Barrier: All processors wait until others done.

Runtime: $\max w_{i}+\max s_{i}$


Pro: Captures Parallelism and Synchronization
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- Map: assigns items to processor by KEY.
- Reduce: processes all items using VALUE. Usually combines many items with same KEY.
Repeat $M+R$ a constant number of times, often only one round.
- Optional post-processing step.


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## General Purpose GPU

Massive parallelism on your desktop. Uses Graphics Processing Unit. Designed for efficient video rasterizing. Each processor corresponds to pixel p

- depth buffer:

$$
D(p)=\min _{i}\left\|x-w_{i}\right\|
$$

- color buffer: $C(p)=\sum_{i} \alpha_{i} \chi_{i}$
- ...


Pro: Fine grain, massive parallelism. Cheap. Harnesses Locality.
Con: Somewhat restrictive model, hierarchy. Small memory.

## Distributed Computing

Many small slow processors with data.
Communication very expensive.

- Report to base station
- Merge tree
- Unorganized (peer-to-peer)


Data collection or Distribution

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## Themes

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- Taste of how to use each model
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Work Plan:

- 1-3 weeks each model.
- Background and Model.
- Example algorithms analysis in each model.

| I/O | Stream | Parallel | MapReduce | GPU | Distributed |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 4 | 5 | 4 | 4 | 3 | 3 |

## Class Work

1 Credit Students:

- Attend Class. (some Fridays less important)
- Ask Questions.
- If above lacking, may have quizzes.
- Scribing Notes, Video-taping Lectures, or Giving Lectures.

3 Credit Students:
Must also do a project!

- Project Proposal (Aug 30). Approved or Rejected by Sept 4.
- Intermediate Report (Oct 23).
- Presentations (Dec 11 or 13).


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## Asymptotics

How large (in seconds) is:

- Searching $(\log n)$
- Max (n)
- Merge-Sort $(n \log n)$
- Bubble-Sort ( $n^{2}$ ) ... or Dynamic Programming

| $n=$ | 10 | $10^{2}$ | $10^{3}$ | $10^{4}$ | $10^{5}$ | $10^{6}$ | $10^{7}$ | $10^{8}$ | 1 |
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- NP: verify solution in P, find solution conjectured EXP (If EXP number parallel machines, then in P time)


## Data Group

Data Group Meeting<br>Thursdays @ 12:15-1:30pm in LCR<br>(to be confirmed)

http://datagroup.cs.utah.edu/dbgroup.php

