

Big Data Mining and Analytics Lecture

Parallel and Distributed Computing


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Material adapted from slides by Christophe Bisciglia, Aaron Kimball, & Sierra Michels-Slettvet, Google Distributed Computing Seminar, 2007 (licensed under Creation Commons Attribution 3.0 License)



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Big Data processing boils down to...

- Divide-and-conquer
- Throwing more hardware at the problem

Simple to understand... a lifetime to master...



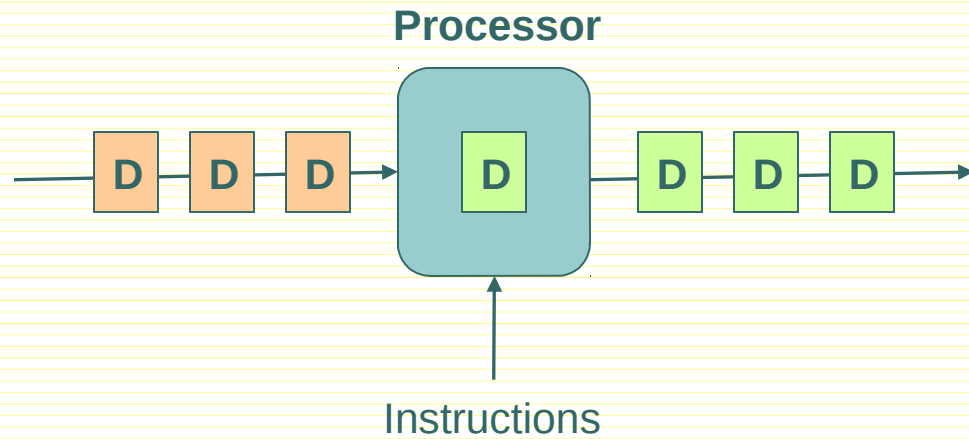
Parallel vs. Distributed

- Parallel computing generally means:
 - Vector processing of data
 - Multiple CPUs in a single computer
- Distributed computing generally means:
 - Multiple CPUs across many computers

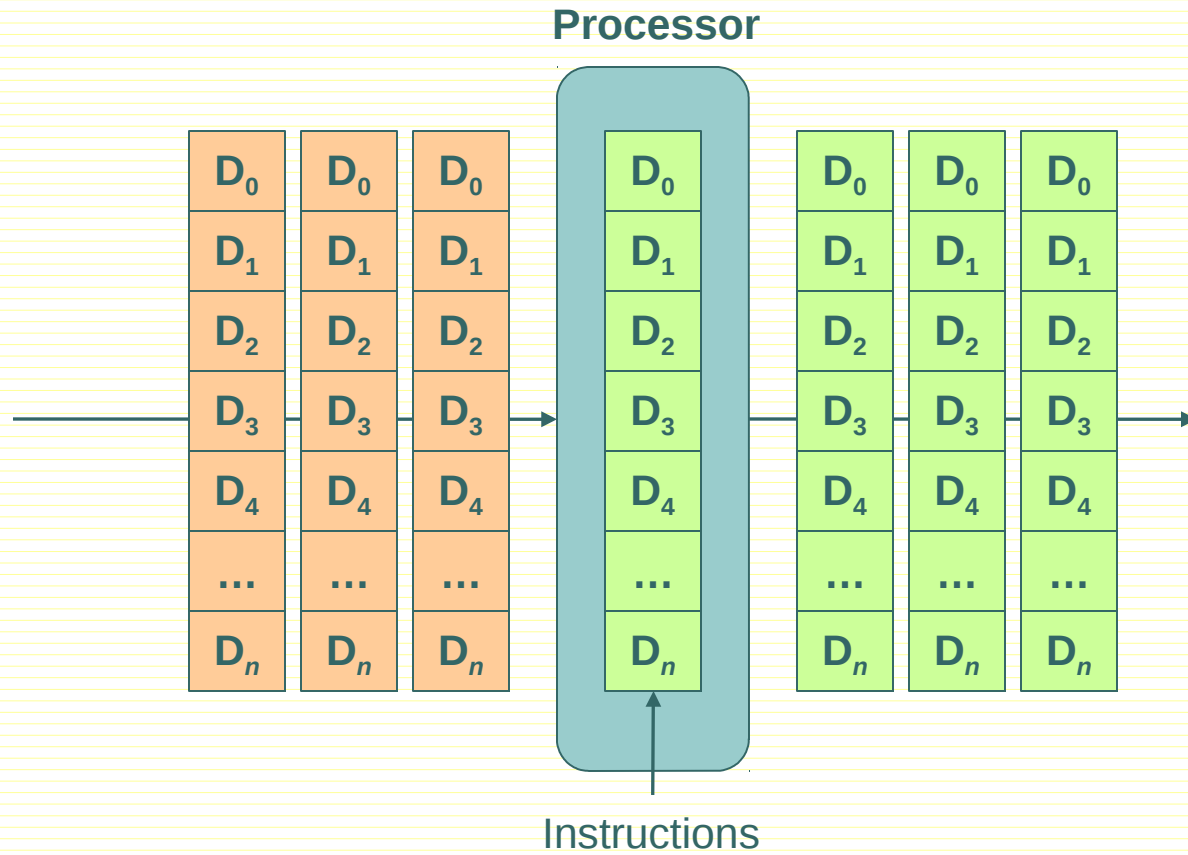
Flynn's Taxonomy

		Instructions	
		Single (SI)	Multiple (MI)
Data	Single (SD)	SISD Single-threaded process	MISD Pipeline architecture
	Multiple (MD)	SIMD Vector Processing	MIMD Multi-threaded Programming

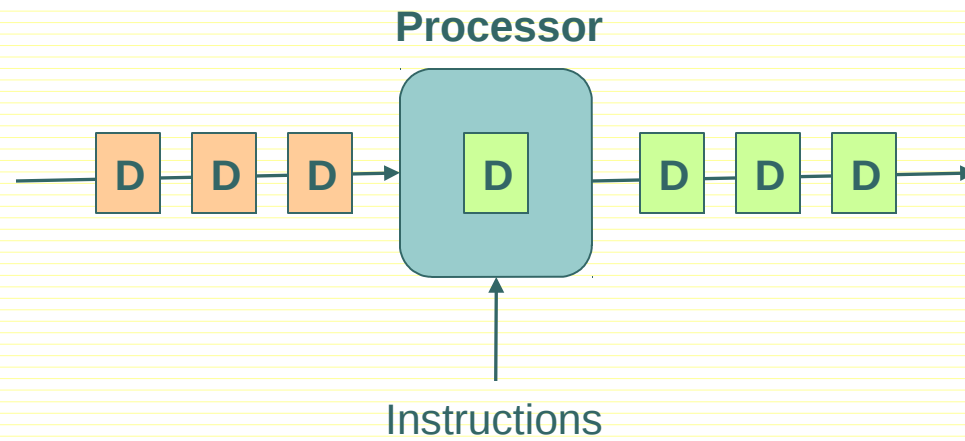
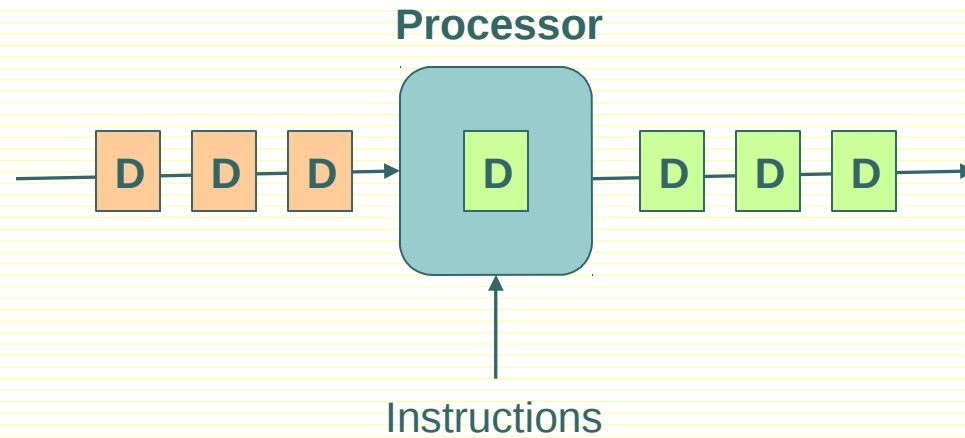
SISD



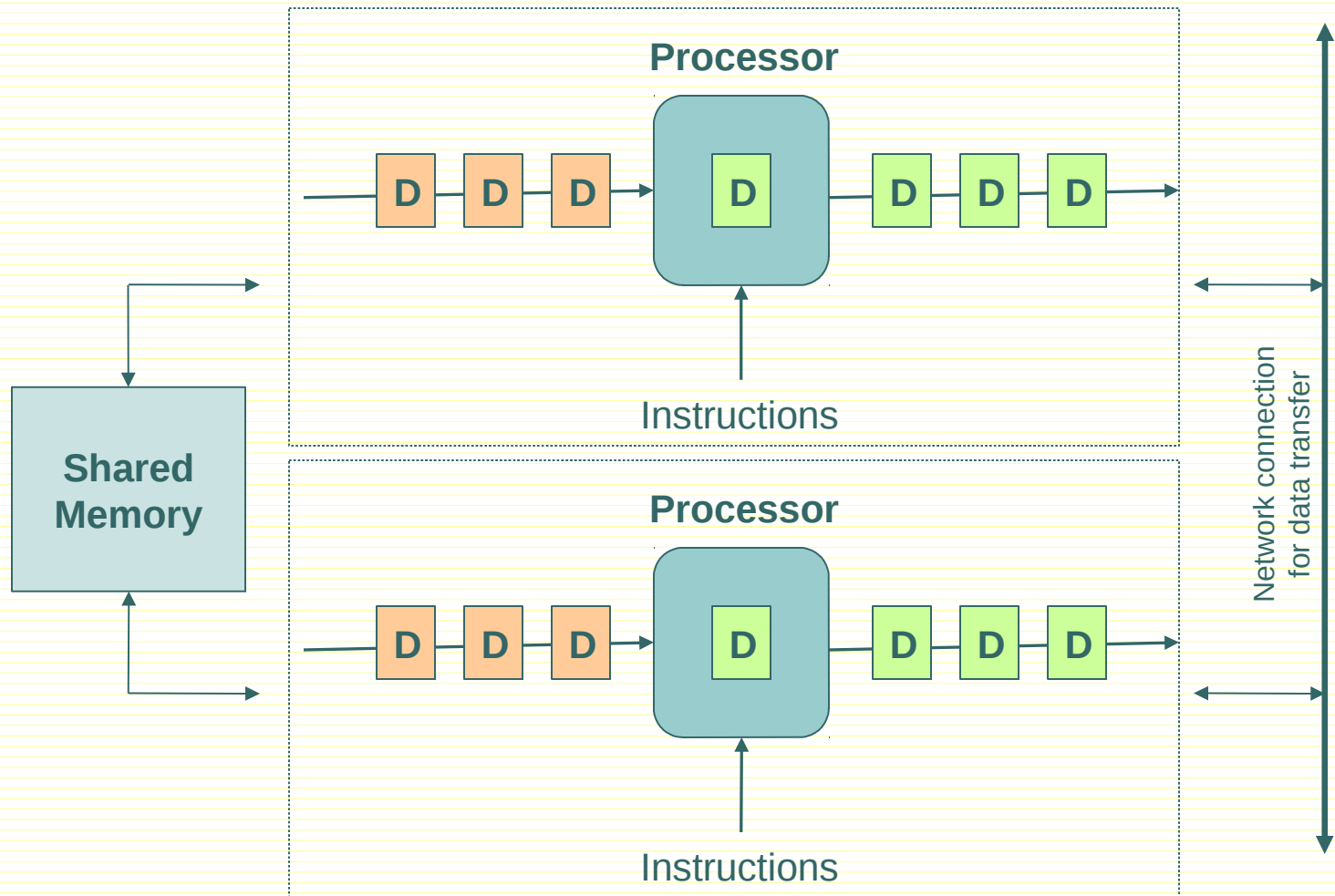
SIMD



MIMD



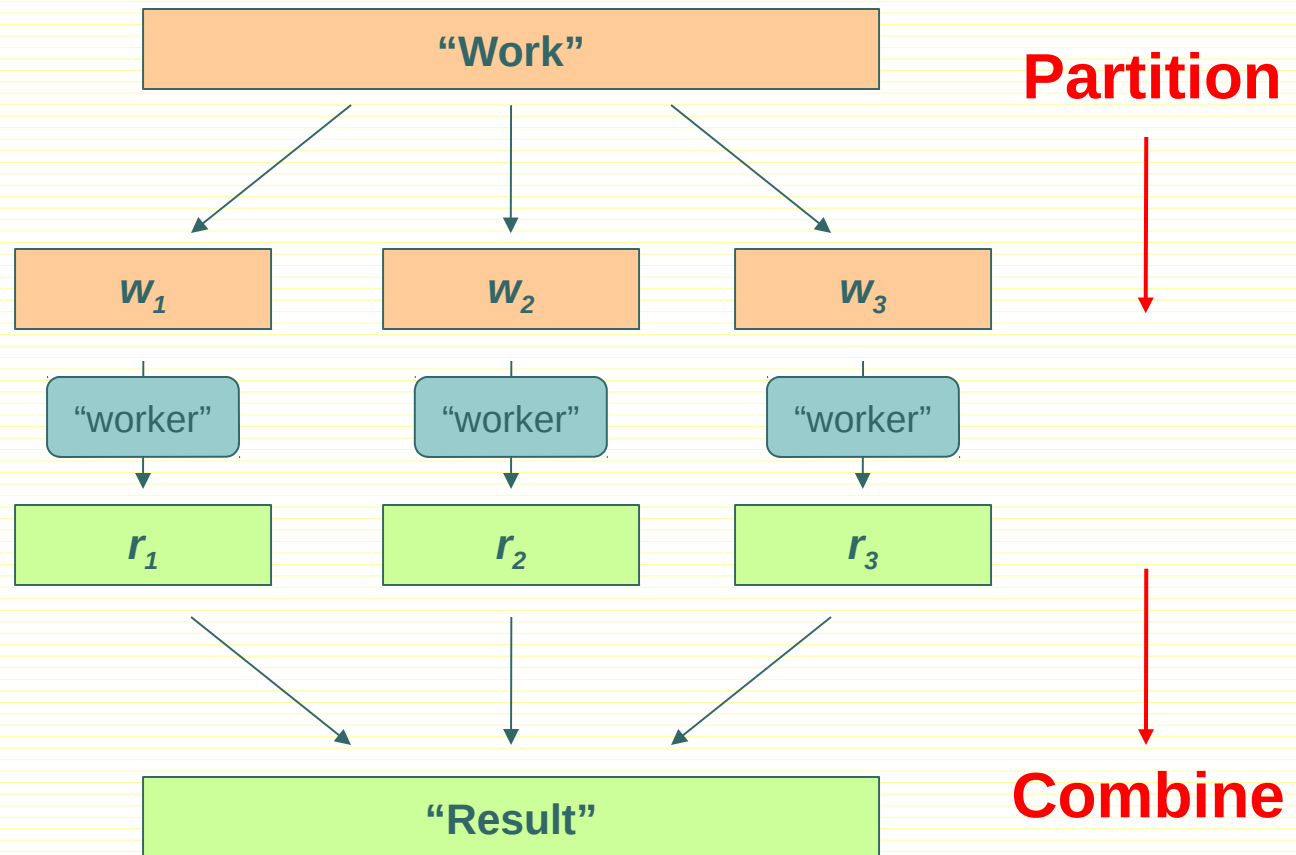
Parallel vs. Distributed



Parallel: Multiple CPUs within a shared memory machine

Distributed: Multiple machines with own memory connected over a network

Divide and Conquer





Parallelization Problems

- How do we assign work units to workers?
- What if we have more work units than workers?
- What if workers need to share partial results?
- How do we aggregate partial results?
- How do we know all the workers have finished?
- What if workers die?

What is the common theme of all of these problems?



General Theme?

- Parallelization problems arise from:
 - Communication between workers
 - Access to shared resources (e.g., data)
- Thus, we need a synchronization system!
- This is tricky:
 - Finding bugs is hard
 - Solving bugs is even harder


Cloud Computing Lecture #2

From Lisp to MapReduce and GFS

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Today's Topics

- Functional Programming
- MapReduce
- Google File System (GFS)

Lisp

MapReduce

GFS



Functional Programming

- MapReduce = functional programming meets distributed processing on steroids
 - Not a new idea... dates back to the 50's (or even 30's)
- What is functional programming?
 - Computation as application of functions
 - Theoretical foundation provided by lambda calculus
- How is it different?
 - Traditional notions of “data” and “instructions” are not applicable
 - Data flows are implicit in program
 - Different orders of execution are possible
- Exemplified by LISP and ML

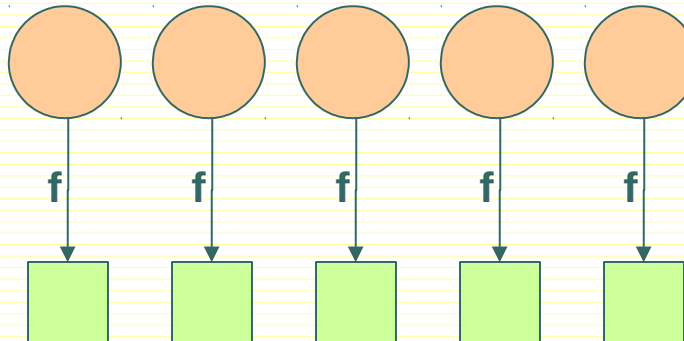


Lisp → MapReduce?

- What does this have to do with MapReduce?
- After all, Lisp is about processing *lists*
- Two important concepts in functional programming
 - Map: do something to everything in a list
 - Fold: combine results of a list in some way

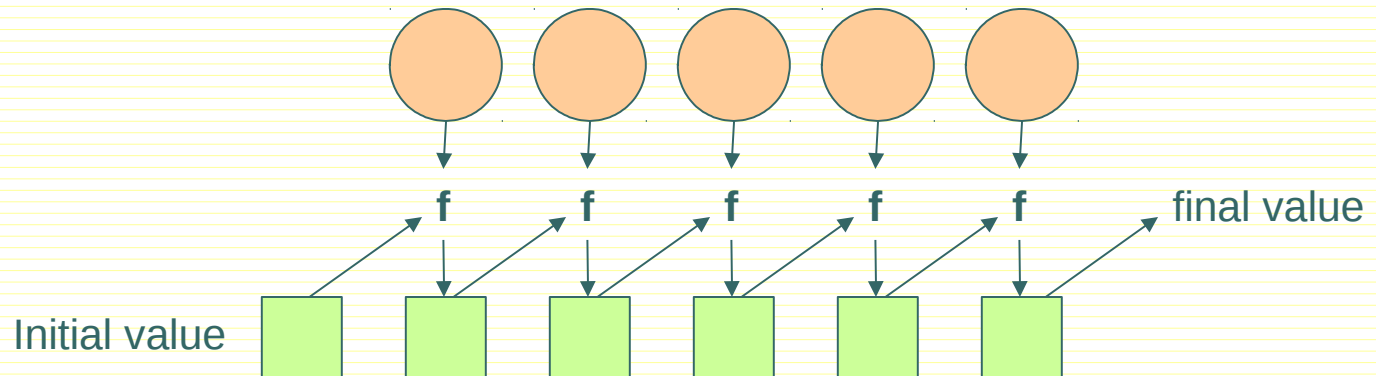
Map

- Map is a higher-order function
- How map works:
 - Function is applied to every element in a list
 - Result is a new list



Fold

- Fold is also a higher-order function
- How fold works:
 - Accumulator set to initial value
 - Function applied to list element and the accumulator
 - Result stored in the accumulator
 - Repeated for every item in the list
 - Result is the final value in the accumulator



Map/Fold in Action

- Simple map example:

```
(map (lambda (x) (* x x))  
      '(1 2 3 4 5))  
→ '(1 4 9 16 25)
```

- Fold examples:

```
(fold + 0 '(1 2 3 4 5)) → 15
```

- Sum of squares:

```
(define (sum-of-squares v)  
  (fold + 0 (map (lambda (x) (* x x)) v)))  
(sum-of-squares '(1 2 3 4 5)) → 55
```



Lisp → MapReduce

- Let's assume a long list of records: imagine if...
 - We can distribute the execution of map operations to multiple nodes
 - We have a mechanism for bringing map results back together in the fold operation
- That's MapReduce! (and Hadoop)
- Implicit parallelism:
 - We can parallelize execution of map operations since they are isolated
 - We can reorder folding if the fold function is commutative and associative



Typical Problem

- Iterate over a large number of records
- **Map**: extract something of interest from each
- Shuffle and sort intermediate results
- **Reduce**: aggregate intermediate results
- Generate final output

Key idea: provide an abstraction at the point of these two operations



MapReduce

- Programmers specify two functions:
 - map** $(k, v) \rightarrow \langle k', v' \rangle^*$
 - reduce** $(k', v') \rightarrow \langle k', v' \rangle^*$
 - All v' with the same k' are reduced together
- Usually, programmers also specify:
 - partition** $(k', \text{number of partitions}) \rightarrow \text{partition for } k'$
 - Often a simple hash of the key, e.g. $\text{hash}(k') \bmod n$
 - Allows reduce operations for different keys in parallel