Data Intensive Scalable Computing

Finding the Right Programming Models

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Outline

Data-Intensive Scalable Computing

- Focus on petabytes, not petaflops
- Rethinking machine design

Map/Reduce Programming Model

- Suitability for wide class of computing tasks

Strengths & Limitations

- Scalability
- Performance

Beyond Map/Reduce

- Small variations
- Other programming models

Our Data-Driven World

Science

- Data bases from astronomy, genomics, natural languages, seismic modeling, …

Humanities

- Scanned books, historic documents, …

Commerce

- Corporate sales, stock market transactions, census, airline traffic, …

Entertainment

- Internet images, Hollywood movies, MP3 files, …

Medicine

- MRI & CT scans, patient records, …

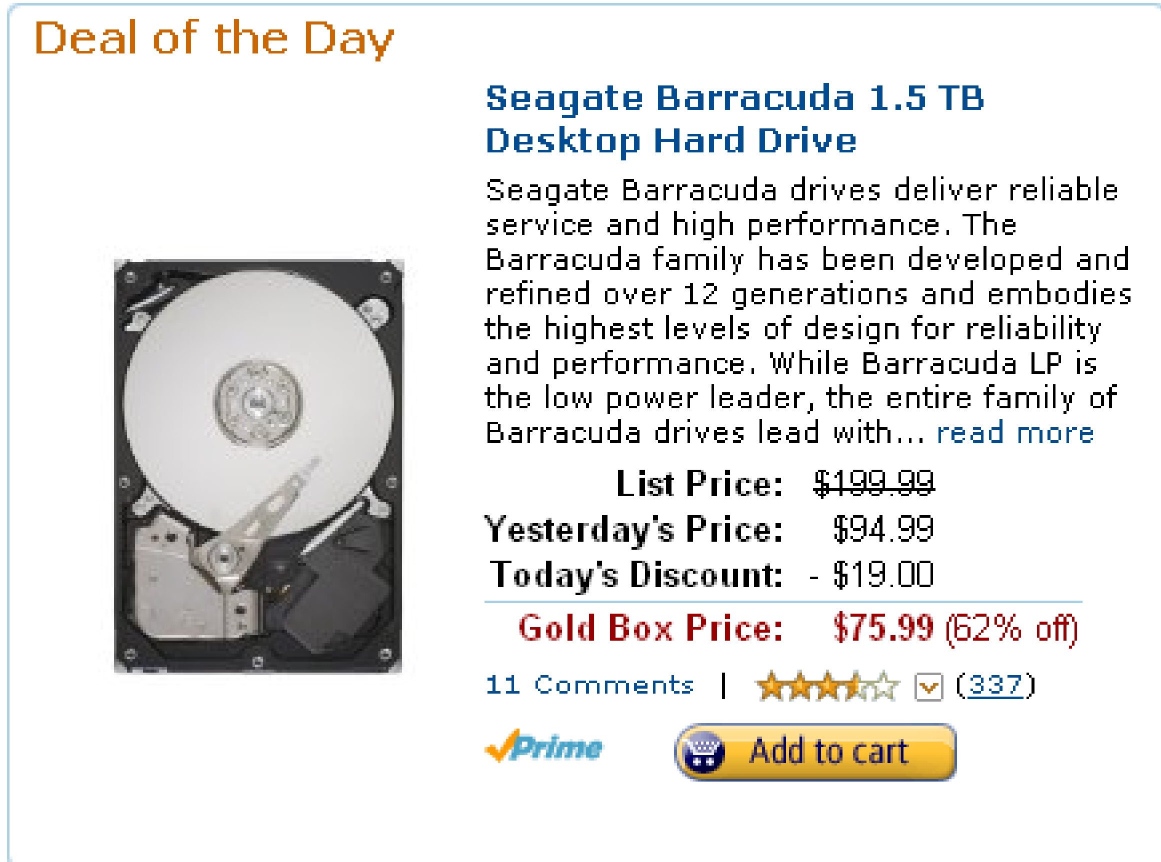
Why So Much Data?

We Can Get It

- Automation + Internet

We Can Keep It

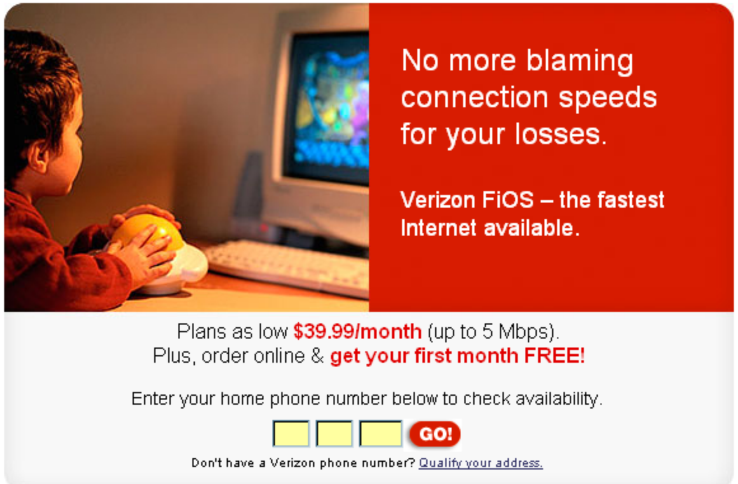
- Seagate Barracuda
- 1.5 TB @ $76
  - 5¢ / GB
  - (vs. 40¢ in 2007)



We Can Use It

- Scientific computation
- Business applications
- Harvesting Internet data

Oceans of Data, Skinny Pipes



Seagate

1 Terabyte

- Easy to store
- Hard to move

Disks	MB / s	Time
Seagate Barracuda	115	2.3 hours
Seagate Cheetah	125	2.2 hours
Networks	**MB / s**	**Time**
Home Internet	< 0.625	> 18.5 days
Gigabit Ethernet	< 125	> 2.2 hours
PSC Teragrid Connection	< 3,750	> 4.4 minutes

Data-Intensive System Challenge

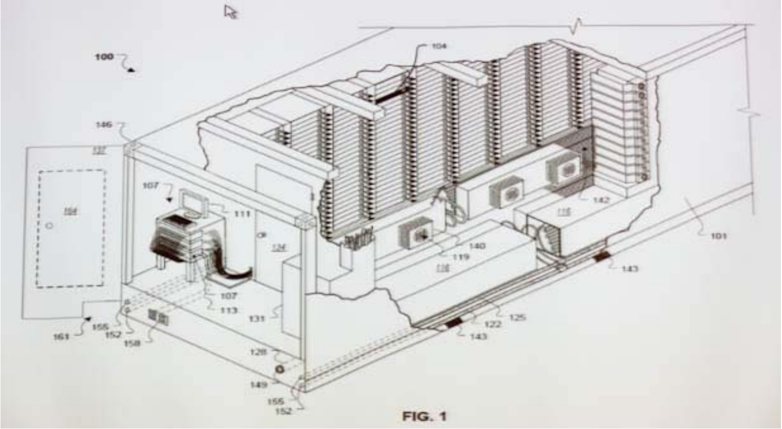
For Computation That Accesses 1 TB in 5 minutes

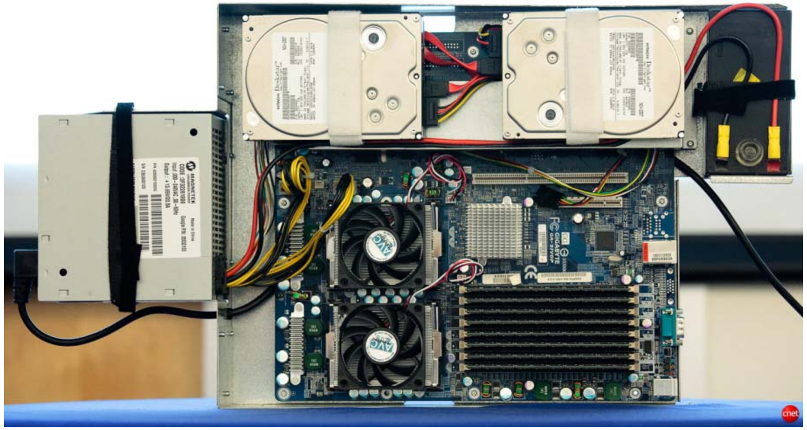
- **Data distributed over 100+ disks**
  - Assuming uniform data partitioning
- **Compute using 100+ processors**
- **Connected by gigabit Ethernet (or equivalent)**

System Requirements

- **Lots of disks**
- **Lots of processors**
- **Located in close proximity**
  - Within reach of fast, local-area network

Google Data Centers





Dalles, Oregon

- **Hydroelectric power @ 2¢ / KW Hr**
- **50 Megawatts**
  - Enough to power 6,000 homes

- **Engineered for maximum modularity & power efficiency**
- **Container: 1160 servers, 250KW**
- **Server: 2 disks, 2 processors**

High-Performance Distributed Computing: Two Versions

Grid Computing

Connect small number of big machines

- Allow resource sharing among supercomputers

Issues

- Programs must usually be specialized for machine
- Hard to get cooperation from multiple organizations

DISC System

Build big system from many small machines

- Use distributed systems principles to construct large-scale machine
- File system provides distribution, reliability, recovery
- Dynamically scheduled task as basic processing unit

Programming Model Comparison

Bulk Synchronous

- **Commonly used for compute-intensive applications**

Map/Reduce

- **Commonly used for data-intensive applications**

Issues

- **Raw performance**
- **Scalability**
  - Cost required to increase machine size by K
    - » $\geq$ K
  - Performance achieved by increasing machine size by K
    - » $\leq$ K
  - Frequency and impact of failures

Bulk Synchronous Programming

Solving Problem Over Grid

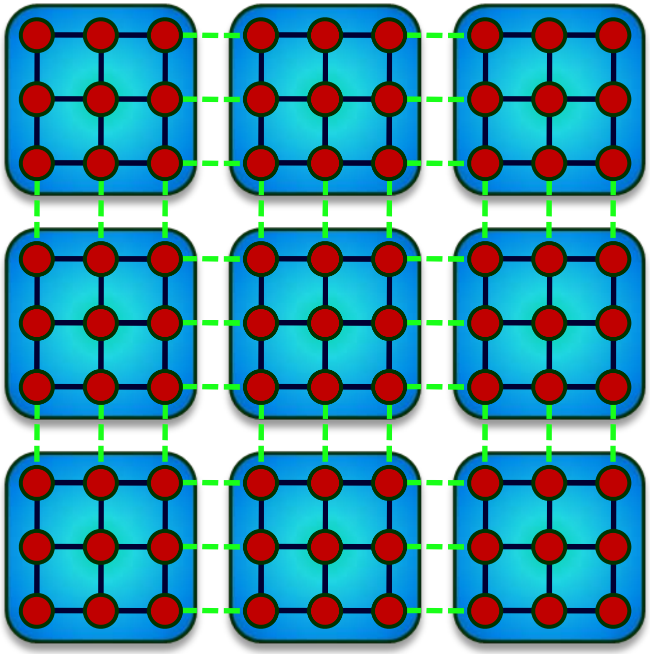
- E.g., finite-element computation

Partition into Regions

- p regions for p processors

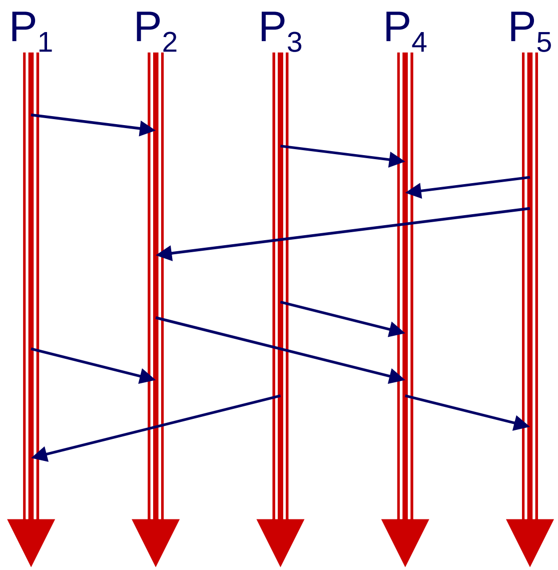
Map Region per Processor

- Local computation sequential
- Periodically communicate boundary values with neighbors

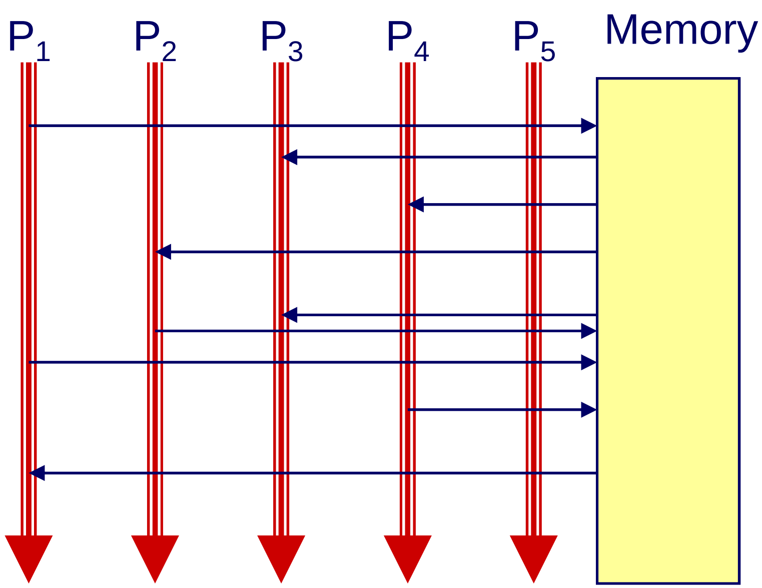


Typical HPC Operation

Message Passing



Shared Memory



Characteristics

- Long-lived processes
- Make use of spatial locality
- Hold all program data in memory (no disk access)
- High bandwidth communication

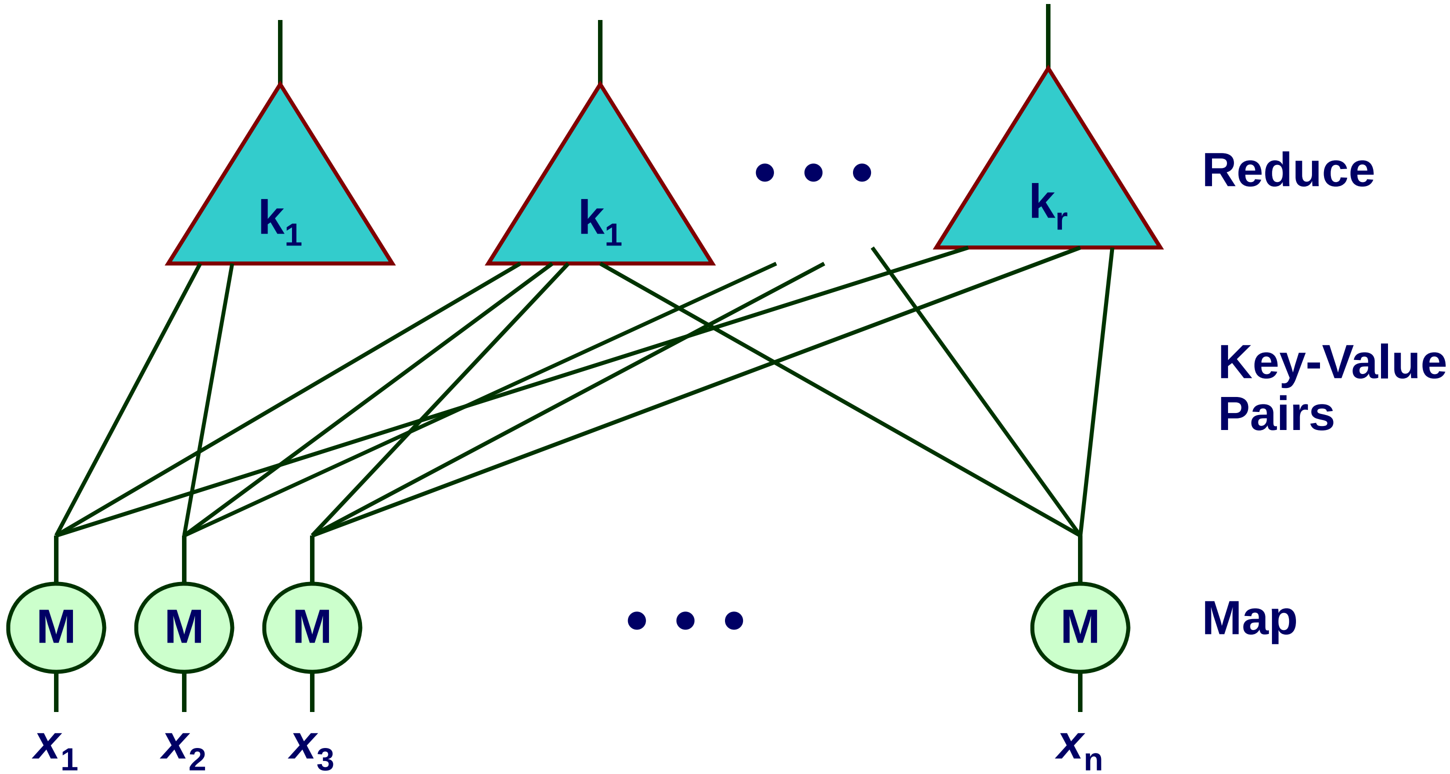
Strengths

- High utilization of resources
- Effective for many scientific applications

Weaknesses

- Requires careful tuning of application to resources
- Intolerant of any variability

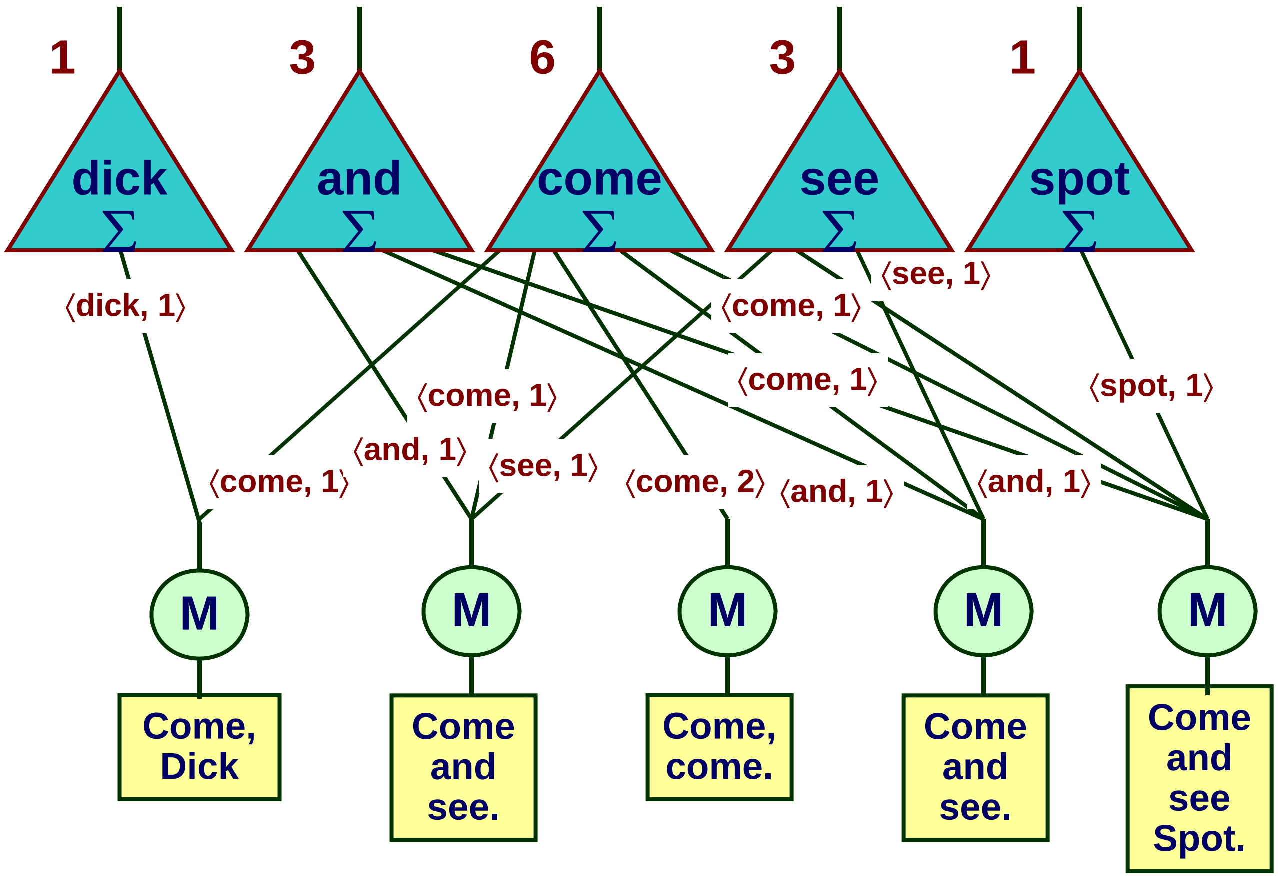
Map/Reduce Programming Model



- **Map computation across many objects**
  - E.g., 10^{10} Internet web pages
- **Aggregate results in many different ways**
- **System deals with issues of resource allocation & reliability**

Dean & Ghemawat: "MapReduce: Simplified Data Processing on Large Clusters", OSDI 2004

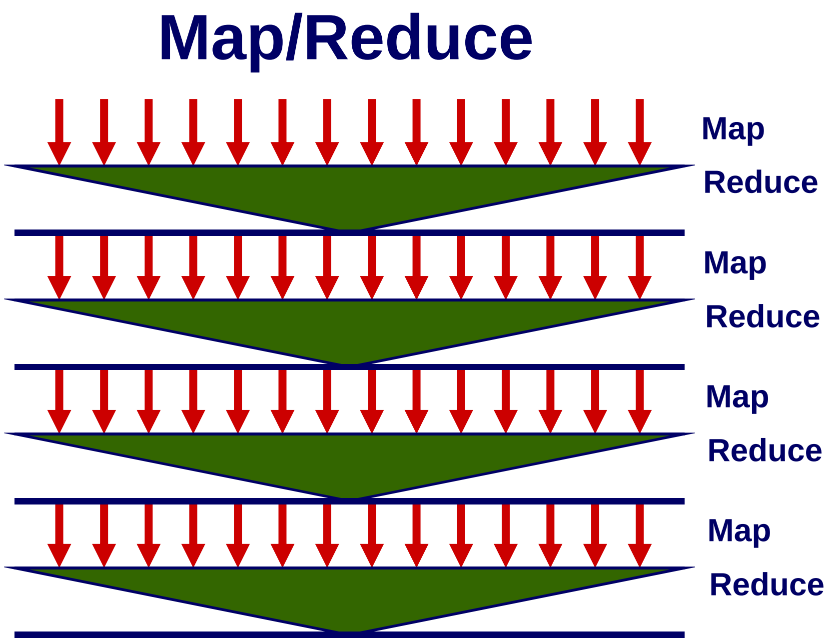
Map/Reduce Example



Extract

- Create an word index of set of documents
- Map: generate ⟨word, count⟩ pairs for all words in document
- Reduce: sum word counts across documents

Map/Reduce Operation



Characteristics

- Computation broken into many, short-lived tasks
  - Mapping, reducing
- Use disk storage to hold intermediate results

Strengths

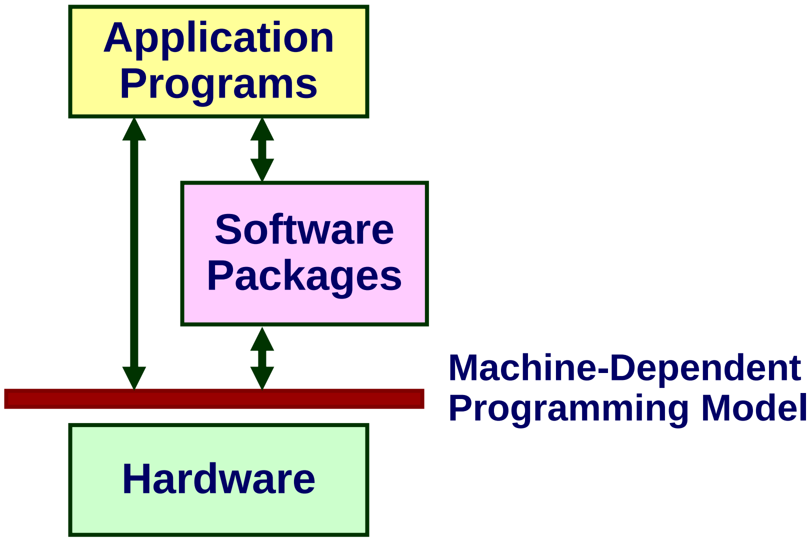
- Great flexibility in placement, scheduling, and load balancing
- Can access large data sets

Weaknesses

- Higher overhead
- Lower raw performance

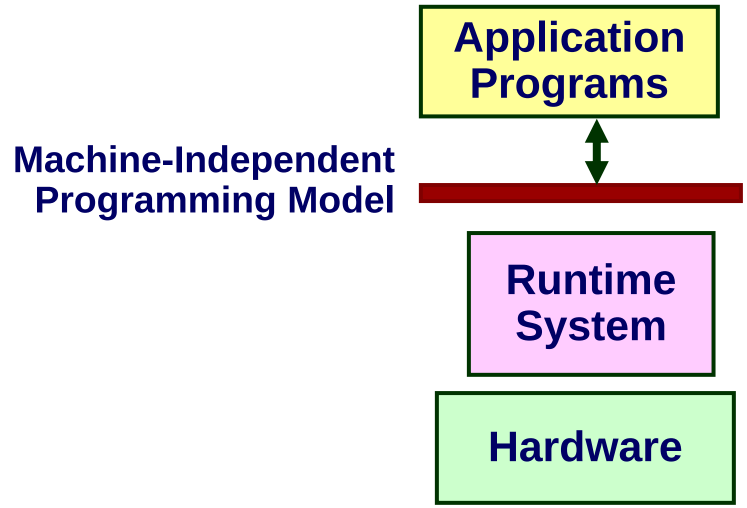
System Comparison: Programming Models

Conventional HPC



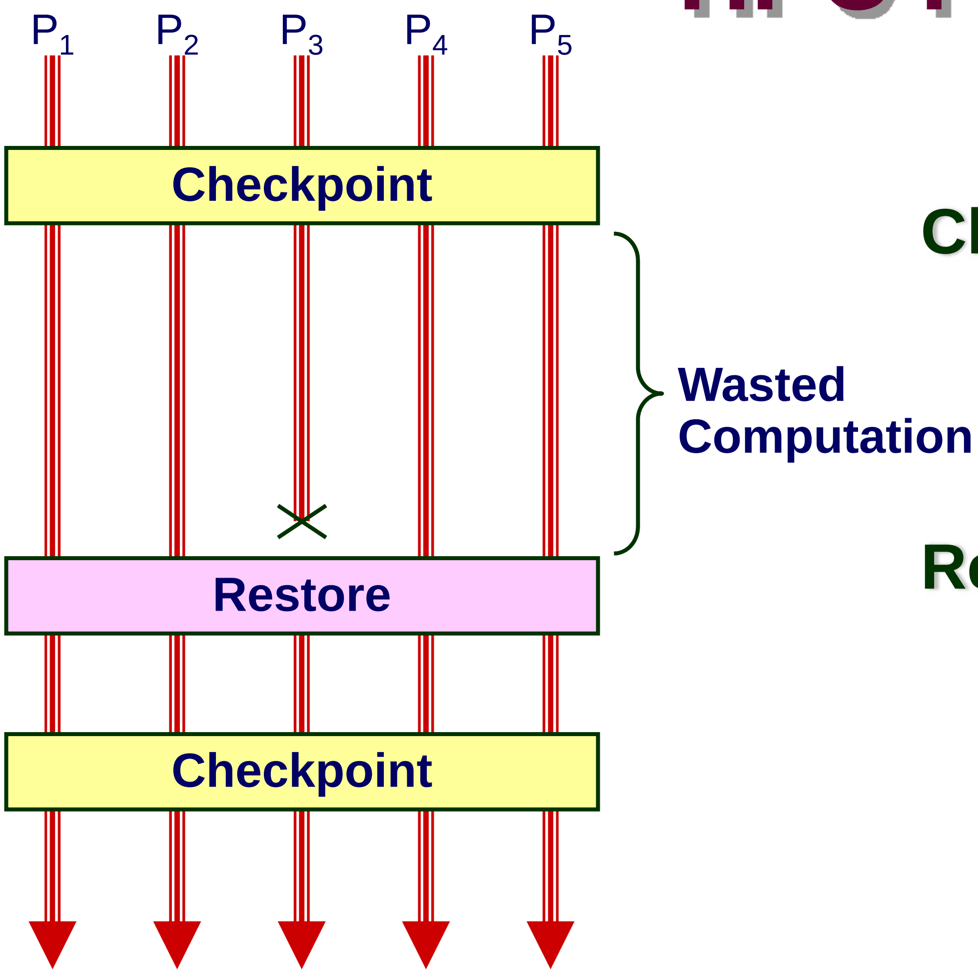
- Programs described at very low level
  - Specify detailed control of processing & communications
- Rely on small number of software packages
  - Written by specialists
  - Limits classes of problems & solution methods

DISC



- Application programs written in terms of high-level operations on data
- Runtime system controls scheduling, load balancing, …

HPC Fault Tolerance



Checkpoint

- Periodically store state of all processes
- Significant I/O traffic

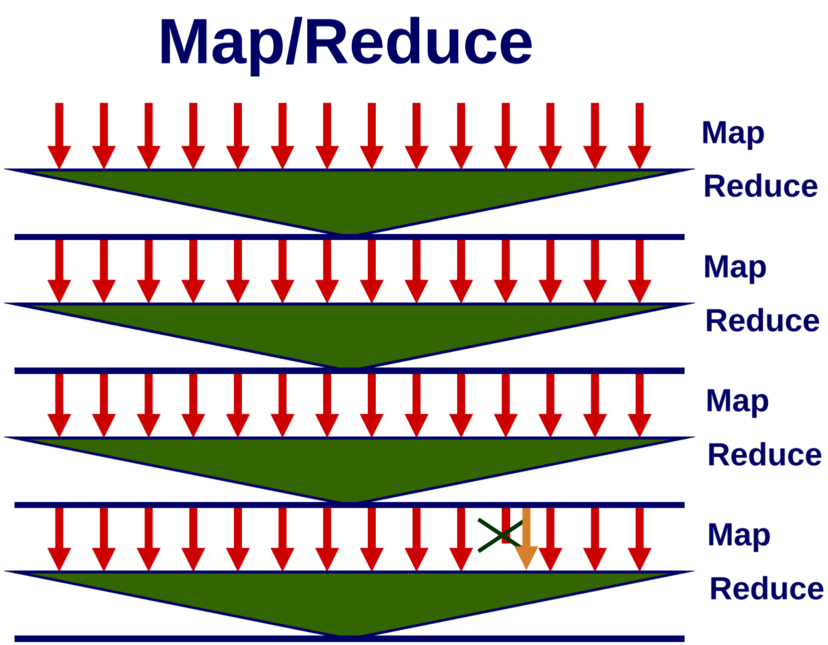
Restore

- When failure occurs
- Reset state to that of last checkpoint
- All intervening computation wasted

Performance Scaling

- Very sensitive to number of failing components

Map/Reduce Fault Tolerance



Data Integrity

- Store multiple copies of each file
- Including intermediate results of each Map / Reduce
  - Continuous checkpointing

Recovering from Failure

- Simply recompute lost result
  - Localized effect
- Dynamic scheduler keeps all processors busy

DISC Scalability Advantages

- **Distributed system design principles lead to scalable design**
- **Dynamically scheduled tasks with state held in replicated files**

Provisioning Advantages

- **Can use consumer-grade components**
  - maximizes cost-peformance
- **Can have heterogenous nodes**
  - More efficient technology refresh

Operational Advantages

- **Minimal staffing**
- **No downtime**

Getting Started

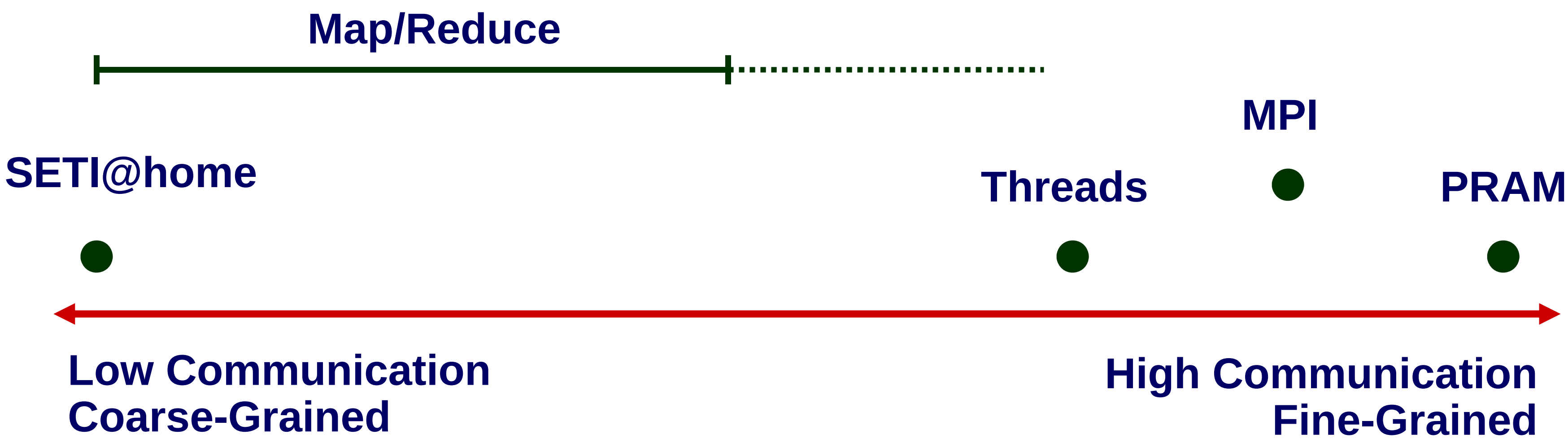
Goal

- **Get people involved in DISC**

Software

- **Hadoop Project**
  - Open source project providing file system and Map/Reduce
  - Supported and used by Yahoo
  - Rapidly expanding user/developer base
  - Prototype on single machine, map onto cluster

Exploring Parallel Computation Models



DISC + Map/Reduce Provides Coarse-Grained Parallelism

- Computation done by independent processes
- File-based communication

Observations

- Relatively “natural” programming model
- Research issue to explore full potential and limits

Example: Sparse Matrices with Map/Reduce

$$
A = \begin{bmatrix} 10 & & 20 \\ & 30 & 40 \\ 50 & 60 & 70 \end{bmatrix}
\times
B = \begin{bmatrix} -1 & \\ -2 & -3 \\ & -4 \end{bmatrix}
=
C = \begin{bmatrix} -10 & -80 \\ -60 & -250 \\ -170 & -460 \end{bmatrix}
$$

- Task: Compute product C = A·B
- Assume most matrix entries are 0

Motivation

- Core problem in scientific computing
- Challenging for parallel execution
- Demonstrate expressiveness of Map/Reduce

Computing Sparse Matrix Product

A

$$A = \begin{bmatrix} 10 & & 20 \\ & 30 & 40 \\ 50 & 60 & 70 \end{bmatrix}$$

1	10 A →	1
1	20 A →	3
2	30 A →	2
2	40 A →	3
3	50 A →	1
3	60 A →	2
3	70 A →	3

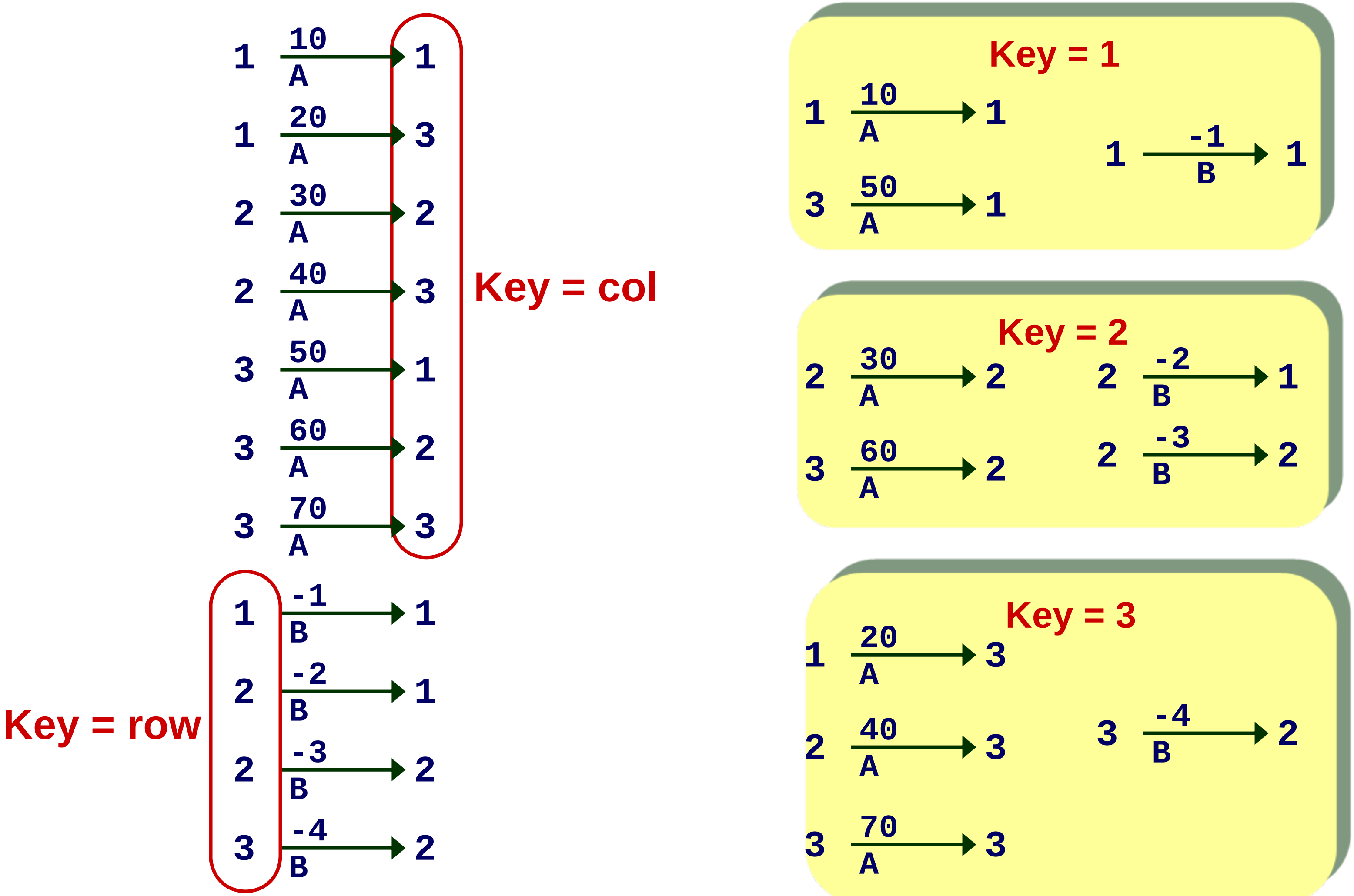
B

$$B = \begin{bmatrix} -1 & \\ -2 & -3 \\ & -4 \end{bmatrix}$$

1	-1 B →	1
2	-2 B →	1
2	-3 B →	2
3	-4 B →	2

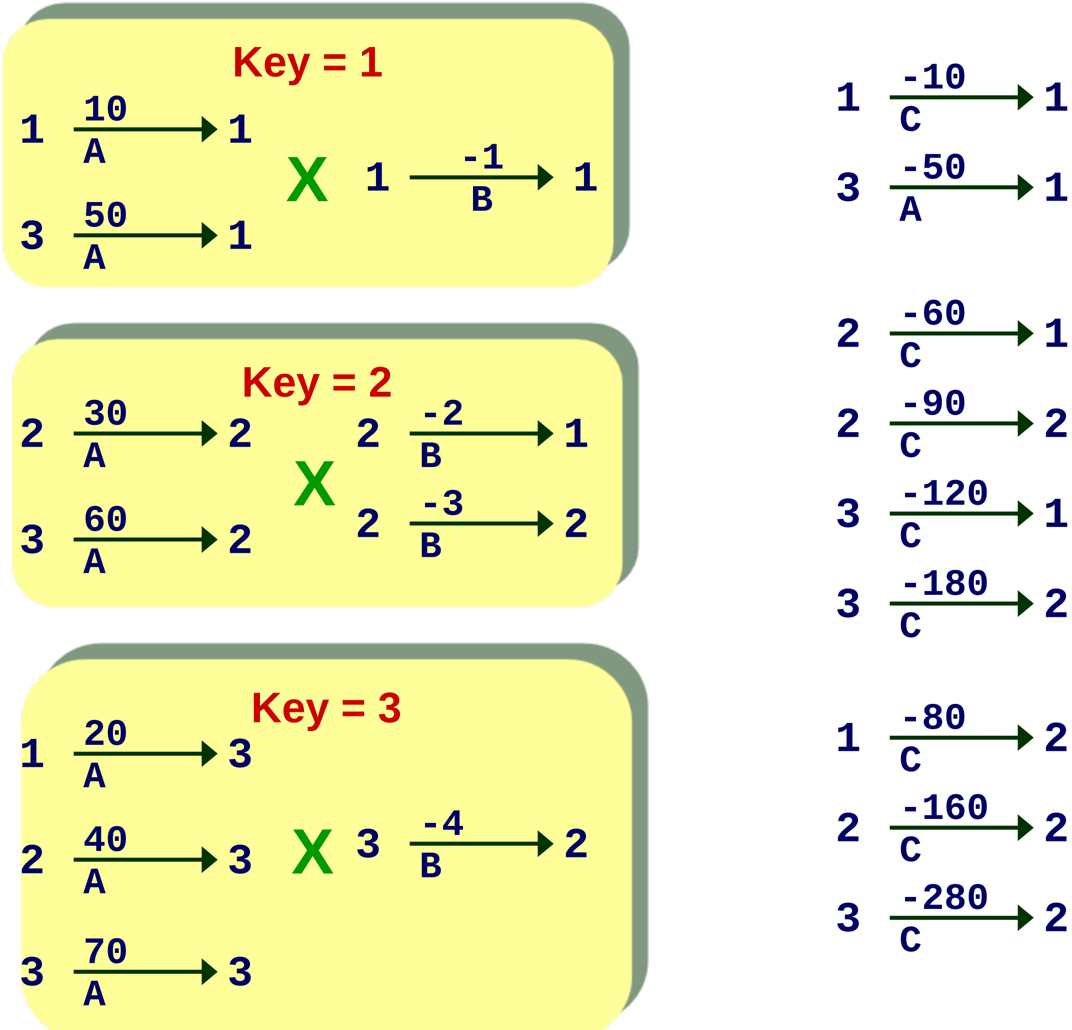
- **Represent matrix as list of nonzero entries**
  - ⟨row, col, value, matrixID⟩
- **Strategy**
  - Phase 1: Compute all products $a_{i,k} \cdot b_{k,j}$
  - Phase 2: Sum products for each entry i,j
  - Each phase involves a Map/Reduce

Phase 1 Map of Matrix Multiply



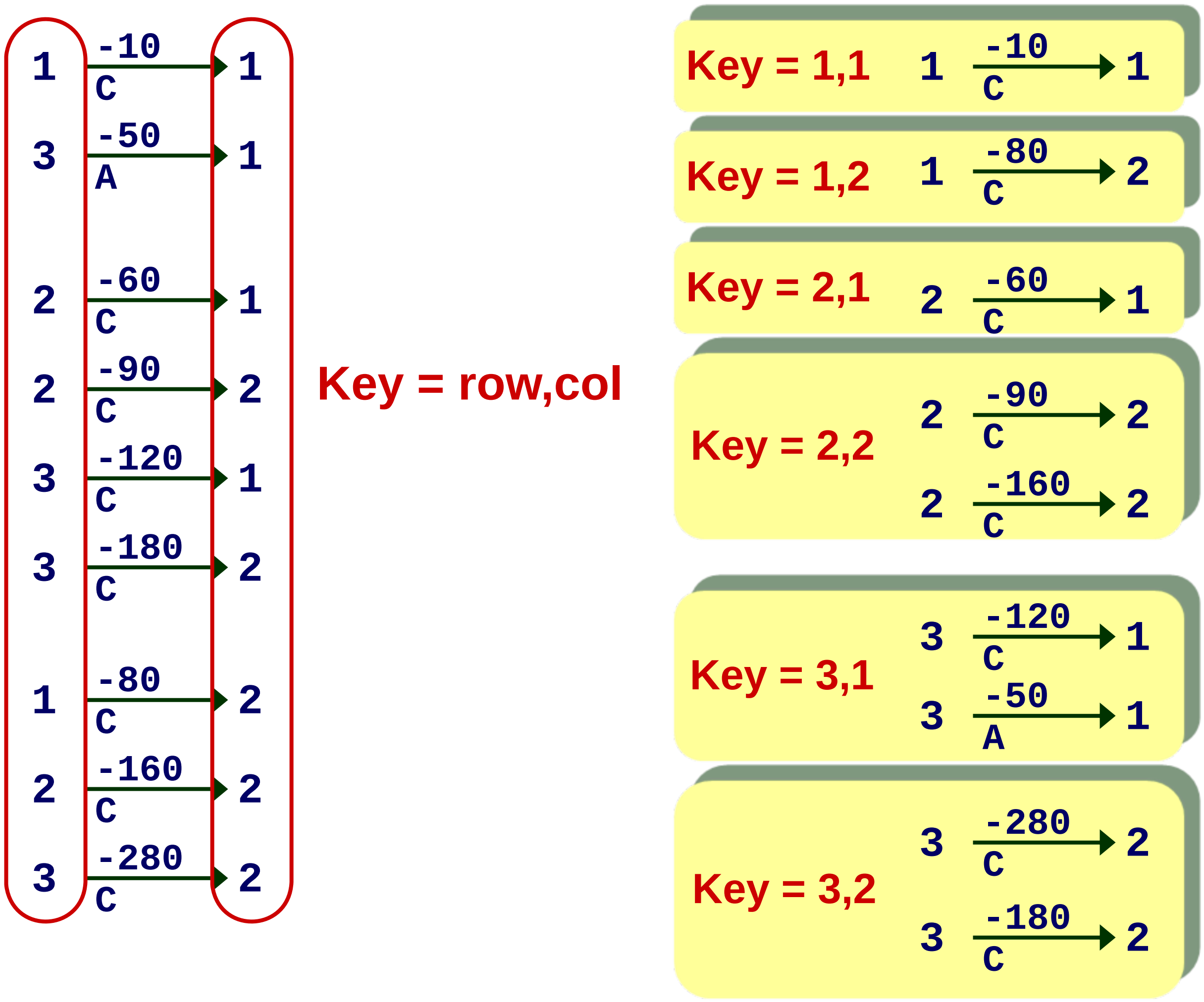
- Group values $a_{i,k}$ and $b_{k,j}$ according to key k

Phase 1 "Reduce" of Matrix Multiply



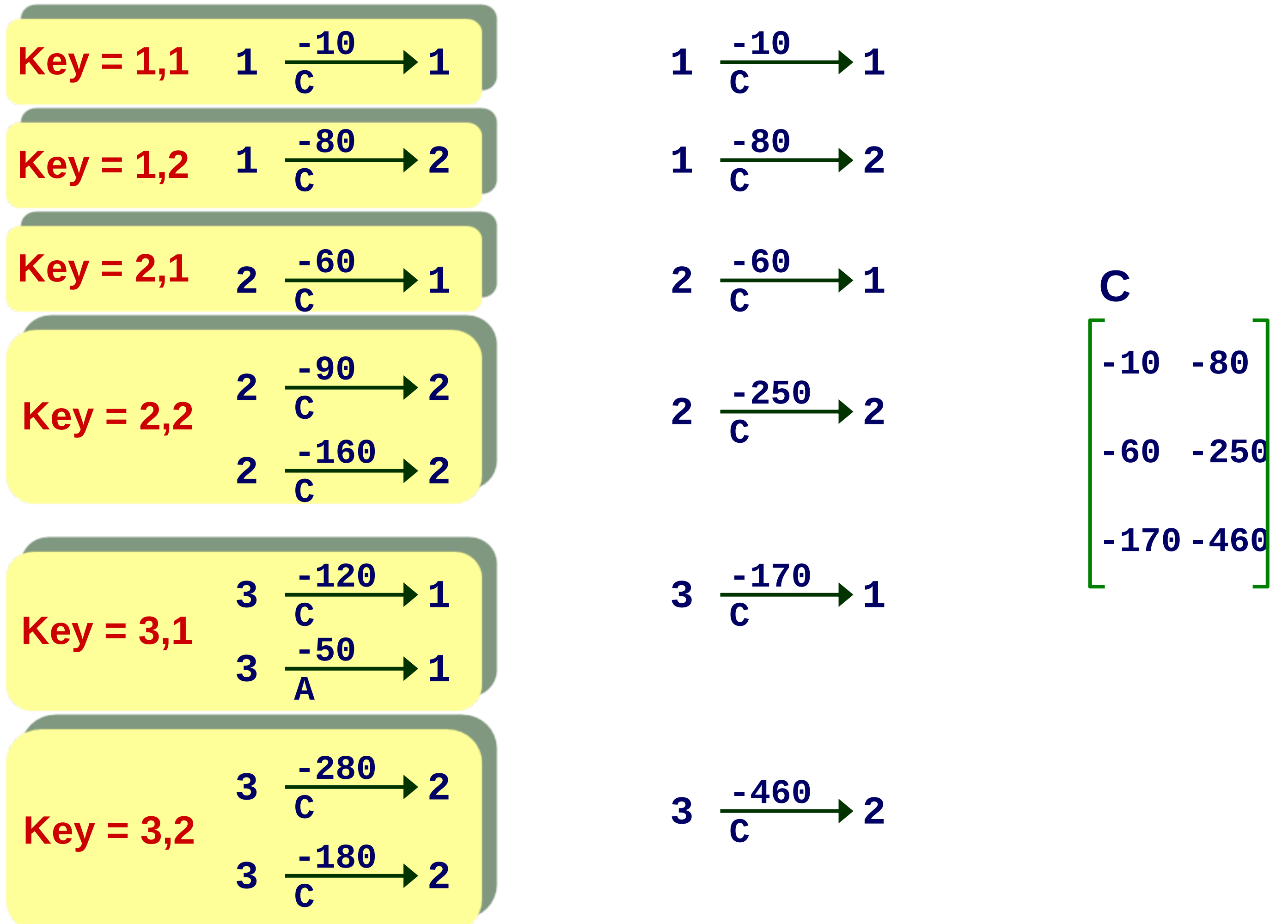
- Generate all products $a_{i,k} \cdot b_{k,j}$

Phase 2 Map of Matrix Multiply



- **Group products $a_{i,k} \cdot b_{k,j}$ with matching values of i and j**

Phase 2 Reduce of Matrix Multiply



- Sum products to get final entries

Lessons from Sparse Matrix Example

Associative Matching is Powerful Communication Primitive

- Intermediate step in Map/Reduce

Similar Strategy Applies to Other Problems

- Shortest path in graph
- Database join

Many Performance Considerations

- Kiefer, Volk, Lehner, TU Dresden
- Should do systematic comparison to other sparse matrix implementations

Tweaking MapReduce

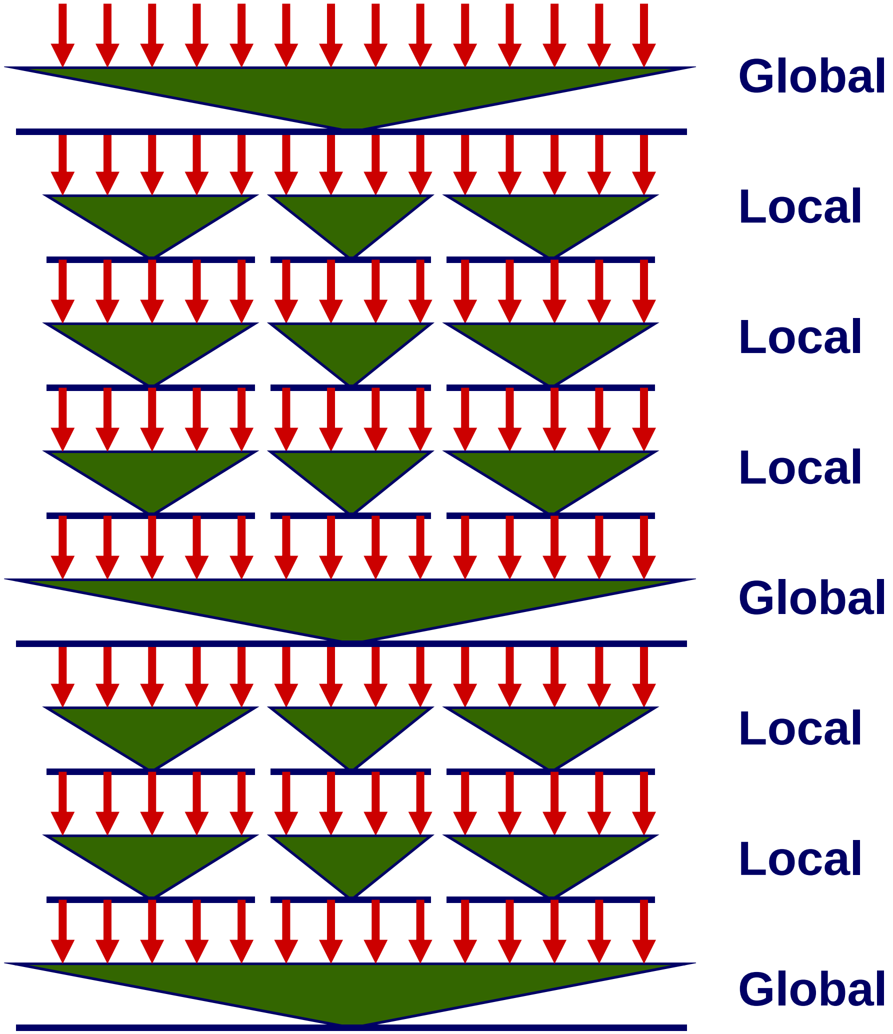
Map/Reduce/Merge

- Yang, et al. Yahoo & UCLA
- Add merge step to do tagged merge of data sets
  - E.g., getting elements from matrices A & B
- Demonstrate expressive power of relational algebra

Local Iterations

- Kambatla, et al., Purdue
- Support local and global iterations
- Step toward bulk synchronous model

Local / Global Map/Reduce



Iterative Computations

- e.g., PageRank

Graph Partitioning

- Partition into clusters
- Colocate data for each cluster

Computation

- Compute solution for each cluster, holding inter-cluster values constant
- Update inter-cluster values

Pig Project

- Chris Olston, Yahoo!
- Part of Apache/Hadoop

Merge Database & Programming

- SQL-like query language
- Set-oriented function application

Implementation

- Map onto Hadoop
- Automatic selection / optimization of algorithm
- Captures low-level tricks programmers have devised for Map/Reduce

Generalizing Map/Reduce

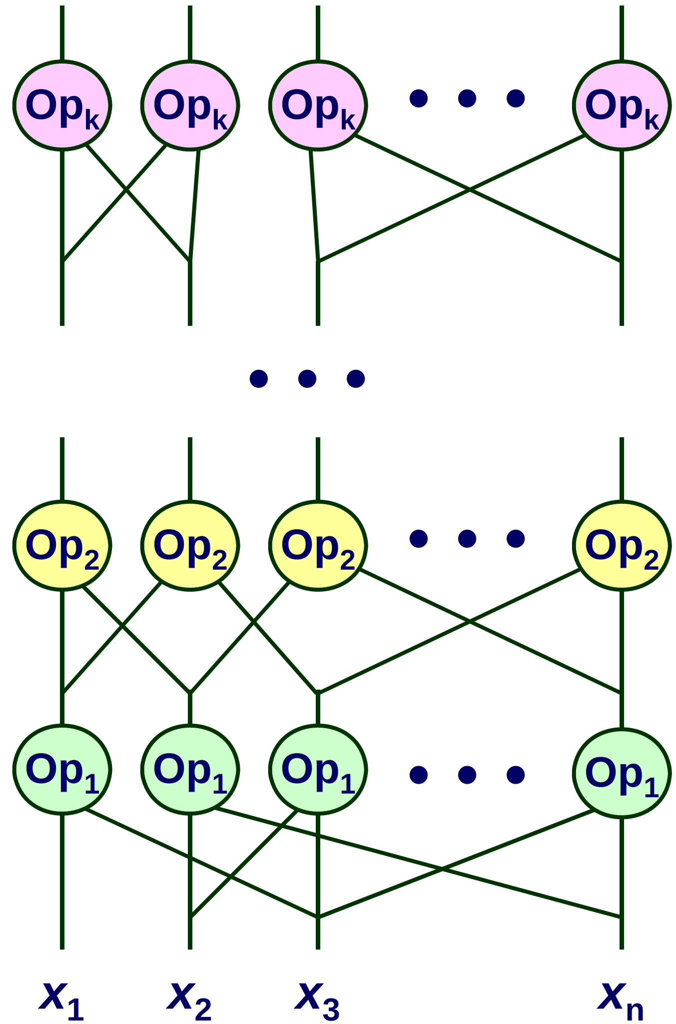
- E.g., Microsoft Dryad Project

Computational Model

- Acyclic graph of operators
  - But expressed as textual program
- Each takes collection of objects and produces objects
  - Purely functional model

Implementation Concepts

- Objects stored in files or memory
- Any object may be lost; any operator may fail
- Replicate & recompute for fault tolerance
- Dynamic scheduling
  - # Operators >> # Processors



Implementation Challenges

Hadoop Platform is Blessing

- Large community adding features, improving performance
- Easy to deploy
- Growing body of documentation and materials
- Works well enough for range of applications

… And Curse

- Map & reduce functionality hardwired
- Not designed as extensible platform

Dryad Not Widely Adopted

- 305 citations on Google Scholar vs. 1759 Map/Reduce
- Built on .NET

Conclusions

Distributed Systems Concepts Lead to Scalable Machines

- **Loosely coupled execution model**
- **Lowers cost of procurement & operation**

Map/Reduce Gaining Widespread Use

- **Hadoop makes it widely available**
- **Great for some applications, good enough for many others**

Lots of Work to be Done

- **Richer set of programming models and implementations**
- **Expanding range of applicability**
  - Problems that are data *and* compute intensive
  - The future of supercomputing?