### **The Gamma Database Machine Project**

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> Slides adopted from those of Deepak Bastakoty, and Ghandeharizadeh and DeWitt, Jianhao Cao

> > Presenter: Tanya Prasad Discussion Leader: Jonas Tai UBC CPSC 504 – 2023.03.06

### U Why parallel databases?

- Obtain faster response time
- Increase query throughput
- Improve robustness to failure
- Reduce processor workload
- Enable scalability

### DIRECT

- Early parallel database project
- Shared memory
- Centralized control of parallel algorithms

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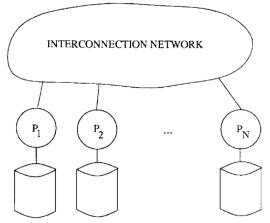
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Impossible to scale the architecture
to hundreds of processors!
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### Share-nothing

• Each processor has it own memory or disk(s)

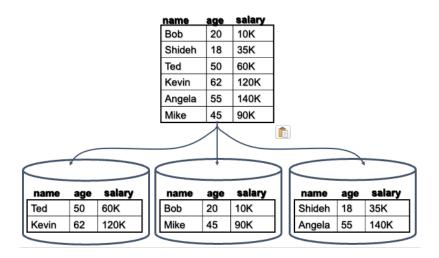
### Hash-based parallel algorithms

No need for centralized control



### Horizontal partitioning (declustering)

- Tuples of a relation distributed over multiple disks.
- Round robin; hashed; range partitioned



## **Hardware Architecture**

### **GAMMA 1.0**

- 17 VAX 11/750 processors, each with 2 MB memory
- Another VAX as the host machine
- An 80 Mb/s token ring to connect processors
- 8 processors attached with 333 MB disk drivers

### Problems

- The token ring network packet size is too small (2K bytes)
- The bandwidth mismatch between the token ring and the Unibus on the 11/750
- Insufficient memory for each processor

## **Hardware Architecture**

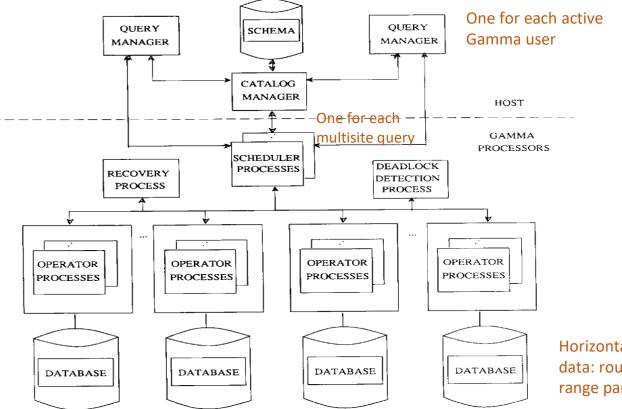
### **GAMMA 2.0**

- 32 processor iPSC/2 hypercube from Intel
- 386 CPU, 8 MB memory
- 330 MB MAXTOR 4380 disk drive with a 45 KB RAM buffer
- Custom VLSI routing modules for network communication
- NOSE (Gamma's OS) run as a thread package inside a process

### Discussion 1 (Groups of 3, at least 1 Systems)

- As some of you pointed out in their reviews, the authors spend a lot of time talking about hardware
  - Issues in Gamma Version 1.0 such as insufficient memory
  - Problems with the disk controller in Gamma Version 2.0
  - Conversion problems because of different addressing schemes
- What do you think was the motivation to include this long section about the hardware and the problems they faced?
- Do you think the experiences they made with the chosen hardware strengthen, weaken or do not impact the paper?

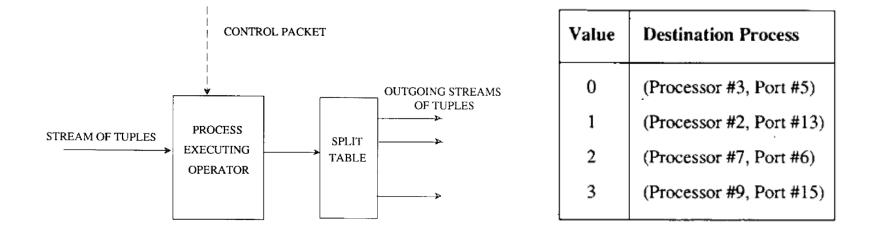
## **Software Architecture**

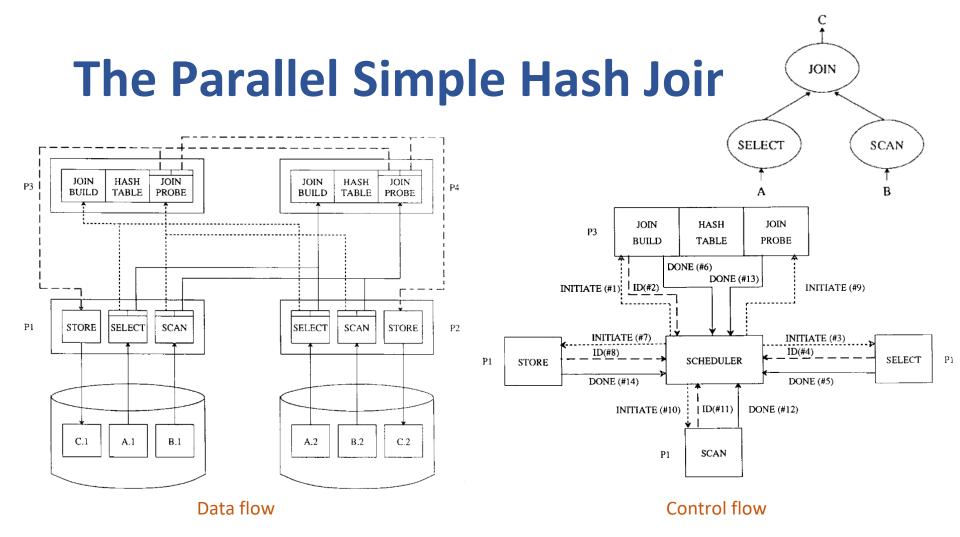


Horizontally partitioned data: round robin; hashed; range partitioned

## **Software Architecture**

The split table defines a mapping of values to a set of destination processes.





# **Query Processing**

### Selection

- Selection on the partitioning attribute
  - Direct the selection to a subset of node if hash or range partitioned.
  - Initiate the selection on all nodes if round-robin partitioned.

### 🖵 Join

- Partition relations into disjoint subsets (buckets) by hashing on the join attribute.
- Four types of parallel joins: sort-merge, Grace, Simple, Hybrid.
- The Hybrid hash join almost always provides the best performance.

# **The Parallel Hybrid Hash Join**

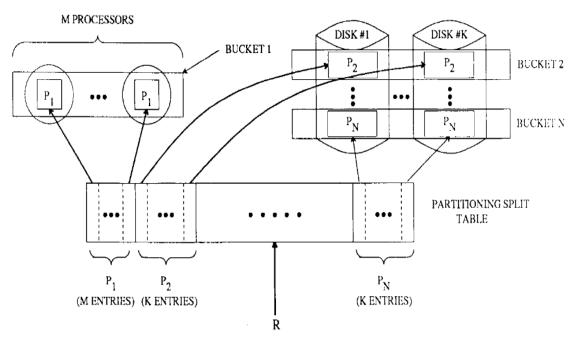


Fig. 8. Partitioning of R into N logical buckets for hybrid hash-join.

- A partitioning split table separates the relations into N logical buckets.
- A joining table sends tuples in the first bucket to M processors for the join operation.
- In-memory hash table for the first bucket of the inner table to be joined with the first bucket of the outer table.
- The N-1 buckets are temporarily stored on disks.

# **Query Processing Algorithms**

### Aggregate functions

- Each processor computes a partial results on its partition.
- The processors redistribute the results on hashing on the "group by" attribute.

### Update operators

- Most operators are implemented with standard techniques.
- A replace operator will send a tuple to the partition to which it belongs.

# **Transaction and Failure Management**

### Concurrency control

- Two-phase locking.
- A local lock manager with a lock table and a transaction wait-for-graph.
- A centralized deadlock detector communicate with each node.

### Recovery and Log manager

- A log record is generated when a tuple is updated.
- Log records are sent to one or more log managers.
- The log manager keeps track of the last flushed record from each node.
- The buffer managers observe the WAL protocol.

### **Data Placement**

#### Chained declustering

Node	0	1	2	3	4	5	6	7
Primary Copy	R0	R1	R2	R3	R4	R5	R6	<b>R</b> 7
Backup Copy	r7	г0	гl	r2	r3	г4	г5	r6

#### Interleaved declustering

_		Clus	ter 0		Cluster 1					
Node	0	1	2	3	4	5	6	7		
Primary Copy	R0	<b>R</b> 1	R2	R3	R4	R5	R6	R7		
Backup Copy		r0.0	r0.1	r0.2		r4.0	r4.1	r4.2		
	r1.2		r1.0	r1.1	r5.2		r5.0	r5.1		
	r2.1	т2.2		r2.0	гб.1	r6.2		r6.0		
	г3.0	г3.1	r3.2		r7.0	r7.1	r7.2			

## Load Balancing When One Node Fails

Node	0	1	2	3	4	5	6	7
Primary Copy	R0	<u> </u>	R2	R3	R4	R5	R6	R7
Backup Copy	r7	.t	r1	r2	r3	r4	r5	r6
Node	0	1	2	3	4	5	6	7
Primary Copy	R0		$\frac{1}{7}$ R2	$\frac{2}{7}$ R3	$\frac{3}{7}$ R4	$\frac{4}{7}$ R5	$\frac{5}{7}$ R6	$\frac{6}{7}$ R7
Backup Copy	$\frac{1}{7}$ r7		r1	$\frac{6}{7}$ r2	$\frac{5}{7}$ r3	$\frac{4}{7}$ r4	$\frac{3}{7}$ r5	$\frac{2}{7}$ r6

Access both the primary and backup copies to balance load on each node.

## **Ideal Parallelism**

### Speedup

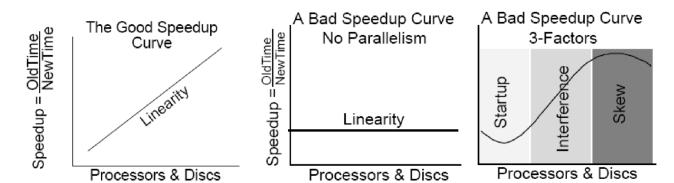
Given a system with 1 node, does adding *n* nodes speed it up with a factor of *n* ?

Speedup =  $\frac{small_system_elapsed_time}{big_system_elapsed_time}$ 

### Scaleup

Given a system with 1 node, does the response time remain the same with *n* nodes ?

Scaleup =  $\frac{small_system_elapsed_time_on_small_problem}{big_system_elapsed_time_on_big_problem}$ 



### **Discussion 2 (Groups of 4)**

- The Gamma database paper is quite old (as you probably also noticed from the used hardware).
- What kind of use cases do you think did the authors have in mind?
- Why do you think parallel databases were not a big breakthrough at the time?
- How do you think the demand for parallel databases has changed since then?

## Conclusion

### Three key ideas that enables Gamma to be scaled to hundreds of processors:

- Horizontally partitioned relations
- Extensive use of hash-based parallel algorithms
- Dataflow scheduling techniques for multioperator queries

# MapReduce: Simplified Data Processing on Large Clusters

Jeff Dean, Sanjay Ghemawat Google, OSDI 2004

Slides based on those by authors and other online sources

Presenter: Tanya Prasad

- Large scale data processing
  - Using hundreds or thousands of machines but without the hassle of management
- MapReduce benefits
  - Automatic parallelization & distribution
  - Fault tolerance
  - I/O scheduling
  - Monitoring & status updates

## **Programming model**

- Input & Output: each a set of key/value pairs
- Programmer specifies two functions:

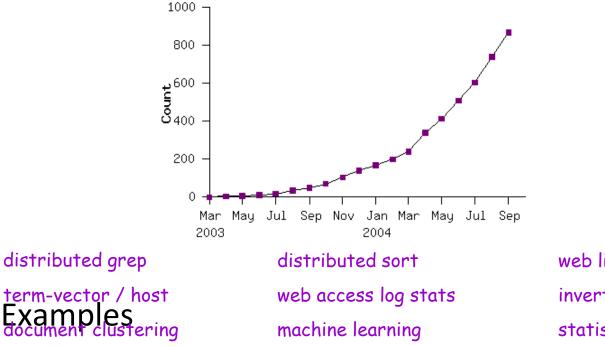
map(in\_key, in\_value) -> list(out\_key, intermediate\_value)

- Processes each input key/value pair
- Produces set of intermediate pairs
   reduce(out\_key, list(intermediate\_value)) ->
   list(out\_value)
  - Combines all intermediate values for a particular key
  - Produces a set of merged output values (usually just one)

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# MapReduce model widely applicable

MapReduce programs in Google source tree (2003-04)



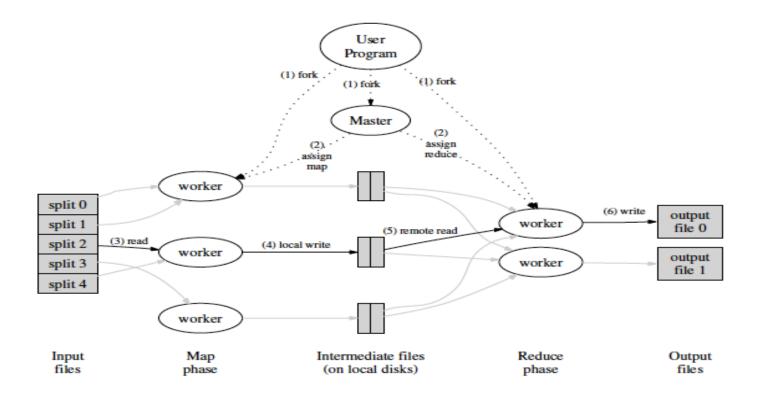
web link-graph reversal inverted index construction statistical machine translation

## **Implementation overview**

### • Typical cluster:

- 100s/1000s of 2-CPU x86 machines, 2-4 GB of memory
- Limited bisection bandwidth
- Storage is on local IDE disks
- GFS: distributed file system manages data (SOSP'03)
- Job scheduling system: jobs made up of tasks, scheduler assigns tasks to machines
- Implementation as C++ library linked into user programs

### **Overall execution workflow**



## **Discussion 3 (Pairs)**

- MapReduce breaks with a lot of conventions: Input data has no schema, programs are written in Java, no indices,...
  - Why do you think MapReduce was still such a huge success?
  - Why or why not is that surprising to you?
- Discuss the questions with the lessons from last week's discussion in mind. How do they hold up here?
  - Lesson 12: Unless there is a big performance or functionality advantage, new constructs will go nowhere
  - Lesson 13: Packages will not sell to users unless they are in "major pain"
  - Lesson 16: Schema-last is probably a niche market

## **Fault-tolerance via re-execution**

### • On worker failure:

- Detect failure via periodic heartbeats
- Re-execute completed and in-progress *map* tasks
  - Output stored on the local disk becomes inaccessible
- Re-execute in progress *reduce* tasks
  - Output stored in a global file system
- Task completion committed through master
- Master failure:
  - Left unhandled as considered unlikely
  - Abort the MapReduce computation

## **Locality Optimization**

- Master scheduling policy:
  - Asks GFS for locations of replicas of input file blocks
  - Map tasks typically split into 64MB (== GFS block size)
  - Map tasks scheduled so GFS input block replica are on same machine or same rack or nearest machine.
  - Goal to reduce communication overhead as much as possible
- Effect: Thousands of machines read input at local disk speed
  - Without this, rack switches limit read rate

### **Task Granularity**

- Fine granularity tasks: map tasks >> machines
  - Minimizes time for fault recovery
  - Can pipeline shuffling with map execution
  - Better dynamic load balancing
- Often use 200K map and 5000 reduce tasks running on 2000 machines

Process	Time>										
User Program	MapReduce()	wait									
Master		Assign tasks to worker machines									
Worker 1		Map 1	Map 3								
Worker 2		Map 2									
Worker 3			Read 1.1		Read 1.3		Read 1.2		Redu	ice 1	
Worker 4			Read 2.1				Read 2.2	Read	12.3	Red	uce 2

### **Backup Execution**

- Slow workers significantly lengthen completion time
  - Other jobs consuming resources on machine
  - Bad disks with soft errors transfer data very slowly
  - Weird things: processor caches disabled (!!)
- Solution: Near end of phase, spawn backup task copies
  - Whichever one finishes first "wins"
- Benefit: Dramatically shortens job completion time

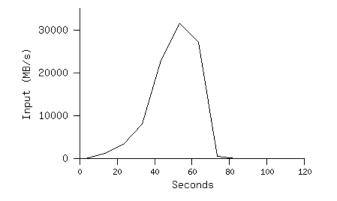
## **Skipping Bad Records**

- Map/Reduce functions sometimes fail for particular inputs
  - Best solution is to debug & fix, but not always possible
- On segmentation fault:
  - Send UDP packet to master from the signal handler
  - Include sequence number of record being processed
- If master sees two failures for the same record:
  - Next worker is told to skip the record
- Effect: Can work around bugs in third-party libraries

### **Some Refinements**

- Sorting guarantees within each reduce partition
- Compression of intermediate data
- Combiner: useful for saving network bandwidth
- Local sequential execution for debugging/testing
- User-defined counters

## **MapReduce Grep**

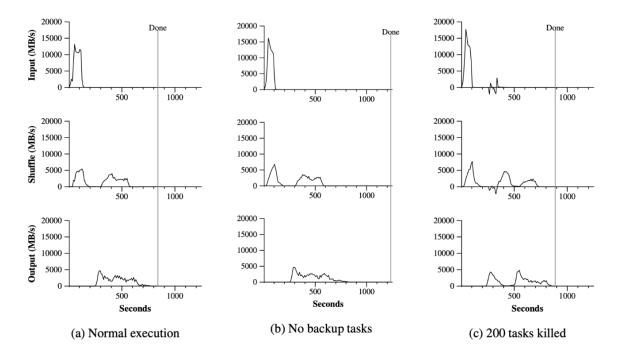


Locality optimization helps:

- 1800 machines read 1 TB at peak ~31 GB/s
- W/out this, rack switches would limit to 10 GB/s

Startup overhead is significant for short jobs

### **MapReduce Sort**



- Backup tasks reduce job completion time a lot!
- System deals well with failures

## Google Experience: Rewrite of Production Indexing System

- Rewrote Google's production indexing system using MapReduce
  - New code is simpler, easier to understand
  - MapReduce takes care of failures, slow machines
  - Easy to make indexing faster by adding more machines

### **Discussion 4 (Groups of 4)**

- With the Gamma database project and MapReduce we have seen two models to parallelize data processing:
  - What are the differences and similarities?
  - Which use cases are they designed for? Do they have the same kind of applications in mind?
  - Which model do you find more convincing and why?
- Gamma Database key features:
  - Parallel Database
  - Horizontally partitioned relations
  - Extensive use of hash-based parallel algorithms
  - Dataflow scheduling techniques for multioperator queries

## **Conclusions**

- MapReduce has proven to be a useful abstraction.
- Network bandwidth is a scarce resource.
- Redundant execution can reduce the impact of slow machines and machine failures.