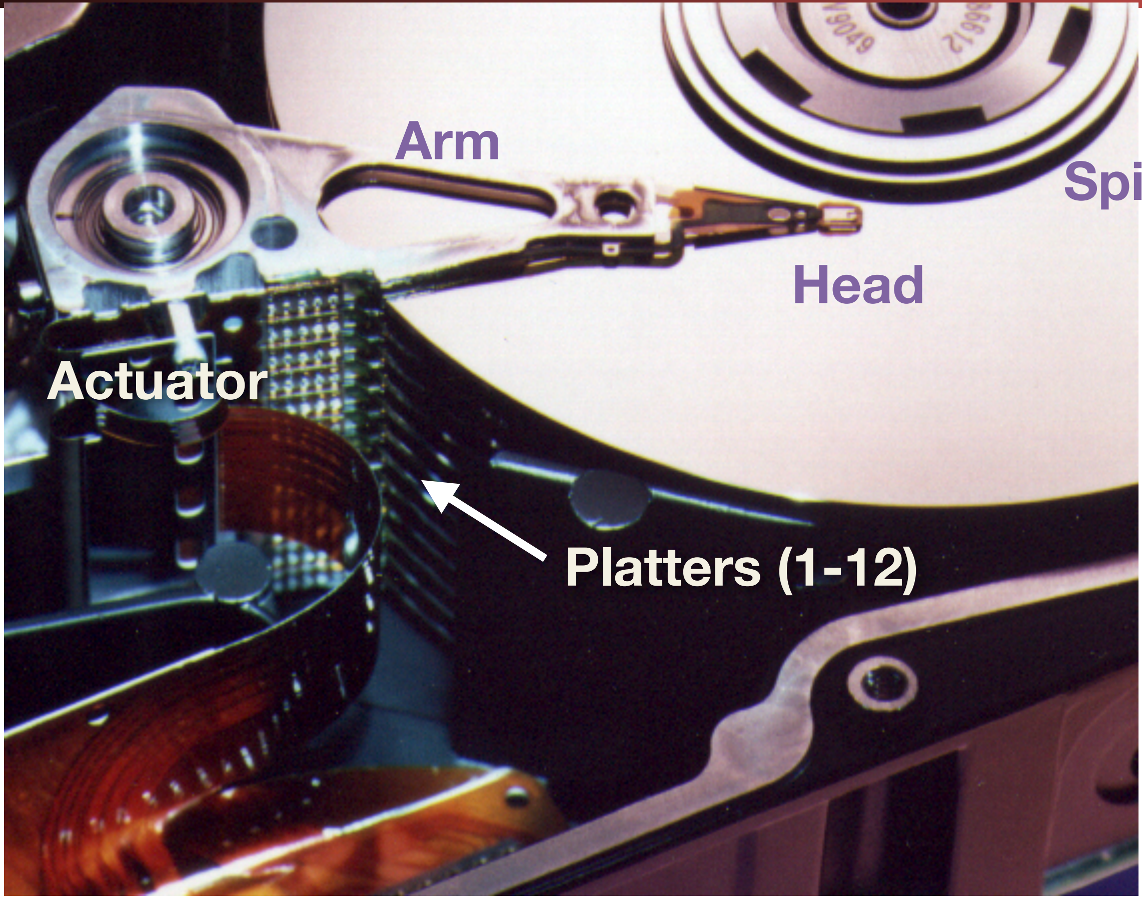
RAID and the Warehouse

Magnetic Disk – common I/O device

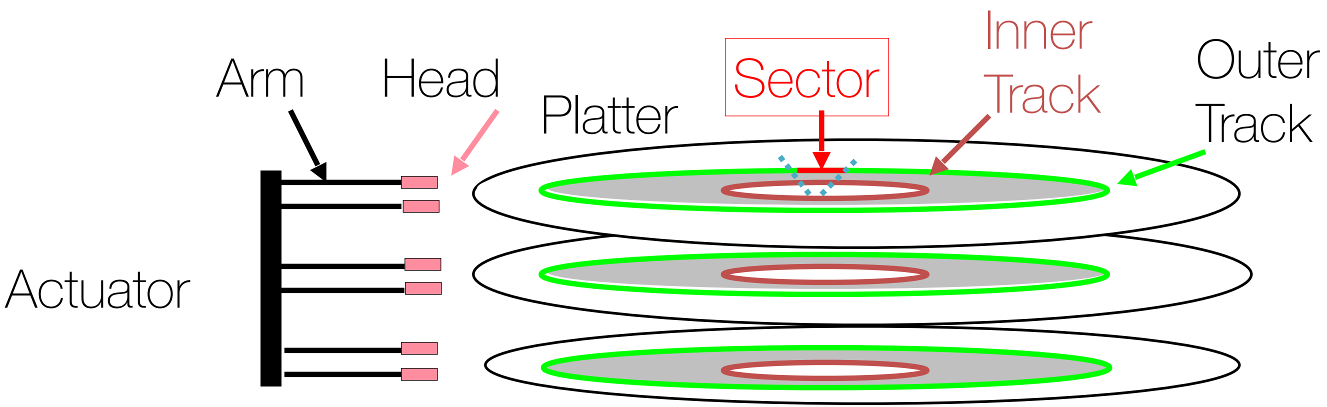
- A kind of computer memory
  - Information stored by magnetizing ferrite material on surface of rotating disk
    - Similar to tape recorder except digital rather than analog data
- A type of *non-volatile* storage
  - Retains its value without applying power to disk.

- Two Types of Magnetic Disk
  - Hard Disk Drives (HDD) – faster, more dense, non-removable.
  - Floppy disks – slower, less dense, removable
    (now replaced by USB "flash drive", only roll these days is as the "Save Icon").
- Purpose in computer systems (Hard Drive):
  - Working file system + long-term backup for files
  - Secondary "backing store" for main-memory. Large, inexpensive, slow level in the memory hierarchy (virtual memory)

Photo of Disk Head, Arm, Actuator



Disk Device Terminology

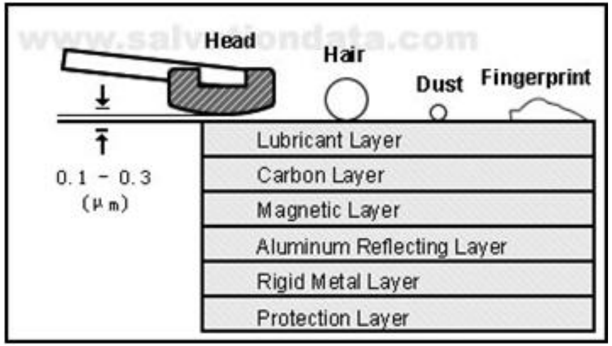


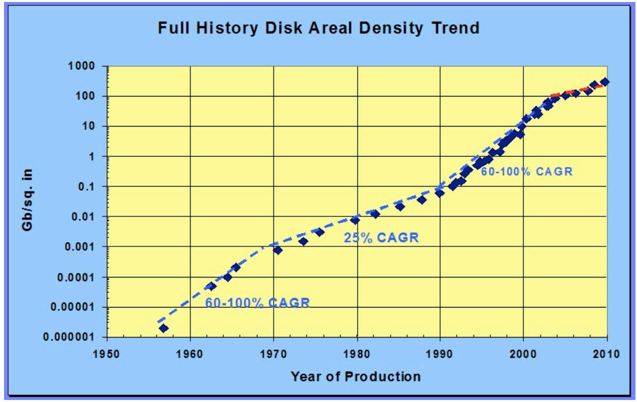
- Several platters, with information recorded magnetically on both surfaces (usually)
- Bits recorded in tracks, which in turn divided into sectors (e.g., 512 Bytes)
- Actuator moves head (end of arm) over track ("seek"), wait for sector rotate under head, then read or write

Hard Drives are Sealed

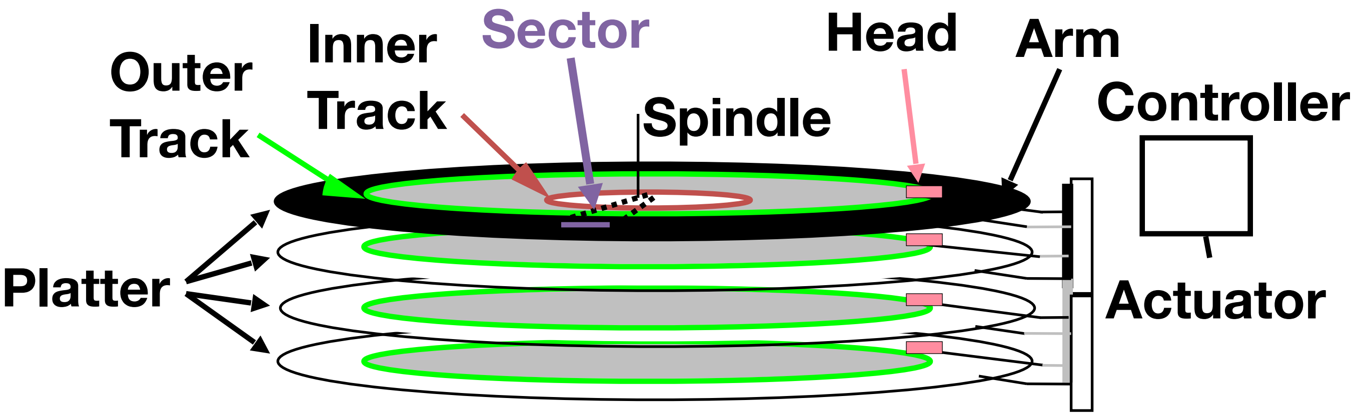
- The closer the head to the disk, the smaller the “spot size” and thus the denser the recording.
    - Modern drives can store up to 20 TB of data
- Disks are sealed to keep the dust out.
    - Heads are designed to “fly” at around 3-20nm above the surface of the disk.
    - 99.999% of the head/arm weight is supported by the air bearing force (air cushion) developed between the disk and the head
- Some drives are even sealed with Helium
    - Lower drag than air

3-20nm



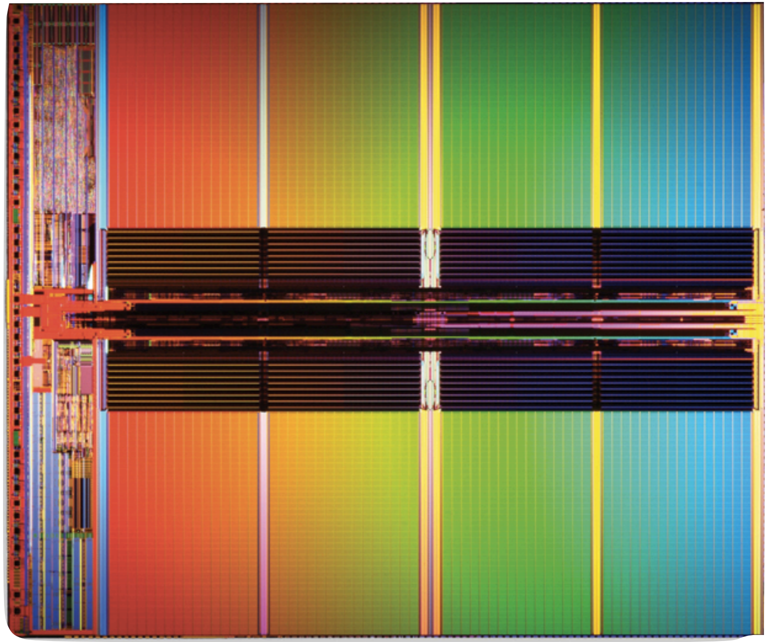


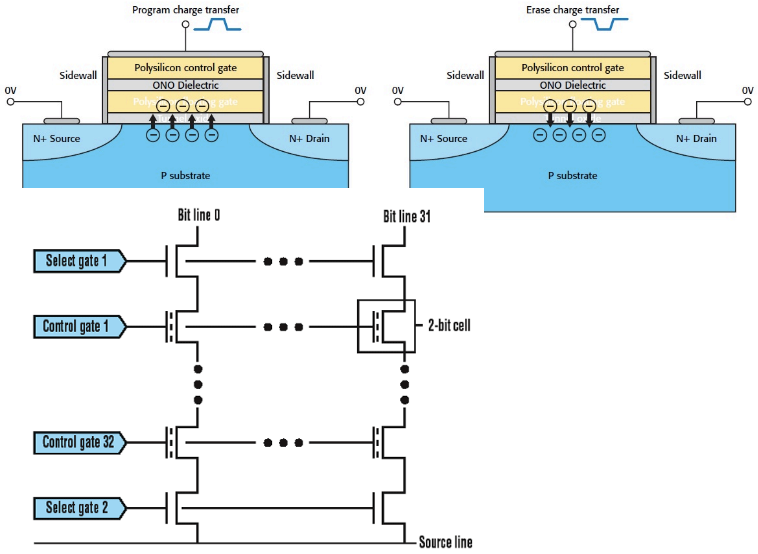
Disk Device Performance



- **Disk Access Time = Seek Time + Rotation Time + Transfer Time + Controller Overhead**
  - Seek Time = time to position the head assembly at the proper cylinder
  - Rotation Time = time for the disk to rotate to the point where the first sectors of the block to access reach the head
  - Transfer Time = time taken by the sectors of the block and any gaps between them to rotate past the head

Flash Memory / SSD Technology

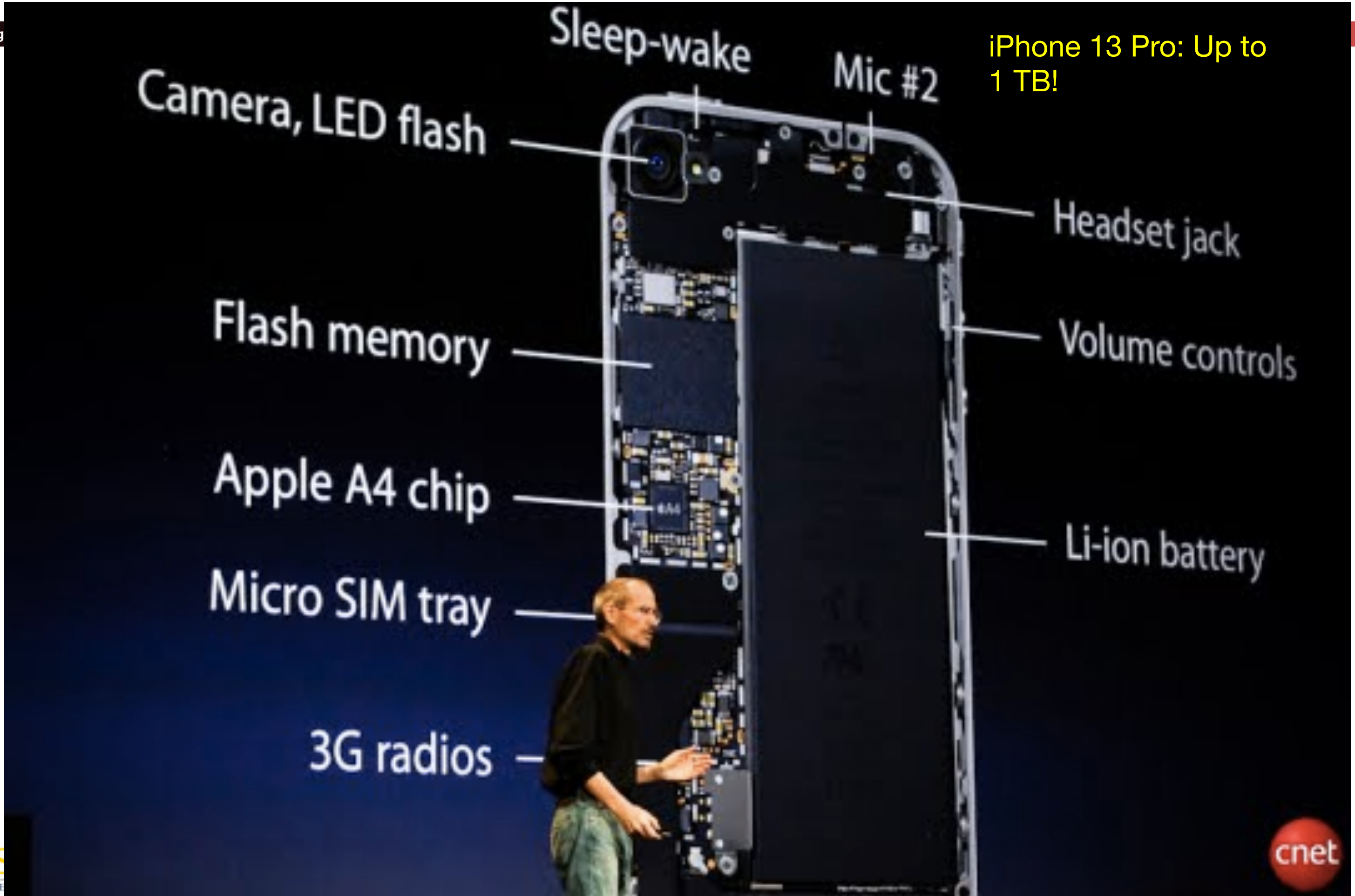




In the basic functional block used in multilevel NAND flash memories, 32 rows of bit lines and 32 control-gate lines form a building block that's repeated many times to form the memory array. The select gate lines are used with the control gate lines to control access to the array.

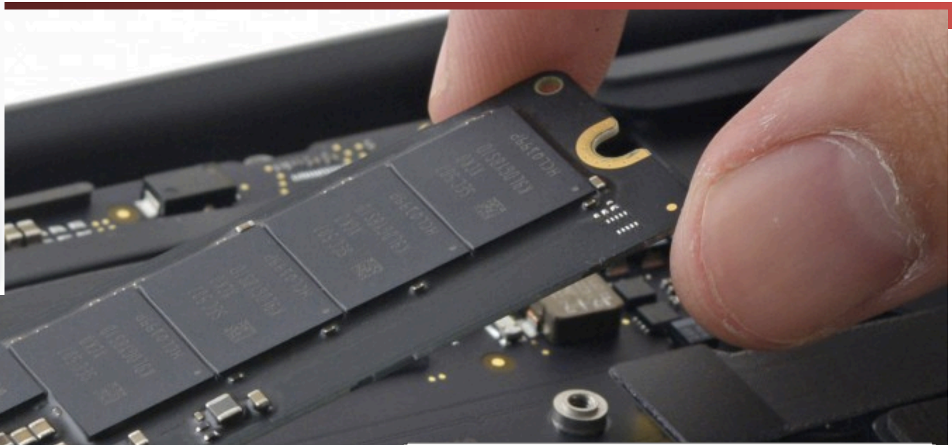
- NMOS transistor with an additional conductor between gate and source/drain which "traps" electrons. The presence/absence is a 1 or 0
- Memory cells can withstand a limited number of program-erase cycles. Controllers use a technique called *wear leveling* to distribute writes as evenly as possible across all the flash blocks in the SSD.
- Erase or write a block, no way to change a block

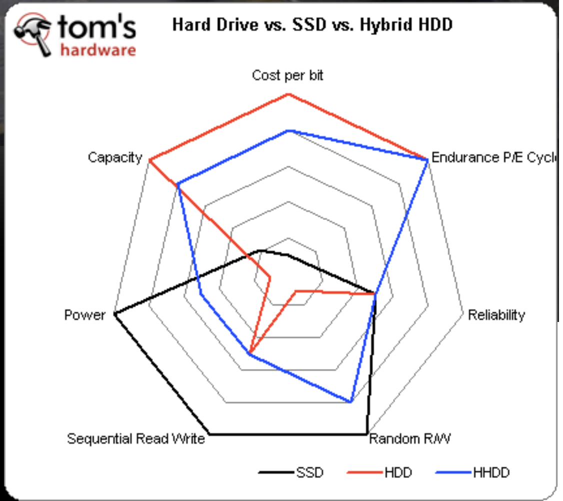
Flash Memory Key to Success of Smart Phones



iPhone 13 Pro: Up to 1 TB!

Flash Memory in Laptops – Solid State Drive (SSD)





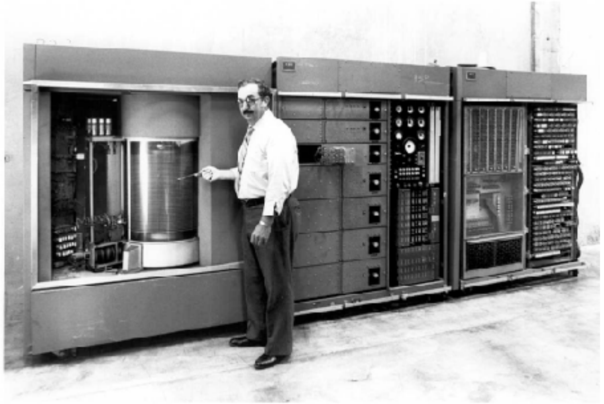
Flash and Latency...

- Flash bandwidth is similar to spinning disk
  - And spinning disk is still a better storage/$ and storage/cm^3
- But Flash's big advantage: ***no seek time!***
  - No additional latency for random access vs sequential access of a block
- This is huge:
  - HDD access times are measured in milliseconds, SSD times are measured in microseconds
- ***NEVER*** put your main OS on a spinning disk!

RAID: Redundancy for Disks

- Spinning disk is still a critical technology
  - Although worse latency than SSD…
- Disk has equal or greater bandwidth and an order of magnitude better storage density (bits/cm^3) and cost density (bits/$)
- So when you need to store a petabyte or three…
  - You need to use disk, not SSDs
- Oh, and SSDs can fail too

Evolution of the Disk Drive



IBM RAMAC 305, 1956

First commercial computer that used a moving-head hard disk drive (magnetic disk storage) for secondary storage.

up to 22.7 billion bytes (gigabytes) of storage

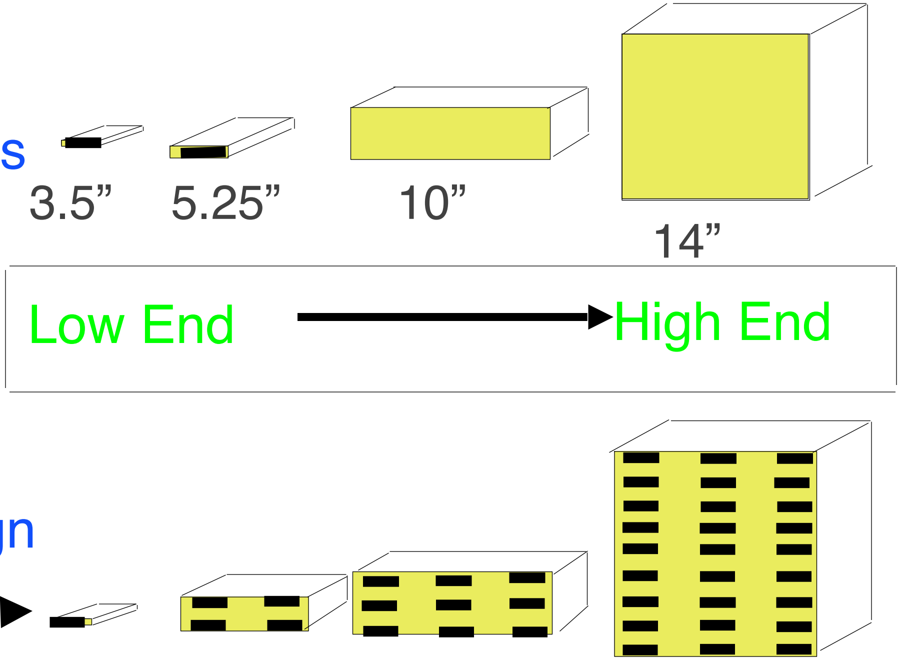
IBM 3390K, 1989

Apple SCSI, 1986

Arrays of Small Disks

Can smaller disks be used to close gap in performance between disks and CPUs?

Conventional:
4 disk designs



Disk Array:
1 disk design

3.5”

Replace Small Number of Large Disks in 1988

	IBM 3390K	IBM 3.5" 0061	x70	
Capacity	20 GBytes	320 MBytes	23 GBytes	
Volume	97 cu. ft.	0.1 cu. ft.	11 cu. ft.	9X
Power	3 KW	11 W	1 KW	3X
Data Rate	15 MB/s	1.5 MB/s	105 MB/s	7X
I/O Rate	600 I/Os/s	55 I/Os/s	3900 IOs/s	6X
MTTF	250 KHrs	50 KHrs	??? Hrs	
Cost	$250K	$2K	$150K	

Disk Arrays have potential for large data and I/O rates, high MB per cu. ft., high MB per KW, but what about reliability?

But MTTF goes through the roof…

- If 1 disk as MTTF of 50k hours…
  - 70 disks will have a MTTF of ~700 hours!!!
  - This is assuming failures are independent…
- But fortunately we know when failures occur!
  - Disks use a lot of CRC coding, so we don't have corrupted data, just no data
- We can have both "Soft" and "Hard" failures
  - Soft failure just the read is incorrect/failed, the disk is still good
  - Hard failures kill the disk, necessitating replacement
    - Most RAID setups are "Hot swap":
Unplug the disk and put in a replacement while things are still going
    - Most modern RAID arrays also have "hot spares":
An already installed disk that is used automatically if another disk fails.

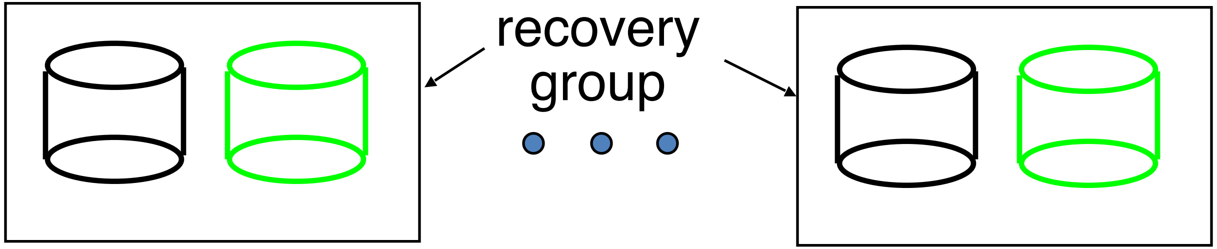
RAID: Redundant Arrays of (Inexpensive) Disks

- Files are "striped" across multiple disks, ex:
- Redundancy yields high data availability
  - Availability: service still provided to user, even if some components failed
- Disks will still fail
- Contents reconstructed from data redundantly stored in the array
  - Capacity penalty to store redundant info
  - Bandwidth penalty to update redundant info on writes
- 6 Raid *Levels,* 0, 1, 5, 6 most common today

RAID 0: Striping

- "RAID 0" is not actually RAID (no redundancy)
  - It is simply spreading the data across multiple disks
- So, e.g, for 4 disks, stripe-unit address 0 is on disk 0, address 1 is on disk 1, address 2 is on disk 2, address 4 on disk 0...
- Improves bandwidth linearly
  - With 4 disks you have 4x the disk bandwidth
- Doesn't really help latency
  - Still have the individual disks seek and rotation time
- Failures will happen...

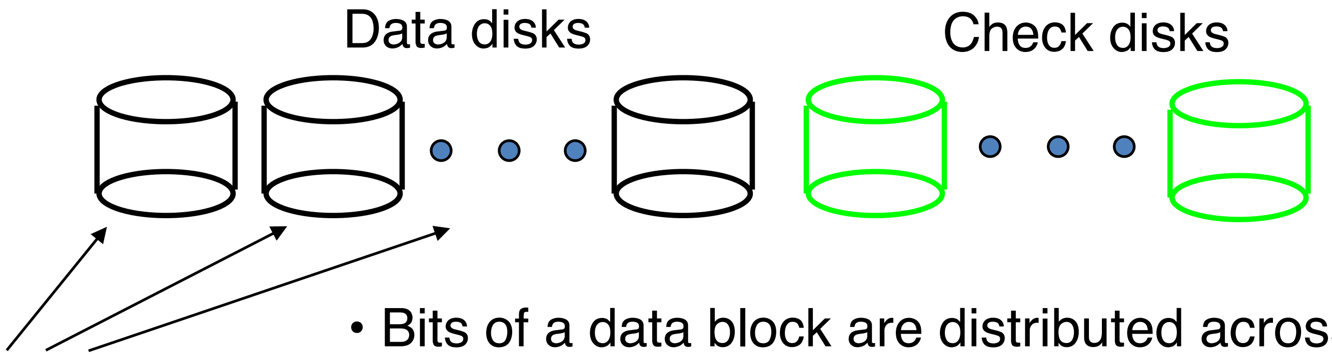
RAID 1: Disk Mirroring/Shadowing (online sparing)



- Each disk is fully duplicated onto its "mirror"
  Very high availability can be achieved
- Writes go to disk and mirror - limited by single-disk speed
- Reads from original disk, unless failure

Most expensive solution: 100% (2x) capacity overhead

RAID 2: Hamming Code for Error Correction



10010011
11001101
10010011
. . .

logical record

- Bits of a data block are distributed across all disks
- Check disks store parity groups of Hamming code

All disks involved in read/write operations

Not actually used, don't worry about remembering it!

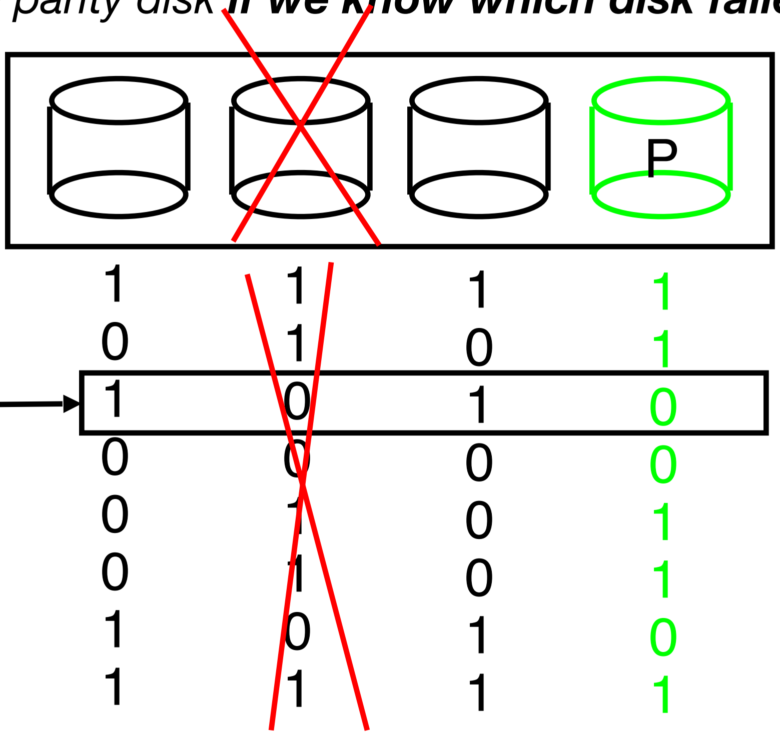
RAID 3: Single Parity Disk

- *Disk drives themselves code data and detect failures*
- *Reconstruction of data can be done with single parity disk **if we know which disk failed***
- *Writes change data disk and P disk*

10010011
11001101
10010011
. . .

logical record

Striped physical records

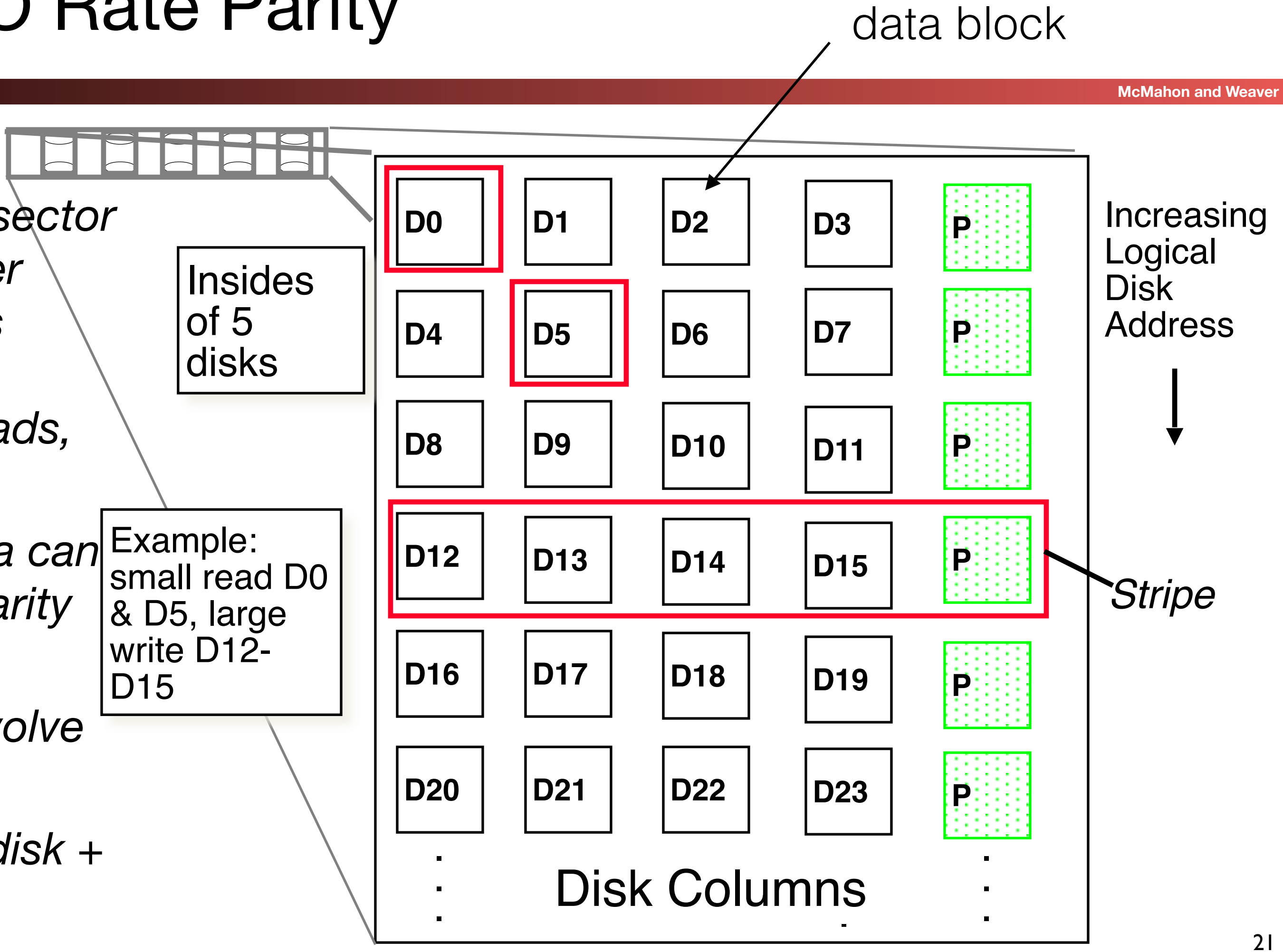


P contains parity of other disks per stripe.

If disk fails, use P and other disks to find missing information

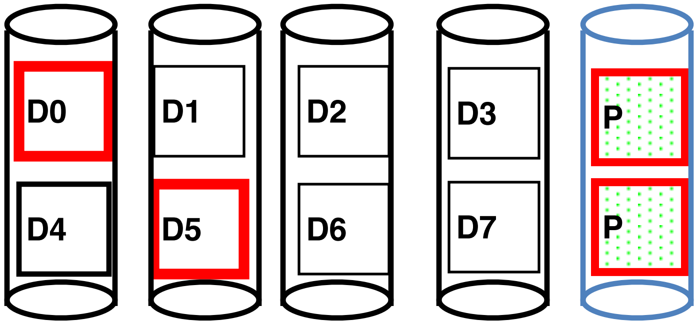
RAID 4: High I/O Rate Parity

- *Interleave data at the sector level (data block) rather than bit level - permits more parallelism (independent small reads, parallel large reads)*
- *Reconstruction of data can be done with single parity disk*
- *Reading (w/o) fault involve only data disk*
- *Writing involves data disk + parity disk*

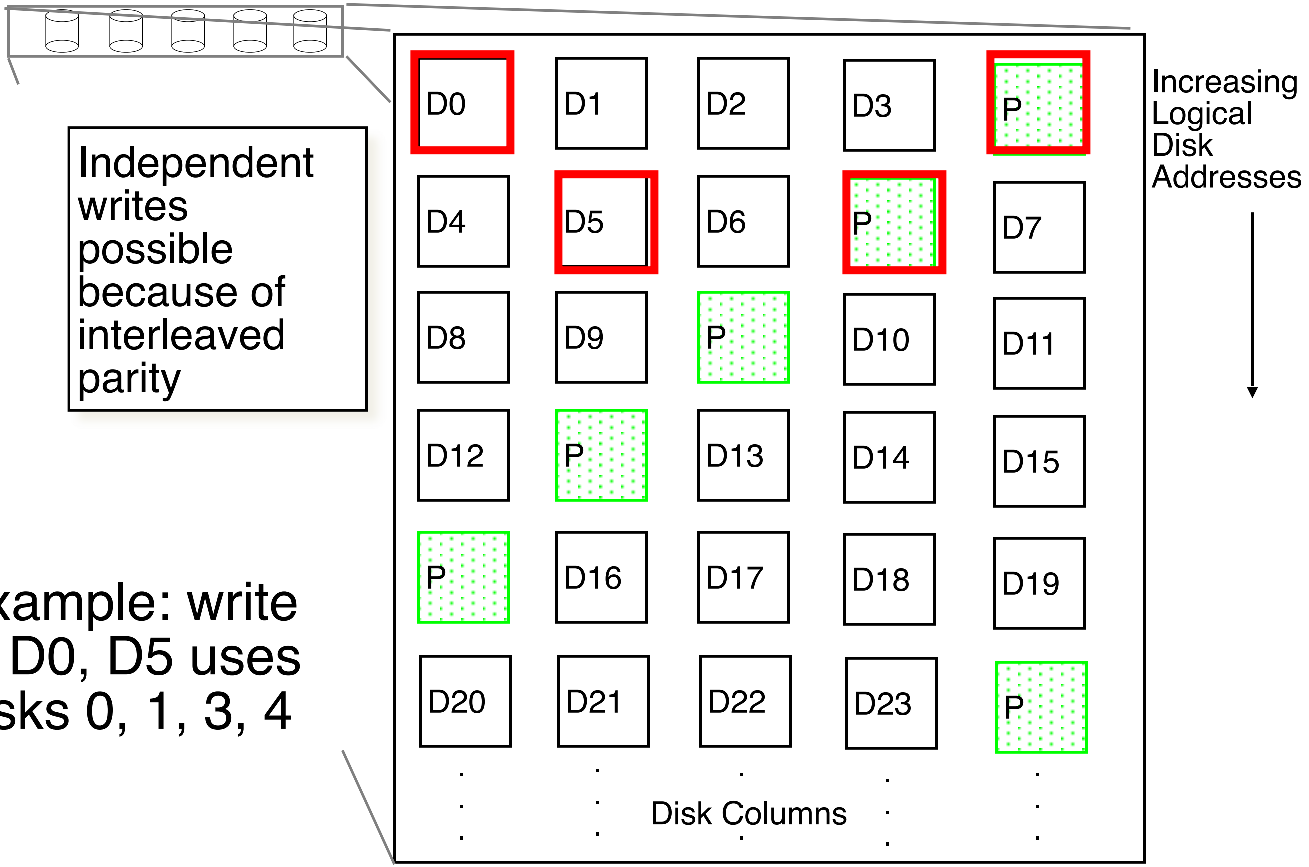


Inspiration for RAID 5

- RAID 4 works well for reads, but
- Parity Disk is the bottleneck for writes: Write to D0, D5 both also write to P disk



RAID 5: High I/O Rate Interleaved Parity



Independent writes possible because of interleaved parity

Example: write to D0, D5 uses disks 0, 1, 3, 4

RAID 6

- RAID 5 is no longer the “gold standard”
- Can experience 1 disk failure and continue operation
  - RAID array is in a “degraded” state
- But disk failures are not actually independent!
  - When one disk has failed, there’s a decent chance another will fail soon
- RAID 6: Add another parity block per stripe
  - Now 2 blocks per stripe rather than 1
  - Sacrifice capacity for increased redundancy
  - Now the array can tolerate **2** disk failures and continue operating

Berkeley's Role in Definition of RAID (December 1987)

A Case for Redundant Arrays of Inexpensive Disks (RAID)

Google

Case for Raid

Scholar

About 138,000 results (0.08 sec)

Articles

Legal documents

Any time

[BOOK] A case for redundant arrays of inexpensive disks (RAID)

DA Patterson, G Gibson, RH Katz - 1988 - dl.acm.org

Abstract Increasing performance of CPUs and memories will be squandered if not matched by a similar performance increase in I/O. While the capacity of Single Large Expensive Disks (SLED) has grown rapidly, the performance improvement of SLED has been modest. ...

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Increasing performance of CPUs and memories will be squandered if not matched by a similar performance increase in I/O. While the capacity of Single Large Expensive Disk (SLED) has grown rapidly, the performance improvement of SLED has been modest. Redundant Arrays of Inexpensive Disks (RAID), based on the magnetic disk technology developed for personal computers, offers an attractive alternative to SLED, promising improvements of an order of magnitude in performance, reliability, power consumption, and scalability.

This paper introduces five levels of RAIDs, giving their relative cost/performance, and compares RAIDs to an IBM 3380 and a Fujitsu Super Eagle.

RAID Version 1

- RAID-I (1989)
  - Consisted of a Sun 4/280 workstation with 128 MB of DRAM, four dual-string SCSI controllers, 28 5.25-inch SCSI disks and specialized disk striping software

RAID Version 2

- 1990-1993
- Early Network Attached Storage (NAS) System running a Log Structured File System (LFS)
- Impact:
  - $25 Billion/year in 2002
  - Over $150 Billion in RAID device sold since 1990-2002
  - 200+ RAID companies (at the peak)
  - Software RAID a standard component of modern OSs

RAID Is Not Enough By Itself

- You don't just have one disk die...
  - You can have more die in a short period of time
  - Thank both the "bathtub curve" and common environmental conditions
- If you care about your data, RAID isn't sufficient
  - You need to also consider a separate backup solution
- A good practice in clusters/warehouse scale computers:
  - RAID-6 in each cluster node with auto-failover and a hot spare
  - Distributed filesystem on top
    - Replicates amongst the cluster nodes so that nodes can fail
  - And then distribute to a different WSC...

In Conclusion …

- We have methods to mitigate faults in electronic systems:
  - Design bugs, Manufacturing defects, and Runtime Faults
- Dependability Measures let us quantify
- Dealing with Runtime Faults requires redundancy
  - either more hardware (cost) or more time (performance)
- Redundancy most commonly used in memory systems (DRAM, SRAM, Disks, SSD), also for communications

Warehouse Scale Cat-puting

Agenda

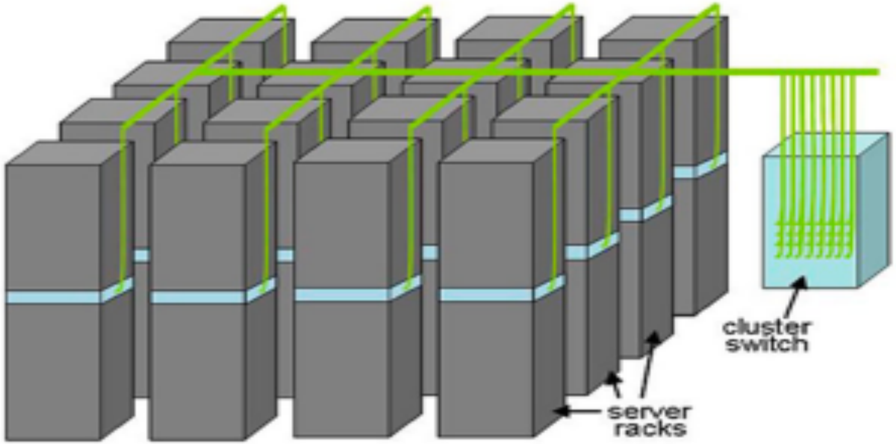
- Warehouse-Scale Computing
- Cloud Computing
- Request-Level Parallelism (RLP)
- Map-Reduce Data Parallelism

Google’s WSCs

WSC Architecture

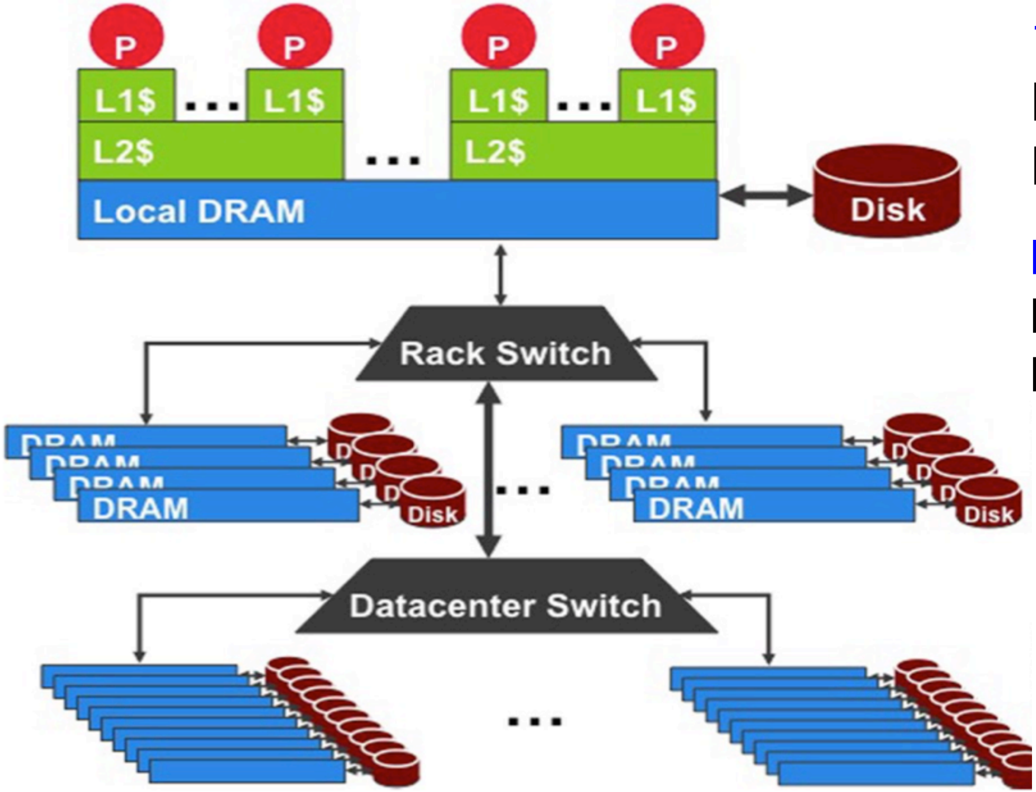
1U Server:
64 cores, 64 GiB DRAM,
4x8 TB disk

Rack:
40-80 servers,
Local Ethernet (1-10Gbps) switch
(30$/1Gbps/server)



Array (aka cluster):
16-32 racks
Expensive switch
(10X bandwidth → 100x cost)

WSC Storage Hierarchy

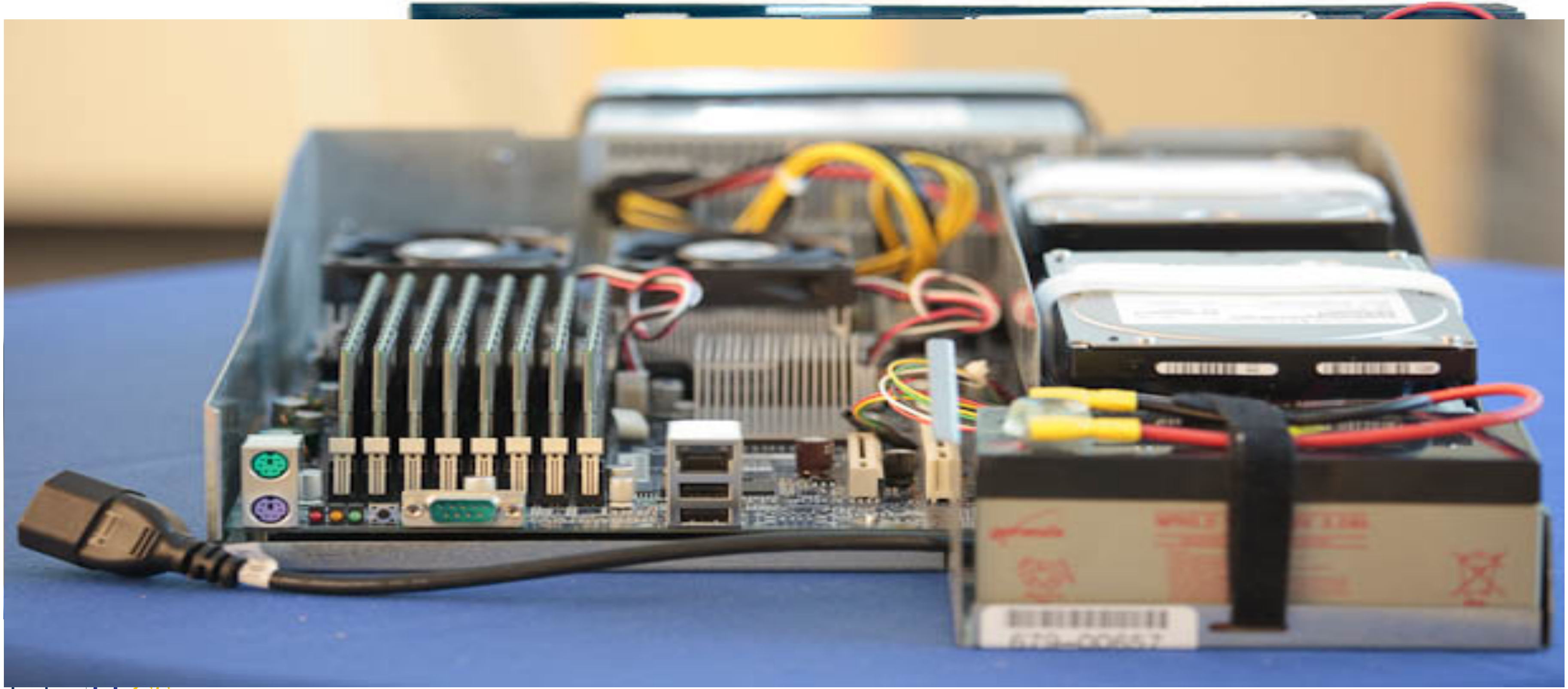


1U Server:
DRAM: 64GB, 100ns
Disk: 10TB, 10ms

Rack (80 severs):
DRAM: 5TB, 300μs
Disk: 800TB, 11ms

Array (30 racks):
DRAM: 150TB, 500μs
Disk: 24PB, 12ms

Early Google Server Internals



Power Usage Effectiveness

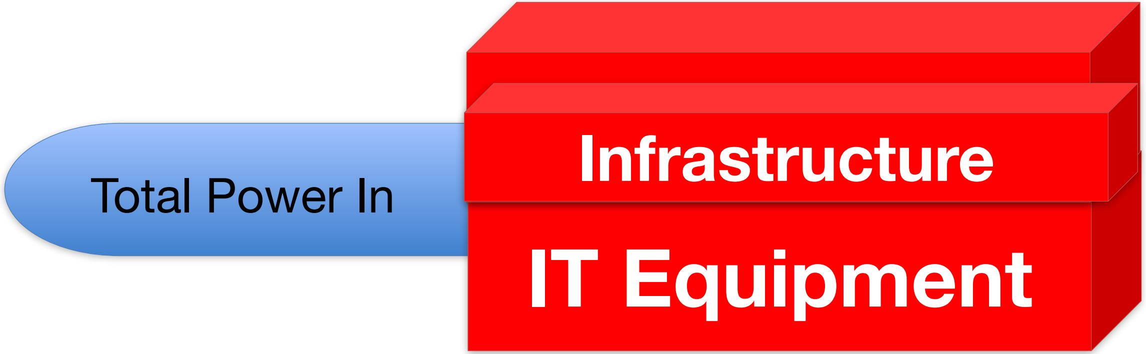
- Energy efficiency
  - Primary concern in the design of WSC
  - Important component of the total cost of ownership
- Power Usage Effectiveness (PUE):

$$\frac{\textbf{Total Building Power}}{\textbf{IT equipment Power}}$$

  - Power efficiency measure for WSC
  - Not considering efficiency of servers, networking
  - Perfection = 1.0
  - Google WSC's PUE = 1.2

Power Usage Effectiveness

Datacenter



Air Conditioning, Power Distribution, UPS, …

Servers, Storage, Networks

PUE = Total Power/IT Power

PUE = 2

PUE = 1.5

Cheating on Cooling

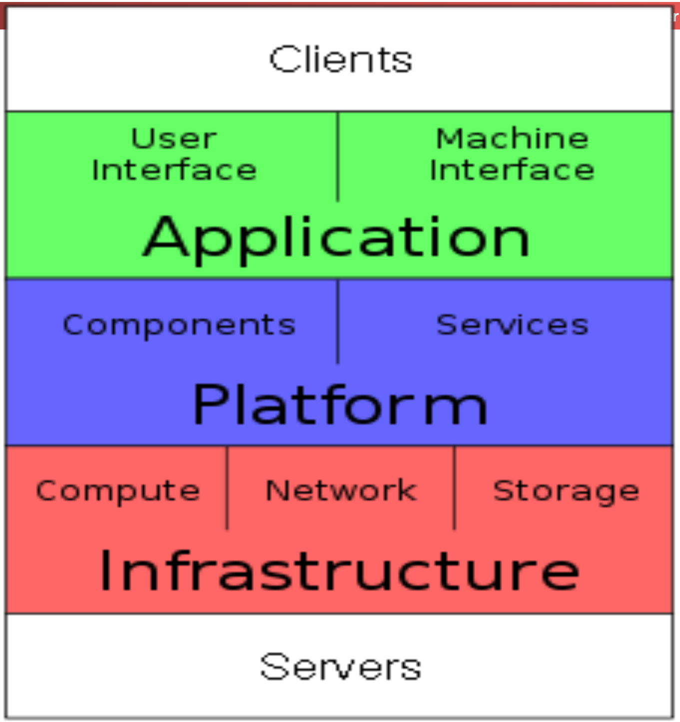
- Normally cooling the air requires big air-conditioning units
  - These suck a lot of power and still consume a lot of water
    - Evaporation of water to dissipate the energy
- Cheat #1: Heat-exchange to a water source
  - Locate your data center on a river or the ocean
  - Or even just put it in a sealed container dropped onto the sea bottom
- Cheat #2: Just have things open to the air!
  - Ups the failure rate, but if the power savings exceed the costs incurred by additional machines dying, it becomes worth it

Cloud Distinguished by …

- Shared platform with illusion of isolation
  - Collocation with other tenants
  - Exploits technology of VMs and hypervisors
  - At best “fair” allocation of resources, but not true isolation
- Attraction of low-cost cycles
  - Economies of scale driving move to consolidation
  - Statistical multiplexing to achieve high utilization/efficiency of resources
- Elastic service
  - Pay for what you need, get more when you need it
  - But no performance guarantees: assumes uncorrelated demand for resources

Cloud Services

- **SaaS**: deliver apps over Internet, eliminating need to install/run on customer's computers, simplifying maintenance and support
  - E.g., Google Docs, Win Apps in the Cloud
- **PaaS**: Deliver computing "stack" as a service, using cloud infrastructure to implement apps. Deploy apps without cost/complexity of buying and managing underlying layers
  - E.g., Hadoop on EC2, Apache Spark on GCP
- **IaaS**: Rather than purchasing servers, software, data center space or net equipment, clients buy resources as an outsourced service. Billed on utility basis. Amount of resources consumed/cost reflect level of activity
  - E.g., Amazon Elastic Compute Cloud, Google Compute Platform

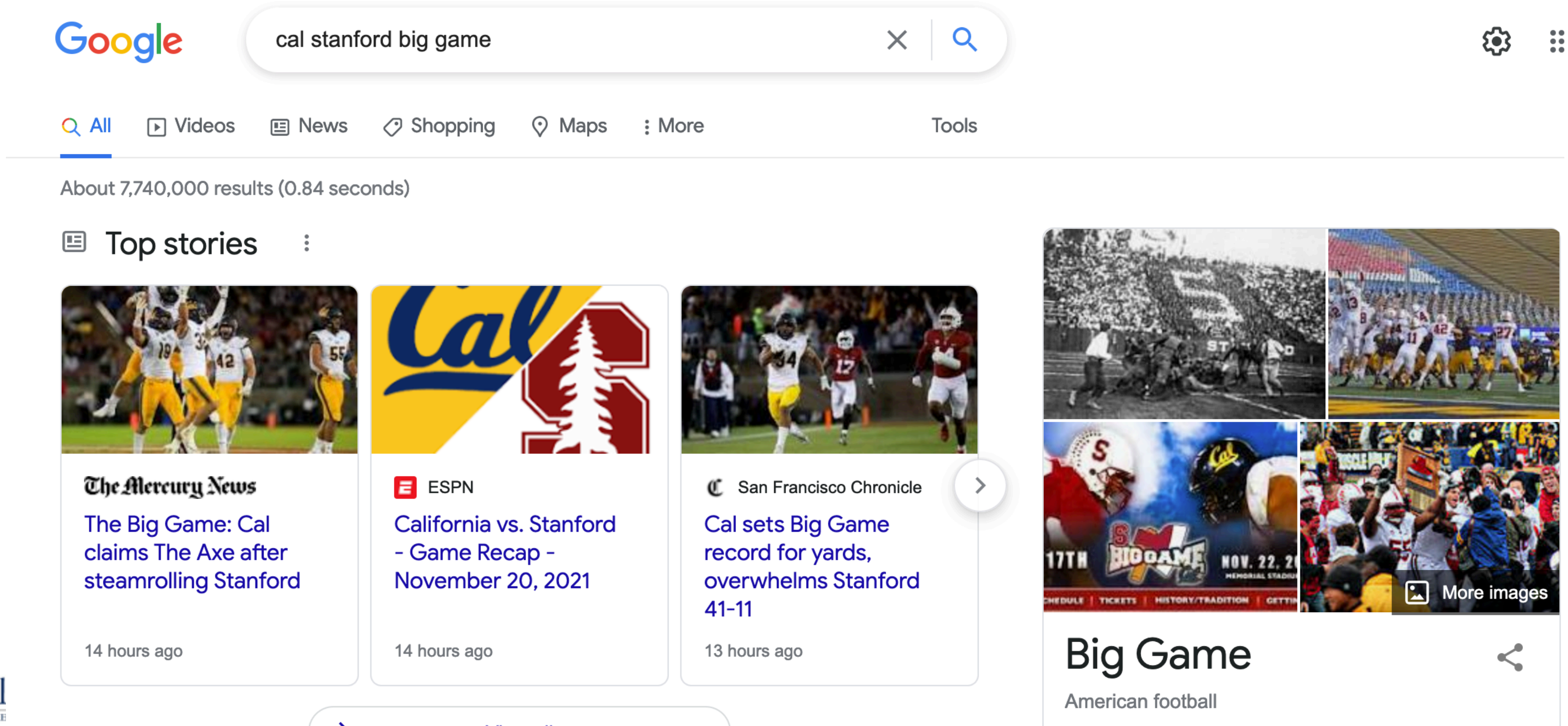


Cloud Computing Stack

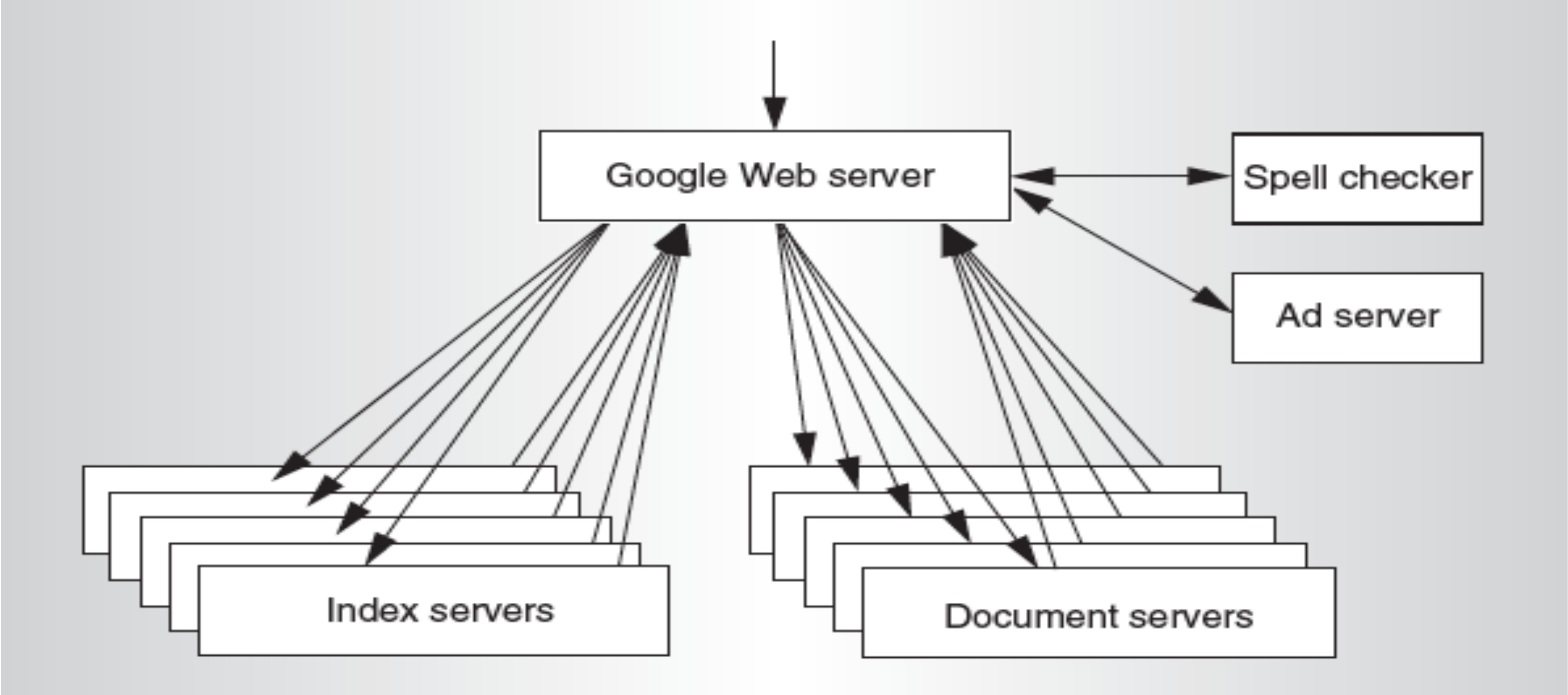
Request-Level Parallelism (RLP)

- Hundreds of thousands of requests per second
  - Popular Internet services like web search, social networking, …
  - Such requests are largely independent
    - Often involve read-mostly databases
    - Rarely involve read-write sharing or synchronization across requests
- Computation easily partitioned across different requests and even within a request
  - Can often "load balance" just at the DNS level:
    Just tell different people to use a different computer

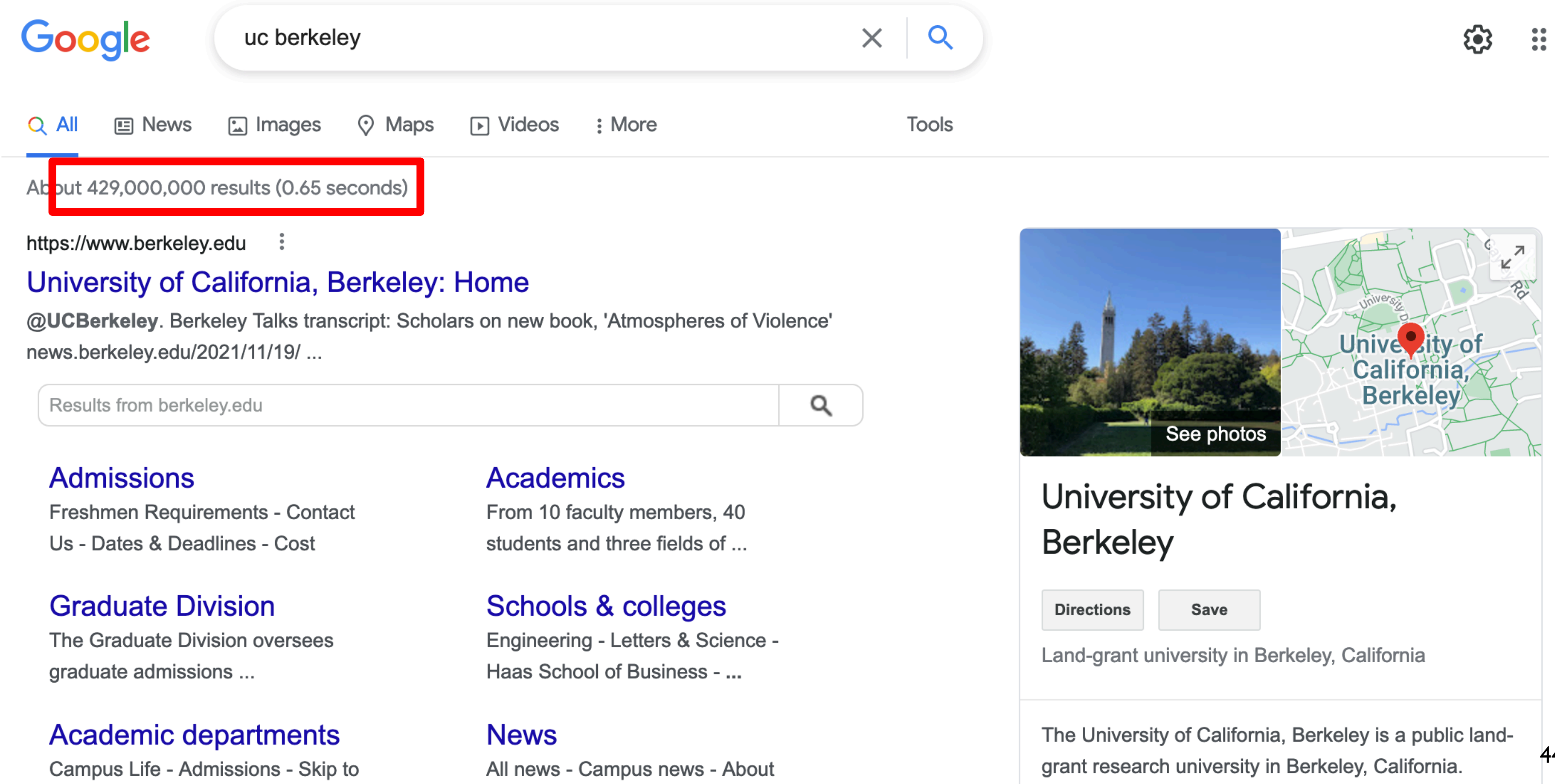
Scaled Communities, Processing, and Data



Google Query-Serving Architecture



Web Search Result



Anatomy of a Web Search (1/3)

- Google "UC Berkeley"
  1. Direct request to "closest" Google Warehouse-Scale Computer
  2. Front-end load balancer directs request to one of many clusters of servers within WSC
  3. Within cluster, select one of many Google Web Servers (GWS) to handle the request and compose the response pages
  4. GWS communicates with Index Servers to find documents that contain the search words, "UC", "Berkeley", uses location of search as well as user information
  5. Send information about this search to the node in charge of tracking you
  6. Return document list with associated relevance score

Anatomy of a Web Search (2/3)

- In parallel,
  - Ad system: if anyone has bothered to advertise for you
  - Customization based on your account
- Use docids (document IDs) to access indexed documents to get snippets of stuff
- Compose the page
  - Result document extracts (with keyword in context) ordered by relevance score
  - A bunch of advertisements (along the top and side)
    - Initially they were easy to see...
      But now they are almost indistinguishable from the desired content

Anatomy of a Web Search (3/3)

- Implementation strategy
  - Randomly distribute the entries
  - Make many copies of data (aka “replicas”)
  - Load balance requests across replicas
- ***Redundant copies*** of indices and documents
  - Breaks up hot spots — especially popular queries
  - Increases opportunities for ***request-level parallelism***
  - Makes the system more ***tolerant of failures***

Data-Level Parallelism (DLP)

- SIMD
  - Supports data-level parallelism in a single machine
  - Additional instructions & hardware (e.g., AVX)

  e.g., Matrix multiplication in memory

- DLP on WSC
  - Supports data-level parallelism across ***multiple machines***
  - MapReduce & scalable file systems

Problem Statement

- How process large amounts of raw data (crawled documents, request logs, …) every day to compute derived data (inverted indices, page popularity, …)
  - Each computation is relatively simple but the input data is huge (petabytes) and distributed across 100s or 1000s of servers
- Challenge: Parallelize computation, distribute data, tolerate faults without obscuring simple computation with complex code to deal with issues

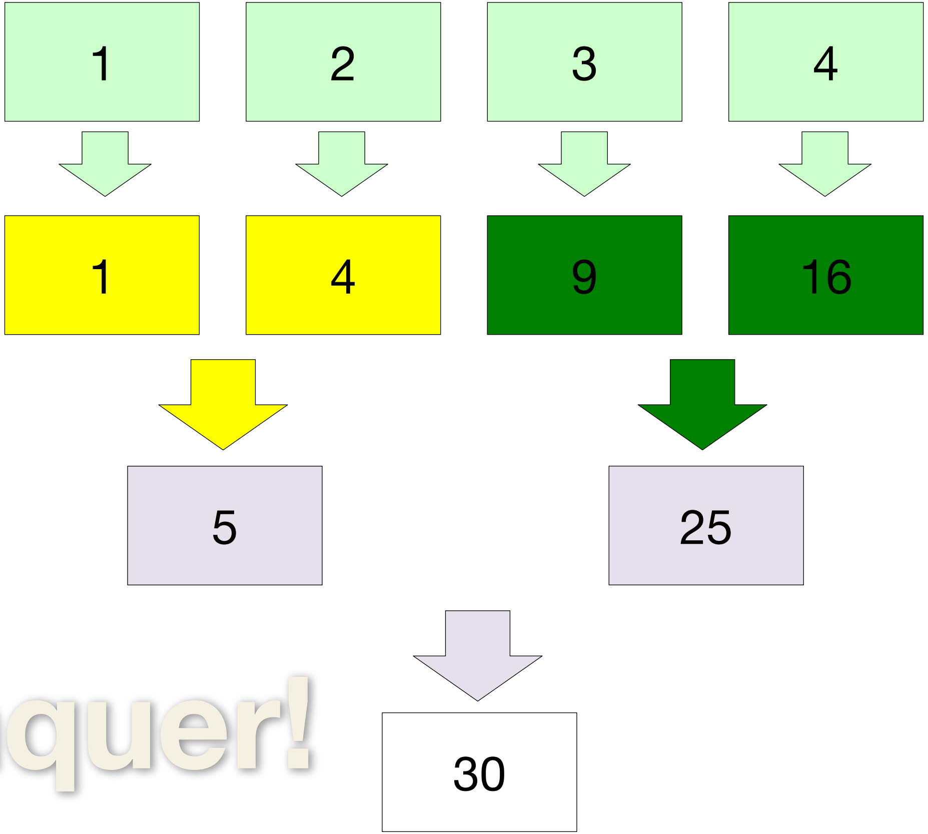
Solution: MapReduce

- Simple data-parallel ***programming model*** and ***implementation*** for processing large datasets
- Users specify the computation in terms of
  - a ***map*** function, and
  - a ***reduce*** function
- Underlying runtime system
  - Automatically ***parallelize*** the computation across large scale clusters of machines
  - ***Handles*** machine ***failure***
  - ***Schedule*** inter-machine communication to make efficient use of the networks

Inspiration: Map & Reduce Functions, ex: Python

Calculate : $\sum_{n=1}^{4} n^2$

```
A = [1, 2, 3, 4]
def square(x):
  return x * x
def sum(x, y):
  return x + y
reduce(sum, map(square,
A))
```



Divide and Conquer!

MapReduce Programming Model

- ***Map***: `(in_key, in_value) → list(interm_key, interm_val)`

```
map(in_key, in_val):
    // DO WORK HERE
    emit(interm_key,interm_val)
```

  - Slice data into “shards” or “splits” and distribute to workers
  - Compute set of intermediate key/value pairs

- ***Reduce***: `(interm_key, list(interm_value)) → list(out_value)`

```
reduce(interm_key, list(interm_val)):
    // DO WORK HERE
    emit(out_key, out_val)
```

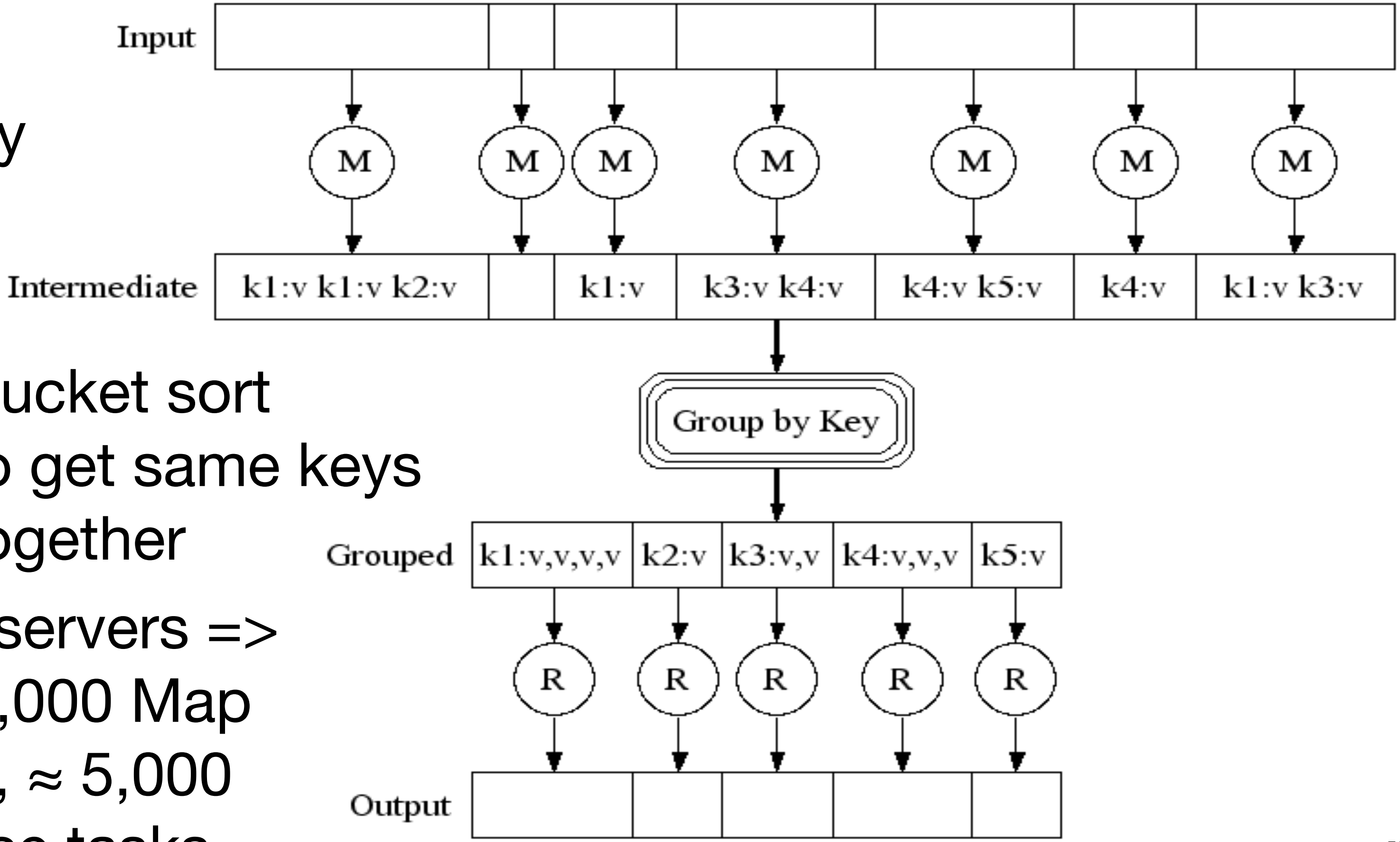
  - Combines all intermediate values for a particular key
  - Produces a set of merged output values (usually just one)

MapReduce Execution

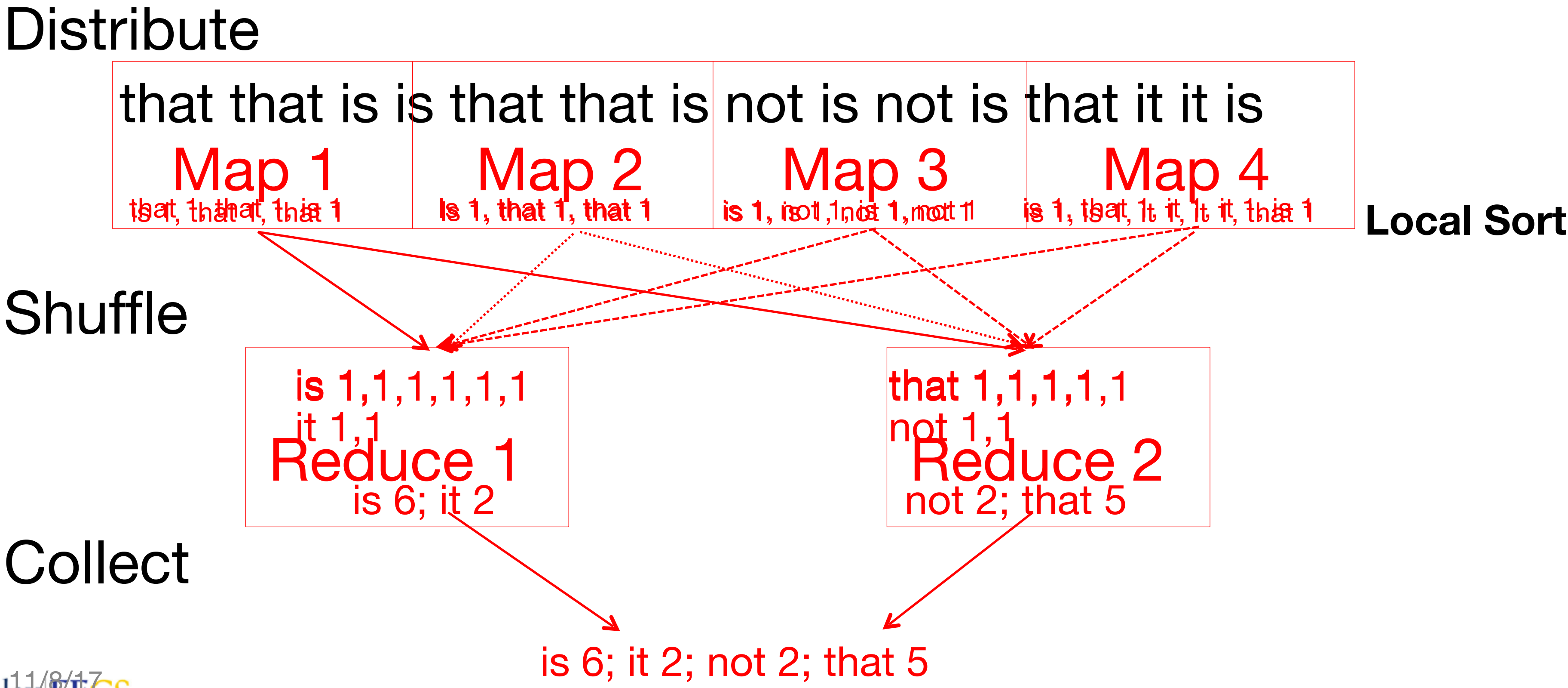
Fine granularity tasks: many more map tasks than machines

Bucket sort to get same keys together

2000 servers => ≈ 200,000 Map Tasks, ≈ 5,000 Reduce tasks



MapReduce Word Count Example



MapReduce Word Count Example

User-written ***Map*** function reads the document data and

parses the words. For each word, it writes the (key, value) pair of (word, 1). The word is treated as the intermediate key and the associated value of 1 means that we saw the word once.

Map phase: (doc name, doc contents) → list(word, count)

```
// "I do I learn" → [("I",1),("do",1),("I",1),("learn",1)]
```

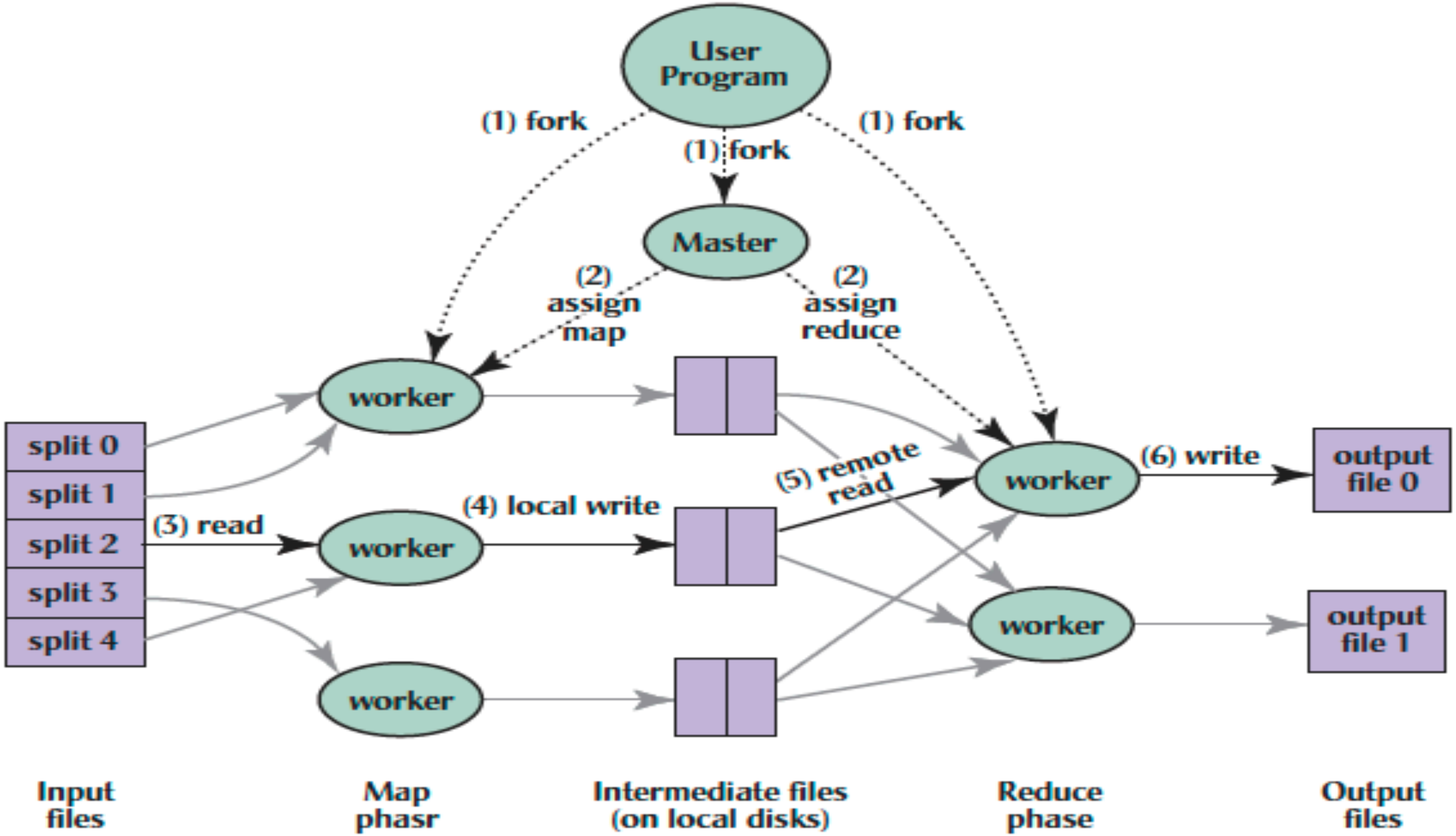
```
map(key, value):
  for each word w in value:
    emit(w, 1)
```

MapReduce Word Count Example

Intermediate data is then sorted by MapReduce by keys and the user's ***Reduce*** function is called for each unique key. In this case, Reduce is called with a list of a "1" for each occurrence of the word that was parsed from the document. The function adds them up to generate a total word count for that word.

Reduce phase: (word, list(counts)) → (word, count_sum)

```
// ("I", [1,1]) → ("I",2)
reduce(key, values):
  result = 0
  for each v in values:
    result += v
  emit(key, result)
```



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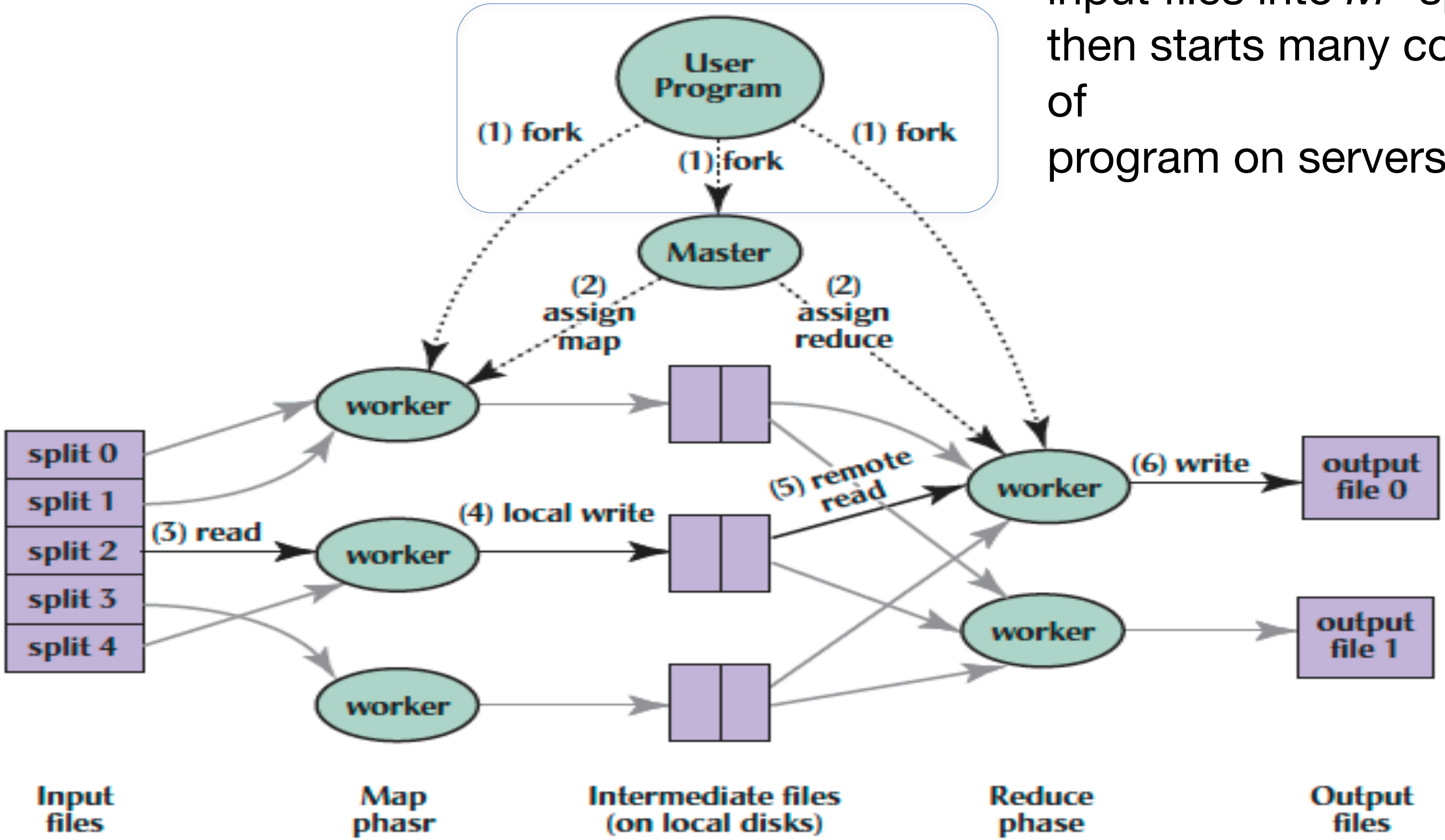
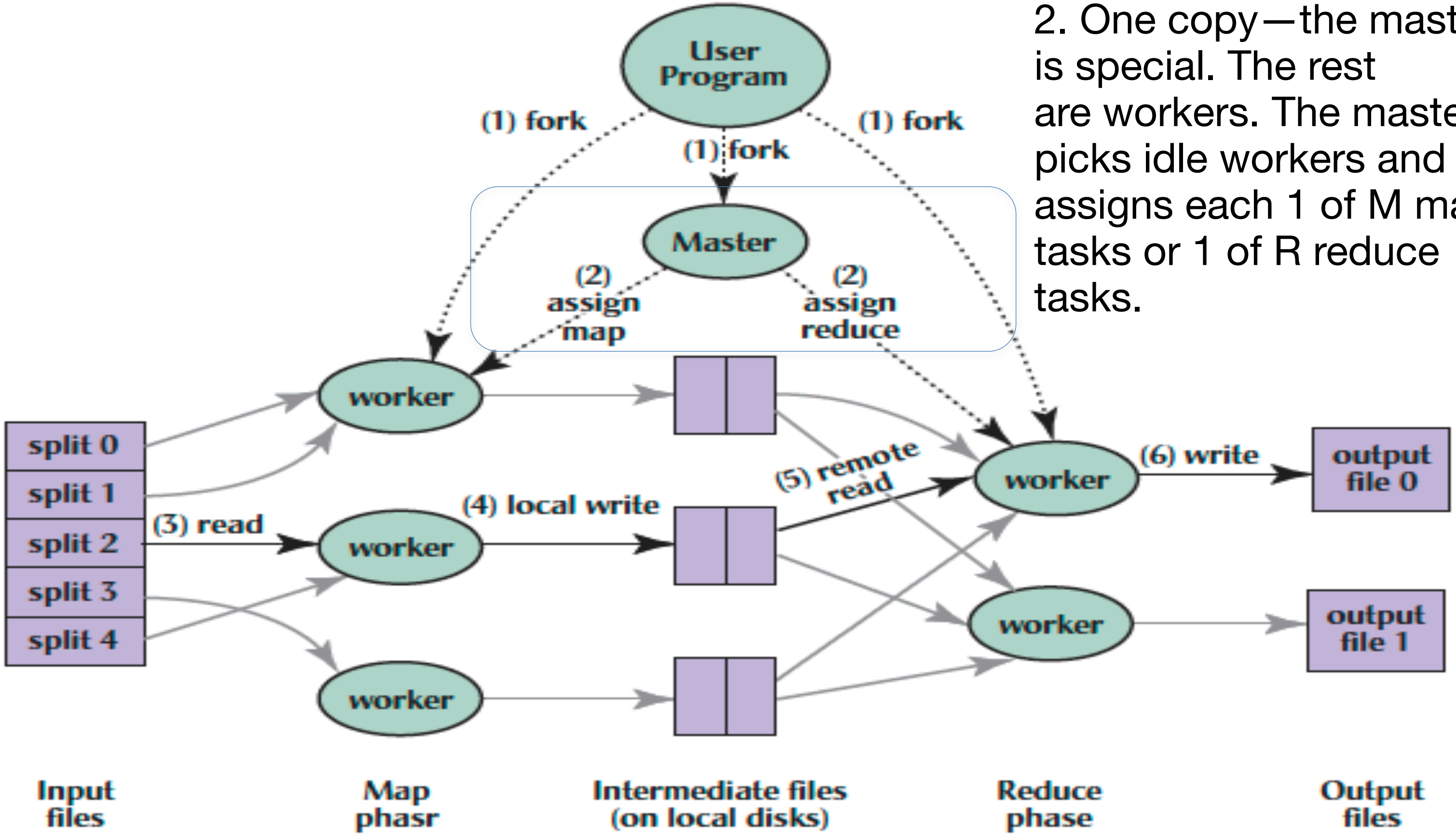
MapReduce Processing

1. MR 1st splits the input files into *M* “splits” then starts many copies of
program on servers



MapReduce Processing

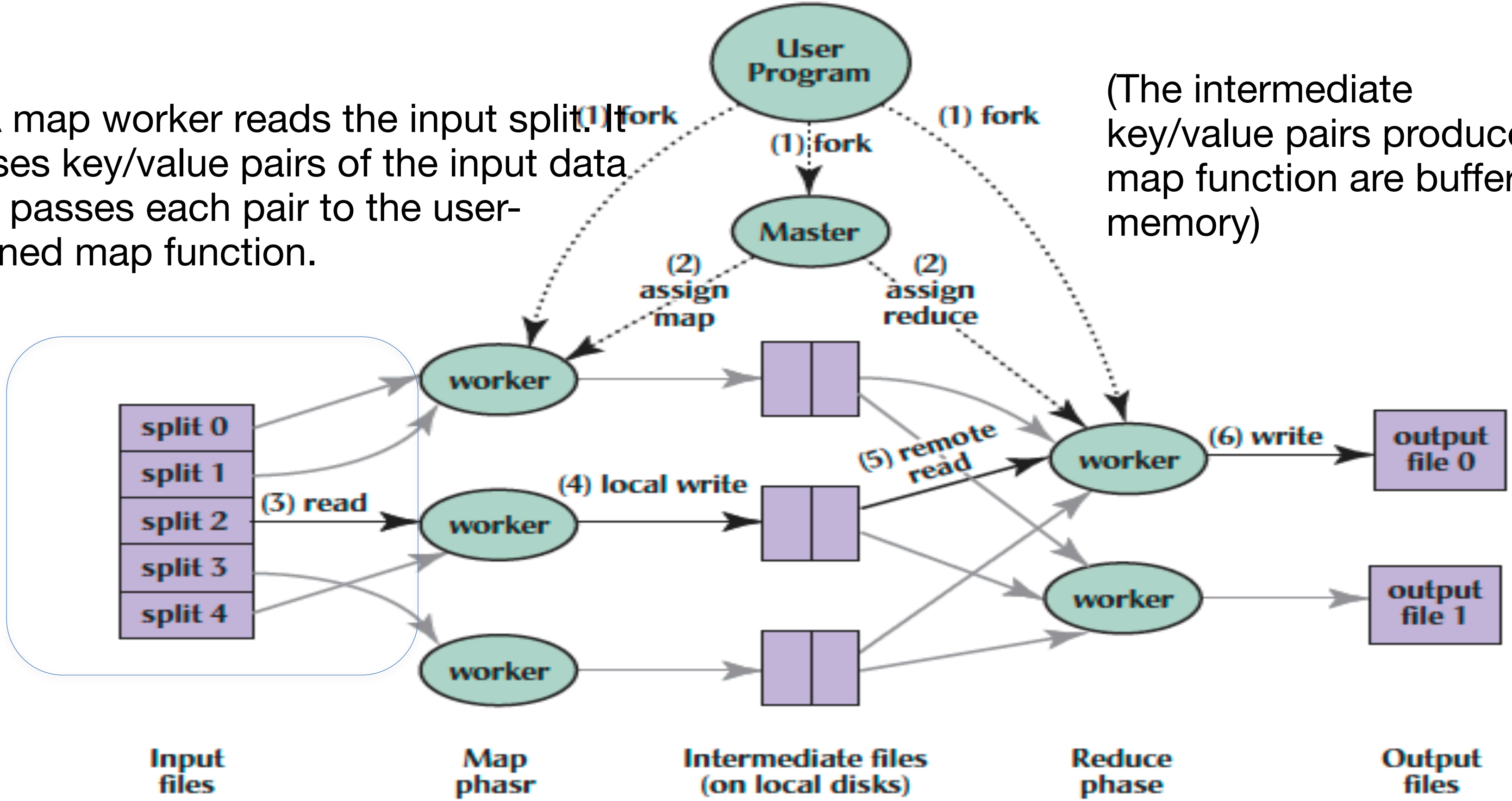


2. One copy—the master—is special. The rest are workers. The master picks idle workers and assigns each 1 of M map tasks or 1 of R reduce tasks.

MapReduce Processing

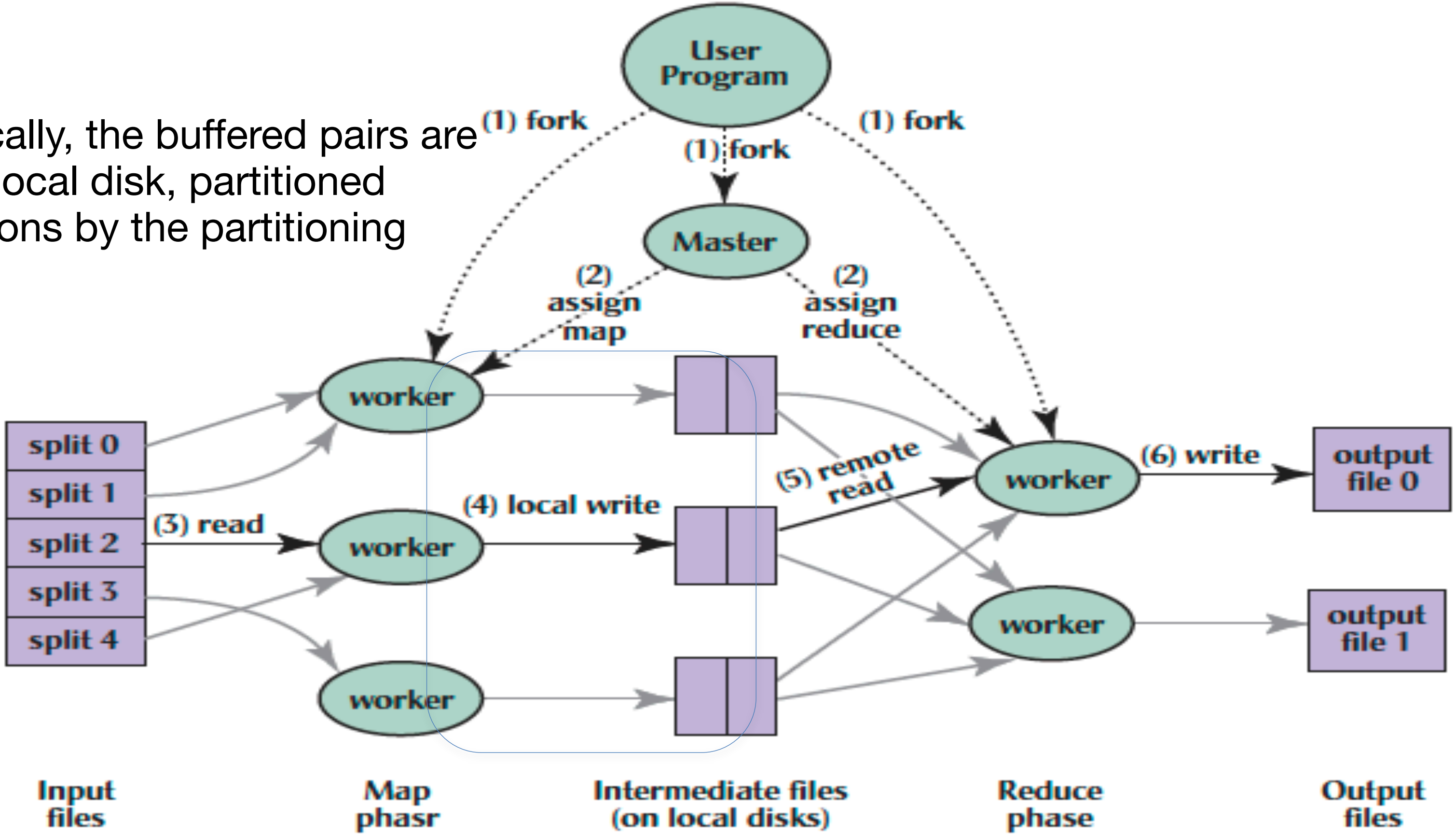
3. A map worker reads the input split. It parses key/value pairs of the input data and passes each pair to the user-defined map function.

(The intermediate key/value pairs produced by the map function are buffered in memory)



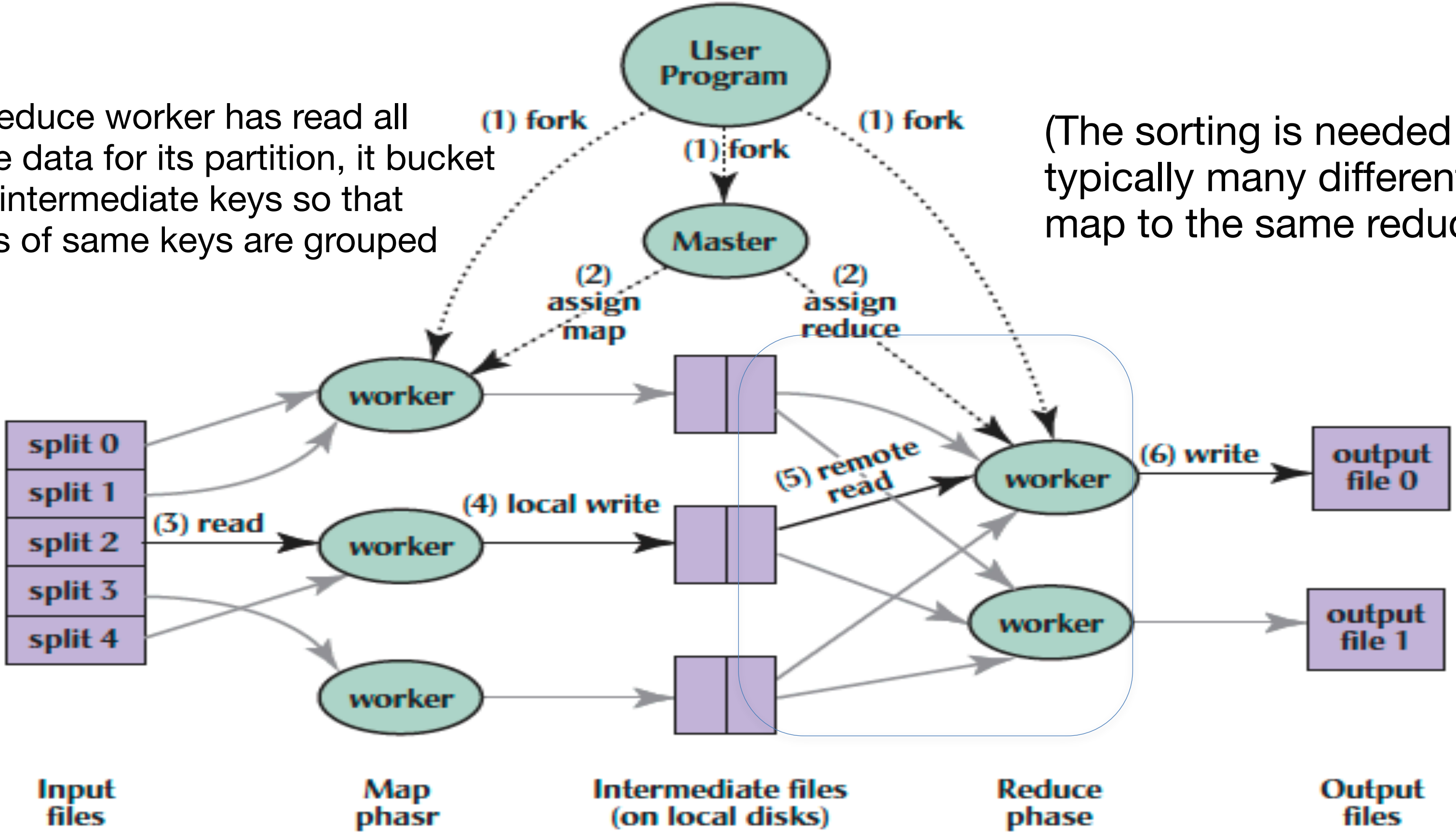
MapReduce Processing

4. Periodically, the buffered pairs are written to local disk, partitioned into *R* regions by the partitioning function.



MapReduce Processing

5. When a reduce worker has read all intermediate data for its partition, it bucket sorts using intermediate keys so that occurrences of same keys are grouped together

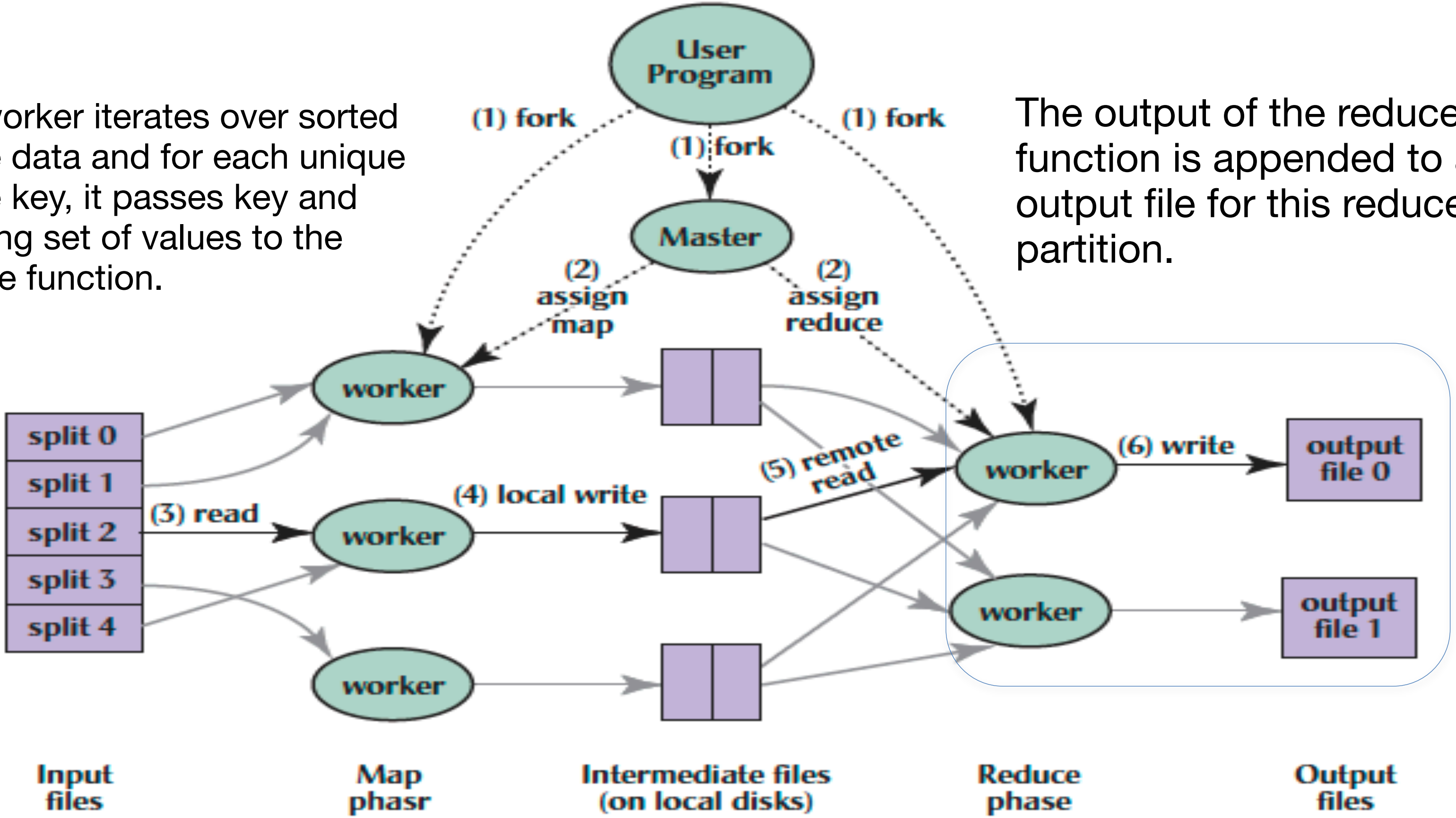


(The sorting is needed because typically many different keys map to the same reduce task)

MapReduce Processing

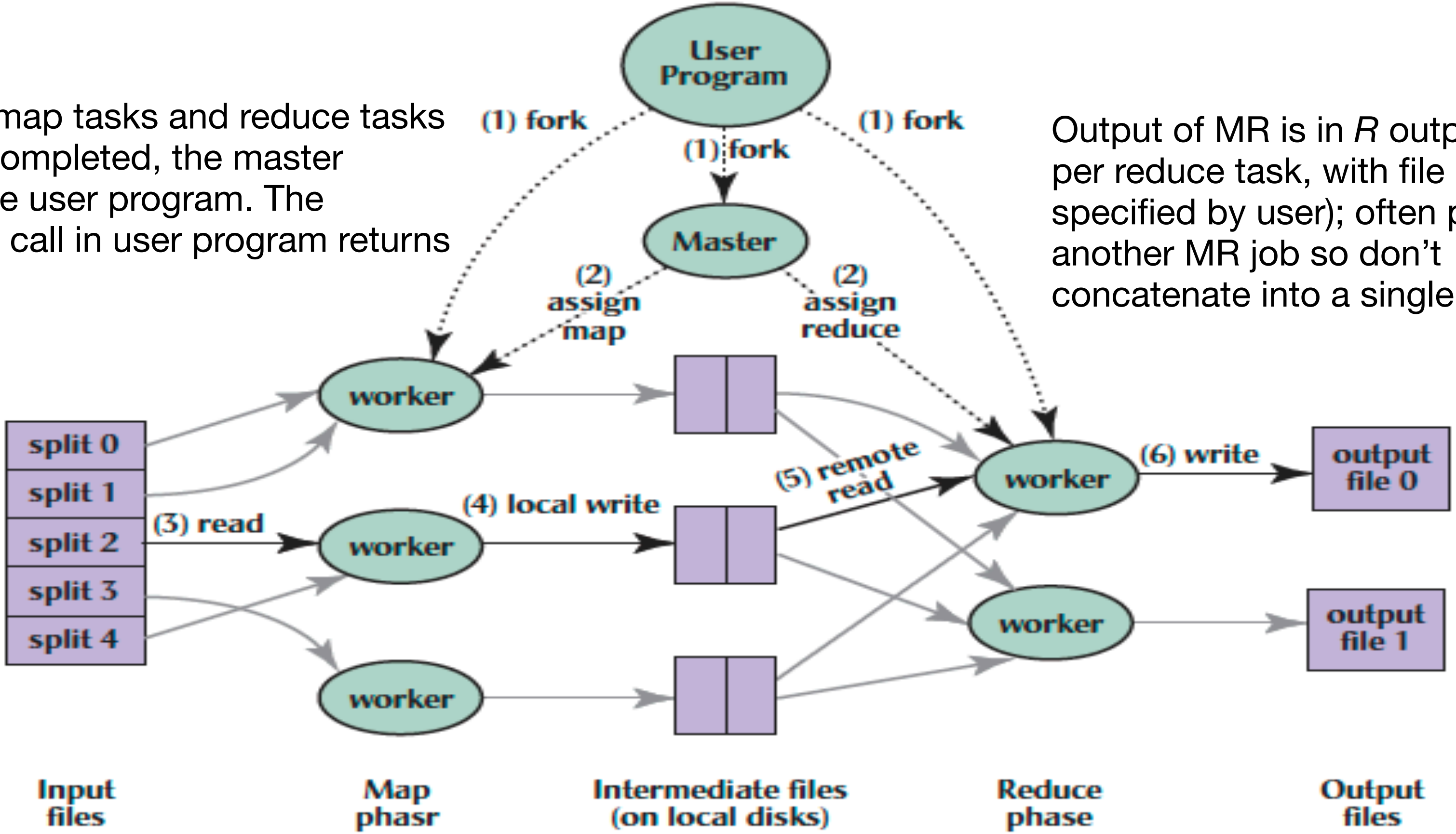
6. Reduce worker iterates over sorted intermediate data and for each unique intermediate key, it passes key and corresponding set of values to the user's reduce function.

The output of the reduce function is appended to a final output file for this reduce partition.



MapReduce Processing

7. When all map tasks and reduce tasks have been completed, the master wakes up the user program. The MapReduce call in user program returns



Output of MR is in *R* output files (1 per reduce task, with file names specified by user); often passed into another MR job so don't concatenate into a single file

Big Data Frameworks: Hadoop & Spark

- Apache Hadoop
  - Open-source MapReduce Framework
  - Hadoop Distributed File System (HDFS)
  - MapReduce Java APIs
- Apache Spark
  - Fast and general engine for large-scale data processing
  - Originally developed in the AMP lab at UC Berkeley
  - Running on top of HDFS
  - Provides Java, Scala, Python APIs for
    - Database
    - Machine learning
    - Graph algorithms

Apache Spark

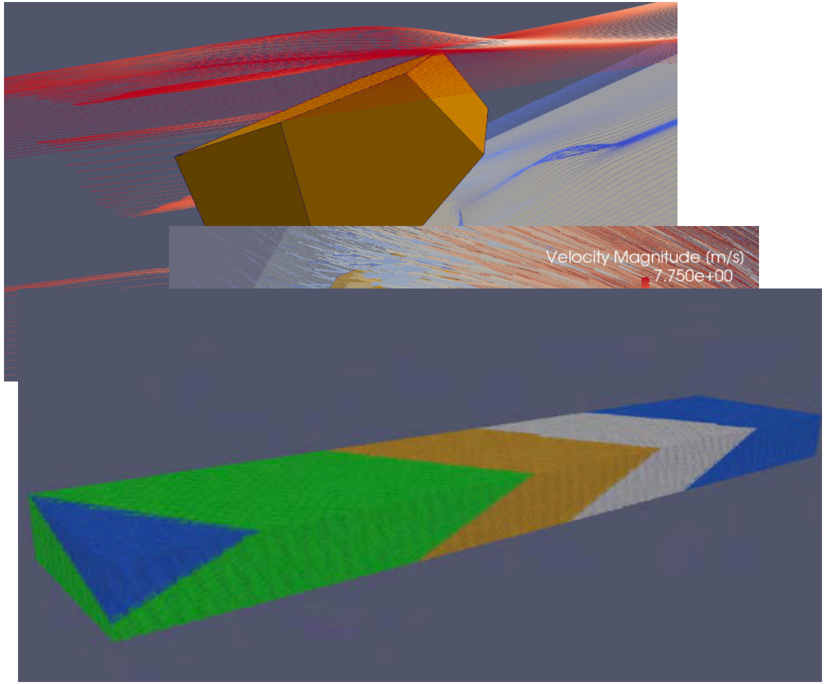
- Resilient Distributed Data Set (RDD): A collection of items partitioned across the members of a cluster
  - Can program against it just like an ordinary list, but operations are carried out in parallel on different machines
- Uses the same file system/infrastructure as Hadoop
  - Reuse existing systems, make it easier for users to transition
- Users can think about writing "ordinary" code to operate against RDDs rather than an explicit map/reduce structure
- Keep intermediate results in memory where possible
  - Issue with Hadoop: Write to disk after each map/reduce cycle, slow and inefficient when we want to compose many operations together (e.g., iterative method)

Word Count in Spark's Python API


```
file = sc.textFile("hdfs://…")
// Two kinds of operations:
// Actions: RDD → Value
// Transformations: RDD → RDD
// e.g. flatMap, Map, reduceByKey
file.flatMap(lambda line: line.split())
     .map(lambda word: (word, 1))
     .reduceByKey(lambda a, b: a + b)
```

See http://spark.apache.org/examples.html

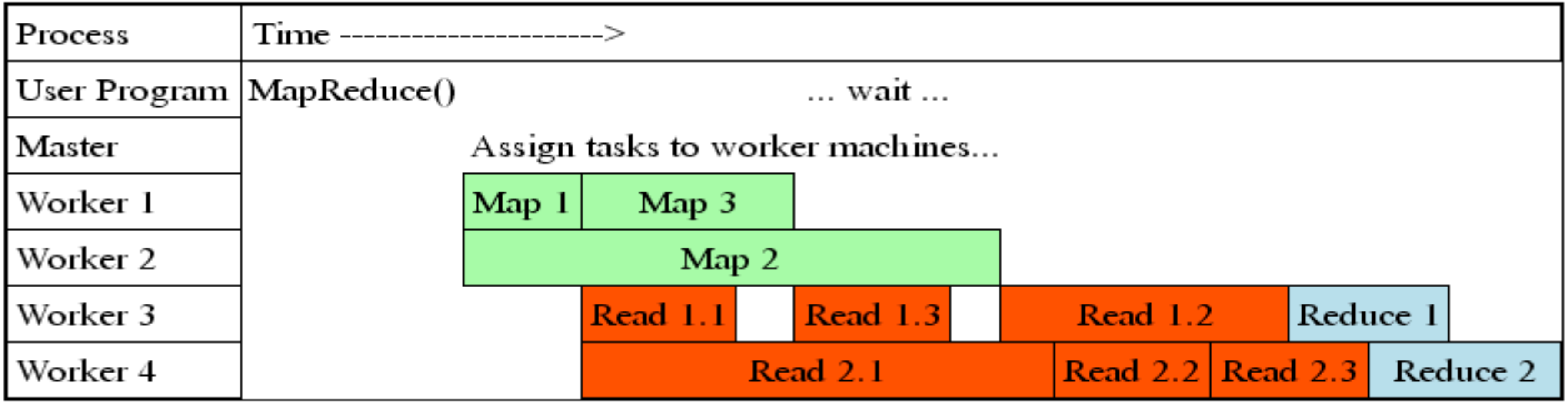
What about a *real* application of Spark?



- 50K Blocks in 15 min. -> 8 million Blocks in 15 min.
- How: Spatial partition of the problem

MapReduce Processing Time Line

- Master assigns map + reduce tasks to “worker” servers
- As soon as a map task finishes, worker server can be assigned a new map or reduce task
- Data shuffle begins as soon as a given Map finishes
- Reduce task begins as soon as all data shuffles finish
- To tolerate faults, reassign task if a worker server “dies”



A 2003 example...

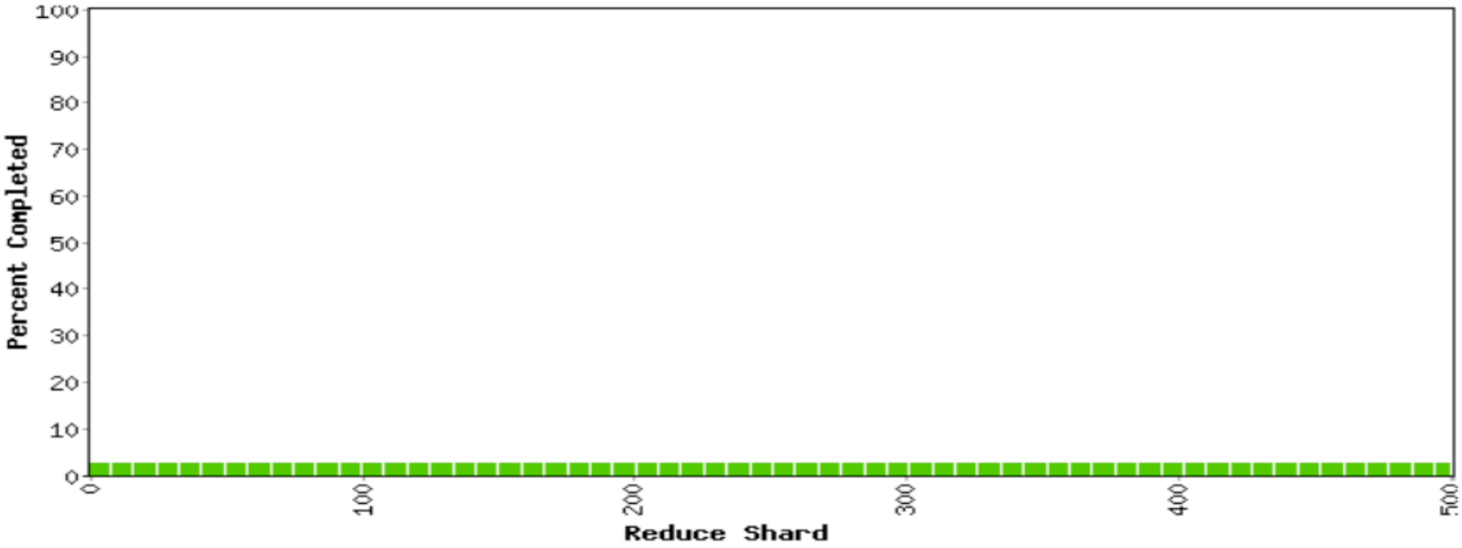
- ~41 minutes total
  - ~29 minutes for Map tasks & Shuffle tasks
  - ~12 minutes for Reduce tasks
  - 1707 worker servers used
- Map (Green) tasks read 0.8 TB, write 0.5 TB
- Shuffle (Red) tasks read 0.5 TB, write 0.5 TB
- Reduce (Blue) tasks read 0.5 TB, write 0.5 TB

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 00 min 18 sec

323 workers; 0 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	0	323	878934.6	1314.4	717.0
Shuffle	500	0	323	717.0	0.0	0.0
Reduce	500	0	0	0.0	0.0	0.0



Counters

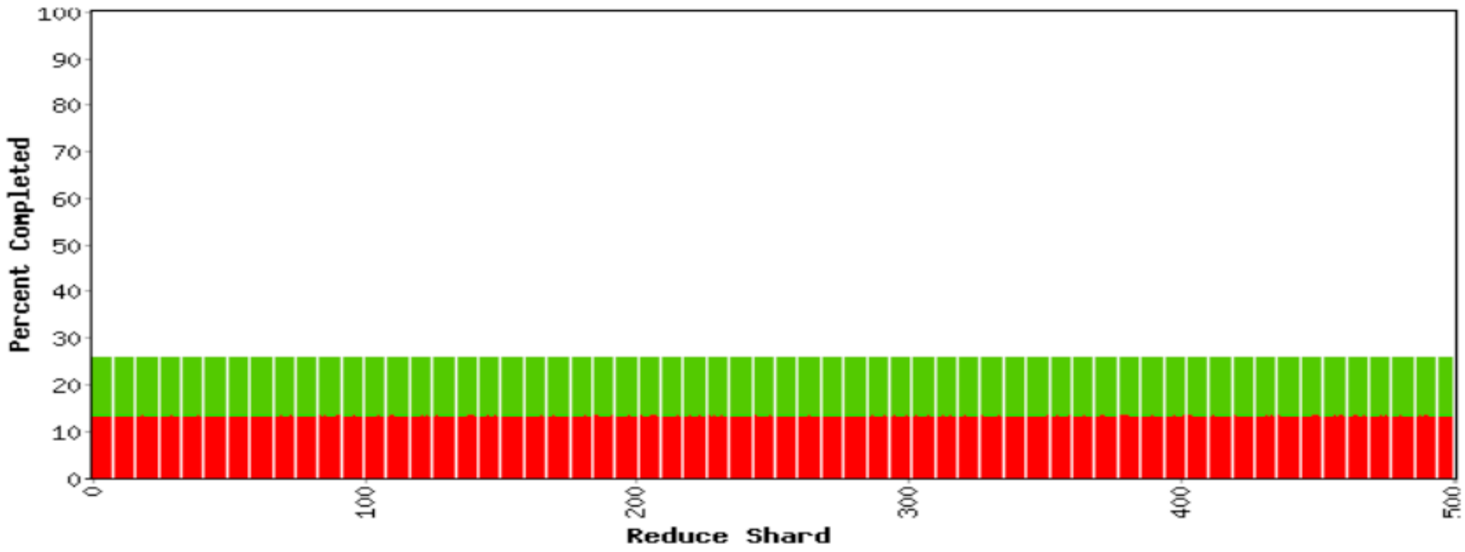
Variable	
Mapped (MB/s)	72.5
Shuffle (MB/s)	0.0
Output (MB/s)	0.0
doc-index-hits	145825686
docs-indexed	506631
dups-in-index-merge	0
mr-operator-calls	508192
mr-operator-outputs	506631

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 05 min 07 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	1857	1707	878934.6	191995.8	113936.6
Shuffle	500	0	500	113936.6	57113.7	57113.7
Reduce	500	0	0	57113.7	0.0	0.0



Counters

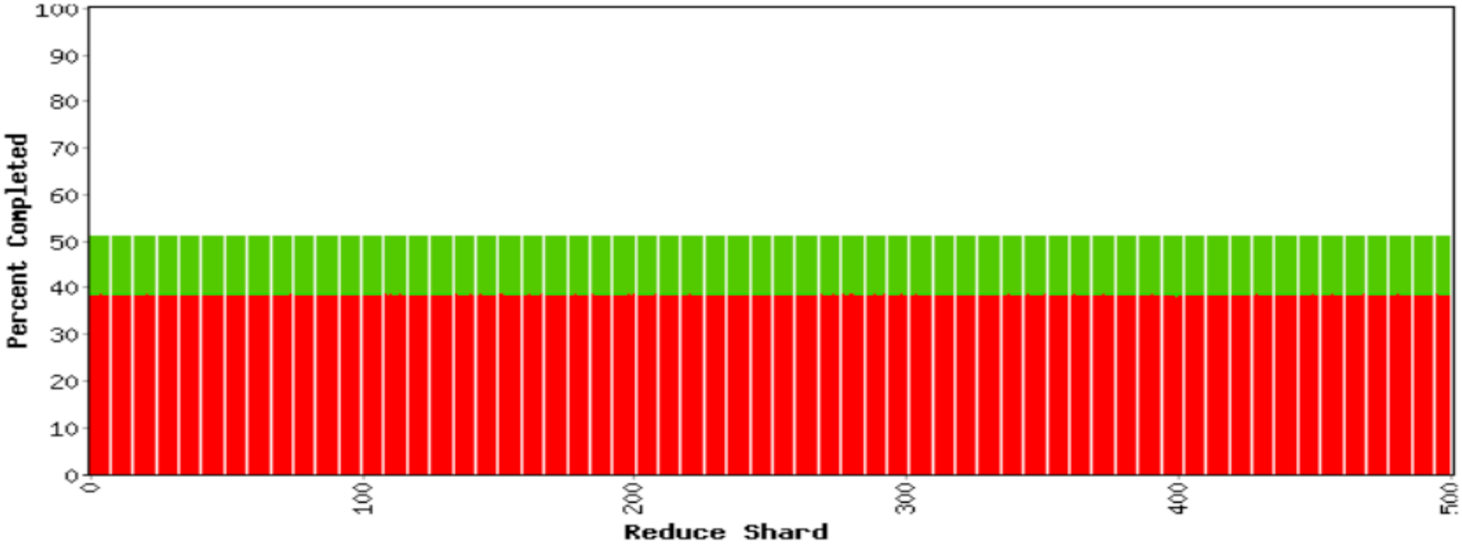
Variable	
Mapped (MB/s)	699.1
Shuffle (MB/s)	349.5
Output (MB/s)	0.0
doc-index-hits	5004411944
docs-indexed	17290135
dups-in-index-merge	0
mr-operator-calls	17331371
mr-operator-outputs	17290135

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 10 min 18 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	5354	1707	878934.6	406020.1	241058.2
Shuffle	500	0	500	241058.2	196362.5	196362.5
Reduce	500	0	0	196362.5	0.0	0.0



Counters

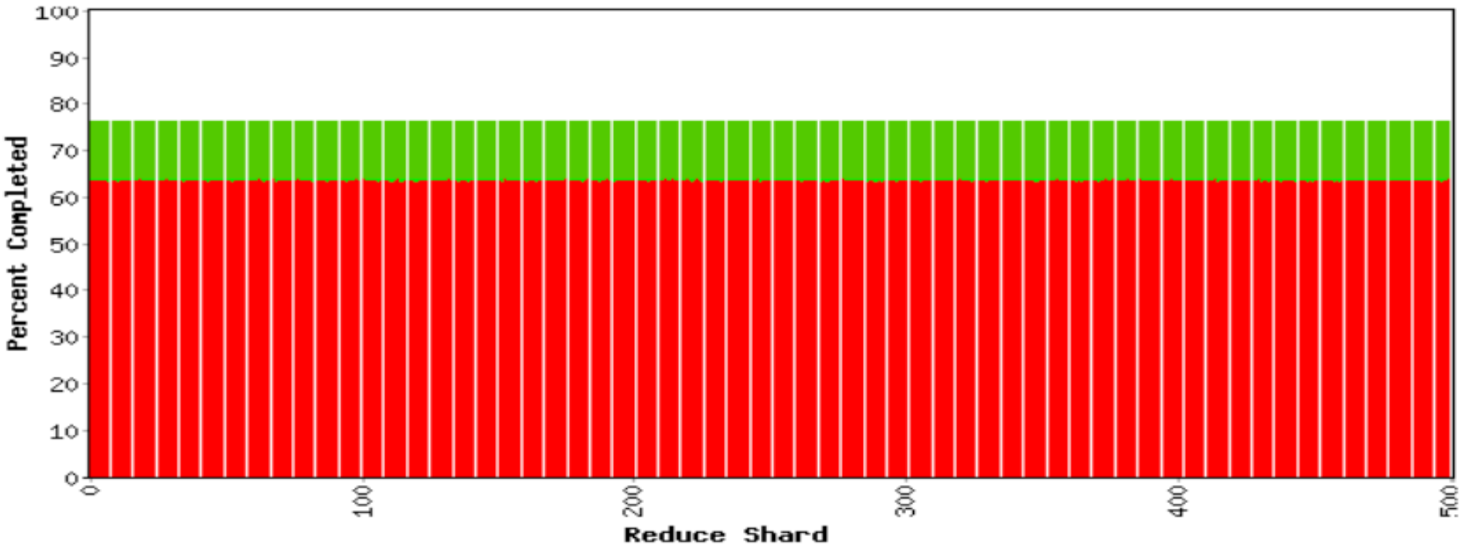
Variable	
Mapped (MB/s)	704.4
Shuffle (MB/s)	371.9
Output (MB/s)	0.0
doc-index-hits	5000364228
docs-indexed	17300709
dups-in-index-merge	0
mr-operator-calls	17342493
mr-operator-outputs	17300709

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 15 min 31 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	8841	1707	878934.6	621608.5	369459.8
Shuffle	500	0	500	369459.8	326986.8	326986.8
Reduce	500	0	0	326986.8	0.0	0.0



Counters

Variable	
Mapped (MB/s)	706.5
Shuffle (MB/s)	419.2
Output (MB/s)	0.0
doc-index-hits	4982870667
docs-indexed	17229926
dups-in-index-merge	0
mr-operator-calls	17272056
mr-operator-outputs	17229926

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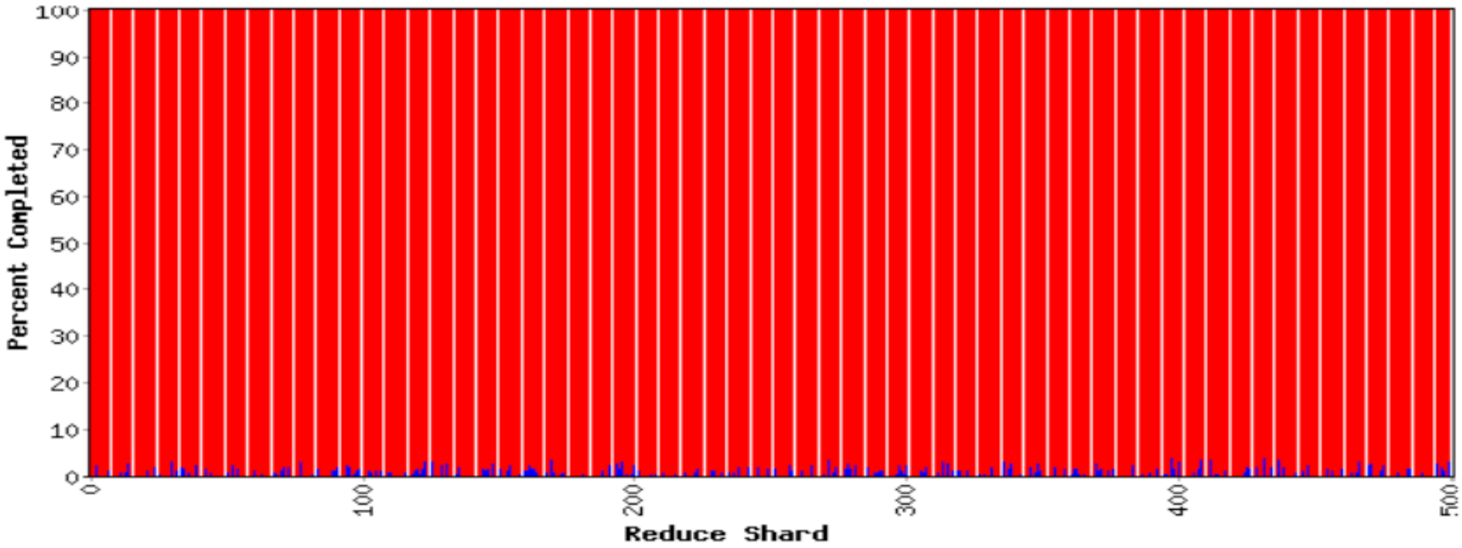
MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 29 min 45 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	195	305	523499.2	523389.6	523389.6
Reduce	500	0	195	523389.6	2685.2	2742.6



Counters

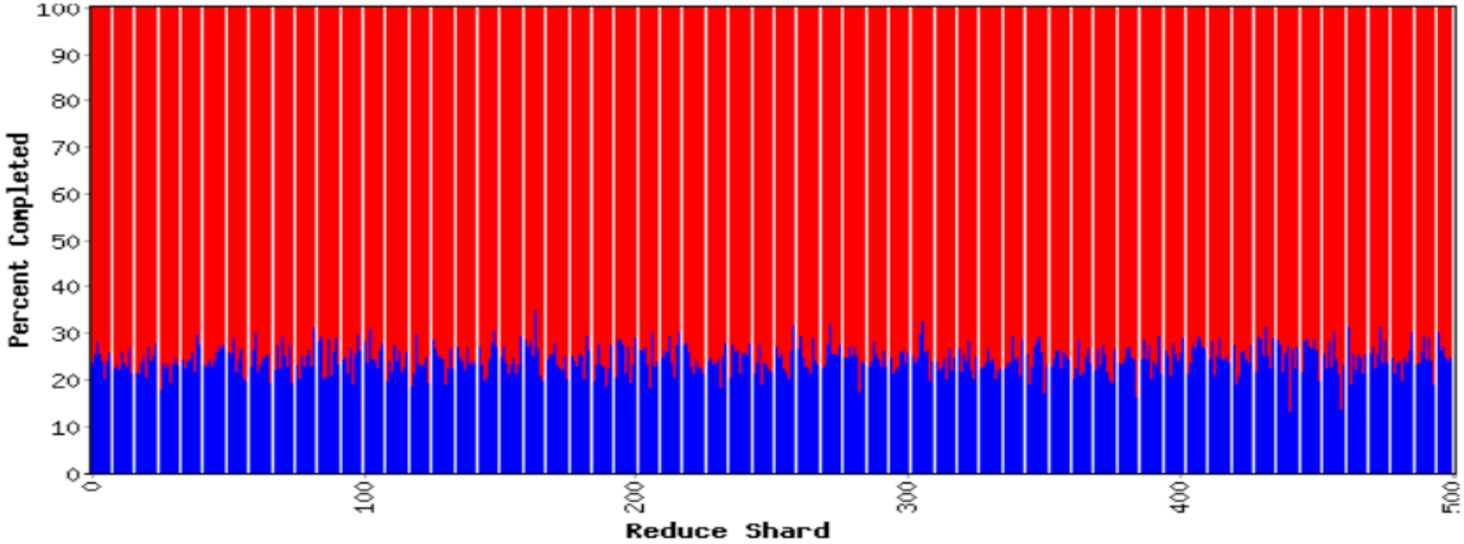
Variable		
Mapped (MB/s)	0.3	
Shuffle (MB/s)	0.5	
Output (MB/s)	45.7	
doc-index-hits	2313178	105
docs-indexed	7936	
dups-in-index-merge	0	
mr-merge-calls	1954105	
mr-merge-outputs	1954105	

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 31 min 34 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	500	0	523499.2	523499.5	523499.5
Reduce	500	0	500	523499.5	133837.8	136929.6



Counters

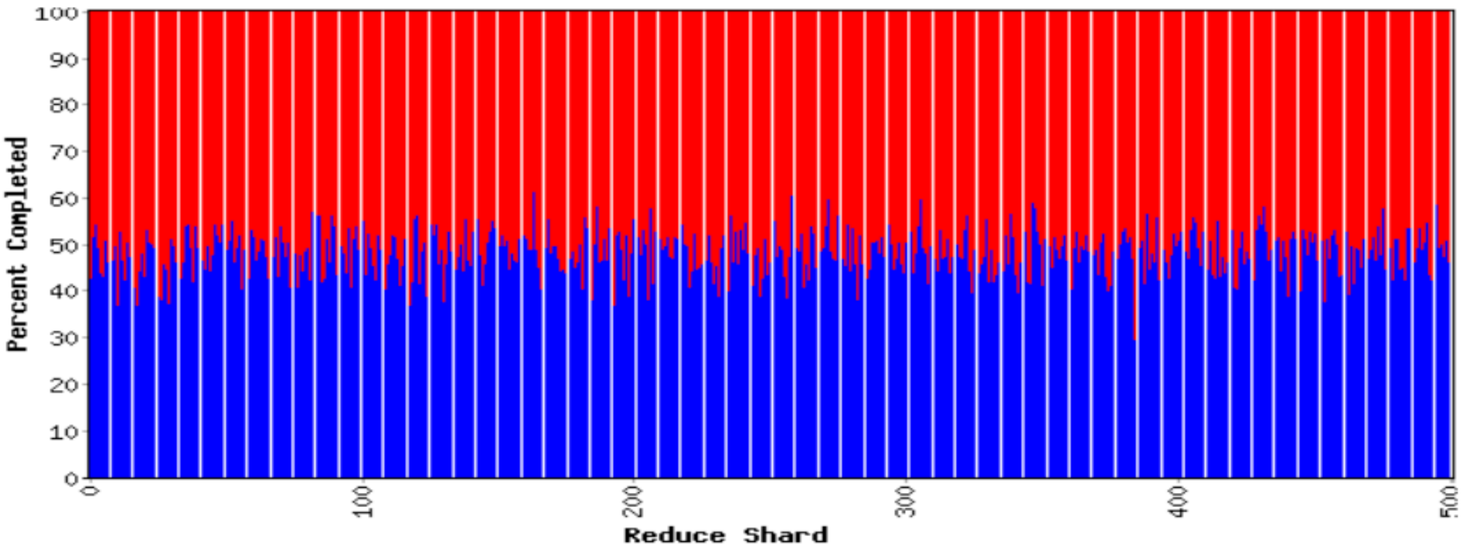
Variable	
Mapped (MB/s)	0.0
Shuffle (MB/s)	0.1
Output (MB/s)	1238.8
doc-index-hits	0
docs-indexed	0
dups-in-index-merge	0
mr-merge-calls	51738599
mr-merge-outputs	51738599

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 33 min 22 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	500	0	523499.2	523499.5	523499.5
Reduce	500	0	500	523499.5	263283.3	269351.2



Counters

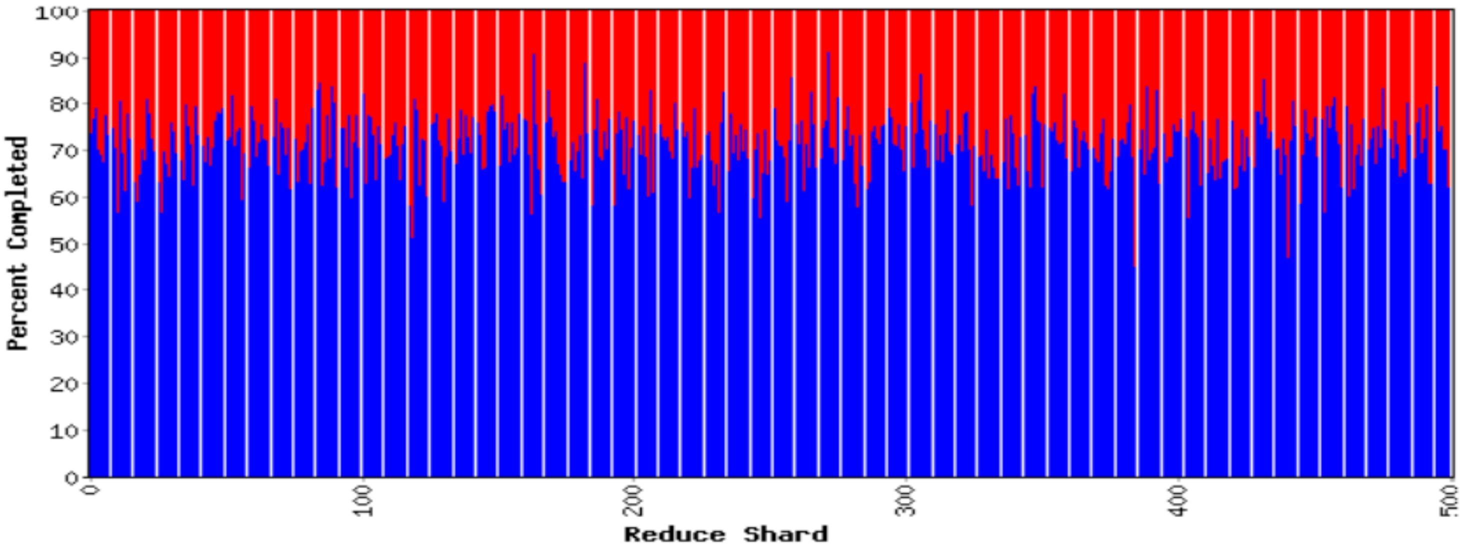
Variable	
Mapped (MB/s)	0.0
Shuffle (MB/s)	0.0
Output (MB/s)	1225.1
doc-index-hits	0
docs-indexed	0
dups-in-index-merge	0
mr-merge-calls	51842100
mr-merge-outputs	51842100

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 35 min 08 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	500	0	523499.2	523499.5	523499.5
Reduce	500	0	500	523499.5	390447.6	399457.2



Counters

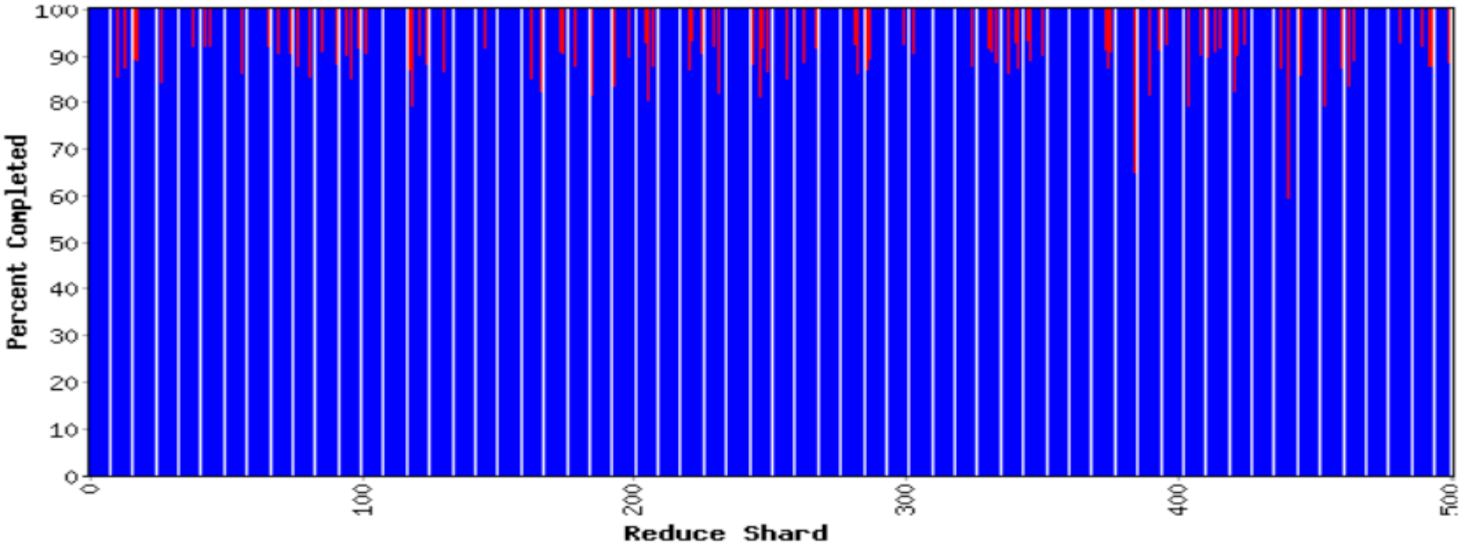
Variable		
Mapped (MB/s)	0.0	
Shuffle (MB/s)	0.0	
Output (MB/s)	1222.0	
doc-index-hits	0	1
docs-indexed	0	
dups-in-index-merge	0	
mr-merge-calls	51640600	
mr-merge-outputs	51640600	

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 37 min 01 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	500	0	523499.2	520468.6	520468.6
Reduce	500	406	94	520468.6	512265.2	514373.3



Counters

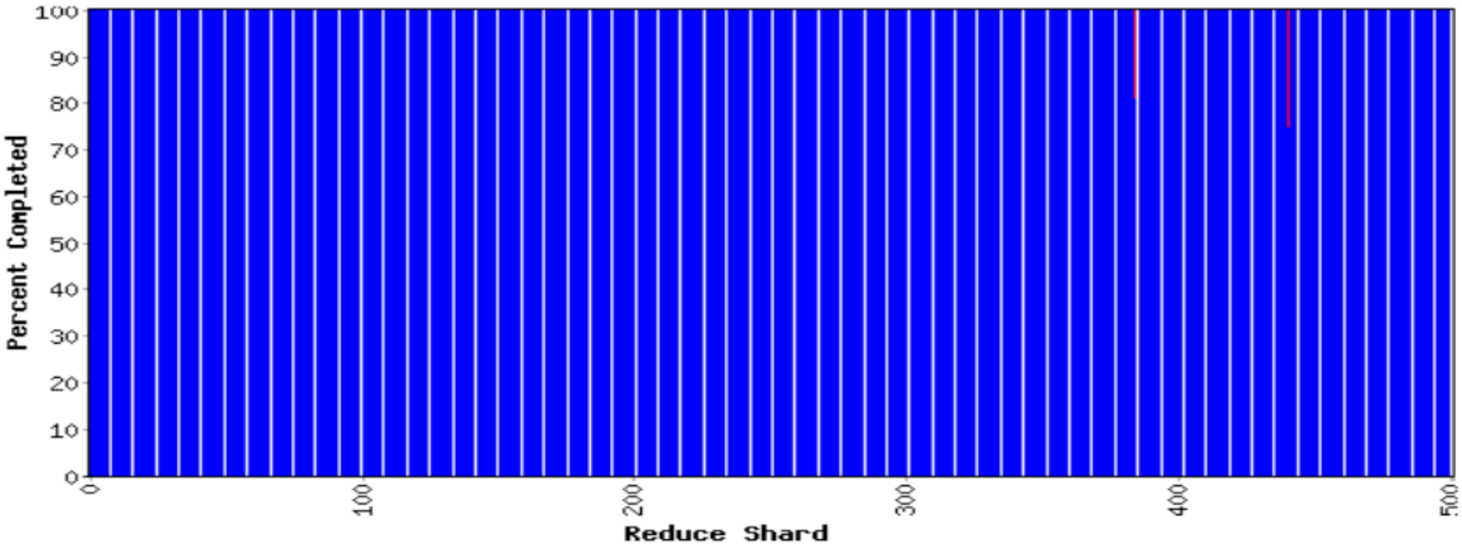
Variable	
Mapped (MB/s)	0.0
Shuffle (MB/s)	0.0
Output (MB/s)	849.5
doc-index-hits	0
docs-indexed	0
dups-in-index-merge	0
mr-merge-calls	35083350
mr-merge-outputs	35083350

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 38 min 56 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	500	0	523499.2	519781.8	519781.8
Reduce	500	498	2	519781.8	519394.7	519440.7



Counters

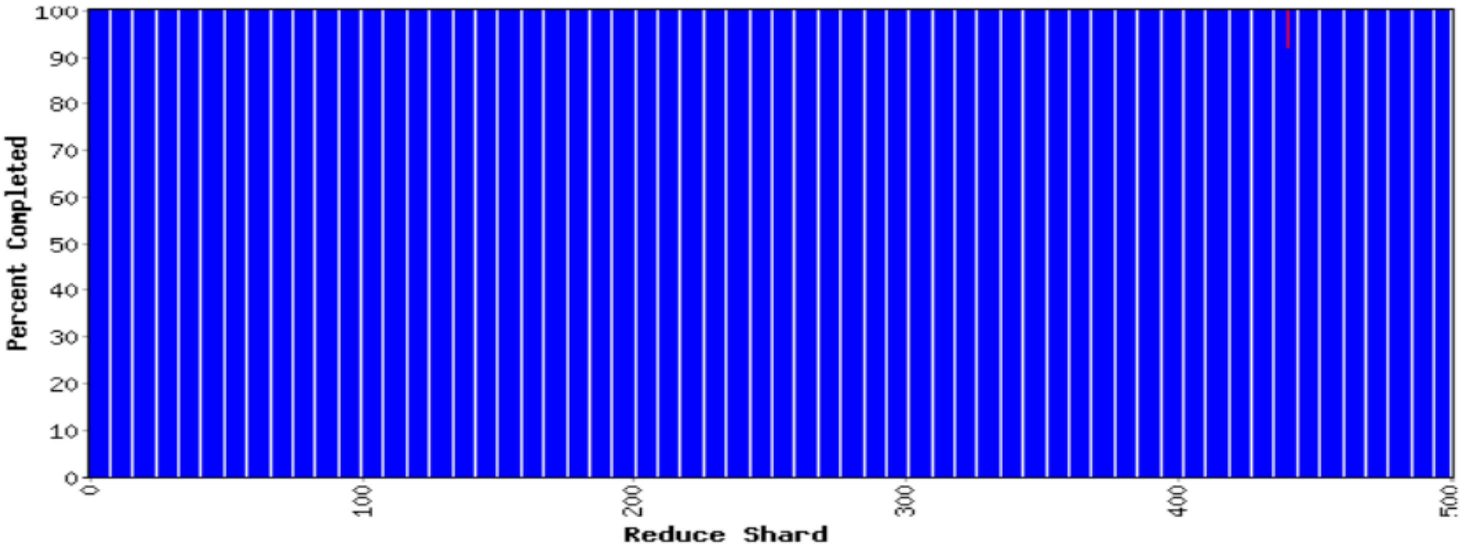
Variable		
Mapped (MB/s)	0.0	
Shuffle (MB/s)	0.0	
Output (MB/s)	9.4	
doc-index-hits	0	1056
docs-indexed	0	
dups-in-index-merge	0	
mr-merge-calls	394792	
mr-merge-outputs	394792	

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 40 min 43 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	500	0	523499.2	519774.3	519774.3
Reduce	500	499	1	519774.3	519735.2	519764.0



Counters

Variable		
Mapped (MB/s)	0.0	
Shuffle (MB/s)	0.0	
Output (MB/s)	1.9	
doc-index-hits	0	105
docs-indexed	0	
dups-in-index-merge	0	
mr-merge-calls	73442	
mr-merge-outputs	73442	

Important Limitations

- This model only works for certain classes of problems
    - Need parallel compute over data and parallel reduction steps
    - **Critically**: Can divide a problem into many independent subproblems, minimal need for communication among workers when performing their computations
        - “Embarrassingly Parallel”
- Significant Overhead
    - Hadoop Distributed File System: 3x+ redundant storage
    - Lots of startup and control overhead:
      So unless you have many GiB/TiB of data, don't bother!
- For many cases, you are still better served sticking with a traditional database approach with big hardware behind it

Summary

- Warehouse-Scale Computers (WSCs)
  - New class of computers
  - Scalability, energy efficiency, high failure rate
- Cloud Computing
  - Benefits of WSC computing for third parties
  - "Elastic" pay as you go resource allocation
- Request-Level Parallelism
  - High request volume, each largely independent of other
  - Use replication for better request throughput, availability
- MapReduce Data Parallelism
  - Map: Divide large data set into pieces for independent parallel processing
  - Reduce: Combine and process intermediate results to obtain final result
  - Hadoop, Spark