# In the news

SILICONVALLEY.COM

**Server farms sprouting in Silicon Valley**

pcarey@mercurynews.com
Posted: 10/06/2011 03:00:00 PM PDT

"The cloud isn't this big fluffy area up in the sky," said Rich Miller, who edits Data Center Knowledge, a publication that follows the data center industry. "It's buildings filled with servers and generators."

"…. you'd be hard-pressed to go three miles here without passing some type of data center. "They're all over the place."



# CS 61C: Great Ideas in Computer Architecture (Machine Structures)

## *Lecture 18 – Data Parallelism 1*

Instructors:
Michael Franklin
Dan Garcia
http://inst.eecs.Berkeley.edu/~cs61c/fa11

# Review

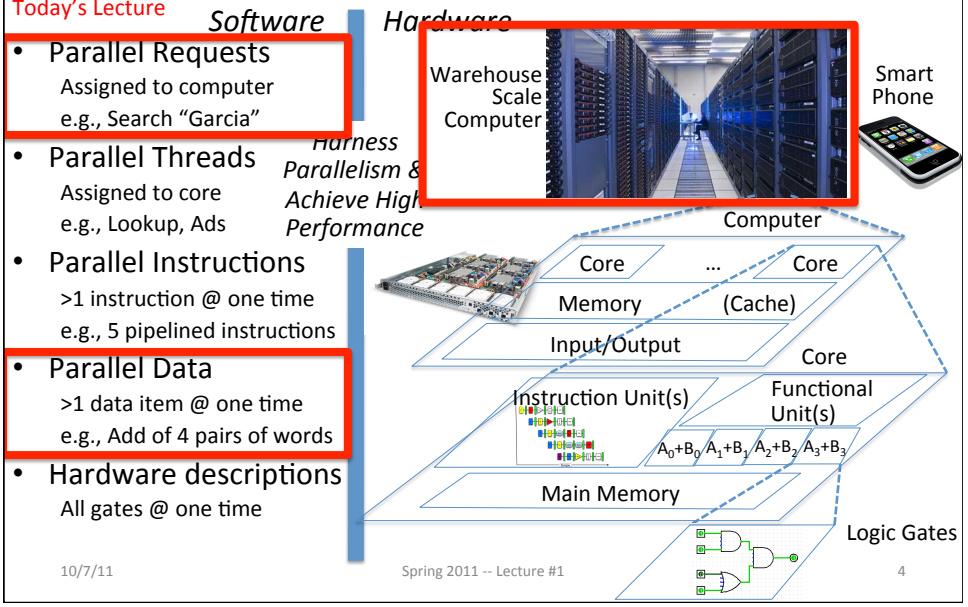
- Great Ideas
  1. Layers of Representation/Interpretation
  2. Moore's Law
  3. Principle of Locality/Memory Hierarchy
  4. Parallelism
  5. Performance Measurement and Improvement
  6. Dependability via Redundancy
- Post PC Era: Parallel processing, smart phones to WSC
- WSC SW must cope with failures, varying load, varying HW latency bandwidth
- WSC HW sensitive to cost, energy efficiency



# New-School Machine Structures (It's a bit more complicated!)

Today's Lecture

- Parallel Requests
  Assigned to computer
  e.g., Search "Garcia"
- Parallel Threads
  Assigned to core
  e.g., Lookup, Ads
- Parallel Instructions
  >1 instruction @ one time
  e.g., 5 pipelined instructions
- Parallel Data
  >1 data item @ one time
  e.g., Add of 4 pairs of words
- Hardware descriptions
  All gates @ one time



# Agenda

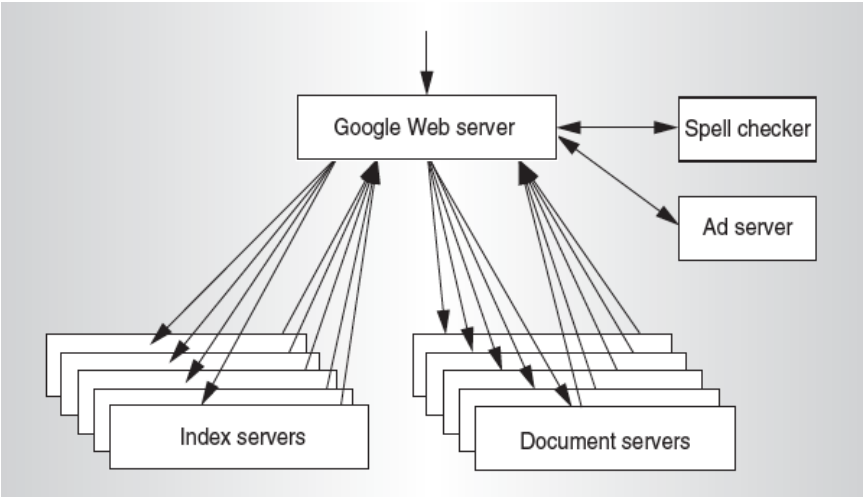
- Request and Data Level Parallelism
- MapReduce
- MapReduce Examples



# Request-Level Parallelism (RLP)

- Hundreds or thousands of requests per second
  - Not your laptop or cell-phone, but popular Internet services like web search, social networking,…
  - Such requests are largely independent
    - Often involve read-mostly databases
    - Rarely involve strict read–write data sharing or synchronization across requests
- Computation easily partitioned within a request and across different requests

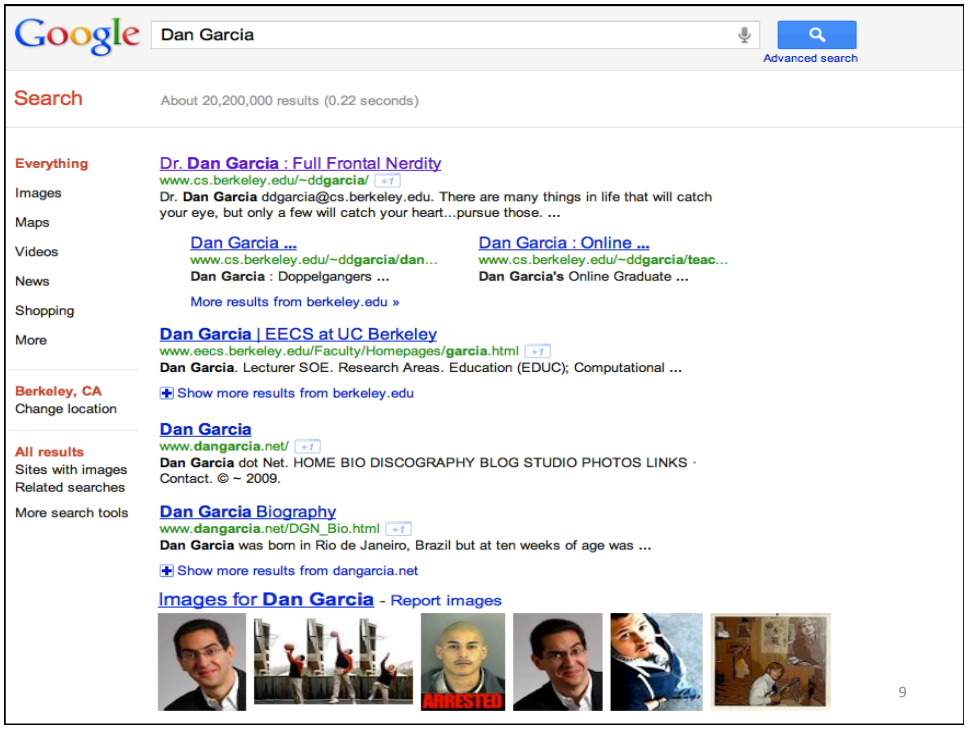
# Google Query-Serving Architecture






# Anatomy of a Web Search

- Google “Dan Garcia”




# Anatomy of a Web Search (1 of 3)

- Google “Dan Garcia”
  - Direct request to “closest” Google Warehouse Scale Computer
  - Front-end load balancer directs request to one of many arrays (cluster of servers) within WSC
  - Within array, select one of many Google Web Servers (GWS) to handle the request and compose the response pages
  - GWS communicates with Index Servers to find documents that contain the search words, “Dan”, “Garcia”, uses location of search as well
  - Return document list with associated relevance score

# Anatomy of a Web Search (2 of 3)

- In parallel,
  - Ad system: run ad auction for bidders on search terms
  - Get Images of various Dan Garcias
- Use docids (document IDs) to access indexed documents
- Compose the page
  - Result document extracts (with keyword in context) ordered by relevance score
  - Sponsored links (along the top) and advertisements (along the sides)



# Anatomy of a Web Search (3 of 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, e.g., "Justin Bieber"
  - Increases opportunities for request-level parallelism
  - Makes the system more tolerant of failures

# Data-Level Parallelism (DLP)

- 2 kinds
  1. Lots of data in memory that can be operated on in parallel (e.g., adding together 2 arrays)
  2. Lots of data on many disks that can be operated on in parallel (e.g., searching for documents)
- Future lecture and 3rd project does Data Level Parallelism (DLP) in memory
- Today's lecture and 2nd project does DLP across many servers and disks using MapReduce



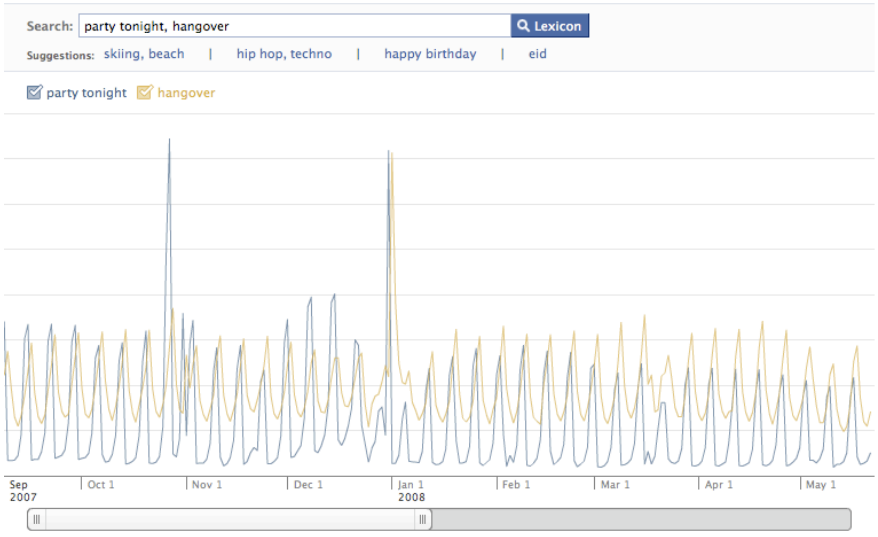
# What is MapReduce?

- Simple data-parallel programming model designed for scalability and fault-tolerance
- Pioneered by Google
  - Processes >25 petabytes of data per day
- Popularized by open-source Hadoop project
  - Used at Yahoo!, Facebook, Amazon, …

# What is MapReduce used for?

- At Google:
  - Index construction for Google Search
  - Article clustering for Google News
  - Statistical machine translation
  - For computing multi-layer street maps
- At Yahoo!:
  - "Web map" powering Yahoo! Search
  - Spam detection for Yahoo! Mail
- At Facebook:
  - Data mining
  - Ad optimization
  - Spam detection

# Example: Facebook Lexicon




www.facebook.com/lexicon (no longer available)

# MapReduce Design Goals

1. **Scalability to large data volumes:**
   - 1000's of machines, 10,000's of disks
2. **Cost-efficiency:**
   - Commodity machines (cheap, but unreliable)
   - Commodity network
   - Automatic fault-tolerance (fewer administrators)
   - Easy to use (fewer programmers)

Jeffrey Dean and Sanjay Ghemawat, "MapReduce: Simplified Data Processing on Large Clusters," *Communications of the ACM*, Jan 2008.

# MapReduce Solution

- Apply Map function to user supplied record of key/value pairs
  - Compute set of intermediate key/value pairs
- Apply Reduce operation to all values that share same key in order to combine derived data properly
- User supplies Map and Reduce operations in functional model
  - so can parallelize,
  - can use re-execution for fault tolerance

# Data-Parallel "Divide and Conquer" (MapReduce Processing)

- Map:
  - Slice data into "shards" or "splits", distribute these to workers, compute sub-problem solutions

```
map(in_key,in_value)->list(out_key,intermediate value)
```

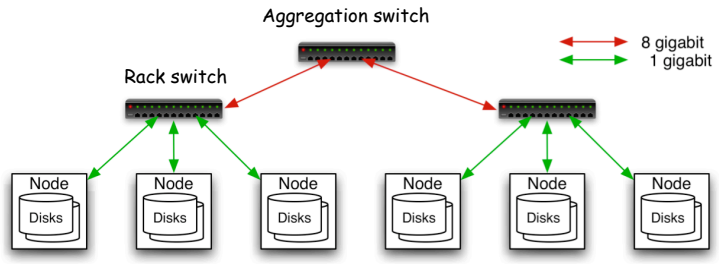
    - Processes input key/value pair
    - Produces set of intermediate pairs
- Reduce:
  - Collect and combine sub-problem solutions

```
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)
- Fun to use: focus on problem, let MapReduce library deal with messy details



# Typical Hadoop Cluster



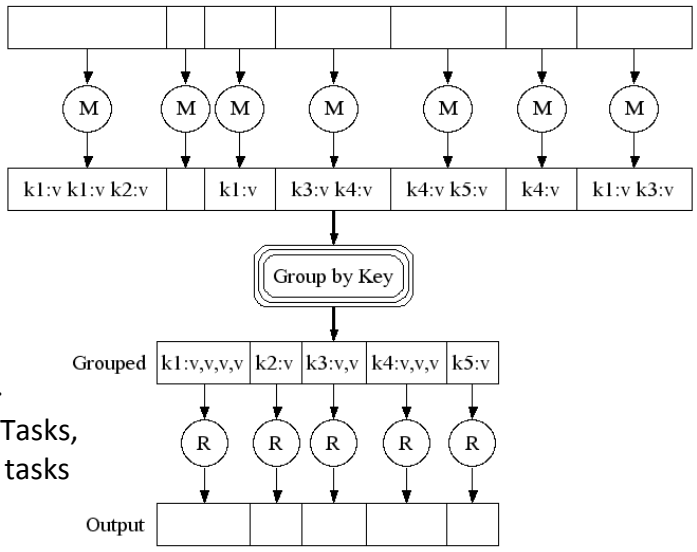

- 40 nodes/rack, 1000-4000 nodes in cluster
- 1 Gbps bandwidth within rack, 8 Gbps out of rack
- Node specs (Yahoo terasort):
  8 x 2GHz cores, 8 GB RAM, 4 disks (= 4 TB?)

Image from http://wiki.apache.org/hadoop-data/attachments/HadoopPresentations/attachments/YahooHadoopIntro-apachecon-us-2008.pdf

# MapReduce Execution

Fine granularity tasks: many more map tasks than machines

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



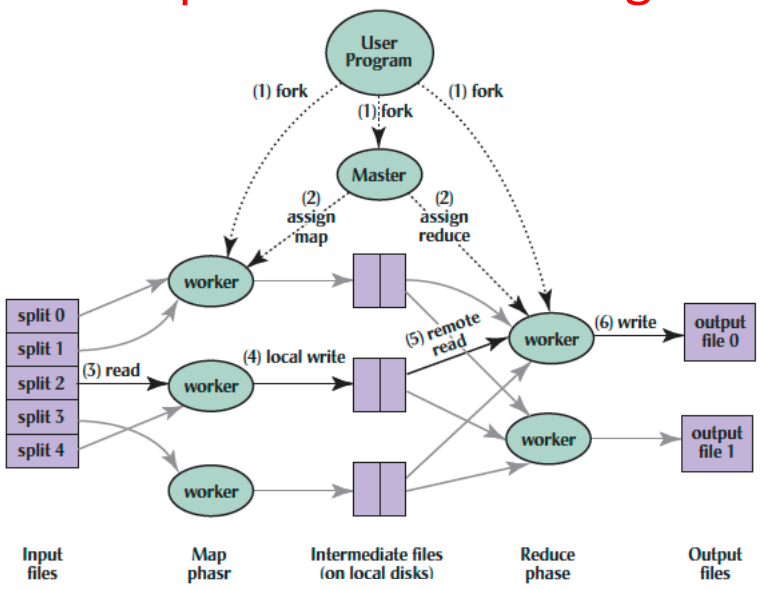



# MapReduce Processing Example: Count Word Occurrences

```
map(String input_key, String input_value):
  // input_key: document name
  // input_value: document contents
  for each word w in input_value:
    EmitIntermediate(w, "1"); // Produce count of words


reduce(String output_key, Iterator intermediate_values):
  // output_key: a word
  // output_values: a list of counts
  int result = 0;
  for each v in intermediate_values:
    result += ParseInt(v); // get integer from key-value
  Emit(AsString(result));
```

# MapReduce Processing

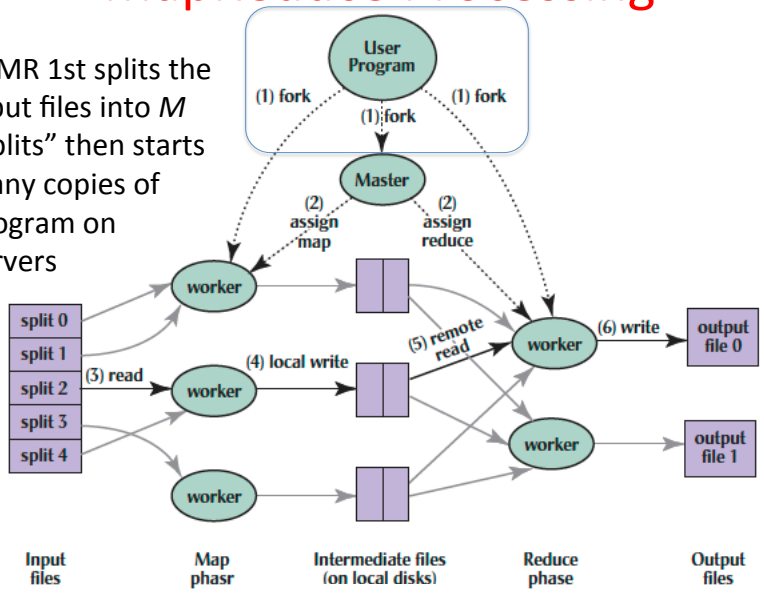



Shuffle phase



# MapReduce Processing

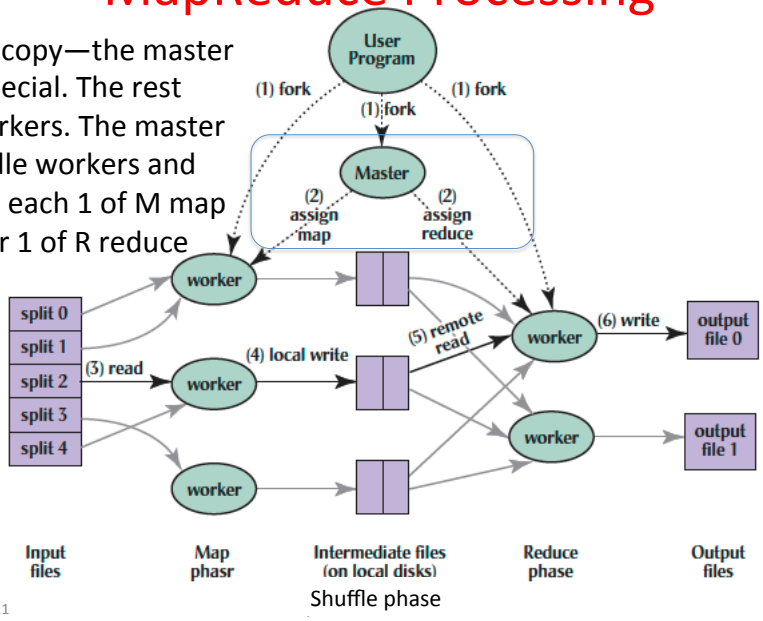
1. MR 1st splits the input files into *M* "splits" then starts many copies of program on servers




Shuffle phase

# 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.



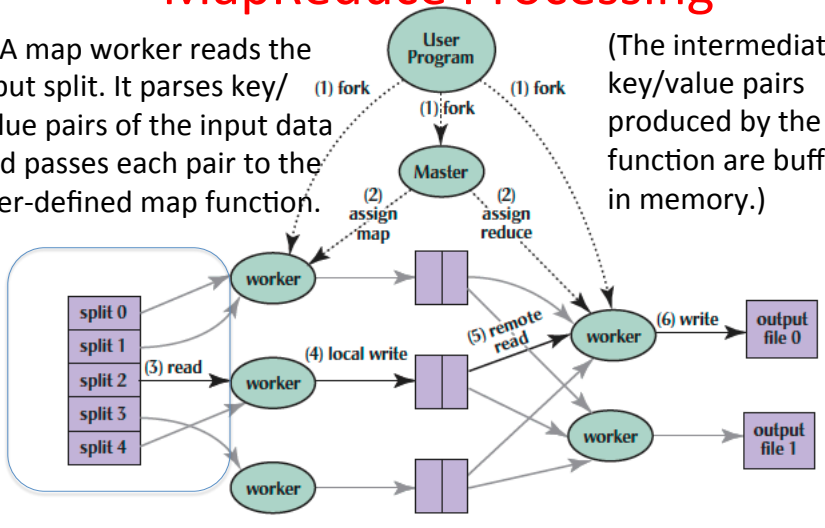

Shuffle phase



# 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.

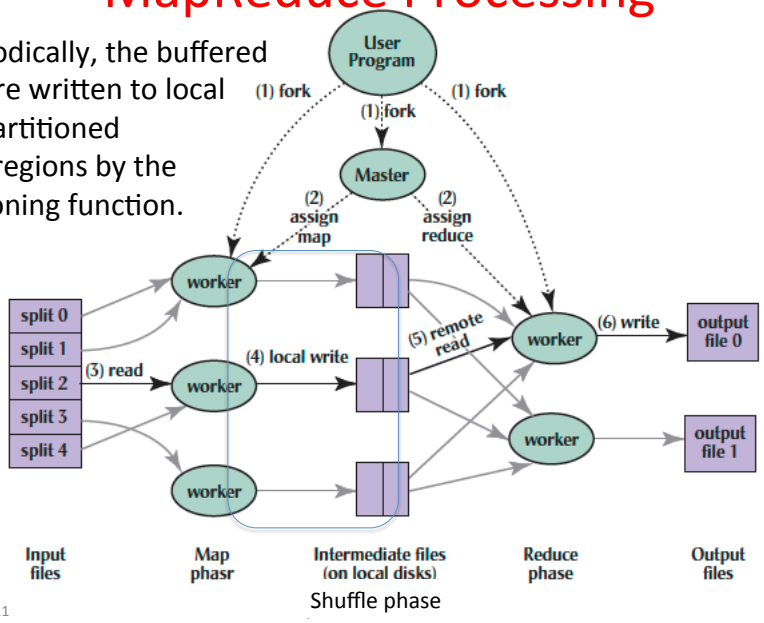
(The intermediate key/value pairs produced by the map function are buffered in memory.)




Shuffle phase

# MapReduce Processing

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

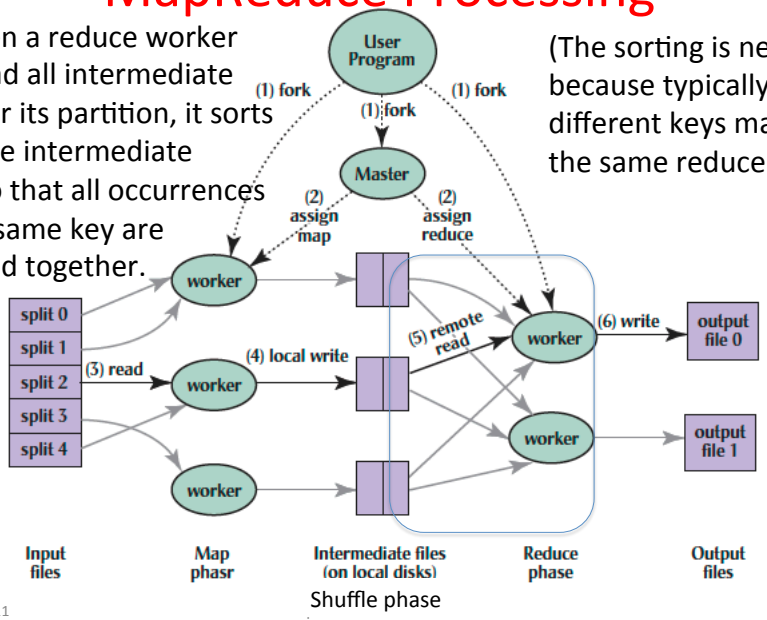





# MapReduce Processing

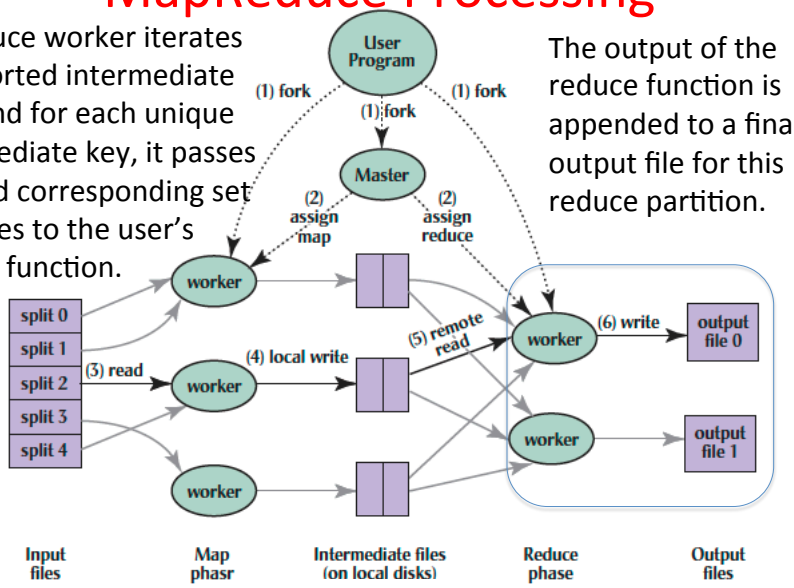
5. When a reduce worker has read all intermediate data for its partition, it sorts it by the intermediate keys so that all occurrences of the same key are grouped together.

(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.

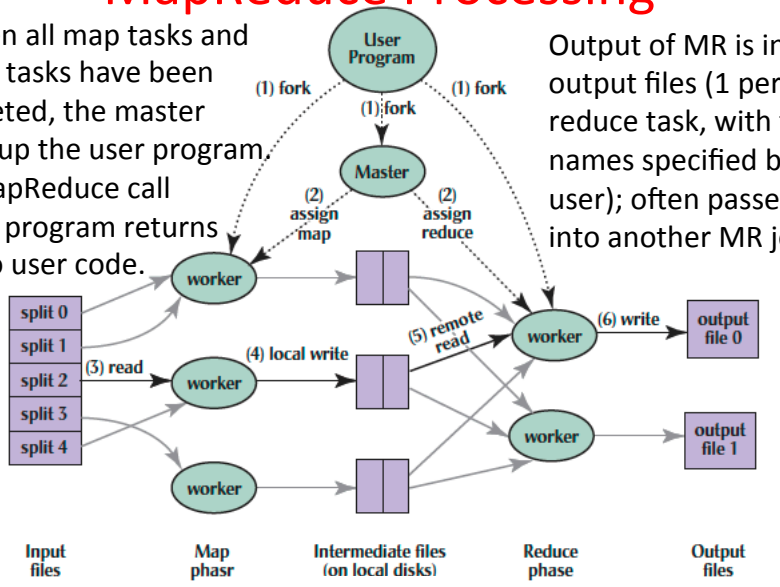



The output of the reduce function is appended to a final output file for this reduce partition.



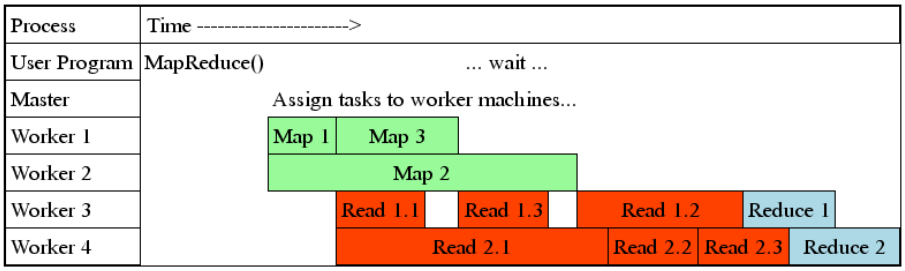
# MapReduce Processing

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 back to user code.




Output of MR is in *R* output files (1 per reduce task, with file names specified by user); often passed into another MR job.

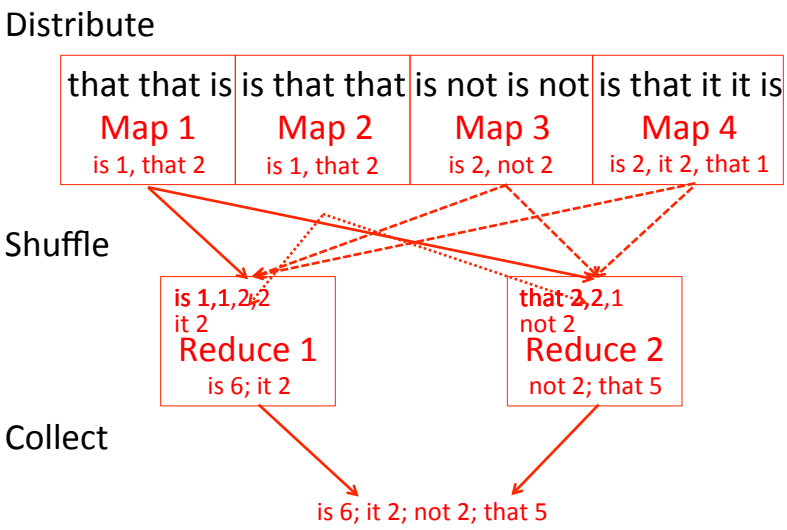
# MapReduce Processing Time Line




- 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"



# Another Example: Word Index (How Often Does a Word Appear?)



## MapReduce Failure Handling

- On worker failure:
  - Detect failure via periodic heartbeats
  - Re-execute completed and in-progress map tasks
  - Re-execute in progress reduce tasks
  - Task completion committed through master
- Master failure:
  - Protocols exist to handle (master failure unlikely)
- Robust: lost 1600 of 1800 machines once, but finished fine (story from Google?)



## MapReduce Redundant 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 copies of tasks
  - Whichever one finishes first "wins"
- Effect: Dramatically shortens job completion time
  - 3% more resources, large tasks 30% faster

# Summary

- Request-Level Parallelism
  - High request volume, each largely independent of other
  - Use replication for better request throughput, availability
- MapReduce Data Parallelism
  - Divide large data set into pieces for independent parallel processing
  - Combine and process intermediate results to obtain final result