TDDD43 HT2015:
Advanced databases and data models
Theme 4: NoSQL, Distributed File System, Map-Reduce

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Slides based on slides by Fang Wei-Kleiner

DFS, Map-Reduce slides based on Material from Chapter 2 in ***Mining of Massive Datasets*** *Anand Rajaraman, Jeffrey David Ullman*

www.mmds.org

Outline

- NoSQL – *Not only* SQL
  - Motivation
  - Concepts
  - Techniques
  - Systems
- Distributed File System
- Map-Reduce

NoSQL: Motivation

30, 40 years history of well-established database technology, all in vain? Not at all! But both setups and demands have drastically changed:

- main memory and CPU speed have exploded, compared to the time when System R (the mother of all RDBMS) was developed
- at the same time, huge amounts of data are now handled in real-time
- both data and use cases are getting more and more dynamic
- social networks (relying on graph data) have gained impressive momentum
- full-texts have always been treated shabbily by relational DBMS

NoSQL: Facebook (Statistics)

royal.pingdom.com/2010/06/18/the-software-behind-facebook

- 500 million users
- 570 billion page views per month
- 3 billion photos uploaded per month
- 1.2 million photos served per second
- 25 billion pieces of content (updates, comments) shared every month
- 50 million server-side operations per second
- 2008: 10,000 servers; 2009: 30,000, …

☞ One RDBMS may not be enough to keep this going on!

NoSQL: Facebook (Architechture)

- Memcached
  - distributed memory caching system
  - caching layer between web and database servers
  - based on a distributed hash table (DHT)
- HipHop for PHP
  - developed by Facebook to improve scalability
  - compiles PHP to C++ code, which can be better optimized
  - PHP runtime system was re-implemented

NoSQL: Facebook (Architechture)

- Cassandra
  - developed by Facebook for inbox searching
  - data is automatically replicated to multiple nodes
  - no single point of failure (all nodes are equal)
- Hadoop/Hive
  - implementation of Google's MapReduce framework
  - performs data-intensive calculations
  - (initially) used by Facebook for data analysis

NoSQL: Facebook (Components)

- Varnish
  - HTTP accelerator, speeds up dynamic web sites
- Haystack
  - object store, used for storing and retrieving photos
- BigPipe
  - web page serving system; serves parts of the page (chat, news feed, ...)
- Scribe
  - aggregates log data from different servers

NoSQL: Facebook

hadoopblog.blogspot.com/2010/05/facebook-has-worlds-largest-hadoop.html

- Architecture: Hadoop Cluster
  - 21 PB in Data Warehouse cluster, spread across 2000 machines:
    - 1200 machines with 8 cores, 800 machines with 16 cores
  - 12 TB disk space per machine, 32 GB RAM per machine
  - 15 map-reduce tasks per machine
- Workload
  - daily: 12 TB of compressed data added, 800 TB of compressed data scanned, and 25 000 map-reduce jobs
  - 65 millions files in HDFS

NoSQL: Facebook

- Conclusion
  - classical database solutions have turned out to be completely insufficient
  - heterogeneous software architecture is needed to match all requirements

NoSQL: *Not only* SQL

- RDBMS are still a great solution for centralized, tabular data sets
- NoSQL gets interesting if data is *heterogeneous* and/or *too large*
- most NoSQL projects are open source and have open communities
- code bases are up-to-date (no 30 years old, closed legacy code)
- they are subject to rapid development and change
- cannot offer general-purpose solutions yet, as claimed by RDBMS

NoSQL: *Not only* SQL

www.techrepublic.com/blog/10things/10-things-you-should-know-about-nosql-databases/1772

10 Things: Five Advantages

- Elastic Scaling → scaling out: distributing data on commodity clusters instead of buying bigger servers
- Economics → based on cheap commodity servers and less costs per transaction/second
- Big Data → opens new dimensions that cannot be handled with RDBMS
- Goodbye DBAs (see you later?) → automatic repair, distribution, tuning, ...
- Flexible Data Models → non-existing/relaxed data schema, structural changes cause no overhead

NoSQL: *Not only* SQL

www.techrepublic.com/blog/10things/10-things-you-should-know-about-nosql-databases/1772

10 Things: Five Challenges

- Maturity → still in pre-production phase, key features yet to be implemented
- Expertise → few NoSQL experts available in the market
- Analytics and Business Intelligence → focused on web apps scenarios, limited ad-hoc querying
- Support → mostly open source, start-ups, limited resources or credibility
- Administration → require lot of skill to install and effort to maintain

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NoSQL: Concepts

nosql-database.org

NoSQL Definition:

Next Generation Databases mostly addressing some of the points: being ***non-relational, distributed, open source*** and ***horizontally scalable***. The original intention has been modern web-scale databases. The movement began early 2009 and is growing rapidly. Often more characteristics apply as: ***schema-free, easy replication support, simple API, eventually consistent/BASE*** (not ACID), a ***huge data amount***, and more.

- Stefan Edlich

NoSQL: Concepts

Scalability: system can handle growing amounts of data without losing performance.

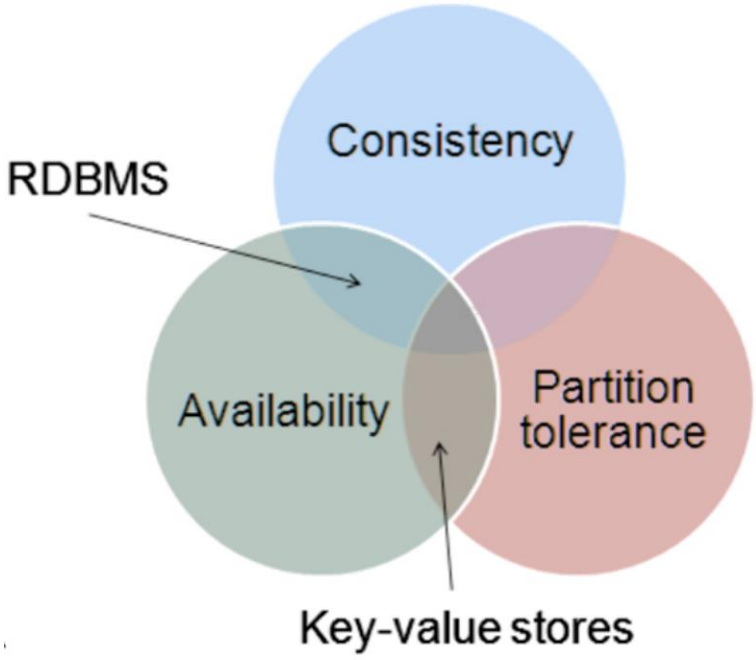
- Vertical Scalability (scale up)
  - add resources (more CPUs, more memory) to a single node
  - using more threads to handle a local problem
- Horizontal Scalability (scale out)
  - add nodes (more computers, servers) to a distributed system
  - gets more and more popular due to low costs for commodity hardware
  - often surpasses scalability of vertical approach

NoSQL: Concepts

CAP Theorem: Consistency, Availability, Partition Tolerance

`Brewer [ACM PODC'2000]: Towards Robust Distributed Systems`

Theorem
(Gilbert, Lynch SIGACT'2002):
only 2 of the 3 guarantees
can be given in a shared-data
system.



NoSQL: Concepts

CAP Theorem: Consistency, Availability, Partition Tolerance

`Brewer [ACM PODC'2000]: Towards Robust Distributed Systems`

- **Consistency**
  - after an update, all readers in a distributed system see the same data
  - all nodes are supposed to contain the same data at all times
- Example
  - single database instance will always be consistent
  - if multiple instances exist, all writes must be duplicated before write operation is completed

NoSQL: Concepts

CAP Theorem: Consistency, Availability, Partition Tolerance

`Brewer [ACM PODC'2000]: Towards Robust Distributed Systems`

- **Availability**
  - all requests will be answered, regardless of crashes or downtimes
- Example
  - a single instance has an availability of 100% or 0%, two servers may be available 100%, 50%, or 0%

NoSQL: Concepts

CAP Theorem: Consistency, Availability, Partition Tolerance

`Brewer [ACM PODC'2000]: Towards Robust Distributed Systems`

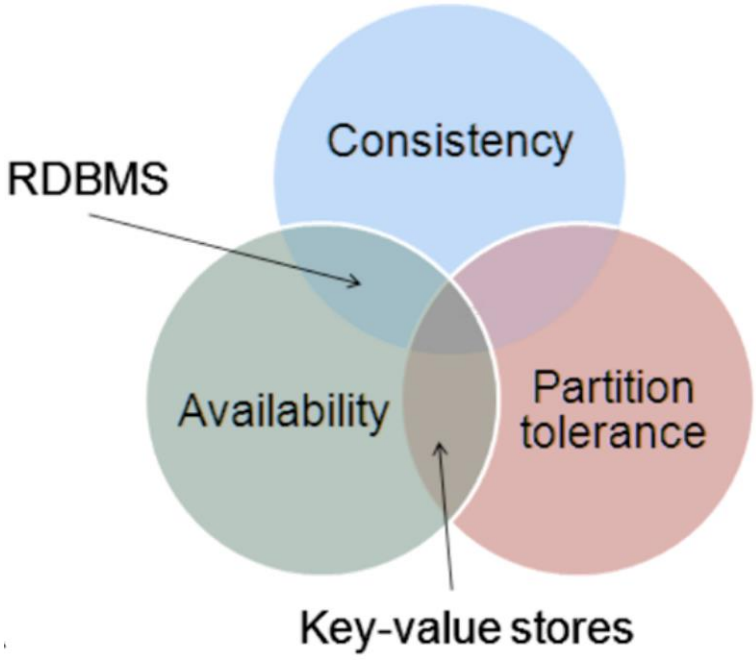
- **Partition Tolerance**
  - system continues to operate, even if two sets of servers get isolated
- Example
  - system gets partitioned if connection between server clusters fails
  - failed connection won't cause troubles if system is tolerant

NoSQL: Concepts

CAP Theorem: Consistency, Availability, Partition Tolerance

`Brewer [ACM PODC'2000]: Towards Robust Distributed Systems`

- (Positive) consequence: we can concentrate on two challenges
- **ACID** properties needed to guarantee consistency and availability
- **BASE** properties come into play if availability and partition tolerance is favored



NoSQL: Concepts

ACID: **Atomicity**, **Consistency**, **Isolation**, **Durability**

- **Atomicity** → all operations in the transaction will complete, or none will
- **Consistency** → before and after the transaction, the database will be in a consistent state
- **Isolation** → operations cannot access data that is currently modified
- **Durability** → data will not be lost upon completion of a transaction

NoSQL: Concepts

BASE: **Basically Available**, **Soft State**, **Eventual Consistency**

`Fox et al. [SOSP'1997]: Cluster-Based Scalable Network Services`

- **Basically Available** → an application works basically all the time (despite partial failures)
- **Soft State** → is in flux and non-deterministic (changes all the time)
- **Eventual Consistency** → will be in some consistent state (at some time in future)

NoSQL: Concepts

CAP Theorem: Consistency, Availability, Partition Tolerance

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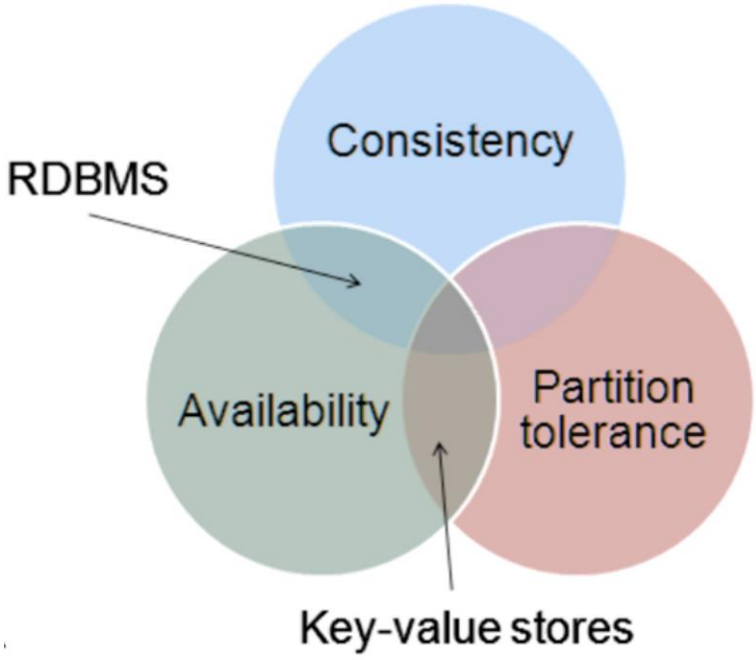

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  - **Techniques**
  - Systems
- Distributed File System
- Map-Reduce

NoSQL: Techniques

Basic techniques (widely applied in NoSQL systems)

- distributed data storage, replication (how to distribute the data which is partition tolerant?) → Consistent hashing
- distributed query strategy (horizontal scalability) → MapReduce
- recognize order of distributed events and potential conflicts → Vector clock

NoSQL: Techniques – Consistent Hashing

Karger et al. [ACM STOC'1997], Consistent Hashing and Random Trees

Task

- find machine that stores data for a specified key k
- trivial hash function to distribute data on n nodes: h(k; n) = k mod n
- if number of nodes changes, all data will have to be redistributed!

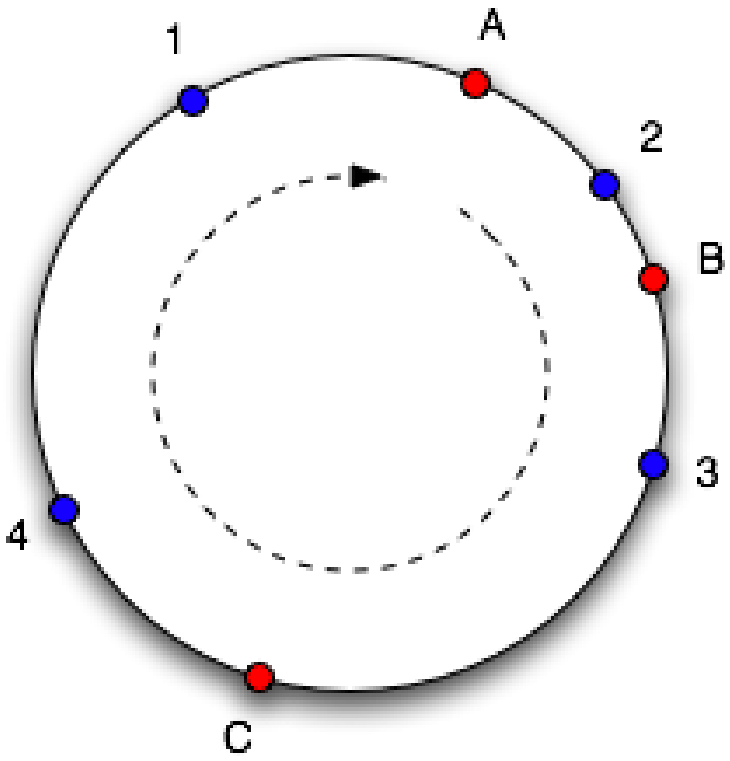
Challenge

- minimize number of nodes to be copied after a configuration change
- incorporate hardware characteristics into hashing model

NoSQL: Techniques – Consistent Hashing

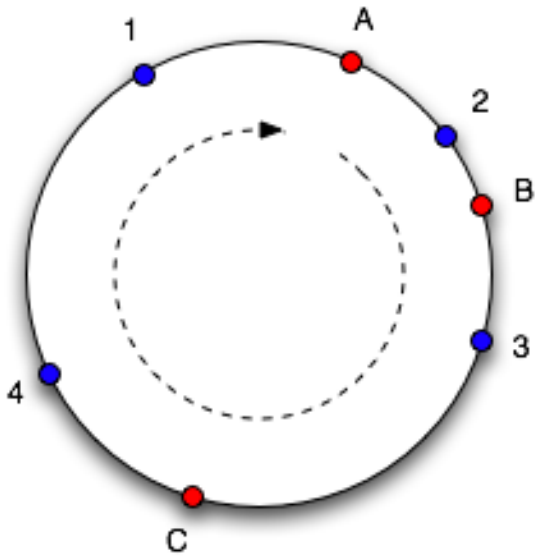
Basic idea

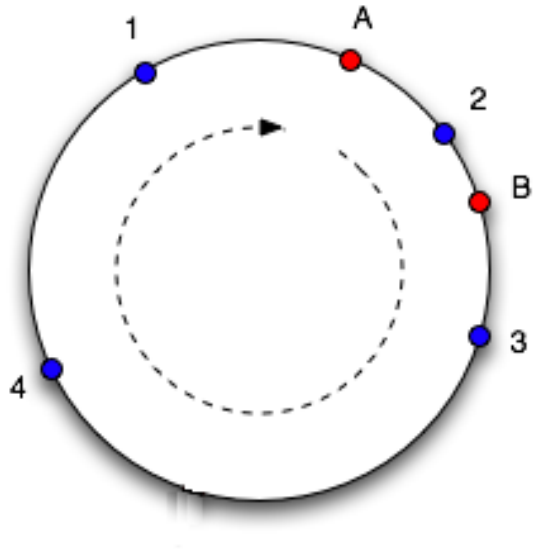
- arrange the nodes in a ring and each node is in charge of the hash values in the range between its neighbor node
- include hash values of all nodes in hash structure
- calculate hash value of the key to be added/retrieved
- choose node which occurs next clockwise in the ring



NoSQL: Techniques – Consistent Hashing

- include hash values of all nodes in hash structure
- calculate hash value of the key to be added/retrieved
- choose node which occurs next clockwise in the ring
- if node is dropped or gets lost, missing data is redistributed to adjacent nodes (replication issue)

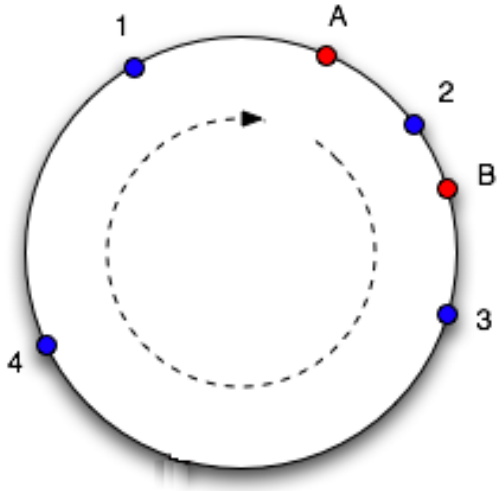


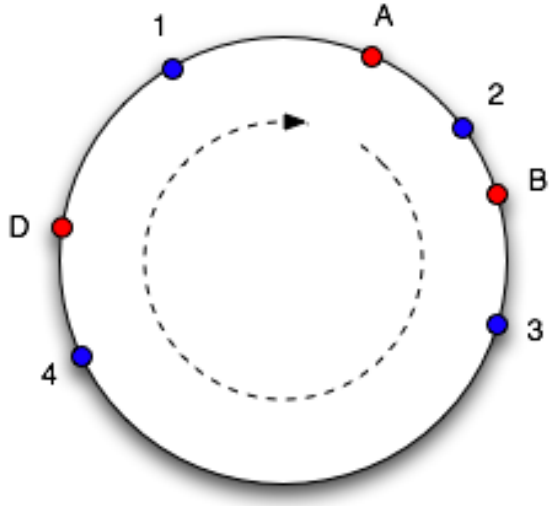


NoSQL: Techniques – Consistent Hashing

- if a new node is added, its hash value is added to the hash table
- the hash realm is repartitioned, and hash data will be transferred to new neighbor

→ no need to update remaining nodes!





NoSQL: Techniques – Consistent Hashing

Karger et al. [ACM STOC'1997], Consistent Hashing and Random Trees

- a replication factor r is introduced: not only the next node but the next r nodes in clockwise direction become responsible for a key
- number of added keys can be made dependent on node characteristics (bandwidth, CPU, ...)
- nifty details are left to the implementation
  e.g.: DeCandia et al. [2007], Dynamo: Amazon's Highly Available Key-value Store

NoSQL: Techniques – Logical Time

Challenge

- recognize order of distributed events and potential conflicts
- most obvious approach: attach timestamp (ts) of system clock to each event e → ts(e)

→ error-prone, as clocks will never be fully synchronized

→ insufficient, as we cannot catch causalities (needed to detect conflicts)

NoSQL: Techniques – Vector Clock

[book] G. Coulouris et al. Distributed Systems: Concepts and Design, 5th Edition

- A vector clock for a system of N nodes is an array of N integers.
- Each process keeps its own vector clock, V_i , which it uses to timestamp local events.
- processes piggyback vector timestamps on the messages they send to one another, and there are simple rules for updating the clocks:
  - VC1: Initially, $V_i[j] = 0$, for i , j = 1, 2, … N
  - VC2: Just before p_i timestamps an event, it sets $V_i[i] := V_i[i] + 1$
  - VC3: p_i includes the value $t = V_i$ in every message it sends
  - VC4: When p_i receives a timestamp t in a message, it sets $V_i[j] := \max(V_i[j]; t[j])$, for j = 1, 2, … N

NoSQL: Techniques – Vector Clock

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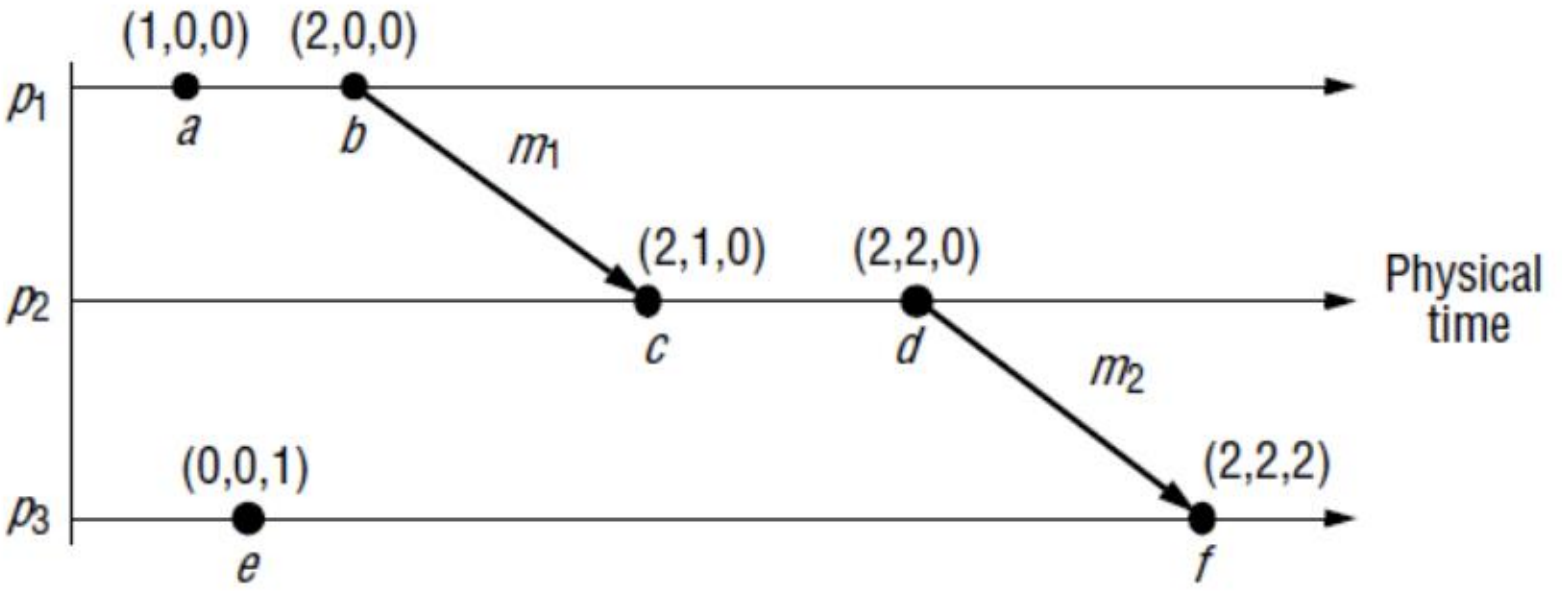


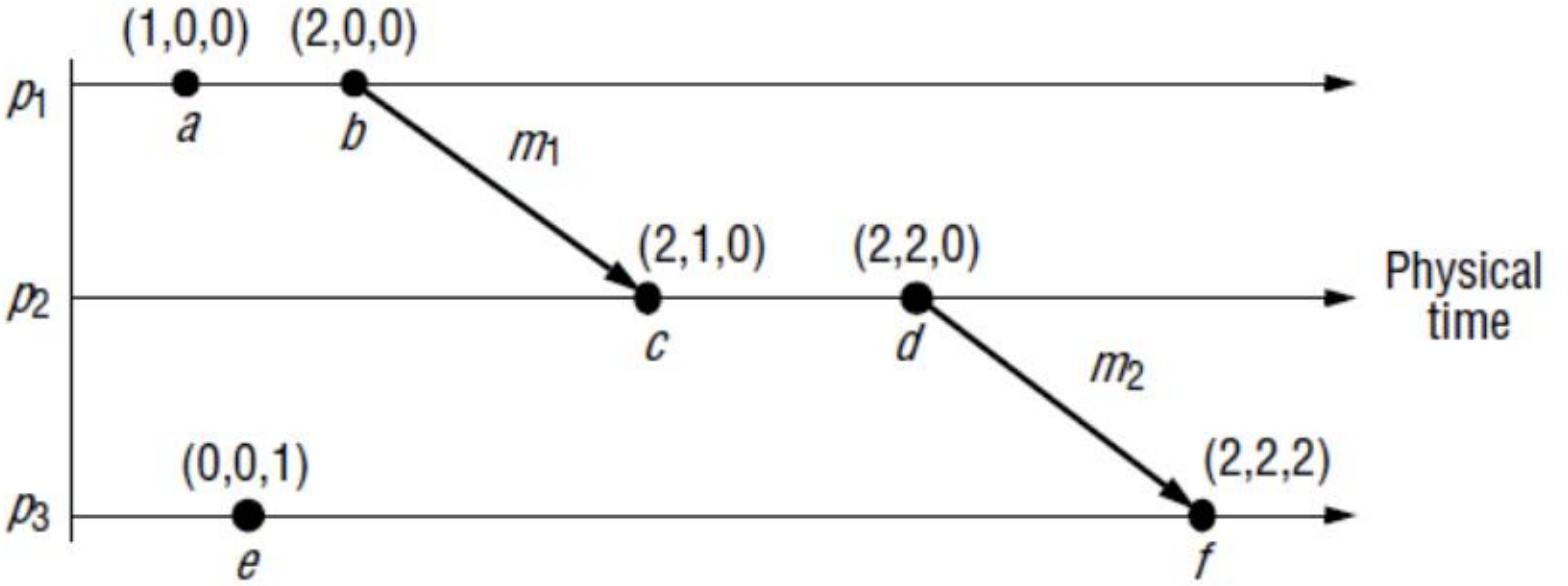
NoSQL: Techniques – Vector Clock

Properties:

- V = V' iff V[j] = V'[j] for j = 1, 2, … N
- V ≤ V‘ iff V[j] ≤ V'[j] for j = 1, 2, … N
- V < V' iff V ≤ V' and V ≠ V'

two events e and e': that e → e' ↔ V(e) < V(e')

→ Conflict detection! (c ‖ e since neither V(c) ≤ V(e) nor V(e) ≤ V(c))



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  - Concepts
  - Techniques
  - **Systems**
- Distributed File System
- Map-Reduce

NoSQL: Systems

Selected Categories from nosql-databases.org

- Key-Value Stores
- Document Stores
- (Wide) Column Stores
- Graph Databases
- Object Databases

→ no taxonomy exists that all parties agree upon

→ might look completely different some years later

NoSQL: Systems

- Key-Value Stores
  - simple common baseline: maps or dictionaries, storing keys and values
  - also called: associative arrays, hash tables/maps
  - keys are unique, values may have arbitrary type
  - focus: high scalability (more important than consistency)
  - traditional solution: BerkeleyDB, started in 1986
  - revived by Amazon Dynamo in 2007 (proprietary)
  - recent solutions: Redis, Voldemort, Tokyo Cabinet, Memcached

→ (very) limited query facilities; usually get(key) and put(key, value)

NoSQL: Systems

- Document Stores
  - basic entities (tuples) are documents
  - schema-less storage
  - document format depends on implementation: XML, JSON, YAML, binary data, …
  - more powerful than key/value stores: offers query and indexing facilities
  - first document store (commercial): LotusDB, developed in 1984
  - recent solutions: CouchDB and MongoDB (free), SimpleDB (commercial)

NoSQL: Systems

- (Wide) Column Stores
  - tight coupling of column data

    → But single tuples are spread across multiple files/pages
  - schema-less storage
  - efficient for calculating aggregations, accessing single columns
  - space saving for dense or identical column data
  - Column Stores implementations: MonetDB, Sybase, Vertica
  - Wide Column Stores implementations: BigTable, HBase, Cassandra

NoSQL: Systems

- Graph Databases
  - based on the property graph model
  - stored as directed adjacency lists
  - vertices: entities
  - edges: similar to relations in RDBMSs
  - majority of graph databases are schema free
  - prominent use cases: location-based services (LBS), social networks, shortest paths, …
  - examples: Neo4J, GraphDB, FlockDB, DEX, InfoGrid, OrientDB

NoSQL: Systems

- Object Databases
  - hot research topic in the 1990s
  - inspired by the success of object-oriented languages
  - requirement: make objects persistent with minimum effort
  - basic entities (tuples) are objects
  - early solutions: GemStone, Objectivity/DB, Versant, Caché
  - new impetus by Open Source movements (db4o)
  - standardization efforts: SQL:1999, ODMG, Native Queries, LINQ
  - query language: OQL (very similar to SQL)

NoSQL: *Not only* SQL

Conclusion

- NoSQL solutions have become essential in distributed environment
- RDBMS are still widespread and often are the only alternative

Choosing a Database

Before you go for a database system/paradigm, clarify for yourself...

1. Which features are needed? Robust storage vs. real-time results vs. querying
2. What limits are most critical? Memory vs. performance vs. bandwidth
3. How large your data will get? Mega- vs. giga- vs. tera- vs. ...bytes

References

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- Ghemawat et al. [SOSP'2003], The Google File System

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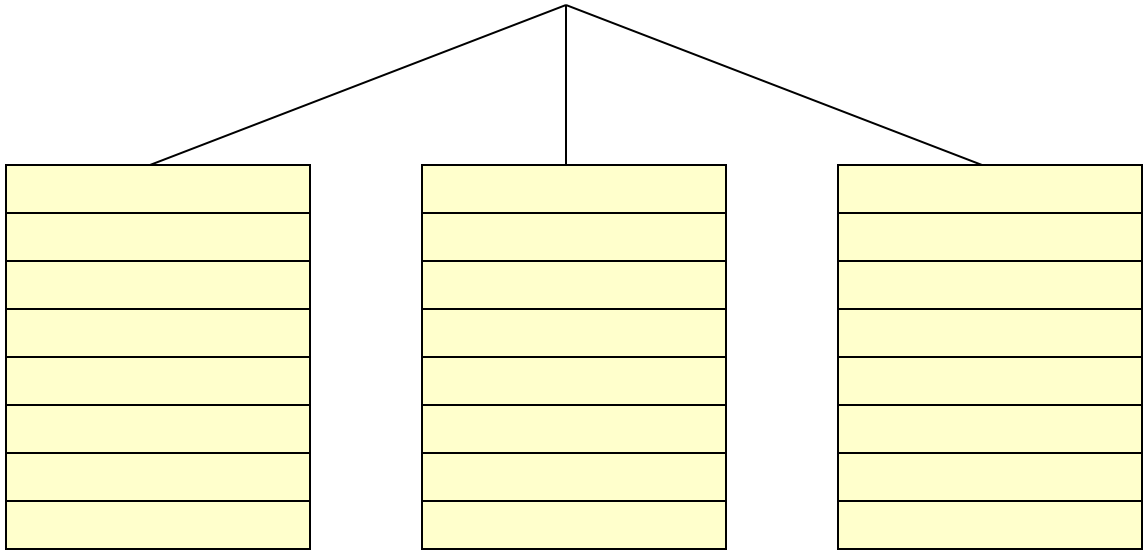
  - Systems
- **Distributed File System**
- Map-Reduce

Compute Nodes

- Compute node – processor, main memory, cache and local disk.
- Organized into racks.
- Intra-rack connection typically gigabit speed.
- Inter-rack connection slower by a small factor.

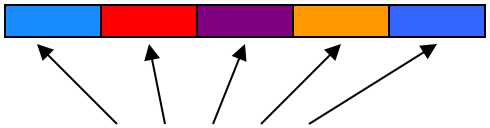
Distributed File System

- Files are very large, read/append.
- They are divided into *chunks*.
  - Typically 64MB to a chunk.
- Chunks are replicated at several *compute-nodes*.
- A *master* (possibly replicated) keeps track of all locations of all chunks.

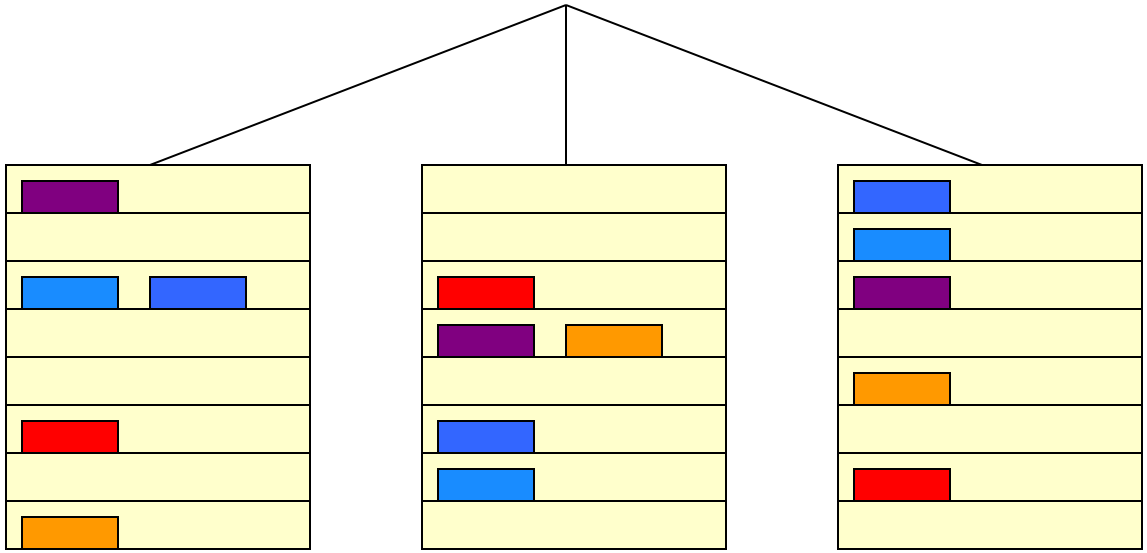


Racks of Compute Nodes

File



Chunks



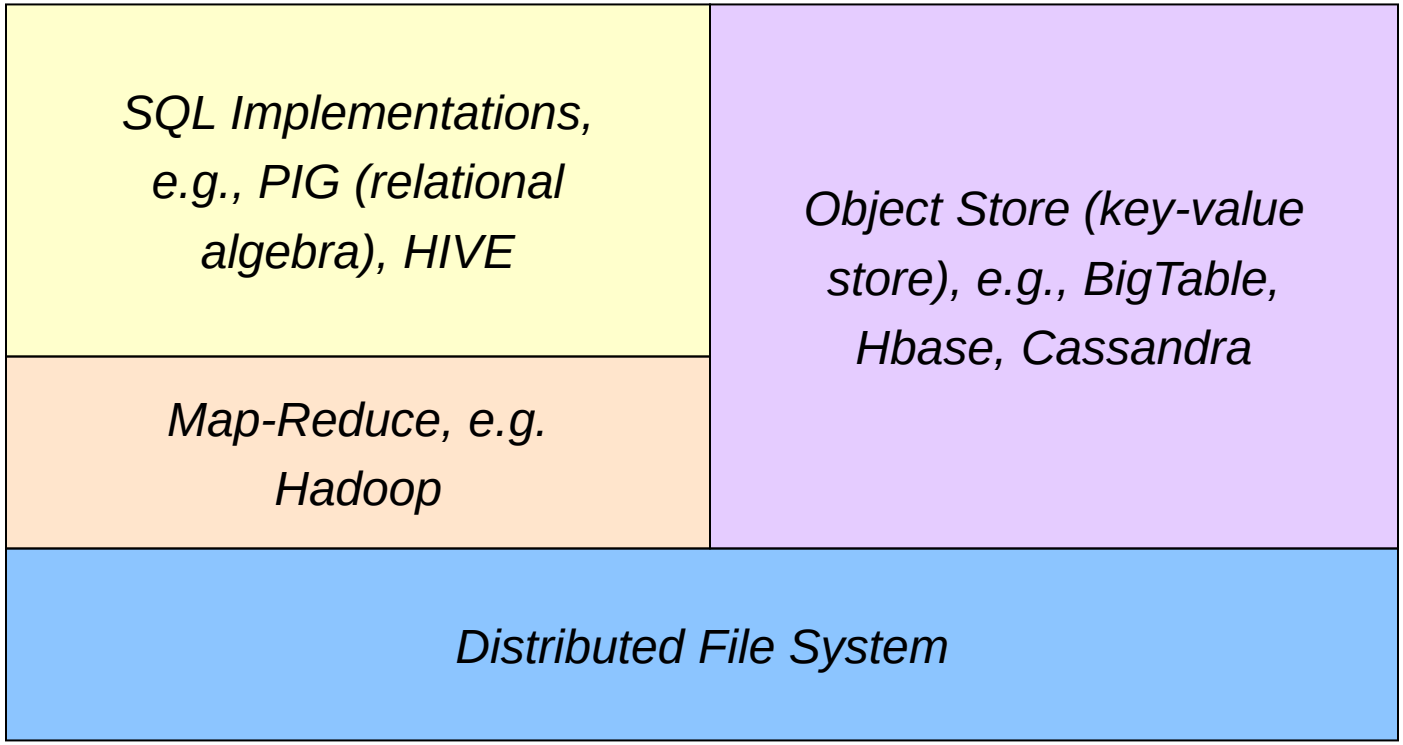
3-way replication of files, with copies on different racks.

Source: J. D. Ullman invited talk EDBT 2011

Implementations

- *GFS* (Google File System – proprietary).
- *HDFS* (Hadoop Distributed File System – open source).
- *CloudStore* (Kosmix File System – open source).

The New Stack



Source: J. D. Ullman invited talk EDBT 2011

What is Hadoop used for?

Slideshare.net - Hadoop Distributed File System by Dhruba Borthaku, 2009

- Search
  - Yahoo, Amazon, Zvents
- Log processing
  - Facebook, Yahoo, ContextWeb, Joost, Last.fm
- Recommendation Systems
  - Facebook
- Data Warehouse
  - Facebook, AOL
- Video and Image Analysis
  - New York Times, Eyealike

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- **Map-Reduce**

MapReduce Overview

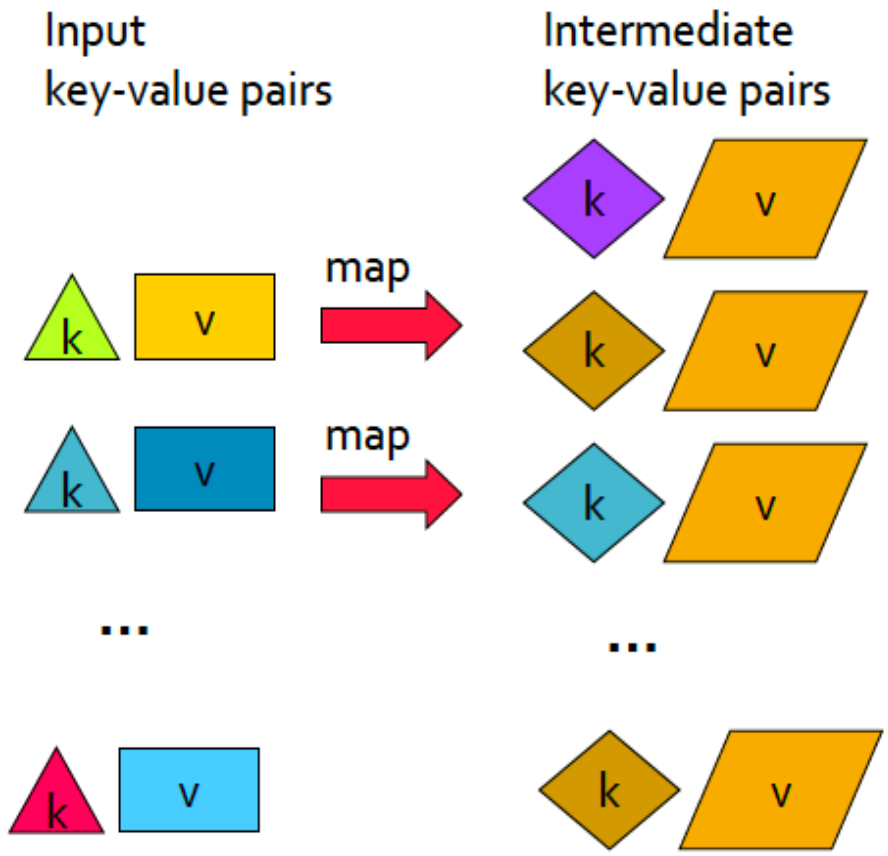
- Sequentially read a lot of data
- **Map:** Extract something you care about

- **Group by key:** Sort and Shuffle

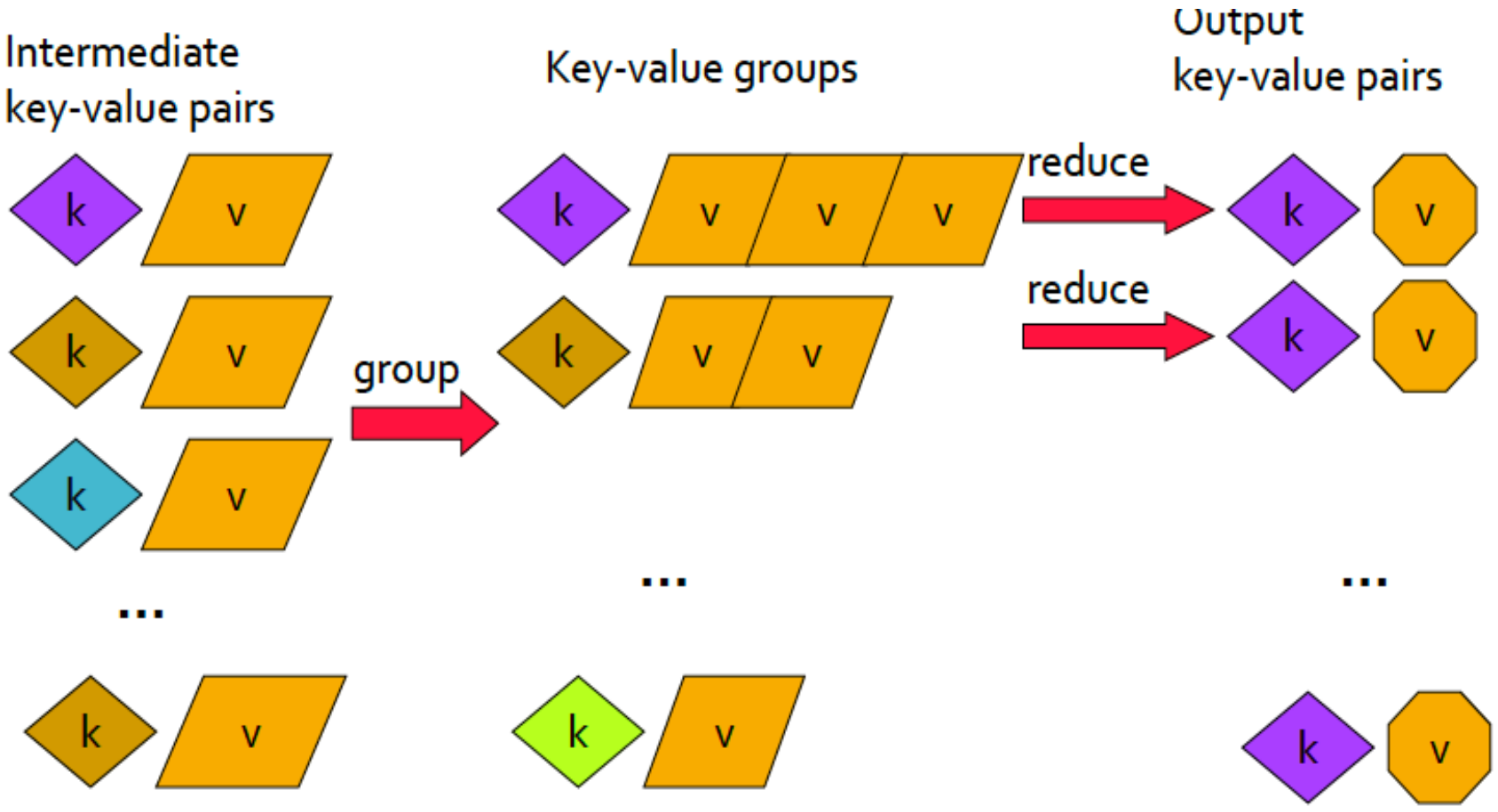
- **Reduce:** Aggregate, summarize, filter or transform
- Write the result

  - ✓ Outline stays the same, **map** and **reduce** change to fit the problem

Map step


Input
key-value pairs
Intermediate
key-value pairs
map
map
k
v
k
v
k
v
k
v
k
v
k
v
k
v
...
...

Reduce step


Intermediate
key-value pairs
Key-value groups
Output
key-value pairs
k
v
group
reduce
reduce
...

More specifically

- **Input:** a set of key/value pairs
- Programmer specifies two methods:
  - **Map(k, v) →** <k',v'>*
    - Takes a key value pair and outputs a set of key value pairs (input: e.g., key is the filename, value is the text of the document;)
    - There is one Map call for every (k,v) pair
  - **Reduce(k', <v'>*) →** <k', v''>*
    - All values v' with same key k' are reduced together and processed in v' order
    - There is one Reduce function call per unique key k'

Word Count

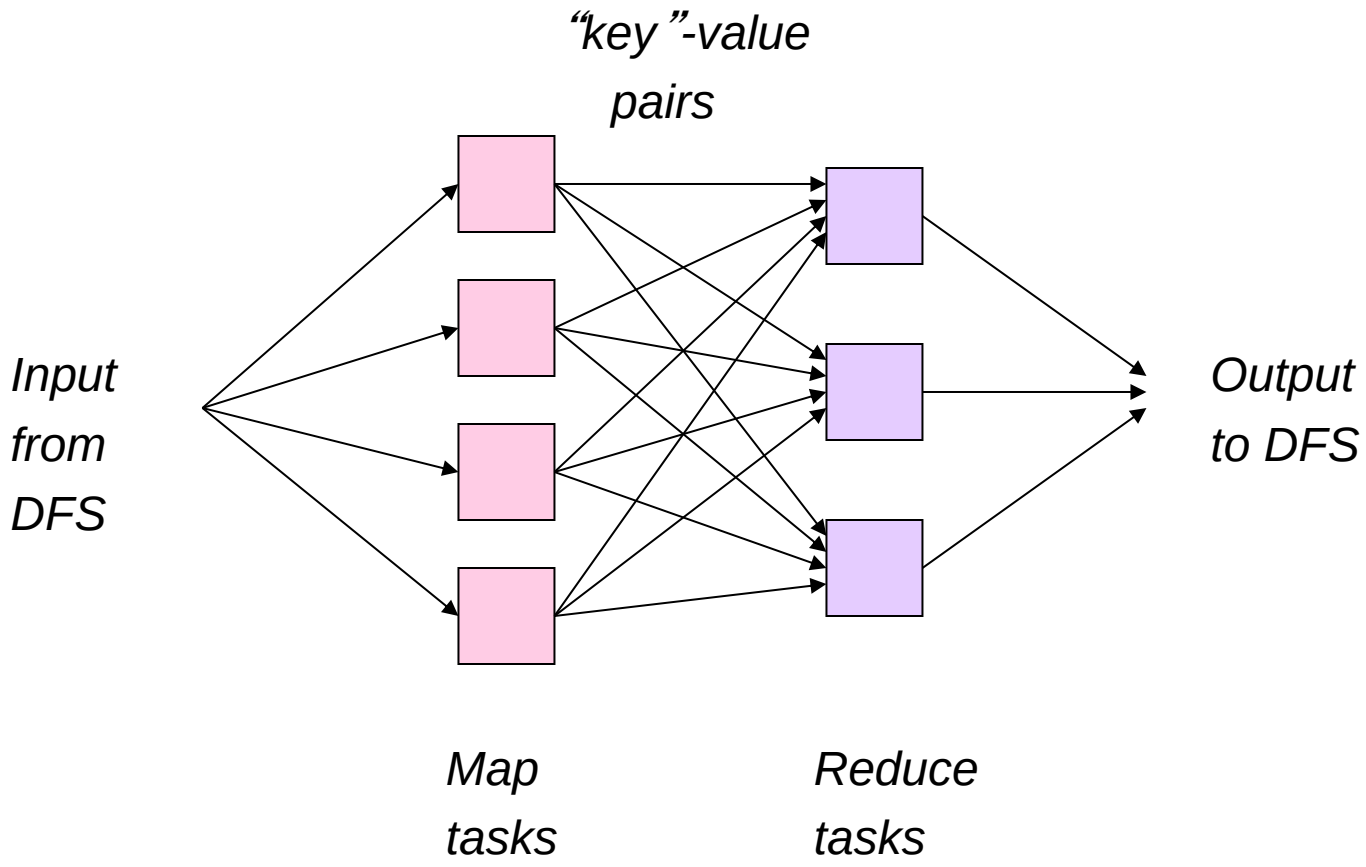
- We have a huge text document
- Count the number of times each distinct word appears in the file

- **Sample application:** Analyze web server logs to find popular URLs

Word Count using MR

```
map(key, value):
// key: document name; value: text of the document
   for each word w in value:
      emit(w, 1)
reduce(key, values):
// key: a word; value: an iterator over counts
   result = 0
   for each count v in values:
      result += v
   emit(key, result)
```

Map-Reduce Pattern



Map-Reduce environment

Map-Reduce environment takes care of:

- **Partitioning** the input data
- **Scheduling** the program's execution across a set of machines
- Handling machine **failures**
- Managing required inter-machine **communication**

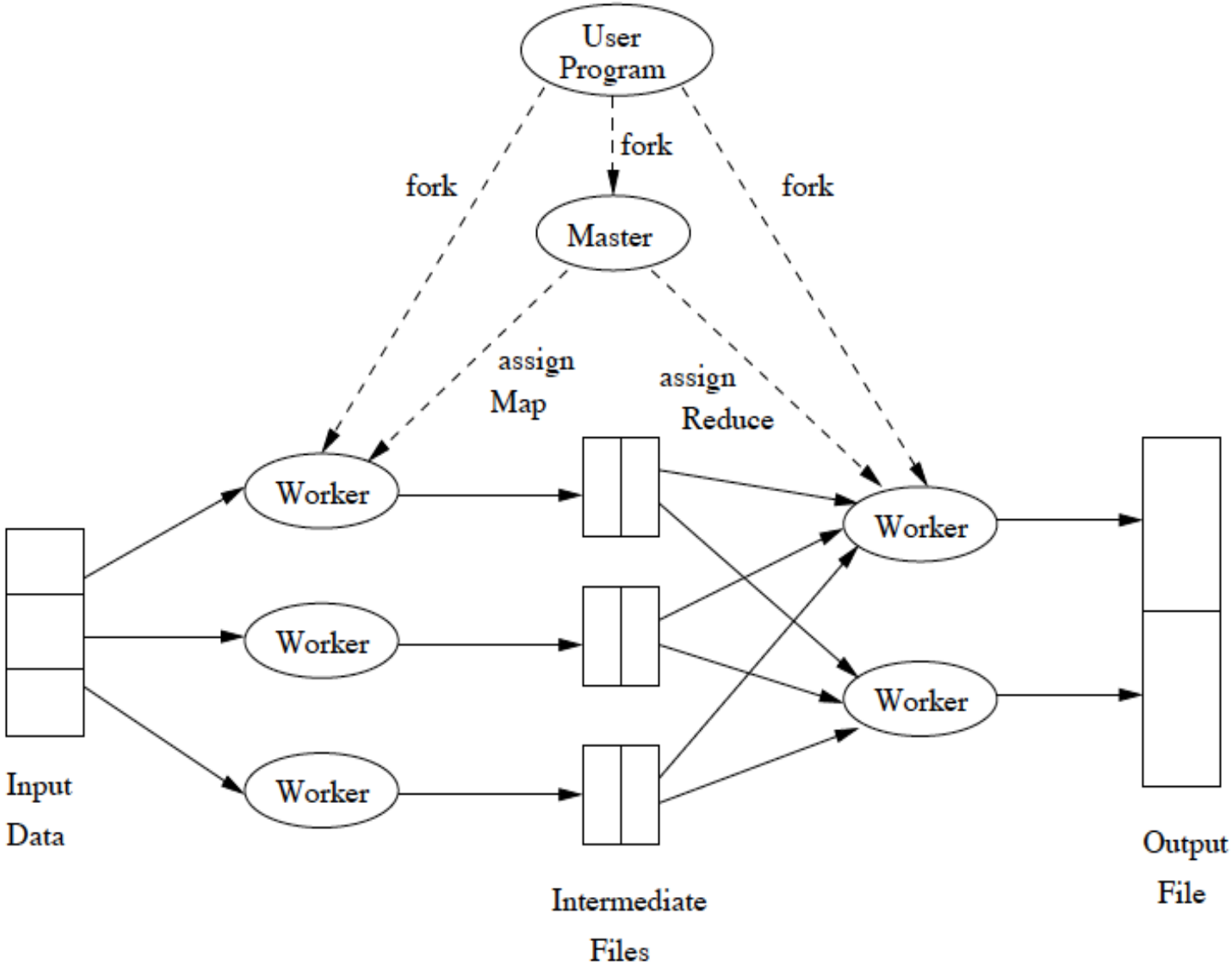


Figure 2.3: Overview of the execution of a map-reduce program

The user program forks a Master controller process and some number of Worker processes at different compute nodes.

Normally, a Worker handles either Map tasks (a Map worker) or Reduce tasks (a Reduce worker), but not both.

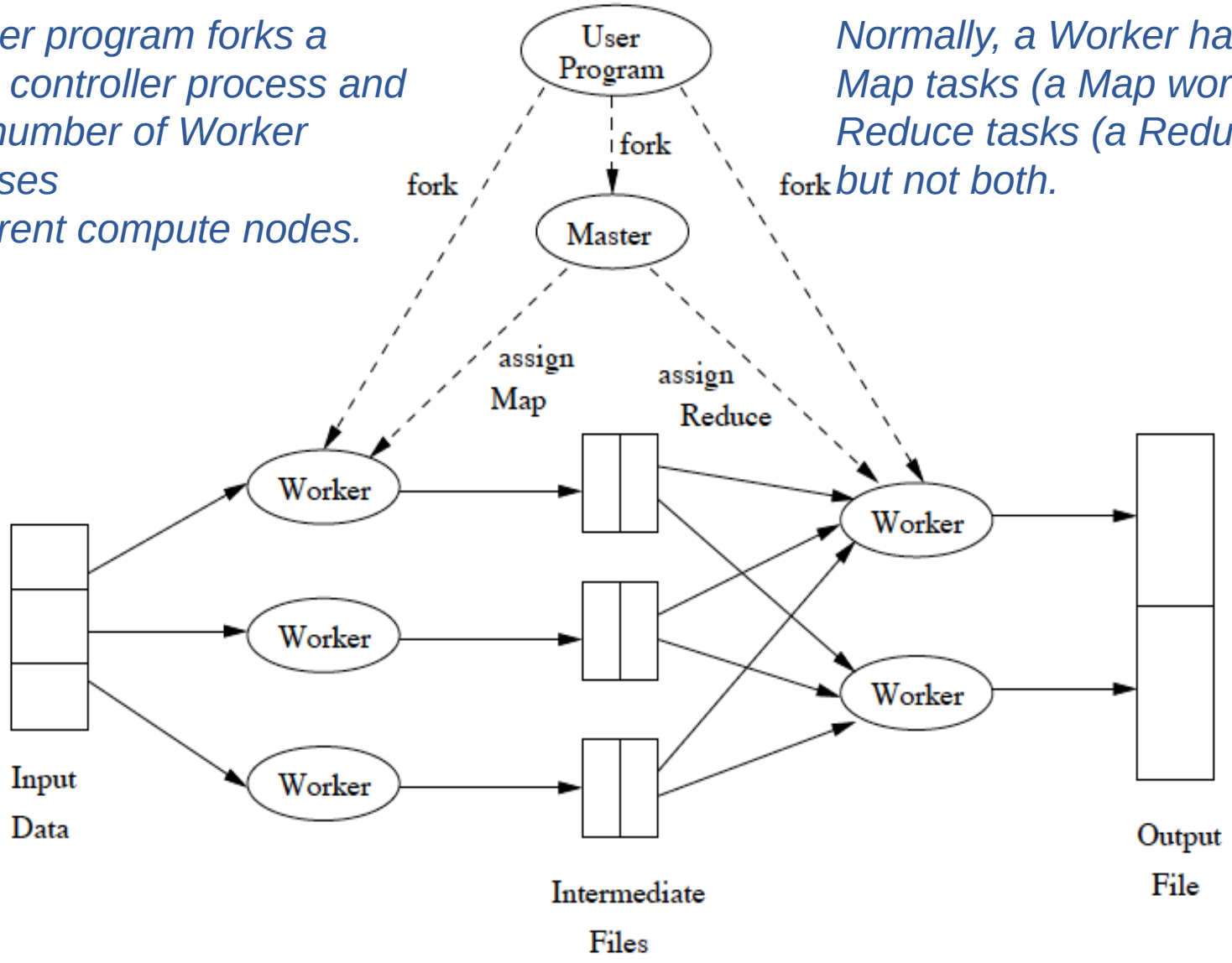


Figure 2.3: Overview of the execution of a map-reduce program

The Master creates some number of Map tasks and some number of Reduce tasks.

These numbers being selected by the user program.

These tasks will be assigned to Worker processes by the Master.

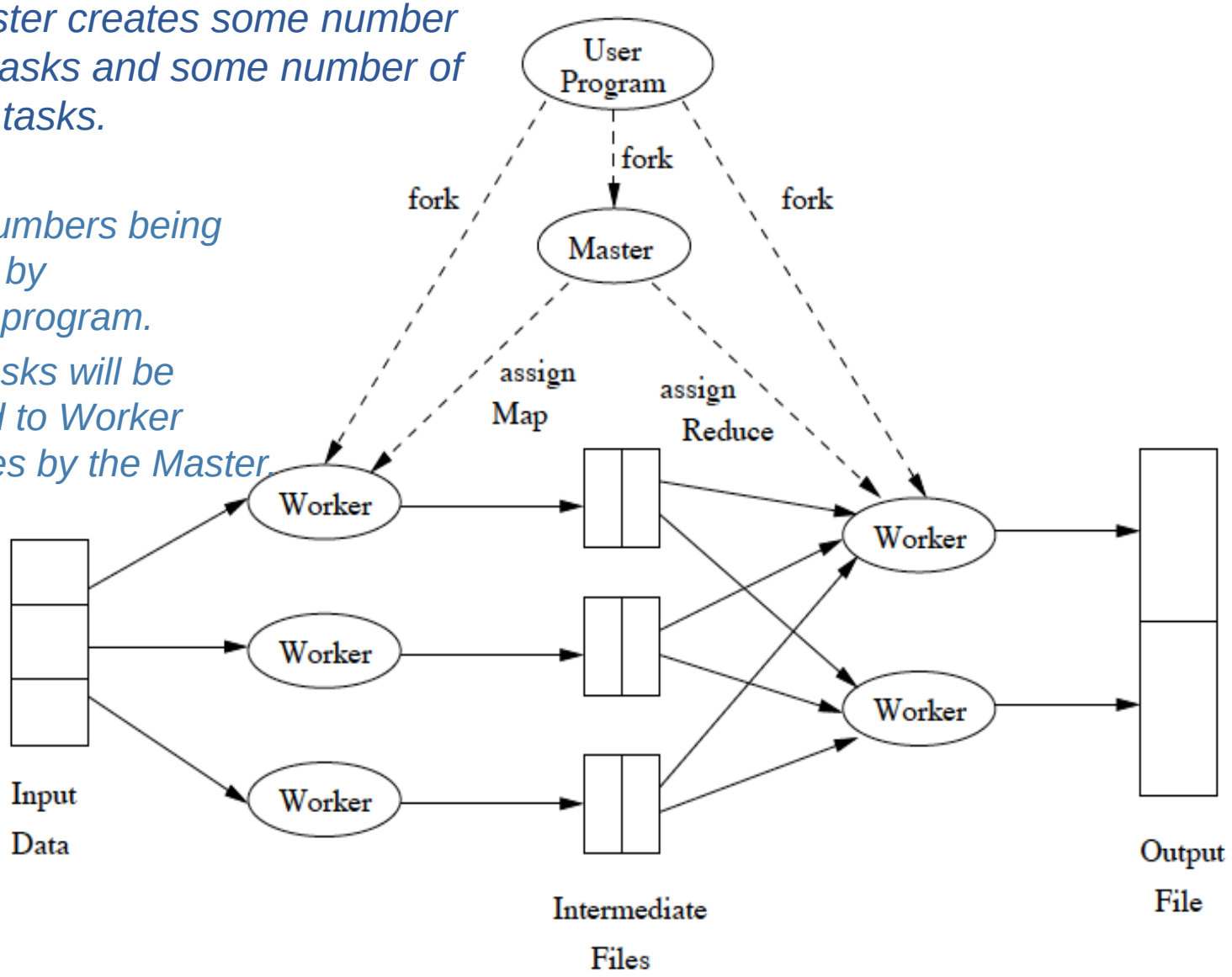


Figure 2.3: Overview of the execution of a map-reduce program

The Master keeps track of the status of each Map and Reduce task (idle, executing at a particular Worker, or completed).

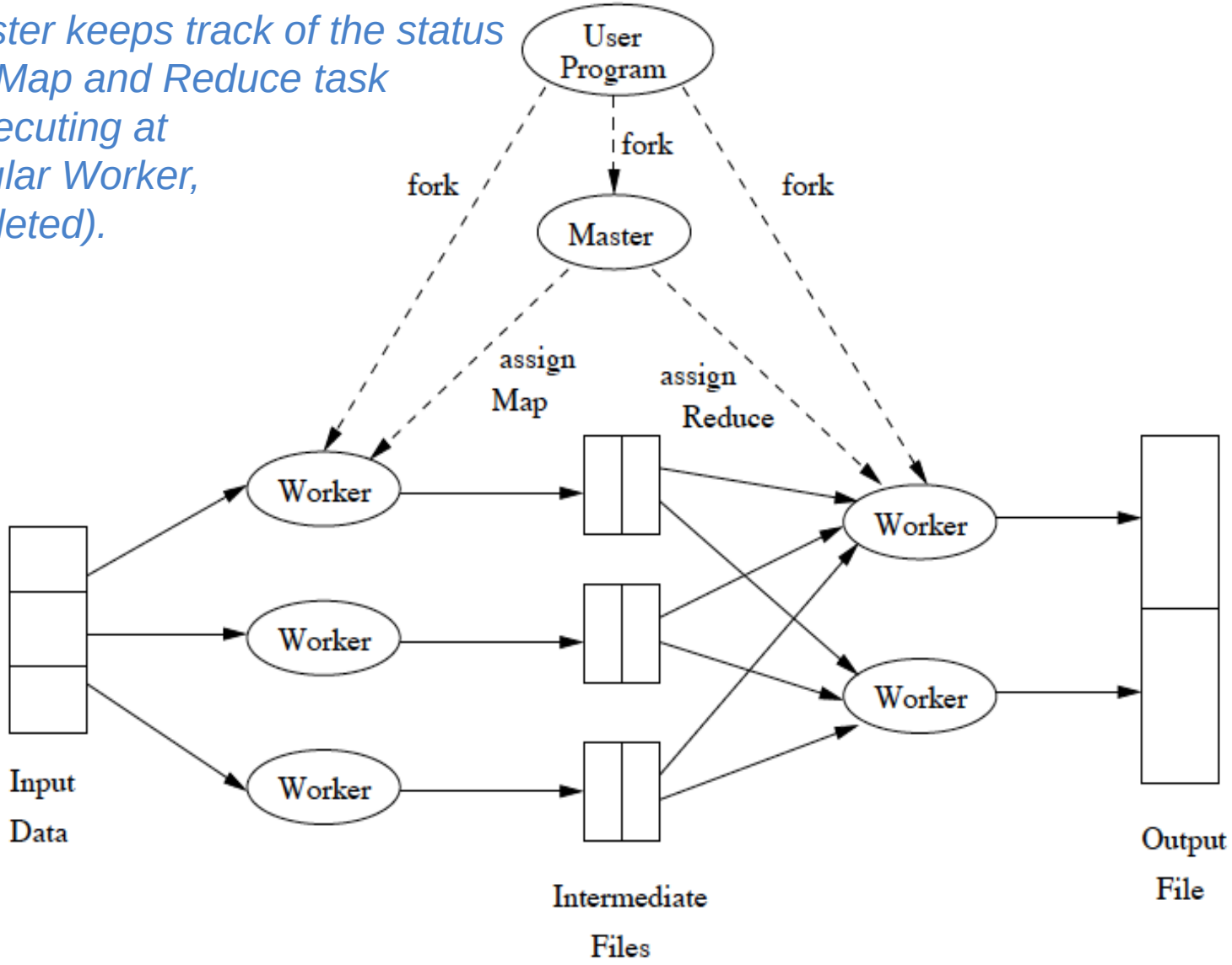


Figure 2.3: Overview of the execution of a map-reduce program

A Worker process reports to the Master when it finishes a task, and a new task is scheduled by the Master for that Worker process.

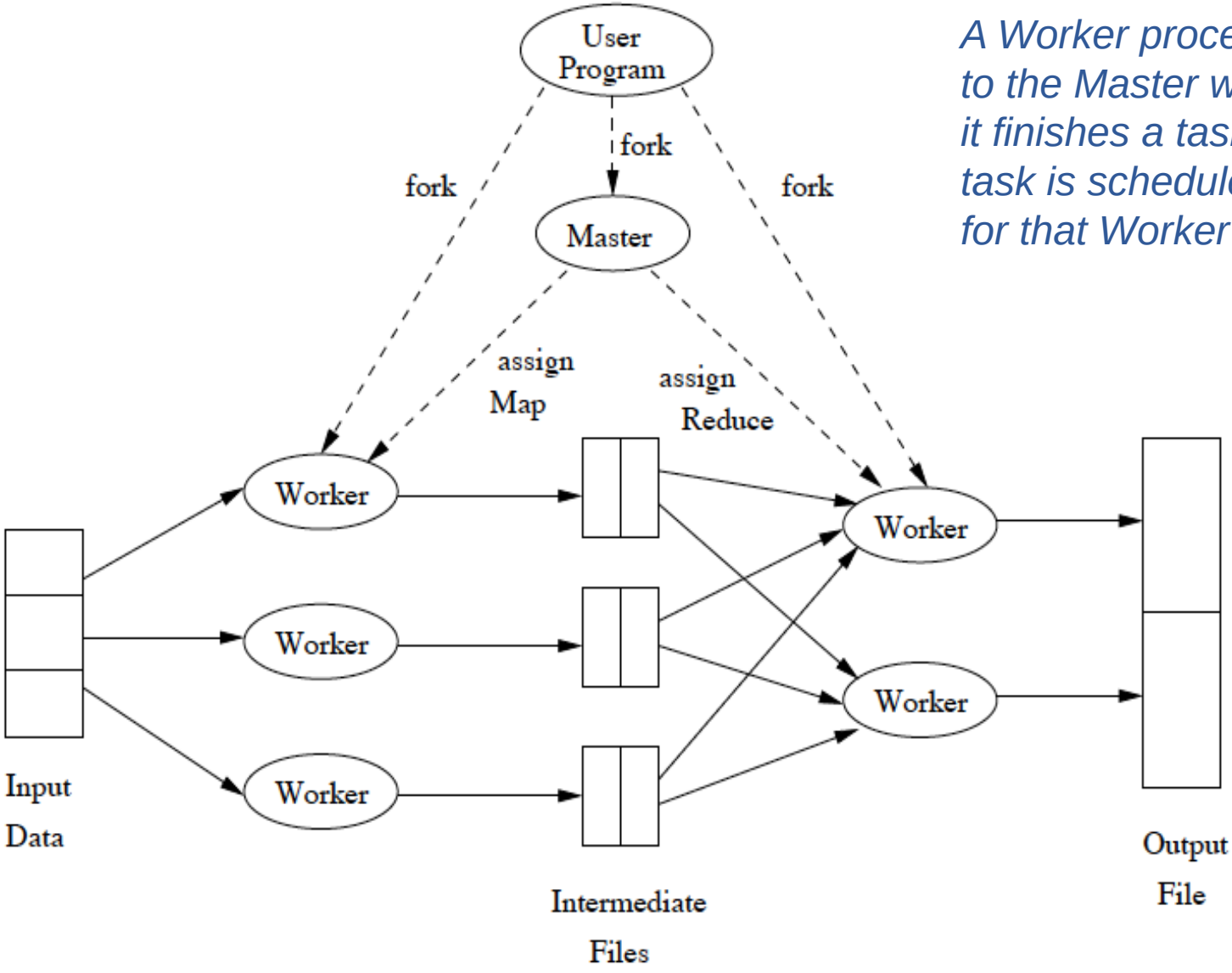


Figure 2.3: Overview of the execution of a map-reduce program

Each Map task is assigned one or more chunks of the input file(s) and executes on it the code written by the user.

The Map task creates a file for each Reduce task on the local disk of the Worker that execute the Map task.

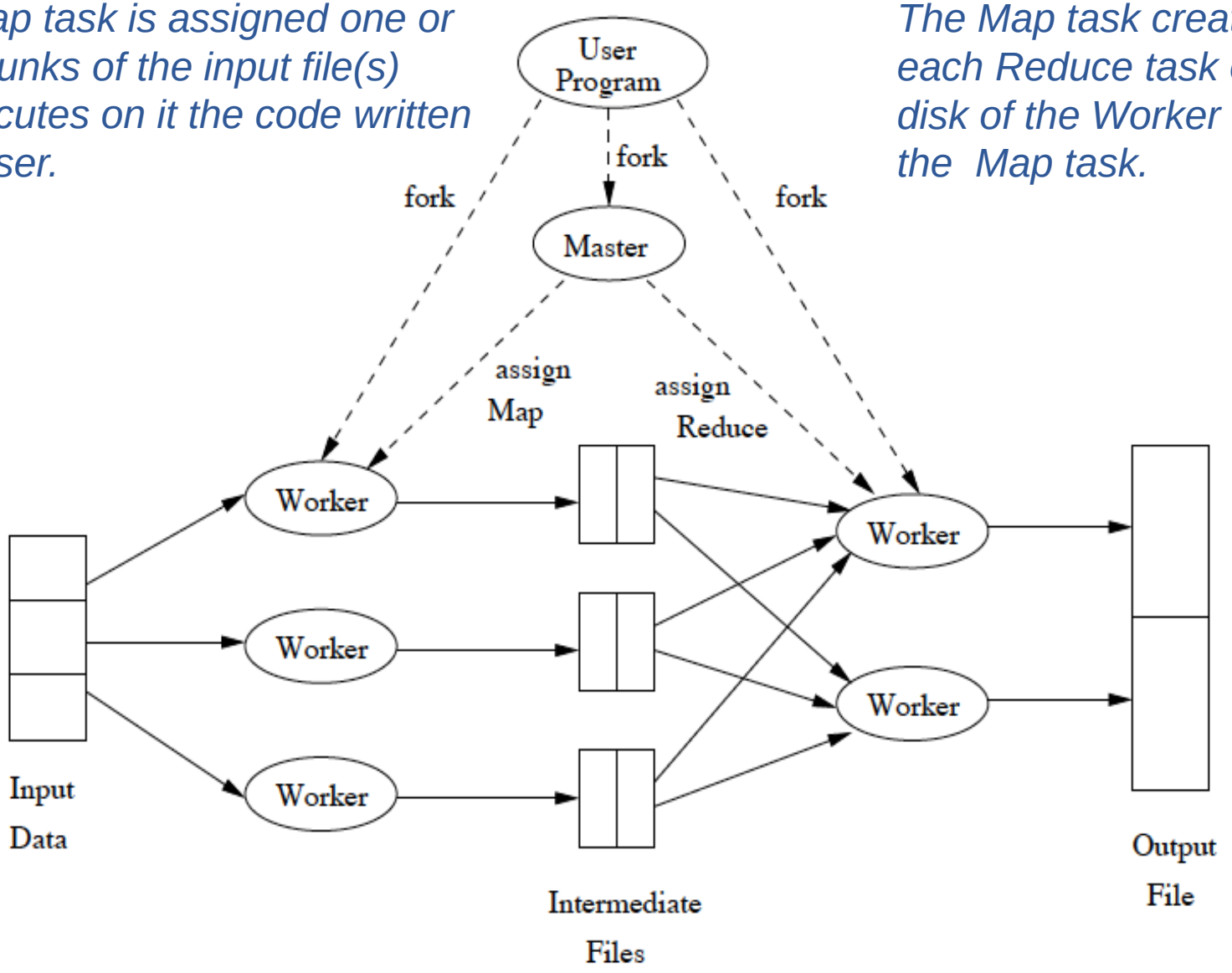


Figure 2.3: Overview of the execution of a map-reduce program

The Master is informed of the location and sizes of each of these files, and the Reduce task for which each is destined.

When a Reduce task is assigned by the Master to a Worker process, that task is given all the files that form its input.

The Reduce task executes code written by the user and writes its output to a file that is part of the surrounding distributed file system.

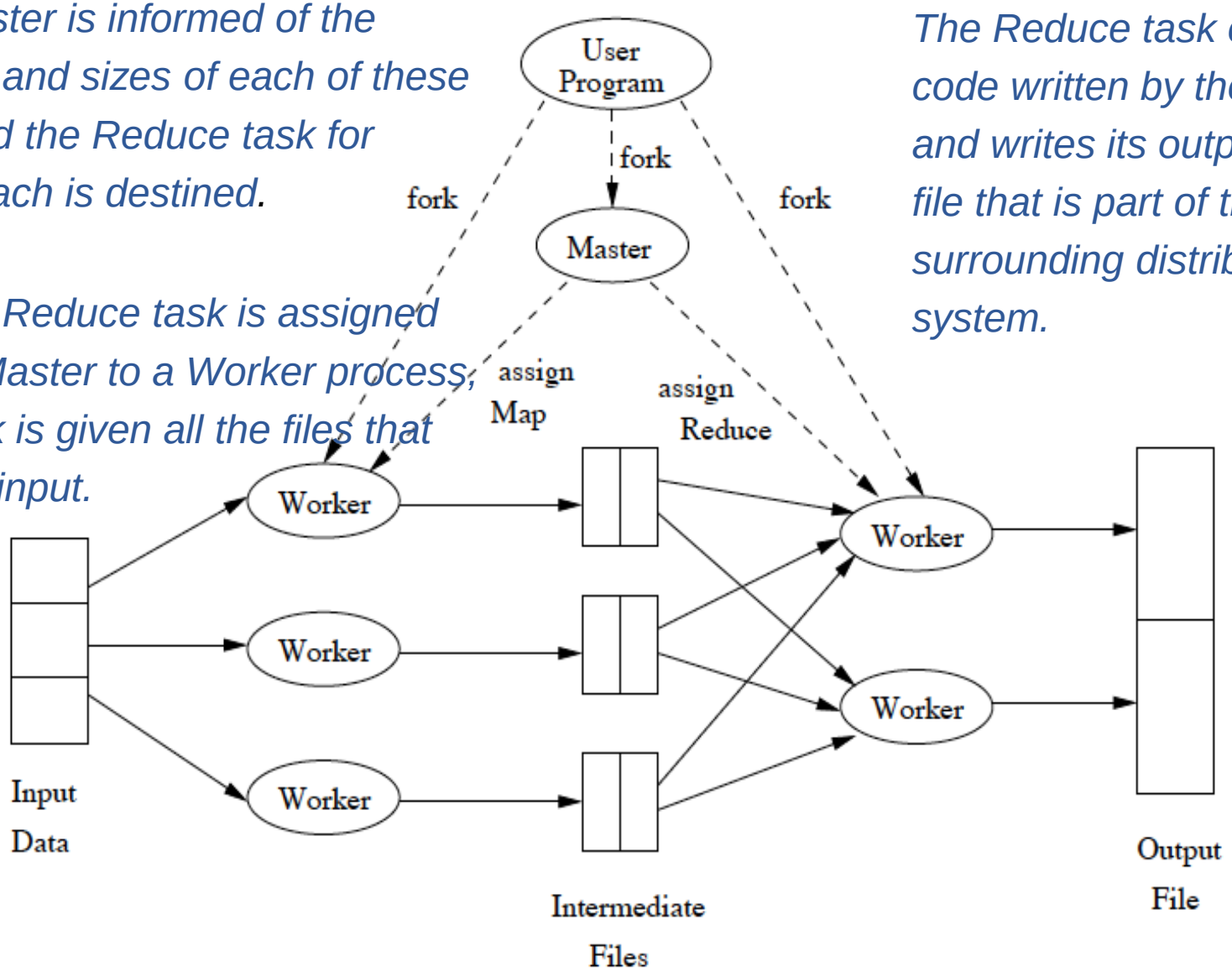


Figure 2.3: Overview of the execution of a map-reduce program

Coping With Failures

- **Map worker failure**
  - Map tasks completed or in-progress at worker are reset to idle
  - Reduce workers are notified when task is rescheduled on another worker
- **Reduce worker failure**
  - Only in-progress tasks are reset to idle
- **Master failure**
  - MapReduce task is aborted and client is notified

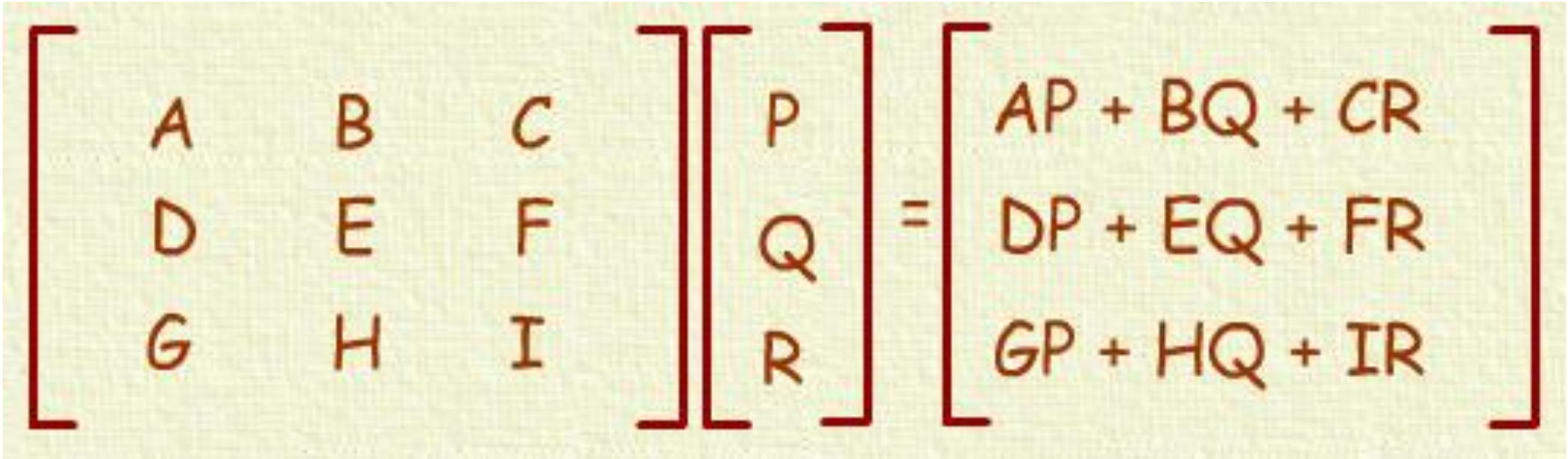
Things Map-Reduce is Good At

- Matrix-Matrix and Matrix-vector multiplication.
  - One step of the PageRank iteration was the original application.
- Relational algebra operations.
- Many other parallel operations.

Matrix-Vector Multiplication

- Suppose we have an ***n*** *x* ***n*** matrix ***M*** , whose element in row ***i*** and column ***j*** will be denoted m_{ij}.
- Suppose we also have a vector **v** of length ***n*** , whose ***j***th element is $\boldsymbol{v}_j$.
- Then the matrix-vector product is the vector *x* of length ***n***, whose ***i***th element $\boldsymbol{x}_i$ is given by

$$x_i = \sum_{j=1}^{n} m_{ij} v_j$$



Matrix-Vector Multiplication

- The matrix *M* and the vector **v** each will be stored in a file of the DFS. We assume that the row-column coordinates of each matrix element will be discoverable, either from its position in the file, or because it is stored with explicit coordinates, as a triple (i, j, m_{ij}).
- We also assume the position of element v_j in the vector **v** will be discoverable in the analogous way.

Matrix-Vector Multiplication

- The Map Function:
  - Each Map task will take the entire vector **v** and a chunk of the matrix *M*.
  - From each matrix element m_{ij} it produces the key-value pair (i, $m_{ij}v_j$). Thus, all terms of the sum that make up the component x_i of the matrix-vector product will get the same key.
- The Reduce Function:
  - A Reduce task has simply to sum all the values associated with a given key i. The result will be a pair (i, x_i).

Relational Algebra

- Selection
- Projection
- Union, Intersection, Difference
- Natural join
- Grouping and Aggregation

✓ A relation can be stored as a file in a distributed file system. The elements of this file are the tuples of the relation.

Union

- Suppose relations R and S have the same schema.
- The input for the Map tasks are chunks from either R or S.

- The Map Function:
  - Turn each input tuple t into a key-value pair (t, t).
- The Reduce Function:
  - Associated with each key t there will be either one or two values. Produce output (t, t) in either case.

Intersection

- Suppose relations R and S have the same schema.
- The input for the Map tasks are chunks from either R or S.

- The Map Function:
  - Turn each input tuple t into a key-value pair (t, t).
- The Reduce Function:
  - If key t has value list [t, t], then produce (t, t). Otherwise, produce (t, NULL).

Difference

- Suppose relations R and S have the same schema.
- The input for the Map tasks are chunks from either R or S.
- The Map Function:
  - For a tuple t in R , produce key-value pair (t, R), and for a tuple t in S , produce key-value pair (t, S). Note that the intent is that the value is the name of R or S, not the entire relation.
- The Reduce Function:
  - For each key **t** , do the following.
    - If the associated value list is [**R**], then produce (**t, t**).
    - If the associated value list is anything else, which could only be [**R, S**],[**S,R**], or [**S**], produce (**t,** NULL).

Natural join

- Joining **R** (**A,B**) with **S** (**B,C**).
- We must find tuples that agree on their B components.
- The Map Function:
  - For each tuple (a, b) of R, produce the key-value pair (b, (R, a)).
  - For each tuple (b, c) of S, produce the key-value pair (b, (S, c)).
- The Reduce Function:
  - Each key value b will be associated with a list of pairs that are either of the form (R, a) or (S, c).
  - Construct all pairs consisting of one with first component R and the other with first component S, say (R, a) and (S, c). The output for key b is (b, [(a**1**, b, c**1**), (a**2**, b, c**2**), . . .]),
  - that is, b associated with the list of tuples that can be formed from an R-tuple and an S-tuple with a common b value.

Grouping and Aggregation

R(A,B,C)

Select SUM(B) From R Group by A

- The Map Function:
  - For each tuple (a, b, c) produce the key-value pair (a, b).
- The Reduce Function:
  - Each key a represents a group. Apply SUM to the list [b**1**, b**2**, . . . , b**n**] of b-values associated with key a. The output is the pair (a, x), where x = b**1** + b**2** + . . . + b**n**.

Thank you!