Data Management for Data Science

Midterm Review 2: MapReduce and NoSQL

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Today's Lecture

1. Review Relational Databases and Relational Algebra

2. Next Lecture: Review MapReduce and NoSQL systems

Select $\longrightarrow \pi$

From $\longrightarrow \times, \bowtie$

Where $\longrightarrow \sigma$

$\bowtie_{A=B}$

join condition

3 Select ~~A~~ DISTINCT A

1 from T_1

2 where $T_1.B = 5$

π_A

$\sigma_{B=5}$ 2

leaves of the Tree T_1 1

$\pi_A(\sigma_{B=5}(T_1))$

$T_1(A, B)$ B refers to C ?

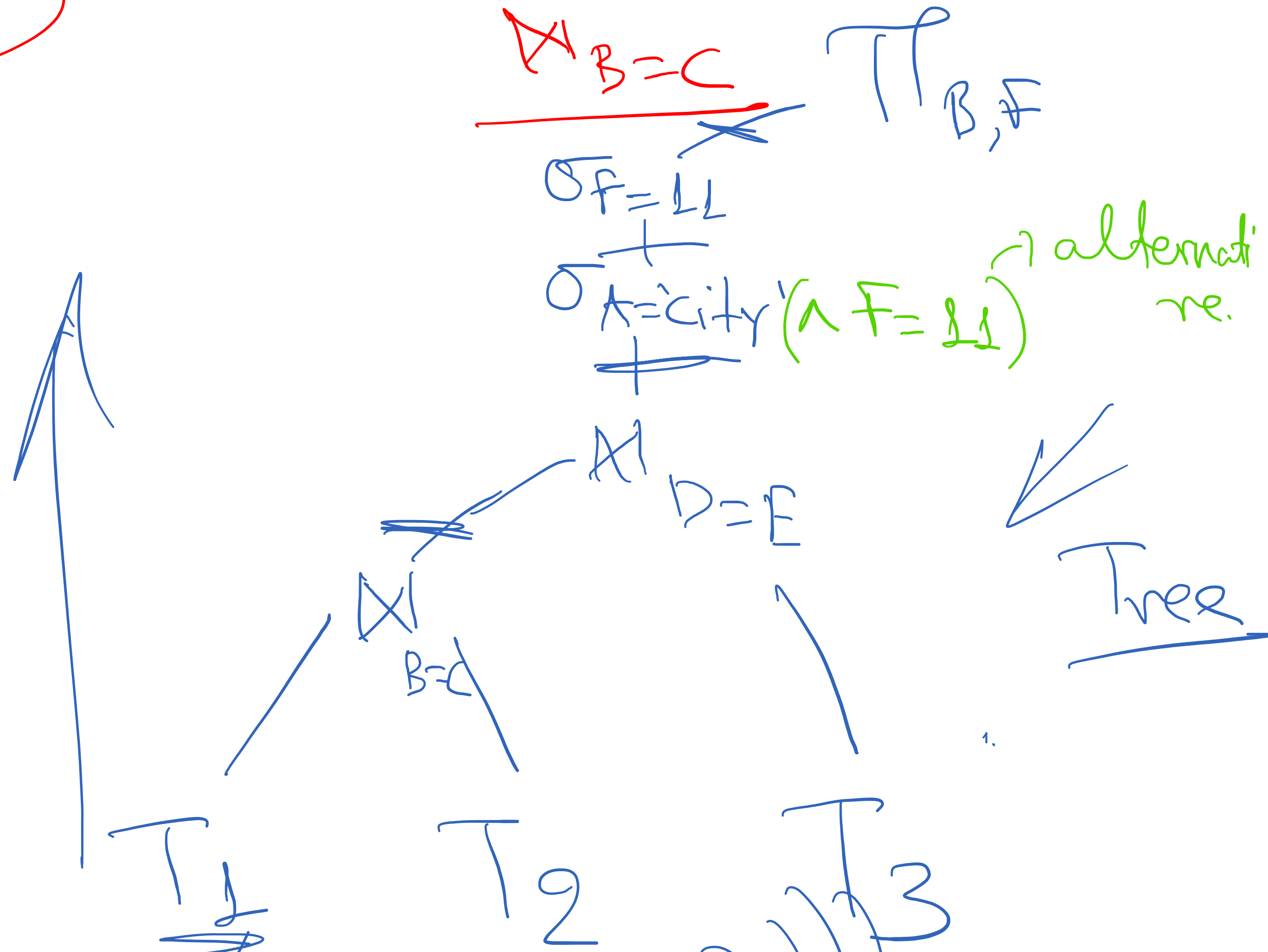
$T_2(C, D)$ D refers to E

$T_3(E, F)$

implies a join condition

Select B, F ③
from T_1, T_2, T_3 ①
where B = C ~~and~~ ②
and D = E
and A = 'city'
and F = 11

$$\Pi_{B,F}(\sigma_{F=11}(\sigma_{A='city'}(((T_1 \bowtie_{B=C} T_2) \bowtie_{D=E} T_3))))$$



$T_1(A,B)$ — B refers to C ?

$T_2(C,D)$ — D refers to E

$T_3(E,F)$

implies a join condition

Select B, F

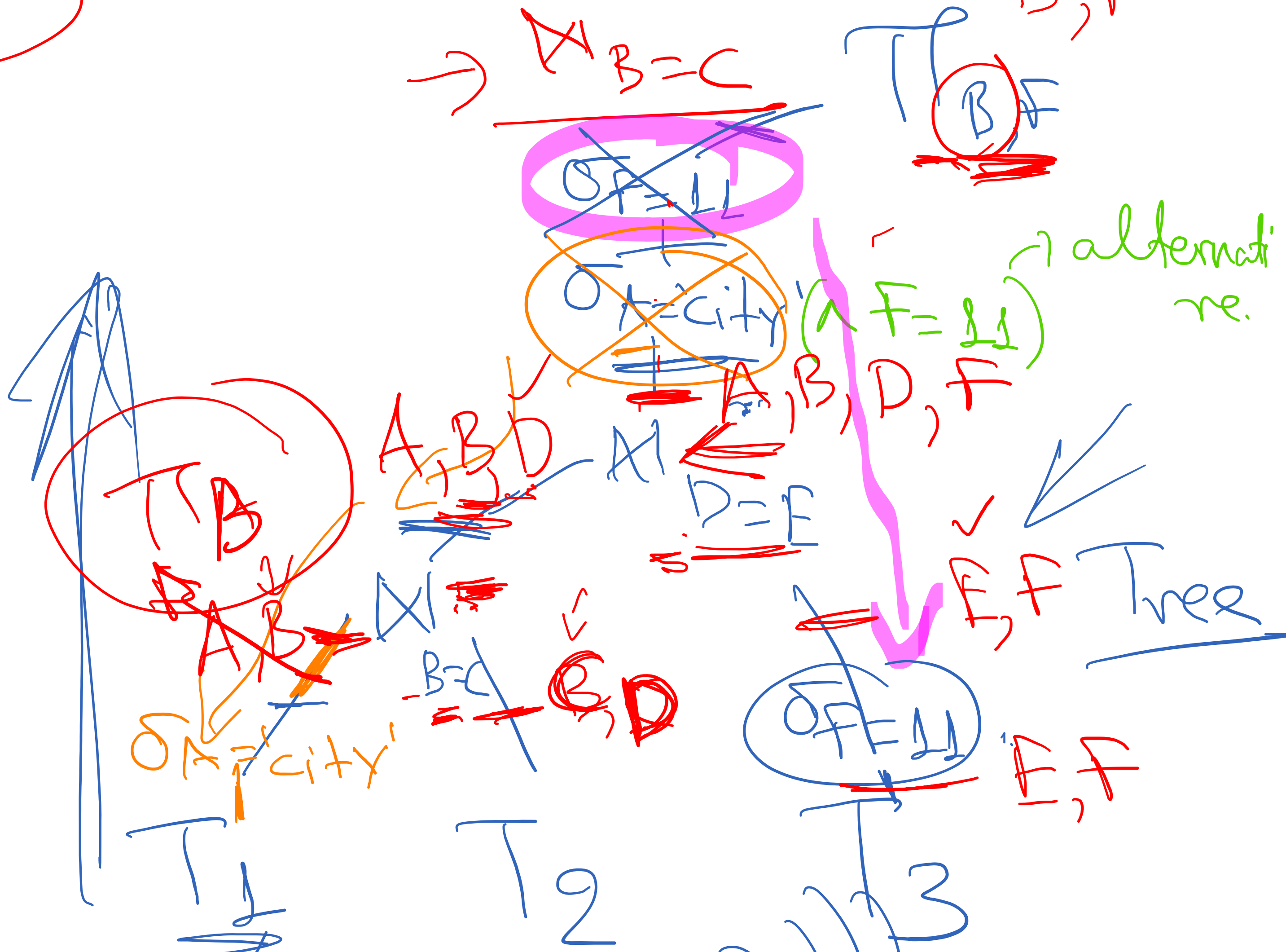
from T_1, T_2, T_3

where B=C

and D=E

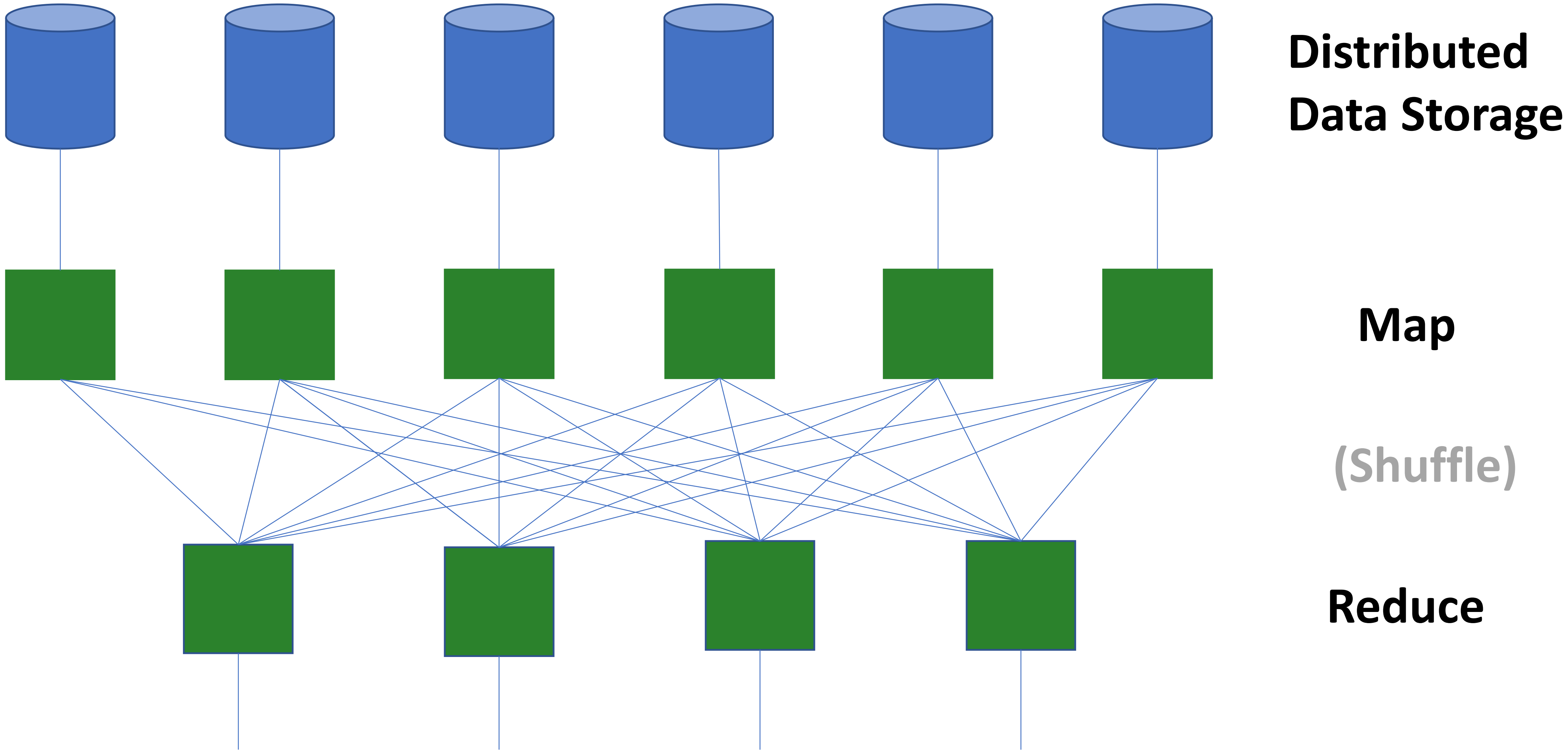
and A='city'

and F=11

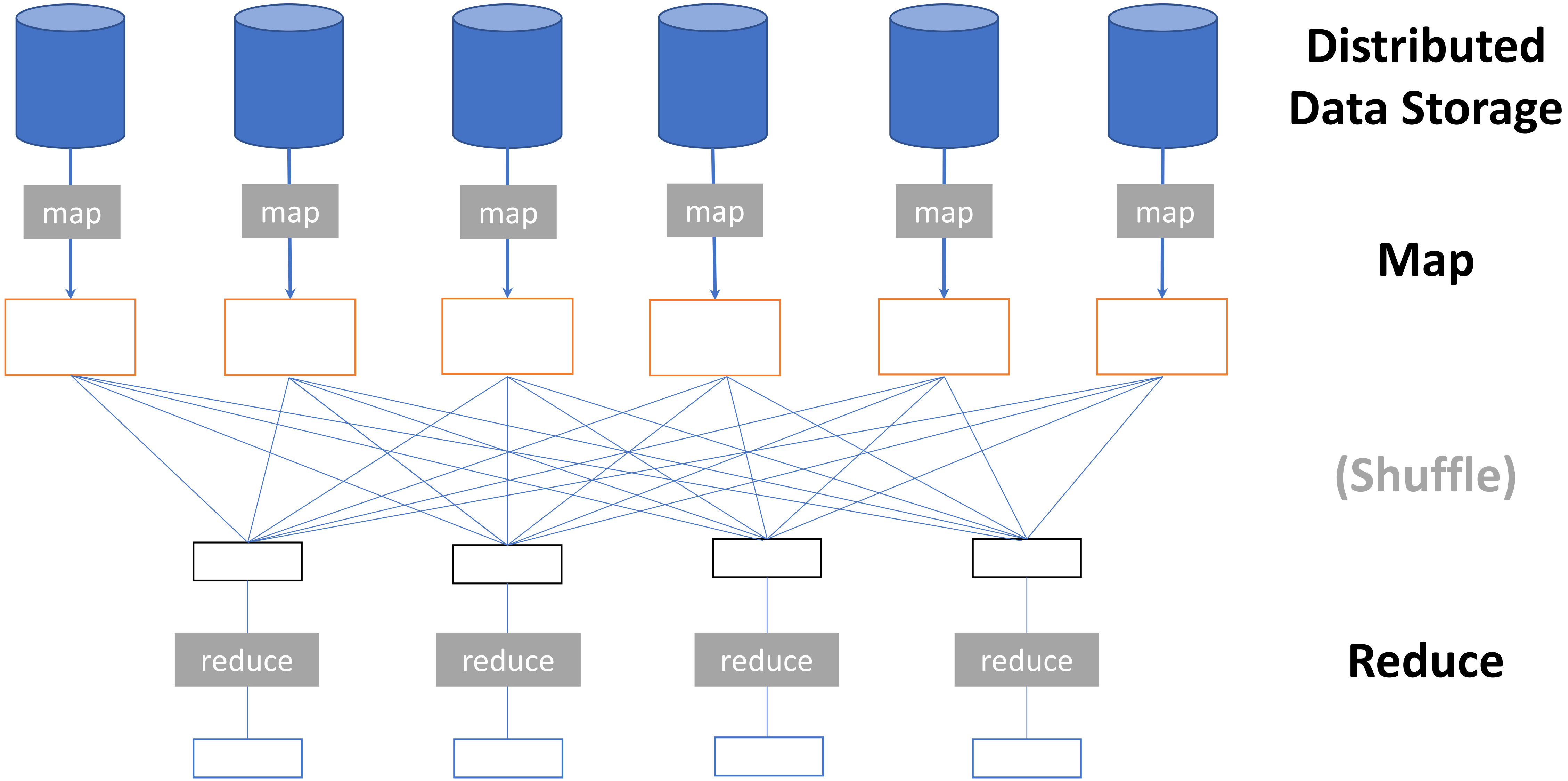


$$\Pi_{B,F}(\sigma_{F=11}(\sigma_{A='city'}(((T_1 \bowtie_{B=C} T_2) \bowtie_{D=E} T_3))))$$

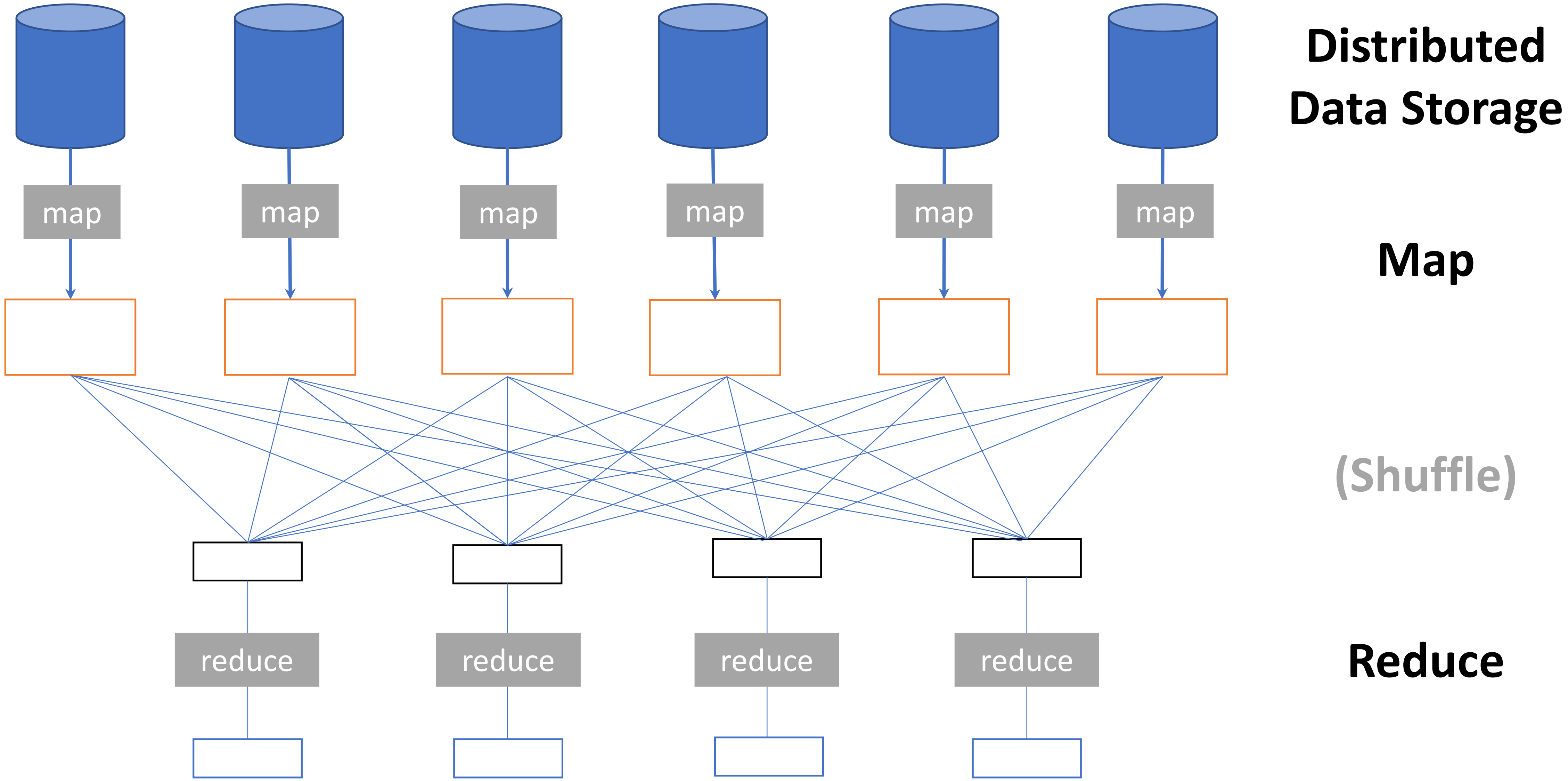
The Map Reduce Abstraction for Distributed Algorithms

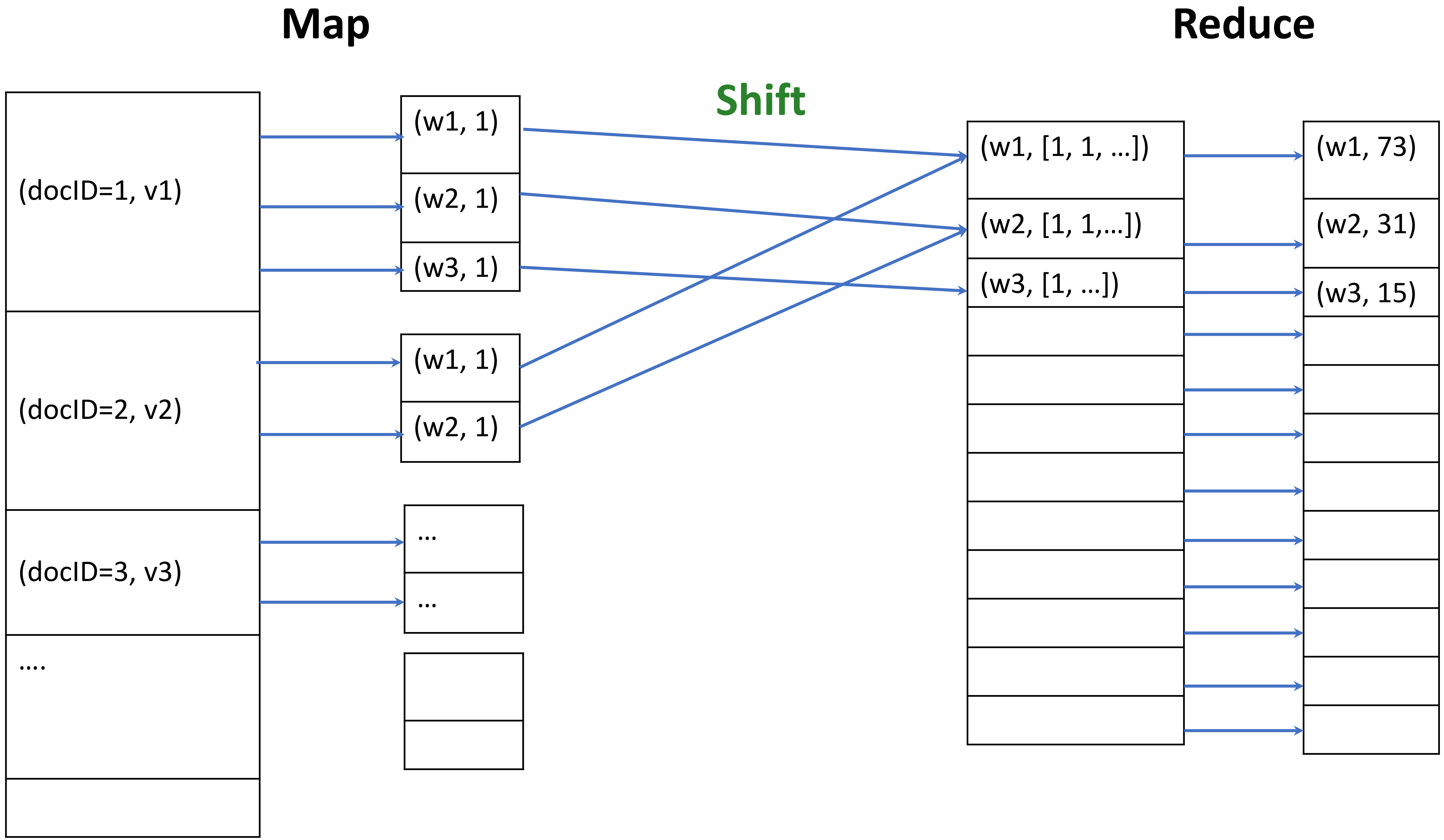


The Map Reduce Abstraction for Distributed Algorithms



The Map Reduce Abstraction for Distributed Algorithms





Map
Reduce
Shift
(docID=1, v1)
(docID=2, v2)
(docID=3, v3)
....
(w1, 1)
(w2, 1)
(w3, 1)
(w1, 1)
(w2, 1)
...
...
(w1, [1, 1, ...])
(w2, [1, 1,...])
(w3, [1, ...])
(w1, 73)
(w2, 31)
(w3, 15)

The Map Reduce Abstraction for Distributed Algorithms

- MapReduce is a high-level programming model and implementation for large-scale parallel data processing
- Like RDBMS adopt the the relational data model, MapReduce has a data model as well

MapReduce's Data Model

- Files!
- A File is a bag of **(key, value)** pairs
  - A bag is a **multiset**
- A map-reduce program:
  - Input: a bag of **(inputkey, value)** pairs
  - Output: a bag of **(outputkey, value)** pairs

User input

- All the user needs to define are the MAP and REDUCE functions

- Execute proceeds in multiple MAP – REDUCE rounds
  - MAP – REDUCE = MAP phase followed REDUCE

MAP Phase

Step 1: the MAP phase

- User provides a MAP-function:
  - Input: **(input key, value)**
  - Output: bag of **(intermediate key, value)**

- System applies the map function in parallel to all (input key, value) pairs in the input file

REDUCE Phase

Step 2: the REDUCE phase

- User provides a REDUCE-function:
  - Input: **(intermediate key, bag of values)**
  - Output: **(intermediate key, values)**

- The system will group all pairs with the same intermediate key, and passes the bag of values to the REDUCE function

MapReduce 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 input key/value pair
- Produces set of intermediate pairs

reduce (out_key, list(intermediate_value)) -> (out_key, list(out_values))

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

MapReduce: what happens in between?

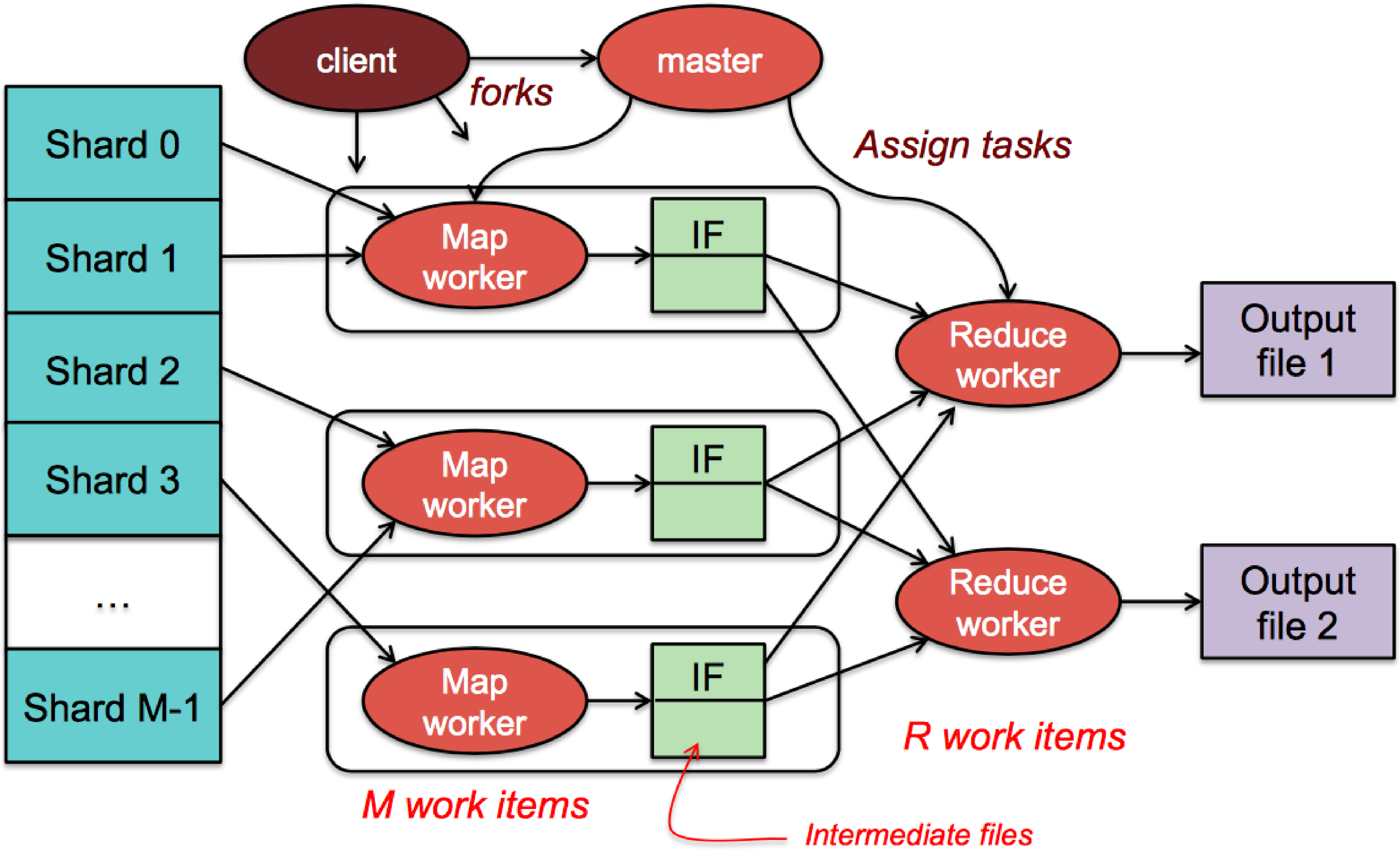
- Map
  - Grab the relevant data from the source (parse into key, value)
  - Write it to an intermediate file
- Partition
  - Partitioning: identify which of *R* reducers will handle which keys
  - Map partitions data to target it to one of *R* Reduce workers based on a partitioning function (both *R* and partitioning function user defined)

Map Worker

- Shuffle & Sort
  - Shuffle: Fetch the relevant partition of the output from <u>all</u> mappers
  - Sort by keys (different mappers may have sent data with the same key)
- Reduce
  - Input is the sorted output of mappers
  - Call the user *Reduce* function per key with the list of values for that key to aggregate the results

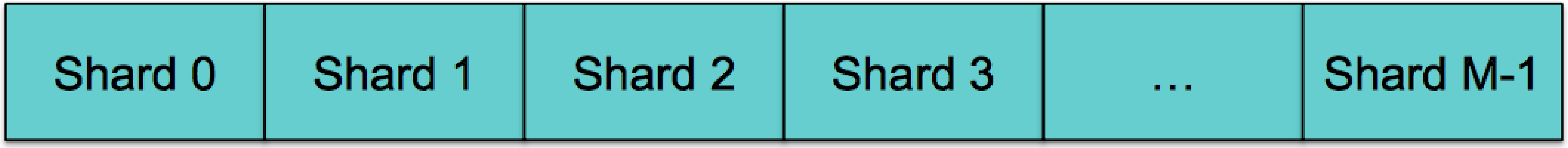
Reduce Worker

MapReduce: the complete picture



Step 1: Split input files into chunks (shards)

- Break up the input data into *M* pieces (typically 64 MB)

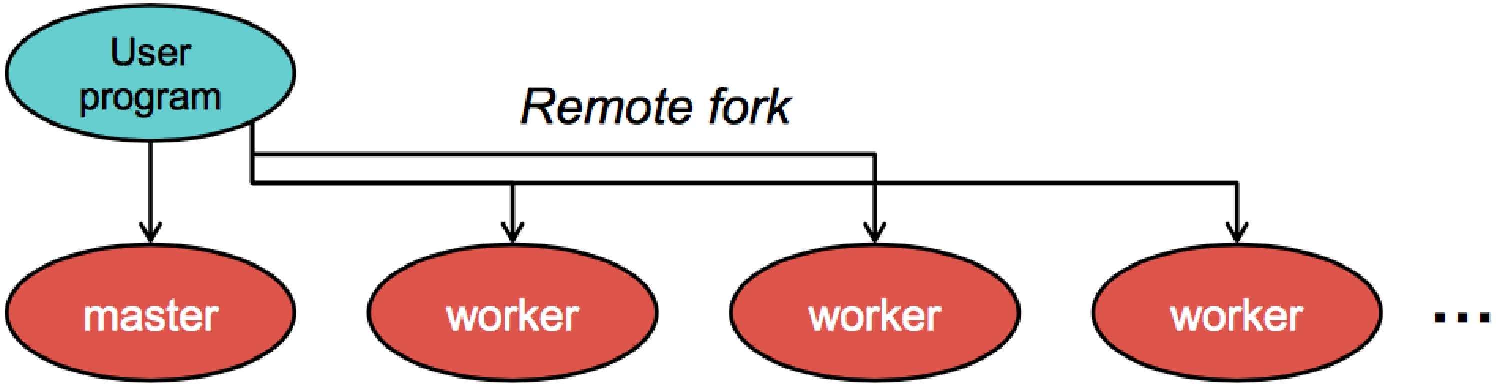


Input files

Divided into *M* shards

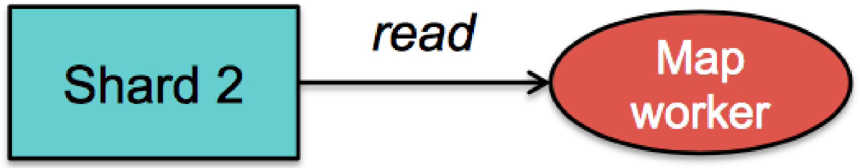
Step 2: Fork processes

- Start up many copies of the program on a cluster of machines
  - **One master**: scheduler & coordinator
  - Lots of workers
- Idle workers are assigned either:
  - map tasks (each works on a shard) – there are *M* map tasks
  - reduce tasks (each works on intermediate files) – there are *R*
    - *R* = # partitions, defined by the user



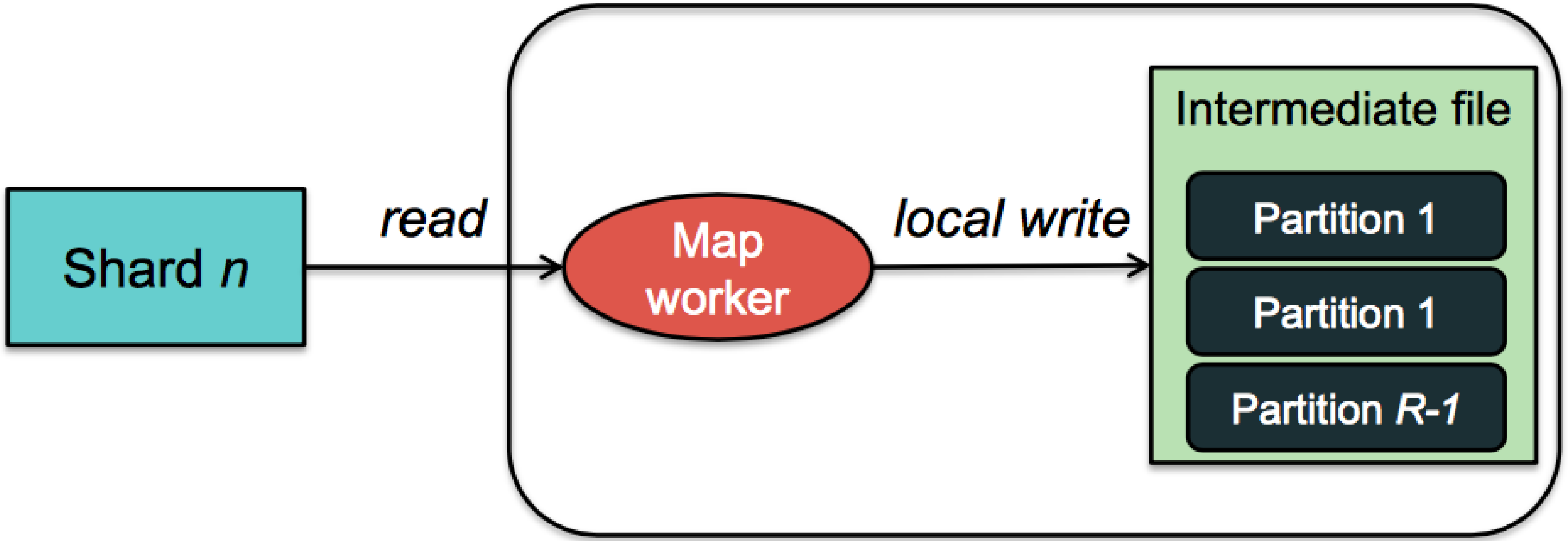
Step 3: Run Map Tasks

- Reads contents of the input shard assigned to it
- Parses key/value pairs out of the input data
- Passes each pair to a user-defined *map* function
  - Produces intermediate key/value pairs
  - These are buffered in memory



Step 4: Create intermediate files

- Intermediate key/value pairs produced by the user's *map* function buffered in memory and are periodically written to the local disk
  - Partitioned into *R* regions by a partitioning function

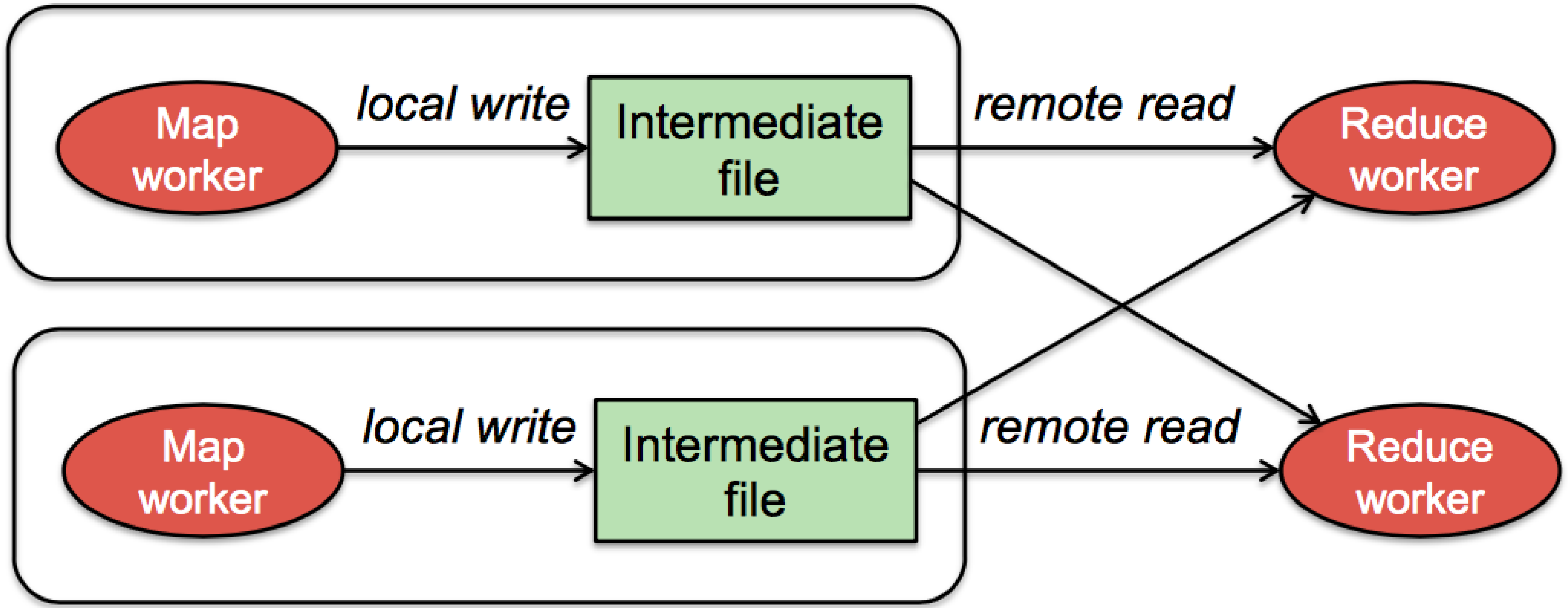


Step 4a: Partitioning

- Map data will be processed by Reduce workers
  - User's *Reduce* function will be called once per unique key generated by *Map*.
- We first need to sort all the (*key, value*) data by keys and decide which Reduce worker processes which keys
  - The Reduce worker will do the sorting
- **Partition function**
  Decides which of *R* reduce workers will work on which key
  - Default function: *hash(key) mod R*
  - Map worker partitions the data by keys
- Each Reduce worker will later read their partition from every Map worker

Step 5: Reduce Task - sorting

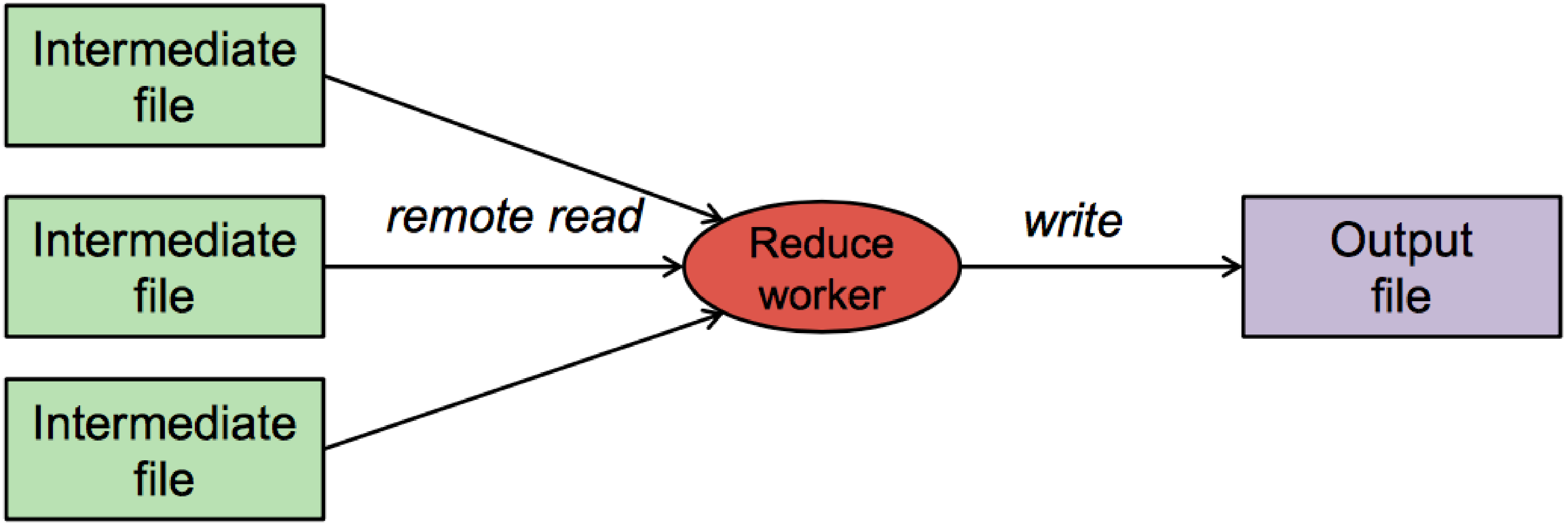
- Reduce worker gets notified by the master about the location of intermediate files for its partition
- Shuffle: Uses RPCs to read the data from the local disks of the map workers
- Sort: When the *reduce* worker reads intermediate data for its partition
  - It sorts the data by the intermediate keys
  - All occurrences of the same key are grouped together



Step 6: Reduce Task - reduce

- The sort phase grouped data with a unique intermediate key
- User's ***Reduce*** function is given the key and the set of intermediate values for that key

  < key, (value1, value2, value3, value4, …) >
- The output of the *Reduce* function is appended to an output file

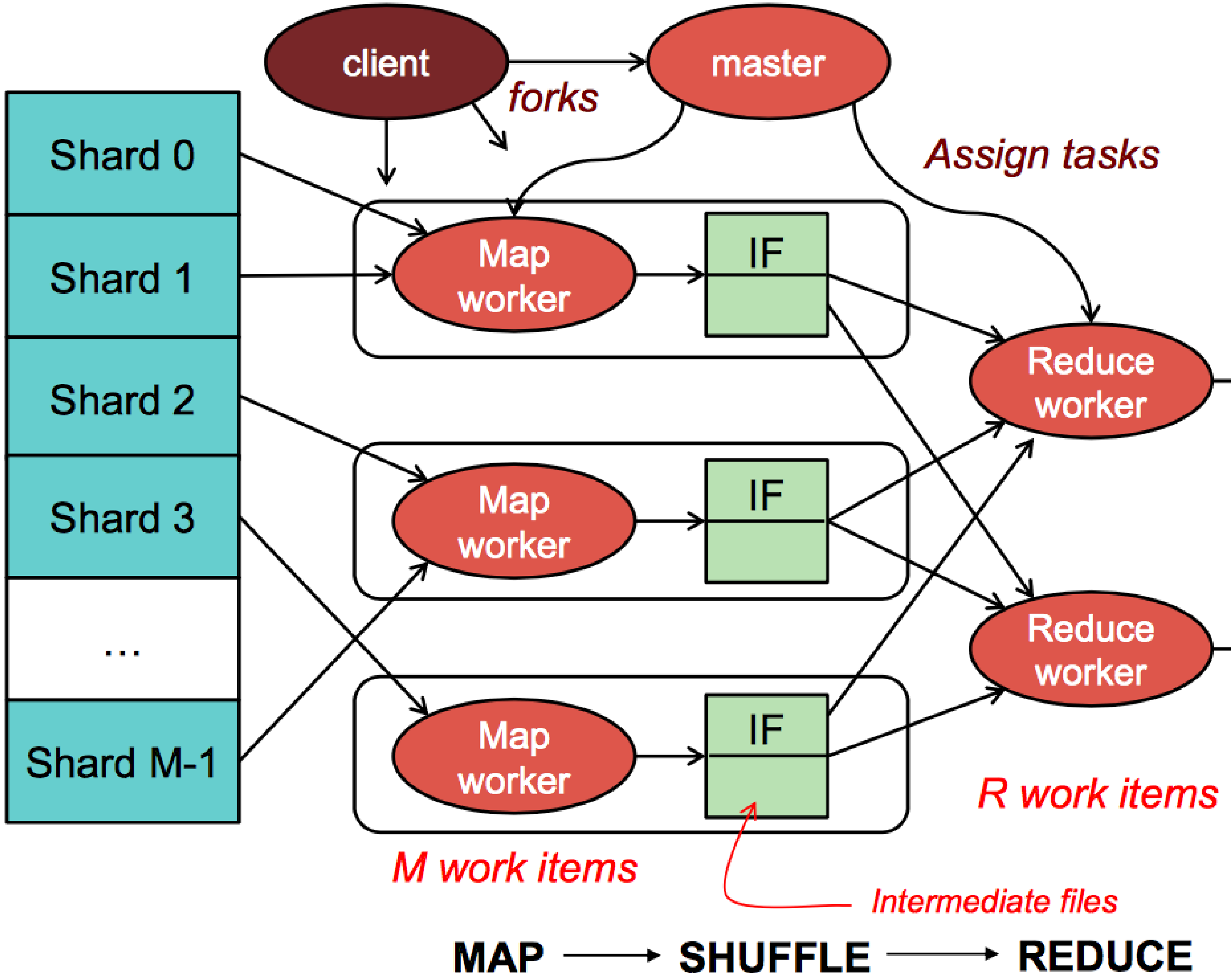


Step 7: Return to user

- When all *map* and *reduce* tasks have completed, the master wakes up the user program

- The *MapReduce* call in the user program returns and the program can resume execution.
  - Output of *MapReduce* is available in *R* output files

MapReduce: the complete picture



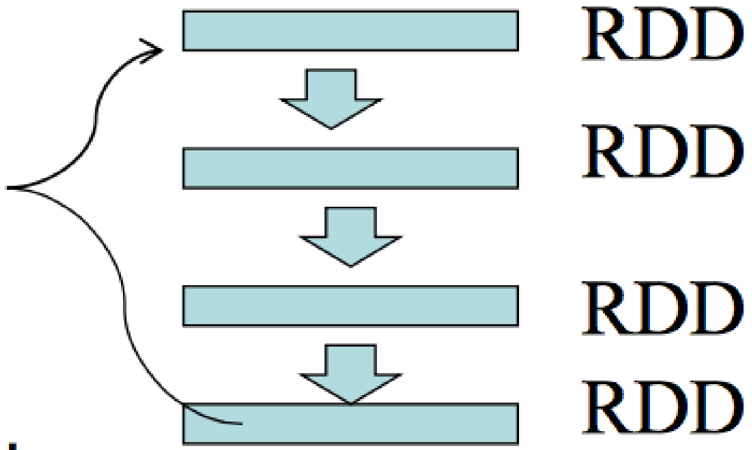
We need a distributed file system!

2. Spark

Intro to Spark

- Spark is really a different implementation of the MapReduce programming model
- What makes Spark different is that it operates on Main Memory
- Spark: we write programs in terms of operations on resilient distributed datasets (RDDs).
- RDD (simple view): a collection of elements partitioned across the nudes of a cluster that can be operated on in parallel.
- RDD (complex view): RDD is an interface for data transformation, RDD refers to the data stored either in persisted store (HDFS) or in cache (memory, memory+disk, disk only) or in another RDD

RDDs in Spark



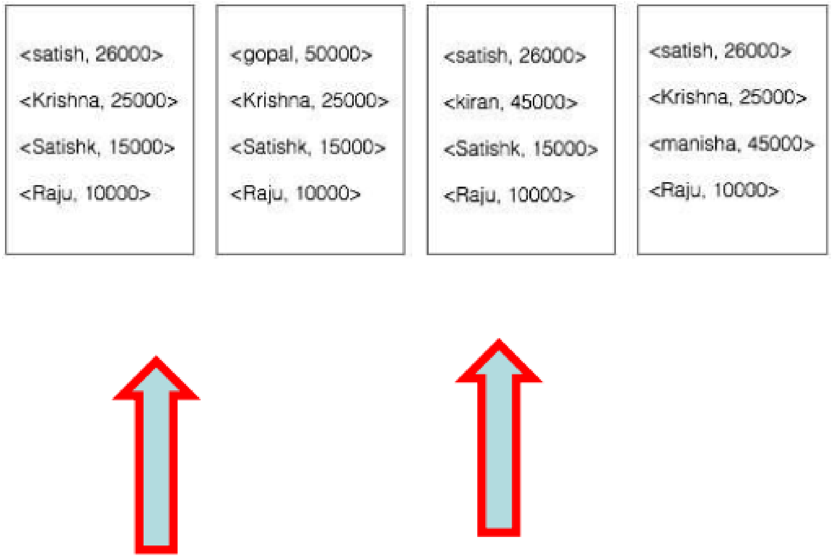
RDD: Resilient Distributed Datasets

- **Like a big list:**
  - Collections of objects spread across a cluster, stored in RAM or on Disk
- **Built through parallel transformations**
- **Automatically rebuilt on failure**

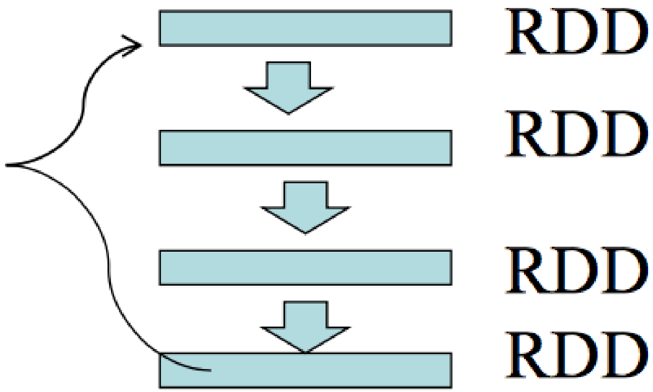
Operations

- **Transformations (e.g. map, filter, groupBy)**
- **Make sure input/output match**

MapReduce vs Spark



Map and reduce tasks operate on key-value pairs

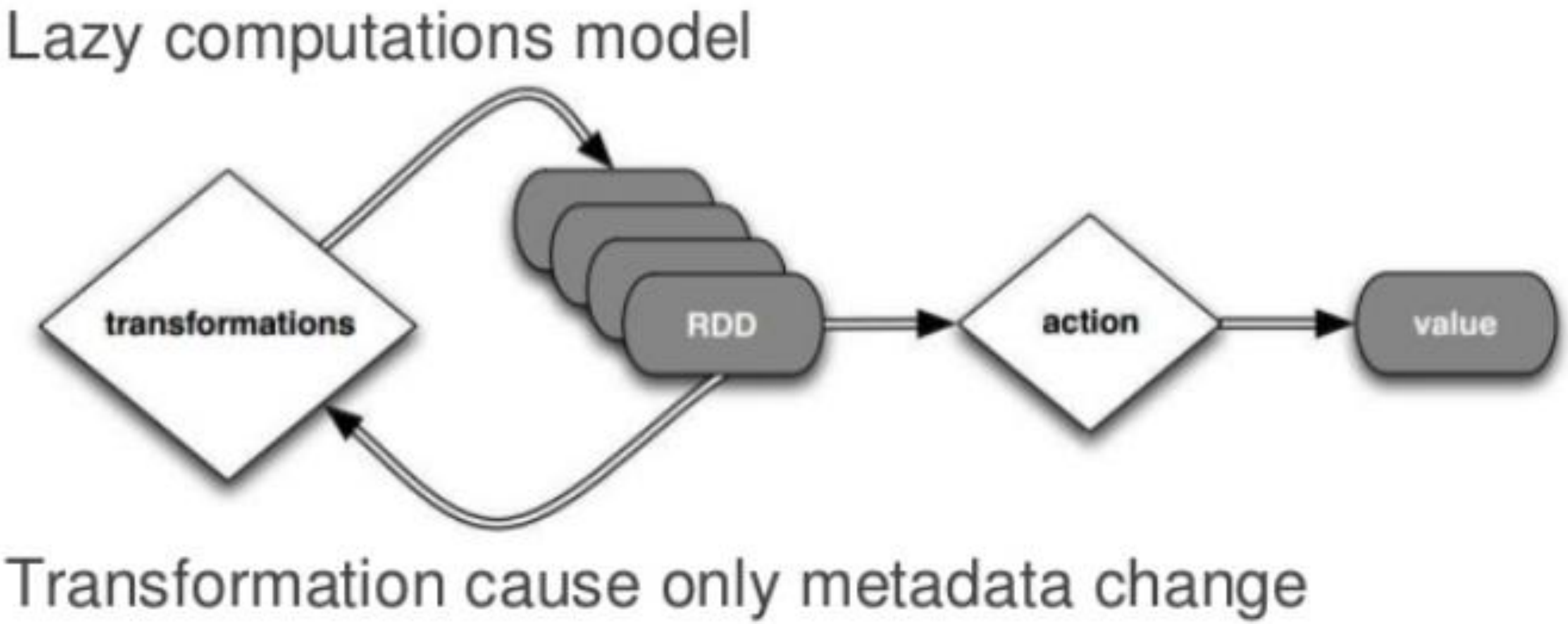


Spark operates on **RDD**

RDDs

- Partitions are recomputed on failure or cache eviction
- Metadata stored for interface:
  - Partitions – set of data splits associated with this RDD
  - Dependencies – list of parent RDDs involved in computation
  - Compute – function to compute partition of the RDD given the parent partitions from the Dependencies
  - Preferred Locations – where is the best place to put computations on this partition (data locality)
  - Partitioner – how the data is split into partitions

RDDs

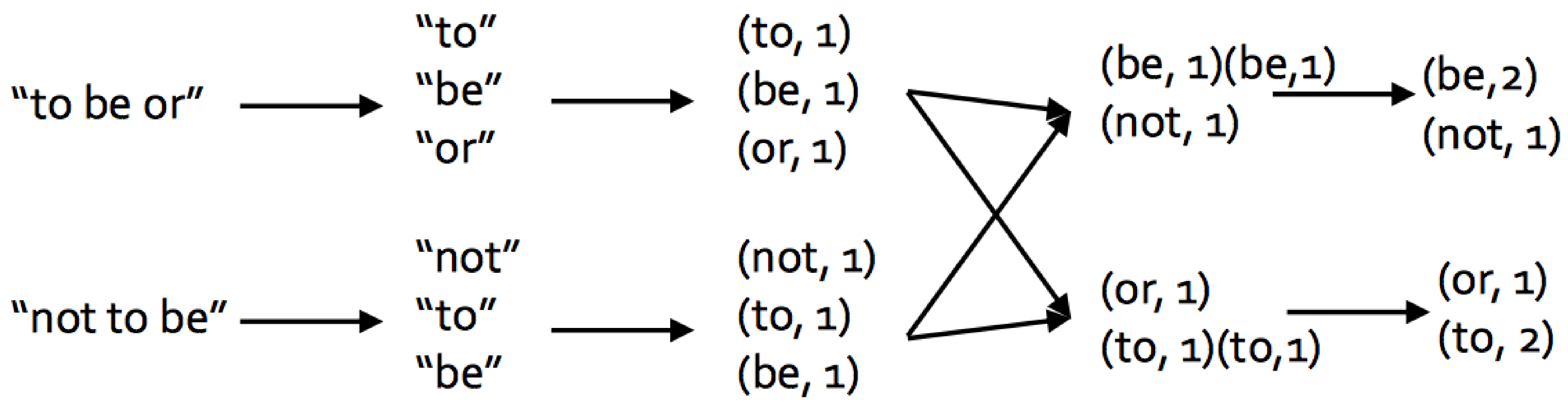

Lazy computations model
transformations
RDD
action
value
Transformation cause only metadata change

DAG

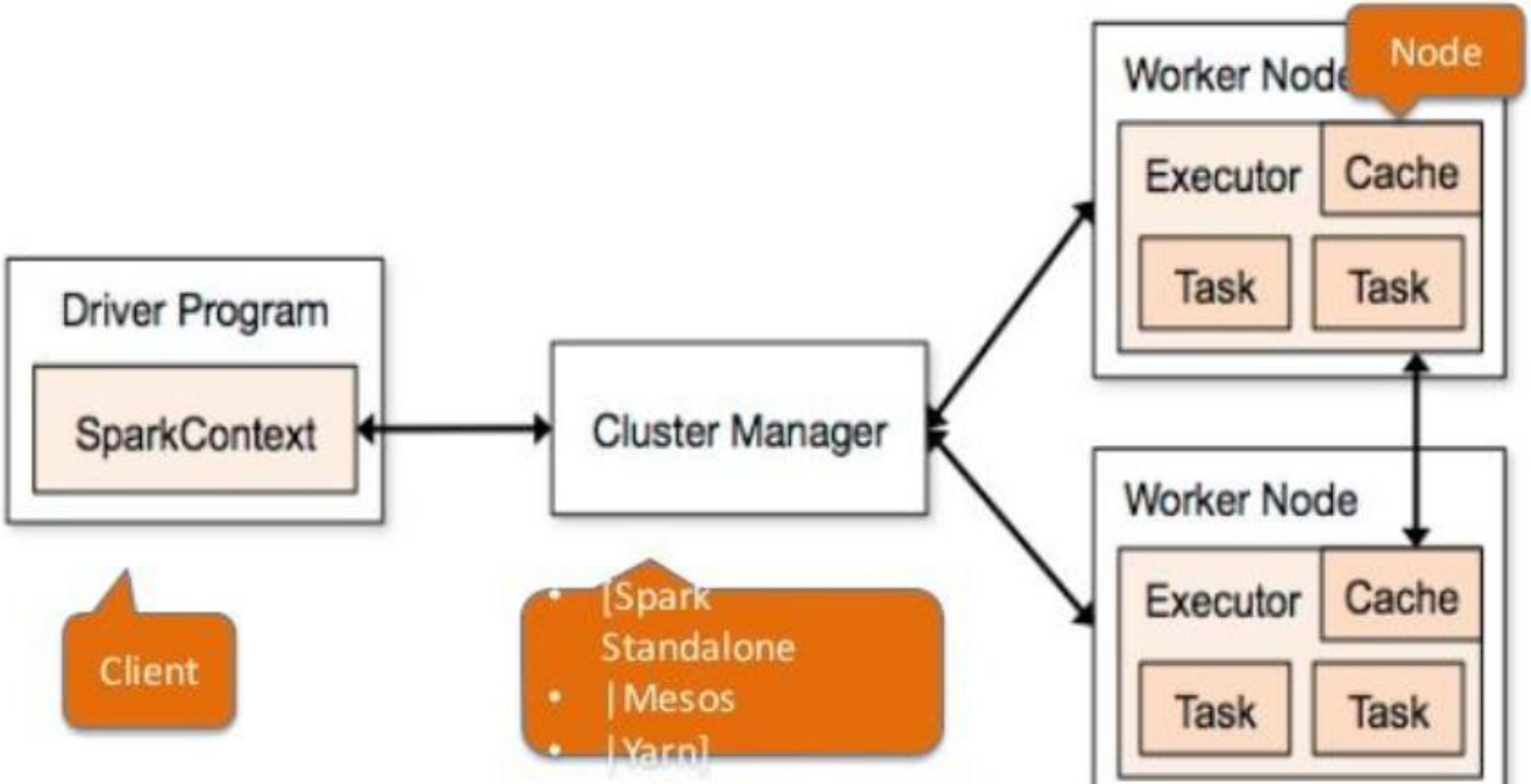
- Directed Acyclic Graph – sequence of computations performed on data
- Node – RDD partition
- Edge – transformation on top of the data
- Acyclic – graph cannot return to the older partition
- Directed – transformation is an action that transitions data partitions state (from A to B)

Example: Word Count

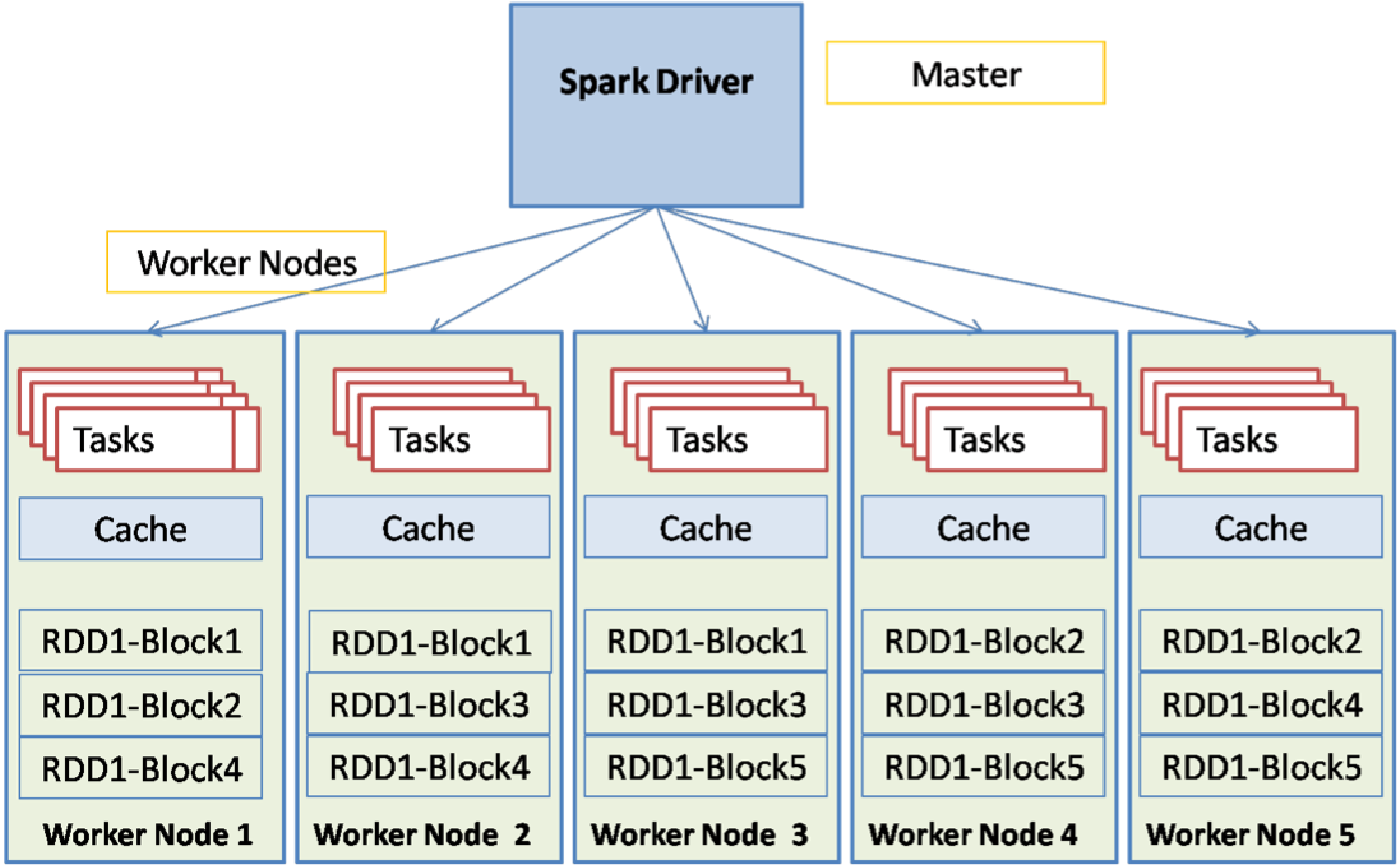
```
> lines = sc.textFile("hamlet.txt")
> counts = lines.flatMap(lambda line: line.split(" "))
                .map(lambda word: (word, 1))
                .reduceByKey(lambda x, y: x + y)
```



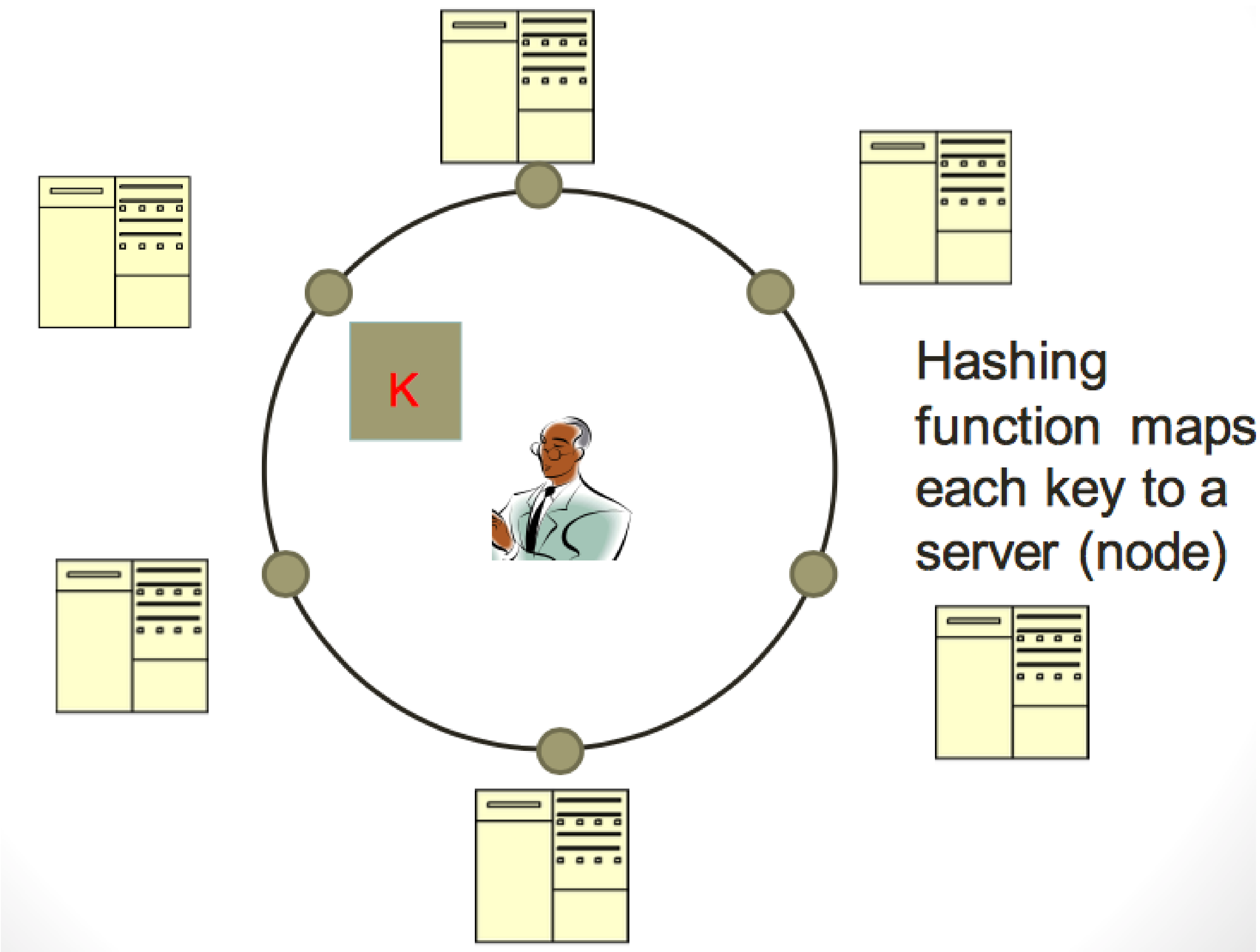
Spark Architecture



Spark Components



Typical NoSQL architecture



CAP theorem for NoSQL

- What the CAP theorem really says: If you cannot limit the number of faults and requests can be directed to any server and you insist on serving every request you receive then you cannot possibly be consistent

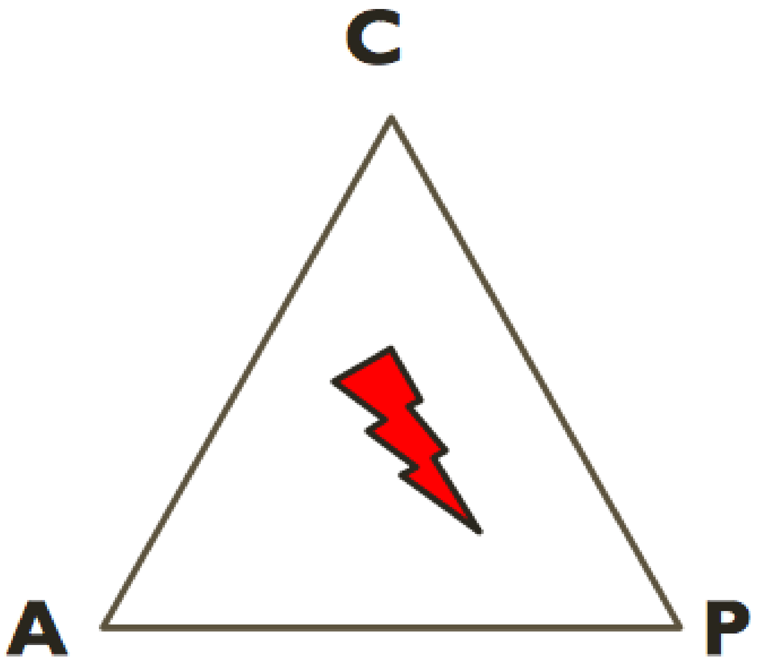
- How it is interpreted: You must always give something up: consistency, availability or tolerance to failure and reconfiguration

CAP theorem for NoSQL

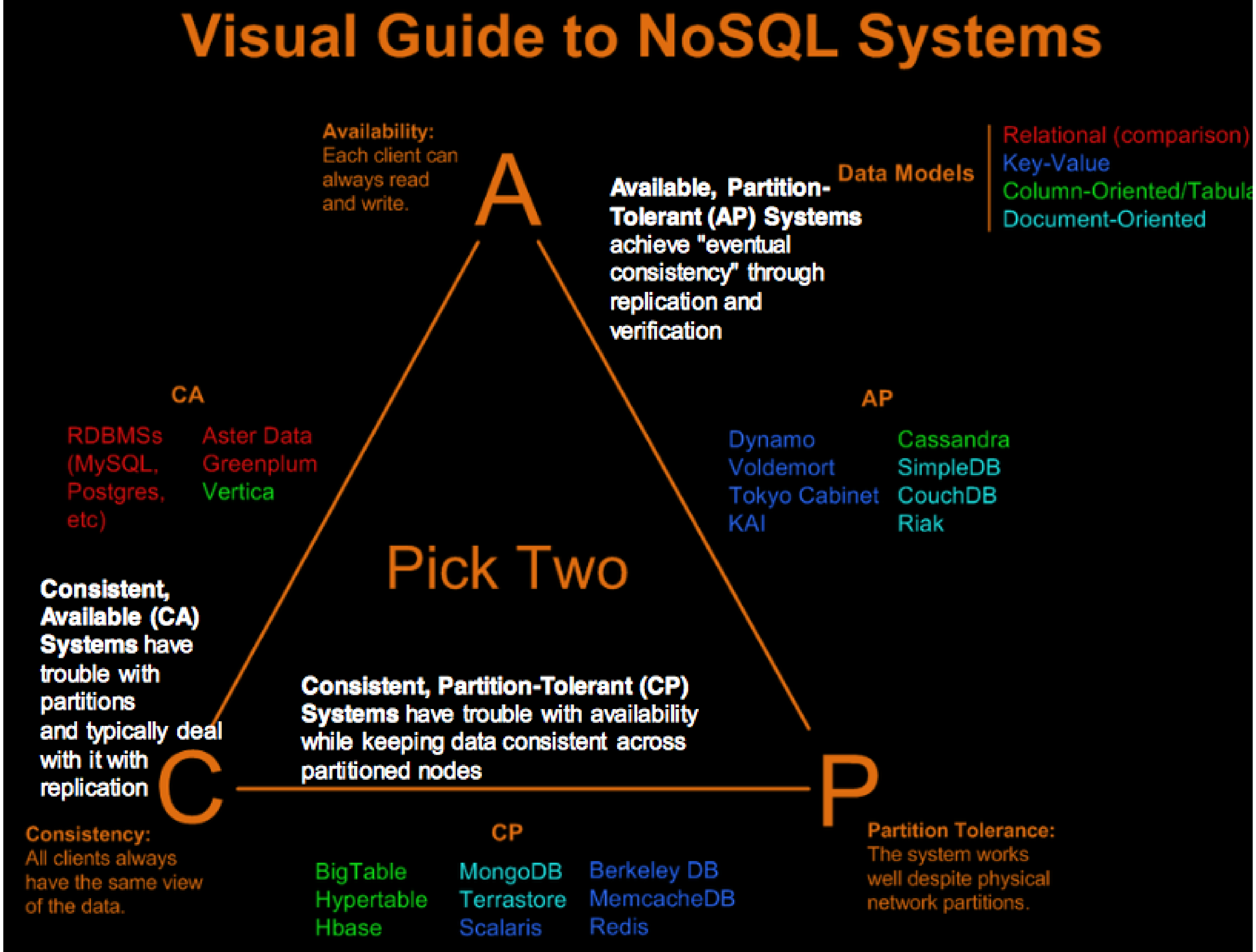
GIVEN:

- Many nodes
- Nodes contain ***replicas of partitions*** of the data

- Consistency
  - All replicas contain the same version of data
  - Client always has the same view of the data (no matter what node)
- Availability
  - System remains operational on failing nodes
  - All clients can always read and write
- Partition tolerance
  - multiple entry points
  - System remains operational on system split (communication malfunction)
  - System works well across physical network partitions



CAP Theorem:
satisfying all three at the same time is impossible


Visual Guide to NoSQL Systems
Availability:
Each client can always read and write.
A
Data Models
Relational (comparison)
Key-Value
Column-Oriented/Tabula
Document-Oriented
Available, Partition-Tolerant (AP) Systems achieve "eventual consistency" through replication and verification
CA
RDBMSs (MySQL, Postgres, etc)
Aster Data
Greenplum
Vertica
AP
Dynamo
Voldemort
Tokyo Cabinet
KAI
Cassandra
SimpleDB
CouchDB
Riak
Pick Two
Consistent, Available (CA) Systems have trouble with partitions and typically deal with it with replication
Consistent, Partition-Tolerant (CP) Systems have trouble with availability while keeping data consistent across partitioned nodes
C
P
Consistency:
All clients always have the same view of the data.
CP
BigTable
Hypertable
Hbase
MongoDB
Terrastore
Scalaris
Berkeley DB
MemcacheDB
Redis
Partition Tolerance:
The system works well despite physical network partitions.

Sharding of data

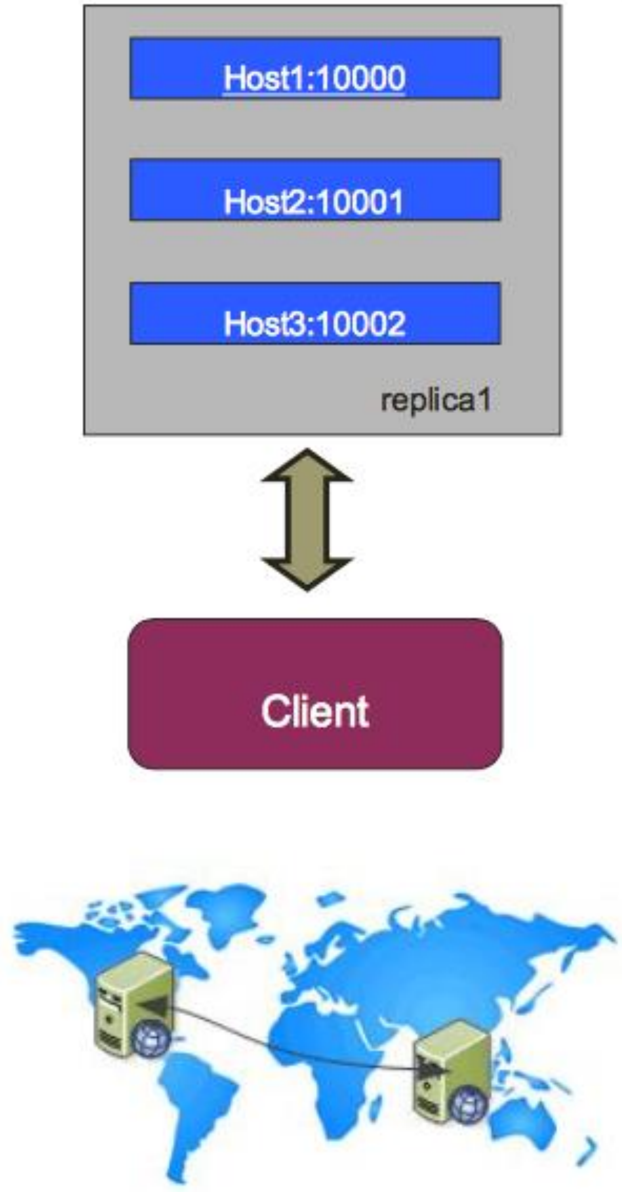
- Distributes a single logical database system across a cluster of machines
- Uses range-based partitioning to distribute documents based on a specific shard key
- Automatically balances the data associated with each shard
- Can be turned on and off per collection (table)

Replica Sets

- Redundancy and Failover
- Zero downtime for upgrades and maintenance

- Master-slave replication
  - Strong Consistency
  - Delayed Consistency

- Geospatial features



How does NoSQL vary from RDBMS?

- Looser schema definition
- Applications written to deal with specific documents/ data
  - Applications aware of the schema definition as opposed to the data
- Designed to handle distributed, large databases
- Trade offs:
  - No strong support for ad hoc queries but designed for speed and growth of database
    - Query language through the API
  - Relaxation of the ACID properties

Benefits of NoSQL

Elastic Scaling

- RDBMS scale up – bigger load , bigger server
- NO SQL scale out – distribute data across multiple hosts seamlessly

DBA Specialists

- RDMS require highly trained expert to monitor DB
- NoSQL require less management, automatic repair and simpler data models

Big Data

- Huge increase in data RDMS: capacity and constraints of data volumes at its limits
- NoSQL designed for big data

Benefits of NoSQL

Flexible data models

- Change management to schema for RDMS have to be carefully managed
- NoSQL databases more relaxed in structure of data
  - Database schema changes do not have to be managed as one complicated change unit
  - Application already written to address an amorphous schema

Economics

- RDMS rely on expensive proprietary servers to manage data
- No SQL: clusters of cheap commodity servers to manage the data and transaction volumes
- Cost per gigabyte or transaction/second for NoSQL can be lower than the cost for a RDBMS

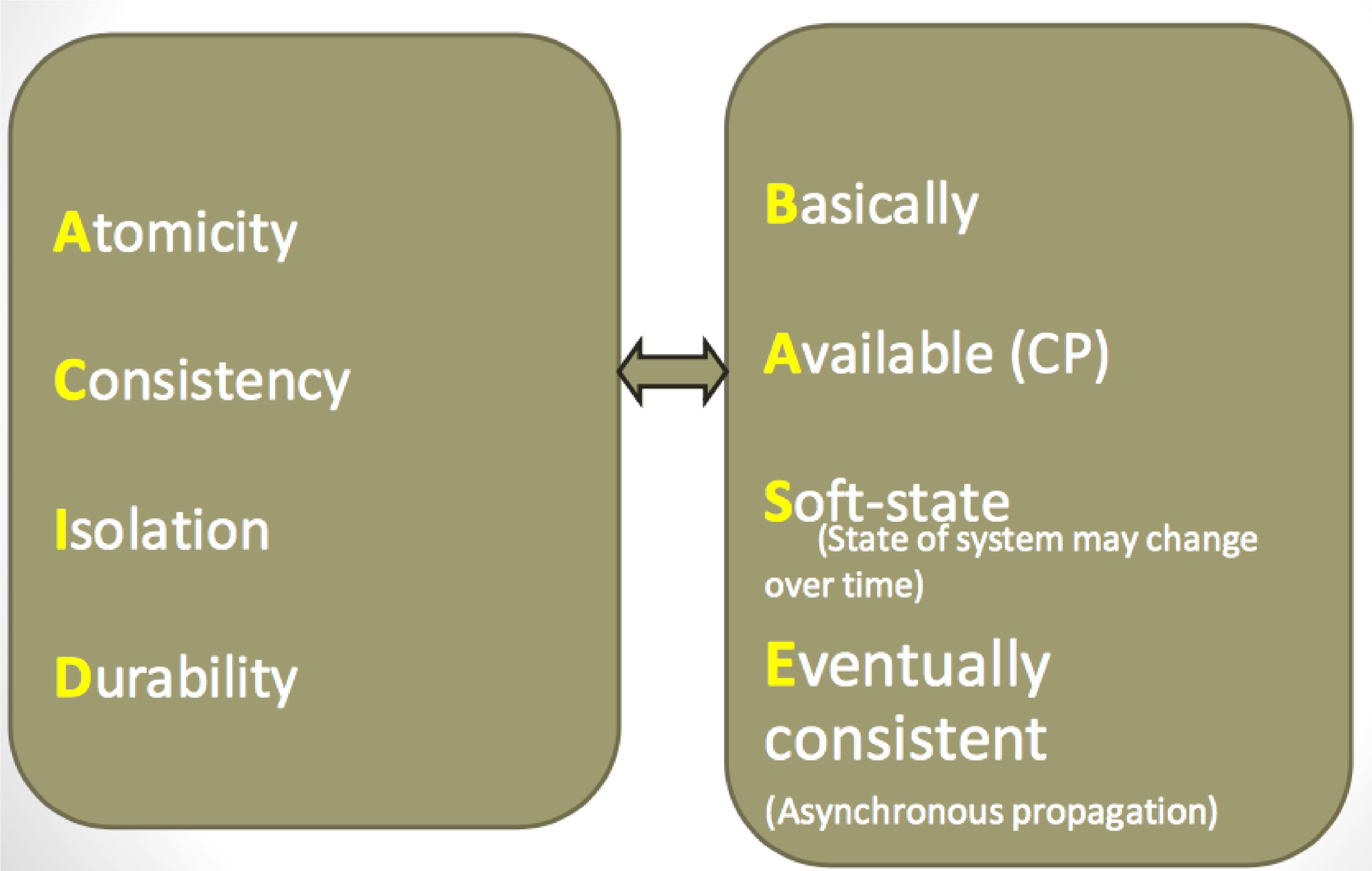
Drawbacks of NoSQL

- Support
  - RDBMS vendors provide a high level of support to clients
    - Stellar reputation
  - NoSQL – are open source projects with startups supporting them
    - Reputation not yet established
- Maturity
  - RDMS mature product: means stable and dependable
    - Also means old no longer cutting edge nor interesting
  - NoSQL are still implementing their basic feature set

Drawbacks of NoSQL

- **Administration**
  - RDMS administrator well defined role
  - No SQL's goal: no administrator necessary however NO SQL still requires effort to maintain
- **Lack of Expertise**
  - Whole workforce of trained and seasoned RDMS developers
  - Still recruiting developers to the NoSQL camp
- **Analytics and Business Intelligence**
  - **RDMS designed to address this niche**
  - NoSQL designed to meet the needs of an Web 2.0 application - not designed for ad hoc query of the data
    - Tools are being developed to address this need

ACID or BASE



Pritchett, D.: BASE: An Acid Alternative (queue.acm.org/detail.cfm?id=1394128)