Data Management for Data Science

Lecture 11: Spark

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Logistics/Announcements

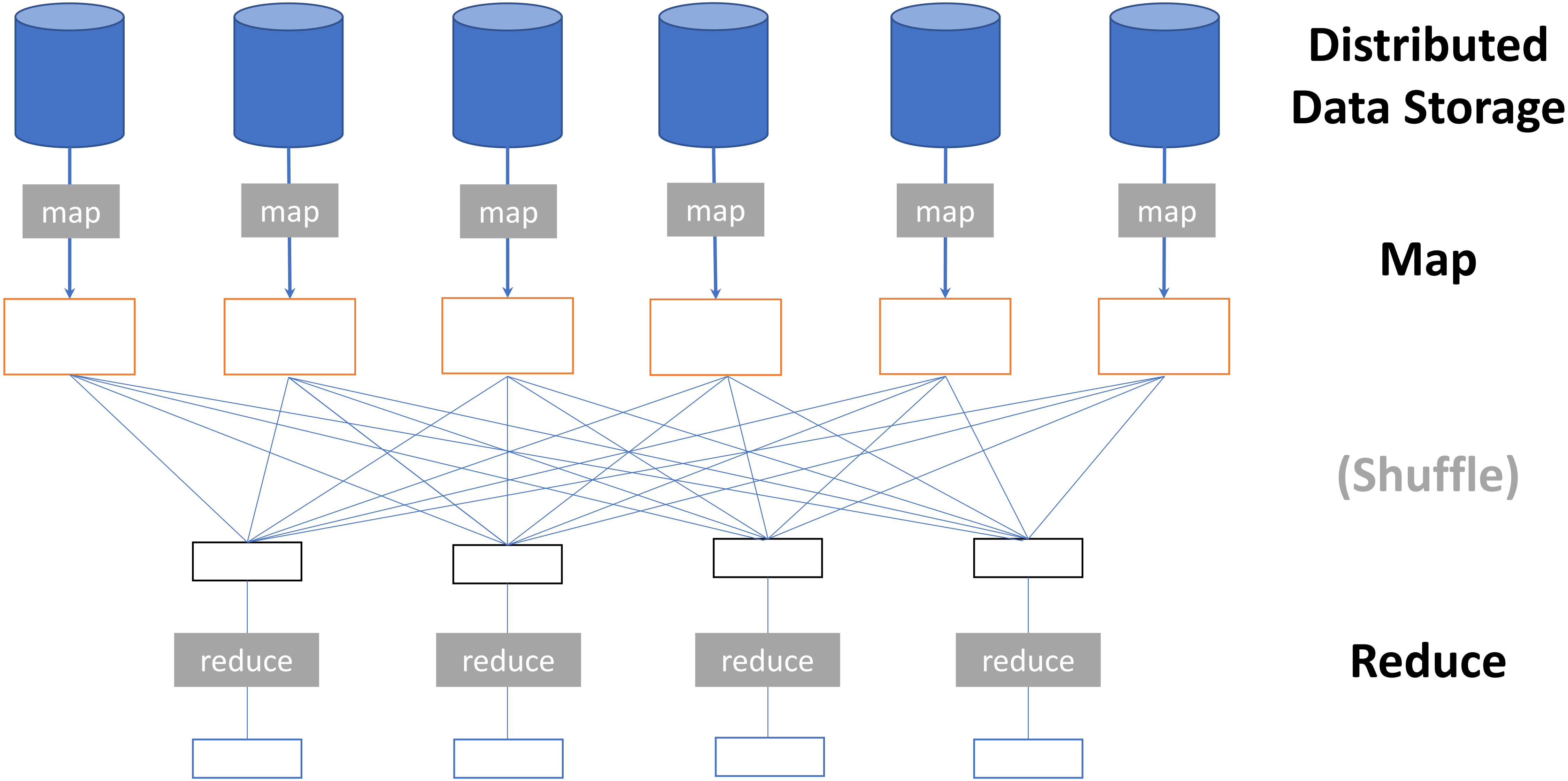
- Questions on PA3?

Today’s Lecture

1. MapReduce Implementation
2. Spark

1. MapReduce Implementation

Recall: The Map Reduce Abstraction for Distributed Algorithms



MapReduce: what happens in between?

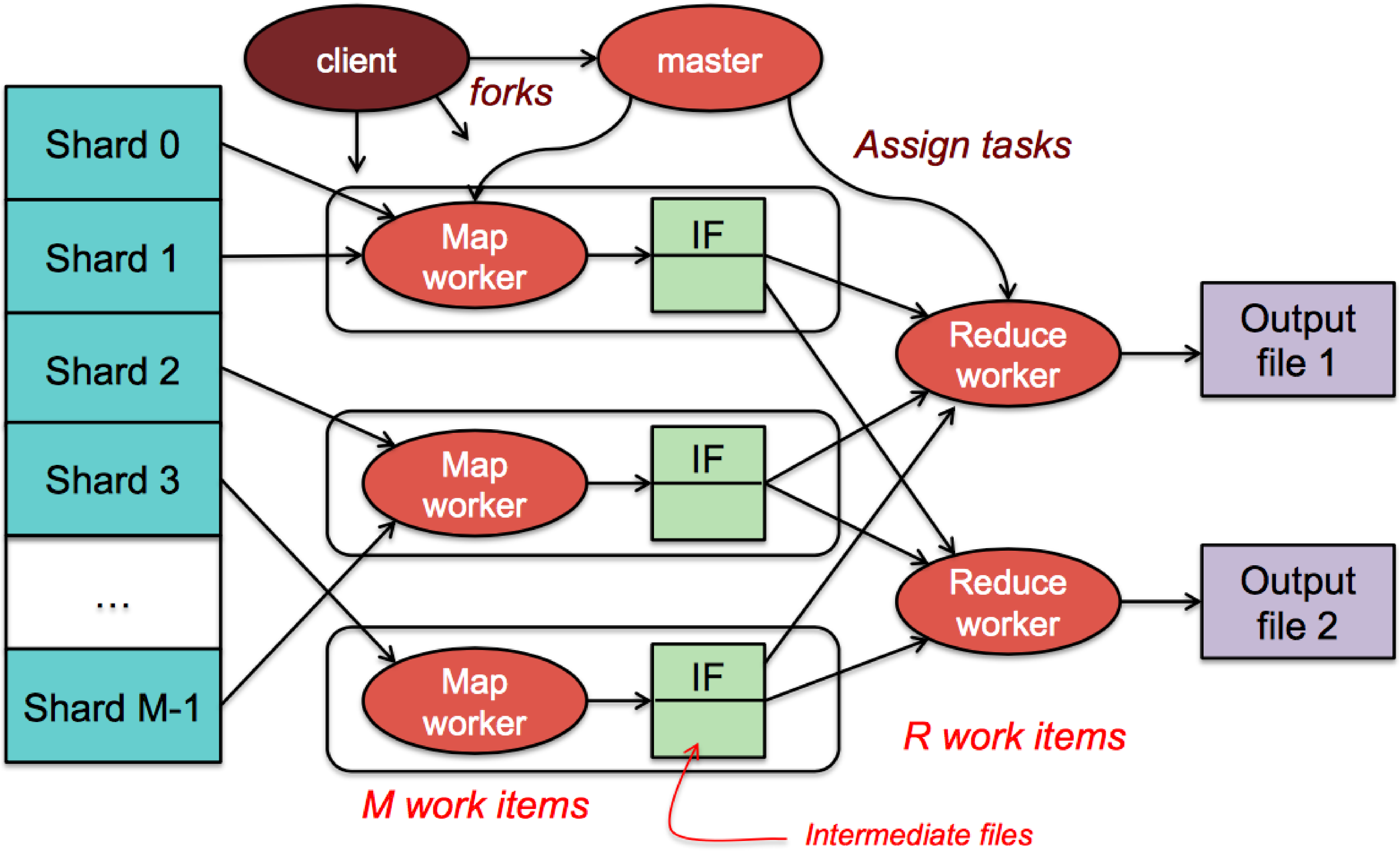
- Map
  - Grab the relevant data from the source (parse into key, value)
  - Write it to an intermediate file
- Partition
  - Partitioning: identify which of *R* reducers will handle which keys
  - Map partitions data to target it to one of *R* Reduce workers based on a partitioning function (both *R*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

Map Worker

- Shuffle & Sort
  - Shuffle: Fetch the relevant partition of the output from all 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

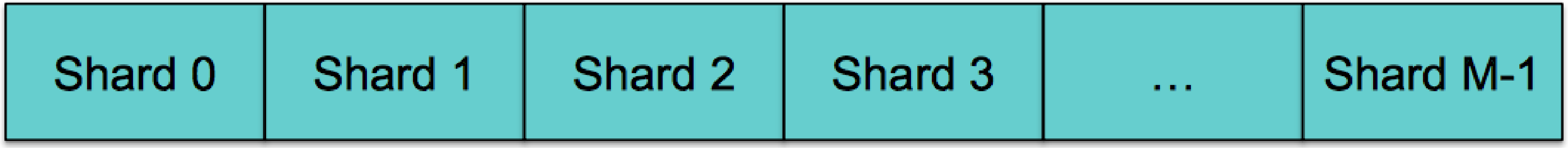
Reduce Worker

MapReduce: the complete picture



Step 1: Split input files into chunks (shards)

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

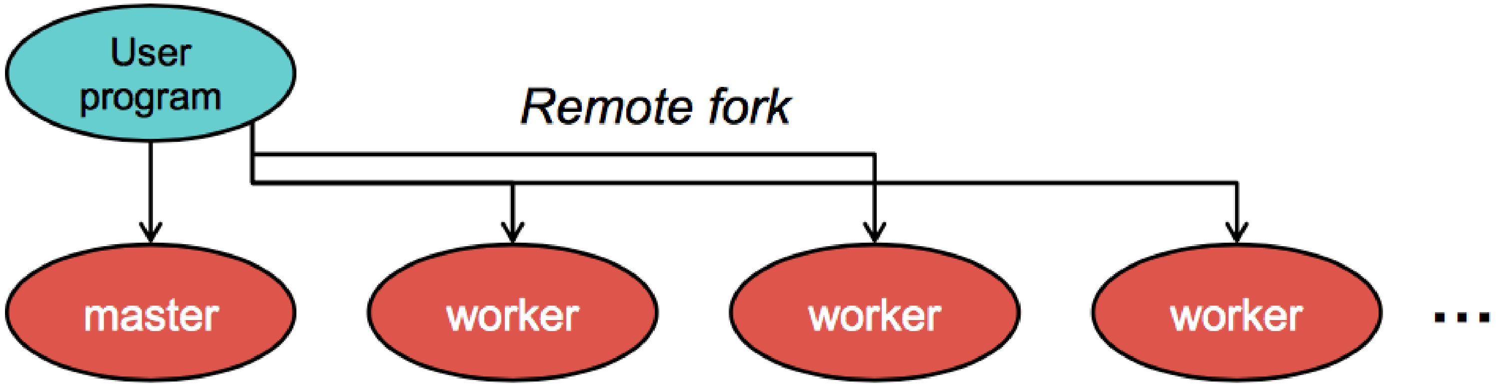


Input files

Divided into *M* shards

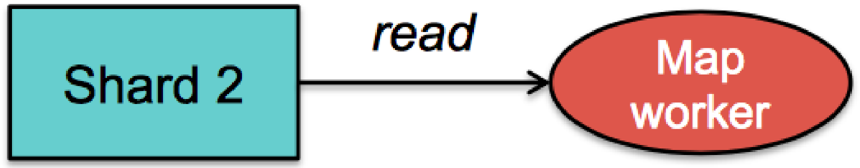
Step 2: Fork processes

- 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



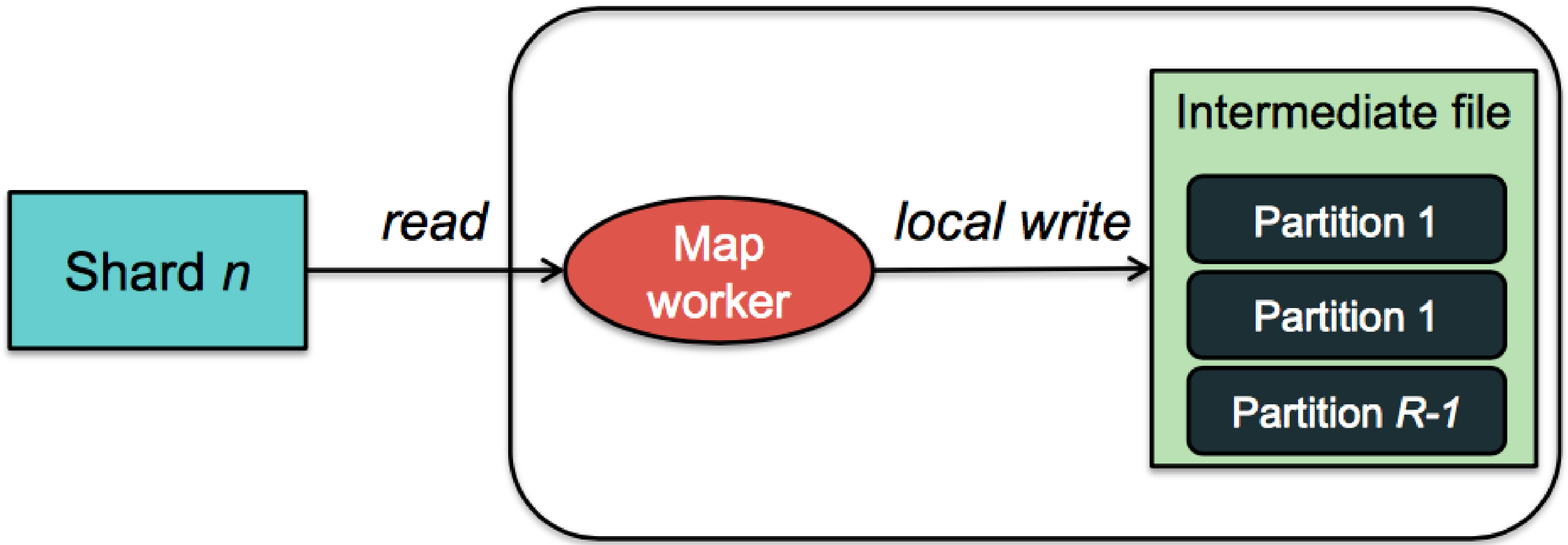
Step 3: Run Map Tasks

- 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

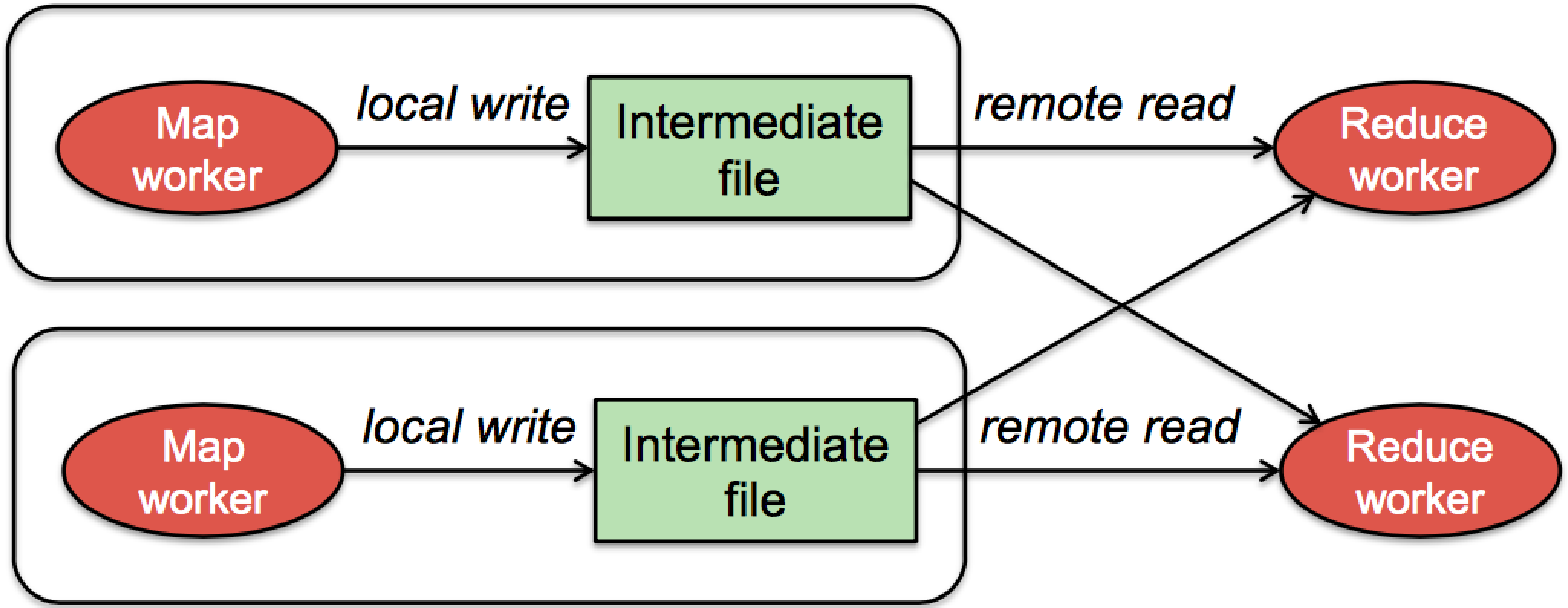


Step 4a: Partitioning

- 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

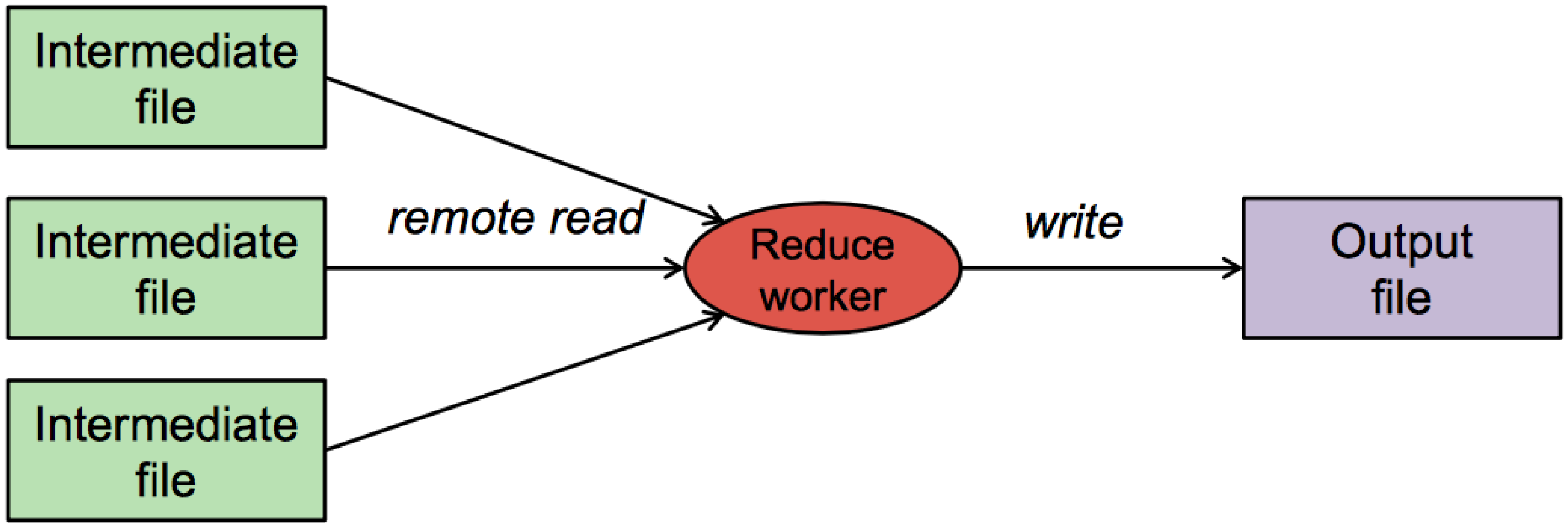
- Reduce worker gets notified by the master about the location of intermediate files for its partition
- Shuffle: Uses RPCs to read the data from the local disks of the map workers
- Sort: When the *reduce* worker reads intermediate data for its partition
  - It sorts the data by the intermediate keys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

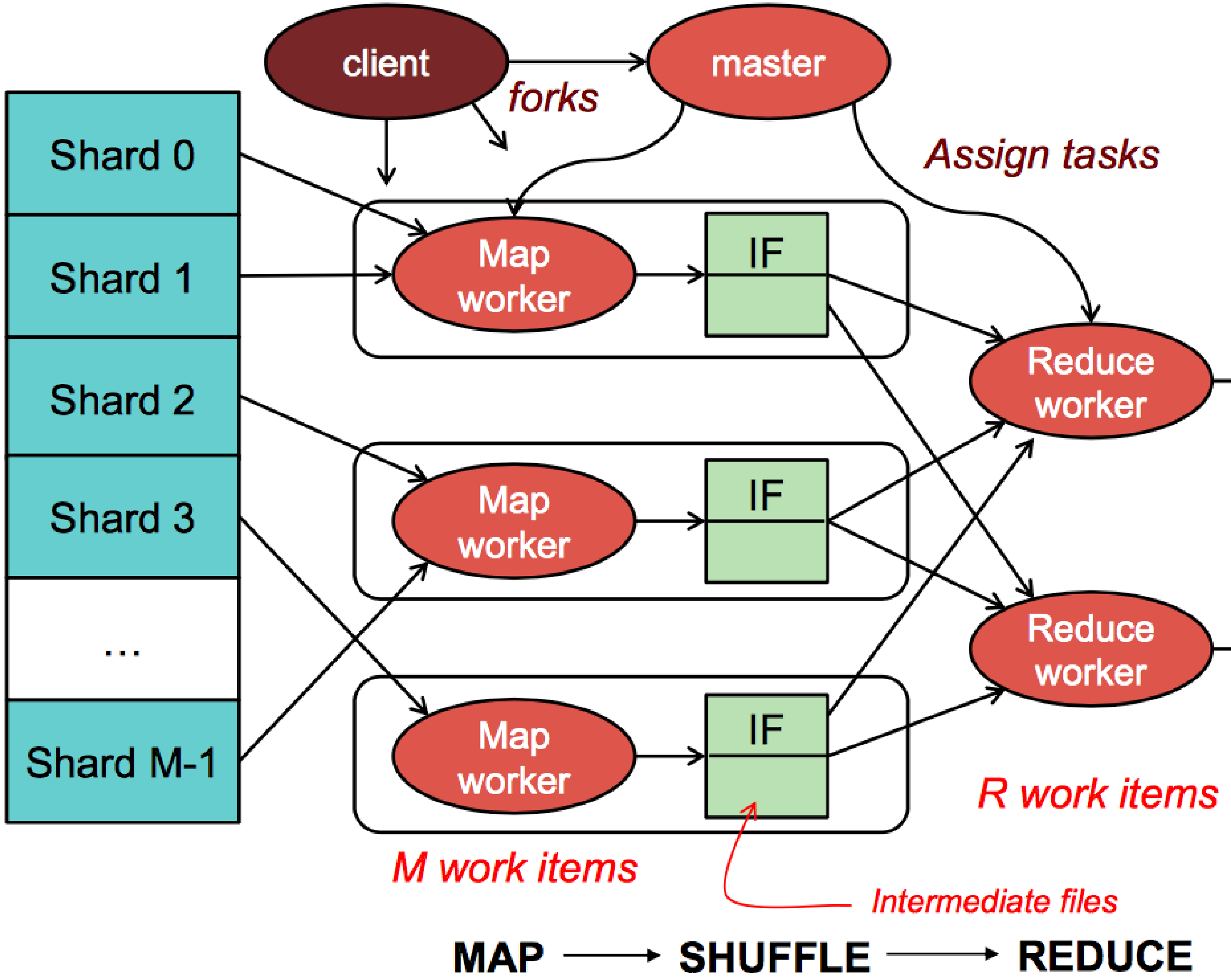


Step 7: Return to user

- 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



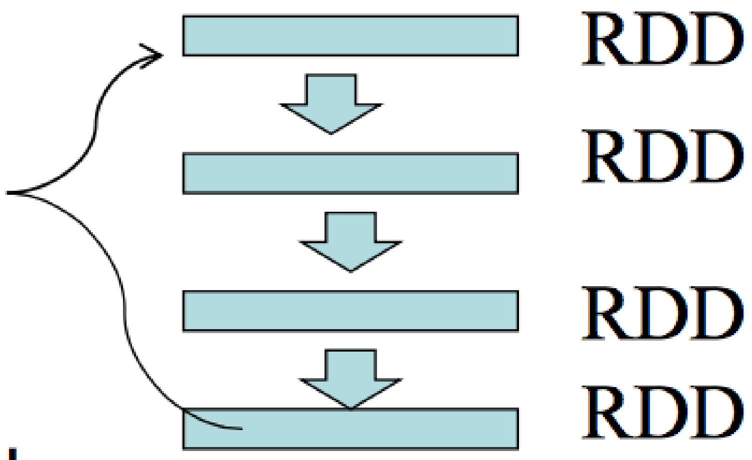
We need a distributed file system!

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



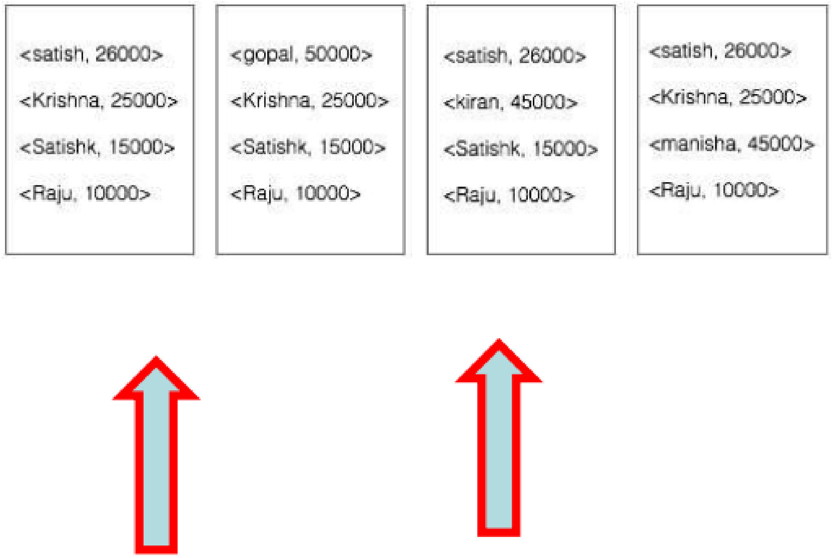
RDD: Resilient Distributed Datasets

- **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**

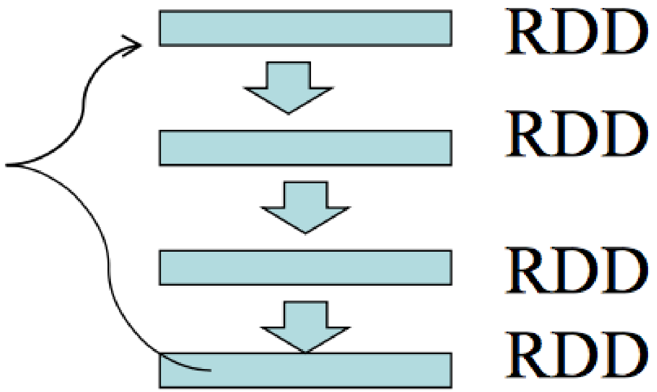
Operations

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

MapReduce vs Spark



Map and reduce tasks operate on key-value pairs



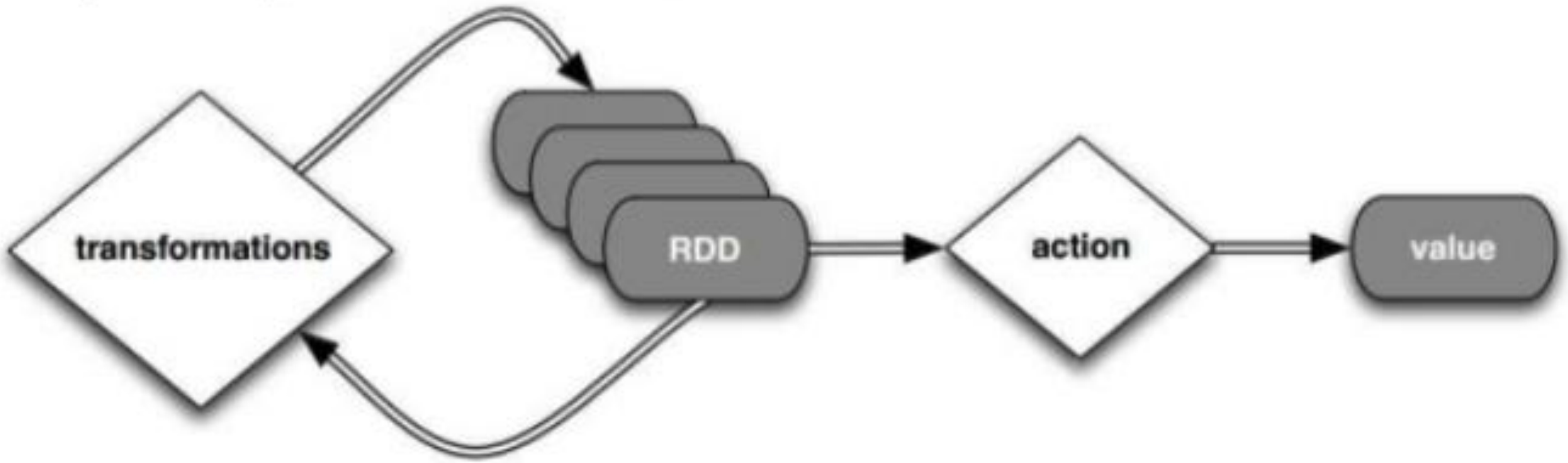
Spark operates on **RDD**

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



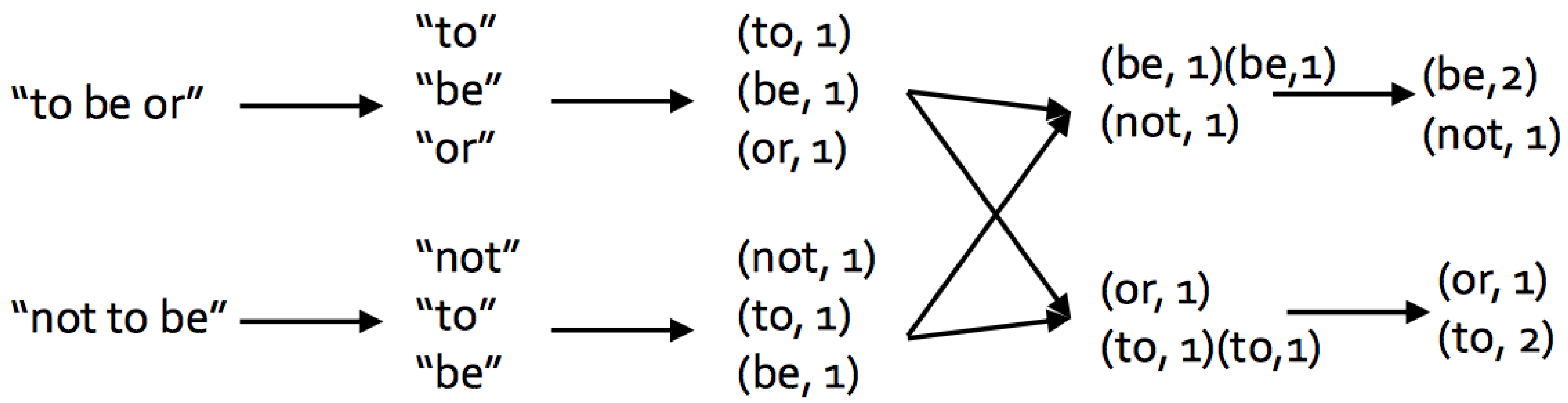
Transformation cause only metadata change

DAG

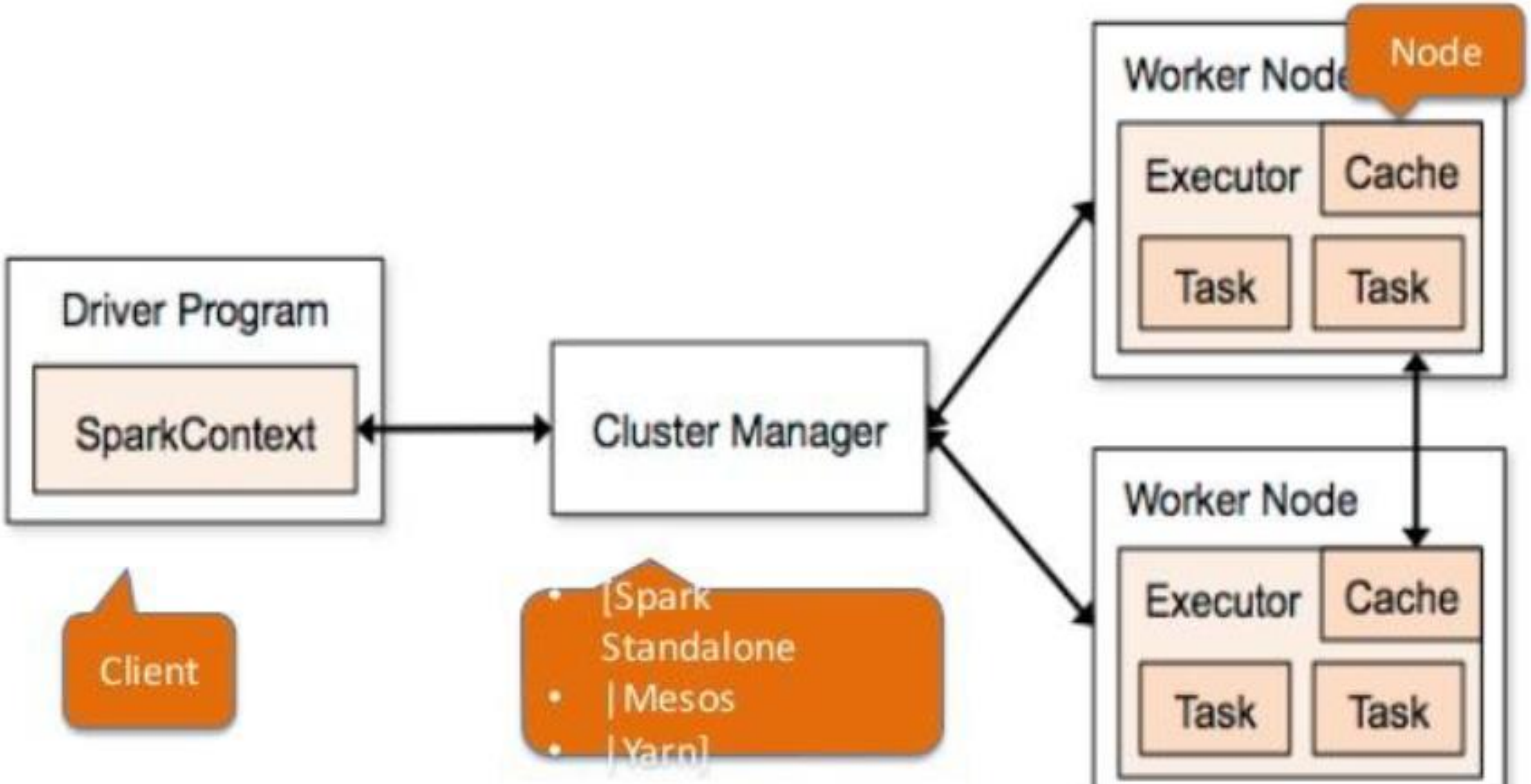
- Directed Acyclic Graph – sequence of computations performed on data
- Node – RDD partition
- Edge – transformation on top of the data
- Acyclic – graph cannot return to the older partition
- Directed – transformation is an action that transitions data partitions state (from A to B)

Example: Word Count

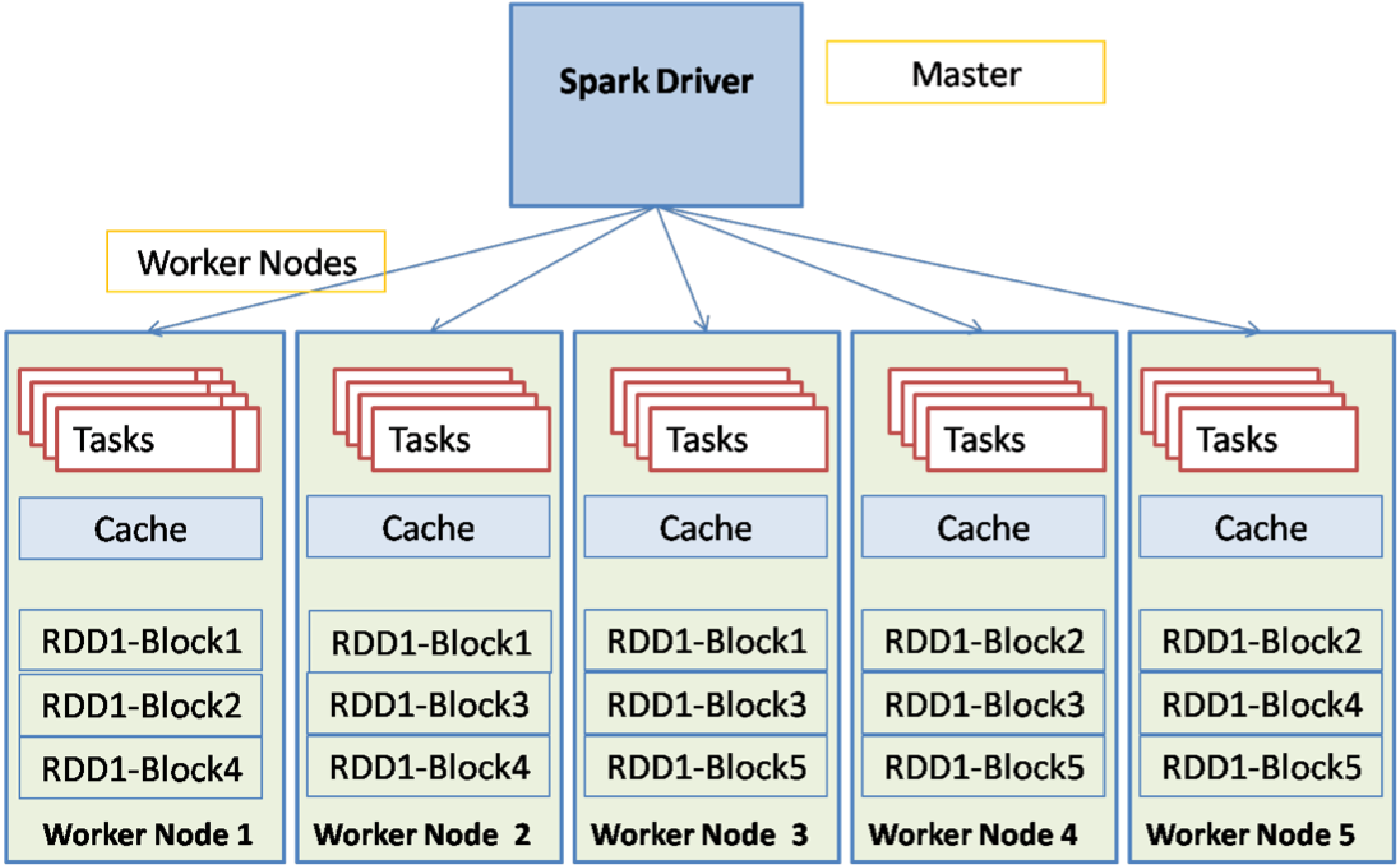
```
> lines = sc.textFile("hamlet.txt")
> counts = lines.flatMap(lambda line: line.split(" "))
                .map(lambda word: (word, 1))
                .reduceByKey(lambda x, y: x + y)
```



Spark Architecture



Spark Components



Spark Driver

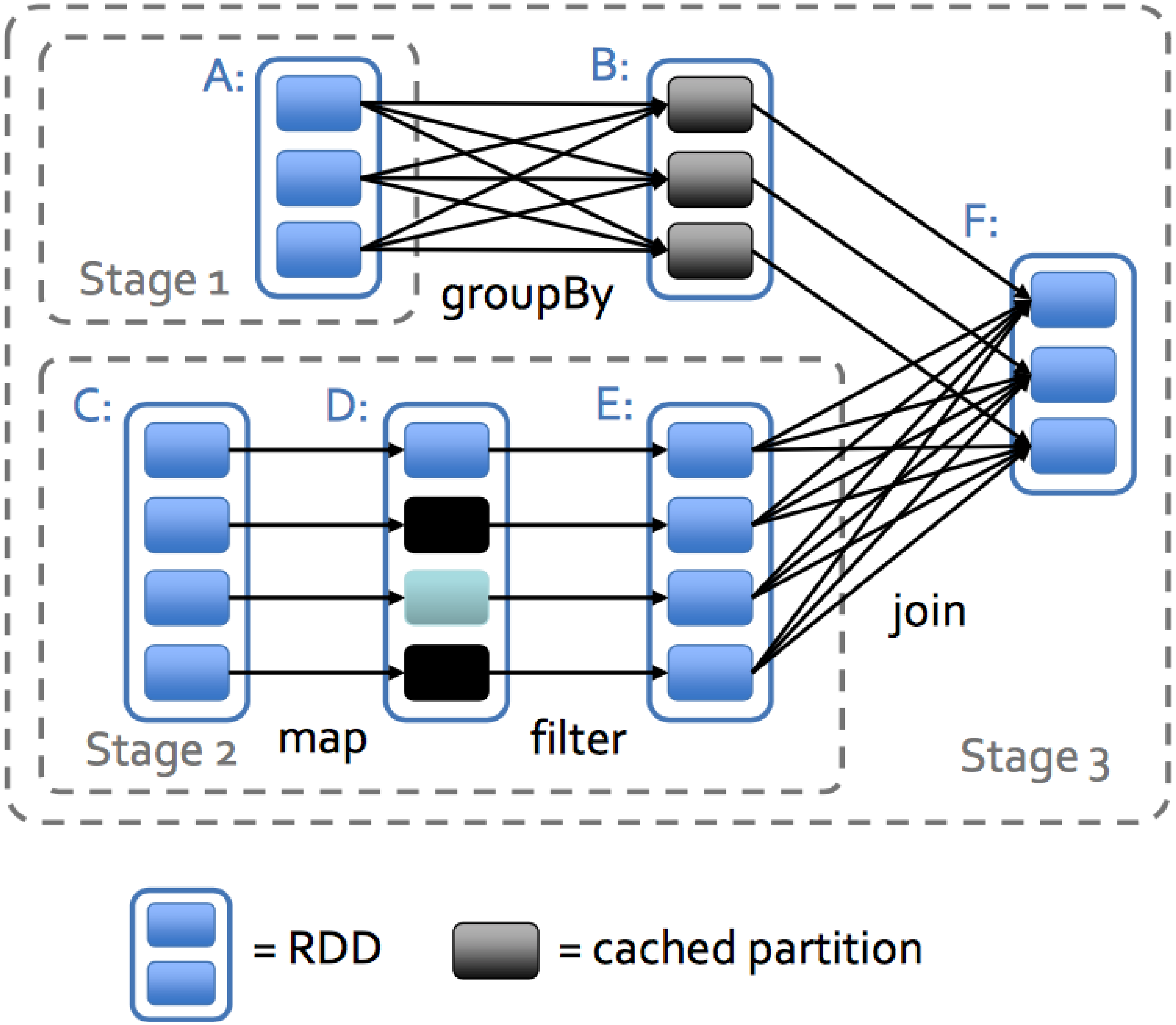
- Entry point of the Spark Shell (Scala, Python, R)
- The place where SparkContext is created
- Translates RDD into the execution graph
- Splits graph into stages
- Schedules tasks and controls their execution
- Stores metadata about all the RDDs and their partitions
- Brings up Spark WebUI with job information

Spark Executor

- Stores the data in cache in JVM heap or on HDDs
- Reads data from external sources
- Writes data to external sources
- Performs all the data processing

Dag Scheduler

- **General task graphs**
- **Automatically pipelines functions**
- **Data locality aware**
- **Partitioning aware to avoid shuffles**



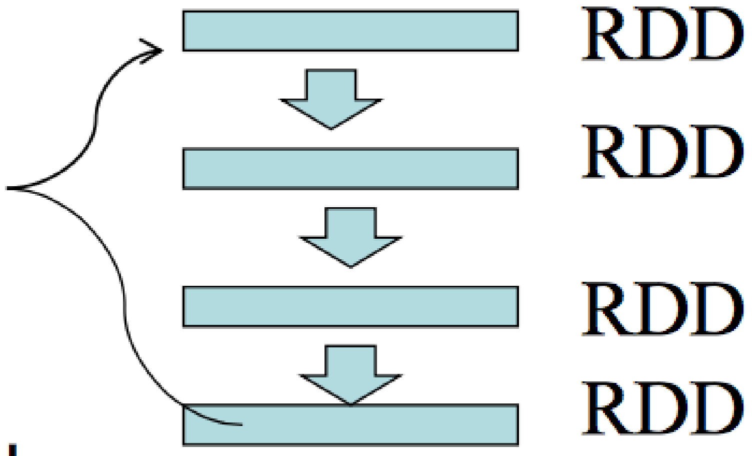
More RDD Operations

- map
- filter
- groupBy
- sort
- union
- join
- leftOuterJoin
- rightOuterJoin

- reduce
- count
- fold
- reduceByKey
- groupByKey
- cogroup
- cross
- zip

sample
take
first
partitionBy
mapWith
pipe
save ...

Spark's secret is really the RDD abstraction



RDD: Resilient Distributed Datasets

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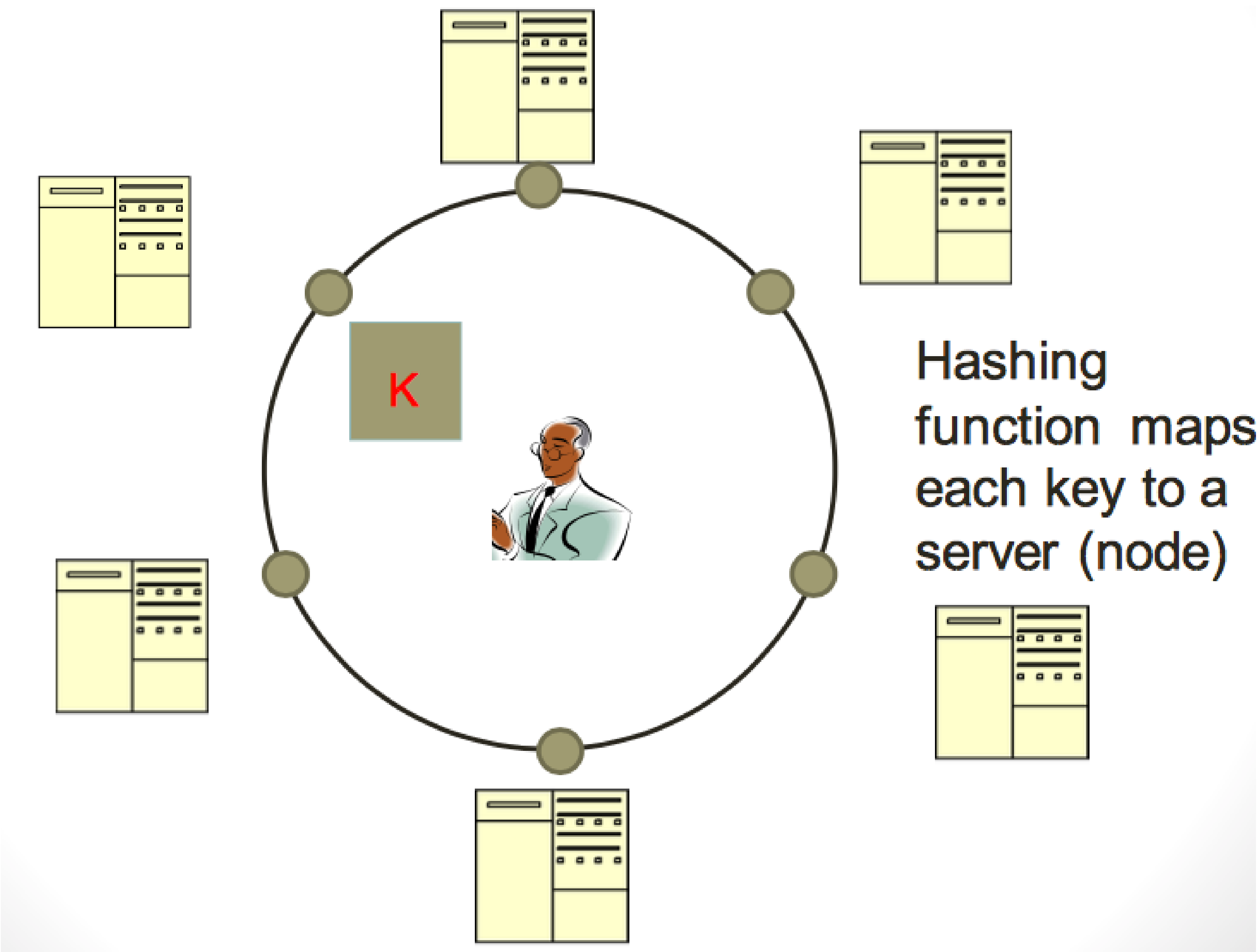
Typical NoSQL architecture



CAP theorem for NoSQL

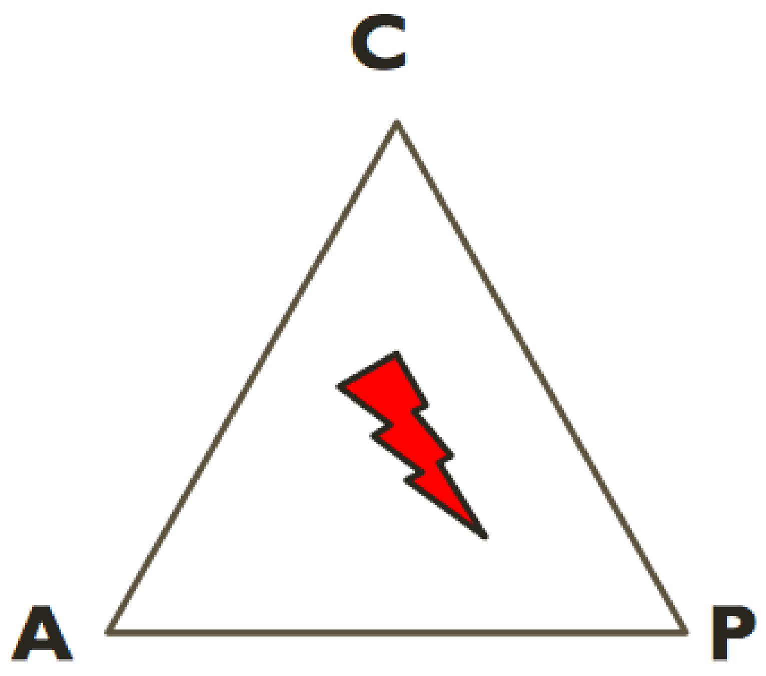
- What the CAP theorem really says: If you cannot limit the number of faults and requests can be directed to any server and you insist on serving every request you receive then you cannot possibly be consistent
- How it is interpreted: You must always give something up: consistency, availability or tolerance to failure and reconfiguration

CAP theorem for NoSQL

GIVEN:

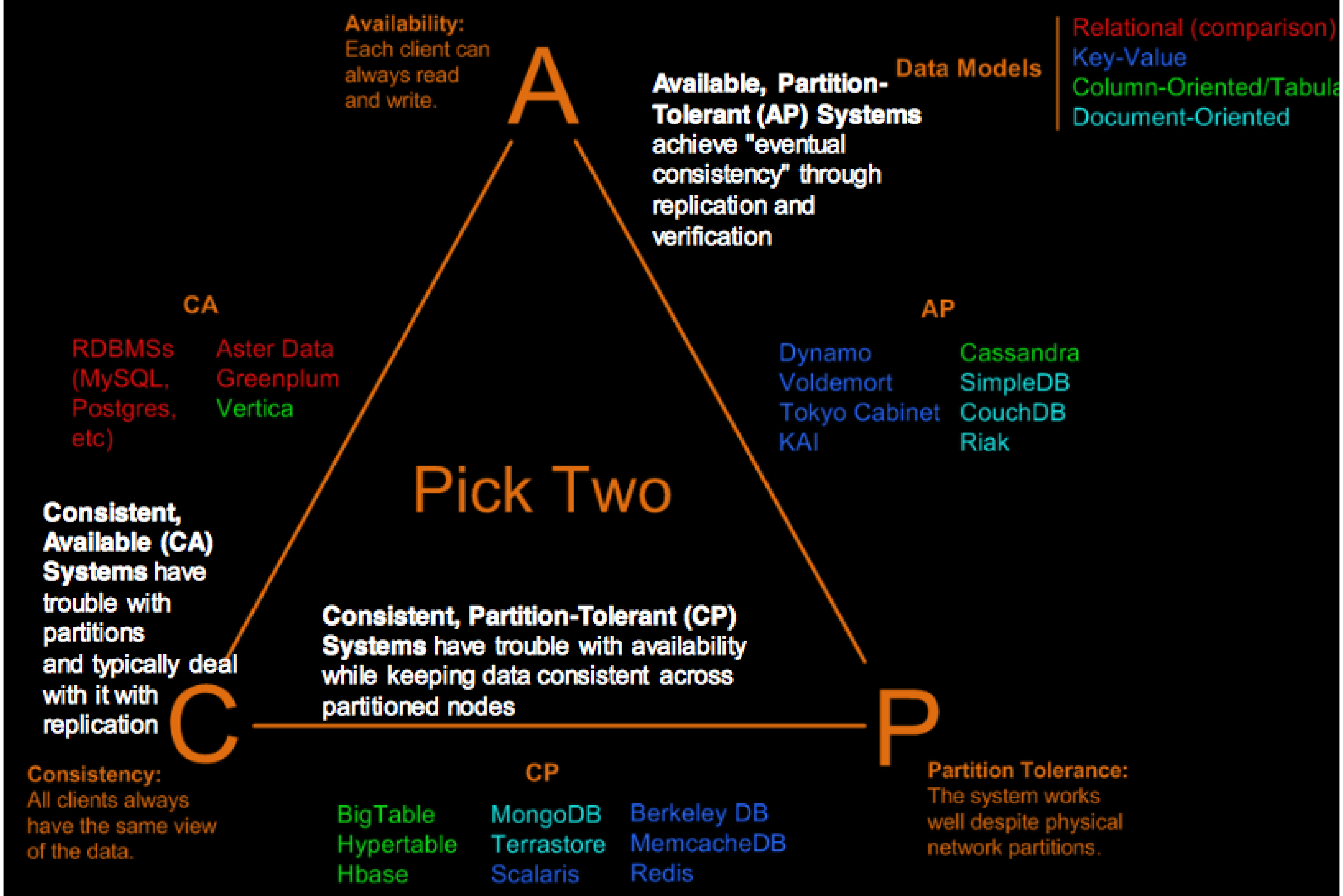
- Many nodes
- Nodes contain ***replicas of partitions*** of the data

- 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



Sharding of data

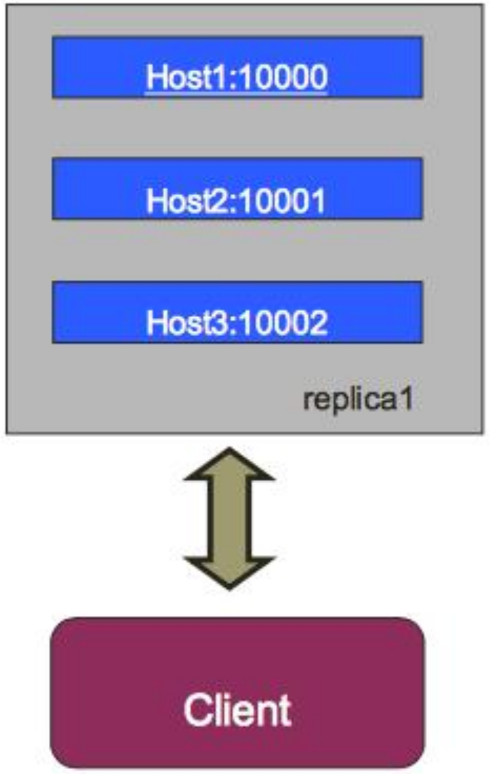
- Distributes a single logical database system across a cluster of machines
- Uses range-based partitioning to distribute documents based on a specific shard key
- Automatically balances the data associated with each shard
- Can be turned on and off per collection (table)

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

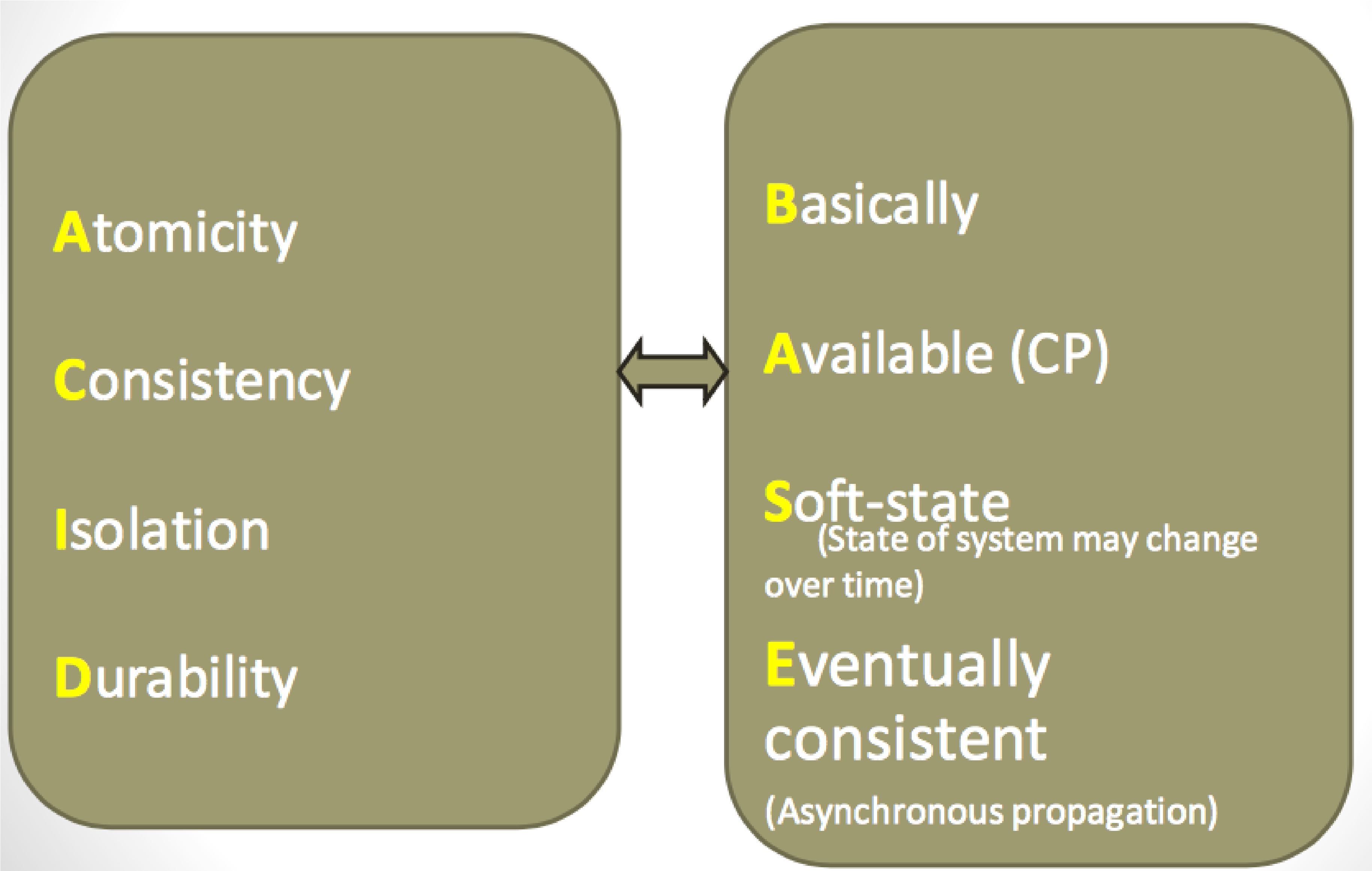
Drawbacks of NoSQL

- 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)