

# **Big Data Algorithm Design and Application**

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**UICBUSINESS**



# More about me...

- Past big data analytics teaching experience
  - Several semester-long big data courses
    - [http://kzhang6.people.uic.edu/teaching/ids594\\_f14/](http://kzhang6.people.uic.edu/teaching/ids594_f14/)
    - Tutorials on big data algorithm and application
      - <http://kzhang6.people.uic.edu/tutorial/amcis2014.html>
- Past big data analytics research experience
  - <http://kzhang6.people.uic.edu/research.html>

# What we'll cover...

- Big data overview
- Hadoop overview
  - Framework
  - MapReduce programming
- Applications
  - Scalable clustering algorithm: K-Means
  - Iterative graph algorithm: single source shortest path
  - Scalable recommender system: Item-based collaborative filtering

**Focus on MapReduce-based algorithm design**

# We can not cover all...



Machine Learning



enterprise infrastructure  
technology operations  
information objectives  
scorecards capitaliz  
analyze text mining  
metrics manage  
applications finance  
connection techniques  
solution stakeholder





**Big data**

# Big data is everywhere...



processed about 24 petabytes of data per day in 2009.



transfers about 30 petabytes of data through its networks each day.

As of January 2013, Facebook users had uploaded over 240 billion photos, with 350 million new photos every day.



S3: 449B objects, peak 290k request/second (7/2011)  
1T objects (6/2012)



By 2012, LHC collision data was being produced at approximately 25 petabytes per year.



Twitter now sends and receives as many as 200 million "tweets" every day.



150 PB on 50k+ servers running 15k apps (6/2011)

# Why big data?

Science  
Engineering  
Business  
Healthcare

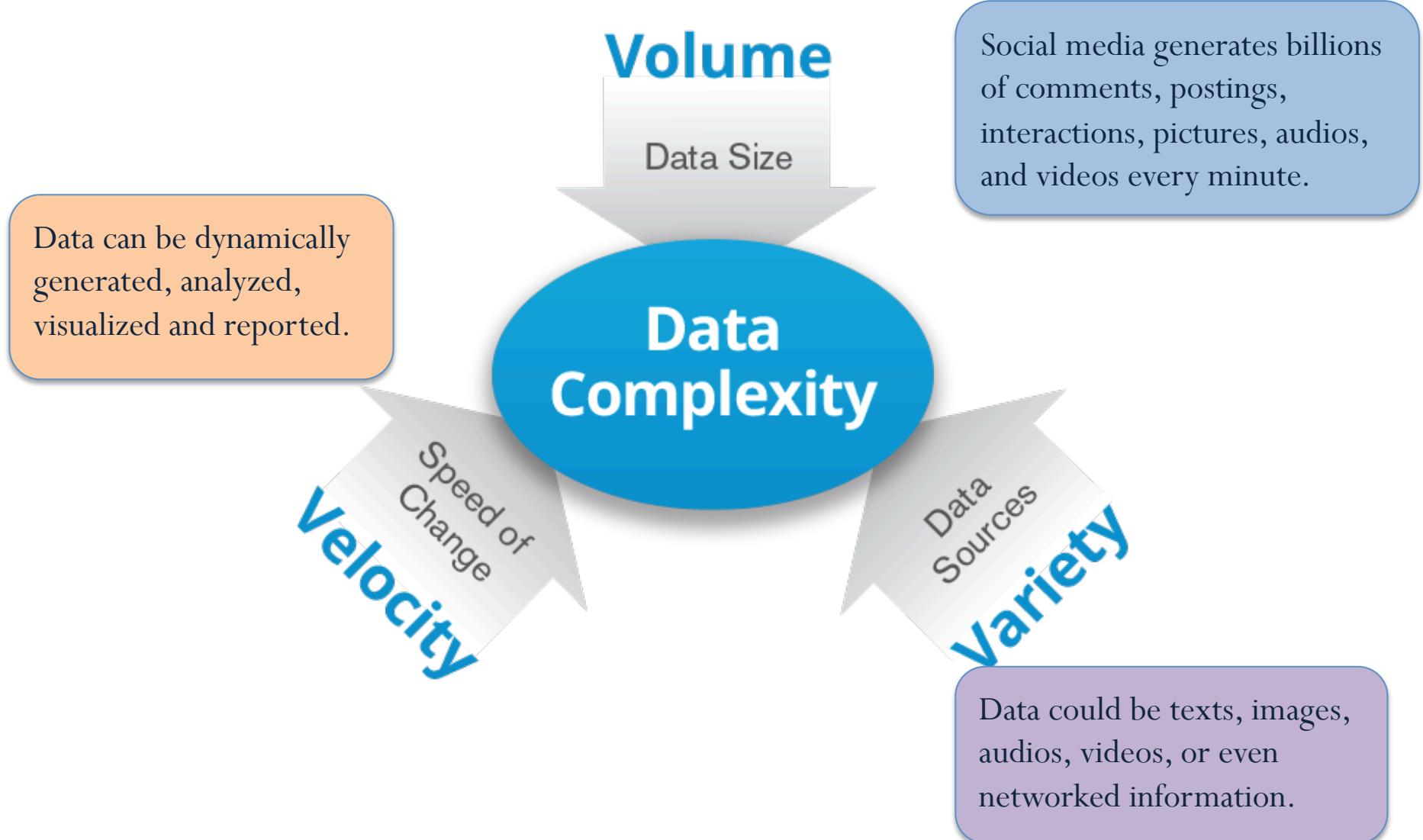
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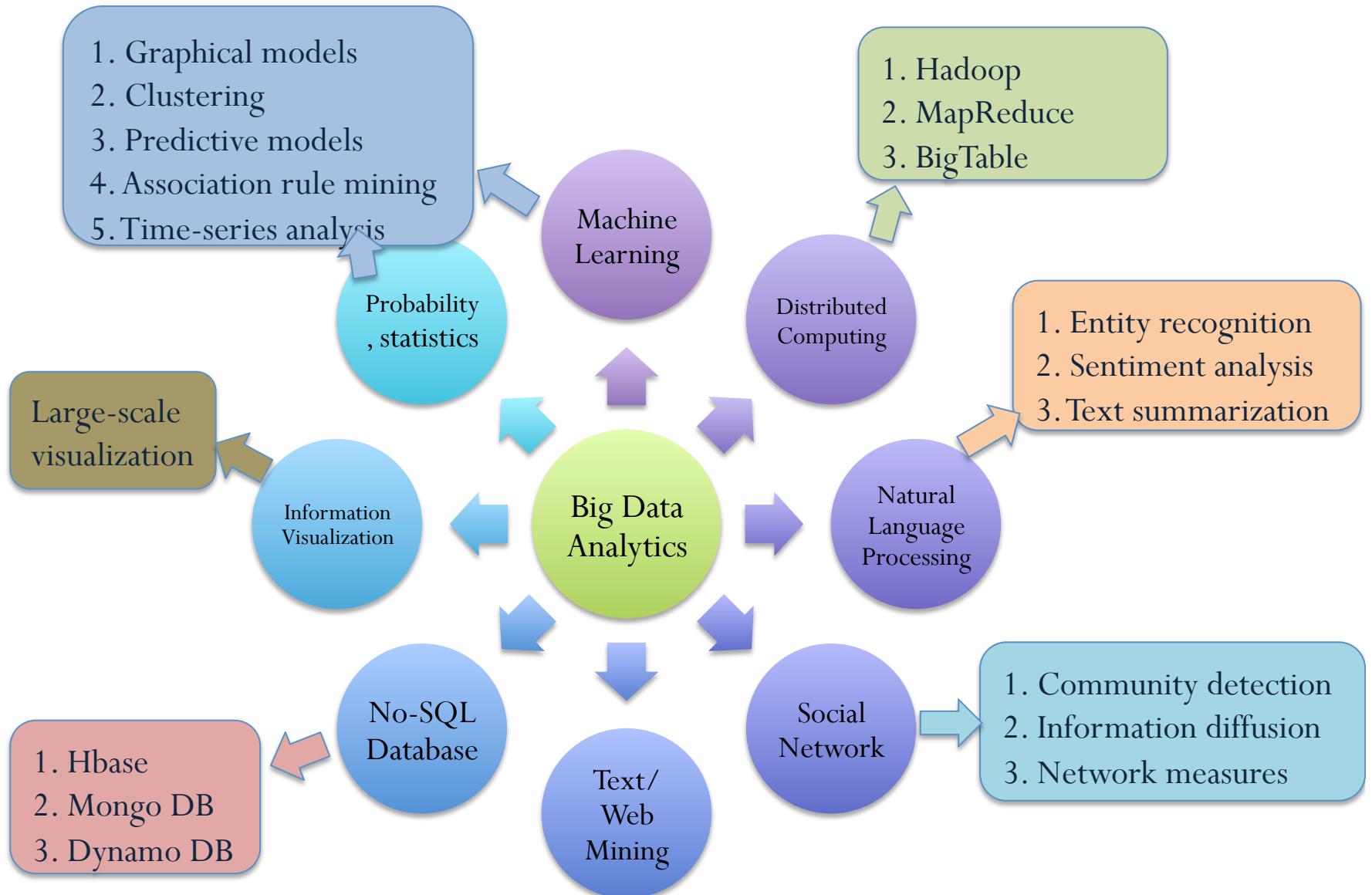
# What is big data?

- Big data is a blanket term for any **types** of data sets so **large** and **complex** that it becomes difficult to process using on-hand **data management tools** or traditional **data processing** applications. [from Wikipedia]

# Big data characteristics (3 Vs)



# Techniques in big data analytics



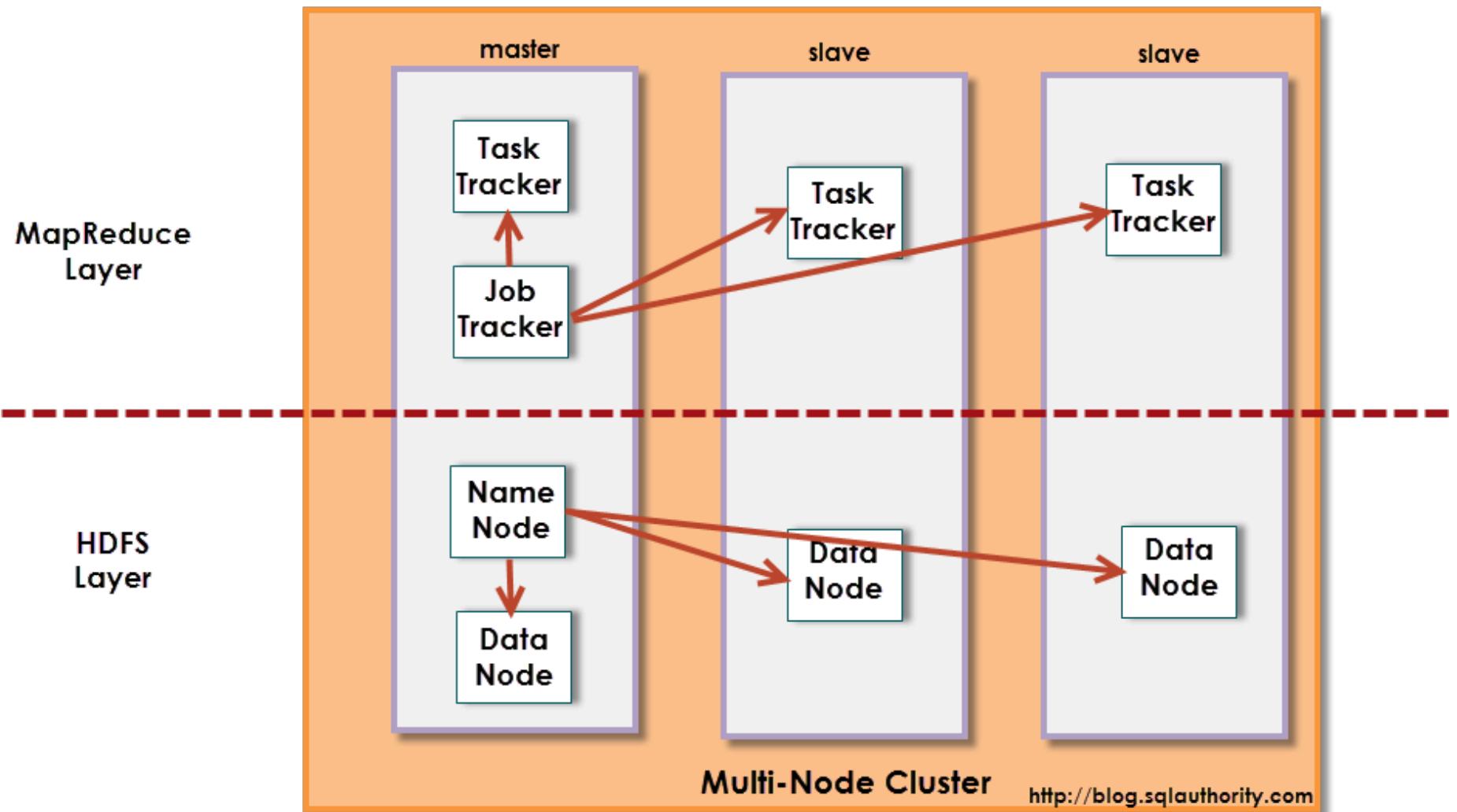


- Hadoop is a **software framework** for distributed processing of large datasets across large clusters of computers.
- It is based on a simple **programming model** called MapReduce.
- It has two main layers:
  - Distributed file system (HDFS)
  - Execution engine (MapReduce)

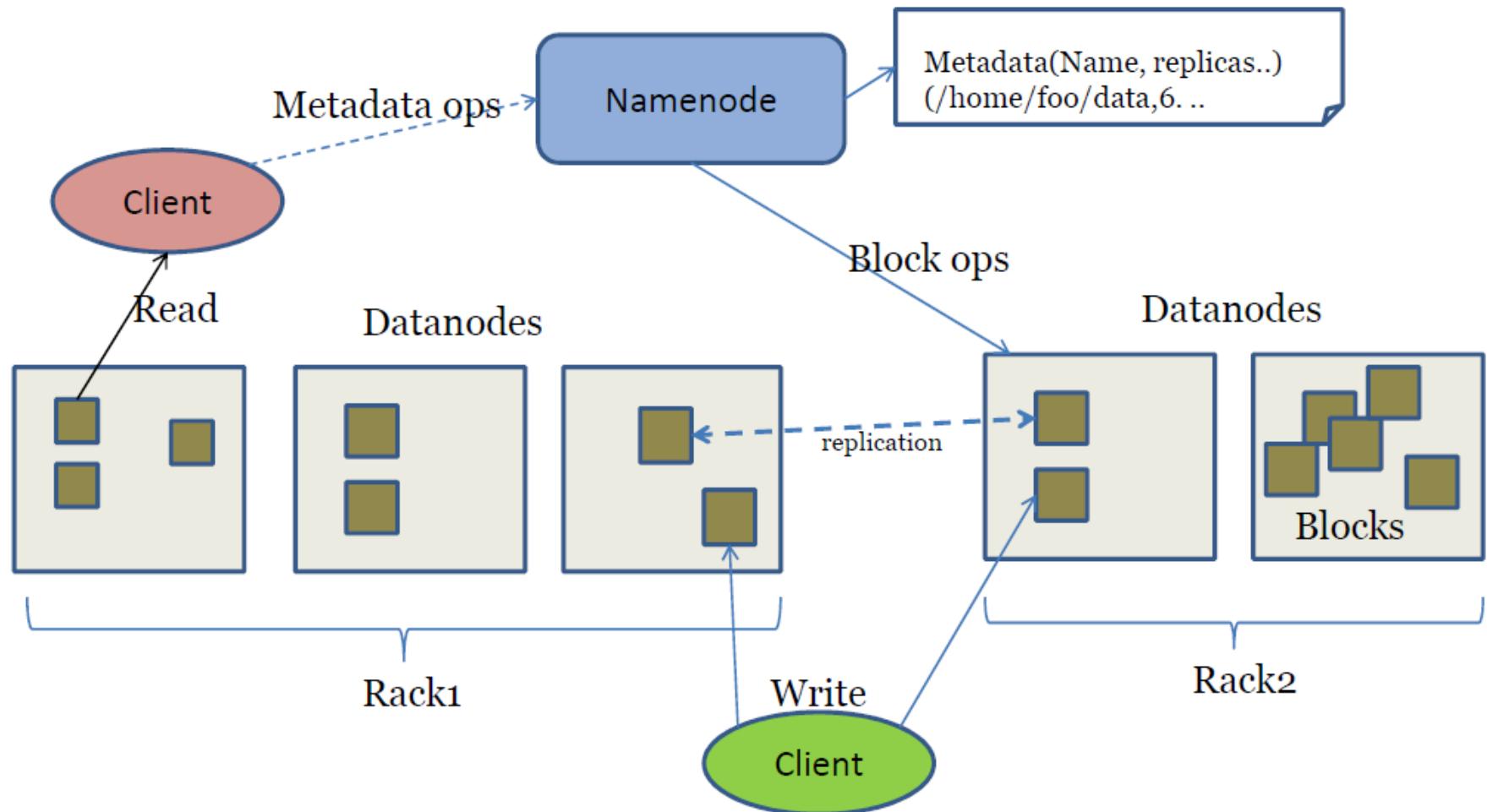
# Usually, big data problems

- Iterate over a large number of records
- Extract something of interest from each → **Map**
- Shuffle and sort intermediate results
- Aggregate intermediate results → **Reduce**
- Generate final output

**Key idea: provide a functional abstraction for these two operations**

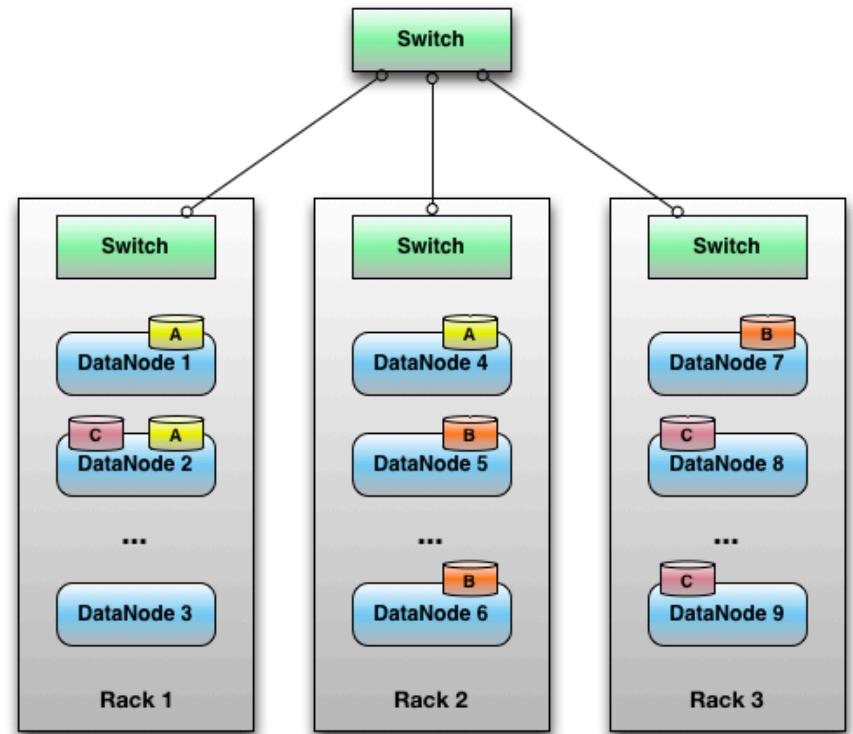


# HDFS Architecture



# Data replication

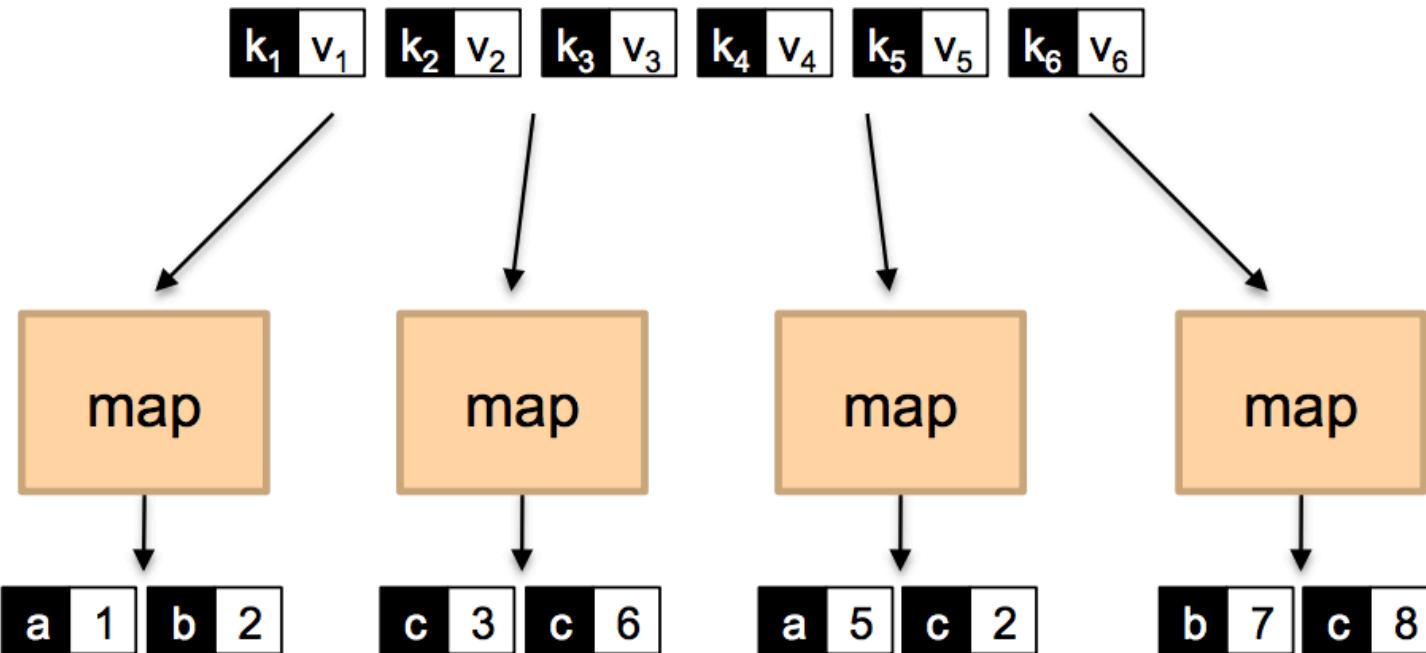
- First copy is written to the local node (write affinity).
- Second copy is written to a DataNode within the same rack.
- Third copy is written to a DataNode in a different rack.



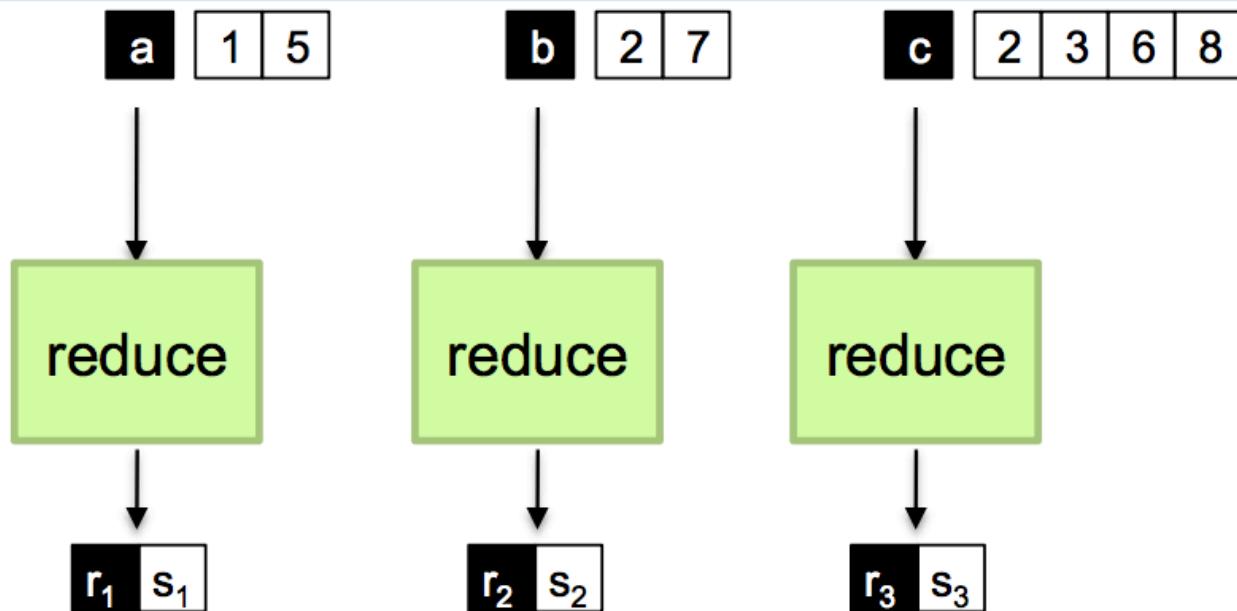
**Objectives: load balancing, fast access, fault tolerance.**

# MapReduce

- Everything in MapReduce is <key, value> pair
- Programmers create two functions/methods:  
 $\text{map}(\text{key1}, \text{value1}) \rightarrow [\text{key2}, \text{value2}]$   
 $\text{reduce}(\text{key2}, [\text{value2}]) \rightarrow [\text{key3}, \text{value3}]$
- The execution framework in Hadoop handles everything else...



### Shuffle and Sort: aggregate values by keys



# MapReduce

- Programmers create two functions/methods:  
 $\text{map}(\text{key1}, \text{value1}) \rightarrow [\langle \text{key2}, \text{value2} \rangle]$   
 $\text{reduce}(\text{key2}, [\text{value2}]) \rightarrow [\langle \text{key3}, \text{value3} \rangle]$
- The execution framework in Hadoop handles everything else...

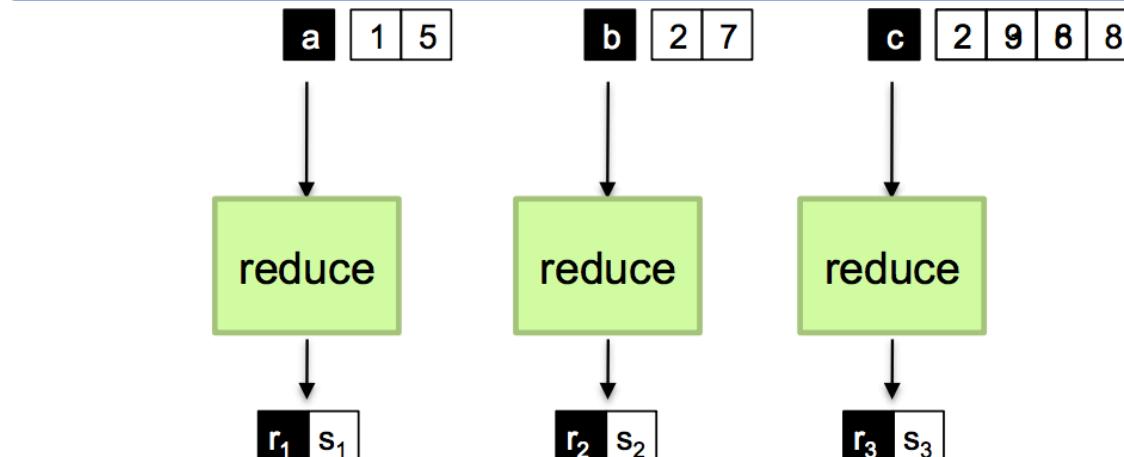
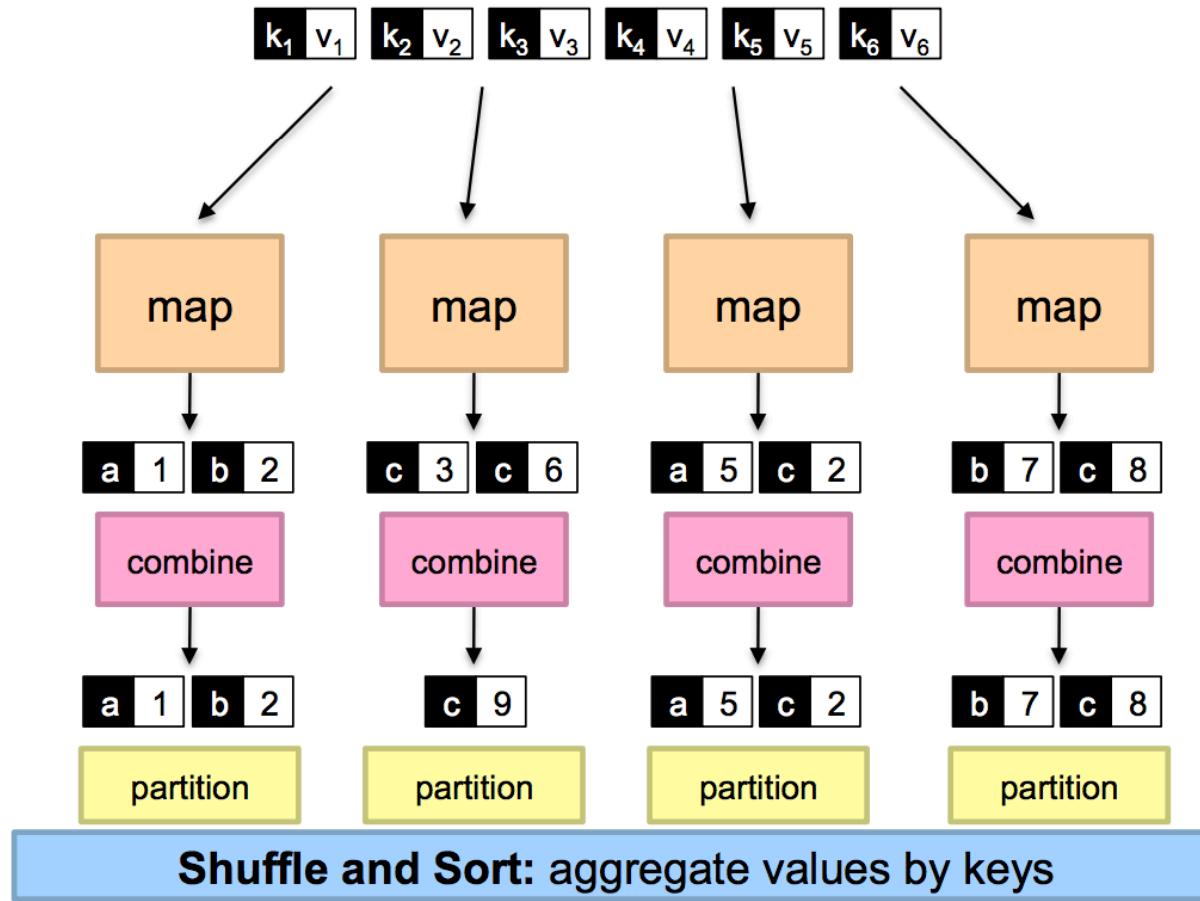
**What's "everything else"?**

# **MapReduce “Runtime”**

- Handles scheduling
  - Assigns mappers and reducers to do tasks
- Handles data distribution
  - Moves processes to data
- Handles synchronization
  - Collects, sorts, and shuffles intermediate data
- Handles errors and faults
  - Detects failures and restarts
- Everything happens on top of a distributed file system

# MapReduce

- Programmers create two functions/methods:  
 $\text{map}(\text{key1}, \text{value1}) \rightarrow [\langle \text{key2}, \text{value2} \rangle]$   
 $\text{reduce}(\text{key2}, [\text{value2}]) \rightarrow [\langle \text{key3}, \text{value3} \rangle]$
- The execution framework in Hadoop handles everything else...
- Usually, programmers also customize:  
 $\text{partition } (k', \text{number of partitions}) \rightarrow \text{partition for } k'$ 
  - Often a simple hash of the key, e.g.,  $\text{hash}(k') \bmod n$
  - Divides up key space for parallel reduce operations $\text{combine } (k', v') \rightarrow \langle k', v' \rangle^*$ 
  - Mini-reducers that run in memory after the map phase
  - Used as an optimization to reduce network traffic



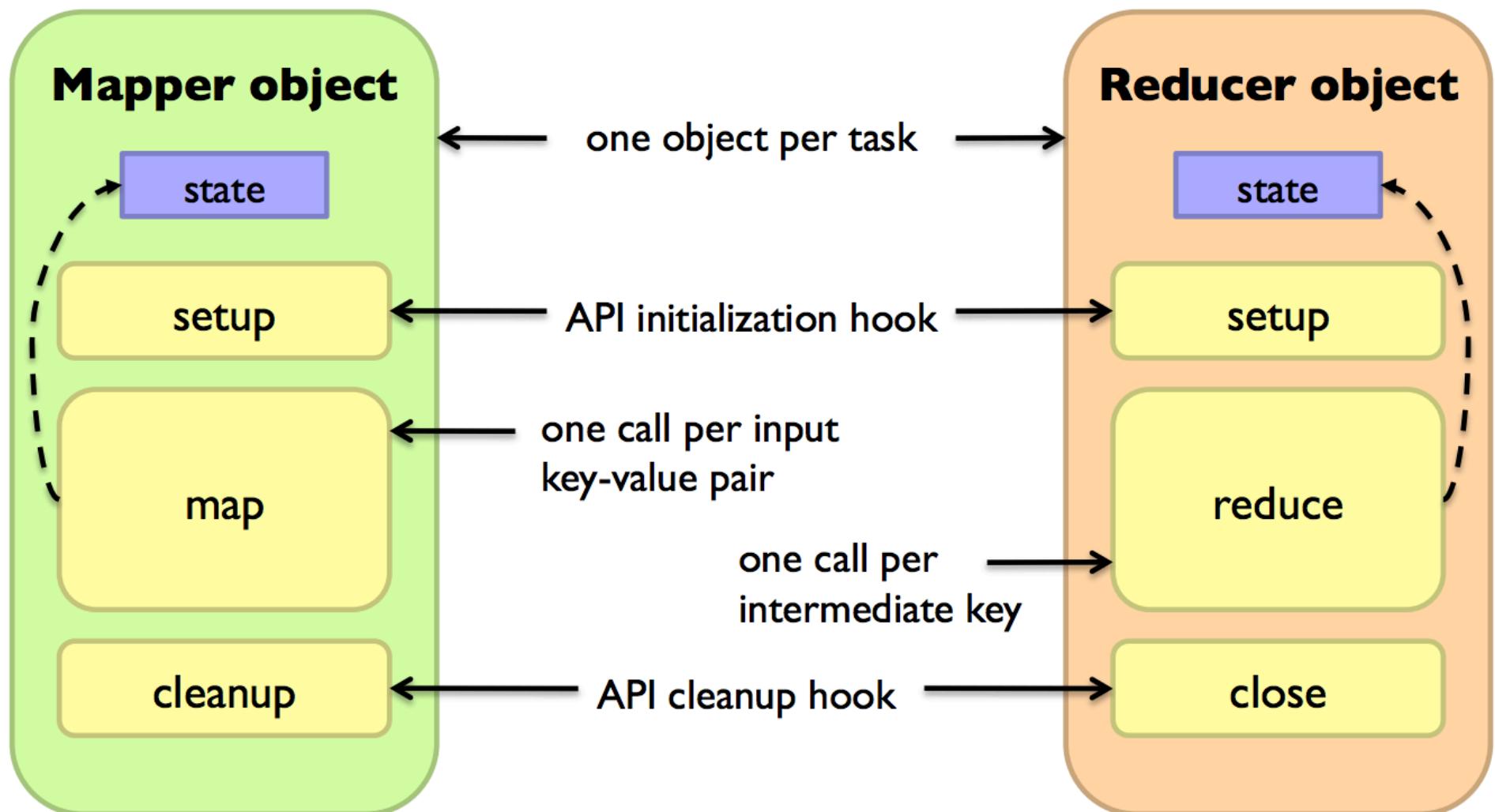
(Lin, WWW 2013)

# More about MapReduce...

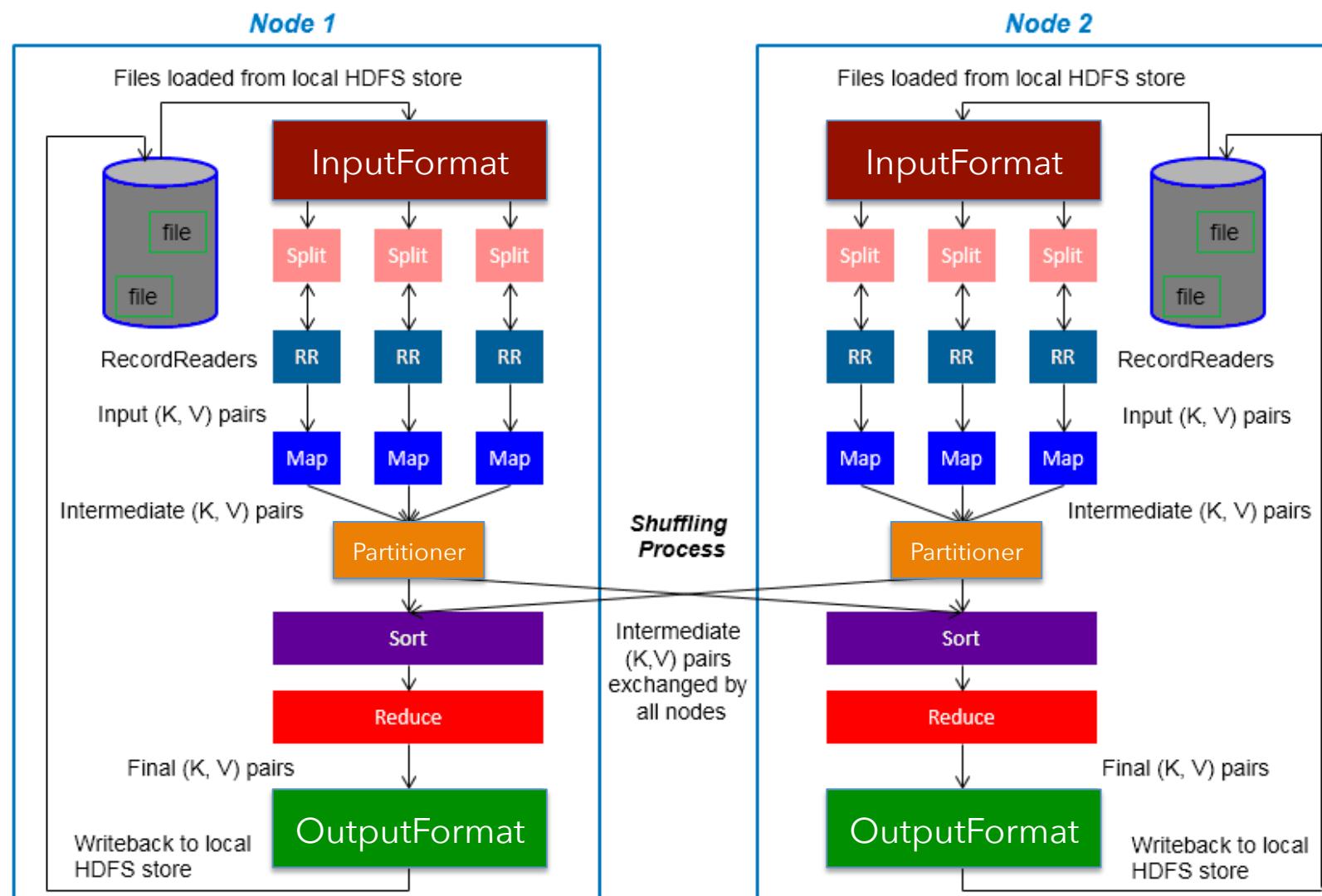


- The same key must be sent to the same reducer for reduce tasks
- Key arrived at each reducer in a sorted order
  - No enforced ordering across reducers
- The number of partitions is based on the number of reducers
- Limitations
  - Limited control over data and execution flow
    - All algorithms must be expressed in map, reduce, combine, or partition
  - You can not control:
    - Where mappers and reducers run
    - When a mapper or reducer begins or finishes
    - Which input a particular mapper is processing
    - Which intermediate key a particular reducer is processing

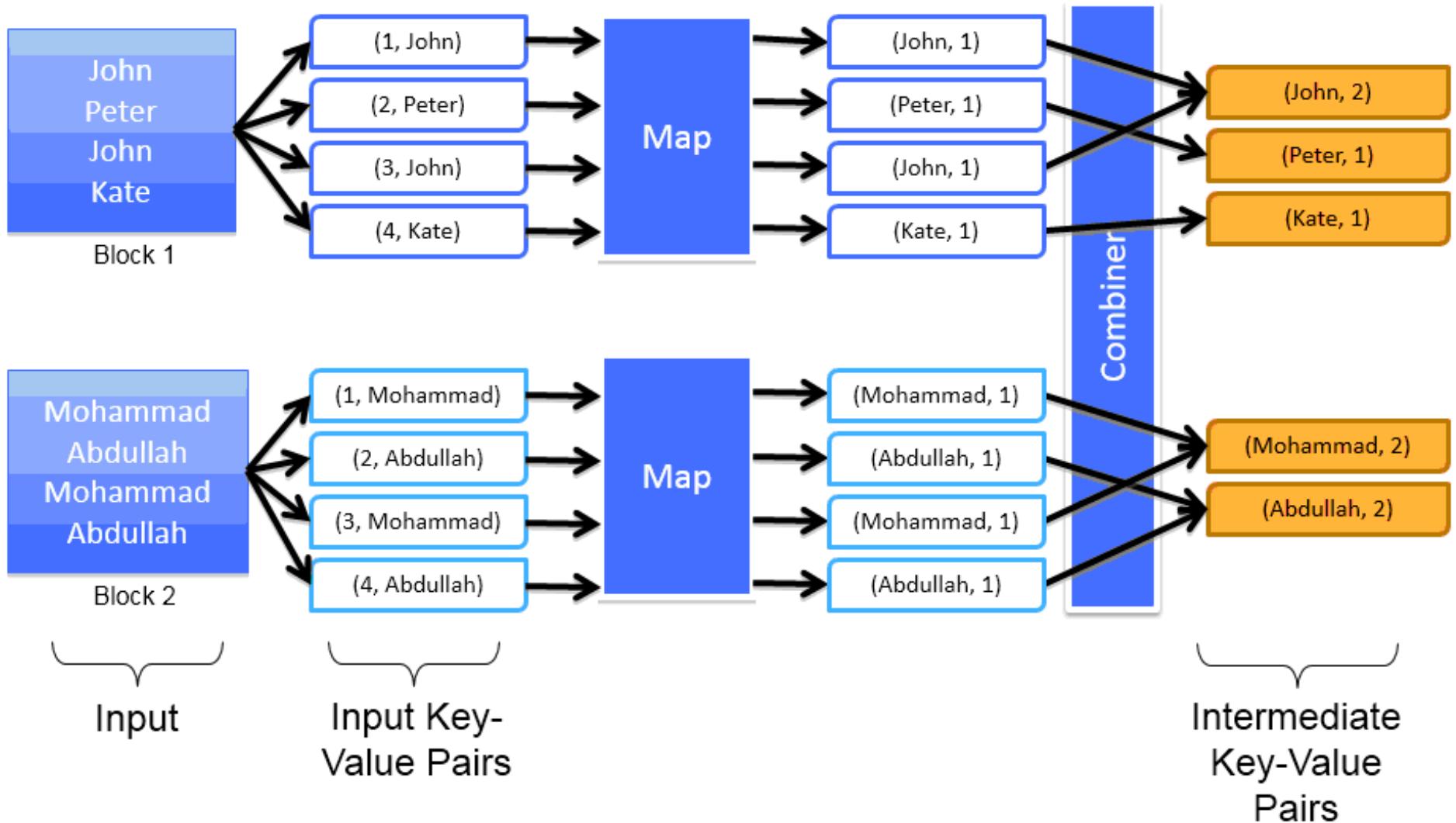
# Mapper and Reducer objects



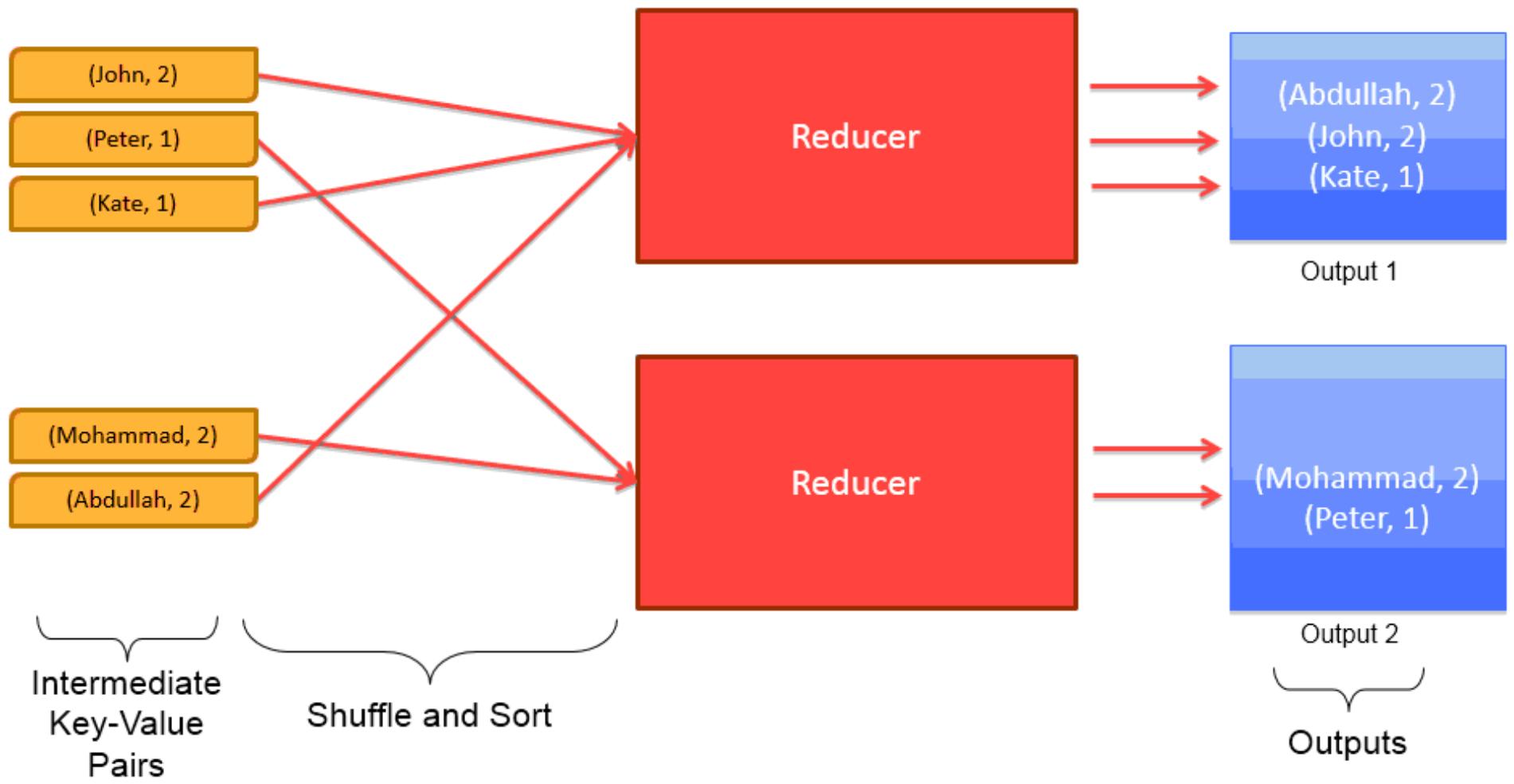
# MapReduce flow



# Wordcount example (1)



# Wordcount example (2)



# More details...

- Driver in Hadoop (job configuration)
  - Specify where to load input and where to put output
  - Specify input format and output format
  - Specify mapper, combiner, partitioner, and reducer
  - Specify number of mappers, reducers, etc.
  - ...
- Chain multiple jobs:
  - Using dependencies among jobs
  - Using internal counter: iterative jobs

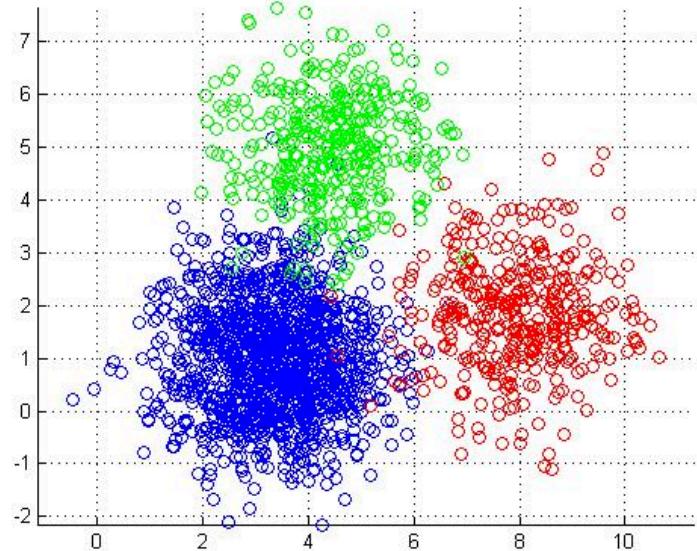




K-Means clustering algorithm (MapReduce)

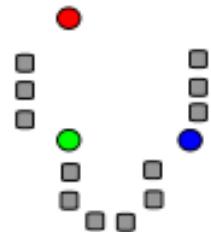
# K-Means

- Unsupervised learning algorithm
- Partition a given data set into a certain number of **K** clusters (**K** is predefined)

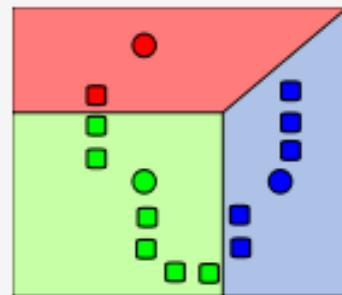


# Algorithm

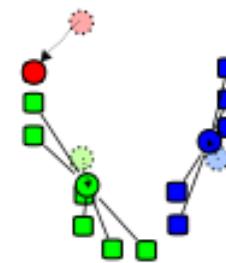
Demonstration of the standard algorithm



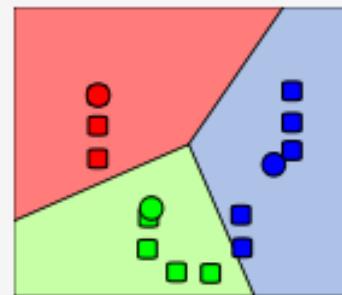
1)  $k$  initial "means" (in this case  $k=3$ ) are randomly selected from the data set (shown in color).



2)  $k$  clusters are created by associating every observation with the nearest mean. The partitions here represent the [Voronoi diagram](#) generated by the means.

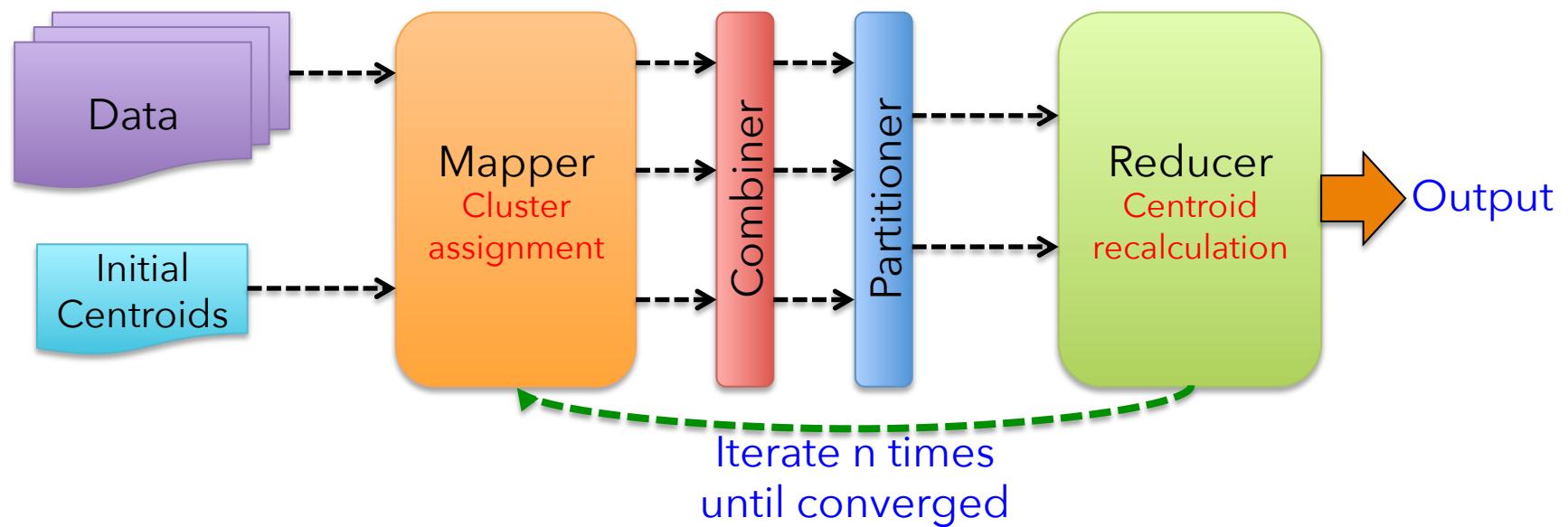


3) The [centroid](#) of each of the  $k$  clusters becomes the new means.



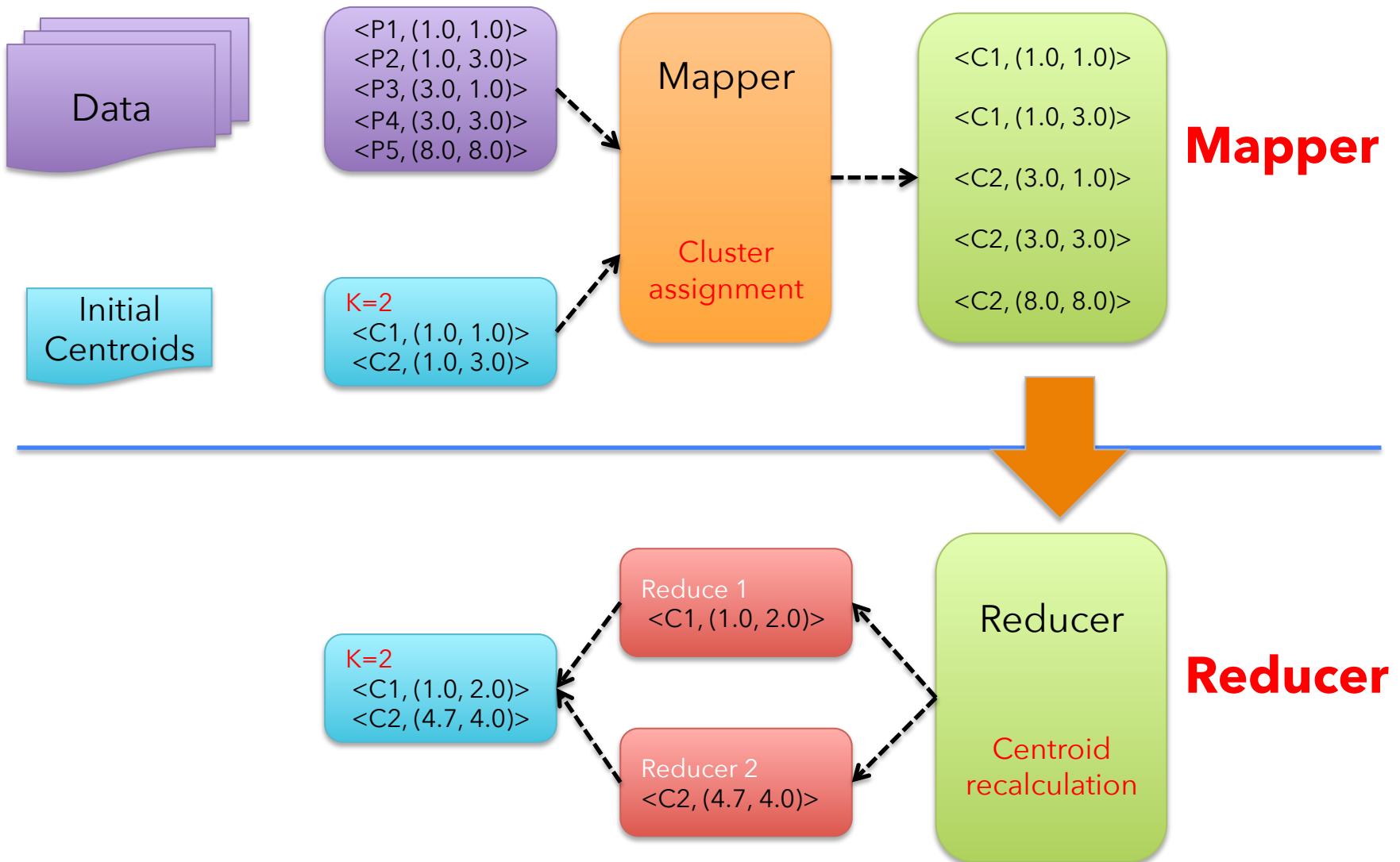
4) Steps 2 and 3 are repeated until convergence has been reached.

# K-Means under MapReduce



Data never changes in the MapReduce process

# Mapper and Reducer



# Remarks



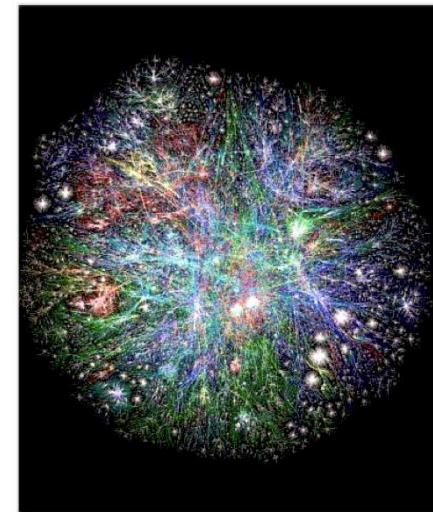
- The way to initialize the means was not specified. One popular way to start is to **randomly choose K** of the samples.
- The results produced depend on the initial values for the means, and it frequently happens that **suboptimal partitions** are found. The standard solution is to try a number of different starting points.
- The results depend on the **metric** used to measure distance between data and centroids.
- The results depend on the **value of K**.



**Iterative graph algorithm: single source shortest path**

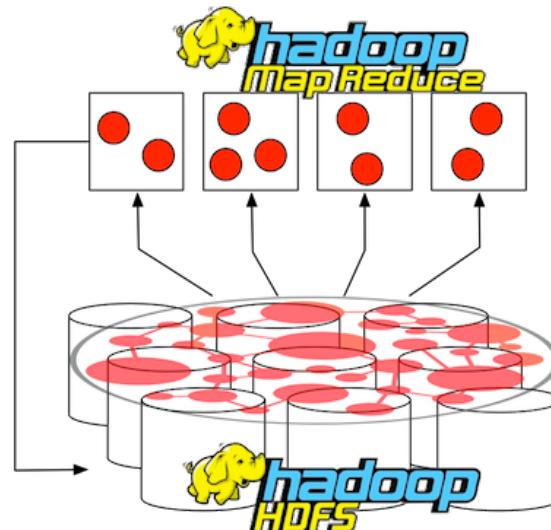
# What is a graph?

- $G = (V, E)$ , where
  - $V$  represents the set of nodes
  - $E$  represents the set of links
  - Links and nodes may contain weights
- Different types of graphs
  - Directed vs. undirected
  - Weighted vs. unweighted
  - Acyclic vs. cyclic
- Networks/graphs are everywhere:
  - Social networks
  - Traffic networks
  - Web link networks



# Graph and MapReduce

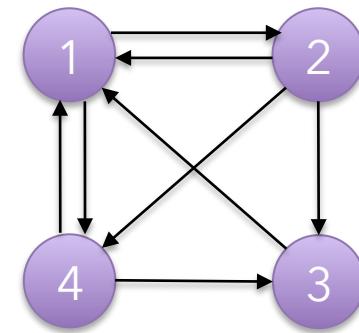
- Graph algorithms typically involves:
  - Computing something about nodes and links
  - Propagating information to the neighbors
- Key issues:
  - Graph representation under MapReduce framework
  - Information propagation under MapReduce framework



# Graph representation

- Adjacency matrix

	1	2	3	4
1	0	1	0	1
2	1	0	1	1
3	1	0	0	0
4	1	0	1	0



- Adjacency list

1: 2, 4

2: 1, 3, 4

3: 1

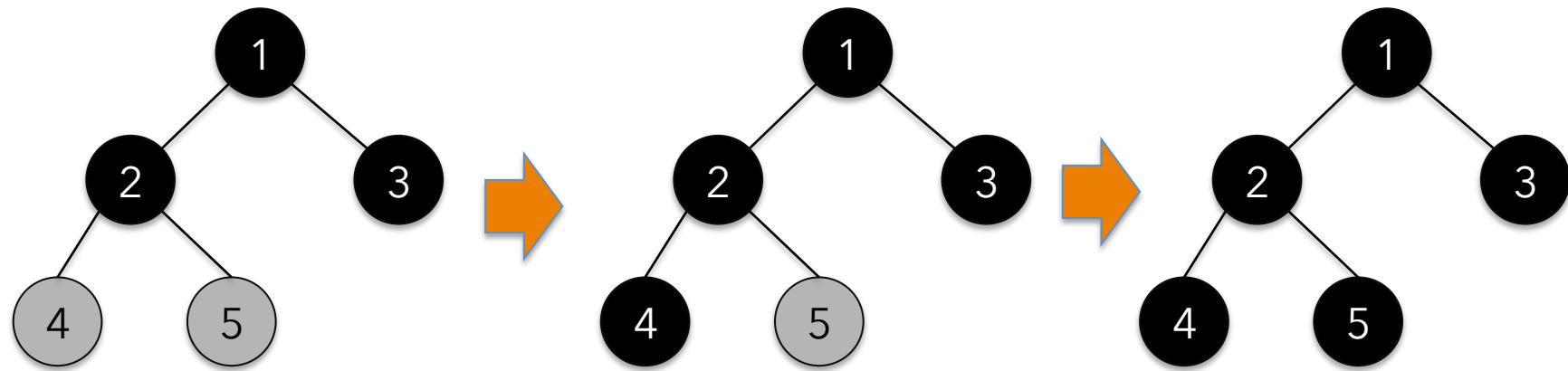
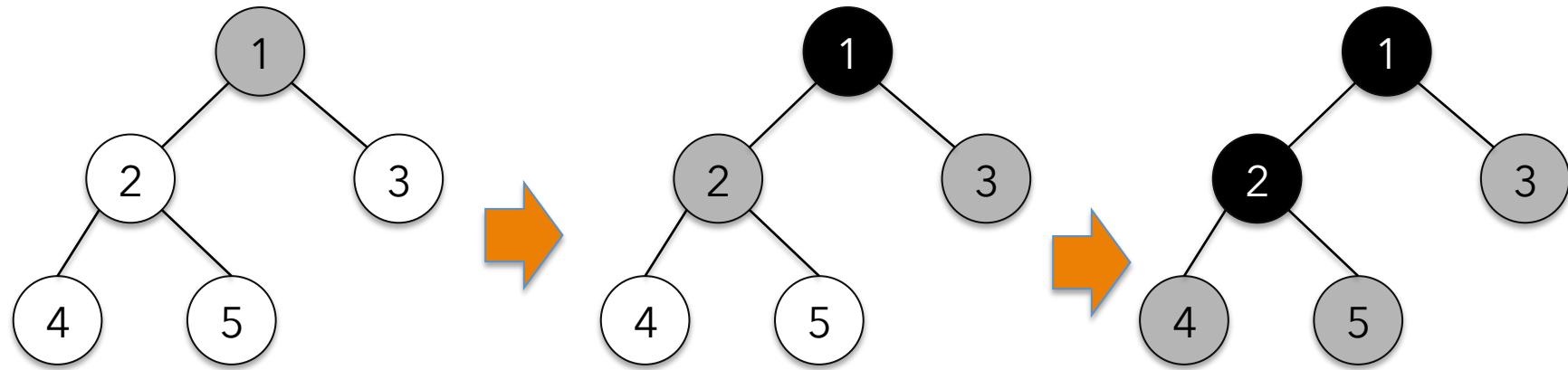
4: 1, 3

# Single source shortest path

- **Problem:** find shortest path from a source node to one or more target nodes
- Single processor: Dijkstra's algorithm
- MapReduce: parallel breadth-first search (BFS)

# Algorithm design

- One way of performing the BFS is by coloring the nodes and traversing according to the color of the nodes.
  - WHITE(unvisited), GRAY(visited) and BLACK(finished)
- At the beginning, all nodes are colored white.
- The source node is colored gray.
- The gray node indicates that it is visited and its neighbors should be processed.
- All the nodes adjacent to a gray node that are white are changed to be gray colored.
- The original gray node is colored.
- The process continues until there are no more gray nodes to process in the graph.



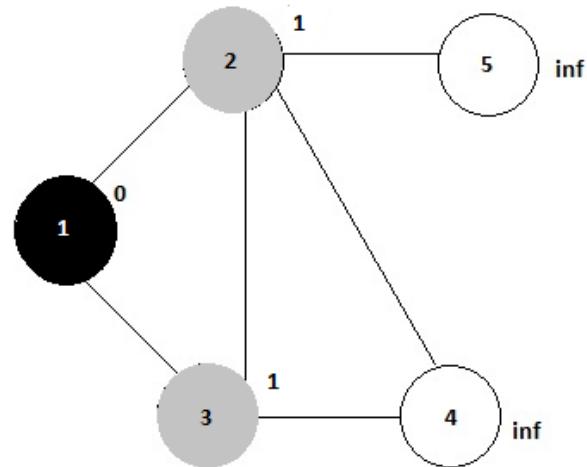
# Algorithm design

- Data preparation (input format)
  - source<tab>adjacency list | distance from source | color | parent node
- Mapper
  - The nodes colored WHITE or BLACK are emitted as such. For each node that is colored GRAY, a new node is emitted with the distance incremented by one and the color set to GRAY. The original GRAY colored node is set to BLACK color and it is also emitted.
- Reducer
  - Make a new node which combines all information for this single node id that is for each key. The new node should have the full list of edges, the **minimum** distance, the **darkest Color**, and the parent/predecessor node

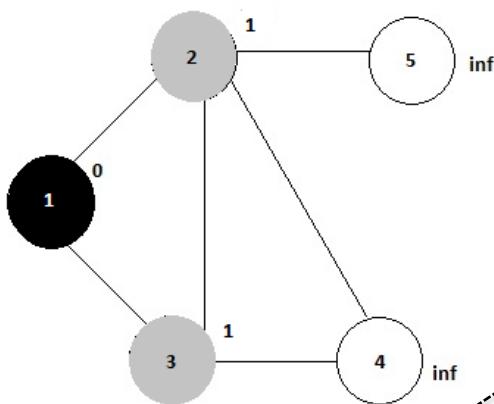
# Example

- Input:

```
1<tab>2,3,|0|BLACK|source  
2<tab>1,3,4,5,|1|GRAY|1  
3<tab>1,4,2,|1|GRAY|1  
4<tab>2,3,|Integer.MAX_VALUE|WHITE|null  
5<tab>2,|Integer.MAX_VALUE|WHITE|null
```



# Mapper



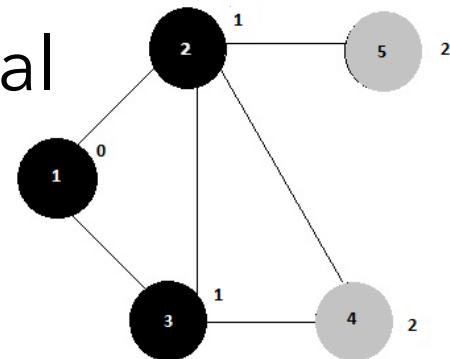
```
1<tab>2,3,|0|BLACK|source  
2<tab>1,3,4,5,|1|GRAY|1  
3<tab>1,4,2,|1|GRAY|1  
4<tab>2,3,|Integer.MAX_VALUE|WHITE|null  
5<tab>2,|Integer.MAX_VALUE|WHITE|null
```

```
1<tab>2,3,|0|BLACK|source  
1<tab>2,3,|2|GRAY|source  
3<tab>1,4,2,|2|GRAY|source  
4<tab>2,3,|2|GRAY|source  
5<tab>2,|2|GRAY|source  
2<tab>1,3,4,5,|1|BLACK|1  
1<tab>2,3,|2|GRAY|source  
4<tab>2,3,|2|GRAY|source  
2<tab>1,3,4,5,|2|GRAY|source  
3<tab>1,4,2,|1|BLACK|1  
>4<tab>2,3,|Integer.MAX_VALUE|WHITE|null  
>5<tab>2,|Integer.MAX_VALUE|WHITE|null
```

# Reducer

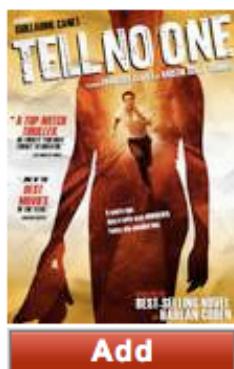
- For the same key, choose the darkest and the minimum distance as the final value

```
1<tab>2,3,|0|BLACK|source
1<tab>2,3,|2|GRAY|source
3<tab>1,4,2,|2|GRAY|source
4<tab>2,3,|2|GRAY|source
5<tab>2,|2|GRAY|source
2<tab>1,3,4,5,|1|BLACK|1
1<tab>2,3,|2|GRAY|source
4<tab>2,3,|2|GRAY|source
2<tab>1,3,4,5,|2|GRAY|source
3<tab>1,4,2,|1|BLACK|1
4<tab>2,3,|Integer.MAX_VALUE|WHITE|null
5<tab>2,|Integer.MAX_VALUE|WHITE|null
```



```
1<tab>2,3,|0|BLACK|source
4<tab>2,3,|2|GRAY|source
5<tab>2,|2|GRAY|source
2<tab>1,3,4,5,|1|BLACK|1
4<tab>2,3,|2|GRAY|source
3<tab>1,4,2,|1|BLACK|1
```

## FOREIGN SUGGESTIONS (about 104) [See all >](#)



### Tell No One

Because you enjoyed:  
Memento  
Syriana  
Children of Men

[Add](#) Not Interested

### Let the Right One In

Because you enjoyed:  
Seven Samurai  
This Is Spinal Tap  
The Big Lebowski

[Add](#) Not Interested

### I've Loved You So Long

Because you enjoyed:  
The Queen  
Syriana  
Good Night, and Good Luck

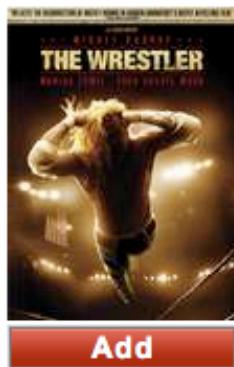
[Add](#) Not Interested

### Downfall

Because you enjoyed:  
Das Boot  
The Killing Fields  
Seven Samurai

[Add](#) Not Interested

## DRAMA SUGGESTIONS (about 82) [See all >](#)



### The Wrestler

Because you enjoyed:  
Sin City  
Reservoir Dogs  
The Big Lebowski

[Add](#) Not Interested

### The Visitor

Because you enjoyed:  
Gandhi  
The Motorcycle Diaries  
The Queen

[Add](#) Not Interested

### Brick

Because you enjoyed:  
The Big Lebowski  
Rushmore  
Fight Club

[Add](#) Not Interested

### The Pianist

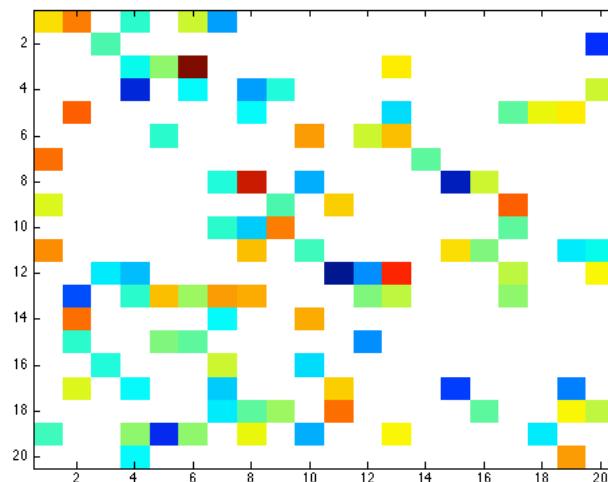
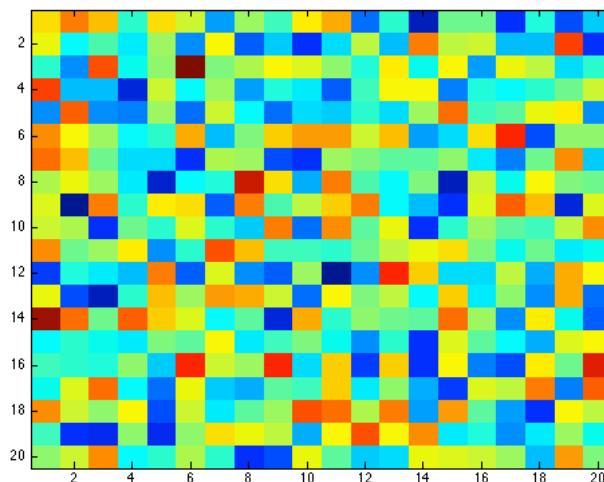
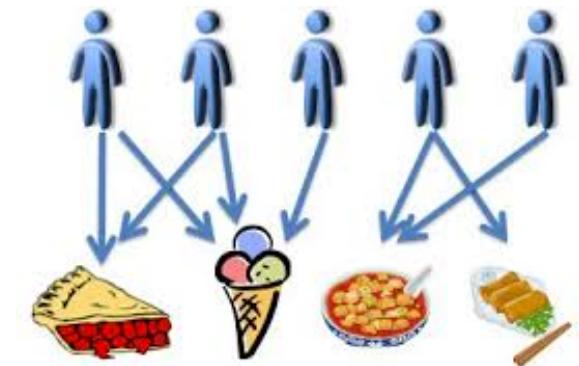
Because you enjoyed:  
Amadeus  
The Killing Fields  
Empire of the Sun

[Add](#) Not Interested

**Recommender system**

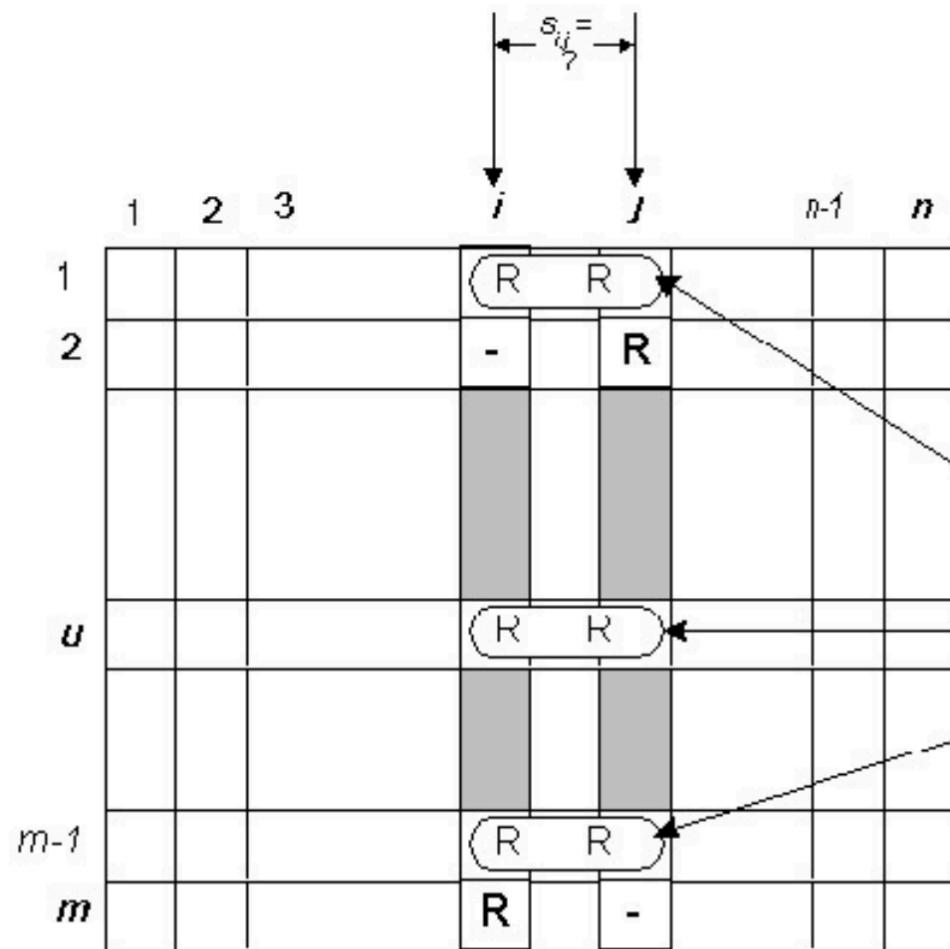
# Recommender systems

- Collaborative filtering (CF) algorithm
  - Item-based
  - User-based
  - Content-based
- Matrix completion algorithm



# Item-based CF

- Key idea: calculate item similarities



Computed by looking into co-rated items only. These co-rated pairs are obtained from different users.

# Item similarity

- Similarity of The Matrix and Inception
  - rating vector of The Matrix: (5, -, 4)
  - rating vector of Inception: (4, 5, 2)
  - isolate all co-occurred ratings (all cases where a user rated both items)
  - Pick a similarity measure to compute a similarity value between -1 and 1. e.g. Pearson correlation, cosine similarity, etc.

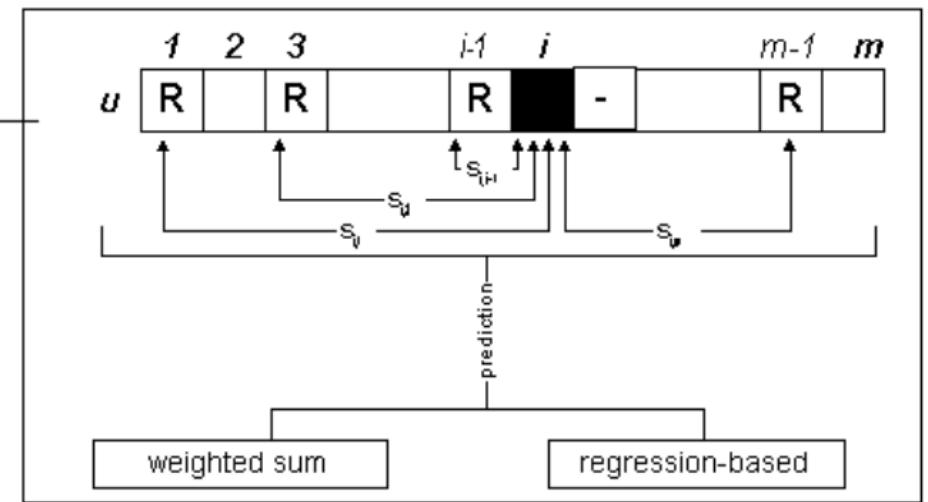
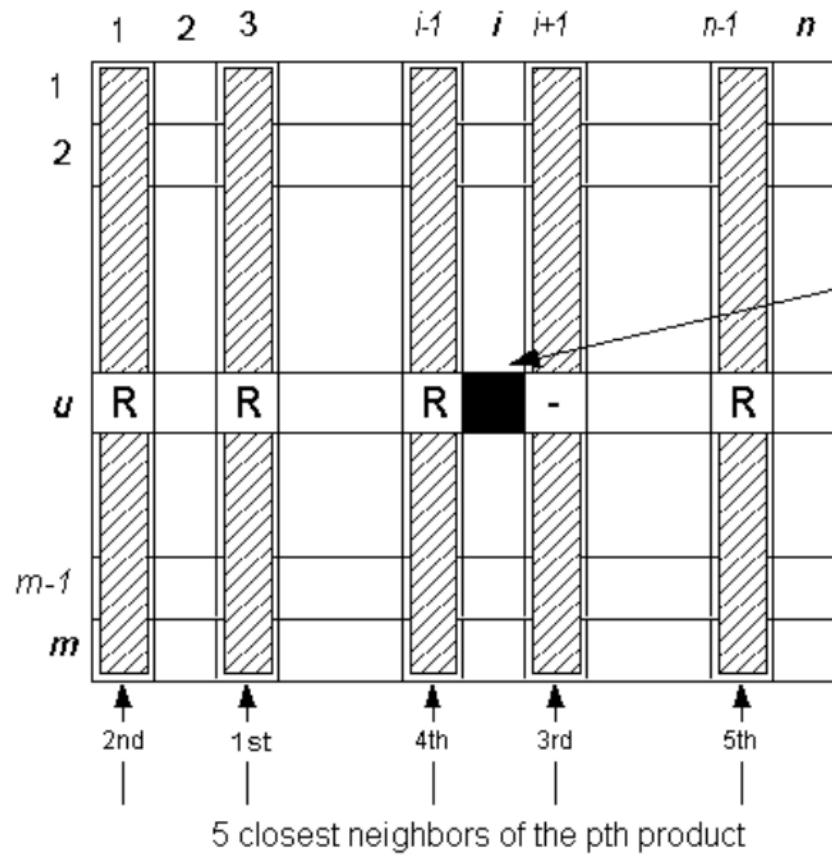
$$sim(i, j) = \frac{\sum_{u \in U} (R_{u,i} - \bar{R}_i)(R_{u,j} - \bar{R}_j)}{\sqrt{\sum_{u \in U} (R_{u,i} - \bar{R}_i)^2} \sqrt{\sum_{u \in U} (R_{u,j} - \bar{R}_j)^2}}$$

$$sim(i, j) = \cos(\vec{i}, \vec{j}) = \frac{\vec{i} \cdot \vec{j}}{\|\vec{i}\|_2 * \|\vec{j}\|_2}$$



5	4
-	5
4	2

# Prediction



$$P_{u,i} = \frac{\sum_{\text{all similar items, } N} (s_{i,N} * R_{u,N})}{\sum_{\text{all similar items, } N} (|s_{i,N}|)}$$

# Algorithm in MapReduce - job 1

- **Map** - make user the key

(Alice,Matrix,5)	→ Alice (Matrix,5)
(Alice,Alien,1)	→ Alice (Alien,1)
(Alice,Inception,4)	→ Alice (Inception,4)
(Bob,Alien,2)	→ Bob (Alien,2)
(Bob,Inception,5)	→ Bob (Inception,2)
(Peter,Matrix,4)	→ Peter (Matrix,4)
(Peter,Alien,3)	→ Peter (Alien,3)
(Peter,Inception,2)	→ Peter (Inception,2)

- **Reduce** - create inverted index

Alice (Matrix,5)	→ Alice (Matrix,5)(Alien,1)(Inception,4)
Alice (Alien,1)	
Alice (Inception,4)	
Bob (Alien,2)	→ Bob (Alien,2)(Inception,5)
Bob (Inception,5)	
Peter (Matrix,4)	→ Peter (Matrix,4)(Alien,3)(Inception,2)
Peter (Alien,3)	
Peter (Inception,2)	

# Algorithm in MapReduce - job 2

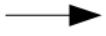
- **Map** – emit all co-occurred ratings

```
Alice (Matrix,5)(Alien,1)  
(Inception,4)
```



```
Matrix,Alien (5,1)  
Matrix,Inception (5,4)  
Alien,Inception (1,4)
```

```
Bob (Alien,2)(Inception,5)
```



```
Alien,Inception (2,5)
```

```
Peter (Matrix,4)(Alien,3)  
(Inception,2)
```



```
Matrix,Alien (4,3)  
Matrix,Inception (4,2)  
Alien,Inception(3,2)
```

- **Reduce** – compute similarities

```
Matrix,Alien (5,1)  
Matrix,Alien (4,3)
```



```
Matrix,Alien (-0.47)
```

```
Matrix,Inception (5,4)  
Matrix,Inception (4,2)
```



```
Matrix,Inception (0.47)
```

```
Alien,Inception (1,4)  
Alien,Inception (2,5)  
Alien,Inception (3,2)
```



```
Alien,Inception (-0.63)
```

# Some good tools

- Spark
  - <http://spark.apache.org>
- Mahout
  - <https://mahout.apache.org>
- D3.js
  - <http://d3js.org>
- Others





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