

The background of the slide is a complex network diagram. It features numerous circular nodes of varying sizes, colored in dark blue, red, and grey. These nodes are interconnected by a web of thin lines, with some lines being red and others dark grey. The overall pattern is dense and abstract, suggesting a large-scale data network or a complex system.

# **BIG DATA MANAGEMENT**

**CE/CZ4123**

# **DISTRIBUTED SYSTEMS AND MAP-REDUCE (MORE EXAMPLES)**

# **MapReduce:**

## **A general distributed paradigm**

**In this lecture, we will see more complicated examples of MapReduce based algorithms.**

- ☐ **Table Join**
- ☐ **Shortest Path Computation**
- ☐ **PageRanks**

# NOTES ON PSEUDOCODE FOR MAPREDUCE ALGORITHMS

- ❑ The pseudocode focuses on “thinking in MapReduce”, and so it is okay to use any understandable syntax (C-like or Java-like).
- ❑ For presenting complicated MapReduce Algorithms, we can use more complicated object class (data structure) than “String” for both key and value. Then we should describe the composition of the complicated data structure as well.

# EXAMPLE: JOINING TWO TABLES

Primary key

A	B	C
a1	b1	c1
a2	b2	c2
a3	b3	c3
a4	b4	c4
a5	b5	c5



Map Input

Key: Line number  
Value: A;B;C

Foreign key

C	D	E
c1	d1	e1
c1	d2	e2
c2	d3	e3
c3	d4	e4
c3	d5	e5



Key: Line number  
Value: C;D;E

# JOINING TWO TABLES

Primary key

A	B	C
a1	b1	c1
a2	b2	c2
a3	b3	c3
a4	b4	c4
a5	b5	c5



Map Input

Key: Line number  
Value: A;B;C

Foreign key

C	D	E
c1	d1	e1
c1	d2	e2
c2	d3	e3
c3	d4	e4
c3	d5	e5



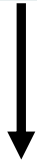
Key: Line number  
Value: C;D;E

- ❑ If the tuples in two tables are in the same file, then we need to know the size of the 1<sup>st</sup> table to classify the tuples.

# JOINING TWO TABLES

Primary key

A	B	C
a1	b1	c1
a2	b2	c2
a3	b3	c3
a4	b4	c4
a5	b5	c5



Key: C  
Value: **T1**;A;B

Foreign key

C	D	E
c1	d1	e1
c1	d2	e2
c2	d3	e3
c3	d4	e4
c3	d5	e5



Key: C  
Value: **T2**;D;E

Map Output



# JOINING TWO TABLES

Primary key

A	B	C
a1	b1	c1
a2	b2	c2
a3	b3	c3
a4	b4	c4
a5	b5	c5

Foreign key

C	D	E
c1	d1	e1
c1	d2	e2
c2	d3	e3
c3	d4	e4
c3	d5	e5

Reduce Input

Key: C

Value: {T1;A;B, T2;D;E}

Key: c1

Value: {T1;a1;b1, T2;d1;e1, T2;d2;e2}

Key: c2

Value: {T1;a2;b2, T2;d3;e3}

Key: c3

Value: {T1;a3;b3, T2;d4;e4, T2;d5;e5}



# JOINING TWO TABLES

Primary key

A	B	C
a1	b1	c1
a2	b2	c2
a3	b3	c3
a4	b4	c4
a5	b5	c5

Foreign key

C	D	E
c1	d1	e1
c1	d2	e2
c2	d3	e3
c3	d4	e4
c3	d5	e5

Reduce

Key: c1

Value: {T1;a1;b1, T2;d1;e1, T2;d2;e2}

→ (T1;a1;b1, T2;d1;e1)  
(T1;a1;b1, T2;d2;e2)  
↘ (a1;b1;c1;d1;e1)  
(a1;b1;c1;d2;e2)

## A FEW TIPS

- ❑ It is crucial to determine which attributes/features should be aggregated on → Intermediate **key**
- ❑ The intermediate **value** can be complex; it can include a lot of useful information for you to finish the task.

# WHAT ABOUT DISTANCE-BASED JOIN?

A	B	C
a1	b1	1
a2	b2	50
a3	b3	100

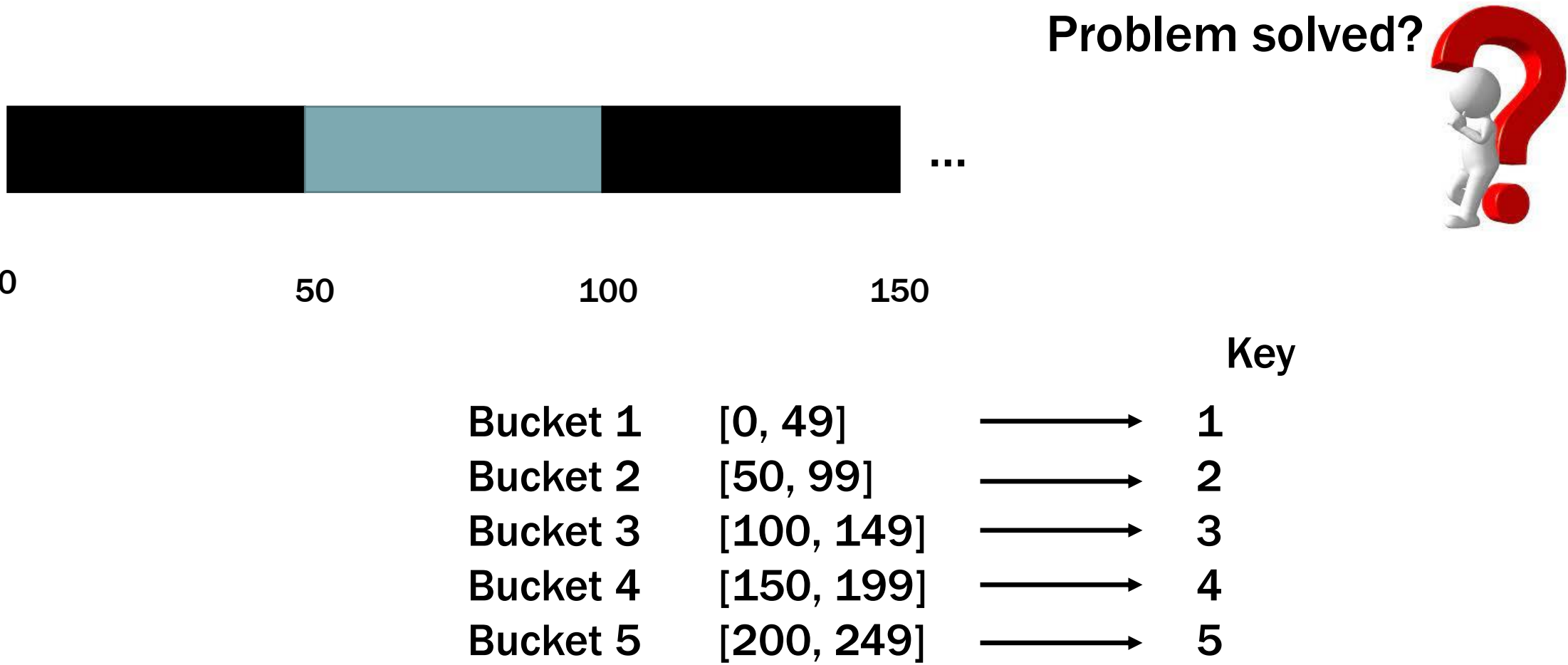
F	D	E
2	d1	e1
99	d2	e2
49	d3	e3
...	...	...
...	...	...

Join Column C of Table 1 and Column F of Table 2 based on the condition that  $|C-F| < 50$ . Assume that the values of Column C and Column F are positive integers.

If we directly use the values of Column C and Column F, qualified tuples will not be joined together. What should we do?

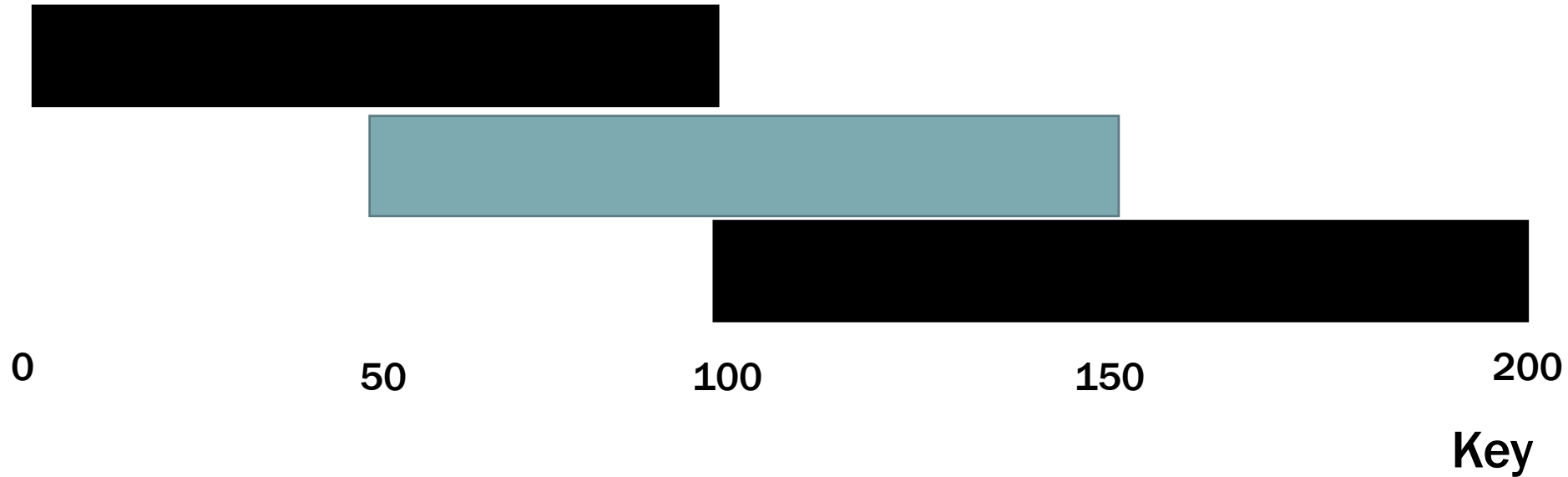


# THE FIRST IDEA



Aggregate the values in the same bucket

# FIXED THE IDEA



Bucket 1	[0, 99]	→	1
Bucket 2	[50, 149]	→	2
Bucket 3	[100, 199]	→	3
Bucket 4	[150, 249]	→	4
Bucket 5	[200, 299]	→	5

Any two values whose difference is at most 50 should fall into **at least one** buckets

# INPUT

Assume the input key-value pairs are the following (corresponding to the example):

- 1 a1;b1;1
- 2 a2;b2;50
- 3 a3;b3;100
- 4 2;d1;e1
- 5 99;d2;e2
- 6 49;d3;e3

# JOB1: MAP (PSEUDOCODE)

```
Map(int key, String value){  
    if (key<table1_size){  
        int value_C=get_value_C(value);  
        Emit-Intermediate(floor(value_C/50), "T1:"+value);  
        Emit-Intermediate(floor(value_C/50)+1, "T1:"+value);  
    }  
    else{  
        int value_F=get_value_F(value);  
        Emit-Intermediate(floor(value_C/50), "T2:"+value);  
        Emit-Intermediate(floor(value_C/50)+1, "T2:"+value);  
    }  
}
```



# JOB1: REDUCE (PSEUDOCODE)

```
Reduce(int key, iterator<String> values){
```

```
    List value_C_list, value_F_list, value_T1_list, value_T2_list;
```

```
    for(String value : values){
```

```
        if(value starts with "T1"){
```

```
            int value_C=get_value_C(value);
```

```
            value_C_list.add(value_C);
```

```
            value_T1_list.add(get_tuple(value));
```

```
        } else{
```

```
            int value_F=get_value_F(value);
```

```
            value_F_list.add(value_F);
```

```
            value_T2_list.add(get_tuple(value));
```

```
        }
```

```
    }
```

```
    for(int i=0;i<value_C_list.size();i++)
```

```
        for(int j=0;j<value_F_list.size();j++){
```

```
            int value_C=value_C_list[i];
```

```
            int value_F=value_F_list[j];
```

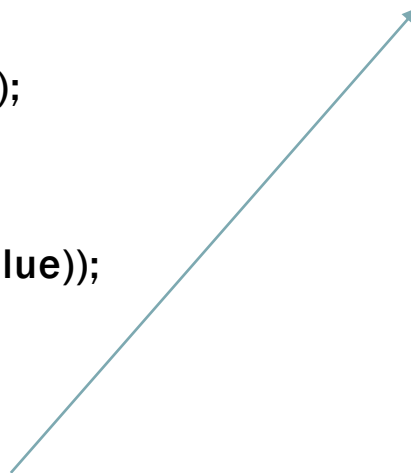
```
            if(|value_C-value_F|<50){
```

```
                Emit("", value_T1_list[i]+value_T2_list[j]);
```

```
            }
```

```
        }
```

```
    }
```



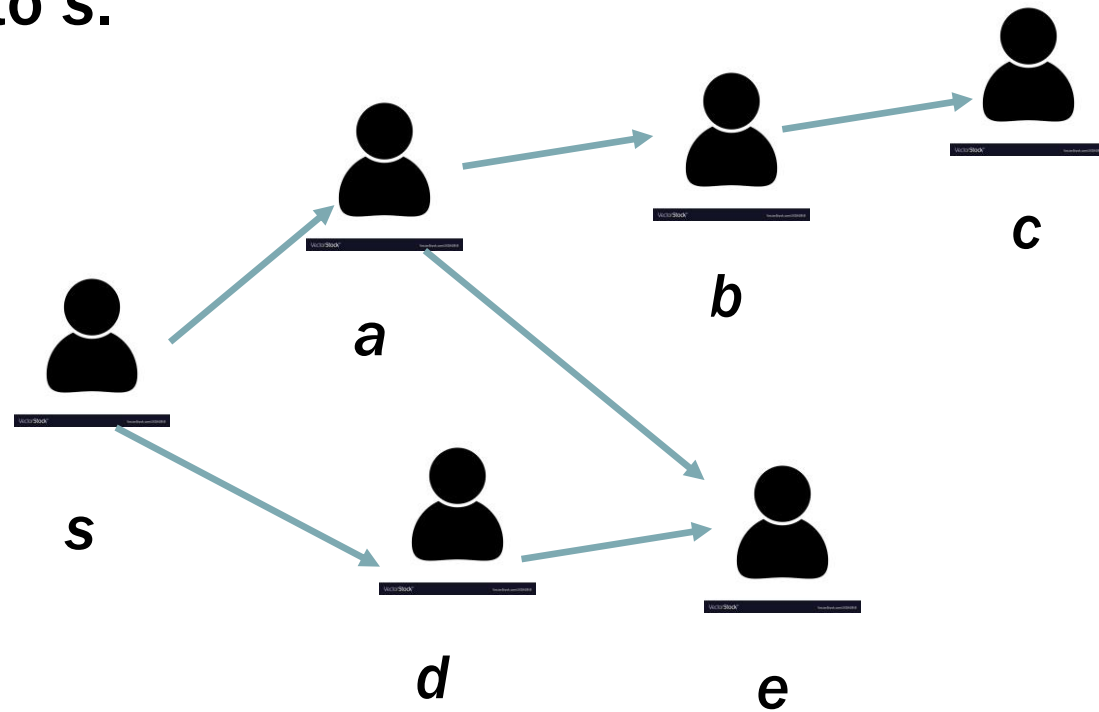
## **JOB2: REMOVE DUPLICATES**

**The output of Job1 may contain duplicates (why?)**

**It is easy to remove duplicates by another MapReduce job.**

# EXAMPLE: SHORTEST PATH COMPUTATION

Given a directed social network in the following form, find all the people within  $k$ -hops from a given source node  $s$ , and the corresponding hop distance to  $s$ .



# EXAMPLE: SHORTEST PATH COMPUTATION

Given a directed social network in the following form, find all the people within k-hops from a given source node  $s$ , and the corresponding hop distance to  $s$ .

Example results ( $k=2$ ):

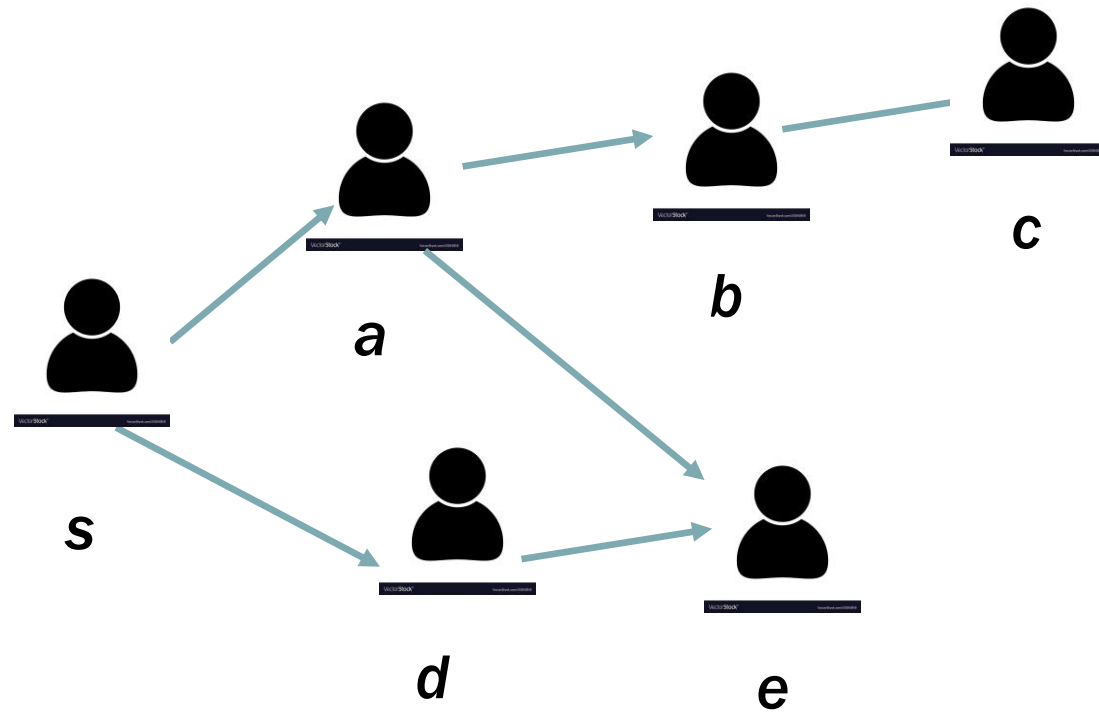
$a, d, e, b$

$\text{dis}(s, a) = 1$

$\text{dis}(s, d) = 1$

$\text{dis}(s, e) = 2$

$\text{dis}(s, b) = 2$



# EXAMPLE: SHORTEST PATH COMPUTATION

Single-Machine Algorithm: Dijkstra's algorithm

- An efficient implementation of Dijkstra's algorithm often uses priorityqueue

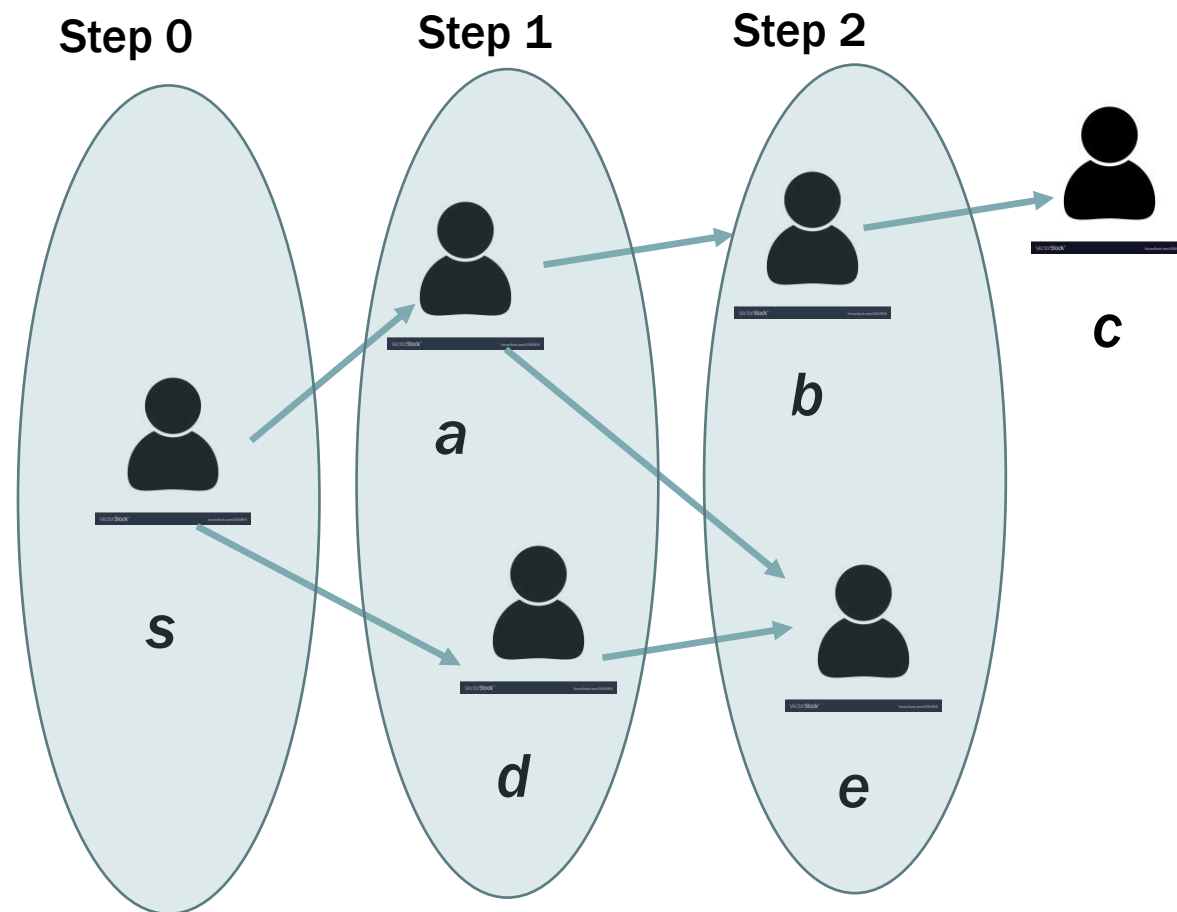
**Not easy to parallelize the computation in MapReduce**

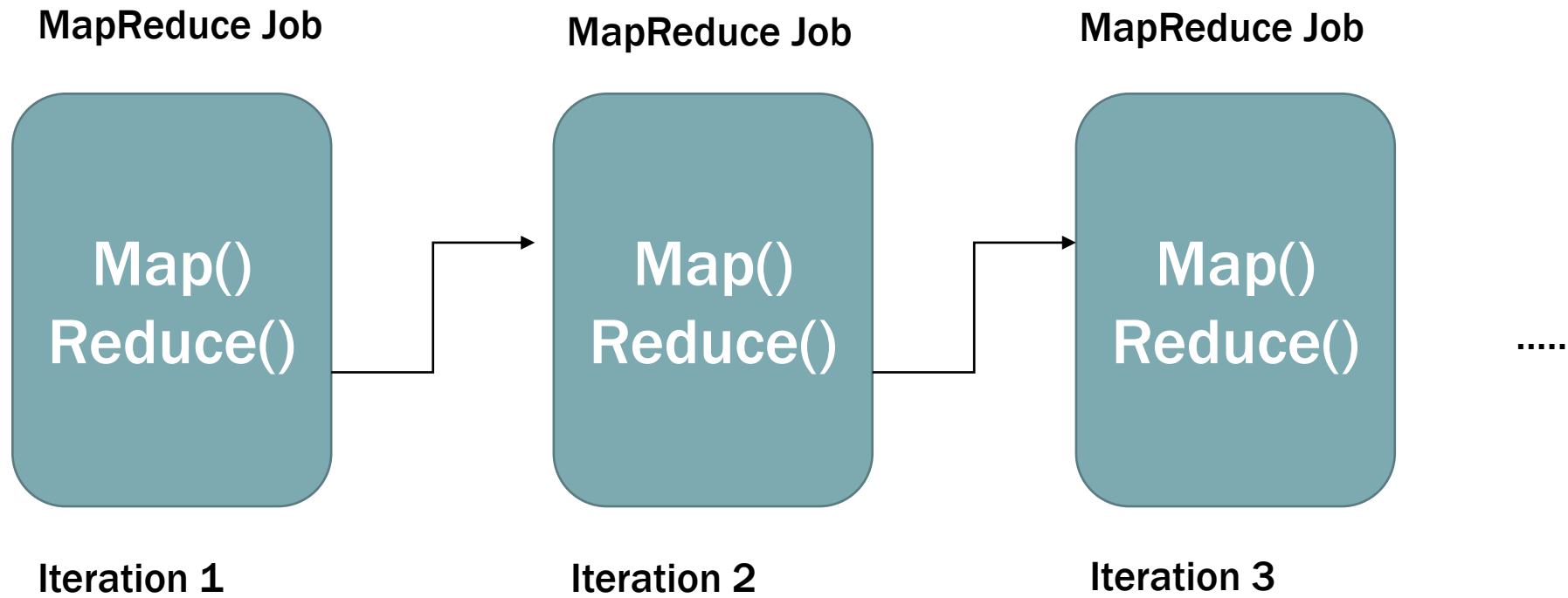
# IDEA FOR DESIGNING MAPREDUCE FUNCTIONS

- ❑ Solution to the problem can be defined inductively

## Intuition

- ❑ Initial step (Step 0):  $\text{dis}(s)=0$   $\text{dis}(v)=+\infty$  for any other  $v$ .
- ❑ Step 1: For any node  $v_1$  that is 1-hop from  $s$ , set  $d(v_1)=\min\{d(v_1), 1\}$
- ❑ Step 2: For any node  $v_2$  that can be reached in 2-hops from  $s$ , set  $d(v_2)=\min\{d(v_2), 2\}$
- ❑ ...
- ❑ Step  $K$  : For any node  $v_k$  that can be reached  $K$ -hops from  $s$ , set  $d(v_k)=\min\{d(v_k), K\}$







# INPUT KEY-VALUE PAIRS

Data representation:

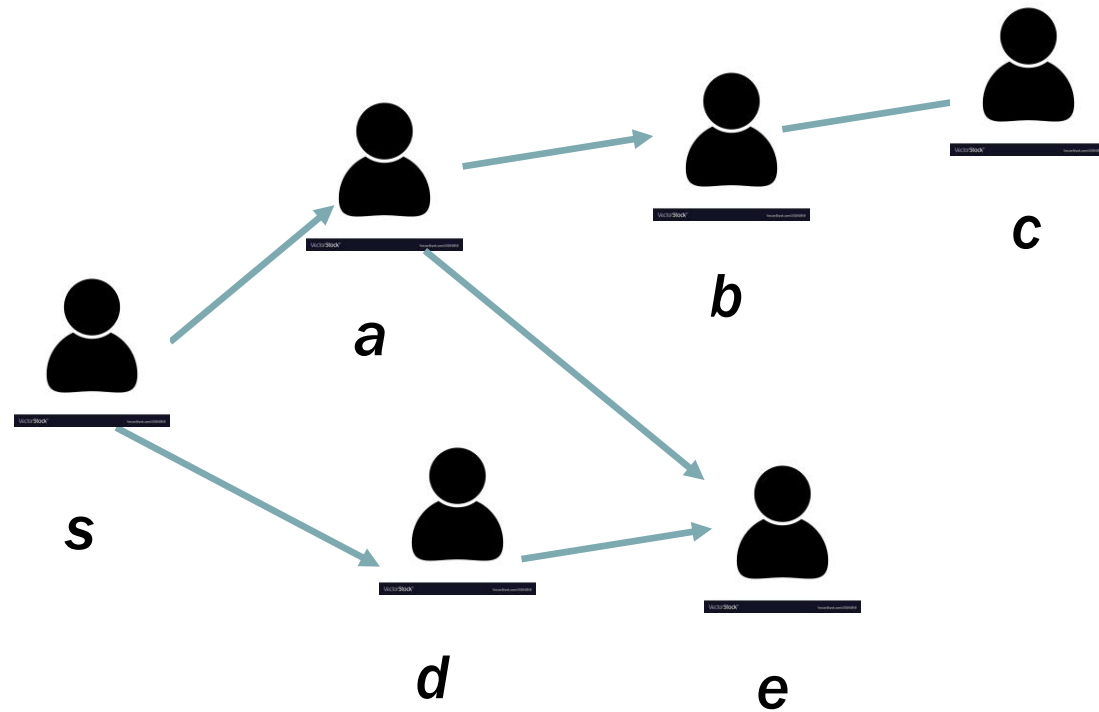
Each key-value pair stores the information of an edge

❑ Key: nodeID

❑ Value: nodeID

❑ Example:

- (s, a)
- (s, d)
- (a, e)
- (d, e)
- (a, b)
- (b, c)



**Each MapReduce iteration advances the “frontier” by one hop**

- Subsequent iterations include more and more reachable nodes as frontier expands
- Multiple iterations are needed to explore the nodes reachable in K hops

**How to preserve the graph structure?**

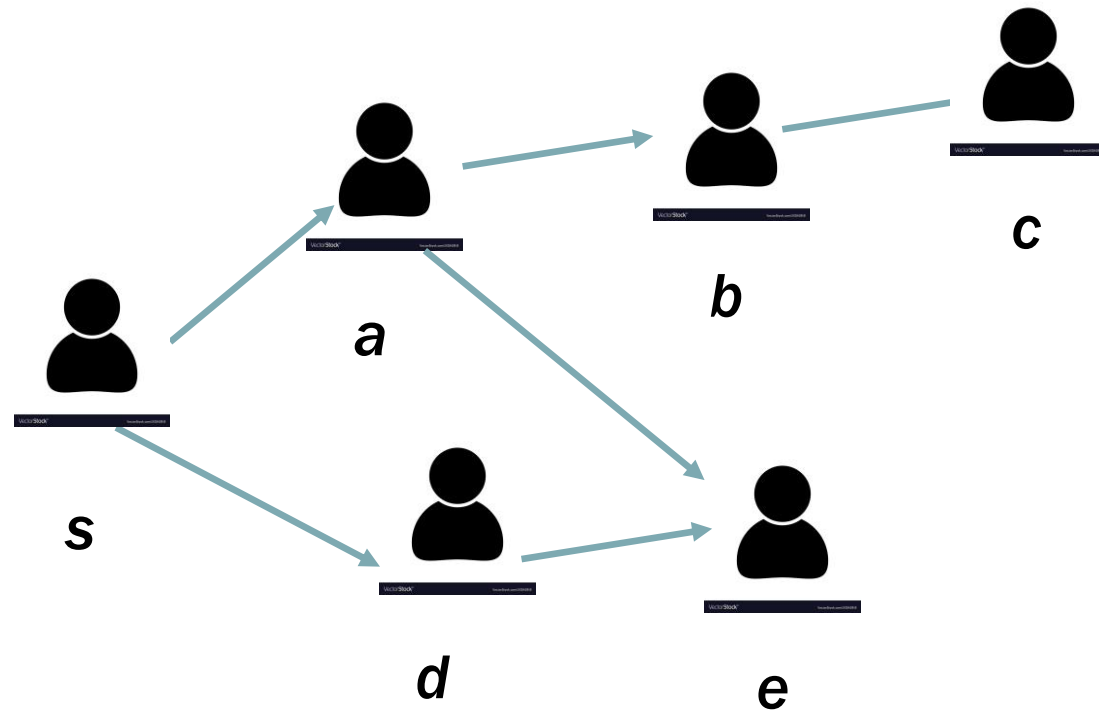
- Solution: map function emits (node, neighbor list) as well

# FIRST MAPREDUCE JOB

## Purpose:

Each key-value pair stores the information of an edge

- Key: nodeID
- Value: nodeID
- Example:
  - (s, a)
  - (s, d)
  - (a, e)
  - (d, e)
  - (a, b)
  - (b, c)



## **JOB0(STEP0):MAP**

```
map(String nodeid_from, String nodeid_to) {  
  {  
    Emit-Intermediate(nodeid_from, nodeid_to);  
  }  
}
```

## **JOB0(STEP0):REDUCE**

```
reduce(String nodeid, Iterator<String> neighbors) {  
    if(nodeid.equals("s")){  
        Emit("s", "D:0");//"D" indicates distance  
    }  
}
```

```
    Emit(nodeid, "N:"+ToString(neighbors));//"N" indicates  
neighbors  
}
```

Note: ToString() makes the list of neighbors as a string

# EXAMPLE FOR JOB0

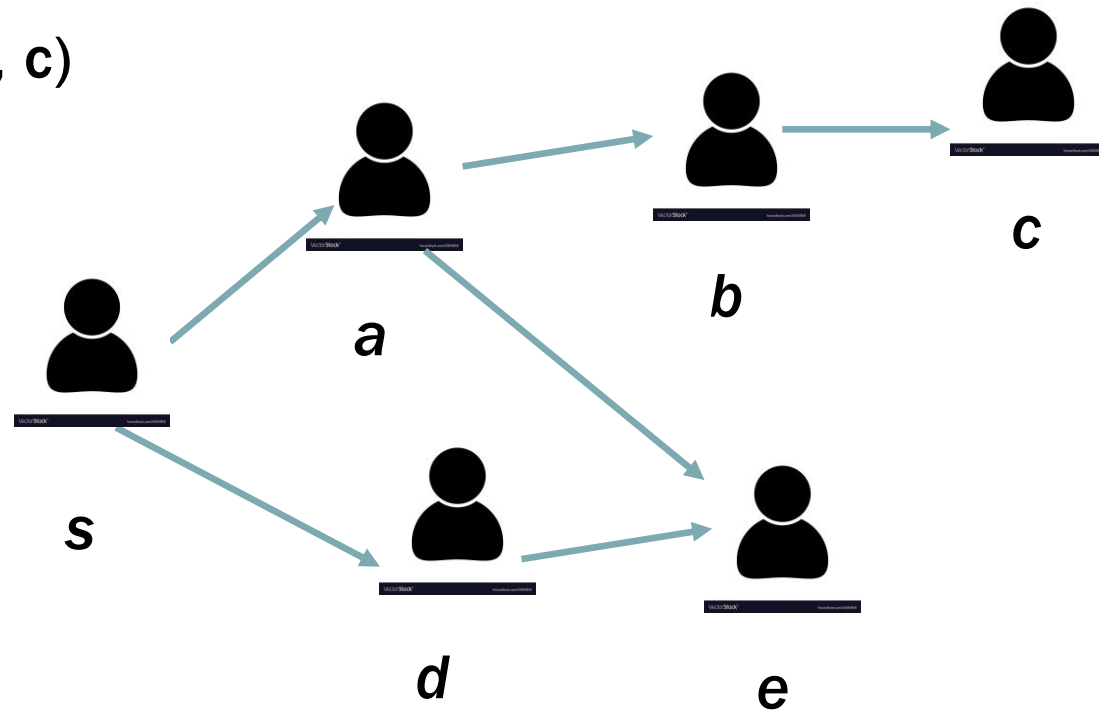
Job0:

Input

- (s, a) (s, d) (a, e) (d, e) (a, b) (b, c)

Output

- (s, "D:0")
- (s, "N:a;d")
- (a, "N:b;e")
- (d, "N:e")
- (b, "N:c")



## SUBSEQUENT JOBS (STEPS 1-K): MAP

```
map(String nodeid, String value) {  
  {  
    Emit-Intermediate(nodeid, value);  
  }  
}
```

# SUBSEQUENT JOBS (STEPS 1-K): REDUCE

```
reduce(String nodeid, Iterator<String> values) {
```

```
    d_min=+∞;
```

```
    Iterator<String> neighbors;
```

```
    for( value in values ){
```

```
        if (value starts with "N"){
```

```
            neighbors= ToNeighbors(value);
```

```
            Emit(nodeid, value); // always send neighbors out
```

```
        }
```

```
    else{
```

```
        if( ToInteger(value)<d_min)
```

```
            d_min=ToInteger(value);
```

```
    }
```

```
}
```

```
    if(d_min!=+∞){
```

```
        for (neighbor in neighbors){
```

```
            Emit(neighbor, ToString("D:",d_min+1));
```

```
            // possible distances for neighbors
```

```
        }
```

```
        Emit(nodeid, ToString("D:",d_min));
```

```
    }
```

```
}
```





# EXAMPLE FOR JOB1

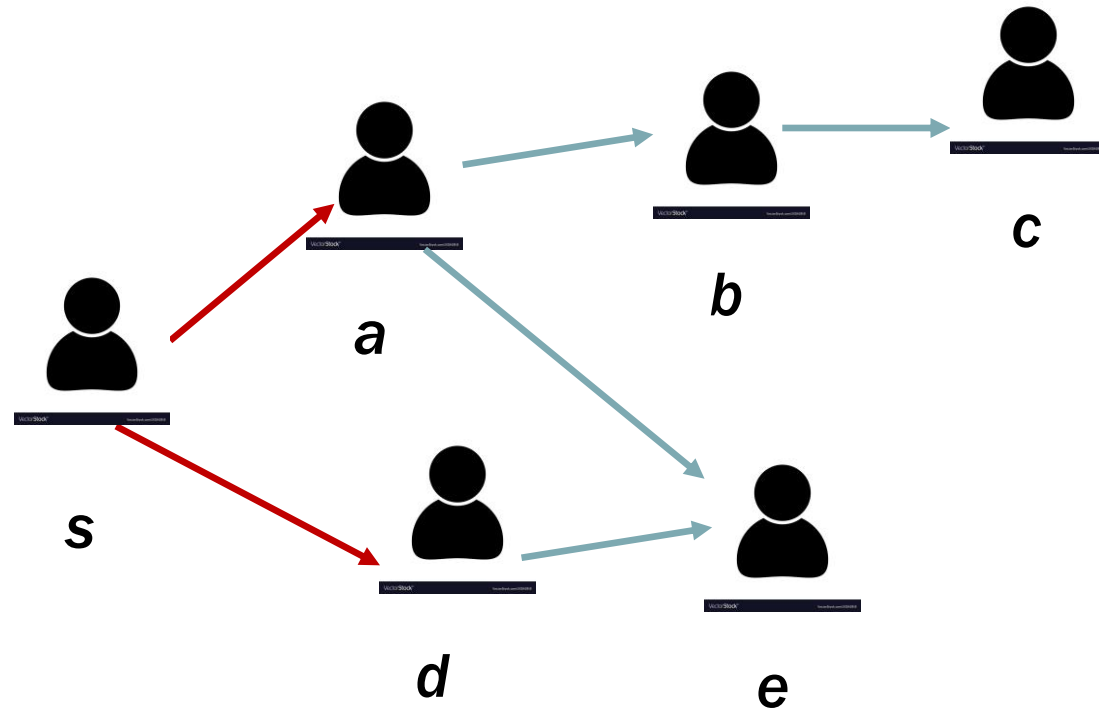
Job1:

Input

- (s,"D:0") (s, "N:a;d") (a, "N:b;e") (d, "N:e") (b, "N:c")

Output

- (s,"D:0")
- (s, "N:a;d")
- (a, "N:b;e")
- (d, "N:e")
- (b, "N:c")
- (a, "D:1")
- (d, "D:1")



# EXAMPLE FOR JOB2

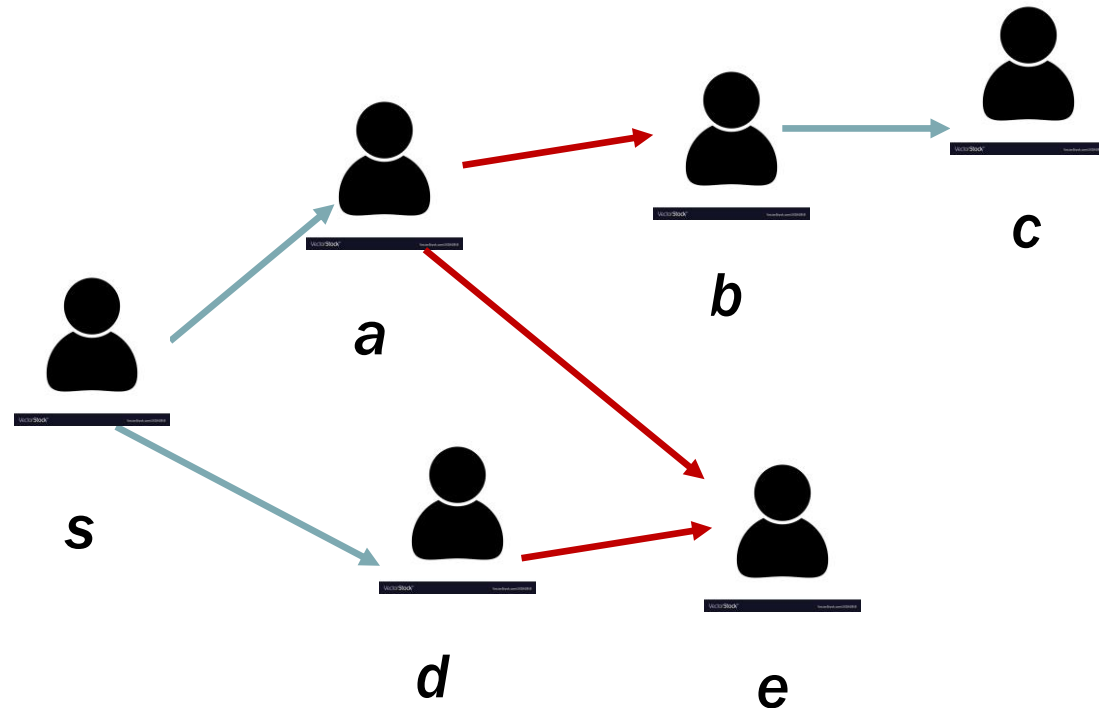
Job2:

Input

- (s,"D:0") (s, "N:a;d") (a, "N:b;e") (d, "N:e") (b, "N:c") (a, "D:1") (b, "D:2")

Output

- (s,"D:0")
- (s, "N:a;d")
- (a, "N:b;e")
- (d, "N:e")
- (b, "N:c")
- (a, "D:1")
- (d, "D:1")
- (b, "D:2")
- (e, "D:2")
- (e, "D:2")



## LAST JOB: MAP

```
map(String nodeid, String value) {  
  {  
    Emit-Intermediate(nodeid, value);  
  }  
}
```

# LAST JOB: REDUCE

```
reduce(String nodeid, Iterator<String> values) {  
    d_min=+∞;  
    for( value in values ){  
        if (value starts with “D”){  
            if( ToInteger(value)<d_min)  
                d_min=ToInteger(value);  
        }  
    }  
    if(d_min!=+∞)  
        Emit(nodeid, ToString(“D:”,d_min));  
}
```

# EXAMPLE LAST JOB

Job2:

Input

- (s,"D:0") (s, "N:a;d") (a, "N:b;e") (d, "N:e") (b, "N:c") (a, "D:1") (d, "D:1") (b, "D:2") (e, "D:2") (e, "D:2")

Output

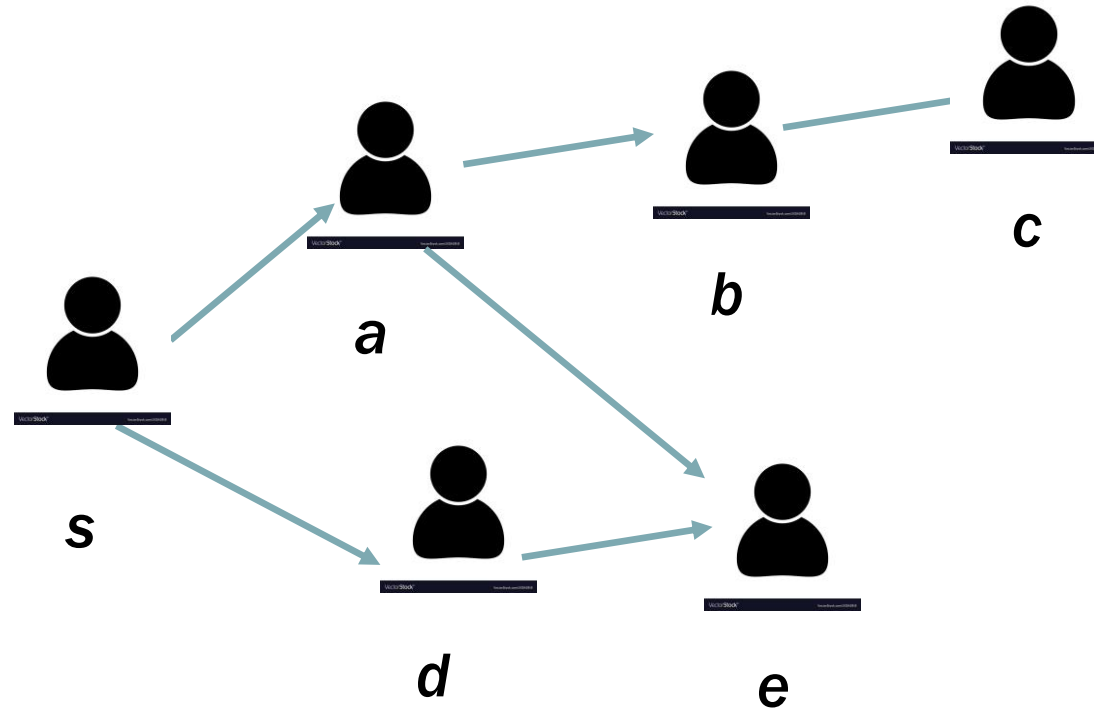
(s,"D:0")

(a, "D:1")

(d, "D:1")

(b, "D:2")

(e, "D:2")



**OPTIMIZATION?**



## FURTHER EXTENSION

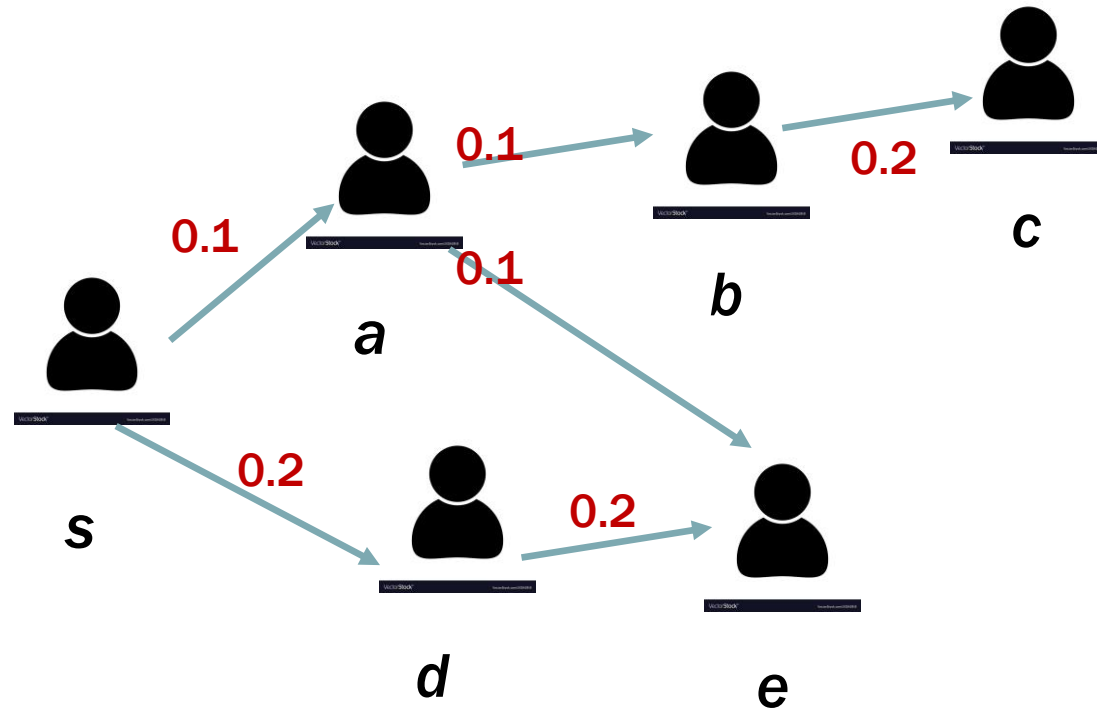
Previously, we considered the  $K$ -hop shortest path computation in social graphs using MapReduce. Extend the pseudo code to handle weighted graph whose edges may have different weights.

# FIRST MAPREDUCE JOB

## Purpose:

Each key-value pair stores the information of an edge

- Key: nodeID
- Value: nodeID; **weight**
- Example:
  - (s, "a; 0.1")
  - (s, "d; 0.2")
  - (a, "e; 0.1")
  - (d, "e; 0.2")
  - (a, "b; 0.1")
  - (b, "c; 0.2")





## JOB0(STEP0):MAP

```
map(String nodeid_from, String nodeid_to_and_weight) {  
  {  
    Emit-Intermediate(nodeid_from, nodeid_to_and_weight);  
  }  
}
```

## **JOB0(STEP0):REDUCE**

```
reduce(String nodeid, Iterator<String> neighbors) {  
    if(nodeid.equals("s")){  
        Emit("s", "D:0");//"D" indicates distance  
    }  
  
    Emit(nodeid, "N:"+ToString(neighbors));//"N" indicates neighbors  
}
```

Note: ToString() makes the list of neighbors as a string

# EXAMPLE FOR JOB0

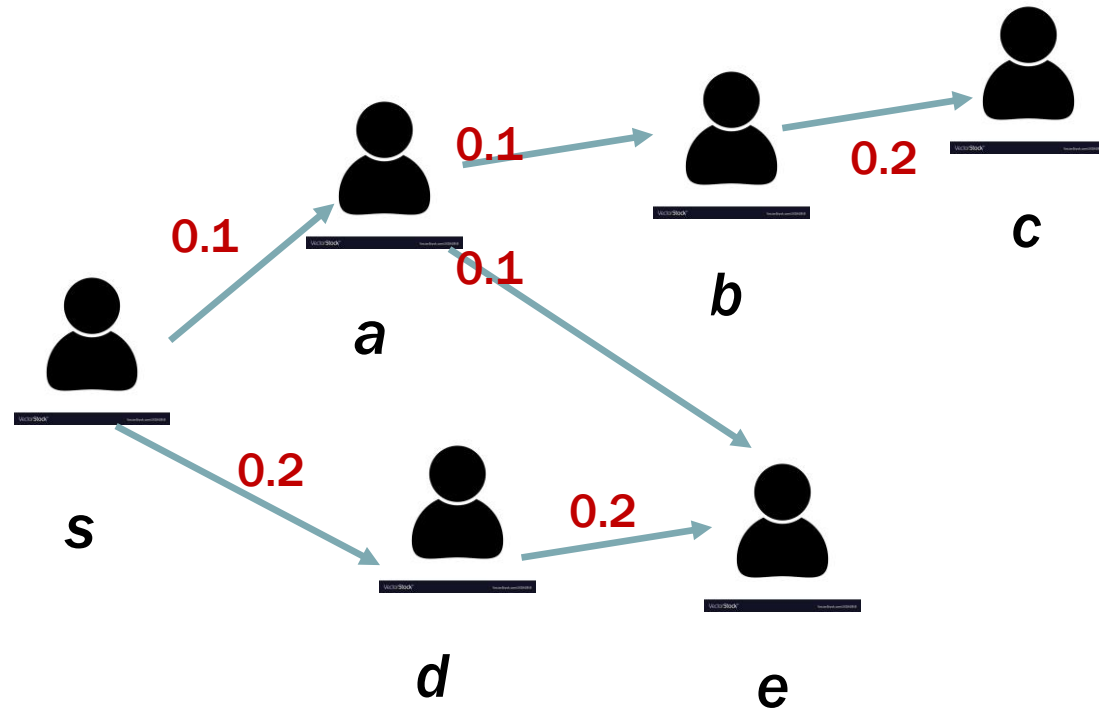
Job0:

Input

- (s, a;0.1) (s, d;0.2) (a, e;0.1) (d, e;0.2) (a, b;0.1) (b, c;0.2)

Output

- (s, "D:0")
- (s, "N:a;0.1;d;0.2")
- (a, "N:b;0.1;e;0.1")
- (d, "N:e;0.2")
- (b, "N:c;0.2")

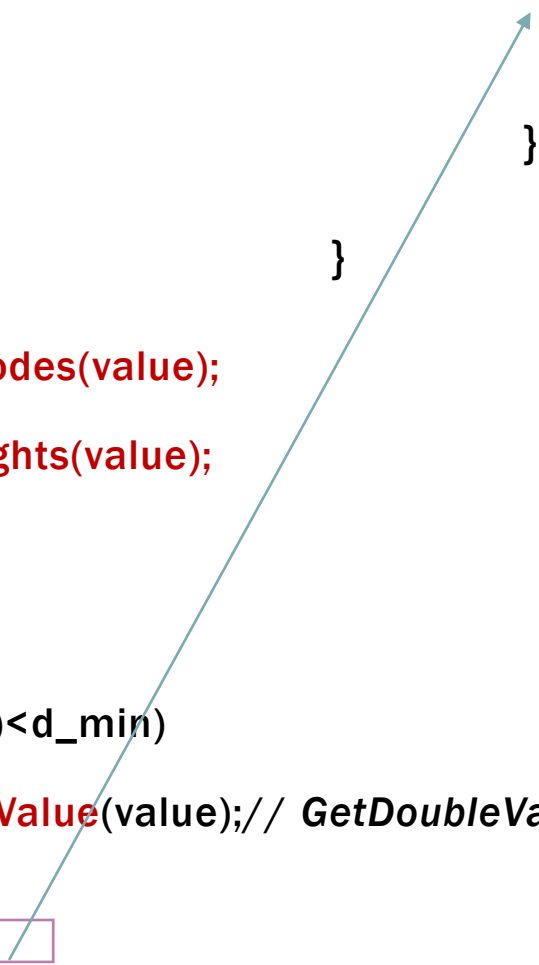


## SUBSEQUENT JOBS (STEPS 1-K): MAP

```
map(String nodeid, String value) {  
  {  
    Emit-Intermediate(nodeid, value);  
  }  
}
```

# SUBSEQUENT JOBS (STEPS 1-K): REDUCE

```
reduce(String nodeid, Iterator<String> values) {  
    d_min=+∞;  
    Iterator<String> neighbors;  
    Iterator<Double> weights;  
    for( value in values ){  
        if (value starts with "N"){  
            neighbors= ToNeighborsNodes(value);  
            weights= ToNeighborsWeights(value);  
            Emit(nodeid, value);  
        }else{  
            if( GetDoubleValue(value)<d_min)  
                d_min=GetDoubleValue(value);  
            // GetDoubleValue removes "N" and convert the value to double.  
        }  
    }  
}
```



The diagram illustrates the flow of the **weights** variable. A light blue arrow originates from the **weights** variable in the left code block and points to the **weights[i]** in the right code block. A light purple rectangular box is positioned at the bottom of the left code block, with a line extending from its right side to the start of the arrow.

## LAST JOB: MAP

```
map(String nodeid, String value) {  
  {  
    Emit-Intermediate(nodeid, value);  
  }  
}
```

# LAST JOB: REDUCE

```
reduce(String nodeid, Iterator<String> values) {  
    d_min=+∞;  
    for( value in values ){  
        if (value starts with "D"){  
            if(GetDoubleValue(value)<d_min)  
                d_min=GetDoubleValue(value);  
        }  
    }  
    if(d_min!=+∞)  
        Emit(nodeid, ToString("D:",d_min));  
}
```

# EXAMPLE: PAGERANK

- ❑ Google's famous algorithms for ranking webpages.
- ❑ A measure of the “importance/quality” of a page.
- ❑ Widely adopted for ranking search results
- ❑ Intuition
  - ❑ Consider a random surfer that starts at a random webpage
  - ❑ He follows out-going links in a random manner with probability  $(1 - \alpha)$   
He jumps to a random webpage with probability  $\alpha$
  - ❑ PageRank is the probability that the random surfer will arrive at a given webpage



# MORE FORMALLY

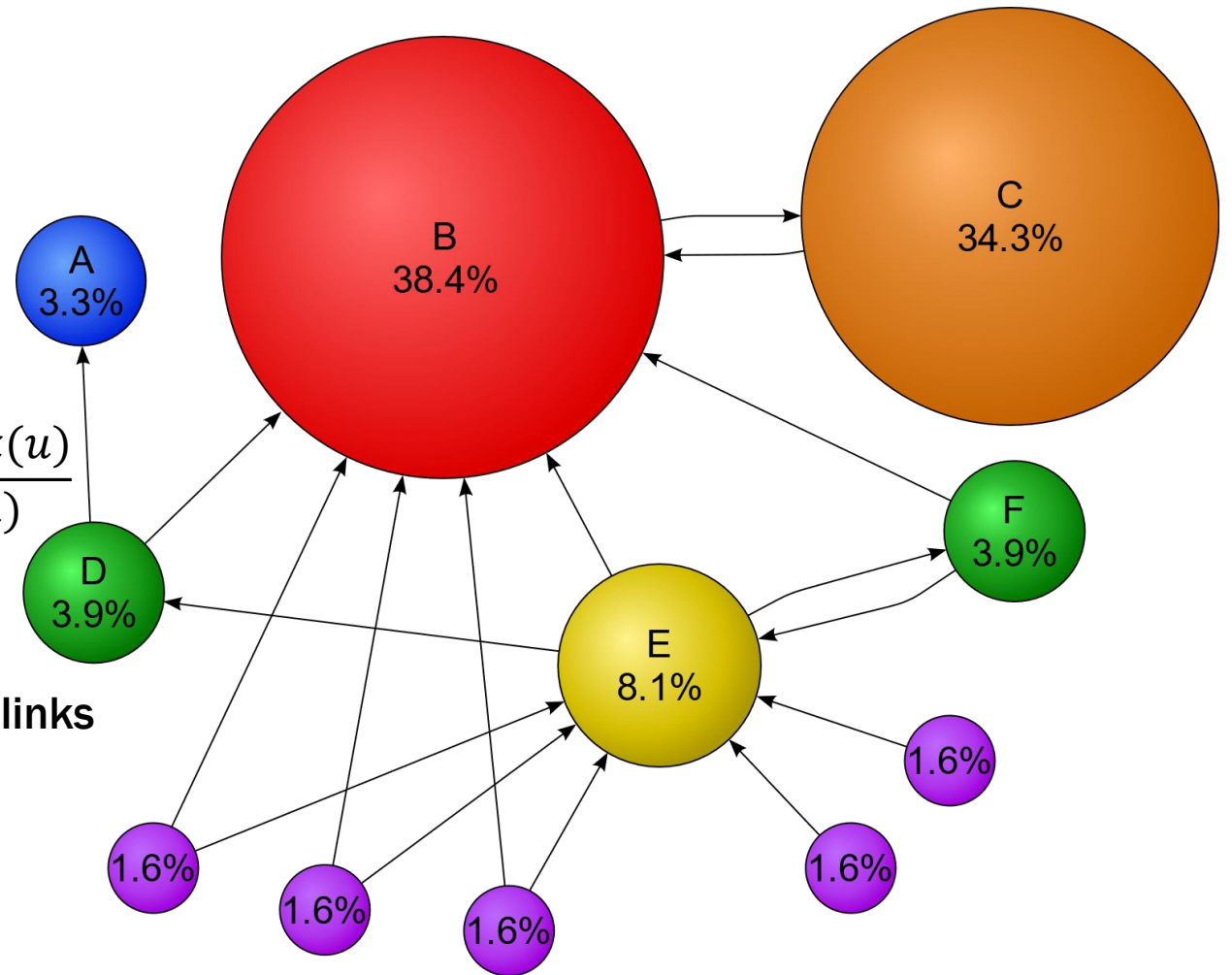
PageRank of a page is based on the PageRank of the pages which link to it

a value in (0, 1)

$$\text{PageRank}(v) = \frac{\alpha}{n} + (1 - \alpha) \times \sum_{u \text{ links to } v} \frac{\text{PageRank}(u)}{d_{\text{out}}(u)}$$

Number of web pages

Number of out-going links



# PAGERANK COMPUTATION

**Step 1:** Initialize  $\text{PageRank}(v) = 1/n$  for every webpage.

**Step 2:** Iteratively apply the formula until convergence

For each webpage  $v$ , compute

$$\text{PageRank}(v) = \frac{\alpha}{n} + (1 - \alpha) \times \sum_{u \text{ links to } v} \frac{\text{PageRank}(u)}{d_{\text{out}}(u)}$$

Value of the previous iteration



# MAPREDUCE DESIGNS

Each iteration is a MapReduce job:

**Question:**

Which features should be aggregated for a page?

$$\text{PageRank}(v) = \frac{\alpha}{n} + (1 - \alpha) \times \sum_{u \text{ links to } v} \frac{\text{PageRank}(u)}{d_{\text{out}}(u)}$$

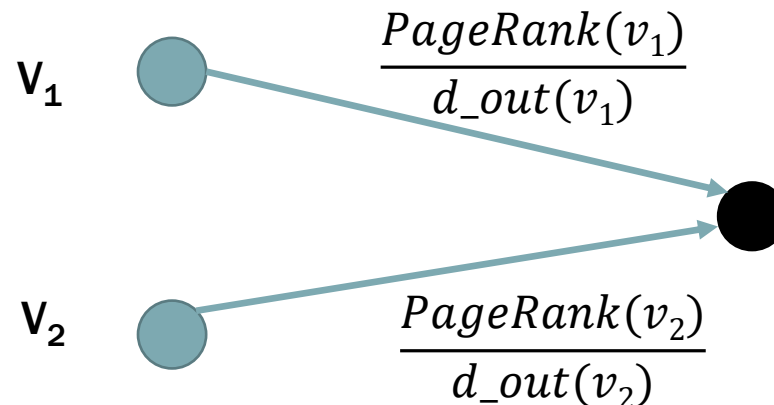
# MAPREDUCE DESIGNS

Each iteration is a MapReduce job:

## Map:

Input with the current PageRank value of a webpage  $v$  (or set to  $\text{PageRank}(v)=1/n$  in the 1<sup>st</sup> job).

For each out-neighbor link ( $u$ ) of current webpage  $v$  (namely,  $v \rightarrow u$ ), compute  $\frac{\text{PageRank}(v)}{d_{\text{out}}(v)}$  and **Emit-Intermediate**( $u, \frac{\text{PageRank}(v)}{d_{\text{out}}(v)}$ )



## Reduce:

Each webpage  $u$  receives the PageRank portion (stored in **values of reduce()**) from its incoming links, and hence it can compute

$$\sum_{u \text{ links to } v} \frac{PageRank(u)}{d_{out}(u)}$$

Use the formula to update PageRanks for the next job

# MAP

```
Map(String nodeid, String value_and_neighbors){  
    // value stores neighbor list and PageRank of nodeid  
    double PR=getPageRank(value_and_neighbors);  
    List<String> neighbors = getNeighbors(value_and_neighbors);  
    for(each neighbor in neighbors){  
        Emit-Intermediate(neighbor, "P:"+PR/neighbors.size());  
    }  
    Emit-Intermediate(nodeid, "N:"+ToString(neighbors));  
}
```

# REDUCE

```
Reduce(String nodeid, Iterator values){  
    double PR=0.0;  
  
    String neighbors;  
  
    for(value in values){  
        if(value starts with "P"){  
            PR = PR + getPageRank(value)  $\times$  (1 -  $\alpha$ );  
        }  
        else{  
            neighbors = getNeighbors(value);  
        }  
    }  
  
    PR=PR+  $\frac{\alpha}{n}$  ;  
  
    Emit(nodeid, PR+";" + neighbors);  
}
```

# SUMMARY AND OPEN DISCUSSIONS

MapReduce model is very powerful.

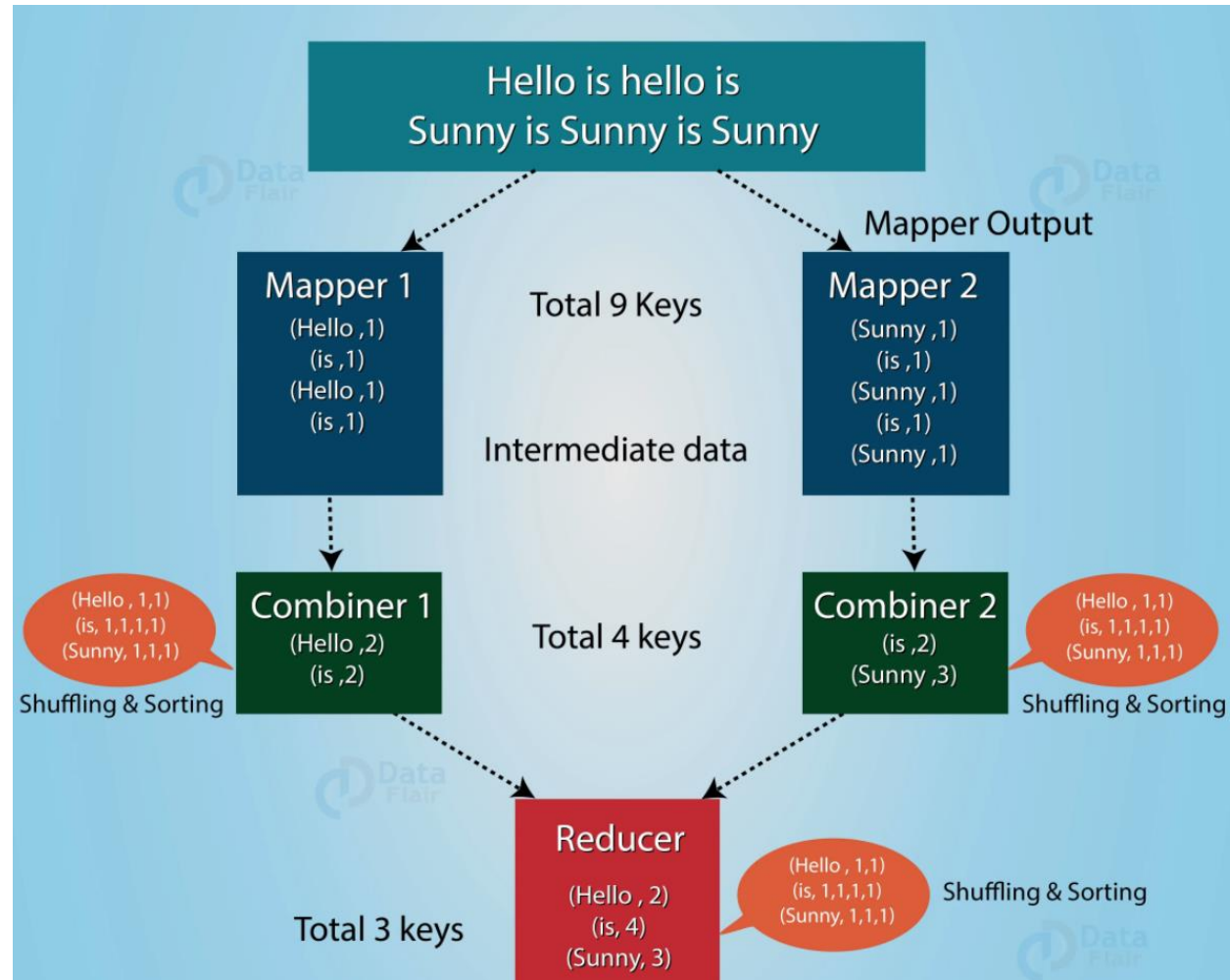
- ❑ Database operations (join)
- ❑ Graph based queries (shortest paths, PageRanks)
- ❑ ...

- 1. Any more examples?**
- 2. Possible optimization**

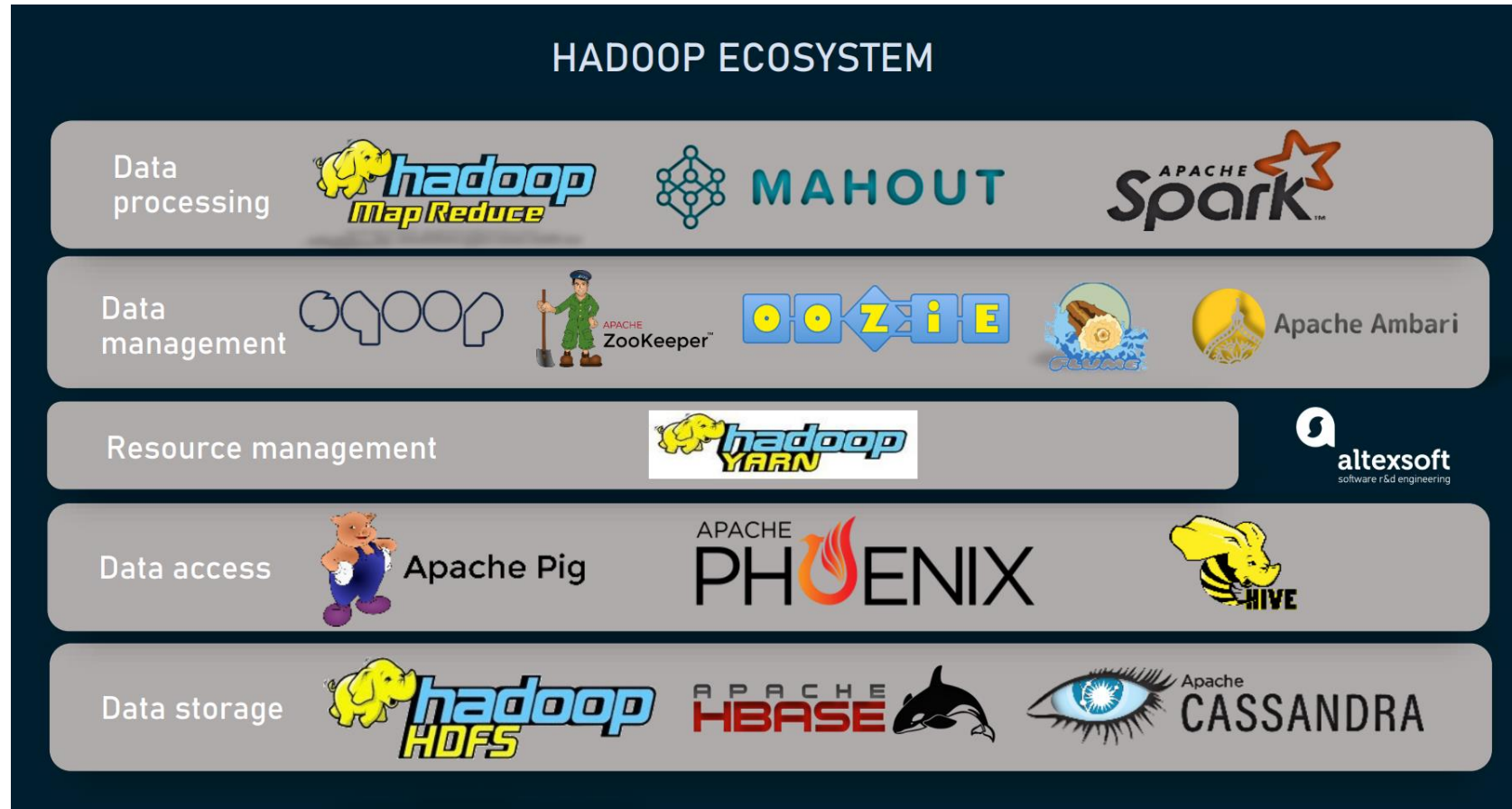




# COMBINER



# HADOOP → SPARK



Source: <https://www.altexsoft.com/blog/hadoop-vs-spark/>

**We finish lectures for Distributed Systems!**



**Next lecture:**

**NoSQL and Key-Value Stores**