



## **BIG DATA**

# **Big Data Algorithm Complexity**

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- Motivation – Algorithm complexity
- Communication Cost Complexity Model
- 3 Way joins with the communication cost complexity
- Key parameters
- Similarity join - analysis

## Motivation – Algorithm Complexity

- So far, we have looked at MapReduce algorithms
- However, for a particular problem, there could be many algorithms
- Which algorithm should we choose?
- This is why we study complexity of MapReduce
- We will actually study complexity of workflow systems
  - Generalization of MapReduce
  - Many important Big Data systems are workflow systems

- Consider the following two problems
  - Matrix multiplication
  - Database query
- What would be the complexity of these algorithms when executing on a single node?
- What does complexity depend on?



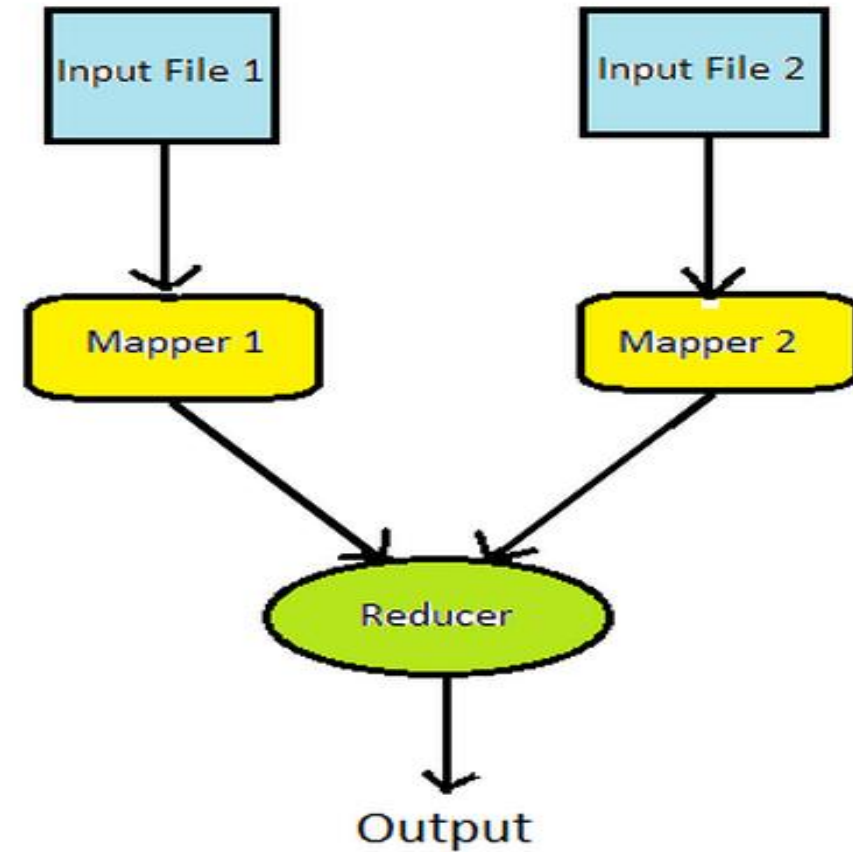
- Matrix multiplication
  - Expressed in terms of the bound on total #computations performed
- Database query
  - Complexity depends on disk read

- Communication cost: size of input
- Why communication cost?
  - Algorithm tends to be linear in data
  - Network speed  $\ll$  CPU speed
  - Disk speed  $\ll$  CPU speed
  - Major time could be communication time

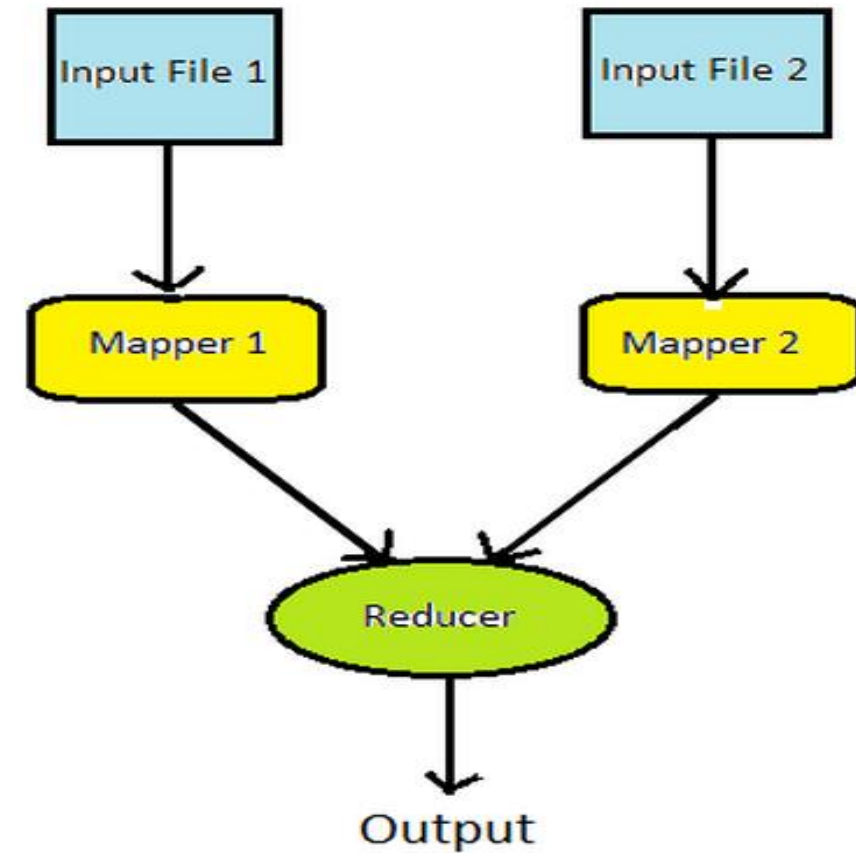
- Why only input size?
  - Output is input to some other task
  - Final output is generally small by aggregation
    - Otherwise not human-readable



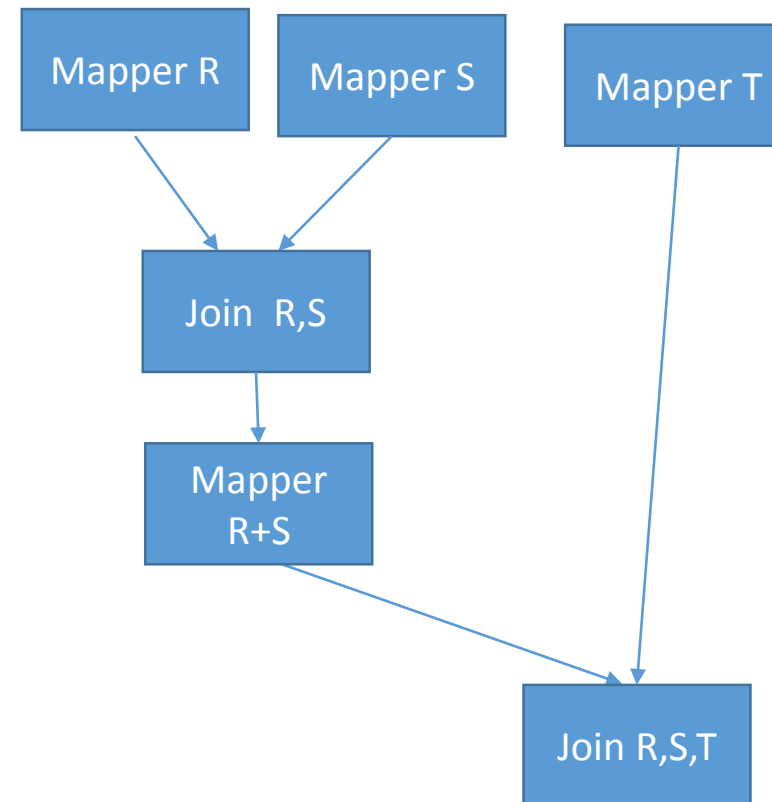
- Mapper input complexity =  $r+s$ 
  - Read data from disk
- Reducer input complexity =  $r+s$ 
  - Network reads
- Total Complexity:  $O(r+s)$



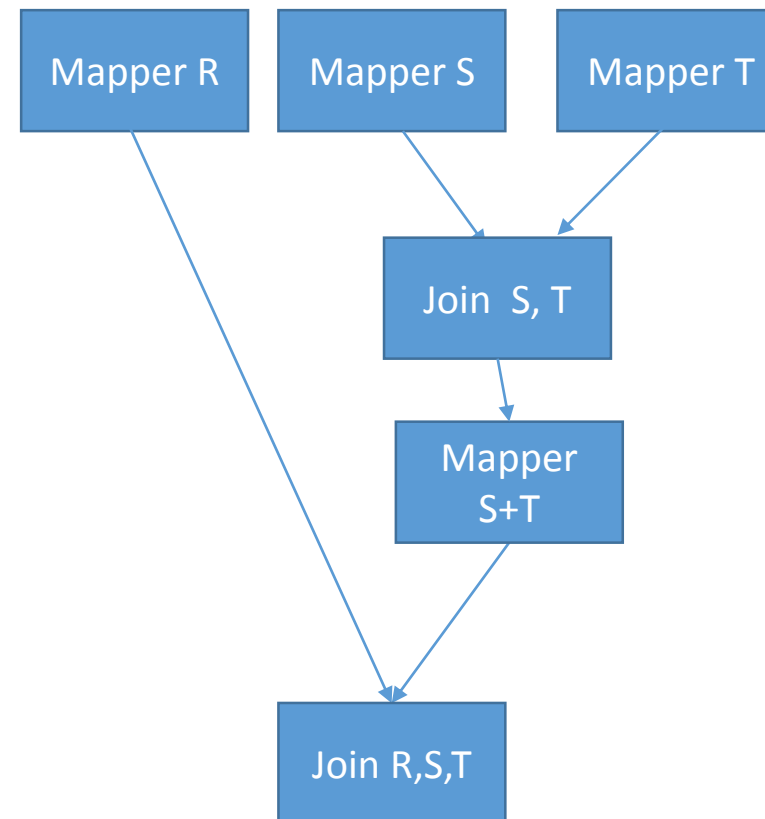
- Consider three relations R, S and T
- How will you perform a join using map reduce across the three?
- Estimate the complexity



- 2 MapReduce phases
- Case 1: Join  $R, S$  and then join  $T$ 
  - Input to Mapper 1:  $r$
  - Input to Mapper 2:  $s$
  - Input to Reducer 1:  $r+s$
  - Let  $p$  be the probability of match between  $r, s$
  - Input to Mapper 3:  $prs$
  - Input to Mapper 4:  $t$
  - Input to Reducer 2:  $t+prs$
- Total Complexity:  $O(r+s+t+prs)$



- Case 1: Join  $S, T$  and then join  $R$ 
  - Input to Mapper 1:  $s$
  - Input to Mapper 2:  $t$
  - Input to Reducer 1:  $s+t$
  - Let  $q$  be the probability of match between  $s, t$
  - Input to Mapper 3:  $qst$
  - Input to Mapper 4:  $r$
  - Input to Reducer 2:  $r+qst$
- Total Complexity:  $O(r+s+t+qst)$ 
  - Depends upon join order
  - If  $p \sim q$ , first join could be whichever of  $rs, st, rt$  is the smallest



- Can make communication cost very low by executing all tasks on single CPU
- However, program may run slowly
- Need to consider *wall clock time*
  - Time taken for entire job to finish
- Dividing jobs could increase communication but reduce wall clock time
  - Need to trade off communication time, wall clock time

- Reducer size  $q$ 
  - Max # of values that can have the same key
    - Not the number of reducers
  - If  $q$  is small, there can be more reducers
    - Suppose the number of Map outputs is  $T$
    - Max number of reducers =  $T/q$
    - This will reduce the wall clock time
    - But increase the communication cost
- Replication rate  $r$ 
  - $r = (\text{\#key value pairs output by Mapper}) / (\text{\# input records to Mapper})$
  - Average communication cost from Map tasks to Reduce tasks

- Assume we have a database of 1 million images
- Each image is 1 MB
- Total DB size = 1 TB
- Assume there is a function  $s(x,y)$  which determines how similar two images  $x,y$  are
  - $s(x,y) = s(y,x)$
- Problem: output all pairs  $x,y$  such that  $s(x,y) > t$

- Assume each image  $P_i$  has an index  $i$
- Mapper
  - Reads in  $(i, P_i)$
  - Generates all pairs  $(\{i, j\}, \{P_i, P_j\})$
- Reducer
  - Reads  $(\{i, j\}, \{P_i, P_j\})$
  - Computes  $s(P_i, P_j)$



- What is the
  - Communication cost of the naïve algorithm?
  - Parallelism of the naïve algorithm?



- What is the
  - Communication cost of the naïve algorithm?
  - Parallelism of the naïve algorithm?
- Algorithm doesn't work
  - Data to be transmitted =  $1,000,000 \times 999,999 \times 1,000,000$  bytes =  $10^{18}$
  - Communication cost is  $\sim n^2$  where  $n$  is the number of images (extremely high)
  - However, potential parallelism is very high

- Do everything on one node
- Mapper
  - Reads in  $(i, P_i)$
  - Generates all pairs  $(\{i, j\}, \{P_i, P_j\})$
- Reducer (runs on same node as mapper)
  - Reads  $(\{i, j\}, \{P_i, P_j\})$
  - Computes  $s(P_i, P_j)$
- No communication cost
- Very low parallelism (wall clock time high)

### **Send one pair to each reducer**

- High communication cost (bad)
- High parallelism (good)

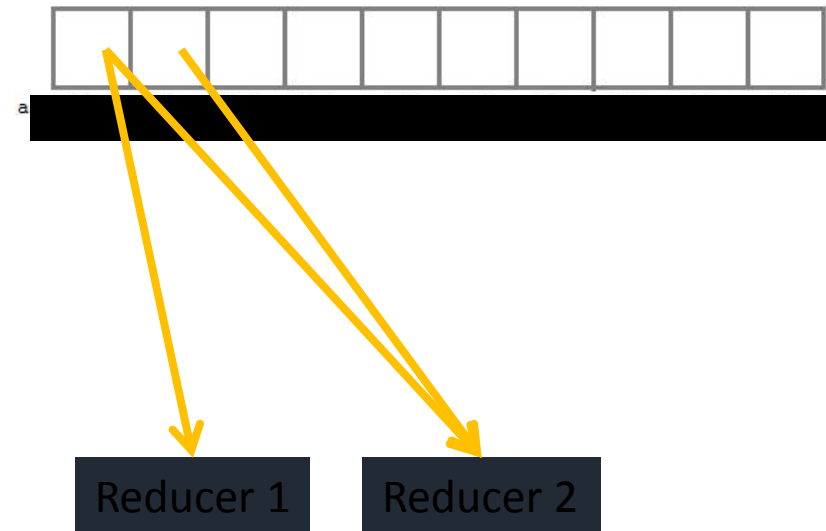
### **Do everything on one node**

- Low parallelism (bad)
- Low communication cost (good)

Can we get something in between?

- Overview

- Group images
- Read in two groups of images in a single reducer
- Store them in memory
- Compare all pairs from those groups
- Output results



- Suppose the groups are  $G_0, \dots, G_{99}$
- Group  $G_0$  is sent to nodes 0, 1, ..., 98
  - Why?
- Group  $G_0$  has to be compared with 99 other groups
- Group  $G_1$  is sent to?
  - ~~0, 1, ..., 98~~
- Group  $G_1$  is sent to 0, 99, 100, ...196 (0+98 other nodes)
- Group  $G_2$  is sent to?
- Group  $G_2$  is sent to 1, 99, 197, 198, ... 293 (1, 99 +97 other nodes)
- Group  $G_3$  is sent to 2, 100, 197, 294, ...389 (2, 100, 197, +96 other nodes)

- If there are  $g$  groups
- The number of images per group  $m=n/g$
- Each group is sent to  $g-1$  servers
- Total number of messages =  $g(g-1)$
- **Total data =  $mg(g-1) = n(g-1) \sim ng$**
- **Parallelism = no of nodes =  $(g-1) + (g-2) + (g-3) + \dots = g(g-1)/2 = O(g^2)$**
- Another way = no of nodes =  ${}^nC_2 = g(g-1)/2$

- Suppose we have groups of 100
  - How many groups are there?
  - How many nodes is each group sent to?
- What is the
  - Communication cost of the algorithm?
  - Parallelism of the algorithm?





- Naïve: approximately  $1,000,000 \times 1,000,000$  images =  $10^{12}$  images, parallelism =  $10^{12}$
- Example: group images into groups of 100
  - Communication cost:  $1,000,000$  images  $\times$   $100$  groups =  $10^8$  images
  - Parallelism =  $10^4$
- Example: group images into groups of 1000
  - Communication cost =  $1,000,000 \times 1000 = 10^9$  images
  - Parallelism =  $10^6$
- Trade-off: increasing group size
  - Increases communication complexity (more reads)
  - Reduces wall clock time (increases parallelism)

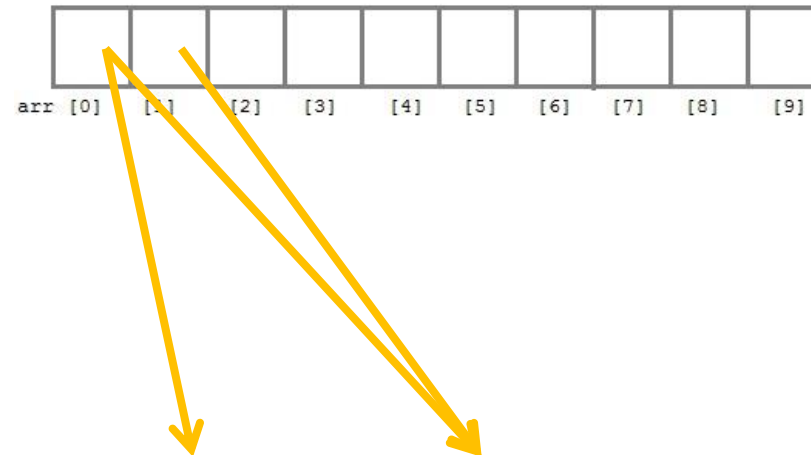
- On next slide
- Note
  - Group-based algorithm is discussed in book as if mapper sends pictures to reducer
  - In previous slides, we have discussed as if reducer reads in pictures from disk
  - From communication cost complexity both are the same
  - Performance: probably better to read from disk

- Overview

- Group images
- Read in two groups of images in a single reducer
- Store them in memory
- Compare all pairs from those groups
- Output results

- Complexity

- Communication cost  $\sim ng$  where  $g$  is the number of groups
- Can still get good parallelism



- Group images into  $g$  groups
- Mapper
  - Input:  $(i, P_i)$
  - Find  $u$  = group to which image  $i$  belongs
  - Output  $g-1$  key-value pairs  $(\{u, v\}, i, P_i)$  for all  $v \neq u$
- Reducer:
  - There is one reducer for each unique key  $\{u, v\}$
  - Use the input to store images for groups  $u, v$
  - Compare all pairs of images in groups  $u, v$
  - If  $v=u+1$ , then compare all pairs of images in group  $u$

- If group size is 1000
- Need ~2GB to store 2000 images in memory
- Need ~500,000 reducers
- If we have a 10,000 node cluster
  - Can do computation in 50 passes
  - Speedup of 10,000

- There could be many MapReduce algorithms to implement a particular functionality
  - Matrix multiplication
  - Multi-way joins
- There are two factors to consider when selecting an algorithm
  - Communication complexity: volume of data that is input to the different phases of the algorithm
  - Wall clock time: Total elapsed time for algorithm
    - Depends upon parallelism
  - Frequently there is a trade-off between these factors
    - Group size

- Mining of Massive Datasets
  - Rajaraman et. Al.
  - Chapter 2.4-2.5



# THANK YOU

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