

# Comparison of MapReduce with Bulk-Synchronous Systems

Review of Bulk-Synchronous  
Communication Costs  
Problem of Semijoin

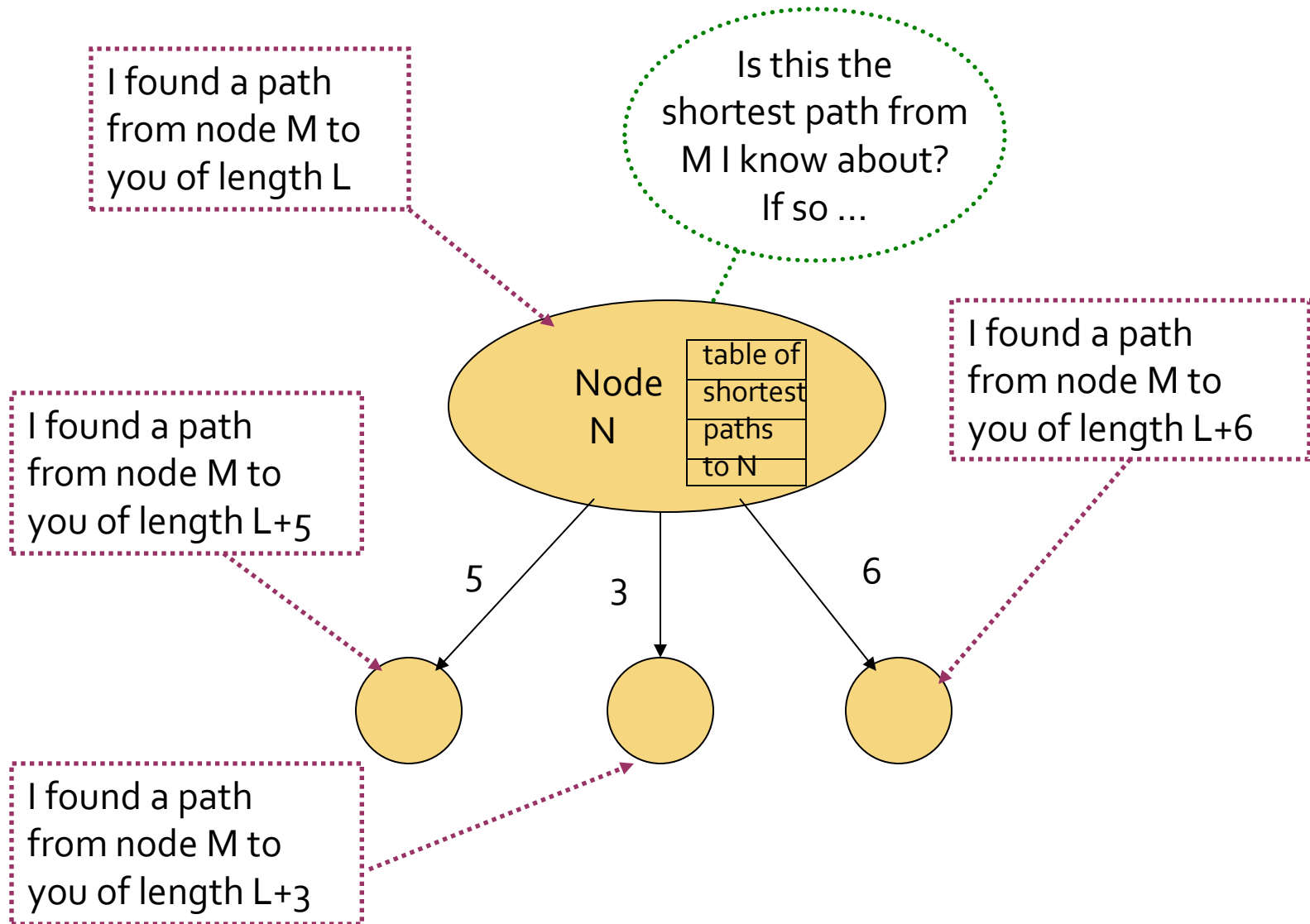
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# The Graph Model

- Views all computation as a recursion on some graph.
- Graph nodes send messages to one another.
  - Messages bunched into *supersteps*, where each graph node processes all data received.
  - Sending individual messages would result in far too much overhead.
- Checkpoint all compute nodes after some fixed number of supersteps.
- On failure, rolls all tasks back to previous checkpoint.

# Example: Shortest Paths



# Some Systems

- *Pregel*: the original, from Google.
- *Giraph*: open-source (Apache) Pregel.
  - Built on Hadoop.
- *GraphX*: a similar front end for Spark.
- *GraphLab*: similar system that deals more effectively with nodes of high degree.
  - Will split the work for such a graph node among several compute nodes.

# The Tyranny of Communication

- All these systems move data between tasks.
  - It is rare that (say) a Map task feeds a Reduce task at the same compute node.
  - And even so, you probably need to do disk I/O.
- Gigabit communication seems like a lot, but it is often the bottleneck.

# Two Approaches

- There is a subtle difference regarding how one avoids moving big data in MapReduce and Bulk-Synchronous systems.
- **Example:** join of  $R(A,B)$  and  $S(B,C)$ , where:
  - A is a really large field – a video.
  - B is the video ID.
  - $S(B,C)$  is a small number of streaming requests, where C is the destination.
- If we join R and S, most R-tuples move to the reducer for the B-value needlessly.

# The Semijoin

- Might want to *semijoin* first: find all the values of B in S, and filter those (a,b) in R that are *dangling* (will not join with anything in S).
- Then Map need not move dangling tuples to any reducer.
- But the obvious approach to semijoin also requires that every R-tuple be sent by its mapper to some reducer.

# Semijoin – (2)

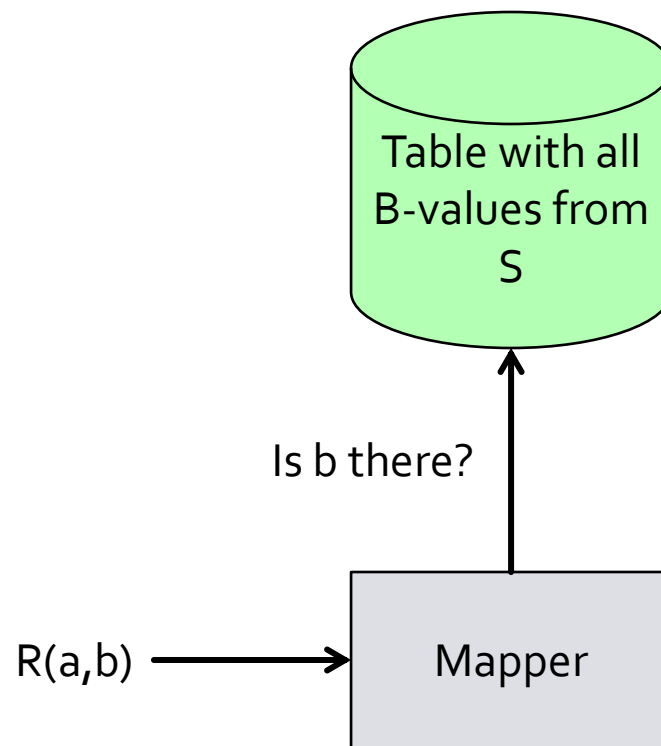
- To semijoin  $R(A,B)$  with  $S(B,C)$ , use  $B$  as the key for both relations.
  - From  $R(a,b)$  create key-value pair  $(b, (R,a))$ .
  - From  $S(b,c)$  create key-value pair  $(b,S)$ .
    - Almost like join, but you don't need the  $C$ -value.



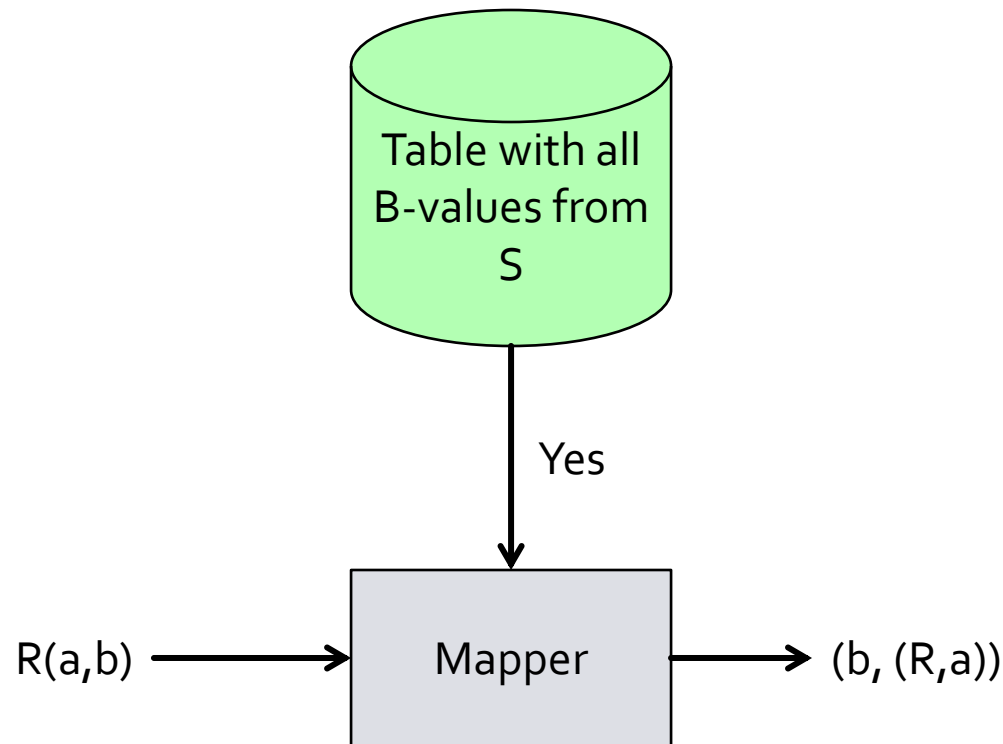
# The MapReduce Solution

- Recent implementations of MapReduce allow distribution of “small” amounts of data to every compute node.
- Project  $S$  onto  $B$  to form set  $S'$  and distribute  $S'$  everywhere.
- Then, run the standard MapReduce join, but have the Map function check that  $(a,b)$  has  $b$  in  $S'$  before emitting it as a key-value pair.
  - If most tuples in  $R$  are dangling, it saves substantial communication.

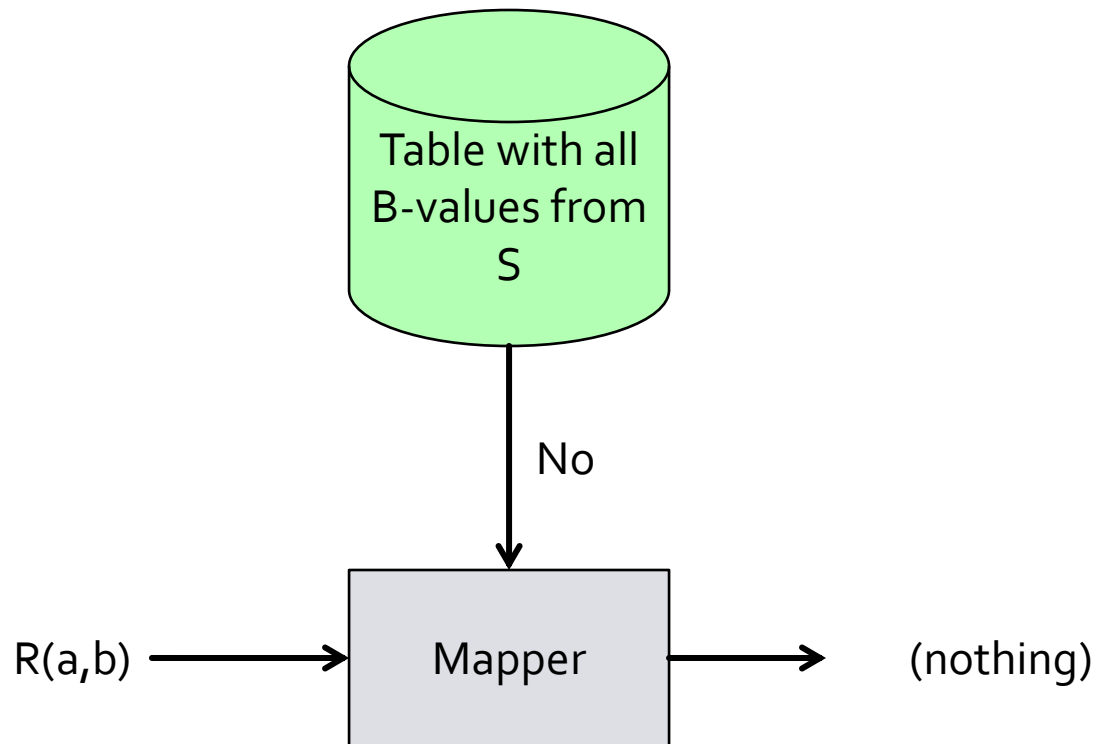
# Semijoin in the Mappers



# Semijoin in the Mappers – “Yes”



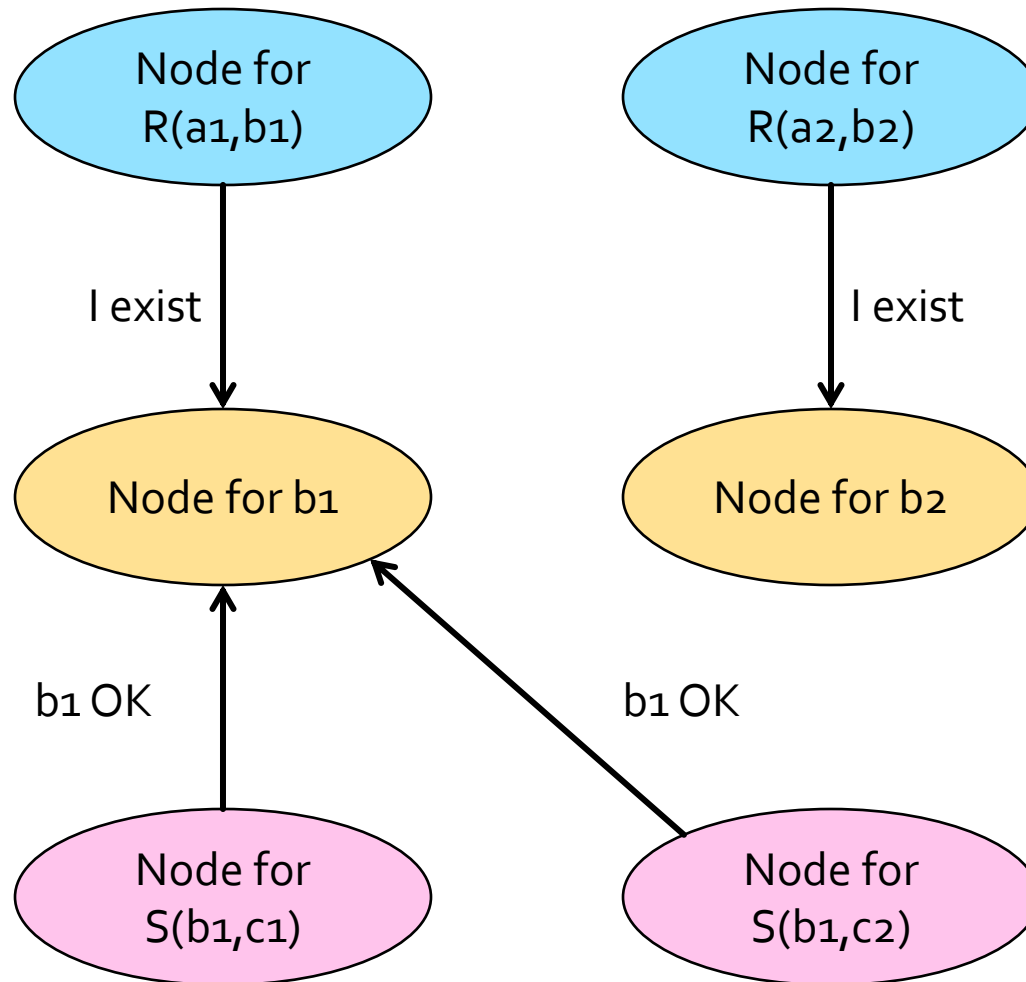
# Semijoin in the Mappers – “No”



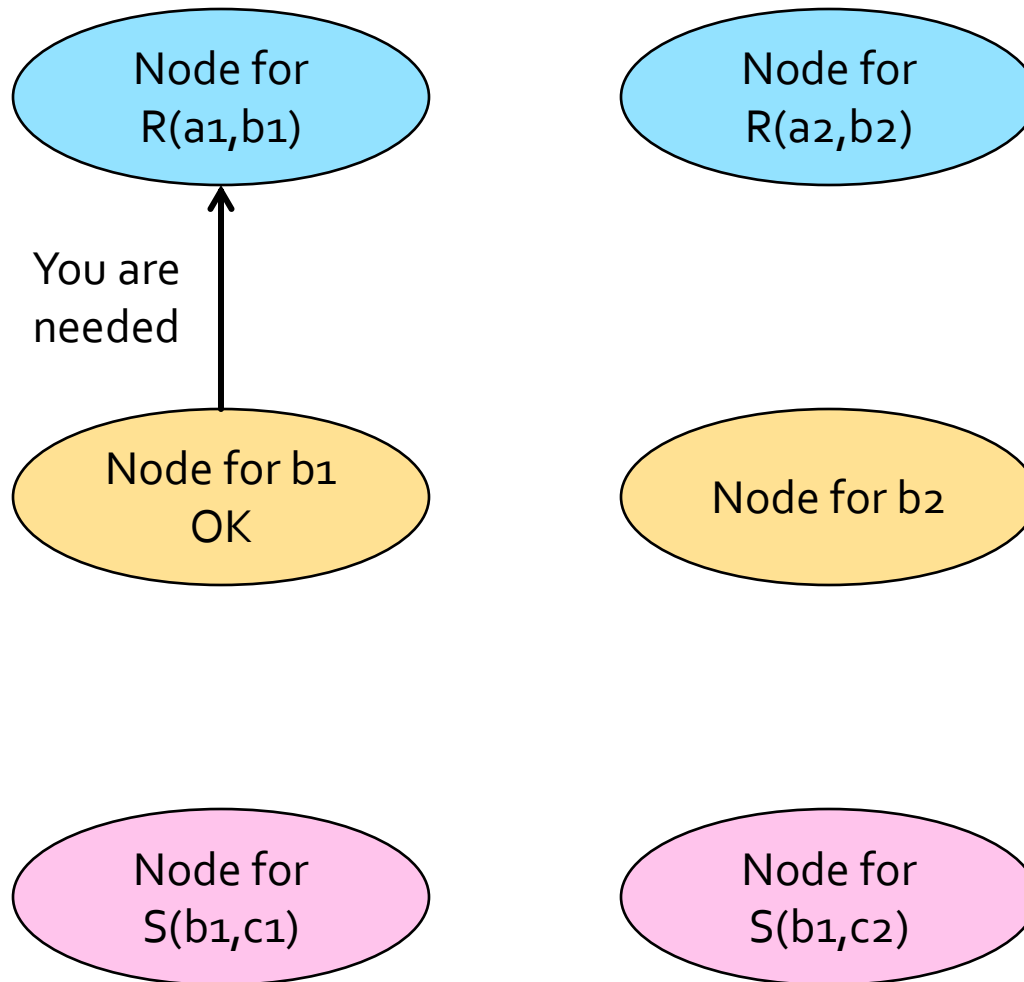
# The Bulk-Synchronous Solution

- Create a graph node for every tuple, and also for every B-value.
- All tuples  $(b,c)$  from  $S$  send a message to the node for B-value  $b$ .
- All tuples  $(a,b)$  from  $R$  send a message with their node name to the node for B-value  $b$ .
- The node for  $b$  sends messages to all  $(a,b)$  in  $R$ , provided it has received at least one message from a tuple in  $S$ .
- Now, we can mimic the MapReduce join without considering dangling tuples.

# Bulk-Synchronous Semijoin



# Bulk-Synchronous Semijoin – (2)



# Bulk-Synchronous Join Phase

