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Chapter 6

Batch processing - part 1

MapReduce

Data processing: MapReduce

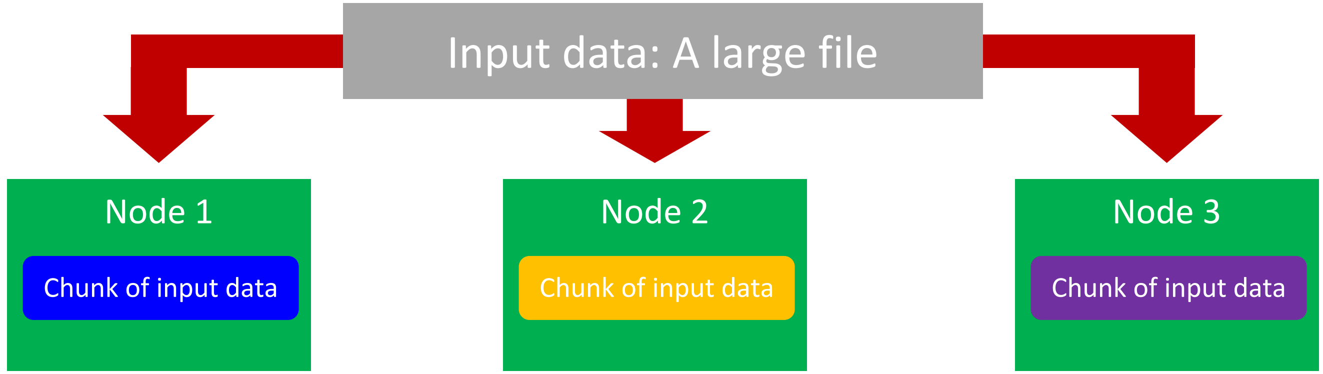
- MapReduce framework is the Hadoop default data processing engine
- MapReduce is a programming model for data processing
    - it is not a language, a style of processing data created by Google
- The beauty of MapReduce
    - Simplicity
    - Flexibility
    - Scalability

a MR job = {Isolated Tasks}n

- MapReduce divides the workload into multiple *independent tasks* and schedule them across cluster nodes
- A work performed by each task is done *in isolation* from one another for scalability reasons
  - The communication overhead required to keep the data on the nodes synchronized at all times would prevent the model from performing reliably and efficiently at large scale

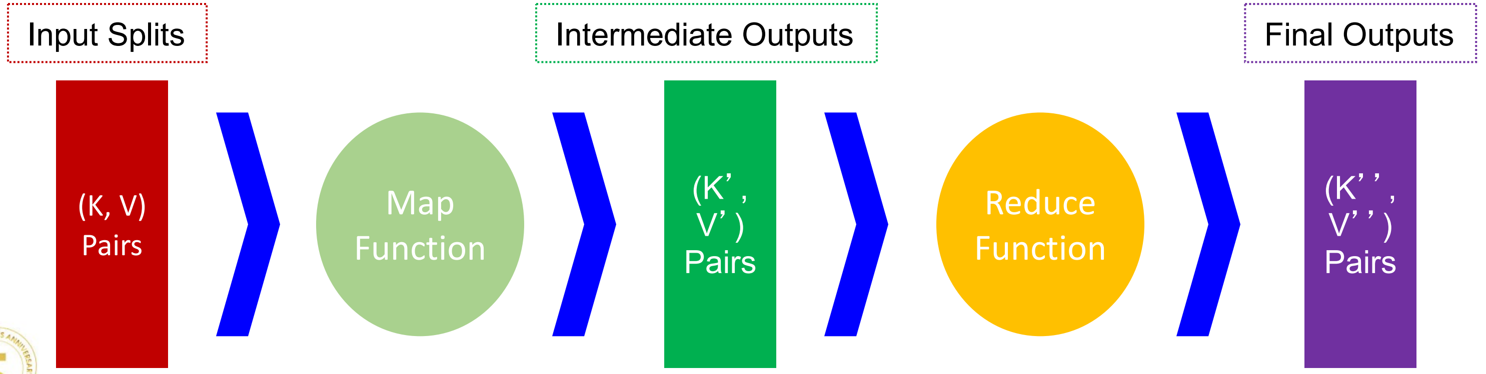
Data Distribution

- In a MapReduce cluster, data is usually managed by a distributed file systems (e.g., HDFS)
- Move code to data and not data to code



Keys and Values

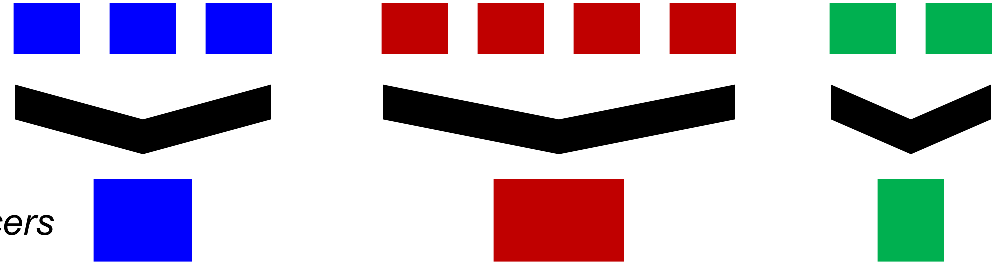
- The programmer in MapReduce has to specify two functions, the *map function* and the *reduce function* that implement the Mapper and the Reducer in a MapReduce program
- In MapReduce data elements are always structured as key-value (i.e., (K, V)) pairs
- The map and reduce functions receive and *emit* (K, V) pairs



Partitions

- A different subset of intermediate key space is assigned to each Reducer
- These subsets are known as *partitions*

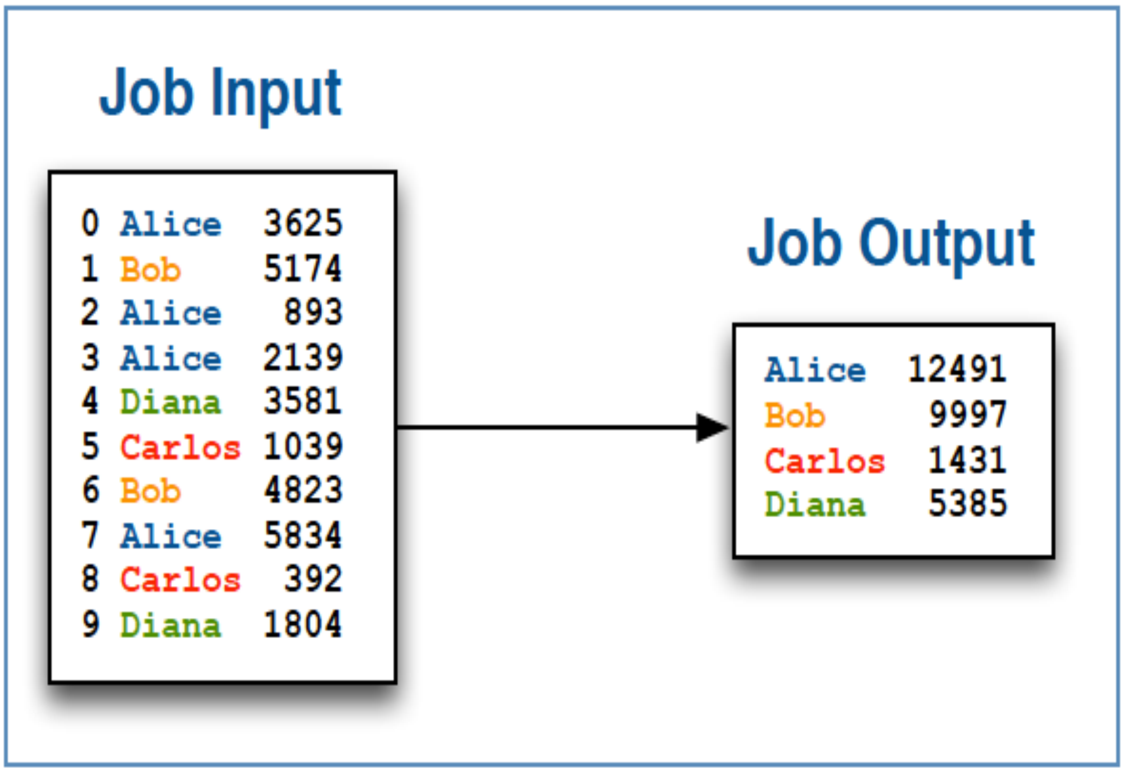
Different colors represent different keys (potentially) from different Mappers



Partitions are the input to Reducers

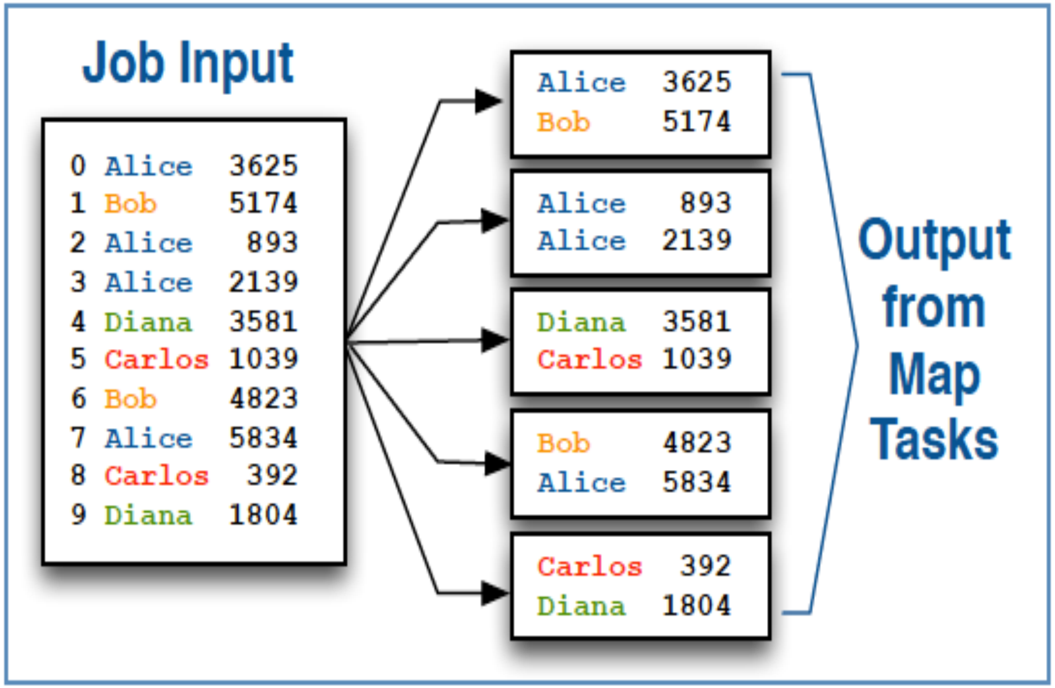
MapReduce example

- Input: text file containing order ID, employee name, and sale amount
- Output: sum of all sales per employee



Map phase

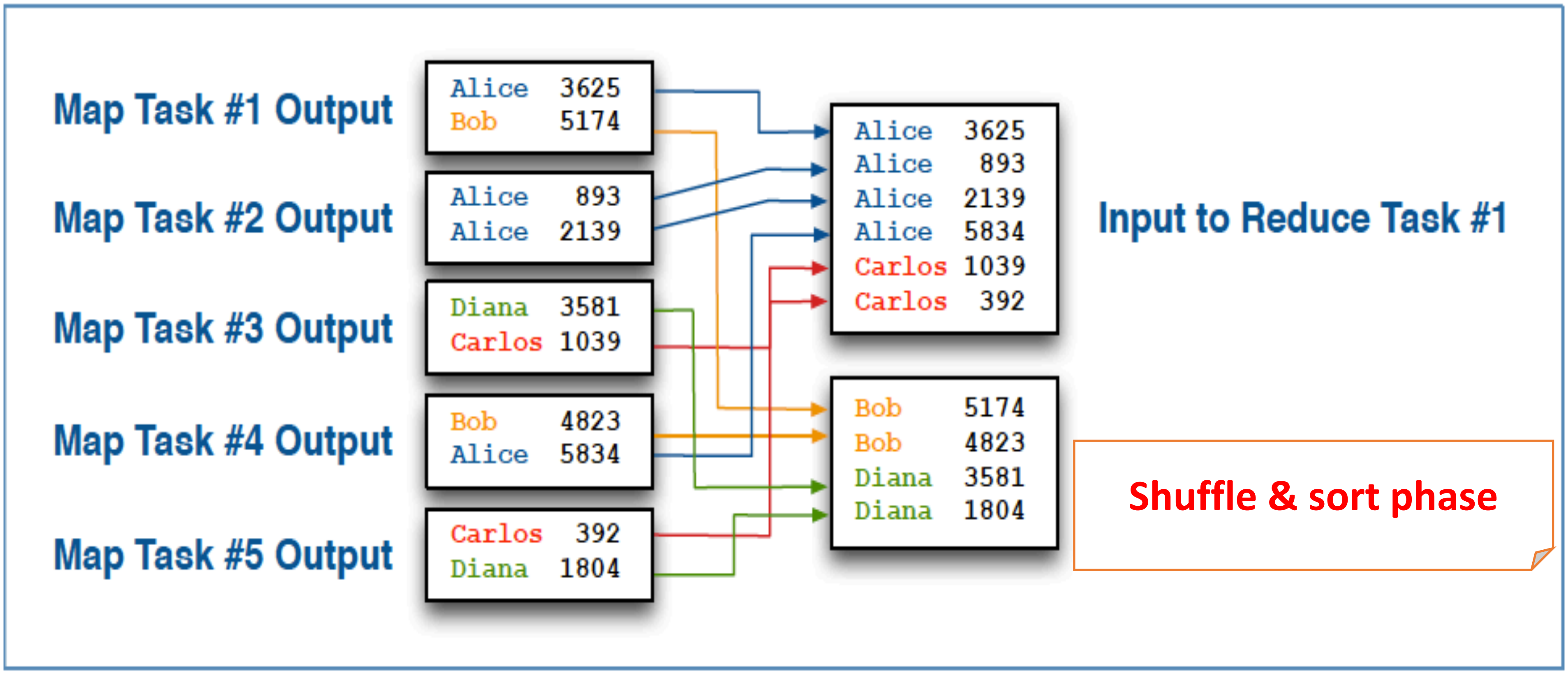
- Hadoop splits job into many individual map tasks
  - Number of map tasks is determined by the amount of input data
  - Each map task receives a portion of the overall job input to process
  - Mappers process one input record at a time
  - For each input record, they emit zero or more records as output
- In this case, the map task simply parses the input record
  - And then emits the name and price fields for each as output



Map phase

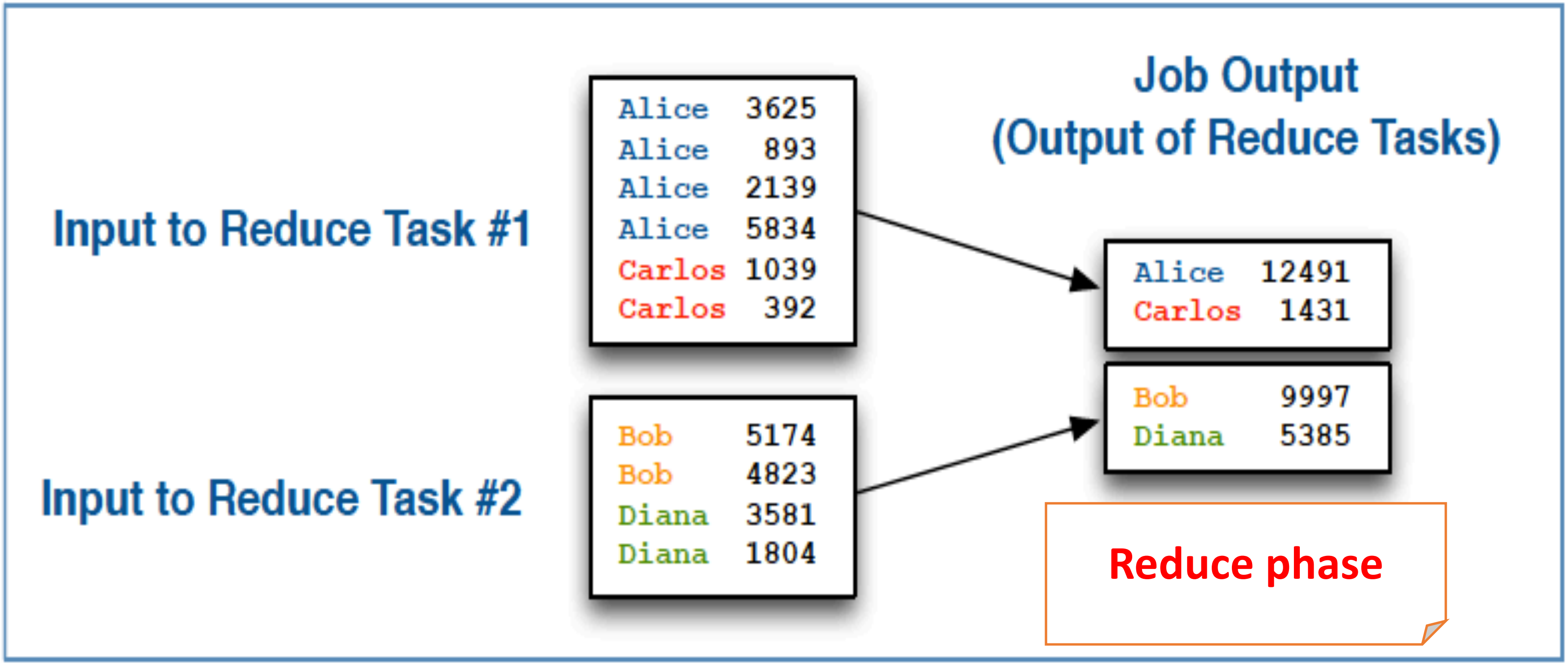
Shuffle & sort

- Hadoop automatically sorts and merges output from all map tasks
  - This intermediate process is known as the **shuffle and sort**
  - The result is supplied to reduce tasks

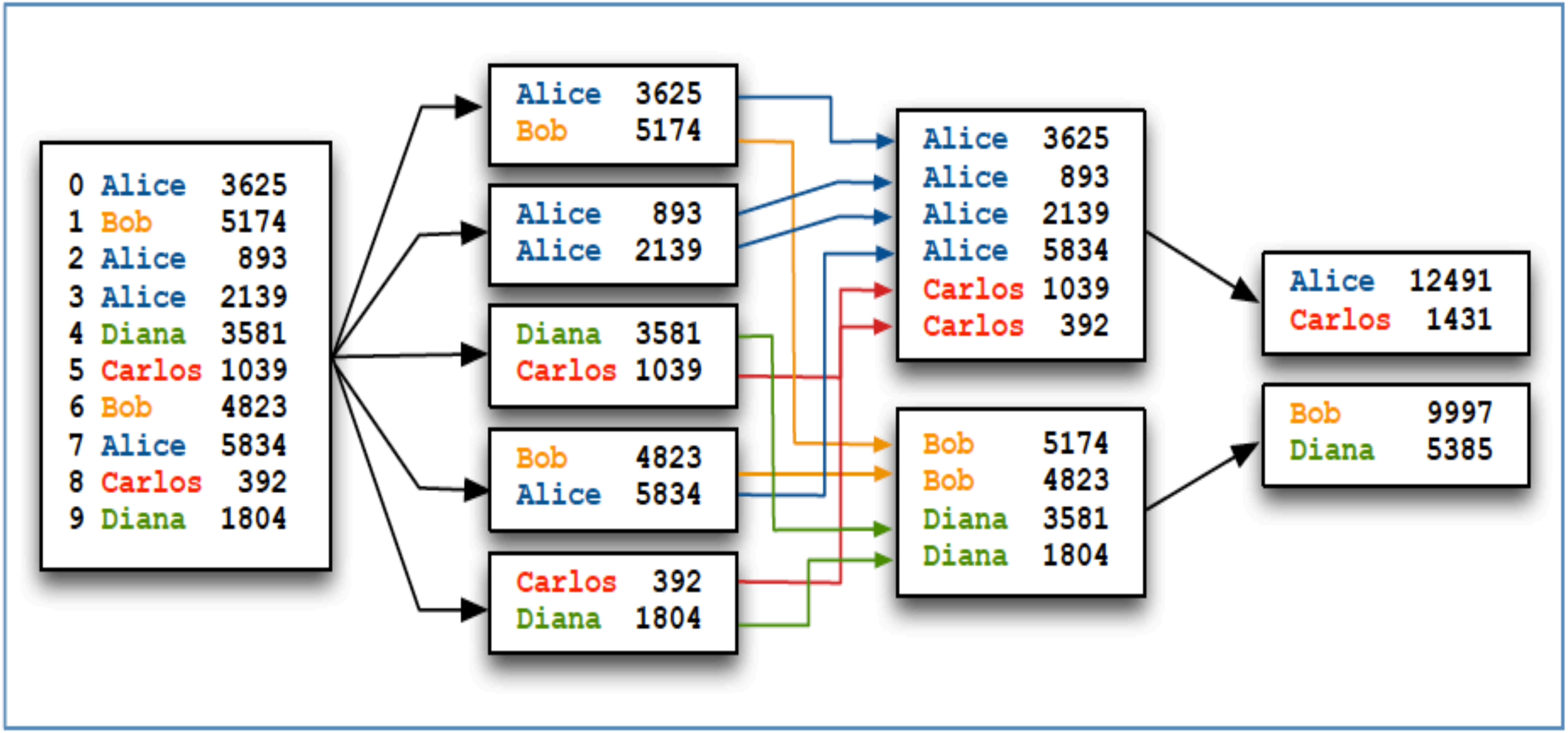


Reduce phase

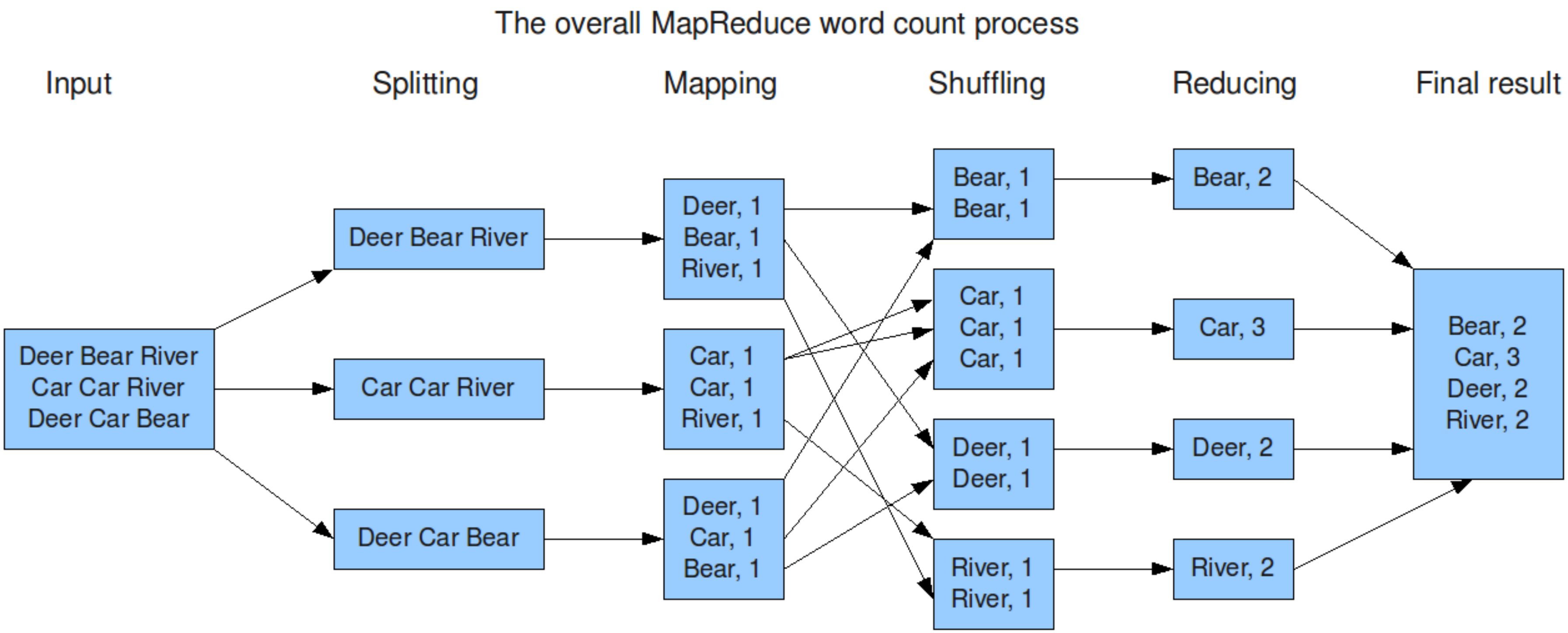
- Reducer input comes from the shuffle and sort process
  - As with map, the reduce function receives one record at a time
  - A given reducer receives all records for a given key
  - For each input record, reduce can emit zero or more output records
- Our reduce function simply sums total per person
  - And emits employee name (key) and total (value) as output



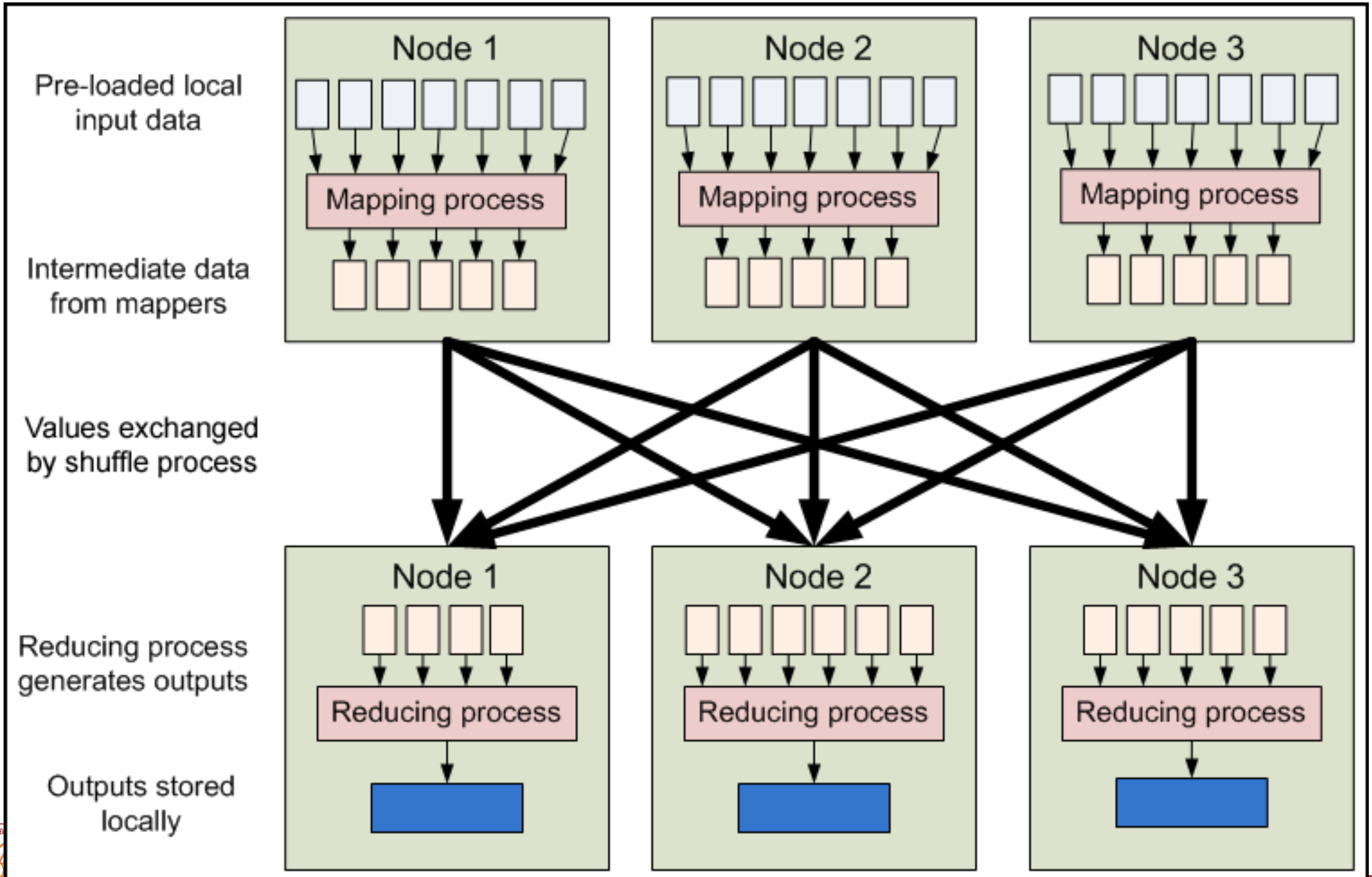
Data flow for the entire MapReduce job



Word Count Dataflow



MapReduce - Dataflow



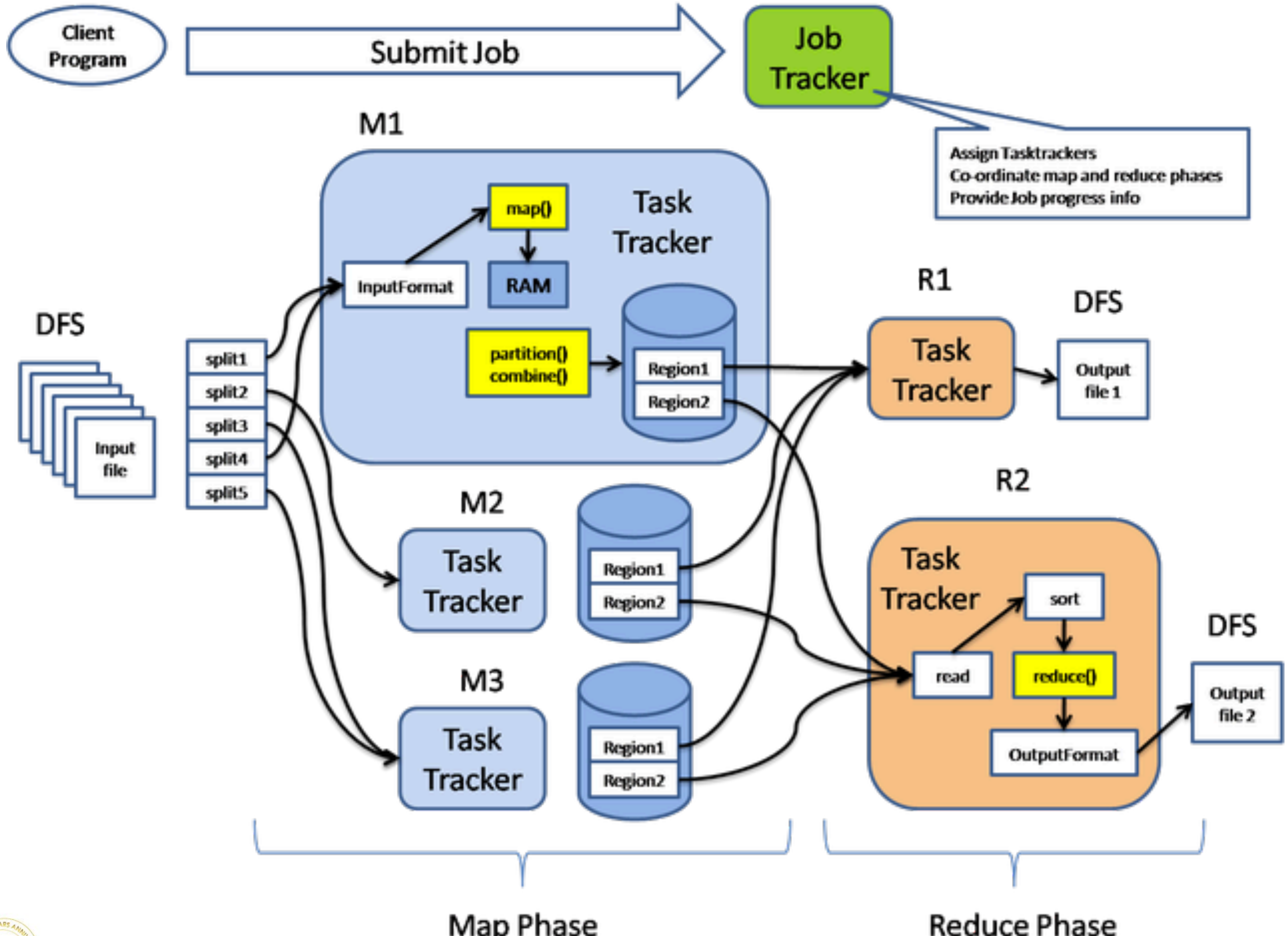
Example: Word Count (1)

```java
import org.apache.hadoop.mapreduce.Job;
import org.apache.hadoop.mapreduce.Mapper;
import org.apache.hadoop.mapreduce.Reducer;
import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;
import org.apache.hadoop.util.GenericOptionsParser;




public class WordCount {
public static void main(String [] args) throws Exception
{
Configuration c=new Configuration();
String[] files=new GenericOptionsParser(c,args).getRemainingArgs();
Path input=new Path(files[0]);
Path output=new Path(files[1]);
Job j=new Job(c,"wordcount");
j.setJarByClass(WordCount.class);
j.setMapperClass(MapForWordCount.class);
j.setReducerClass(ReduceForWordCount.class);
j.setOutputKeyClass(Text.class);
j.setOutputValueClass(IntWritable.class);
FileInputFormat.addInputPath(j, input);
FileOutputFormat.setOutputPath(j, output);
System.exit(j.waitForCompletion(true)?0:1);
}
```

Example: Word Count (2)

```
public static class MapForWordCount extends Mapper<LongWritable, Text, Text, IntWritable>{
public void map(LongWritable key, Text value, Context con) throws IOException, InterruptedException
{
String line = value.toString();
String[] words=line.split(",");
for(String word: words )
{
      Text outputKey = new Text(word.toUpperCase().trim());
  IntWritable outputValue = new IntWritable(1);
  con.write(outputKey, outputValue);
}
}
}

public static class ReduceForWordCount extends Reducer<Text, IntWritable, Text, IntWritable>
{
public void reduce(Text word, Iterable<IntWritable> values, Context con) throws IOException, InterruptedE
{
int sum = 0;
   for(IntWritable value : values)
   {
   sum += value.get();
   }
   con.write(word, new IntWritable(sum));
}
```

Map reduce life cycle



MapReduce algorithms

(C) https://courses.cs.washington.edu/courses/cse490h/08au/lectures.htm

Algorithms for MapReduce

- Sorting
- Searching
- TF-IDF
- BFS
- PageRank
- More advanced algorithms

Sort algorithm

- Used as a test of Hadoop’s raw speed
- Essentially “IO drag race”
- Input
  - A set of files, one value per line
  - Mapper key is file name, line number
  - Mapper value is the contents of the line

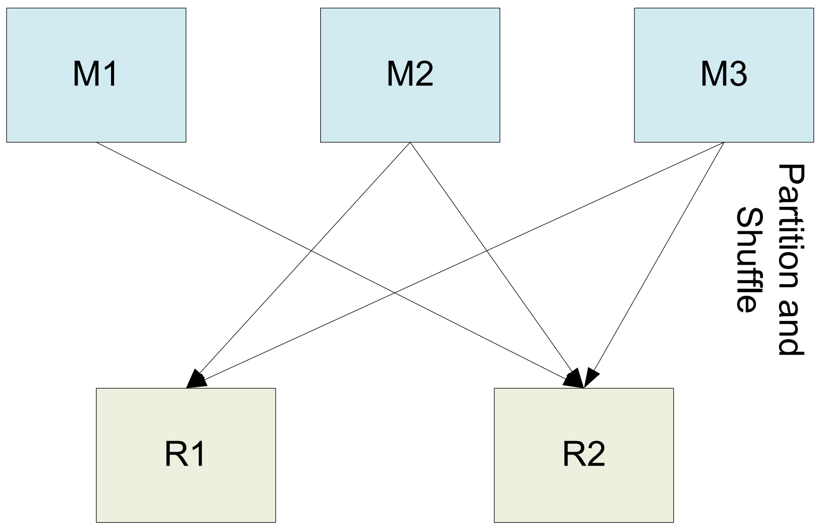
Idea

- Takes advantage of reducer properties: (key, value) pairs are processed in order by key; reducers are themselves ordered
- Mapper: Identity function for value

$$(k, v) \rightarrow (v, \_)$$

- Reducer: Identity function (k’, _) -> (k’, “”)

Idea (2)



- (key, value) pairs from mappers are sent to a particular reducer based on hash(key)
- Must pick the hash function for your data such that k1 < k2 => hash(k1) < hash(k2)

Search algorihtm

- Input
  - A set of files containing lines of text
  - A search pattern to find
- Mapper key is file name, line number
- Mapper value is the contents of the line
- Search pattern sent as special parameter

Search algorithm

- Mapper
  - Given (filename, some text) and “pattern”, if “text” matches “pattern” output (filename, _)
- Reducer
  - Identity function

Optimization

- Once a file is found to be interesting, we only need to mark it that way once
- Use *Combiner* function to fold redundant (filename, _) pairs into a single one
  - Reduces network I/O

TF-IDF algorithm

- Term Frequency – Inverse Document Frequency
  - Relevant to text processing
  - Common web analysis algorithm

$$\mathrm{tf_i} = \frac{n_i}{\sum_k n_k}$$

$$\mathrm{idf_i} = \log \frac{|D|}{|\{d : t_i \in d\}|}$$

$$\mathrm{tfidf} = \mathrm{tf} \cdot \mathrm{idf}$$

- $|D|$: total number of documents in the corpus
- $|\{d : t_i \in d\}|$ number of documents where the term t_i appears (that is $n_i \neq 0$).

Obervation

- Information needed
  - Number of times term X appears in a given document
  - Number of terms in each document
  - Number of documents X appears in total number of documents

Job 1: Word frequency in each document

- Mapper
  - Input: (docname, contents)
  - Output: ((word, docname), 1)
- Reducer
  - Sums counts for word in document
  - Outputs ((word, docname), *n*)
- Combiner is same as Reducer

Job 2: Word counts for documents

- Mapper
  - Input: ((word, docname), *n*)
  - Output: (docname, (word, *n*))
- Reducer
  - Sums frequency of individual *n*'s in same doc
  - Feeds original data through
  - Outputs ((word, docname), (*n*, *N*))
  - $N = \sum n_i \ sums\ frequency$

Job 3: Word frequency in corpus

- Mapper
  - Input: ((word, docname), (n, N))
  - Output: (word, (docname, n, N, 1))
- Reducer
  - Number of documents where the term *word* appear d
  - Outputs ((word, docname), (n, N, d))

Job 4: Calculate TF-IDF

- Mapper
  - Input: ((word, docname), (n, N, d))
  - Assume D is known (or, easy MR to find it)
  - Output ((word, docname), TF*IDF)
- Reducer
  - Just the identity function

Final thoughts on TF-IDF

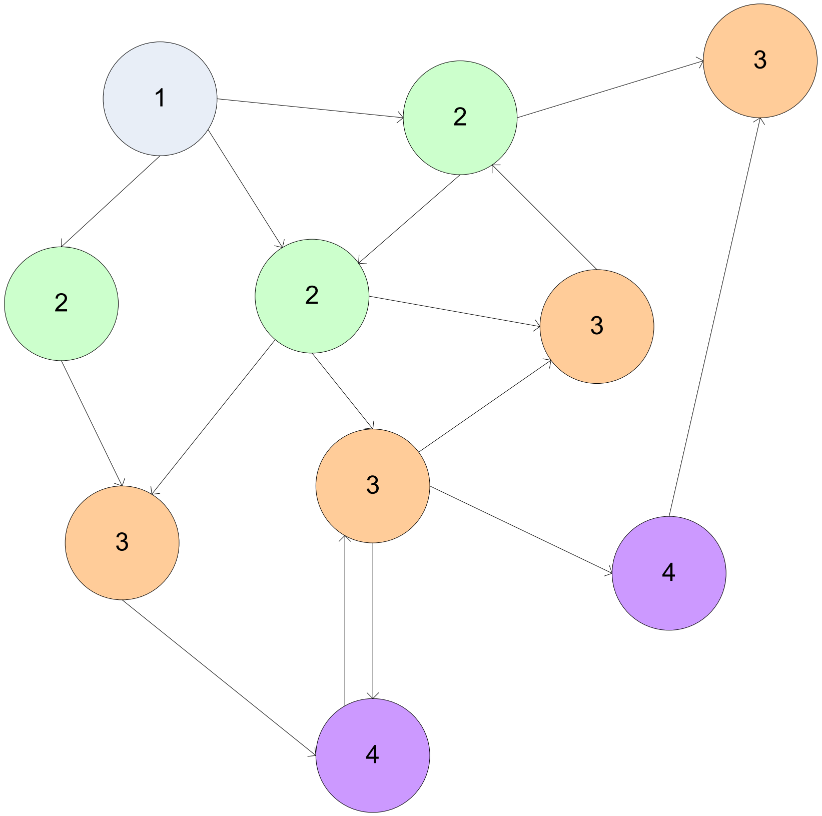
- Several small jobs add up to full algorithm
- Lots of code reuse possible
  - Stock classes exist for aggregation, identity
- Jobs 3 and 4 can really be done at once in same reducer, saving a write/read cycle
- Very easy to handle medium-large scale, but must take care to ensure flat memory usage for largest scale

Breadth-first search algorithm

- Performing computation on a graph data structure requires processing at each node
- Each node contains node-specific data as well as links (edges) to other nodes
- Computation must traverse the graph and perform the computation step
- How do we traverse a graph in MapReduce? How do we represent the graph for this?

Breadth-first search

- Breadth-First Search is an iterated algorithm over graphs
- Frontier advances from origin by one level with each pass



Breadth-first search & MapReduce

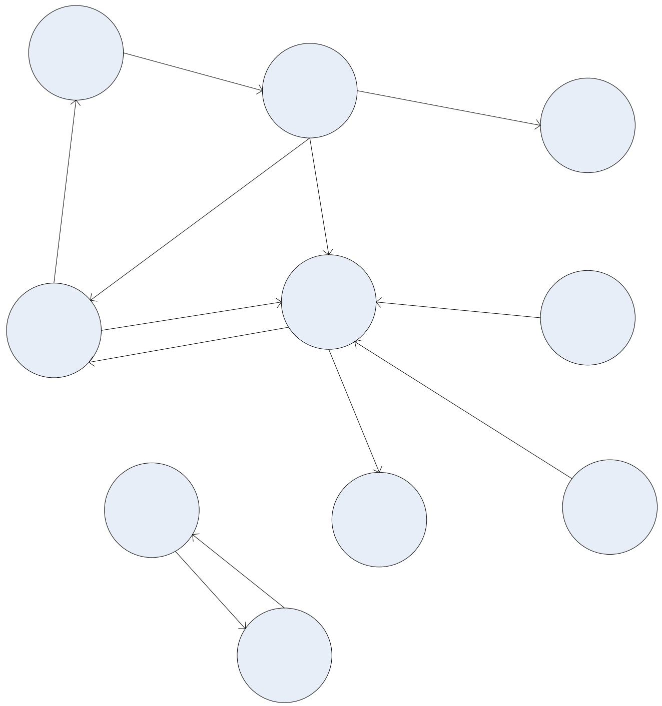
- Problem
  - This doesn't “fit” into MapReduce
- Solution
  - Iterated passes through MapReduce – map some nodes, result includes additional nodes which are fed into successive MapReduce passes

Breadth-first search & MapReduce

- Problem
  - Sending the entire graph to a map task (or hundreds/thousands of map tasks) involves an enormous amount of memory
- Solution
  - Carefully consider how we represent graphs

Graph representations

- The most straightforward representation of graphs uses references from each node to its neighbors



Direct references

- Structure is inherent to object
- Iteration requires linked list “threaded through” graph
- Requires common view of shared memory (synchronization!)
- Not easily serializable

```
class GraphNode
{
  Object data;
  Vector<GraphNode>
    out_edges;
  GraphNode
    iter_next;
}
```

Adjacency matrices

- Another classic graph representation. M[i][j]= '1' implies a link from node i to j.
- Naturally encapsulates iteration over nodes

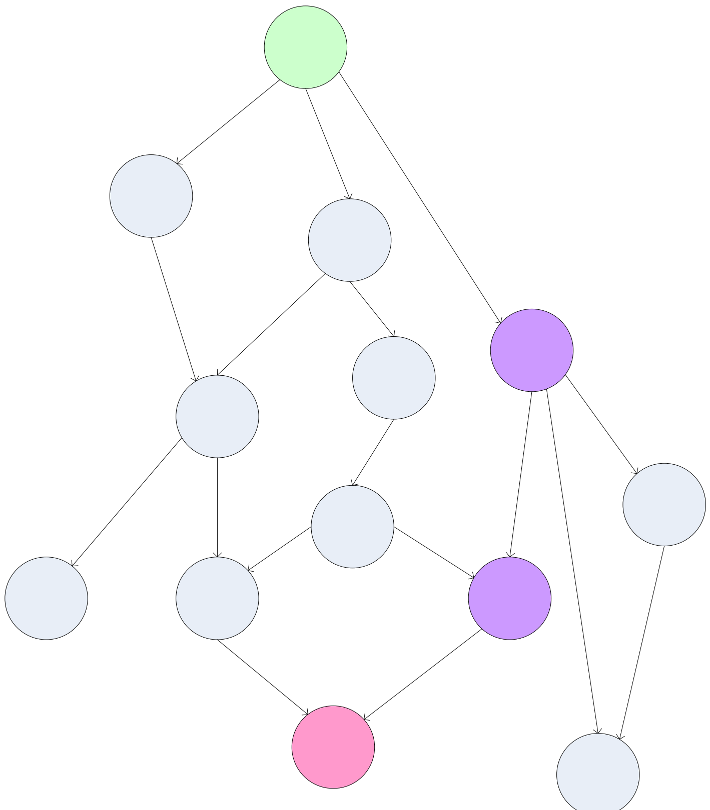
0	1	2	3	4
1	0	1	0	1
2	1	0	1	1
3	0	1	0	0
4	1	0	1	0

Adjacency matrices: Sparse representation

- Adjacency matrix for most large graphs (e.g., the web) will be overwhelmingly full of zeros.
- Each row of the graph is absurdly long
- Sparse matrices only include non-zero elements
  - 1: (3, 1), (18, 1), (200, 1)
  - 2: (6, 1), (12, 1), (80, 1), (400, 1)
  - 3: (1, 1), (14, 1)
  - …
  - 1: 3, 18, 200
  - 2: 6, 12, 80, 400
  - 3: 1, 14
  - …

Finding the shortest path

- A common graph search application is finding the shortest path from a start node to one or more target nodes
- Commonly done on a single machine with Dijkstra's Algorithm
- Can we use BFS to find the shortest path via MapReduce?



This is called the single-source shortest path problem. (a.k.a. SSSP)

Finding the shortest path: Intuition

- We can define the solution to this problem inductively:
  - DistanceTo(startNode) = 0
  - For all nodes n directly reachable from startNode, DistanceTo(n) = 1
  - For all nodes n reachable from some other set of nodes S,
    - DistanceTo(n) = 1 + min(DistanceTo(m), m □ S)

From intuition to algorithm

- A map task receives a node n as a key, and (D, points-to) as its value
  - D is the distance to the node from the start
  - points-to is a list of nodes reachable from n
  - $\forall p \in$ points-to, emit (p, D+1)
- Reduce task gathers possible distances to a given p and selects the minimum one

Discussion

- This MapReduce task can advance the known frontier by one hop
- To perform the whole BFS, a non-MapReduce component then feeds the output of this step back into the MapReduce task for another iteration
  - Problem: Where'd the points-to list go?
  - Solution: Mapper emits (n, points-to) as well

Blow-up and termination

- This algorithm starts from one node
- Subsequent iterations include many more nodes of the graph as frontier advances
- Does this ever terminate?
  - Yes! Eventually, routes between nodes will stop being discovered and no better distances will be found. When distance is the same, we stop
  - Mapper should emit (n, D) to ensure that “current distance” is carried into the reducer

Adding weights

- Weighted-edge shortest path is more useful than cost==1 approach
- Simple change: points-to list in map task includes a weight 'w' for each pointed-to node
  - emit (p, D+wp) instead of (p, D+1) for each node p
  - Works for positive-weighted graph

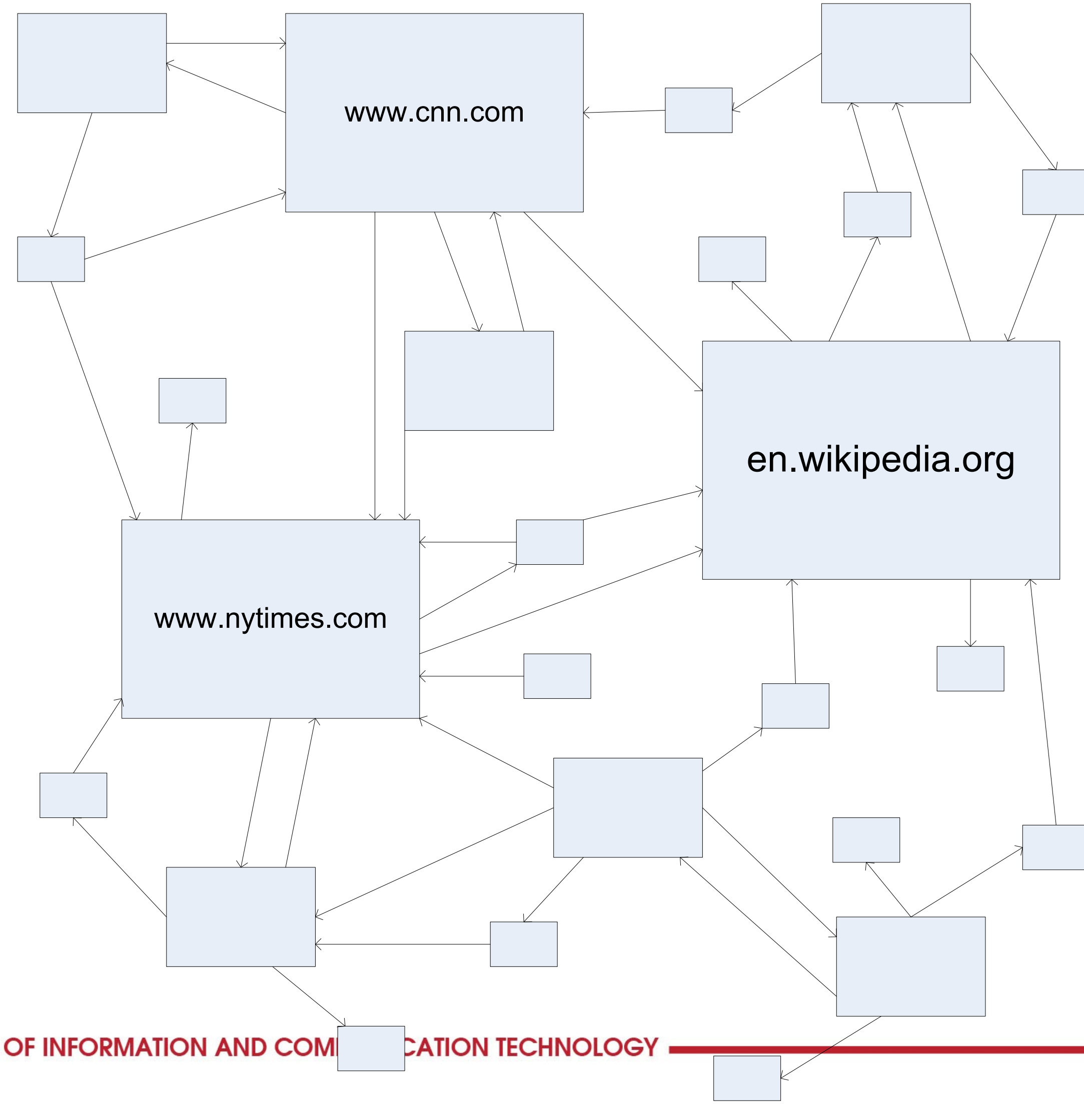
Comparison to Dijkstra

- Dijkstra's algorithm is more efficient because at any step it only pursues edges from the minimum-cost path inside the frontier
- MapReduce version explores all paths in parallel; not as efficient overall, but the architecture is more scalable
- Equivalent to Dijkstra for weight=1 case

PageRank: Random walks over the Web

- If a user starts at a random web page and surfs by clicking links and randomly entering new URLs, what is the probability that s/he will arrive at a given page?
- The PageRank of a page captures this notion
  - More “popular” or “worthwhile” pages get a higher rank

PageRank: Visually



PageRank: Formula

- Given page A, and pages T_1 through T_n linking to A, PageRank is defined as:
  - $PR(A) = (1-d) + d\,(PR(T_1)/C(T_1) + ... + PR(T_n)/C(T_n))$
- C(P) is the cardinality (out-degree) of page P
- d is the damping (“random URL”) factor

PageRank: Intuition

- Calculation is iterative: PR_{i+1} is based on PR_i
- Each page distributes its PR_i to all pages it links to. Linkees add up their awarded rank fragments to find their PR_{i+1}
- d is a tunable parameter (usually = 0.85) encapsulating the "random jump factor"

$$PR(A) = (1-d) + d\,(PR(T_1)/C(T_1) + ... + PR(T_n)/C(T_n))$$

PageRank: First implementation

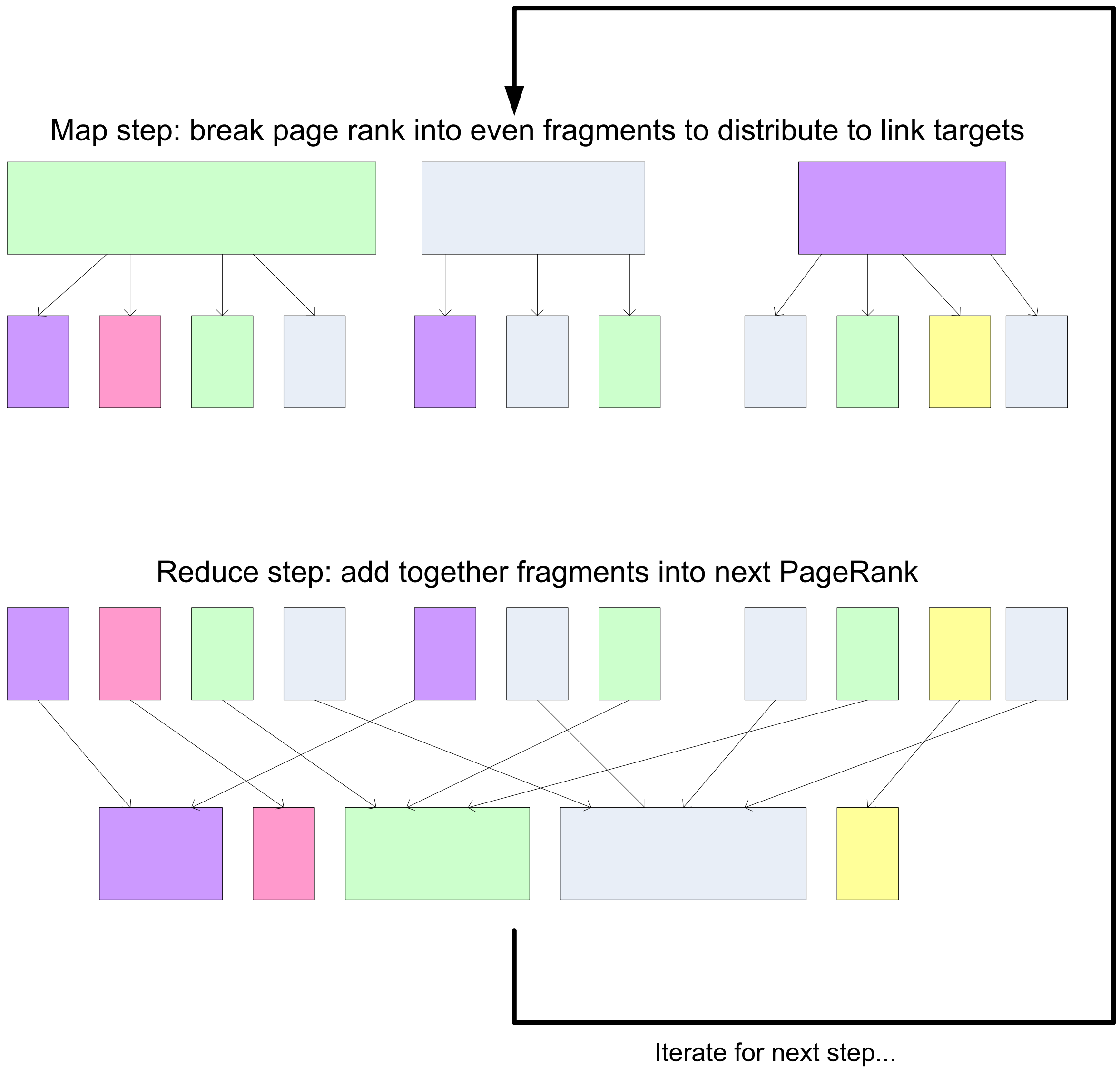
- Create two tables 'current' and 'next' holding the PageRank for each page. Seed 'current' with initial PR values
- Iterate over all pages in the graph, distributing PR from 'current' into 'next' of linkees
- current := next; next := fresh_table();
- Go back to iteration step or end if converged

Distribution of the algorithm

- Key insights allowing parallelization:
  - The 'next' table depends on 'current', but not on any other rows of 'next'
  - Individual rows of the adjacency matrix can be processed in parallel
  - Sparse matrix rows are relatively small

Distribution of the algorithm

- Consequences of insights:
  - We can map each row of 'current' to a list of PageRank “fragments” to assign to linkees
  - These fragments can be reduced into a single PageRank value for a page by summing
  - Graph representation can be even more compact; since each element is simply 0 or 1, only transmit column numbers where it's 1


Map step: break page rank into even fragments to distribute to link targets
Reduce step: add together fragments into next PageRank
Iterate for next step...

Phase 1: Parse HTML

- Map task takes (URL, page content) pairs and maps them to (URL, (PRinit, list-of-urls))
  - PRinit is the “seed” PageRank for URL
  - list-of-urls contains all pages pointed to by URL
- Reduce task is just the identity function

Phase 2: PageRank distribution

- Map task takes (URL, (cur_rank, url_list))
  - For each u in url_list, emit (u, cur_rank/|url_list|)
  - Emit (URL, url_list) to carry the points-to list along through iterations
- Reduce task gets (URL, url_list) and many (URL, val) values
  - Sum vals and fix up with d
  - Emit (URL, (new_rank, url_list))

$$PR(A) = (1\text{-}d) + d\,(PR(T_1)/C(T_1) + \ldots + PR(T_n)/C(T_n))$$

Finishing up...

- A subsequent component determines whether convergence has been achieved (Fixed number of iterations? Comparison of key values?)
- If so, write out the PageRank lists - done!
- Otherwise, feed output of Phase 2 into another Phase 2 iteration

Remark

- MapReduce runs the “heavy lifting” in iterated computation
- Key element in parallelization is independent PageRank computations in a given step
- Parallelization requires thinking about minimum data partitions to transmit (e.g., compact representations of graph rows)
  - Even the implementation shown today doesn't actually scale to the whole Internet; but it works for intermediate-sized graphs

References

- Dean, Jeffrey, and Sanjay Ghemawat. "MapReduce: simplified data processing on large clusters." *Communications of the ACM* 51.1 (2008): 107-113.
- Lin, Jimmy, and Chris Dyer. "Data-intensive text processing with MapReduce." *Synthesis Lectures on Human Language Technologies* 3.1 (2010): 1-177.
- Lee, Kyong-Ha, et al. "Parallel data processing with MapReduce: a survey." *AcM sIGMoD Record* 40.4 (2012): 11-20.

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