Chương 6

Các kĩ thuật xử lý dữ liệu lớn theo khối - phần 1

MapReduce

Mô thức xử lý dữ liệu MapReduce

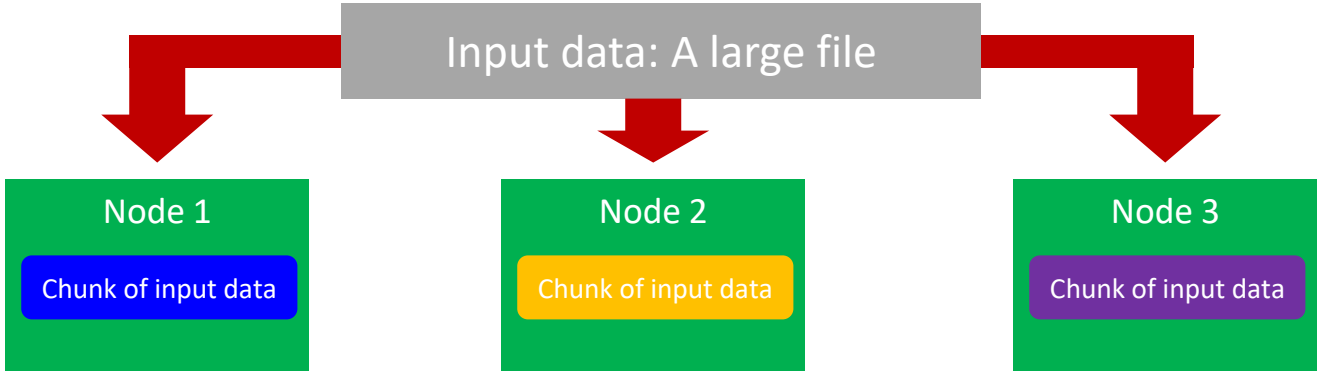
- MapReduce là mô thức xử lý dữ liệu mặc định trong Hadoop
- MapReduce không phải là ngôn ngữ lập trình, được đề xuất bởi Google
- Đặc điểm của MapReduce
  - Đơn giản (Simplicity)
  - Linh hoạt (Flexibility)
  - Khả mở (Scalability)

A MR job = {Isolated Tasks}n

- Mỗi chương trình MapReduce là một công việc (job) được phan rã làm nhiều tác vụ độc lập (task) và các tác vụ này được phân tán trên các nodes khác nhau của cụm để thực thi
- Mỗi tác vụ được thực thi độc lập với các tác vụ khác để đạt được tính khả mở
  - Giảm truyền thông giữa các node máy chủ
  - Tránh phải thực hiện cơ chế đồng bộ giữa các tác vụ

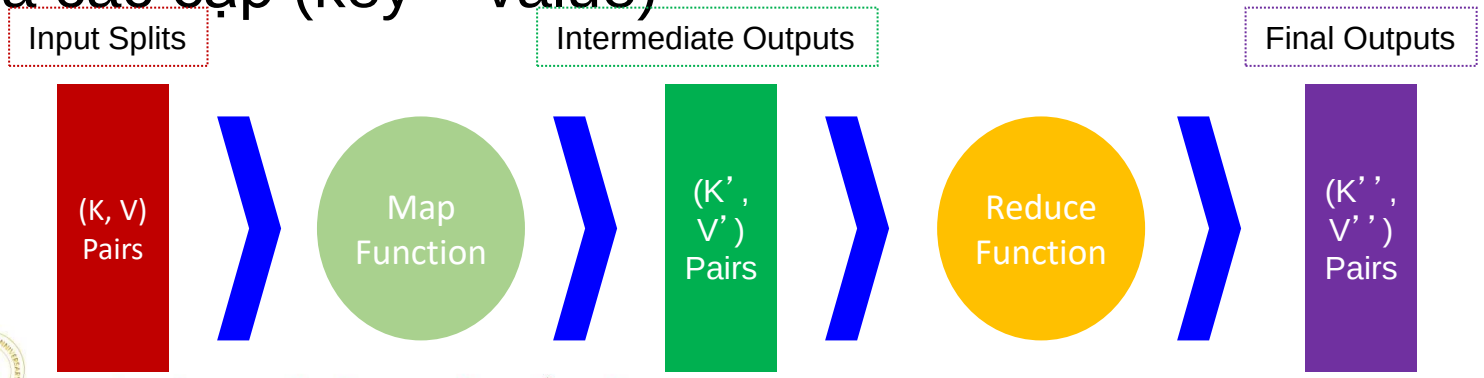
Dữ liệu cho MapReduce

- MapReduce trong môi trường Hadoop thường làm việc với dữ liệu đa có sẵn trên HDFS
- Khi thực thi, mã chương trình MapReduce được gửi tới các node đã có dữ liệu tương ứng



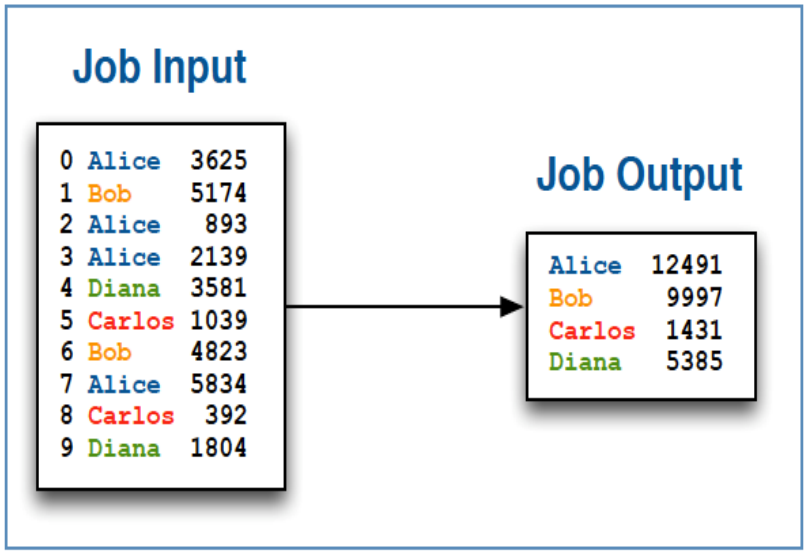
Chương trình MapReduce

- Lập trình với MapReduce cần cài đặt 2 hàm Map và Reduce
  - 2 hàm này được thực thi bởi các tiến trình Mapper và Reducer tương ứng.
- Trong chương trình MapReduce, dữ liệu được nhìn nhận như là các cặp khóa – giá trị (key – value)
- Các hàm Map và Reduce nhận đầu vào và trả về đầu ra các cặp (key – value)



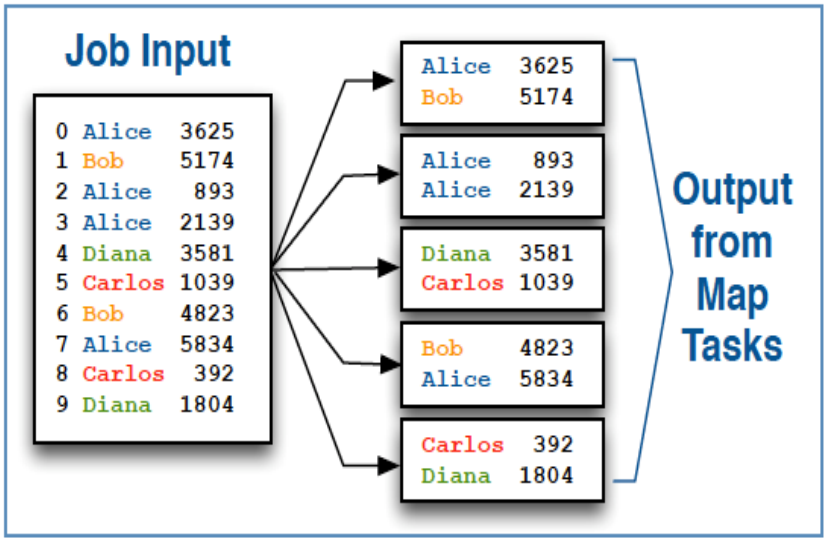
Ví dụ về MapReduce

- Đầu vào: tệp văn bản chứa thông tin về order ID, employee name, and sale amount
- Đầu ra : Doanh số bán (sales) theo từng nhân viên (employee)



Bước Map

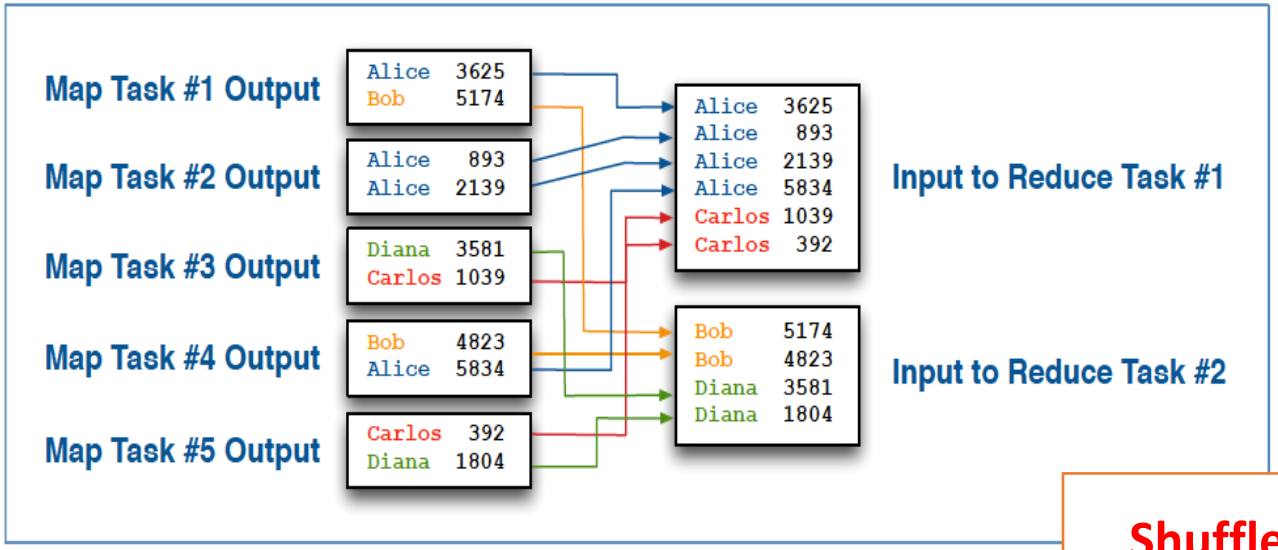
- Dữ liệu đầu vào được xử lý bởi nhiều tác vụ Mapping độc lập
  - Số lượng các tác vụ Mapping được xác định theo lượng dữ liệu đầu vào (~ số chunks)
  - Mỗi tác vụ Mapping xử lý một phần dữ liệu (chunk) của khối dữ liệu ban đầu
  - Với mỗi tác vụ Mapping, Mapper xử lý lần lượt từng bản ghi đầu vào
  - Với mỗi bản ghi đầu vào (key-value), Mapper đưa ra 0 hoặc nhiều bản ghi đầu ra (key – value trung gian)
- Trong ví dụ này, tác vụ Mapping đơn giản đọc từng dòng văn bản và đưa ra tên nhân viên và doanh số tương ứng



Map phase

Bước shuffle & sort

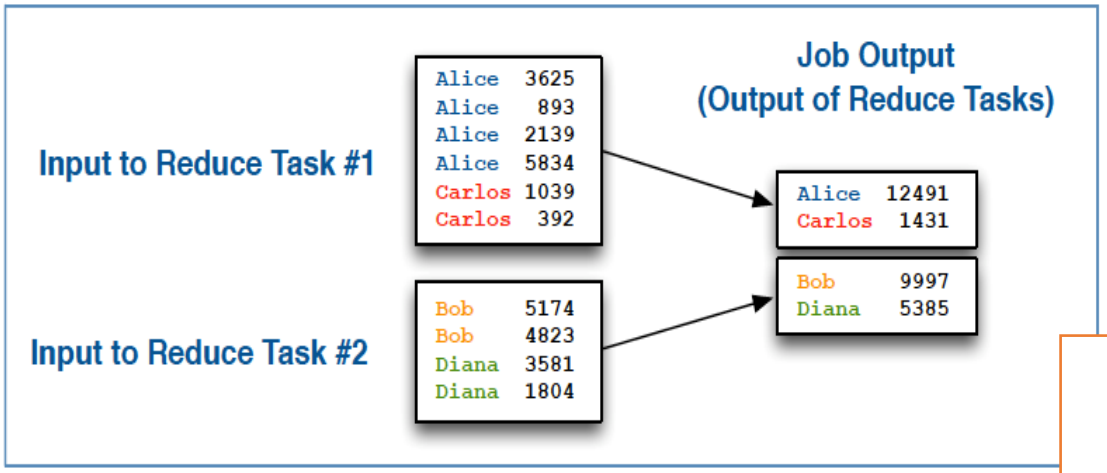
- Hadoop tự động sắp xếp và gộp đầu ra của các Mappers theo các partitions
  - Mỗi partitions là đầu vào cho một Reducer



Shuffle & sort phase

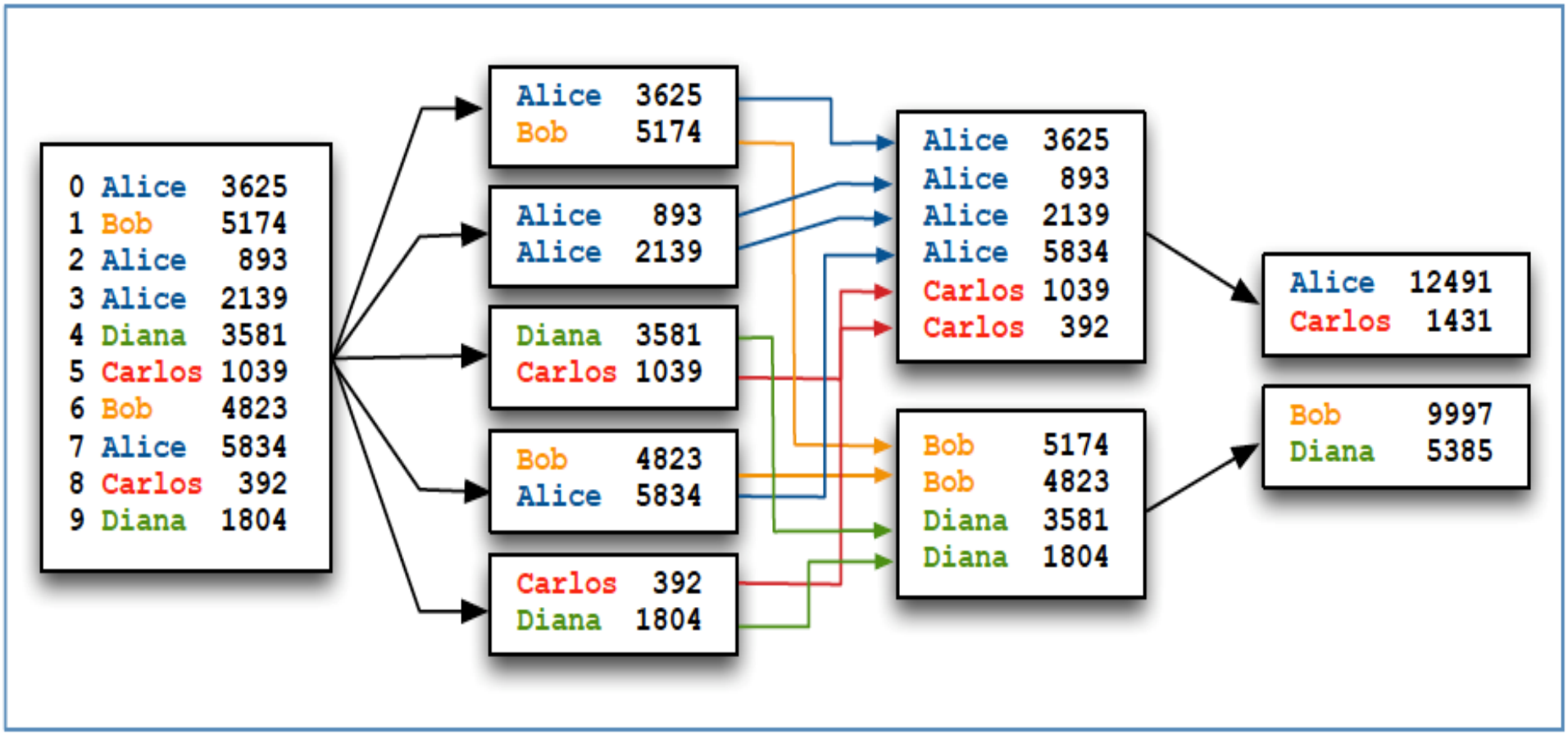
Bước Reduce

- Reducer nhận dữ liệu đầu vào từ bước shuffle & sort
  - Tất cả các bản ghi key – value tương ứng với một key được xử lý bởi một Reducer duy nhất
  - Giống bước Map, Reducer xử lý lần lượt từng key, mỗi lần với toàn bộ các values tương ứng
- Trong ví dụ, hàm reduce đơn giản là tính tổng doanh số cho từng nhân viên, đầu ra là các cặp key – value tương ứng với tên nhân viên – doanh số tổng

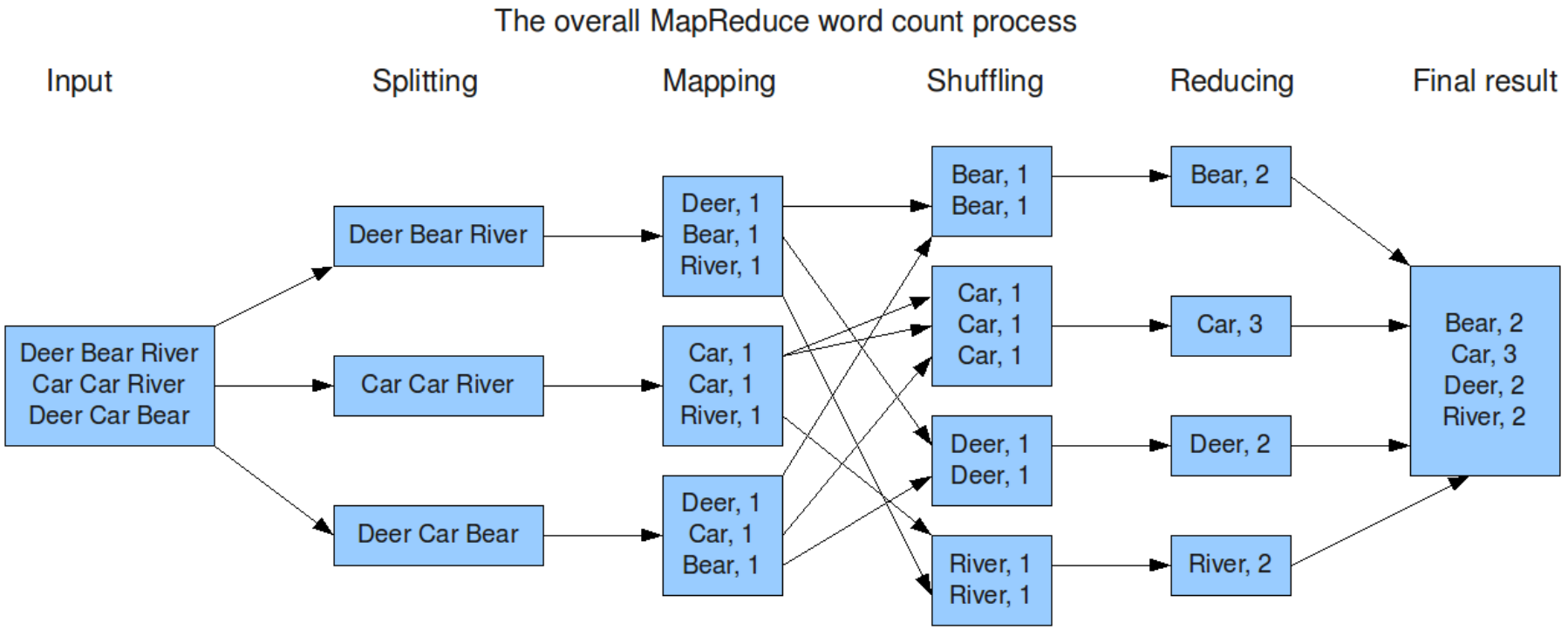


Reduce phase

Luồng dữ liệu cho ví dụ MapReduce



Luồng dữ liêu với bài toán Word Count



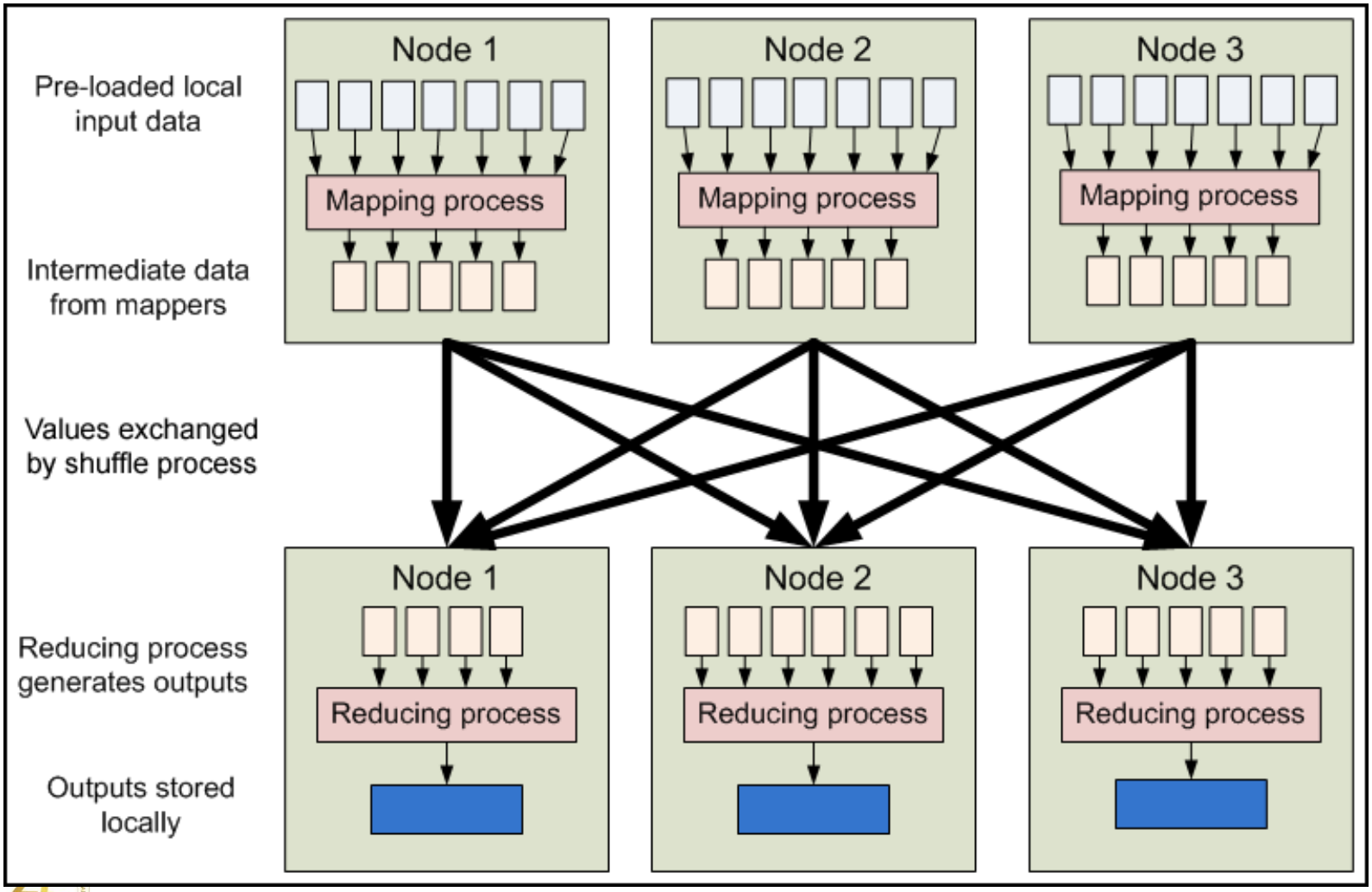
Chương trình Word Count thực tế (1)

```
9  import org.apache.hadoop.mapreduce.Job;
10 import org.apache.hadoop.mapreduce.Mapper;
11 import org.apache.hadoop.mapreduce.Reducer;
12 import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
13 import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;
14 import org.apache.hadoop.util.GenericOptionsParser;
15
16
17
18
19 public class WordCount {
20 public static void main(String [] args) throws Exception
21 {
22 Configuration c=new Configuration();
23 String[] files=new GenericOptionsParser(c,args).getRemainingArgs();
24 Path input=new Path(files[0]);
25 Path output=new Path(files[1]);
26 Job j=new Job(c,"wordcount");
27 j.setJarByClass(WordCount.class);
28 j.setMapperClass(MapForWordCount.class);
29 j.setReducerClass(ReduceForWordCount.class);
30 j.setOutputKeyClass(Text.class);
31 j.setOutputValueClass(IntWritable.class);
32 FileInputFormat.addInputPath(j, input);
33 FileOutputFormat.setOutputPath(j, output);
34 System.exit(j.waitForCompletion(true)?0:1);
35 }
```

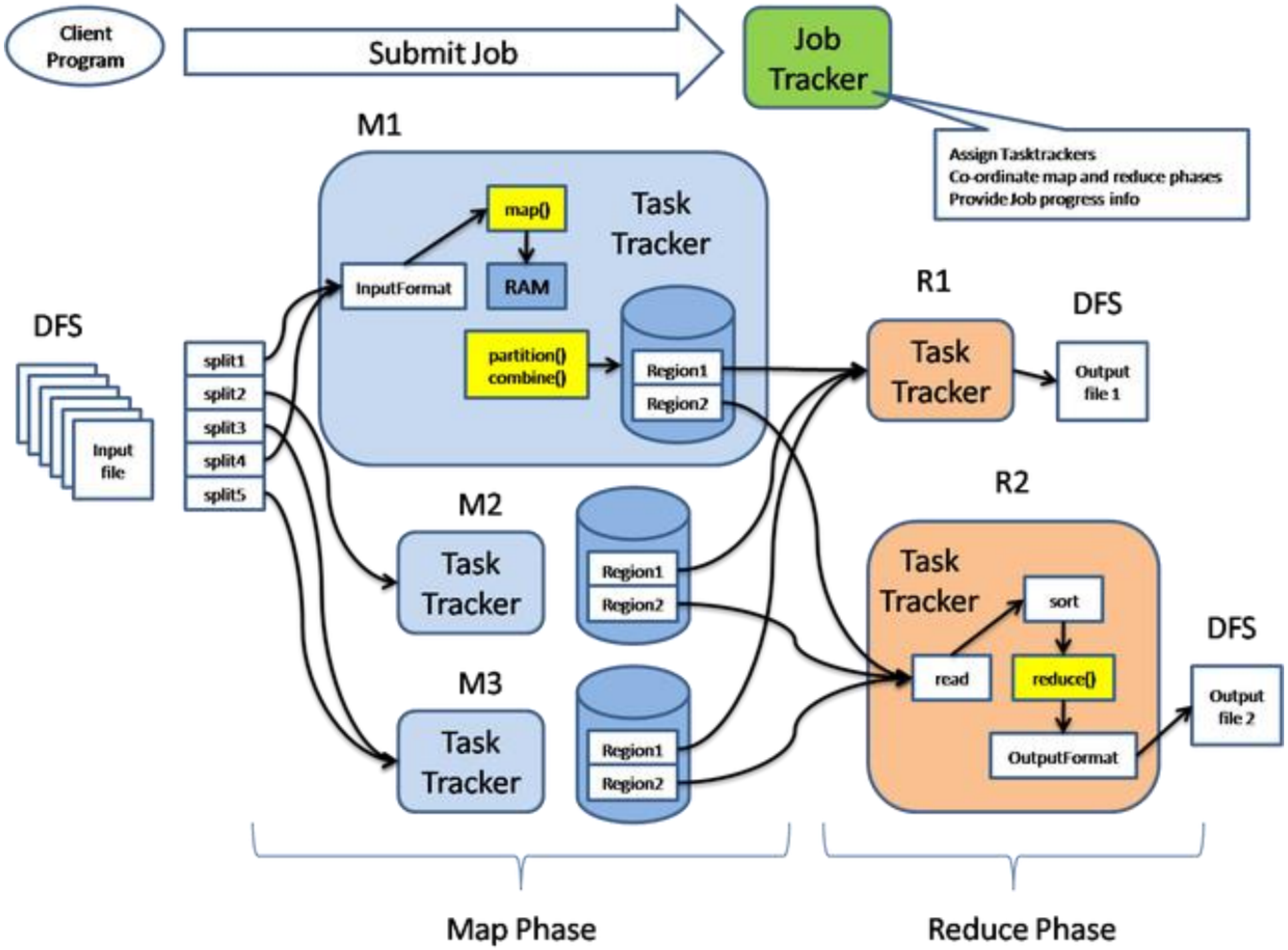
Chương trình Word Count thực tế (2)

```
36 public static class MapForWordCount extends Mapper<LongWritable, Text, Text, IntWritable>{
37 public void map(LongWritable key, Text value, Context con) throws IOException, InterruptedException
38 {
39 String line = value.toString();
40 String[] words=line.split(",");
41 for(String word: words )
42 {
43       Text outputKey = new Text(word.toUpperCase().trim());
44   IntWritable outputValue = new IntWritable(1);
45   con.write(outputKey, outputValue);
46 }
47 }
48 }
49
50 public static class ReduceForWordCount extends Reducer<Text, IntWritable, Text, IntWritable>
51 {
52 public void reduce(Text word, Iterable<IntWritable> values, Context con) throws IOException, InterruptedE
53 {
54 int sum = 0;
55    for(IntWritable value : values)
56    {
57    sum += value.get();
58    }
59    con.write(word, new IntWritable(sum));
60 }
```

MapReduce trên môi trường phân tán



Vai trò của Job tracker và Task tracker



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

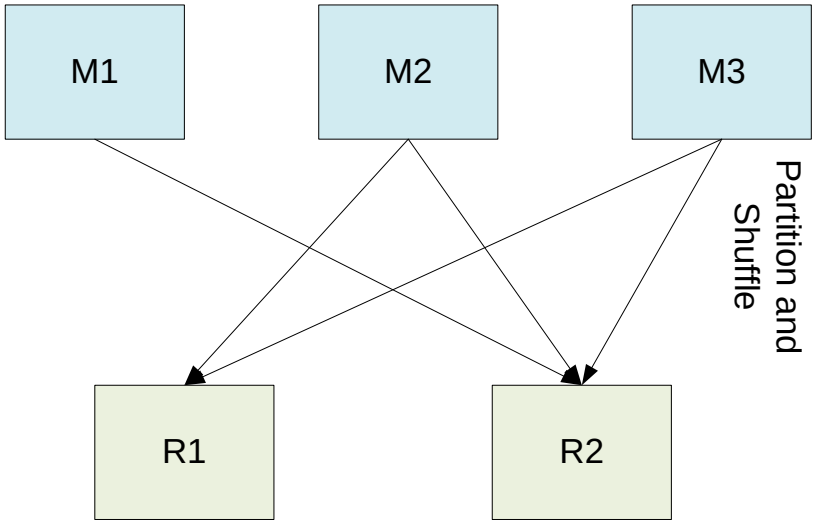
Idea

- 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

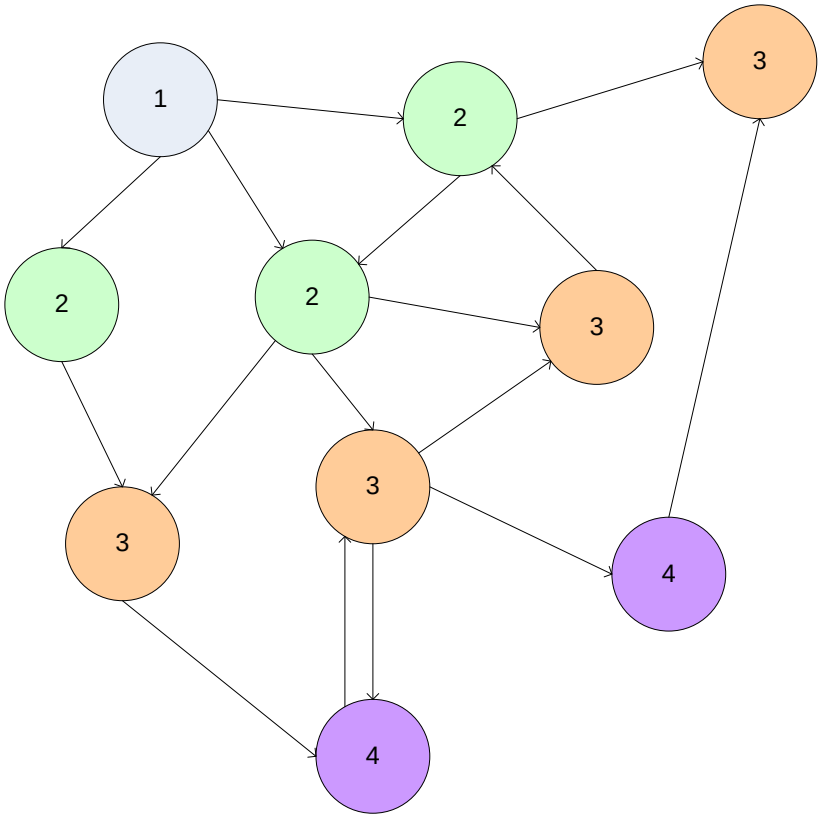
- Several small jobs add up to full algorithm
- Lots of code reuse possible
  - Stock classes exist for aggregation, identity
- Jobs 3 and 4 can really be done at once in same reducer, saving a write/read cycle
- Very easy to handle medium-large scale, but must take care to ensure flat memory usage for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

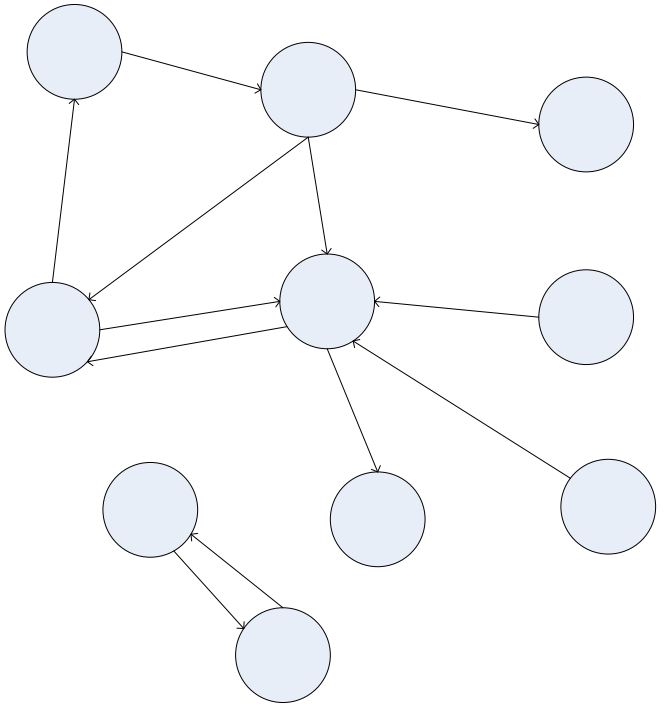
- Problem
  - This doesn't “fit” into MapReduce
- Solution
  - Iterated passes through MapReduce – map some nodes, result includes additional nodes which are fed into successive MapReduce passes

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

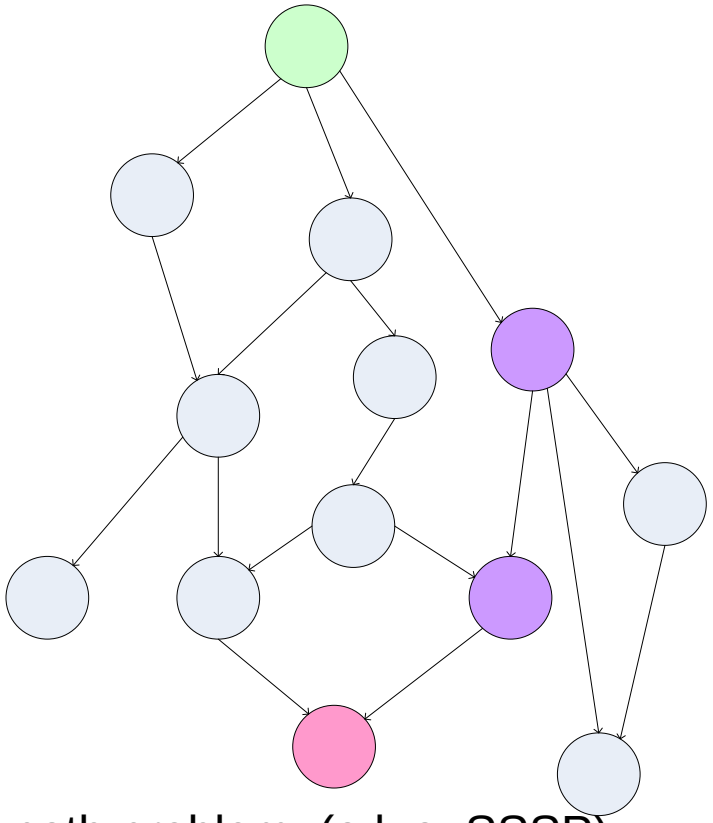
0	1	2	3	4
1	0	1	0	1
2	1	0	1	1
3	0	1	0	0
4	1	0	1	0

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

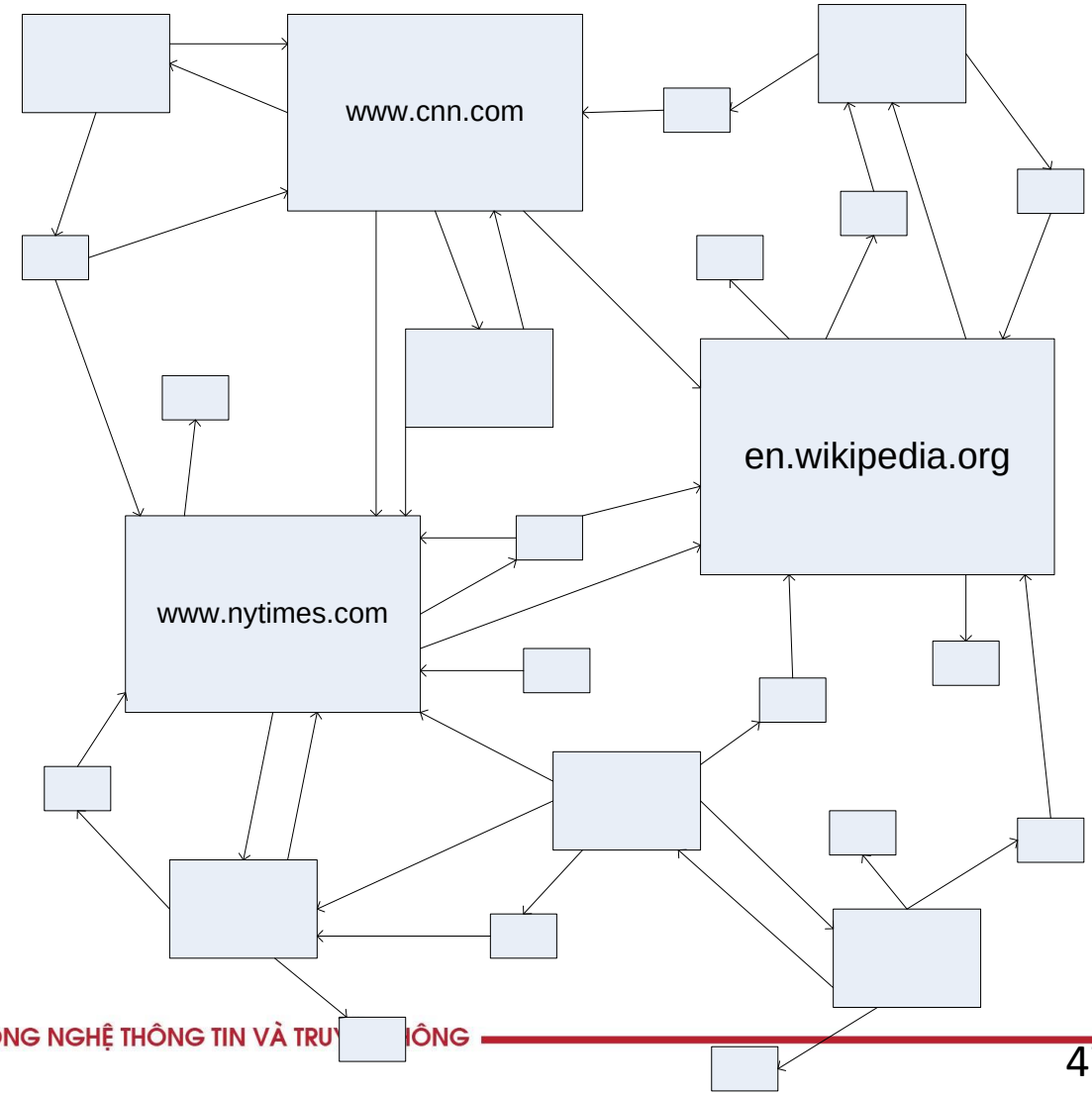
Comparison to Dijkstra

- 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

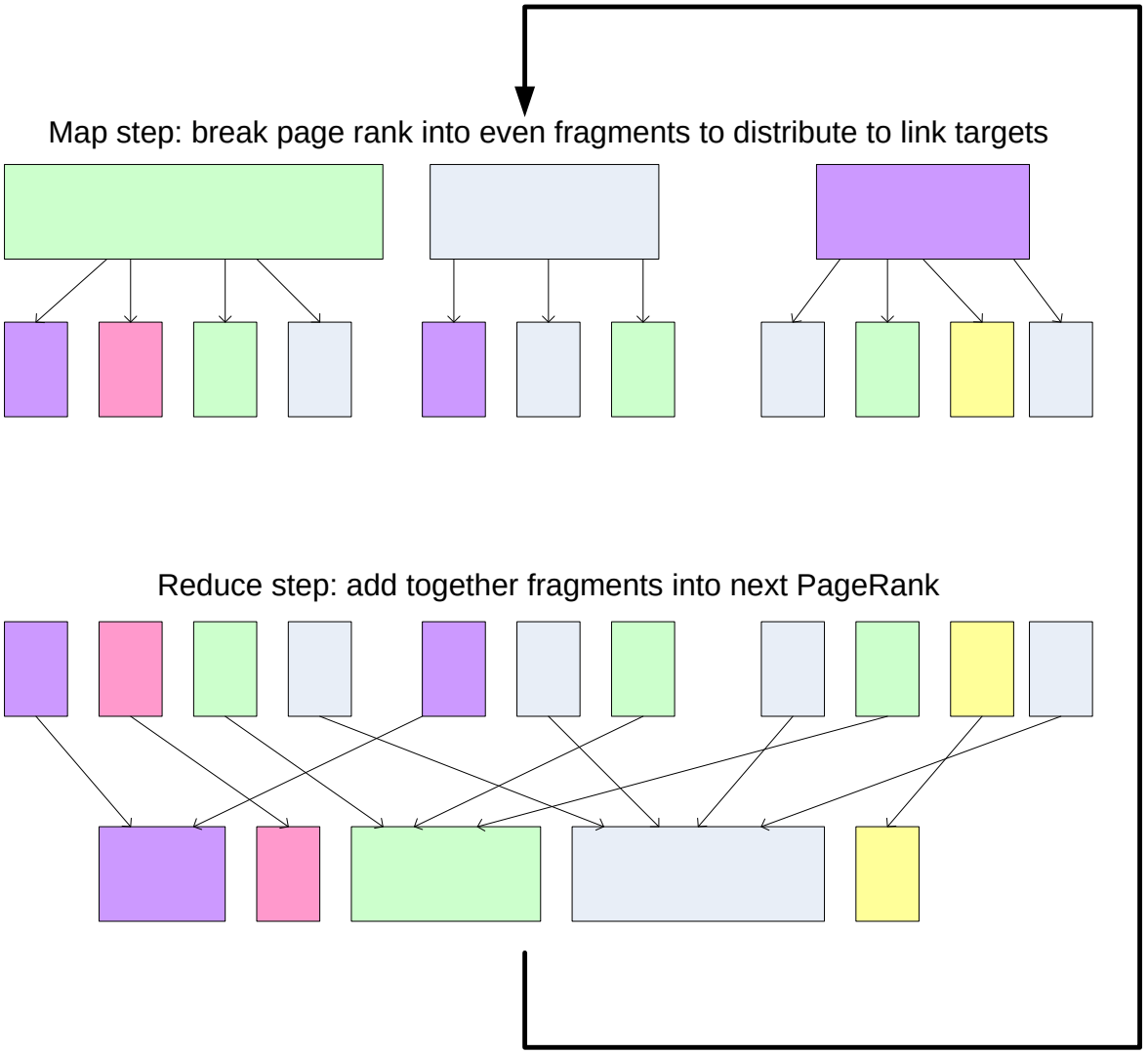
- Create two tables 'current' and 'next' holding the PageRank for each page. Seed 'current' with initial PR values
- Iterate over all pages in the graph, distributing PR from 'current' into 'next' of linkees
- current := next; next := fresh_table();
- Go back to iteration step or end if converged

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))

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

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

Thank you for your attention!

Q&A