COMP9313: Big Data Management

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Course web site: http://www.cse.unsw.edu.au/~cs9313/

Chapter 4: MapReduce IV

Graph Data Processing in MapReduce

What’s a Graph?

- G = (V,E), where
  - V represents the set of vertices (nodes)
  - E represents the set of edges (links)
  - Both vertices and edges may contain additional information
- Different types of graphs:
  - Directed vs. undirected edges
  - Presence or absence of cycles
- Graphs are everywhere:
  - Hyperlink structure of the Web
  - Physical structure of computers on the Internet
  - Interstate highway system
  - Social networks

Graph Analytics

- General Graph
  - Count the number of nodes whose degree is equal to 5
  - Find the diameter of the graphs
- Web Graph
  - Rank each webpage in the web graph or each user in the twitter graph using PageRank, or other centrality measure
- Transportation Network
  - Return the shortest or cheapest flight/road from one city to another
- Social Network
  - Detect a group of users who have similar interests
- Financial Network
  - Find the path connecting two suspicious transactions;
- … …

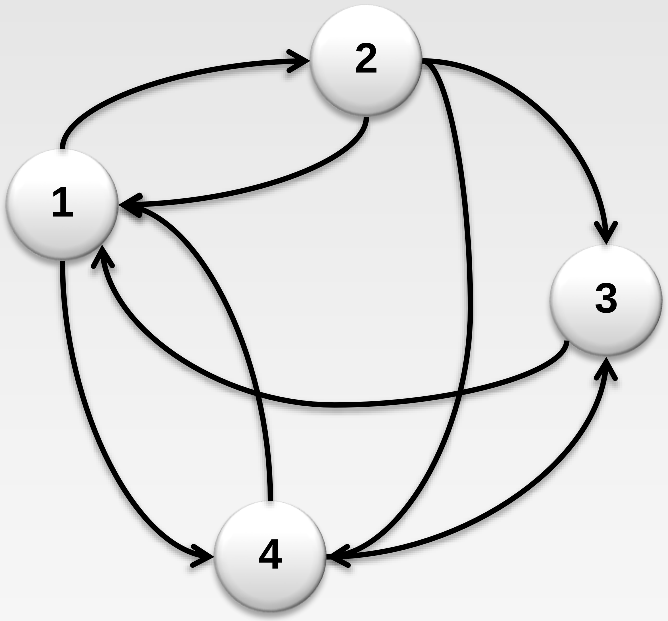
Graphs and MapReduce

- Graph algorithms typically involve:
  - Performing computations at each node: based on node features, edge features, and local link structure
  - Propagating computations: “traversing” the graph
- Key questions:
  - How do you represent graph data in MapReduce?
  - How do you traverse a graph in MapReduce?

Representing Graphs

- Adjacency Matrices: Represent a graph as an *n* x *n* square matrix *M*
  - $n = |V|$
  - $M_{ij} = 1$ means a link from node *i* to *j*

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



Adjacency Matrices: Critique

- Advantages:
  - Amenable to mathematical manipulation
  - Iteration over rows and columns corresponds to computations on outlinks and inlinks
- Disadvantages:
  - Lots of zeros for sparse matrices
  - Lots of wasted space

Representing Graphs

- Adjacency Lists: Take adjacency matrices… and throw away all the zeros

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

$\Rightarrow$

1: 2, 4
2: 1, 3, 4
3: 1
4: 1, 3

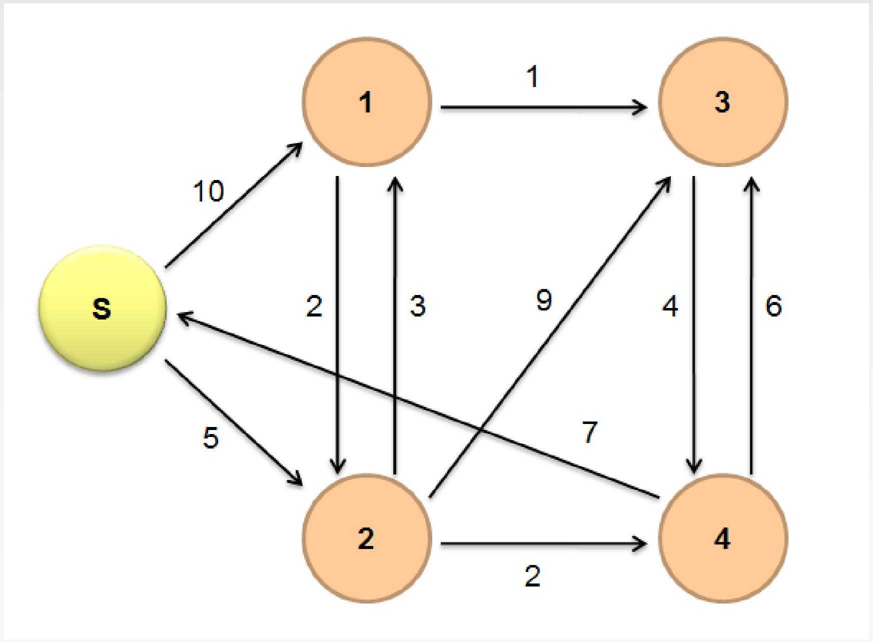
Adjacency Lists: Critique

- Advantages:
  - Much more compact representation
  - Easy to compute over outlinks
- Disadvantages:
  - Much more difficult to compute over inlinks

Single-Source Shortest Path

Single-Source Shortest Path (SSSP)

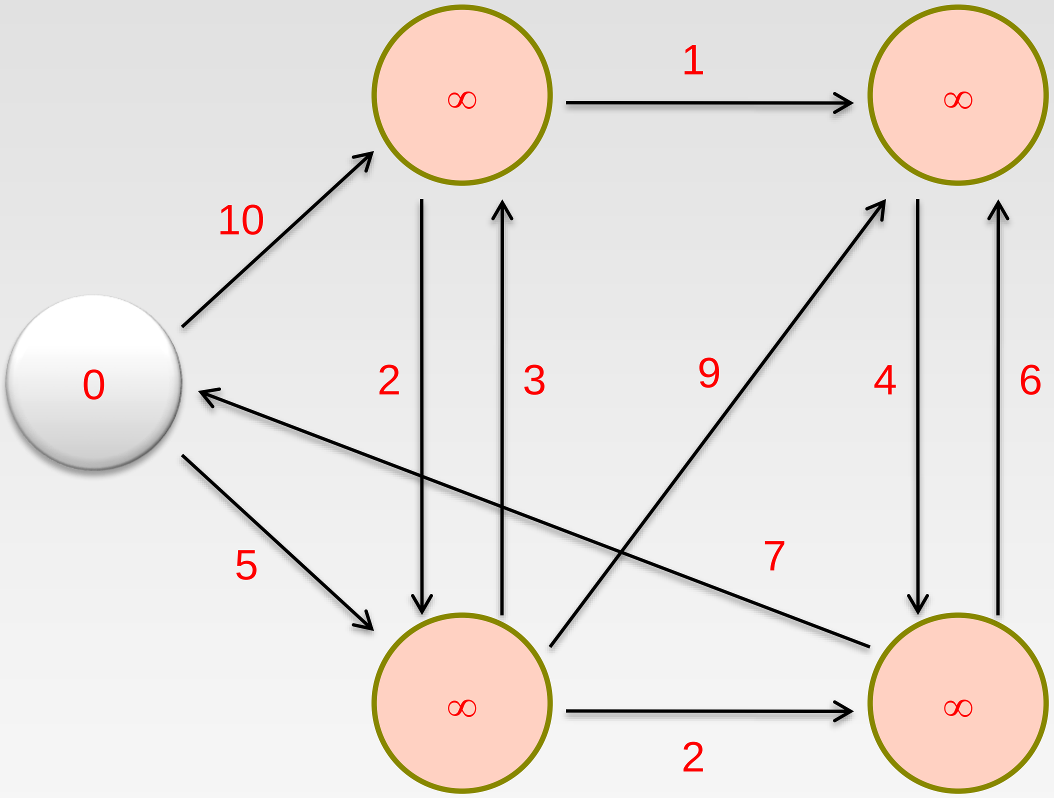
- **Problem:** find shortest path from a source node to one or more target nodes
  - Shortest might also mean lowest weight or cost
- Dijkstra's Algorithm:
  - For a given source node in the graph, the algorithm finds the shortest path between that node and every other



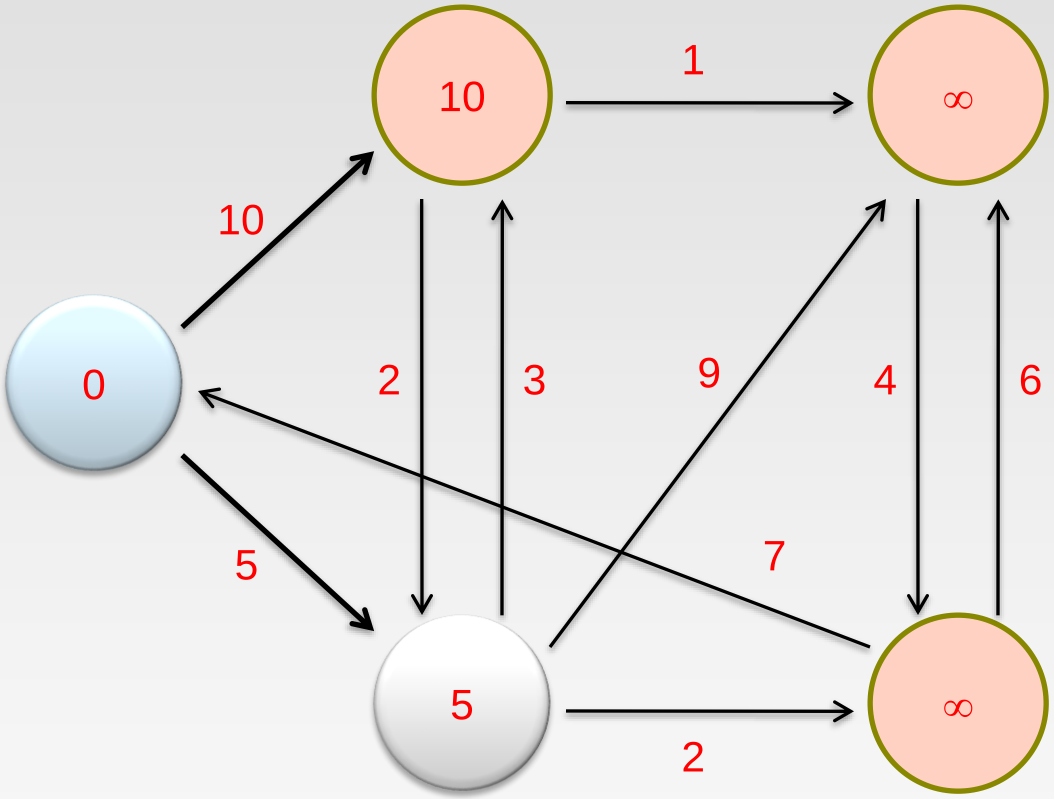
Dijkstra’s Algorithm

```
DIJKSTRA$(G, w, s)$
    $d[s] \leftarrow 0$
    for all vertex $v \in V$ do
        $d[v] \leftarrow \infty$
    $Q \leftarrow \{V\}$
    while $Q \neq \emptyset$ do
        $u \leftarrow$ EXTRACTMIN$(Q)$
        for all vertex $v \in u.$ADJACENCYLIST do
            if $d[v] > d[u] + w(u, v)$ then
                $d[v] \leftarrow d[u] + w(u, v)$
```

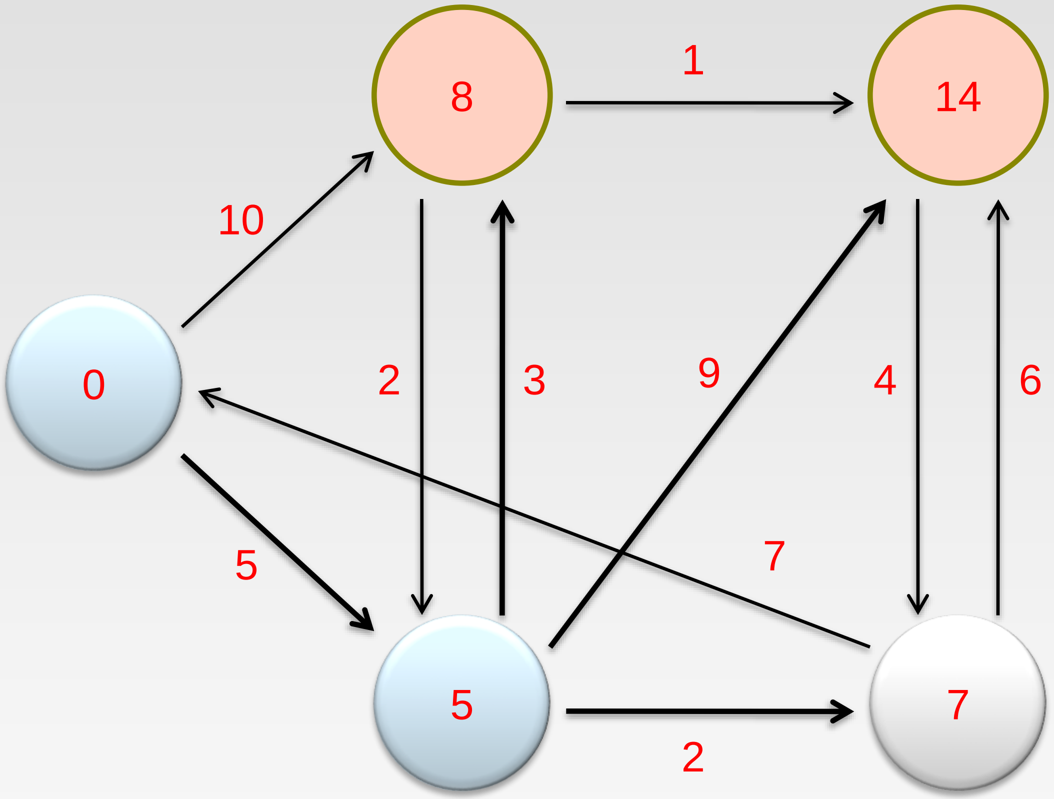
Dijkstra's Algorithm Example



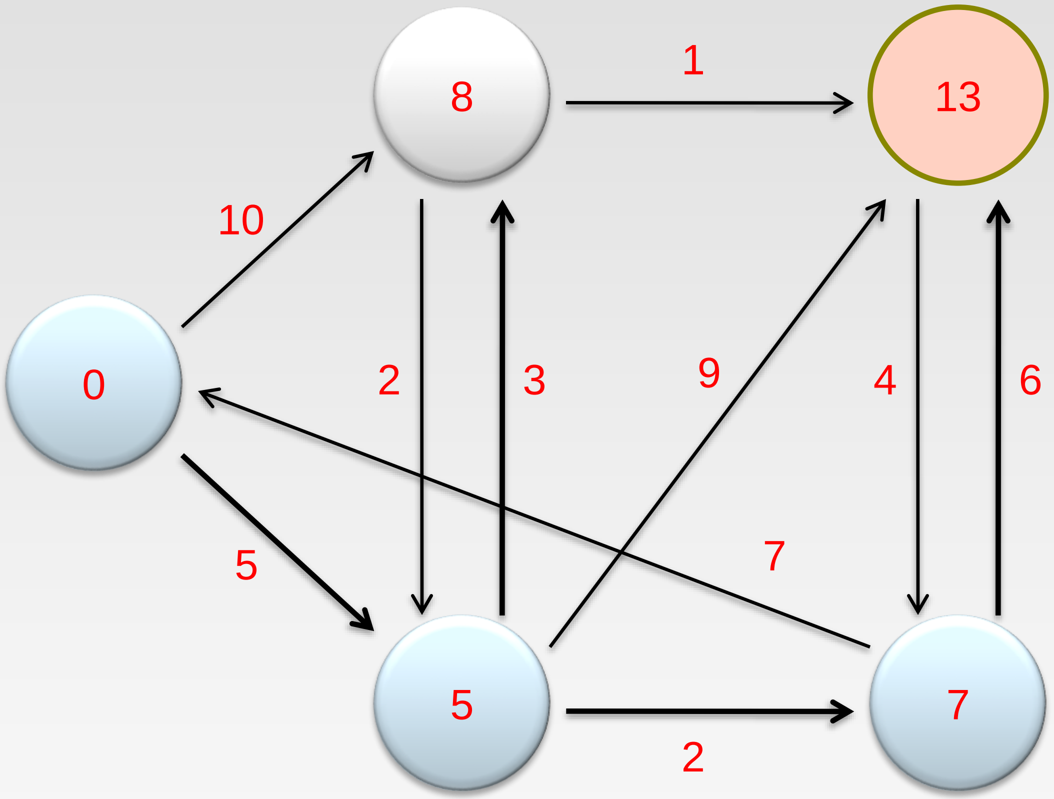
Dijkstra's Algorithm Example



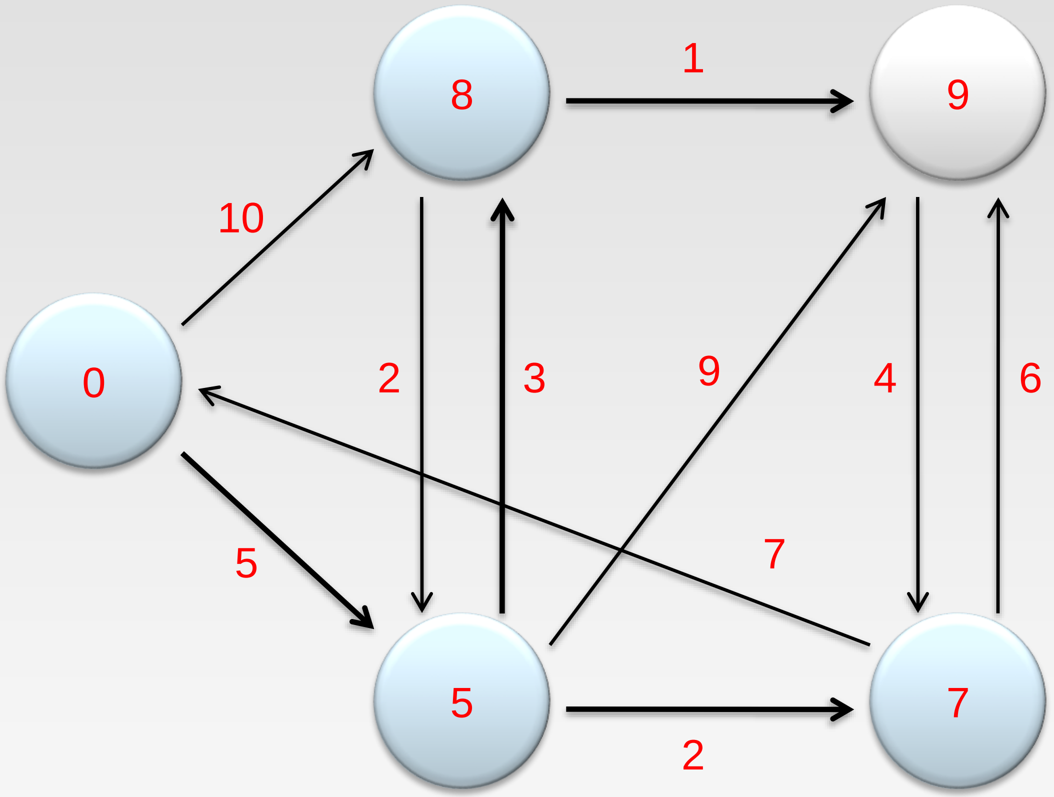
Dijkstra's Algorithm Example



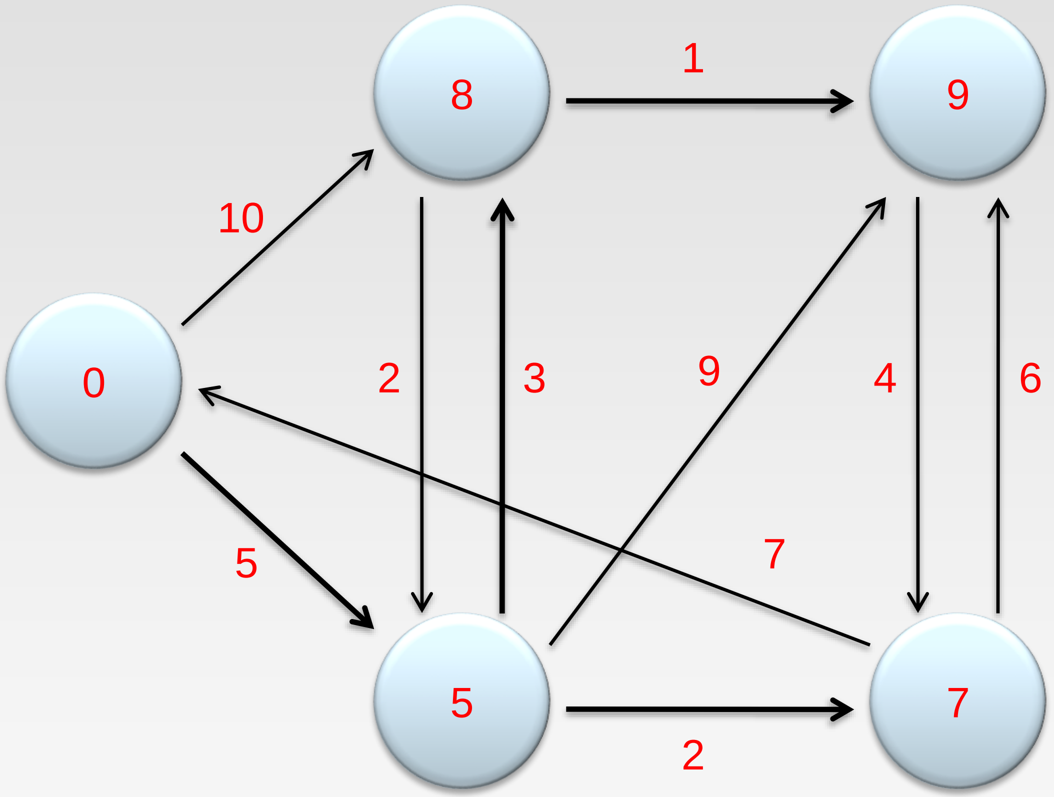
Dijkstra's Algorithm Example



Dijkstra's Algorithm Example



Dijkstra's Algorithm Example



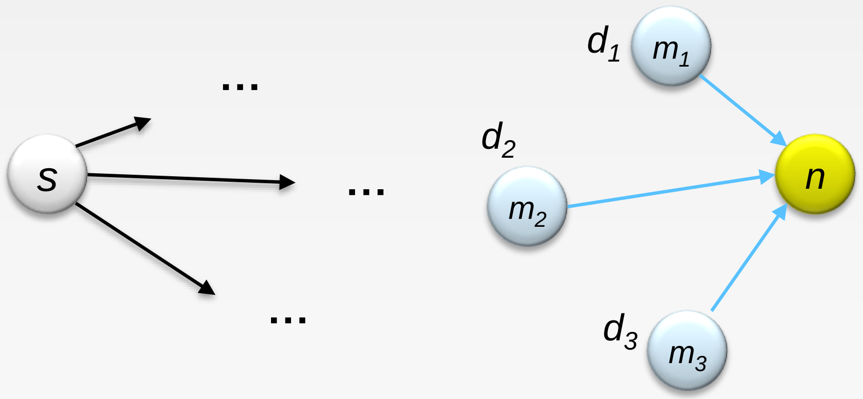
Finish!

Single Source Shortest Path

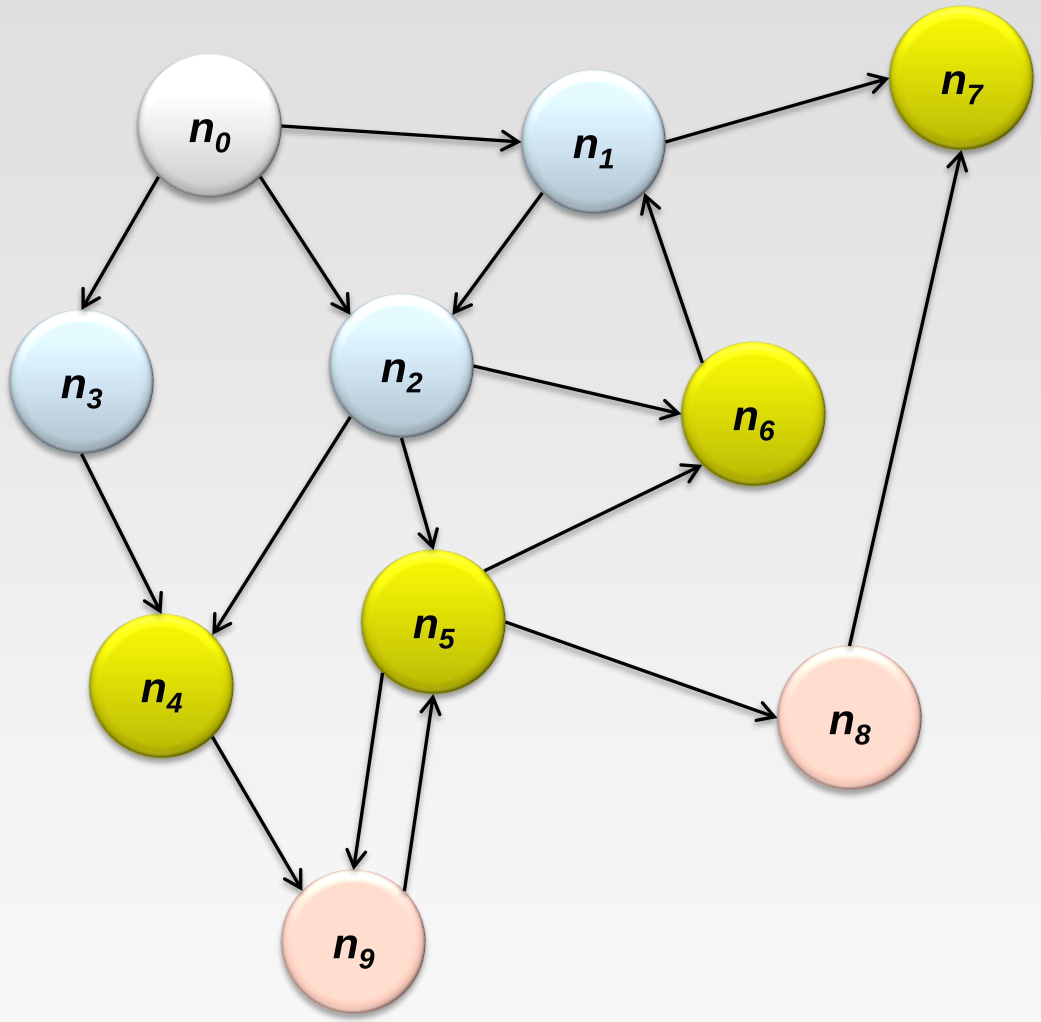
- **Problem:** find shortest path from a source node to one or more target nodes
  - Shortest might also mean lowest weight or cost
- Single processor machine: Dijkstra’s Algorithm
- MapReduce: parallel Breadth-First Search (BFS)

Finding the Shortest Path

- Consider simple case of equal edge weights
- Solution to the problem can be defined inductively
- Here's the intuition:
  - Define: *b* is reachable from *a* if *b* is on adjacency list of *a*
  - DISTANCETO(*s*) = 0
  - For all nodes *p* reachable from *s*,
    DISTANCETO(*p*) = 1
  - For all nodes *n* reachable from some other set of nodes *M*,
    DISTANCETO(*n*) = 1 + min(DISTANCETO(*m*), $m \in M$)



Visualizing Parallel BFS



From Intuition to Algorithm

- Data representation:
  - Key: node *n*
  - Value: *d* (distance from start), adjacency list (list of nodes reachable from *n*)
  - Initialization: for all nodes except for start node, $d = \infty$
- Mapper:
  - $\forall m \in$ adjacency list: emit $(m, d + 1)$
- Sort/Shuffle
  - Groups distances by reachable nodes
- Reducer:
  - Selects minimum distance path for each reachable node
  - Additional bookkeeping needed to keep track of actual path

Multiple Iterations Needed

- Each MapReduce iteration advances the “known frontier” by one hop
  - Subsequent iterations include more and more reachable nodes as frontier expands
  - The input of Mapper is the output of Reducer in the previous iteration
  - Multiple iterations are needed to explore entire graph
- Preserving graph structure:
  - Problem: Where did the adjacency list go?
  - Solution: mapper emits (*n*, adjacency list) as well

BFS Pseudo-Code

- Equal Edge Weights (how to deal with weighted edges?)
- Only distances, no paths stored (how to obtain paths?)

```
class Mapper
    method Map(nid n, node N)
    d ← N.Distance
    Emit(nid n,N.AdjacencyList)                    //Pass along graph structure
    for all nodeid m ∈ N.AdjacencyList do
        Emit(nid m, d+1)             //Emit distances to reachable nodes
```

```
class Reducer
    method Reduce(nid m, [d1, d2, . . .])
    $d_{min}$←∞
    M ← ∅
    for all d ∈ counts [d1, d2, . . .] do
        if IsNode(d) then
            M.AdjacencyList ← d                    //Recover graph structure
        else if d < $d_{min}$ then           //Look for shorter distance
            $d_{min}$ ← d
    M.Distance ← $d_{min}$                   //Update shortest distance
    Emit(nid m, node M)
```

Stopping Criterion

- How many iterations are needed in parallel BFS (equal edge weight case)?
- Convince yourself: when a node is first “discovered”, we’ve found the shortest path
- Now answer the question...
  - The diameter of the graph, or the greatest distance between any pair of nodes
  - Six degrees of separation?
    - If this is indeed true, then parallel breadth-first search on the global social network would take at most six MapReduce iterations.

Implementation in MapReduce

- The actual checking of the termination condition must occur outside of MapReduce.
- The driver (main) checks to see if a termination condition has been met, and if not, repeats.
- Hadoop provides a lightweight API called “counters”.
  - It can be used for counting events that occur during execution, e.g., number of corrupt records, number of times a certain condition is met, or anything that the programmer desires.
  - Counters can be designed to count the number of nodes that have distances of ∞ at the end of the job, the driver program can access the final counter value and check to see if another iteration is necessary.

Chained MapReduce Job (Java)

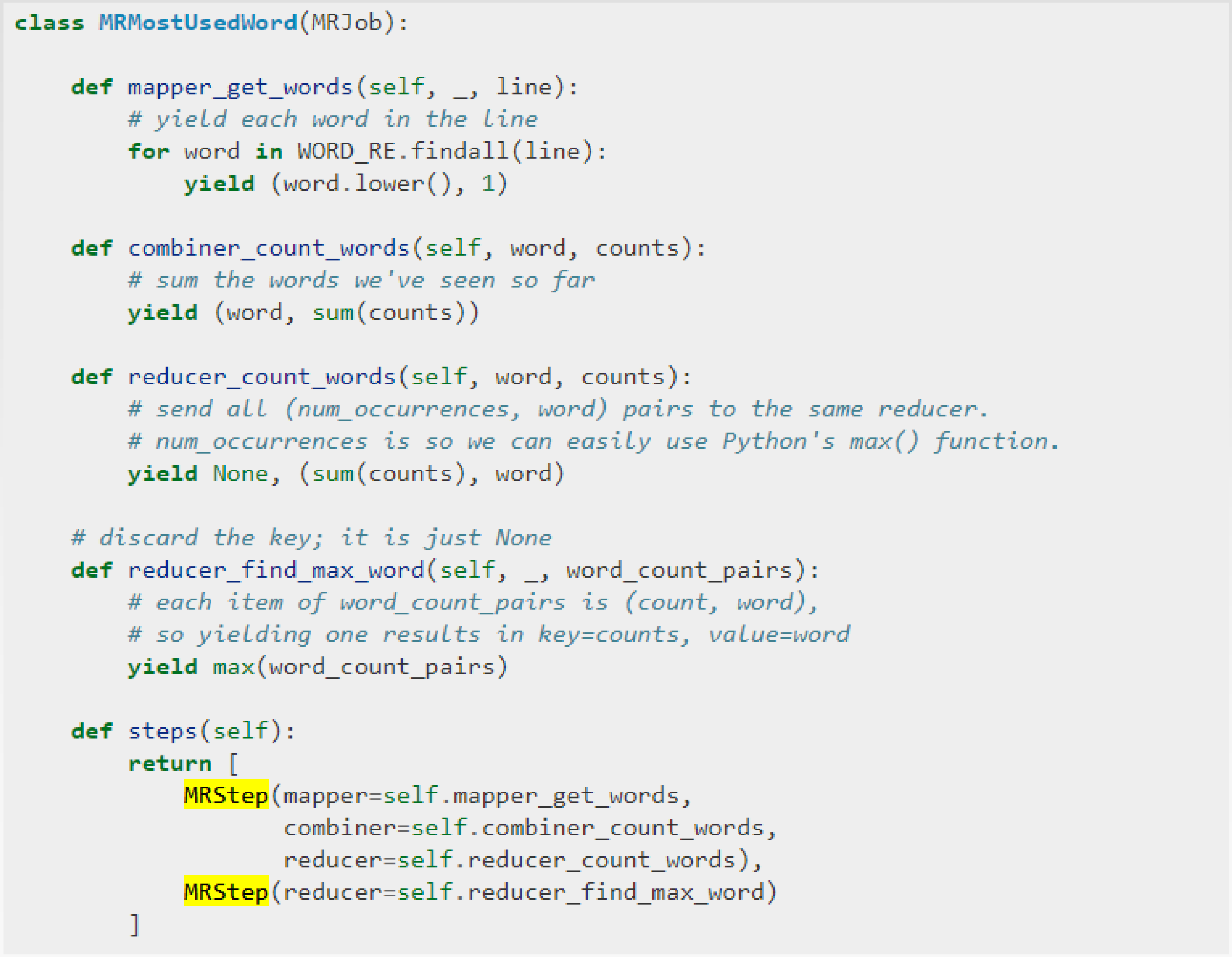
- In the main function, you can configure like:

```
String input = IN;
String output = OUT + System.nanoTime();
boolean isdone = false;
while (isdone == false) {
        Job job = Job.getInstance(conf, "traverse job");
        //configure your jobs here such as mapper and reducer classes

        FileInputFormat.addInputPath(job, new Path(input));
        FileOutputFormat.setOutputPath(job, new Path(output));

        job.waitForCompletion(true);          //start the job

        Counters counters = job.getCounters();
        Counter counter = counters.findCounter(MY_COUNTERS.REACHED);

        if(counter.getValue() == 0){          //use the counter to check the termination
                isdone = true;
        }
        input = output;                       //make the current output as the next input
        output = OUT + System.nanoTime();
}
```

https://github.com/himank/Graph-Algorithm-MapReduce/blob/master/src/DijikstraAlgo.java

Chained MapReduce Job (MRJob)

- To define multiple steps, override steps() to return a list of MRSteps:



```python
class MRMostUsedWord(MRJob):

    def mapper_get_words(self, _, line):
        # yield each word in the line
        for word in WORD_RE.findall(line):
            yield (word.lower(), 1)

    def combiner_count_words(self, word, counts):
        # sum the words we've seen so far
        yield (word, sum(counts))

    def reducer_count_words(self, word, counts):
        # send all (num_occurrences, word) pairs to the same reducer.
        # num_occurrences is so we can easily use Python's max() function.
        yield None, (sum(counts), word)

    # discard the key; it is just None
    def reducer_find_max_word(self, _, word_count_pairs):
        # each item of word_count_pairs is (count, word),
        # so yielding one results in key=counts, value=word
        yield max(word_count_pairs)

    def steps(self):
        return [
            MRStep(mapper=self.mapper_get_words,
                   combiner=self.combiner_count_words,
                   reducer=self.reducer_count_words),
            MRStep(reducer=self.reducer_find_max_word)
        ]
```

MapReduce Counters

- Instrument Job’s metrics
  - Gather statistics
    - Quality control – confirm what was expected.
      - E.g., count invalid records
    - Application-level statistics.
  - Problem diagnostics
  - Try to use counters for gathering statistics instead of log files
- Framework provides a set of built-in metrics
  - For example, bytes processed for input and output
- User can create new counters
  - Number of records consumed
  - Number of errors or warnings

Built-in Counters

- Hadoop maintains some built-in counters for every job.
- Several groups for built-in counters
  - File System Counters – number of bytes read and written
  - Job Counters – documents number of map and reduce tasks launched, number of failed tasks
  - Map-Reduce Task Counters– mapper, reducer, combiner input and output records counts, time and memory statistics

User-Defined Counters

- You can create your own counters
  - Counters are defined by a Java enum
    - serves to group related counters
    - E.g.,

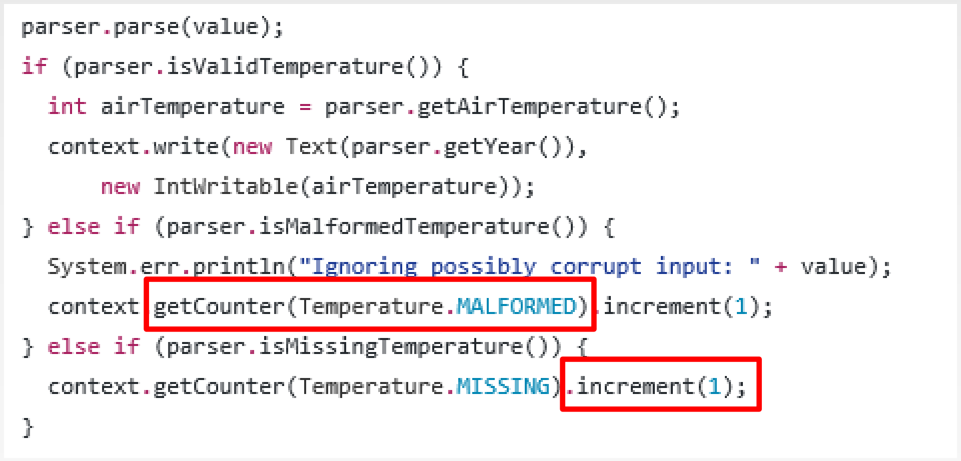
```
enum Temperature {
        MISSING,
        MALFORMED
}
```

- Increment counters in Reducer and/or Mapper classes
  - Counters are global: Framework accurately sums up counts across all maps and reduces to produce a grand total at the end of the job

Implement User-Defined Counters

- Retrieve Counter from Context object
  - Framework injects Context object into map and reduce methods

- Increment Counter's value
  - Can increment by 1 or more



```
parser.parse(value);
if (parser.isValidTemperature()) {
  int airTemperature = parser.getAirTemperature();
  context.write(new Text(parser.getYear()),
      new IntWritable(airTemperature));
} else if (parser.isMalformedTemperature()) {
  System.err.println("Ignoring possibly corrupt input: " + value);
  context.getCounter(Temperature.MALFORMED).increment(1);
} else if (parser.isMissingTemperature()) {
  context.getCounter(Temperature.MISSING).increment(1);
}
```

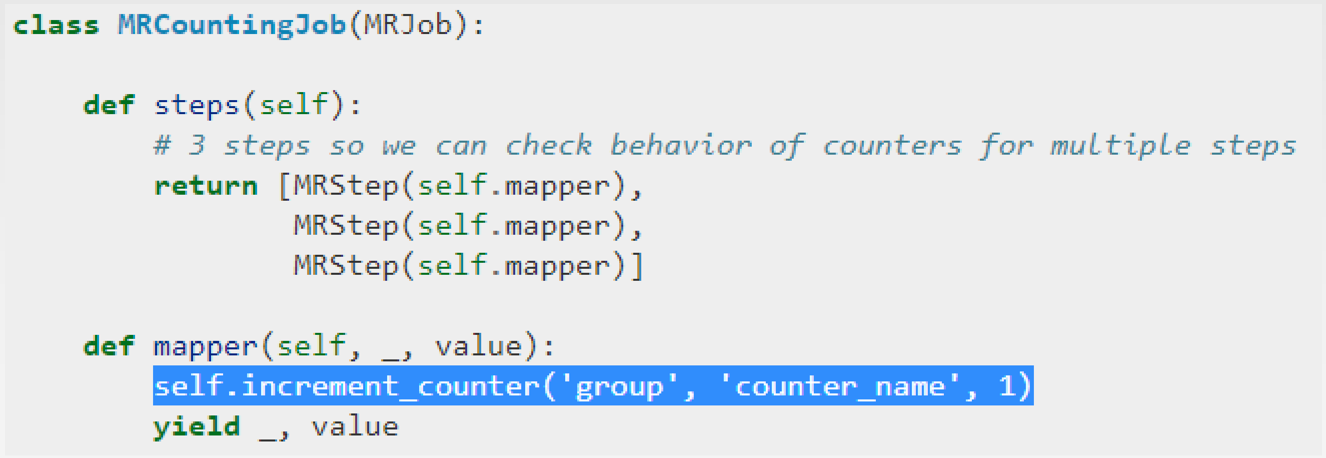
Implement User-Defined Counters

- Get Counters from a finished job in Java
  - Counter counters = job.getCounters()
- Get the counter according to name
  - Counter c1 = counters.findCounter(Temperature.MISSING)
- Enumerate all counters after job is completed

```
for (CounterGroup group : counters) {
        System.out.println("* Counter Group: " + group.getDisplayName() + " (" +
        group.getName() + ")");
        System.out.println("  number of counters in this group: " + group.size());
        for (Counter counter : group) {
                System.out.println("  - " + counter.getDisplayName() + ": " +
                counter.getName() + ": "+counter.getValue());
        }
}
```

Counters in MRJob

- A counter has a group, a name, and an integer value. Hadoop itself tracks a few counters automatically. mrjob prints your job's counters to the command line when your job finishes, and they are available to the runner object if you invoke it programmatically.
- To increment a counter from anywhere in your job, use the increment_counter() method:



```
class MRCountingJob(MRJob):

    def steps(self):
        # 3 steps so we can check behavior of counters for multiple steps
        return [MRStep(self.mapper),
                MRStep(self.mapper),
                MRStep(self.mapper)]

    def mapper(self, _, value):
        self.increment_counter('group', 'counter_name', 1)
        yield _, value
```

- At the end of your job, you'll get the counter's total value.
- You can also read the counters by using "runner.counters()"

https://mrjob.readthedocs.io/en/latest/guides/runners.html

How to Find the Shortest Path?

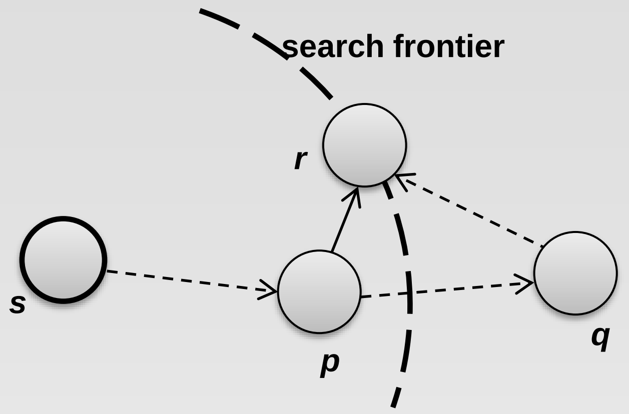
- The parallel breadth-first search algorithm only finds the shortest distances.
- Store “back-pointers” at each node, as with Dijkstra's algorithm
  - Not efficient to recover the path from the back-pointers
- A simpler approach is to emit paths along with distances in the mapper, so that each node will have its shortest path easily accessible at all times
  - The additional space requirement is acceptable

BFS Pseudo-Code (Weighted Edges)

- The adjacency lists, which were previously lists of node ids, must now encode the edge distances as well
    - Positive weights!
- In line 6 of the mapper code, instead of emitting d + 1 as the value, we must now emit d + w, where w is the edge distance
- **The termination behaviour is very different!**
    - How many iterations are needed in parallel BFS (positive edge weight case)?
    - Convince yourself: when a node is first "discovered", we've found the shortest path

Not true!

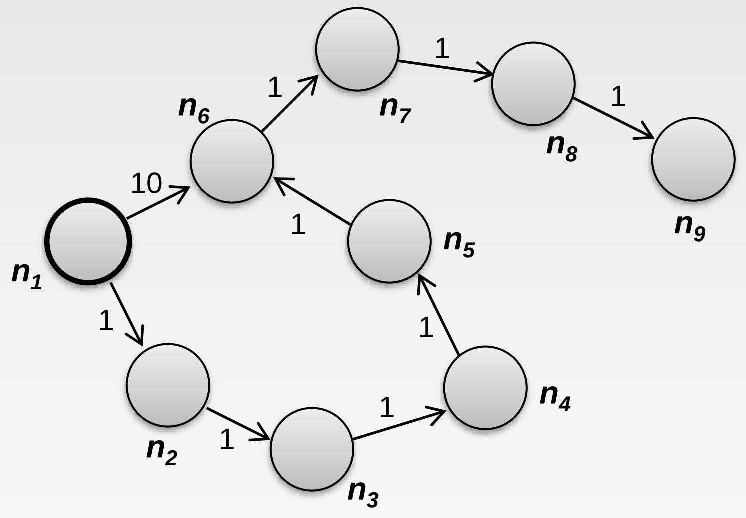
Additional Complexities



- Assume that *p* is the current processed node
  - In the current iteration, we just “discovered” node r for the very first time.
  - We've already discovered the shortest distance to node *p*, and that the shortest distance to *r* so far goes through *p*
  - Is *s*->*p*->*r* the shortest path from *s* to *r*?
- The shortest path from source *s* to node *r* may go outside the current search frontier
  - It is possible that *p*->*q*->*r* is shorter than *p*->*r*!
  - We will not find the shortest distance to *r* until the search frontier expands to cover *q*.

How Many Iterations Are Needed?

- In the worst case, we might need as many iterations as there are nodes in the graph minus one
  - A sample graph that elicits worst-case behaviour for parallel breadth-first search.
  - Eight iterations are required to discover shortest distances to all nodes from n_1.



Example (only distances)

- Input file:

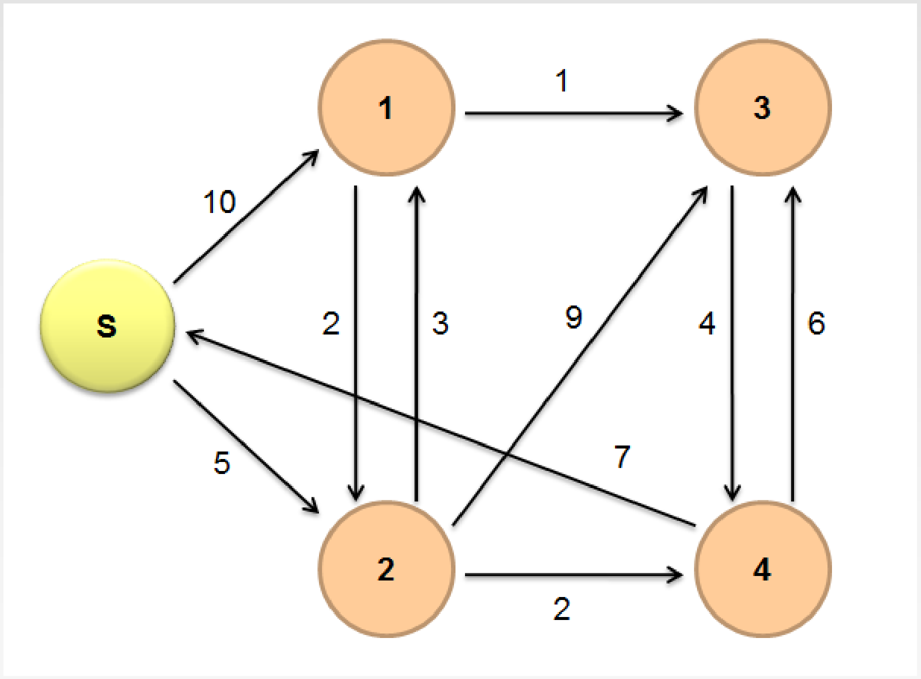
s --> 0 | n1: 10, n2: 5

n1 --> ∞ | n2: 2, n3:1

n2 --> ∞ | n1: 3, n3:9, n4:2

n3 --> ∞ | n4:4

n4 --> ∞ | s:7, n3:6



Iteration 1

- Map:

Read s --> 0 | n1: 10, n2: 5

Emit: (n1, 10), (n2, 5), and the adjacency list (s, n1: 10, n2: 5)

The other lists will also be read and emit, but they do not contribute, and thus ignored

- Reduce:

Receives: (n1, 10), (n2, 5), (s, <0, (n1: 10, n2: 5)>)

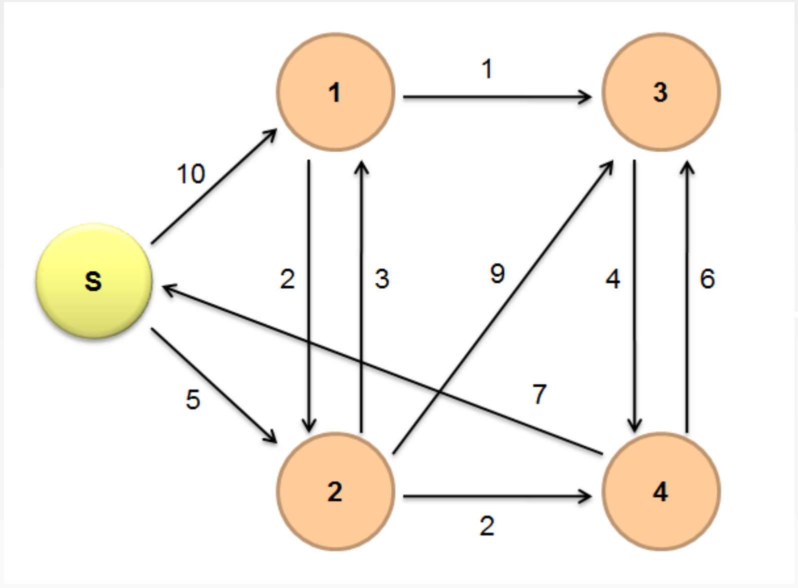
The adjacency list of each node will also be received, ignored in example

Emit:

s --> 0 | n1: 10, n2: 5

n1 --> 10 | n2: 2, n3:1

n2 --> 5 | n1: 3, n3:9, n4:2



Iteration 2

- Map:

Read: n1 --> 10 | n2: 2, n3:1

Emit: (n2, 12), (n3, 11), (n1, <10, (n2: 2, n3:1)>)

Read: n2 --> 5 | n1: 3, n3:9, n4:2

Emit: (n1, 8), (n3, 14), (n4, 7), (n2, <5, (n1: 3, n3:9, n4:2)>)

Ignore the processing of the other lists

- Reduce:

Receives: (n1, (8, <10, (n2: 2, n3:1)>)), (n2, (12, <5, n1: 3, n3:9, n4:2>)), (n3, (11, 14)), (n4, 7)

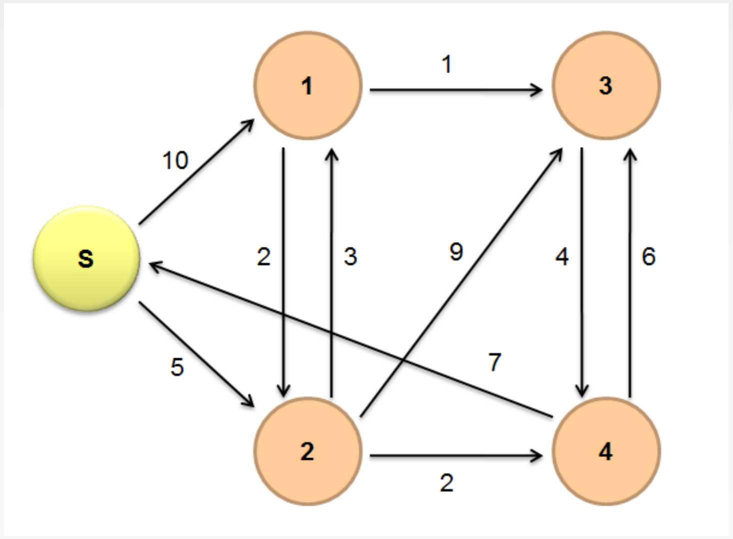
Emit:

n1 --> 8 | n2: 2, n3:1

n2 --> 5 | n1: 3, n3:9, n4:2

n3 --> 11 | n4:4

n4 --> 7 | s:7, n3:6



Iteration 3

- Map:

Read: n1 --> 8 | n2: 2, n3:1

Emit: (n2, 10), (n3, 9), (n1, <8, (n2: 2, n3:1)>)

Read: n2 --> 5 | n1: 3, n3:9, n4:2 (**Again!**)

Emit: (n1, 8), (n3, 14), (n4, 7), (n2, <5, (n1: 3, n3:9, n4:2)>)

Read: n3 --> 11 | n4:4

Emit: (n4, 15), (n3, <11, (n4:4)>)

Read: n4 --> 7 | s:7, n3:6

Emit: (s, 14), (n3, 13), (n4, <7, (s:7, n3:6)>)

- Reduce:

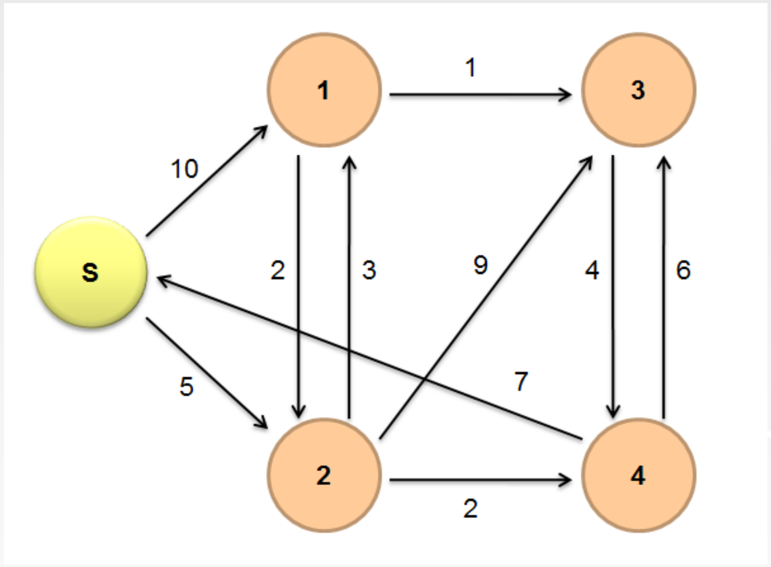
Emit:

n1 --> 8 | n2: 2, n3:1

n2 --> 5 | n1: 3, n3:9, n4:2

n3 --> 9 | n4:4

n4 --> 7 | s:7, n3:6



Iteration 4

In order to avoid duplicated computations, you can use a status value to indicate whether the distance of the node has been modified in the previous iteration.

- Map:

Read: n1 --> 8 | n2: 2, n3:1 (**Again!**)

Emit: (n2, 10), (n3, 9), (n1, <8, (n2: 2, n3:1)>)

Read: n2 --> 5 | n1: 3, n3:9, n4:2 (**Again!**)

Emit: (n1, 8), (n3, 14), (n4, 7), (n2, <5, (n1: 3, n3:9, n4:2)>)

Read: n3 --> 9 | n4:4

Emit: (n4, 13), (n3, <9, (n4:4)>)

Read: n4 --> 7 | s:7, n3:6 (**Again!**)

Emit: (s, 14), (n3, 13), (n4, <7, (s:7, n3:6)>)

- Reduce:

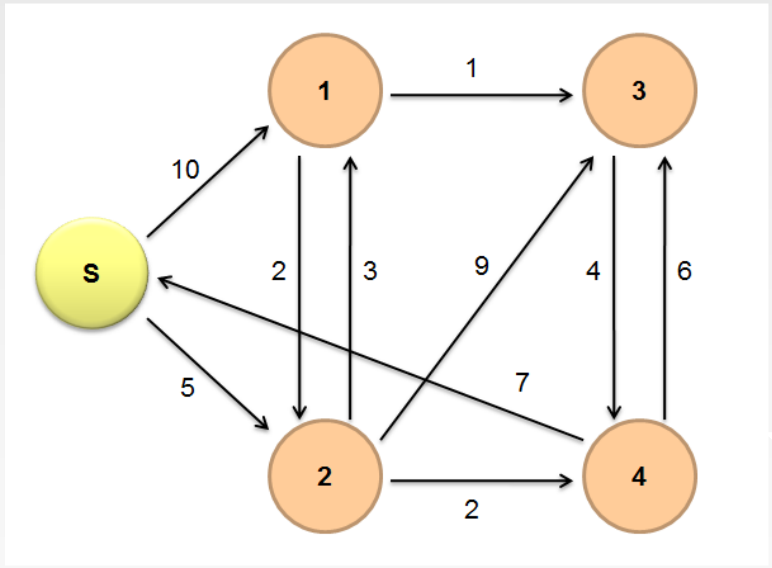
Emit:

n1 --> 8 | n2: 2, n3:1

n2 --> 5 | n1: 3, n3:9, n4:2

n3 --> 9 | n4:4

n4 --> 7 | s:7, n3:6



No updates. Terminate.

Comparison to Dijkstra

- Dijkstra's algorithm is more efficient
  - At any step it only pursues edges from the minimum-cost path inside the frontier
- MapReduce explores all paths in parallel
  - Lots of "waste"
  - Useful work is only done at the "frontier"
- Why can't we do better using MapReduce?

Graphs and MapReduce

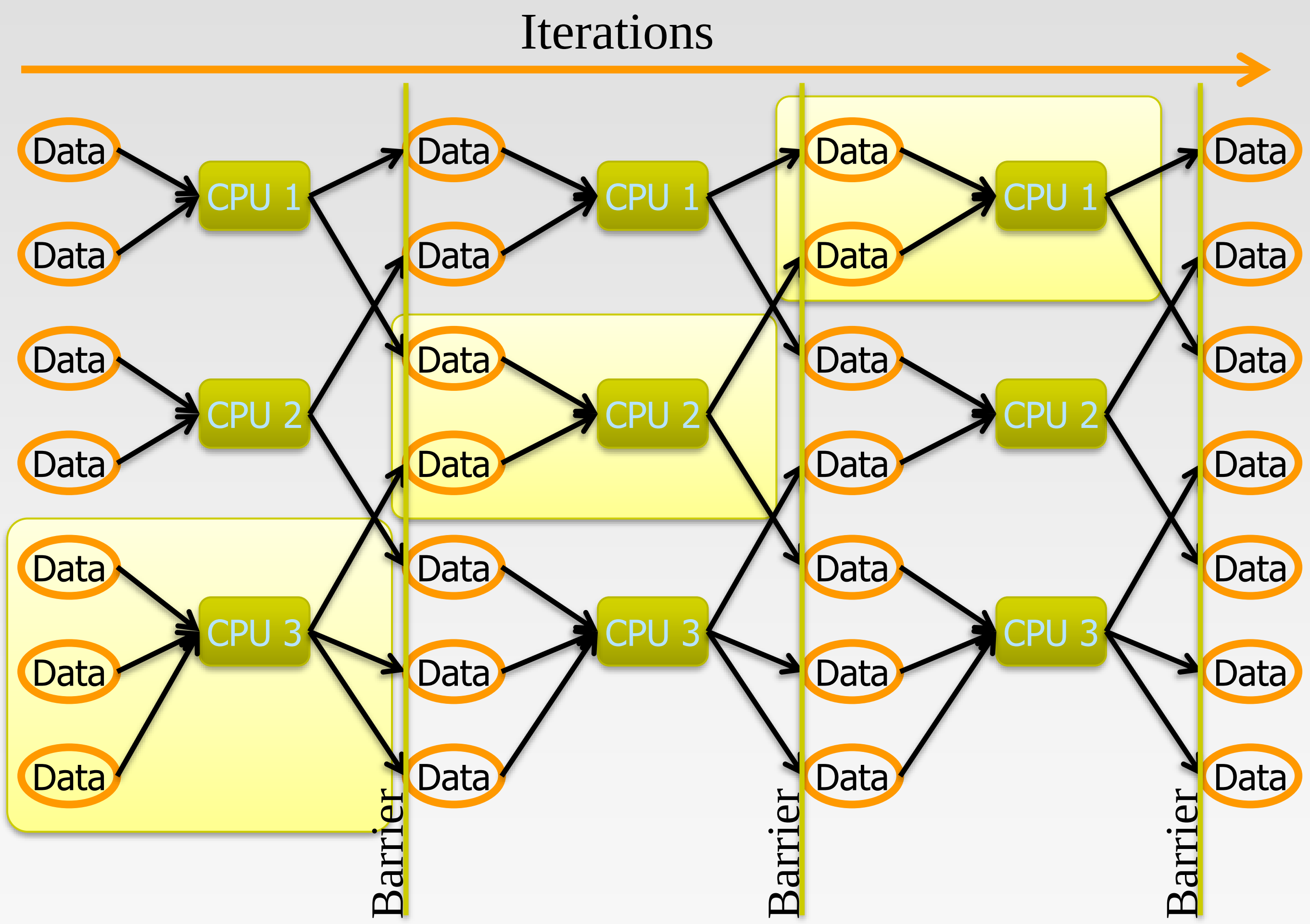
- Graph algorithms typically involve:
  - Performing computations at each node: based on node features, edge features, and local link structure
  - Propagating computations: “traversing” the graph
- Generic recipe:
  - Represent graphs as adjacency lists
  - Perform local computations in mapper
  - Pass along partial results via outlinks, keyed by destination node
  - Perform aggregation in reducer on inlinks to a node
  - Iterate until convergence: controlled by external “driver”
  - Don’t forget to pass the graph structure between iterations

Issues with MapReduce on Graph Processing

- MapReduce Does not support iterative graph computations:
  - External driver. Huge I/O incurs
  - No mechanism to support global data structures that can be accessed and updated by all mappers and reducers
    - Passing information is only possible within the local graph structure – through adjacency list
    - Dijkstra's algorithm on a single machine: a global priority queue that guides the expansion of nodes
    - Dijkstra‘s algorithm in Hadoop, no such queue available. Do some “wasted” computation instead
- MapReduce algorithms are often impractical on large, dense graphs.
  - The amount of intermediate data generated is on the order of the number of edges.
  - For dense graphs, MapReduce running time would be dominated by copying intermediate data across the network.

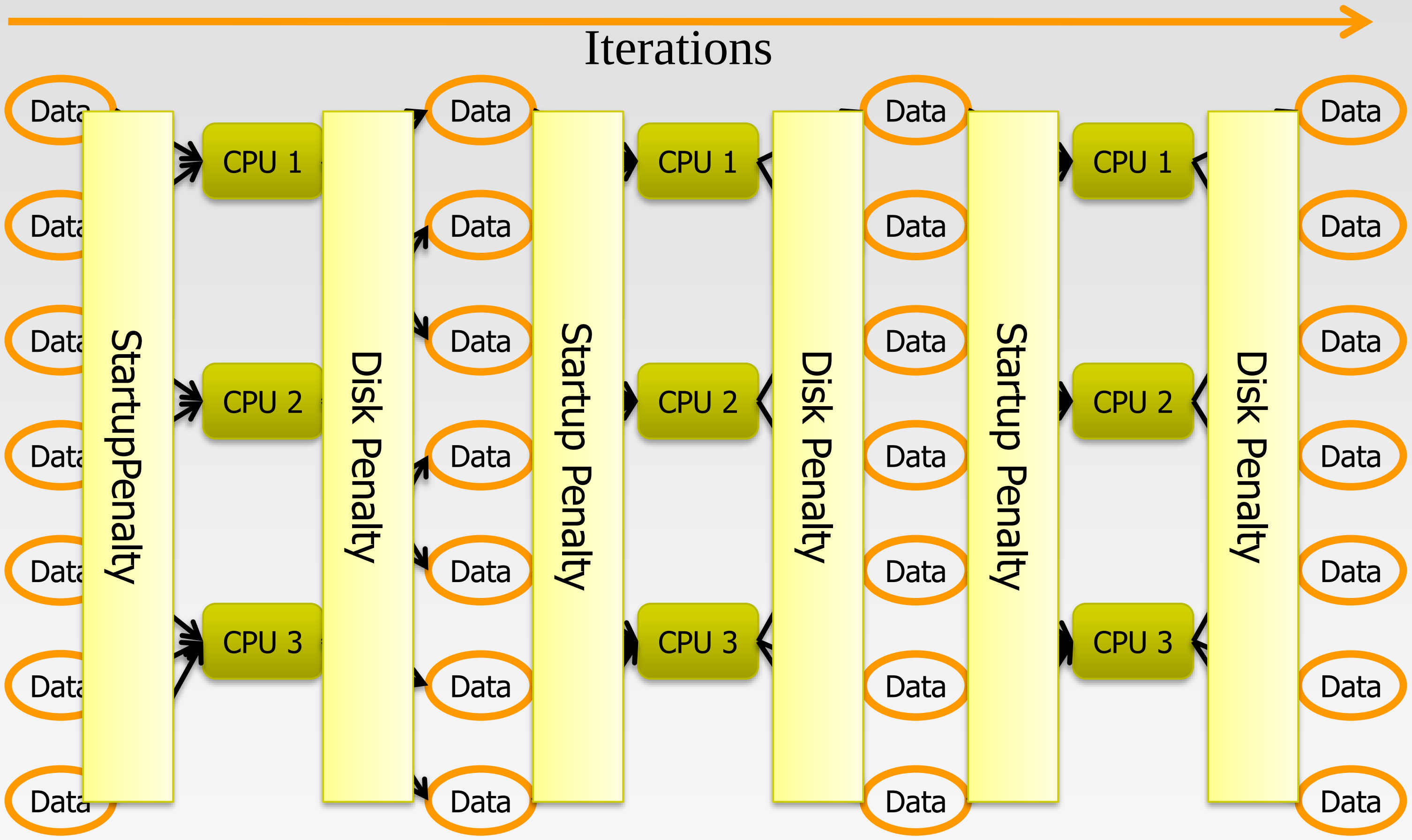
Iterative MapReduce

Only a subset of data needs computation:



Iterative MapReduce

System is not optimized for iteration:



Better Partitioning

- Default: hash partitioning
  - Randomly assign nodes to partitions
- Observation: many graphs exhibit local structure
  - E.g., communities in social networks
  - Better partitioning creates more opportunities for local aggregation
- Unfortunately, partitioning is **hard**!
  - Sometimes, chick-and-egg…
  - But cheap heuristics sometimes available
  - For webgraphs: range partition on domain-sorted URLs

References

- Chapter 5, Data-Intensive Text Processing with MapReduce. Jimmy Lin and Chris Dyer. University of Maryland, College Park.

End of Chapter 3.2

Practices

Practice: Design MapReduce Algorithms

- Counting total enrollments of two specified courses

- Input Files: A list of students with their enrolled courses

  Jamie: COMP9313, COMP9318

  Tom: COMP9331, COMP9313

  … …

- Mapper selects records and outputs initial counts
  - Input: Key – student, value – a list of courses
  - Output: (COMP9313, 1), (COMP9318, 1), …

- Reducer accumulates counts
  - Input: (COMP9313, [1, 1, …]), (COMP9318, [1, 1, …])
  - Output: (COMP9313, 16), (COMP9318, 35)

Practice: Design MapReduce Algorithms

- Remove duplicate records
- Input: a list of records

  2013-11-01 aa
  2013-11-02 bb
  2013-11-03 cc
  2013-11-01 aa
  2013-11-03 dd

- Mapper
  - Input (record_id, record)
  - Output (record, “”)
    - E.g., (2013-11-01 aa, “”), (2013-11-02 bb, “”), …
- Reducer
  - Input (record, [“”, “”, “”, …])
    - E.g., (2013-11-01 aa, [“”, “”]), (2013-11-02 bb, [“”]), …
  - Output (record, “”)

Practice: Design MapReduce Algorithms

- Assume that in an online shopping system, a huge log file stores the information of each transaction. Each line of the log is in format of "userID***\t*** product***\t*** price***\t*** time". Your task is to use MapReduce to find out the top-5 expensive products purchased by each user in 2016

- Mapper:
  - Input(transaction_id, transaction)
  - initialize an associate array H(UserID, priority queue Q of log record based on price)
  - map(): get local top-5 for each user
  - cleanup(): emit the entries in H

- Reducer:
  - Input(userID, list of queues[])
  - get top-5 products from the list of queues

Practice: Design MapReduce Algorithms

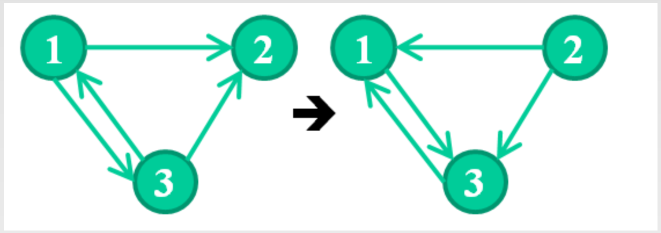
- Reverse graph edge directions & output in node order

  Input: adjacency list of graph (3 nodes and 4 edges)

  (3, [1, 2]) (1, [3])

  (1, [2, 3]) ➔ (2, [1, 3])

  (3, [1])



- Note, the node_ids in the output values are also sorted. But Hadoop only sorts on keys!

- Solutions: Secondary sort

Practice: Design MapReduce Algorithms

- Map
  - Input: (3, [1, 2]), (1, [2, 3]).
  - Intermediate: (1, [3]), (2, [3]), (2, [1]), (3, [1]). (reverse direction)
  - Output: (<1, 3>, [3]), (<2, 3>, [3]), (<2, 1>, [1]), (<3, 1>, [1]).
    - Copy node_ids from value to key.
- Partition on Key.field1, and Sort on whole Key (both fields)
  - Input: (<1, 3>, [3]), (<2, 3>, [3]), (<2, 1>, [1]), (<3, 1>, [1])
  - Output: (<1, 3>, [3]), (<2, 1>, [1]), (<2, 3>, [3]), (<3, 1>, [1])
- Grouping comparator
  - Merge according to part of the key
  - Output: (<1, 3>, [3]), (<2, 1>, [1, 3]), (<3, 1>, [1])
    this will be the reducer's input
- Reducer
  - Merge according to part of the key
  - Output: (1, [3]), (2, [1, 3]), (3, [1])

Practice: Design MapReduce Algorithms

- Calculate the common friends for each pair of users in Facebook. Assume the friends are stored in format of Person->[List of Friends], e.g.: A -> [B C D], B -> [A C D E], C -> [A B D E], D -> [A B C E], E -> [B C D]. Note that the “friendship” is bi-directional, which means that if A is in B’s list, B would be in A’s list as well. Your result should be like:
  - (A B) -> (C D)
  - (A C) -> (B D)
  - (A D) -> (B C)
  - (B C) -> (A D E)
  - (B D) -> (A C E)
  - (B E) -> (C D)
  - (C D) -> (A B E)
  - (C E) -> (B D)
  - (D E) -> (B C)

Practice: Design MapReduce Algorithms

- Mapper:
  - Input(user u, List of Friends [f_1, f_2, …,])
  - map(): for each friend f_i, emit (<u, f_i>, List of Friends [f_1, f_2, …,])
    - Need to generate the pair <u, f_i> according to an order! Thus <u, fi> and <fi, u> will be the same key

- Reducer:
  - Input(user pair, list of friends lists[])
  - Get the intersection from all friends lists

- Example: http://scaryscientist.blogspot.com/2015/04/common-friends-using-mapreduce.html