

Map-Reduce Applications: Counting, Graph Shortest Paths

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Overview

- Simple counting, averaging
- Graph problems and representations
- Parallel breadth-first search



MapReduce: Recap

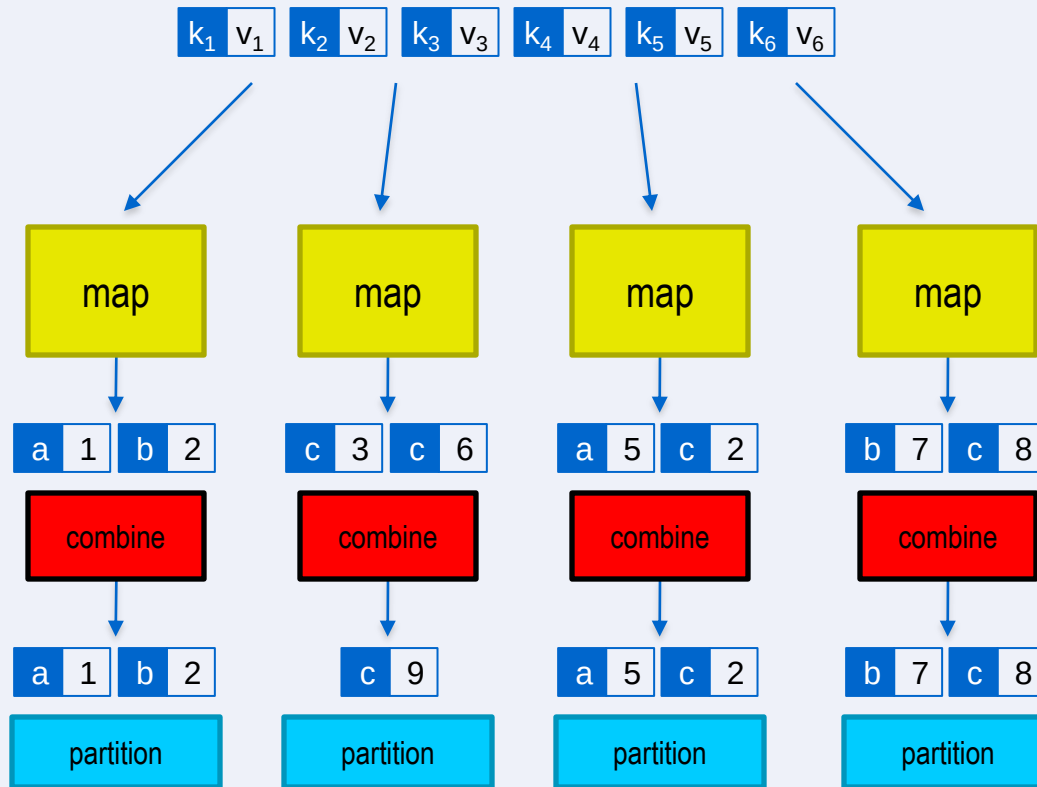
- Programmers must specify:
 - map** $(k, v) \rightarrow \langle k', v' \rangle^*$
 - reduce** $(k', v') \rightarrow \langle k', v' \rangle^*$
 - All values with the same key are reduced together
- Optionally, also:
 - partition** $(k', \text{number of partitions}) \rightarrow \text{partition for } k'$
 - Often a simple hash of the key, e.g., $\text{hash}(k') \bmod n$
 - Divides up key space for parallel reduce operations
 - combine** $(k', v') \rightarrow \langle k', v' \rangle^*$
 - Mini-reducers that run in memory after the map phase
 - Used as an optimization to reduce network traffic
- The execution framework handles everything else...



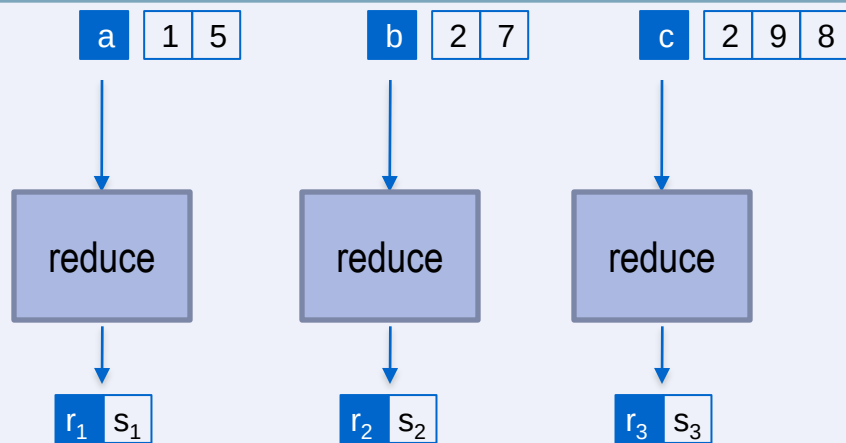
“Everything Else”

- The execution framework handles everything else...
 - Scheduling: assigns workers to map and reduce tasks
 - “Data distribution”: moves processes to data
 - Synchronization: gathers, sorts, and shuffles intermediate data
 - Errors and faults: detects worker failures and restarts
- Limited control over data and execution flow
 - All algorithms must be expressed in m, r, c, p
- You don't know:
 - Where mappers and reducers run
 - When a mapper or reducer begins or finishes
 - Which input a particular mapper is processing
 - Which intermediate key a particular reducer is processing





Shuffle and Sort: aggregate values by keys



Word Count: Baseline

```
1: class MAPPER
2:   method MAP(docid  $a$ , doc  $d$ )
3:     for all term  $t \in \text{doc } d$  do
4:       EMIT(term  $t$ , count 1)

1: class REDUCER
2:   method REDUCE(term  $t$ , counts  $[c_1, c_2, \dots]$ )
3:      $sum \leftarrow 0$ 
4:     for all count  $c \in \text{counts } [c_1, c_2, \dots]$  do
5:        $sum \leftarrow sum + c$ 
6:     EMIT(term  $t$ , count  $s$ )
```

What's the impact of combiners?



Word Count: Version 1

```
1: class MAPPER
2:   method MAP(docid  $a$ , doc  $d$ )
3:      $H \leftarrow$  new ASSOCIATIVEARRAY
4:     for all term  $t \in$  doc  $d$  do
5:        $H\{t\} \leftarrow H\{t\} + 1$                                 ▷ Tally counts for entire document
6:     for all term  $t \in H$  do
7:       EMIT(term  $t$ , count  $H\{t\}$ )
```



Word Count: Version 2

```
1: class MAPPER
2:   method INITIALIZE
3:      $H \leftarrow \text{new ASSOCIATIVEARRAY}$ 
4:   method MAP(docid  $a$ , doc  $d$ )
5:     for all term  $t \in \text{doc } d$  do
6:        $H\{t\} \leftarrow H\{t\} + 1$ 
7:   method CLOSE
8:     for all term  $t \in H$  do
9:        $\text{EMIT}(\text{term } t, \text{count } H\{t\})$ 
```

Key: preserve state across
input key-value pairs!

▷ Tally counts *across* documents



Design Pattern for Local Aggregation

- “In-mapper combining”
 - Fold the functionality of the combiner into the mapper by preserving state across multiple map calls
- Advantages
 - Speed
 - Faster than actual combiners
- Disadvantages
 - Explicit memory management required
 - Potential for order-dependent bugs



Combiner Design

- Combiners and reducers share same method signature
 - Sometimes, reducers can serve as combiners
 - Often, not...
- Remember: combiner are optional optimizations
 - Should not affect algorithm correctness
 - May be run 0, 1, or multiple times
- Example: find average of all integers associated with the same key



Computing the Mean: Version 1

```
1: class MAPPER
2:   method MAP(string  $t$ , integer  $r$ )
3:     EMIT(string  $t$ , integer  $r$ )

1: class REDUCER
2:   method REDUCE(string  $t$ , integers  $[r_1, r_2, \dots]$ )
3:      $sum \leftarrow 0$ 
4:      $cnt \leftarrow 0$ 
5:     for all integer  $r \in$  integers  $[r_1, r_2, \dots]$  do
6:        $sum \leftarrow sum + r$ 
7:        $cnt \leftarrow cnt + 1$ 
8:      $r_{avg} \leftarrow sum / cnt$ 
9:     EMIT(string  $t$ , integer  $r_{avg}$ )
```

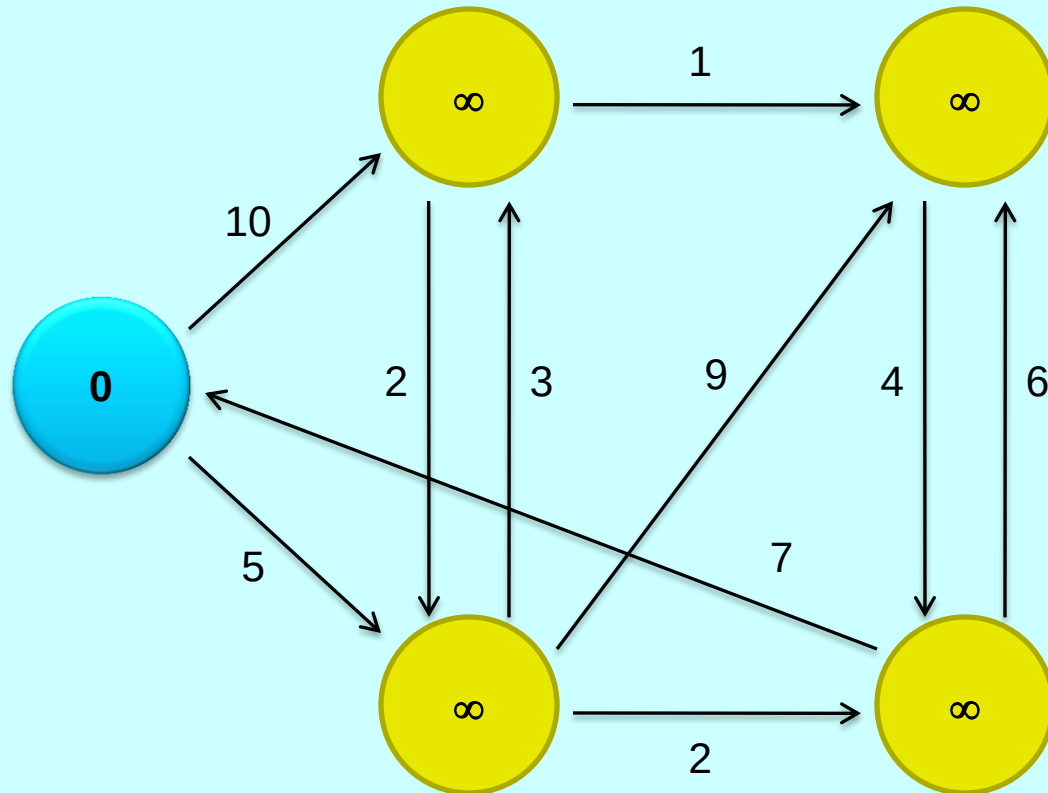


Single Source Shortest Path

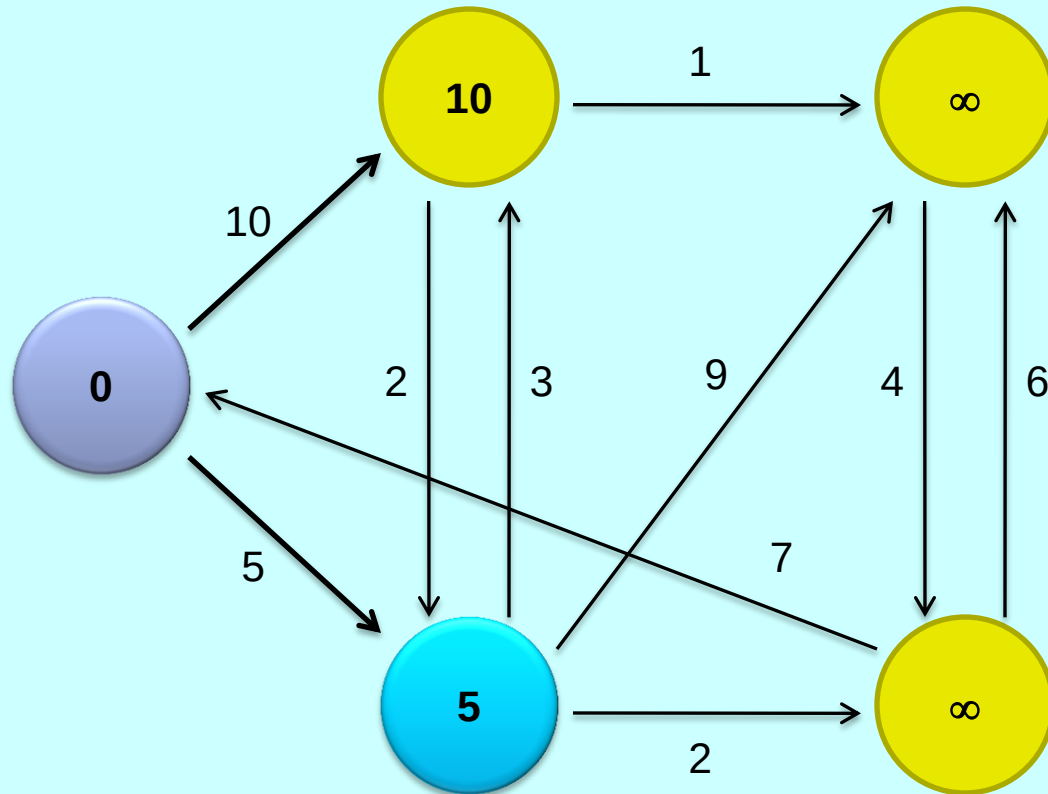
- Problem: find shortest path from a source node to one or more target nodes
 - Shortest might also mean lowest weight or cost
- First, a refresher: Dijkstra's Algorithm



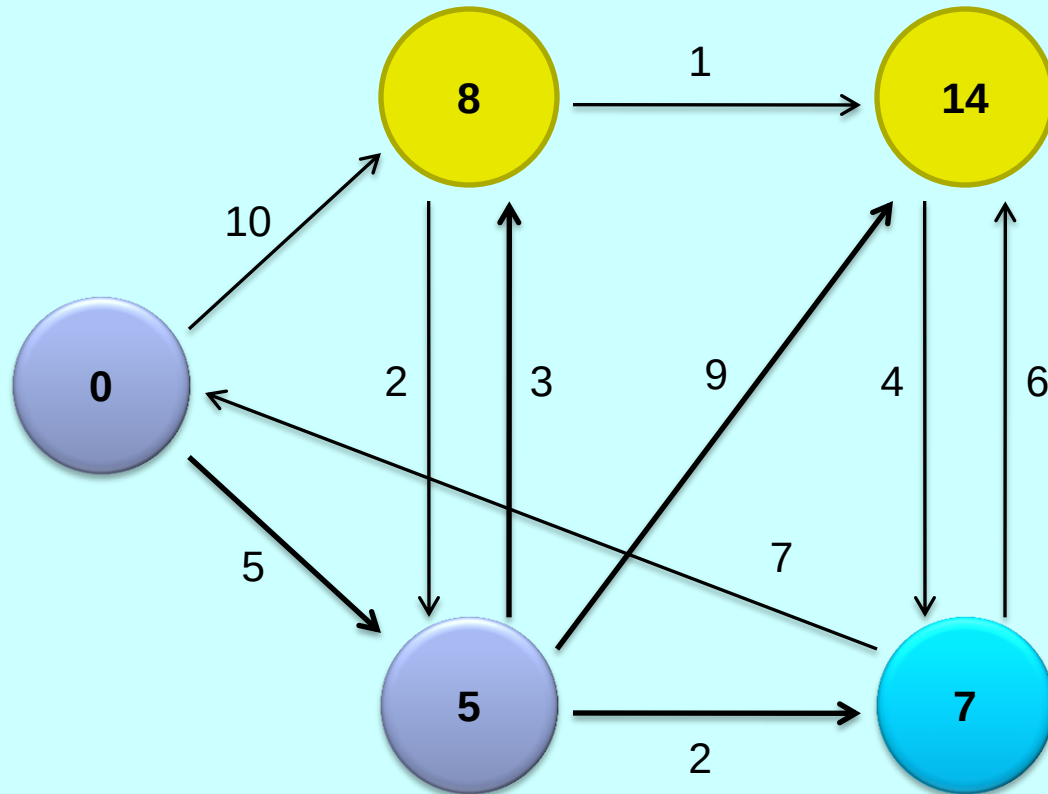
Dijkstra's Algorithm Example



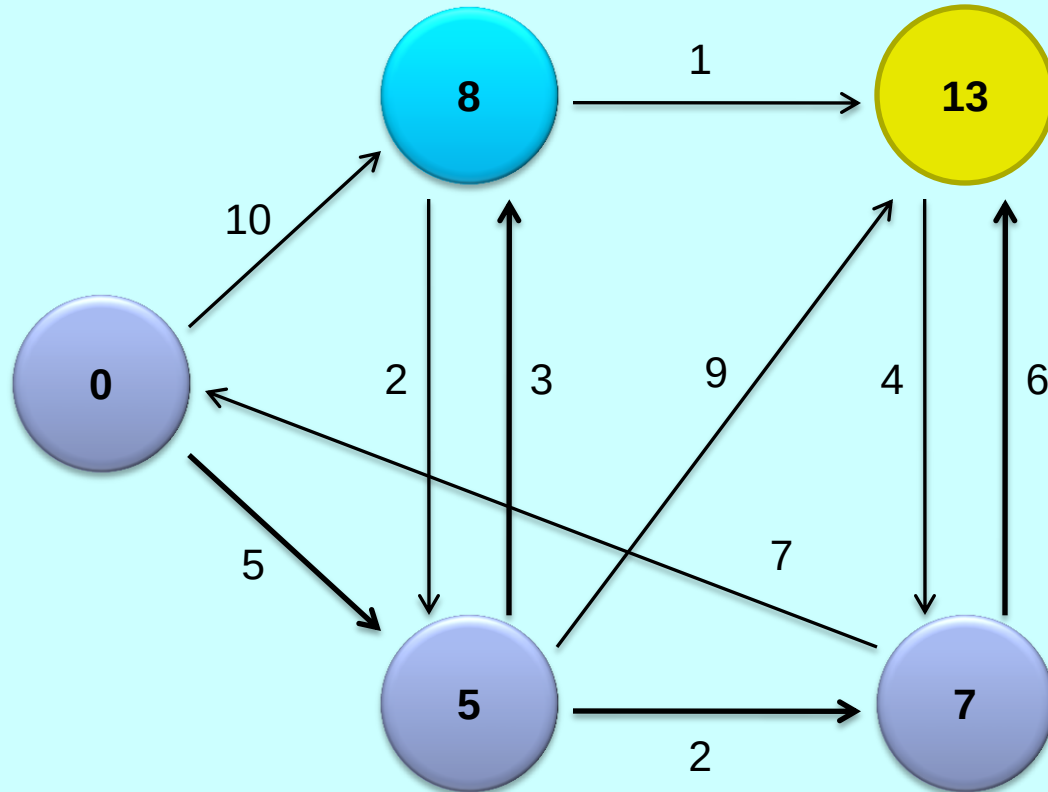
Dijkstra's Algorithm Example



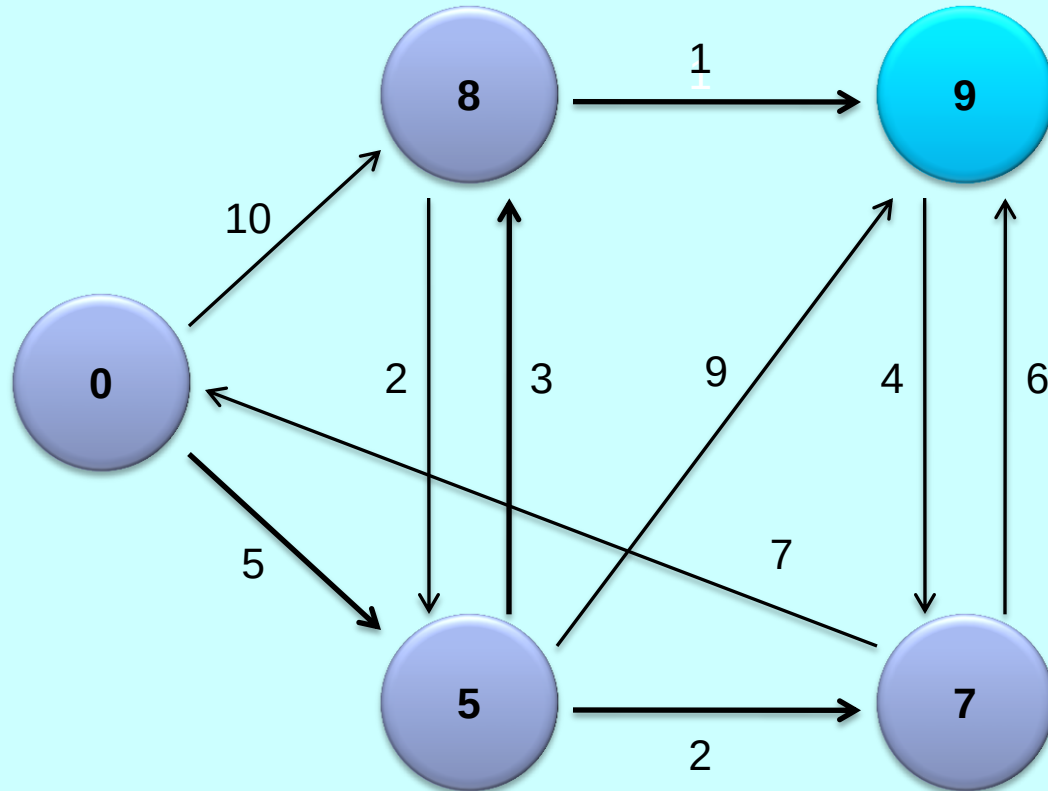
Dijkstra's Algorithm Example



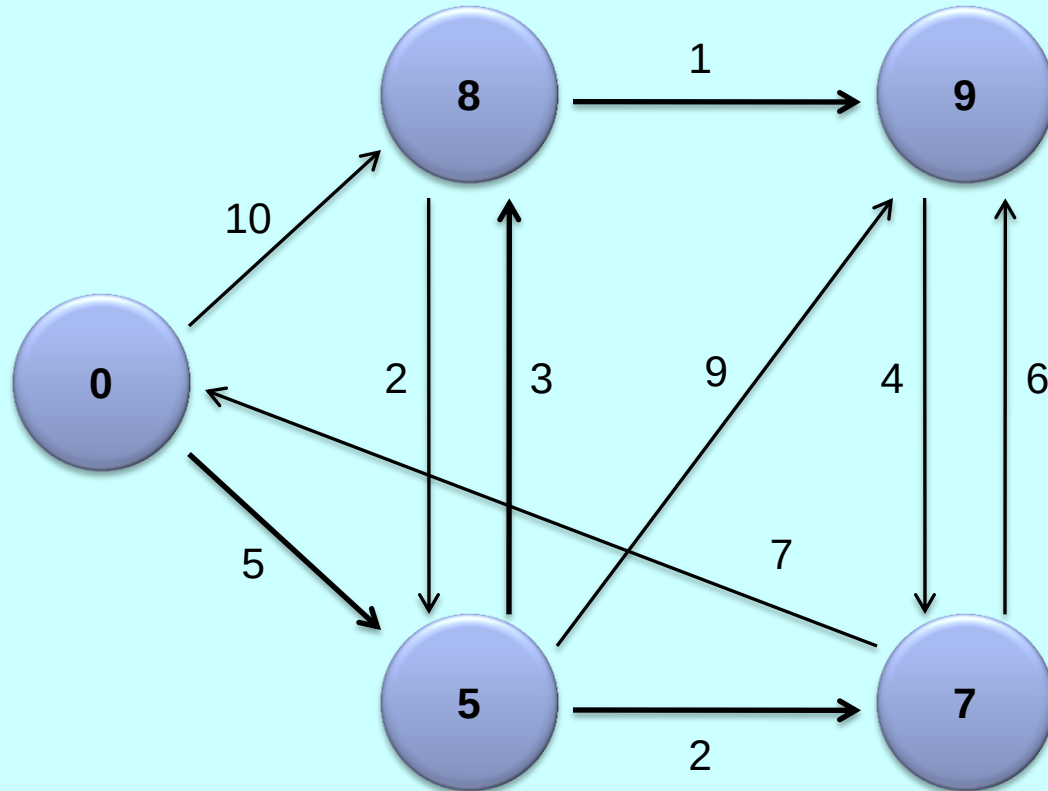
Dijkstra's Algorithm Example



Dijkstra's Algorithm Example



Dijkstra's Algorithm Example



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)



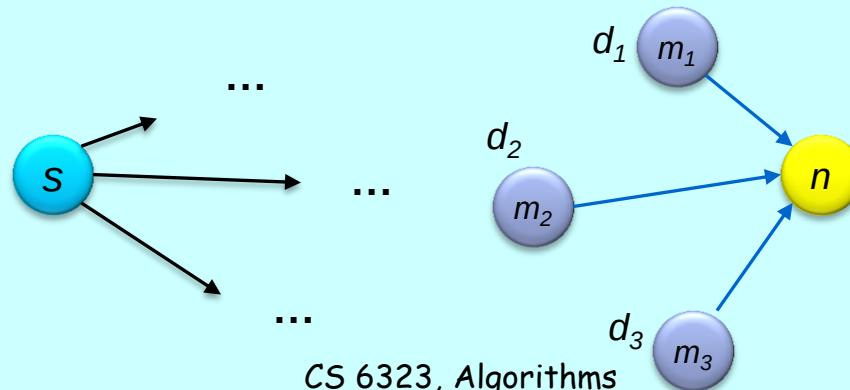


Source: Wikipedia (Wave)

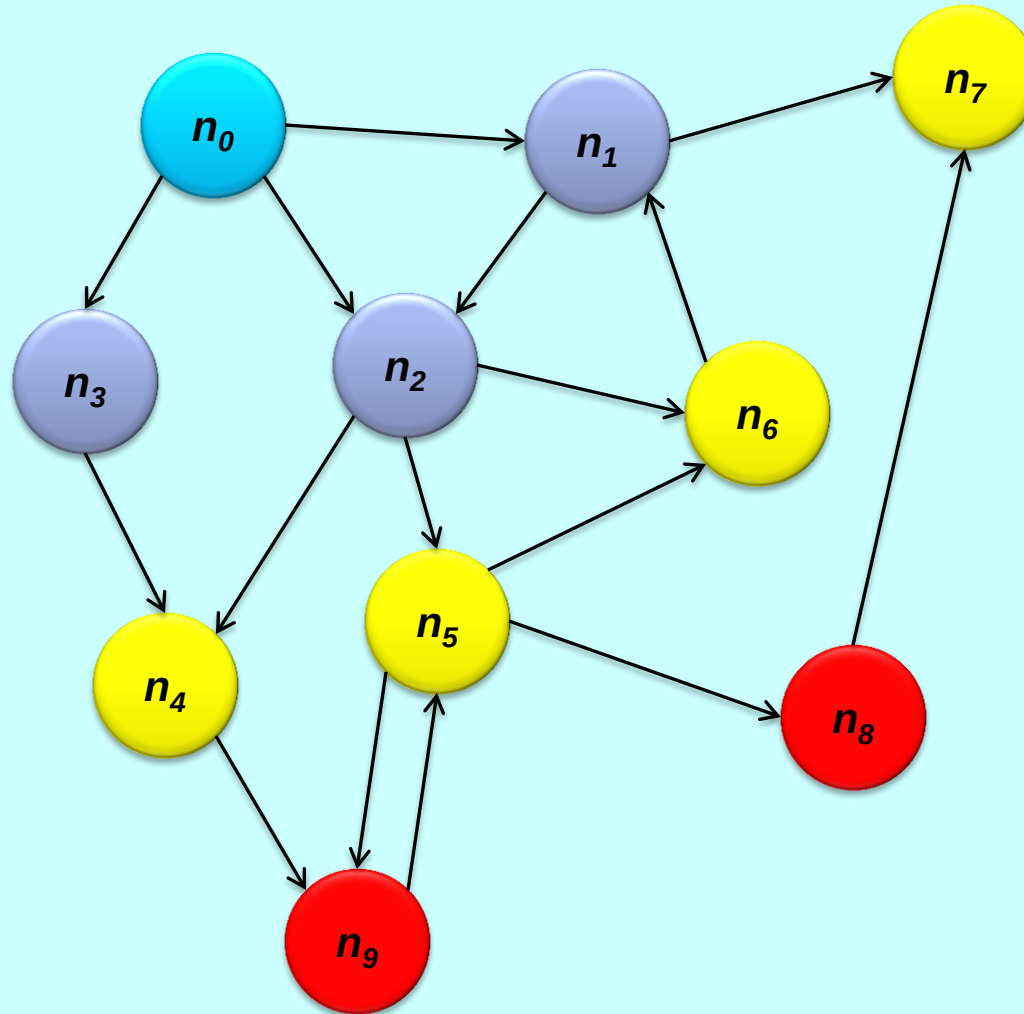
University College Cork,
Gregory M. Provan

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
 - $\text{DISTANCETo}(s) = 0$
 - For all nodes p reachable from s ,
 $\text{DISTANCETo}(p) = 1$
 - For all nodes n reachable from some other set of nodes M ,
 $\text{DISTANCETo}(n) = 1 + \min(\text{DISTANCETo}(m), m \in M)$



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:**
 - $\forall m \in \text{adjacency list: emit } (m, d + 1)$
- **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
 - Multiple iterations are needed to explore entire graph
- Preserving graph structure:
 - Problem: Where did the adjacency list go?
 - Solution: mapper emits $(n, \text{adjacency list})$ as well



BFS Pseudo-Code

```
1: class MAPPER
2:   method MAP(nid  $n$ , node  $N$ )
3:      $d \leftarrow N.DISTANCE$ 
4:     EMIT(nid  $n$ ,  $N$ )                                ▷ Pass along graph structure
5:     for all nodeid  $m \in N.ADJACENCYLIST$  do
6:       EMIT(nid  $m$ ,  $d + 1$ )                            ▷ Emit distances to reachable nodes

1: class REDUCER
2:   method REDUCE(nid  $m$ , [ $d_1, d_2, \dots$ ])
3:      $d_{min} \leftarrow \infty$ 
4:      $M \leftarrow \emptyset$ 
5:     for all  $d \in \text{counts } [d_1, d_2, \dots]$  do
6:       if ISNODE( $d$ ) then
7:          $M \leftarrow d$                                 ▷ Recover graph structure
8:       else if  $d < d_{min}$  then                          ▷ Look for shorter distance
9:          $d_{min} \leftarrow d$ 
10:     $M.DISTANCE \leftarrow d_{min}$                         ▷ Update shortest distance
11:    EMIT(nid  $m$ , node  $M$ )
```



Example: SSSP – Parallel BFS in MapReduce

Adjacency matrix

	A	B	C	D	E
A		10		5	
B			1	2	
C					4
D		3	9		2
E	7		6		

Adjacency List

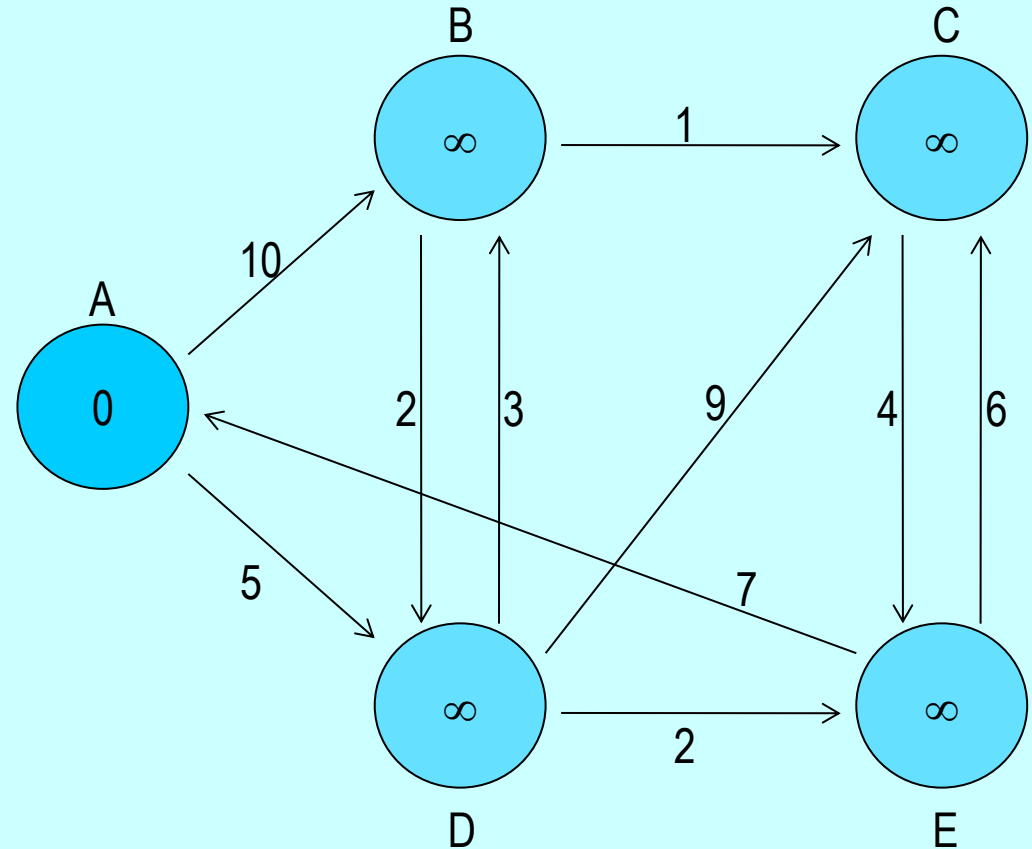
A: (B, 10), (D, 5)

B: (C, 1), (D, 2)

C: (E, 4)

D: (B, 3), (C, 9), (E, 2)

E: (A, 7), (C, 6)



Example: SSSP – Parallel BFS in MapReduce

- Map input: $\langle \text{node ID}, \langle \text{dist}, \text{adj list} \rangle \rangle$

$\langle A, \langle 0, \langle (B, 10), (D, 5) \rangle \rangle \rangle$

$\langle B, \langle \text{inf}, \langle (C, 1), (D, 2) \rangle \rangle \rangle$

$\langle C, \langle \text{inf}, \langle (E, 4) \rangle \rangle \rangle$

$\langle D, \langle \text{inf}, \langle (B, 3), (C, 9), (E, 2) \rangle \rangle \rangle$

$\langle E, \langle \text{inf}, \langle (A, 7), (C, 6) \rangle \rangle \rangle$

- Map output: $\langle \text{dest node ID}, \text{dist} \rangle$

$\langle B, 10 \rangle \langle D, 5 \rangle$

$\langle C, \text{inf} \rangle \langle D, \text{inf} \rangle$

$\langle E, \text{inf} \rangle$

$\langle B, \text{inf} \rangle \langle C, \text{inf} \rangle \langle E, \text{inf} \rangle$

$\langle A, \text{inf} \rangle \langle C, \text{inf} \rangle$

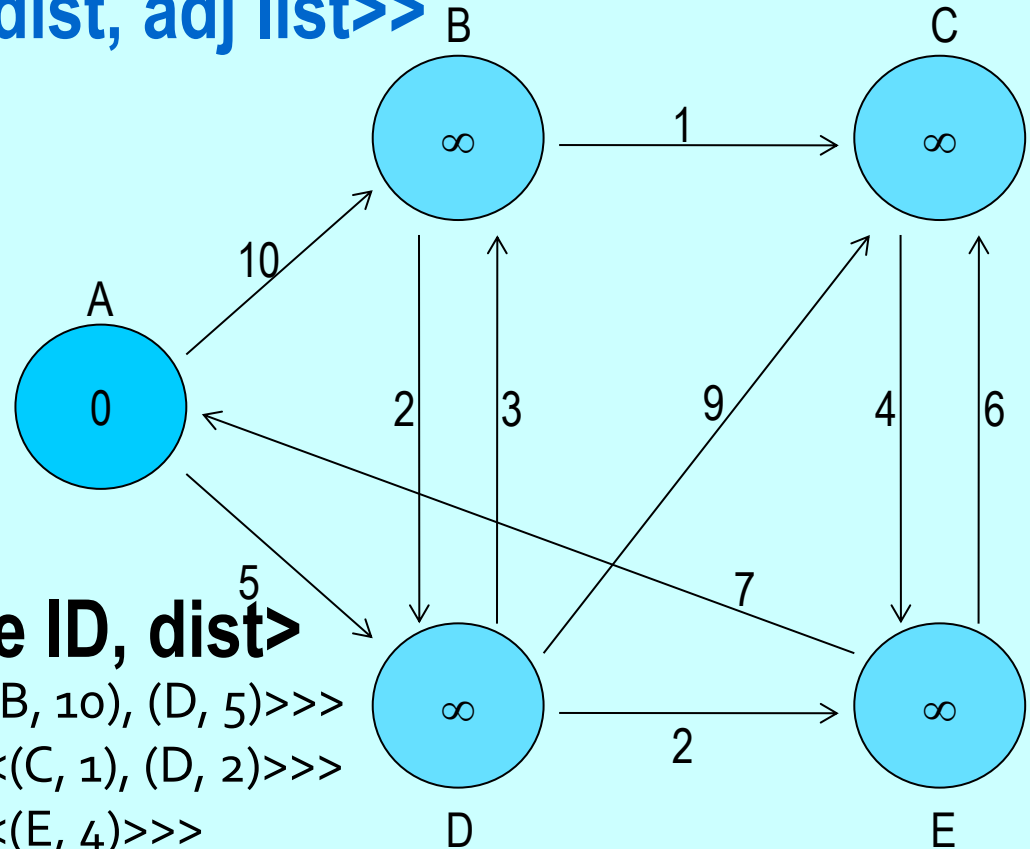
$\langle A, \langle 0, \langle (B, 10), (D, 5) \rangle \rangle \rangle$

$\langle B, \langle \text{inf}, \langle (C, 1), (D, 2) \rangle \rangle \rangle$

$\langle C, \langle \text{inf}, \langle (E, 4) \rangle \rangle \rangle$

$\langle D, \langle \text{inf}, \langle (B, 3), (C, 9), (E, 2) \rangle \rangle \rangle$

$\langle E, \langle \text{inf}, \langle (A, 7), (C, 6) \rangle \rangle \rangle$



Flushed to local disk!!



Example: SSSP – Parallel BFS in MapReduce

- Reduce input: <node ID, dist>

<A, <0, <(B, 10), (D, 5)>>>

<A, inf>

<B, <inf, <(C, 1), (D, 2)>>>

<B, 10> <B, inf>

<C, <inf, <(E, 4)>>>

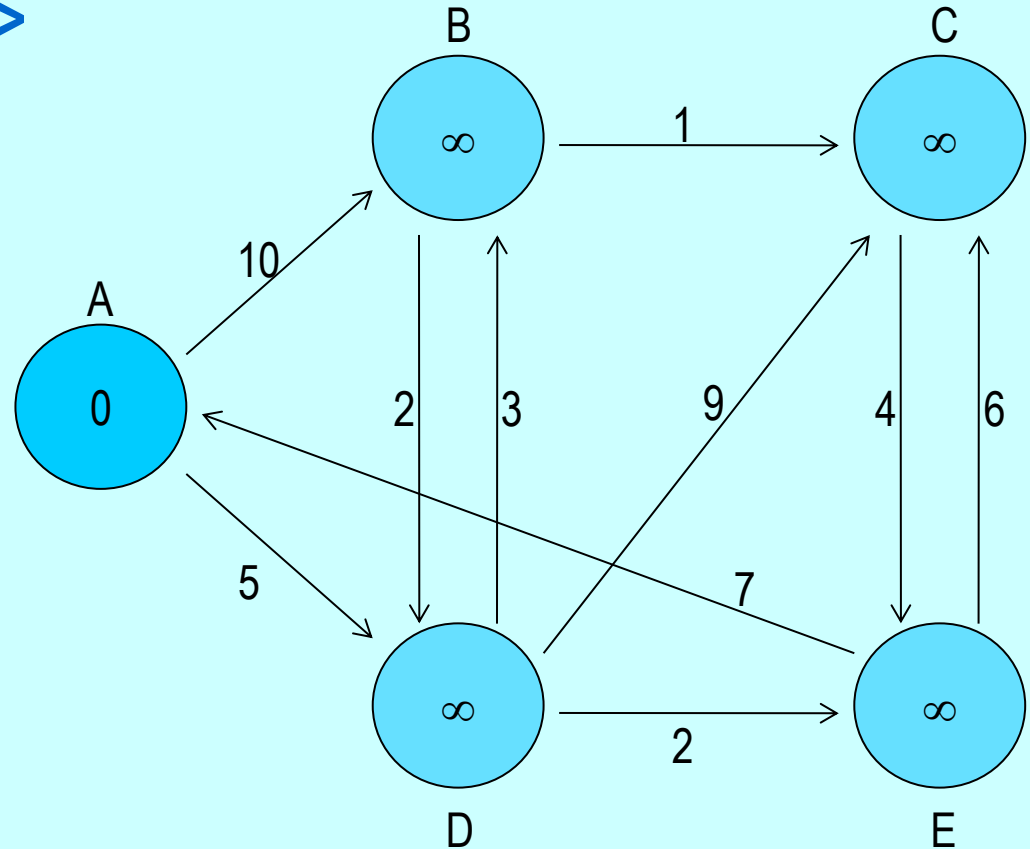
<C, inf> <C, inf> <C, inf>

<D, <inf, <(B, 3), (C, 9), (E, 2)>>>

<D, 5> <D, inf>

<E, <inf, <(A, 7), (C, 6)>>>

<E, inf> <E, inf>



Example: SSSP – Parallel BFS in MapReduce

- Reduce input: <node ID, dist>

<A, <0, <(B, 10), (D, 5)>>>

~~<A, inf>~~

<B, <inf, <(C, 1), (D, 2)>>>

<B, 10> ~~<B, inf>~~

<C, <inf, <(E, 4)>>>

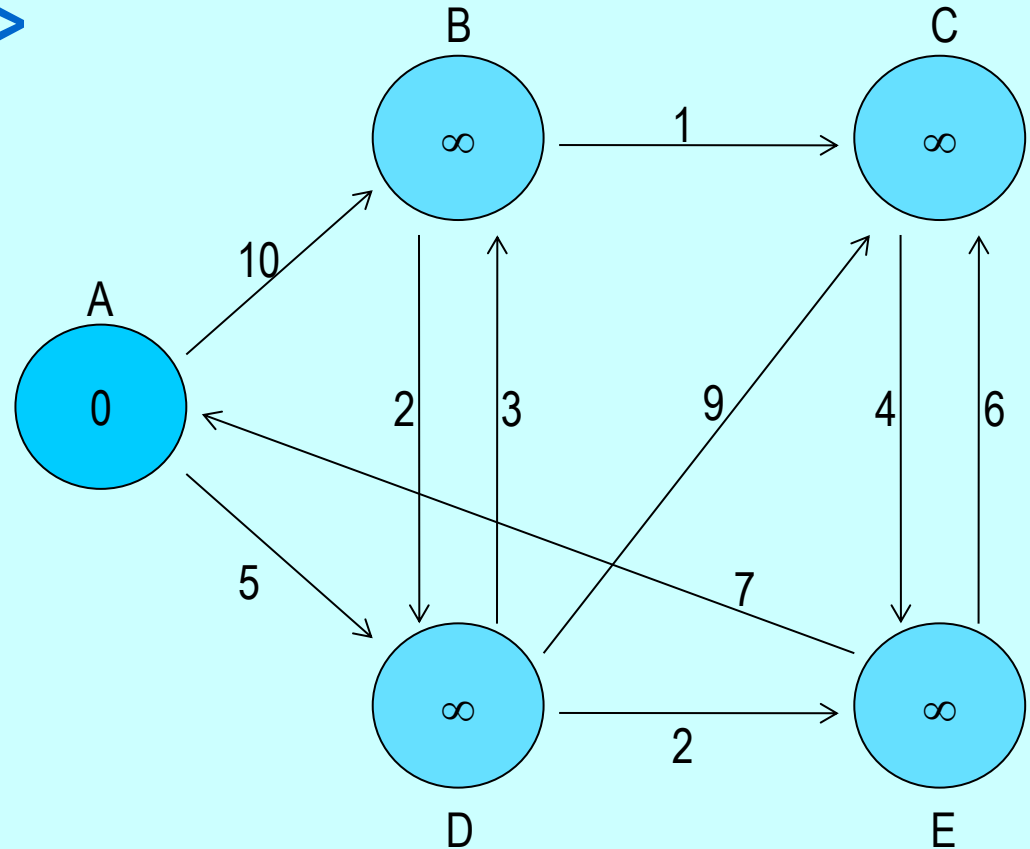
~~<C, inf>~~ ~~<C, inf>~~ ~~<C, inf>~~

<D, <inf, <(B, 3), (C, 9), (E, 2)>>>

<D, 5> ~~<D, inf>~~

<E, <inf, <(A, 7), (C, 6)>>>

~~<E, inf>~~ ~~<E, inf>~~



Example: SSSP – Parallel BFS in MapReduce

- Reduce output: $\langle \text{node ID}, \langle \text{dist}, \text{adj list} \rangle \rangle$
= Map input for next iteration

$\langle A, \langle 0, \langle (B, 10), (D, 5) \rangle \rangle \rangle$ Flushed to DFS!!

$\langle B, \langle 10, \langle (C, 1), (D, 2) \rangle \rangle \rangle$

$\langle C, \langle \text{inf}, \langle (E, 4) \rangle \rangle \rangle$

$\langle D, \langle 5, \langle (B, 3), (C, 9), (E, 2) \rangle \rangle \rangle$

$\langle E, \langle \text{inf}, \langle (A, 7), (C, 6) \rangle \rangle \rangle$

- Map output: $\langle \text{dest node ID}, \text{dist} \rangle$

$\langle B, 10 \rangle \langle D, 5 \rangle$

$\langle C, 11 \rangle \langle D, 12 \rangle$

$\langle E, \text{inf} \rangle$

$\langle B, 8 \rangle \langle C, 14 \rangle \langle E, 7 \rangle$

$\langle A, \text{inf} \rangle \langle C, \text{inf} \rangle$

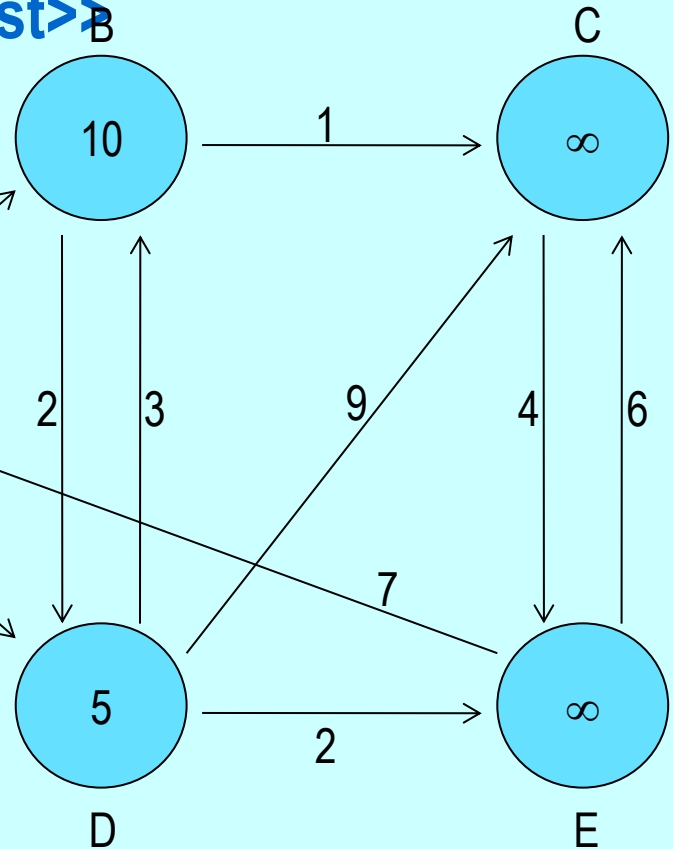
$\langle A, \langle 0, \langle (B, 10), (D, 5) \rangle \rangle \rangle$

$\langle B, \langle 10, \langle (C, 1), (D, 2) \rangle \rangle \rangle$

$\langle C, \langle \text{inf}, \langle (E, 4) \rangle \rangle \rangle$

$\langle D, \langle 5, \langle (B, 3), (C, 9), (E, 2) \rangle \rangle \rangle$

$\langle E, \langle \text{inf}, \langle (A, 7), (C, 6) \rangle \rangle \rangle$



Flushed to local disk!!



Example: SSSP – Parallel BFS in MapReduce

- Reduce input: $\langle \text{node ID, dist} \rangle$

$\langle A, \langle 0, \langle (B, 10), (D, 5) \rangle \rangle \rangle$

$\langle A, \text{inf} \rangle$

$\langle B, \langle 10, \langle (C, 1), (D, 2) \rangle \rangle \rangle$

$\langle B, 10 \rangle \langle B, 8 \rangle$

$\langle C, \langle \text{inf}, \langle (E, 4) \rangle \rangle \rangle$

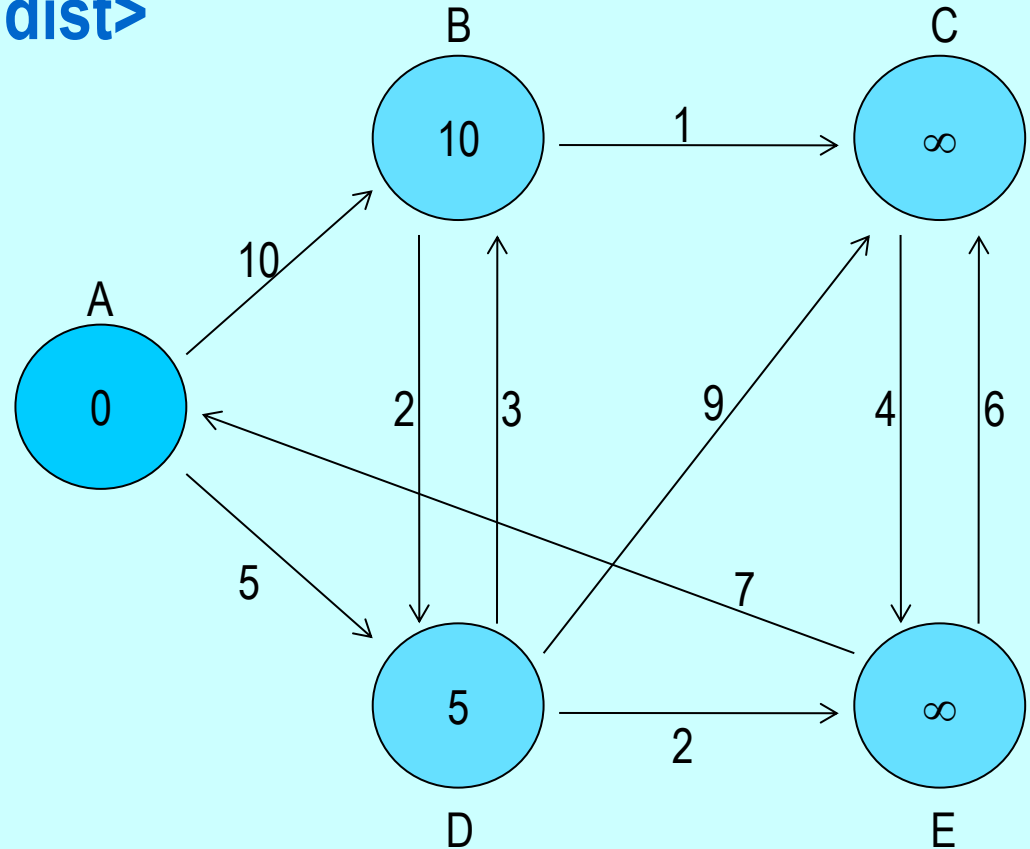
$\langle C, 11 \rangle \langle C, 14 \rangle \langle C, \text{inf} \rangle$

$\langle D, \langle 5, \langle (B, 3), (C, 9), (E, 2) \rangle \rangle \rangle$

$\langle D, 5 \rangle \langle D, 12 \rangle$

$\langle E, \langle \text{inf}, \langle (A, 7), (C, 6) \rangle \rangle \rangle$

$\langle E, \text{inf} \rangle \langle E, 7 \rangle$



Example: SSSP – Parallel BFS in MapReduce

- Reduce input: $\langle \text{node ID, dist} \rangle$

$\langle A, \langle 0, \langle (B, 10), (D, 5) \rangle \rangle \rangle$

$\langle A, \text{inf} \rangle$

$\langle B, \langle 10, \langle (C, 1), (D, 2) \rangle \rangle \rangle$

$\langle B, 10 \rangle \langle B, 8 \rangle$

$\langle C, \langle \text{inf}, \langle (E, 4) \rangle \rangle \rangle$

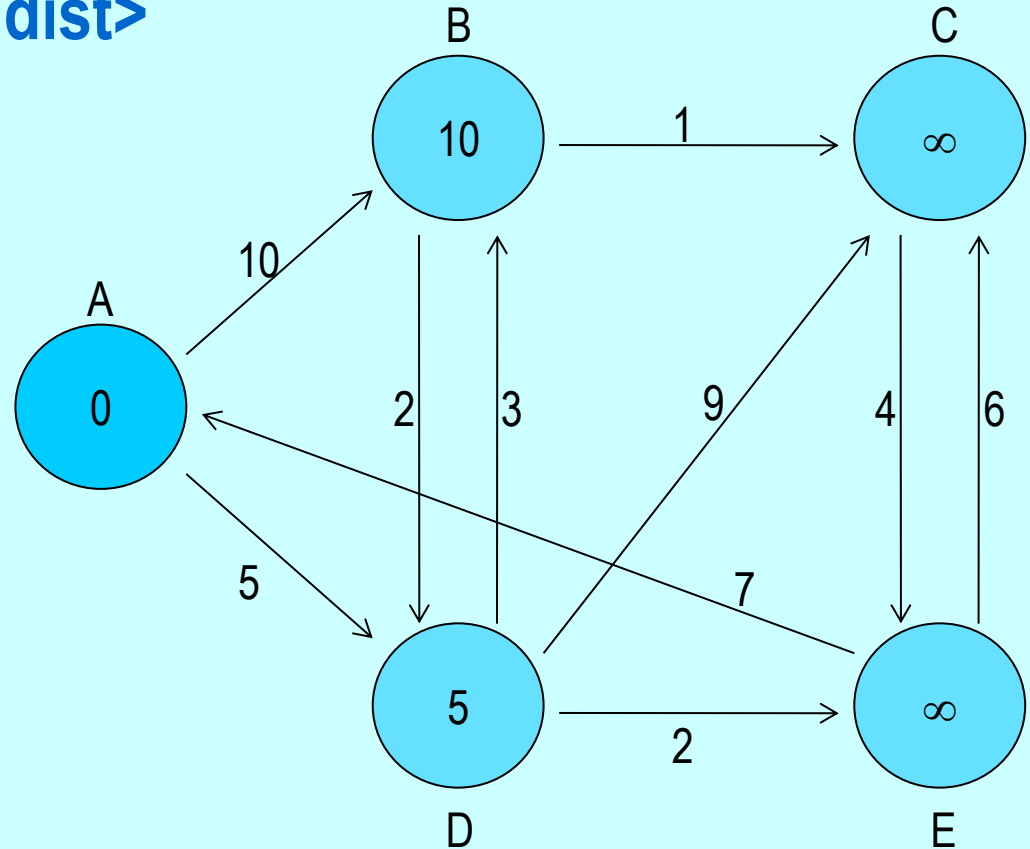
$\langle C, 11 \rangle \langle C, 14 \rangle \langle C, \text{inf} \rangle$

$\langle D, \langle 5, \langle (B, 3), (C, 9), (E, 2) \rangle \rangle \rangle$

$\langle D, 5 \rangle \langle D, 12 \rangle$

$\langle E, \langle \text{inf}, \langle (A, 7), (C, 6) \rangle \rangle \rangle$

$\langle E, \text{inf} \rangle \langle E, 7 \rangle$



Example: SSSP – Parallel BFS in MapReduce

- Reduce output: $\langle \text{node ID}, \langle \text{dist}, \text{adj list} \rangle \rangle$
= Map input for next iteration

$\langle A, \langle 0, \langle (B, 10), (D, 5) \rangle \rangle \rangle$

Flushed to DFS!!

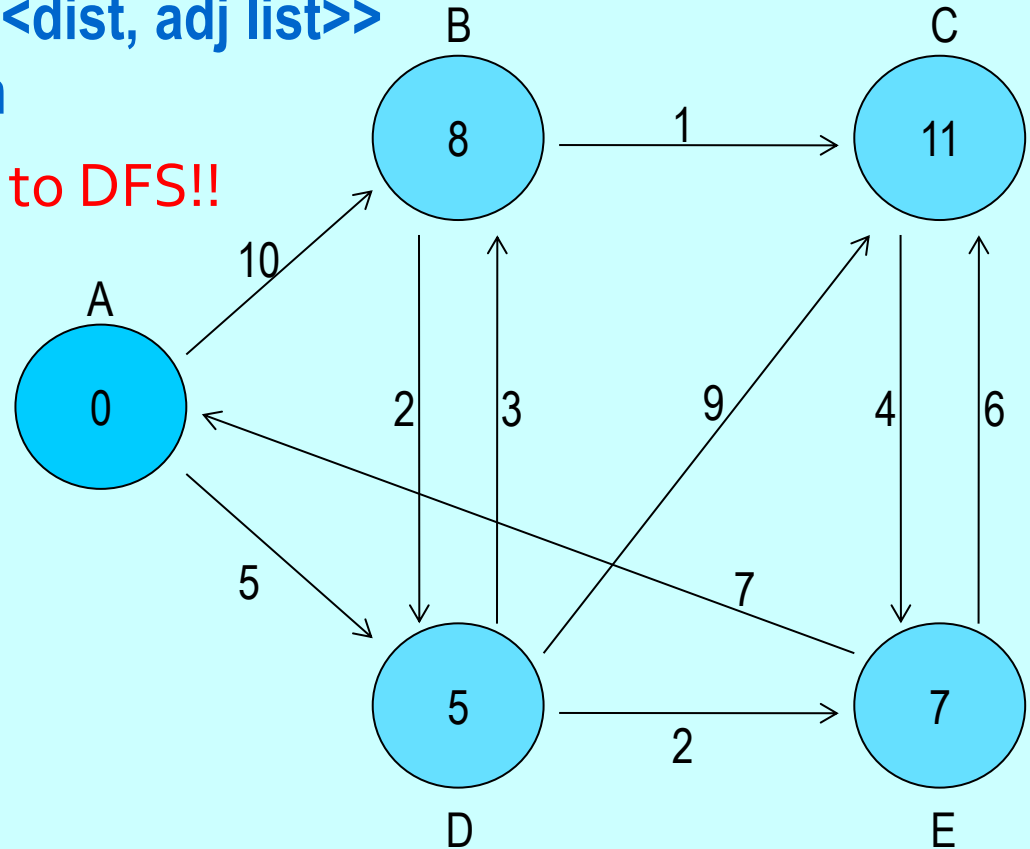
$\langle B, \langle 8, \langle (C, 1), (D, 2) \rangle \rangle \rangle$

$\langle C, \langle 11, \langle (E, 4) \rangle \rangle \rangle$

$\langle D, \langle 5, \langle (B, 3), (C, 9), (E, 2) \rangle \rangle \rangle$

$\langle E, \langle 7, \langle (A, 7), (C, 6) \rangle \rangle \rangle$

... the rest omitted ...



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...
 - Six degrees of separation?
- Practicalities of implementation in MapReduce



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?



Weighted Edges

- Now add positive weights to the edges
 - Why can't edge weights be negative?
- Simple change: adjacency list now includes a weight w for each edge
 - In mapper, emit $(m, d + w_p)$ instead of $(m, d + 1)$ for each node m



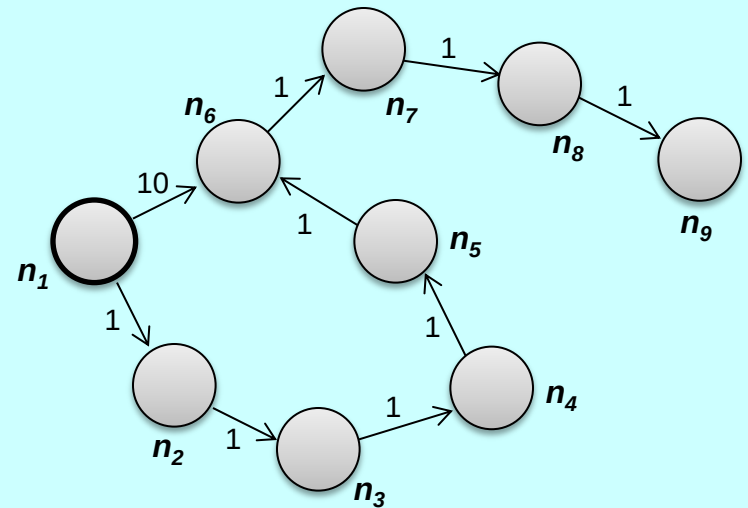
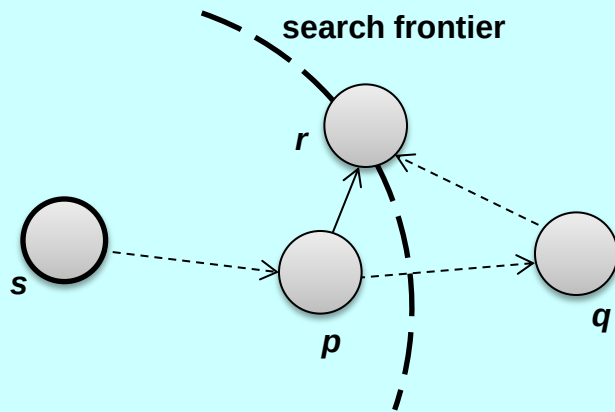
Stopping Criterion

- How many iterations are needed in parallel BFS (positive edge weight case)
 - Graph diameter D
- Convince yourself: when a node is first “discovered”, we’ve found the shortest path

Not true!



Additional Complexities



Stopping Criterion

- How many iterations are needed in parallel BFS (positive edge weight case)?
- Practicalities of implementation in 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




```
public class Dijkstra extends Configured implements Tool {
    public static String OUT = "outfile";
    public static String IN = "inputlarger";
    public static class TheMapper extends Mapper<LongWritable, Text, LongWritable, Text> {
        public void map(LongWritable key, Text value, Context context) throws IOException, InterruptedException {
            Text word = new Text();
            String line = value.toString();//looks like 1 0 2:3:
            String[] sp = line.split(" ");//splits on space
            int distanceadd = Integer.parseInt(sp[1]) + 1;
            String[] PointsTo = sp[2].split(":");
            for(int i=0; i<PointsTo.length; i++){
                word.set("VALUE "+distanceadd);//tells me to look at distance value
                context.write(new LongWritable(Integer.parseInt(PointsTo[i])), word);
                word.clear(); }
            //pass in current node's distance (if it is the lowest distance)
            word.set("VALUE "+sp[1]);
            context.write( new LongWritable( Integer.parseInt( sp[0] ) ), word );
            word.clear();
            word.set("NODES "+sp[2]);//tells me to append on the final tally
            context.write( new LongWritable( Integer.parseInt( sp[0] ) ), word );
            word.clear();
        }
    }
}
```



```
public static class TheReducer extends Reducer<LongWritable, Text, LongWritable, Text> {  
    public void reduce(LongWritable key, Iterable<Text> values, Context context) throws  
IOException, InterruptedException {  
String nodes = "UNMODDED";
```

```
    Text word = new Text();  
    int lowest = 10009; //start at infinity
```

for (Text val : values) { //looks like NODES/VALUES 1 0 2:3, we need to use the first
as a key

```
    String[] sp = val.toString().split(" "); //splits on space  
    //look at first value  
    if(sp[0].equalsIgnoreCase("NODES")){  
        nodes = null;  
        nodes = sp[1];  
    }else if(sp[0].equalsIgnoreCase("VALUE")){  
        int distance = Integer.parseInt(sp[1]);  
        lowest = Math.min(distance, lowest);  
    }  
}  
word.set(lowest+" "+nodes);  
context.write(key, word);  
word.clear();
```



```
public int run(String[] args) throws Exception {
```

```
//http://code.google.com/p/joycrawler/source/browse/NetflixChallenge/src/org/niubility/learning/knn/KNNDriver.java?r=2  
getConf().set("mapred.textoutputformat.separator", " "); //make the key -> value space separated (for iterations)
```

```
.....  
while(isdone == false){  
    Job job = new Job(getConf());  
    job.setJarByClass(Dijkstra.class);  
    job.setJobName("Dijkstra");  
    job.setOutputKeyClass(LongWritable.class);  
    job.setOutputValueClass(Text.class);  
    job.setMapperClass(TheMapper.class);  
    job.setReducerClass(TheReducer.class);  
    job.setInputFormatClass(TextInputFormat.class);  
    job.setOutputFormatClass(TextOutputFormat.class);
```

```
    FileInputFormat.addInputPath(job, new Path(infile));  
    FileOutputFormat.setOutputPath(job, new Path(outputfile));  
    success = job.waitForCompletion(true);
```

```
    //remove the input file
```

```
    //http://eclipse.sys-con.com/node/1287801/mobile
```

```
    if(infile != IN){  
        String indir = infile.replace("part-r-00000", "");  
        Path ddir = new Path(indir);  
        FileSystem dfs = FileSystem.get(getConf());  
        dfs.delete(ddir, true);
```

