Search Engine Architecture

6. Link Analysis

Noted slides adapted from: Lin et al.'s Big Data Infrastructure, UMD Spring 2015 with cosmetic changes.

Today's Agenda

- Graph problems and representations
- Parallel breadth-first search
- PageRank
- Optimizing graph algorithms

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

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Some Graph Problems

- Finding shortest paths
  - Routing Internet traffic and UPS trucks
- Finding minimum spanning trees
  - Telco laying down fiber
- Finding Max Flow
  - Airline scheduling
- Identify “special” nodes and communities
  - Breaking up terrorist cells, spread of avian flu
- Bipartite matching
  - Monster.com, Match.com
- And of course... PageRank

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Graphs and MapReduce

- A large class of graph algorithms 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?

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Representing Graphs

- G = (V, E)
- Two common representations
  - Adjacency matrix
  - Adjacency list

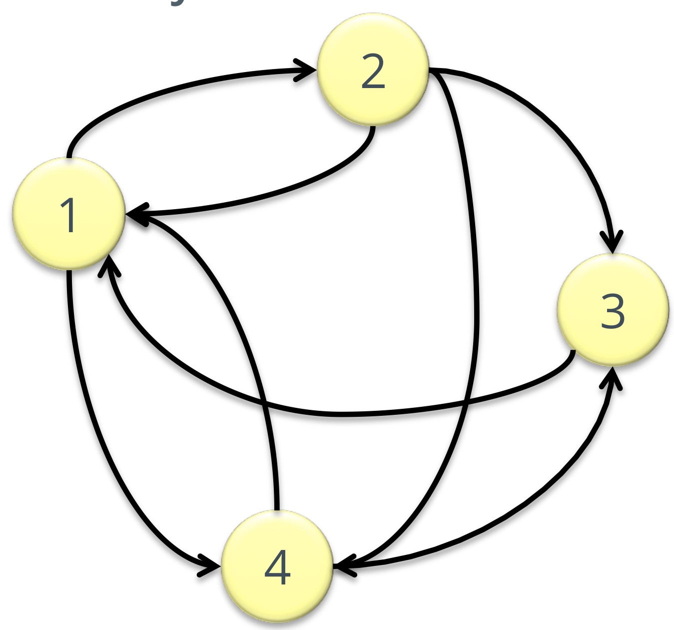
Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

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



Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

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

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

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

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

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Adjacency Lists: Critique

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

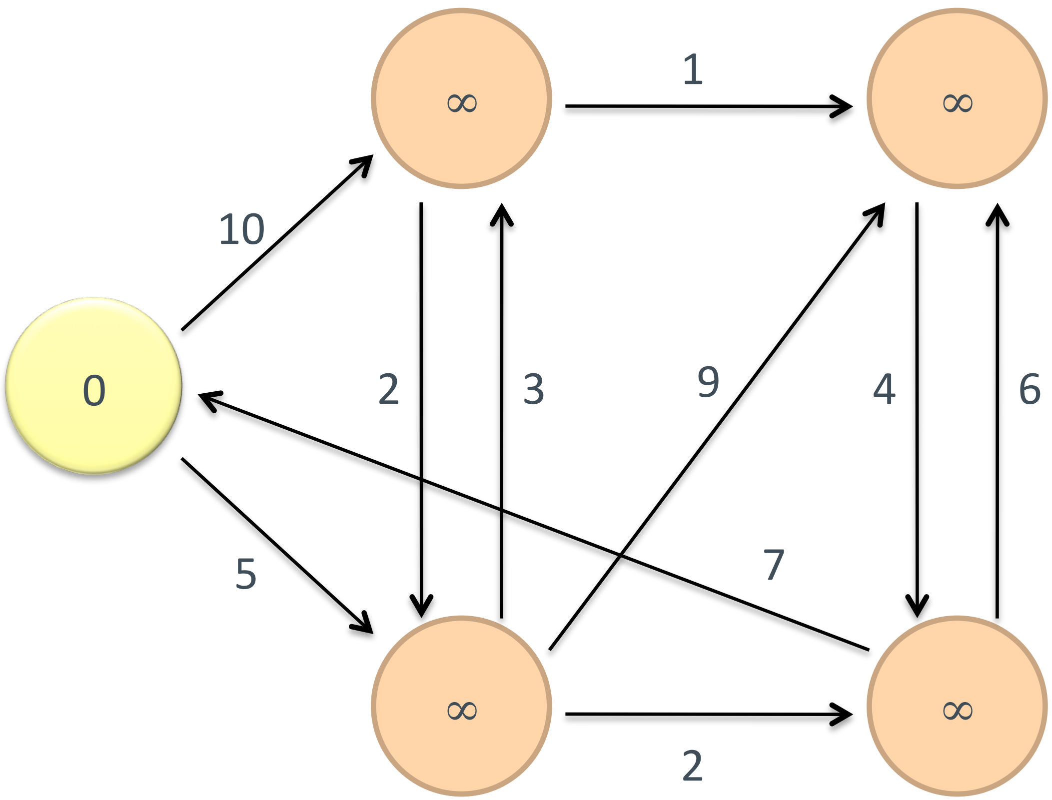
Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

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

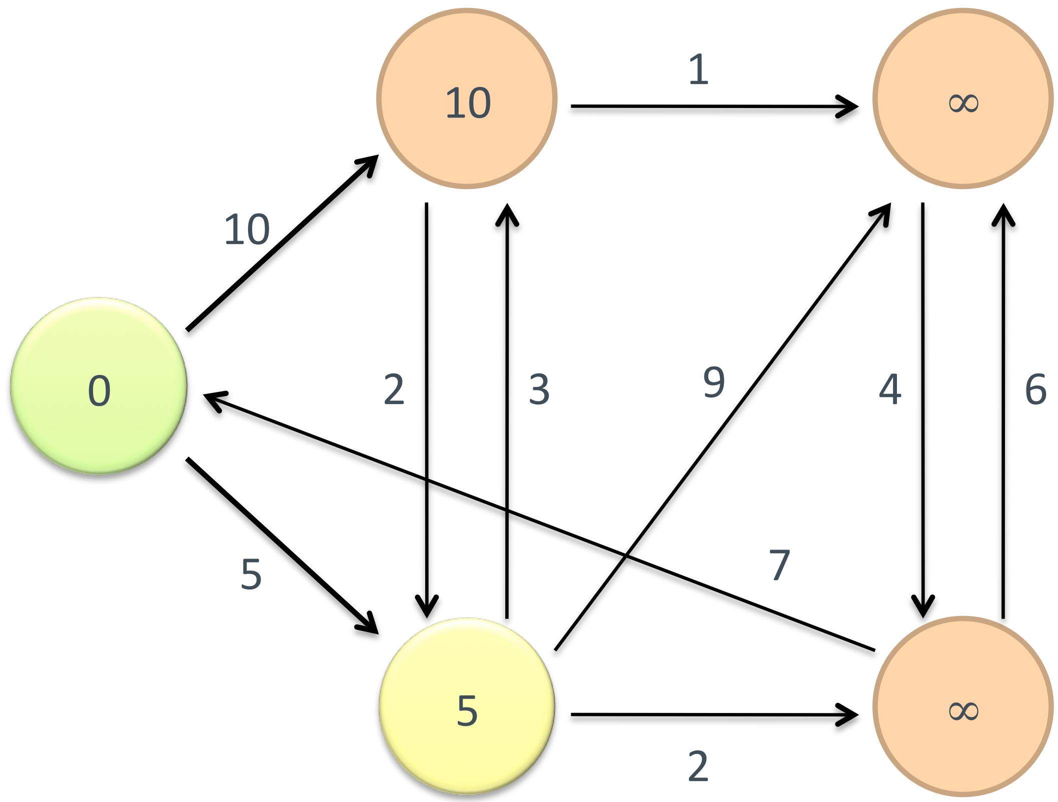
Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Dijkstra’s Algorithm Example



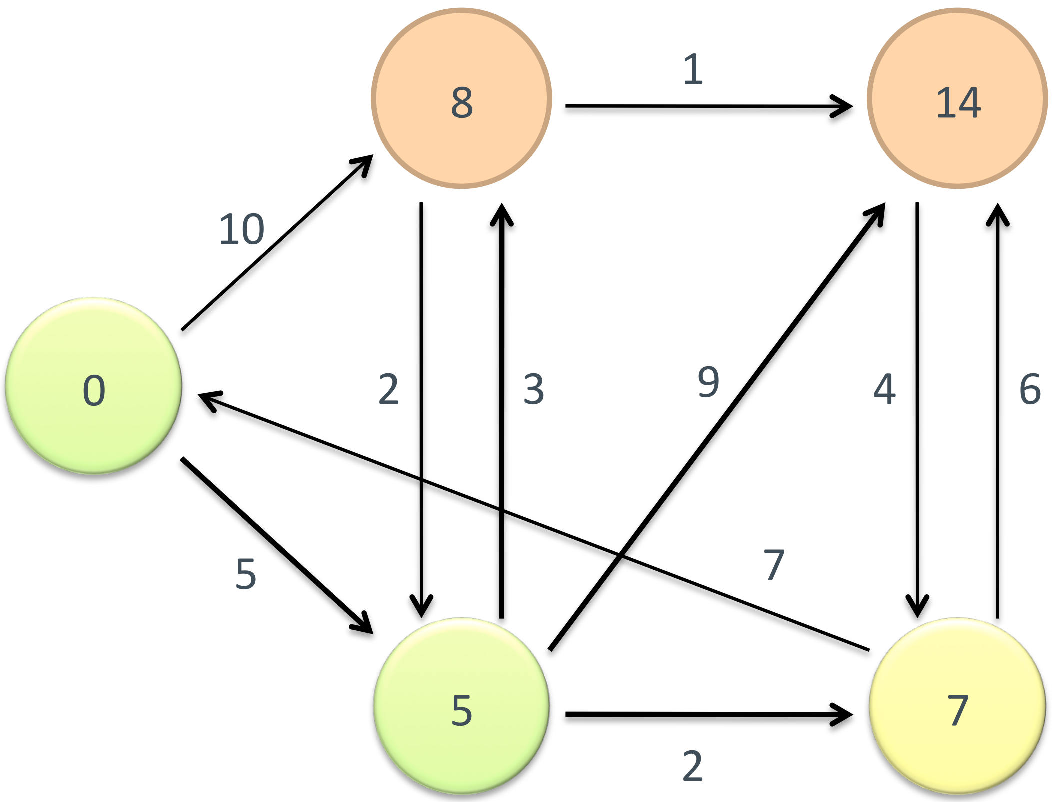
Example from CLR
Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Dijkstra's Algorithm Example



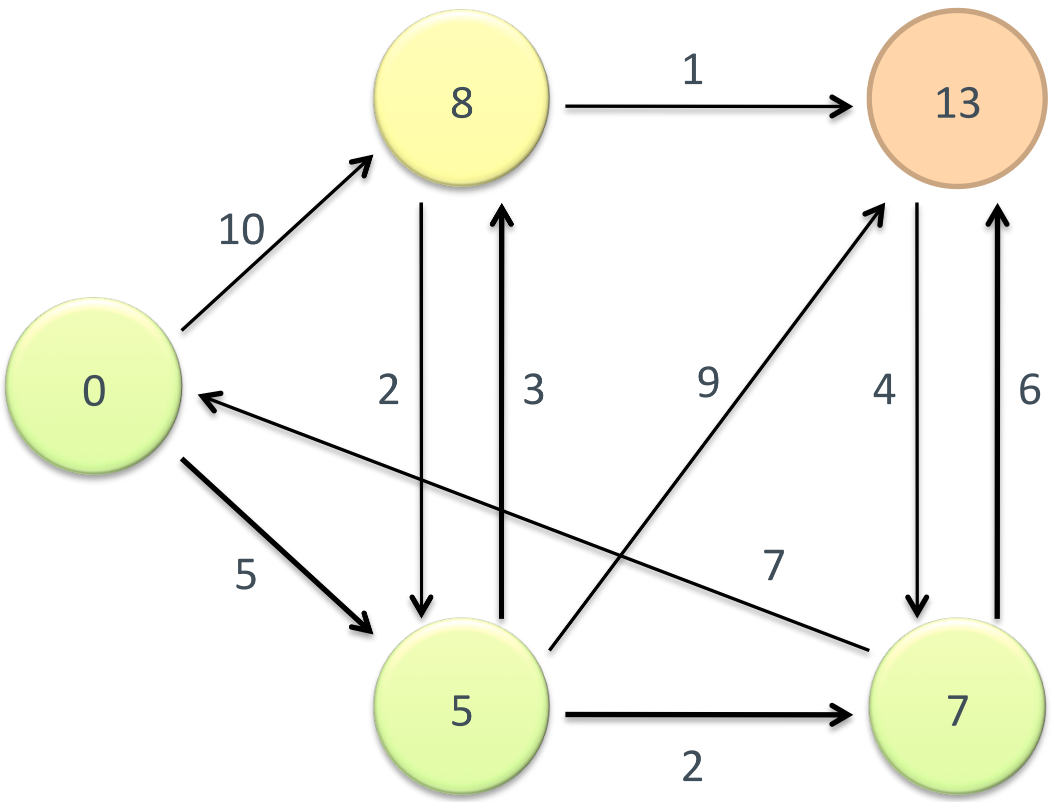
Example from CLR
Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Dijkstra's Algorithm Example



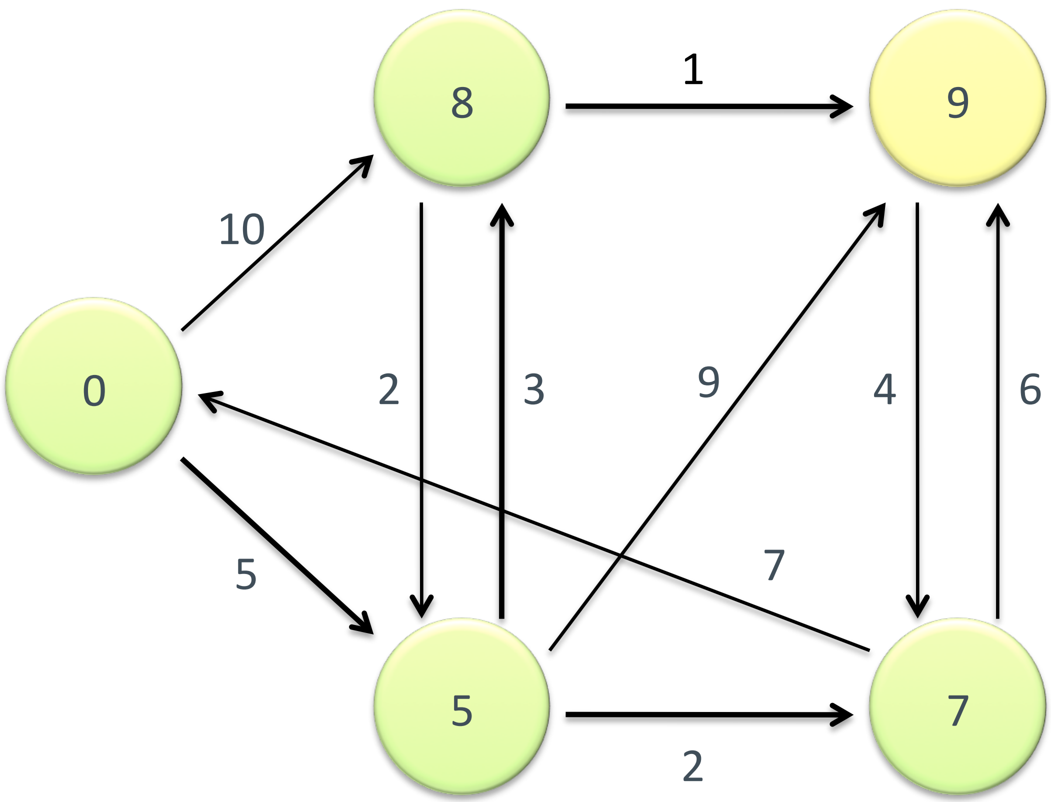
Example from CLR
Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Dijkstra’s Algorithm Example



Example from CLR
Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Dijkstra's Algorithm Example



Example from CLR
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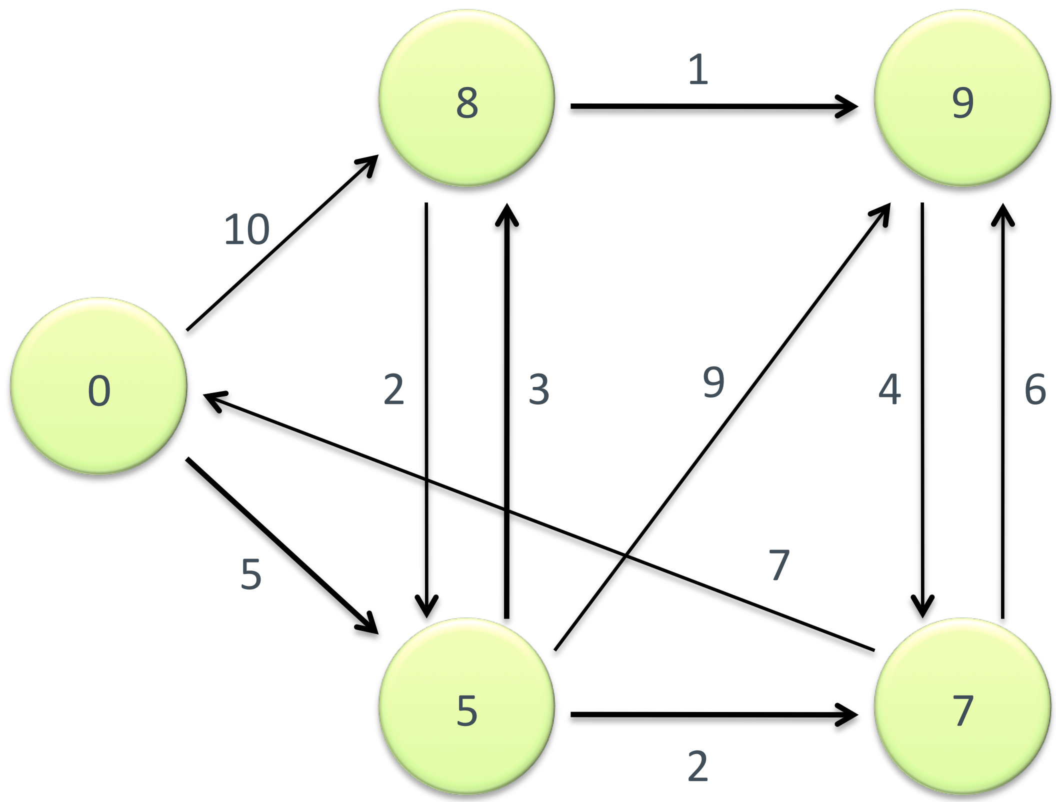
Dijkstra's Algorithm Example



Example from CLR
Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Single-Source Shortest Path

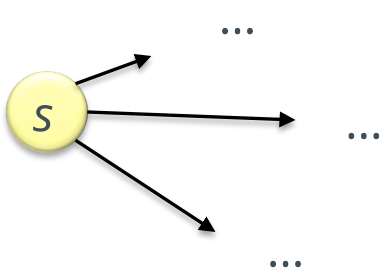
- **Problem:** find shortest path from a source node to one or more target nodes
    - Shortest might also mean lowest weight or cost
- Single processor machine: Dijkstra's Algorithm
- MapReduce: parallel breadth-first search (BFS)

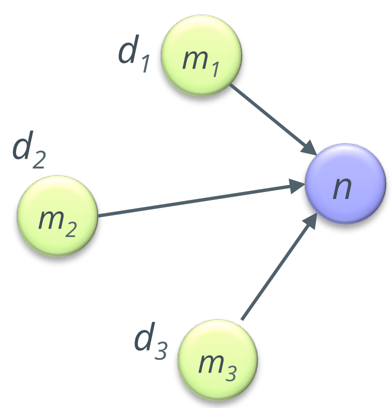
Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

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*

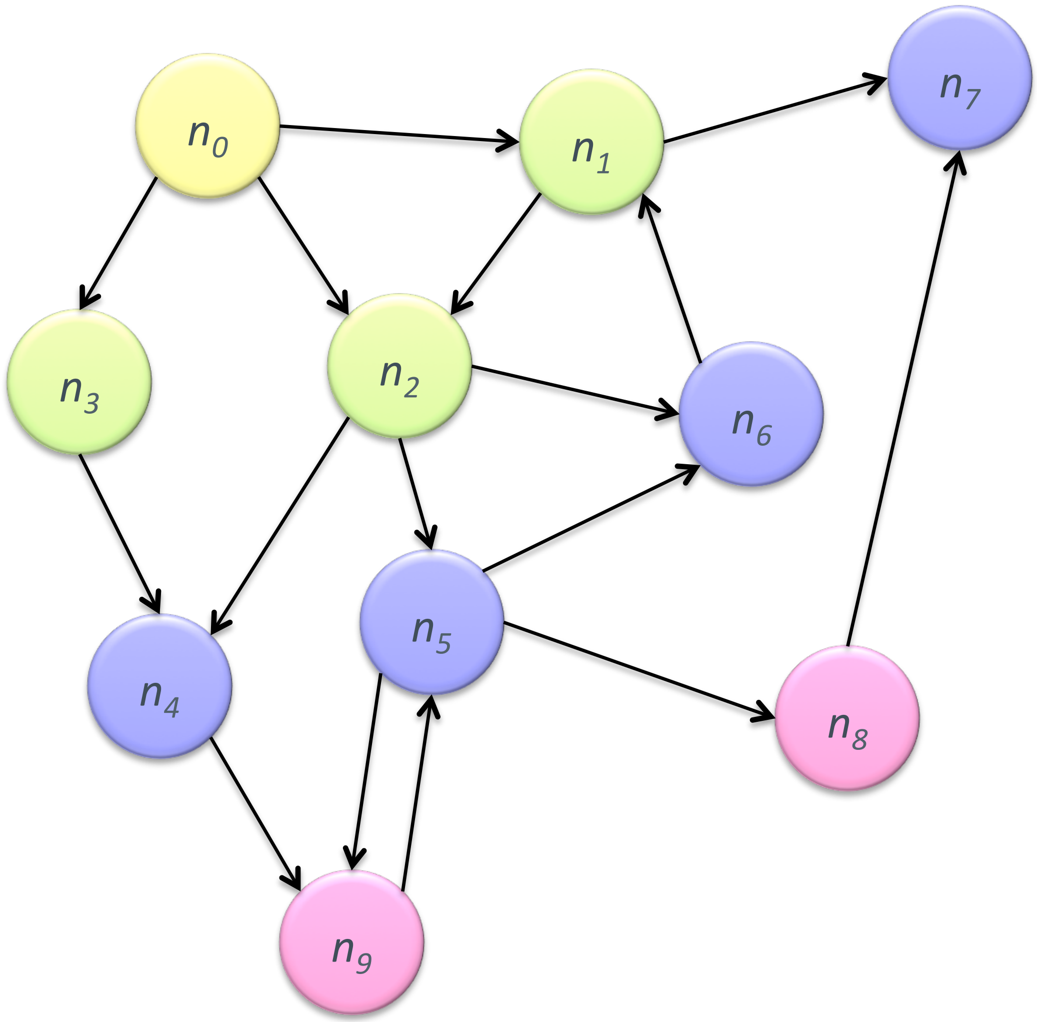
    DISTANCETO(*s*) = 0
  - For all nodes *p* reachable from *s*,
    DISTANCETO(*p*) = 1
  - For all nodes *n* reachable from some other set of nodes *M*,
    DISTANCETO(*n*) = 1 + min(DISTANCETO(*m*), $m \in M$)





Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Visualizing Parallel BFS



Source: Wikipedia (Wave)
Via Lin et al. Big Data Infrastructure, UMD Spring 2015.

From Intuition to Algorithm

- Data representation:
  - Key: node n
  - Value: d (distance from start), adjacency list (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

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Multiple Iterations Needed

- Each MapReduce iteration advances the “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*, adjacency list) as well

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

BFS Pseudo-Code

```
class Mapper
    method Map(nid n, node N)
        d ← N.Distance
        Emit(nid n, N)                              ▷ 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, [d_1, d_2, ...])
        d_min ← ∞
        M ← ∅
        for all d ∈ counts [d_1, d_2, ...] do
            if IsNode(d) then
                M ← 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)
```

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Single Source: Weighted Edges

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

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Stopping Criterion

- 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

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Stopping Criterion

- 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!

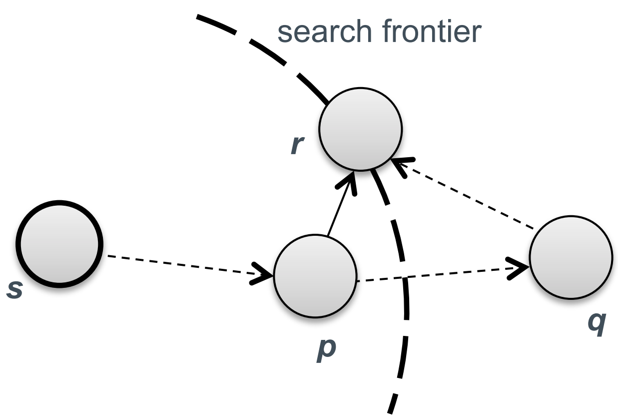
Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

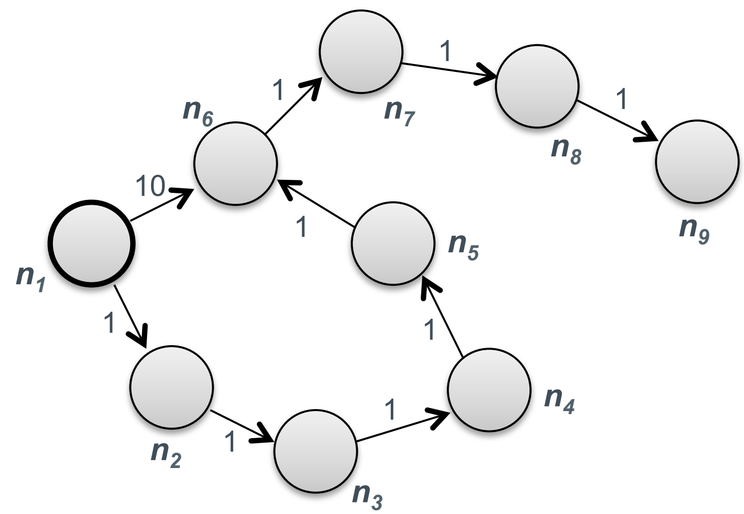
Comparison to Dijkstra

- Dijkstra's algorithm is more efficient
  - At each step, only pursues edges from minimum-cost path inside 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?

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Additional Complexities





Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

PageRank

Graphs and MapReduce

- A large class of graph algorithms 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

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Random Walks Over the Web

- Random surfer model:
  - User starts at a random Web page
  - User randomly clicks on links, surfing from page to page
- PageRank
  - Characterizes the amount of time spent on any given page
  - Mathematically, a probability distribution over pages
- PageRank captures notions of page importance
  - Correspondence to human intuition?
  - One of thousands of features used in web search (query-independent)

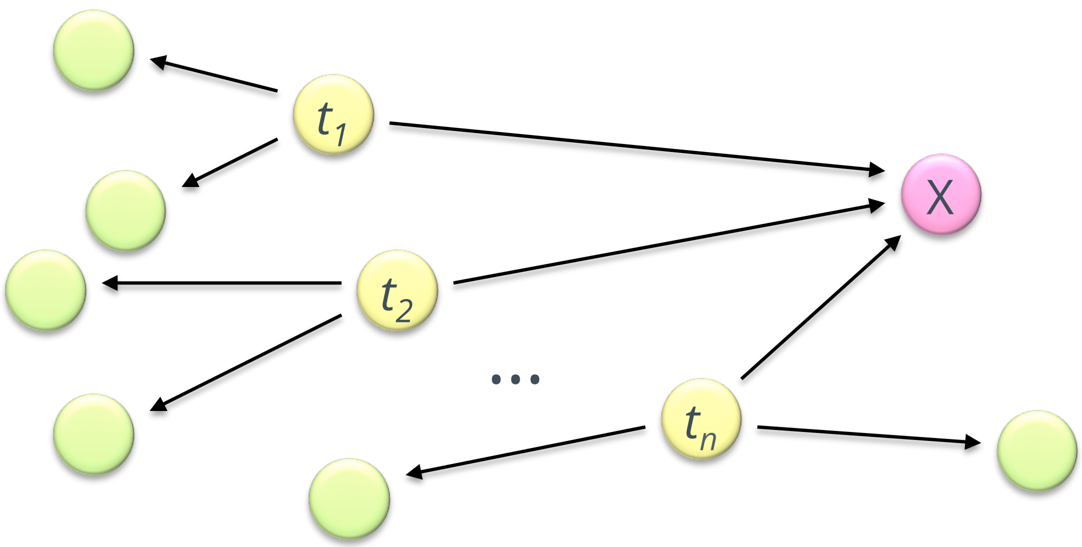
Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

PageRank: Defined

Given page *x* with inlinks $t_1 \ldots t_n$, where

- *C(t)* is the out-degree of *t*
- α is probability of random jump
- *N* is the total number of nodes in the graph

$$PR(x) = \alpha \left(\frac{1}{N} \right) + (1 - \alpha) \sum_{i=1}^{n} \frac{PR(t_i)}{C(t_i)}$$



Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Computing PageRank

- Properties of PageRank
  - Can be computed iteratively
  - Effects at each iteration are local
- Sketch of algorithm:
  - Start with seed PR_i values
  - Each page distributes PR_i "credit" to all pages it links to
  - Each target page adds up "credit" from multiple in-bound links to compute PR_{i+1}
  - Iterate until values converge

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

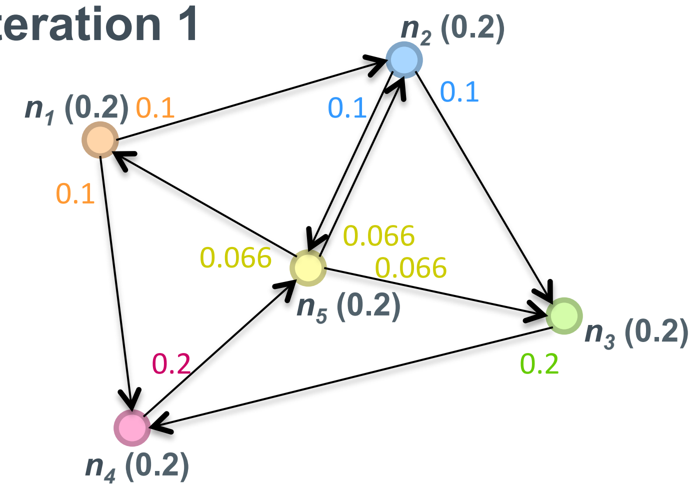
Simplified PageRank

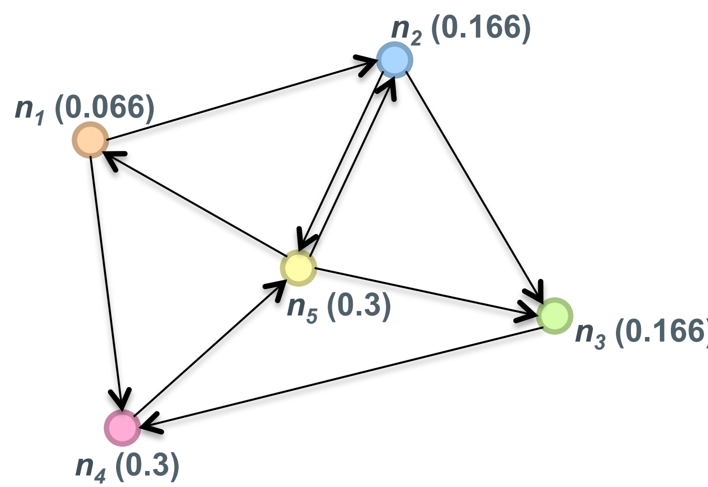
- First, tackle the simple case:
  - No random jump factor
  - No dangling nodes
- Then, factor in these complexities…
  - Why do we need the random jump?
  - Where do dangling nodes come from?

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Sample PageRank Iteration (1)

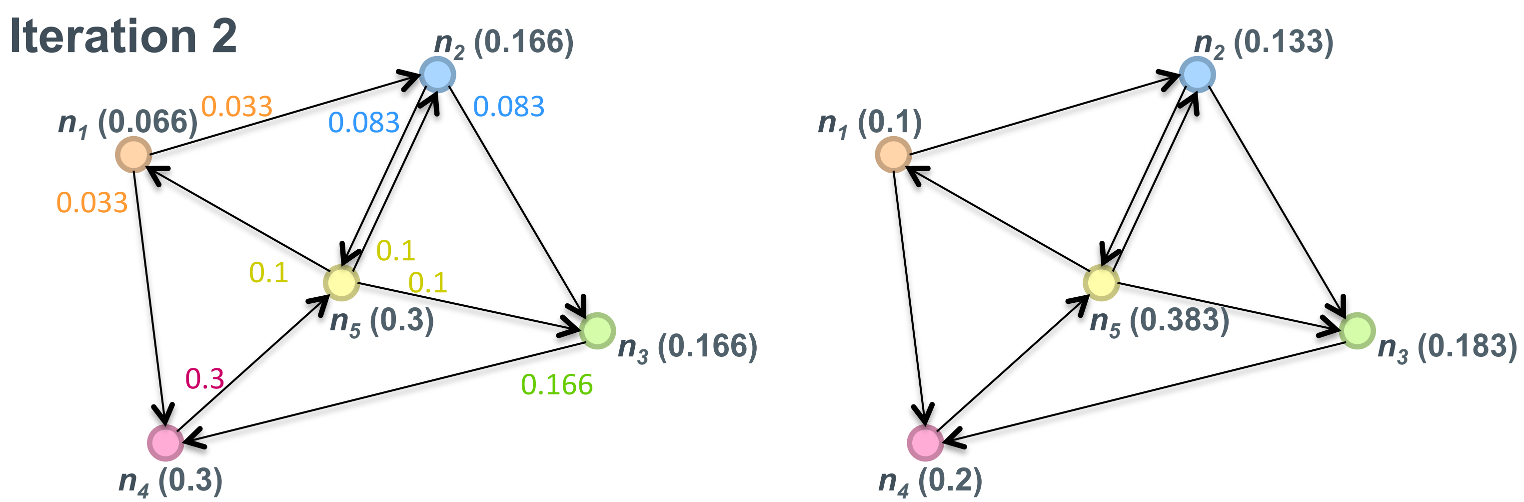
Iteration 1



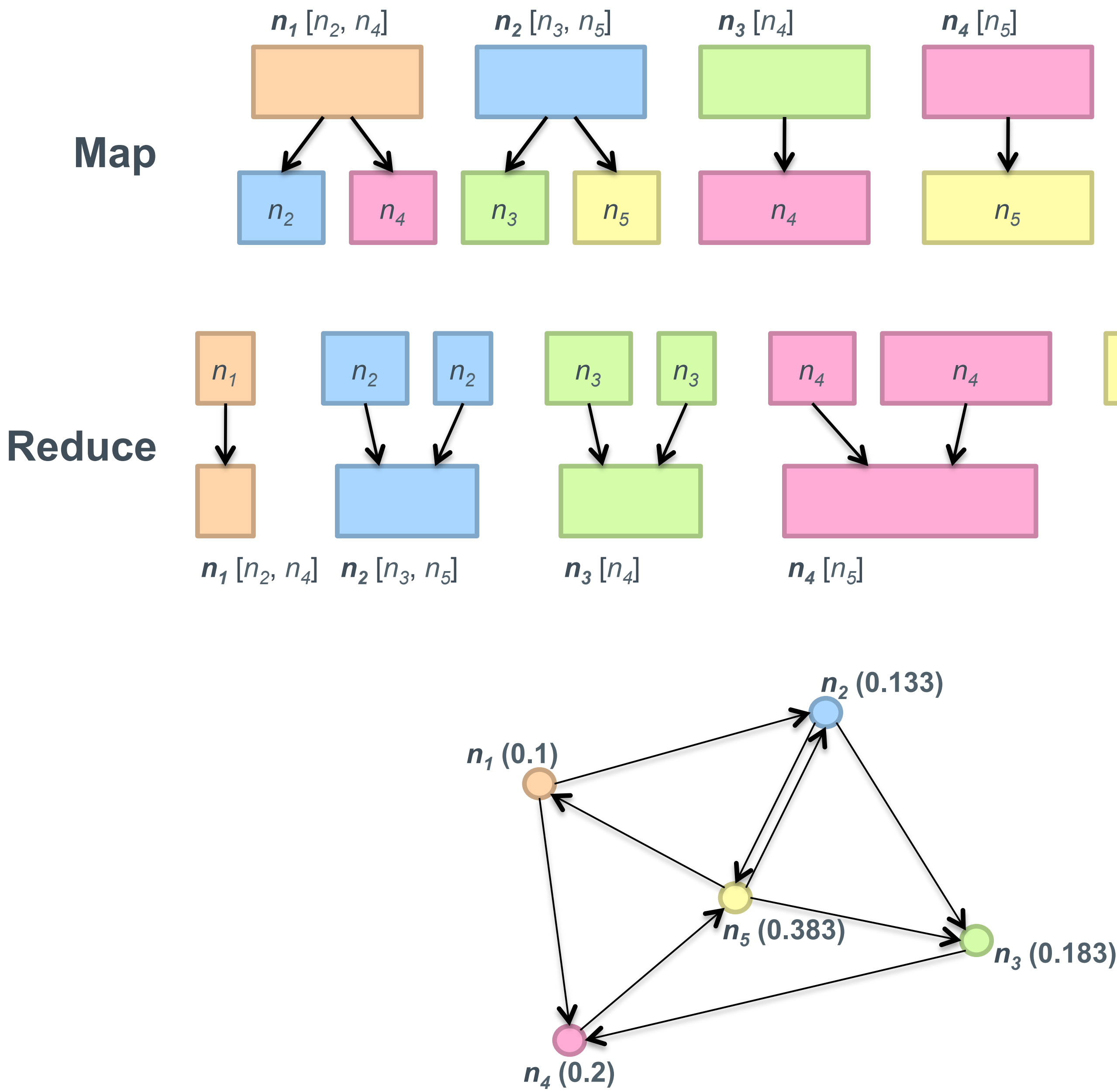


Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Sample PageRank Iteration (2)



Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.



Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

PageRank Pseudo-Code

```
class Mapper
    method Map(nid n, node N)
        p ← N.PageRank/|N.AdjacencyList|
        Emit(nid n, N)                                   ▷ Pass along graph structure
        for all nodeid m ∈ N.AdjacencyList do
            Emit(nid m, p)                               ▷ Pass PageRank mass to neighbors

class Reducer
    method Reduce(nid m, [p1, p2, ...])
        M ← ∅
        for all p ∈ counts [p1, p2, ...] do
            if IsNode(p) then
                M ← p                                    ▷ Recover graph structure
            else
                s ← s + p                                ▷ Sums incoming PageRank contributions
        M.PageRank ← s
        Emit(nid m, node M)
```

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Complete PageRank

- Two additional complexities
  - What is the proper treatment of dangling nodes?
  - How do we factor in the random jump factor?
- Solution:
  - Second pass to redistribute “missing PageRank mass” and account for random jumps

$$p' = \alpha \left(\frac{1}{N} \right) + (1 - \alpha) \left(\frac{m}{N} + p \right)$$

  - p is PageRank value from before, p' is updated PageRank value
  - N is the number of nodes in the graph
  - m is the missing PageRank mass
- Additional optimization: make it a single pass!

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

PageRank Convergence

- Alternative convergence criteria
  - Iterate until PageRank values don’t change
  - Iterate until PageRank rankings don’t change
  - Fixed number of iterations
- Convergence for web graphs?
  - Not a straightforward question
- Watch out for link spam:
  - Link farms
  - Spider traps
  - …

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Beyond PageRank

- Variations of PageRank
  - Weighted edges
  - Personalized PageRank
- Variants on graph random walks
  - Hubs and authorities (HITS)
  - SALSA

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Applications

- Static prior for web ranking
- Identification of “special nodes” in a network
- Link recommendation
- Additional feature in any machine learning problem

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Other Classes of Graph Algorithms

- Subgraph pattern matching
- Computing simple graph statistics
  - Degree vertex distributions
- Computing more complex graph statistics
  - Clustering coefficients
  - Counting triangles

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Iterative Algorithms

MapReduce Sucks

- Needless graph shuffling
- Checkpointing at each iteration

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

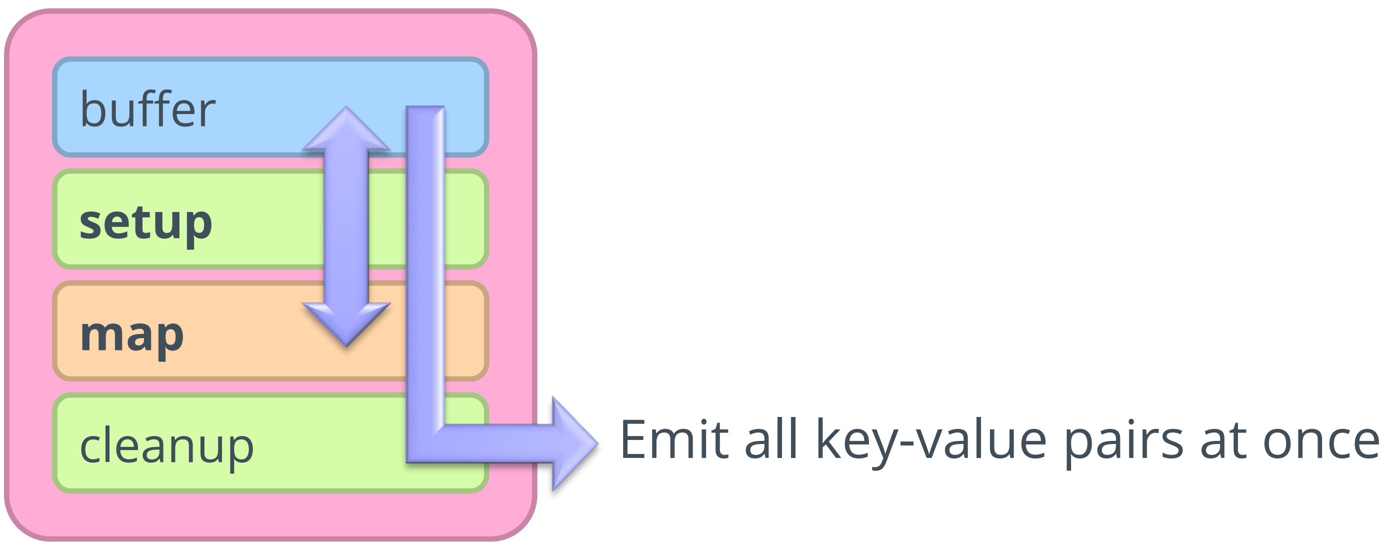
MapReduce sucks at iterative algorithms

- Alternative programming models (later)
- Easy fixes (now)

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

In-Mapper Combining

- Use combiners
  - Perform local aggregation on map output
  - Downside: intermediate data is still materialized
- Better: in-mapper combining
  - Preserve state across multiple map calls, aggregate messages in buffer, emit buffer contents at end
  - Downside: requires memory management



Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

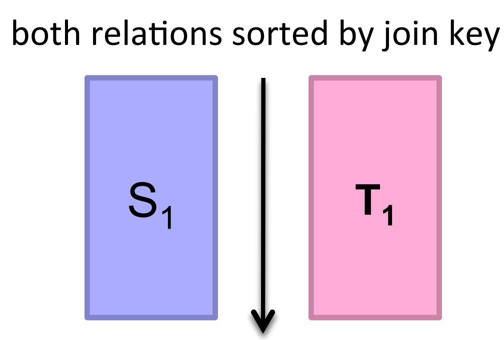
Better Partitioning

- 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, chicken-and-egg…
  - But cheap heuristics sometimes available
  - For webgraphs: range partition on domain-sorted URLs

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Schimmy Design Pattern

- Basic implementation contains two dataflows:
  - Messages (actual computations)
  - Graph structure ("bookkeeping")
- Schimmy: separate the two dataflows, shuffle only the messages
  - Basic idea: merge join between graph structure and messages



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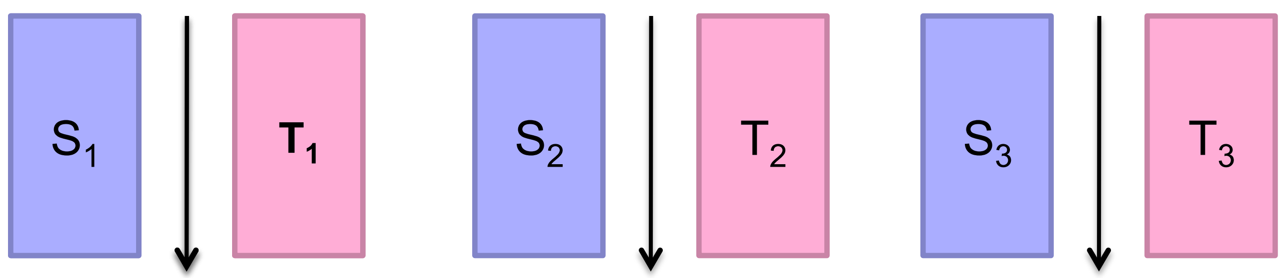
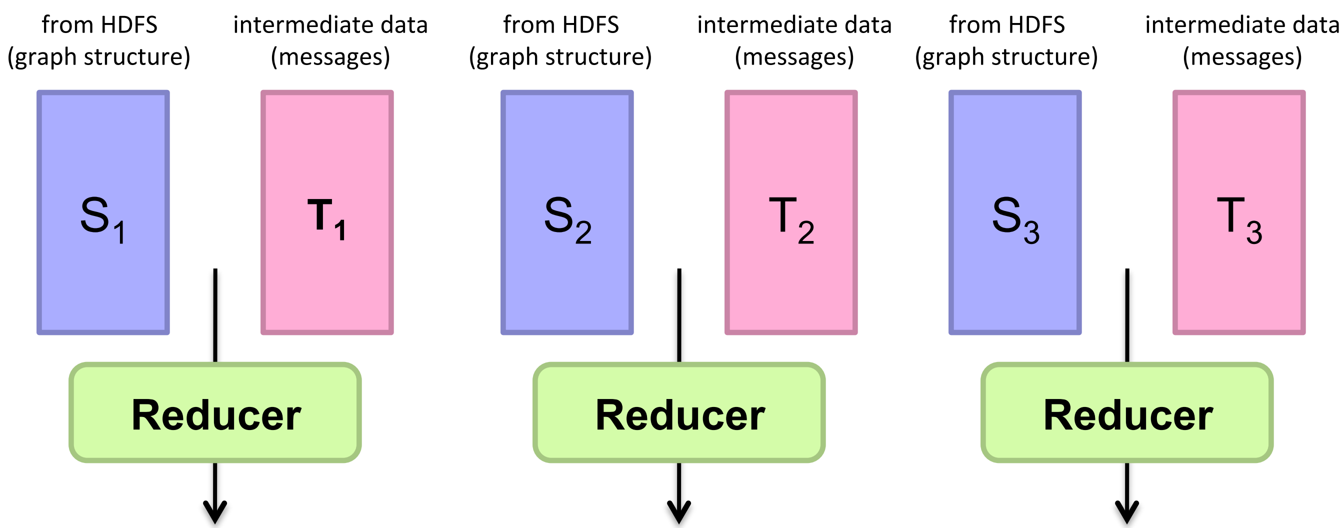
both relations consistently partitioned and sorted by join key



Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Do the Schimmy!

- Schimmy = reduce side parallel merge join between graph structure and messages
  - Consistent partitioning between input and intermediate data
  - Mappers emit only messages (actual computation)
  - Reducers read graph structure directly from HDFS



Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Pregel

What makes graph processing hard?

- Lessons learned so far:
  - Partition
  - Replicate
  - Reduce cross-partition communication
- What makes MapReduce “work”?

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Characteristics of Graph Algorithms

- What are some common features of graph algorithms?
  - Graph traversals
  - Computations involving vertices and their neighbors
  - Passing information along graph edges
- What’s the obvious idea?
  - Keep “neighborhoods” together!

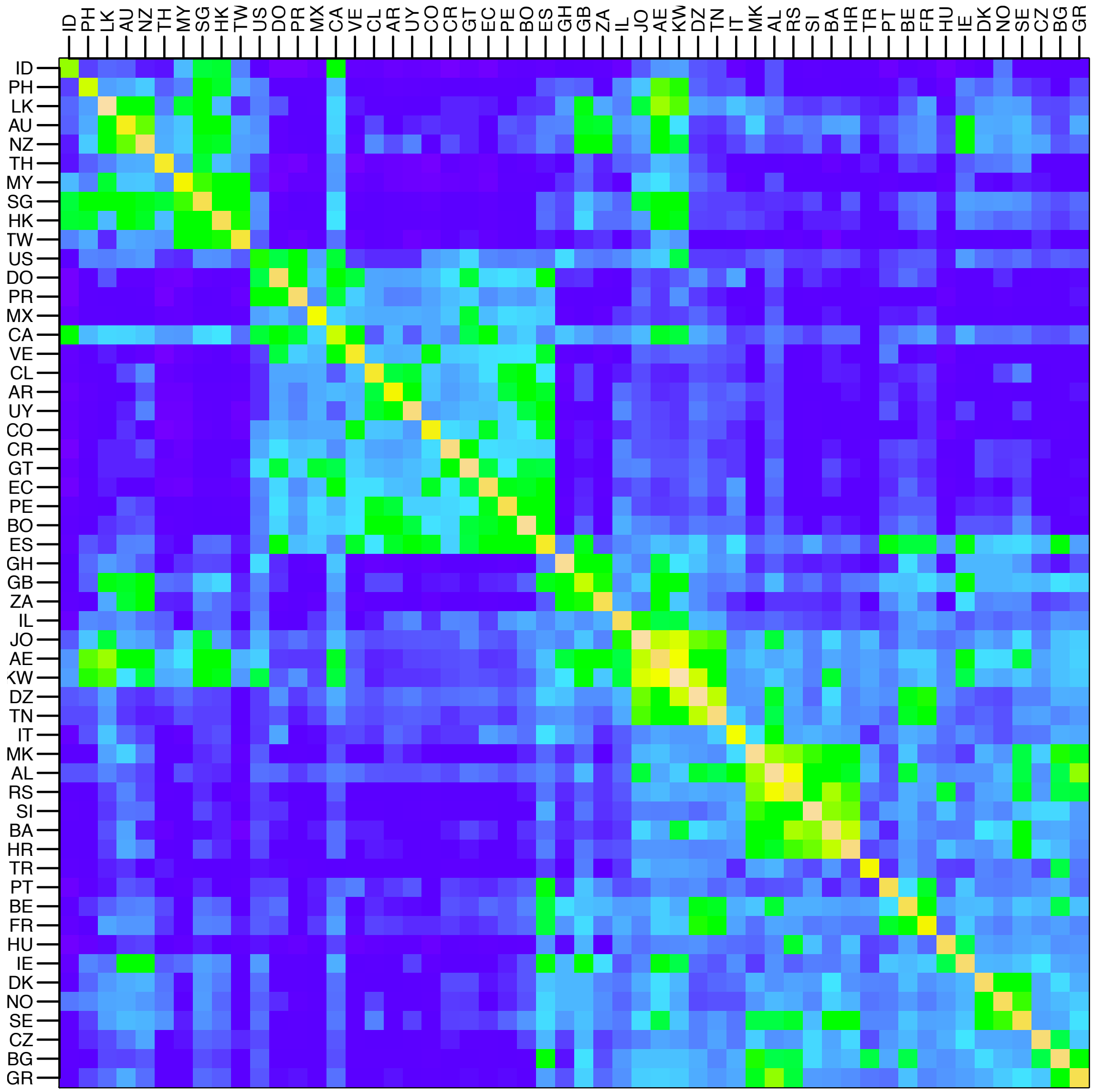
Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Simple Partitioning Techniques

- Hash partitioning
- Range partitioning on some underlying linearization
  - Web pages: lexicographic sort of domain-reversed URLs
  - Social networks: sort by demographic characteristics

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Country Structure in Facebook



Analysis of 721 million active users (May 2011)

54 countries w/ >1m active users, >50% penetration

Ugander et al. (2011) The Anatomy of the Facebook Social Graph.

What makes graph processing hard?

- It’s tough to apply our “usual tricks” :
  - Partition
  - Replicate
  - Reduce cross-partition communication

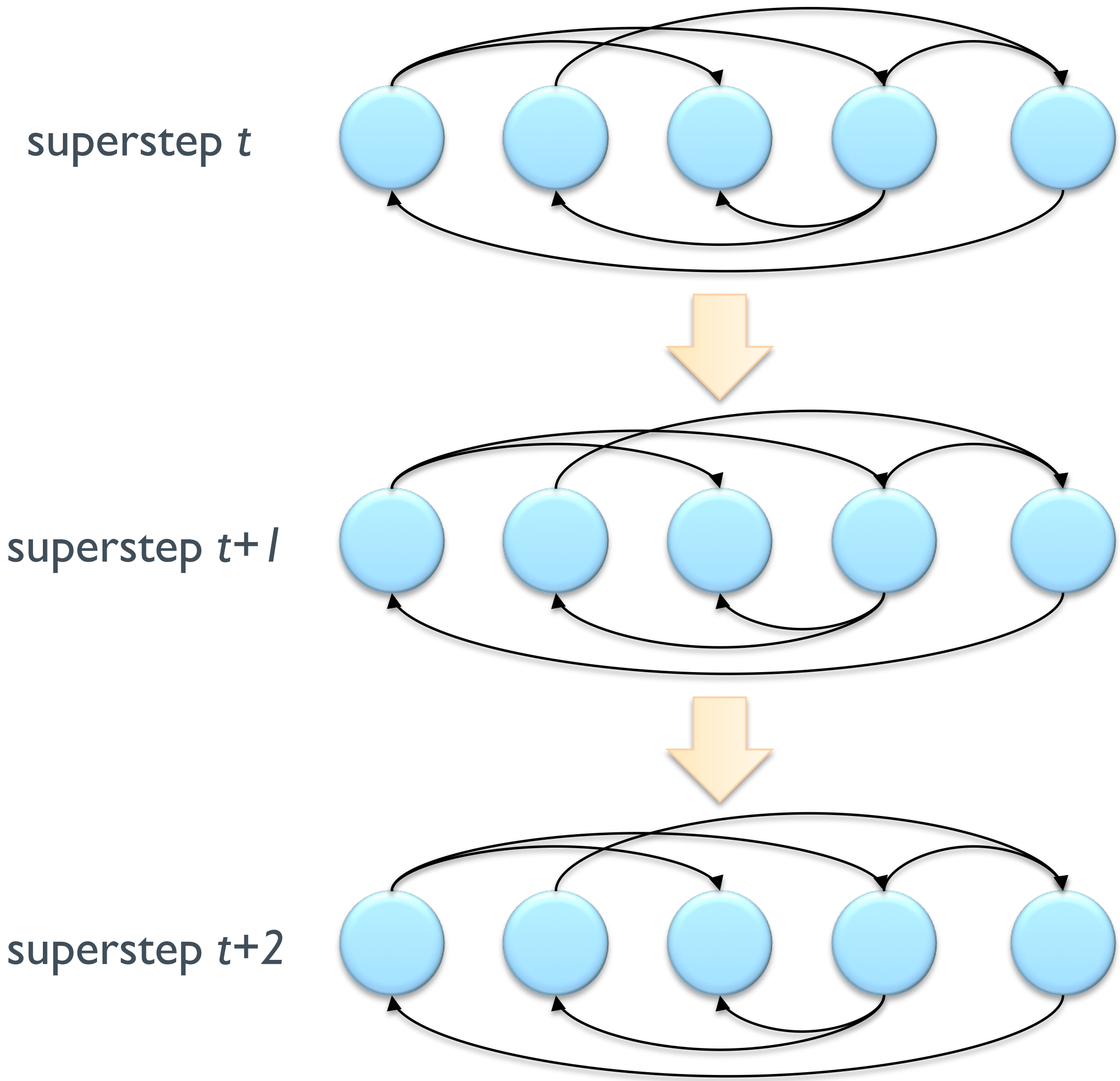
Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Pregel: Computational Model

- Based on Bulk Synchronous Parallel (BSP)
  - Computational units encoded in a directed graph
  - Computation proceeds in a series of supersteps
  - Message passing architecture
- Each vertex, at each superstep:
  - Receives messages directed at it from previous superstep
  - Executes a user-defined function (modifying state)
  - Emits messages to other vertices (for the next superstep)
- Termination:
  - A vertex can choose to deactivate itself
  - Is “woken up” if new messages received
  - Computation halts when all vertices are inactive

Source: Malewicz et al. (2010) Pregel: A System for Large-Scale Graph Processing. SIGMOD via Lin et al. Big Data Infrastructure, UMD Spring 2015.

Pregel



Source: Malewicz et al. (2010) Pregel: A System for Large-Scale Graph Processing. SIGMOD via Lin et al. Big Data Infrastructure, UMD Spring 2015.

Pregel: Implementation

- Master-Slave architecture
  - Vertices are hash partitioned (by default) and assigned to workers
  - Everything happens in memory
- Processing cycle:
  - Master tells all workers to advance a single superstep
  - Worker delivers messages from previous superstep, executing vertex computation
  - Messages sent asynchronously (in batches)
  - Worker notifies master of number of active vertices
- Fault tolerance
  - Checkpointing
  - Heartbeat/revert

Source: Malewicz et al. (2010) Pregel: A System for Large-Scale Graph Processing. SIGMOD via Lin et al. Big Data Infrastructure, UMD Spring 2015.

Pregel: PageRank

```
class PageRankVertex : public Vertex<double, void, double> {
public:
  virtual void Compute(MessageIterator* msgs) {
    if (superstep() >= 1) {
      double sum = 0;
      for (; !msgs->Done(); msgs->Next())
        sum += msgs->Value();
      *MutableValue() = 0.15 / NumVertices() + 0.85 * sum;
    }

    if (superstep() < 30) {
      const int64 n = GetOutEdgeIterator().size();
      SendMessageToAllNeighbors(GetValue() / n);
    } else {
      VoteToHalt();
    }
  }
};
```

Source: Malewicz et al. (2010) Pregel: A System for Large-Scale Graph Processing. SIGMOD via Lin et al. Big Data Infrastructure, UMD Spring 2015.

Questions?