Design Patterns for Efficient Graph Algorithms in MapReduce

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Talk Outline

- Graph algorithms
- Graph algorithms in MapReduce
- Making it efficient
- Experimental results

Punch line: per-iteration running time -69% on 1.4b link webgraph!
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

- Graphs are everywhere:
  - E.g., hyperlink structure of the web, interstate highway system, social networks, etc.

- Graph problems are everywhere:
  - E.g., random walks, shortest paths, MST, max flow, bipartite matching, clustering, etc.
Graph Representation

- $G = (V, E)$
- Typically represented as adjacency lists:
  - Each node is associated with its neighbors (via outgoing edges)

```
1: 2, 4
2: 1, 3, 4
3: 1
4: 1, 3
```
“Message Passing” Graph Algorithms

- Large class of iterative algorithms on sparse, directed graphs

- At each iteration:
  - Computations at each vertex
  - Partial results (“messages”) passed (usually) along directed edges
  - Computations at each vertex: messages aggregate to alter state

- Iterate until convergence
A Few Examples...

- Parallel breadth-first search (SSSP)
  - Messages are distances from source
  - Each node emits current distance + 1
  - Aggregation = MIN

- PageRank
  - Messages are partial PageRank mass
  - Each node evenly distributes mass to neighbors
  - Aggregation = SUM

- DNA Sequence assembly
  - Michael Schatz’s dissertation

Boring!

Still boring!
PageRank in a nutshell....

- Random surfer model:
  - User starts at a random Web page
  - User randomly clicks on links, surfing from page to page
  - With some probability, user randomly jumps around

- PageRank...
  - Characterizes the amount of time spent on any given page
  - Mathematically, a probability distribution over pages
PageRank: Defined

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

- $C(t)$ is the out-degree of $t$
- $\alpha$ is probability of random jump
- $N$ is the total number of nodes in the graph

$$PR(x) = \alpha \left( \frac{1}{N} \right) + (1 - \alpha) \sum_{i=1}^{n} \frac{PR(t_i)}{C(t_i)}$$
Sample PageRank Iteration (1)
Sample PageRank Iteration (2)
PageRank in MapReduce

Map

Reduce
PageRank Pseudo-Code

1: class Mapper
2:     method Map(nid n, node N)
3:         p ← |N.PageRank|/|N.AdjacencyList|
4:         Emit(nid n, N)  ▶ Pass along graph structure
5:         for all nodeid m ∈ N.AdjacencyList do
6:             Emit(nid m, p)  ▶ Pass PageRank mass to neighbors

1: class Reducer
2:     method Reduce(nid m, [p₁, p₂, ...])
3:         M ← ∅
4:         for all p ∈ counts [p₁, p₂, ...] do
5:             if IsNode(p) then
6:                 M ← p  ▶ Recover graph structure
7:             else
8:                 s ← s + p  ▶ Sums incoming PageRank contributions
9:                 M.PageRank ← s
10:                Emit(nid m, node M)
Why don’t distributed algorithms scale?
Three Design Patterns

- In-mapper combining: efficient local aggregation
- Smarter partitioning: create more opportunities
- Schimmy: avoid shuffling the graph
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
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 in some domains (e.g., webgraphs) take advantage of cheap heuristics
  - For webgraphs: range partition on domain-sorted URLs
Schimmy Design Pattern

- Basic implementation contains two dataflows:
  - Messages (actual computations)
  - Graph structure ("bookkeeping")

- Schimmy: separate the two data flows, shuffle only the messages
  - Basic idea: merge join between graph structure and messages

Both relations consistently partitioned and sorted by join key
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

![Diagram showing Schimmy process with S1, T1, S2, T2, S3, T3 stages](image)
Experiments

- Cluster setup:
  - 10 workers, each 2 cores (3.2 GHz Xeon), 4GB RAM, 367 GB disk
  - Hadoop 0.20.0 on RHELS 5.3

- Dataset:
  - First English segment of ClueWeb09 collection
  - 50.2m web pages (1.53 TB uncompressed, 247 GB compressed)
  - Extracted webgraph: 1.4 billion links, 7.0 GB
  - Dataset arranged in crawl order

- Setup:
  - Measured per-iteration running time (5 iterations)
  - 100 partitions
Results

“Best Practices”

- Combining
- Baseline
+ IMC
+ range partitioning
+ Schimmy
Results

[Bar chart showing per-iteration running time in seconds for different scenarios: -Combining, Baseline, +IMC, +range partitioning, +Schimmy. The chart indicates a +18% improvement with +1.4b 674m.]
Results

![Bar chart showing per-iteration running time (seconds) with labels: -Combining, Baseline, +IMC, +range partitioning, +Schimmy. The chart indicates +18% for 1.4b and -15% for 674m.](chart.png)
Results

- Combining: 1.4b
- Baseline: 674m
- +IMC: -15%
- +range partitioning: -60%
- +Schimmy: 86m
Results

The diagram shows the per-iteration running time in seconds for different scenarios. The bars represent:

- **Combining**: +18% increase, 1.4b
- **Baseline**: 674m
- **+IMC**: -15%
- **+range partitioning**: -60%, 86m
- **+Schimmy**: -69%

The diagram compares the performance of these scenarios, indicating improvements and increases in running time.
Take-Away Messages

- Lots of interesting graph problems!
  - Social network analysis
  - Bioinformatics

- Reducing intermediate data is key
  - Local aggregation
  - Better partitioning
  - Less bookkeeping

http://mapreduce.me/

Source code available in Cloud⁹
http://cloud9lib.org/