max planck institut informatik

Seminar: Massive-Scale Graph Analysis
Summer Semester 2015

MapReduce for Graph Algorithms

Modeling & Approach

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Agenda

Big Data: Definition

- Sources? : Web pages, social network, tweets, messages and many more
- How Big? : Google's Index is larger than 100 Peta Bytes and consumed over 1M computing hours to build [a]
- Number of webpages indexed: 48B (Google) & 5B (Bing)[b]
- Big Data Market will account $50 Billion by 2017[c]

[a] https://www.google.com/search/about/insidesearch/howsearchworks/crawling-indexing.html

[b] www.worldwidewebsize.com

[c] www.wikibon.org

Big Data: Processing

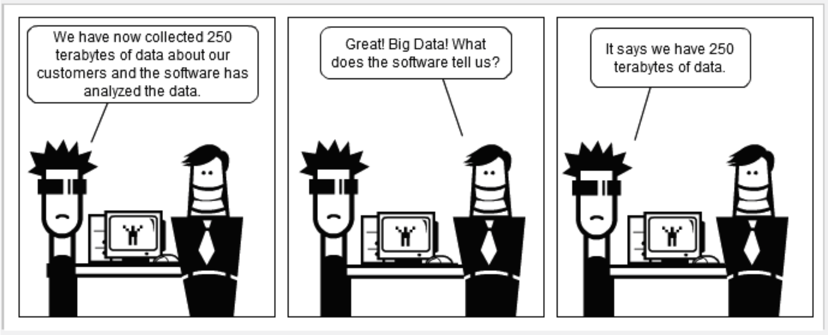

Figure: Comic from Socmedsean[1]

[1] Source: www.socmedsean.com

Big Data: Processing

- Quick and efficient analysis of *Big Data* requires extreme parallelism.
- A lot of systems were developed in late 1990s for parallel data processing such as SRB[a]
- These systems were efficient but lacked nice wrapper for average developer.
- In 2004, *Jeffrey Dean* and *Sanjay Ghemawat* from *Google* introduced *MapReduce*[b] which is a part of company's proprietary infrastructure.
- Similar open source infrastructure *Hadoop*[c] was developed in late 2005 by Doug Cutting & Mike Cafarella.

[a] Wan et. al. *The SDSC storage resource broker*, CASCON '98

[b] Ghemawat et. al. *MapReduce: Simplified data processing on large clusters*, OSDI'14

[c] www.hadoop.apache.org

MapReduce: Framework

Introduction

- MapReduce motivates from LISP's map and reduce operations
  - $(\textit{map square}\,'(1\ 2\ 3\ 4\ 5)) \rightarrow (1\ 4\ 9\ 16\ 25)$
  - $(\textit{reduce}\ +\ '(1\ 2\ 3\ 4\ 5)) \rightarrow (15)$
- Framework provides *automatic parallelism, fault-tolerance, I/O scheduling and monitoring* for data processing

MapReduce: Framework

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MapReduce: Programming Model

- Input / Output are a set of key value pairs
- User only needs to provide simple functions map(), reduce() and combine()[a]
  - $map(in\_k, in\_v) \rightarrow list(out\_k,\ imt\_v)$
  - $combine(in\_k, list(in\_v)) \rightarrow list(out\_k,\ imt\_v)$
  - $reduce(out\_k, list(imt\_v)) \rightarrow list(out\_v)$

[a] optional

MapReduce: Execution Model

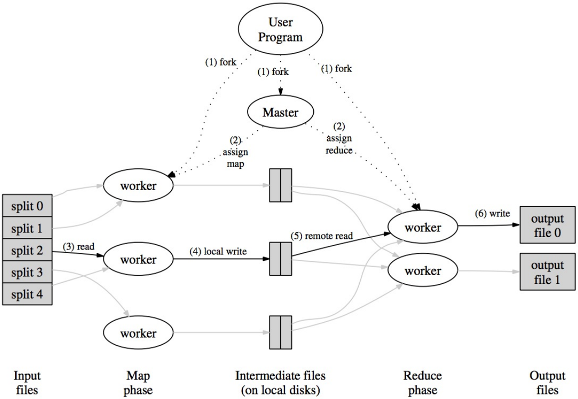

Figure: Overview: Map-Reduce execution model[2]

[2] Source: Ghemawat et. al. *MapReduce: Simplified data processing on large clusters*, OSDI'14

MapReduce: Example
Word Count

Map

```
function M(in_k, in_v)
    for each word in in_v:
        emit(word, 1)
end function
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function C_R(out_k, list{imt_v})
emit(word, $\sum imt\_v$)
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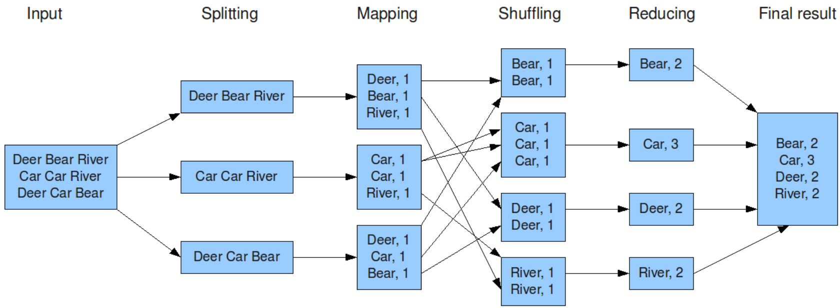

Graphs

- Graph are everywhere: social graphs representing connections or citation graphs representing hierarchy in scientific research
- Due to massive scale, it is impractical to use conventional techniques for graph storage and in-memory analysis
- These constraints had driven the development of scalable systems such as distributed file systems like Google File System[a] and Hadoop File System[b]
- MapReduce provides a good way to partition and analyze graphs as suggested by Cohen et. al. [c]

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[a] Ghemawat et. al. *The Google File System*, SOSP '03

[b] www.hadoop.apache.org

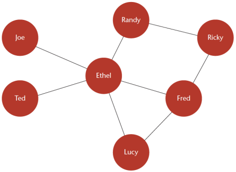
[c] Jonathan Cohen, Graph twiddling in a MapReduce world, Computing in Science & Engineering 2009

Augmenting edge with vertex degree

Input: All edges as *Key Value Pair* $\rightarrow$ <-,e_{ij}> : edge connecting v_i & v_j

MapReduce Job I

- map(<-,e_{ij}>)$\rightarrow$ list[<v_i, e_{ij}>, <v_j, e_{ij}>]
- reduce(v_k, list[e_{pk}, e_{qk} ...]>) $\rightarrow$ [<e_{pk}, deg(v_k)>, <e_{qk}, deg(v_k)>, ...]
  - where deg(v_k) = size of the list in the parameter



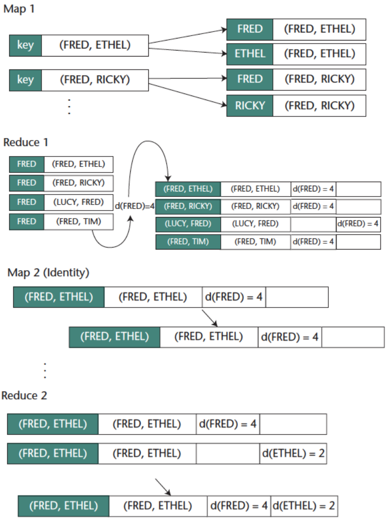
Input: Output of Job I

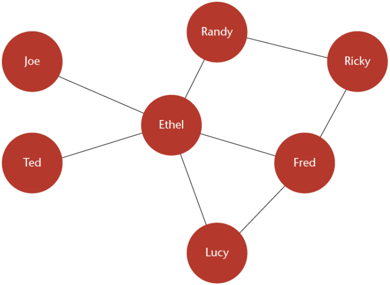
MapReduce Job II

- map() is an *identity* function: does no modification to input
- reduce(<e_{ij}, list[deg(v_i), deg(v_j)]>) $\rightarrow$ <e_{ij}, deg(v_i), deg(v_j)>

Augmenting edge ... contd

Example



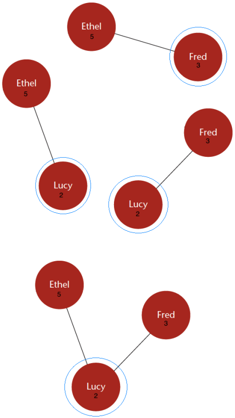


Enumerating Triangles

- The main idea behind enumerating the triangles is to find triad and an edge joining the open ends together
- **Input**: Augmented edges with vertex valency

MapReduce Job 1

- map(<e_{ij}, deg(v_i), deg(v_j)>) $\rightarrow$
  - output: *deg(v_i) < deg(v_j)* **?** <v_i, e_{ij}> **:** <v_j, e_{ij}>
  - If *deg(v_i) == deg(v_j)*, we can break the tie by any consistent method such as using vertex names
- reduce(<v_i, list[edges connecting v_i]>) $\rightarrow$
  - For each pair of edge connected by v_i, emit <e_1, e_2> with key as <v_p, v_q>, where v_p and v_q represent the open end of triad
  - The order of v_p and v_q is decided using some consistent technique like vertex names



Enumerating Triangles ...contd

- **Input**: Augmented edge set and output of Job I

MapReduce Job 2

- map(<R>) $\rightarrow$
  - if R is a record from Augmented Edge Set, change key to $<v_i, v_j>$ such that $\deg(v_i) < \deg(v_j)$
  - if R is a record from MR Job I and hence a **triad**, change key to $<v_i, v_j>$ such that $\deg(v_i) < \deg(v_j)$, where v_i & v_j are vertices of open ends
- reduce($<[v_i, v_j]$, list[containing a triad, edge]^a>) $\rightarrow$
  - If there is a record corresponding to an edge and a triad with same key, emit a triangle $<e_{ij}, e_{jk}, e_{ki}>$

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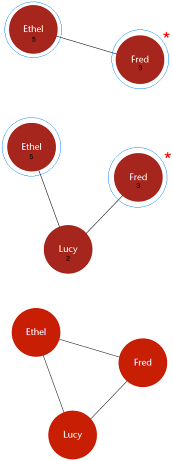
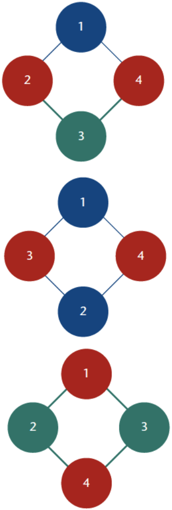
[a] may or may not be there



Enumerating Rectangles

Idea: Two triads joining with a common edge can be merged to form a rectangle



- $4! = 24$ different orderings. Since symmetry group(S_4) on 4 elements has $|S_4| = 8$, we have $\frac{24}{8} = 3$ distinct orderings

Enumerating Rectangles

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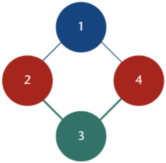

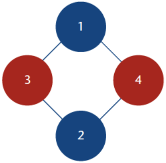

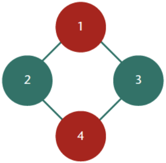

- $4! = 24$ different orderings. Since symmetry group(S_4) on 4 elements has $|S_4| = 8$, we have $\frac{24}{8} = 3$ distinct orderings

MapReduce Job I

- map($<e_{ij}$, deg(v_i), deg(v_j)$>$) $\rightarrow$
  - [$<v_i$, H, $e_{ij}>$, $<v_j$, L, $e_{ij}>$]
- reduce($<v_k$, list[edges incident on v_k]$>$) $\rightarrow$
  - emit a triad for L-L & H-L record
- if we express $deg(v) = deg_L(v) + deg_H(v)$, each vertex appears in $O(deg_L^2(v))$ low triads and $O(deg_L(v) deg_H(v))$ mixed triads

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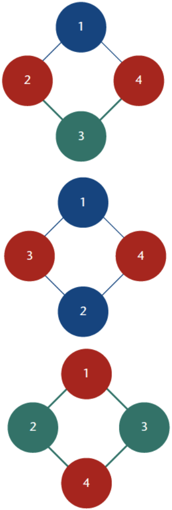

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MapReduce Job I

- map(<e_{ij}, deg(v_i), deg(v_j)>) $\rightarrow$
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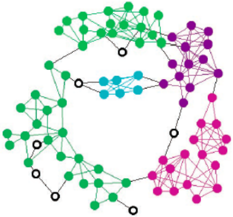
- if we express deg(v) = deg_L(v) + deg_H(v), each vertex appears in $O(deg_L^2(v))$ low triads and $O(deg_L(v)deg_H(v))$ mixed triads

MapReduce Job II

- map(<v_k, list[triads]>) $\rightarrow$
  - list[<key: edge joining open ends, value: triad>]
- reduce(<e_{ij}, list[triads open at same end]>) $\rightarrow$
  - emit rectangle: [e_{ij}, e_{jk}, e_{kl}, & e_{li}]

Finding k-truss

Definition: A k-truss is a sub-graph in which each edge is a part of atleast k-2 triangles



MapReduce Job

Input: Augmented edge set & enumerated triangles of the graph

- map(<e_{ij}, $triangle_i$>) $\rightarrow$
  - if ($e_{ij} \in triangle_i$) : <e_{ij},1>
- reduce(<e_{ij}, list[1,1......,1]>) $\rightarrow$
  - if ($\sum list_i$) $\geq$ k : emit e_{ij}

All edges emitted by map-reduce job belongs to the *k*-truss

Barycentric Clustering

Clusters are sub-graphs that partitions graph without loosing the co-relevant information. ***Barycentric Clustering*** is a highly scalable approach of finding tighly connected sub-graphs.

- w_{ij} : weight of edge e_{ij} and $d_i = \sum w_{ij}$: weighted degree of vertex v_i
- If x = $(x_1, x_2, .., x_n)^T$ denotes the position of n vertices, then $x' =$ Mx modifies the vertex position by the average of its old position and position of its neighborhood.
- The process is repeated and literature[3] suggests that 5 repetitions are adequate.
- If the length of edge > threshold, it can be cut

$$M = \begin{pmatrix} 1/(d_1+1) & w_{12}1/(d_1+1) & \cdots & w_{1n}1/(d_1+1) \\ w_{21}1/(d_2+1) & 1/(d_2+1) & \cdots & w_{2n}1/(d_2+1) \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1}1/(d_n+1) & w_{n2}1/(d_n+1) & \cdots & 1/(d_n+1) \end{pmatrix}$$

[3] Cohen et. at. Barycentric Graph Clustering, 2008

Barycentric Clustering ... contd

MapReduce Job I

- map(<e_{ij}>) $\rightarrow$ [<v_i, e_{ij}>, <v_j, e_{ij}>]
- reduce(<v_i, list[e_{ij}, e_{ik},...]>) $\rightarrow$ [<e_{ij}, P(v_i)>, <e_{ik}, P(v_i)>,...], where P(v) denotes the position vector of vertex v.

Barycentric Clustering ... contd

MapReduce Job I

- map(<e_{ij}>) $\rightarrow$ [<v_i, e_{ij}>, <v_j, e_{ij}>]
- reduce(<v_i, list[e_{ij}, e_{ik},...]>) $\rightarrow$ [<e_{ij}, P(v_i)>, <e_{ik}, P(v_i)>,...], where P(v) denotes the position vector of vertex v.

MapReduce Job II

- map : (identity)
- reduce(<e_{ij}, list[P(v_i), P(v_j)]>) $\rightarrow$ <e_{ij}, P(v_i), P(v_j)>

Barycentric Clustering ... contd

MapReduce Job I

- map(<e_{ij}>) $\rightarrow$ [<v_i, e_{ij}>, <v_j, e_{ij}>]
- reduce(<v_i, list[e_{ij}, e_{ik},...]>) $\rightarrow$ [<e_{ij}, P(v_i)>, <e_{ik}, P(v_i)>,...], where P(v) denotes the position vector of vertex v.

MapReduce Job II

- map : (identity)
- reduce(<e_{ij}, list[P(v_i), P(v_j)]>) $\rightarrow$ <e_{ij}, P(v_i), P(v_j)>

Now we execute 5 iterations of next two map reduce jobs

MapReduce Job III

- map(<e_{ij}, P(v_i), P(v_j)>) $\rightarrow$ [<v_i, e_{ij}, P(v_i), P(v_j)>, <v_j, e_{ij}, P(v_i), P(v_j)>]
- reduce(<v_i, list[<e_{ij}, P(v_i), P(v_j)>, <e_{ik}, P(v_i), P(v_k)>...]>) $\rightarrow$ calculates modified P'(v_i) = M*P'(v_i)and emits [<e_{ij}, P'(v_i), P(v_j)>, <e_{ik}, P'(v_i), P(v_k)>, ...]

Barycentric Clustering ... contd

MapReduce Job IV

- map: (identity)
- reduce(<e_{ij}, list[<e_{ij}, P'(v_i), P(v_j)>, <e_{ij}, P(v_i), P'(v_j)>]>) $\rightarrow$ <e_{ij}, P'(v_i), P'(v_j)>

Barycentric Clustering ... contd

MapReduce Job IV

- map: (identity)
- reduce(<e_{ij}, list[<e_{ij}, P'(v_i), P(v_j)>, <e_{ij}, P(v_i), P'(v_j)>]>) $\rightarrow$ <e_{ij}, P'(v_i), P'(v_j)>

MapReduce Job V

- map(e_{ij}, list[P_1, P_2, ..., P_r]) $\rightarrow$ [<v_i, AVG(P_i), AVG(P_j)>, <v_j, AVG(P_j)>]
- reduce(<v_i, list[<e_{ij}, P_j>, <e_{ik}, P_k>..]>) $\rightarrow$ [<e_{ij}, >, <e_{ik}, $\sum P_j, P_k, \ldots$>...], $\sum P_j, P_k, \ldots$, a_{ij} = $\sum P_j, P_k, \ldots$ represents the weight of edge e_{ij}.

Barycentric Clustering ... contd

MapReduce Job IV

- map: (identity)
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MapReduce Job VI

- map : (identity)
- reduce(<e_{ij}, list[weights emitted by previous map reduce job]>) : computes $\bar{a}_{ij}$, if $\bar{a}_{ij} > a_{ij}$, emit the edge

$$\overline{a_{ij}} = \frac{\sum_{k \in N_i} a_{jk} + \sum_{k \in N_j} a_{jk} - a_{ij}}{\mid N_i \mid + \mid N_j \mid -1}$$

- where N_k represents the set of vertices in the neighborhood of v_k

Finding Components

Algorithm using MapReduce

- ***Step 1*** → *consists of two MapReduce Jobs focussing on translating the vertex-vertex information into zone zone information*
  - **MapReduce 1** assigns edges with zones, producing 1 record for each vertex in edge and then translating this information to assign 1 zone to both the vertices
  - **MapReduce 2** merges the result of Job 1. If distinct zones are connected by an edge, then the zone with lower zone_id captures the other
- ***Step 2*** → *consists of one MapReduce Job*
  - **MapReduce 1** It record any updates to zone information for each vertex
- Step 1 and 2 alternate until step 1 produces no new record, which marks the completion of zone assignment

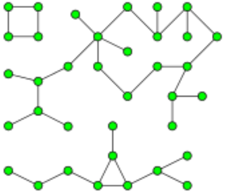

Figure: Graph with three components

Lin et. al[a] suggested following design patterns for efficiently implementing graph algorithms using MapReduce.

- ***Local aggregation*** done using combiners reduce the amount intermediate data. It is effective only in case of high duplication factor of intermediate key-value pair.
- ***In-Mapper Combining*** performs better than than regular combiner. Combiner often have to create and destroy objects and perform object serialization and de-serialization which is often costly.
- ***Schimmy Pattern*** divides the graph into n partitions each sorted by *vertex id*. Number of reducers are then set to n and it is guaranteed that reducer R_i processes same *vertex ids* as in partition P_i in sorted manner. Hence reducing the cost of shuffle and sort.
- ***Range Partitioning*** proposes to maximize intra-block connectivity and minimize inter-block connectivity. Dividing a graph into blocks with such a property helps reducing the amount of communication over network.

[a] Jimmy Lin, Michael Schatz, Design patterns for efficient graph algorithms in MapReduce, MLG'10

Design Patterns ... contd
Performance Comparison

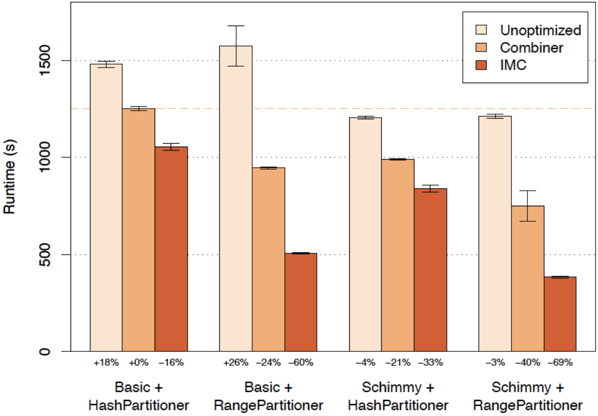

Figure: Performance comparison for PageRank using suggested strategies.[4]

[4] Jimmy Lin, Michael Schatz, Design patterns for efficient graph algorithms in MapReduce, MLG'10

Summary & Conclusion

- In general, it is a good contribution to attract MapReduce community to develop distributed systems for graph processing.
- Author focused on breaking down smaller problems in map-reduce jobs and merging them together to solve bigger problem.
- The contribution provides no information about the performance of the implementation. No comparison to standard approach.
- Most of the algorithms need complete re-transformation for implementation using MR framework. Some may become easy and some like finding component becomes complex.
- Lin et. al. introduced some really good strategies for efficient MapReduce implementation which can be used even for non-graph algorithms.

Thank You
Questions?