PowerGraph

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New Problem

Previous frameworks are inefficient for power law graphs

Challenges

1 – Work Balance

2 – Communication

3 – Storage

4 – Partitioning

5 – Computation

GAS system

`interface` *GASVertexProgram*(u) {

  `// Run on gather_nbrs(u)`

  gather$(D_u, D_{(u,v)}, D_v) \rightarrow Accum$

  sum$(Accum$ left, $Accum$ right$) \rightarrow Accum$

  apply$(D_u, Accum) \rightarrow D_u^{\text{new}}$

  `// Run on scatter_nbrs(u)`

  scatter$(D_u^{\text{new}}, D_{(u,v)}, D_v) \rightarrow (D_{(u,v)}^{\text{new}}, Accum)$

}

Delta Caching

```
// gather_nbrs: IN_NBRS
gather(D_u, D_(u,v), D_v):
   return D_v.rank / #outNbrs(v)
sum(a, b): return a + b
apply(D_u, acc):
   rnew = 0.15 + 0.85 * acc
   D_u.delta = (rnew - D_u.rank)/
               #outNbrs(u)
   D_u.rank = rnew
// scatter_nbrs: OUT_NBRS
scatter(D_u,D_(u,v),D_v):
   if(|D_u.delta|>ε) Activate(v)
   return delta
```

– Avoids re-gather-ing of data of unchanged neighbors.

- Optional

- Not always possible

– Useful for power law graphs.

Interface Comparison

```
// gather_nbrs: IN_NBRS
gather(D_u, D_(u,v), D_v):
   return D_v.rank / #outNbrs(v)
sum(a, b): return a + b
apply(D_u, acc):
   rnew = 0.15 + 0.85 * acc
   D_u.delta = (rnew - D_u.rank)/
               #outNbrs(u)
   D_u.rank = rnew
// scatter_nbrs: OUT_NBRS
scatter(D_u,D_(u,v),D_v):
   if(|D_u.delta|>ε) Activate(v)
   return delta
```

```
Message combiner(Message m1, Message m2) :
  return Message(m1.value() + m2.value());
void PregelPageRank(Message msg) :
  float total = msg.value();
  vertex.val = 0.15 + 0.85*total;
  foreach(nbr in out_neighbors) :
    SendMsg(nbr, vertex.val/num_out_nbrs);
```

```
void GraphLabPageRank(Scope scope) :
  float accum = 0;
  foreach (nbr in scope.in_nbrs) :
    accum += nbr.val / nbr.nout_nbrs();
  vertex.val = 0.15 + 0.85 * accum;
```

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Vertex Cut vs. Edge Cut

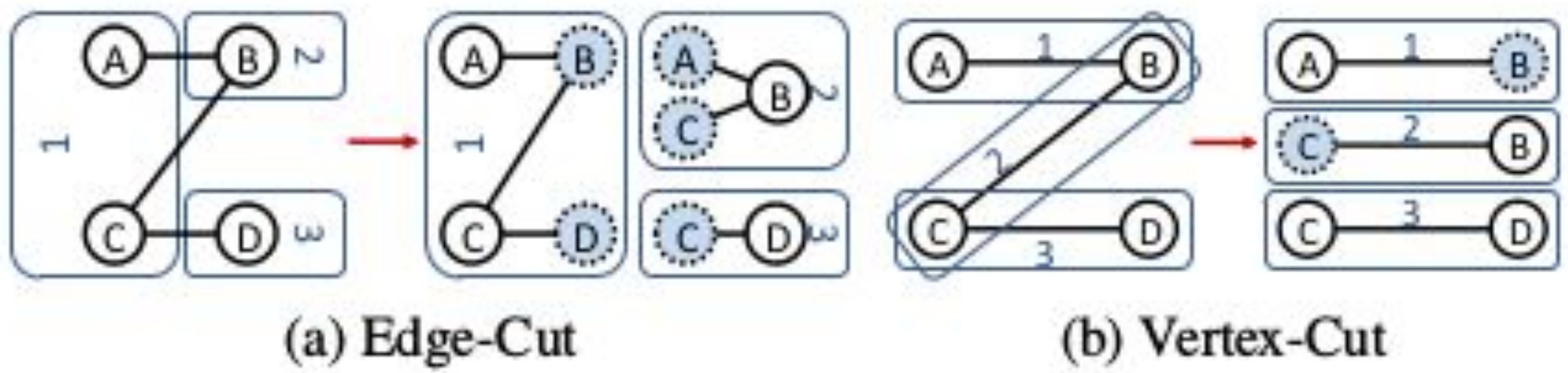

Figure 4: **(a)** An edge-cut and **(b)** vertex-cut of a graph into three parts. Shaded vertices are ghosts and mirrors respectively.

Partition Design Decisions

1 – Put each edge on one machine.

2 – Put replicas of vertices on different machines.

3 – Elect one replica as master and others as mirrors, maintain consistency in a centralized fashion.

4 – Minimize replicas to minimize communication and duplication of data.

Communication

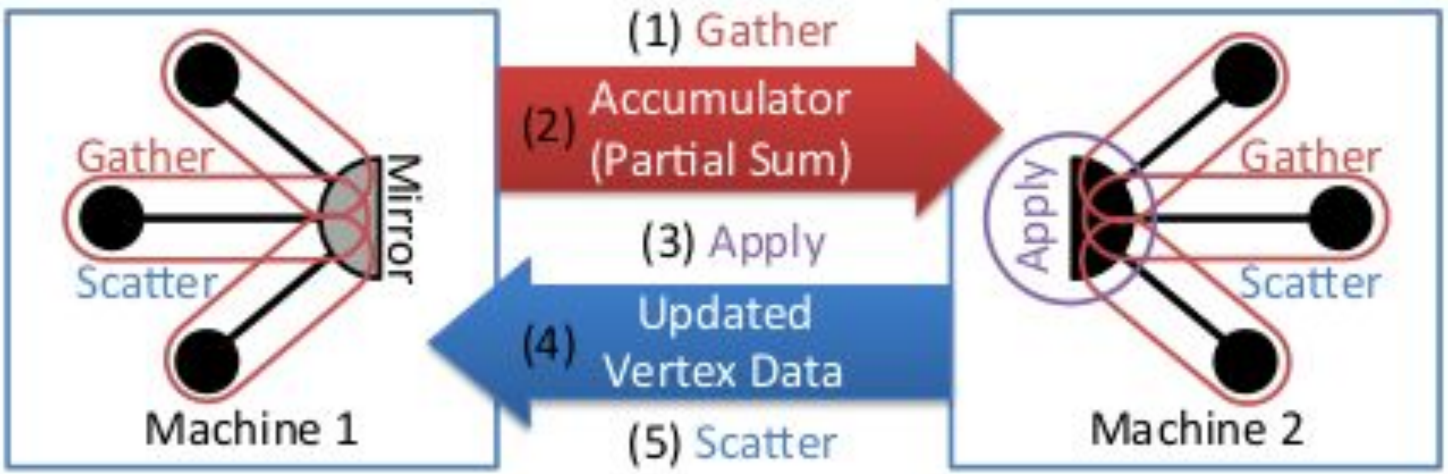

Figure 5: The communication pattern of the PowerGraph abstraction when using a vertex-cut. Gather function runs locally on each machine and then one accumulators is sent from each mirror to the master. The master runs the apply function and then sends the updated vertex data to all mirrors. Finally the scatter phase is run in parallel on mirrors.

New Problem

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Vertex Cut vs. Edge Cut

Vertex Cut

1 – Minimizes vertex cuts - replicas in powerGraph

2 – Efficient to compute

Edge Cut

1 – Hard to compute with power law graphs.

2 – Even if computed, not suitable for PowerGraph.

3 – When random, most edges will be cut.

New Problem

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Vertex Cut Computation

Random

Assign each edge to a different machine in parallel.

Greedy

Case 1: If $A(u)$ and $A(v)$ intersect, then the edge should be assigned to a machine in the intersection.

Case 2: If $A(u)$ and $A(v)$ are not empty and do not intersect, then the edge should be assigned to one of the machines from the vertex with the most unassigned edges.

Case 3: If only one of the two vertices has been assigned, then choose a machine from the assigned vertex.

Case 4: If neither vertex has been assigned, then assign the edge to the least loaded machine.

Implementations

1 – Coordinated

2 – Oblivious

3 – Random

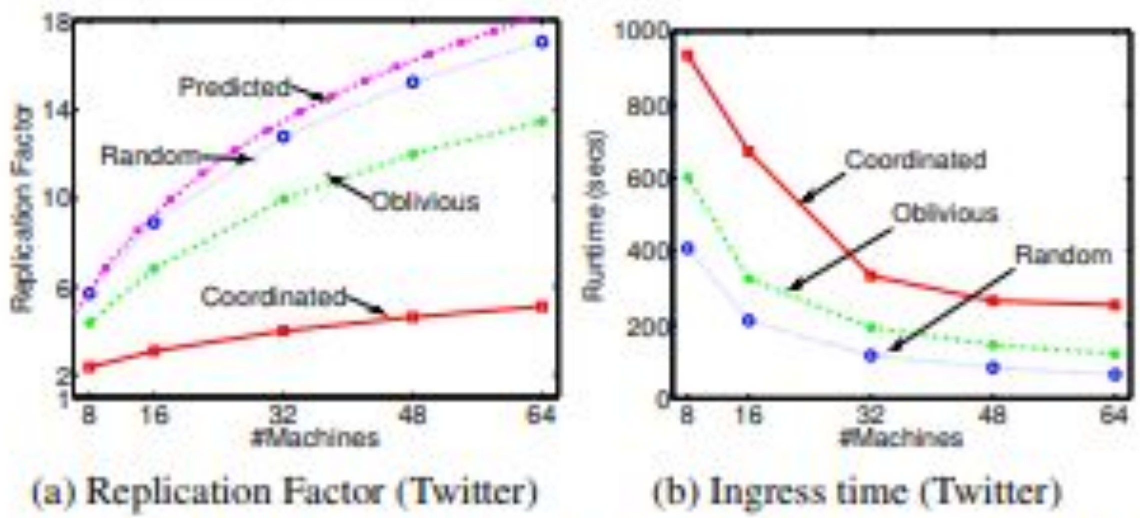


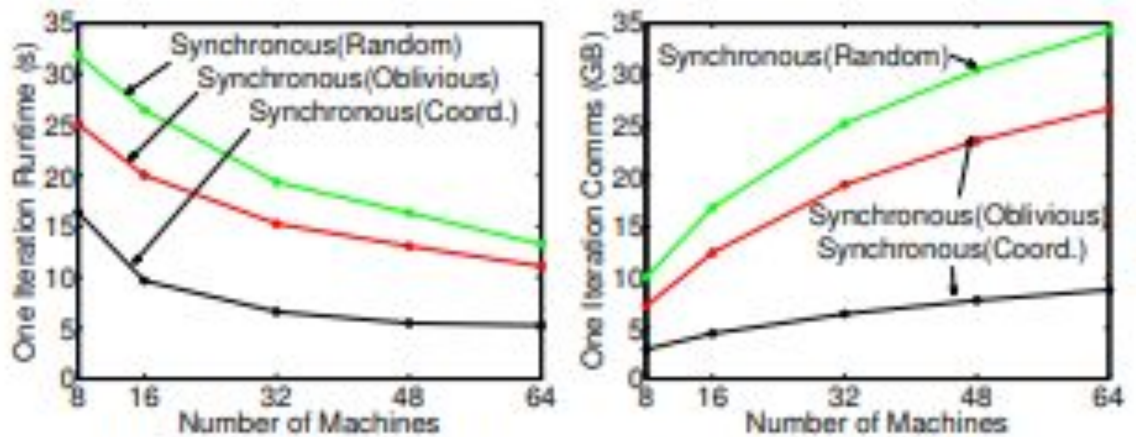
Figure 8: **(a,b)** Replication factor and runtime of graph ingress for the Twitter follower network as a function of the number of machines for random, oblivious, and coordinated vertex-cuts.

Implementations

1 – Coordinated

2 – Oblivious

3 – Random



(a) Twitter PageRank Runtime (b) Twitter PageRank Comms

New Problem

Challenges

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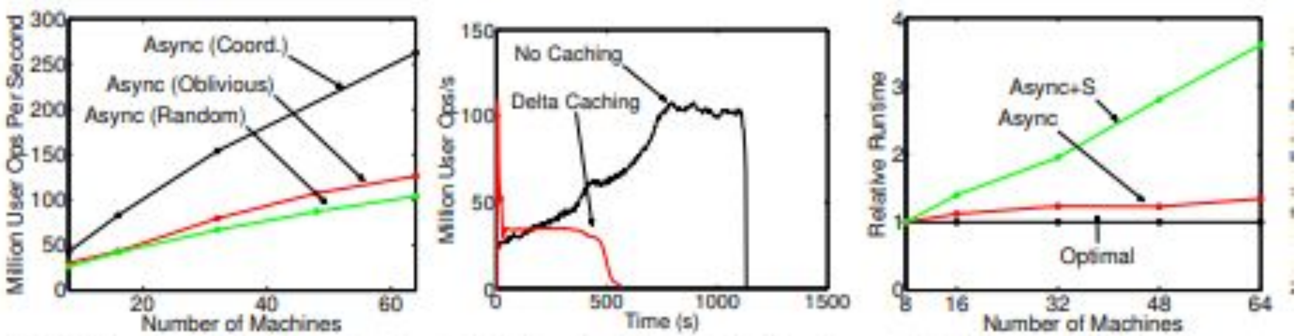
Implementations

1 – Synchronized

2 – Asynchronized

3 – Asynchronized and Serializable



(a) Twitter PageRank Throughput (b) Twitter PageRank Delta Cache (c) Coloring Weak Scaling

Parallel Locking

Async Serializable PowerGraph

1 – Use Parallel Locking

2 – Extend Chandy-Misra Solution

3 – Each mirror attempts to acquire its own locks.

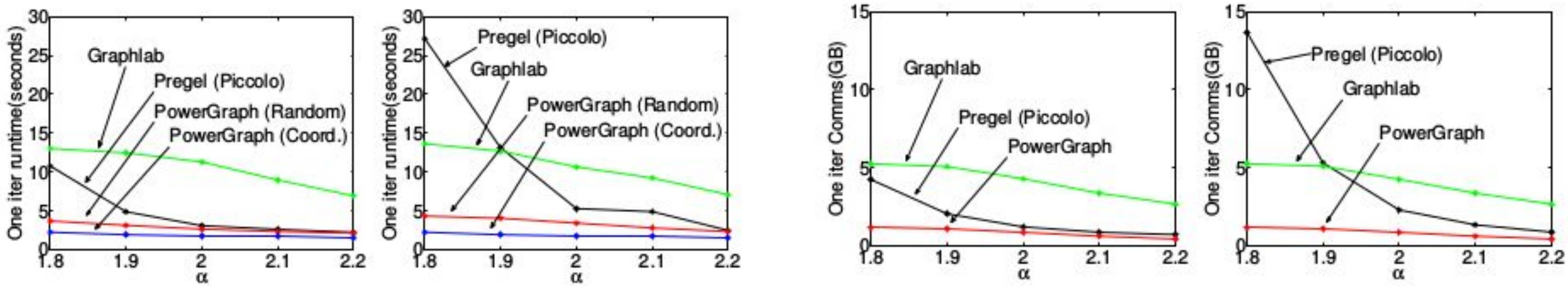
GraphLab

1 – Sequential Locking

2 – Use Dijkstra

3 – Suitable only when nodes degrees are small.

Comparison with Pregel and GraphLab



(a) Power-law Fan-In Runtime (b) Power-law Fan-Out Runtime (c) Power-law Fan-In Comm. (d) Power-law Fan-Out Comm.

Summary of the solution

Essence of the solution:

1 – Decouple different types of operations (read-only, write to adjacent nodes, changing node data) .

2 – Use smart partitioning strategies to decrease communication.

3 – Shared memory; data not need to be moved.

4 – Optimized for power law graph.

Contributions and Notes

1. An analysis of the challenges of power-law graphs in distributed graph computation and the limitations of existing graph parallel abstractions (Sec. 2 and 3).
2. The PowerGraph abstraction (Sec. 4) which factors individual vertex-programs.
3. A delta caching procedure which allows computation state to be dynamically maintained (Sec. 4.2).
4. A new fast approach to data layout for power-law graphs in distributed environments (Sec. 5).
5. An theoretical characterization of network and storage (Theorem 5.2, Theorem 5.3).
6. A high-performance open-source implementation of the PowerGraph abstraction (Sec. 7).
7. A comprehensive evaluation of three implementations of PowerGraph on a large EC2 deployment using real-world MLDM applications (Sec. 6 and 7).

1 – Achieved the five goals, with minimal trade-offs.

2 – Thorough analysis

3 – The research is built on assuming natural graphs are power laws.

References

1 – Gonzalez, Joseph E., Yucheng Low, Haijie Gu, Danny Bickson, and Carlos Guestrin. "Powergraph: distributed graph-parallel computation on natural graphs." In OSDI, vol. 12, no. 1, p. 2. 2012.

2 – Low, Yucheng, Joseph E. Gonzalez, Aapo Kyrola, Danny Bickson, Carlos E. Guestrin, and Joseph Hellerstein. "Graphlab: A new framework for parallel machine learning." arXiv preprint arXiv:1408.2041 (2014).

3 – Malewicz, Grzegorz, Matthew H. Austern, Aart JC Bik, James C. Dehnert, Ilan Horn, Naty Leiser, and Grzegorz Czajkowski. "Pregel: a system for large-scale graph processing." In Proceedings of the 2010 ACM SIGMOD International Conference on Management of data, pp. 135-146. ACM, 2010.

Questions

- The paper makes use of power law, what about other properties in natural graphs?

- How does the nature of the algorithm impacts the framework?

- How does PowerGraph compares with GraphLab and Pregel?