PowerGraph: Distributed Graph-Parallel Computation on Natural Graphs

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Background

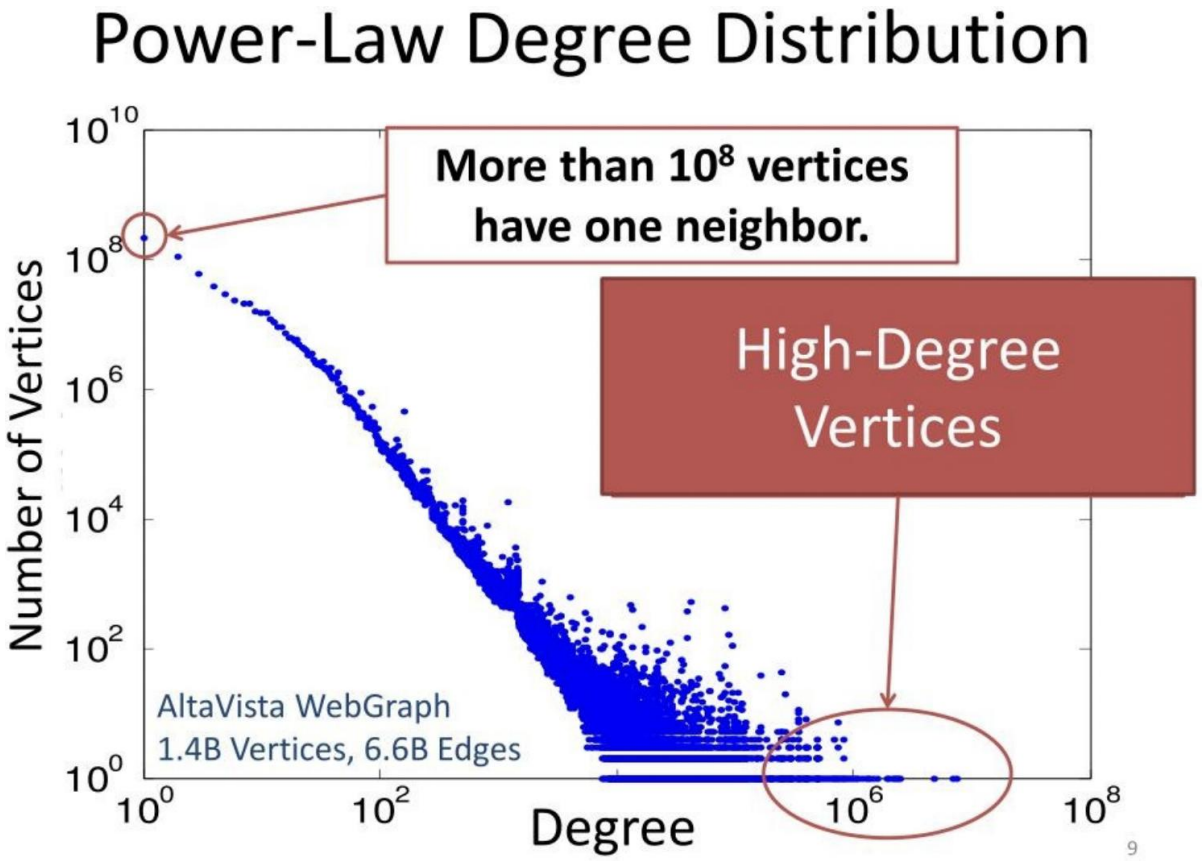
1. **Why Graph?**
   Machine Learning and Data Mining (MLDM) problems represented as graphs ---> Graph structured computation is important

2. Current distributed graph computation systems
   - Pregel
   - GraphLab

3. **Problems**: Existing distributed graph computation systems perform poorly on Natural Graphs.

Challenges of Natural Graphs

Many Graphs have skewed degree distribution: a small fraction of the vertices are adjacent to a large fraction of the edges



Source: Joseph Gonzalez. (2012).

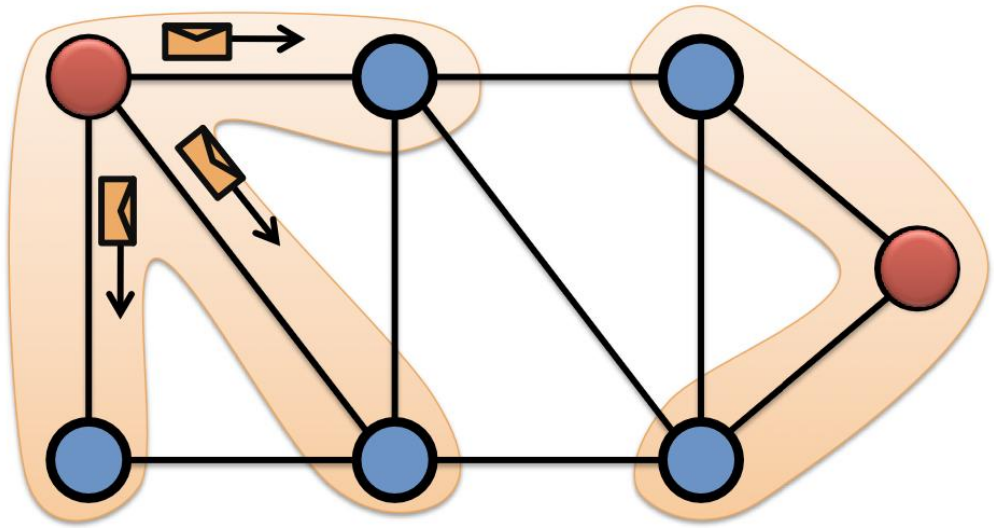
How do we *program* **graph** computation?

"Think like a Vertex."

-Malewicz et al. [SIGMOD'10]

The **Graph-Parallel** Abstraction

1. A user-defined **Vertex-Program** runs on each vertex
2. **Graph** constrains **interaction** along edges
   - Using **messages** (e.g. **Pregel** [PODC'09, SIGMOD'10])
   - Through **shared state** (e.g., **GraphLab** [UAI'10, VLDB'12])
3. **Parallelism**: run multiple vertex programs simultaneously



Source: Joseph Gonzalez. (2012).

PageRank Algorithm

$$R[i] = 0.15 + \sum_{j \in \mathrm{Nbrs}(i)} w_{ji} R[j]$$

Rank of user *i*

Weighted sum of neighbors' ranks

- Update ranks in parallel
- Iterate until convergence

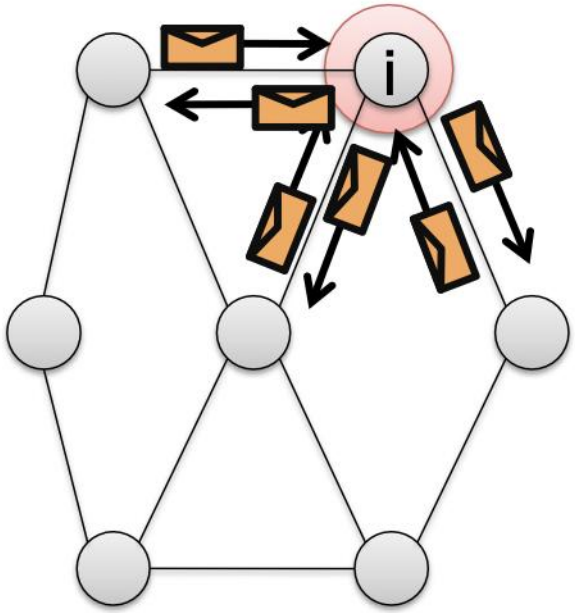
The Pregel Abstraction

Vertex-Programs interact by sending **messages**.

```
Pregel_PageRank(i, messages) :
  // Receive all the messages
  total = 0
  foreach( msg in messages) :
    total = total + msg

  // Update the rank of this vertex
  R[i] = 0.15 + total

  // Send new messages to neighbors
  foreach(j in out_neighbors[i]) :
    Send  msg(R[i] * w_ij) to vertex j
```



Malewicz et al. [PODC'09, SIGMOD'10]

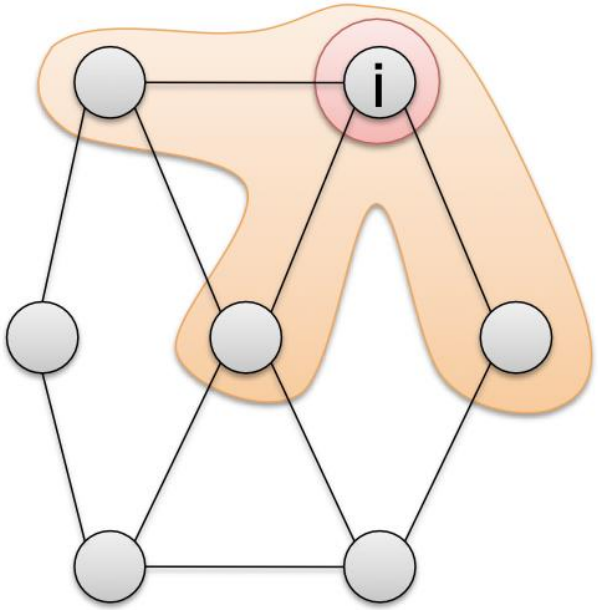
The GraphLab Abstraction

Vertex-Programs directly **read** the neighbors state

```
GraphLab_PageRank(i)
  // Compute sum over neighbors
  total = 0
  foreach( j in in_neighbors(i)):
    total = total + R[j] * w_ji

  // Update the PageRank
  R[i] = 0.15 + total

  // Trigger neighbors to run again
  if R[i] not converged then
    foreach( j in out_neighbors(i)):
      signal vertex-program on j
```

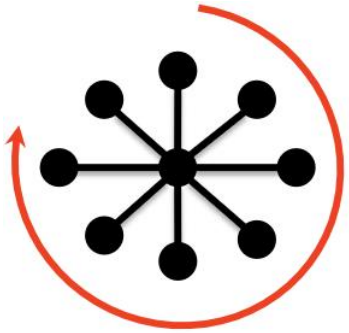


Low et al. [UAI'10, VLDB'12]

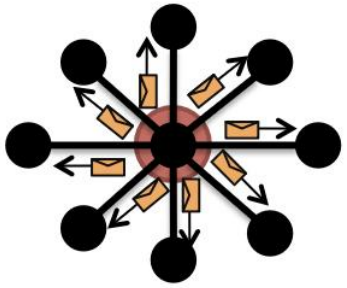
Problem: Challenges of High-Degree Vertices

GraphLab and Pregel on Natural Graphs:

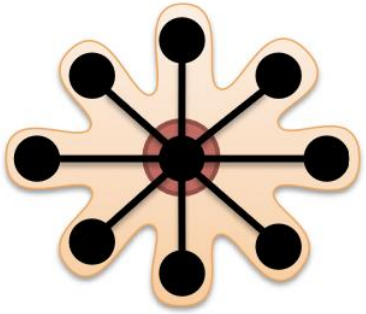
1. Work Imbalance
2. Partitioning
3. Communication
4. Storage
5. Computation



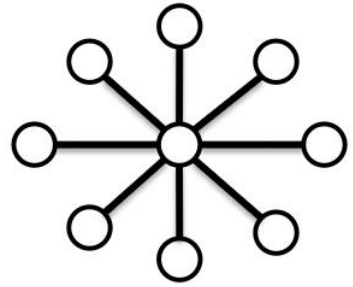
Sequentially process edges



Sends many messages (Pregel)

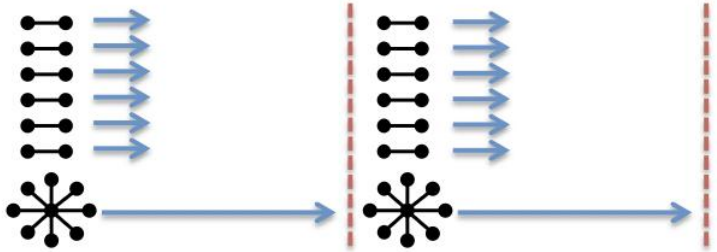


Touches a large fraction of graph (GraphLab)



Edge meta-data too large for single machine

Asynchronous Execution requires heavy locking (GraphLab)

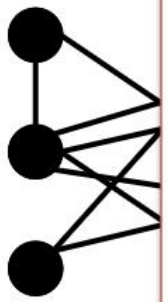


Synchronous Execution prone to stragglers (Pregel)

Source: Joseph Gonzalez. (2012).

Problem: Random Partitioning

- Both GraphLab and Pregel resort to **random** (hashed) partitioning on **natural graphs**



$$\mathbb{E}\left[\frac{|Edges\ Cut|}{|E|}\right] = 1 - \frac{1}{p}$$

10 Machines → 90% of edges cut

100 Machines → 99% of edges cut!

Source: Joseph Gonzalez. (2012).

In Summary

GraphLab and **Pregel** are not well suited for **natural graphs**

- Challenges of **high-degree vertices**
- Low quality **partitioning**

PowerGraph

- **GAS Decomposition**: distribute vertex-programs
  - Move computation to data
  - Parallelize **high-degree** vertices

- **Vertex Partitioning:**
  - Effectively distribute large power-law graphs

A **Common Pattern** for Vertex-Programs

GraphLab_PageRank(i)

```
// Compute sum over neighbors
total = 0
foreach( j in in_neighbors(i)):
  total = total + R[j] * w_ji
```

Gather Information About Neighborhood

```
// Update the PageRank
R[i] = 0.1 + total
```

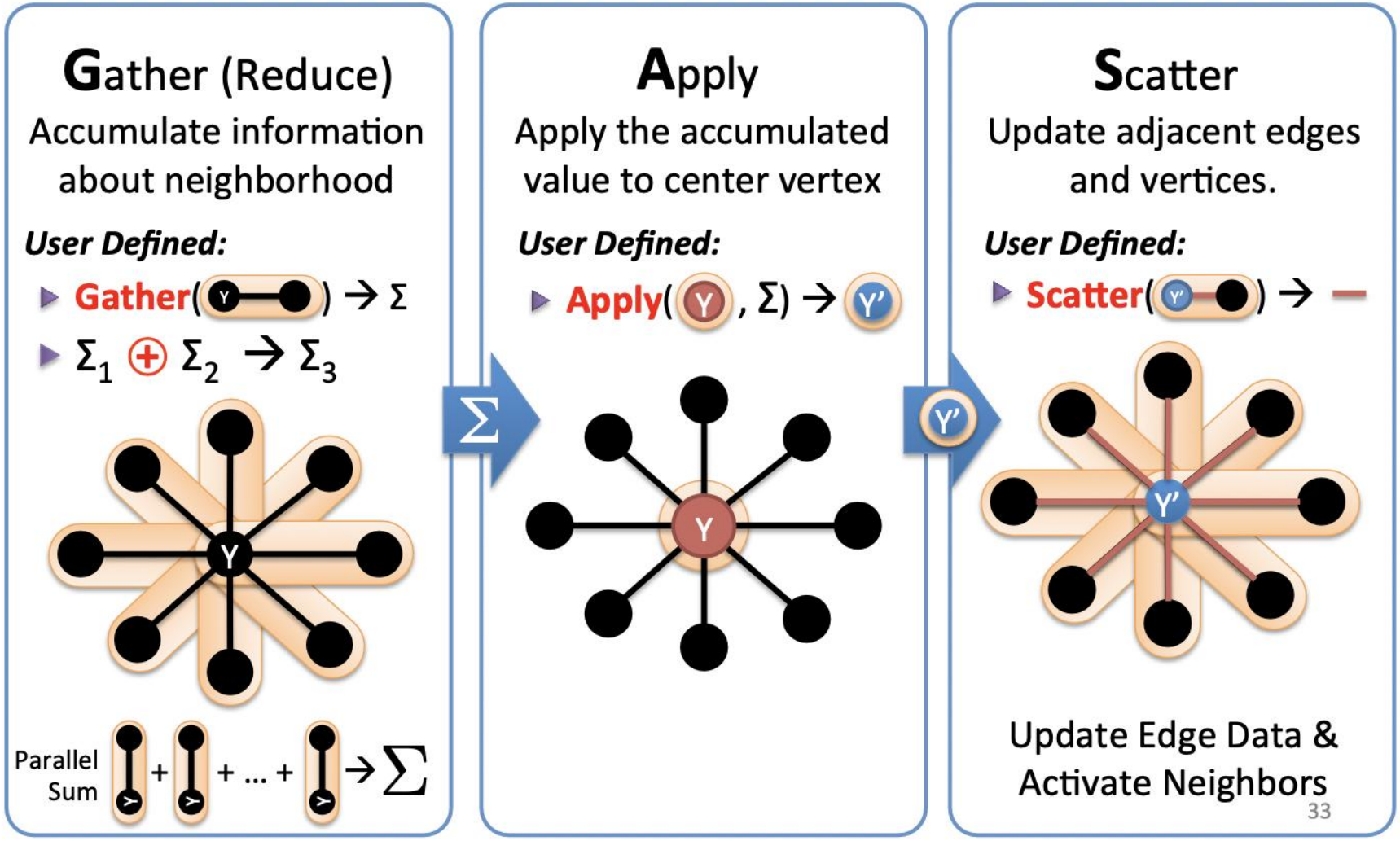
Update Vertex

```
// Trigger neighbors to run again
if R[i] not converged then
  foreach( j in out_neighbors(i))
    signal vertex-program on j
```

Signal Neighbors & Modify Edge Data

Source: Joseph Gonzalez. (2012).

GAS Decomposition



Source: Joseph Gonzalez. (2012).

PageRank in PowerGraph

$$R[i] = 0.15 + \sum_{j \in \text{Nbrs}(i)} w_{ji} R[j]$$

PowerGraph_PageRank(i)

Gather(j → i) : return w_{ji} * R[j]

sum(a, b) : return a + b;

Apply(i, Σ) : R[i] = 0.15 + Σ

Scatter(i → j) :

if *R[i]* changed then trigger *j* to be **recomputed**

Source: Joseph Gonzalez. (2012).

Edge Cut vs Vertex Cut

Two methods for partitioning the graph in a distributed environment:

- Edge Cut (Used by Pregel and GraphLab abstractions)

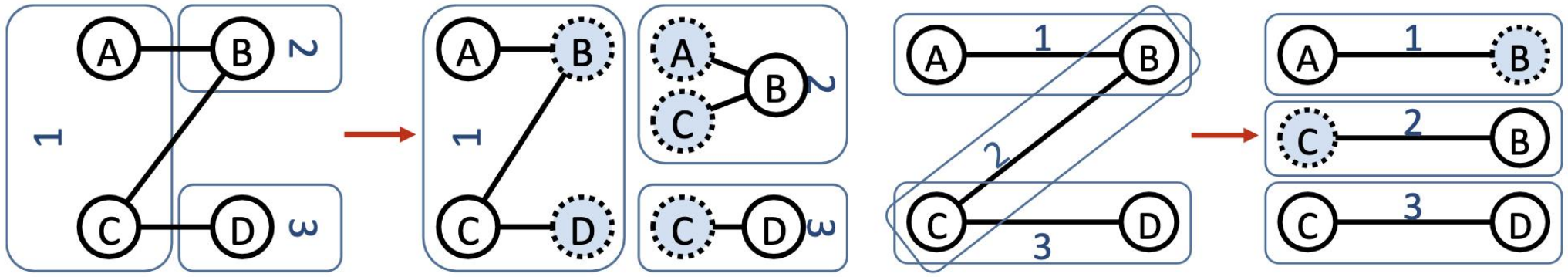
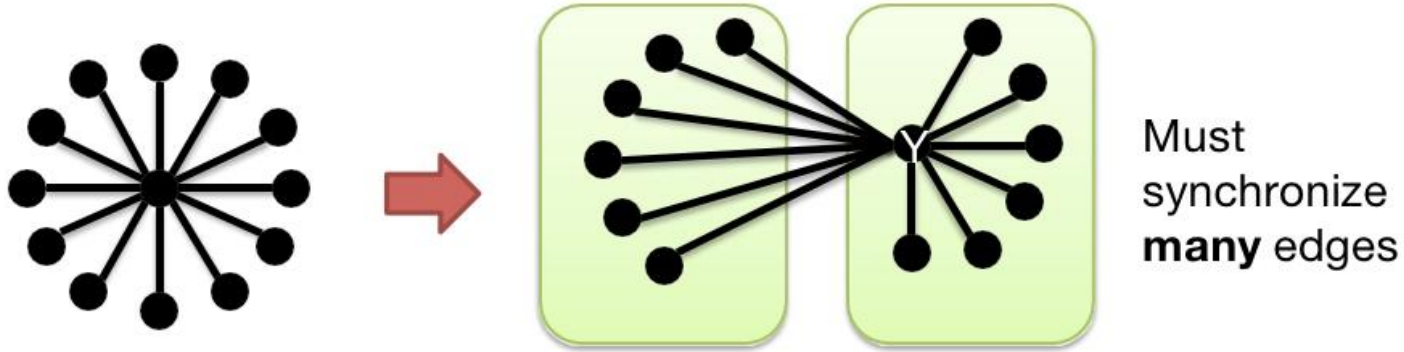


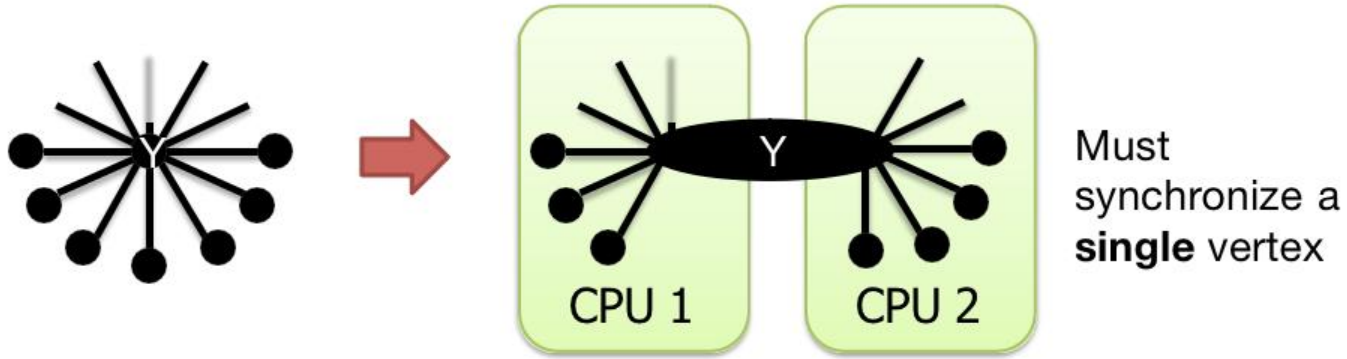
Figure 4: **(a)** An edge-cut and **(b)** vertex-cut of a graph into three parts. Shaded vertices are ghosts and mirrors respectively.

New Approach to Partitioning

- Rather than cut edges:



- We cut vertices



Source: Joseph Gonzalez. (2012).

New Approach to Partitioning

New Theorem:

*For **any edge-cut** we can directly construct a vertex-cut which requires **strictly less** communication and storage.*

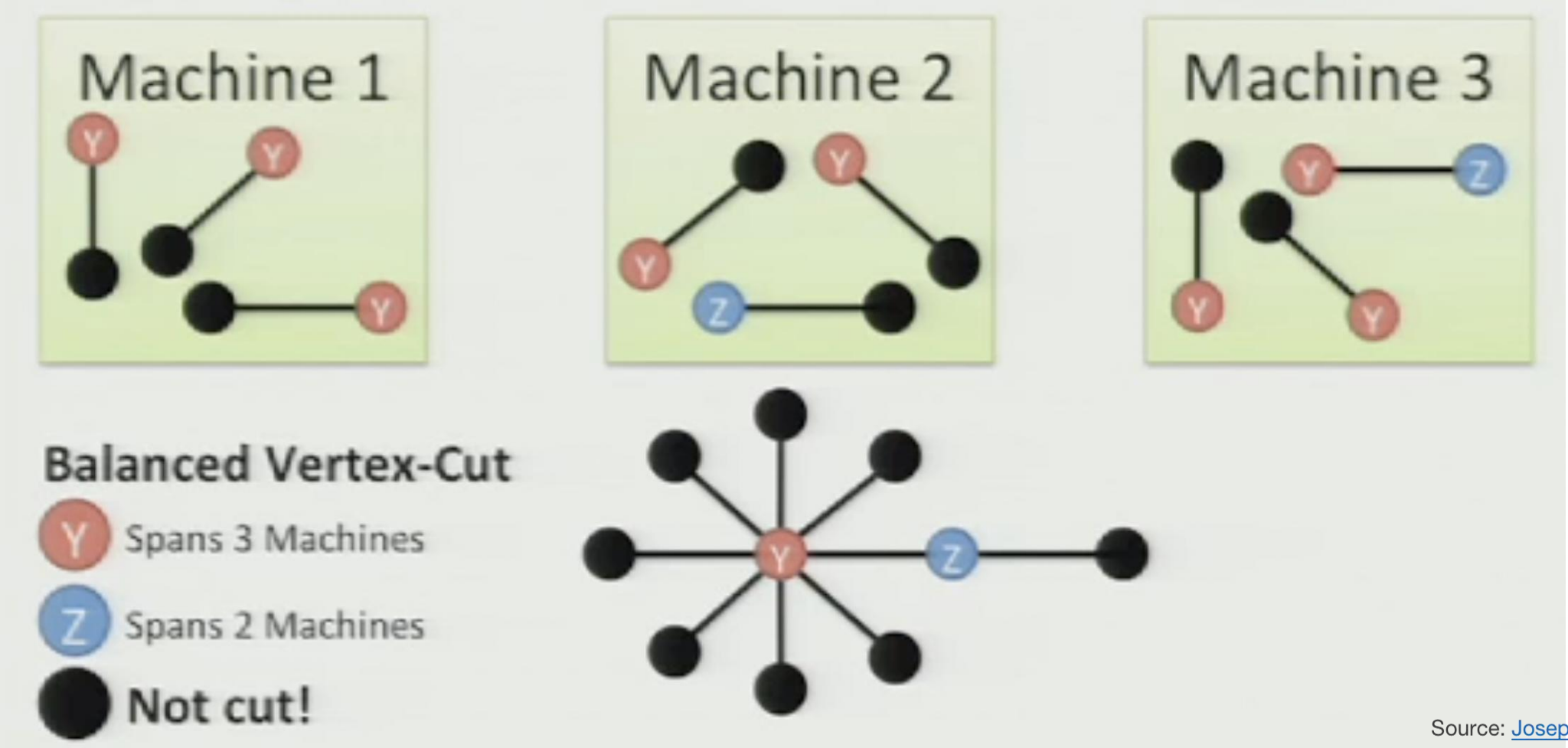
Source: Joseph Gonzalez. (2012).

Constructing Vertex-Cuts

- **Evenly** assign **edges** to machines
  - Minimize machines spanned by each vertex
- Assign each edge **as it is loaded**
  - Touch each edge only once
- Propose three **distributed** approaches:
  - ***Random*** *Edge Placement*
  - ***Coordinated Greedy*** *Edge Placement*
  - ***Oblivious Greedy*** *Edge Placement*

Random Edge-Placement

- Randomly assign edges to machines



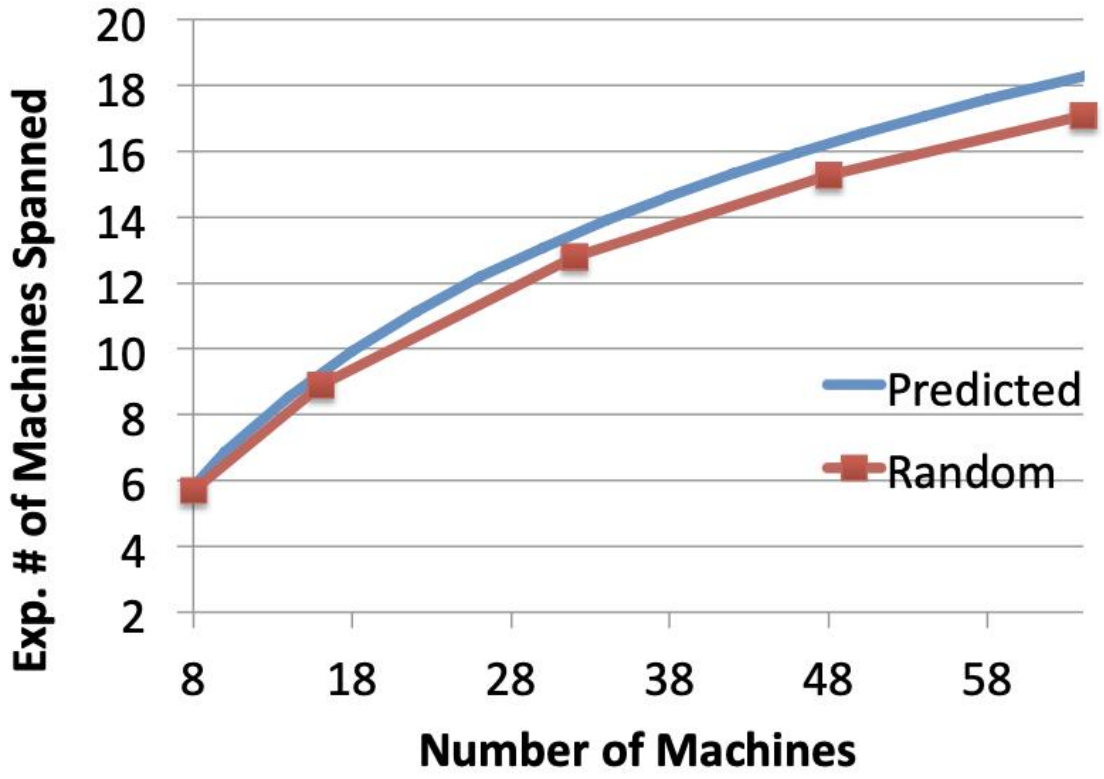
Source: Joseph Gonzalez. (2012).

Analysis Random Edge-Placement

- Expected number of machines spanned by a vertex:

Twitter Follower Graph
41 Million Vertices
1.4 Billion Edges

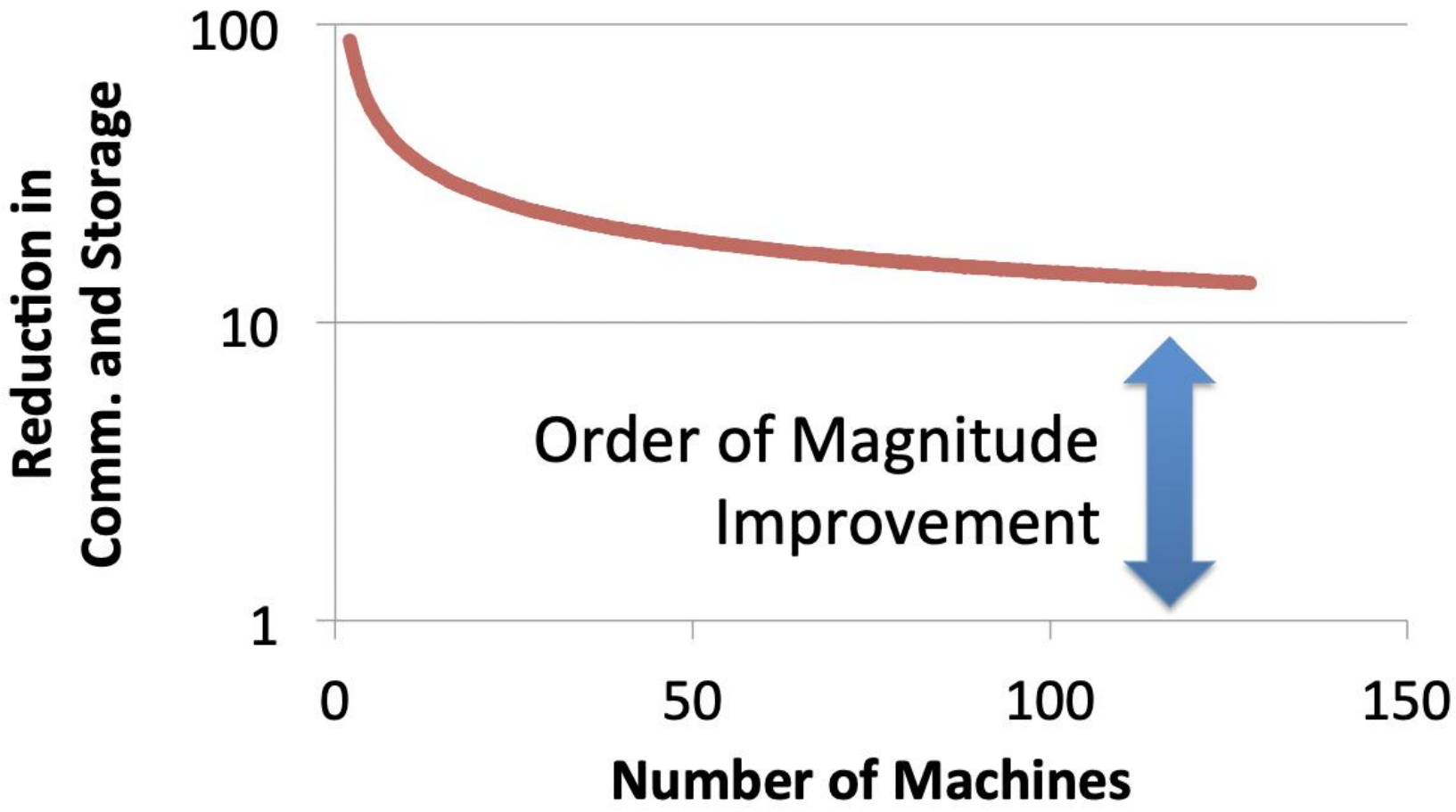
Accurately Estimate Memory and Comm. Overhead



Source: Joseph Gonzalez. (2012).

Random Vertex-Cuts vs. Edge-Cuts

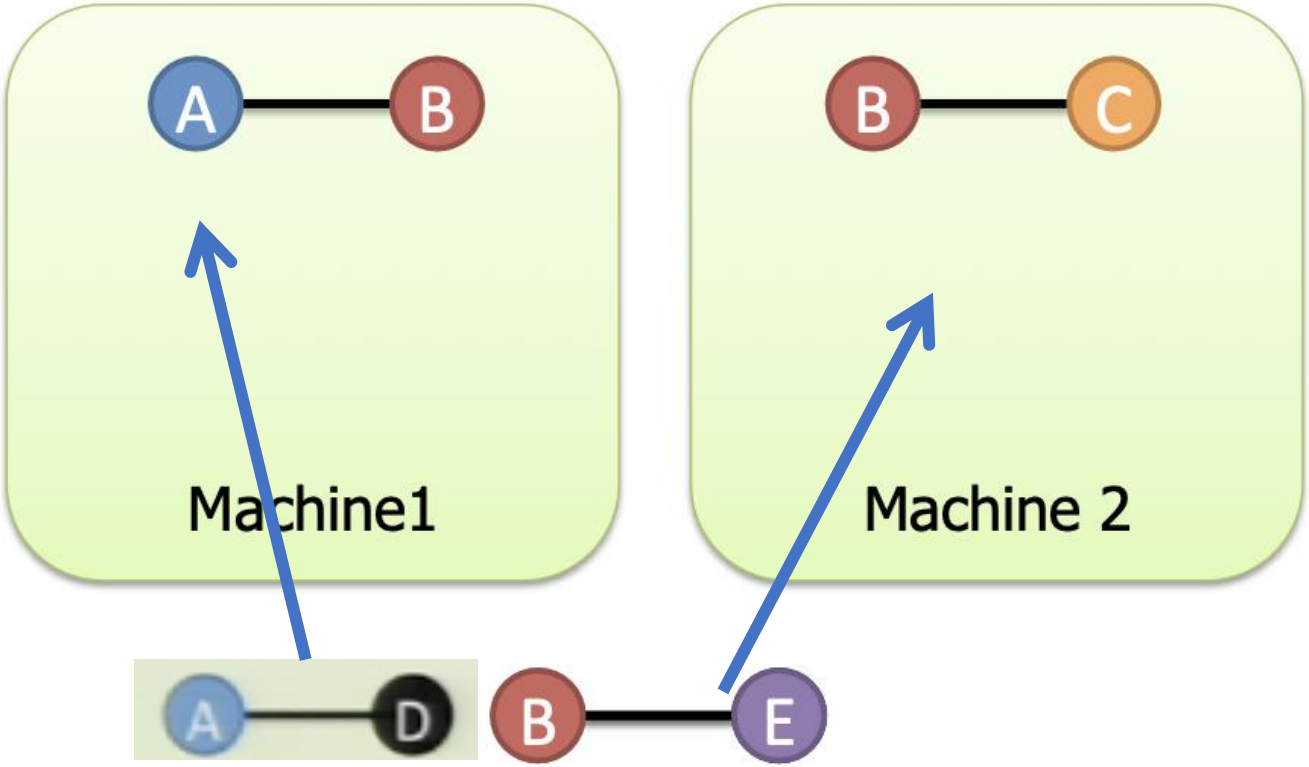
- Expected improvement from vertex-cuts:



Source: Joseph Gonzalez. (2012).

Greedy Vertex-Cuts

- Place edges on machines which already have the vertices in that edge.



Source: Joseph Gonzalez. (2012).

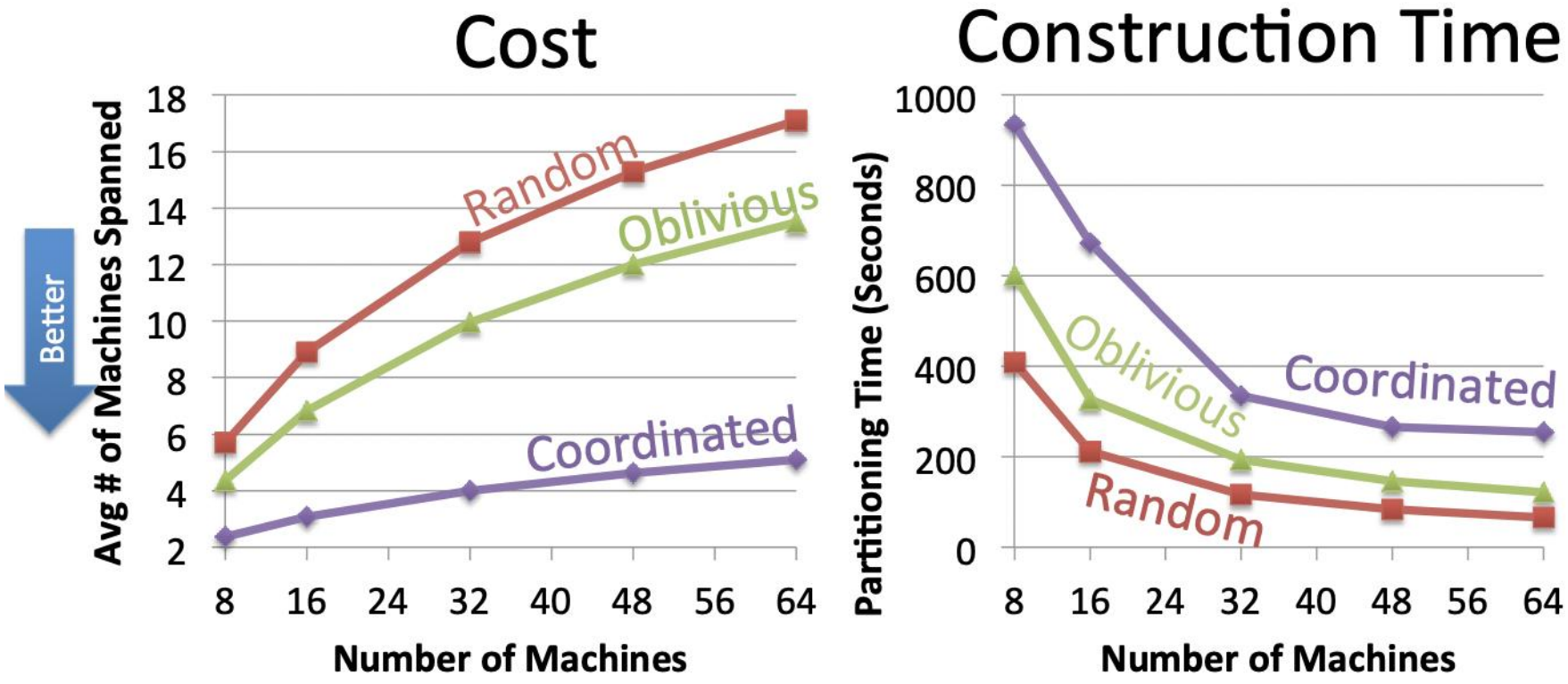
Greedy Vertex-Cuts

- **De-randomization** → greedily minimizes the expected number of machines spanned

- **Coordinated** Edge Placement
  - Requires coordination to place each edge
  - Slower: higher quality cuts
- **Oblivious** Edge Placement
  - Approx. greedy objective without coordination
  - Faster: lower quality cuts

Partitioning Performance

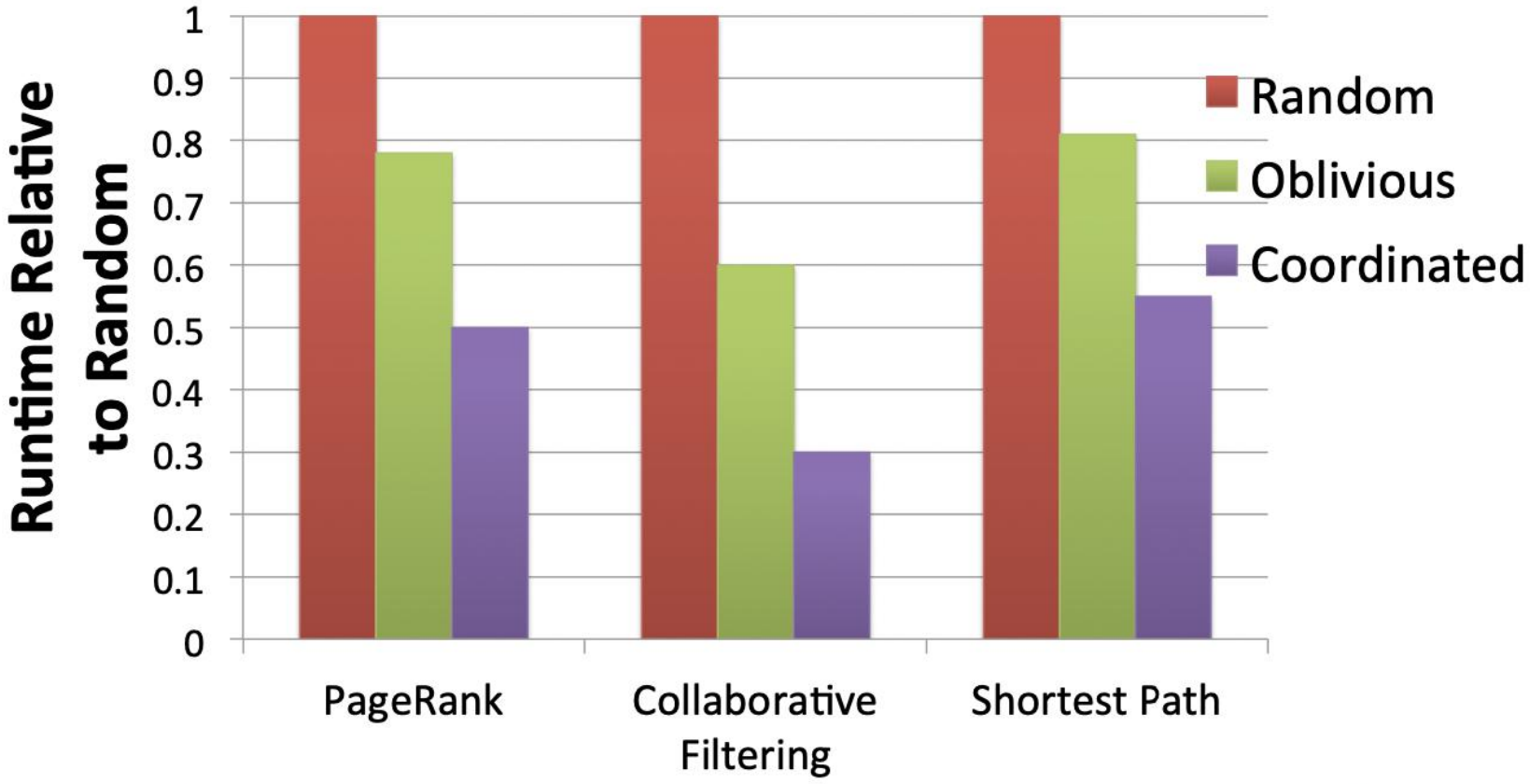
Twitter Graph: 41M vertices, 1.4B edges



Oblivious balances cost and partitioning time.

Source: Joseph Gonzalez. (2012).

Greedy Vertex-Cuts Improve Performance



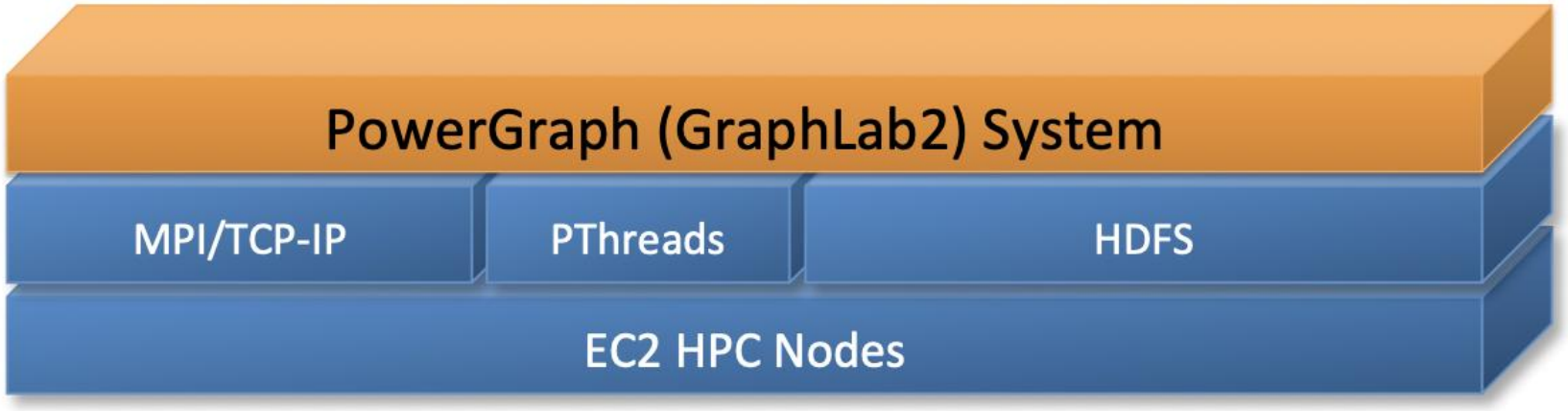
Greedy partitioning improves computation performance.

Source: Joseph Gonzalez. (2012).

Other Features (See Paper)

- Supports three execution modes:
  - **Synchronous:** Bulk-Synchronous GAS Phases
  - **Asynchronous:** Interleave GAS Phases
  - **Asynchronous + Serializable:** Neighboring vertices do not run simultaneously
- Delta Caching
  - Accelerate gather phase by **caching** partial sums for each vertex

System Design



Source: Joseph Gonzalez. (2012).

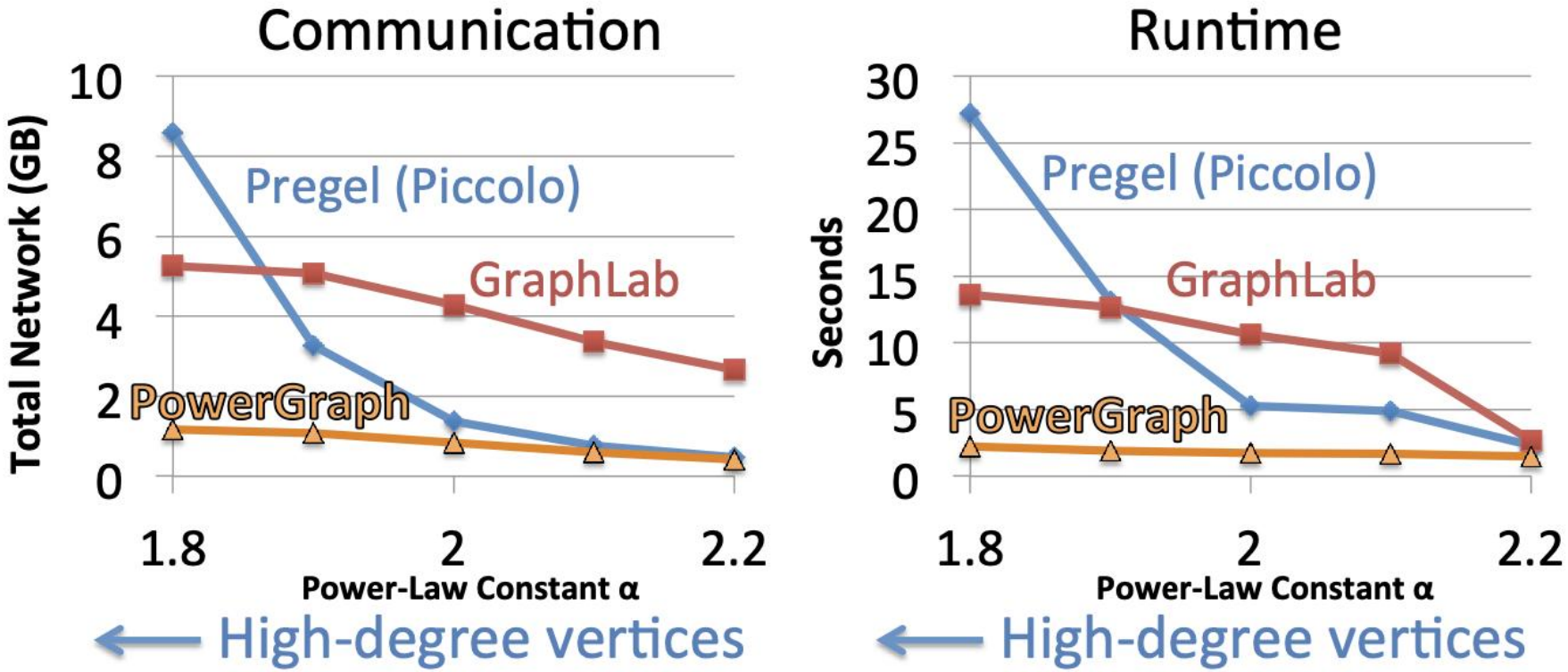
- Implemented as C++ API
- Uses HDFS for Graph Input and Output
- Fault-tolerance is achieved by check-pointing
  - Snapshot time < 5 seconds for twitter network

Implemented Many Algorithms

- **Collaborative Filtering**
  - Alternating Least Squares
  - Stochastic Gradient Descent
  - SVD
  - Non-negative MF
- **Statistical Inference**
  - Loopy Belief Propagation
  - Max-Product Linear Programs
  - Gibbs Sampling
- **Graph Analytics**
  - PageRank
  - Triangle Counting
  - Shortest Path
  - Graph Coloring
  - K-core Decomposition
- **Computer Vision**
  - Image stitching
- **Language Modeling**
  - LDA

Comparison with GraphLab & Pregel

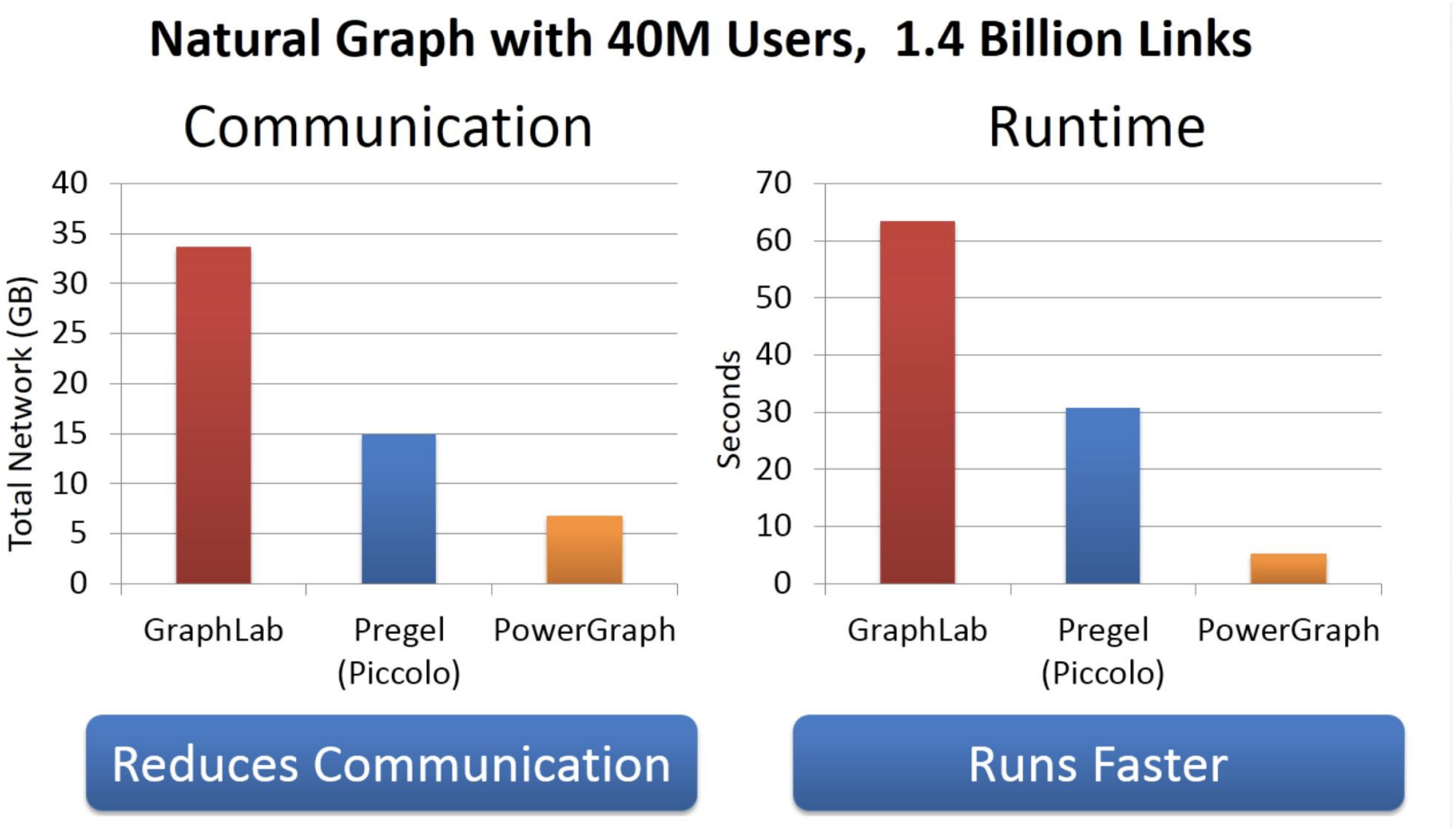
- PageRank on Synthetic Power-Law Graphs:



PowerGraph is robust to **high-degree** vertices.

Source: Joseph Gonzalez. (2012).

PageRank on the Twitter Follower Graph



Source: Joseph Gonzalez. (2012).

PowerGraph is Scalable

Yahoo Altavista Web Graph (2002):

One of the largest publicly available web graphs

1.4 Billion Webpages, 6.6 Billion Links

7 Seconds per Iter.

1B links processed per second

30 lines of user code

Summary

- *Problem*: Computation on **Natural Graphs** is challenging
  - High-degree vertices
  - Low-quality edge-cuts

- *Solution*: **PowerGraph System**
  - **GAS Decomposition**: split vertex programs
  - **Vertex-partitioning**: distribute natural graphs

- PowerGraph **theoretically** and **experimentally** outperforms existing graph-parallel systems.

Criticism - pros/cons

- PowerGraph, uses intelligent partitioning of vertices across servers. While this pre-processing reduces per iteration runtime, it is an expensive step by itself. [1]
- High Memory: store in, edges, mirror values
- Out-of-core storage: Support graphs that don’t fit in memory (GraphChi)
- Maintenance of vertex replicas, communication-bound apply phase in the GAS abstraction [2]

Goal	PowerGraph
Computation	2 passes
Communication	$\propto$ #vertex mirrors
Pre-Processing	Expensive (Intelligent)
Memory	High(store in- and out-edges + mirror values)
Scalability	Good but needs a min #servers

source: link

References

[1] Hoque I, Gupta I. LFGraph: Simple and fast distributed graph analytics[C]//Proceedings of the First ACM SIGOPS Conference on Timely Results in Operating Systems. 2013: 1-17.

[2] Zhu X, Chen W, Zheng W, et al. Gemini: A {Computation-Centric} Distributed Graph Processing System[C]//12th USENIX Symposium on Operating Systems Design and Implementation (OSDI 16). 2016: 301-316.