PowerGraph: Distributed Graph-Parallel Computation on Natural Graphs

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Introduction

- New framework for distributed graph paralleled computation on natural graphs
- Transition from big data to big graphs

NATURAL GRAPHS

- Graphs are ubiquitous…

- Graphs encode relationships between

People Products Ideas

Facts Interests

♥ Billions of vertices and edges and rich metadata

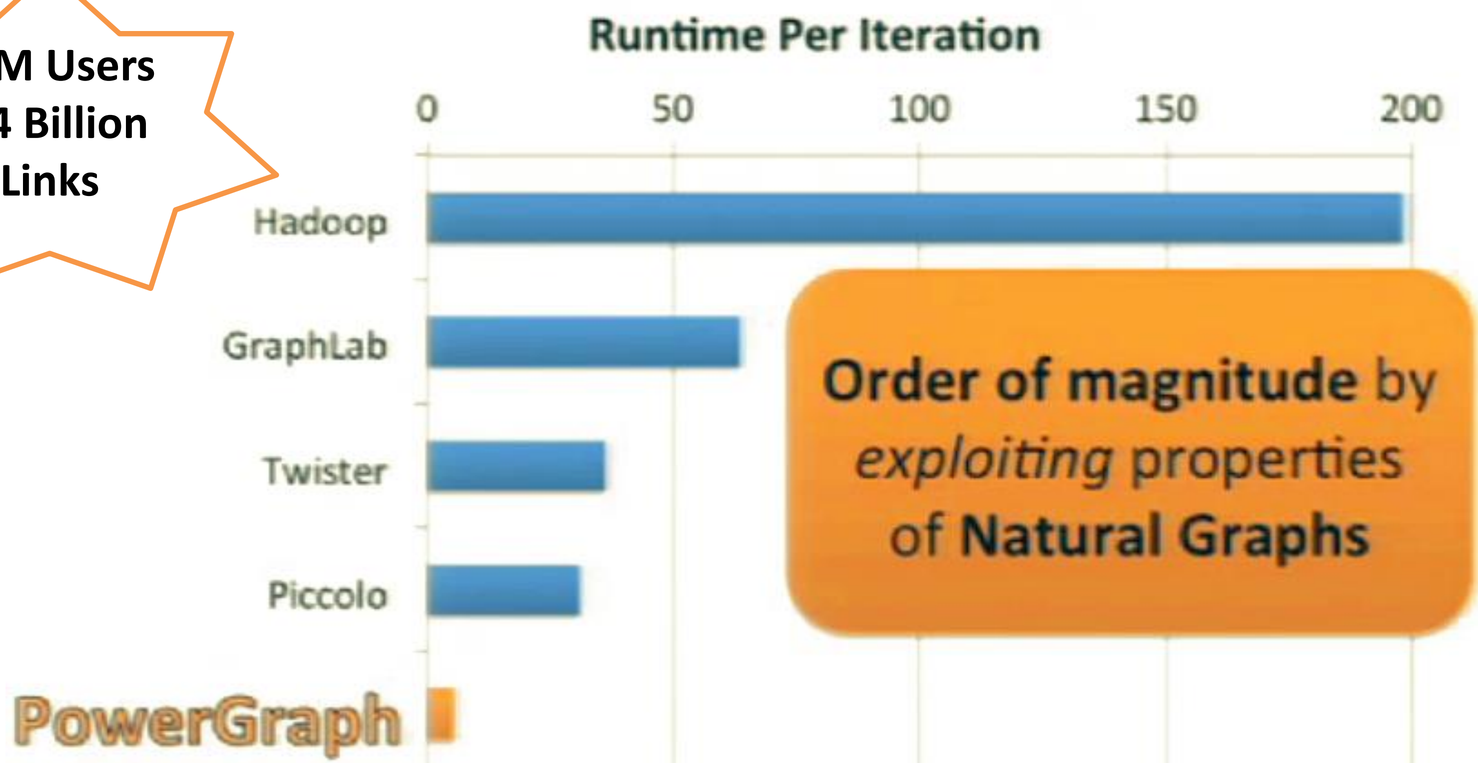
Graphs are essential for Data-Mining and Machine Learning

- They help us identify influential people and information
- Find communities
- Target ads and products
- Model complex data dependencies

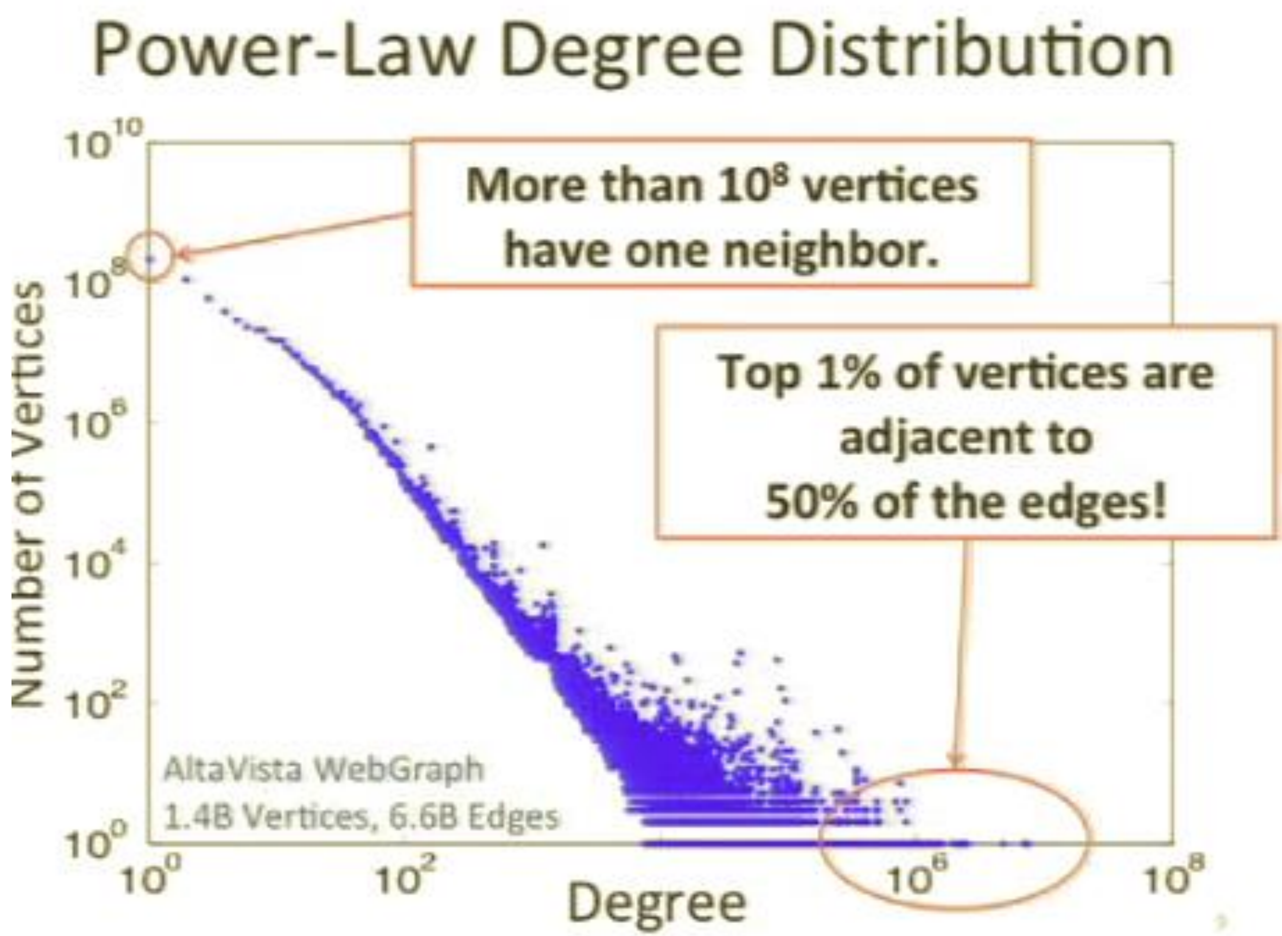
Problem: Existing **distributed** graph computation systems perform poorly on **Natural Graphs**

- Example: PageRank on Twitter Follower Graph

40M Users
1.4 Billion Links



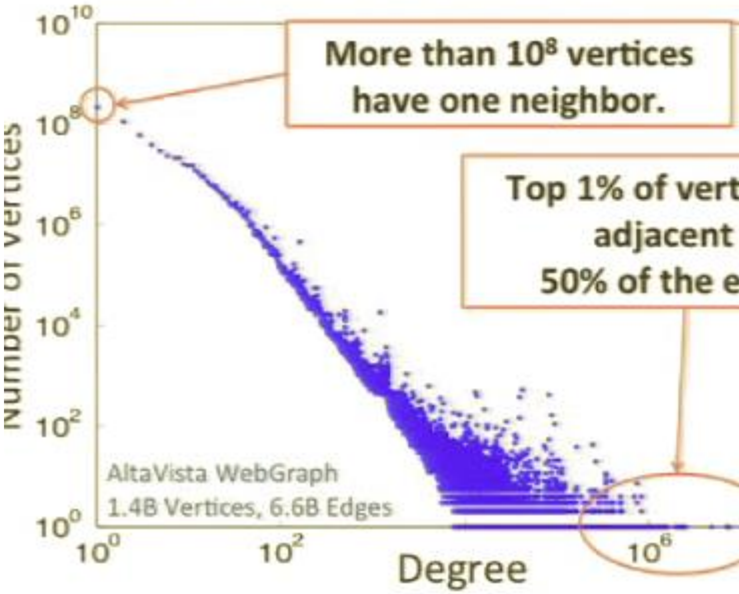
Properties of the Natural Graphs



Challenges of Natural Graphs

- Sparsity structure of natural graphs presents a unique challenge to efficient distributed graph-parallel computation
- Hallmark property: most vertices have relatively few neighbours while a few have many neighbours

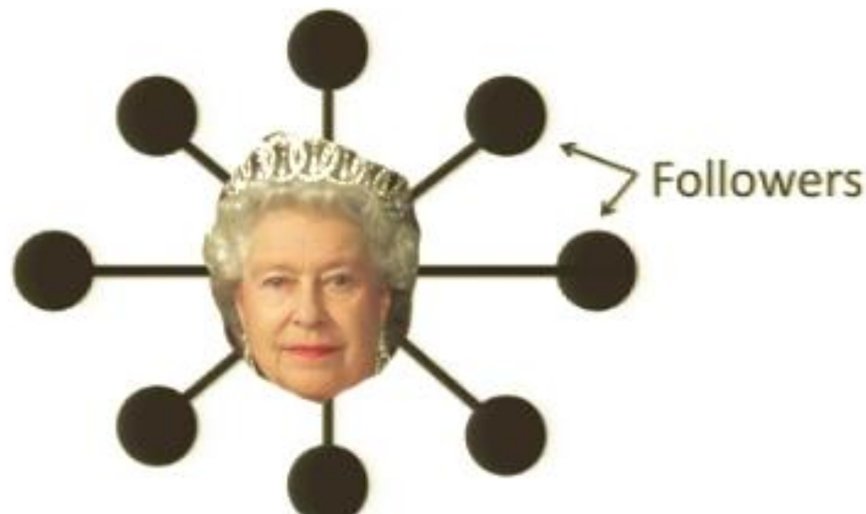
Power-Law Degree Distribution



High-degree Vertices

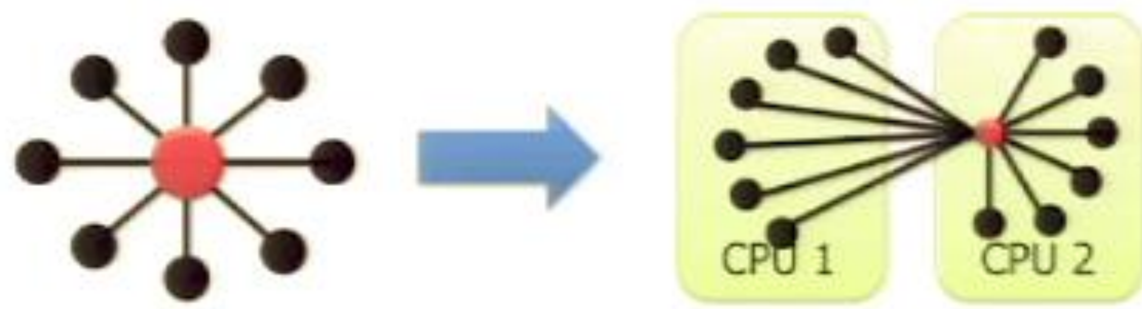
Power-Law Degree Distribution

"Star Like" Motif



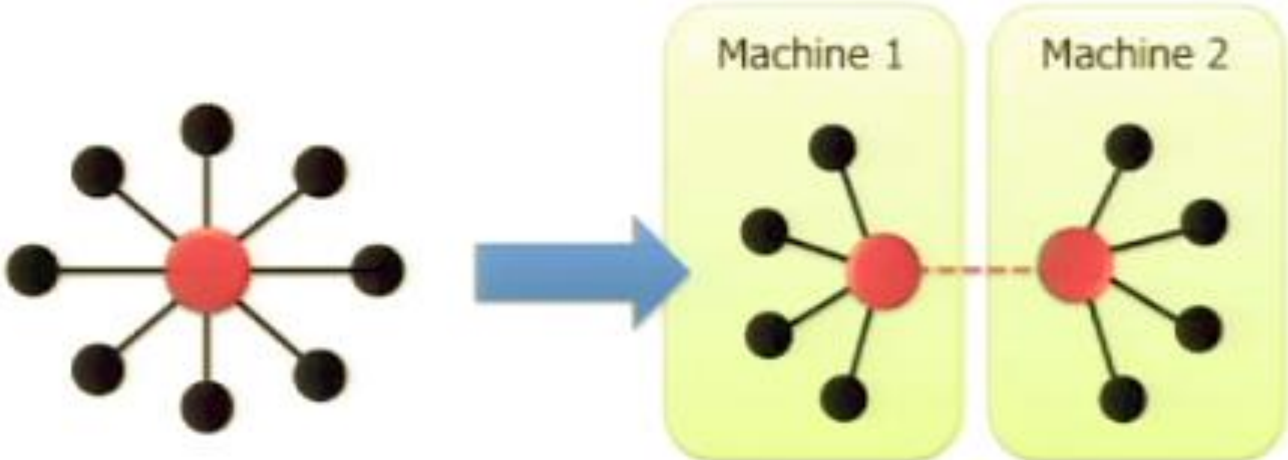
Properties of the Natural Graphs

- Difficult to Partition
  - Power-Law graphs do not have low-cost balanced cuts
  - Traditional graph-partitioning algorithms perform poorly on Power-Law Graphs



PowerGraph

- Split High-Degree vertices:



- Introduction of new abstraction:

♥ EQUIVALENCE on Split Vertices ♥

How do we program graph computation?

- Graph-Parallel Abstraction
  - A user-defined Vertex-program runs on each vertex
- Pregel
  - Graph constrains interact using **messages**
- GraphLab
  - Graph constrains interact through shared state
- Parallelism: run multiple vertex program at the same time

PageRank Algorithm

- Example: The popularity of a user depends of the popularity of her followers, which depends of the popularity of their followers

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

Rank of user i

Weighted sum of neighbors' ranks

- Update ranks in parallel
- Iterate process until convergence

Pregel PageRank

Receive all the messages

Update the rank of the vertex

```
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);
```

Send new messages to neighbors

GraphLab PageRank

Compute sum over neighbors

```
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;
```

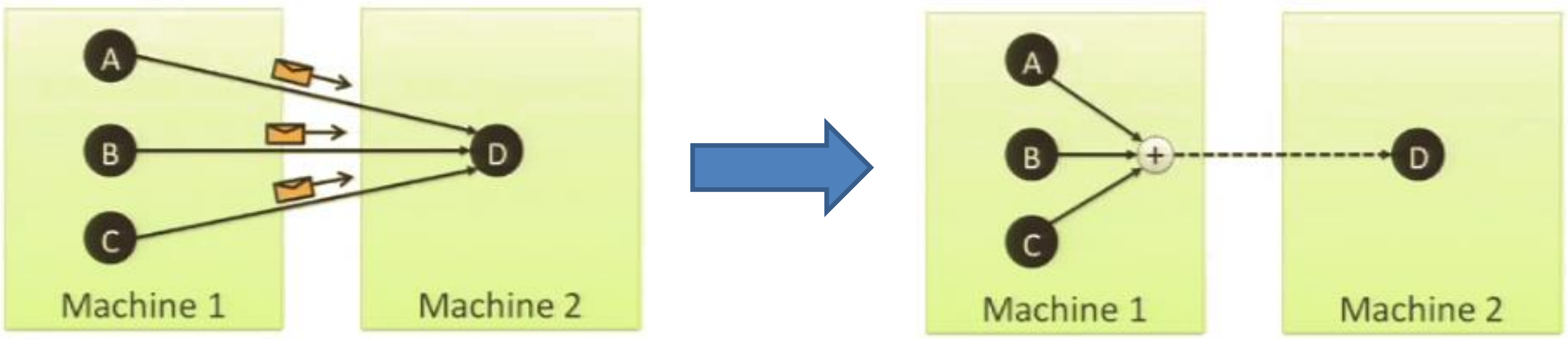
Update the rank of the vertex

Challenges of High-Degree Vertices

- A lot of iterating over our neighborhood
- Pregel: many messages
- GraphLab: Touches a large number of states

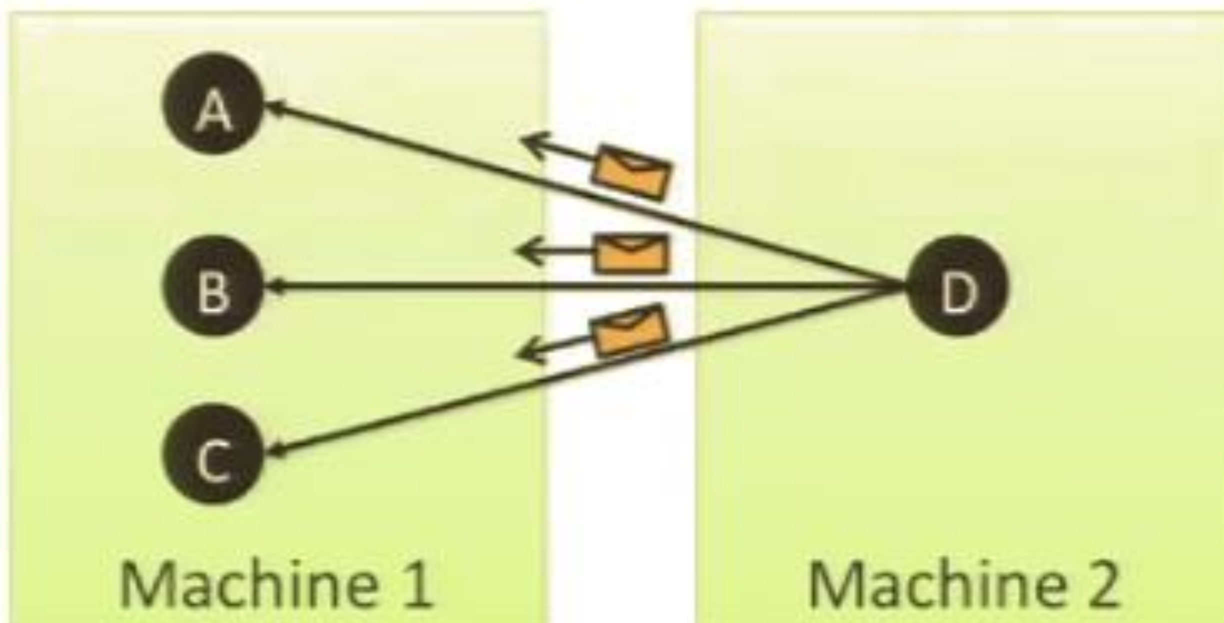
Pregel Message Combiners on Fan-IN

- User defines commutative associative message operations:

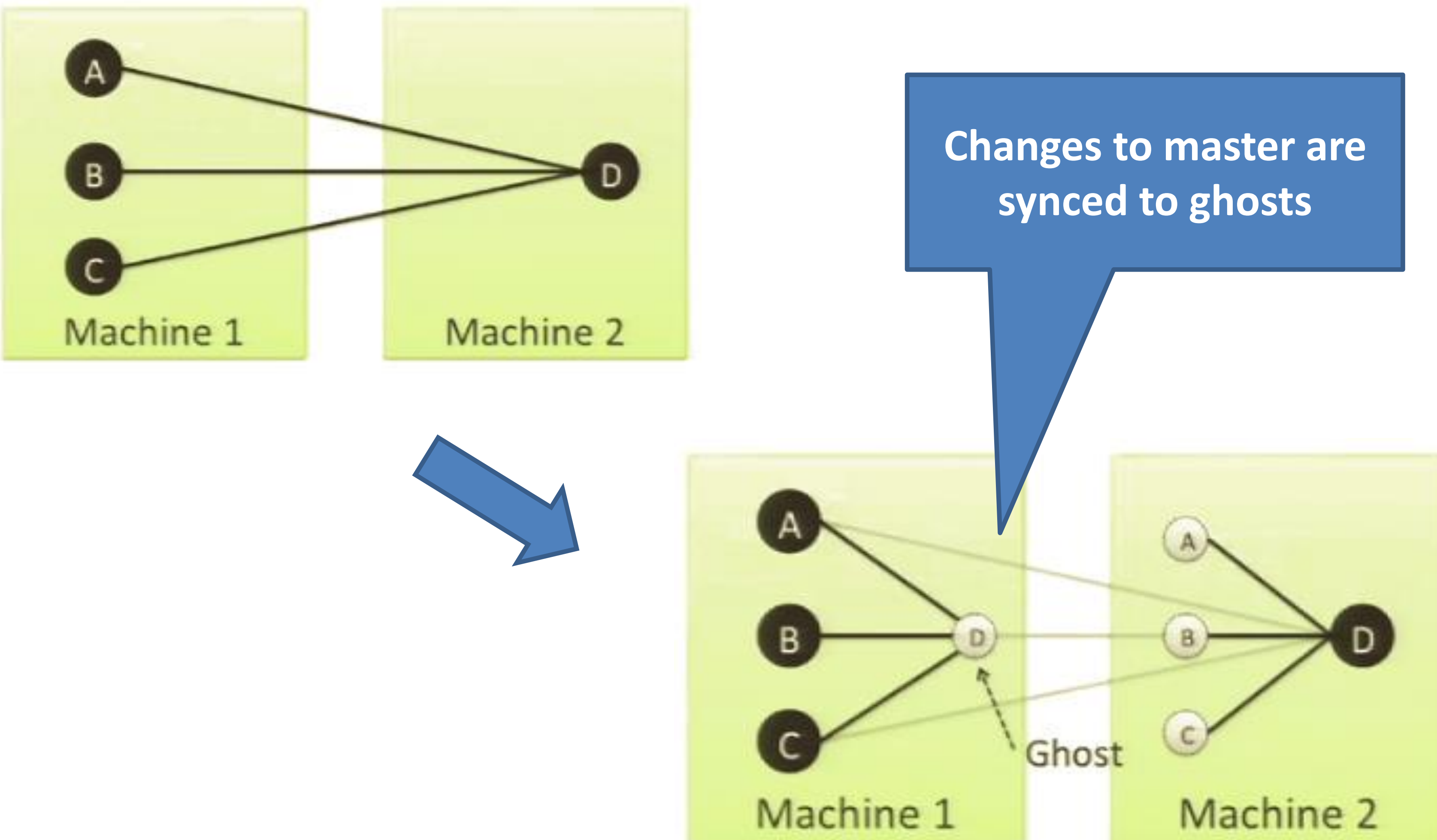


Pregel Struggles with Fan-OUT

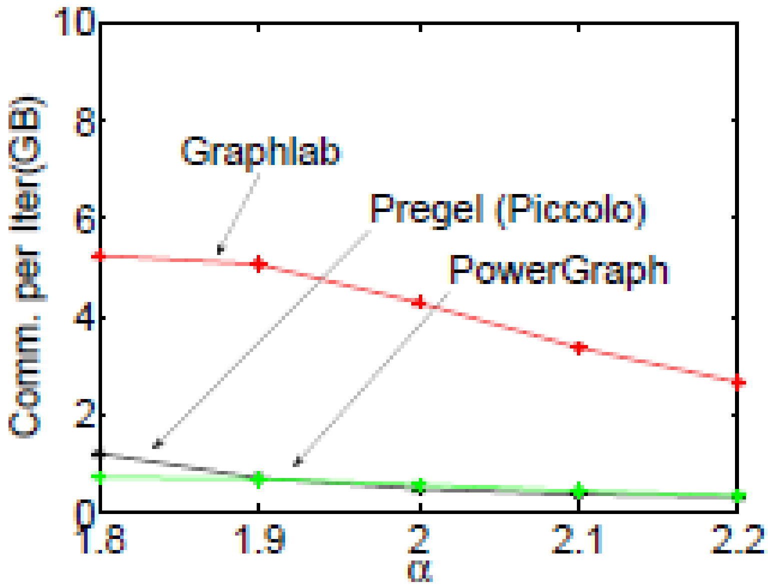
- Fan-OUT: Broadcast sends many copies of the same message to the same machine



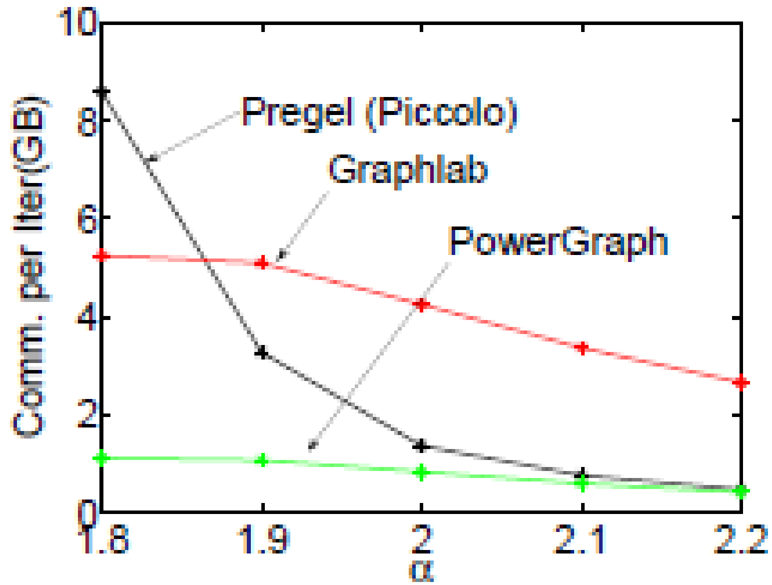
GraphLab Ghosting



Fan-IN and Fan-Out performance



(c) Power-law Fan-In Comm.



(d) Power-law Fan-Out Comm.

More high-degree vertices

Graph Partitioning

- Graph parallel abstractions rely on partitioning:
  - Minimize communication
  - Balance computation and storage
- Both GraphLab and Pregel resort to **random** partitioning on natural graphs
  - They randomly split vertices over machines

Theorem 5.1. *If vertices are randomly assigned to p machines then the expected fraction of edges cut is:*

$$\mathbb{E}\left[\frac{|Edges\ Cut|}{|E|}\right] = 1 - \frac{1}{p}. \tag{5.1}$$

10 Machines => 90% of edges cut
100 Machines => 99% of edges cut

In Summary

- GraphLab and Pregel are not well suited for computation of natural graphs
- Challenges of high-degree vertices
- Low quality partitioning

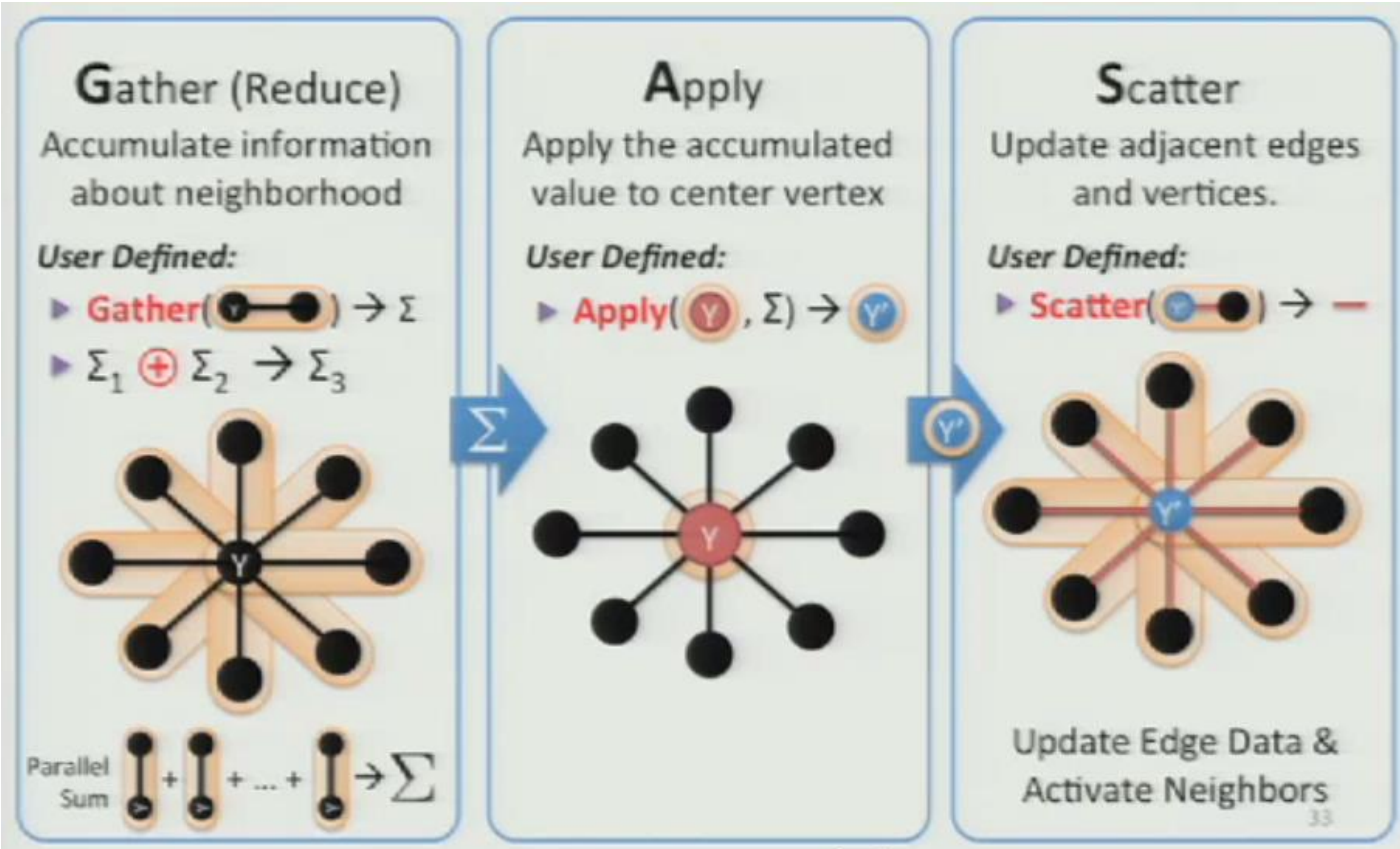
Main idea of PowerGraph

- GAS decomposition: distribute vertex – programs
  - Move computation to data
  - Parallelize high-degree vertices
- Represents three conceptual phases of a vertex-program:
  - Gather
  - Apply
  - Scatter

PowerGraph Abstraction

- Combines the best features from both Pregel and GraphLab
  - From GraphLab it borrows the data-graph and shared memory view of computation
  - From Pregel it borrows the commutative, associative gather concept

GAS Decomposition



PageRank in PowerGraph

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

PowerGraph_PageRank(i)

Gather(j → i) : return $w_{ji} * R[j]$

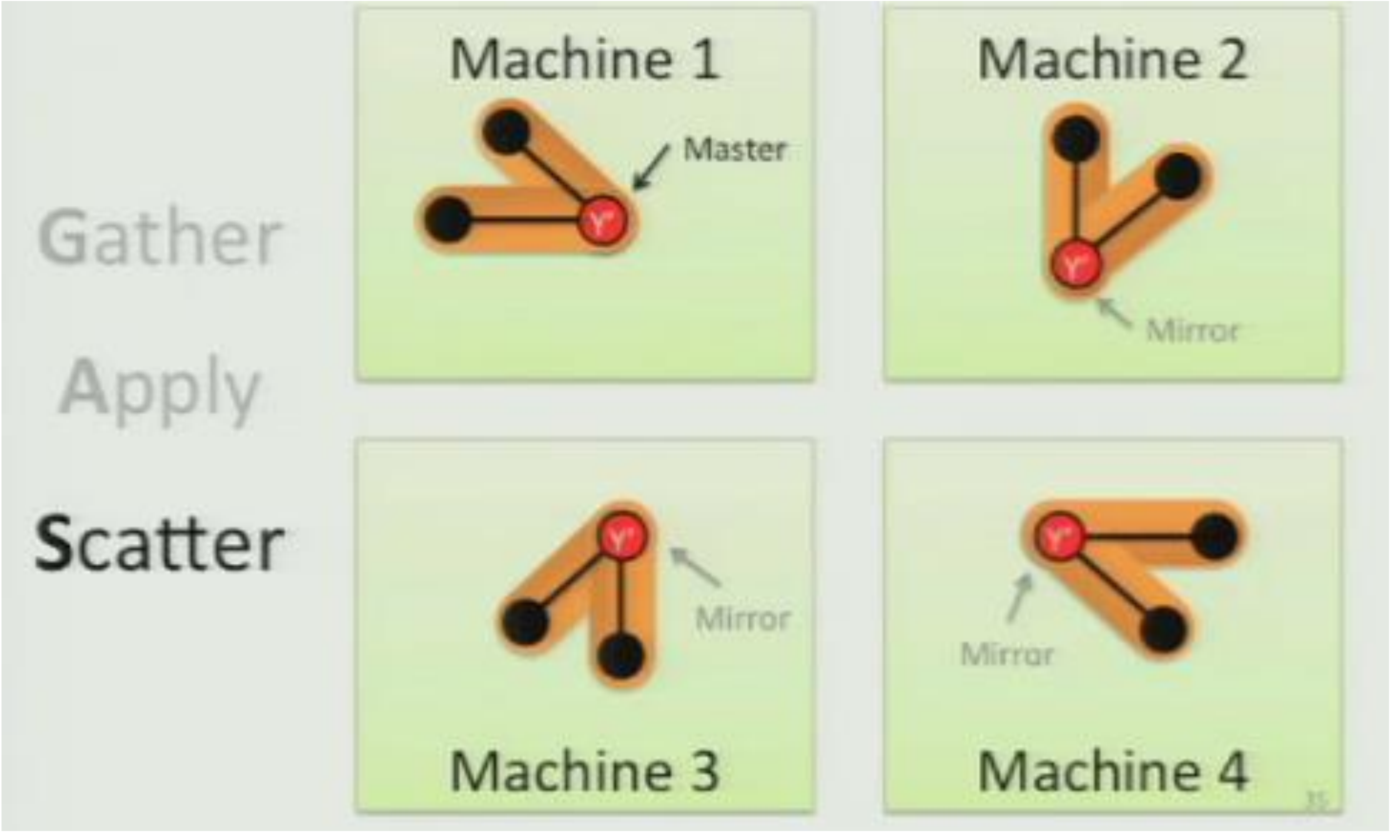
sum(a, b) : return a + b;

Apply(i, Σ) : $R[i] = 0.15 + \Sigma$

Scatter(i → j) :

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

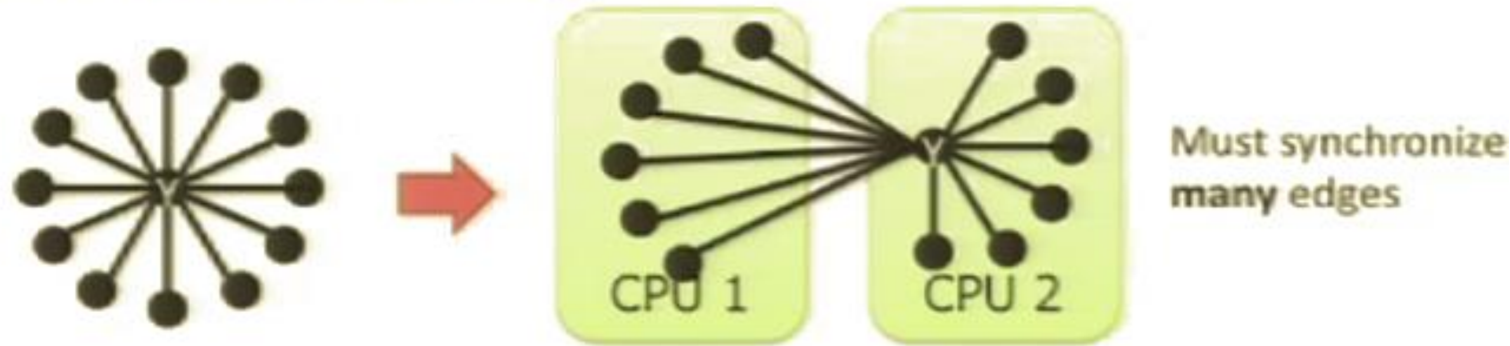
Example



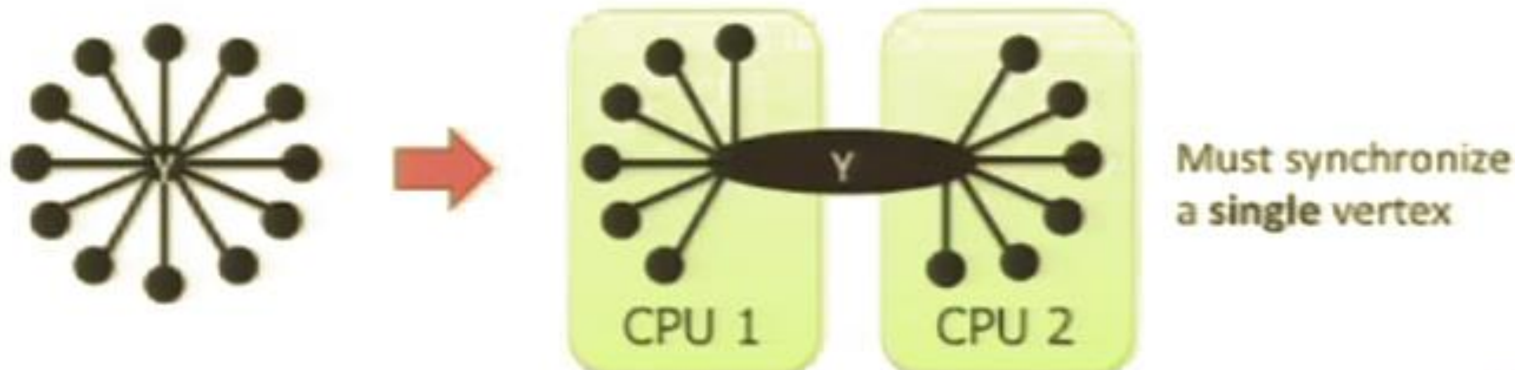
Gather
Apply
Scatter
Machine 1
Master
Machine 2
Mirror
Mirror
Machine 3
Mirror
Machine 4

New Approach to Partitioning

- Rather than cut edges:



- we cut vertices:

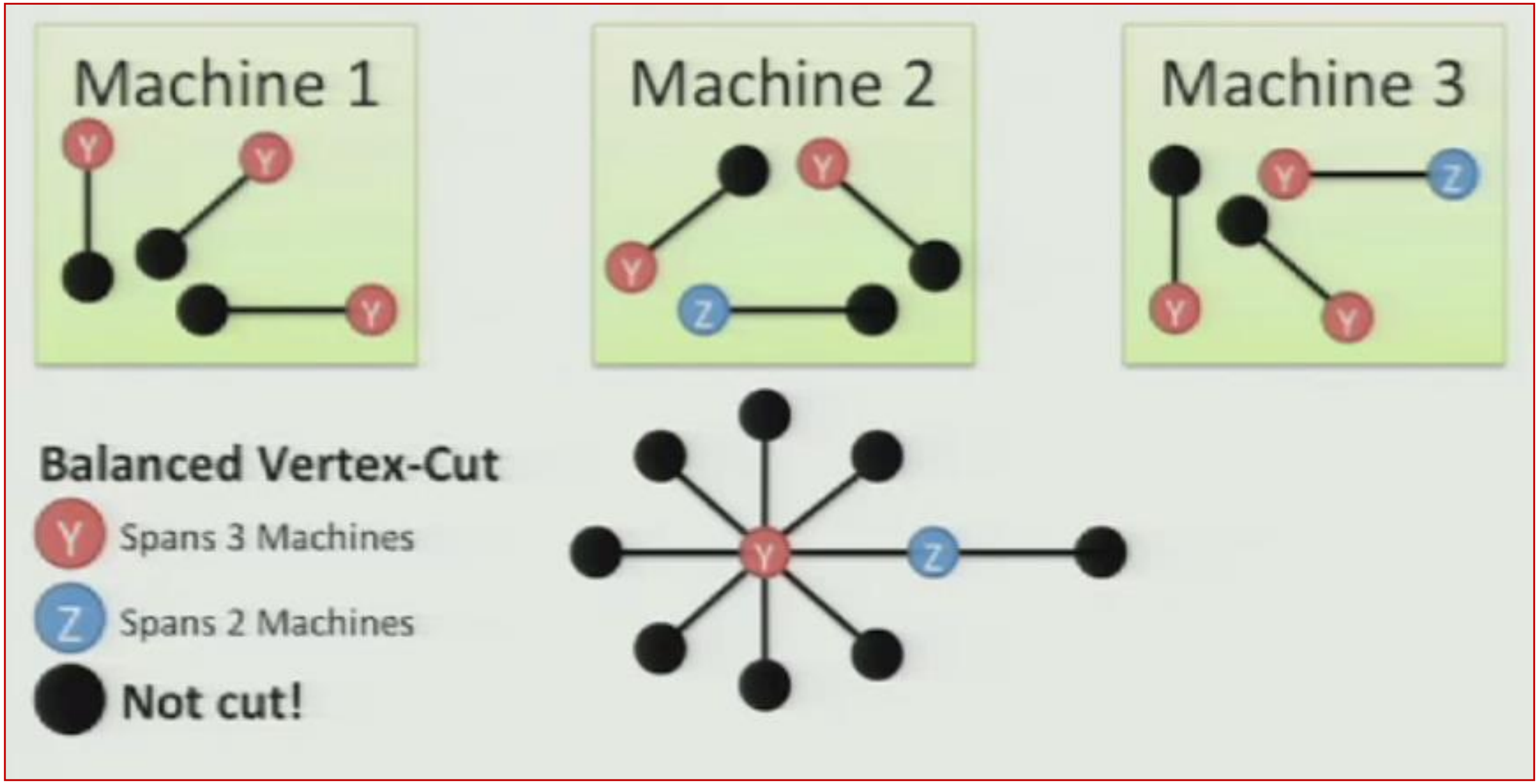


New Theorem: For any edge cut we can construct a vertex cut which requires strictly less communication and storage.

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
- Three distributed approaches:
  - Random Edge Placement
  - Coordinated Greedy Edge Placement
  - Oblivious Greedy Edge Placement

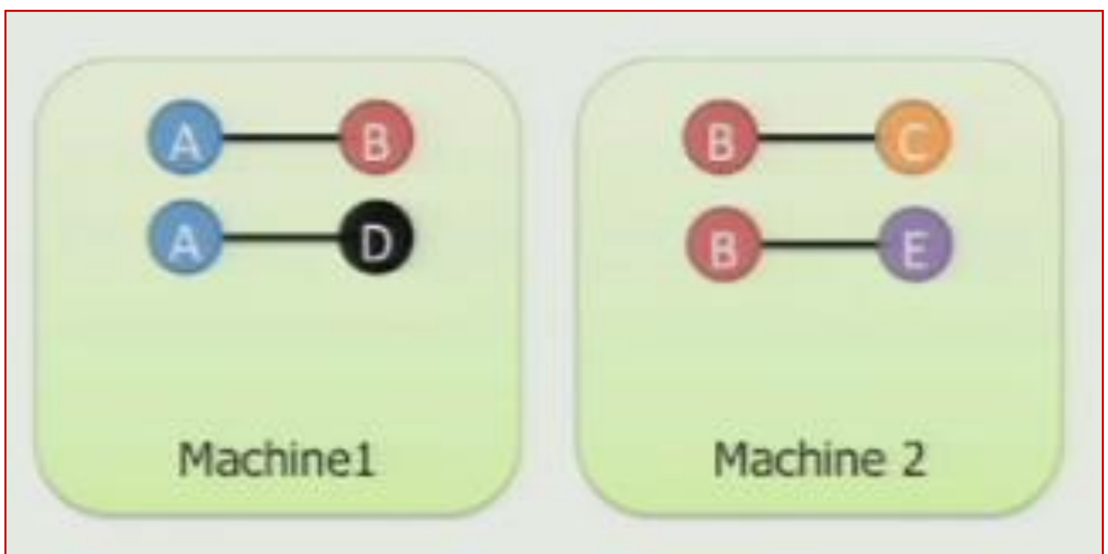
Random Edge Placement



- Uniquely assigned to one machine
- Balanced cut

Greedy Vertex-Cuts

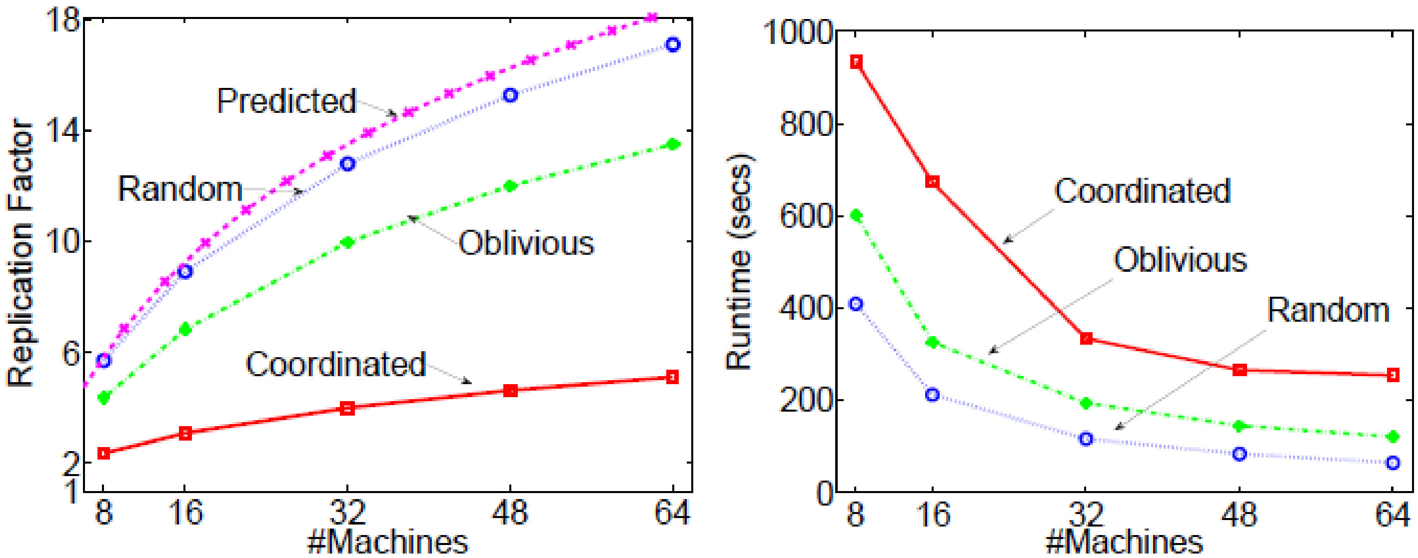
- Place edges on machines which already have the vertices in that edge.
- If more machines have the same vertex, place edge on less loaded machine



Greedy Vertex-Cuts

- Greedy minimizes the expected number of machines spanned
- Coordinated
  - Requires coordination to place each edge
  - Slower: higher quality cuts
- Oblivious
  - Approx. greedy objective without coordination
  - Faster: lower quality cuts

Partitioning Performance



(a) Replication Factor (Twitter) (b) Ingress time (Twitter)

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.

Partitioning Performance

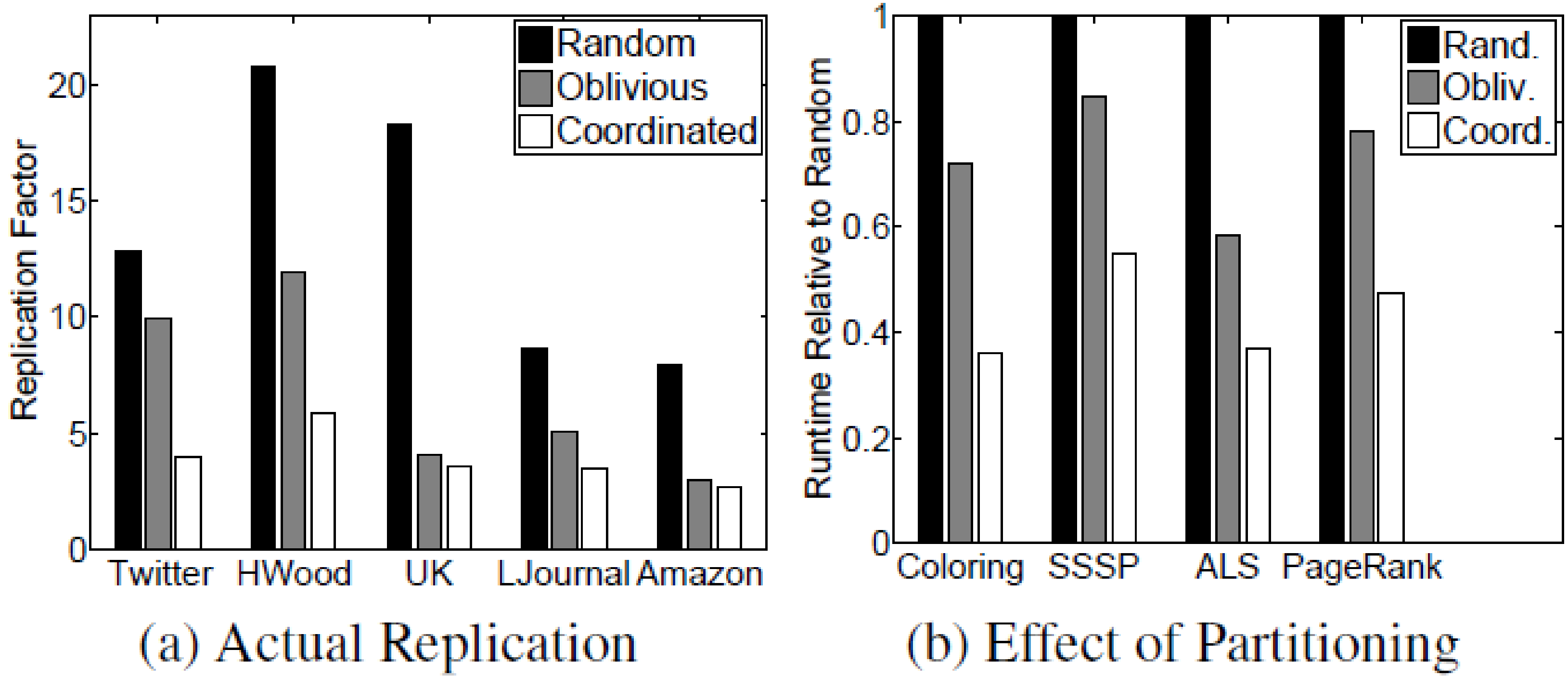


Figure 7: **(a)** The actual replication factor on 32 machines. **(b)** The effect of partitioning on runtime.

Other Features

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

Implementation and Evaluation

- Technical details:
  - Experiments were performed on a 64 node cluster of Amazon EC2 Linux instances
  - Each instance has two quad core Intel Xeon X5570 processor with 23GB RAM and is connected via 10 GigE Ethernet
  - PowerGraph was written in C++ and compiled with GCC 4.5

System Design

- Built on top of
  - MPI/TCP-IP
  - Pthreads
  - HDFS
- Uses HDFS for Graph input and output
- Fault-tolerance is achieved by check-poining
  - Snapshot time <5 sec. for twitter network

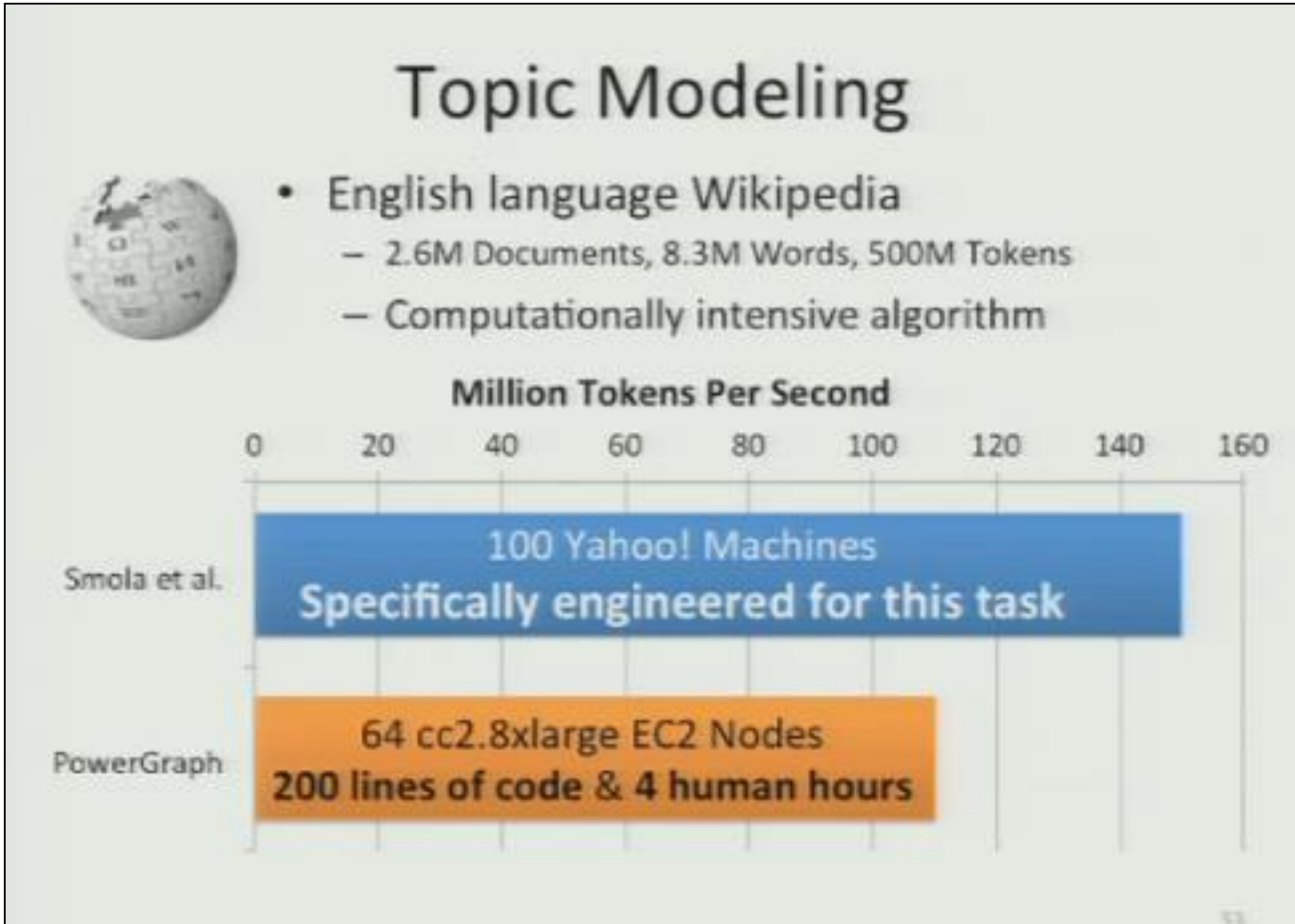
Implemented Algorithms

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

Results


Topic Modeling
English language Wikipedia
2.6M Documents, 8.3M Words, 500M Tokens
Computationally intensive algorithm
Million Tokens Per Second
0
20
40
60
80
100
120
140
160
Smola et al.
100 Yahoo! Machines
Specifically engineered for this task
PowerGraph
64 cc2.8xlarge EC2 Nodes
200 lines of code & 4 human hours

More results

Thank you for your attention!

http://graphlab.org

Some of the slides were taken from the talk by J. E. Gonzalez, available on the website:
https://www.usenix.org/conference/osdi12/technical-sessions/presentation/gonzalez