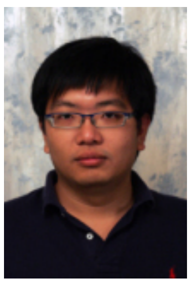
Big Learning with **Graphs**

Joseph Gonzalez

jegonzal@cs.cmu.edu

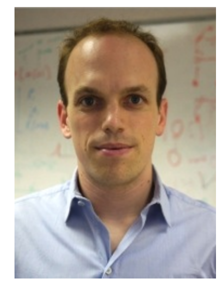


Yucheng
Low

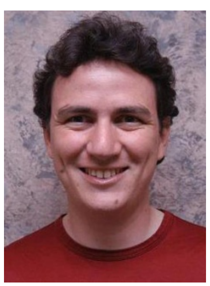
Aapo
Kyrola

Haijie
Gu

Danny
Bickson



Arthur
Gretto
n

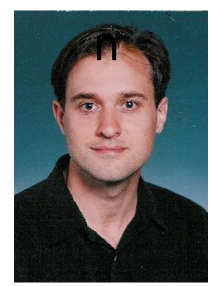


Carlos
Guestrin

Alex
Smola

Joe
Hellerstein

David
O'Hallaron



Guy
Blelloch

The Age of Big Data

28 Million
Wikipedia Pages

6 Billion
Flickr Photos

900 Million
Facebook Users

72 Hours a Minute
YouTube

The New York Times
SundayReview

WORLD U.S. N.Y. / REGION BUSINESS TEC

NEWS ANALYSIS
The Age of Big Data
By STEVE LOHR
Published: February 11, 2012

"…growing at 50 percent a year…"

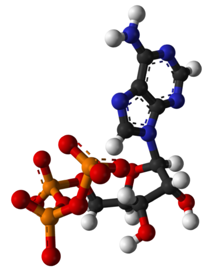
"… data a new class of economic asset, like currency or gold."

Big Data

⬇

Big Graphs

Social Media **Science** **Advertising** **Web**



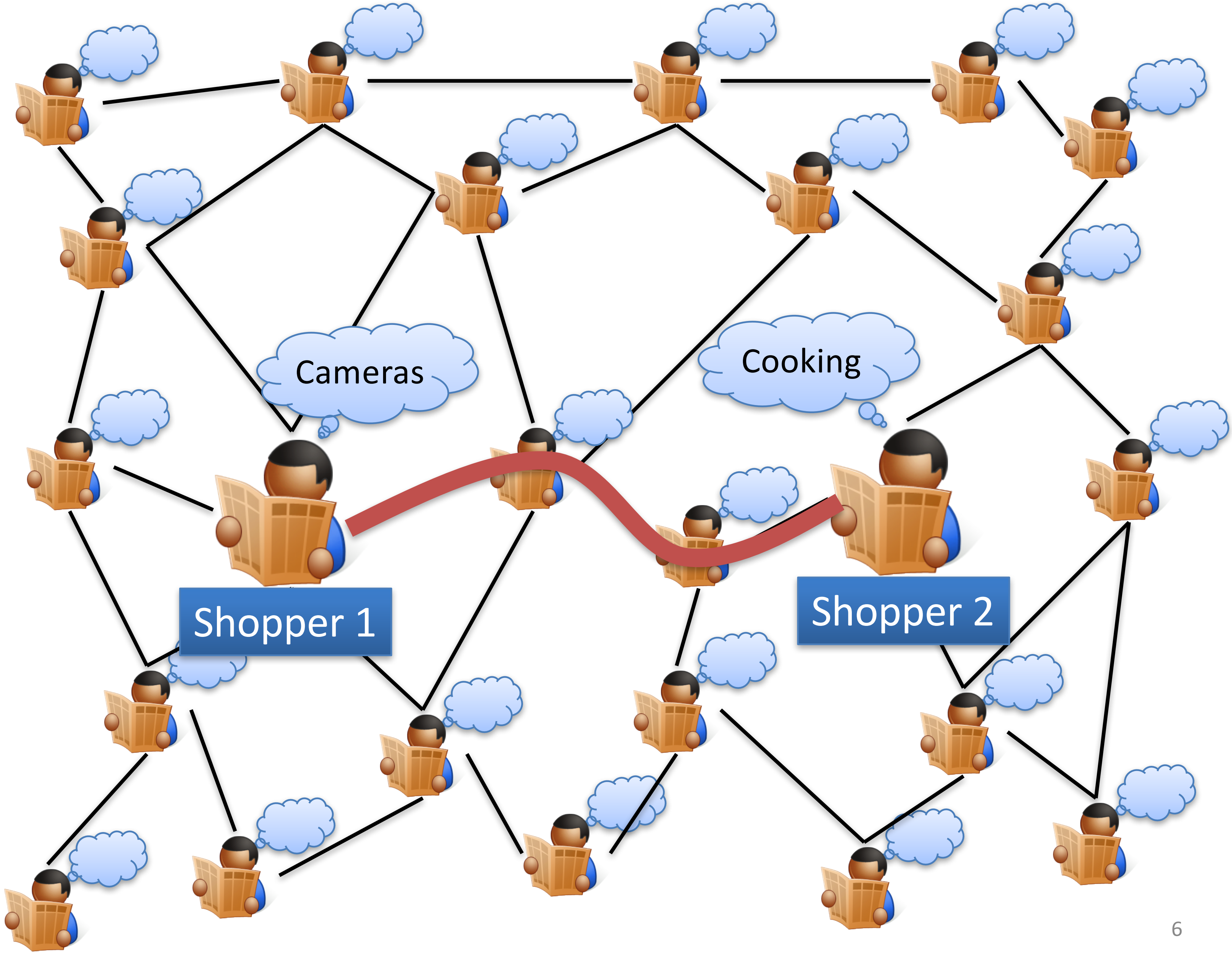
- **Graphs** *encode* **relationships** between:

People Products Ideas

Facts Interests

- **Big**: **billions** of **vertices** and **edges** and rich metadata

Big graphs *present*
exciting new ***opportunities*** *…*


Cameras
Cooking
Shopper 1
Shopper 2

Big-Graphs are Essential to **Data-Mining** and **Machine Learning**

- Identify influential people and information
- Find communities
- Target ads and products
- Model complex data dependencies

Big Learning with **Graphs**

Understanding and *using*
large-scale **structured** data.

Examples

PageRank (Centrality Measures)

- Iterate:

$$R[i] = \alpha + (1 - \alpha) \sum_{(j,i) \in E} \frac{1}{L[j]} R[j]$$

- Where:
  - α is the random reset probability
  - $L[j]$ is the number of links on page j

$$R[5] = \alpha + (1 - \alpha) \left(\frac{1}{3} R[1] + \frac{1}{1} R[4] \right)$$

http://ilpubs.stanford.edu:8090/422/1/1999-66.pdf

Label Propagation (Structured Prediction)

- Social Arithmetic:

  50% What I list on my profile
  40% Sue Ann Likes
  \+ 10% Carlos Like

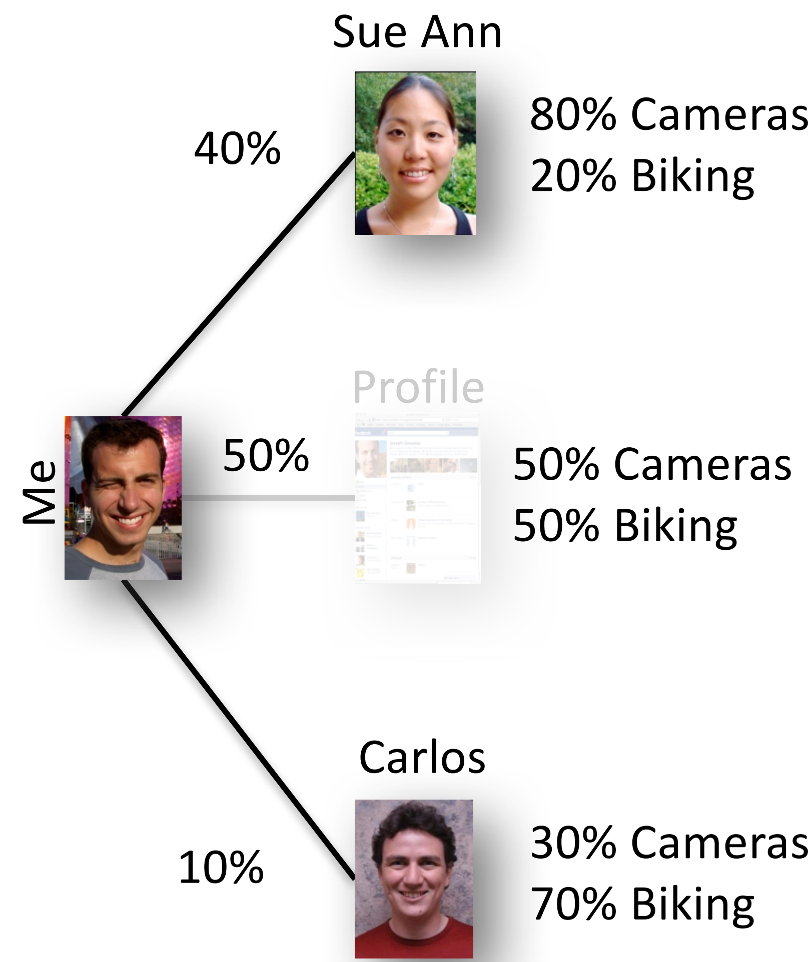
  I Like: 60% Cameras, 40% Biking

- Recurrence Algorithm:

$$Likes[i] = \sum_{j \in Friends[i]} W_{ij} \times Likes[j]$$

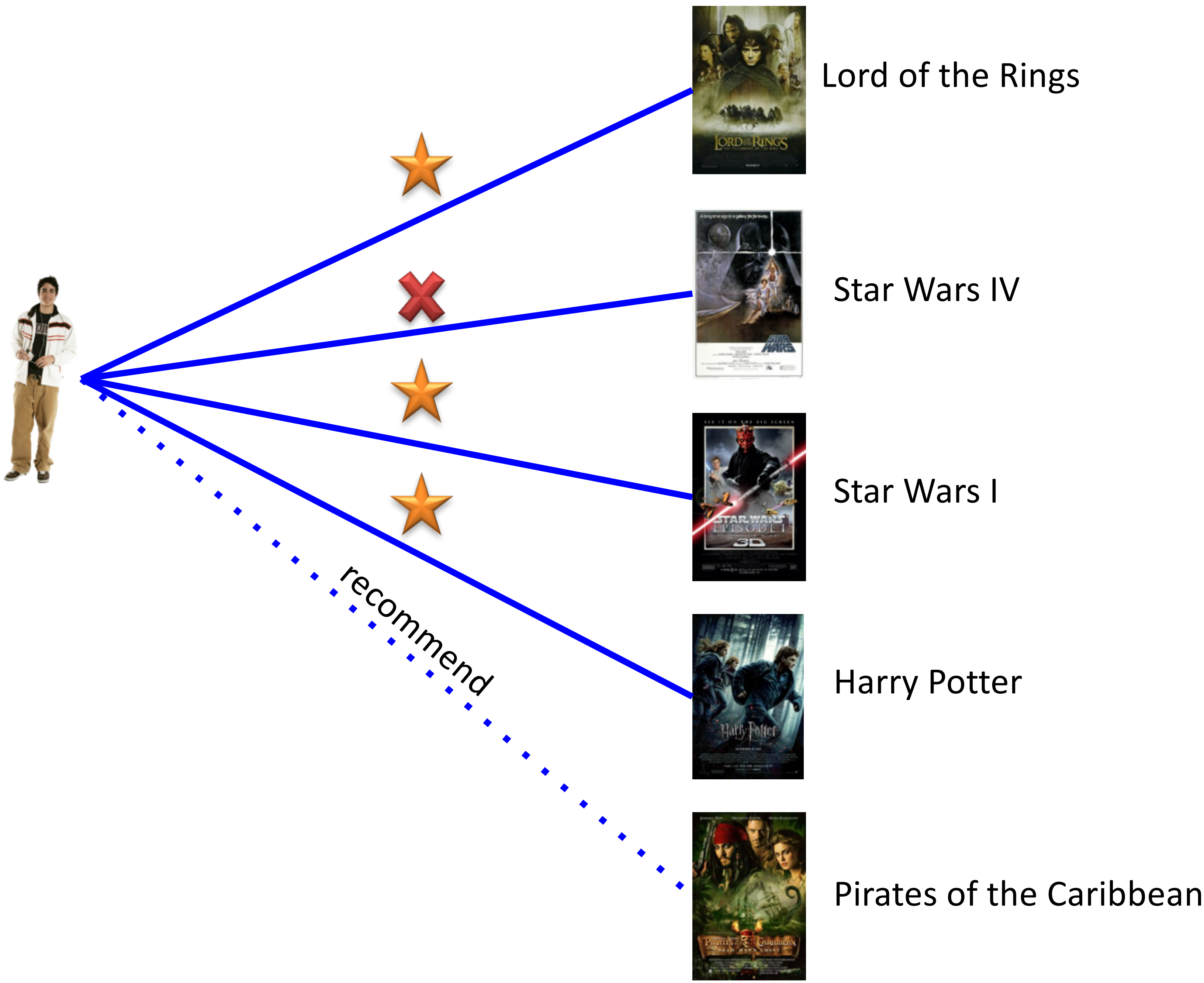
  – iterate until convergence

- Parallelism:
  – Compute all *Likes[i]* in parallel

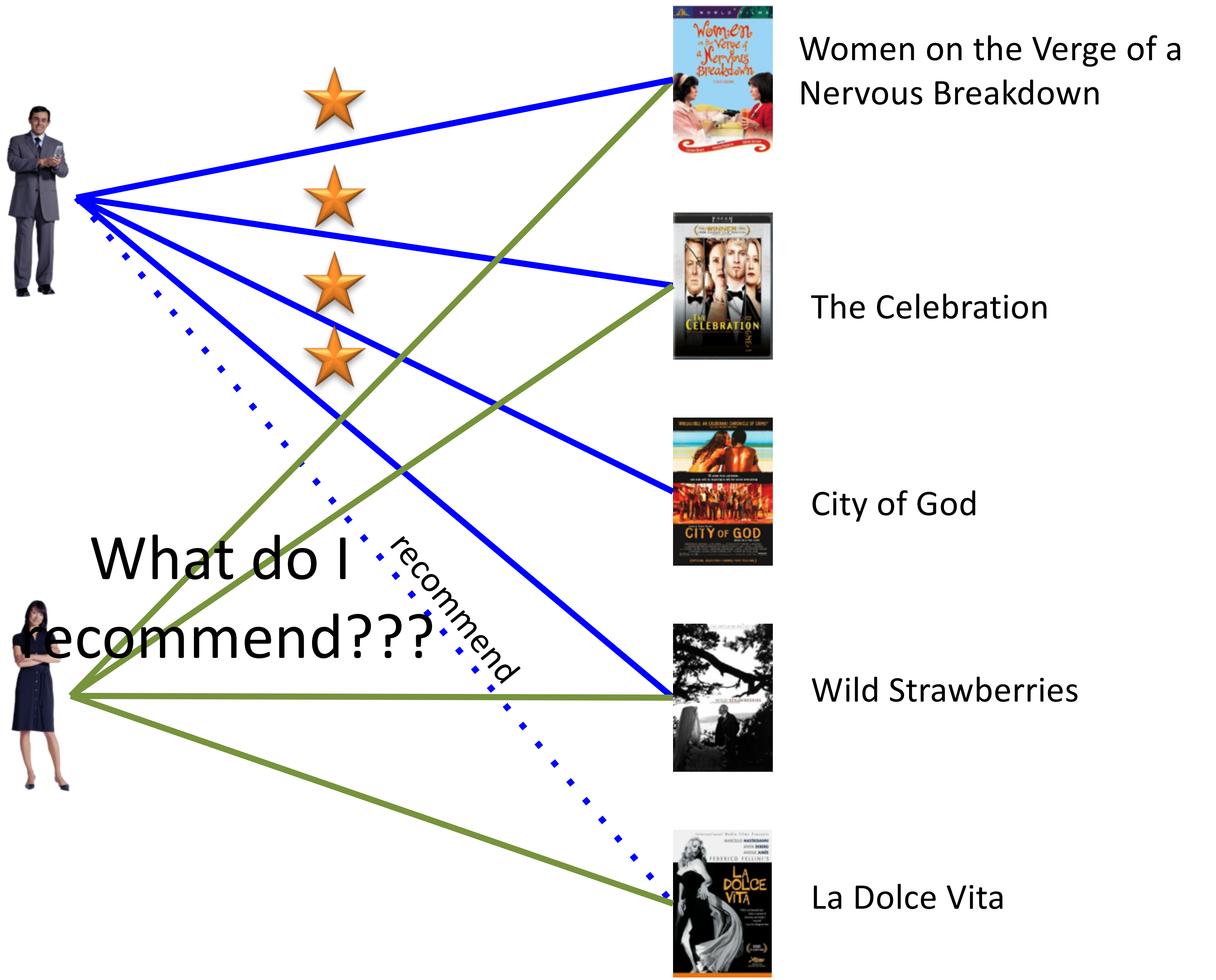


http://www.cs.cmu.edu/~zhuxj/pub/CMU-CALD-02-107.pdf

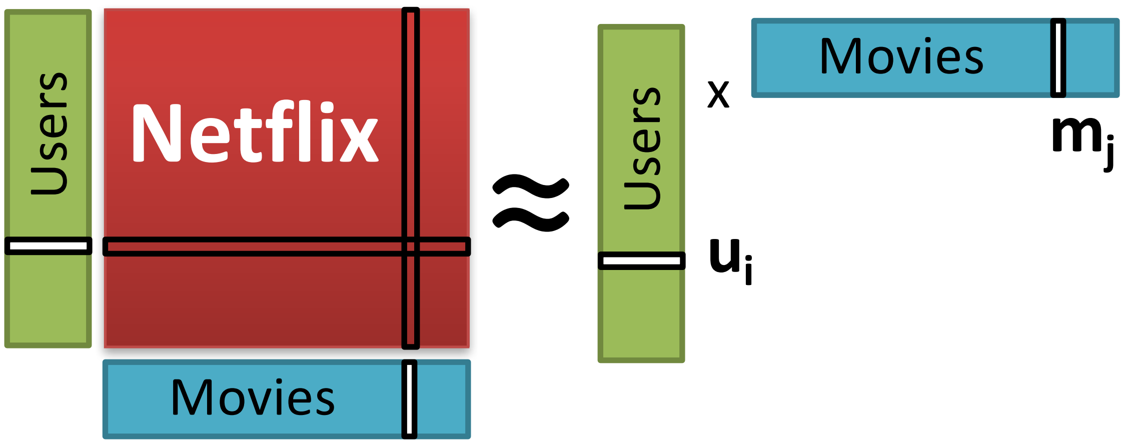
Collaborative Filtering: Independent Case

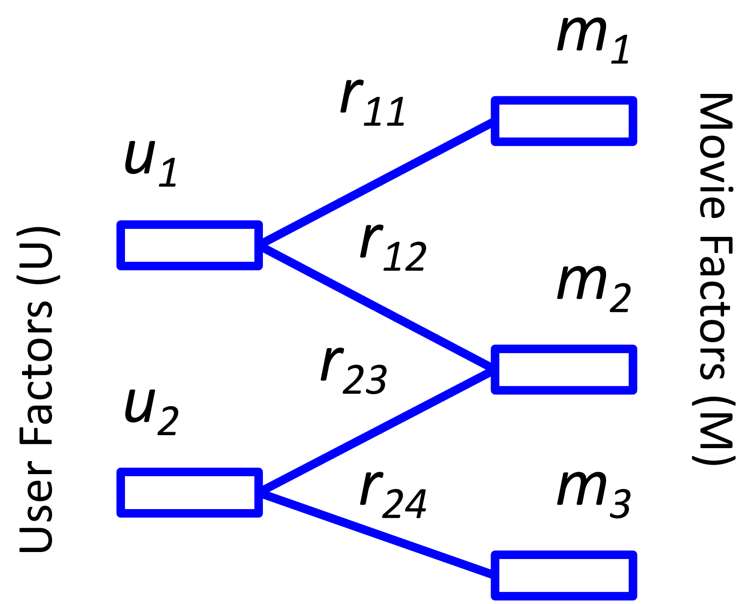


Collaborative Filtering: Exploiting Dependencies



Matrix Factorization
Alternating Least Squares (ALS)





Iterate:

$$u_i = \arg\min_{w} \sum_{j \in N[i]} (r_{ij} - m_j \cdot w)^2$$

$$m_j = \arg\min_{w} \sum_{i \in N[j]} (r_{ij} - u_i \cdot w)^2$$

http://dl.acm.org/citation.cfm?id=1424269

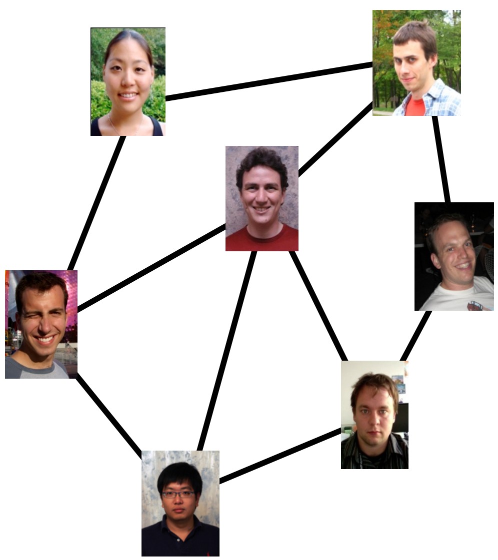
Many More Algorithms

- **Collaborative Filtering**
  - Alternating Least Squares
  - Stochastic Gradient Descent
  - Tensor Factorization
  - SVD
- **Structured Prediction**
  - Loopy Belief Propagation
  - Max-Product Linear Programs
  - Gibbs Sampling
- **Semi-supervised ML**
  - Graph SSL
  - CoEM
- **Graph Analytics**
  - PageRank
  - Single Source Shortest Path
  - Triangle-Counting
  - Graph Coloring
  - K-core Decomposition
  - Personalized PageRank
- **Classification**
  - Neural Networks
  - Lasso

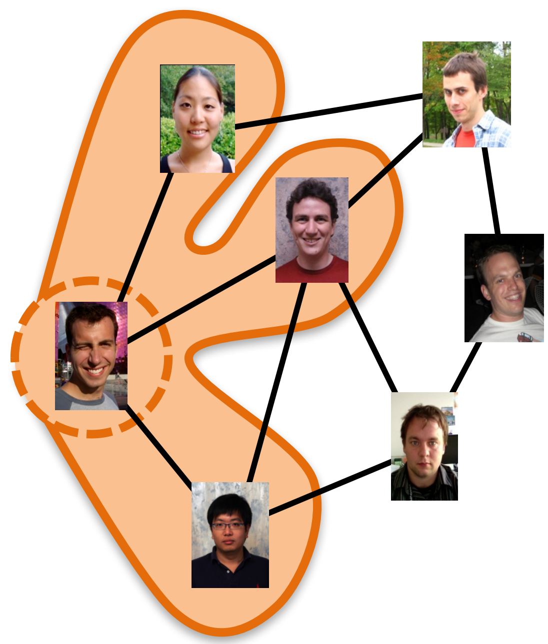
…

Graph Parallel Algorithms

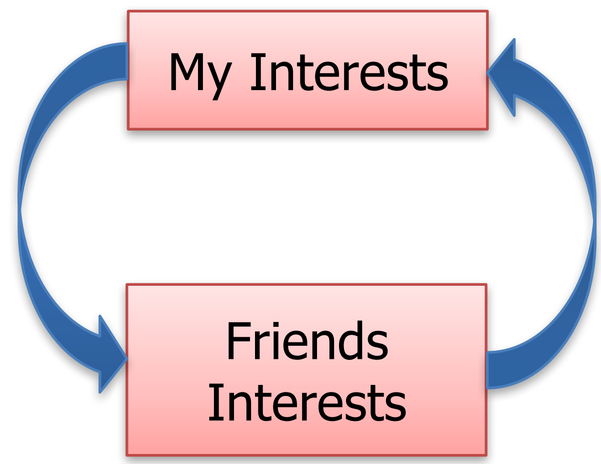
Dependency **Graph**



Local Updates



Iterative Computation



What is the right tool for Graph-Parallel ML

Data-Parallel ↔ Graph-Parallel

Map Reduce

Feature Extraction

Cross Validation

Computing Sufficient Statistics

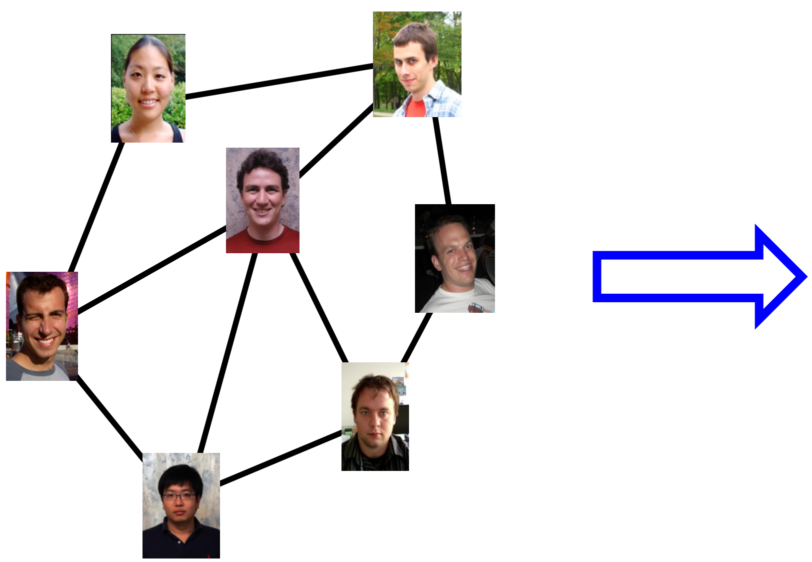
Map Reduce?

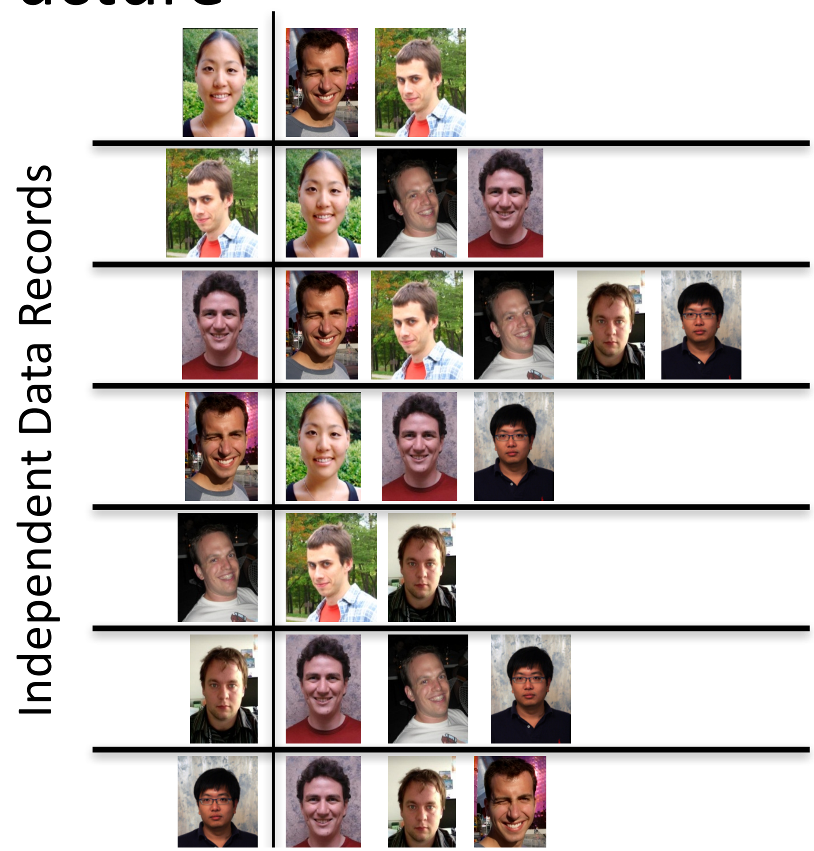
Collaborative Filtering
Graph Analytics
Structured Prediction
Clustering

Why not use *Map-Reduce* for **Graph Parallel** algorithms?

Data Dependencies are Difficult

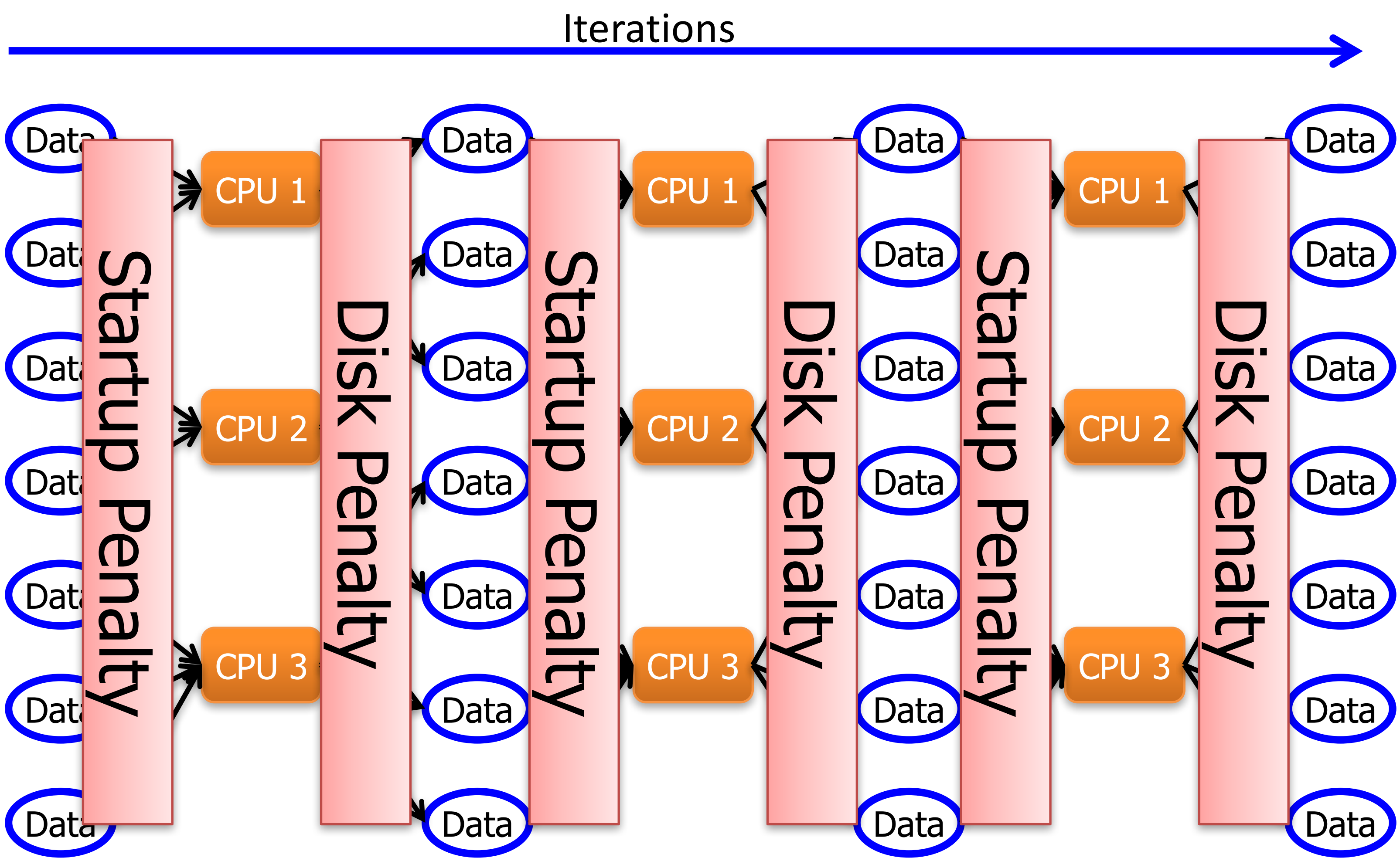
- Difficult to express dependent data in Map Reduce
  - Substantial data transformations
  - User managed graph structure
  - Costly data replication





Iterative Computation is Difficult

- System is not optimized for iteration:



Map-Reduce for Data-Parallel ML

- Excellent for large data-parallel tasks!

Data-Parallel ⟷ Graph-Parallel

Map Reduce

Feature Extraction

Cross Validation

Computing Sufficient Statistics

MPI/Pthreads

Collaborative Filtering

Graph Analytics

Structured Prediction

Clustering

We could use ….

Threads, Locks, & Messages

"low level parallel primitives"

Threads, Locks, and Messages

- Graduate students **repeatedly** solve the same parallel design challenges:
  - Implement and debug complex parallel system
  - Tune for a specific parallel platform
  - Six months later the conference paper contains:

"We implemented ______ in parallel."

- The resulting code:
  - is difficult to maintain
  - is difficult to extend
    - couples learning model to parallel implementation

Addressing Graph-Parallel ML

- We need alternatives to Map-Reduce

Map Reduce

Feature Extraction

Cross Validation

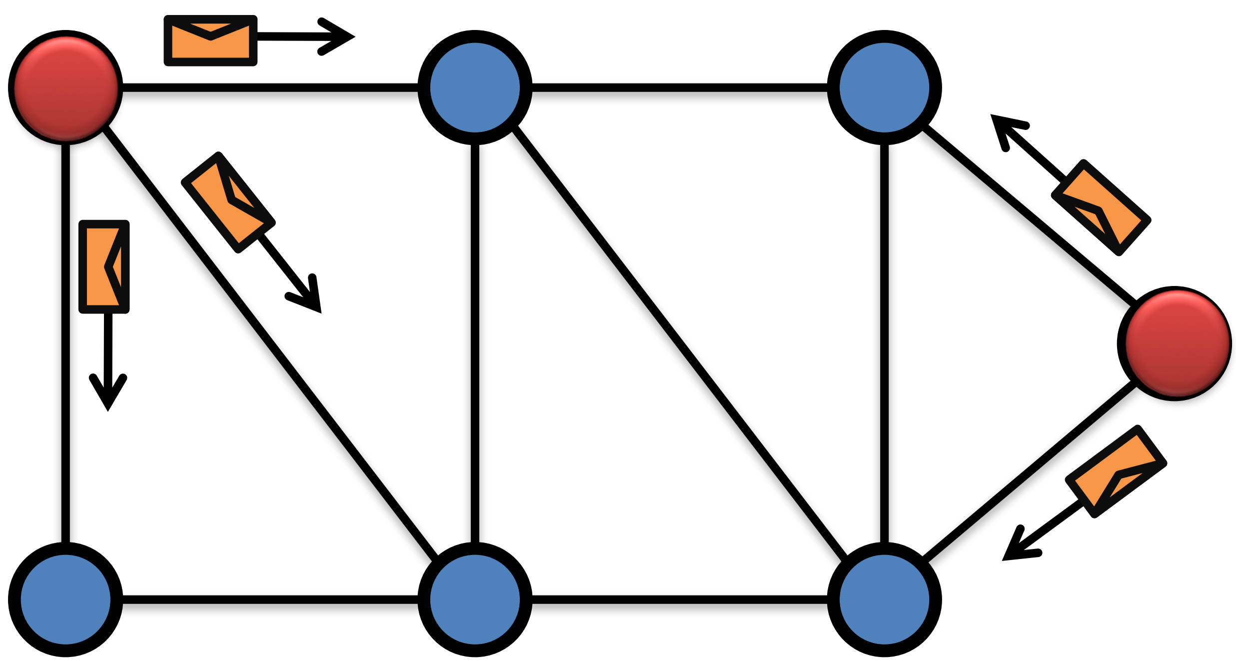
Computing Sufficient Statistics

Pregel

Collaborative Filtering
Graph Analytics
Structured Prediction
Clustering

Pregel Abstraction

- User-defined **Vertex-Program** on each vertex
- Vertex-programs interact along edges in the **Graph**
  - Programs interact through Messages
- **Parallelism**: Multiple vertex programs run simultaneously



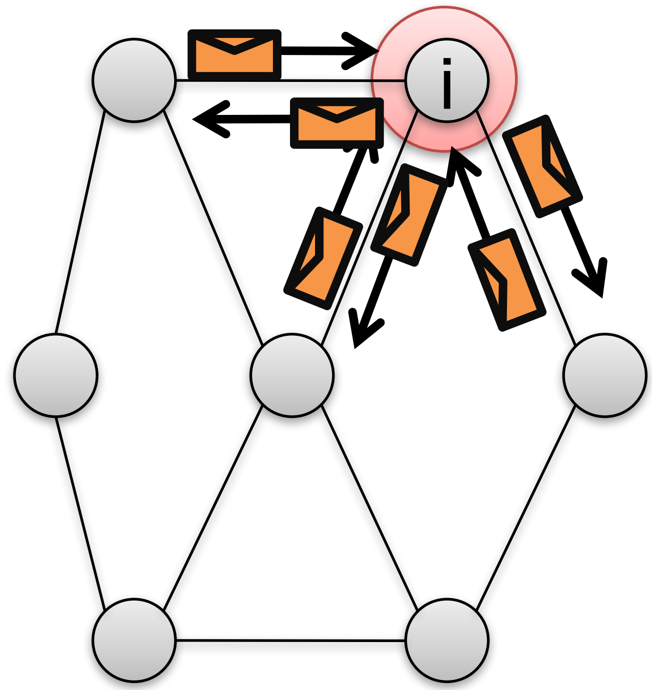
The Pregel Abstraction

Vertex-Programs communicate through messages

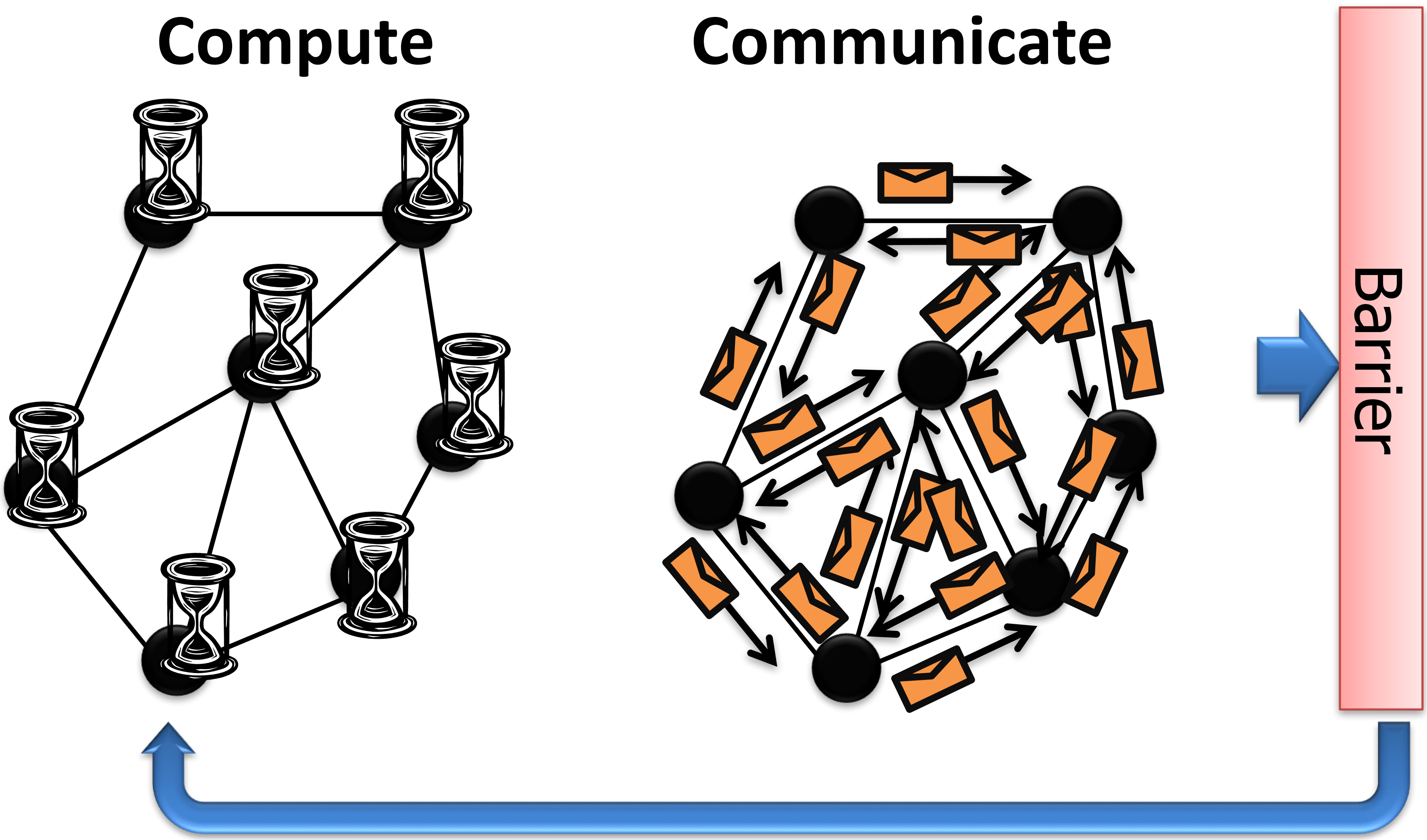
```
void Pregel_PageRank(i, msgs) :
  // Receive all the messages
  float total = sum(m in msgs)

  // Update the rank of this vertex
  R[i] = β + (1-β)*total

  // Send Messages to neighbors
  foreach(j in out_neighbors[i]) :
    SendMsg(nbr, R[i] * w_ij)
```



Pregel is Bulk Synchronous Parallel



http://dl.acm.org/citation.cfm?id=1807184

Open Source Implementations

- Giraph: http://incubator.apache.org/giraph/
- Golden Orb: http://goldenorbos.org/
- Stanford GPS: http://infolab.stanford.edu/gps/

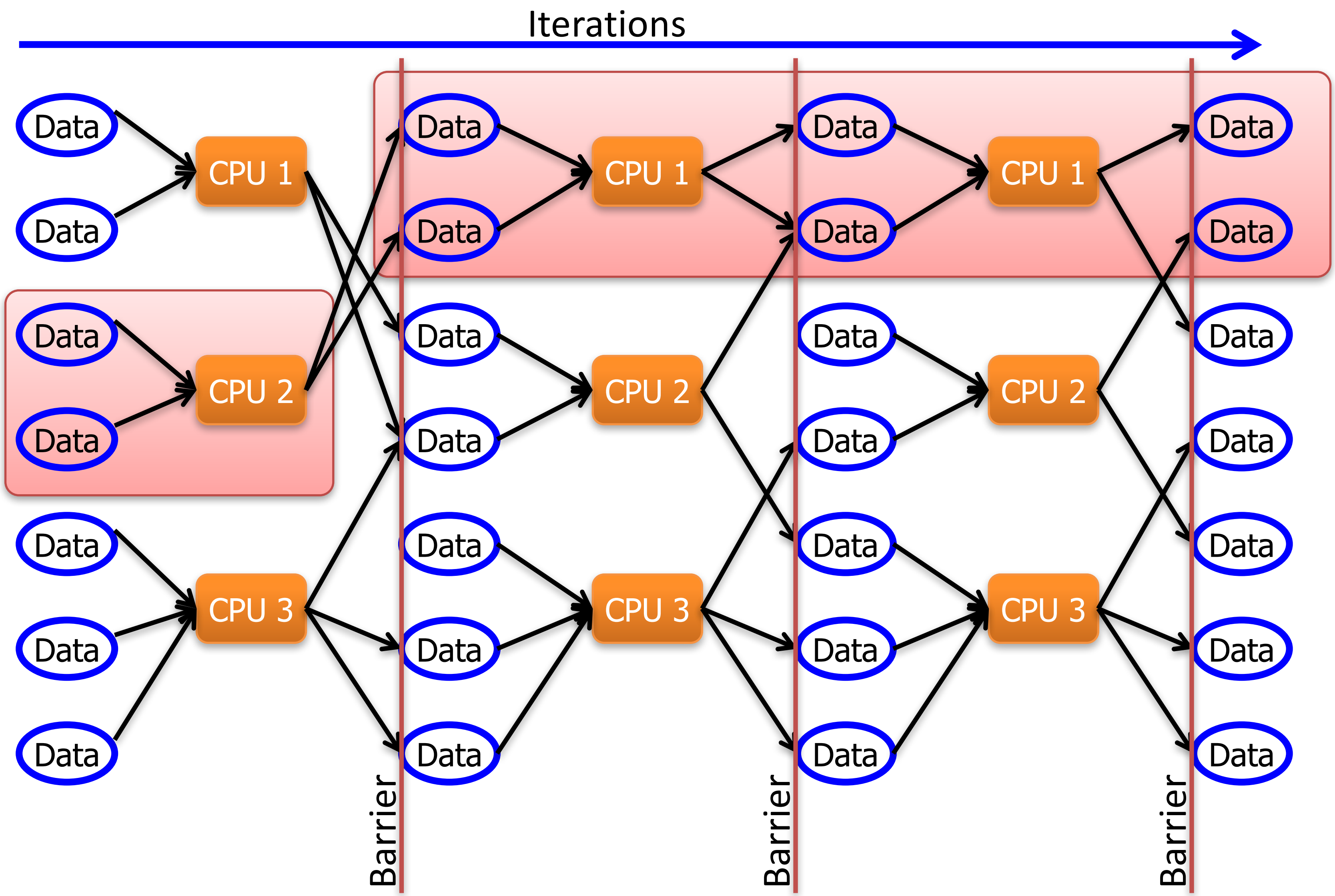
An asynchronous variant:

- GraphLab: http://graphlab.org/

Tradeoffs of the BSP Model

- Pros:
  - *Graph Parallel*
  - Relatively easy to implement and reason about
  - **Deterministic execution**
- Cons:
  - User must architect the movement of information
    - Send the correct information in messages
  - Bulk synchronous abstraction inefficient

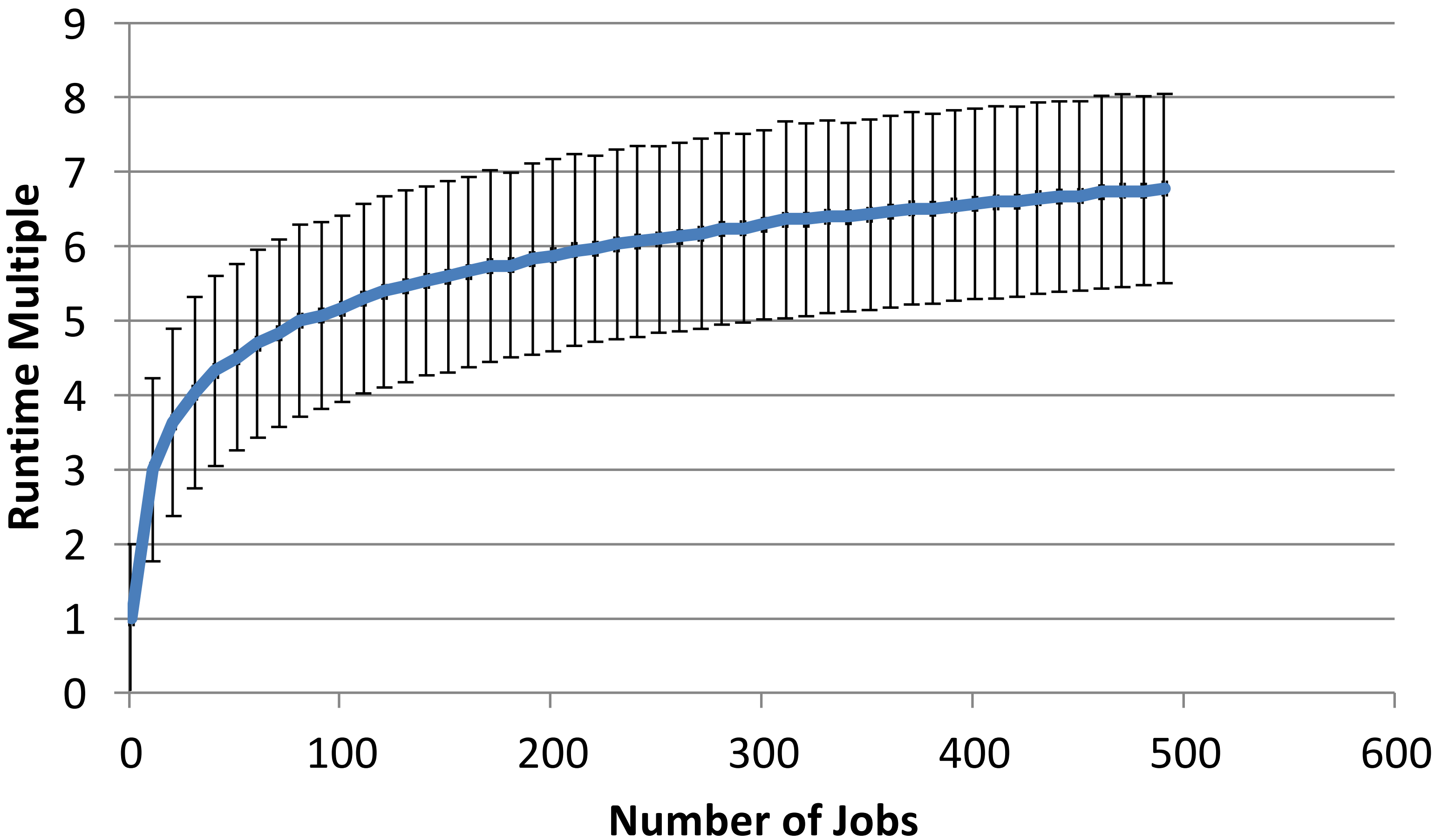
Curse of the Slow Job



http://www.www2011india.com/proceeding/proceedings/p607.pdf

Curse of the Slow Job

- Assuming runtime is drawn from an exponential distribution with mean 1.

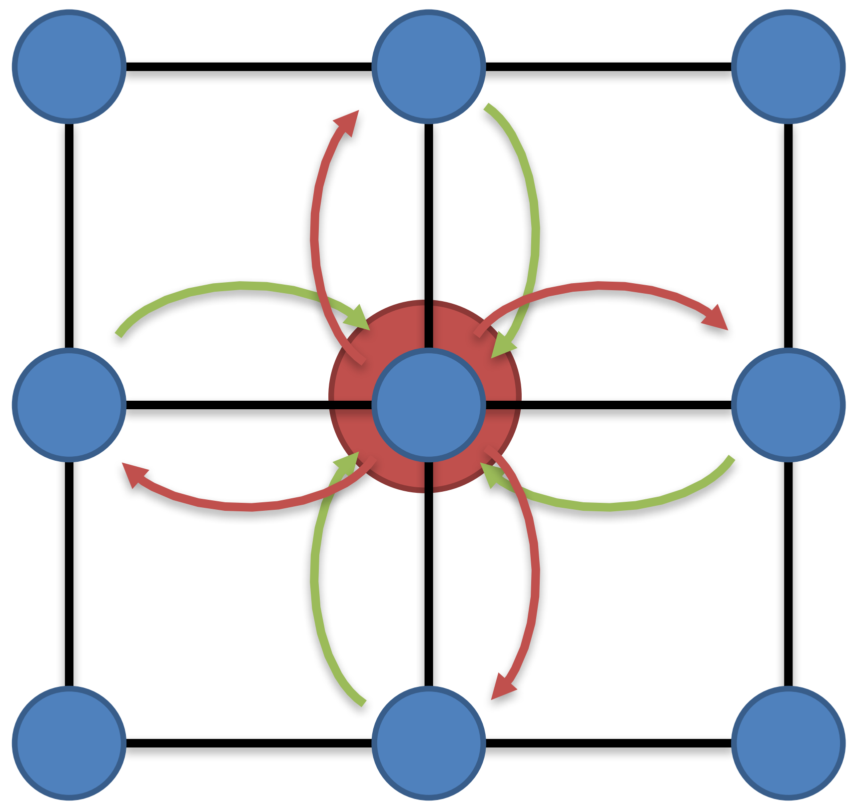


http://www.www2011india.com/proceeding/proceedings/p607.pdf

Bulk synchronous parallel model ***provably inefficient*** *for some graph-parallel tasks*

Example:
Loopy Belief Propagation (Loopy BP)

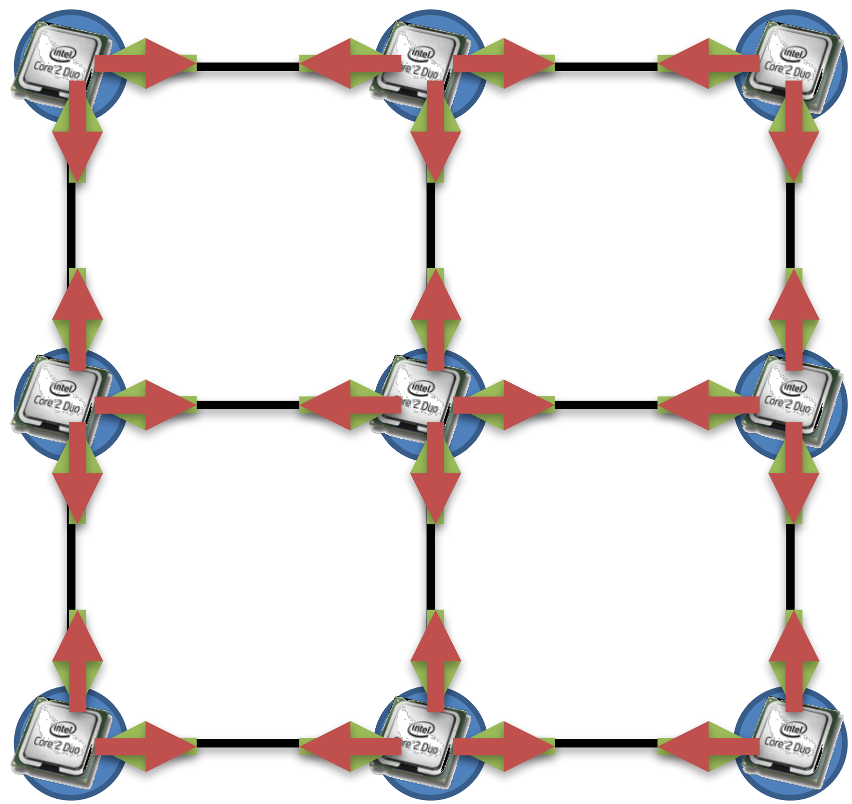
- Iteratively estimate the "beliefs" about vertices
  - Read in messages
  - Updates marginal estimate (**belief**)
  - Send updated out messages
- Repeat for all variables until convergence



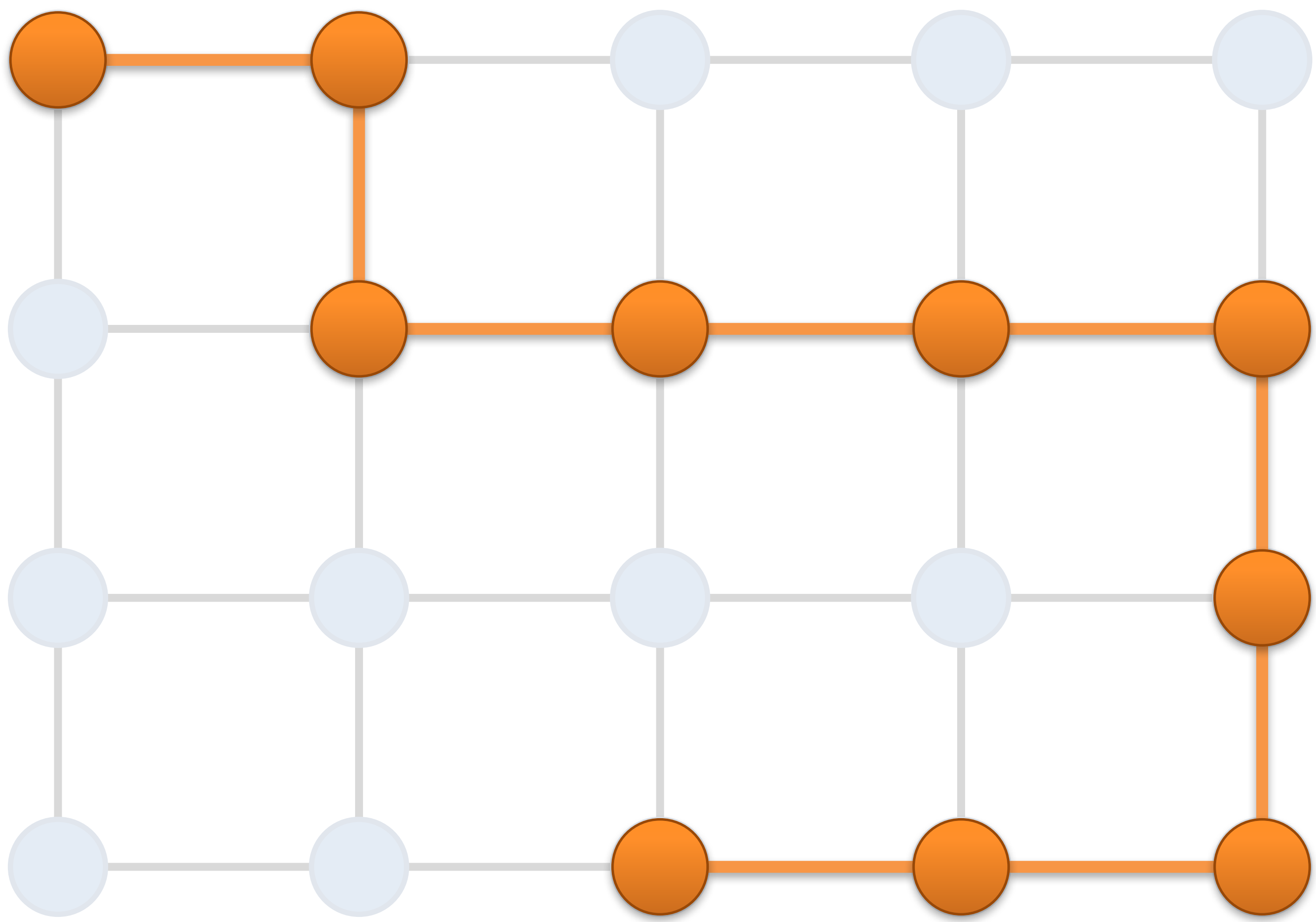
http://www.merl.com/papers/docs/TR2001-22.pdf

Bulk Synchronous Loopy BP

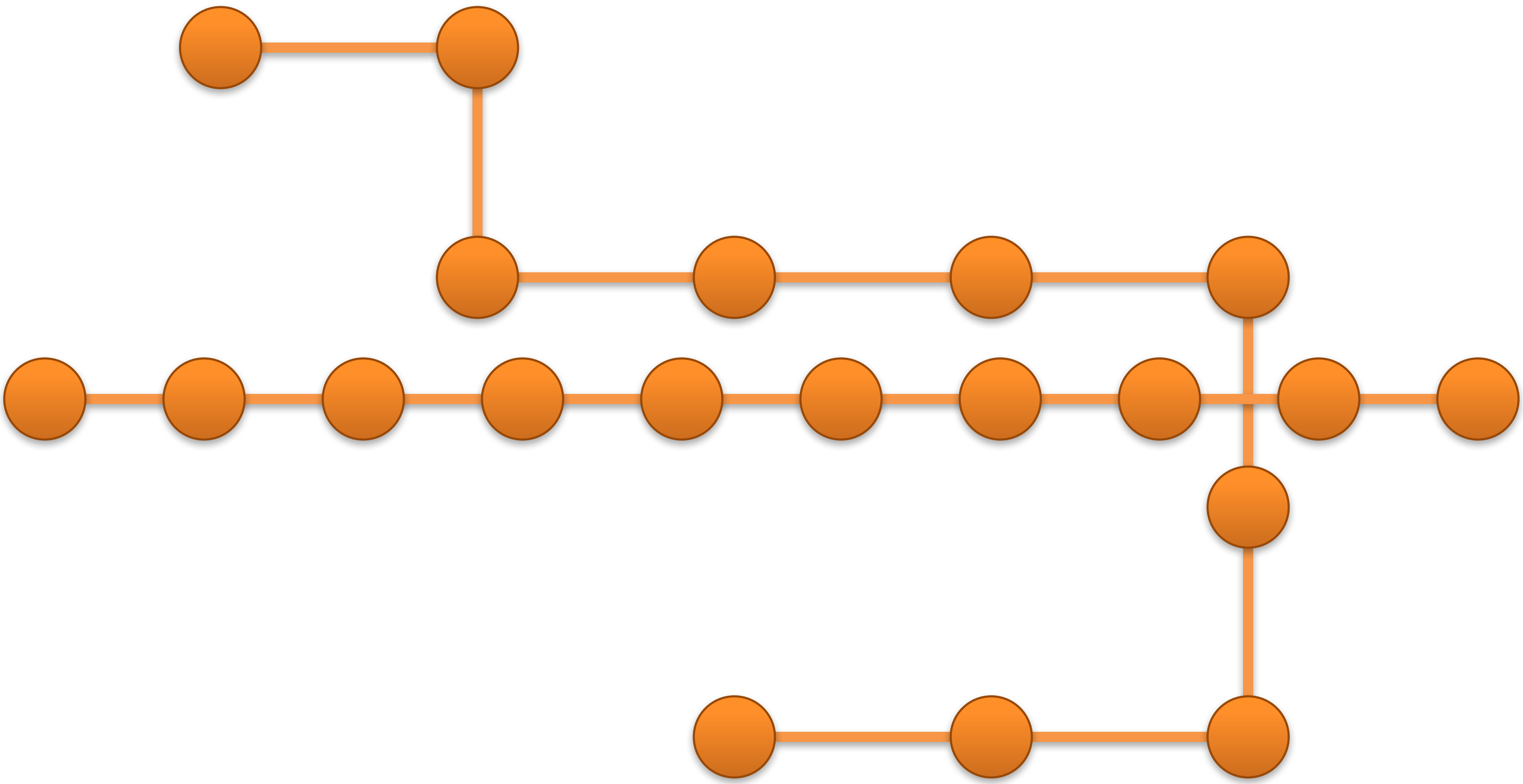
- Often considered embarrassingly parallel
  - Associate processor with each vertex
  - Receive all messages
  - Update all beliefs
  - Send all messages
- Proposed by:
  - Brunton et al. CRV'06
  - Mendiburu et al. GECC'07
  - Kang,et al. LDMTA'10
  - …



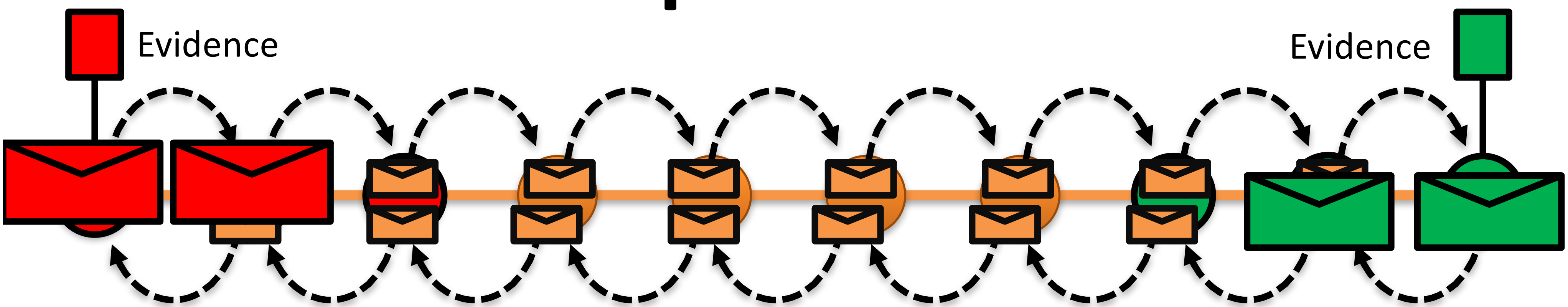
Sequential Computational Structure



Hidden Sequential Structure



Hidden **Sequential** Structure



- Running Time:

$$\frac{2n \text{ Messages Calculations}}{p \text{ Processors}} \times (n \text{ Iterations to Converge}) = \frac{2n^2}{p}$$

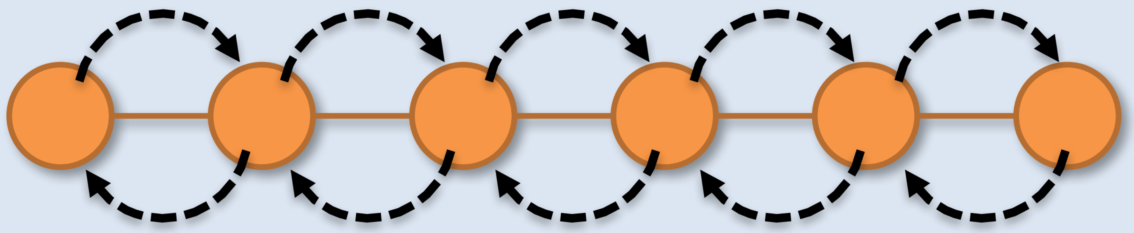
Time for a single parallel iteration

Number of Iterations

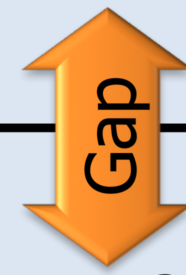
Optimal Sequential Algorithm

Running Time

Bulk Synchronous

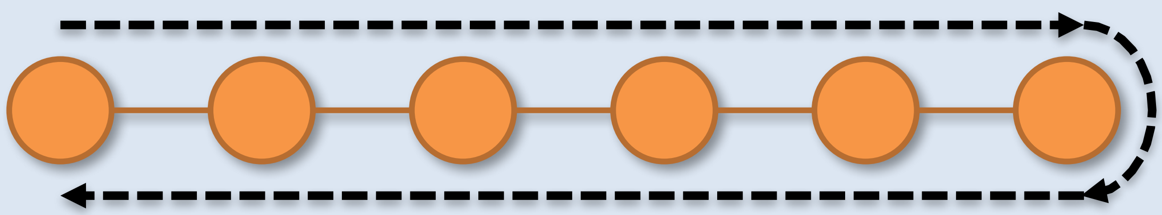


$2n^2/p$



$p \leq 2n$

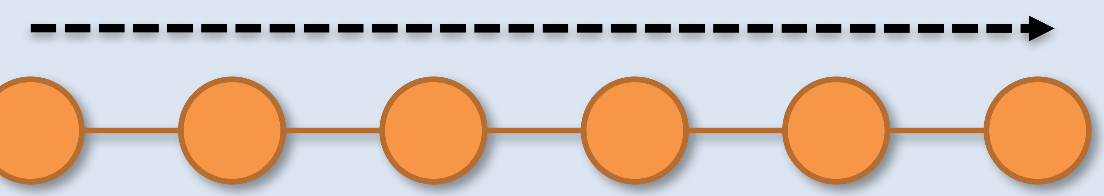
Forward-Backward



$2n$

$p = 1$

Optimal Parallel

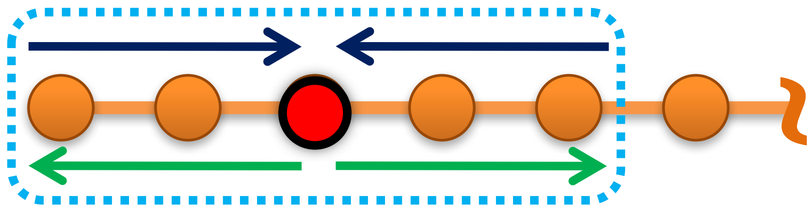


n

$p = 2$

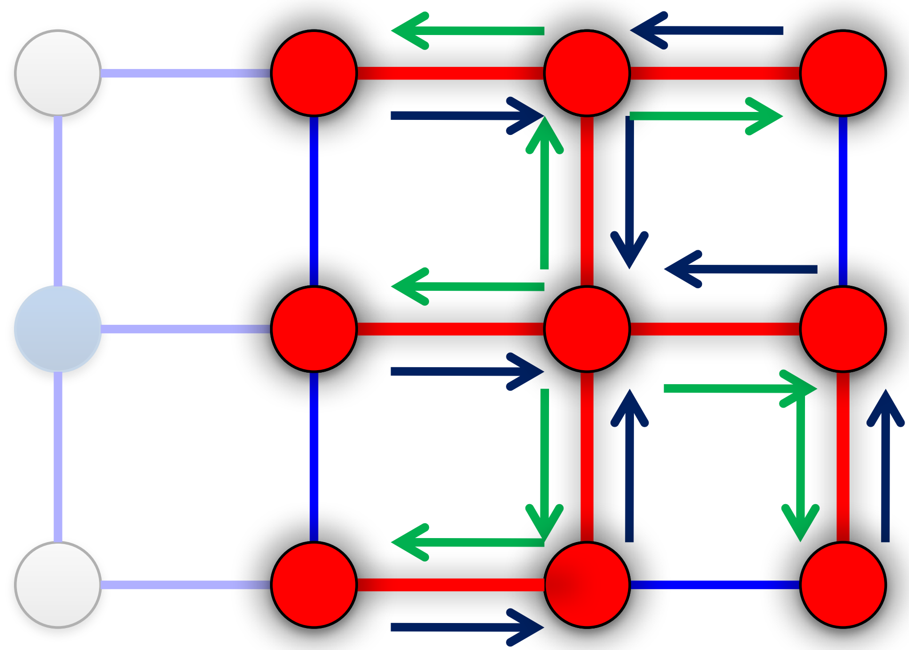
The Splash Operation

- Generalize the optimal chain algorithm:



to arbitrary cyclic graphs:

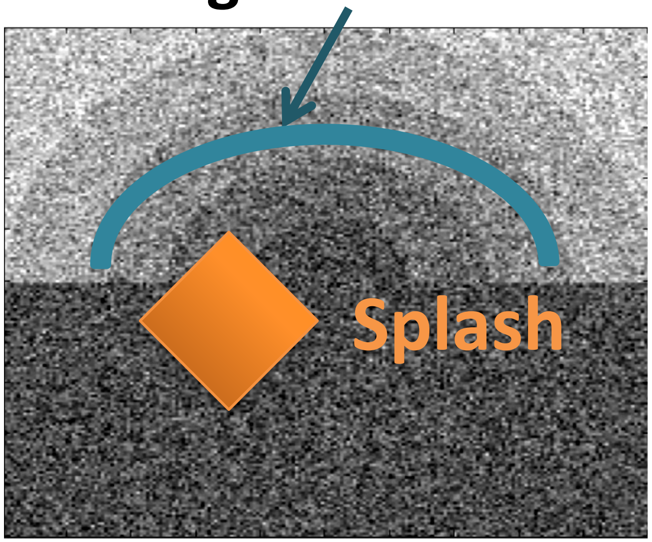
1) Grow a BFS Spanning tree with fixed size
2) Forward Pass computing all messages at each vertex
3) Backward Pass computing all messages at each vertex



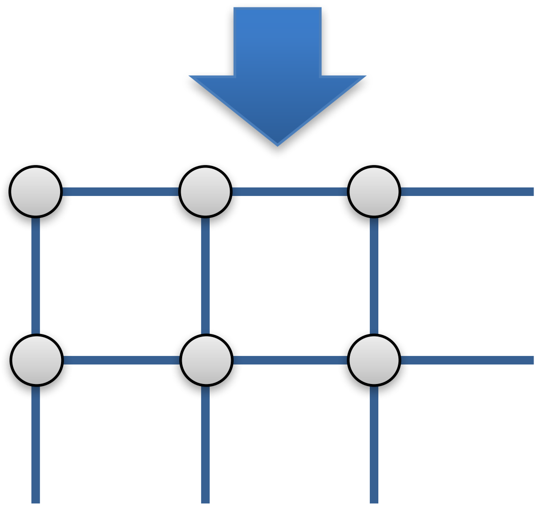
http://www.select.cs.cmu.edu/publications/paperdir/aistats2009-gonzalez-low-guestrin.pdf

Prioritize Computation

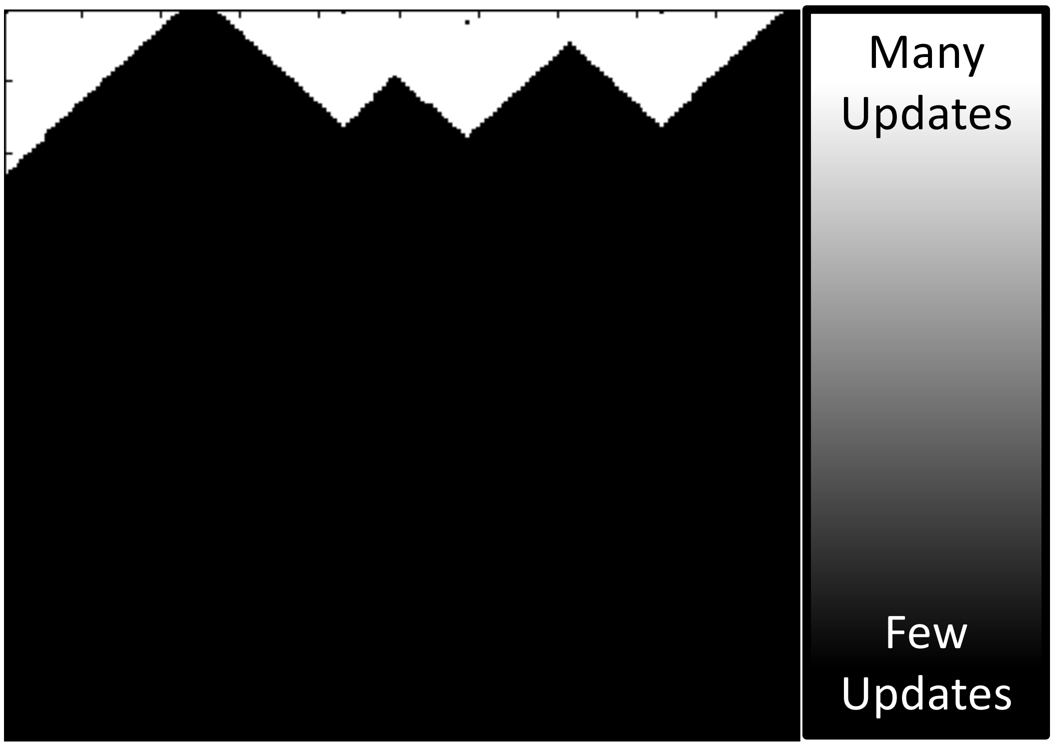
Challenge = Boundaries



Synthetic Noisy Image



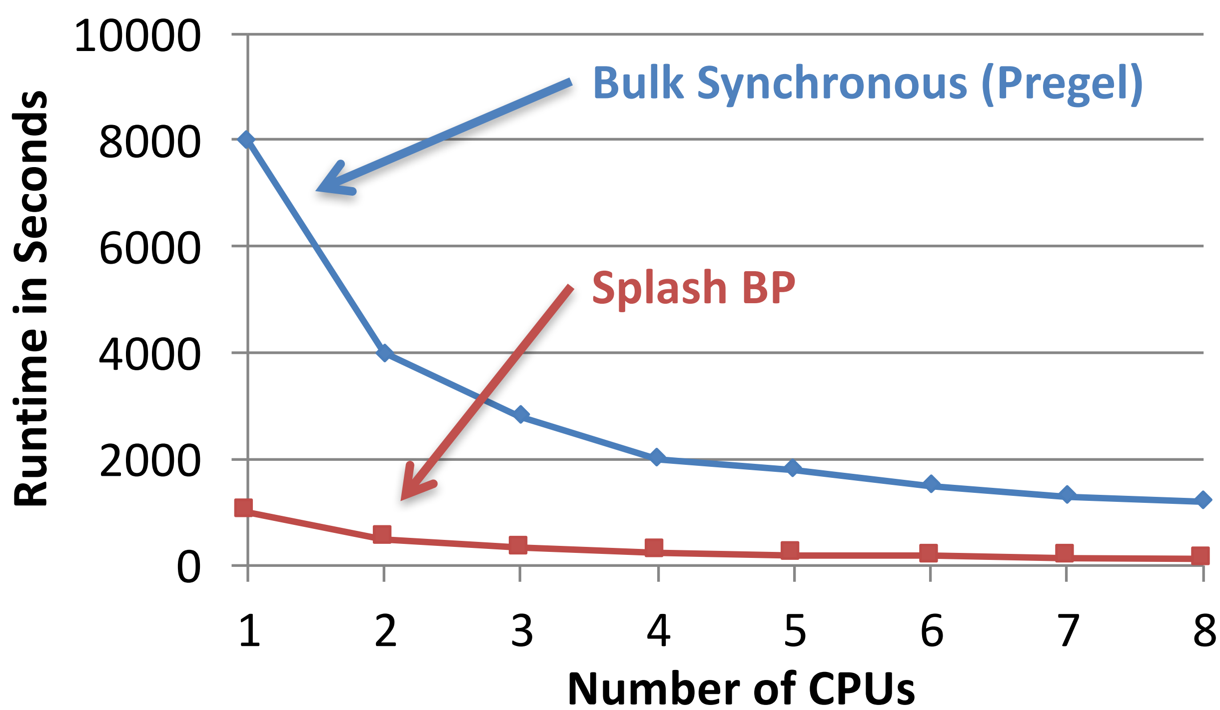
Graphical Model



Vertex Updates

Algorithm identifies and focuses on hidden sequential structure

Comparison of Splash and Pregel Style Computation



Limitations of bulk synchronous model can lead to ***provably*** inefficient parallel algorithms

The Need for a New Abstraction

- Need: Asynchronous, Dynamic Parallel Computations

Data-Parallel ⟷ Graph-Parallel

Map Reduce

Feature Extraction

Cross Validation

Computing Sufficient Statistics

BSP, e.g., Pregel

Carnegie Mellon

Graphical Models
Gibbs Sampling
Belief Propagation
Variational Opt.

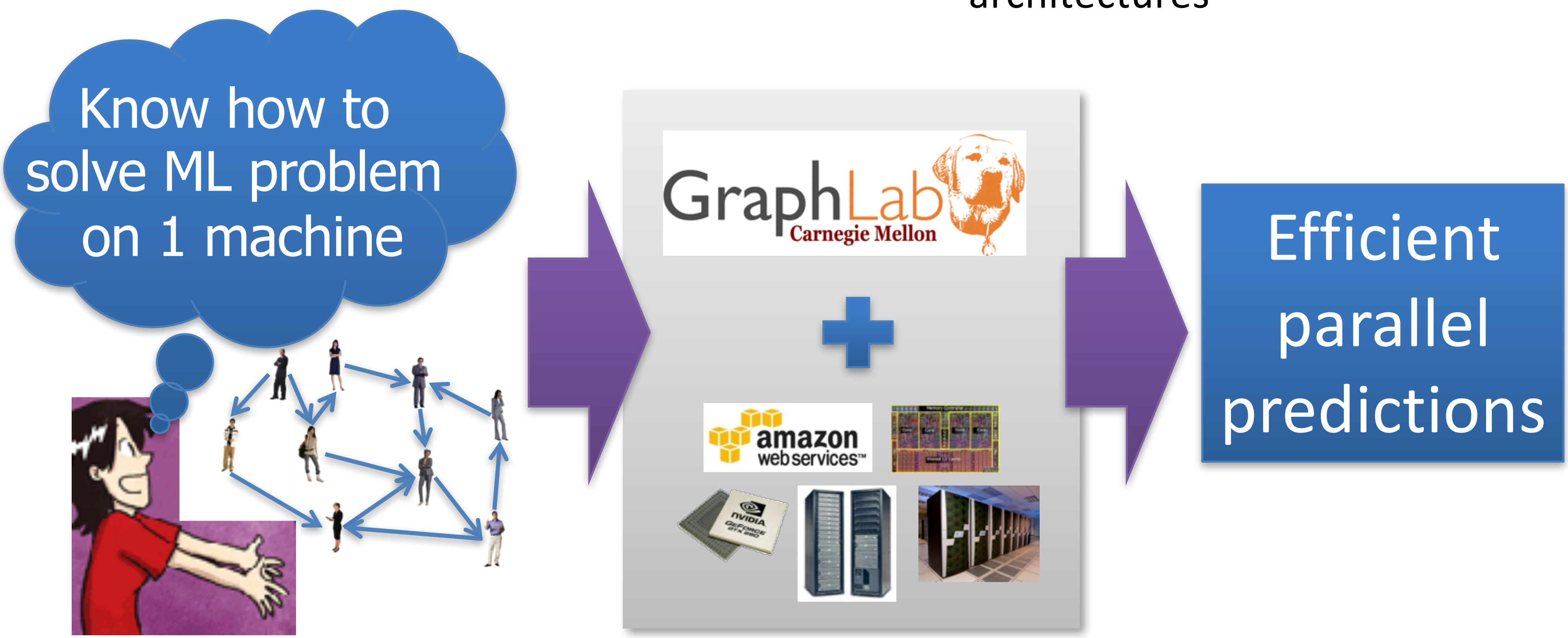
Semi-Supervised Learning
Label Propagation
CoEM

Collaborative Filtering
Tensor Factorization

Data-Mining
PageRank
Triangle Counting

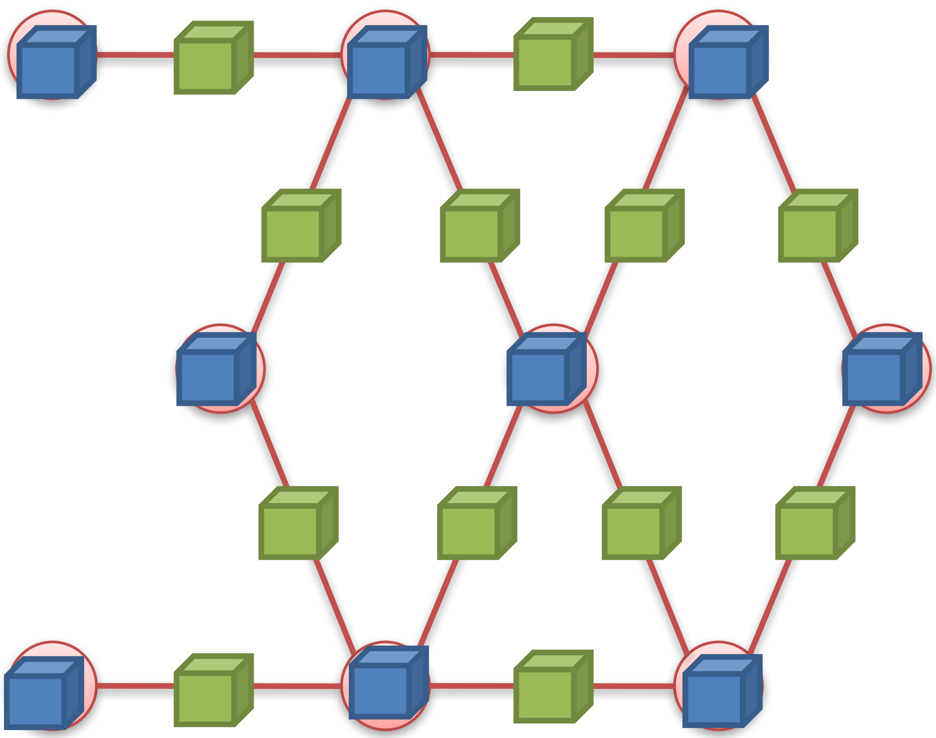
The **GraphLab** Goals

- Designed specifically for ML
  - Graph dependencies
  - Iterative
  - Asynchronous
  - Dynamic
- Simplifies design of parallel programs:
  - Abstract away hardware issues
  - Automatic data synchronization
  - Addresses multiple hardware architectures



Data Graph

Data associated with vertices and edges



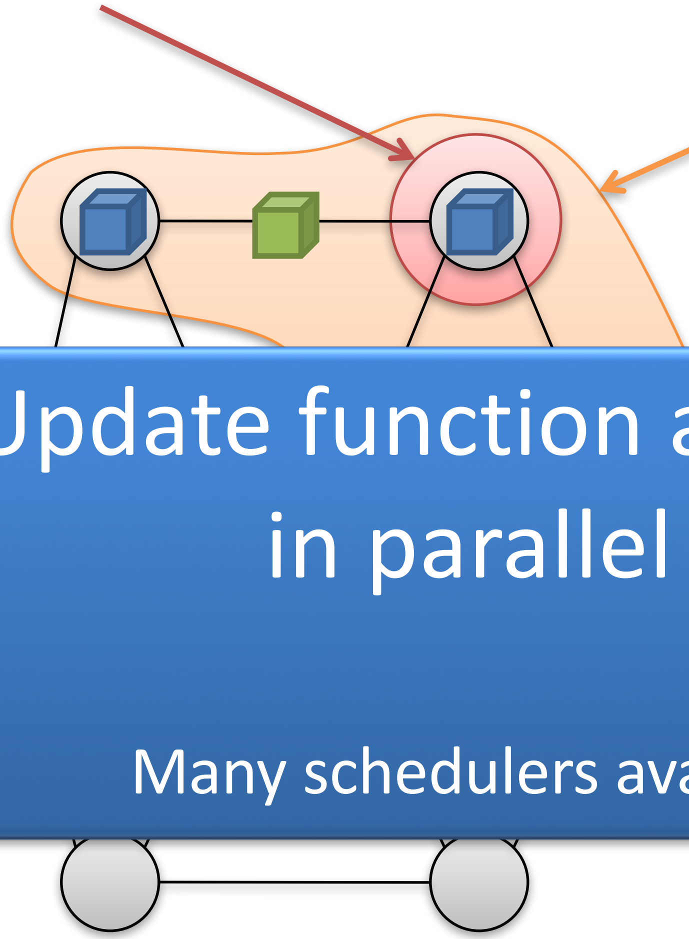
Graph:
- Social Network

Vertex Data:
- User profile text
- Current interests estimates

Edge Data:
- Similarity weights

Update Functions

User-defined program: applied to **vertex** transforms data in **scope** of vertex



pagerank(i, scope){
// Get Neighborhood data
$(R[i], w_{ij}, R[j]) \leftarrow$ scope;

}

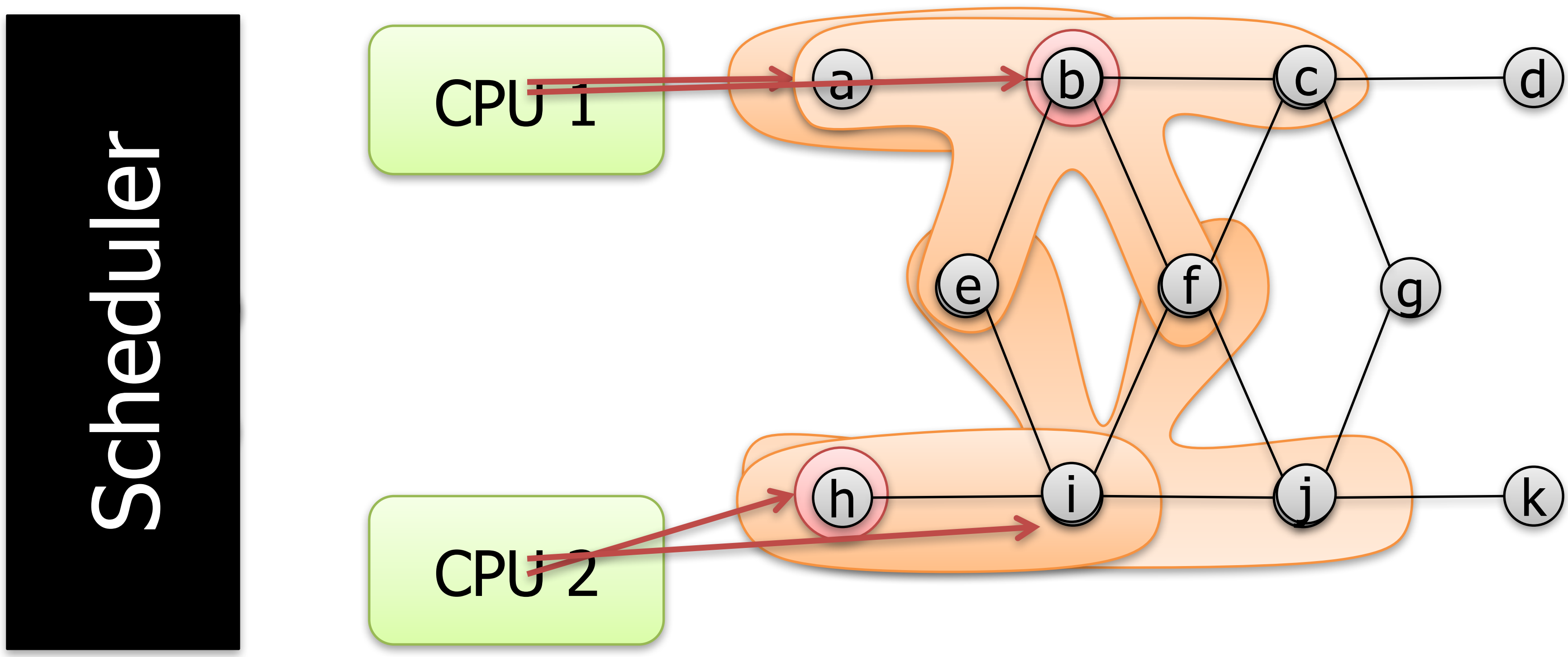
Update function applied (asynchronously) in parallel until convergence

Many schedulers available to prioritize computation

Dynamic computation

The Scheduler

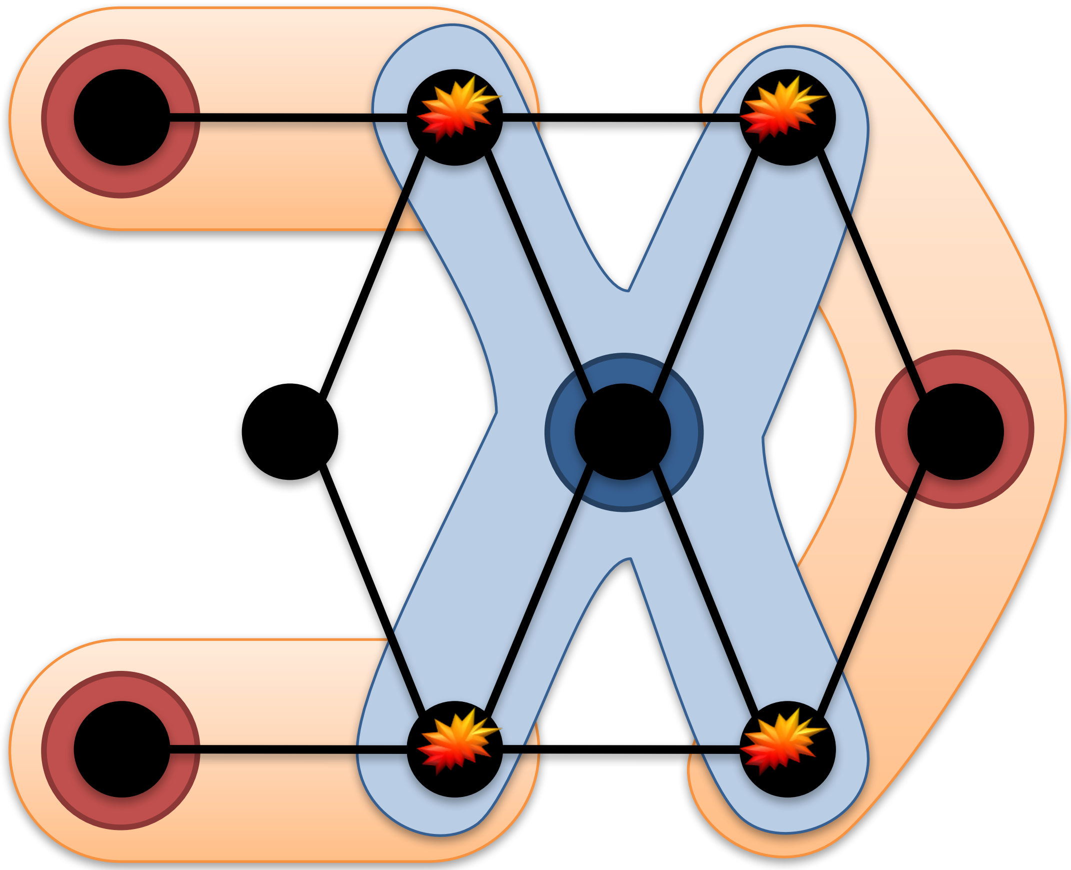
The **scheduler** determines the order that vertices are updated



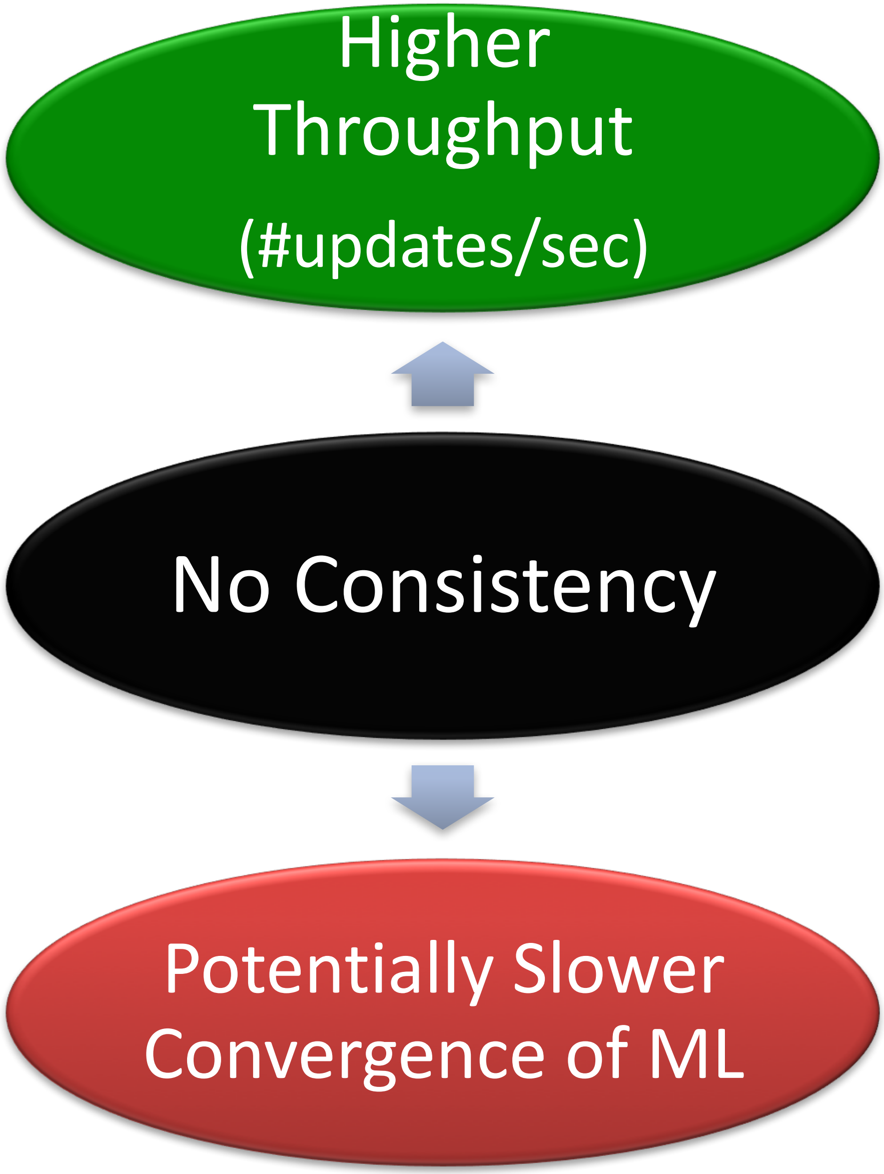
The process repeats until the scheduler is empty

Ensuring Race-Free Code

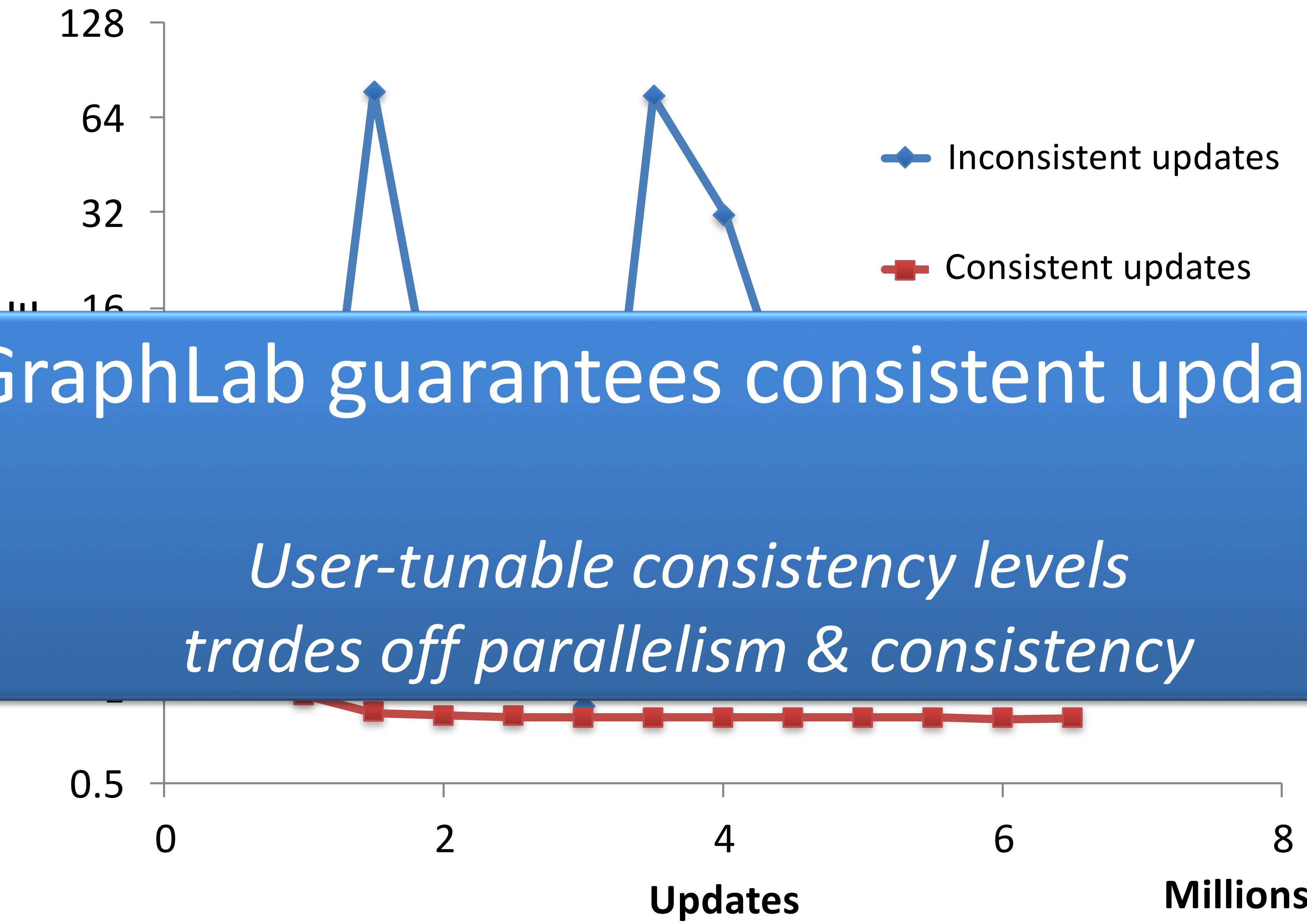
How much can computation **overlap**?



Need for Consistency?



Consistency in Collaborative Filtering



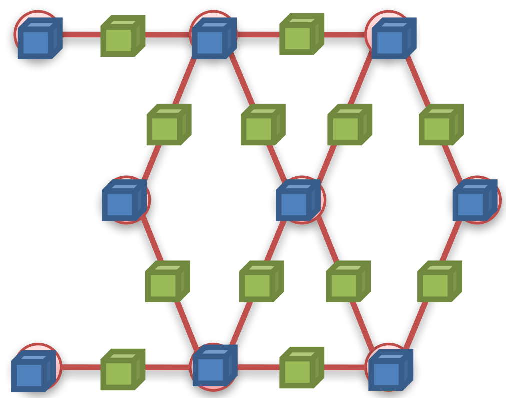
GraphLab guarantees consistent updates

User-tunable consistency levels trades off parallelism & consistency

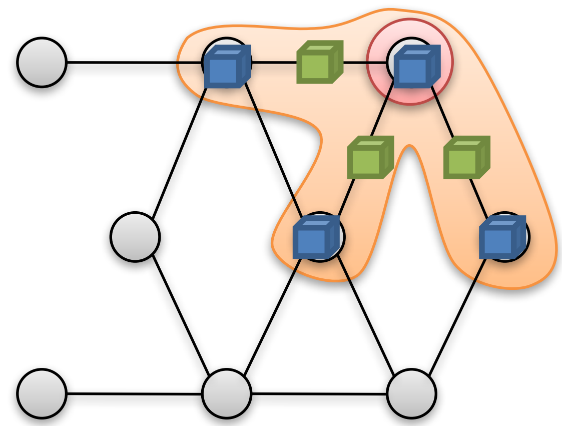
Netflix data, 8 cores

The GraphLab Framework

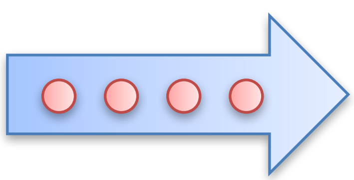
Graph Based
Data Representation



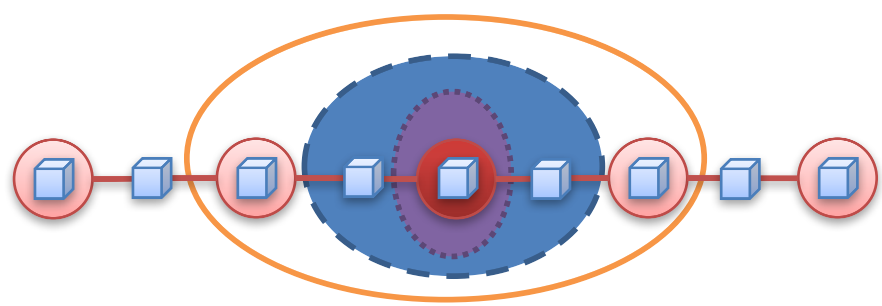
Update Functions
User Computation



Scheduler



Consistency Model



Alternating Least Squares

SVD

Splash Sampler

CoEM

Bayesian Tensor Factorization

Lasso

Belief Propagation

PageRank

LDA

SVM

Gibbs Sampling

Dynamic Block Gibbs Sampling

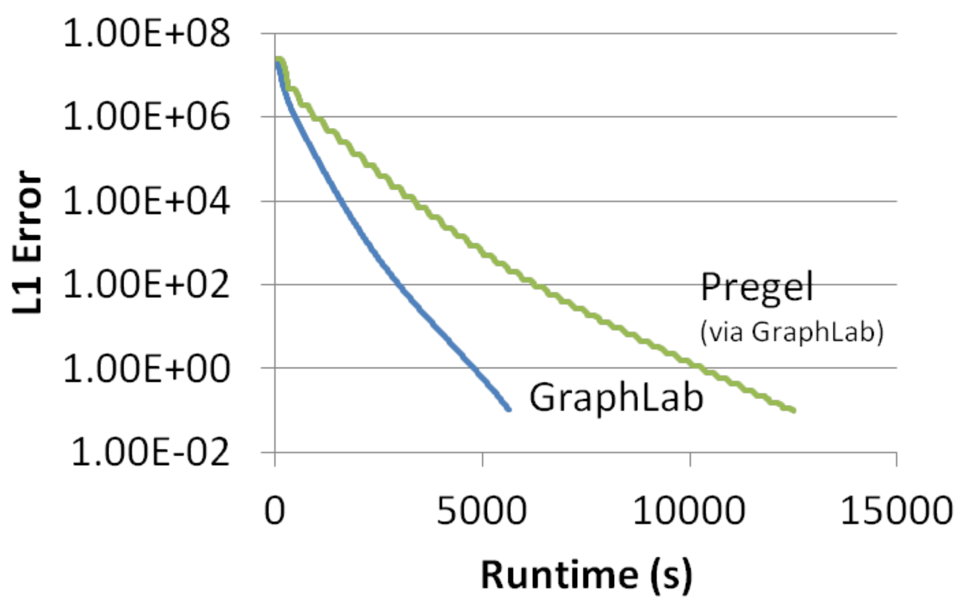
K-Means

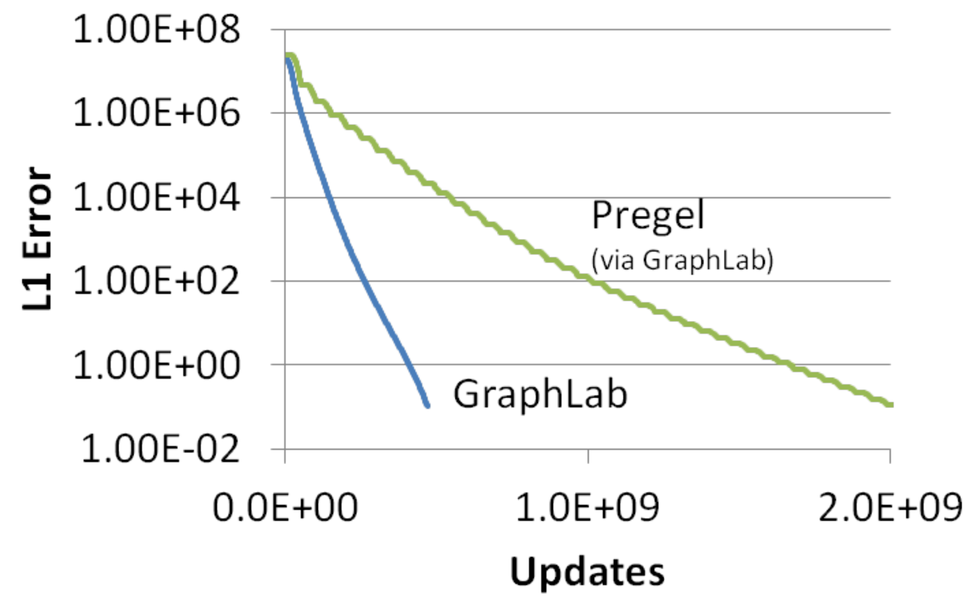
…Many others…

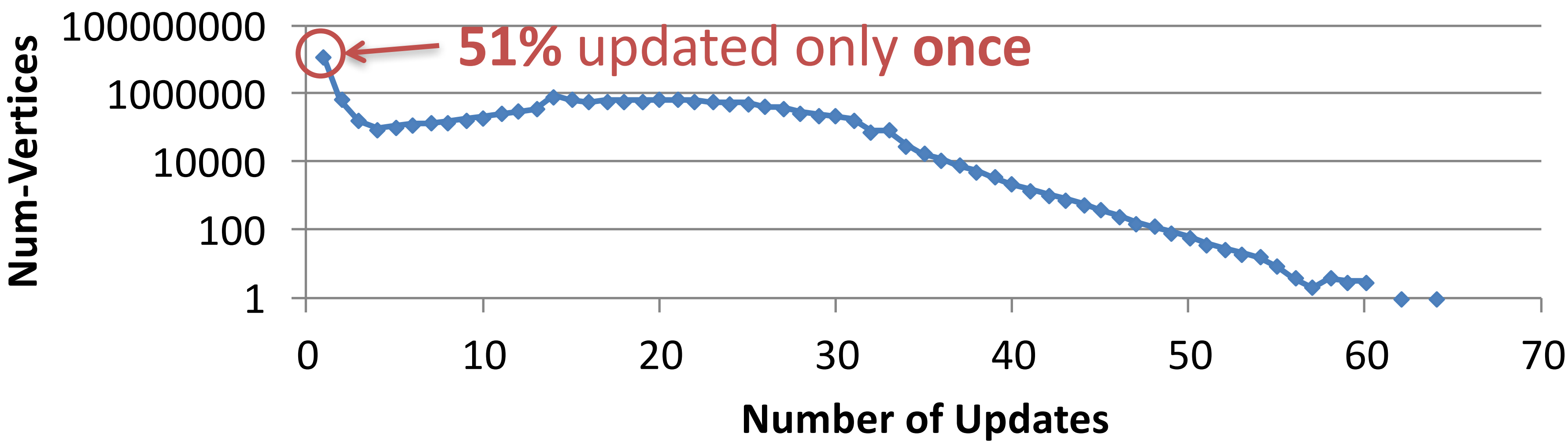
Matrix Factorization

Linear Solvers

GraphLab vs. Pregel (BSP)

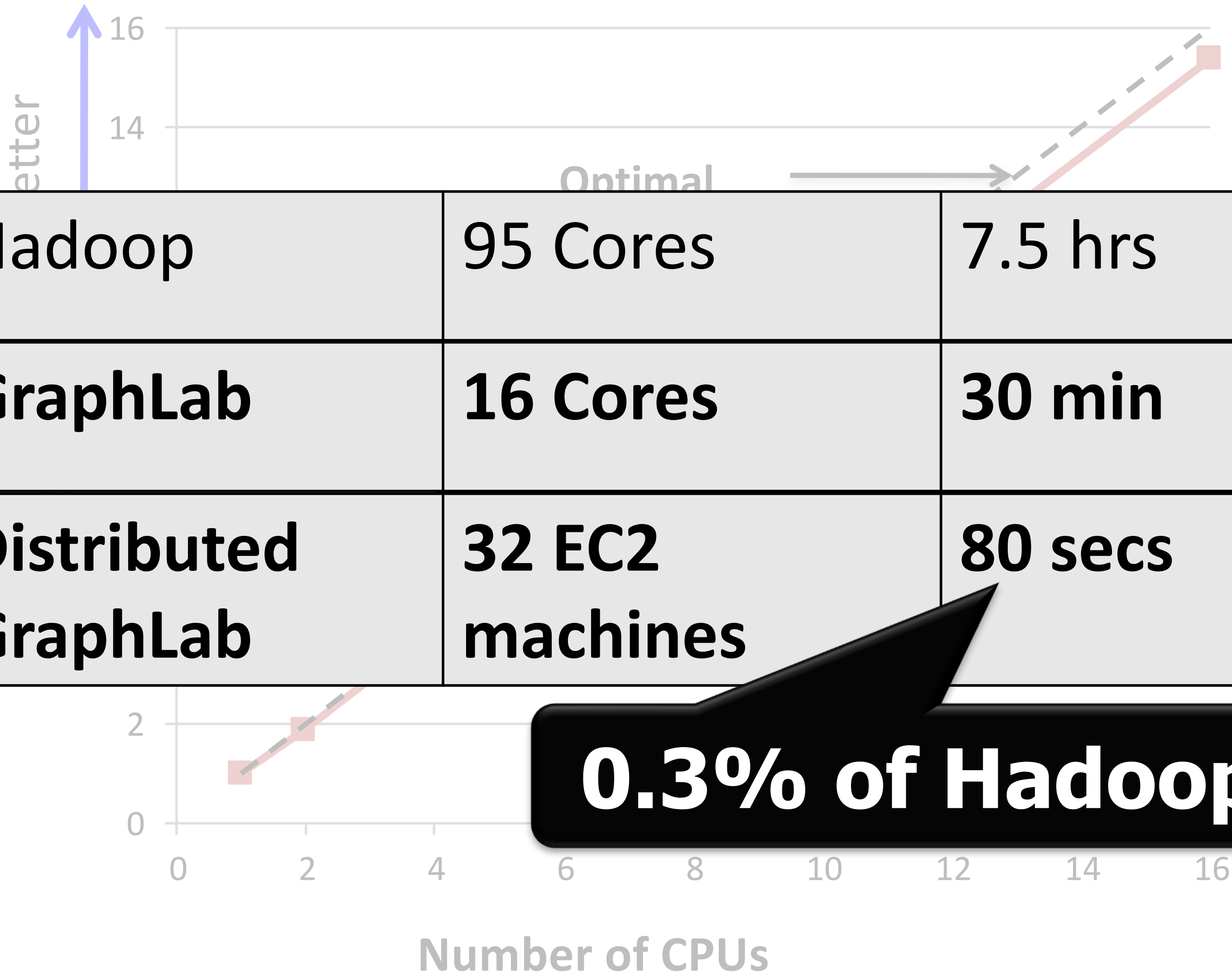






- PageRank (25M Vertices, 355M Edges)

Never Ending Learner Project (CoEM)

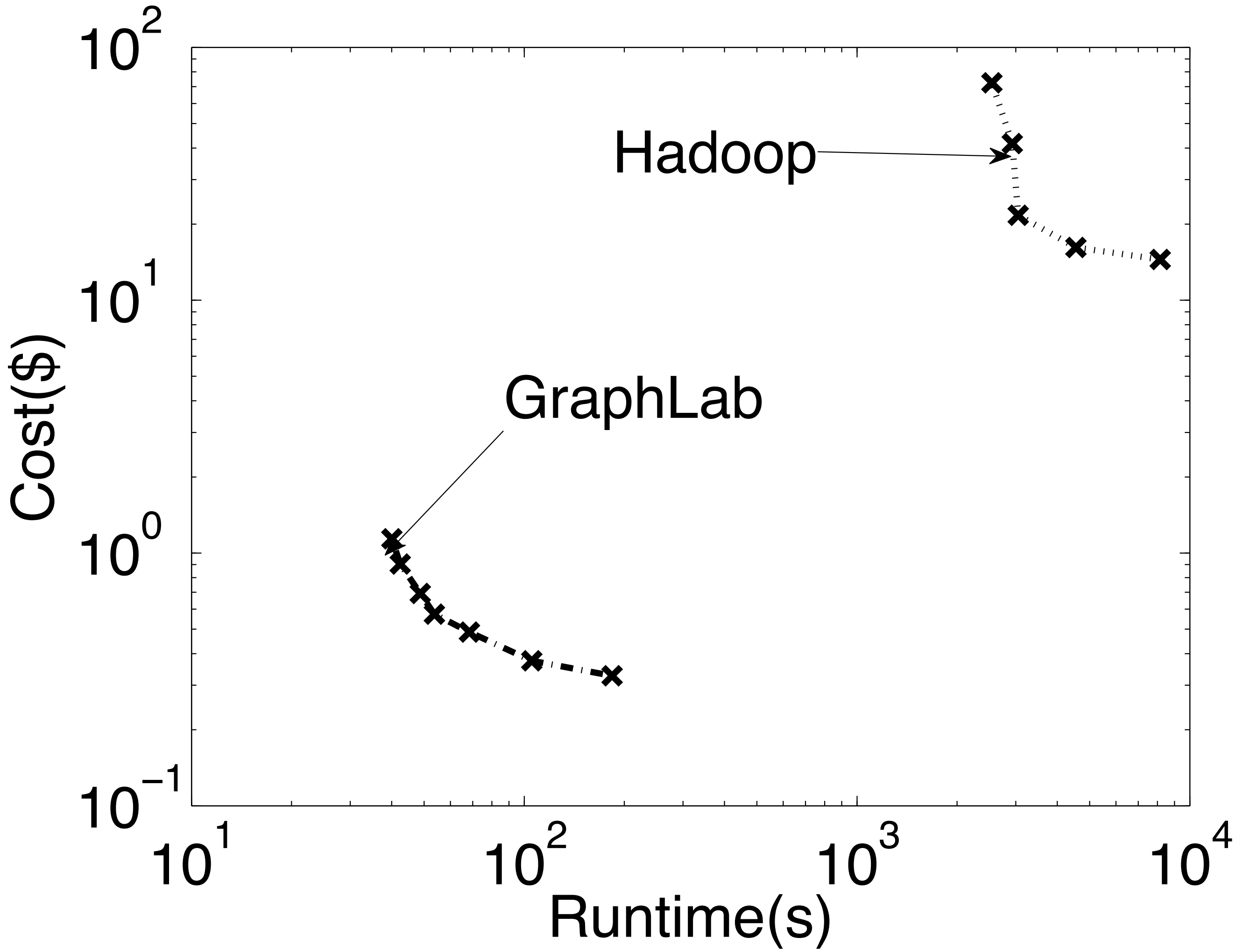


Hadoop	95 Cores	7.5 hrs
GraphLab	**16 Cores**	**30 min**
Distributed GraphLab	**32 EC2 machines**	**80 secs**

0.3% of Hadoop time

The Cost of the Wrong Abstraction

Log-Scale!



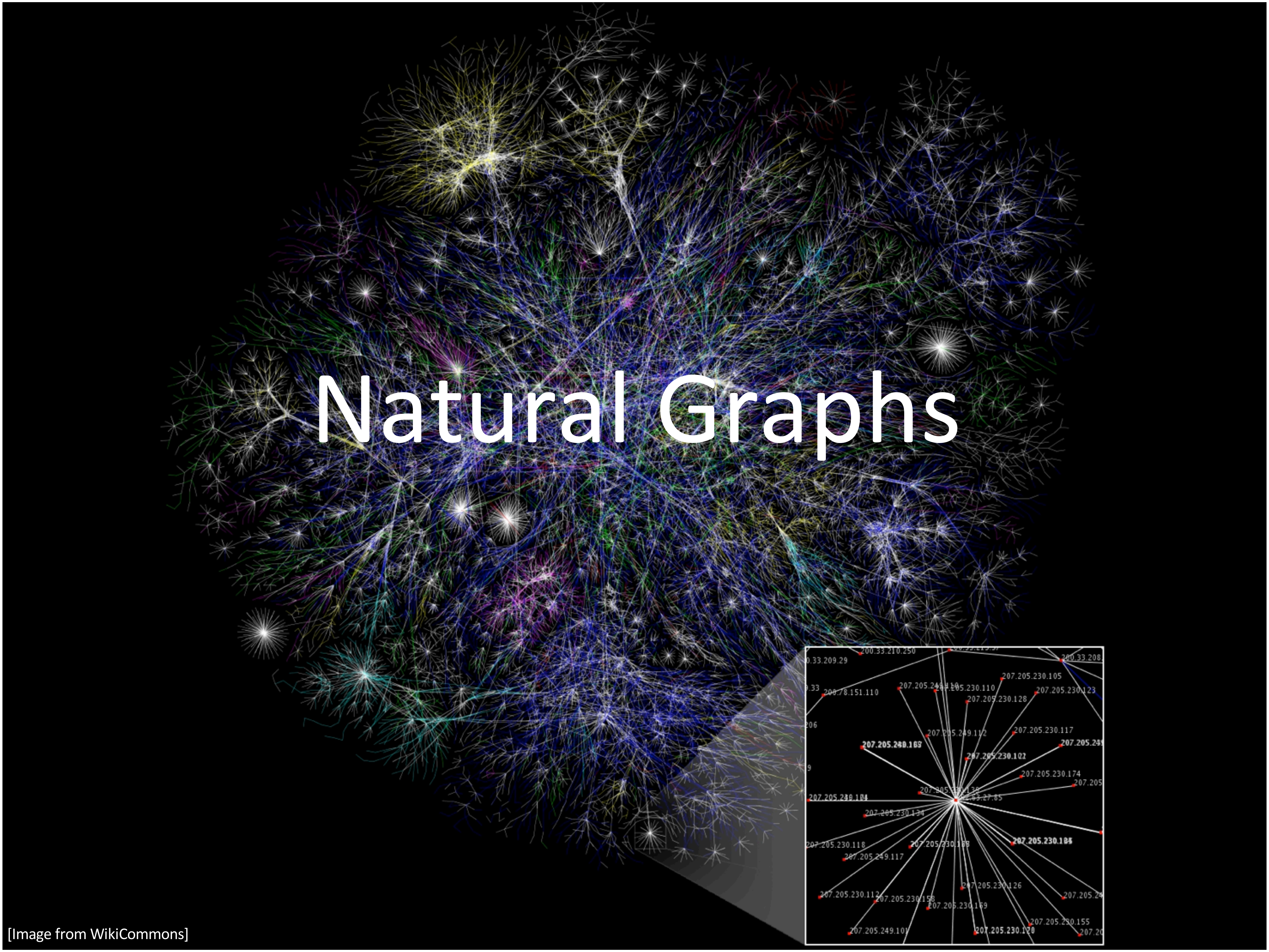
Thus far…

GraphLab1 provided exciting scaling performance

But…

We couldn't scale up to Altavista Webgraph 2002 1.4B vertices, 6.7B edges

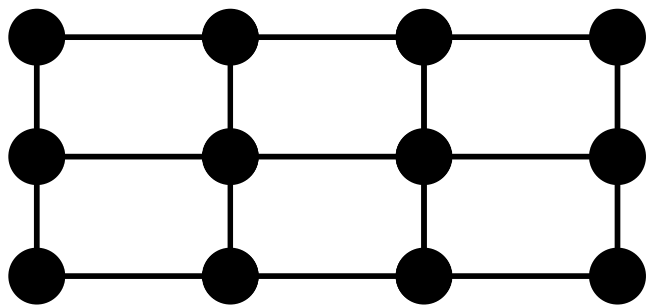
Natural Graphs



[Image from WikiCommons]

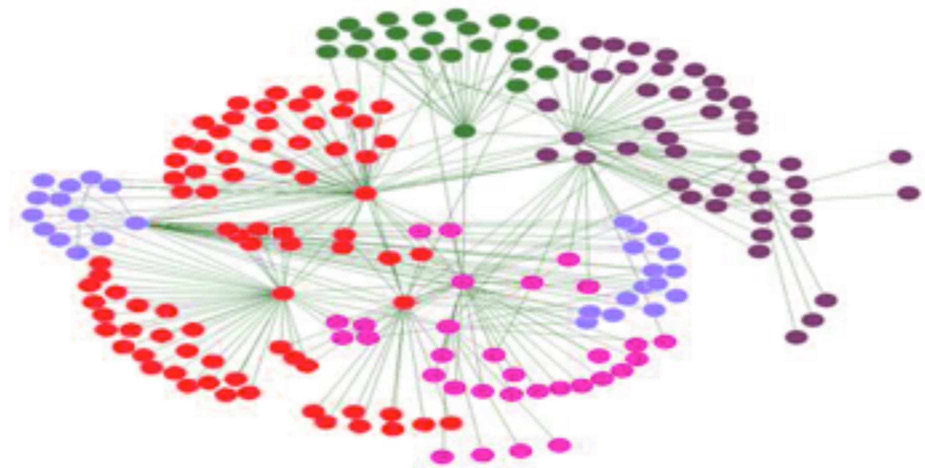
Assumptions of **Graph-Parallel** Abstractions

Idealized Structure



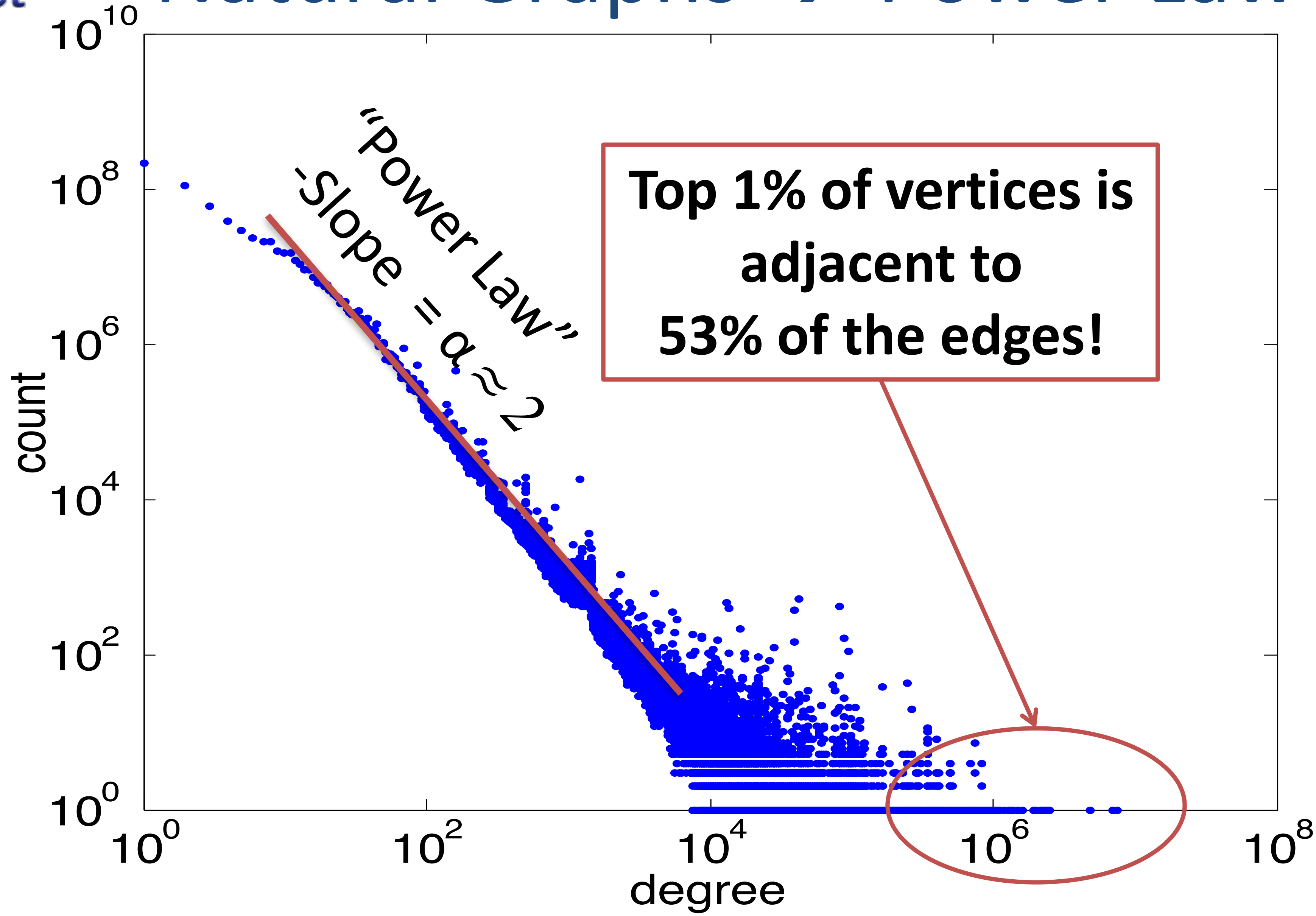
- ***Small*** neighborhoods
  - Low degree vertices
- Similar degree
- Easy to partition

Natural Graph



- ***Large*** Neighborhoods
  - High degree vertices
- ***Power-Law*** degree distribution
- ***Difficult to partition***

Natural Graphs → Power Law

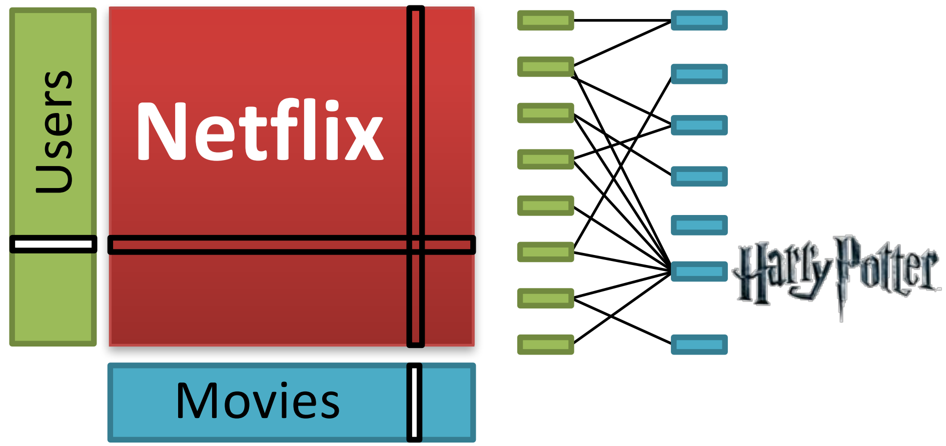


Altavista Web Graph: 1.4B Vertices, 6.7B Edges

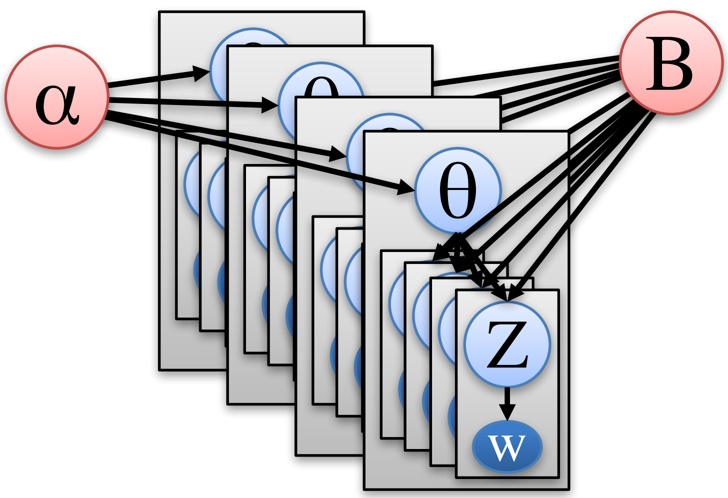
High Degree Vertices are Common

"Social" People

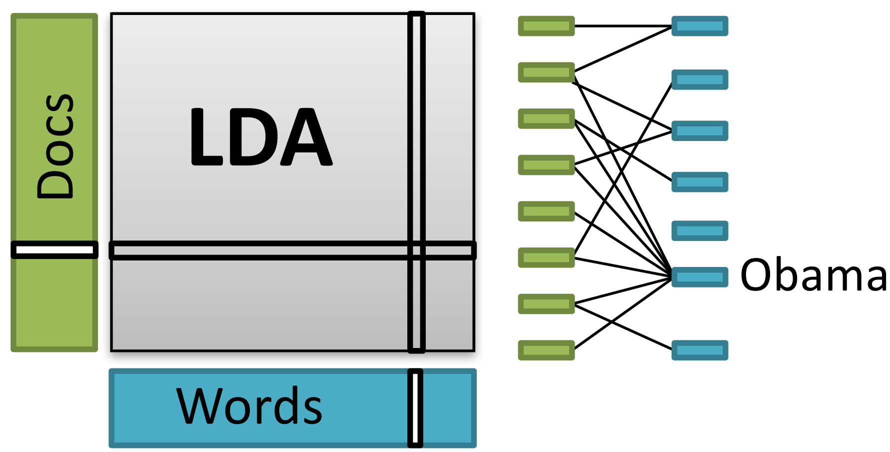
Popular Movies



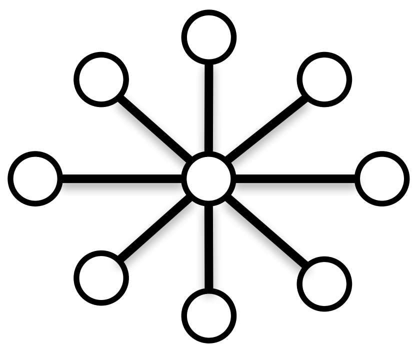
Hyper Parameters



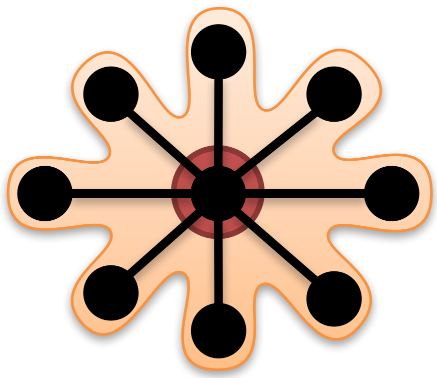
Common Words



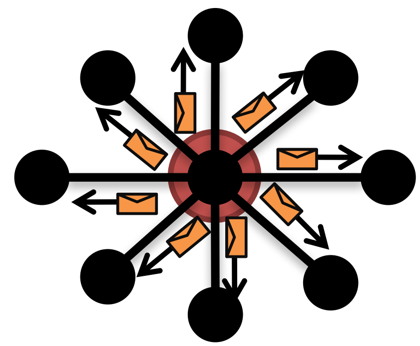
Problem:
High Degree Vertices Limit Parallelism



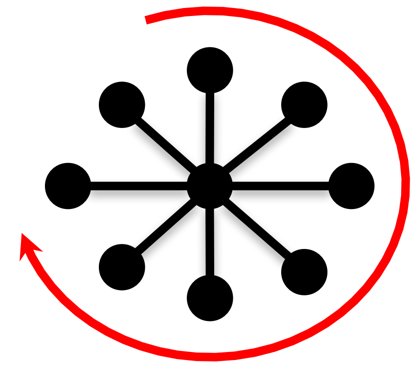
Edge information too large for single machine



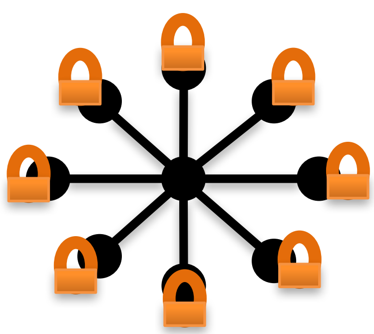
Touches a large fraction of graph (GraphLab 1)



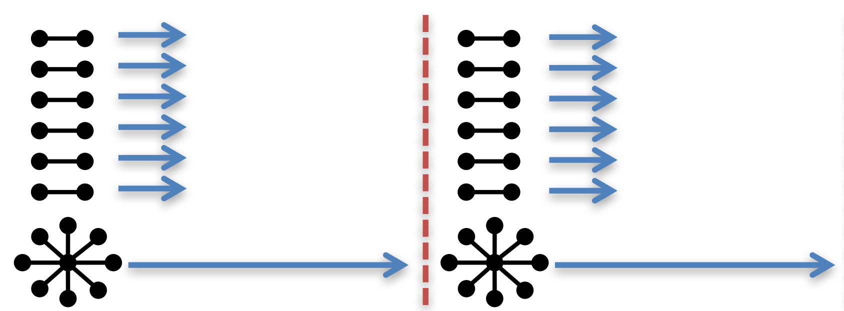
Produces many messages (Pregel)



Sequential Vertex-Updates

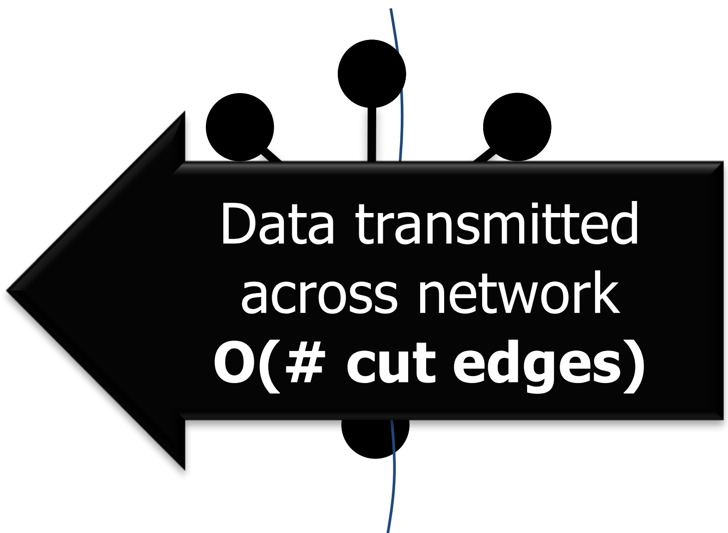


Asynchronous consistency requires heavy locking (GraphLab 1)



Synchronous consistency is prone to stragglers (Pregel)

Problem:
High Degree Vertices → High Communication for Distributed Updates



Natural graphs do not have low-cost balanced cuts

[Leskovec et al. 08, Lang 04]

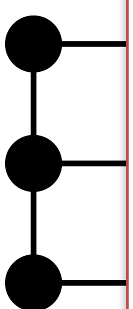
Popular partitioning tools (Metis, Chaco,…) perform poorly

[Abou-Rjeili et al. 06]

Extremely slow and require substantial memory

Random Partitioning

- Both GraphLab1 and Pregel proposed Random (hashed) partitioning for Natural Graphs



For *p* Machines:

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

10 Machines → 90% of edges cut

100 Machines → 99% of edges cut!

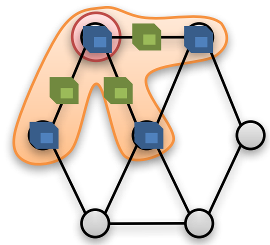
In Summary

GraphLab1 and Pregel are not well suited for natural graphs

- Poor performance on high-degree vertices
- Low Quality Partitioning

- Distribute a single vertex-update
  - Move computation to data
  - Parallelize high-degree vertices
- Vertex Partitioning
  - Simple online approach, effectively partitions large power-law graphs

Factorized Vertex Updates



Split update into 3 phases

PageRank in GraphLab2

$$R[i] = \beta + (1-\beta)\boxed{\sum_{(j,i)\in E} w_{ji} R[j]}$$

PageRankProgram(i)

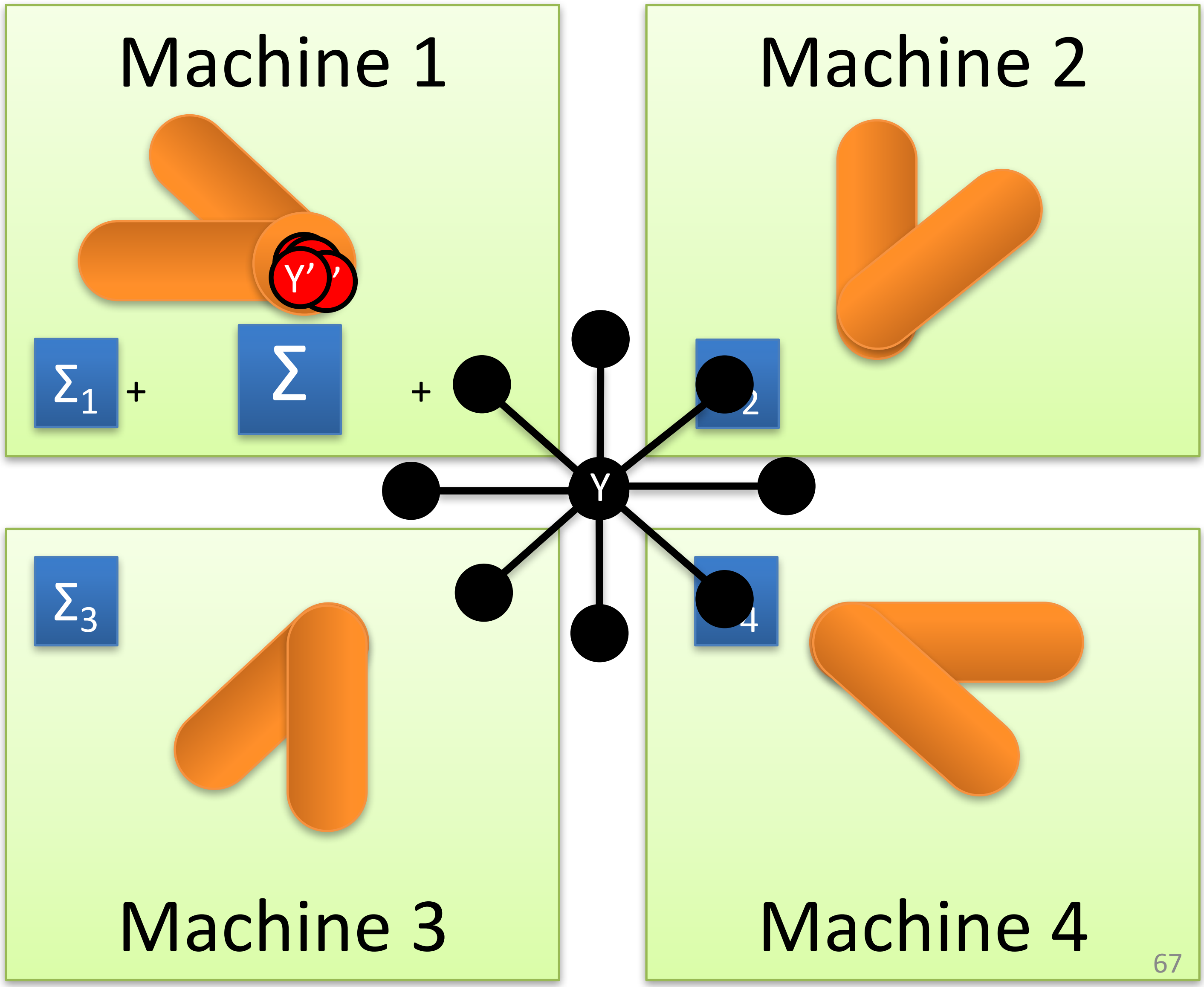
- **Gather**(j → i) : return w_{ji} * R[j]
- **sum**(a, b) : return a + b;
- **Apply**(i, Σ) : R[i] = β + (1 – β) * Σ
- **Scatter**(i → j) :
  - if (R[i] changes) then *activate*(j)

Distributed Execution of a GraphLab2 Vertex-Program

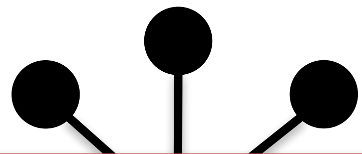
Gather

Apply

Scatter



Minimizing Communication in GraphLab2

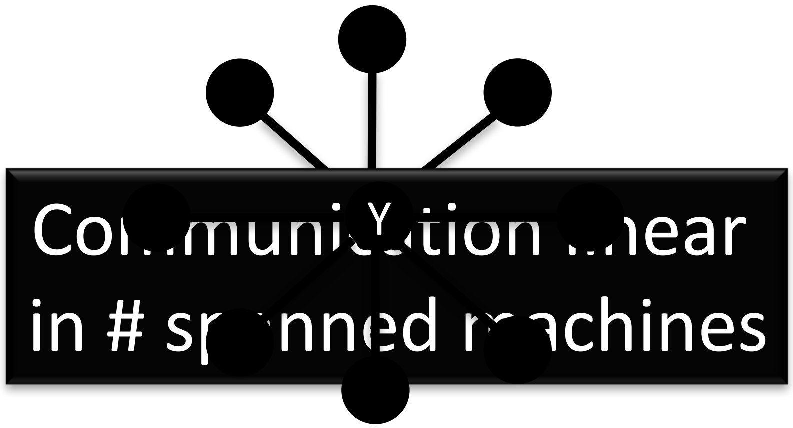


Communication is linear in the number of machines each vertex spans

A **vertex-cut** minimizes machines each vertex spans

Percolation theory suggests that power law graphs have good vertex cuts. [Albert et al. 2000]

Minimizing Communication in GraphLab2: **Vertex Cuts**



A **vertex-cut** minimizes
machines per vertex

Percolation theory suggests Power Law graphs can be split by removing only a small set of vertices [Albert et al. 2000]

➔

Small vertex cuts possible!

Constructing Vertex-Cuts

- **Goal:** *Parallel graph partitioning on ingress*
- GraphLab 2 provides three **simple** approaches:
  - ***Random** Edge Placement*
    - Edges are placed randomly by each machine
      - Good theoretical guarantees
  - ***Greedy** Edge Placement with **Coordination***
    - Edges are placed using a shared objective
      - Better theoretical guarantees
  - ***Oblivious-Greedy** Edge Placement*
    - Edges are placed using a local objective

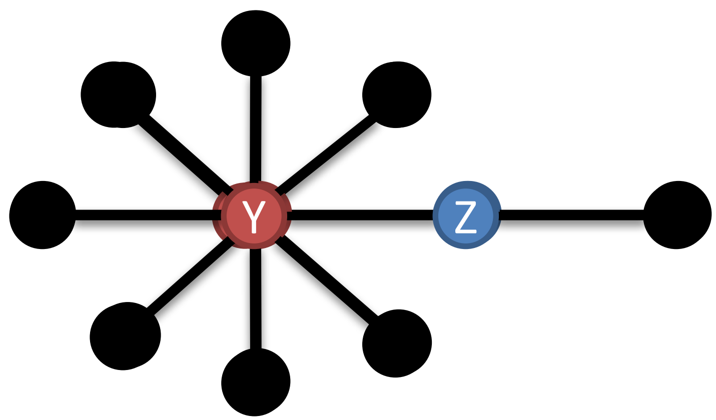
Random Vertex-Cuts

- Randomly assign edges to machines

Machine 1

Machine 2

Machine 3



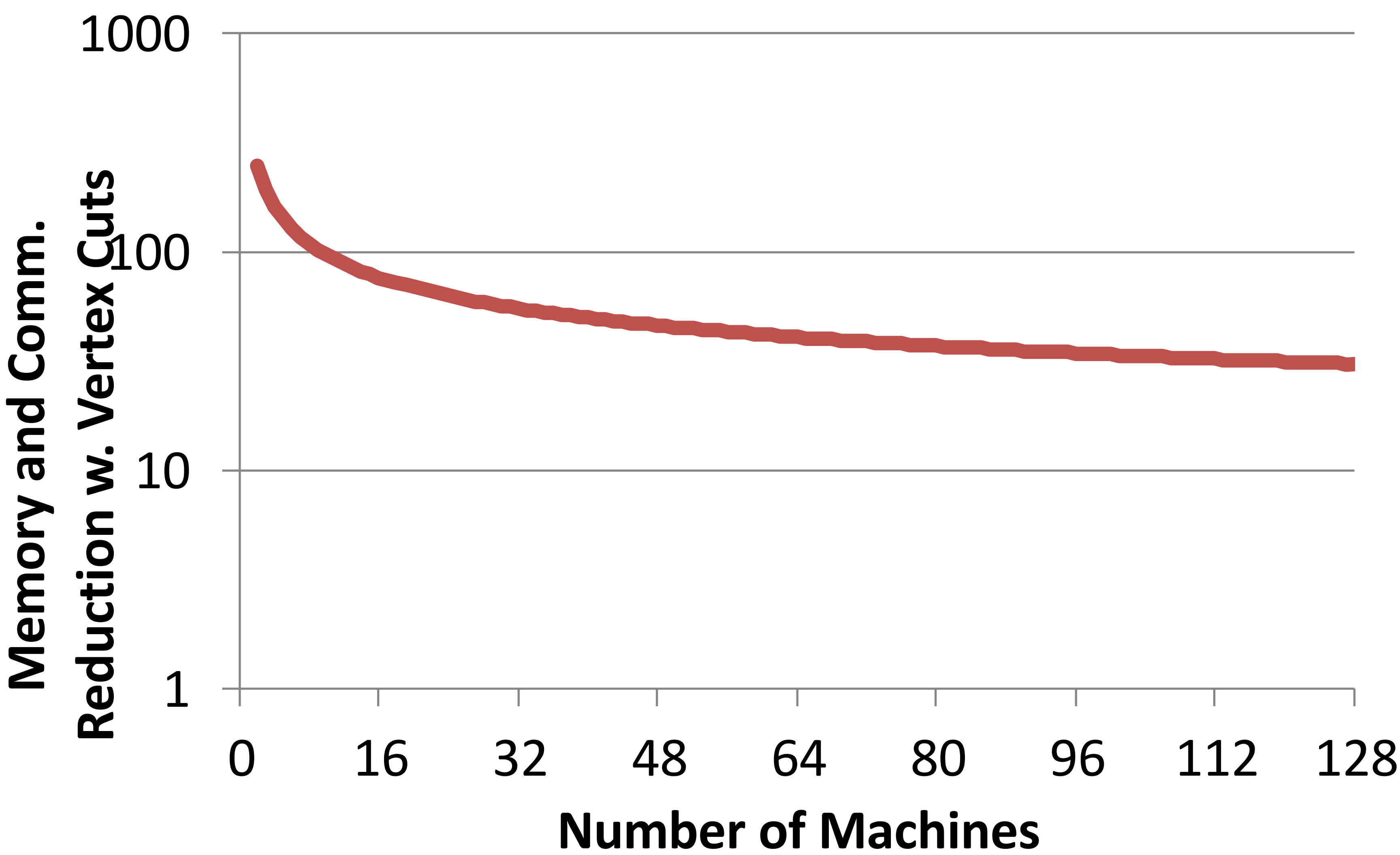
Balanced Cut

Y Spans 3 Machines

Z Spans 2 Machines

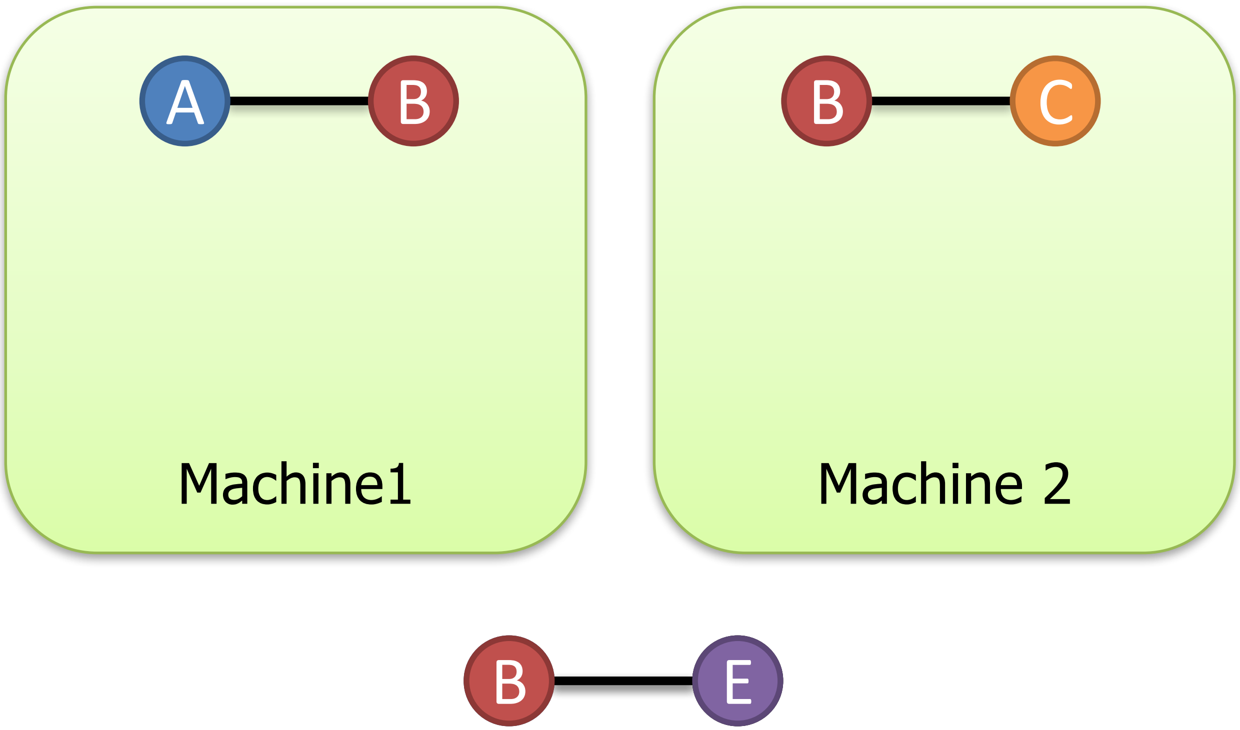
Spans only 1 machine

Random Vertex Cuts vs Edge Cuts



Greedy Vertex-Cuts

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

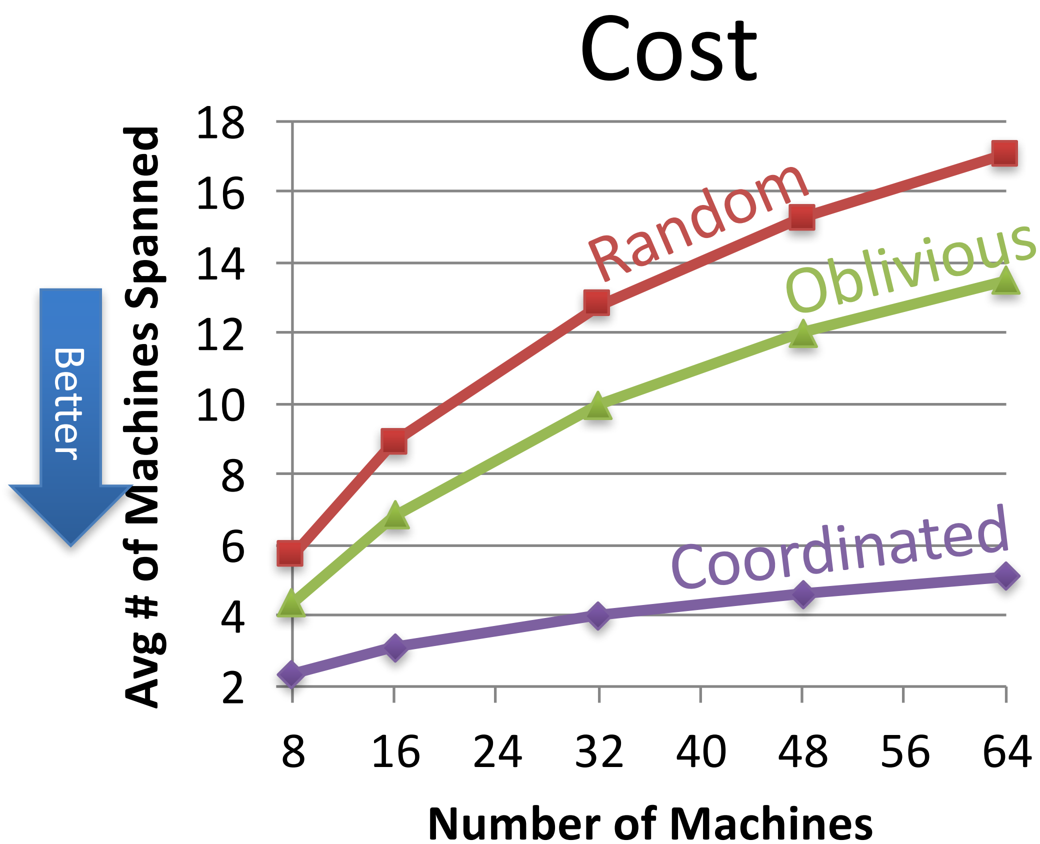


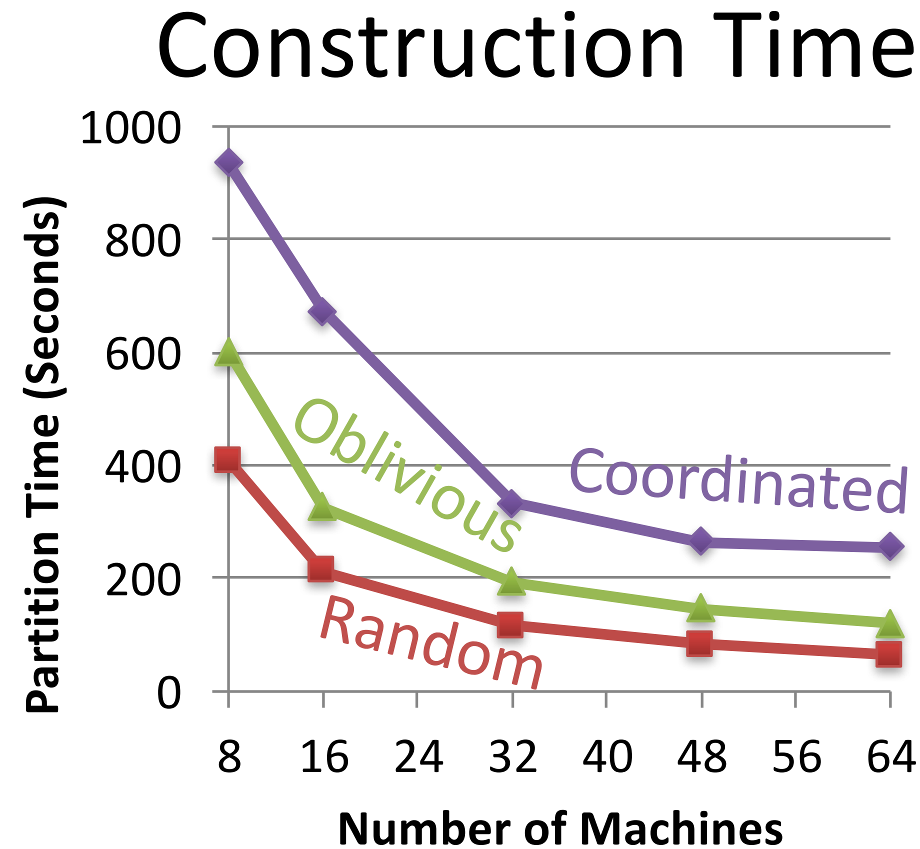
Greedy Vertex-Cuts

- **Derandomization**: Minimizes the expected number of machines spanned by each vertex.
- **Coordinated**
  - Maintain a shared placement history (DHT)
  - Slower but higher quality
- **Oblivious**
  - Operate only on local placement history
  - Faster but lower quality

Partitioning Performance

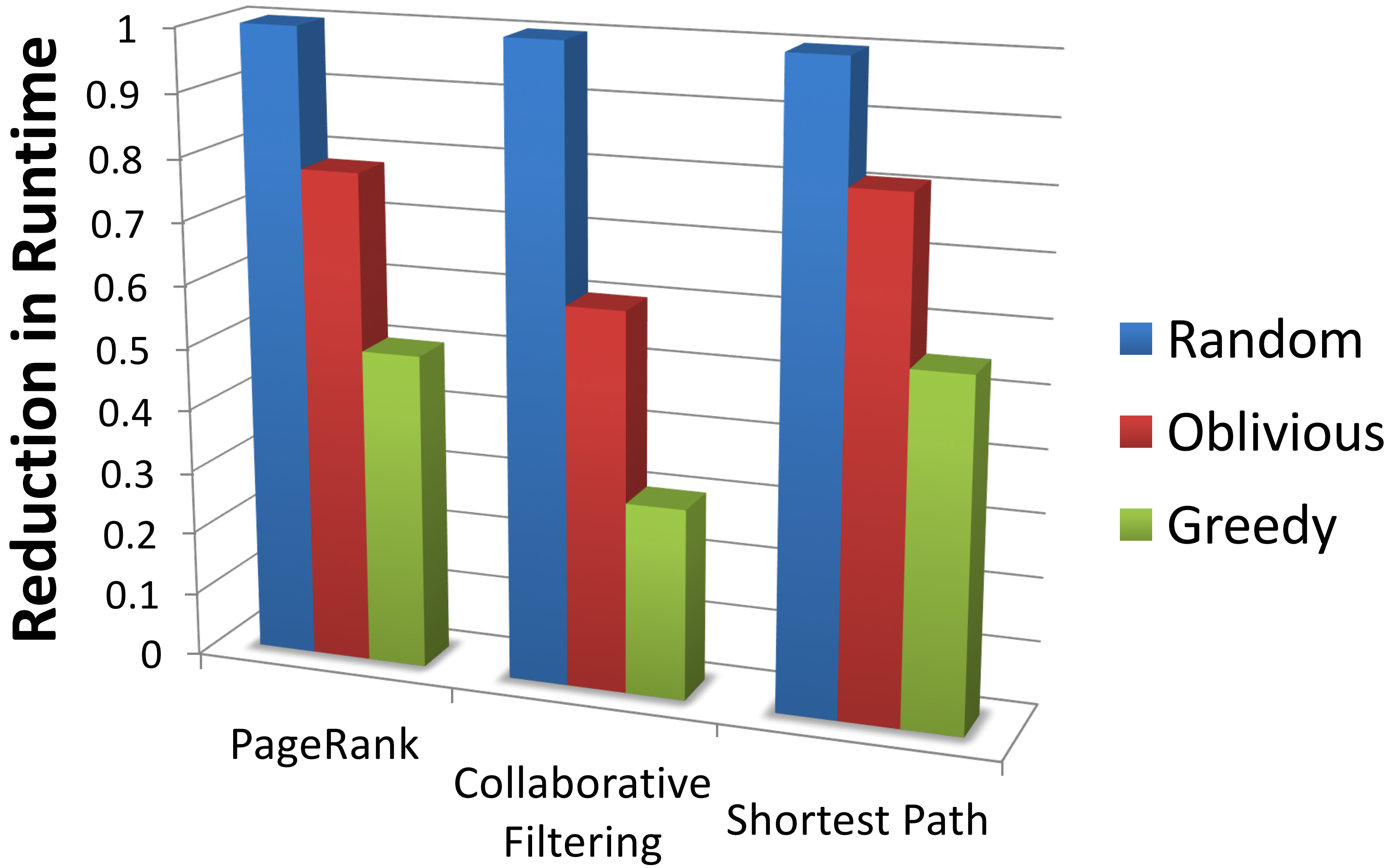
Twitter Graph: 41M vertices, 1.4B edges





Oblivious balances partition quality and partitioning time.

Beyond Random Vertex Cuts!

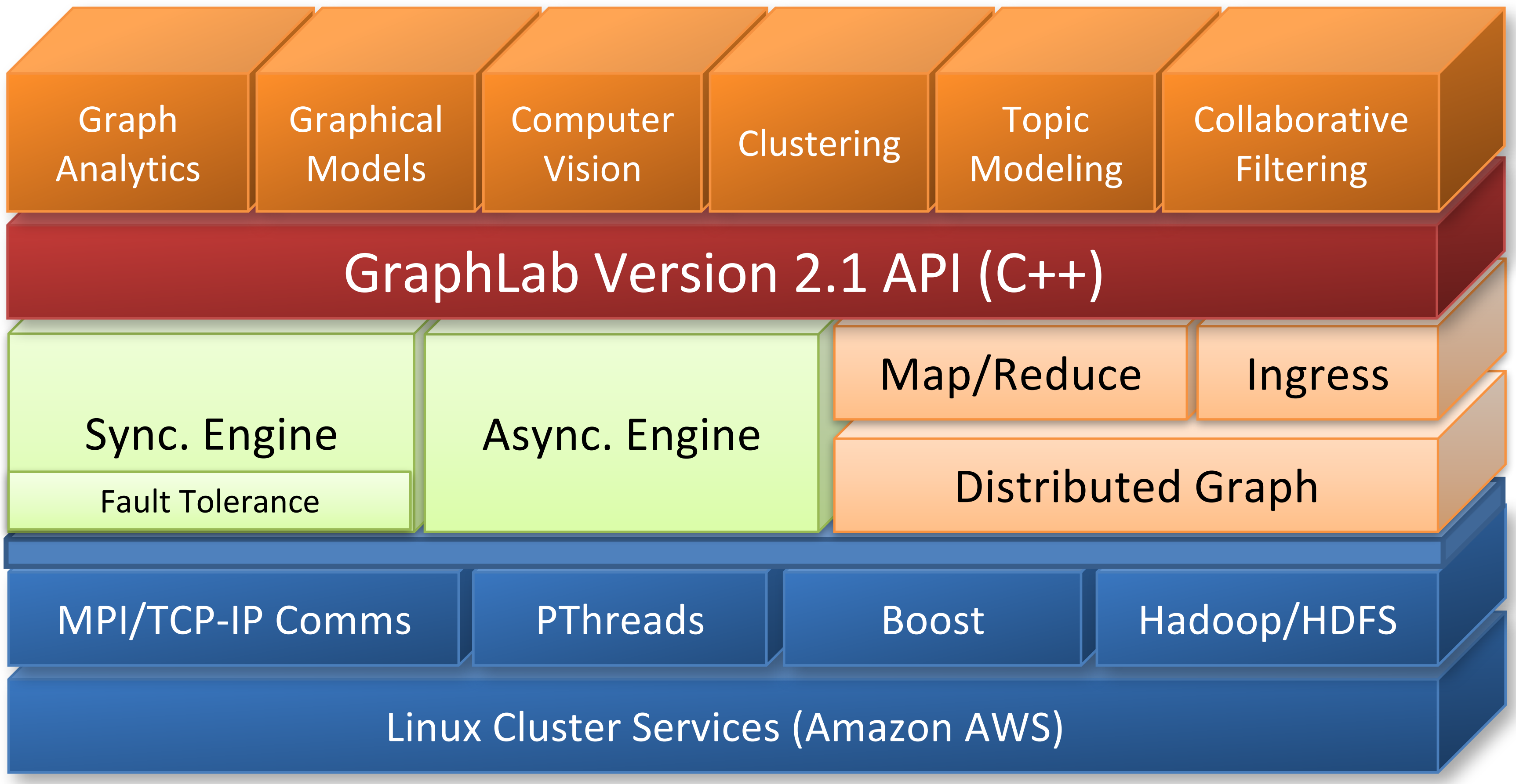


GraphLab2

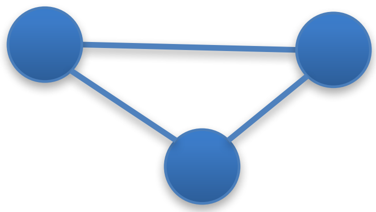
From the Abstraction to a System

Select Lab

Carnegie Mellon

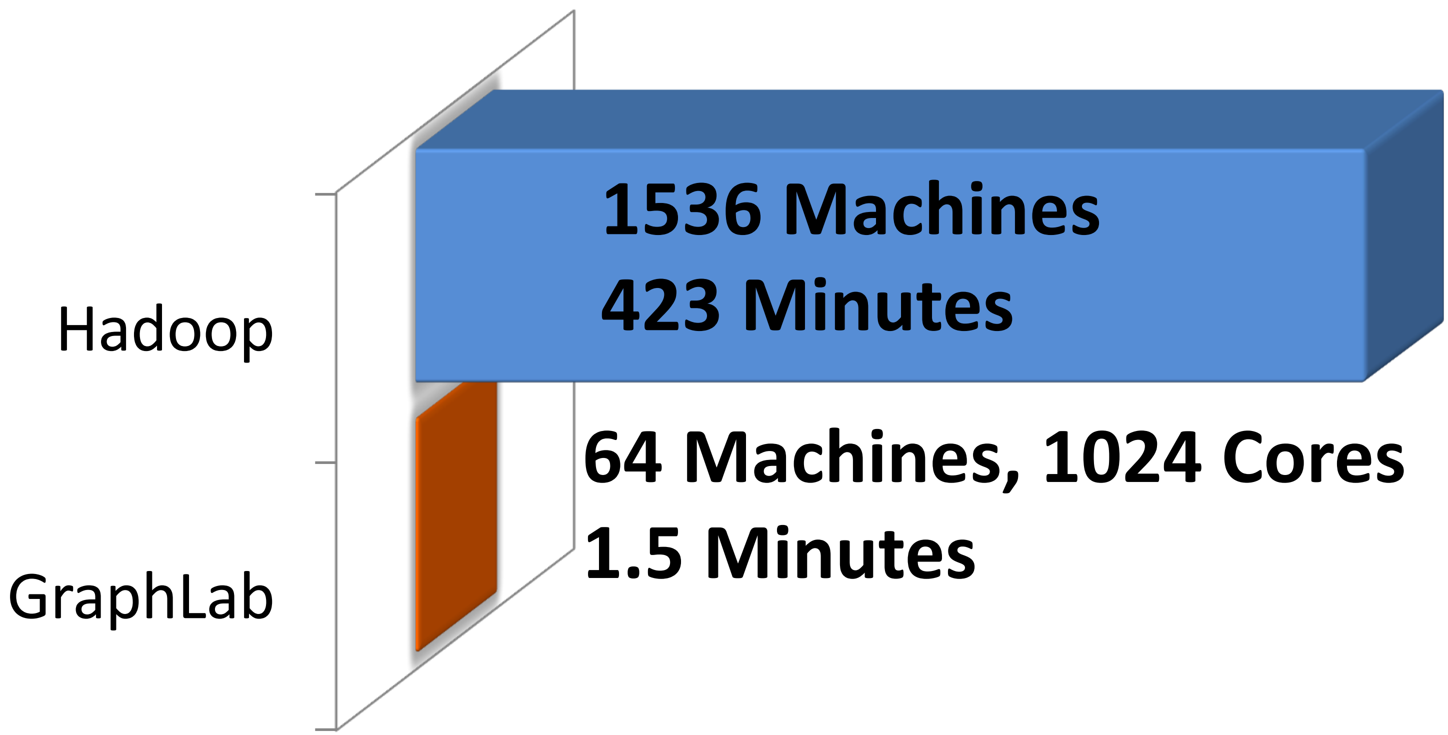

Graph Analytics
Graphical Models
Computer Vision
Clustering
Topic Modeling
Collaborative Filtering
GraphLab Version 2.1 API (C++)
Sync. Engine
Fault Tolerance
Async. Engine
Map/Reduce
Ingress
Distributed Graph
MPI/TCP-IP Comms
PThreads
Boost
Hadoop/HDFS
Linux Cluster Services (Amazon AWS)

Triangle Counting in Twitter Graph



40M Users
1.2B Edges

Total:
34.8 Billion Triangles

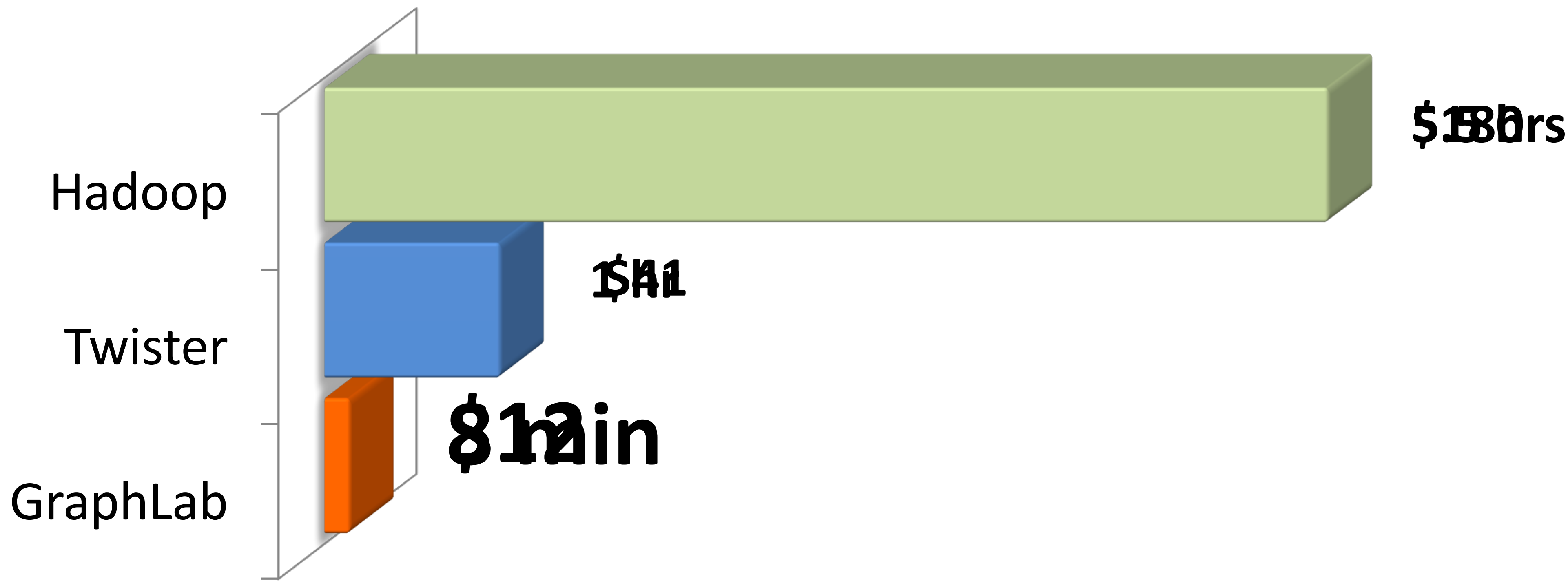


Hadoop results from [Suri & Vassilvitskii '11]

LDA Performance

- All English language Wikipedia
  - 2.6M documents, 8.3M words, 500M tokens
- LDA state-of-the-art sampler (100 Machines)
  - *Alex Smola*: 150 Million tokens per Second
- GraphLab Sampler (64 cc2.8xlarge EC2 Nodes)
  - **100 Million Tokens per Second**
  - Using only 200 Lines of code and 4 human hours

PageRank



40M Webpages, 1.4 Billion Links

Hadoop results from [Kang et al. '11]
Twister (in-memory MapReduce) [Ekanayake et al. '10]

How well does GraphLab scale?

Yahoo Altavista Web Graph (2002):

One of the largest publicly available webgraphs

1.4B Webpages, 6.6 Billion Links

11 Mins

64 HPC Nodes

1B links processed per second

30 lines of user code

1024 Cores (2048 HT)

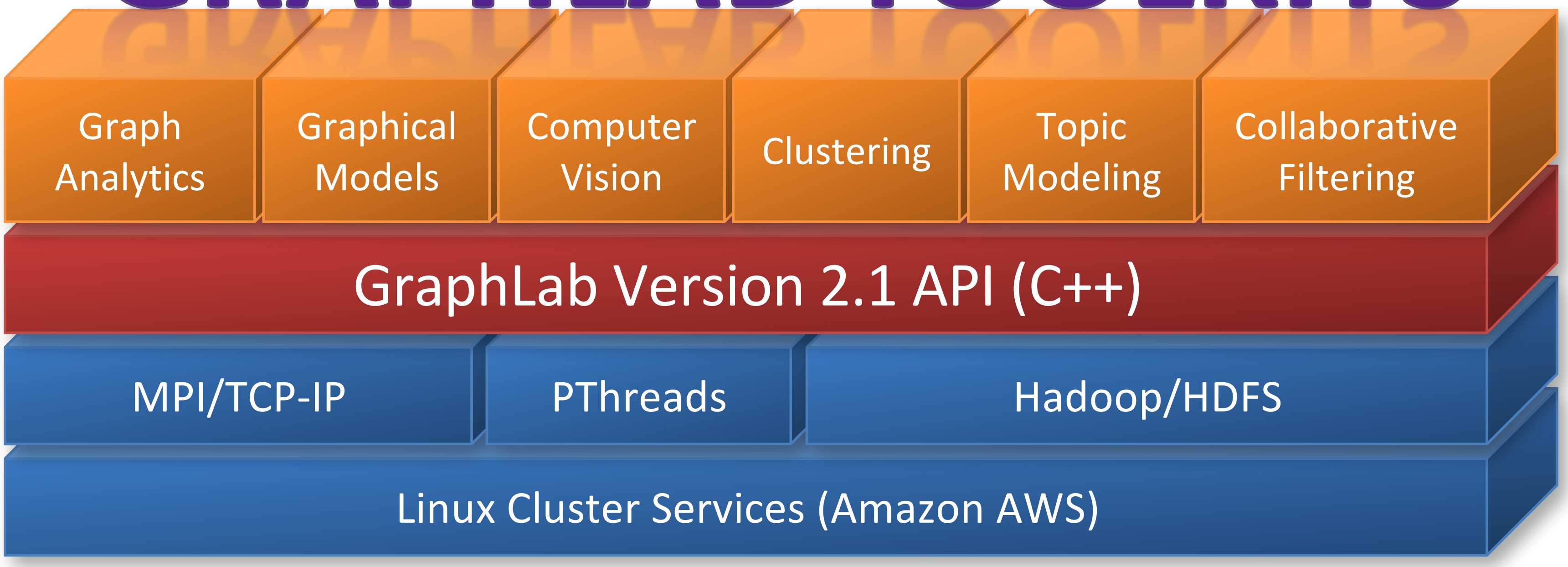
4.4 TB RAM

GraphLab

Release 2.1 available now

Apache 2 License

GRAPHLAB TOOLKITS

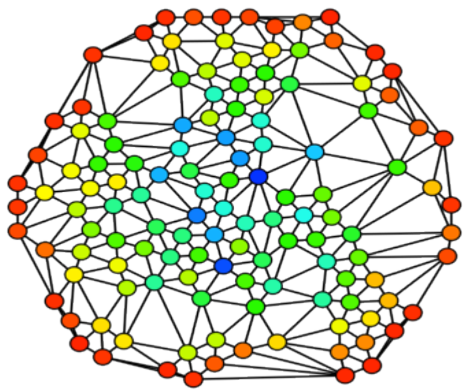


GraphLab easily incorporates external toolkits

Automatically detects and builds external toolkits

Graph Processing

Extract knowledge from graph structure



- Find communities
- Identify important individuals
- Detect vulnerabilities

Algorithms

- **Triangle Counting**
- **Pagerank**
- **K-Cores**
- **Shortest Path**

Coming soon:

- Max-Flow
- Matching
- Connected Components
- Label propagation

Collaborative Filtering

Understanding Peoples

***Shared** Interests*

- Target advertising
- Improve shopping experience

Algorithms

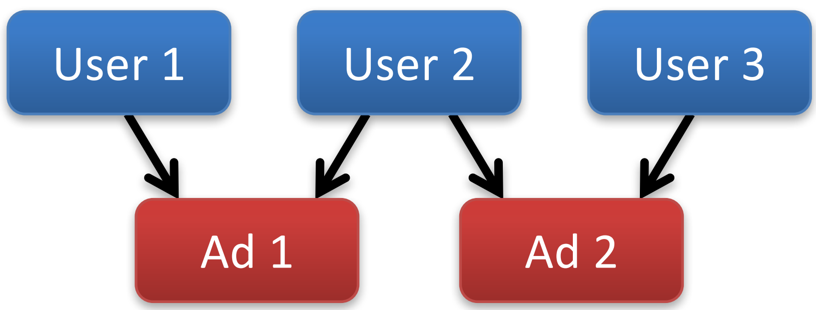
- **ALS, Weighted ALS**
- **SGD, Biased SGD**

Proposed:

- SVD++
- Sparse ALS
- Tensor Factorization

Graphical Models

Probabilistic analysis for correlated data.



- Improved predictions
- Quantify uncertainty
- Extract relationships

Algorithms

- **Loopy Belief Propagation**
- **Max Product LP**

Coming soon:

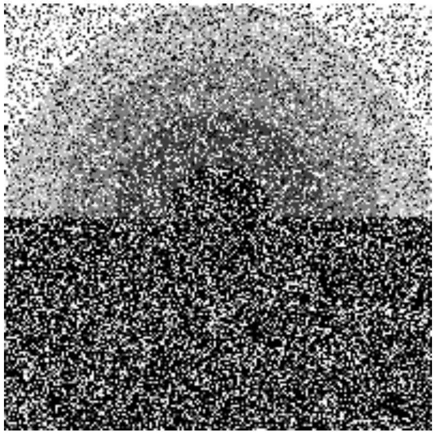
- Gibbs Sampling
- Parameter Learning
- L_1 Structure Learning
- M^3 Net
- Kernel Belief Propagation

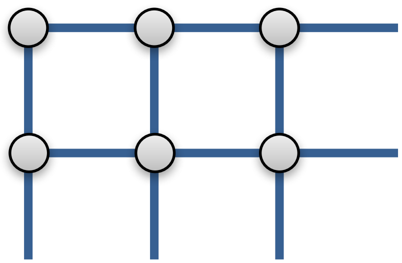
Structured Prediction

- Input:
  - Prior probability for each vertex

User Id	Pr(Conservative)	Pr(Not Conservative)
1	0.8	0.2
2	0.5	0.5
3	0.3	0.7
…	…	…

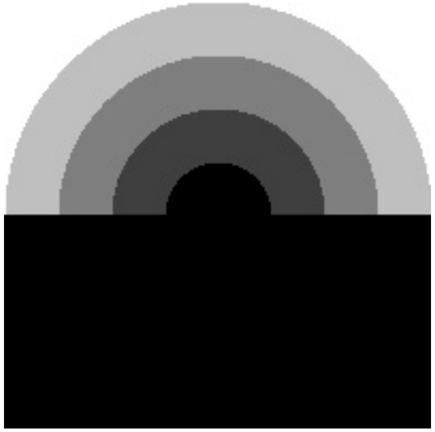
  - Edge List
  - Smoothing Parameter (e.g., 2.0)





- Output: posterior

User Id	Pr(Conservative)	Pr(Not Conservative)
1	0.7	0.3
2	0.3	0.7
3	0.1	0.8
…	…	…



sense
learn
act

Computer Vision (CloudCV)

Making sense of pictures.

- Recognizing people
- Medical imaging
- Enhancing images

Algorithms

- **Image stitching**
- **Feature extraction**

Coming soon:

- Person/object detectors
- Interactive segmentation
- Face recognition

Clustering

Identify groups of related data

- Group customer and products
- Community detection
- Identify outliers

Algorithms

- **K-Means++**

Coming soon:

- Structured EM
- Hierarchical Clustering
- Nonparametric *-Means

Topic Modeling

Extract meaning from raw text

- Improved search
- Summarize textual data
- Find related documents

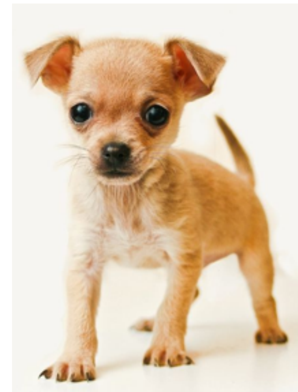
Algorithms

- **LDA Gibbs Sampler**

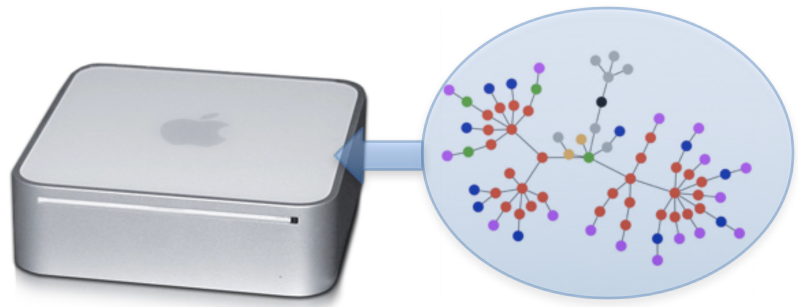
Coming soon:

- CVB0 for LDA
- LSA/LSI
- Correlated topic models
- Trending Topic Models

GraphChi: Going small with GraphLab



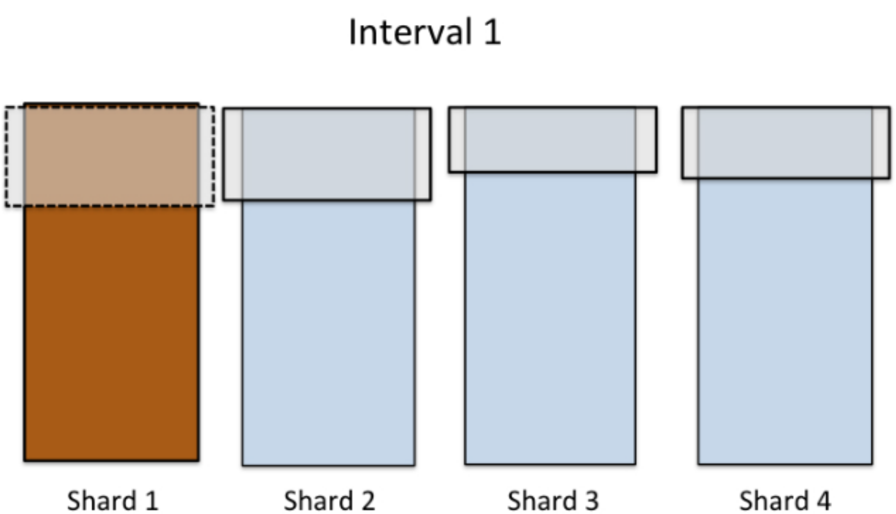
Solve huge problems on small or embedded devices?



Key: Exploit non-volatile memory (starting with SSDs and HDs)

GraphChi – disk-based GraphLab

Novel Parallel Sliding Windows algorithm

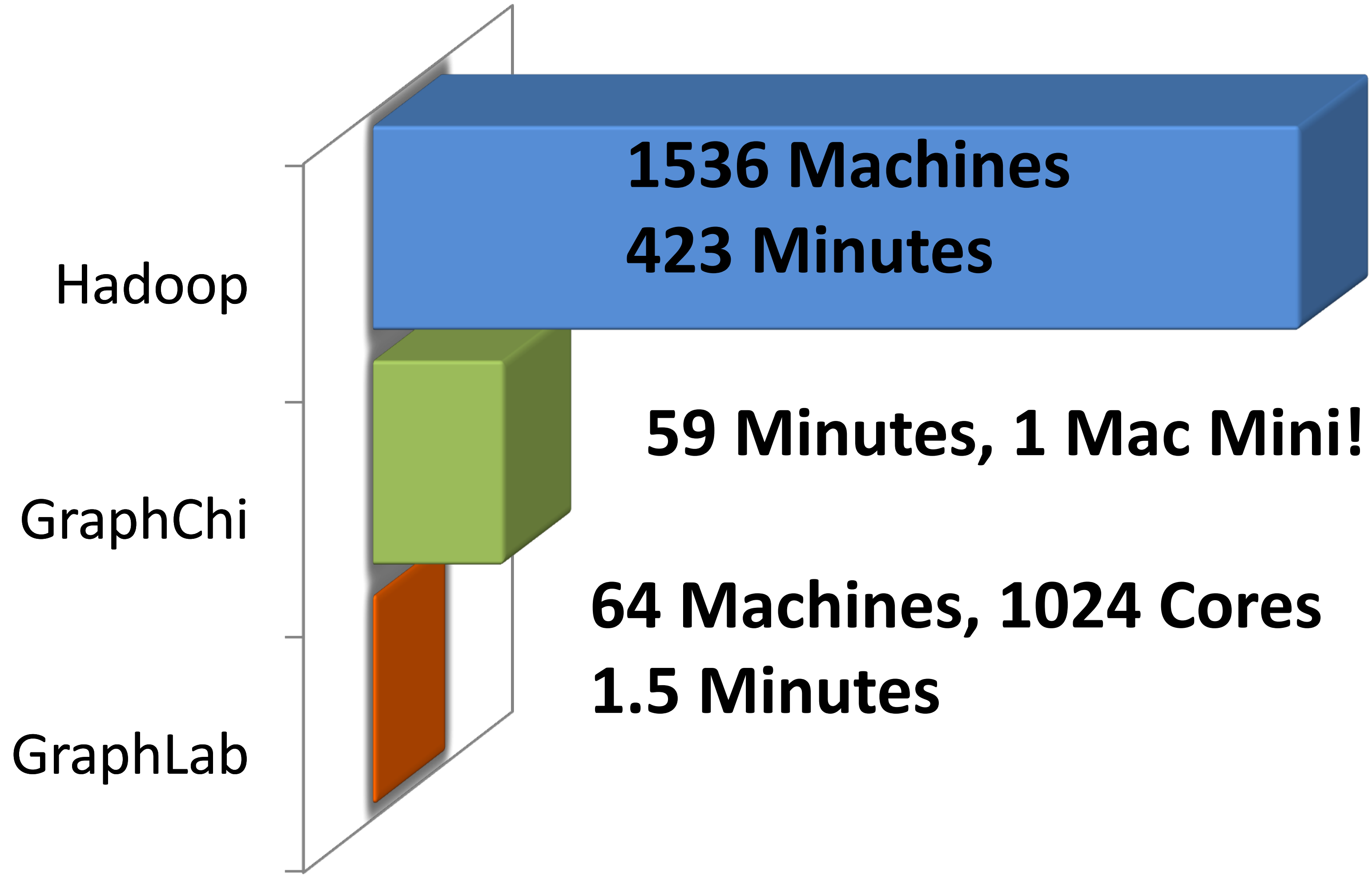


- Fast!
- Solves tasks as large as current distributed systems
- Minimizes disk seeks
  - Efficient on *both* SSD and hard-drive
- Multicore Asynchronous execution

Triangle Counting in Twitter Graph

40M Users
1.2B Edges

Total: 34.8 Billion Triangles



Hadoop results from [Suri & Vassilvitskii '11]

GraphLab

Release 2.1 available now

http://graphlab.org

Documentation… Code… Tutorials… (more on the way)

GraphChi 0.1 available now

http://graphchi.org


SUPPORT VECTOR MACHINES
REPEA POWE LAWS
END DUALITy GAP
Map Reduce
Map Reuse
Map Recycle
BAYeSIANS AGAINST DISCRIMINATION
FREE VARIABLES!
BAN GENETIC ALGORITHMS

Open Challenges

Dynamically Changing Graphs

- **Example:** *Social Networks*
  - New users → New Vertices
  - New Friends → New Edges
- How do you adaptively maintain computation:
  - Trigger computation with changes in the graph
  - Update "interest estimates" only where needed
  - Exploit asynchrony
  - Preserve consistency

Graph Partitioning

- How can you quickly place a large data-graph in a distributed environment:
- Edge separators fail on large power-law graphs
  - Social networks, Recommender Systems, NLP
- Constructing vertex separators at scale:
  - No large-scale tools!
  - How can you adapt the placement in changing graphs?

Graph Simplification for Computation

- Can you construct a “sub-graph” that can be used as a proxy for graph computation?
- See Paper:
  - *Filtering: a method for solving graph problems in MapReduce.*
    - http://research.google.com/pubs/pub37240.html

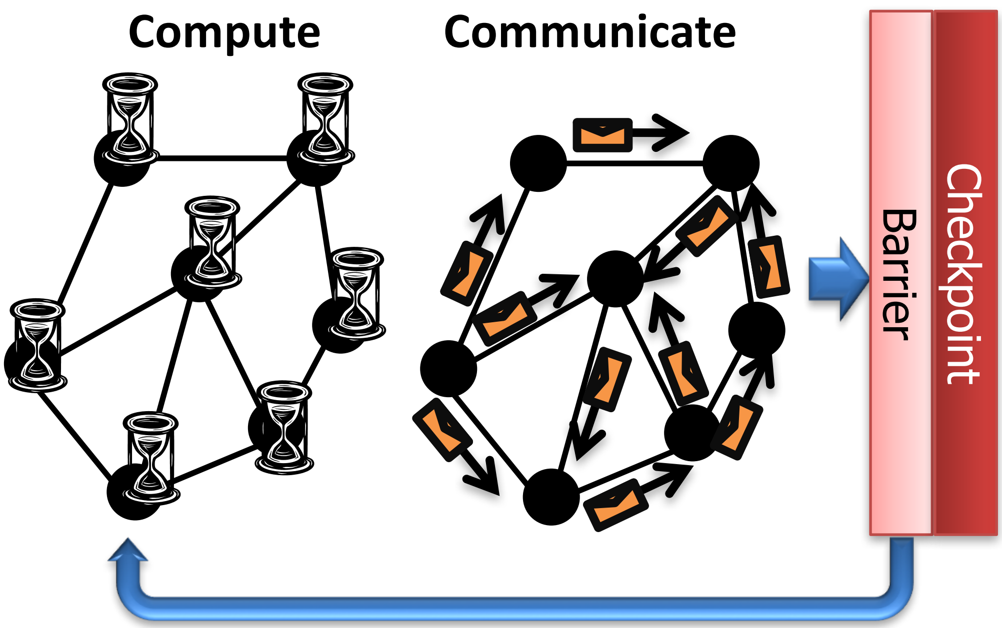
Concluding **BIG Ideas**

- Modeling Trend: Independent Data → Dependent Data
  - Extract more signal from noisy structured data
- Graphs model data dependencies
  - Captures locality and communication patterns
- Data-Parallel tools not well suited to Graph Parallel problems
- Compared several Graph Parallel Tools:
  - Pregel / BSP Models:
    - Easy to Build, **Deterministic**
    - Suffers from several key inefficiencies
  - GraphLab:
    - Fast, efficient, and expressive
    - Introduces non-determinism
  - GraphLab2:
    - Addresses the challenges of computation on Power-Law graphs
- Open Challenges: *Enormous Industrial Interest*

Fault Tolerance

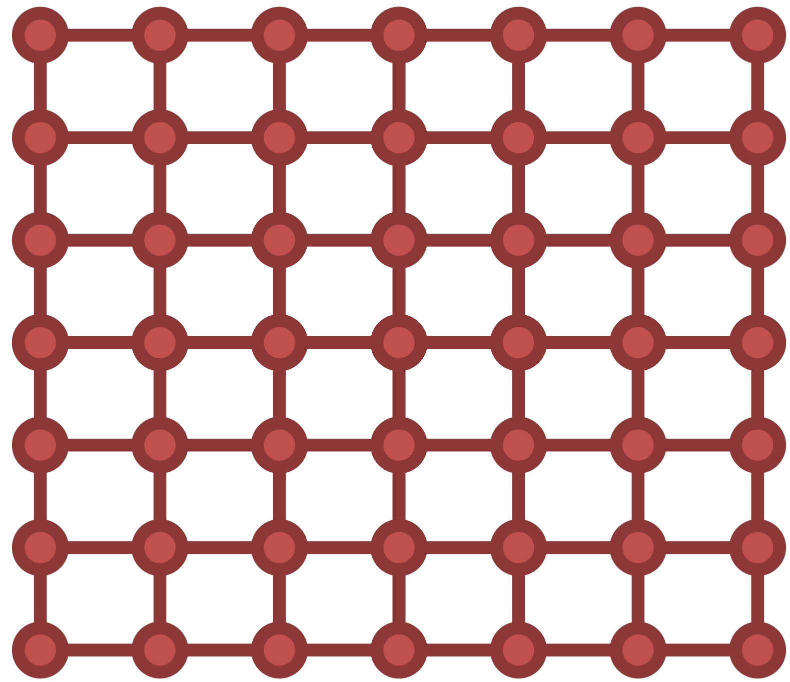
Checkpoint Construction

Pregel (BSP)



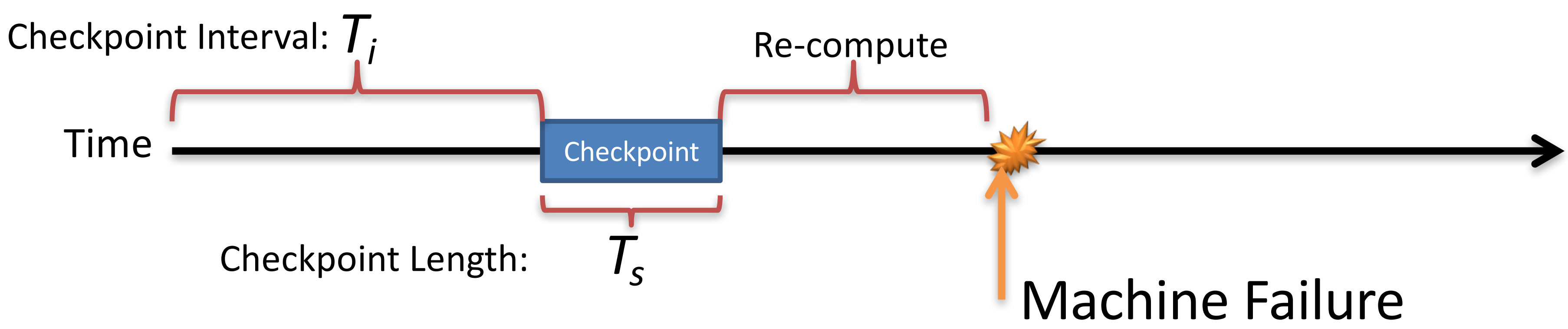
Synchronous Checkpoint Construction

GraphLab



Asynchronous Checkpoint Construction

Checkpoint Interval



- Tradeoff:
  - **Short** T_i: Checkpoints become too costly

  - **Long** T_i : Failures become too costly

Optimal Checkpoint Intervals

- Construct a first order approximation:

$$T_i \approx \sqrt{2 T_c T_{\mathrm{mtbf}}}$$

Checkpoint Interval

Length of Checkpoint

Mean time between failures

- Example:
  - 64 machines with a per machine MTBF of 1 year
    - T_{mtbf} = 1 year / 64 ≈ **130 Hours**
  - T_c = of 4 minutes
  - T_i ≈ of 4 hours

From: http://dl.acm.org/citation.cfm?id=361115