Case Study 4: Collaborative Filtering

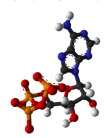
GraphLab

Machine Learning/Statistics for Big Data
CSE599C1/STAT592, University of Washington

Carlos Guestrin

March 14th, 2013

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

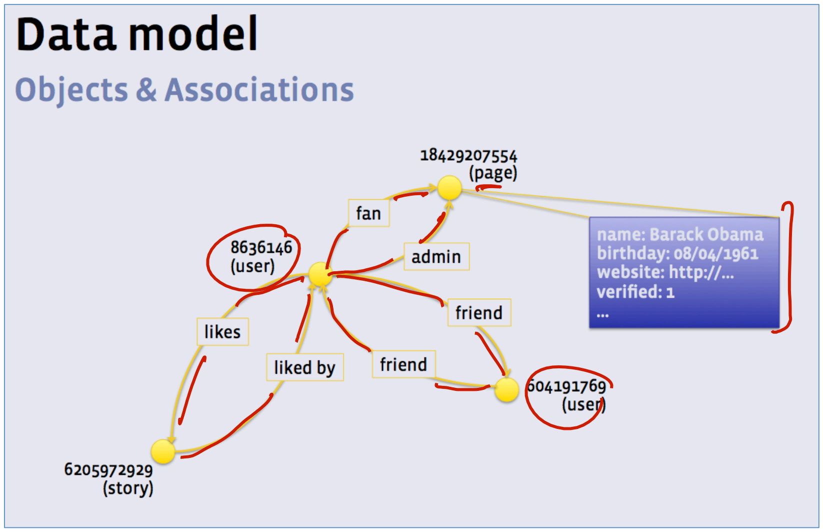


- **Graphs** encode the **relationships** between:

People Products Ideas
Facts Interests

- **Big: 100 billions** of **vertices** and **edges** and rich metadata
  - Facebook (10/2012): 1B users, 144B friendships
  - Twitter (2011): 15B follower edges

Facebook Graph



Slide from Facebook Engineering presentation 3

Addressing Graph-Parallel ML

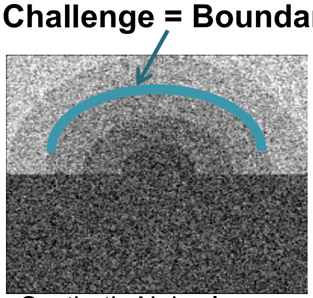
Data-Parallel ⟷ Graph-Parallel

Map Reduce	Graph-Parallel Abstraction
Feature Extraction; Cross Validation; Computing Sufficient Statistics	**Graphical Models**: Gibbs Sampling, Belief Propagation, Variational Opt.; **Semi-Supervised Learning**: Label Propagation, CoEM; **Collaborative Filtering**: Tensor Factorization; **Data-Mining**: PageRank, Triangle Counting

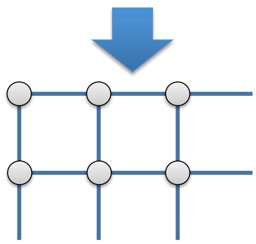
4

Asynchronous Belief Propagation

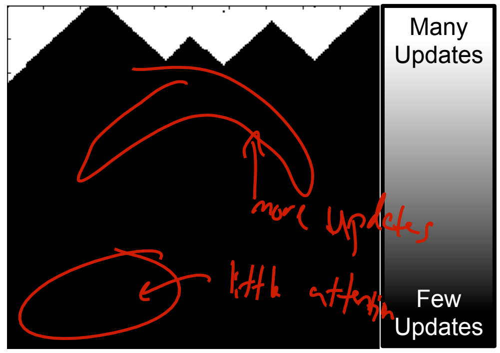
Challenge = Boundaries



Synthetic Noisy Image



Graphical Model



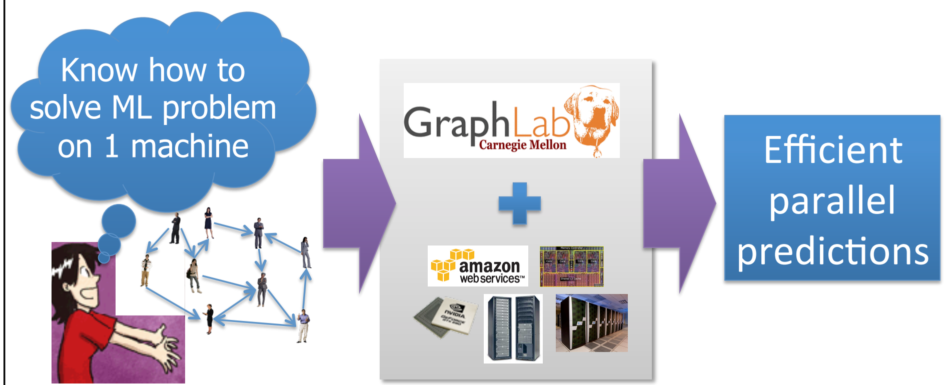
Cumulative Vertex Updates

Algorithm identifies and focuses on hidden sequential structure

Synchronous v. Asynchronous

- Bulk synchronous processing:
  - Computation in phases
    - All vertices participate in a phase
      - Though OK to say no-op
    - All messages are sent
  - Simpler to build, like Map-Reduce
    - No worries about race conditions, barrier guarantees data consistency
    - Simpler to make fault-tolerant, save data on barrier
  - Slower convergence for many ML problems
  - In matrix-land, called Jacobi Iteration
  - Implemented by Google Pregel 2010
- Asynchronous processing:
  - Vertices see latest information from neighbors
    - Most closely related to sequential execution
  - Harder to build:
    - Race conditions can happen all the time
      - Must protect against this issue
    - More complex fault tolerance
    - When are you done?
    - Must implement scheduler over vertices
  - Faster convergence for many ML problems
  - In matrix-land, called Gauss-Seidel Iteration
  - Implemented by GraphLab 2010, 2012

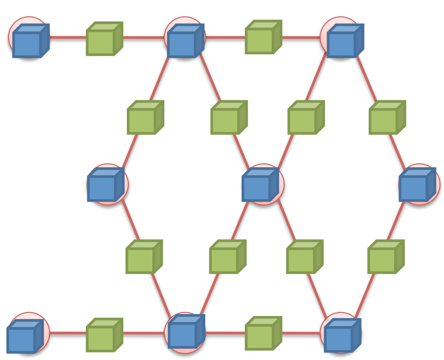
The **GraphLab** Goals



 7

Data Graph

Data associated with vertices and edges



Graph:
- Social Network

Vertex Data:
- User profile text
- Current interests estimates

Edge Data:
- Similarity weights

 8

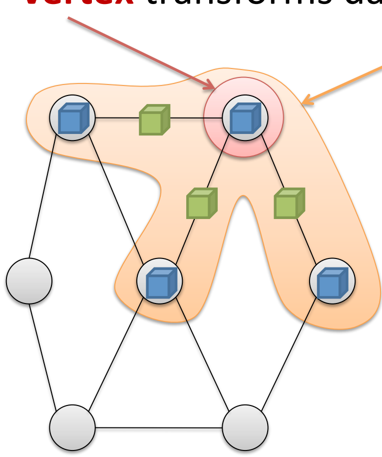
How do we *program* **graph** computation?

"Think like a Vertex."

-Malewicz et al. [SIGMOD'10]

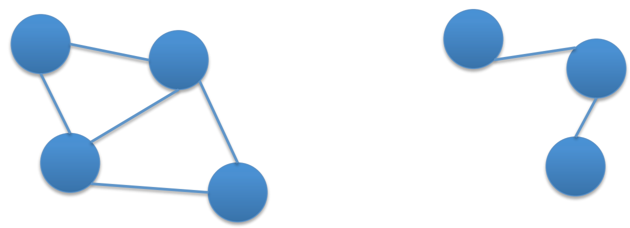
Update Functions

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

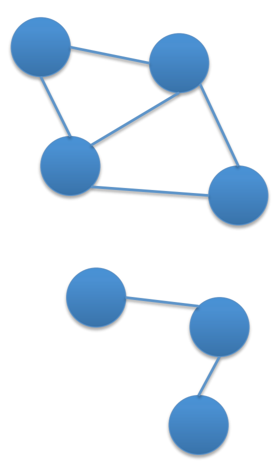


```
pagerank(i, scope){



}
```

Connected Components

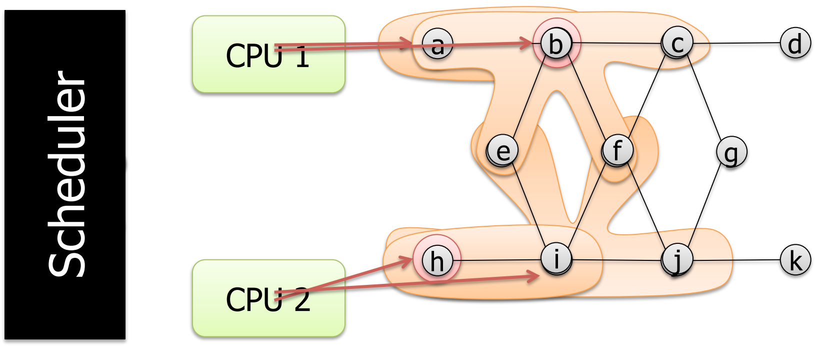


Update Function Example: Connected Components



The Scheduler

The **scheduler** determines order vertices are updated

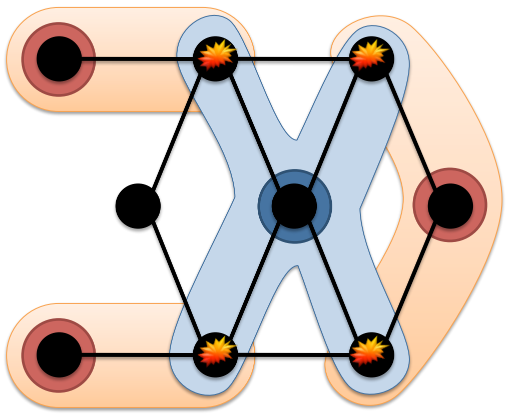


Example Schedulers

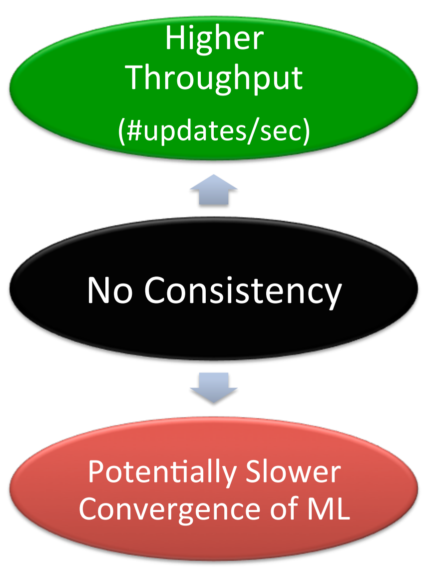
- Round-robin
- Selective scheduling (skipping):
  - round robin but jump over un-scheduled vertice
- FIFO
- Prioritize scheduling
  - Hard to implement in a distributed fashion
    - Approximations used (each machine has its own priority queue)

Ensuring Race-Free Code

How much can computation **overlap**?

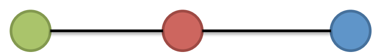


Need for Consistency?



GraphLab Ensures **Sequential Consistency**

For **each parallel execution**, there exists a **sequential execution** of update functions which produces the same result



Parallel

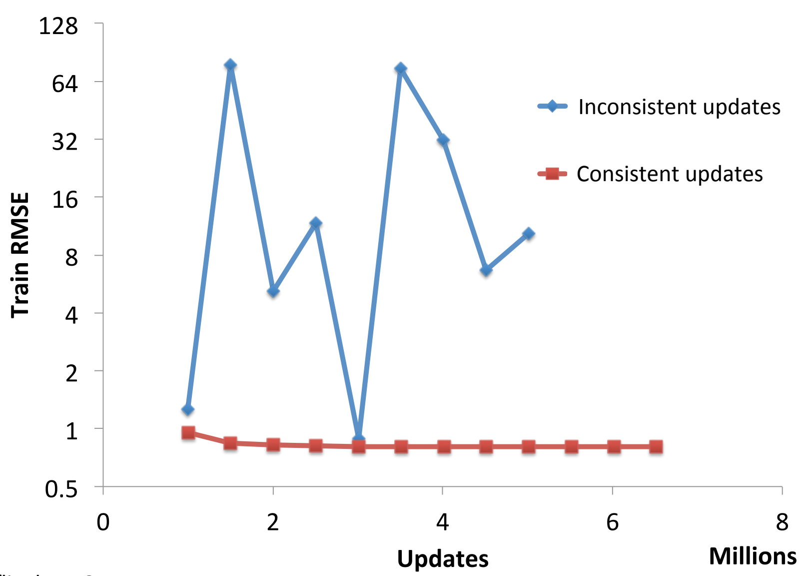
CPU 1

CPU 2

Sequential

Single CPU

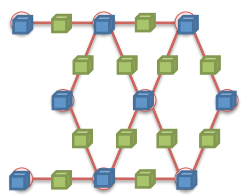
Consistency in Collaborative Filtering



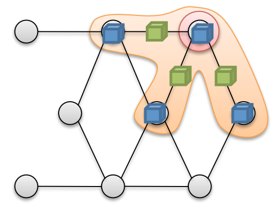
Netflix data, 8 cores

The GraphLab Framework

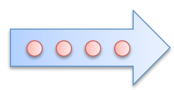
Graph Based
Data Representation



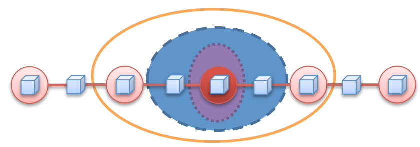
Update Functions
User Computation



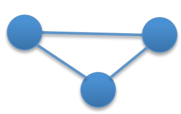
Scheduler



Consistency Model

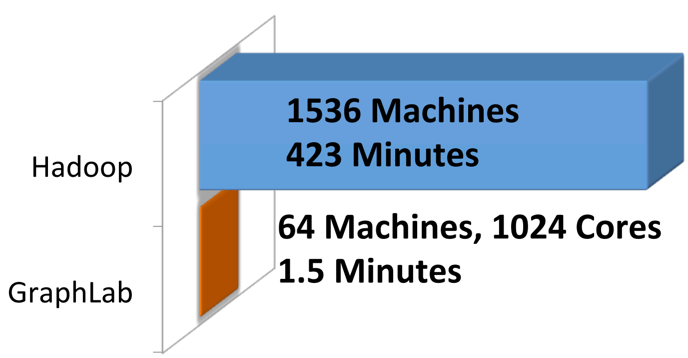


Triangle Counting in Twitter Graph



40M Users
1.2B Edges

Total:
34.8 Billion Triangles

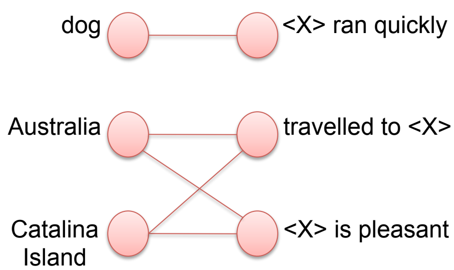


Hadoop results from [Suri & Vassilvitskii '11]

CoEM (Jones et al., 2005)

Named Entity Recognition Task

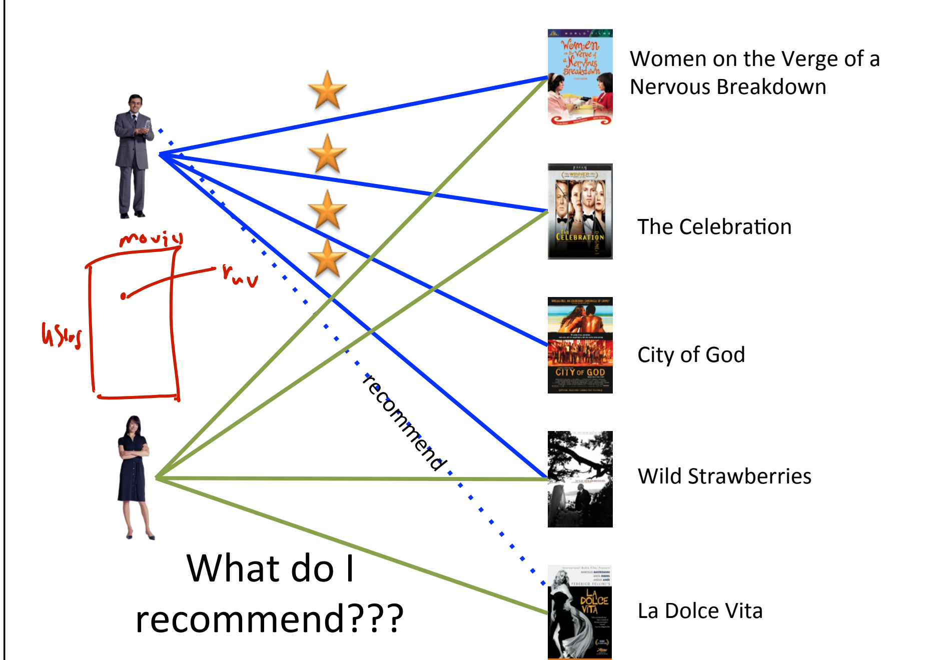
Is “Dog” an animal?
Is “Catalina” a place?



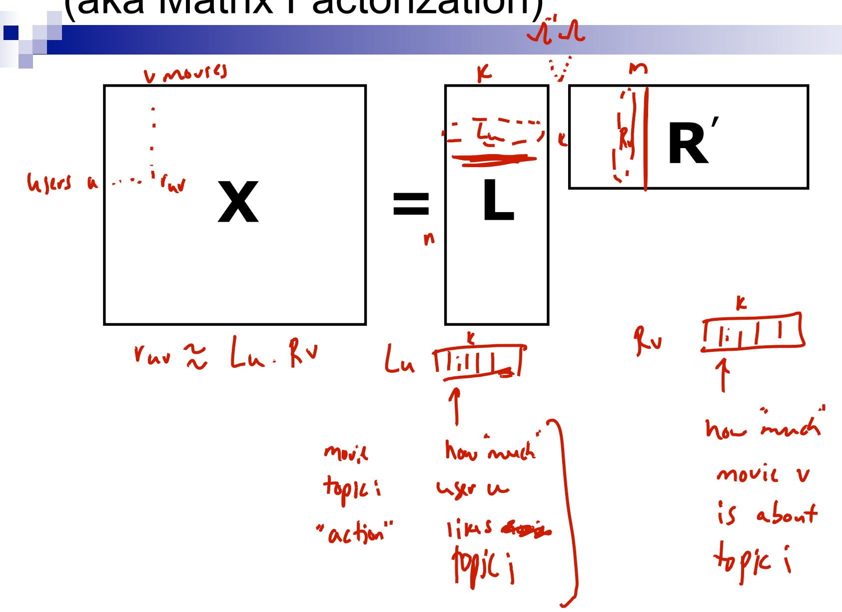
Never Ending Learner Project (CoEM)

Vertices: 2 Million
Edges: 200 Million

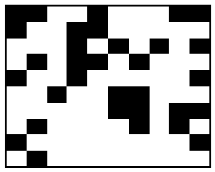
Hadoop	95 Cores	7.5 hrs
Distributed GraphLab	**32 EC2 machines**	**80 secs**



Interpreting Low-Rank Matrix Completion (aka Matrix Factorization)



Matrix Completion as a Graph

X = 

X_{ij} known for black cells
X_{ij} unknown for white cells
Rows index users
Columns index movies

Coordinate Descent for Matrix Factorization: Alternating Least-Squares

$$\min_{L,R} \sum_{(u,v,r_{uv})\in X: r_{uv}\neq ?} (L_u \cdot R_v - r_{uv})^2 + \lambda_u \|L\| + \lambda_v \|R\|$$

- Fix movie factors, optimize for user factors
  - Independent least-squares over users

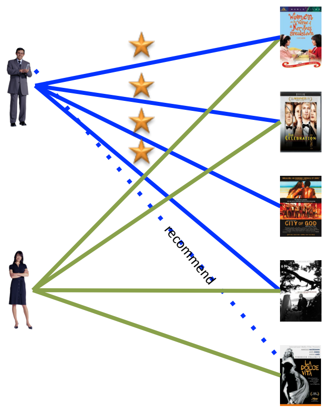
$$\min_{L_u} \sum_{v \in V_u} (L_u \cdot R_v - r_{uv})^2 + \lambda_u \|L_u\|$$

- Fix user factors, optimize for movie factors
  - Independent least-squares over movies

$$\min_{R_v} \sum_{u \in U_v} (L_u \cdot R_v - r_{uv})^2 + \lambda_v \|R_v\|$$

- System may be underdetermined: use regularization
- Converges to local optima

Alternating Least Squares Update Function

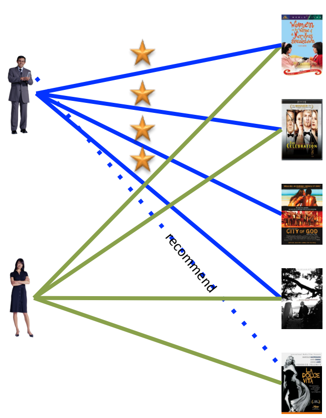


$$\min_{L_u} \sum_{v \in V_u} (L_u \cdot R_v - r_{uv})^2 \qquad \min_{R_v} \sum_{u \in U_v} (L_u \cdot R_v - r_{uv})^2$$

SGD for Matrix Factorization in Map-Reduce?

$$\epsilon_t = L_u^{(t)} \cdot R_v^{(t)} - r_{uv}$$

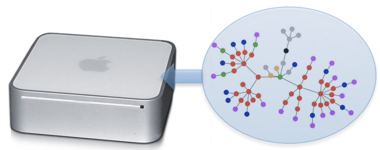
$$\begin{bmatrix} L_u^{(t+1)} \\ R_v^{(t+1)} \end{bmatrix} \leftarrow \begin{bmatrix} (1-\eta_t \lambda_u) L_u^{(t)} - \eta_t \epsilon_t R_v^{(t)} \\ (1-\eta_t \lambda_v) R_v^{(t)} - \eta_t \epsilon_t L_u^{(t)} \end{bmatrix}$$



GraphChi: Going small with GraphLab

GraphLab

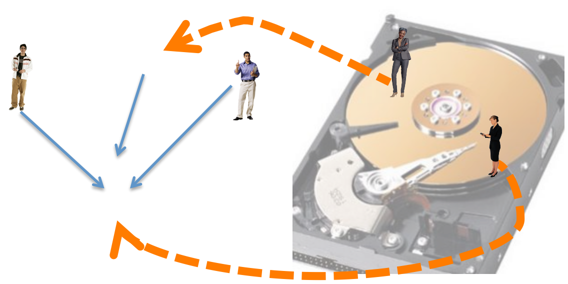
Solve huge problems on small or embedded devices?



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

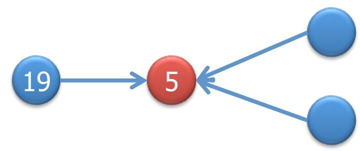
GraphChi – disk-based GraphLab

Challenge:
Random Accesses



Novel GraphChi solution:
Parallel sliding windows method ➔ minimizes number of random accesses

Naive Graph Disk Layouts



- Symmetrized adjacency file with values,

vertex	in-neighbors	out-neighbors
5	**3**:2.3, **19**: 1.3, **49**: 0.65,...	**781**: 2.3, **881**: 4.2..
....		
19	**3**: 1.4, **9**: 12.1, ...	**5**: 1.3, 28: 2.2, ...

synchronize

Random write

- … or with file index pointers

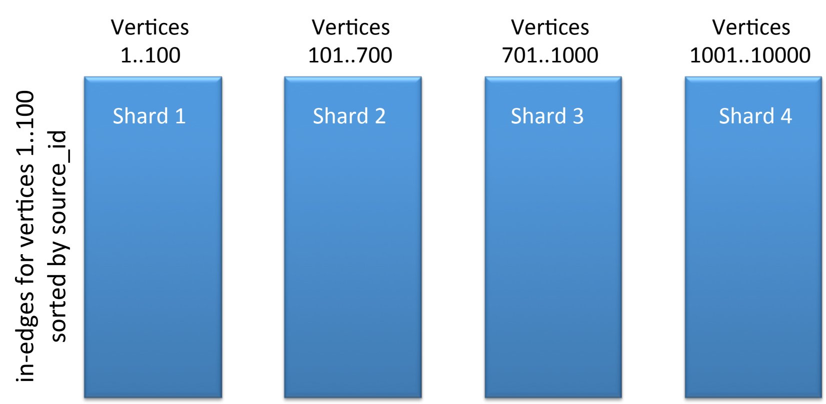
vertex	in-neighbor-ptr	out-neighbors
5	**3**: 881, **19**: 10092, **49**: 20763,...	**781**: 2.3, **881**: 4.2..
....		
19	**3**: 882, **9**: 2872, ...	**5**: 1.3, 28: 2.2, ...

read

Random read/write

Parallel Sliding Windows Layout

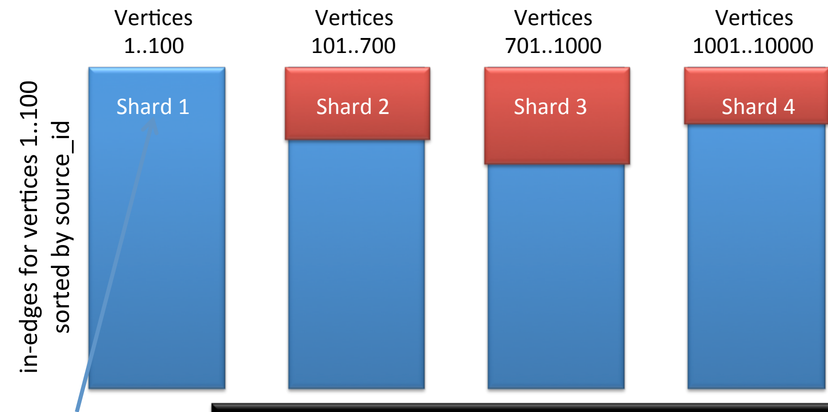
Shard: in-edges for subset of vertices; sorted by source_id



Shards small enough to fit in memory; balance size of shards

Parallel Sliding Windows Execution

Load subgraph for vertices 1..100

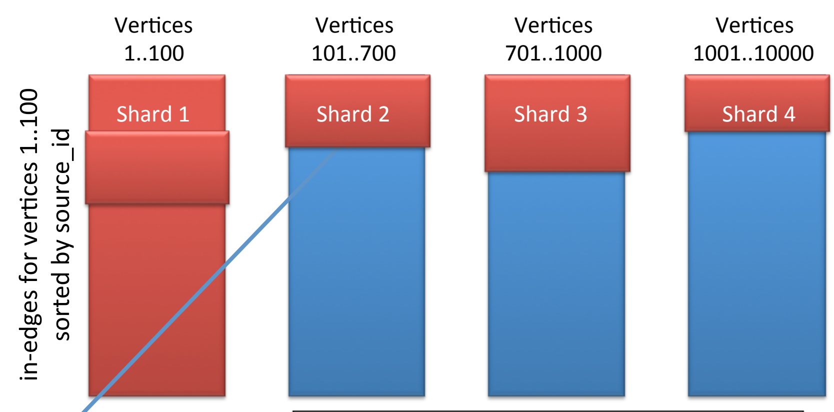


Load all in-edges in memory

What about out-edges?
- Arranged in sequence in other shards!
- And sequential writes!

Parallel Sliding Windows Execution

Load subgraph for vertices 101..700



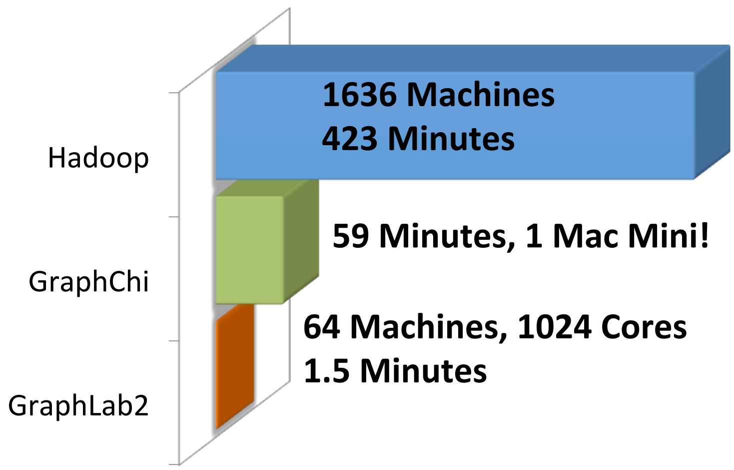
Load all in-edges in memory

Only $O(P^2)$ random reads per pass on entire graph

Triangle Counting on Twitter Graph

40M Users
1.2B Edges

Total: 34.8 Billion Triangles



©Carlos Guestrin 2013

Hadoop results from [Suri & Vassilvitskii '11]

35

GraphLab

Release 2.1 available now

http://graphlab.org

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

GraphChi 0.1 available now

http://graphchi.org

What you need to know…

- Data-parallel versus graph-parallel computation
- Bulk synchronous processing versus asynchronous processing
- GraphLab system for graph-parallel computation
  - Data representation
  - Update functions
  - Scheduling
  - Consistency model