OSDI'12

GraphChi: Large-Scale Graph Computation on Just a PC

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In co-operation with the GraphLab team.

Carnegie Mellon

BigData with *Structure*: BigGraph

social graph

social graph

follow-graph

consumer-products graph

user-movie ratings graph

DNA interaction graph

WWW link graph

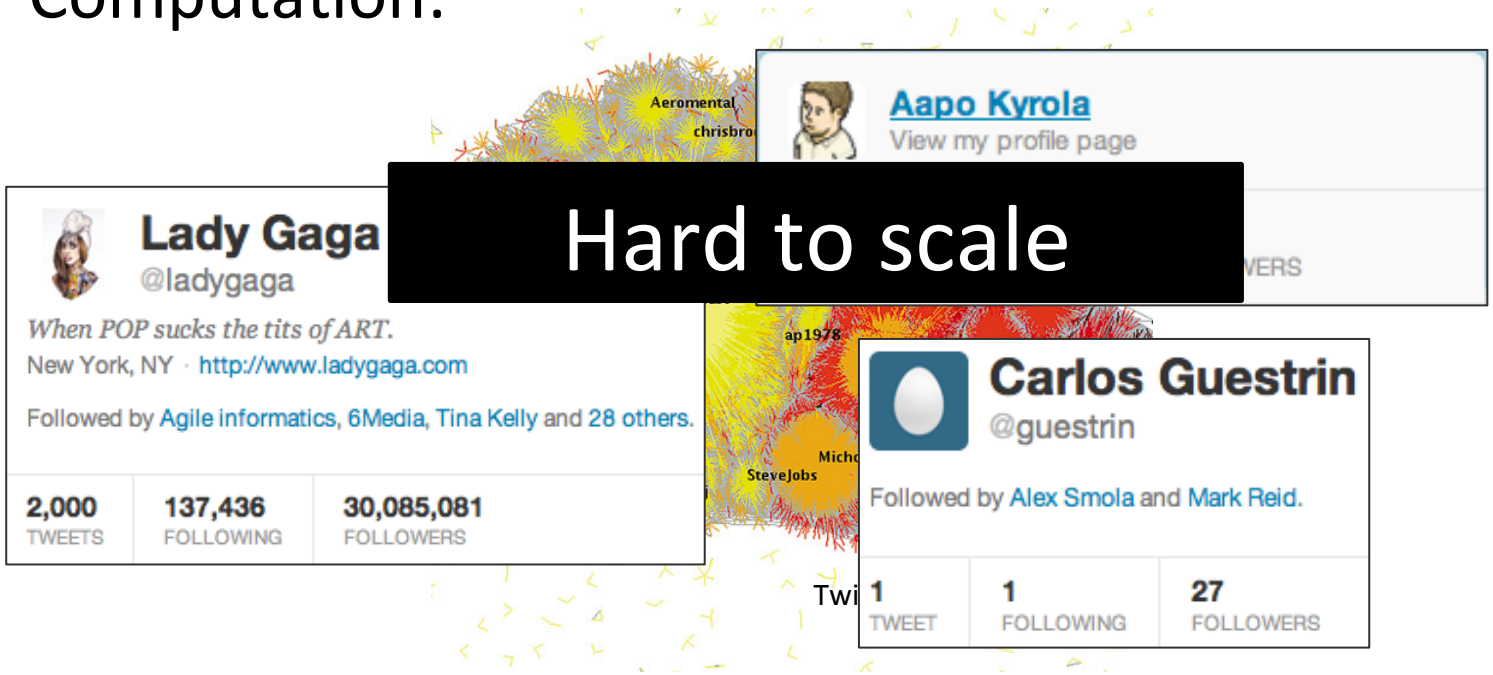
etc.

Big Graphs != Big Data

Data size: facebook 140 billion connections ≈ 1 TB

Not a problem!

Computation:

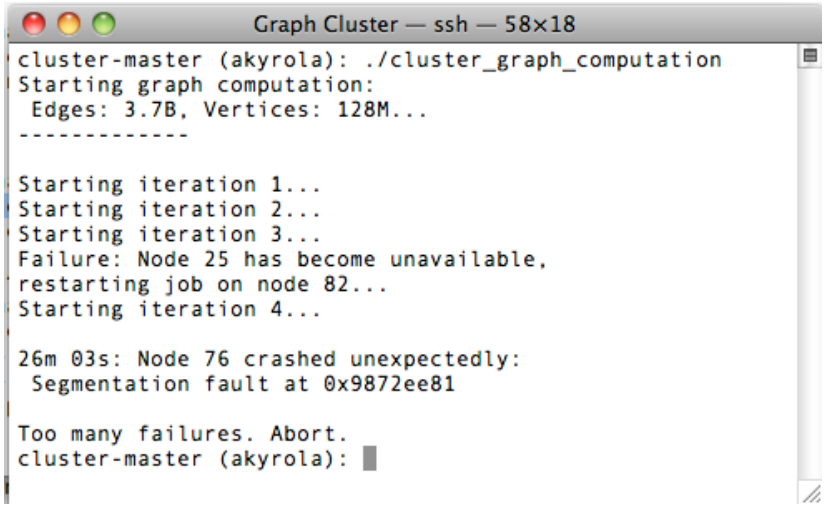


Could we compute Big Graphs on a *single machine?*

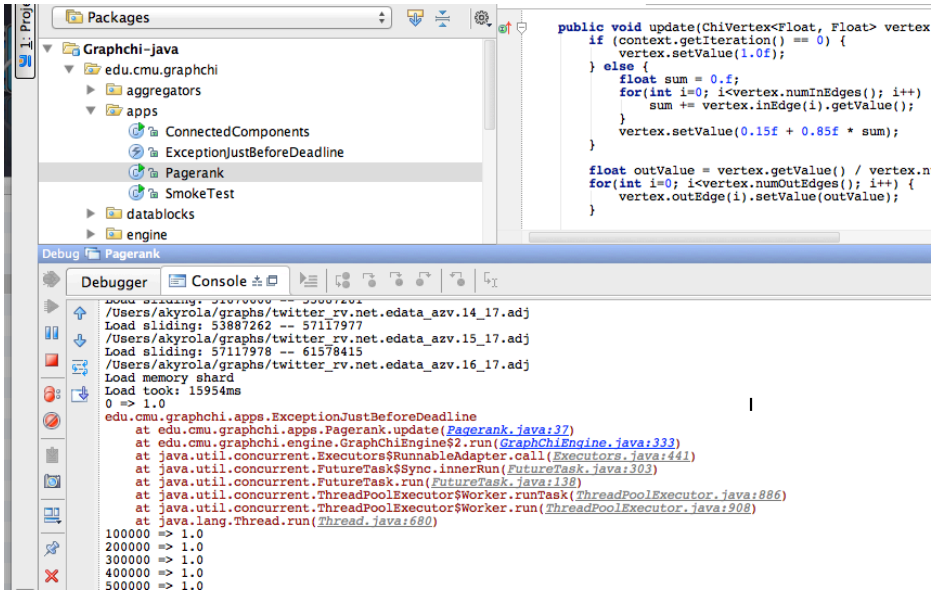
Disk-based Graph Computation

Distributed State is Hard to Program

Writing distributed applications remains cumbersome.



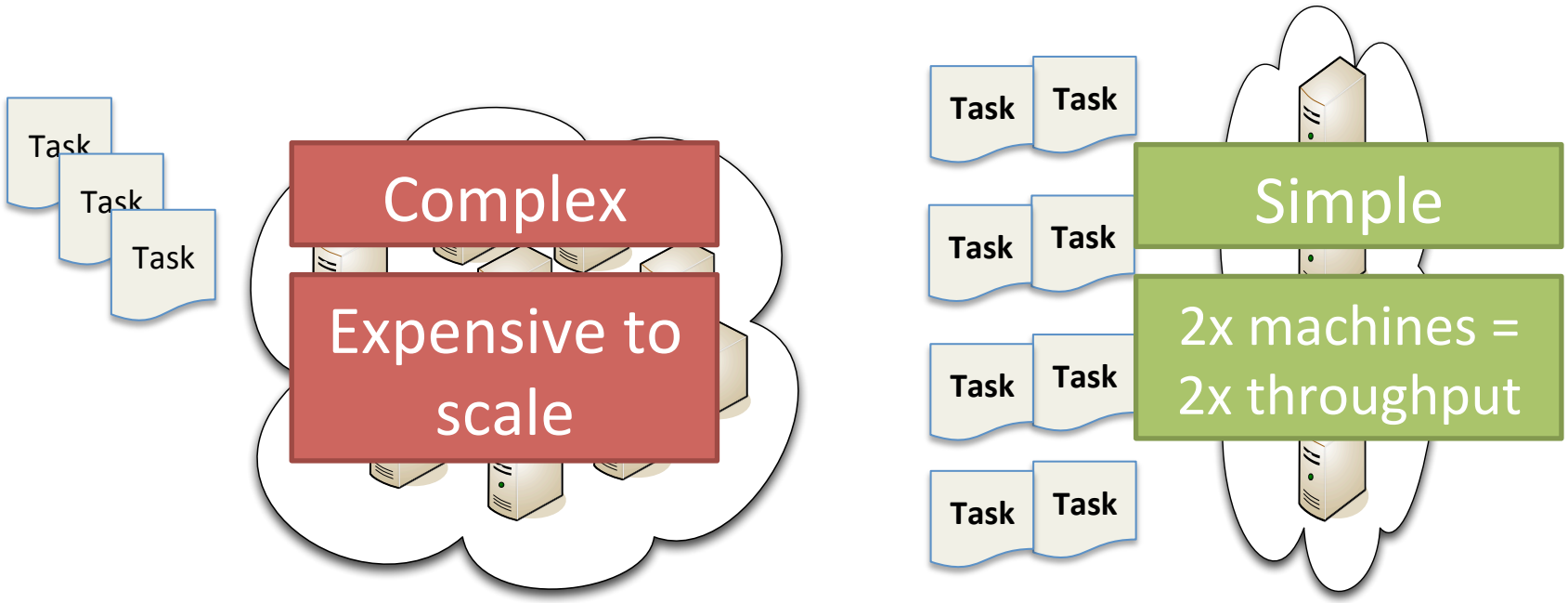
Cluster crash



Crash in your IDE

Efficient Scaling

- Businesses need to compute hundreds of distinct tasks on the same graph
  - Example: personalized recommendations.



Parallelize each task

Parallelize across tasks

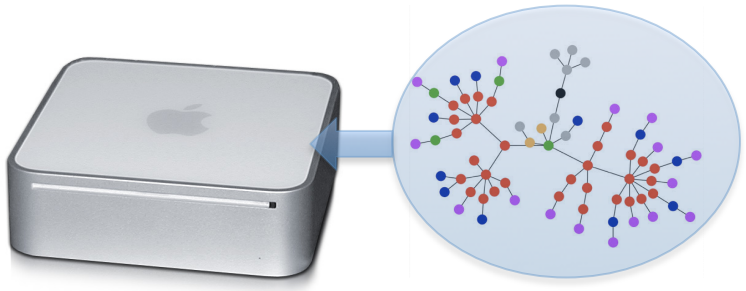
Other Benefits

- **Costs**
  - Easier management, simpler hardware.
- **Energy Consumption**
  - Full utilization of a single computer.
- Embedded systems, mobile devices
  - A basic flash-drive can fit a huge graph.

Research Goal

Compute on graphs with billions of edges, in *a reasonable time,* on a single PC.

– *Reasonable* = close to numbers previously reported for distributed systems in the literature.

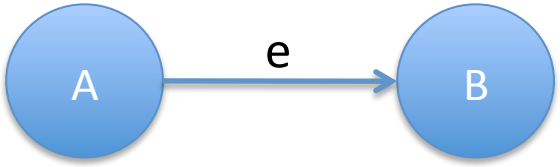


Experiment PC: Mac Mini (2012)

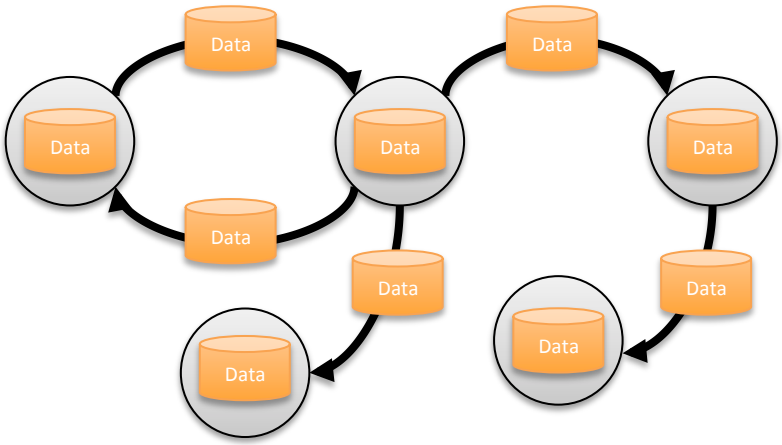
Computational Model

Computational Model

- Graph G = (V, E)
  - **directed edges**: e = (source, destination)
  - each edge and vertex **associated with a value** (user-defined type)
  - vertex and edge **values can be modified**
    - (structure modification also supported)

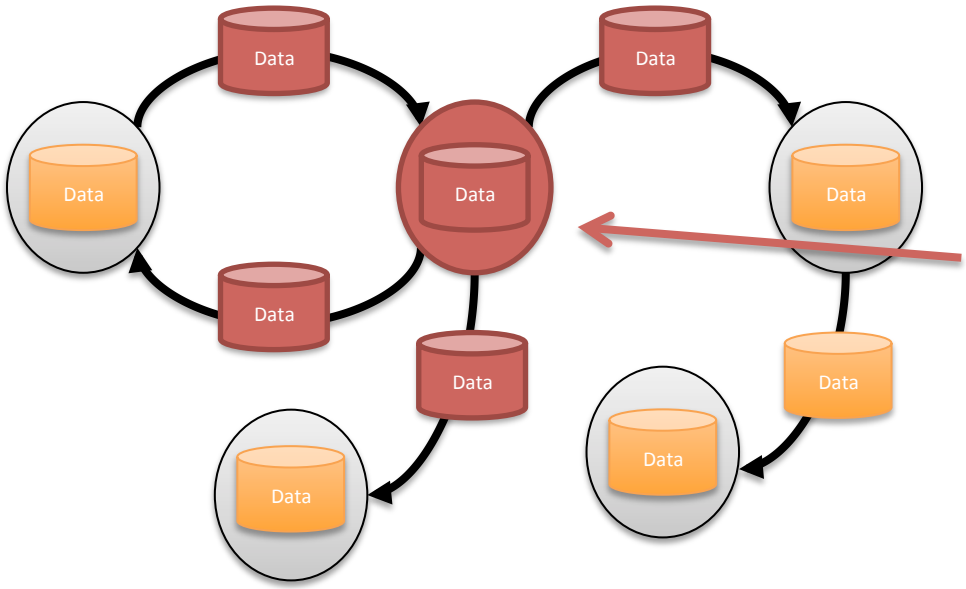


Terms: **e** is an **out-edge** of A, and **in-edge** of B.



Vertex-centric Programming

- "Think like a vertex"
- Popularized by the Pregel and GraphLab projects
  - Historically, systolic computation and the Connection Machine

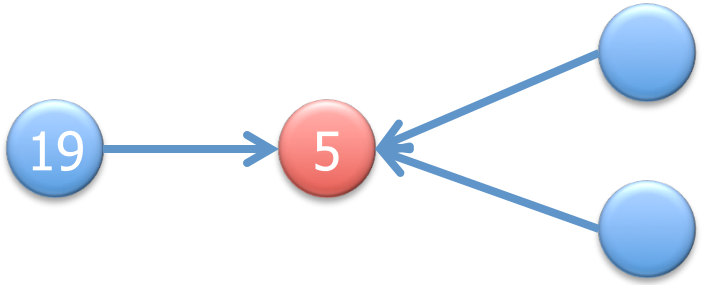


MyFunc(vertex)
{ // modify neighborhood }

The Main Challenge of Disk-based Graph Computation:

Random Access

Random Access Problem



- 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	2, …

Random write

For sufficient performance, millions of random accesses / second would be needed. Even for SSD, this is too much.

- … or with

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

Possible Solutions

1. Use SSD as a memory-extension? [SSDAlloc, NSDI'11]

Too many small objects, need millions / sec.

2. Compress the graph structure to fit into RAM? [→ WebGraph framework]

Associated values do not compress well, and are mutated.

3. Cluster the graph and handle each cluster separately in RAM?

Expensive; The number of inter-cluster edges is big.

4. Caching of hot nodes?

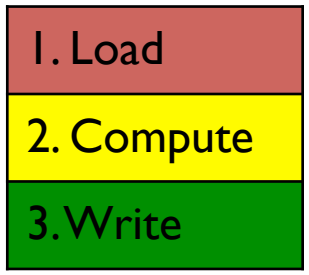
Unpredictable performance.

Our Solution

Parallel Sliding Windows (PSW)

Parallel Sliding Windows: Phases

- PSW processes the graph one **sub-graph** a time:

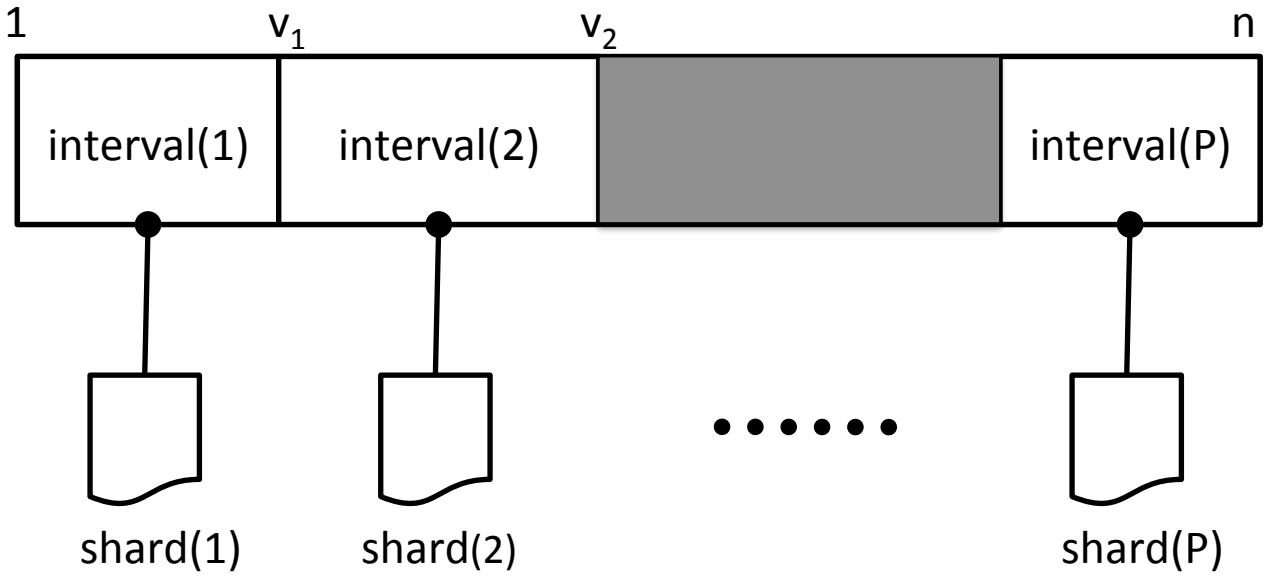


- In one **iteration**, the whole graph is processed.
  - And typically, next iteration is started.

PSW: Shards and Intervals

1. Load
2. Compute
3. Write

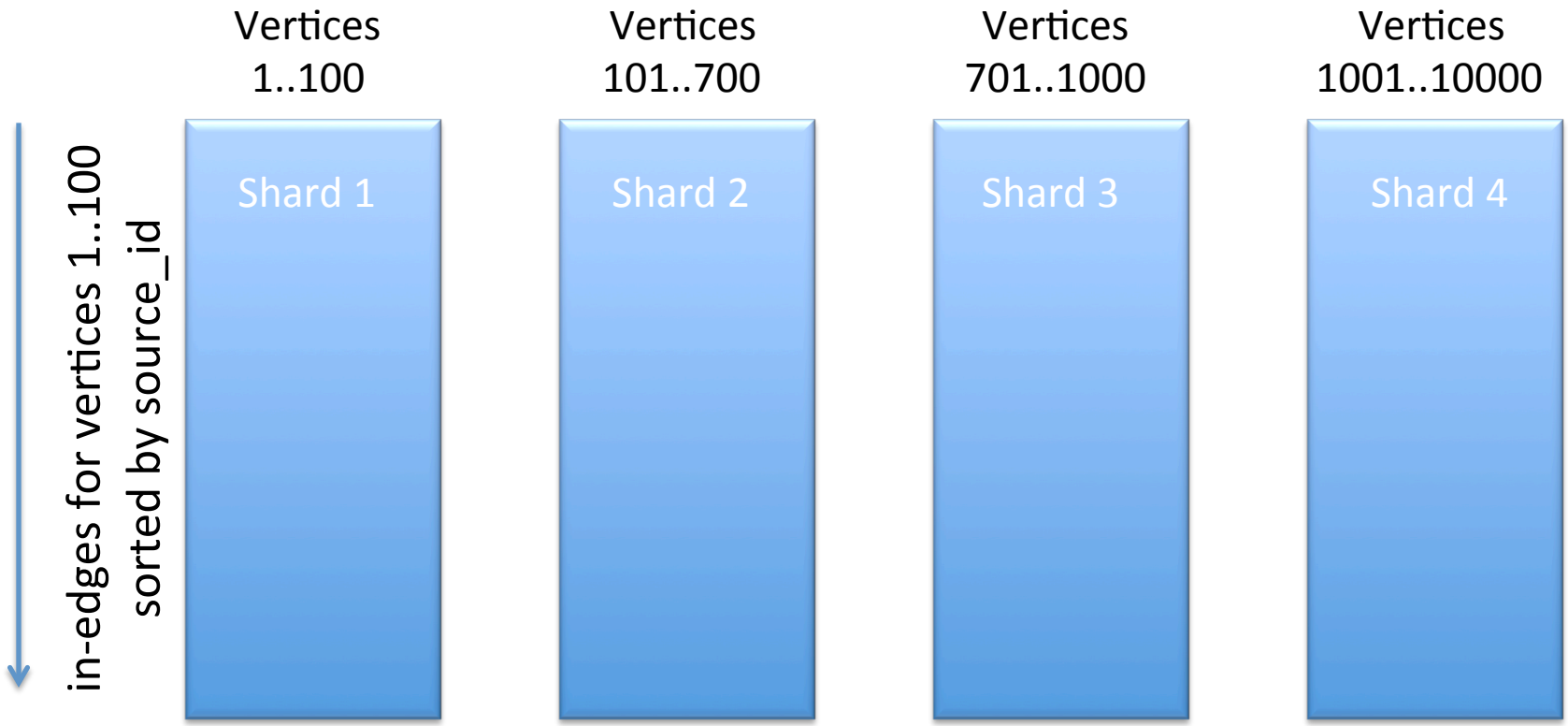
- Vertices are numbered from 1 to n
  - **P** intervals, each associated with a **shard** on disk.
  - **sub-graph =** interval of vertices



PSW: Layout

1. Load
2. Compute
3. Write

Shard: in-edges for **interval** of vertices; sorted by source-id

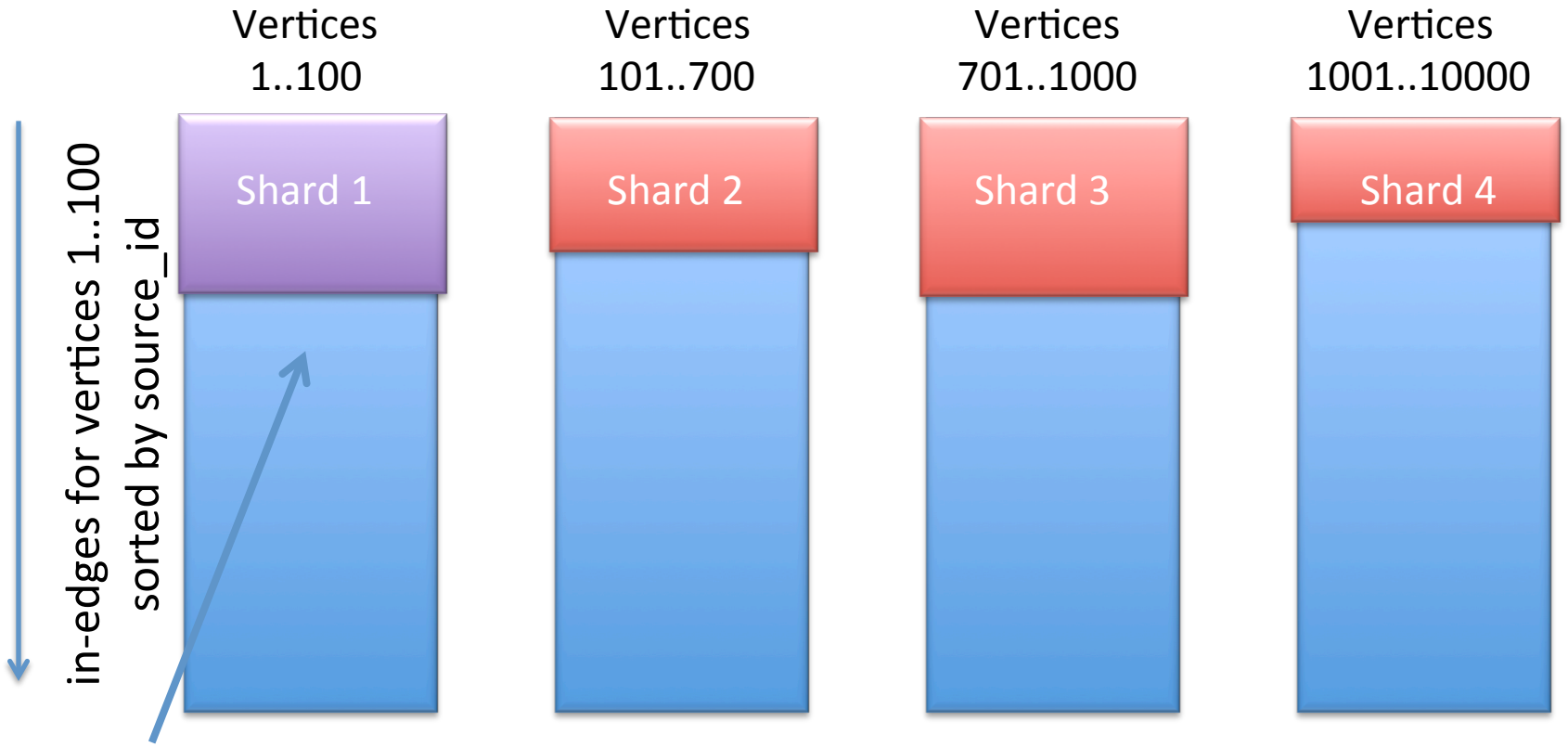


Shards small enough to fit in memory; balance size of shards

PSW: Loading Sub-graph

1. Load
2. Compute
3. Write

Load subgraph for vertices 1..100



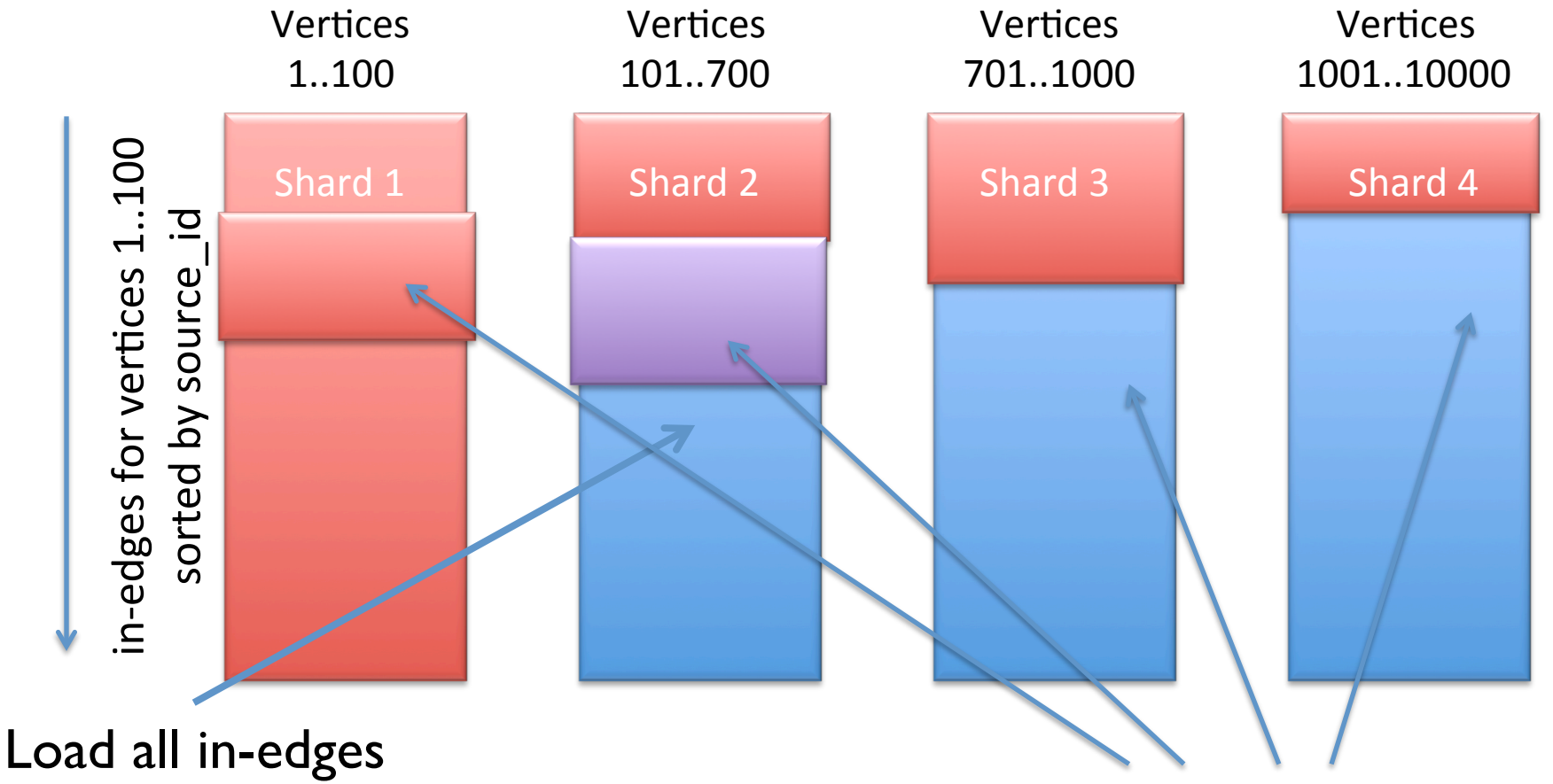
Load all in-edges in memory

What about out-edges?
Arranged in sequence in other shards

PSW: Loading Sub-graph

Load subgraph for vertices 101..700

1. Load
2. Compute
3. Write

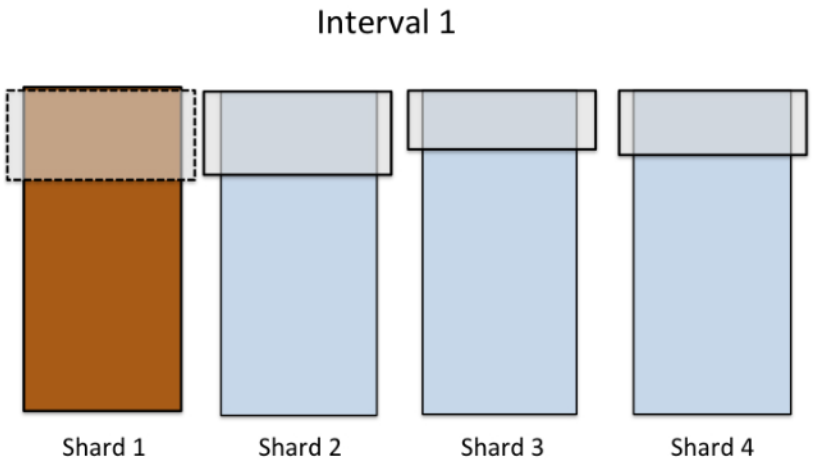


PSW Load-Phase

1. Load
2. Compute
3. Write

Only P large reads for each interval.

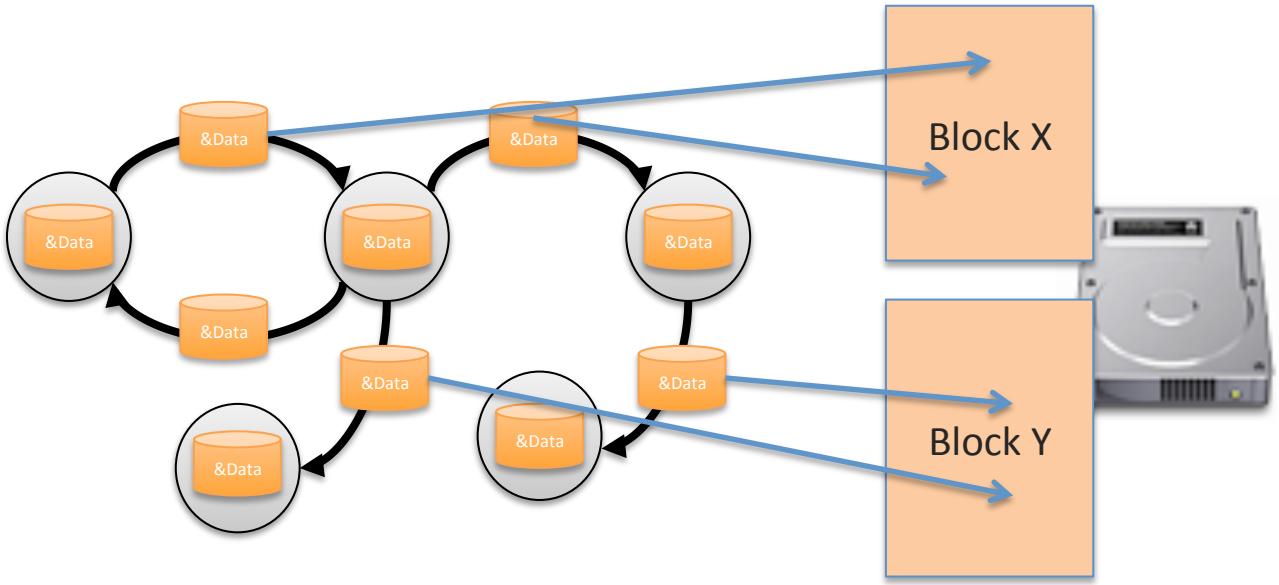
P^2 reads on one full pass.



PSW: Execute updates

1. Load
2. Compute
3. Write

- Update-function is executed on interval's vertices
- Edges have pointers to the loaded data blocks
  - Changes take effect immediately → asynchronous.



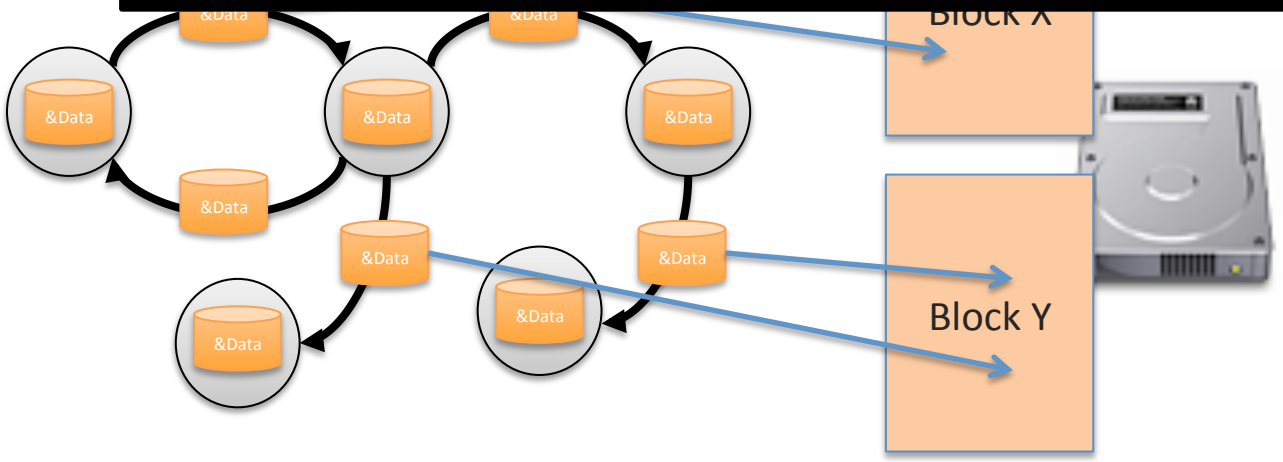
Deterministic scheduling prevents races between neighboring vertices.

PSW: Commit to Disk

1. Load
2. Compute
3. Write

- In write phase, the blocks are written *back* to disk
  - Next load-phase sees the preceding writes → asynchronous.

In total:
P^2 reads and writes / full pass on the graph.
→ Performs well on *both* SSD and hard drive.



GraphChi: Implementation

Evaluation & Experiments

GraphChi

- C++ implementation: 8,000 lines of code
  - Java-implementation also available (~ 2-3x slower), with a Scala API.
- Several optimizations to PSW (see paper).

Source code and examples: http://graphchi.org

EVALUATION: APPLICABILITY

Evaluation: Is PSW expressive enough?

Graph Mining
- Connected components
- Approx. shortest paths
- Triangle counting
- Community Detection

SpMV
- PageRank
- Generic

Recommendations
- Random walks

Collaborative Filtering
(by Danny Bickson)
- ALS
- SGD
- Sparse-ALS
- SVD, SVD++
- Item-CF

Probabilistic Graphical Models
- Belief Propagation

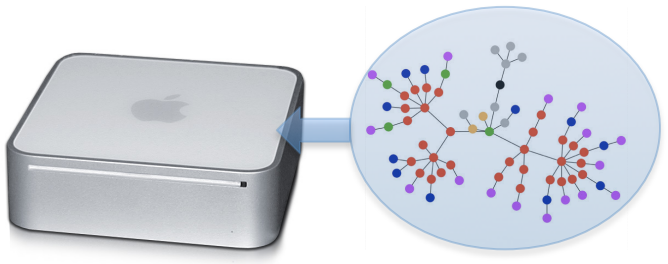
Algorithms implemented for GraphChi (Oct 2012)

Comparisons to existing systems

IS GRAPHCHI FAST ENOUGH?

Experiment Setting

- Mac Mini (Apple Inc.)
  - 8 GB RAM
  - 256 GB SSD, 1TB hard drive
  - Intel Core i5, 2.5 GHz
- Experiment graphs:



Graph	Vertices	Edges	P (shards)	Preprocessing
live-journal	4.8M	**69M**	3	0.5 min
netflix	0.5M	**99M**	20	1 min
twitter-2010	42M	**1.5B**	20	2 min
uk-2007-05	106M	**3.7B**	40	31 min
uk-union	133M	**5.4B**	50	33 min
yahoo-web	1.4B	**6.6B**	50	37 min

See the paper for more comparisons.

Comparison to Existing Systems

PageRank

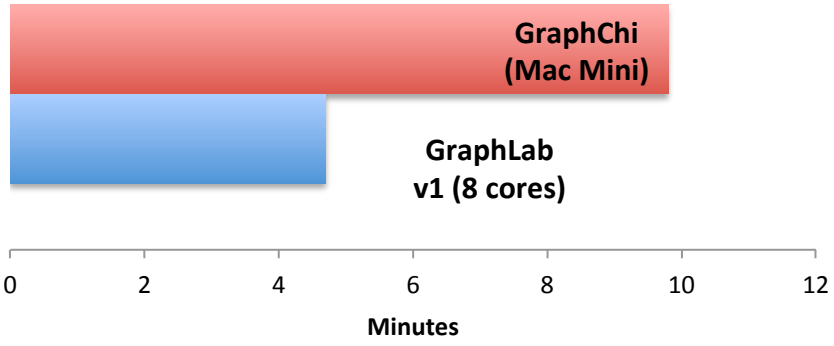
WebGraph Belief Propagation (U Kang et al.)

On a Mac Mini:

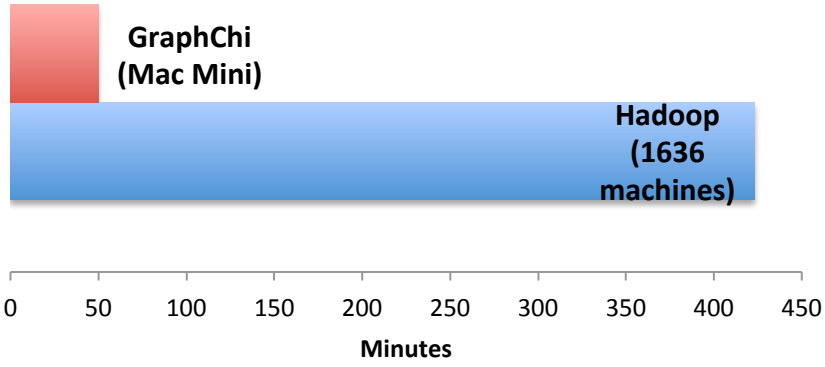
- ✓ GraphChi can solve as big problems as existing large-scale systems.
- ✓ Comparable performance.

Matrix F

Netflix (99B edges)



twitter-2010 (1.5B edges)



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Notes: comparison results do not include time to transfer the data to cluster, preprocessing, or the time to load the graph from disk. GraphChi computes asynchronously, while all but GraphLab synchronously.

OSDI'12

PowerGraph Comparison

- **PowerGraph / GraphLab 2** outperforms previous systems by a wide margin on natural graphs.
- With 64 more machines, 512 more CPUs:
  - **Pagerank**: 40x faster than GraphChi
  - **Triangle counting**: 30x faster than GraphChi.

vs.

GraphChi

GraphChi has state-of-the-art performance / CPU.

Consult the paper for a comprehensive evaluation:

- *HD vs. SSD*
- *Striping data across multiple hard drives*
- *Comparison to an in-memory version*
- *Bottlenecks analysis*
- *Effect of the number of shards*
- *Block size and performance.*

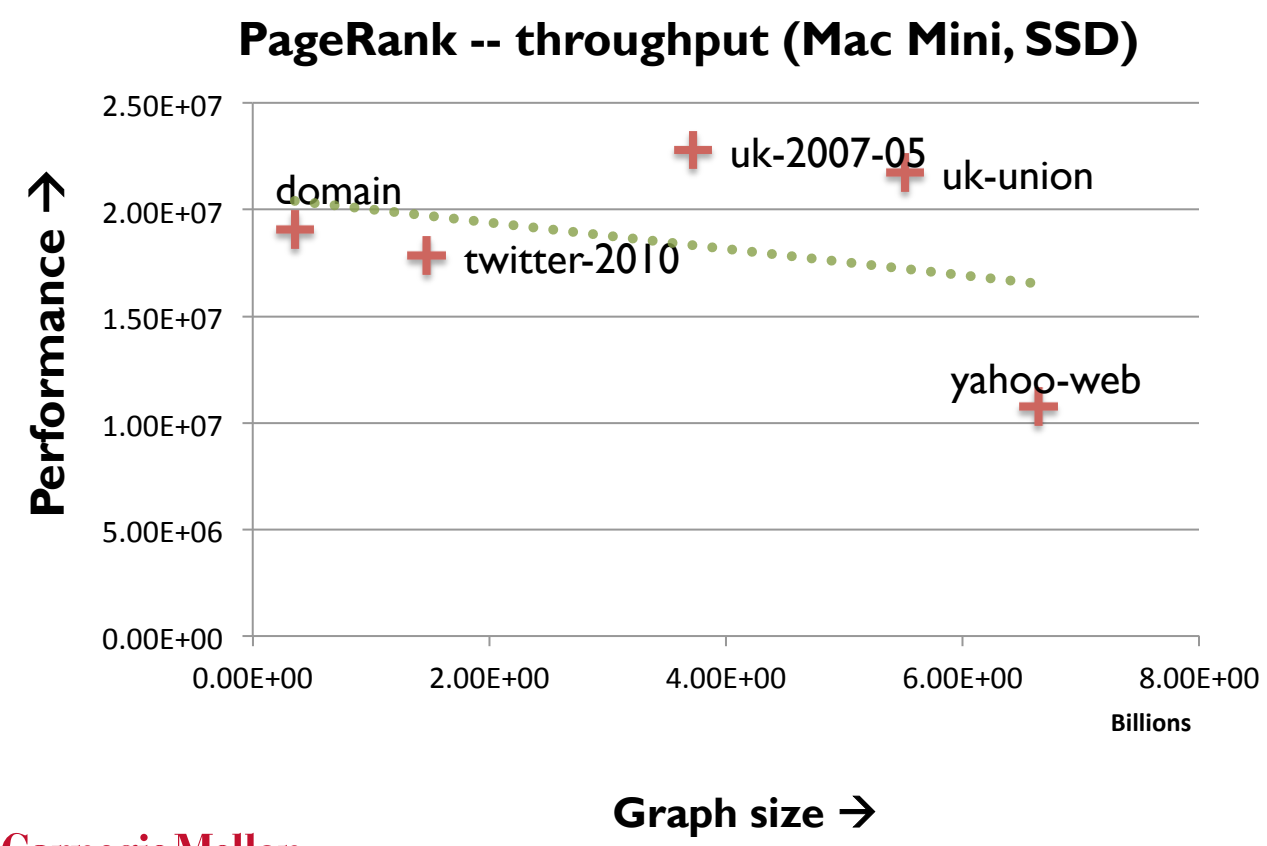
Sneak peek

SYSTEM EVALUATION

Paper: scalability of other applications.

Scalability / Input Size [SSD]

- Throughput: number of edges processed / second.

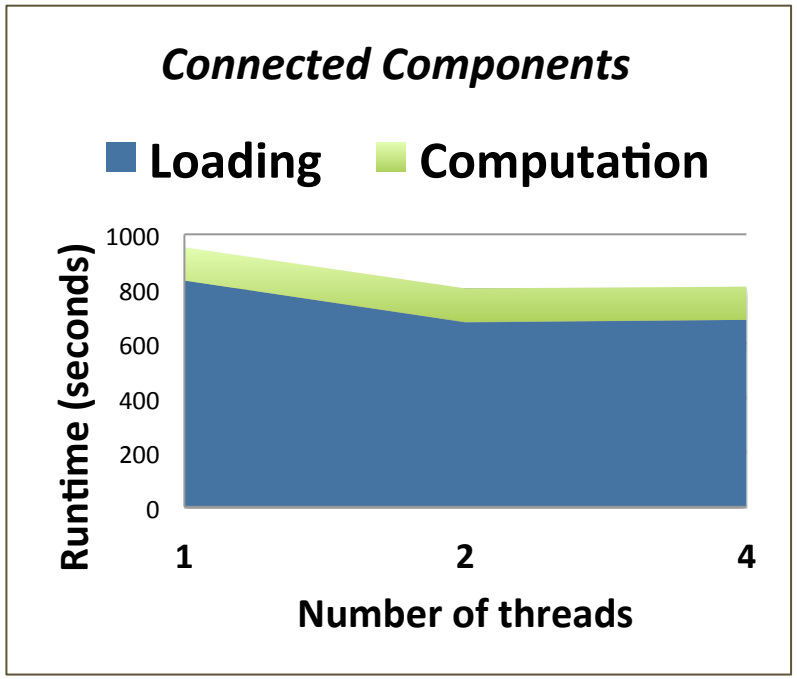


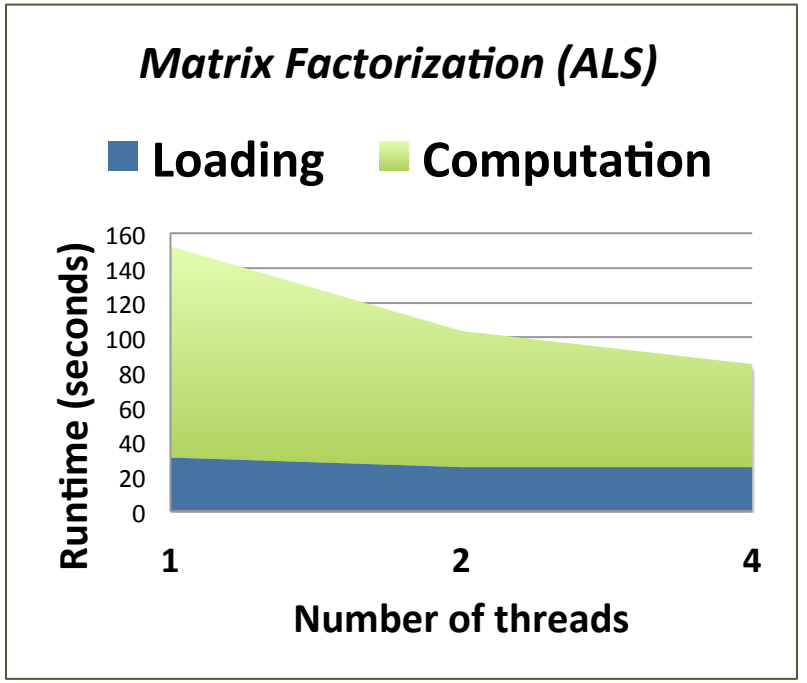
Conclusion: the throughput remains roughly constant when graph size is increased.

GraphChi with hard-drive is ~ 2x slower than SSD (if computational cost low).

Bottlenecks / Multicore

- Computationally intensive applications benefit substantially from parallel execution.
- GraphChi saturates SSD I/O with 2 threads.





Experiment on MacBook Pro with 4 cores / SSD.

Evolving Graphs

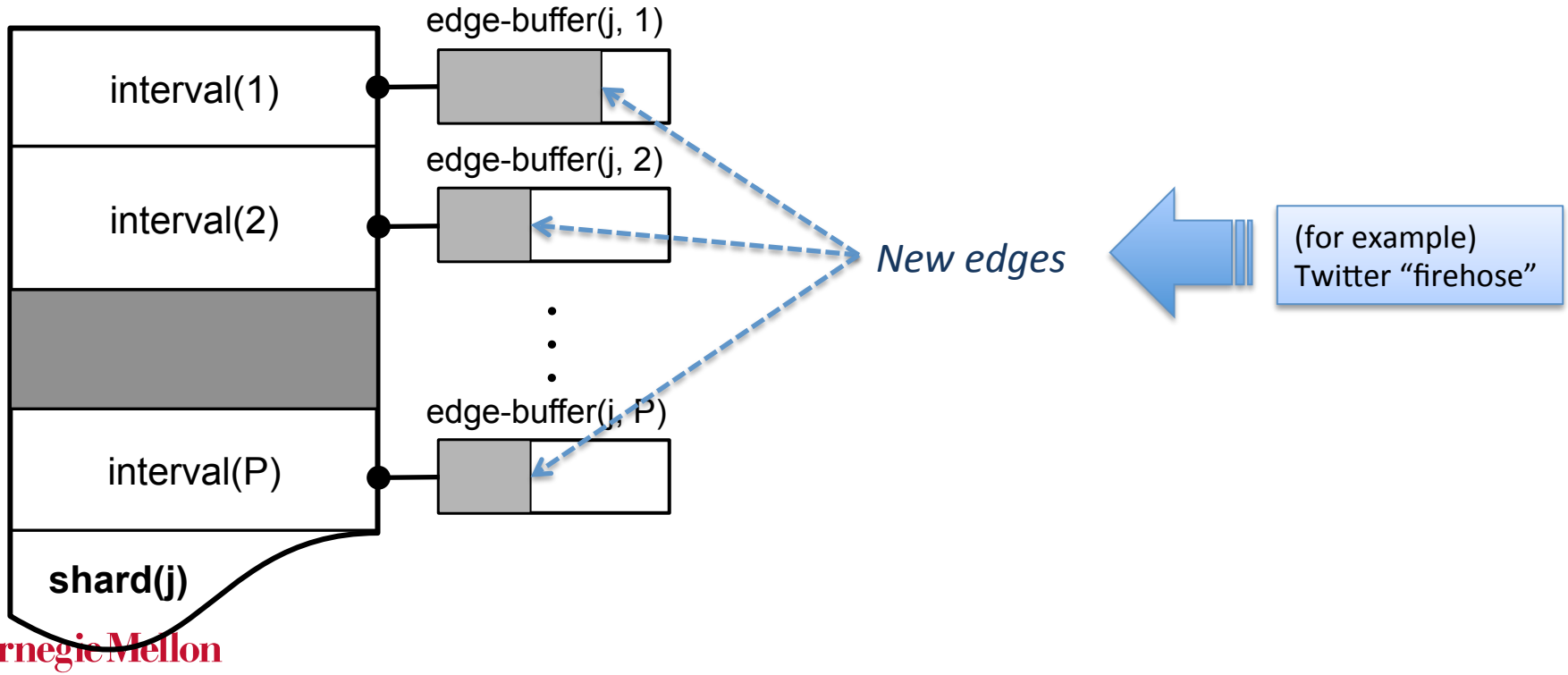
Graphs whose structure changes over time

Evolving Graphs: Introduction

- Most interesting networks grow continuously:
  - New connections made, some 'unfriended'.
- Desired functionality:
  - Ability to add and remove edges in streaming fashion;
  - ... while continuing computation.
- Related work:
  - *Kineograph* (EuroSys '12), distributed system for computation on a changing graph.

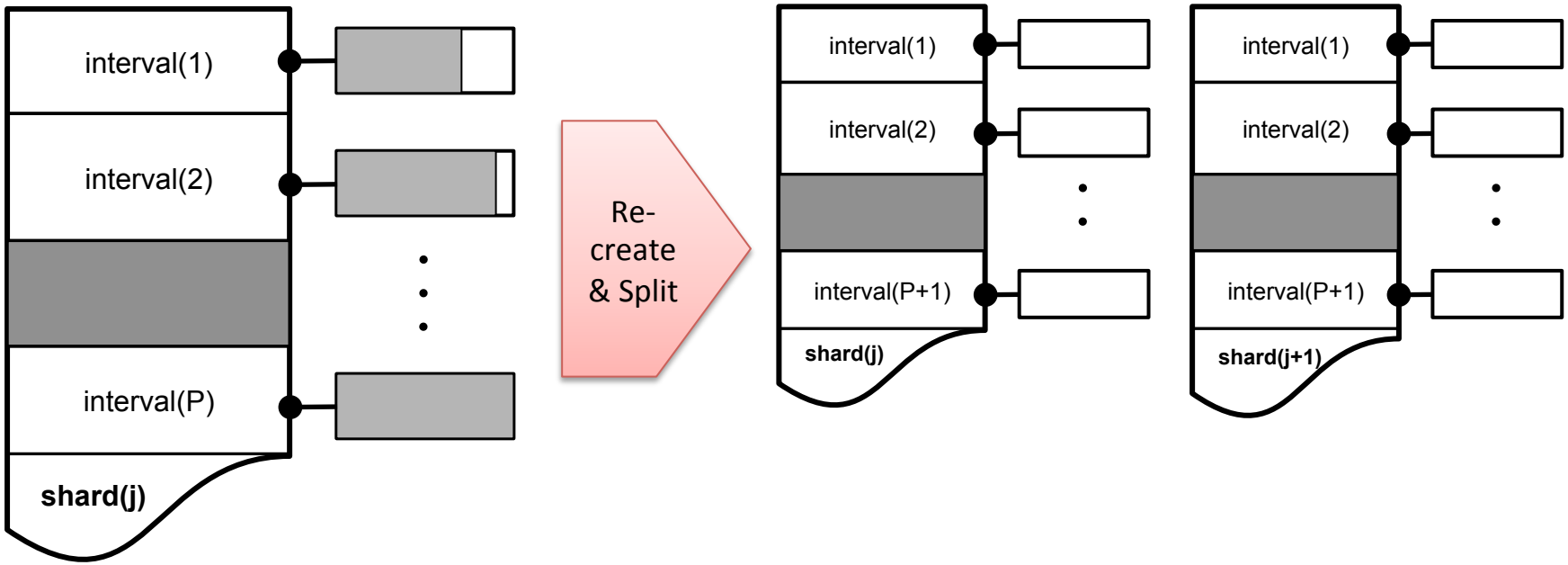
PSW and Evolving Graphs

- Adding edges
  - Each (shard, interval) has an associated edge-buffer.
- Removing edges: Edge flagged as "removed".



Recreating Shards on Disk

- When buffers fill up, shards a **recreated** on disk
  - Too big shards are **split**.
- During recreation, deleted edges are permanently removed.



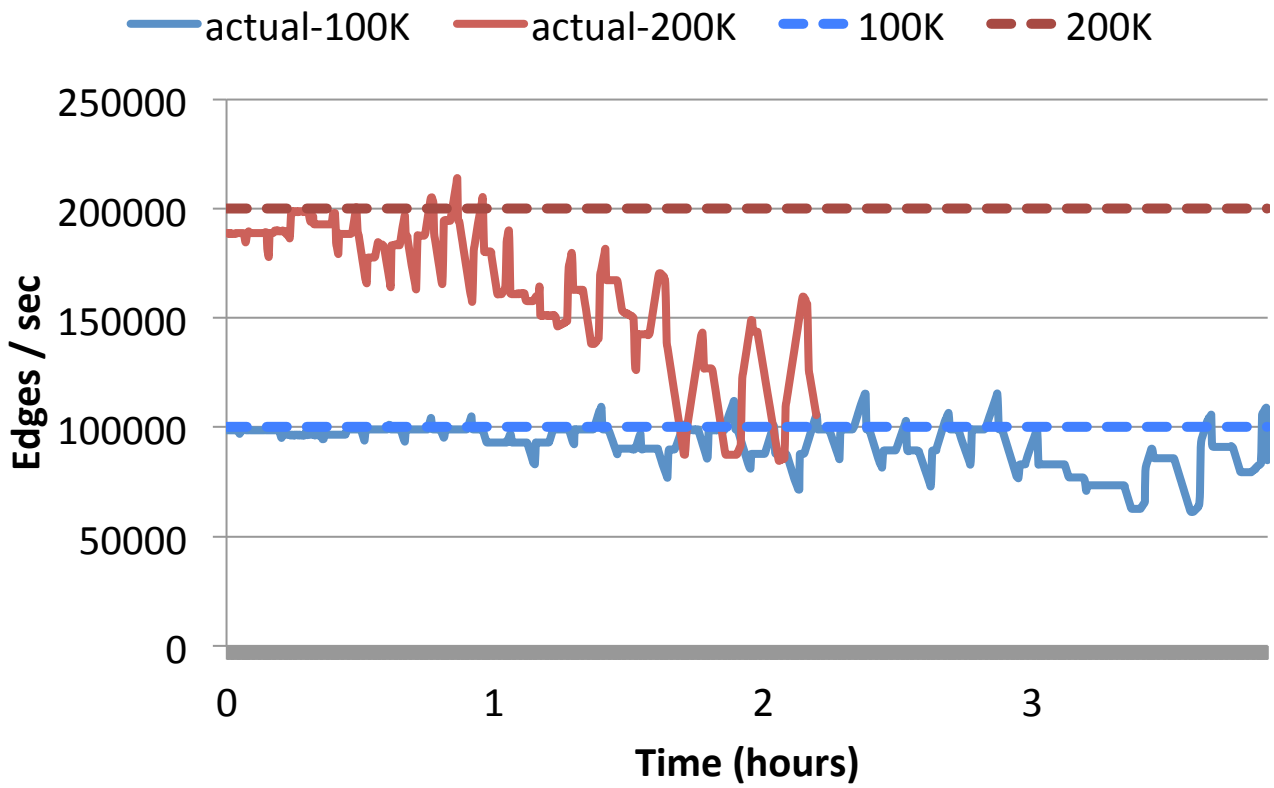
Streaming Graph experiment

EVALUATION: EVOLVING GRAPHS

Streaming Graph Experiment

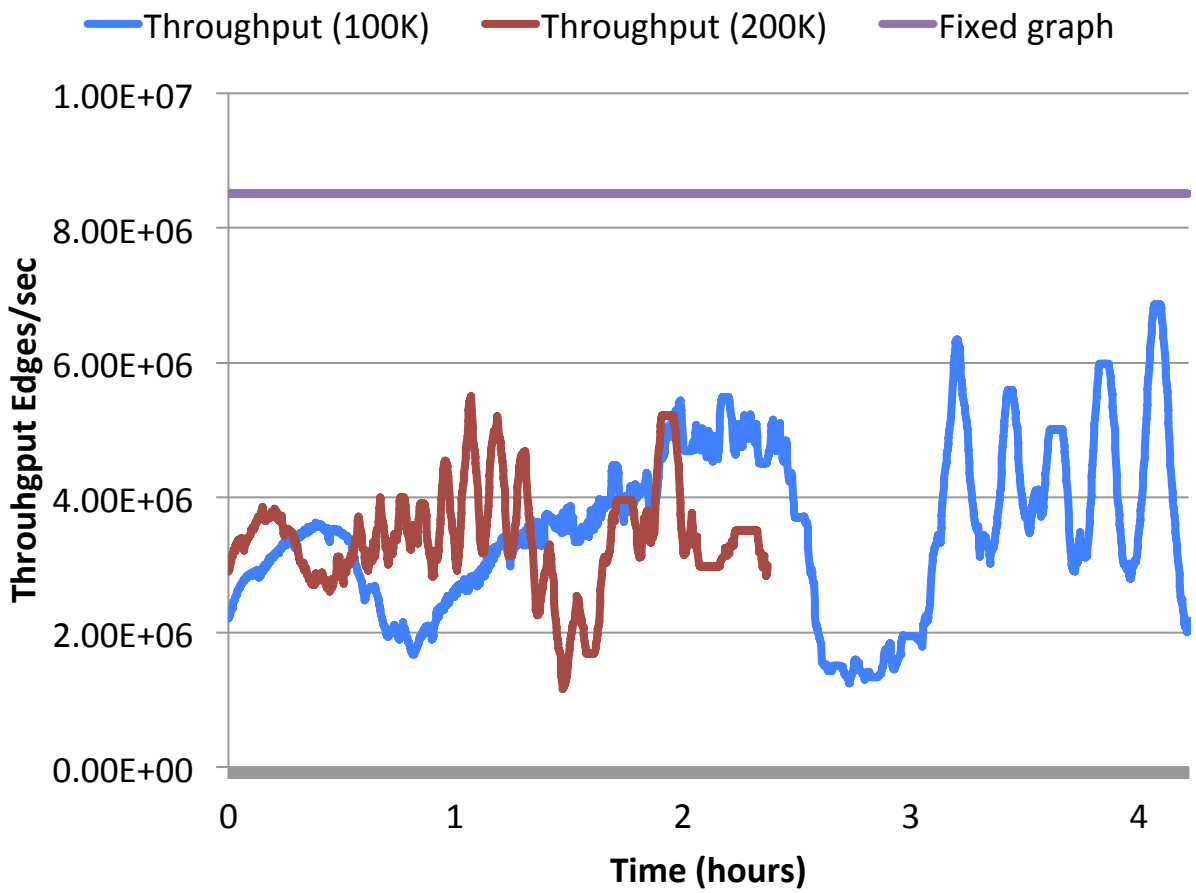
- On the Mac Mini:
  - Streamed edges in random order from the *twitter-2010* graph (1.5 B edges)
    - With maximum rate of 100K or 200K edges/sec. (very high rate)
  - Simultaneously run PageRank.
  - Data layout:
    - Edges were streamed from hard drive
    - Shards were stored on SSD.

Ingest Rate



When graph grows, shard recreations become more expensive.

Streaming: Computational Throughput

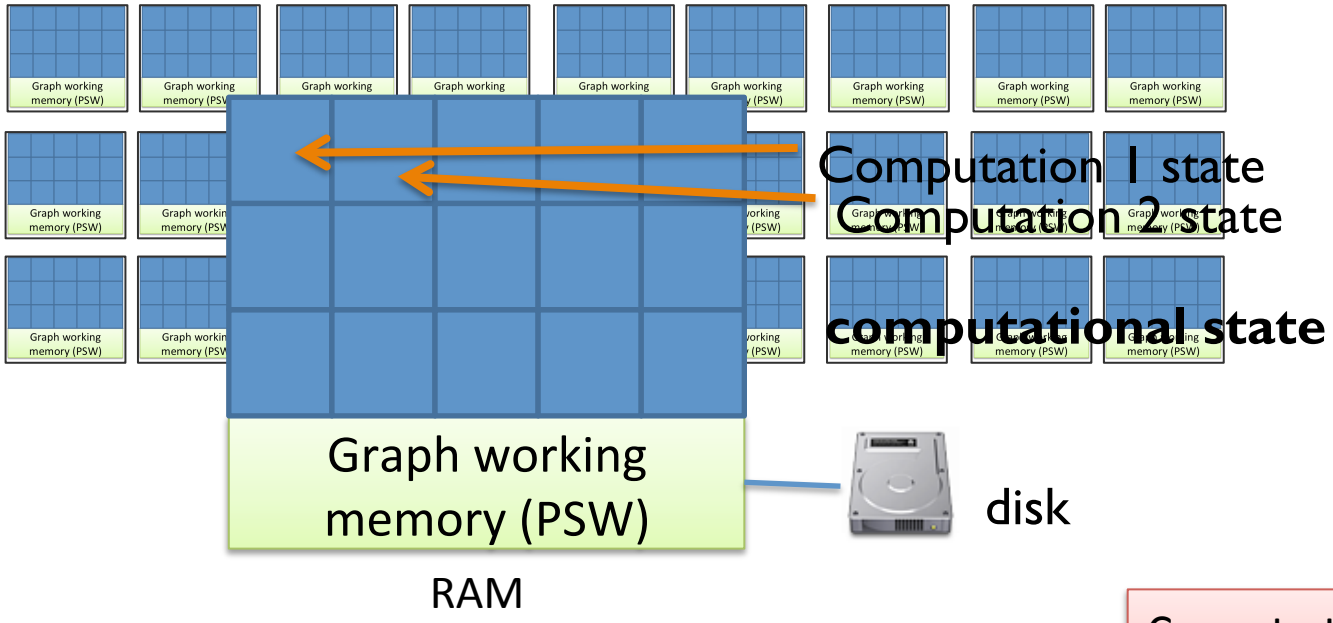


Throughput varies strongly due to shard rewrites and asymmetric computation.

Conclusion

Future Directions

- This work: small amount of memory.
- What if have hundreds of GBs of RAM?



Come to the the poster on Monday to discuss!

Conclusion

- Parallel Sliding Windows algorithm enables processing of large graphs with very few non-sequential disk accesses.
- For the system researchers, GraphChi is a solid baseline for system evaluation
  - It can solve as big problems as distributed systems.
- Takeaway: Appropriate data structures as an alternative to scaling up.

Source code and examples: http://graphchi.org
License: Apache 2.0

Extra Slides

Extended edition

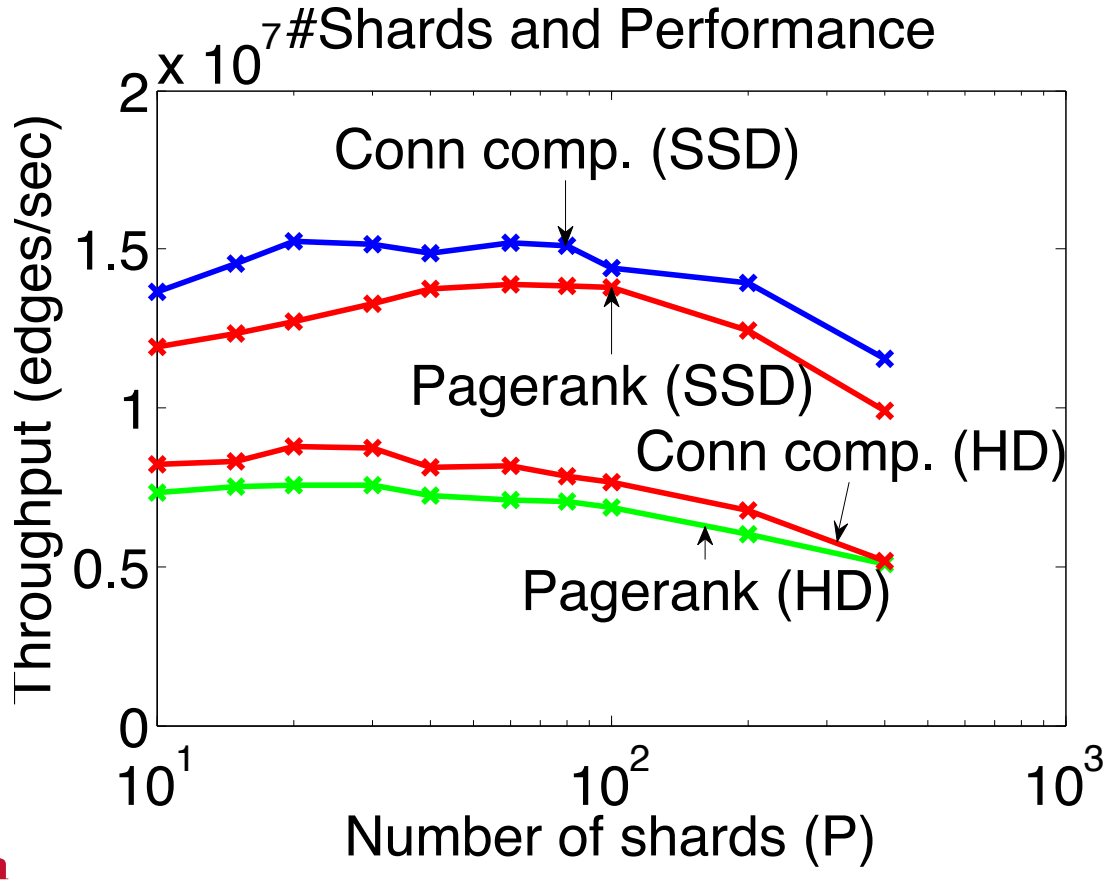
PSW is Asynchronous

- If V > U, and there is edge (U,V, &x) = (V, U, &x), update(V) will observe change to x done by update(U):
  - Memory-shard for interval (j+1) will contain writes to shard(j) done on previous intervals.
  - Previous slide: If U,V in the same interval.
- PSW implements the **Gauss-Seidel (asynchronous)** model of computation
  - Shown to allow, in many cases, clearly faster convergence of computation than Bulk-Synchronous Parallel (BSP).
  - Each edge stored only once.

$$V_i^t \Leftarrow F(V_0^t, V_1^t, \ldots, V_{i-1}^t, V_i^{t-1}, V_{i+1}^{t-1}, \ldots)$$

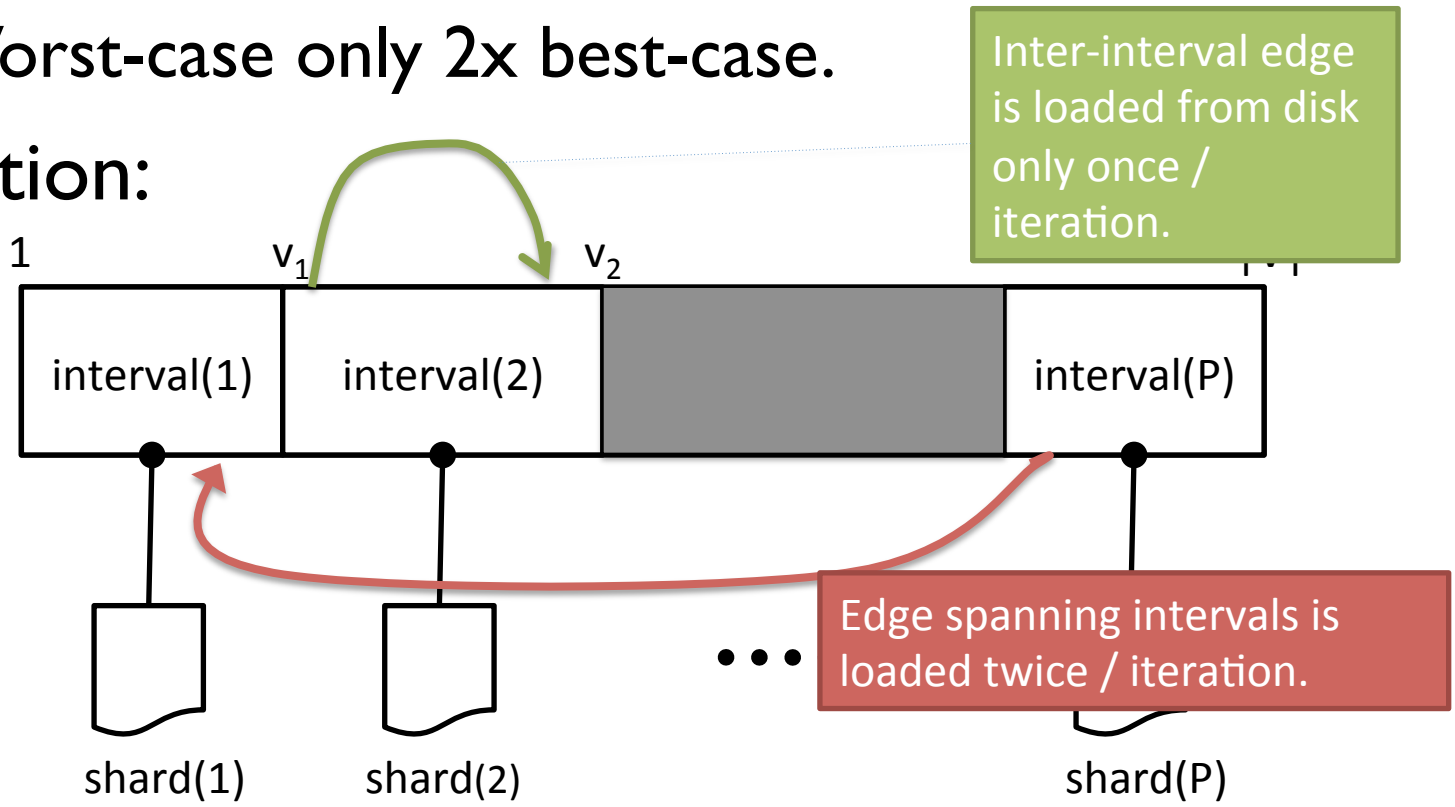
Number of Shards

- If P is in the "dozens", there is not much effect on performance.



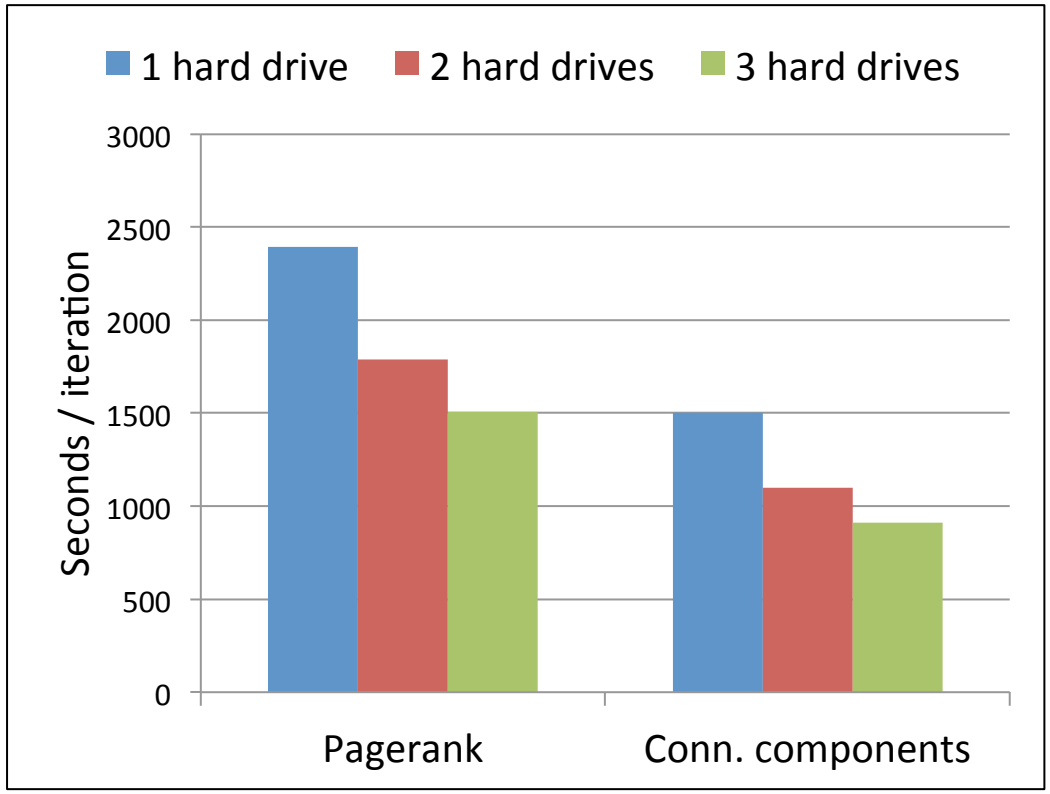
I/O Complexity

- See the paper for theoretical analysis in the Aggarwal-Vitter's I/O model.
  - Worst-case only 2x best-case.
- Intuition:



Multiple hard-drives (RAIDish)

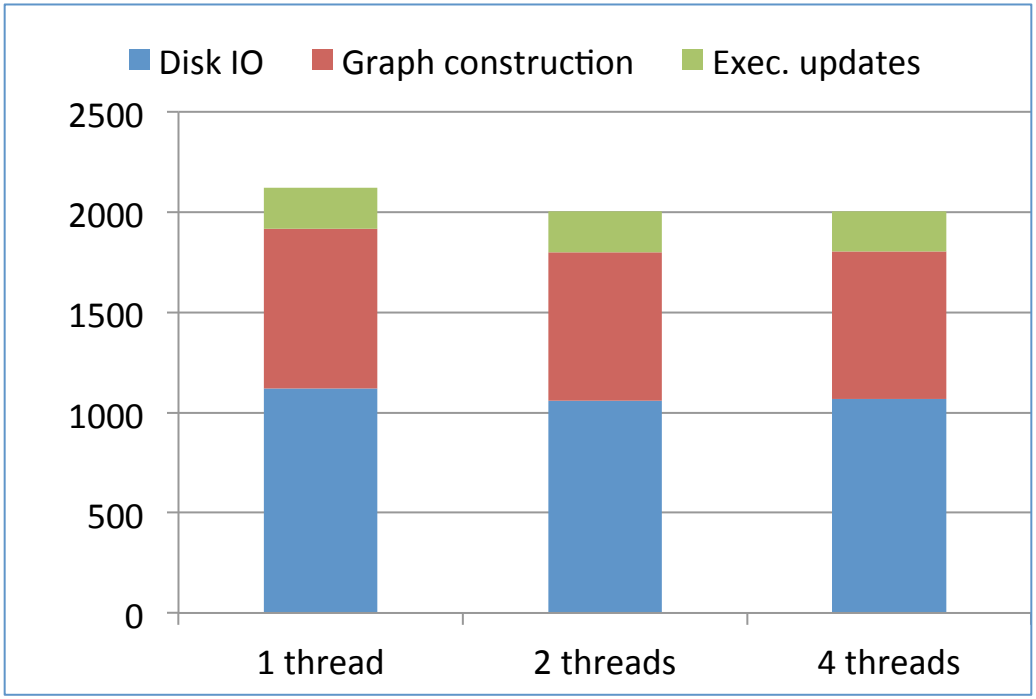
- GraphChi supports *striping* shards to multiple disks → Parallel I/O.



Experiment on a 16-core AMD server (from year 2007).

Bottlenecks

- Cost of constructing the sub-graph in memory is almost as large as the I/O cost on an SSD
  - Graph construction requires a lot of random access in RAM → memory bandwidth becomes a bottleneck.



Connected Components on Mac Mini / SSD

Computational Setting

- Constraints:
  A. Not enough memory to store the whole graph in memory, nor all the vertex values.
  B. Enough memory to store one vertex and its edges w/ associated values.
- Largest example graph used in the experiments:
  – Yahoo-web graph: 6.7 B edges, 1.4 B vertices

Recently GraphChi has been used on a MacBook Pro to compute with the most recent Twitter follow-graph (last year: 15 B edges)