GraphChi: Large-Scale Graph Computation on Just a PC

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In co-operation with the GraphLab team.

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BigData with *Structure*: BigGraph

social graph

social graph

follow-graph

consumer-
products graph

user-movie
ratings
graph

DNA
interaction
graph

WWW
link graph

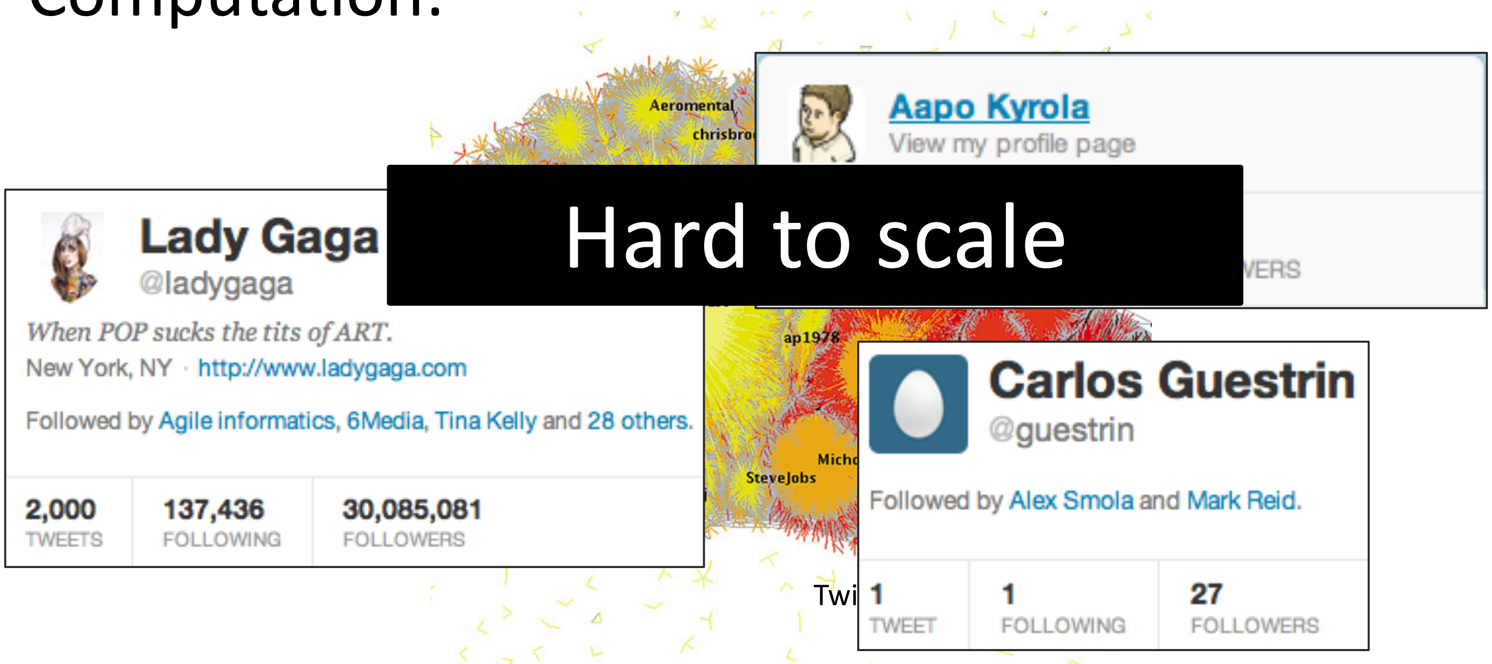
etc.

Big Graphs != Big Data

Data size: facebook 140 billion connections ≈ 1 TB

Not a problem!

Computation:



Hard to scale

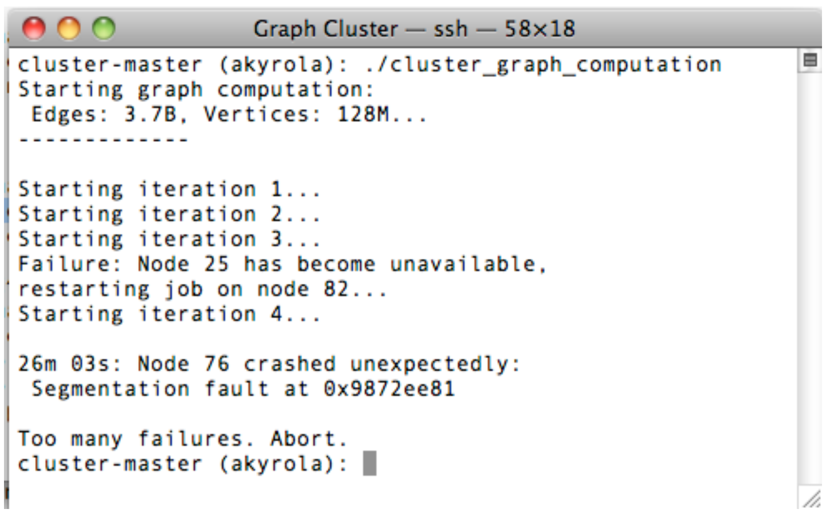
Could we compute Big Graphs on a *single machine*?

Disk-based Graph Computation

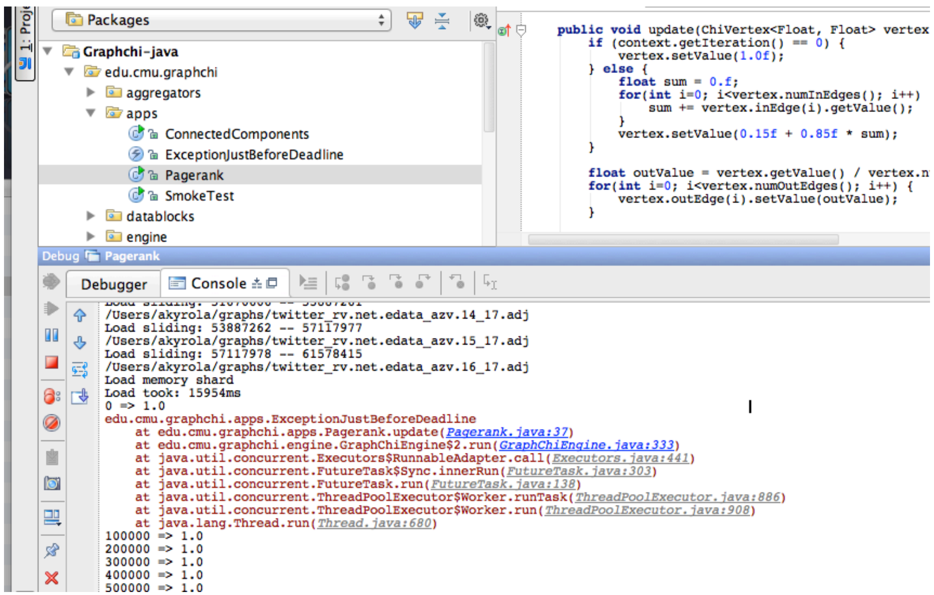
Can't we just use the Cloud?

Distributed State is Hard to Program

Writing distributed applications remains cumbersome.



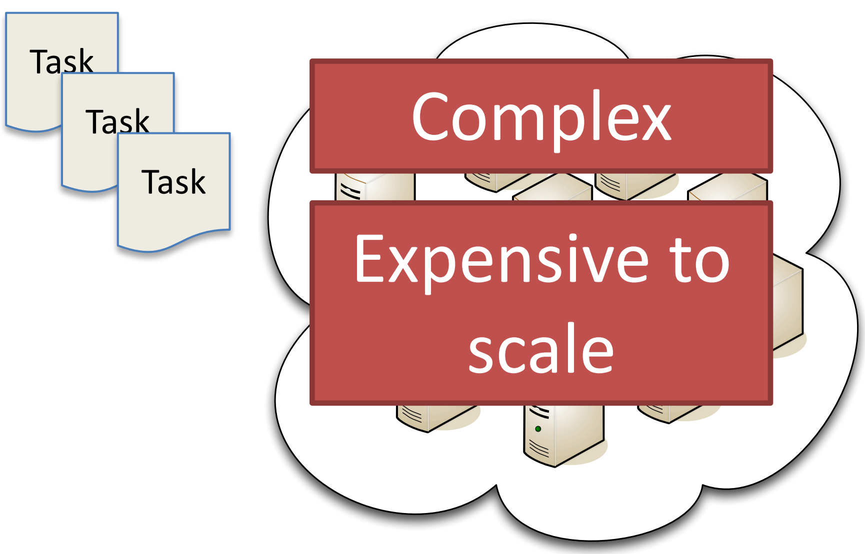
Cluster crash



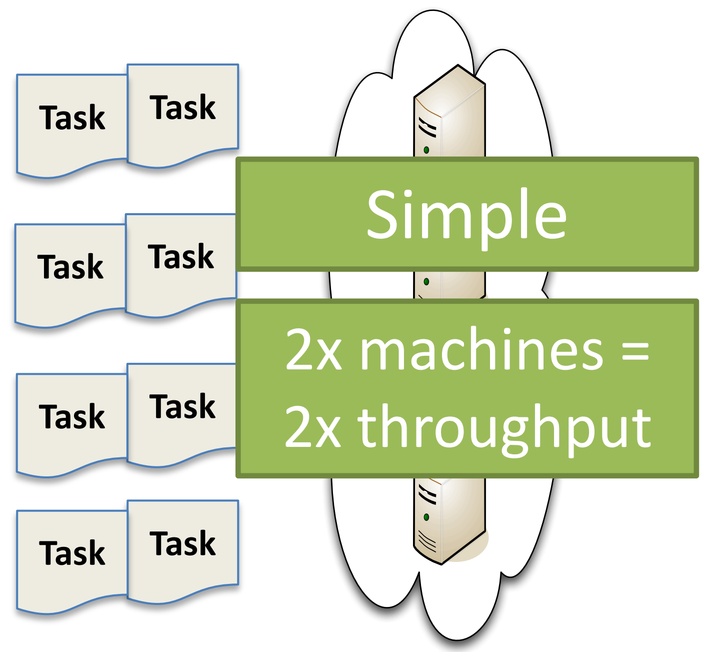
Crash in your IDE

Efficient Scaling

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



Parallelize each task

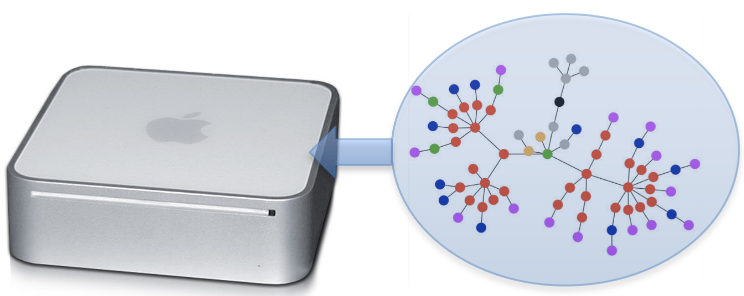


Parallelize across tasks

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.

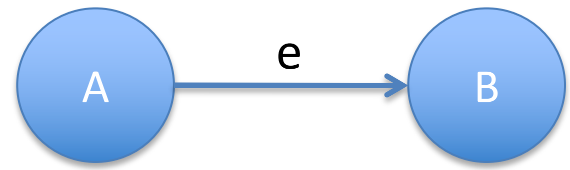


Experiment PC: Mac Mini (2012)

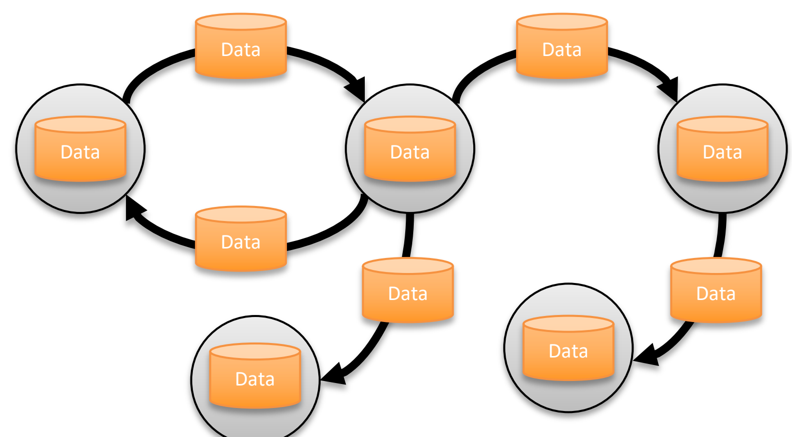
Computational Model

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)

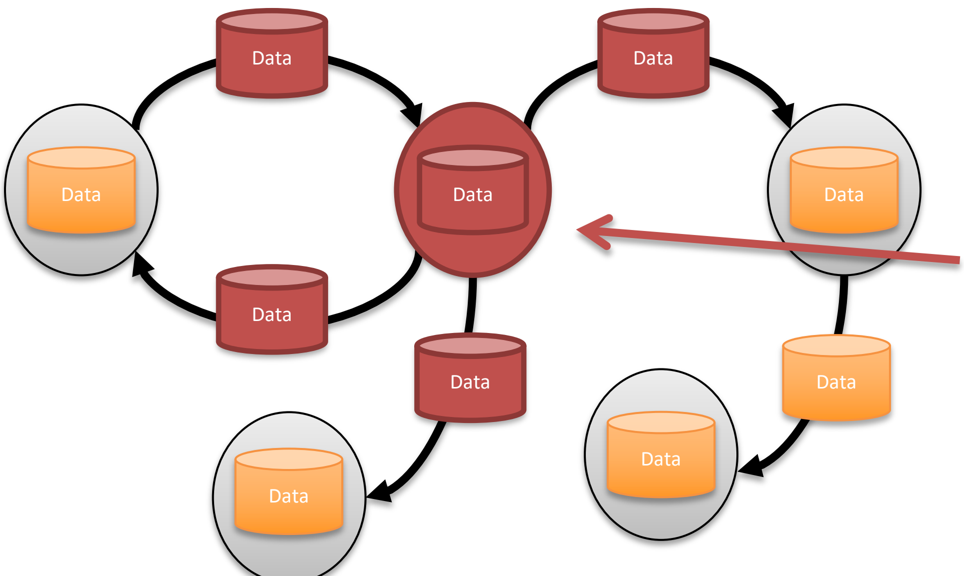


Terms: **e** is an **out-edge** of A, and **in-edge** of B.



Vertex-centric Programming

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



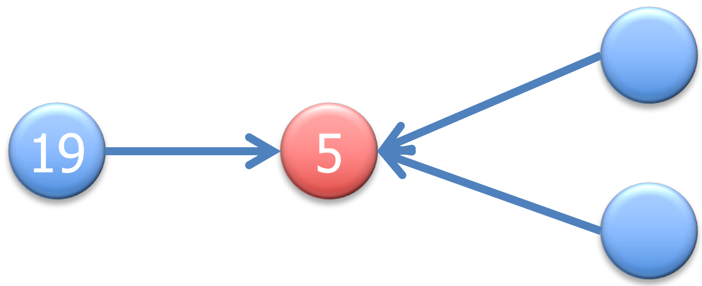
MyFunc(vertex)

{ // 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

- ... or with

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

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

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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:

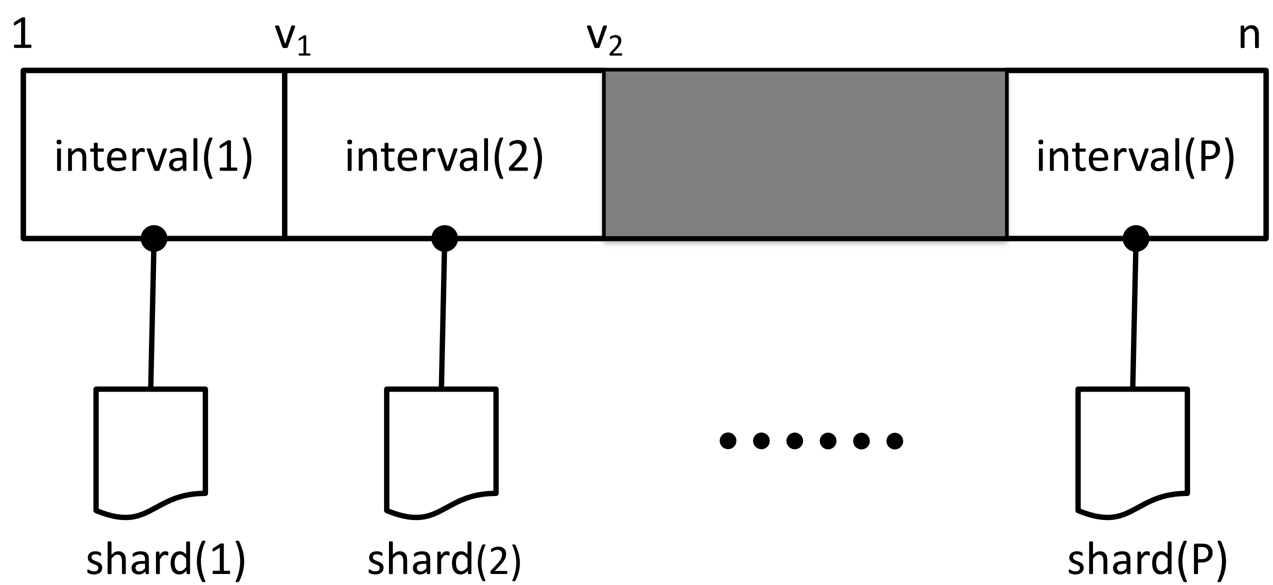
1. Load
2. Compute
3. Write

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

PSW: Shards and Intervals

1. Load
2. Compute
3. Write

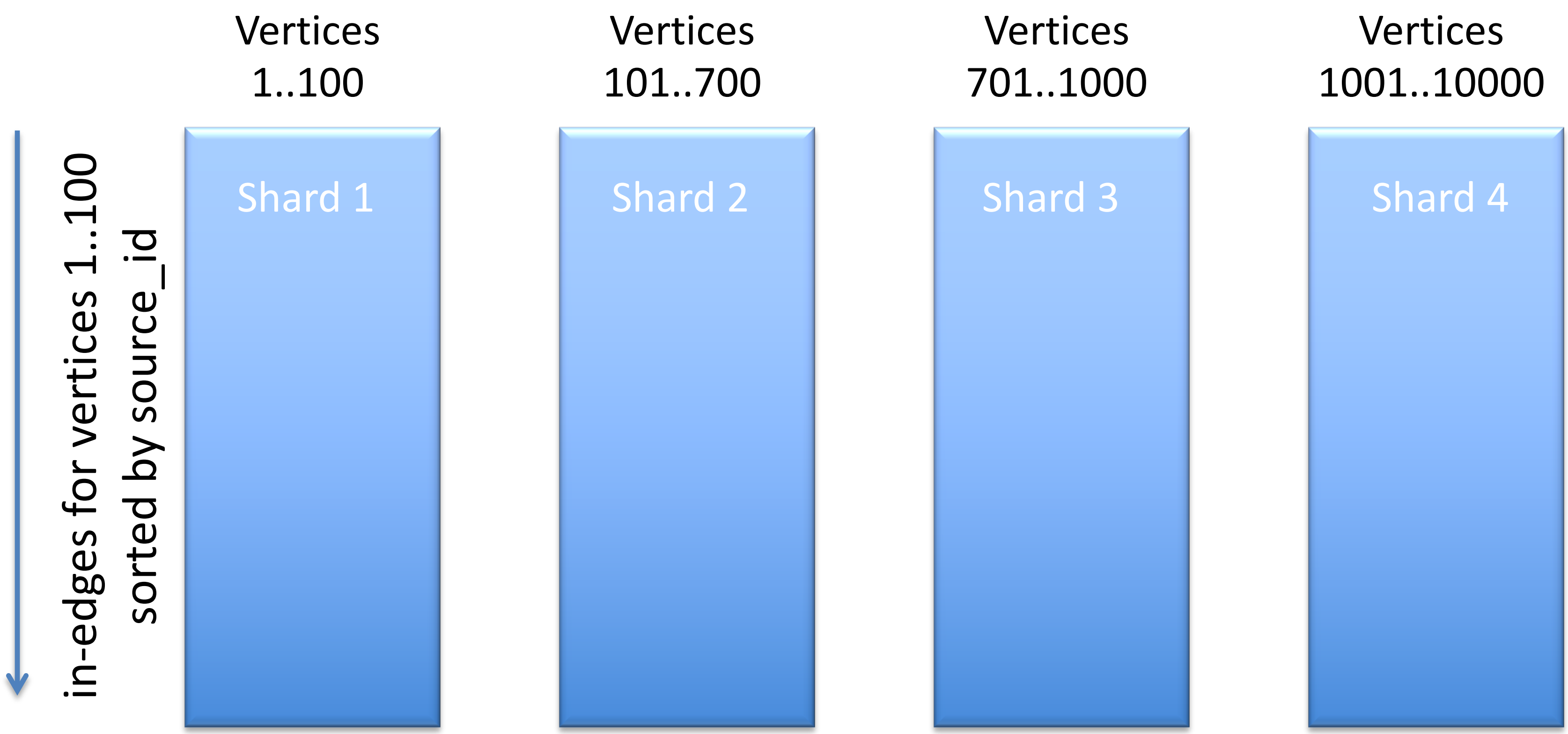
- Vertices are numbered from 1 to n
  - **P** intervals, each associated with a **shard** on disk.
  - **sub-graph =** interval of vertices



PSW: Layout

1. Load
2. Compute
3. Write

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

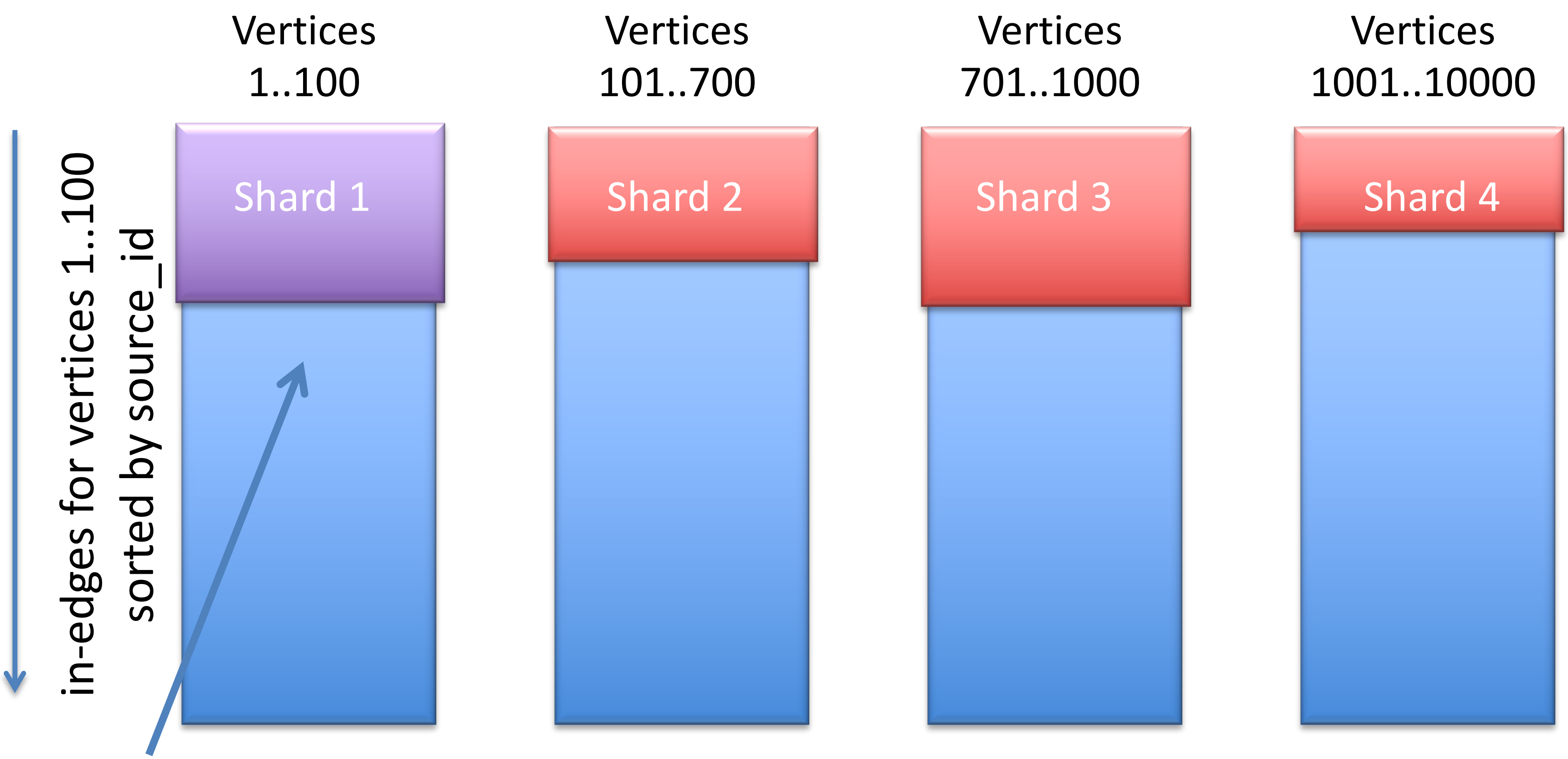


Shards small enough to fit in memory; balance size of shards

PSW: Loading Sub-graph

1. Load
2. Compute
3. Write

Load subgraph for vertices 1..100



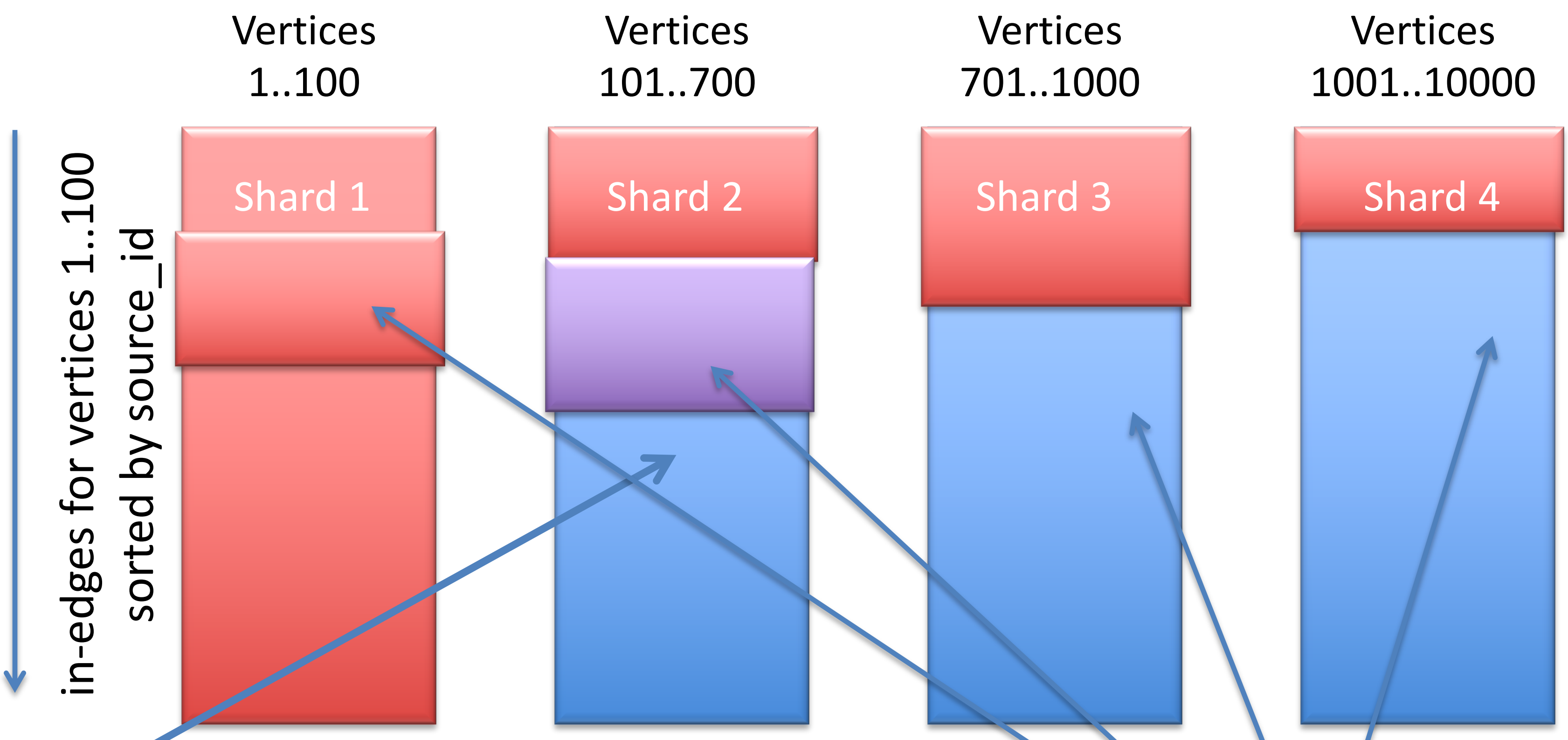
Load all in-edges in memory

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

PSW: Loading Sub-graph

1. Load
2. Compute
3. Write

Load subgraph for vertices 101..700



Load all in-edges in memory

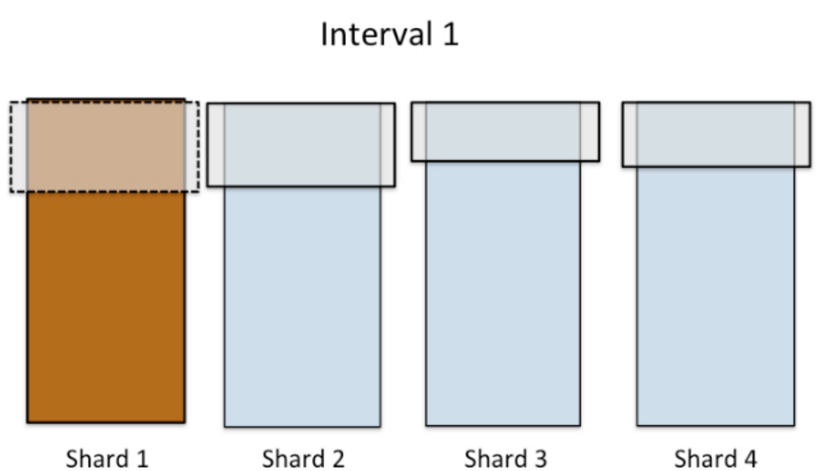
Out-edge blocks in memory

1. Load
2. Compute
3. Write

PSW Load-Phase

Only P large reads for each interval.

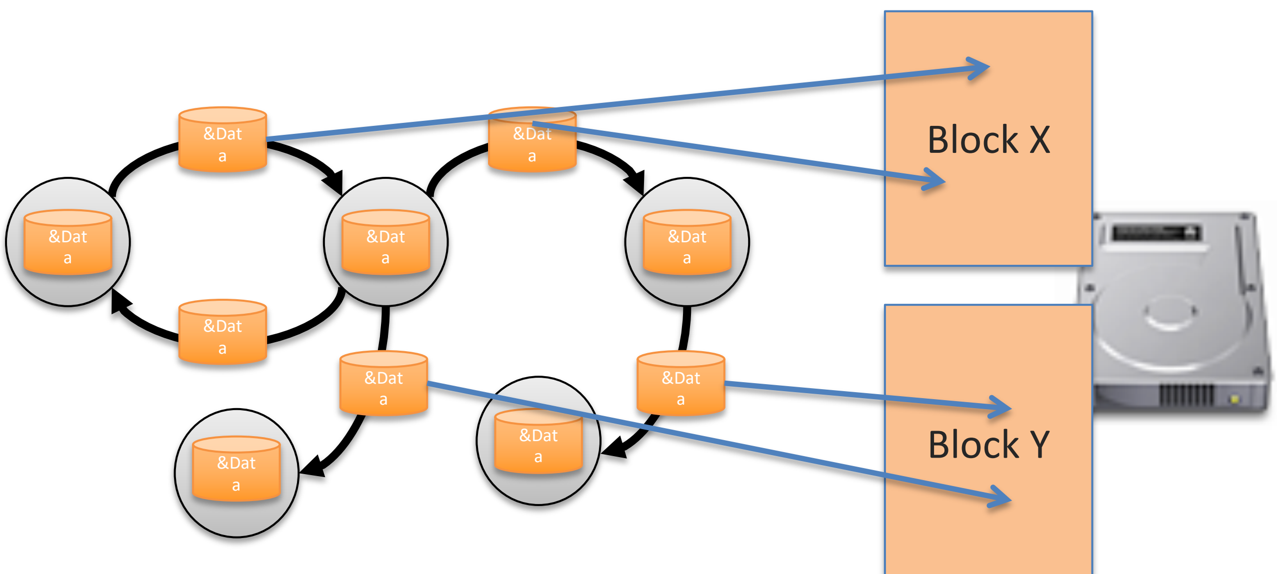
P^2 reads on one full pass.



1. Load
2. Compute
3. Write

PSW: Execute updates

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



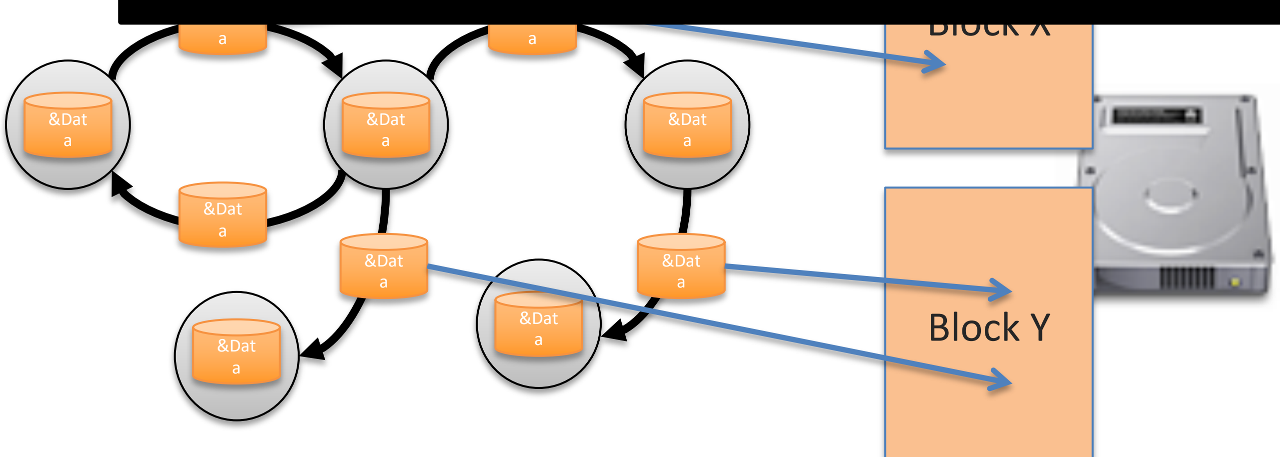
Deterministic scheduling prevents races between neighboring vertices.

1. Load
2. Compute
3. Write

PSW: Commit to Disk

- 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

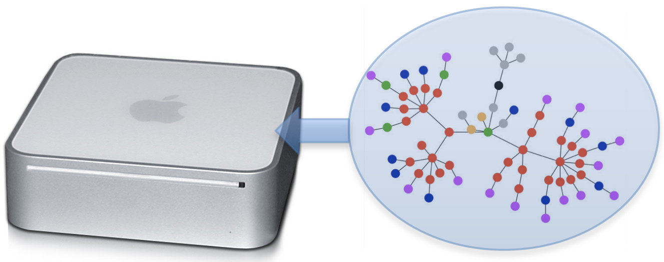
Algorithms implemented for GraphChi (Oct 2012)

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



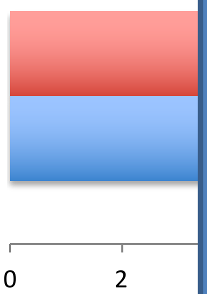
- Experiment graphs:

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

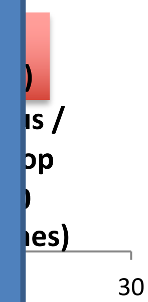
See the paper for more comparisons.

Comparison to Existing Systems

PageRank



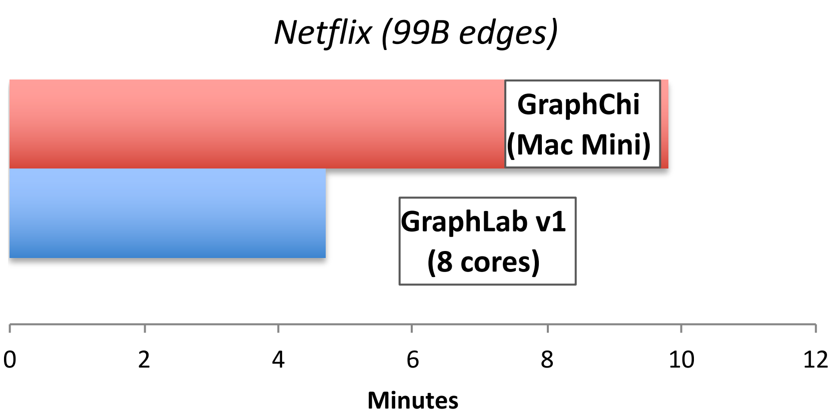
WebGraph Belief Propagation (U Kang et al.)

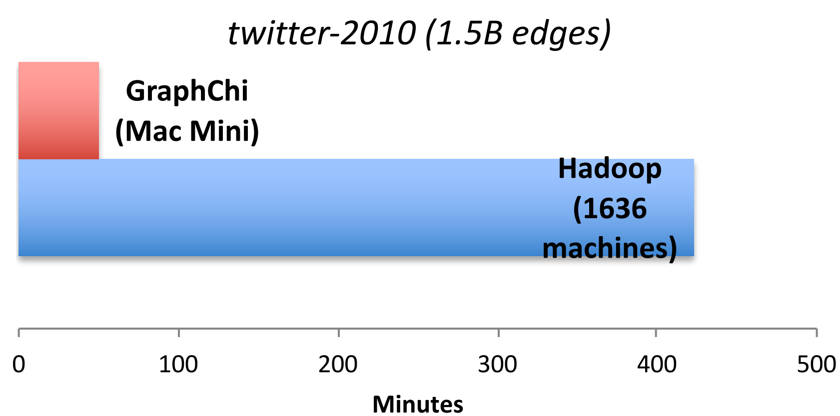


On a Mac Mini:

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

Matrix F





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.

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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.

GraphLab 2

vs.

GraphChi

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

Consult the paper for a comprehensive evaluation:

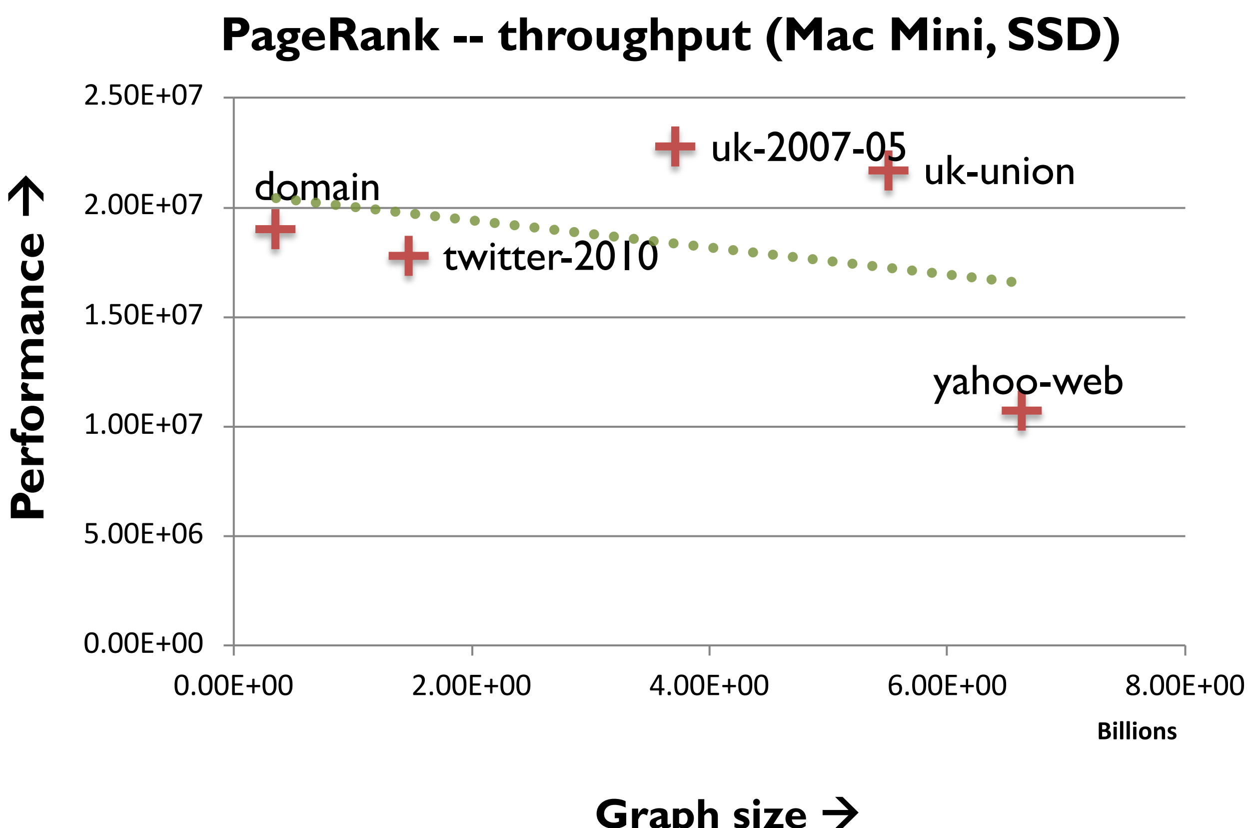
- *HD vs. SSD*
- *Striping data across multiple hard drives*
- *Comparison to an in-memory version*
- *Bottlenecks analysis*
- *Effect of the number of shards*
- *Block size and performance.*

Sneak peek

SYSTEM EVALUATION

Scalability / Input Size [SSD]

- Throughput: number of edges processed / second.

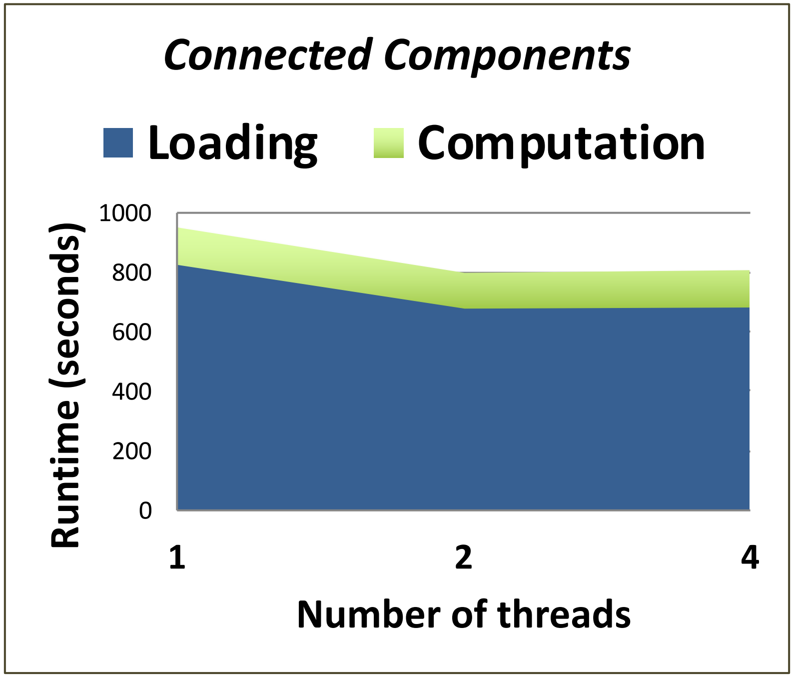


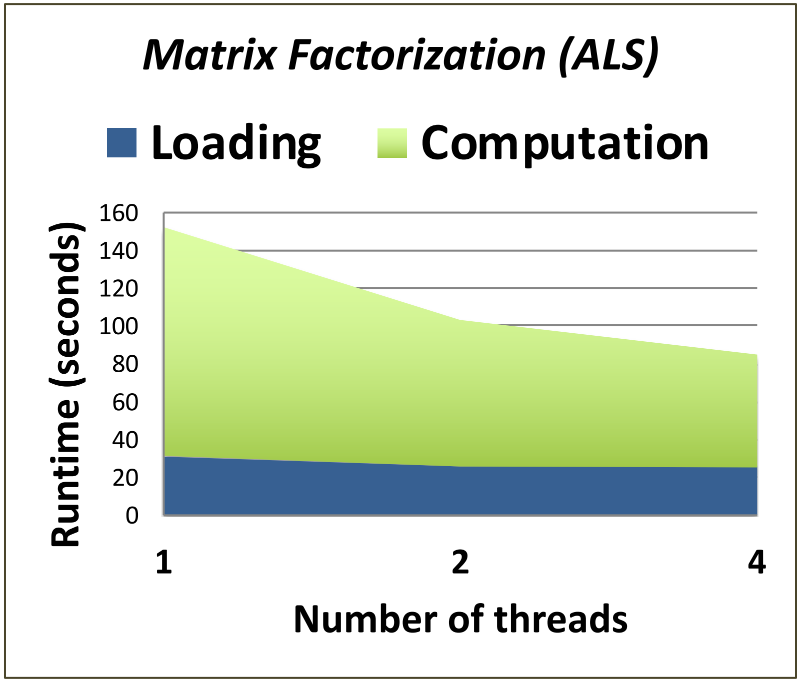
Conclusion: the throughput remains roughly constant when graph size is increased.

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

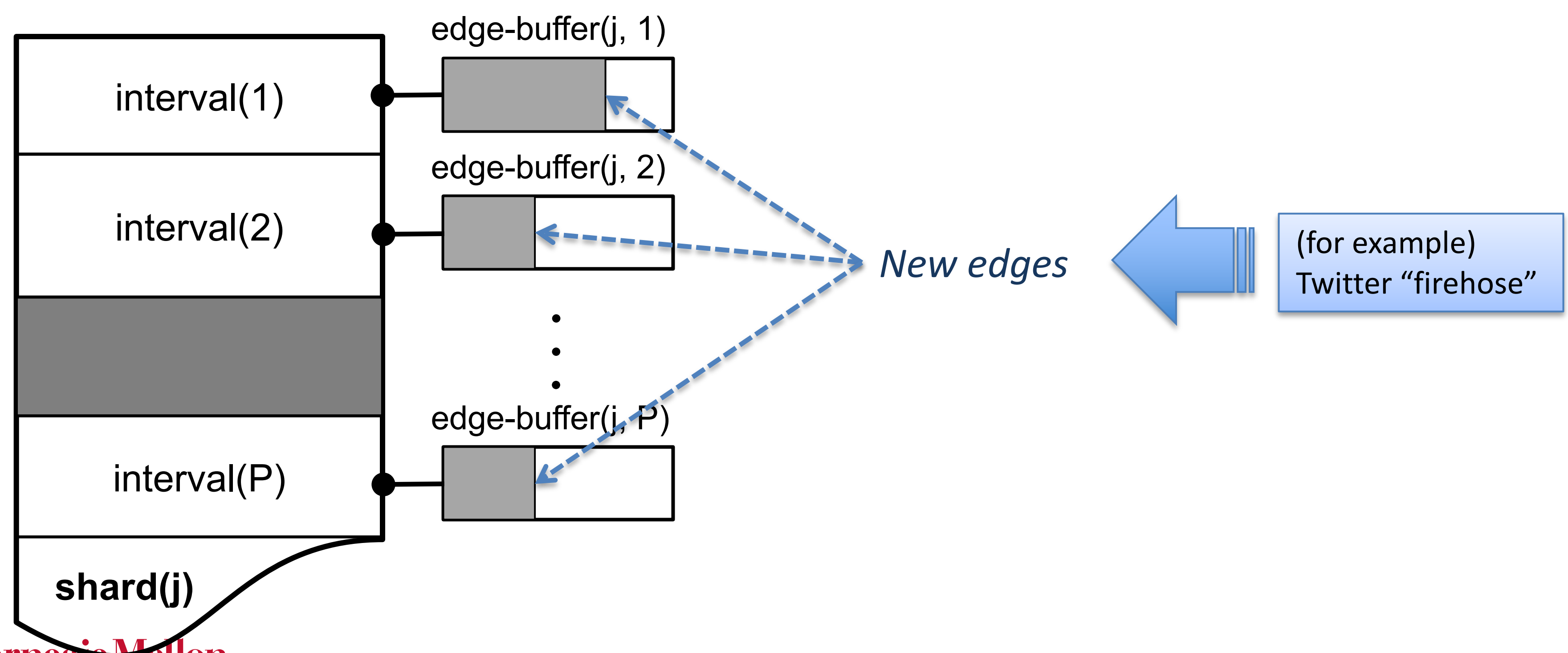
Graphs whose structure changes over time

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.

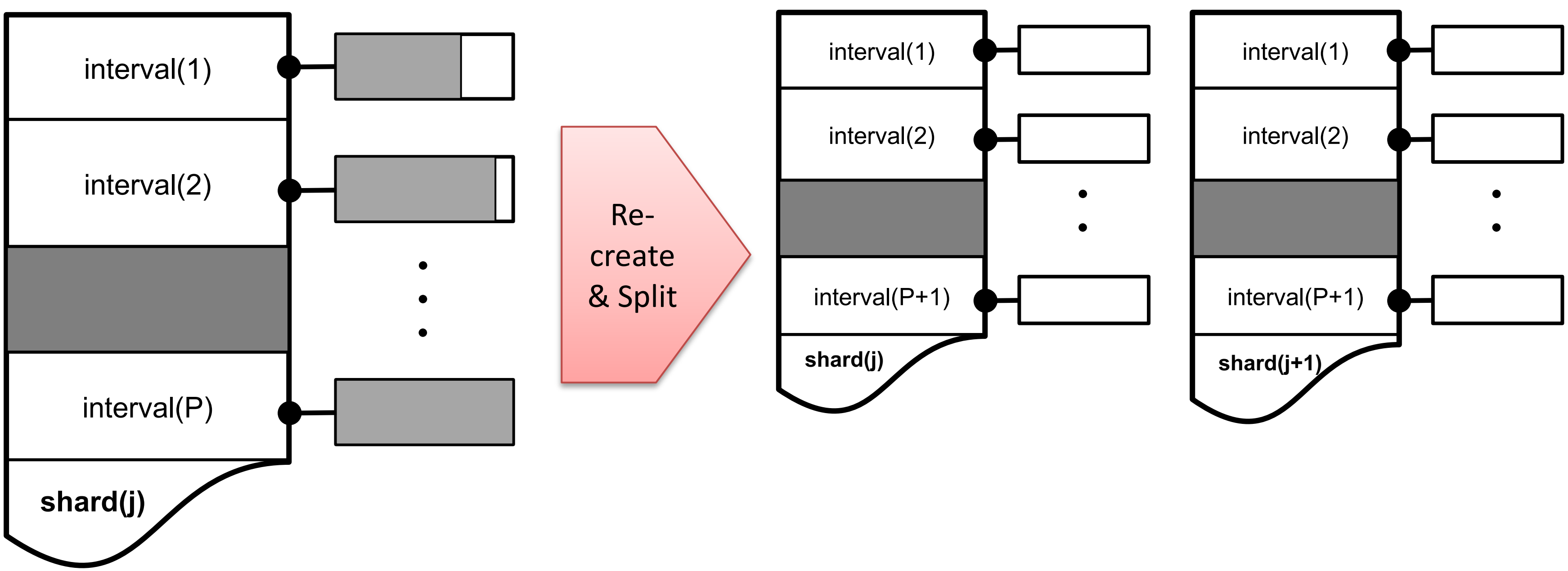
PSW and Evolving Graphs

- 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.

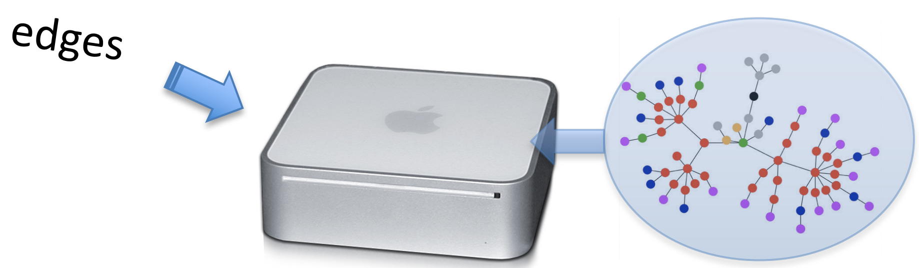


Streaming Graph experiment

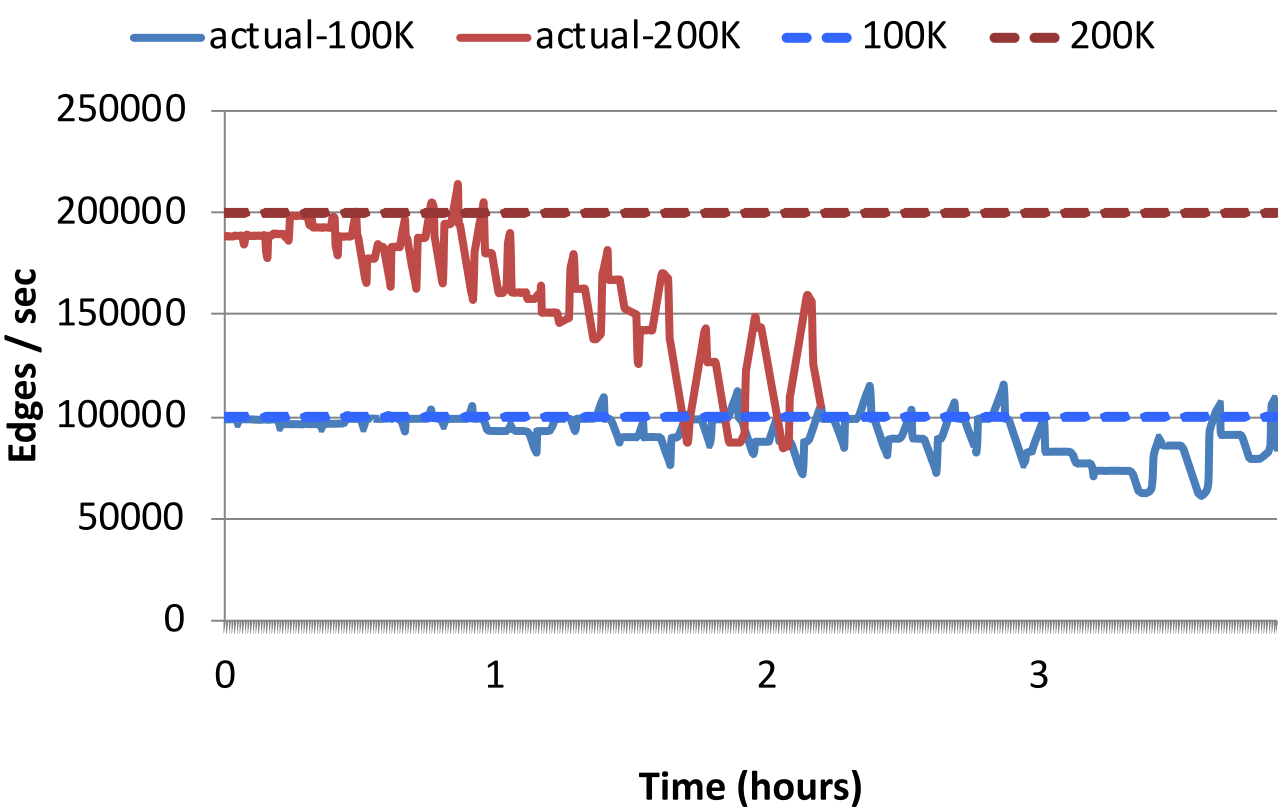
EVALUATION: EVOLVING GRAPHS

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.

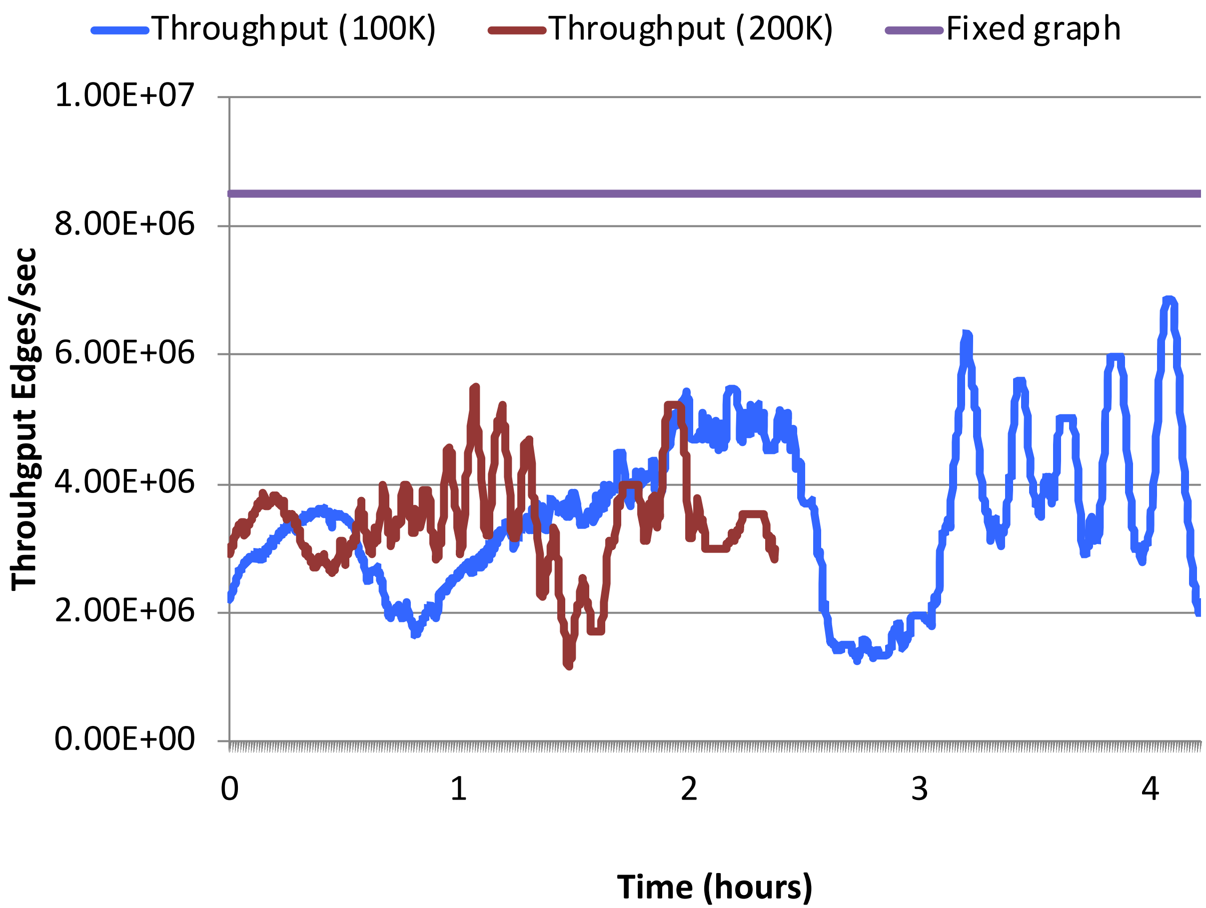


Ingest Rate



When graph grows, shard recreations become more expensive.

Streaming: Computational Throughput



Throughput varies strongly due to shard rewrites and asymmetric computation.

Conclusion

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