FlashGraph: Processing Billion-Node Graphs on an Array of Commodity SSDs

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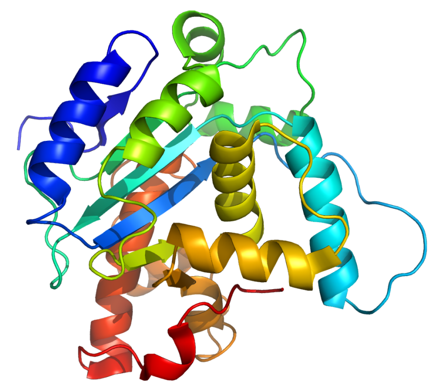
Overview

- Large-scale graph analysis using a commodity SSD array.
- We built a *semi-external memory* [1] graph processing framework called FlashGraph.
  - Achieve performance comparable to in-memory graph engines.
  - Scale to graphs with billions of vertices and hundreds of billions of edges.

[1] J. Abello, A.L. Buchsbaum, J.R. Westbrook, A functional approach to external graph algorithms. In Algorithmica (1998), Springer-Verlag, pp. 332–343.

Motivation

- Graph analysis is ubiquitous:
  - Many real-world problems are modeled with graphs.



Challenges in Graph analysis

- Many real-world graphs are massive.
  - Facebook's social graph has billions of vertices.
  - Web page graph has tens of billions of vertices.
- Seemingly random vertex connection.
  - Small random memory access.
  - Hard to explore data locality.
  - Efficient graph analysis requires RAM.
- Power-law distribution in vertex degree.
  - Load balance.

Alternatives for scaling

- Option 1: Buy a machine with large RAM.
  - Examples: SNAP, Galois, Ligra
  - Problems: Price & Scalability.
- Option 2: Scale out in a cluster.
  - Examples: Pregel, GraphLab/PowerGraph, GraphX
  - Problem: Network is the bottleneck.
- Option 3: Scale with hard drives.
  - Examples: GraphChi, X-Streams
  - Problem: Slow.

Why Scale with SSDs?

- SSD properties:
  - Throughput: over 1M random IOPS.
  - Latency: 20μs.
  - Much cheaper and much larger than RAM.
- Questions:
  - How much can we approach to the performance of in-memory graph analysis?
  - How do we maximize the benefits SSDs bring for graph analysis?

Challenges in using SSDs

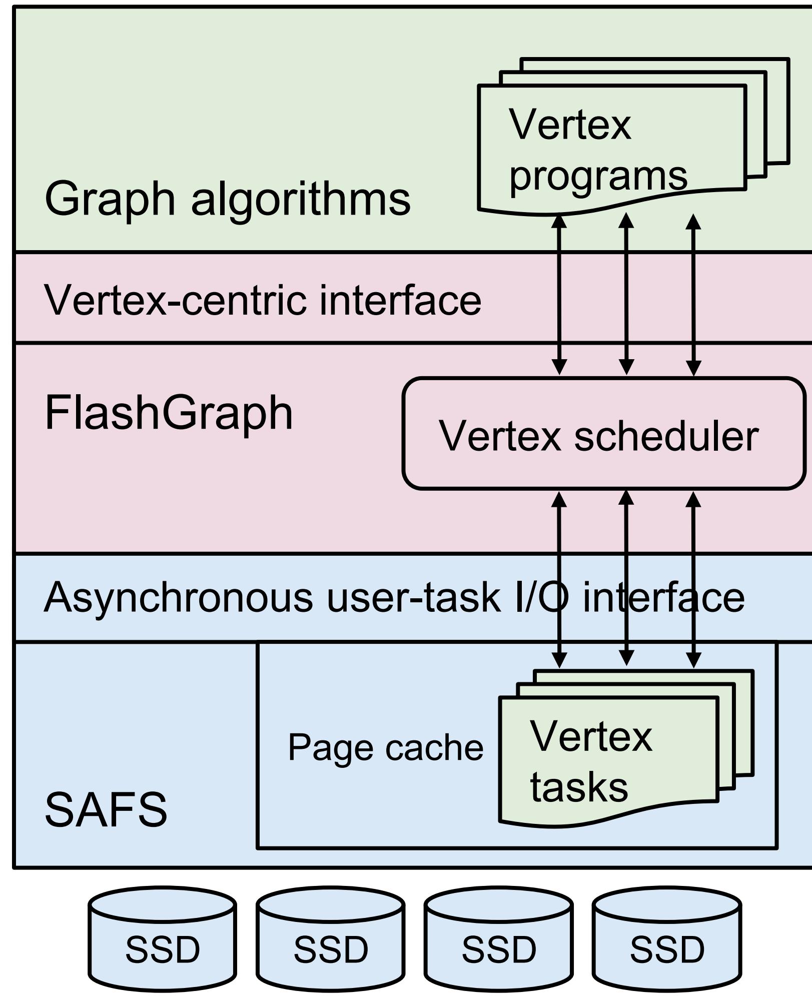
- High OS overhead in fast I/O.
  - Heavy locking overhead in the OS block subsystem.
  - We tackle it with SAFS, a user-space filesystem optimized for a large SSD array [1].
- High latency and low throughput compared with RAM.
  - Latency: three orders of magnitude higher.
  - Throughput: almost an order of magnitude lower.

Design principles for I/O optimization:
- Reduce I/O.
- Overlap I/O and computation.
- Perform sequential I/O.

[1] D. Zheng, R. Burns, A. S. Szalay, Toward Millions of File System IOPS on Low-Cost, Commodity Hardware, in Supercomputing 2013

Architecture

- Three layers for graph analysis using a large SSD array.
  - SAFS: a user-space file system for delivering maximal I/O performance.
  - FlashGraph: schedules vertex programs to optimize I/O.
  - Graph algorithms: part of vertex computation in the page cache.



Semi-external memory

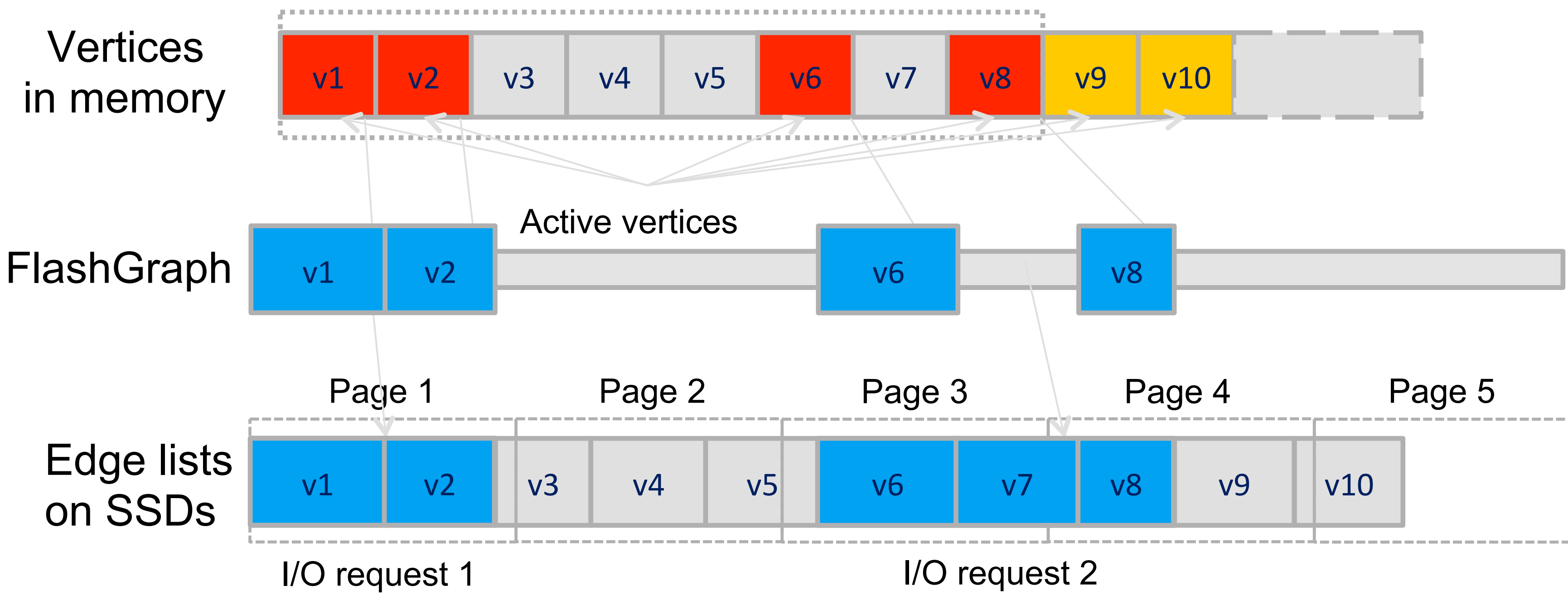
- Algorithmic vertex state in memory.
- Edge lists of vertices on SSDs.
- Scalability:
  - In proportion to the ratio of edges to vertices in a graph.
- Advantage:
  - vs. distributed memory:
    - Enable in-memory vertex communication.
  - vs. external memory:
    - Reduce reads and avoid writes to SSDs.

I/O access in FlashGraph

- Access edge lists only required by an application.
  - Reduce I/O.
- Conservatively merge I/O requests.
  - Increase sequential I/O.
  - Merge criteria:
    - Two edge lists are on the same SSD page.
    - Two edge lists are on adjacent SSD pages.
  - Never increase the amount of data read from SSD.

I/O merging in FlashGraph

- The most common case:
  - A vertex only accesses its own edge list.

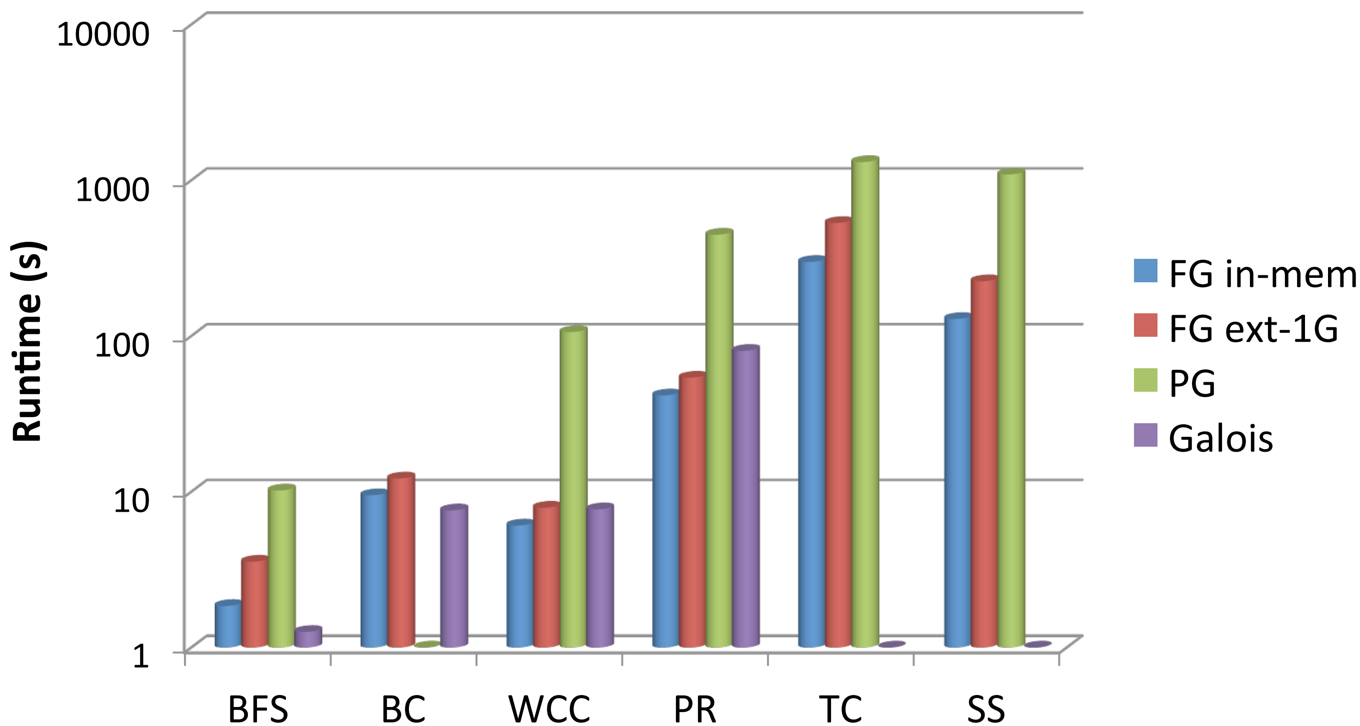


Applications

- Class 1: subset of vertices access their own edge lists.
  - Breadth-first search (BFS).
  - Betweenness centrality (BC).
- Class 2: all vertices access their own edge lists.
  - PageRank (PR).
  - Weakly connected components (WCC).
- Class 3: a vertex accesses multiple edges lists.
  - Triangle counting (TC).
  - Scan statistics (SS).

FlashGraph Performance

- FlashGraph has performance comparable to Galois.
- Ext-mem FlashGraph has performance comparable to in-mem FlashGraph.
- Ext-mem FlashGraph significantly outperforms PowerGraph.



FlashGraph Scalability

- Largest graph publicly available: 3.5B vertices and 129B edges.

Algorithm	Runtime (min)	Memory (GB)
BFS	5	22
Betweenness	10	81
Triangle	130	55
WCC	8	47
PageRank	34	46
Scan statistics	6	83

Previous Results:

- Google Pregel used **300 multi-core machines** for SSSP in +10 min on **1B vertex** and **127B edge** graph.
- Microsoft Trinity used **14 12-core machines** for BFS in +10 min on **1B vertex** and **13B edge** graph.

FlashGraph uses one machine with 32 CPU cores.

We can scale to a much larger graph!

Conclusion

- SSD-based graph analysis has performance comparable to in-memory counterparts.
- FlashGraph offers unprecedented opportunities to perform massive graph analysis efficiently with commodity hardware.

Thank you!

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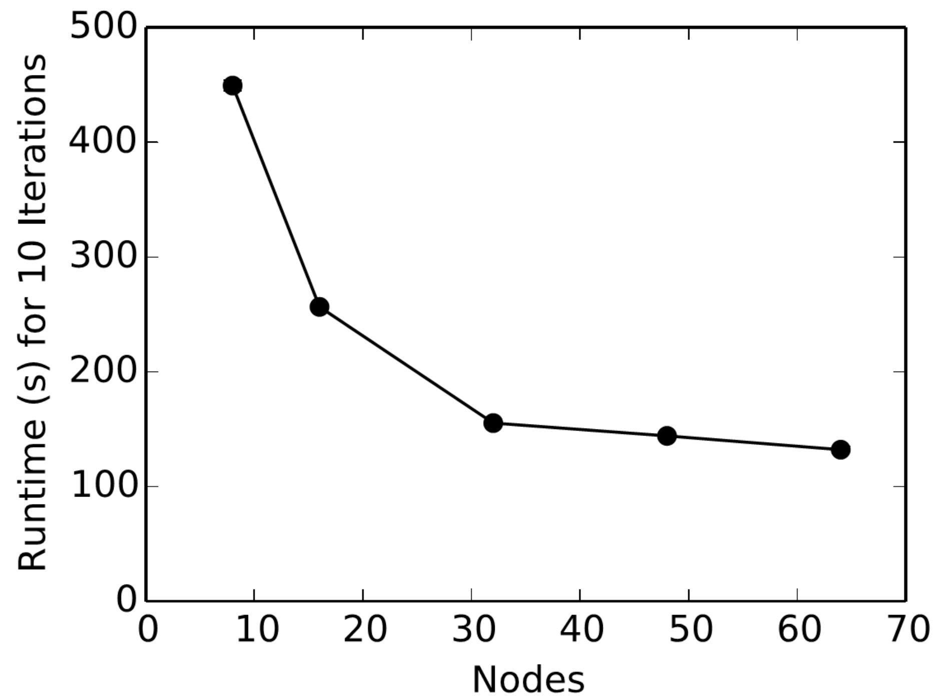
- FlashGraph: https://github.com/icoming/FlashGraph

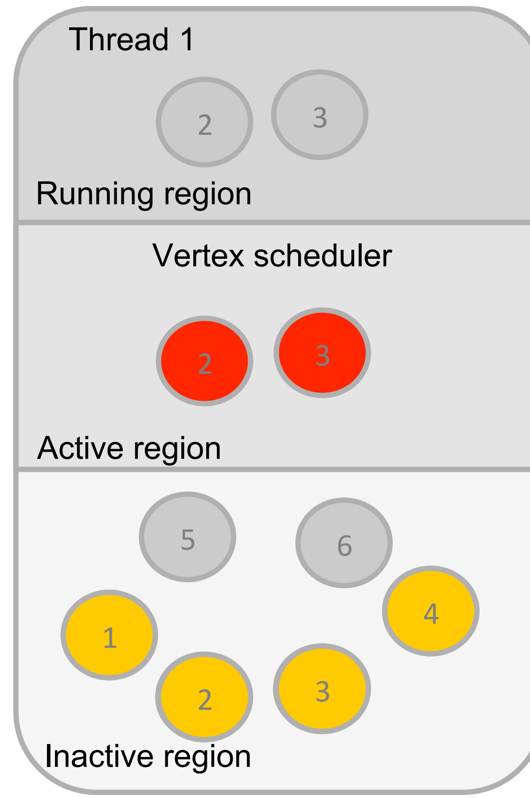
Scale out

- Graph analysis in distributed memory.
- PageRank on EC2 m2.4xlarge.
- Problems:
  - Network is the bottleneck.



Execution model

- A graph is partitioned for parallel processing.
- Each thread schedules and executes vertex programs independently.
- Vertex status:
  - Running.
  - Active.
  - Inactive.



FlashGraph programming interface

- Vertex centric
  - Users write programs from the perspective of vertices

```
class vertex {
    void run(graph_engine &g);
    void run_on_vertex(graph_engine &g, page_vertex &v);
    void run_on_message(graph_engine &g, vertex_message &msg);
    void run_on_iteration_end(graph_engine &g);
};
```

Run in the page cache asynchronously

Asynchronous