A shared-memory algorithm for updating single-source shortest paths in large weighted dynamic networks

Presented by
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github.com/DynamicSSSP/HIPC18
The graph problem

Given a weighted graph, a source vertex, a single-source shortest paths (SSSP) tree, and a batch of graph edge insertions and deletions, update the SSSP tree.
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Given a weighted graph, a source vertex, a single-source shortest paths (SSSP) tree, and a batch of graph edge insertions and deletions, update the SSSP tree.
The naïve approach

Recompute from scratch
Generate new graph after updates, perform SSSP again

Can we do better than recomputing from scratch?
Contributions

A new two-step parallel algorithm for updating the SSSP optimizations to improve scalability optimizations to reduce redundant/wasteful computation

Correctness proof (see paper)

Empirical evaluation to demonstrate speedup over recomputing SSSP from scratch

Why dynamic SSSP?

Many applications
Maps and GPS
Internet routing
Path planning for robots
Discrete event simulations
Centrality analysis in complex networks
Related Work

Parallel algorithms, implementations for SSSP in static graphs
   e.g., Delta-stepping, DSMR

Libraries for dynamic data/graph analysis
   e.g., Sandia PHISH, Georgia Tech Stinger

Dynamic graph algorithms
   e.g., Ramalingam-Reps, Narvez et al.
Assume batched updates

Consider a sequence of insertions and deletions

Edge operations considered

Vertex insertions and deletions can be modeled by adding and deleting edges
Observations about graph updates

Updates may only affect a subgraph and the complete graph need not be analyzed

Not all updates affect the property (SSSP in this paper) updates can be processed in parallel

Not all updates affect the same subgraph affected subgraphs can be processed in parallel
A template for parallel dynamic graph algorithms

Sparsification
Preprocessing step before graph updates

Selection
Identify vertices and edges affected by graph updates
Can be parallelized for each update

Updating
Update set of key edges according to changes
Might require multiple iterations for convergence
Previously-unaffected entities may also be affected
New algorithm for dynamic SSSP

**Sparsification:** use rooted SSSP tree

**Selection:** identify affected vertices and edges with a simple distance label check

**Updating:** propagate changes, iterate until convergence
Selection step

Assume \( \text{dist}(s, v) > \text{dist}(s, u) \)

An edge insertion update \([u, v, w(u, v)]\) affects the SSSP tree if \( \text{dist}(s, v) > \text{dist}(s, u) + w(u, v) \). If this condition is met, \( v \) is marked as affected.

An edge deletion update \([u, v, w(u, v)]\) affects the SSSP tree if the edge is present in the SSSP tree. \( v \)'s distance label is set to Infinity.
Selection step

Graph updates

Insert edge [a, f] of weight 1
Insert edge [c, d] of weight 4
Delete edge [a, c]
Delete edge [a, b]
Updating step

The effect of each inserted edge can percolate to a large subgraph, possibly the entire graph.

Reduces to edge relaxations from affected vertices.

Relaxations can be performed concurrently. Convergence when there are no more affected vertices.
Updating step with single edge insertion

Iteration 1

Iteration 2
Shared-memory parallelization

The Selection step is easy to implement and shows good load balance.

The parallel performance of the Updating step is dependent on the number of affected vertices and the size of the subgraphs they alter. Vertex degree distributions can cause further load imbalance.

Asynchronous updates: can process longer paths instead of just neighbors. Reduce number of synchronization steps.
Empirical results

Results on a 36-core Intel Haswell system with 256 GB memory

OpenMP implementation

Comparison to SSSP implementation in Galois v2.2.1

Synthetic RMAT-G (skewed degree distribution) and RMAT-ER (normal degree distribution) graphs, three real-world graphs from SNAP
Comparison to recomputation-based approach

New algorithm is up to 4X faster.
Strong scaling (synthetic graphs)
Strong scaling (real-world graphs)
Strong scaling (vertex insertion/deletion)
Empirical evaluation summary

For low thread counts, update algorithm is significantly faster than recomputation. However, recomputation shows better scaling.

Possible parallel scaling bottlenecks
- Set of changed edges not known apriori
- Redundant work in parallel setting
Brainstorming on how to analyze dynamic networks
August 2015

Brainstorming on how to update MST and SSSP.
June 2016

Solved Connected Components. Presented in IPDPS 2016

Solved SSSP, SC18 (Accepted @ HIPC 18)
Dec 2016

Solved MST, Presented in SIAM CS17, and IPDPS (Ph.D.forum) 2017. IEEE Transactions on Big data Journal (Accepted at 06/2018)
May 2017

March 2018
Conclusions and Future Work

New shared-memory algorithm for updating SSSP in dynamic networks

Performance results demonstrate up to a 4X performance improvement over a parallel recomputation-based SSSP code

Plan to extend the general approach to centrality algorithms

Future GPU and distributed-memory implementations
Acknowledgments & Collaborators

Dr. Boyana Norris,
University of Oregon

Dr. Sajal Das,
Missouri S&T
Thank you!

If you want to go fast, go alone.
If you want to go far, go together.
—African proverb

Questions?
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