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Title: A Parallel Algorithm Template for Updating Single-Source Shortest Paths in Large-Scale Dynamic Networks

1. Problem Statement

- **Core Challenge:** Traditional SSSP algorithms (e.g., Dijkstra's) assume static graphs, but real-world networks (e.g., social, transportation) are dynamic—edges/weights change over time.
- **Gap:** Recomputing SSSP from scratch after each change is inefficient for large-scale dynamic networks.
- **Goal:** Develop a parallel framework to *update* SSSP incrementally when edges are added/deleted, minimizing redundant computations.

2. Proposed Parallel Algorithm

Key Idea:

- **Step 1:** Identify subgraphs affected by edge changes (parallelizable).
- **Step 2:** Update only affected subgraphs iteratively (avoids global recomputation).

Parallelization Strategy:

MPI (Inter-node):

- Partition graph using **METIS** (not explicitly mentioned but implied for distributed memory).
- Each process handles a subset of vertices/edges.
- OpenMP (Intra-node):
- Parallelize edge relaxation and tree updates within a node using dynamic scheduling.
- **GPU** (Alternative):
- Uses CUDA with a Vertex-Marking Functional Block (VMFB) to avoid atomic operations and reduce synchronization overhead.

Data Structures:

- SSSP Tree: Stored as an adjacency list with Parent, Dist, and Affected flags per vertex.
- Dynamic Updates:
- o **Edge Insertion:** Update distances if a shorter path is found.
- Edge Deletion: Disconnect affected subtrees and mark vertices for reprocessing.

3. Results

- Speedup:
- GPU: Up to 5.6× faster than Gunrock (static recomputation) for 100M edge changes (≥50% insertions).
- CPU (OpenMP): Outperforms Galois by up to 5× for similar conditions.
- Scalability:
- Efficiently handles graphs with millions of vertices/edges (e.g., LiveJournal: 12.6M vertices, 161M edges).
- Performance degrades if >75% changes are deletions (recomputation becomes better).

4. Key Contributions

- 1. **Unified Framework:** Works for both CPUs (shared memory) and GPUs.
- 2. **Iterative Convergence:** Avoids locks by iteratively updating distances until stability.

- Load Balancing: Uses dynamic scheduling for uneven workloads (e.g., varying subtree sizes).
- 4. **Batch Processing:** Handles **100M edge changes** efficiently by processing in batches.

5. Tools/Datasets Used

- **Graphs:** Real-world (e.g., LiveJournal, Orkut) and synthetic R-MAT networks.
- **GPU:** NVIDIA Tesla V100 (CUDA).
- CPU: Intel Xeon Gold (OpenMP).

Parallelization Strategy for Dynamic SSSP Updates

(Based on Paper 3: "A Parallel Algorithm Template for Updating SSSP in Dynamic Networks")

1. MPI Strategy (Inter-Node Parallelism)

- Graph Partitioning with METIS:
- Use **METIS** to split the graph into k partitions (one per MPI process).
- Partitioning Goal: Minimize edge cuts while balancing vertex counts across nodes.
- Output: Each MPI process gets a subgraph + boundary vertices (shared with neighbors).
- Communication Patterns:
- o Master-Worker: Designate one process (e.g., rank 0) to coordinate batch updates.
- All-to-All: Sync Dist/Parent arrays for boundary vertices after each iteration (MPI_Allreduce).
- Sparse Updates: Only communicate changes to affected vertices (MPI_Isend/MPI_Irecv).

2. OpenMP Strategy (Intra-Node Parallelism)

Thread-Level Parallelism:

Parallelize loops in Step 1 (identifying affected vertices) and Step 2 (updating distances) using #pragma omp parallel for schedule(dynamic).

- o **Dynamic Scheduling:** Handles uneven workloads (e.g., subtrees of varying sizes).
- Critical Sections:
- Avoid locks by using **iterative convergence** (no atomic updates; recompute until stable).
- Example:

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```
#pragma omp parallel for
for (Vertex v : AffectedVertices) {
   relax_neighbors(v); // No locks; redundant updates allowed
}
```

3. METIS Integration

- Preprocessing:
- o Run METIS on the initial graph to generate partitions (mpmetis -kway graph.txt N, where N = MPI ranks).
- Dynamic Updates:
- After edge changes, re-partition only if imbalance exceeds a threshold (e.g., >20% vertex count variance).
- Optimization: Cache partition data to avoid recomputing for small changes.

4. OpenCL Alternative (GPU Acceleration)

(Optional, if GPUs are available)

- Kernel Design:
- Step 1 (Edge Processing): Launch one GPU thread per changed edge (massively parallel).
- Step 2 (Vertex Updates): Use VMFB (Vertex-Marking Functional Block) to:

- 1. Mark affected vertices in parallel (no atomics).
- 2. Filter/Sync via GPU ballot operations.
- o Data Structure: Store graph in CSR format for coalesced memory access.

Implementation Workflow

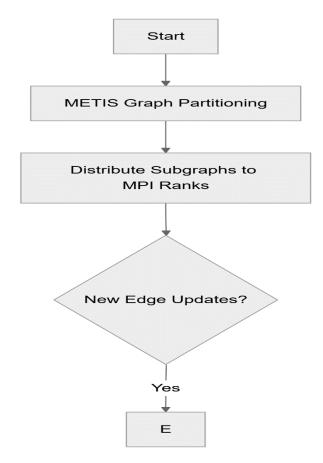
1. Initialization:

- o Partition graph with METIS → Distribute subgraphs to MPI processes.
- o Compute initial SSSP sequentially (Dijkstra's) on each partition.
- 2. Dynamic Update:
- o MPI: Broadcast batch of edge changes (Ins k, Del k).
- o **OpenMP:** Parallelize Steps 1–2 within each node.
- o **Sync:** Aggregate updates to boundary vertices via MPI.
- 3. Termination:
- o Check global convergence (no further distance updates).

Challenges & Mitigations

- Load Imbalance:
- Use METIS to balance partitions; dynamic scheduling in OpenMP.
- Synchronization Overhead:

Limit MPI syncs to boundary vertices; tolerate redundant OpenMP updates.



Key Interactions Explained:

1. METIS (Yellow):

- o Partitions the initial graph into k subgraphs (1 per MPI rank).
- o Output: Balanced partitions with minimal edge cuts.

2. MPI (Purple):

- o Distributes subgraphs to ranks.
- Broadcasts edge updates (Ins_k/Del_k) to all ranks.
- Synchronizes boundary vertex distances after local updates.

3. OpenMP (Blue):

- Within each MPI rank:
- **Step 1:** Parallel edge processing (mark affected vertices).
- Step 2: Parallel distance updates (dynamic scheduling).

4. Convergence Check:

0	Iterates until	no fu	urther	distance	updates	occur (global	sync via	MPI).