Lux
A Distributed Multi-GPU System for Fast Graph Processing

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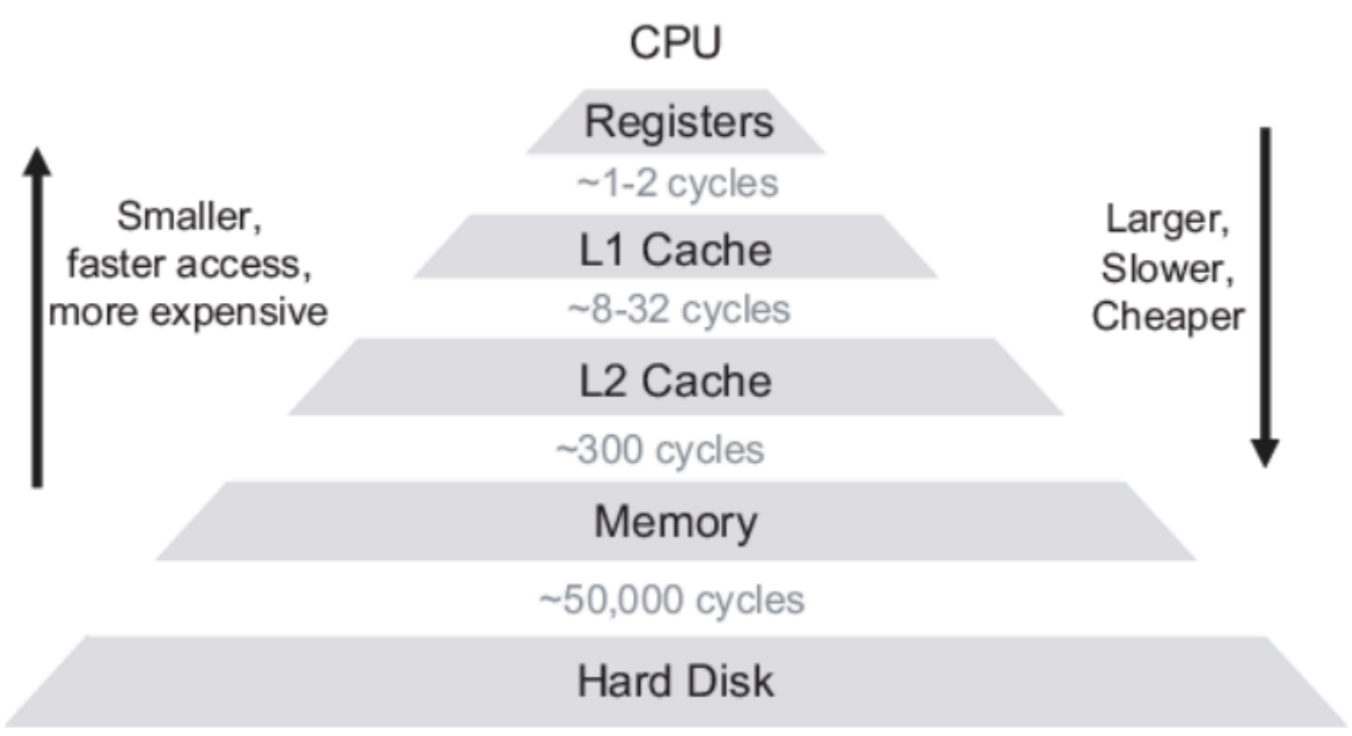
Background

Prior work

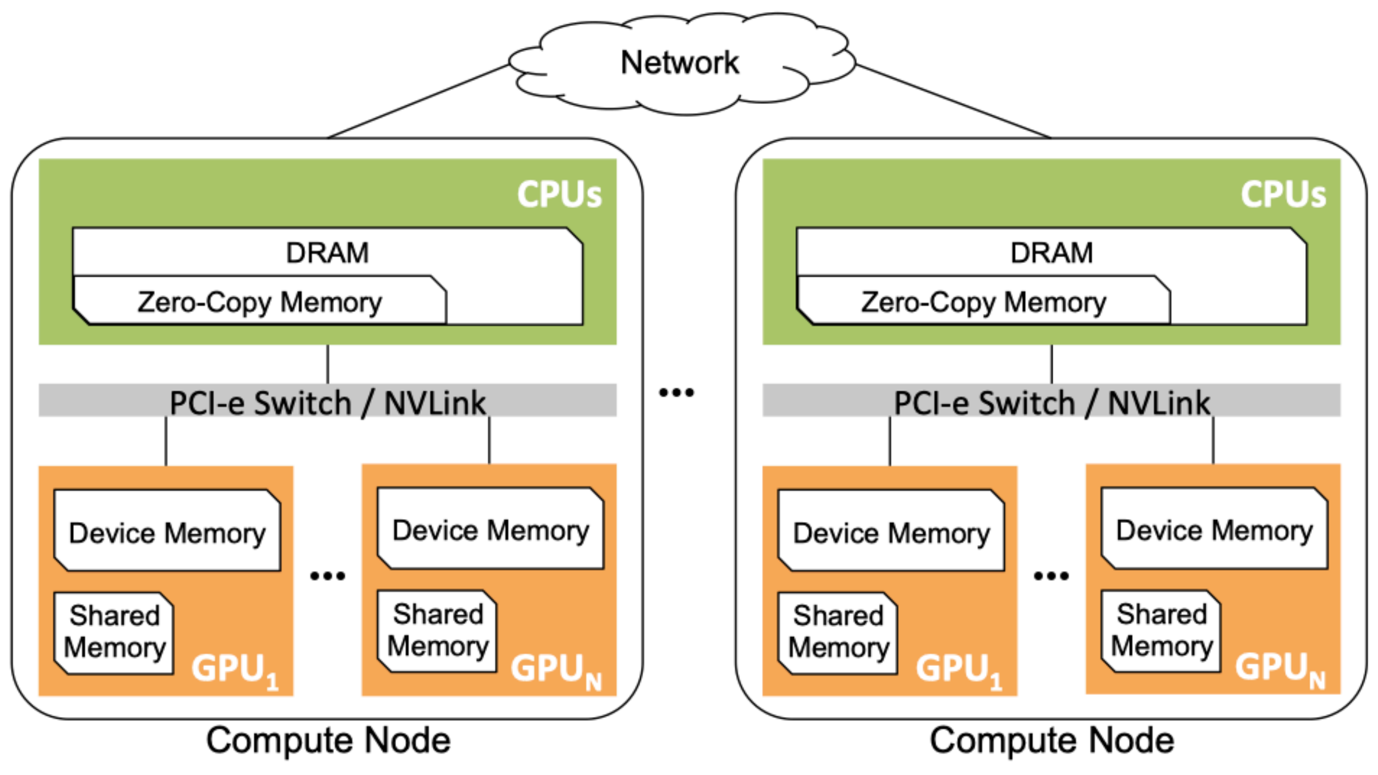
- Distributed CPU-based systems: Pregel, PowerGraph, GraphX…
- Single-node CPU-based systems: Ligra, Galois, and Polymer…
- Single-node GPU-based systems:
  - Single GPU: CuSha, MapGraph…
  - Single machine: Groute, Medusa, GTS…
- Lux: Distributed multi-GPU system that achieves fast graph processing

Background

Motivation



- GPU vs CPU
- GPUs provide much higher memory bandwidth than today's CPU architectures.
- Prior work cannot be easily adapted to multi-GPU clusters:
  - graph placement and data transfers
  - Optimisation interference
  - load balancing



- Lux: Distributed multi-GPU system that achieves fast graph processing

Introduction

Graph Tasks

- PageRank (PR)
- connected components (CC)
- single-source shortest path (SSSP)
- betweenness centrality (BC)
- collaborative filtering (CF)

- Up to 20× speedup over Ligra, Galois, and Polymer
- Two orders of magnitude speedup over PowerGraph and GraphX

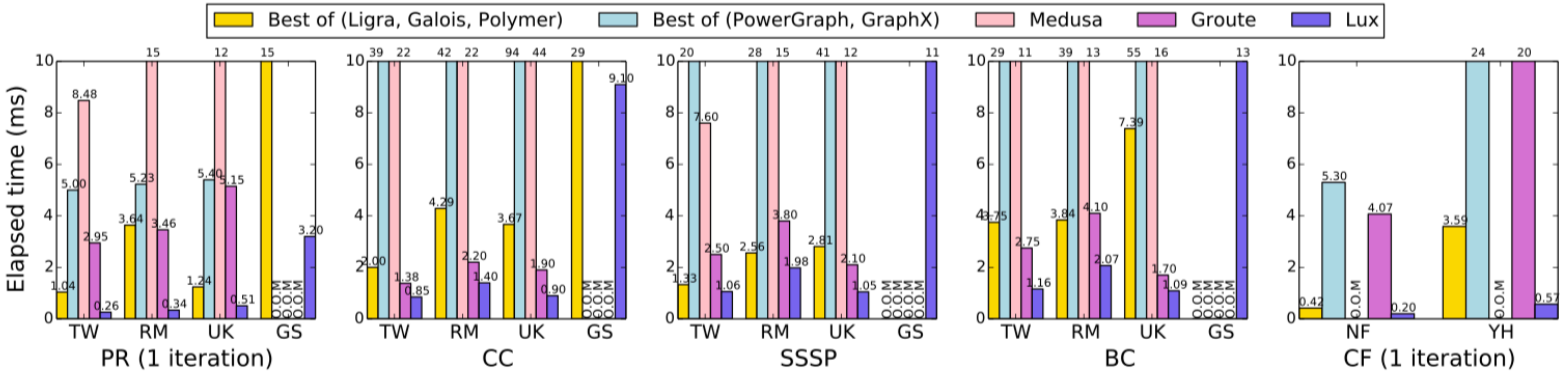


Figure 16: The execution time for different graph processing frameworks (lower is better).

Lux Details

Programming Model

- Gather-Apply-Scatter concepts, Vertex-centric algorithms
- Vertex contain mutable states
- Edges do not contain states AND topology cannot change

```
interface Program(V, E) {
  void init(Vertex v, Vertex v^old);
  void compute(Vertex v, Vertex u^old,
               Edge e);
  bool update(Vertex v, Vertex v^old);
}
```

Lux Details

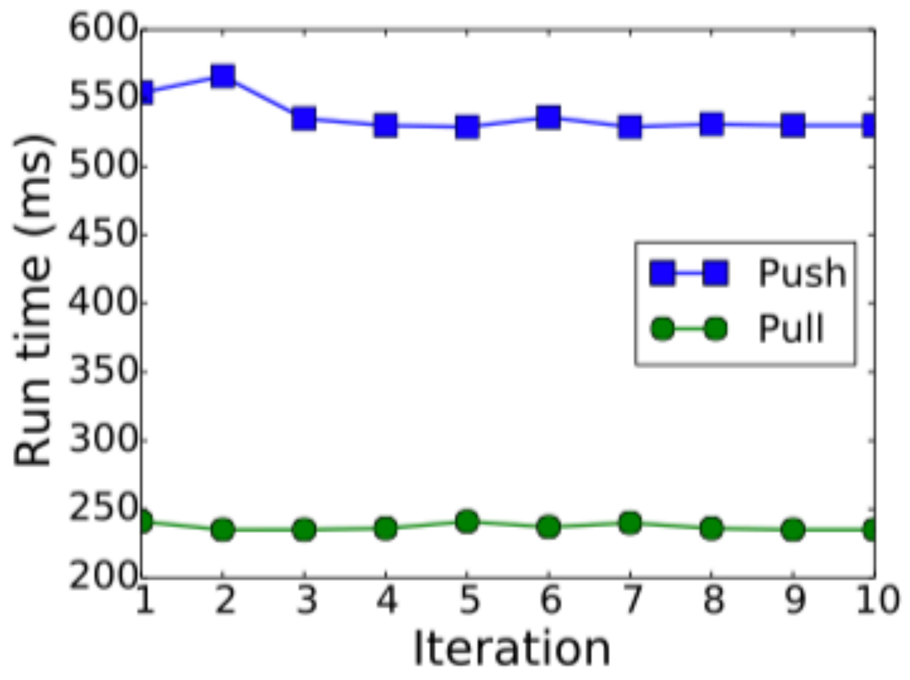
Two Execution models

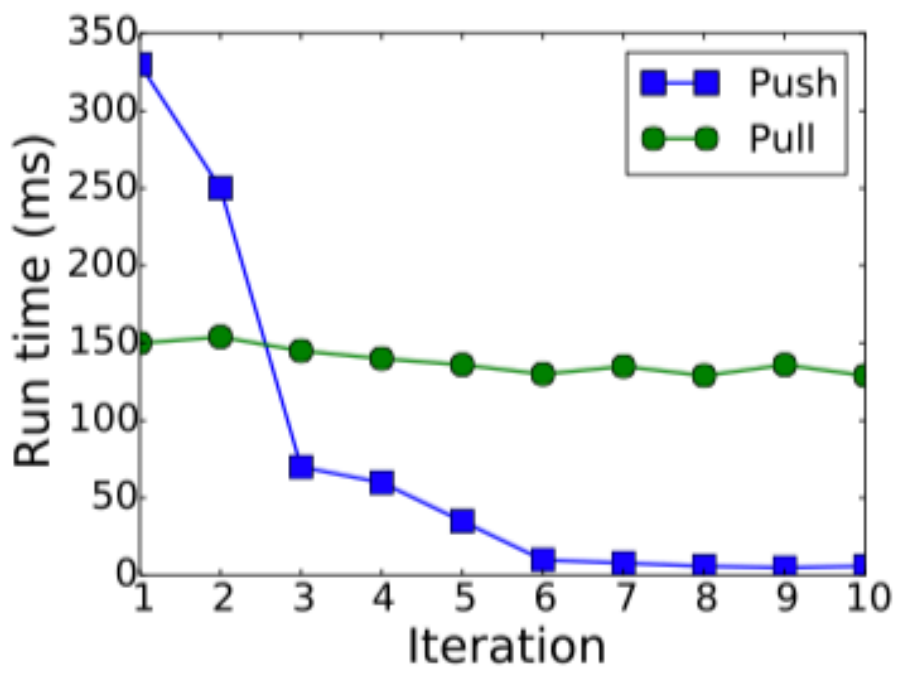
- **Push** execution model
  - optimize algorithmic efficiency
- **Pull** execution model
  - enable important GPU optimizations
  - applications with a large proportion of active vertices over iterations benefit substantially

(e.g., PageRank, collaborative filtering)

```
define Vertex {rank:float}
void init(Vertex v, Vertex v^old) {
  v.rank = 0
}
void compute(Vertex v, Vertex u^old, Edge e) {
  atomicAdd(&v.rank, u^old.rank)
}
bool update(Vertex v, Vertex v^old) {
  v.rank = (1 - d) / |V| + d * v.rank
  v.rank = v.rank / deg+(v)
  return (|v.rank - v^old.rank| > δ)
}
```

```
define Vertex {rank, delta:float}
void init(Vertex v, Vertex v^old) {
  v.delta = 0
}
void compute(Vertex v, Vertex u^old, Edge e) {
  atomicAdd(&v.delta, u^old.delta)
}
bool update(Vertex v, Vertex v^old) {
  v.rank = v^old.rank + d * v.delta
  v.delta = d * v.delta / deg+(v)
  return (|v.delta| > δ)
}
```





Lux Details

Distributed Graph Placement and Data Transfers

- vertex-cut partitioning: PowerGraph, GraphX
  - takes too long
  - not a good estimate of data transfers
- edge partitioning
  - each partition holds contiguously numbered vertices and the edges pointing to them
  - GPU can coalesce reads and writes to consecutive memory
  - very efficient

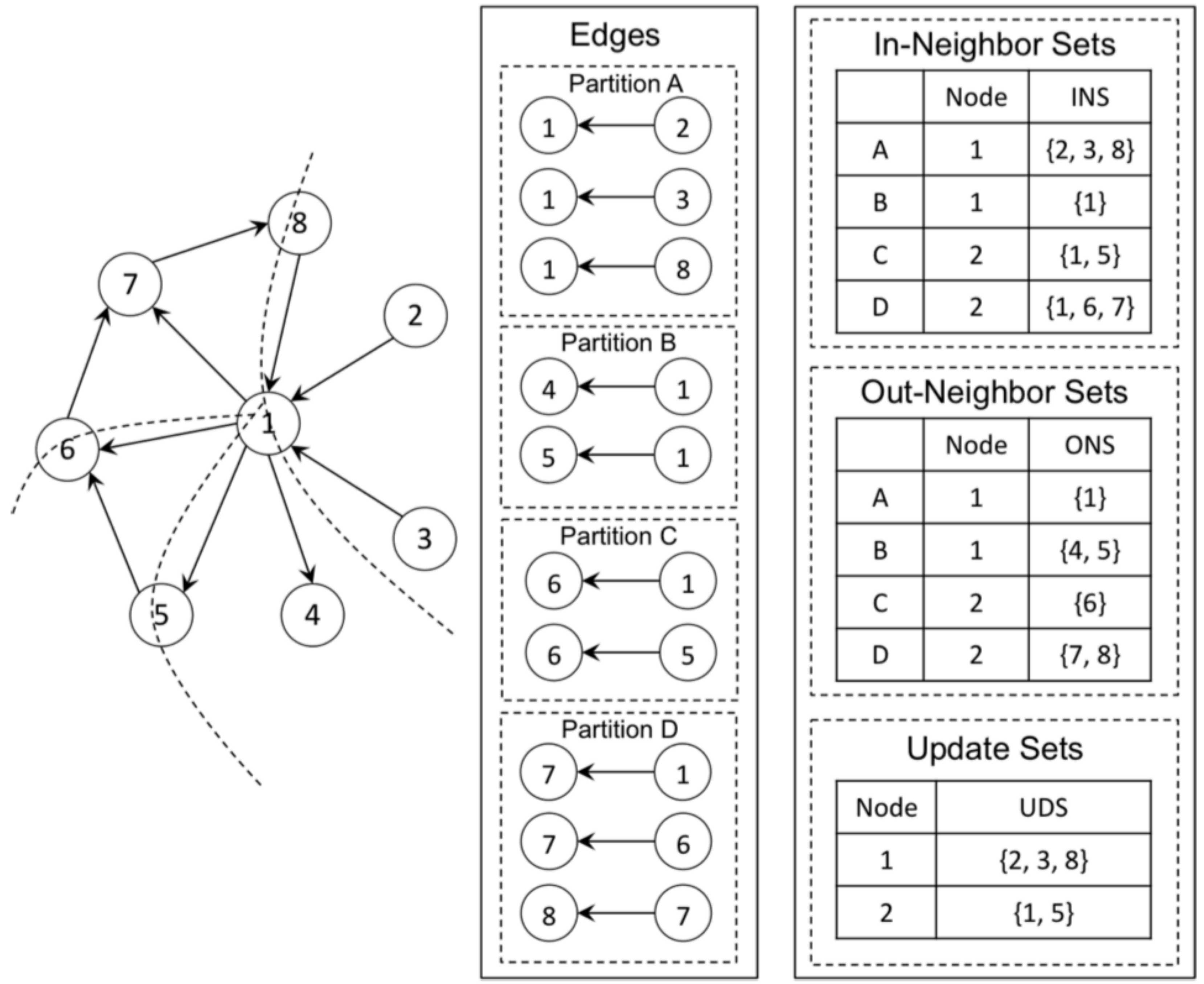


Figure 7: Edge partitioning in Lux: a graph is divided into 4 partitions, which are assigned to 4 GPUs on 2 nodes.

$$
\begin{aligned}
INS(P_i) &= \{u \mid (u, v) \in P_i\} \\
ONS(P_i) &= \{v \mid (u, v) \in P_i\}
\end{aligned}
$$

Lux Details

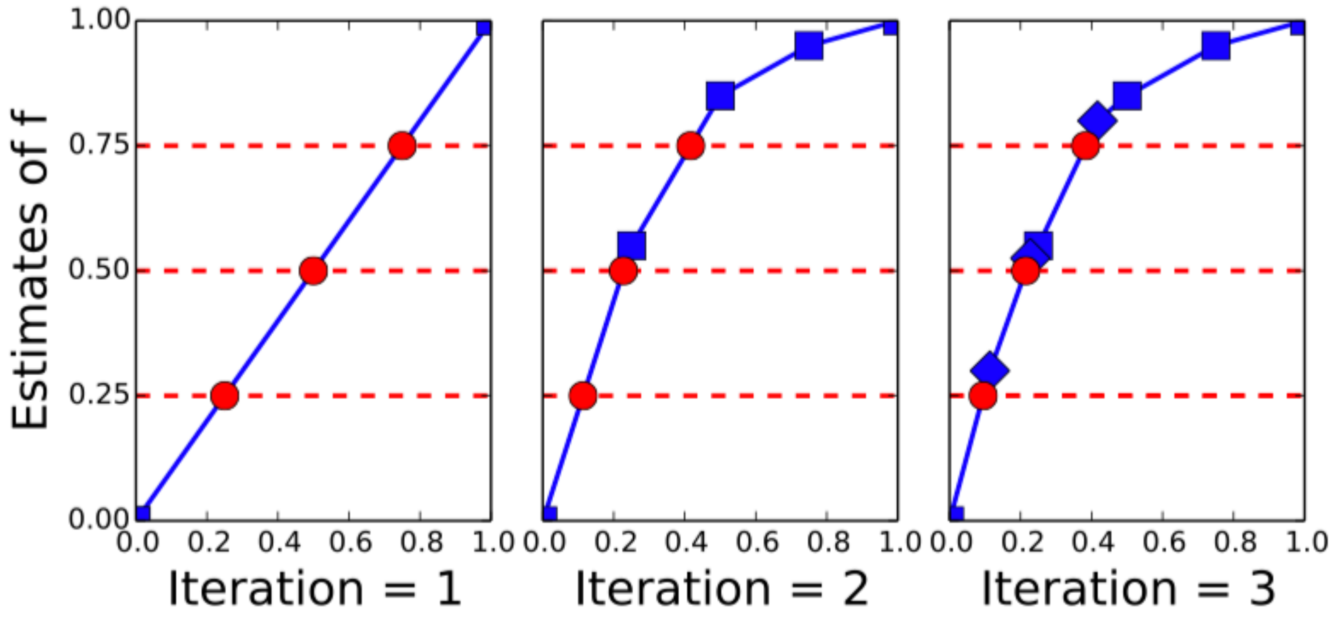
Load Balancing

- Static load balancing: Pregel, Giraph, GraphLab, PGX.D
- Dynamic load balancing: Giraph, Presto

A Dynamic graph repartitioning strategy

- global: multiple nodes
- local: multiple GPUs on a node

1. Collect t_i per P_i, update f, calculate partitioning
2. Compare $\Delta_{gain}(G)$ (improvement) vs $\Delta_{cost}(G)$ (inter-node transfer)
3. Globally repartition depending on 2
4. Local repartition



Estimates of $f(x) = \sum_{i=0}^{x} w_i$ used to pick pivot vertices.

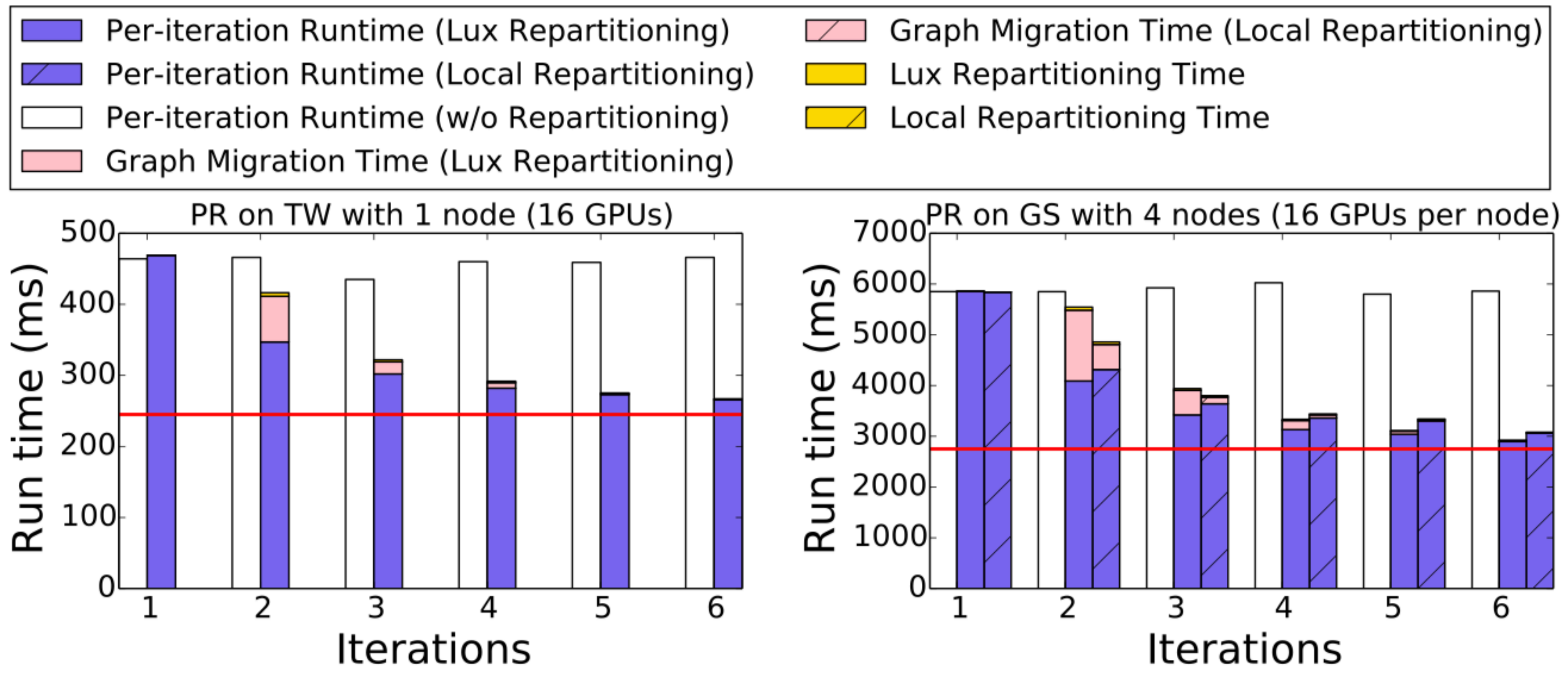


Figure 18: Performance comparison for different dynamic repartitioning approaches. The horizontal line shows the expected per-iteration run time with perfect load balancing.

Lux Details

Performance Model

- To preselect an execution model and runtime configuration
- Models performance for a single iteration

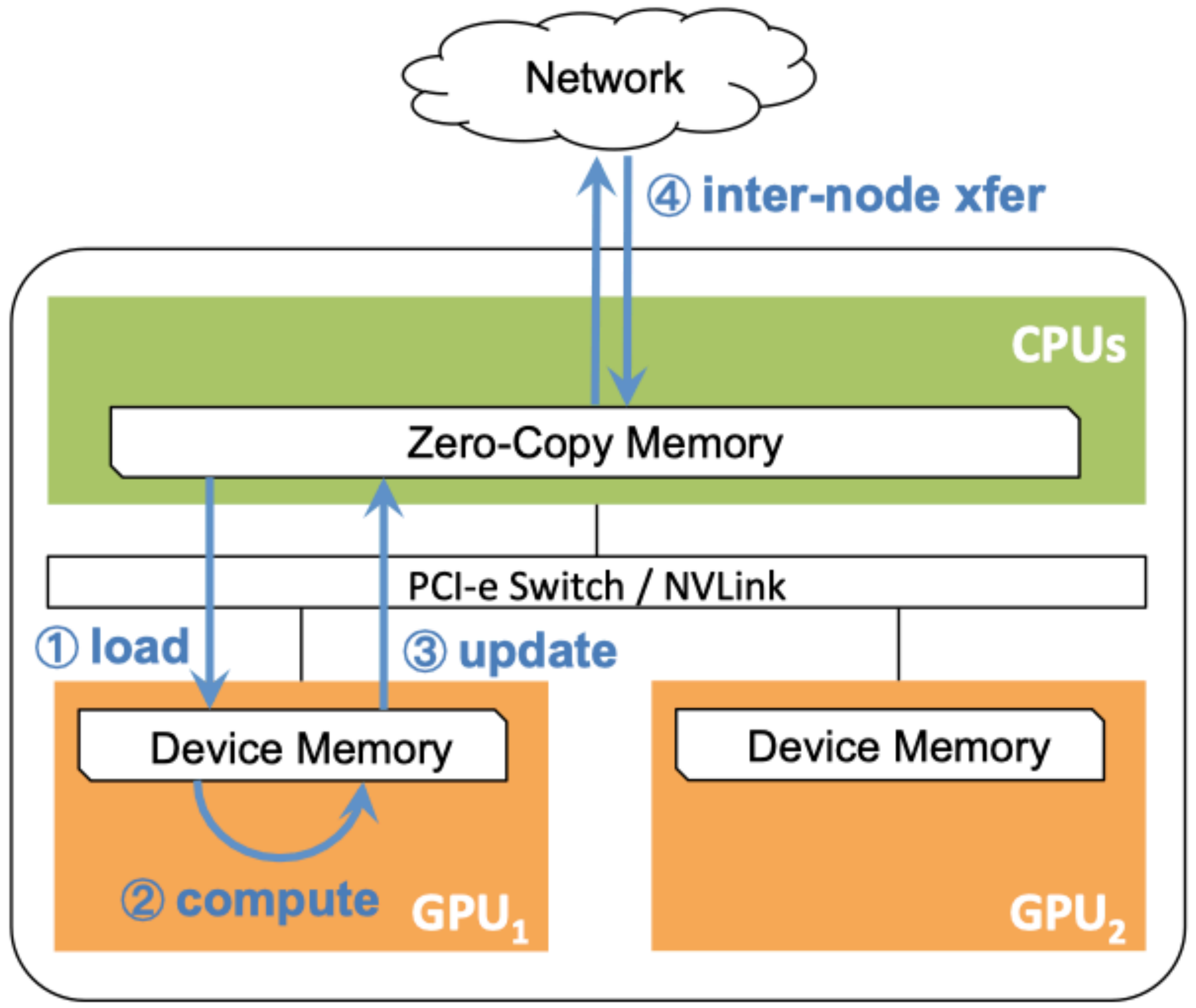


Figure 9: Data flow for one iteration.

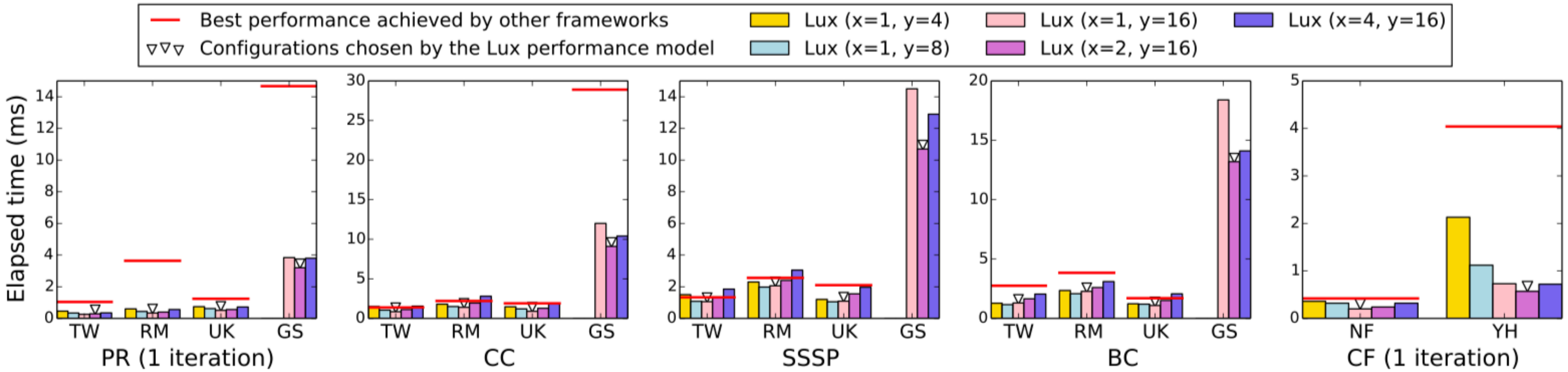


Figure 17: The execution time for different Lux configurations (lower is better). x and y indicate the number of nodes and the number of GPUs on each node.

Opinions

key takeaway

- Lux, a distributed multi-GPU system that achieves fast graph processing by:
    - a distributed **graph placement** to minimize **data transfers** within the memory hierarchy.
    - two **execution models** optimizing algorithmic efficiency and enabling GPU optimizations.
    - a dynamic graph repartitioning strategy that achieves good **load balance across GPUs**.
    - a **performance model** that chooses the number of nodes and GPUs for the best possible performance.

Opinions

Criticism

- The paper is hard to follow
- Absence of fault tolerance
- Abstract claims up to 20x speedup over shared-memory systems (more like 5-10)
- For evaluation all parameters were highly tuned. Can't guarantee others were as tuned as Lux
- The prediction for the push-based execution is not as accurate as the pull-based execution

Thanks for listening!

Q&A