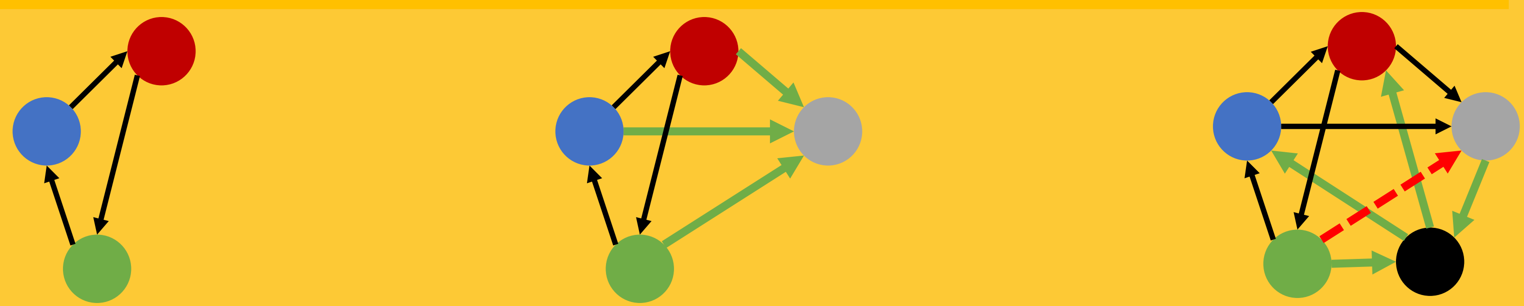
Tegra

Time-evolving Graph Processing on Commodity Clusters



SIAM CSE 17
2 March 2017

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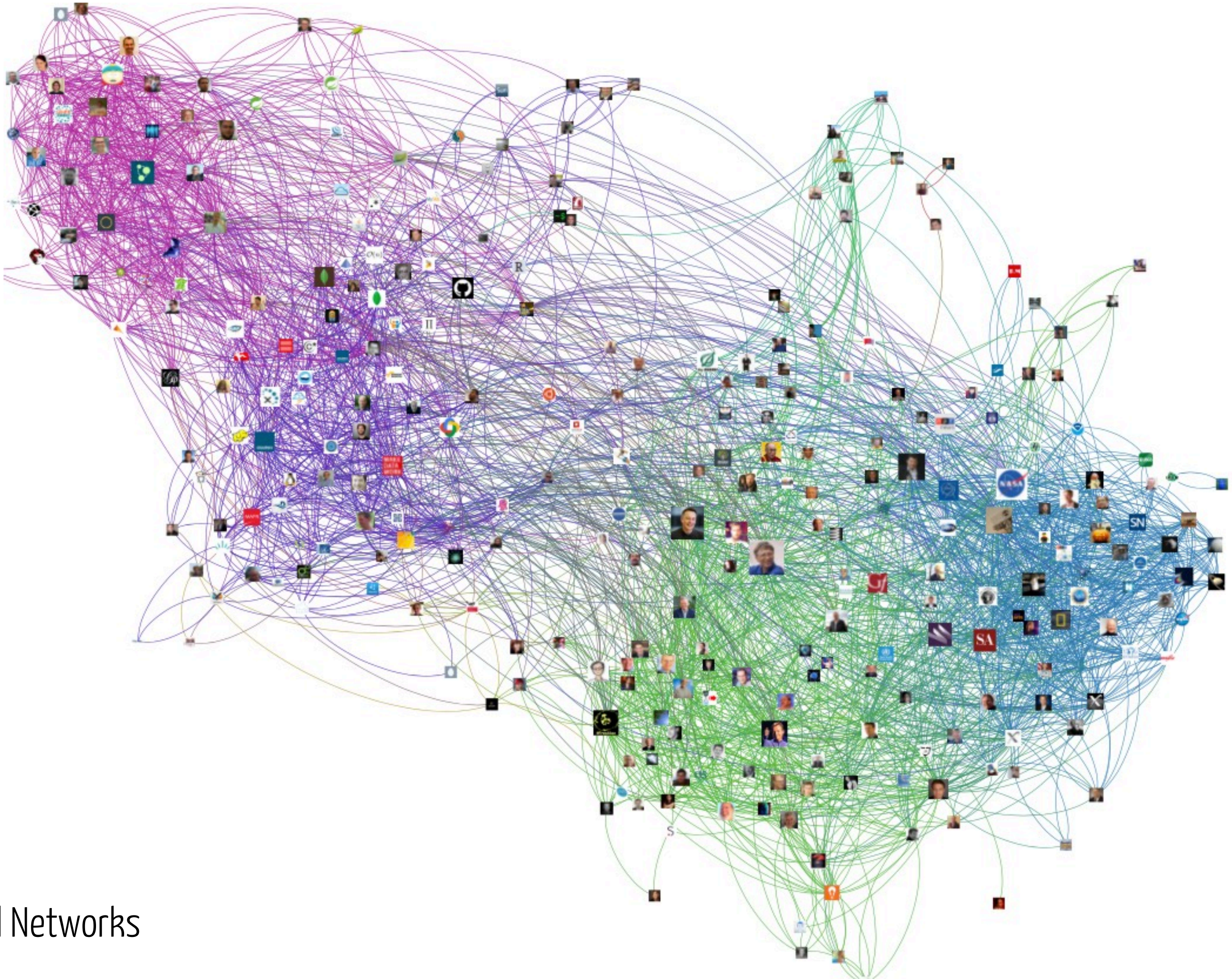
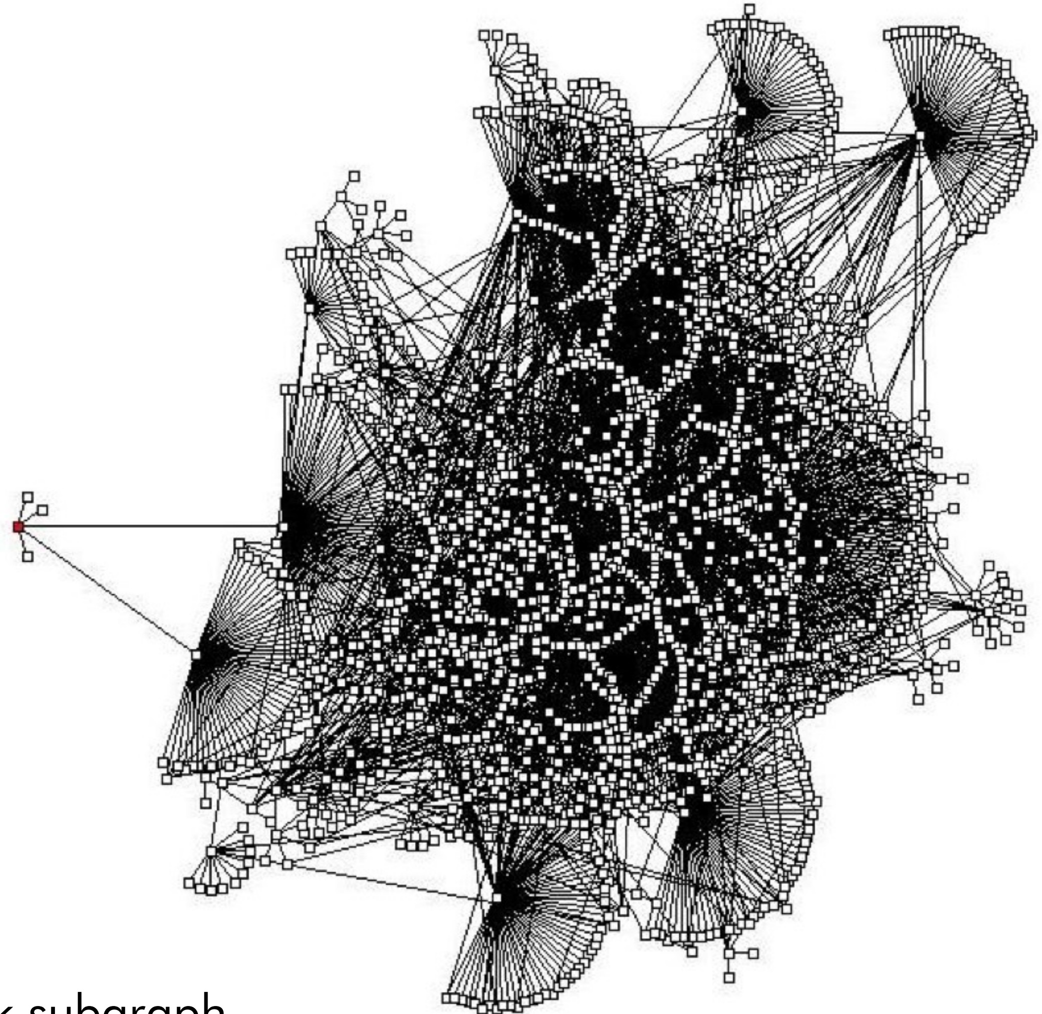
riselab UC Berkeley

Graphs are everywhere…



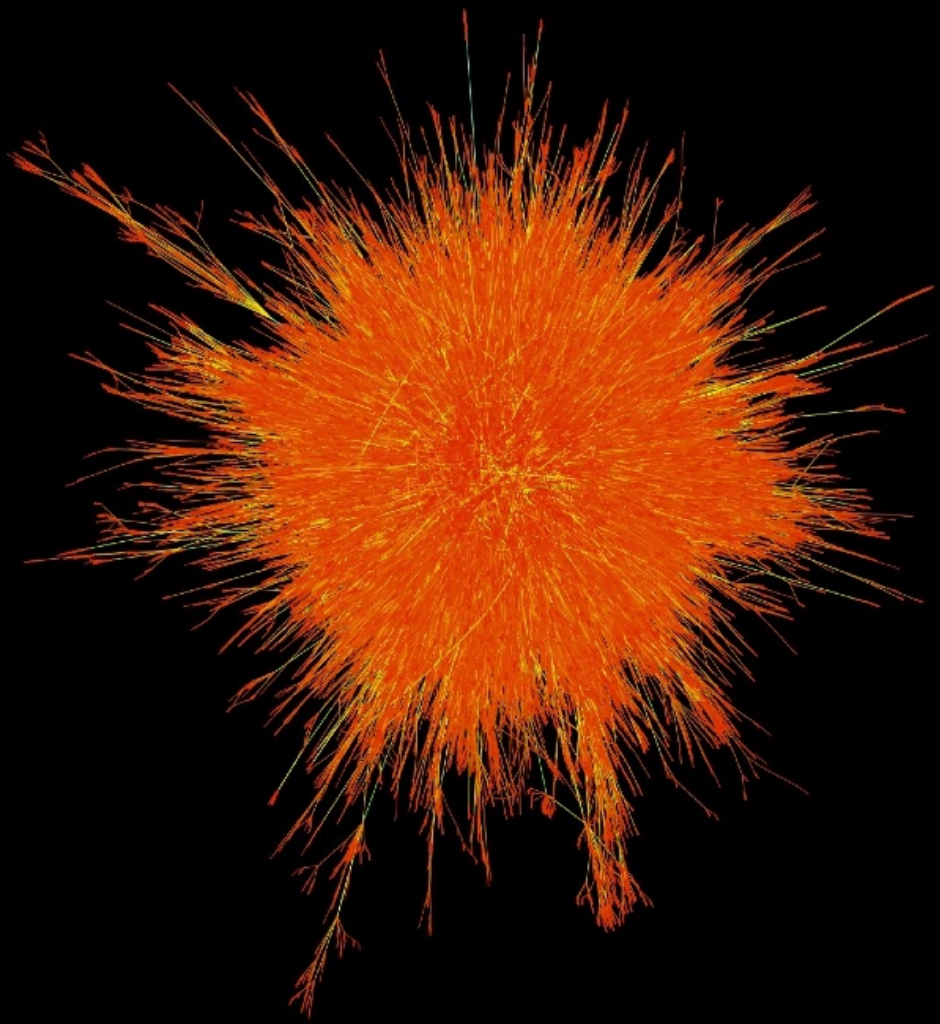
Social Networks

Graphs are everywhere…



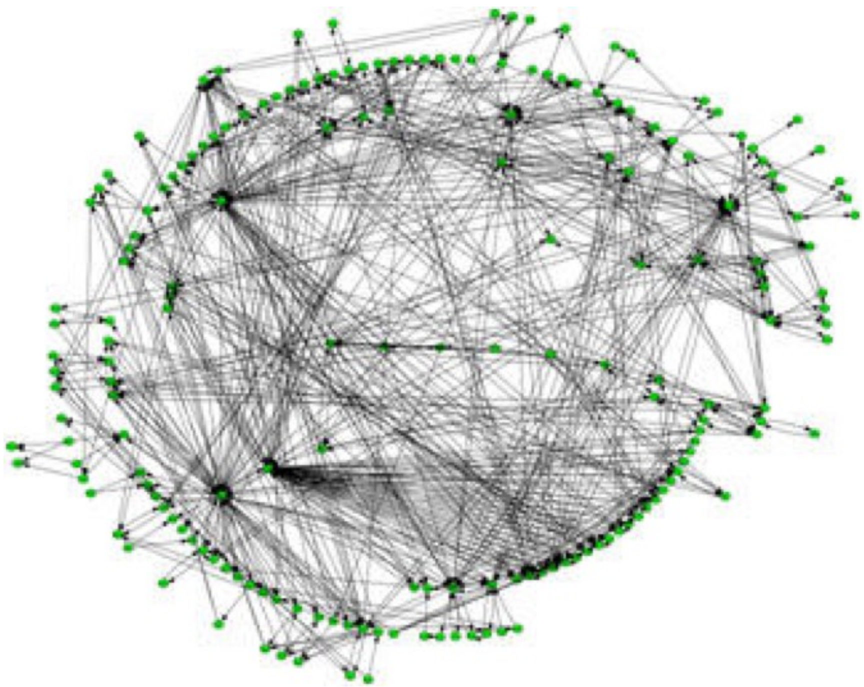
Gnutella network subgraph

Graphs are everywhere...

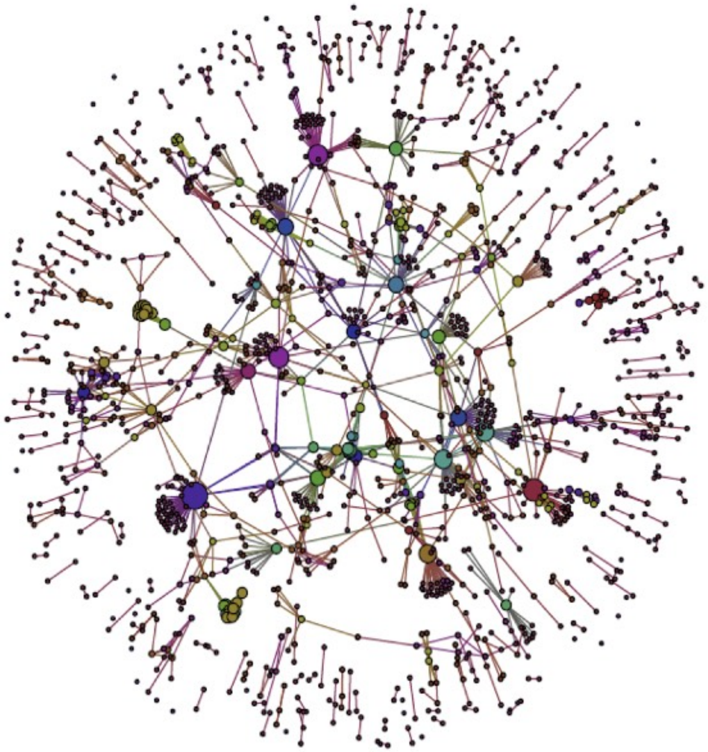


SNAP@web-Google. 1316100 nodes, 4925011 edges.

Graphs are everywhere…



Metabolic network of a single cell organism



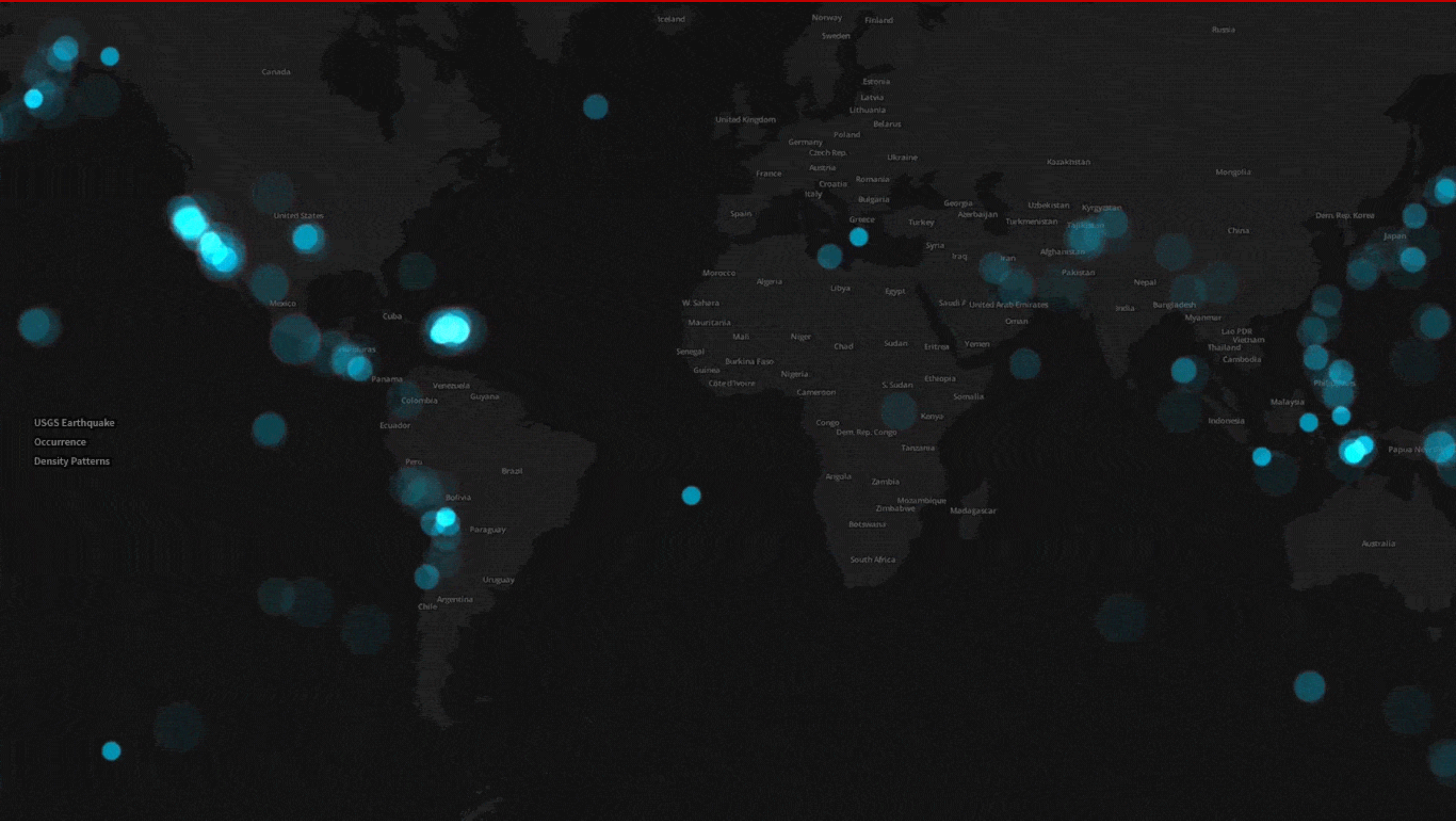
Tuberculosis

Plenty of interest in processing them

- Graph DBMS 25% of all enterprises by end of 2017[1]
- Many open-source and research prototypes on distributed graph processing frameworks: Giraph, Pregel, GraphLab, GraphX, ...

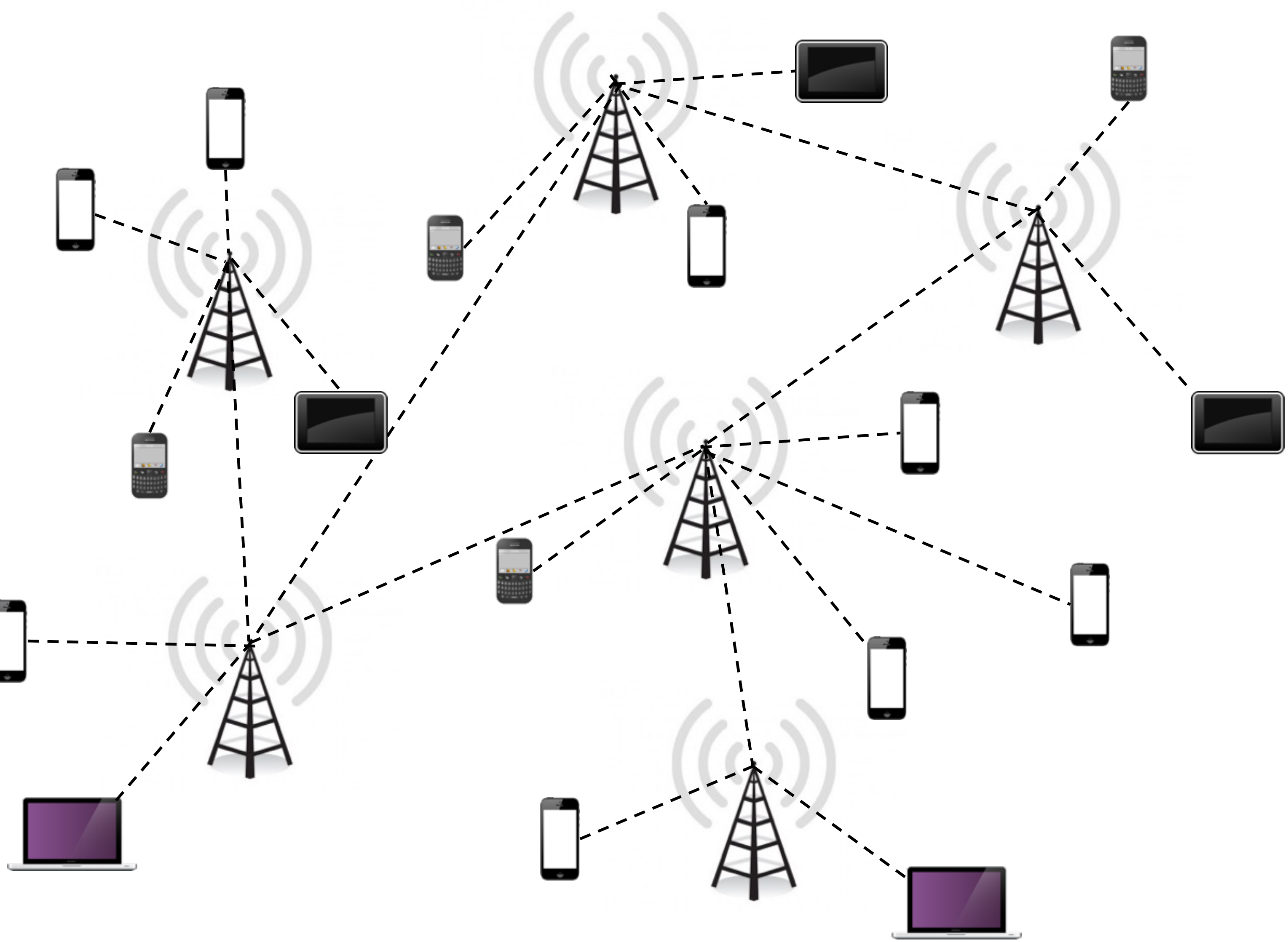
[1]Forrester Research

Real-world Graphs are Dynamic



Earthquake Occurrence Density

Real-world Graphs are Dynamic



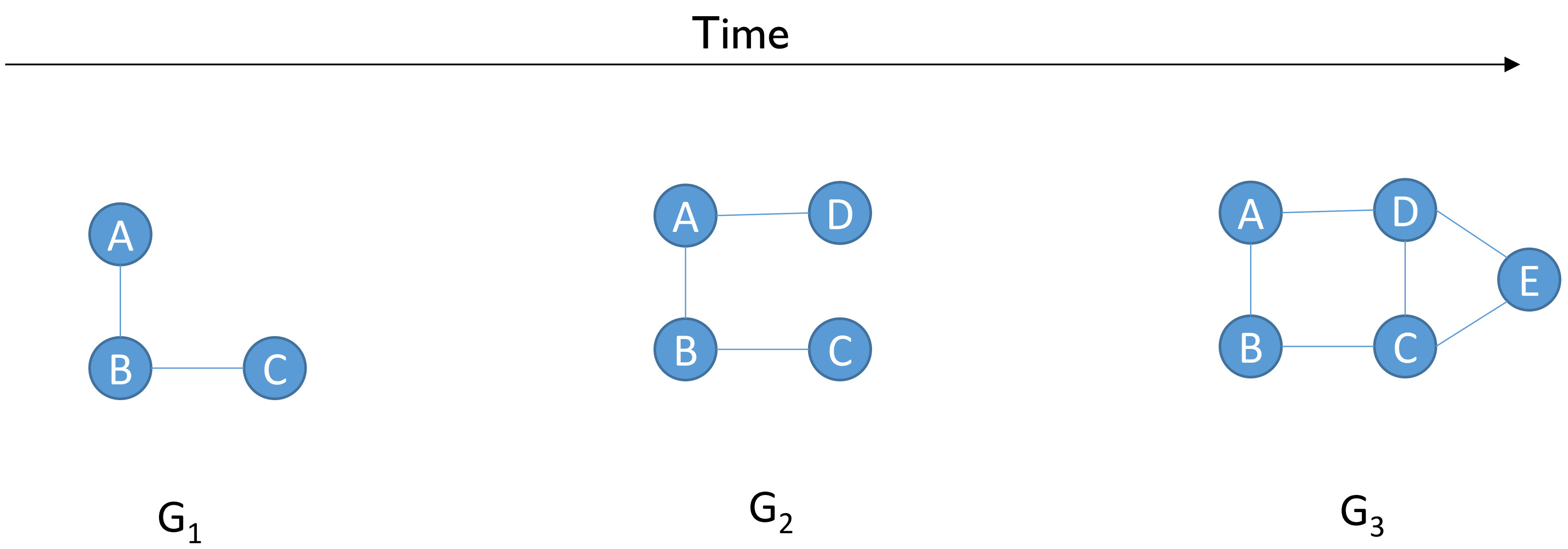
Real-world Graphs are Dynamic

Processing Time-evolving Graphs

Many interesting business and research insights possible by processing such dynamic graphs…

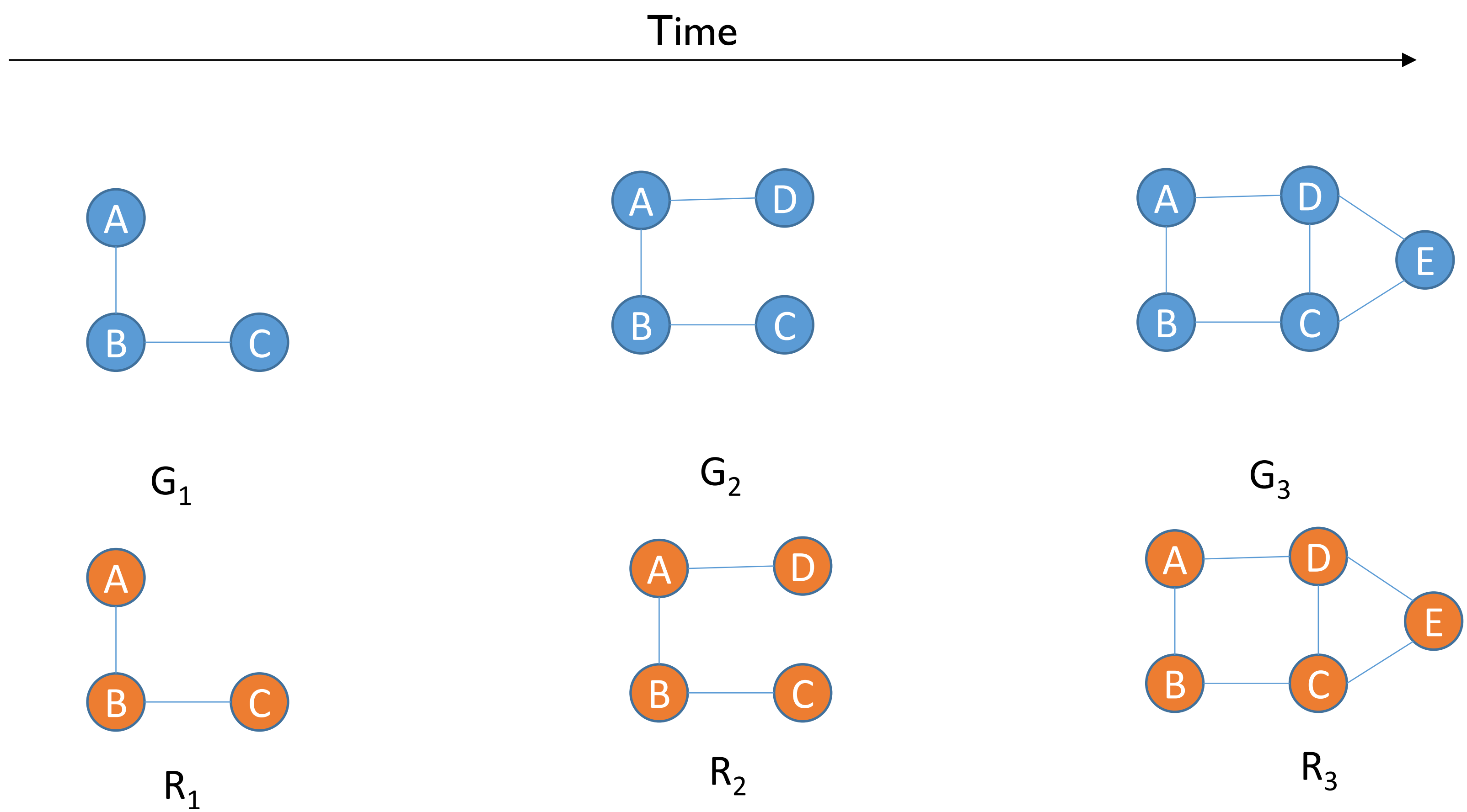
… little or no work in supporting such workloads in existing big-data graph-processing frameworks

Challenge #1: Storage



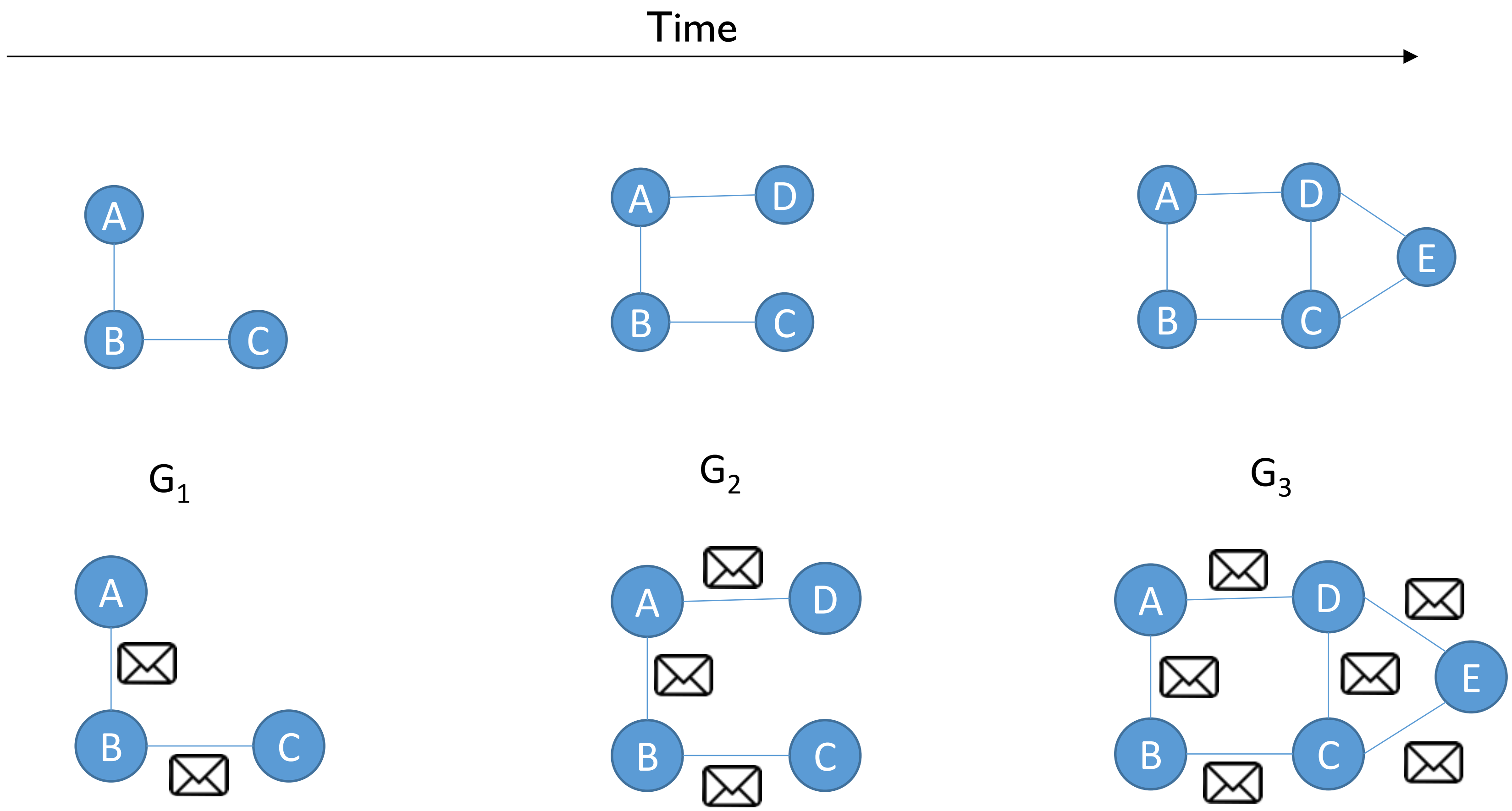
Redundant storage of graph entities over time

Challenge #2: Computation



Wasted computation across snapshots

Challenge #3: Communication



Duplicate messages sent over the network

How do we process time-evolving, dynamically changing graphs efficiently?

Share

Storage

Communication

Computation

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How do we process time-evolving, dynamically changing graphs efficiently?

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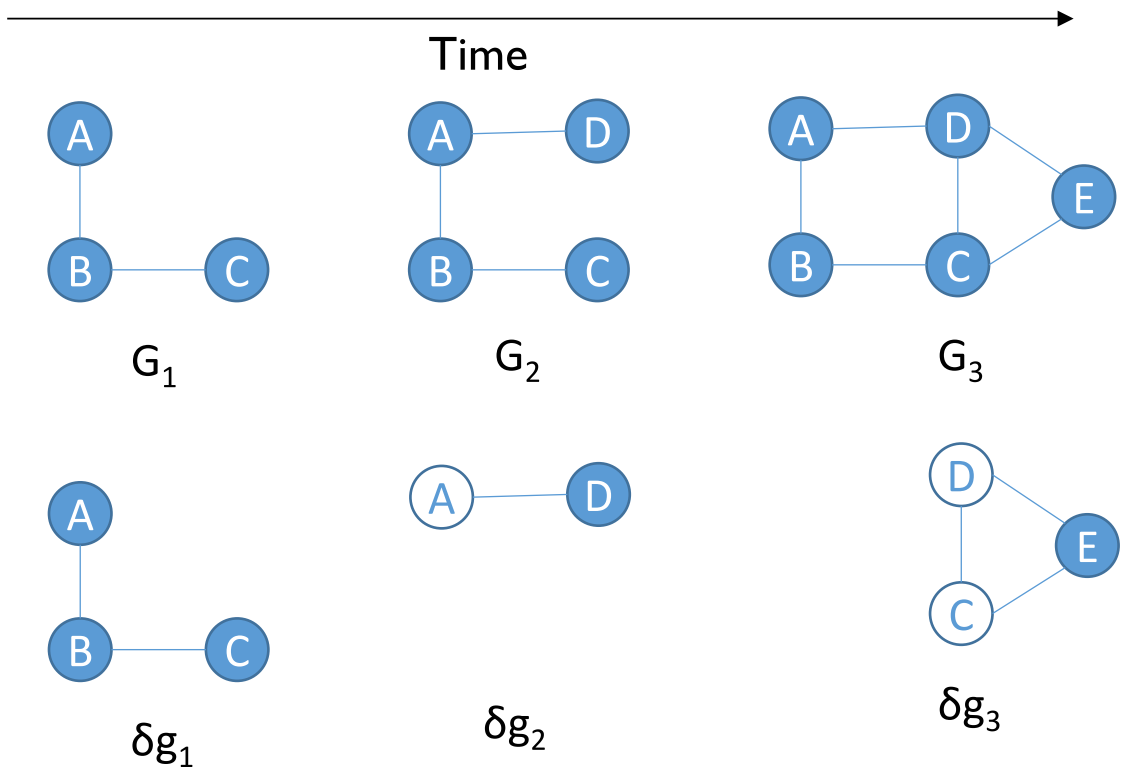
Tegra

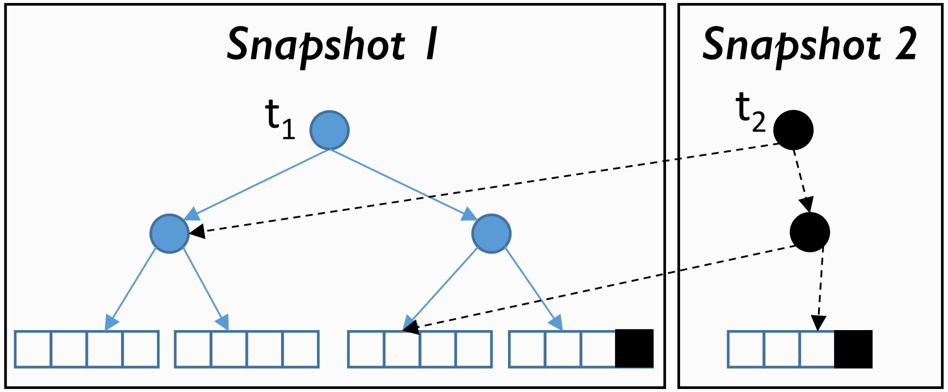
Sharing Storage



Storing deltas result in the most optimal storage, but creating snapshot from deltas can be expensive!

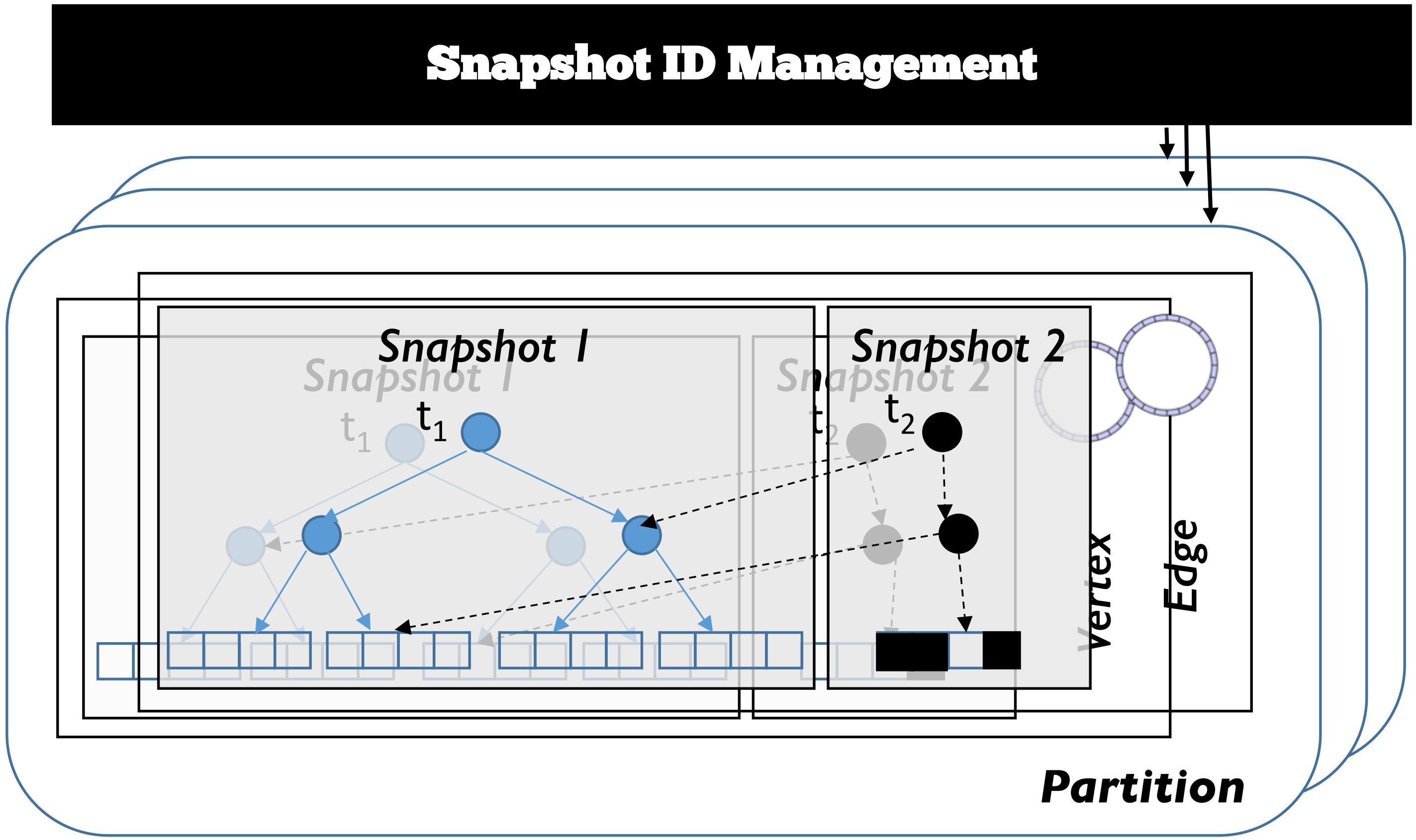
A Better Storage Solution

Use a persistent datastructure



Store snapshots in Persistent Adaptive Radix Trees (PART)

Graph Snapshot Index



Shares structure between snapshots, and enables efficient operations

How do we process time-evolving, dynamically changing graphs efficiently?

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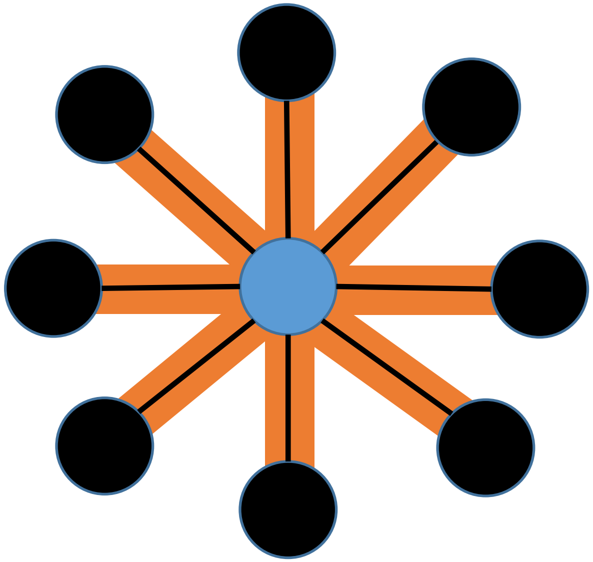
Graph Parallel Abstraction - GAS

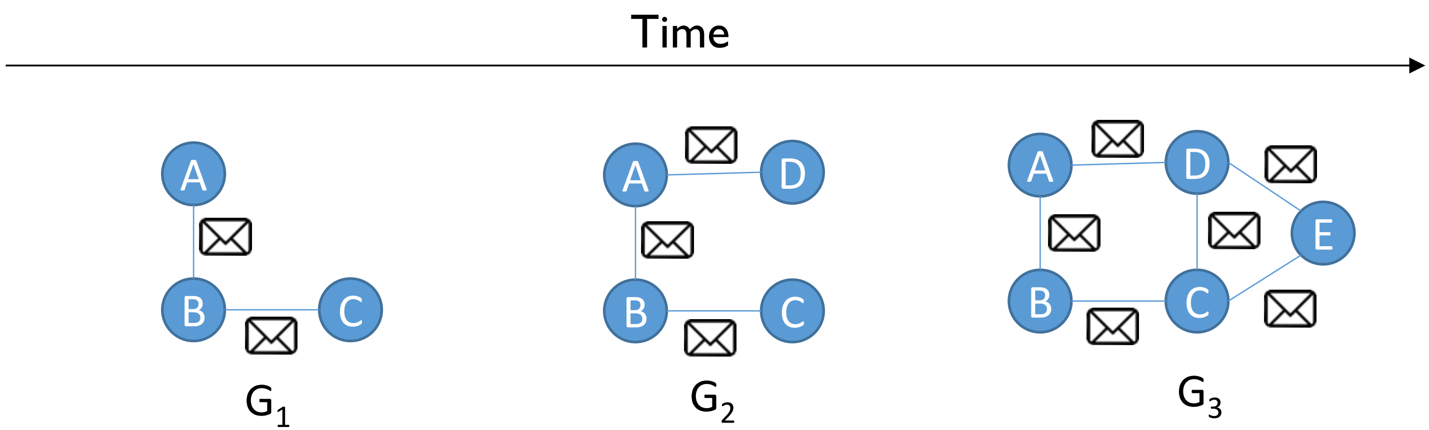
Gather: Accumulate information from neighborhood

Apply: Apply the accumulated value

Scatter: Update adjacent edges & vertices with updated value



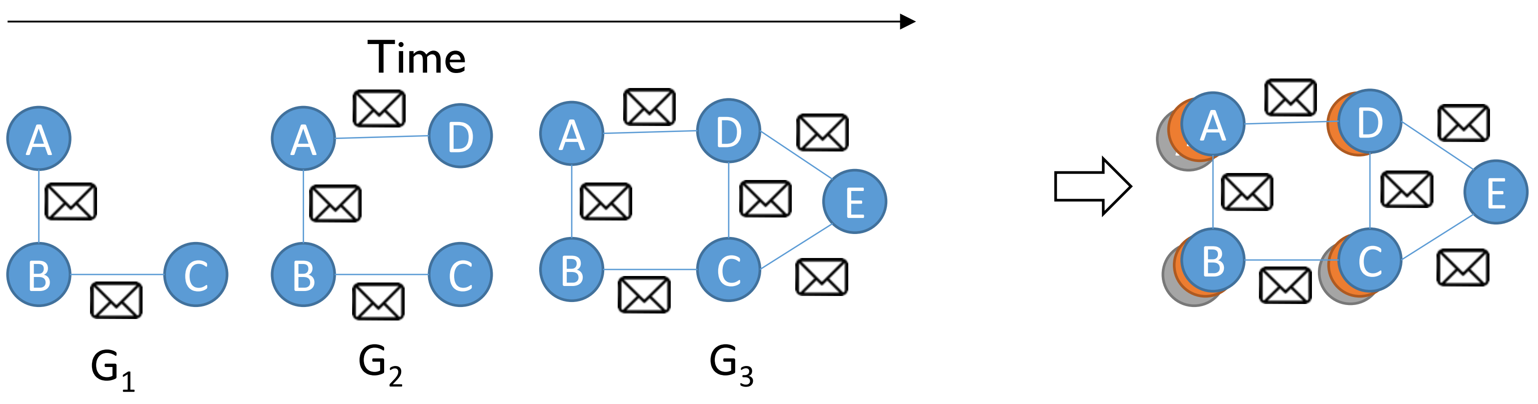
Processing Multiple Snapshots




```
for (snapshot in snapshots) {
    for (stage in graph-parallel-computation) {…}
}
```

Reducing Redundant Messages

```
for (step in graph-parallel-computation) {
      for (snapshot in snapshots) {…}
}
```



Can potentially avoid large number of redundant messages

How do we process time-evolving, dynamically changing graphs efficiently?

Share

Storage
Communication
Computation

Tegra

Updating Results

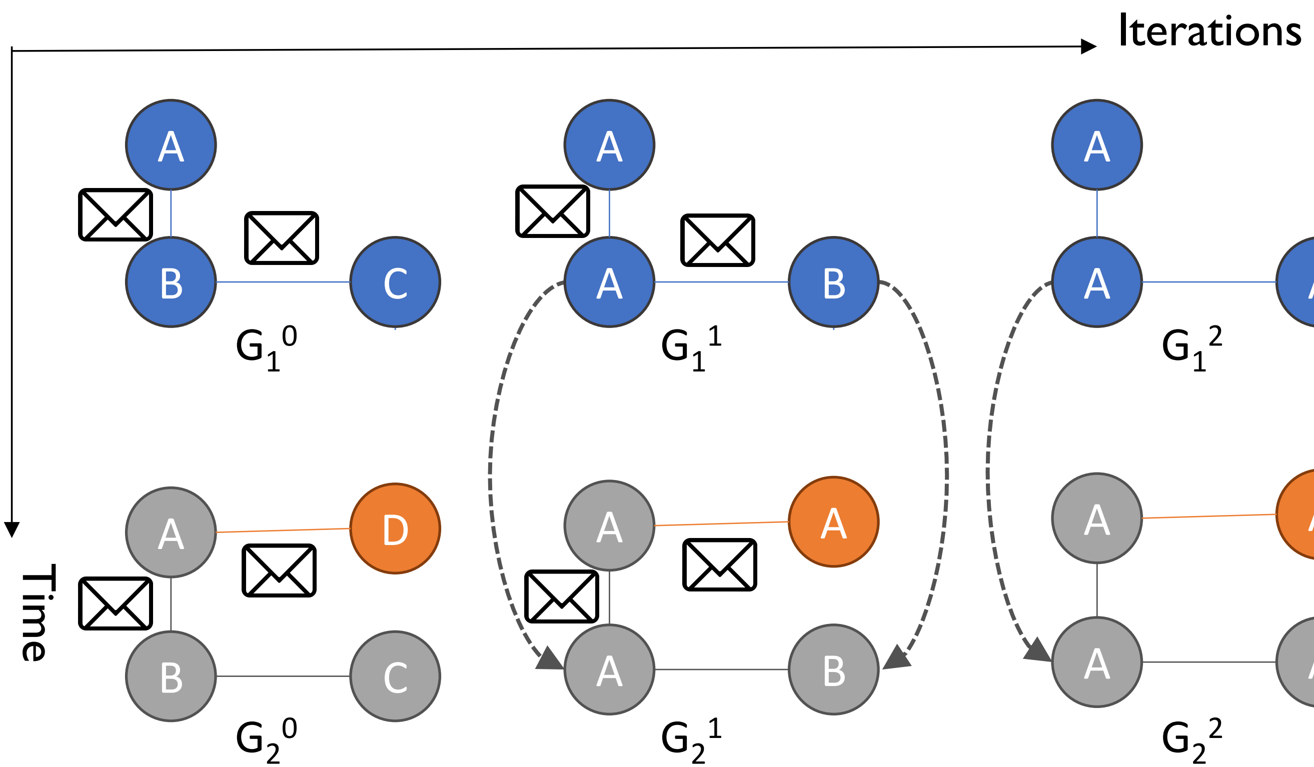
- If result from a previous snapshot is available, how can we reuse them?
- Three approaches in the past:
  - Restart the algorithm
    - Redundant computations
  - Memoization (GraphInc[1])
    - Too much state
  - Operator-wise state (Naiad[2,3])
    - Too much overhead
    - Fault tolerance

[1]Facilitating real- time graph mining, CloudDB '12
[2] Naiad: A timely dataflow system, SOSP '13
[3] Differential dataflow, CIDR '13

Key Idea

- Leverage how GAS model executes computation
- Each iteration in GAS modifies the graph by a little
  - Can be seen as another time-evolving graph!
- Upon change to a graph:
  - Mark parts of the graph that changed
  - Expand the marked parts to involve regions for recomputation in every iteration
  - Borrow results from parts not changed

Incremental Computation

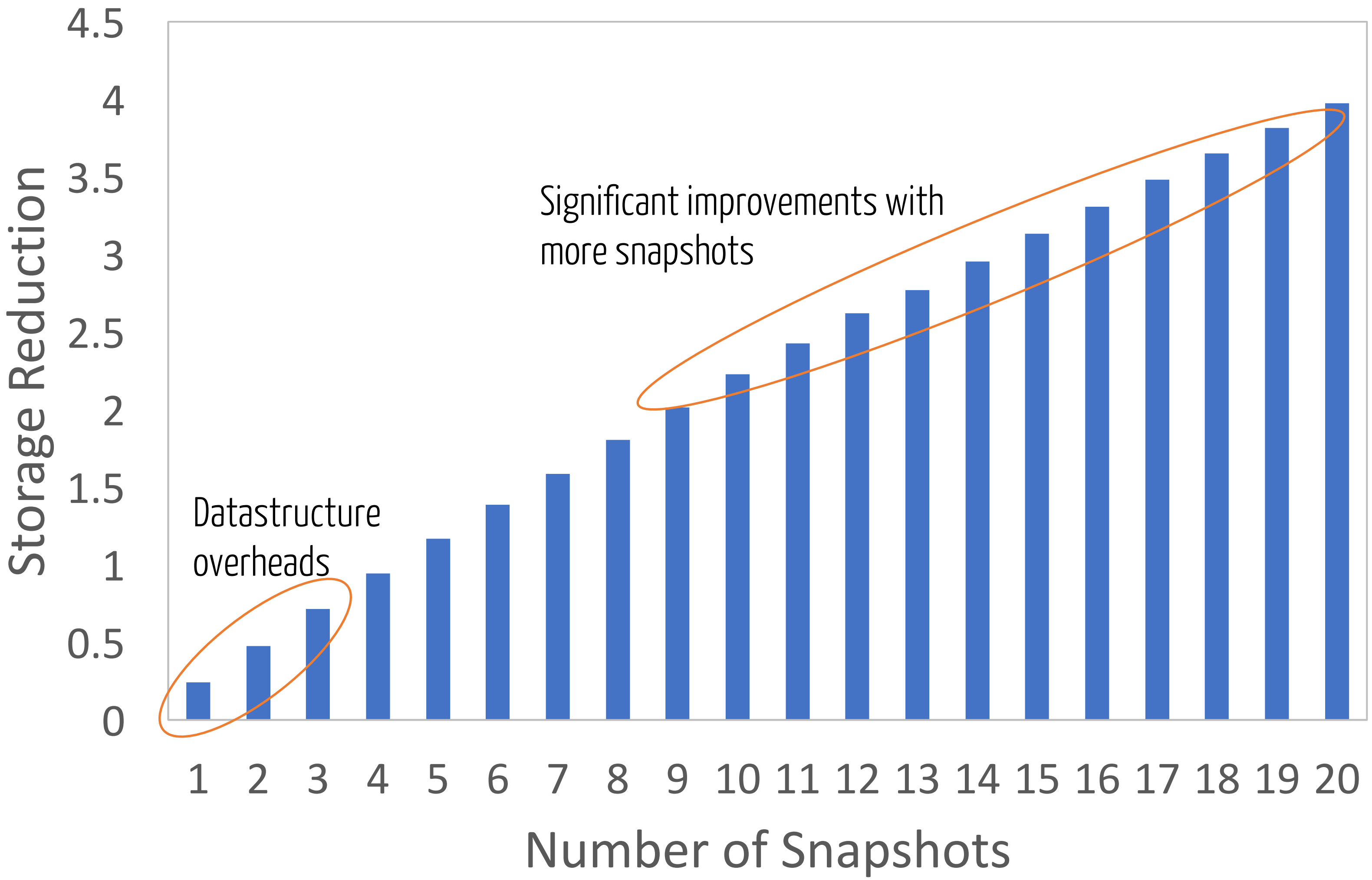


Larger graphs and more iterations can yield significant improvements

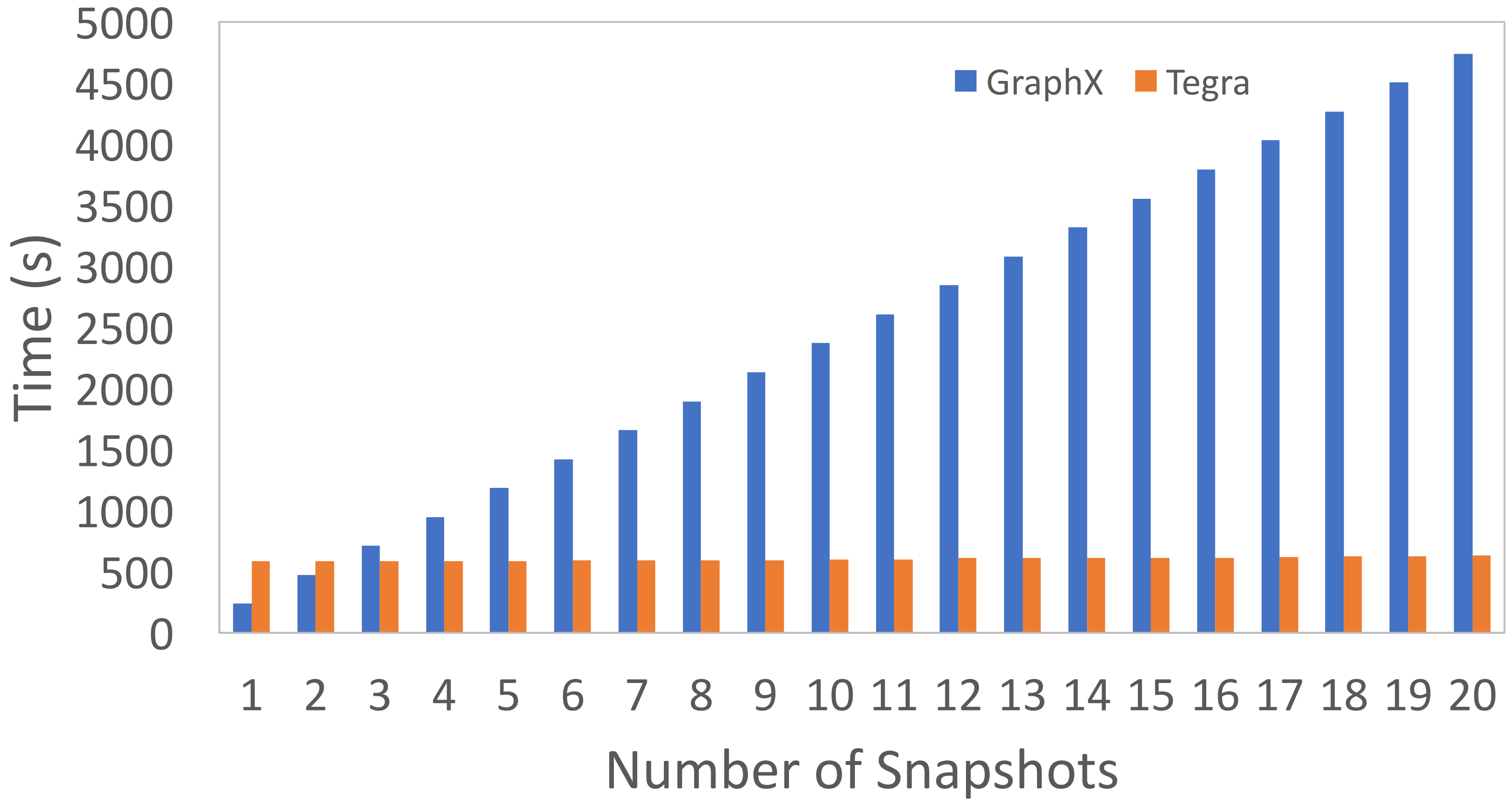
Implementation & Evaluation

- Implemented on Spark 2.0
  - Extended dataframes with versioning information and iterate operator
  - Extended GraphX API to allow computation on multiple snapshots
- Preliminary evaluation on two real-world graphs
  - **Twitter:** 41,652,230 vertices, 1,468,365,182 edges
  - **uk-2007:** 105,896,555 vertices, 3,738,733,648 edges

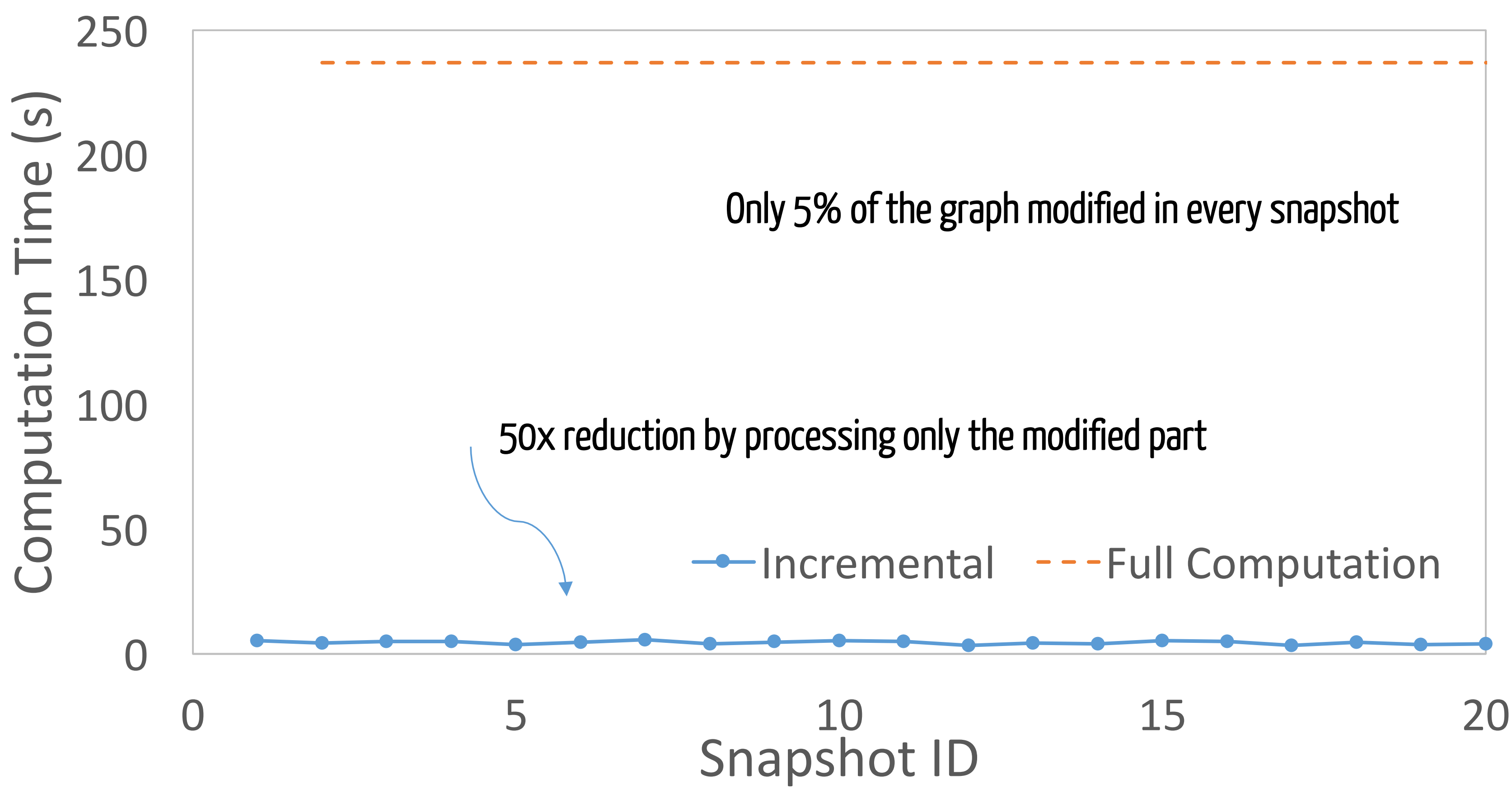
Benefits of Storage Sharing



Benefits of sharing communication



Benefits of Incremental Computing



Summary & Future Work

- Processing time-evolving graph efficiently can be useful
- Sharing storage, computation and communication key to efficient time-evolving graph analysis
- Code release
- Incremental pattern matching
- Approximate graph analytics
- Geo-distributed graph analytics

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