Large Scale Graph Processing - Pregel and GraphLab

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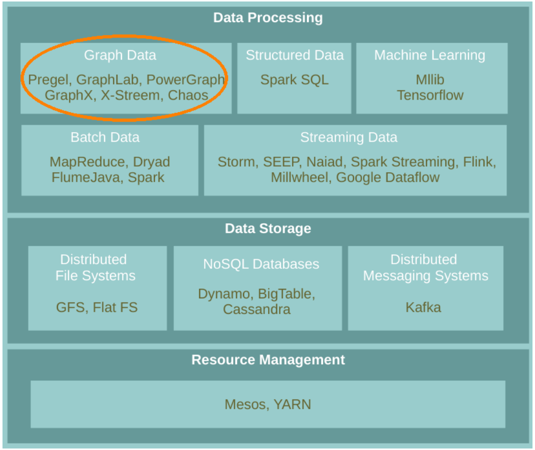
2020-09-23

The Course Web Page

https://id2221kth.github.io

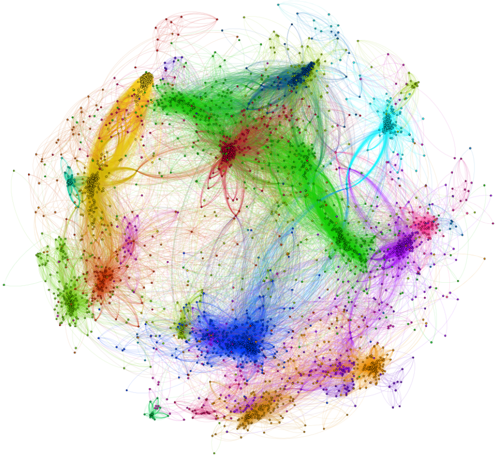
https://tinyurl.com/y4qph82u

Where Are We?


Data Processing
Graph Data
Pregel, GraphLab, PowerGraph
GraphX, X-Streem, Chaos
Structured Data
Spark SQL
Machine Learning
Mllib
Tensorflow
Batch Data
MapReduce, Dryad
FlumeJava, Spark
Streaming Data
Storm, SEEP, Naiad, Spark Streaming, Flink,
Millwheel, Google Dataflow
Data Storage
Distributed
File Systems
GFS, Flat FS
NoSQL Databases
Dynamo, BigTable,
Cassandra
Distributed
Messaging Systems
Kafka
Resource Management
Mesos, YARN

- A flexible abstraction for describing relationships between discrete objects.

Large Graph



Graph Algorithms Challenges

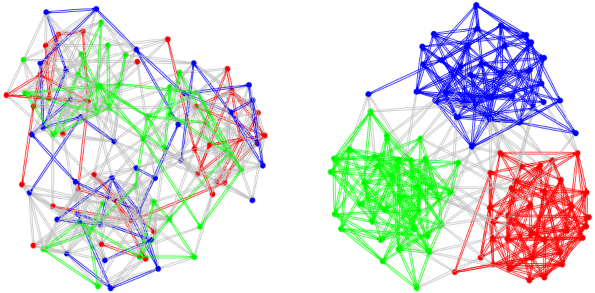
- Difficult to extract parallelism based on partitioning of the data.
- Difficult to express parallelism based on partitioning of computation.

Graph Algorithms Challenges

- Difficult to extract parallelism based on partitioning of the data.
- Difficult to express parallelism based on partitioning of computation.
- Graph partition is a challenging problem.

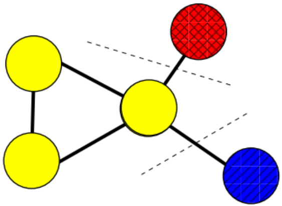
Graph Partitioning

- Partition large scale graphs and distribut to hosts.



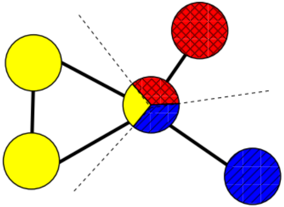
Edge-Cut Graph Partitioning

- Divide vertices of a graph into disjoint clusters.
- Nearly equal size (w.r.t. the number of vertices).
- With the minimum number of edges that span separated clusters.



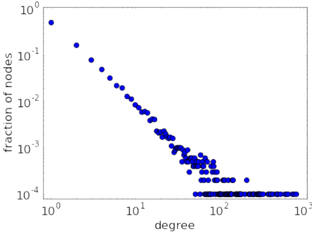
Vertex-Cut Graph Partitioning

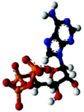
- Divide edges of a graph into disjoint clusters.
- Nearly equal size (w.r.t. the number of edges).
- With the minimum number of replicated vertices.



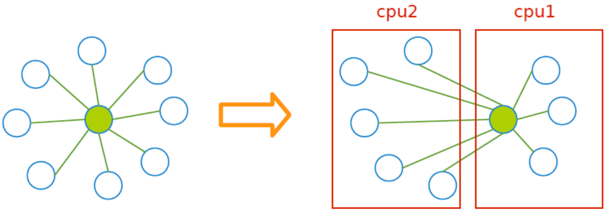
Edge-Cut vs. Vertex-Cut Graph Partitioning (1/2)

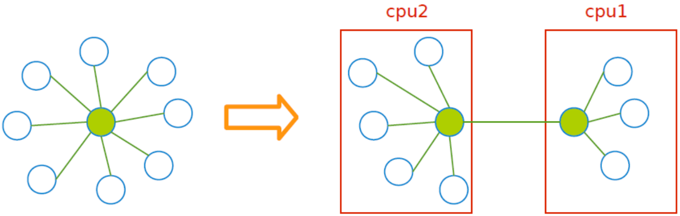
- Natural graphs: skewed Power-Law degree distribution.
- Edge-cut algorithms perform poorly on Power-Law Graphs.





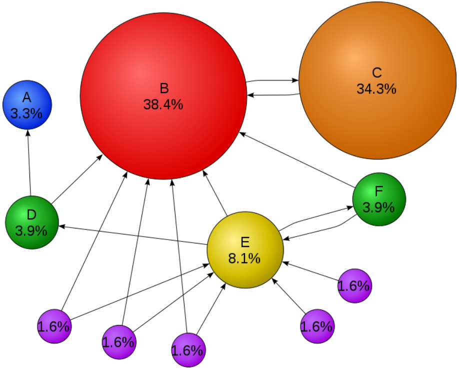
Edge-Cut vs. Vertex-Cut Graph Partitioning (2/2)





PageRank with MapReduce

PageRank



$$\mathtt{R[i]} = \sum_{\mathtt{j} \in \mathtt{Nbrs(i)}} \mathtt{w_{ji} R[j]}$$

PageRank Example (1/2)

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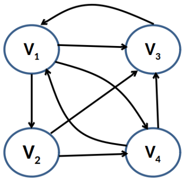

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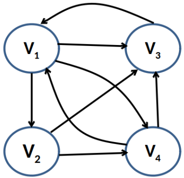
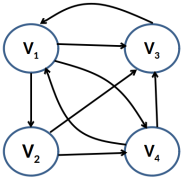


- Input

```
V1: [0.25, V2, V3, V4]
V2: [0.25, V3, V4]
V3: [0.25, V1]
V4: [0.25, V1, V3]
```

PageRank Example (1/2)

- $\mathtt{R[i]} = \sum_{\mathtt{j} \in \mathtt{Nbrs(i)}} \mathtt{w_{ji}R[j]}$



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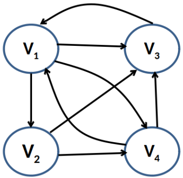
V2: [0.25, V3, V4]
V3: [0.25, V1]
V4: [0.25, V1, V3]
```

- Share the rank among all outgoing links

```
V1: (V2, 0.25/3), (V3, 0.25/3), (V4, 0.25/3)
V2: (V3, 0.25/2), (V4, 0.25/2)
V3: (V1, 0.25/1)
V4: (V1, 0.25/2), (V3, 0.25/2)
```

PageRank Example (2/2)

- $\mathtt{R[i]} = \sum_{\mathtt{j} \in \mathtt{Nbrs(i)}} \mathtt{w_{ji}R[j]}$




```
V1: (V2, 0.25/3), (V3, 0.25/3), (V4, 0.25/3)
V2: (V3, 0.25/2), (V4, 0.25/2)
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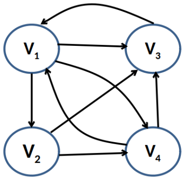
```

PageRank Example (2/2)

- $\mathtt{R[i]} = \sum_{\mathtt{j \in Nbrs(i)}} \mathtt{w_{ji} R[j]}$



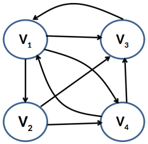

```
V1: (V2, 0.25/3), (V3, 0.25/3), (V4, 0.25/3)
V2: (V3, 0.25/2), (V4, 0.25/2)
V3: (V1, 0.25/1)
V4: (V1, 0.25/2), (V3, 0.25/2)
```

- Output after one iteration

```
V1: [0.37, V2, V3, V4]
V2: [0.08, V3, V4]
V3: [0.33, V1]
V4: [0.20, V1, V3]
```

PageRank in MapReduce - Map (1/2)

- Map function




```
map(key: [url, pagerank], value: outlink_list)
  for each outlink in outlink_list:
        emit(key: outlink, value: pagerank / size(outlink_list))

  emit(key: url, value: outlink_list)
```

PageRank in MapReduce - Map (1/2)

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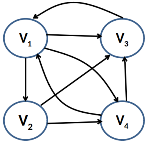


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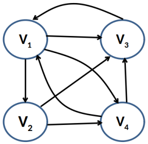
```

- Input (key, value)

```
((V1, 0.25), [V2, V3, V4])
((V2, 0.25), [V3, V4])
((V3, 0.25), [V1])
((V4, 0.25), [V1, V3])
```

PageRank in MapReduce - Map (2/2)

- Map function

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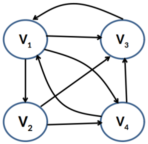


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  emit(key: url, value: outlink_list)
```

- Intermediate (key, value)

```
(V2, 0.25/3), (V3, 0.25/3), (V4, 0.25/3), (V3, 0.25/2), (V4, 0.25/2), (V1, 0.25/1),
(V1, 0.25/2), (V3, 0.25/2)
(V1, [V2, V3, V4])
(V2, [V3, V4])
(V3, [V1])
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```

PageRank in MapReduce - Shuffle

- Intermediate (key, value)

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```

PageRank in MapReduce - Shuffle

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(V1, 0.25/2), (V3, 0.25/2)
(V1, [V2, V3, V4])
(V2, [V3, V4])
(V3, [V1])
(V4, [V1, V3])
```

- After shuffling

```
(V1, 0.25/1), (V1, 0.25/2), (V1, [V2, V3, V4])
(V2, 0.25/3), (V2, [V3, V4])
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```

PageRank in MapReduce - Reduce (1/2)

- Reduce function

```
reducer(key: url, value: list_pr_or_urls)
  outlink_list = []
  pagerank = 0

  for each pr_or_urls in list_pr_or_urls:
    if is_list(pr_or_urls):
      outlink_list = pr_or_urls
    else
      pagerank += pr_or_urls

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```

- Input of the Reduce function

```
(V1, 0.25/1), (V1, 0.25/2), (V1, [V2, V3, V4])
(V2, 0.25/3), (V2, [V3, V4])
(V3, 0.25/3), (V3, 0.25/2), (V3, 0.25/2), (V3, [V1])
(V4, 0.25/3), (V4, 0.25/2), (V4, [V1, V3])
```

PageRank in MapReduce - Reduce (2/2)

- Reduce function

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Problems with MapReduce for Graph Analytics

- MapReduce does not directly support iterative algorithms.
  - Invariant graph-topology-data re-loaded and re-processed at each iteration is wasting I/O, network bandwidth, and CPU

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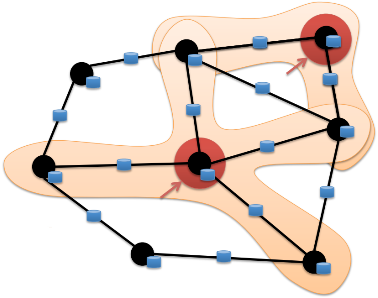
- MapReduce does not directly support iterative algorithms.
  - Invariant graph-topology-data re-loaded and re-processed at each iteration is wasting I/O, network bandwidth, and CPU
- Materializations of intermediate results at every MapReduce iteration harm performance.

Think Like a Vertex

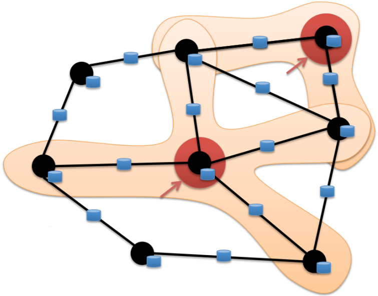
Think Like a Vertex

- Each vertex computes individually its value (in parallel).
- Computation typically depends on the neighbors.

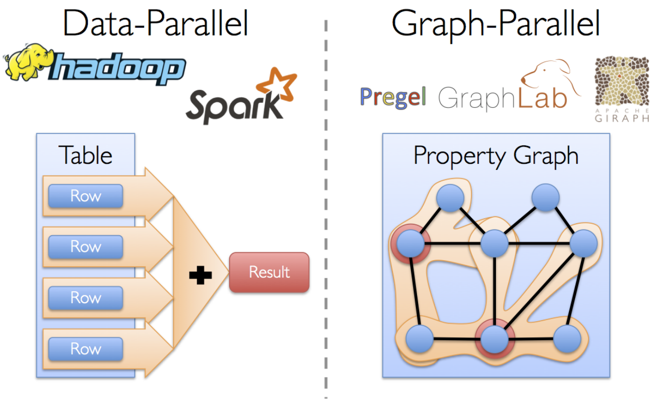


Think Like a Vertex

- Each vertex computes individually its value (in parallel).
- Computation typically depends on the neighbors.
- Also know as graph-parallel processing model.



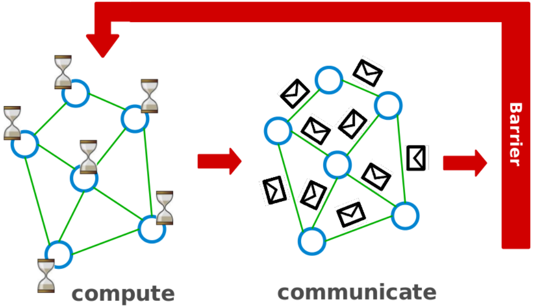
Data-Parallel vs. Graph-Parallel Computation



Pregel

Pregel

- Large-scale graph-parallel processing platform developed at Google.
- Inspired by bulk synchronous parallel (BSP) model.



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  - sends messages to other vertices: receiving at superstep S+1.
  - modifies its state.

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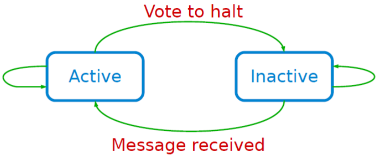
- A vertex in superstep `S` can:
  - reads messages sent to it in superstep `S-1`.
  - sends messages to other vertices: receiving at superstep `S+1`.
  - modifies its state.
- Vertices communicate directly with one another by sending messages.

Execution Model (2/2)

- Superstep 0: all vertices are in the active state.



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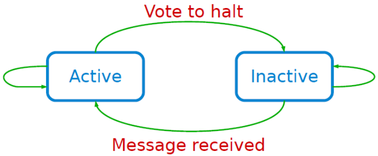

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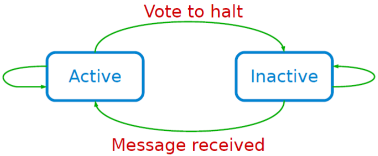
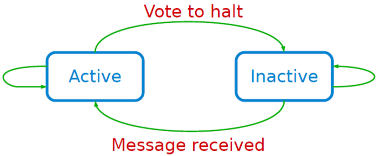


Execution Model (2/2)

- Superstep 0: all vertices are in the active state.
- A vertex deactivates itself by voting to halt: no further work to do.
- A halted vertex can be active if it receives a message.
- The whole algorithm terminates when:
  - All vertices are simultaneously inactive.
  - There are no messages in transit.

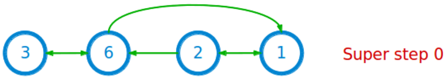


Example: Max Value (1/4)

```
i_val := val

for each message m
  if m > val then val := m

if i_val == val then
  vote_to_halt
else
  for each neighbor v
    send_message(v, val)
```



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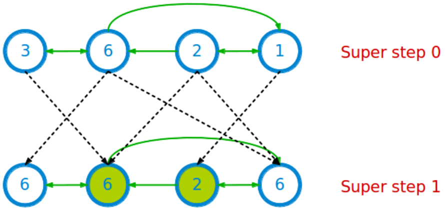
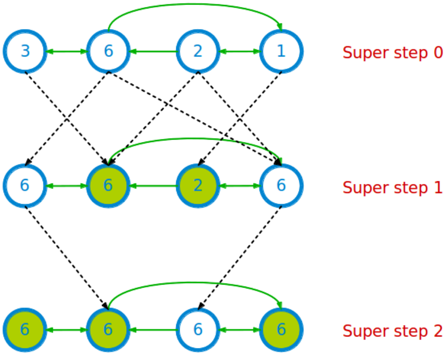


Example: Max Value (3/4)

```
i_val := val

for each message m
  if m > val then val := m

if i_val == val then
  vote_to_halt
else
  for each neighbor v
    send_message(v, val)
```

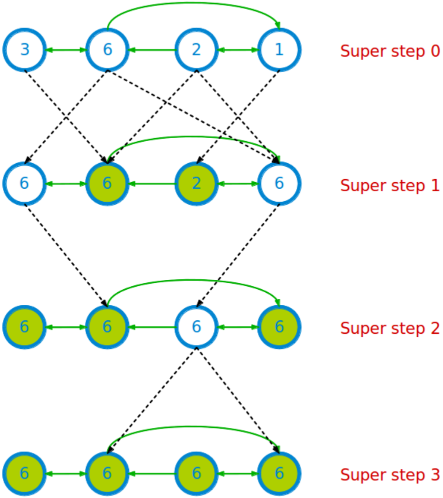


Example: Max Value (4/4)

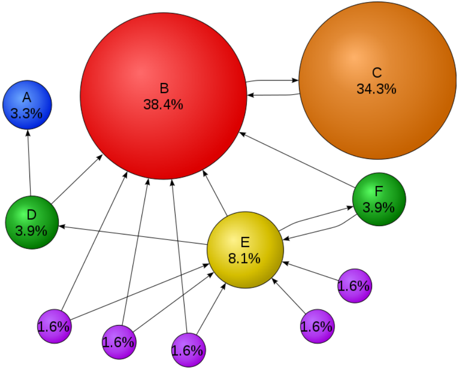
```
i_val := val

for each message m
  if m > val then val := m

if i_val == val then
  vote_to_halt
else
  for each neighbor v
    send_message(v, val)
```



Example: PageRank



$$\mathtt{R[i]} = \sum_{\mathtt{j} \in \mathtt{Nbrs(i)}} \mathtt{w_{ji} R[j]}$$

Example: PageRank

```
Pregel_PageRank(i, messages):
  // receive all the messages
  total = 0
  foreach(msg in messages):
    total = total + msg

  // update the rank of this vertex
  R[i] = total

  // send new messages to neighbors
  foreach(j in out_neighbors[i]):
    sendmsg(R[i] * wij) to vertex j
```

$$\mathtt{R[i]} = \sum_{\mathtt{j} \in \mathtt{Nbrs(i)}} \mathtt{w_{ji}} \mathtt{R[j]}$$

Graph Partitioning

- Edge-cut partitioning

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- The pregel library divides a graph into a number of partitions.
- Each partition consists of vertices and all of those vertices' outgoing edges.
- Vertices are assigned to partitions based on their vertex-ID (e.g., hash(ID)).

System Model

- Master-worker model.
- The master
  - Coordinates workers.
  - Assigns one or more partitions to each worker.
  - Instructs each worker to perform a superstep.

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- The master
  - Coordinates workers.
  - Assigns one or more partitions to each worker.
  - Instructs each worker to perform a superstep.
- Each worker
  - Executes the local computation method on its vertices.
  - Maintains the state of its partitions.
  - Manages messages to and from other workers.

Fault Tolerance

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- When master detects one or more worker failures:
  - All workers revert to last checkpoint.

Pregel Limitations

- Inefficient if different regions of the graph converge at different speed.
- Runtime of each phase is determined by the slowest machine.

GraphLab/Turi

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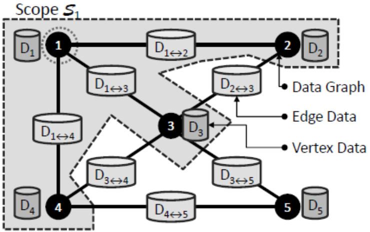
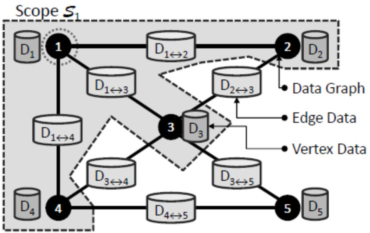


GraphLab

- GraphLab allows asynchronous iterative computation.
- Vertex scope of vertex v: the data stored in v, and in all adjacent vertices and edges.
- A vertex can read and modify any of the data in its scope (shared memory).



Example: PageRank (GraphLab)

```
GraphLab_PageRank(i)
  // compute sum over neighbors
  total = 0
  foreach(j in in_neighbors(i)):
    total = total + R[j] * wji

  // update the PageRank
  R[i] = total

  // trigger neighbors to run again
  foreach(j in out_neighbors(i)):
    signal vertex-program on j
```

$$\mathtt{R[i]} = \sum_{\mathtt{j} \in \mathtt{Nbrs(i)}} \mathtt{w_{ji}R[j]}$$

Consistency (1/5)

- Overlapped scopes: race-condition in simultaneous execution of two update functions.

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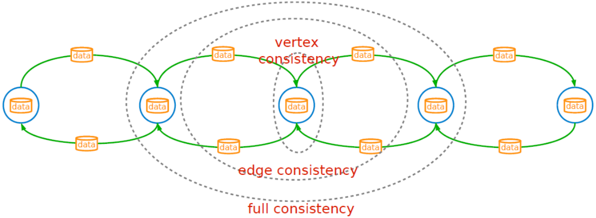
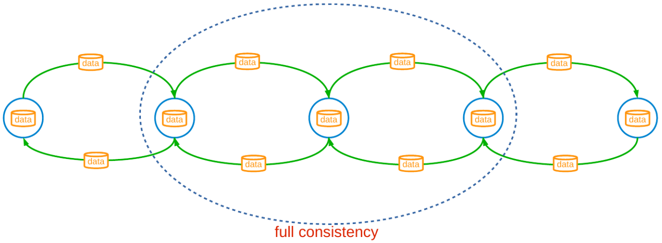
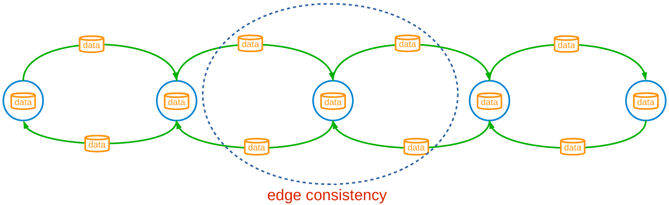


Consistency (2/5)



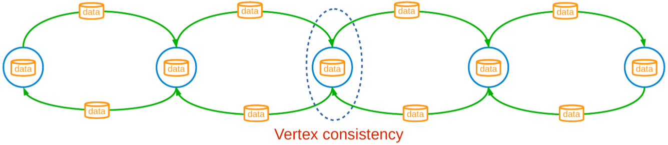
- Full consistency: during the execution `f(v)`, no other function reads or modifies data within the `v` scope.

Consistency (3/5)



- Edge consistency: during the execution `f(v)`, no other function reads or modifies any of the data on `v` or any of the edges adjacent to `v`.

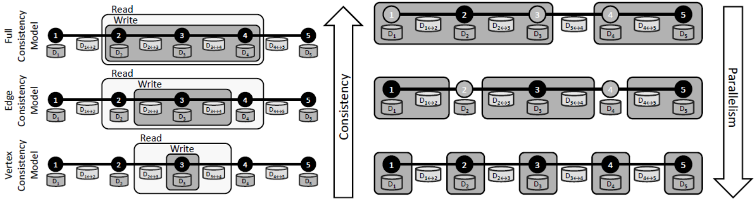
Consistency (4/5)



- Vertex consistency: during the execution `f(v)`, no other function will be applied to `v`.

Consistency (5/5)

Consistency vs. Parallelism



[Low, Y., GraphLab: A Distributed Abstraction for Large Scale Machine Learning (Doctoral dissertation, University of California), 2013.]

Consistency Implementation

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Consistency Implementation

- Distributed locking: associating a readers-writer lock with each vertex.
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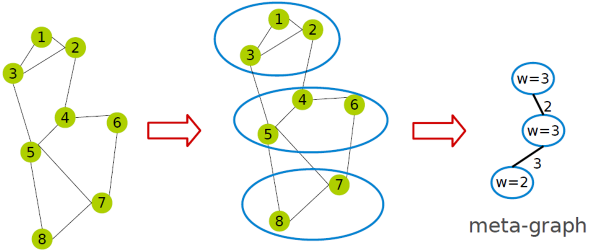
  - Central vertex (write-lock), Adjacent vertices (read-locks)
- Full consistency
  - Central vertex (write-locks), Adjacent vertices (write-locks)
- Deadlocks are avoided by acquiring locks sequentially following a canonical order.

Graph Partitioning

- Edge-cut partitioning.
- Two-phase partitioning:
  1. Convert a large graph into a small meta-graph
  2. Partition the meta-graph



Fault Tolerance - Synchronous

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- The systems periodically signals all computation activity to halt.
- Then synchronizes all caches, and saves to disk all data which has been modified since the last snapshot.
- Simple, but eliminates the systems advantage of asynchronous computation.

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- Based on the Chandy-Lamport algorithm.
- The snapshot function is implemented as a function in vertices.
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if *v was already snapshotted* **then**
    Quit
Save D_v `// Save current vertex`
`// Save all edges connected to un-snapshotted vertices`
foreach $u \in \mathbf{N}[v]$ **do** `// Loop over neighbors`
    if *u was not snapshotted* **then**
        Save $D_{u \to v}$ if edge $u \to v$ exists
        Save $D_{v \to u}$ if edge $v \to u$ exists
        `Reschedule` u for a Snapshot Update
Mark v as snapshotted

GraphLab2/Turi (PowerGraph)

PowerGraph

- Factorizes the local vertices functions into the Gather, Apply and Scatter phases.

Programming Model

- Gather-Apply-Scatter (GAS)
- Gather: accumulate information from neighborhood.
- Apply: apply the accumulated value to center vertex.
- Scatter: update adjacent edges and vertices.

Execution Model (1/2)

- Initially all vertices are active.
- It executes the vertex-program on the active vertices until none remain.
  - Once a vertex-program completes the scatter phase it becomes inactive until it is reactivated.
  - Vertices can activate themselves and neighboring vertices.

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  - Once a vertex-program completes the scatter phase it becomes inactive until it is reactivated.
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- PowerGraph can execute both synchronously and asynchronously.

Execution Model (2/2)

- Synchronous scheduling like Pregel.
  - Executing the gather, apply, and scatter in order.
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- Asynchronous scheduling like GraphLab.
  - Changes made to the vertex/edge data during the apply and scatter functions are immediately committed to the graph.
  - Visible to subsequent computation on neighboring vertices.

Example: PageRank (PowerGraph)

```
PowerGraph_PageRank(i):
  Gather(j -> i):
    return wji * R[j]

  sum(a, b):
    return a + b

  // total: Gather and sum
  Apply(i, total):
    R[i] = total

  Scatter(i -> j):
    if R[i] changed then activate(j)
```

$$\mathtt{R[i]} = \sum_{\mathtt{j} \in \mathtt{Nbrs(i)}} \mathtt{w_{ji} R[j]}$$

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- Random vertex-cuts: randomly assign edges to machines.
- Completely parallel and easy to distribute.
- High replication factor.

Graph Partitioning (2/2)

- Greedy vertex-cuts
- `A(v)`: set of machines that vertex `v` spans.

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- Case 4: If $\mathtt{A}(\mathtt{u}) = \mathtt{A}(\mathtt{v}) = \emptyset$, then assign the edge $(\mathtt{u}, \mathtt{v})$ to the least loaded machine.

Summary

Summary

- Think like a vertex
  - Pregel: BSP, synchronous parallel model, message passing, edge-cut
  - GraphLab: asynchronous model, shared memory, edge-cut
  - PowerGraph: synchronous/asynchronous model, GAS, vertex-cut

References

- G. Malewicz et al., “Pregel: a system for large-scale graph processing”, ACM SIGMOD 2010
- Y. Low et al., “Distributed GraphLab: a framework for machine learning and data mining in the cloud”, VLDB 2012
- J. Gonzalez et al., “Powergraph: distributed graph-parallel computation on natural graphs”, OSDI 2012

Questions?