Big Data Analytics

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GraphLab

Outline

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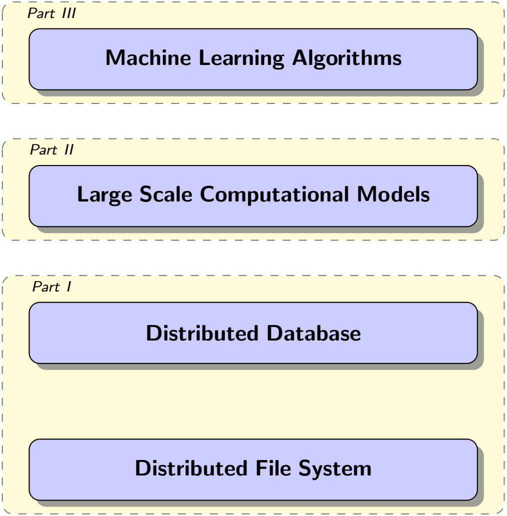
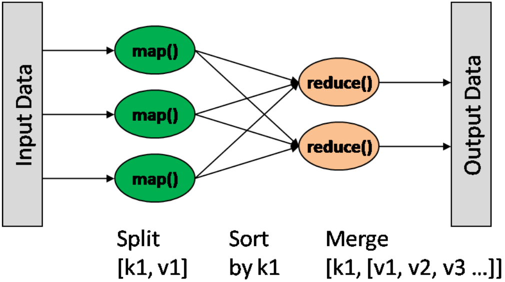
Overview

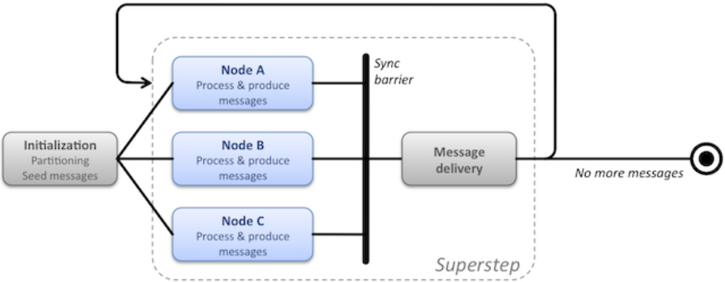

Part III
Machine Learning Algorithms
Part II
Large Scale Computational Models
Part I
Distributed Database
Distributed File System

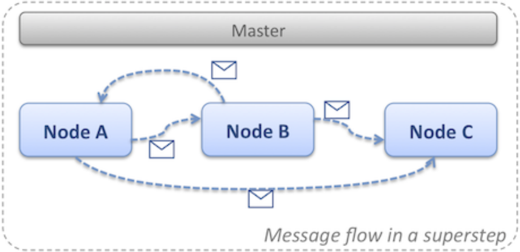
MapReduce - Review

1. Each mapper transforms a set key-value pairs into a list of output keys and intermediate value pairs
2. all intermediate values are grouped according to their output keys
3. each reducer receives all the intermediate values associated with a given keys
4. each reducer associates one final value to each key



Pregel - Review





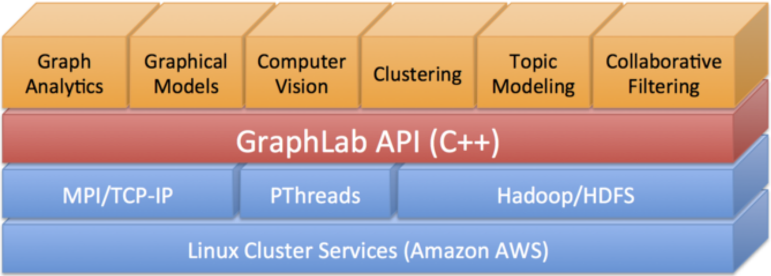
Outline

GraphLab

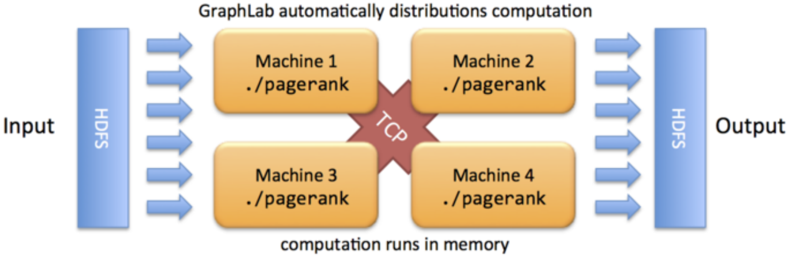
- A new framework for parallel machine learning
- Represents data as a directed graph
- Blocks of data stored in vertices and edges
- Globally shared data table
- Shared memory (GraphLab 1.0) distributed (GraphLab 2.1)

Available for download at: `http://graphlab.org`

GraphLab Software Stack



GraphLab System Overview



GraphLab Abstraction

The **GraphLab abstraction** consists of the following main components:

- A **Data Graph** provides a high level representation for data and complex computational dependencies
- Configurable **consistency models** for automatically guaranteeing data consistency
- **Scheduling Primitives** able to express iterative parallel algorithms
- **User defined computation** consisting of:
  - **Update Functions**: local computation
  - **Sync Mechanism**: global aggregation

Outline

Graphlab Data Model

Consists of two parts:

1. **A directed data graph:**

$$G := (V, E)$$

where V is the set of vertices and $E \subseteq V \times V$ the directed edges

2. **A globally shared data table:**

$$\mathbf{T}[\text{Key}] \rightarrow \text{Value}$$

which maps keys to arbitrary blocks of data

Graphlab Data Model

Users can associate with each graph vertice and edge:

- Arbitrary **data blocks**
- Program or model **parameters**

Some notation:

Data associated with a vertex v: D_v

Data associated with an edge (u, v): $D_{u,v}$

Set of all *outbound* edges from v: $(v \rightarrow *)$

Set of all *inbound* edges from v: $(* \rightarrow v)$

Neighboring vertices of v: $\mathcal{N}_v := \{u | (u, v) \in E \vee (v, u) \in E\}$

GraphLab - User defined computation

There are two types of user defined computation on GraphLab:

- **Update function**:
  - local computation
  - executed on small neighborhoods
  - different functions may access and modify overlapping contexts
- **Sync Mechanism**:
  - global aggregation
  - runs concurrently with the update functions

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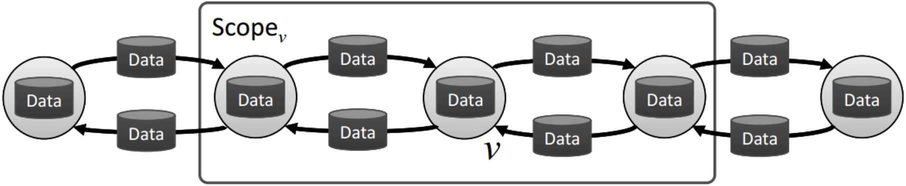
Update Function - Scope of a Vertex

The **Update Function** is a *stateless* user defined function

It operates on the **scope** $\mathcal{S}_v$ of a vertex v:

$$\mathcal{S}_v := \{v\} \cup (v \rightarrow *) \cup (* \rightarrow v) \cup \mathcal{N}_v$$



Once executed on a vertex v, it may trigger the execution of the update functions on other vertices $\mathcal{T}$

Update Function

Be $\mathcal{S}_v$ the scope of a vertex v and $\mathbf{T}$ the globally shared table.

The application of an update function f to a vertex v can be defined as

$$(D_{\mathcal{S}_v}, \mathcal{T}) \leftarrow f(D_{\mathcal{S}_v}, \mathbf{T})$$

Where:

- $D_{\mathcal{S}_v}$ is the data associated with the scope of v
- f has read-only access to $\mathbf{T}$
- $\mathcal{T}$ is a set of vertices

Update Function and Vertex Programs

In the most recent version of the GraphLab abstraction, Update Functions are called **Vertex Programs**

A Vertex Program implements the *Gather-Apply-Scatter (GAS)* model, and has three phases:

- **Gather:** executed in parallel on each edge of the current vertex (usually to read data)
- **Apply:** atomic function that modifies the vertex data
- **Scatter:** Executed in parallel on each edge of the current vertex (usually to update edge data and signaling neighboring nodes)

This decomposition allows us to execute a single vertex program on several machines simultaneously and move computation to the data.

Structure of an Update Function

procedure UPDATEFUNCTION
input: vertex v, scope $\mathcal{S}_v$, data $D_{\mathcal{S}_v}$, shared table $\mathbf{T}$

  GatherType: g ▷ stores the results of the gather phase
  for $(u, v) \in (* \to v)$ **do** ▷ In Parallel
    $g \leftarrow g + \text{gather}((u, v))$
  end for
  $\text{apply}(g, D_v)$
  for $(v, u) \in (v \to *)$ **do** ▷ In Parallel
    $\text{scatter}((v, u))$
  end for
end procedure

Outline

Sync Mechanism

Aggregates data accross all vertices in the graph

Associates the result with a particular entry in $\mathbf{T}$

The user provides:

- a key k
- an initial value r_k^0
- a fold function: $r_k^{i+1} \leftarrow \text{Fold}_k\left(D_v, r_k^i\right)$
- an optional merge function: $r_k^l \leftarrow \text{Merge}_k\left(r_k^i, r_k^j\right)$
- an apply function: $\mathbf{T}[k] \leftarrow \text{Apply}_k\left(r_k^{|V|}\right)$

Sync Mechanism

procedure SYNC ALGORITHM
input: key k, vertices V, data $\{D_v\}_{v \in V}$, initial value r_k^0, shared table $\mathbf{T}$

$t \leftarrow r_k^0$
for $v \in V$ **do**
$t \leftarrow \text{Fold}_k(D_v, t)$
end for
$\mathbf{T}[k] \leftarrow \text{Apply}_k(t)$
end procedure

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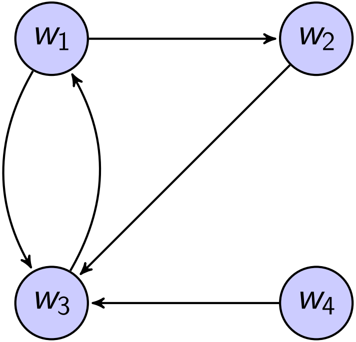
Pagerank: Data Model

- $G := \{w_1, w_2, w_3, w_4\}$
- $E := \{(w_1, w_2), (w_1, w_3), (w_3, w_1), (w_2, w_3), (w_4, w_3)\}$
- $D_v := PR(v)$
- $D_{v,u} := \emptyset$



Pagerank: Update function

procedure PAGERANKUPDATEFUNCTION
input: vertex v, scope $\mathcal{S}_v$, ingoing edges $(* \to v)$

$\mathcal{T} \leftarrow \emptyset$
$D_v^{old} \leftarrow D_v$
$p \leftarrow 0$
for $u \in \{u | (u, v) \in (* \to v)\}$ **do**
  $p \leftarrow p + \frac{D_u}{|(u \to *)|}$
end for
$D_v \leftarrow (1 - \beta) + \beta * p$
if $|D_v - D_v^{old}| > \epsilon$ **then**
  $\mathcal{T} \leftarrow \mathcal{N}_v$
end if
return $(D_{\mathcal{S}_v}, \mathcal{T})$
end procedure

Pagerank: Vertex Program

procedure PAGERANKGATHER
input: vertex v, scope $\mathcal{S}_v$, ingoing edge $(u \to v)$

    return $\frac{D_u}{|(u \to *)|}$

end procedure

procedure PAGERANKAPPLY
input: vertex v, scope $\mathcal{S}_v$, gather result p,

    $D_v^{old} \leftarrow D_v$
    $D_v \leftarrow (1-\beta) + \beta * p$
    if $|D_v - D_v^{old}| > \epsilon$ **then**
        Signal to perform scatter
    end if

end procedure

Pagerank: Scatter

procedure PAGERANKSCATTER
input: outgoing edge $(v \rightarrow u)$, set of vertices to be rescheduled $\mathcal{T}$

Add u to $\mathcal{T}$

end procedure

PageRank Implementation: Data Types

```
struct web_page {
  std::string pagename;
  double pagerank;

  explicit web_page(std::string name):
          pagename(name),pagerank(0.0){ }

  void save(graphlab::oarchive& oarc) const{
     oarc << pagename << pagerank;
  }
  void load(graphlab::iarchive& iarc) {
     iarc >> pagename >> pagerank;
  }
};
typedef graphlab::distributed_graph
          <web_page, graphlab::empty> graph_type;
```

PageRank Implementation: Reading the Data

```
bool line_parser(graph_type& graph,
                 const std::string& filename, const std::string&
  std::stringstream strm(textline);
  graphlab::vertex_id_type vid;
  std::string pagename;

  strm >> vid >> pagename;

  graph.add_vertex(vid, web_page(pagename));

  while(1){
    graphlab::vertex_id_type other_vid;
    strm >> other_vid;
    if (strm.fail()) return true;
    graph.add_edge(vid, other_vid);
  }
  return true;
}
```

PageRank Implementation: Vertex Program

```
class pagerank_program :
  public graphlab::ivertex_program<graph_type, double>,
  public graphlab::IS_POD_TYPE {

  public:
  bool perform_scatter;

  edge_dir_type gather_edges(icontext_type& context,
                             const vertex_type& vertex);
  edge_dir_type scatter_edges(icontext_type& context,
                              const vertex_type& vertex);

  double gather(icontext_type& context,
                const vertex_type& vertex, edge_type& edge);
  void apply(icontext_type& context, vertex_type& vertex,
             const gather_type& total);

  void scatter(icontext_type& context,
               const vertex_type& vertex, edge_type& edge);
};
```

PageRank Implementation: Gather

```
// we are going to gather on all the in−edges
edge_dir_type gather_edges(icontext_type& context,
                           const vertex_type& vertex) const {

   return graphlab::IN_EDGES;

}

// for each in−edge gather the weighted sum of the edge.
double gather(icontext_type& context,
                     const vertex_type& vertex,
                     edge_type& edge) const {

   return    edge.source().data().pagerank
                  / edge.source().num_out_edges();

}
```

PageRank Implementation: Apply

```
// Use the total rank of adjacent pages
// to update this page
void apply(icontext_type& context,
           vertex_type& vertex,
           const gather_type& total) {

   double newval = total * 0.85 + 0.15;
   double oldval = vertex.data().pagerank;
   vertex.data().pagerank = newval;
   perform_scatter = (std::fabs(prevval - oldval) > 1E-3);

}
```

PageRank Implementation: Scatter

```
edge_dir_type scatter_edges(icontext_type& context,
                            const vertex_type& vertex) {

  if (perform_scatter) return graphlab::OUT_EDGES;
  else return graphlab::NO_EDGES;

}

void scatter(icontext_type& context,
             const vertex_type& vertex,
             edge_type& edge) const {

  context.signal(edge.target());

}
```

Outline

Execution Model

```
procedure GraphLabExec
input:  Graph G := (V, E), data D, initial vertex set 𝒯 ⊆ V

    while |𝒯| > 0 do
        v ← RemoveNext(𝒯)
        (𝒯′, D_{S_v}) ← f(D_{S_v}, T)
        𝒯 ← 𝒯 ∪ 𝒯′
    end while
end procedure
```

Serializability

- The GraphLab abstraction provides a rich *sequential model*
- Parallel Execution:
  - Multiple processors to execute the same loop on the same graph
  - Simutaneous execution of update functions on different vertices
- We desire a **serializable execution**:

Definition

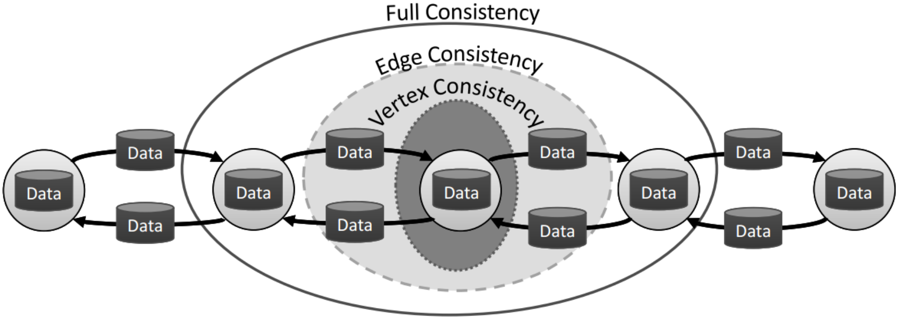
A GraphLab program is sequentially consistent if for every parallel execution, there exists a sequential execution of update functions that produces the same values in the data graph

Data Consistency

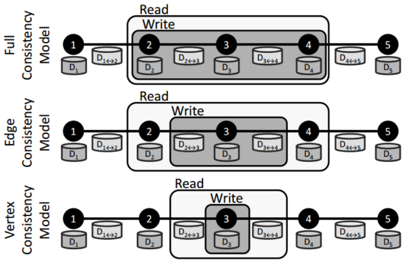
To ensure Serializability we need **consistency models**
GraphLab supports three types of consistency models:

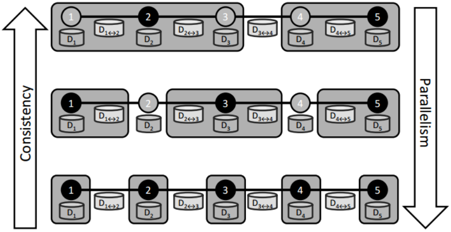
- **Full Consistency**: the scope of two concurrently executing update functions do not overlap
- **Edge Consistency**: each update function has R/W access to its vertex and adjacent edges but only read access to neighboring vertices
- **Vertex Consistency**: only ensures that no concurrently update functions are executed on the same vertice

Data Consistency - Exclusion Sets



Data Consistency



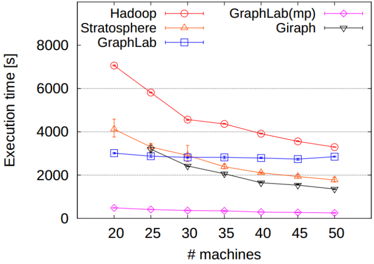


Data Consistency

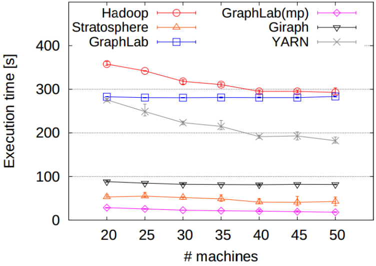
GraphLab *guarantees* sequential consistency under the following three conditions:

- The **full consistency** model is used
- The **edge consistency** model is used and update functions do not modify data in adjacent vertices
- The **vertex consistency** model is used and update functions only access local vertex data

Benchmarks - Horizontal Scaling



Dataset 1



Dataset 2

Dataset	$\|V\|$	$\|E\|$	Size
1	61.2K	50.9 M	655 MB
2	65.6 M	1.8 B	31 GB

Yong Guo, Marcin Biczak, Ana Lucia Varbanescu, Alexandru Iosup, Claudio Martella, Theodore L. Willke. *Towards Benchmarking Graph-Processing Platforms*. Super Computing 2013

Summary

A GraphLab program consists of:

- A **data graph**
- An **update function**
  - Gather Function
  - Apply Function
  - Scatter Function
- A **sync mechanism**
- A **consistency model**