MapReduce & GraphLab: Programming Models for Large-Scale Parallel/Distributed Computing

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Outline

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  - Design Issues & Abstractions
  - Examples and Results
  - Pros and Cons
- Graph Lab
  - Graph Parallel Abstraction
  - MapReduce vs Pregel vs GraphLab
  - Implementation Issues
  - Pros and Cons

Motivation

- The Age of "Big Data"

~ 45 Billion Webpages

~ 1.06 Billion Facebook Users

~24 Million Wikipedia Pages

~6 Billion Flickr Photos

- Infeasible to analyze on a single machine
- Solution: Distribute across many computers

Motivation

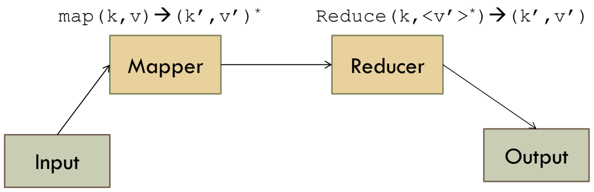
- Challenges: We repeatedly solve the same system-level problems
  - Communication/Coordination among the nodes
  - Synchronization, Race Conditions
  - Load Balancing, Locality, Fault Tolerance, …
- Need a higher level programming Model
  - That hides these messy details
  - Applies to a large number of problems

MapReduce: Overview

- A programming model for large-scale data-parallel applications
  - Introduced by Google (Dean & Ghemawat, OSDI'04)
- Petabytes of data processed on clusters with thousands of commodity machines
  - Suitable for programs that can be decomposed in many embarrassingly parallel tasks
- Hides low level parallel programming details

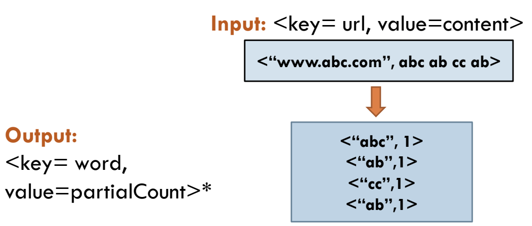
MapReduce: Overview

- Programmers have to specify two primary methods
  - **Map**: processes input data and generates intermediate key/value pairs
  - **Reduce**: aggregates and merges all intermediate values associated with the same key



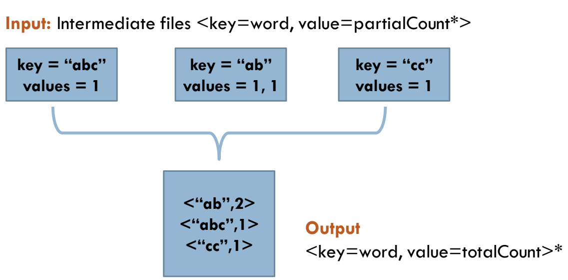
Example: Count word frequencies from web pages

- Input: Web documents
  - Key = web document URL, Value = document content
- Output: Frequencies of individual words
- Steps 1: specify a Map function



Example: Count word frequencies from web pages

- Step 2: specify a Reduce function
  - Collect the partial sums provided by the map function
  - Compute the total sum for each individual word

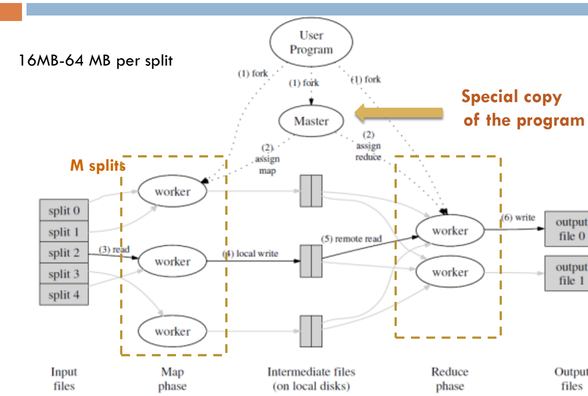


Example code: Count word

```
void map(String key, String value):
// key: webpage url
// value: webpage contents
for each word w in value:
  EmitIntermediate(w, "1");

void reduce(String key, Iterator partialCounts):
// key: a word
// partialCounts: a list of aggregated partial
  counts
int result = 0;
for each pc in partialCounts:
  result += ParseInt(pc);
Emit(AsString(result));
```

How MapReduce Works?



Ref: J. Dean, S. Ghemawat, MapReduce: Simplified Data Processing on Large Clusters, OSDI, 2004

Implementation Details: Scheduling

- One Master, many workers
  - MapReduce Library splits input data into M pieces (16MB or 64MB per piece, uses GFS)
- Master assigns each idle worker to a map or reduce task
- Worker completes the map task, buffers the intermediate (key,value) in memory, and periodically writes to local disk
  - Location of buffered pairs are returned to Master
- Master assigns completed map tasks to Reduce workers
  - Reduce worker reads the intermediate files using RPC
  - Sorts the keys and performs reduction

Fault Tolerance

- Worker Failure: Master pings the workers periodically
  - If no response, then master marks the worker as failed
  - Any map task or reduce task in progress is marked for rescheduling
  - Completed reduce tasks don't have to be recomputed
- Master Failure
  - Master writes periodic checkpoints to GFS. On failure, new master recovers to that checkpoint and continues
  - Often not handled, aborts if master fails (failure of master is less probable)

Locality

- Bandwidth is an important resource
  - Communicating large datasets to worker nodes can be very expensive
- Do not transfer data to worker
  - Assign task to the worker that has the data locally
- Create multiple replications of data (Typically 3)
- Master assigns to one of these computers having the data in local file system

Other Refinements

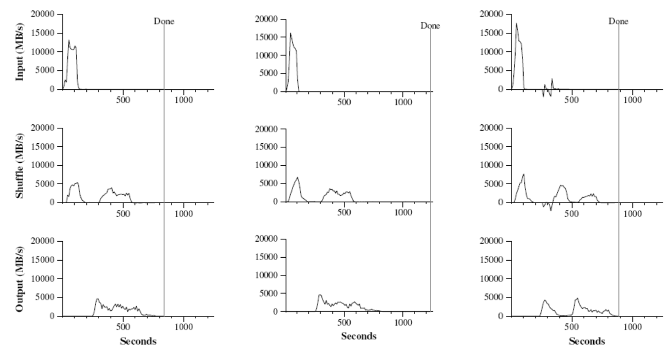
- Task Granularity:
  - M map tasks, R reduce tasks
  - We want to make M and R larger
    - Dynamic load balancing
    - Faster recovery from failure
    - BUT, increases the number of scheduling decisions increases with M and R
  - Finally we'll get R output files. So R should not be too large
  - Typical settings: for 2000 worker machines:
    - M = 200,000 and R = 5000

Other Refinements: Backup Tasks

- Some machines can be extremely slow ("straggler")
  - Perhaps a bad disk that frequently encounters correctable errors
- Solution: Backup tasks
  - Near the end of map reduce, master schedules some backup tasks for each of the remaining tasks
  - A task is marked as complete if either the primary or the backup execution completes

Results: Sorting

M=15k, R=4k,
~1800 machines



(a) Normal execution (b) No backup tasks (c) 200 tasks killed

Figure 3: Data transfer rates over time for different executions of the sort program

Example: Word Frequency: MAP

```
#include “mapreduce/mapreduce.h“
// User's map function
class WordCounter : public Mapper {
  public:
  virtual void Map(const MapInput& input) {
      //perform map operation, parse input
      ...
      //for each word
      Emit(word,”1”)
  }
};
REGISTER_MAPPER(WordCounter);
```

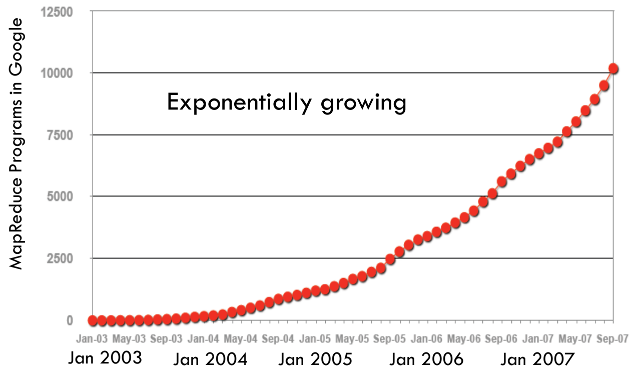
Word Frequency: REDUCE

```
// User's reduce function
class Adder: public Reducer {
  virtual void Reduce(ReduceInput* input) {
      // Iterate over all entries with the
      // same key and add the values
      int64 value = 0;
      while (!input->done()) {
            value += StringToInt(input->value());
            input->NextValue();
      }
  // Emit sum for input->key()
  Emit(IntToString(value));
  }
};
REGISTER_REDUCER(Adder);
```

Word Frequency: MAIN (Simplified)

```
int main(int argc, char** argv) {
  MapReduceSpecification spec;
  // Store list of input files into "spec“
  MapReduceInput* input = spec.add_input();
  input->set_mapper_class("WordCounter");
  //specify output files
  MapReduceOutput* out = spec.output();
  out->set_reducer_class("Adder");
  // Tuning parameters: use at most 2000
  spec.set_machines(2000);
  // Now run it
  MapReduceResult result;
  MapReduce(spec, &result));
  return 0;
}
```

MapReduce Instances at Google



Ref: PACT 06’ Keynote slides by Jeff Dean, Google, Inc.

Pros: MapReduce

- Simplicity of the model
  - Programmers specifies few simple methods that focuses on the functionality not on the parallelism
  - Code is generic and portable across systems
- Scalability
  - Scales easily for large number of clusters with thousands of machines
- Applicability to many different systems and a wide variety of problems
  - Distributed Grep, Sort, Inverted Index, Word Frequency count, etc.

Cons: MapReduce

- Restricted programming constructs (only map & reduce)
- Does not scale well for dependent tasks (for example Graph problems)
- Does not scale well for iterative algorithms (very common in machine learning)

Summary: MapReduce

- MapReduce
  - Restricted but elegant solution
  - High level abstraction
  - Implemented in C++
- Many Open-source Implementation
  - Hadoop (Distributed, Java)
  - Phoenix, Metis (Shared memory, for multicore, C++)

GraphLab

GraphLab: Motivation

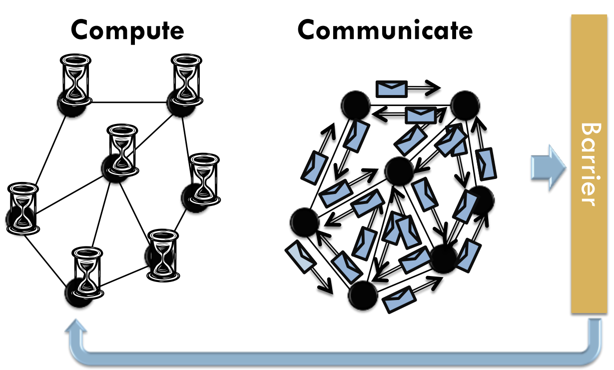
- MapReduce is great for Data Parallel applications
  - Can be easily decomposed using map/reduce
  - Assumes independence among the tasks
- Independence assumption can be too restrictive
- Many interesting problems involve graphs
  - Need to model dependence/interactions among entities
  - Extract more signal from noisy data
  - MapReduce is not well suited for these problems

Graph-based Abstraction

- Machine learning practitioners typically had two choices:
  - Simple algorithms + "Big data" vs
  - Powerful algorithms (with dependency)+ "Small data"
- Graph-based Abstraction
  - Powerful algorithms + "Big data"
- Graph parallel programming models:
  - Pregel: Bulk Synchronous Parallel Model (Google, SIGMOD 2010)
  - GraphLab: asynchronous model [UAI 2010, VLDB 2012]

Bulk Synchronous Parallel Model: Pregel

[Malewicz et al. '2010]



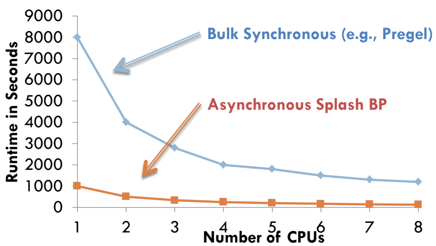
http://graphlab.org/powergraph-presented-at-osdi/

Tradeoffs of the BSP Model

- Pros:
  - Scales better than MapReduce for *Graphs*
  - Relatively easy to build
  - Deterministic execution
- Cons:
  - Inefficient if different regions of the graph converge at different speed
  - Can suffer if one task is more expensive than the others
  - Runtime of each phase is determined by the slowest machine

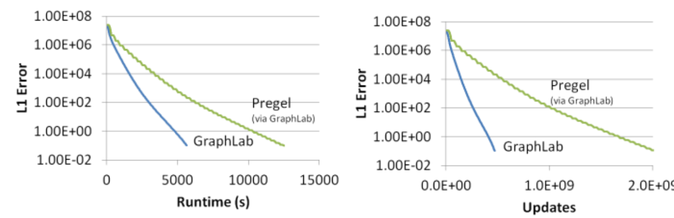
Synchronous vs Asynchronous Belief Propagation

[Gonzalez, Low, Guestrin. '09]



GraphLab vs. Pregel (Page Rank)

[Low et al. PVLDB'12]



- PageRank (25M Vertices, 355M Edges, 16 processors)

GraphLab Framework: Overview

- GraphLab allows asynchronous iterative computation
- The GraphLab abstraction consists of 3 key elements:
  - Data Graph
  - Update Functions
  - Sync Operation
- We explain GraphLab using PageRank example

http://graphlab.org/powergraph-presented-at-osdi/

Case Study: PageRank

- Iterate:

$$R[i] = \alpha + (1-\alpha) \sum_{(j,i)\in E} \frac{1}{L[j]} R[j]$$

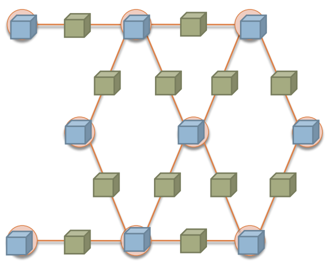
- Where:
  - α is the random reset probability
  - $L[j]$ is the number of links on page j

$$R[5] = \alpha + (1-\alpha)\left(\frac{1}{3}R[1] + \frac{1}{1}R[4]\right)$$

http://graphlab.org/powergraph-presented-at-osdi/

1. Data Graph

- Data Graph: a directed acyclic graph G=(V,E,D)
  - Data D refers to model parameters, algorithm states and other related data



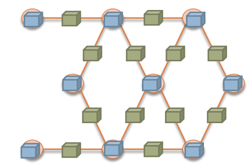
Graph:
- Social Network

Vertex Data:
- User profile text
- Current interests estimates

Edge Data:
- Similarity weights

1. Data Graph

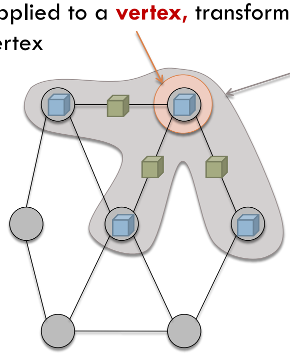
- PageRank: G = (V,E,D)
  - Each vertex (*v*) corresponds to a webpage
  - Each edge *(u,v)* corresponds to a link from (*u* → *v*)
  - Vertex data D_v stores the rank of the webpage i.e. *R*(*v*)
  - Edge data: $D_{u \to v}$ stores the weight of the link (*u* → *v*)



$$R[v] \leftarrow \alpha + (1-\alpha) \sum_{u \in N[v]} W_{uv} \times R[u]$$

2. Update Functions

An **update function** is a user defined program (similar to map)
Applied to a **vertex,** transforms the data in the scope of the vertex



pagerank(*v*, scope){
// Get Neighborhood data
($R[v]$, W_{uv}, $R[u]$) ←scope;
// Get old page rank
$R_{old}[v] \leftarrow R[v]$

// Update the vertex data
$$R[v] \leftarrow \alpha + (1-\alpha) \sum_{u \in N[v]} W_{uv} \times R[u];$$
// Reschedule Neighbors if needed
if $|R_{old}[v] - R[v]| > \varepsilon$
reschedule_neighbors_of(v);
}

2. Update Function

$$R[v] \leftarrow \alpha + (1-\alpha) \sum_{u \in N[v]} W_{uv} \times R[u];$$

```
struct pagerank : public iupdate_functor<graph, pagerank> {
  void operator()(icontext_type& context) {
    double sum = 0;
    foreach ( edge_type edge, context.in_edges() )
      sum += 1/context.num_out_edges(edge.source()) *
        context.vertex_data(edge.source());
    double& rank = context.vertex_data();
    double old_rank = rank;
    rank = RESET_PROB + (1-RESET_PROB) * sum;
    double residual = abs(rank – old_rank)
    if (residual > EPSILON)
      context.reschedule_out_neighbors(pagerank());
  }
};
```

3. Sync Operation

- Global operation, usually performed periodically in the background
  - Useful for maintaining some global statistics of the algorithm
    - Example: PageRank may want to return a list of 100 top ranked web pages
  - Determine the global convergence criteria. For example, estimate log-likelihood.
    - Estimate total log-likelihood for Expectation Maximization
- Similar to Reduce functionality in MapReduce

Scheduling

Algorithm 2: GraphLab Execution Model

Input: Data Graph $G = (V, E, D)$
Input: Initial vertex set $\mathcal{T} = \{v_1, v_2, ...\}$
while $\mathcal{T}$ *is not Empty* **do**
  $v \leftarrow \texttt{RemoveNext}\,(\mathcal{T})$
  $(\mathcal{T}', \mathcal{S}_v) \leftarrow f(v, \mathcal{S}_v)$
  $\mathcal{T} \leftarrow \mathcal{T} \cup \mathcal{T}'$
Output: Modified Data Graph $G = (V, E, D')$

[Low et al. PVLDB'12]

GraphLab: Hello World!

```
#include <graphlab.hpp>
int main(int argc, char** argv) {
  graphlab::mpi_tools::init(argc, argv);
  Graphlab::distributed_control dc;
  dc.cout()<< "Hello World!\n";
  graphlab::mpi_tools::finalize();
}
```

- Let the file name: *my_first_app.cpp*
- Use "make" to build
- Excecute: `mpiexec -n 4 ./my_first_app`

dc.cout() provides a wrapper around standard std::cout
When used in a distributed environment, only one copy will print, even though all machines execute it.

GraphLab Tutorials

- For more interesting examples, check:
  - http://docs.graphlab.org/using_graphlab.html
- A step by step tutorial for implementing PageRank in GraphLab

Few Additional Details

- Fault Tolerance using checkpointing
- The GraphLab described here is GraphLab 2.1
  - GraphLab for distributed systems
- The first version was proposed only for multicore systems
- Recently, PowerGraph was proposed
  - GraphLab on Cloud

Tradeoffs of GraphLab

- Pros:
  - Allows dynamic asynchronous scheduling
  - More expressive consistency model
  - Faster and more efficient runtime performance
- Cons:
  - Non-deterministic execution
  - Substantially more complicated to implement

Summary

- MapReduce: efficient for independent tasks
  - Simple framework
  - Independence assumption can be too restrictive
  - Not scalable for graphs or dependent tasks, or iterative tasks
- Pregel : Bulk Synchronous Parallel Models
  - Can model dependent and iterative tasks
  - Easy to Build, Deterministic
  - Suffers from inefficiencies due to synchronous scheduling
- GraphLab: Asynchrnous Model
  - Can model dependent and iterative tasks
  - Fast, efficient, and expressive
  - Introduces non-determinism, relatively complex implementation

References

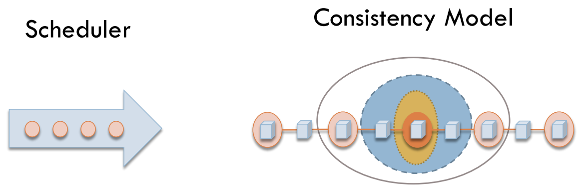
- MapReduce: Simplified Data Processing on Large Clusters, Jeffrey Dean & Sanjay Ghemawat, OSDI 2004.
- GraphLab: A new framework for parallel machine learning, Low et al., UAI 2010.
- GraphLab: a distributed framework for machine learning in the cloud, Low et al., PVLDB 2012.
- Pregel: a system for large-scale graph processing, Malewicz et al., SIGMOD 2010.
- Parallel Splash Belief Propagation, Gonzalez et al., Journal of Machine Learning Research, 2010.

Disclaimer

- Many figures and illustrations were collected from Carlos Guestrin's GraphLab tutorials

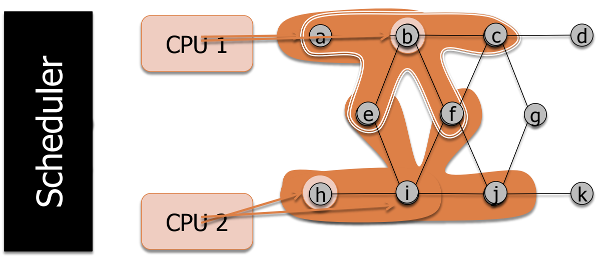
  http://docs.graphlab.org/using_graphlab.html

Additional GraphLab Implementation Issues



Scheduling

The **scheduler** determines the order that vertices are updated



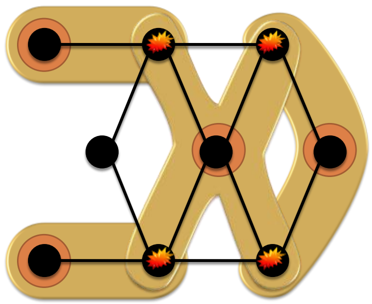
The process repeats until the scheduler is empty

Scheduling

- What happens for boundary vertices (across machines)?
- Data is classified as edge data and vertex data
- Partition a huge graph across multiple machines
  - Ghost vertices (along the cut) maintains adjacency information
  - Graph must be cut efficiently. Use parallel graph partitioning tools (ParMetis)

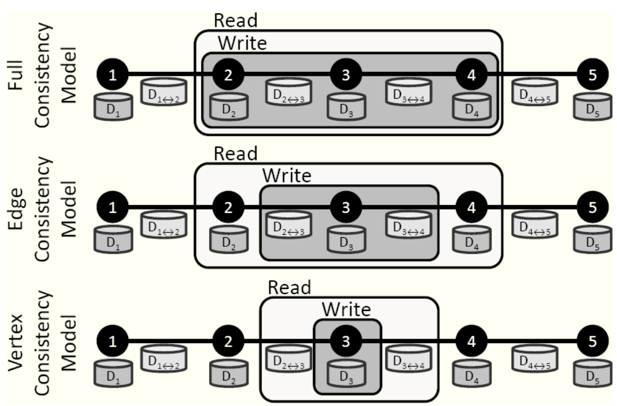
Consistency Model

- Race conditions may occur if updating shared data
  - If overlapping computations run simultaneously



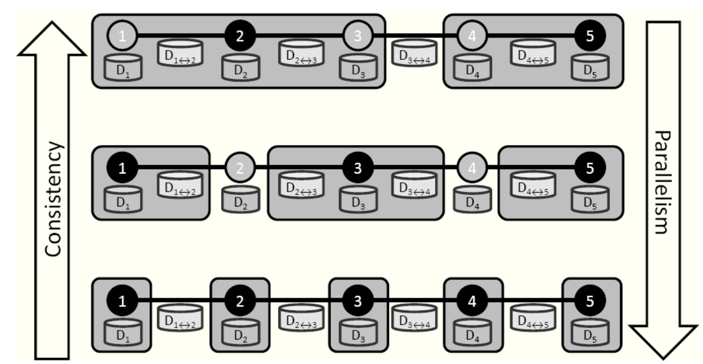
Consistency Model: How to Avoid Race?

- Ensure update functions for two vertices simultaneously operate only if
  - two scopes do not overlap
- Three consistency models:
  - Full consistency
  - Edge consistency
  - Vertex consistency



(b) Consistency Models

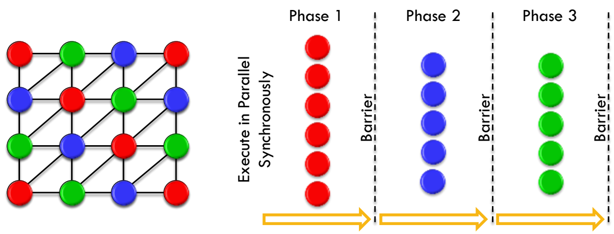
Consistency vs Parallelism



(c) Consistency and Parallelism

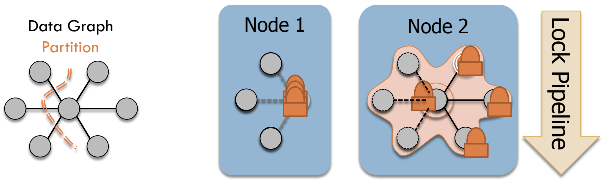
Consistency Model: Implementation

- Option 1: Chromatic Engine:
  - Graph coloring: neighboring vertices have different colors
  - Simultaneous update only for vertices with same color



Consistency using Distributed Locks

- Distributed Locking



- Non-blocking locks allow computation to proceed while locks/data are requested.
- Request locks in a canonical order to avoid deadlock