

Graph-structured Analytics (I)

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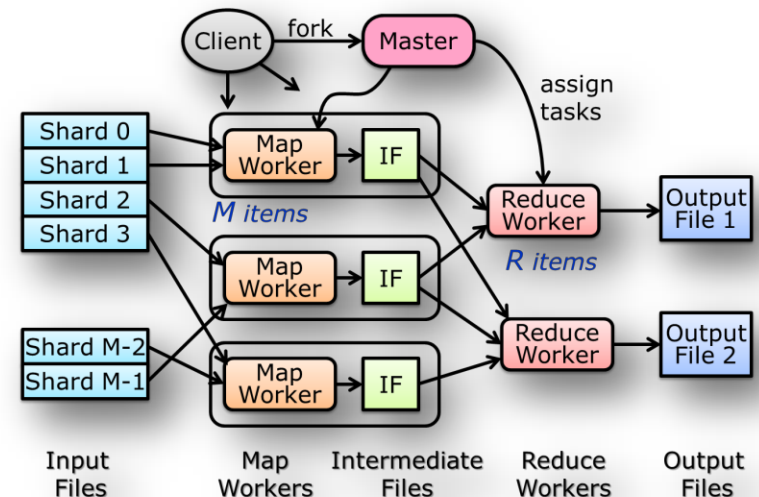
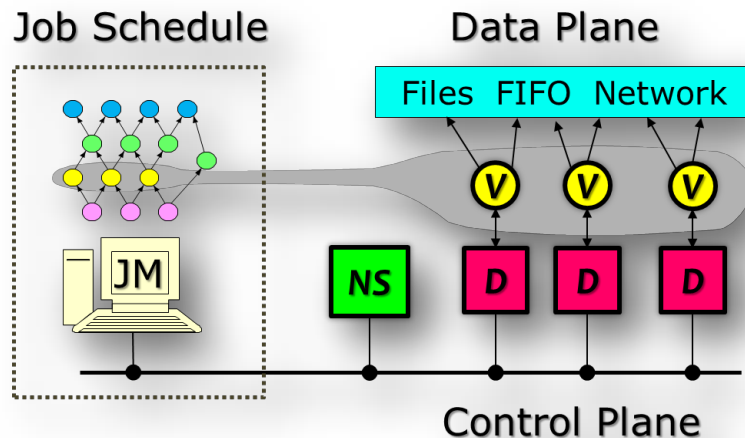
http://ipads.se.sjtu.edu.cn/rong_chen

Credits: some slides and figures from J. Gonzalez (CMU) , Y. Low (CMU),
G. Malewicz (Google), A. Khan (ETH) and S. Elnikety (MSR)

Programming Model so far

Data-parallel Programming Model

- MapReduce & Dryad
 - Parallelism
 - Load balance
 - Locality and data distribution
 - Fault tolerance



Big Data already Happened

1 Billion Tweets
Per Week



facebook

750 Million
Facebook Users

6 Billion
Flickr Photos

flickr

You Tube

48 Hrs of Video
Per Minute

Big Learning



“...growing at 50 percent a year...”

“... data a new class of economic asset,
like currency or gold.”

How do we understand and use Big Data?

Big Learning Example

Social Arithmetic

50% What I list on my profile
40% Sue Ann Likes
+ 10% Carlos Like

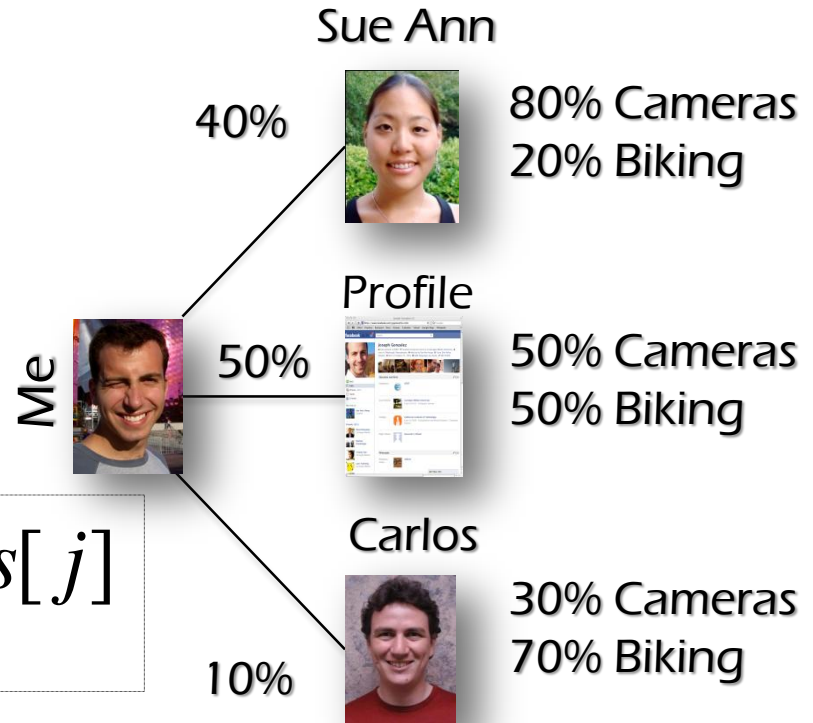
I Like: 60% Cameras, 40% Biking

Recurrence Algorithm

$$Likes[i] = \sum_{j \in Friends[i]} W_{ij} \times Likes[j]$$

iterate until **convergence**

Label Propagation



Parallelism: Compute all Likes[i] in **parallel**

Big Learning Example

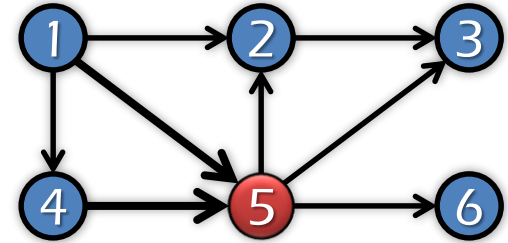
PageRank

<http://ilpubs.stanford.edu:8090/422/1/1999-66.pdf>

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

α is the random reset probability

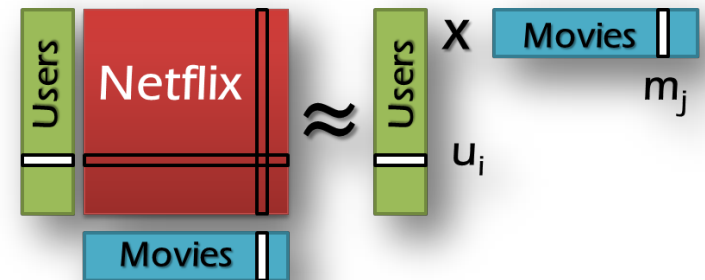
$L[j]$ is the number of links on page j



Alternating Least Squares

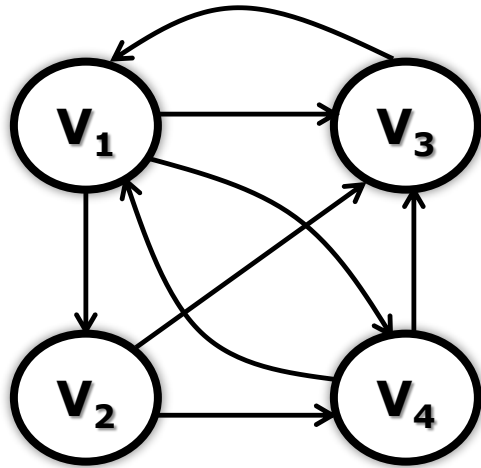
$$u_i = \arg \min_w \sum_{j \in N[i]} (r_{ij} - m_j \cdot w)^2$$

$$m_j = \arg \min_w \sum_{i \in N[j]} (r_{ij} - u_i \cdot w)^2$$



<http://dl.acm.org/citation.cfm?id=1424269>

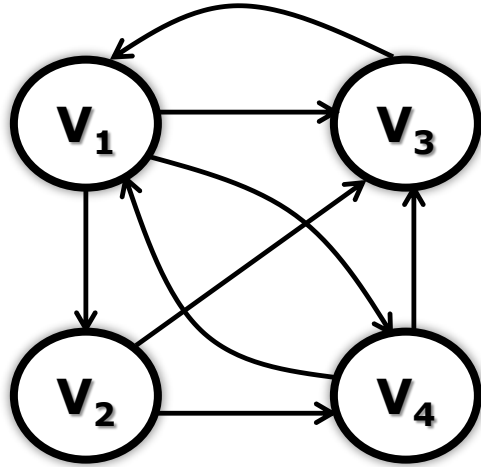
Example: PageRank



$$PR_{k+1}(u) = \sum_{v \in B_u} \frac{PR_k(v)}{|F_v|}$$

- $PR(u)$: Page Rank of node u
- F_u : Out-neighbors of node u

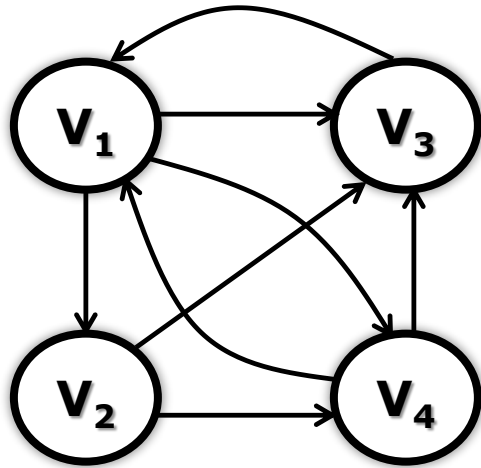
Example: PageRank



$$PR_{k+1}(u) = \sum_{v \in B_u} \frac{PR_k(v)}{|F_v|}$$

	K=0
PR(V ₁)	0.25
PR(V ₂)	0.25
PR(V ₃)	0.25
PR(V ₄)	0.25

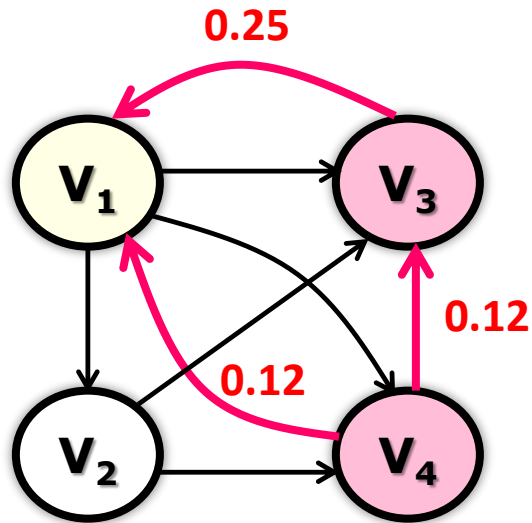
Example: PageRank



$$PR_{k+1}(u) = \sum_{v \in B_u} \frac{PR_k(v)}{|F_v|}$$

	K=0	K=1
PR(V ₁)	0.25	???
PR(V ₂)	0.25	
PR(V ₃)	0.25	
PR(V ₄)	0.25	

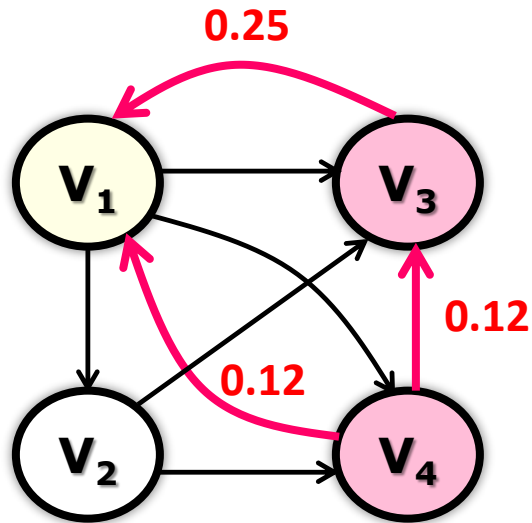
Example: PageRank



$$PR_{k+1}(u) = \sum_{v \in B_u} \frac{PR_k(v)}{|F_v|}$$

	K=0	K=1
PR(V_1)	0.25	???
PR(V_2)	0.25	
PR(V_3)	0.25	
PR(V_4)	0.25	

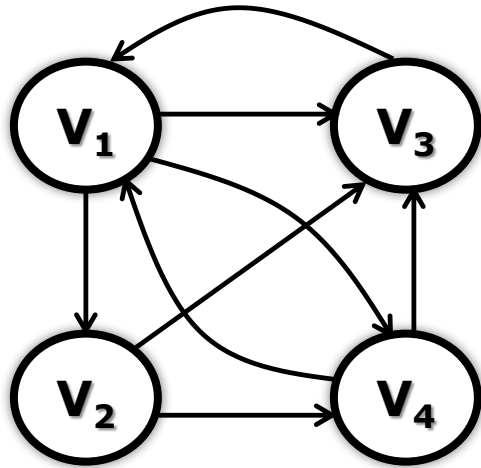
Example: PageRank



$$PR_{k+1}(u) = \sum_{v \in B_u} \frac{PR_k(v)}{|F_v|}$$

	K=0	K=1
PR(V_1)	0.25	0.37
PR(V_2)	0.25	
PR(V_3)	0.25	
PR(V_4)	0.25	

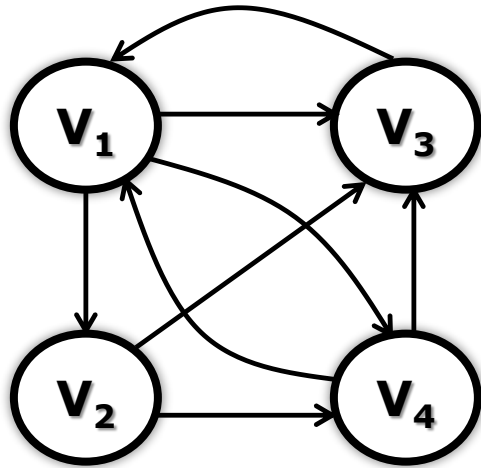
Example: PageRank



$$PR_{k+1}(u) = \sum_{v \in B_u} \frac{PR_k(v)}{|F_v|}$$

	K=0	K=1
PR(V ₁)	0.25	0.37
PR(V ₂)	0.25	0.08
PR(V ₃)	0.25	0.33
PR(V ₄)	0.25	0.20

Example: PageRank

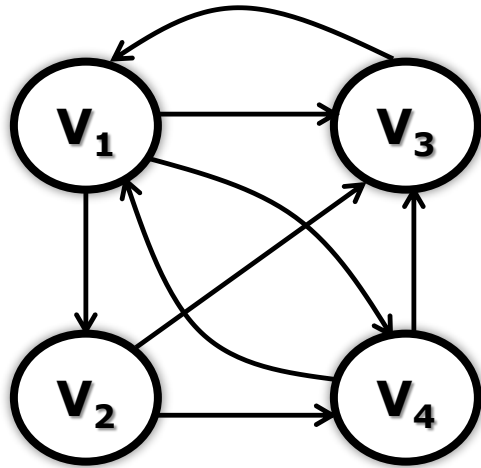


$$PR_{k+1}(u) = \sum_{v \in B_u} \frac{PR_k(v)}{|F_v|}$$

Iterative Batch Processing

	K=0	K=1	K=2
PR(V ₁)	0.25	0.37	0.43
PR(V ₂)	0.25	0.08	0.12
PR(V ₃)	0.25	0.33	0.27
PR(V ₄)	0.25	0.20	0.16

Example: PageRank

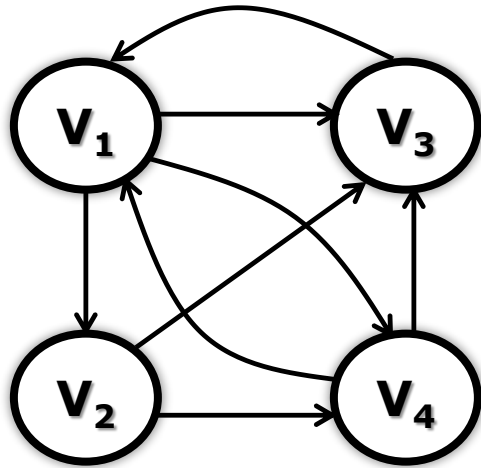


$$PR_{k+1}(u) = \sum_{v \in B_u} \frac{PR_k(v)}{|F_v|}$$

Iterative Batch Processing

	K=0	K=1	K=2	K=3
PR(V ₁)	0.25	0.37	0.43	0.35
PR(V ₂)	0.25	0.08	0.12	0.14
PR(V ₃)	0.25	0.33	0.27	0.29
PR(V ₄)	0.25	0.20	0.16	0.20

Example: PageRank

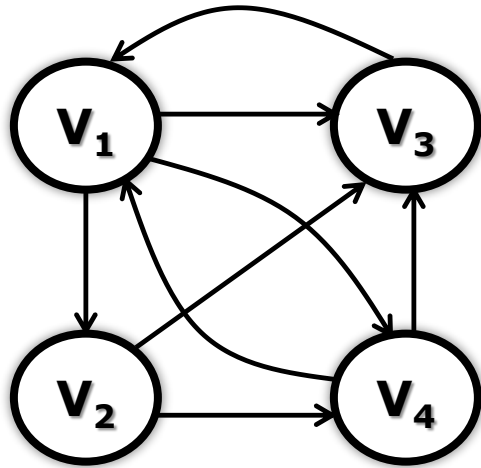


$$PR_{k+1}(u) = \sum_{v \in B_u} \frac{PR_k(v)}{|F_v|}$$

Iterative Batch Processing

	K=0	K=1	K=2	K=3	K=4
PR(V ₁)	0.25	0.37	0.43	0.35	0.39
PR(V ₂)	0.25	0.08	0.12	0.14	0.11
PR(V ₃)	0.25	0.33	0.27	0.29	0.29
PR(V ₄)	0.25	0.20	0.16	0.20	0.19

Example: PageRank

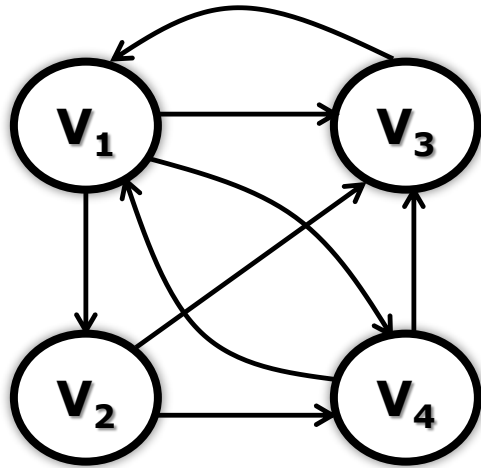


$$PR_{k+1}(u) = \sum_{v \in B_u} \frac{PR_k(v)}{|F_v|}$$

Iterative Batch Processing

	K=0	K=1	K=2	K=3	K=4	K=5
PR(V ₁)	0.25	0.37	0.43	0.35	0.39	0.39
PR(V ₂)	0.25	0.08	0.12	0.14	0.11	0.13
PR(V ₃)	0.25	0.33	0.27	0.29	0.29	0.28
PR(V ₄)	0.25	0.20	0.16	0.20	0.19	0.19

Example: PageRank

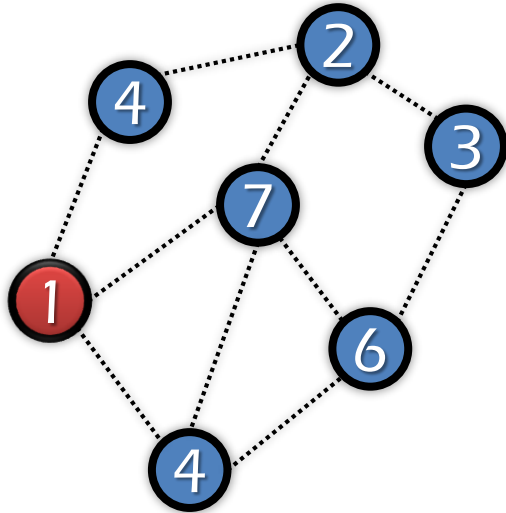


$$PR_{k+1}(u) = \sum_{v \in B_u} \frac{PR_k(v)}{|F_v|}$$

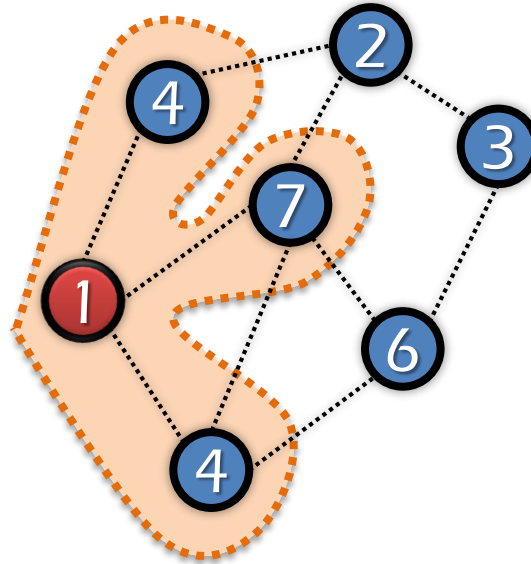
Convergence

	K=0	K=1	K=2	K=3	K=4	K=5	K=6
PR(V ₁)	0.25	0.37	0.43	0.35	0.39	0.39	0.38
PR(V ₂)	0.25	0.08	0.12	0.14	0.11	0.13	0.13
PR(V ₃)	0.25	0.33	0.27	0.29	0.29	0.28	0.28
PR(V ₄)	0.25	0.20	0.16	0.20	0.19	0.19	0.19

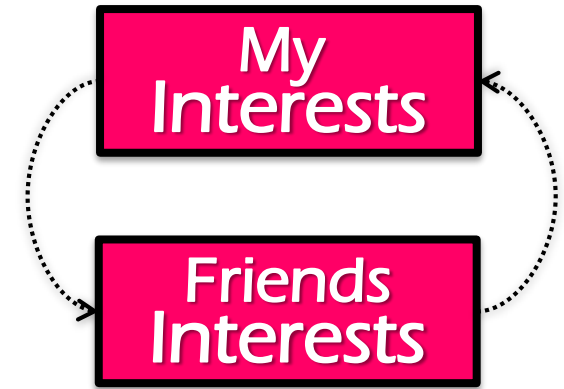
Graph Parallel Algorithm



Dependency
Graph



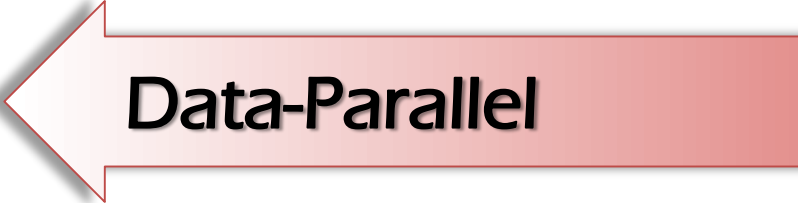
Predictable
Updates



Iterative
Computation

What is the Right Tool

Graph-parallel ML



Data-Parallel

MapReduce

Feature
Extraction

Cross
Validation

Computing Sufficient
Statistics

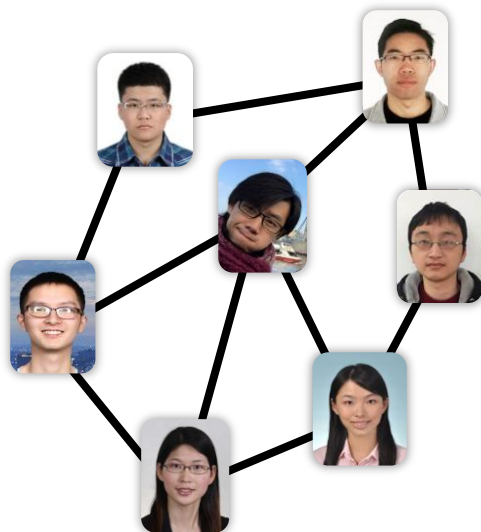
MapReduce

Lasso PageRank Label
Kernel Methods Propagation
Tensor Belief
Factorization Propagation
Deep Belief Neural
Networks Networks

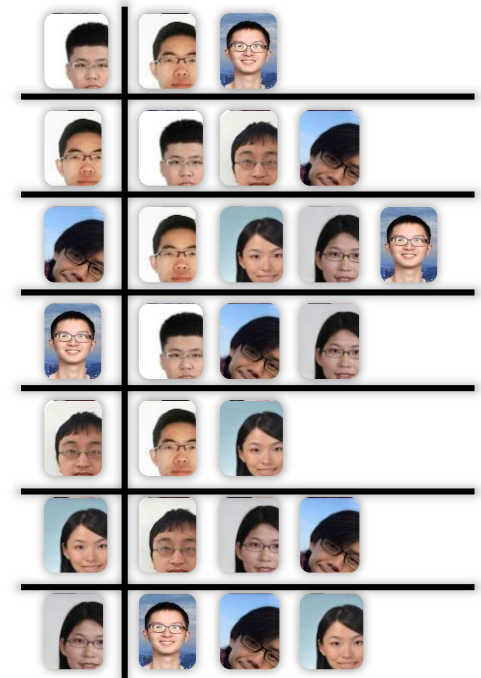
Dependencies are Difficult

Difficult to express dependent data in MR

- Substantial data transformations
- User managed graph structure
- Costly data replication



Independent Data
Records



PageRank on MapReduce

Multiple **MapReduce** iterations

Each PageRank iteration:

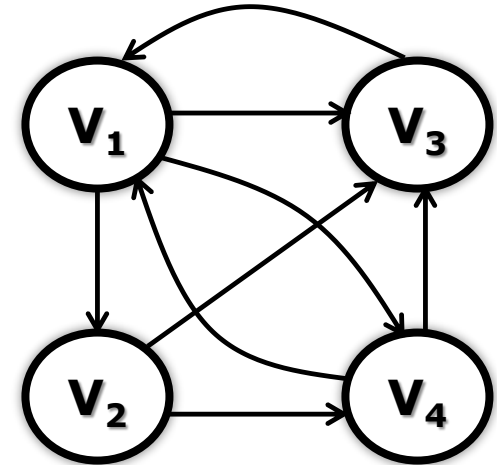
→ **Input:**

1. $(id_1, [PR_t(1), out_{11}, out_{12}, \dots])$,
2. $(id_2, [PR_t(2), out_{21}, out_{22}, \dots])$,
- ..

→ **Output:**

1. $(id_1, [PR_{t+1}(1), out_{11}, out_{12}, \dots])$,
2. $(id_2, [PR_{t+1}(2), out_{21}, out_{22}, \dots])$,
- ..

Iterate until **convergence**



Input:

$V_1, [0.25, V_2, V_3, V_4]$
 $V_2, [0.25, V_3, V_4]$
 $V_3, [0.25, V_1]$
 $V_4, [0.25, V_1, V_3]$

One MapReduce Iteration

Output:

$V_1, [0.37, V_2, V_3, V_4]$
 $V_2, [0.08, V_3, V_4]$
 $V_3, [0.33, V_1]$
 $V_4, [0.20, V_1, V_3]$

PageRank on MapReduce

Map

→ Input:

$(V_1, [0.25, V_2, V_3, V_4]);$

$(V_2, [0.25, V_3, V_4]); (V_3, [0.25, V_1]);$

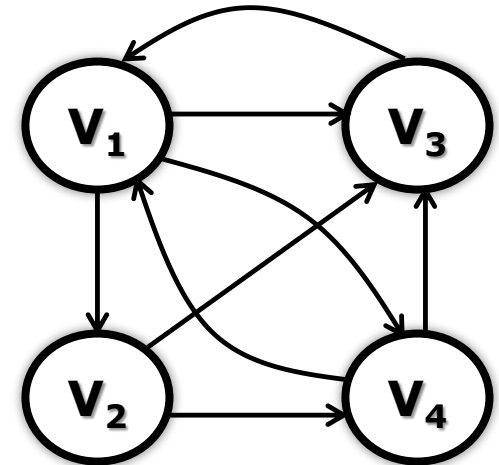
$(V_4, [0.25, V_1, V_3])$

→ Output:

$(V_2, 0.25/3), (V_3, 0.25/3), (V_4, 0.25/3),$

$\dots, (V_1, 0.25/2), (V_3, 0.25/2);$

$(V_1, [V_2, V_3, V_4]), (V_2, [V_3, V_4]), (V_3, [V_1]), \dots$



PageRank on MapReduce

Map

→ Input:

$(V_1, [0.25, V_2, V_3, V_4]);$

$(V_2, [0.25, V_3, V_4]); (V_3, [0.25, V_1]);$

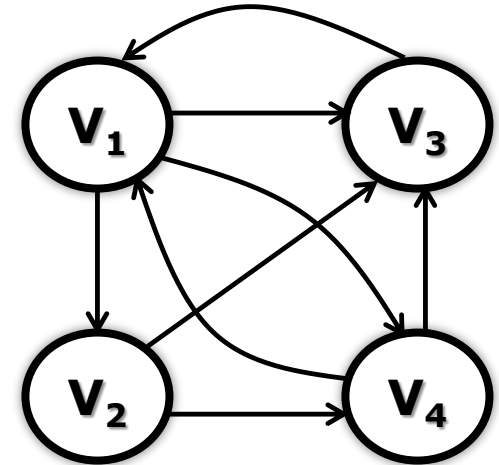
$(V_4, [0.25, V_1, V_3])$

→ Output:

$(V_2, 0.25/3), (V_3, 0.25/3), (V_4, 0.25/3),$

$\dots, (V_1, 0.25/2), (V_3, 0.25/2);$

$(V_1, [V_2, V_3, V_4]), (V_2, [V_3, V_4]), (V_3, [V_1]), \dots$



PageRank on MapReduce

Map

→ Input:

$(V_1, [0.25, V_2, V_3, V_4]);$

$(V_2, [0.25, V_3, V_4]); (V_3, [0.25, V_1]);$

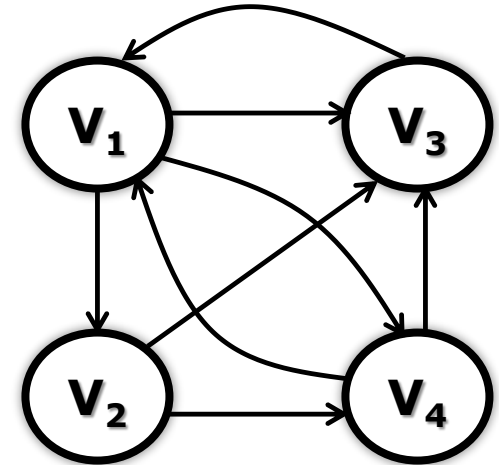
$(V_4, [0.25, V_1, V_3])$

→ Output:

$(V_2, 0.25/3), (V_3, 0.25/3), (V_4, 0.25/3),$

$\dots, (V_1, 0.25/2), (V_3, 0.25/2);$

$(V_1, [V_2, V_3, V_4]), (V_2, [V_3, V_4]), (V_3, [V_1]), \dots$



Shuffle

→ Output:

$(V_1, 0.25/2), (V_1, 0.25/1), (V_1, [V_2, V_3, V_4]); \dots;$

$(V_4, 0.25/3), (V_4, 0.25/2), (V_4, [V_1, V_3])$

PageRank on MapReduce

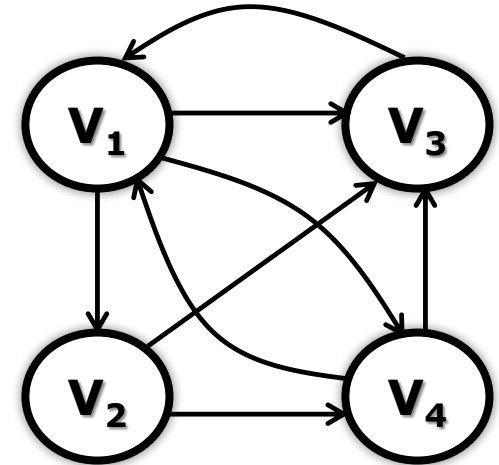
Map

→ Input:

$(V_1, [0.25, V_2, V_3, V_4]);$
 $(V_2, [0.25, V_3, V_4]); (V_3, [0.25, V_1]);$
 $(V_4, [0.25, V_1, V_3])$

→ Output:

$(V_2, 0.25/3), (V_3, 0.25/3), (V_4, 0.25/3),$
 $\dots, (V_1, 0.25/2), (V_3, 0.25/2);$
 $(V_1, [V_2, V_3, V_4]), (V_2, [V_3, V_4]), (V_3, [V_1]), \dots$



Shuffle

→ Output:

$(V_1, 0.25/2), (V_1, 0.25/1), (V_1, [V_2, V_3, V_4]); \dots;$
 $(V_4, 0.25/3), (V_4, 0.25/2), (V_4, [V_1, V_3])$

Reduce

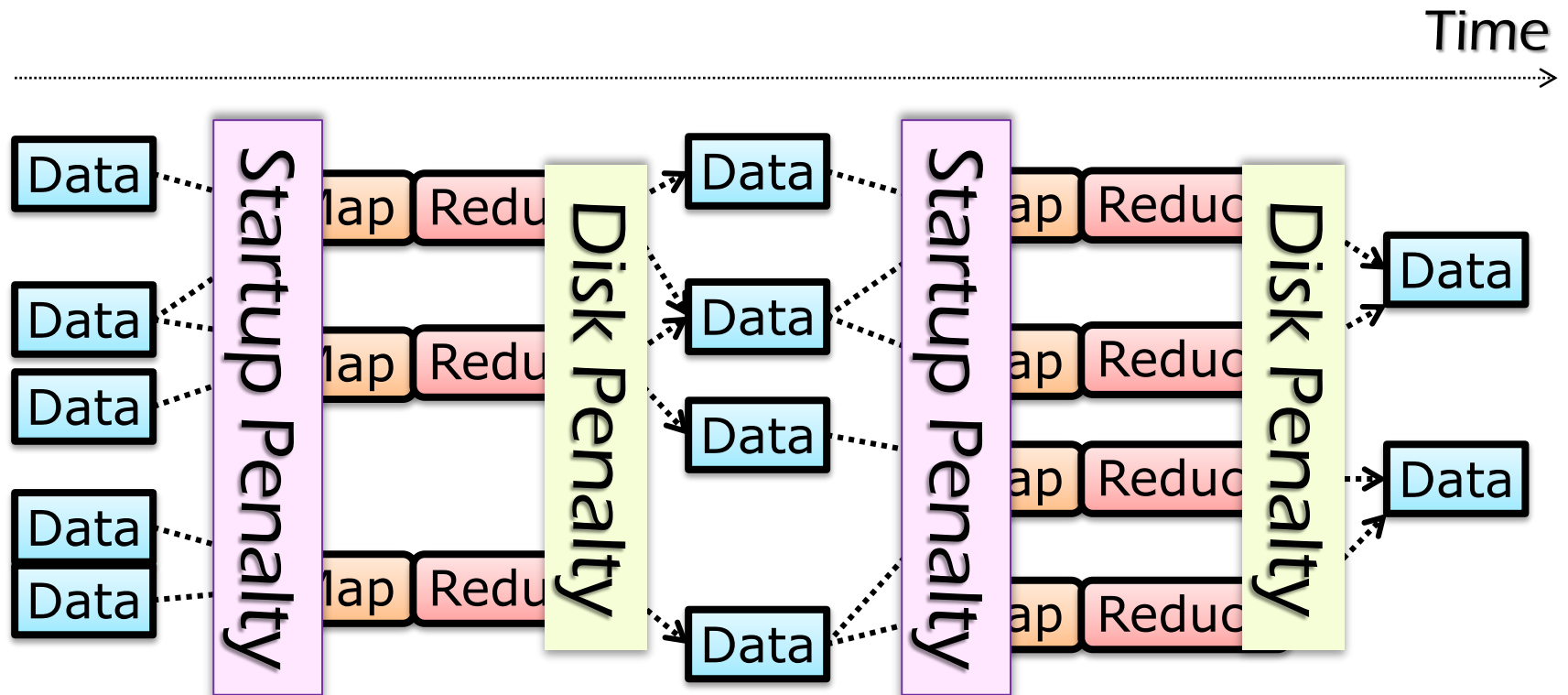
→ Output:

$(V_1, [0.37, V_2, V_3, V_4]); (V_2, [0.08, V_3, V_4]); (V_3, [0.33, V_1]); \dots$

Iterative Comp. is Difficult

MR runtime is not optimized for iteration

- Persistent I/O (e.g., GFS)



What is the Right Tool

Graph-parallel ML



Map Reduce

MPI/Pthreads

Feature
Extraction

Cross
Validation

Computing Sufficient
Statistics

Lasso
Kernel Methods

PageRank
Label
Propagation

Tensor
Factorization

Belief
Propagation

Deep Belief
Networks
Neural
Networks

Threads, Locks and Messages

ML experts repeatedly solve the same parallel design challenges

- Impl. and debug complex parallel systems
- Tune for a specific parallel platform

Threads, Locks and Messages

Graduate Student

~~ML experts~~ repeatedly solve the same parallel design challenges

- Impl. and debug complex parallel systems
- Tune for a specific parallel platform

6 months later, the conference paper contains:

“We implemented ____ in parallel.”

The resulting code

- difficult to maintain and extend

couples **learning model** to **parallel impl.**

What is the Right Tool

Graph-parallel ML



Map Reduce

Feature
Extraction

Cross
Validation

Computing Sufficient
Statistics

Graph-structured
Computation

Lasso PageRank Label
Kernel Methods Propagation
Tensor Belief
Factorization Propagation
Deep Belief Neural
Networks Networks

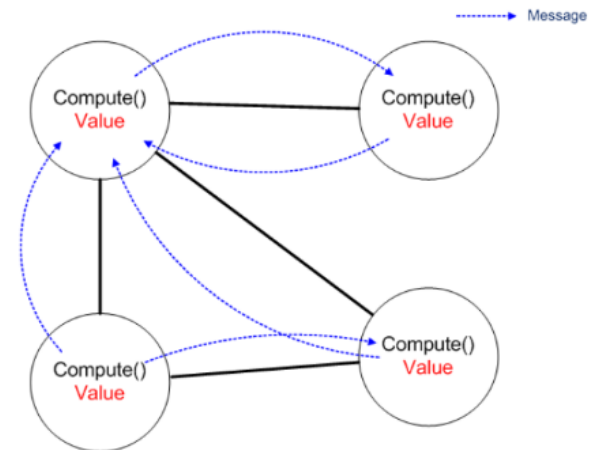
PREGEL

Pregel (Google, 2010)

Inspired by Valiant's
Bulk Synchronous Parallel (BSP) model

Communication through pure **message-passing**
(usually sent along the outgoing edges from each vertex)
+ **shared-nothing**

Vertex-centric programming
"Think like a vertex"

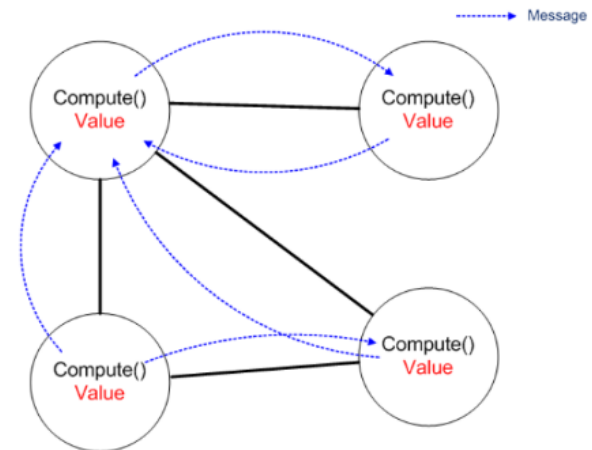


Pregel (Google, 2010)

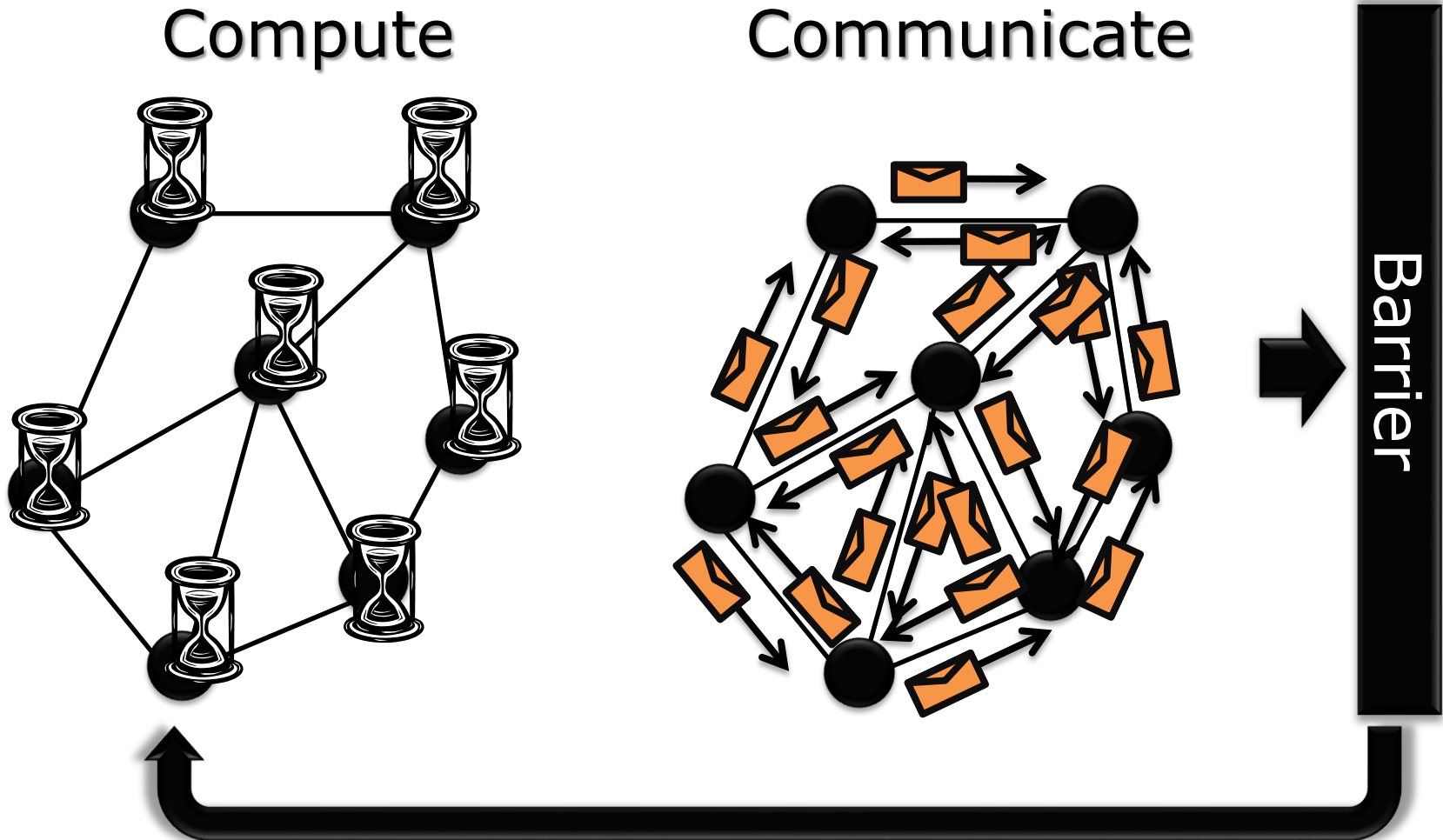
Each vertex

1. **Receives messages** sent in the **previous** superstep
2. Executes the same **user-defined function**
3. Modifies its value
4. If active, sends messages to other vertices (received in the **next** superstep)
5. Votes to halt if it has no further work to do → inactive

Terminate when
all vertices are **inactive** and
no messages in transit

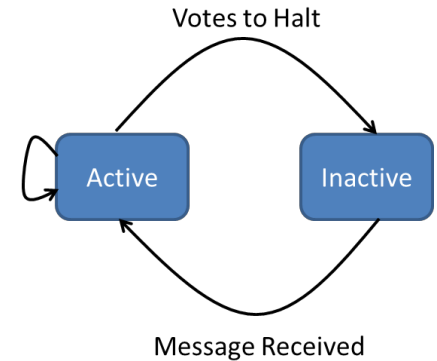
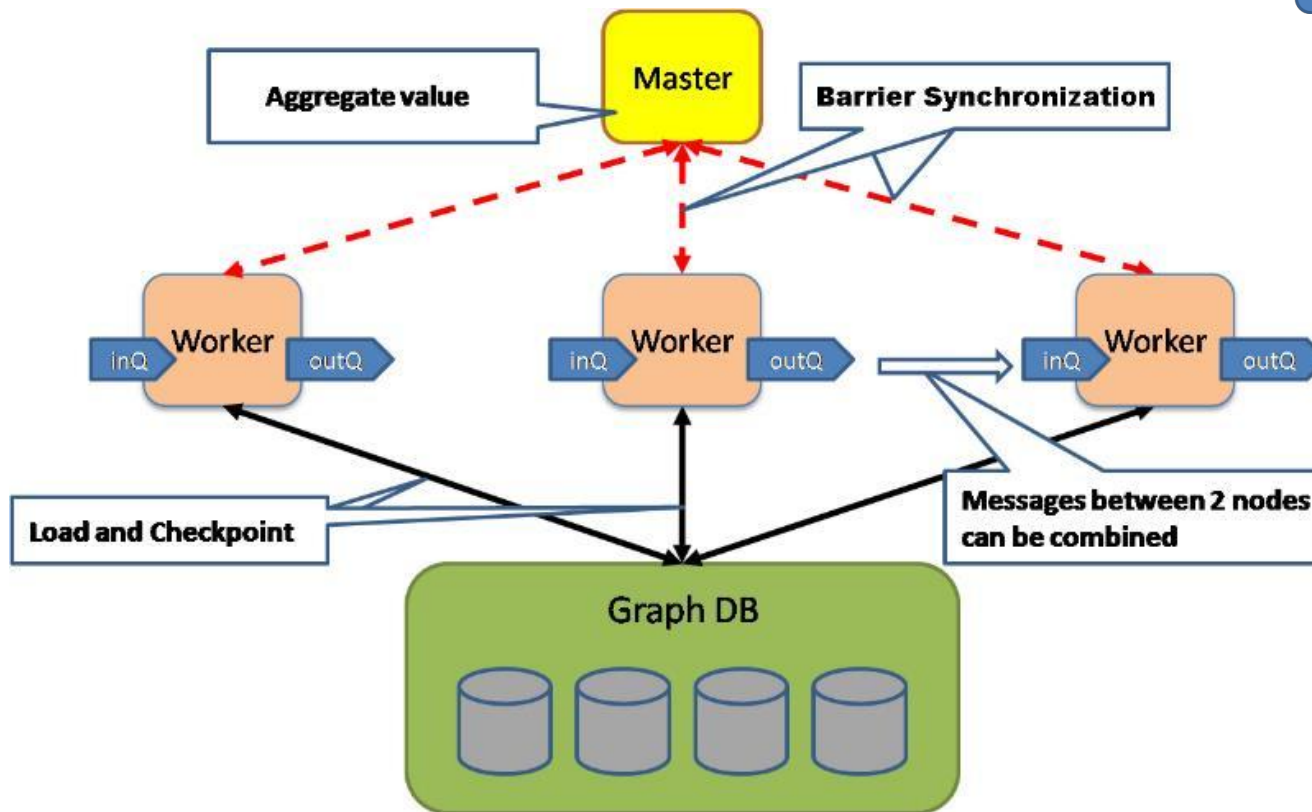


Bulk Synchronous Parallel Model



System Architecture of Pregel

Master-Slave architecture

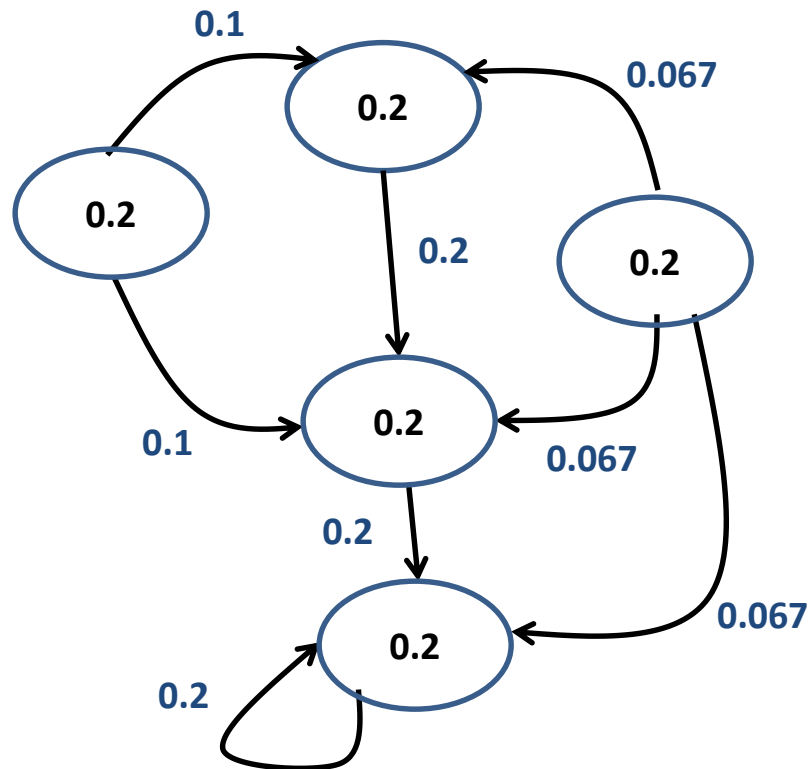


PageRank on Pregel

Superstep 0: PR value of each vertex $1/\text{NumVertices}()$

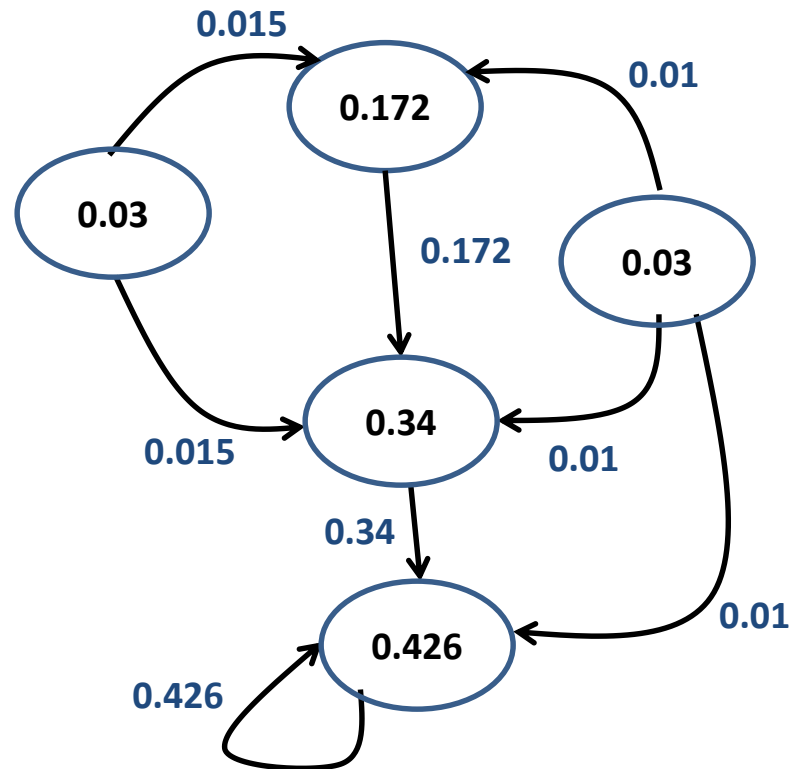
```
Class PageRankVertex {
public:
    virtual void Compute(MessageIterator* msgs) {
        if (superstep () >= 1) {
            double sum = 0;
            for (; !msgs->Done(); msgs->Next())
                sum += msgs->Value();
            *MutableValue() = 0.15/NumVertices() + 0.85*sum;
        }
        if (superstep() < 30) {
            const int64 n = GetOutEdgeIterator().size();
            SendMessageToAllNeighbors(GetValue() / n);
        } else {
            VoteToHalt();
        }
    }
}
```

PageRank on Pregel



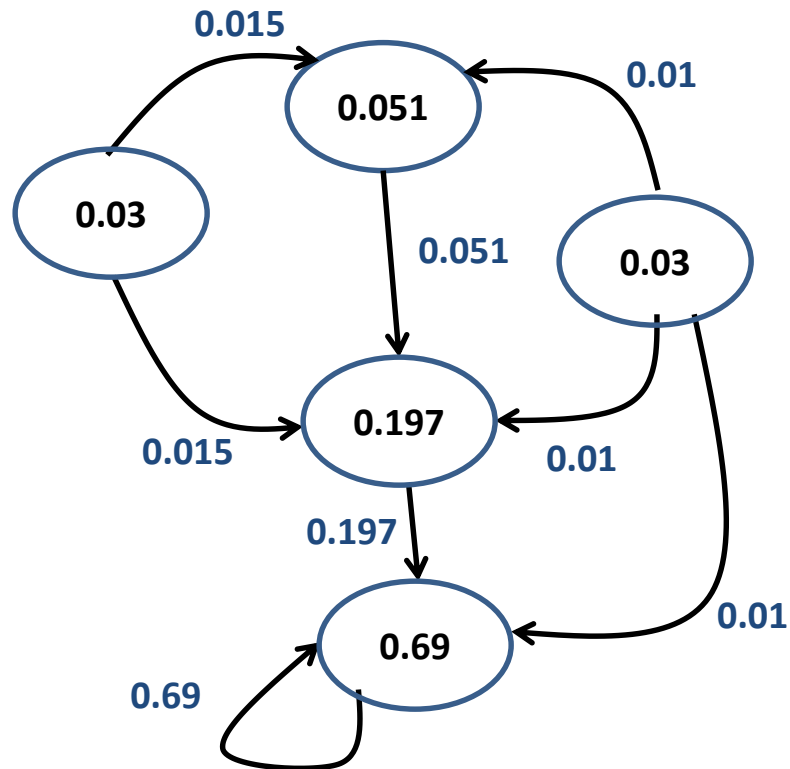
Superstep = 0

PageRank on Pregel



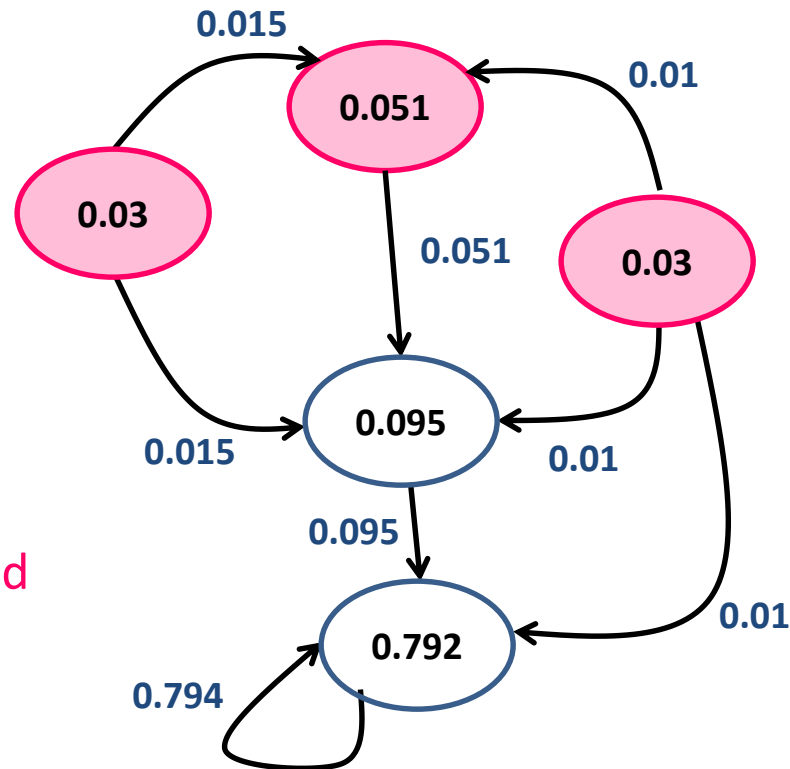
Superstep = 1

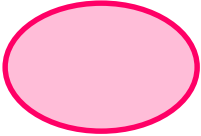
PageRank on Pregel



Superstep = 2

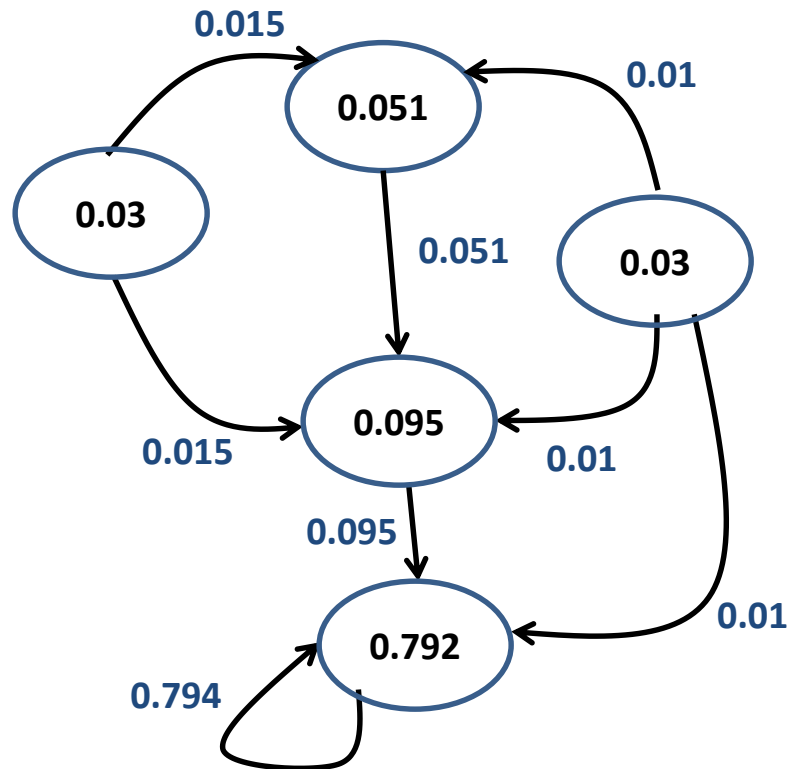
PageRank on Pregel




Computation converged

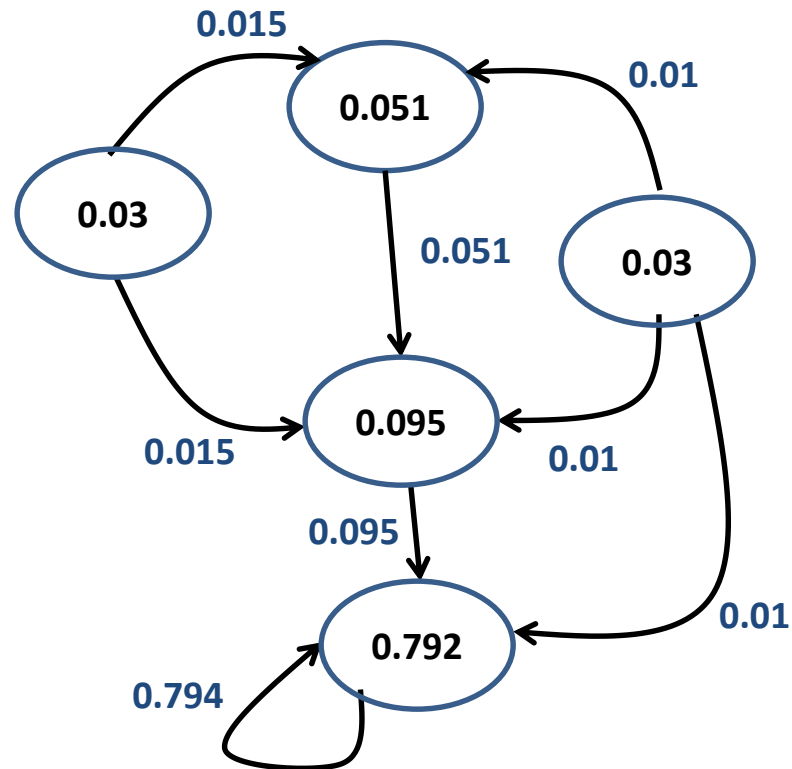
Superstep = 3

PageRank on Pregel



Superstep = 4

PageRank on Pregel

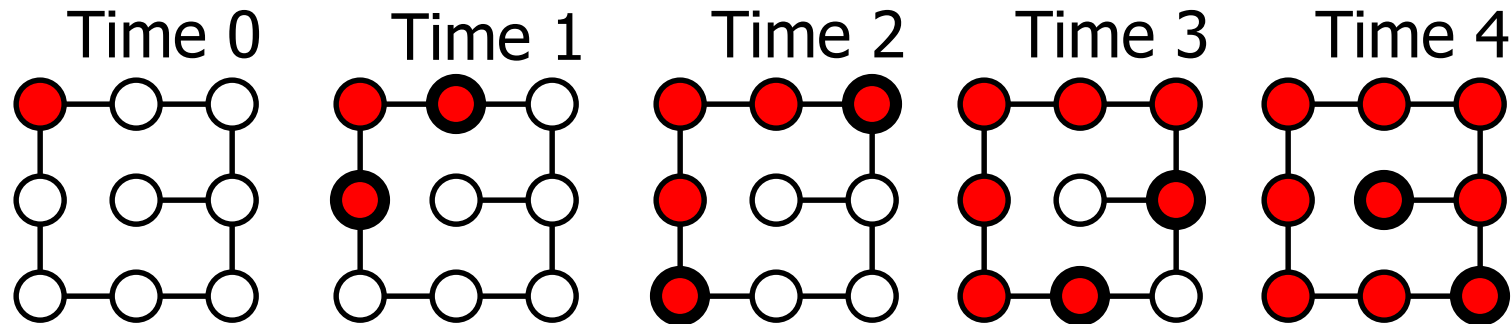


Superstep = 5

GRAPHLAB

Problem with BSP Model

Example Algorithm: If Red neighbor then turn Red



Bulk Synchronous Parallel Computation :

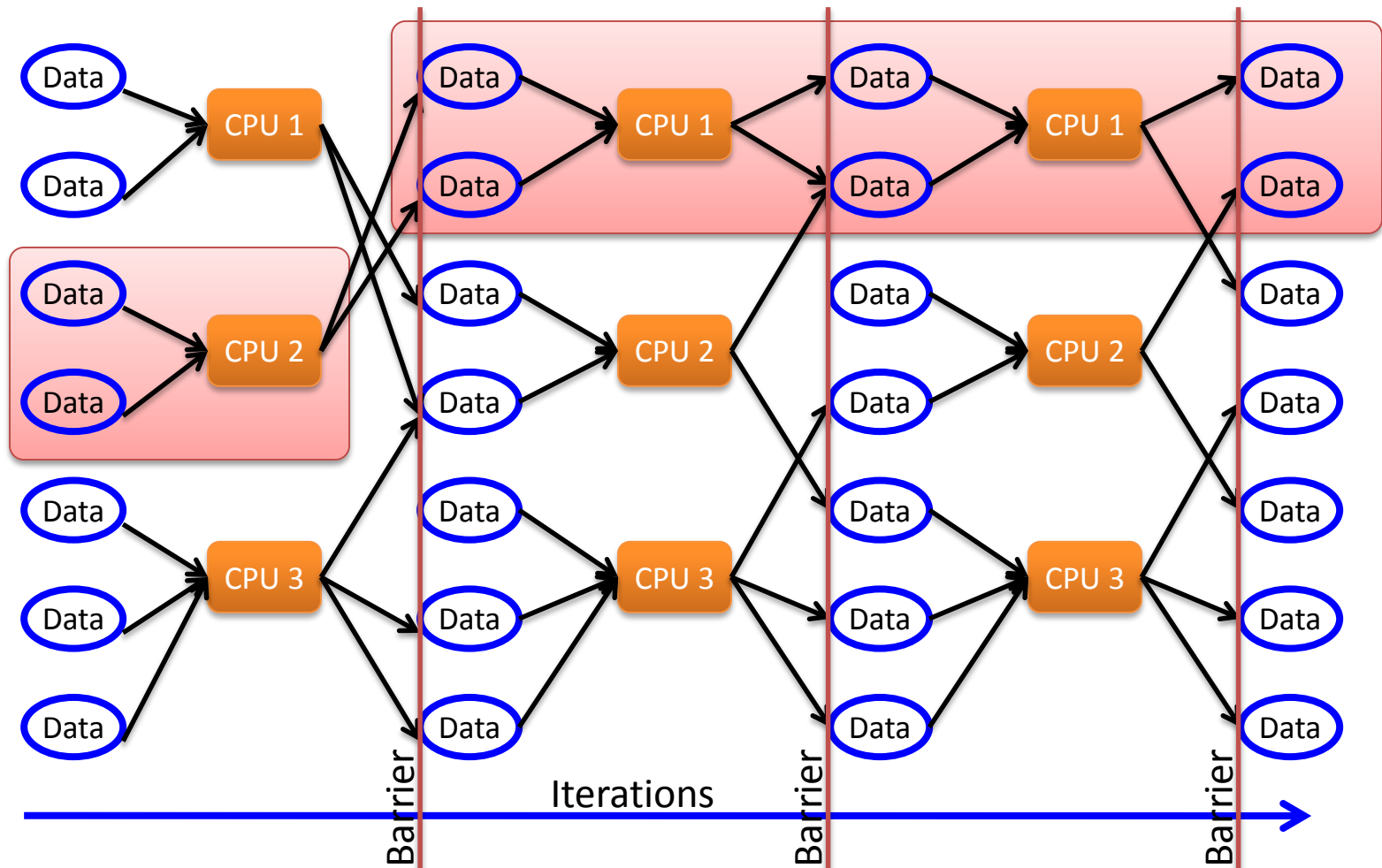
- Evaluate condition on all vertices for every phase
4 Phases each with 9 computations → 36 Computations

Asynchronous Computation:

- Evaluate condition only when neighbor changes
4 Phases each with 2 computations → 8 Computations

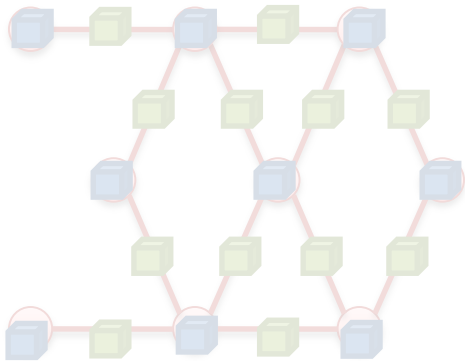
Problem with BSP Model

performance is limited by the slowest machine

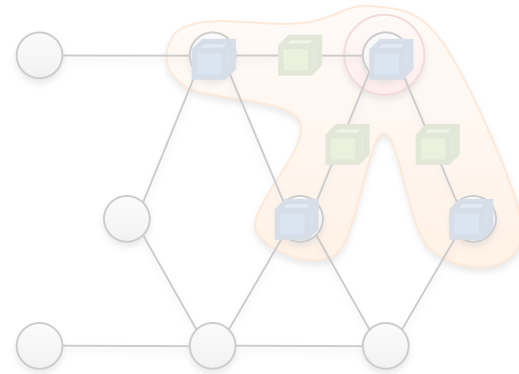


GraphLab Framework

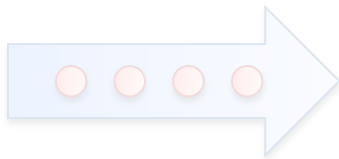
Graph Based
Data Representation



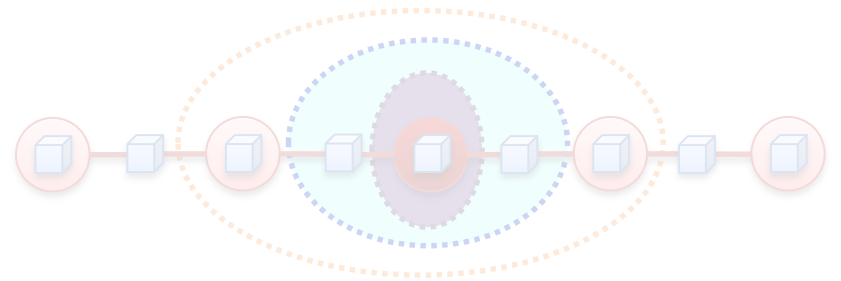
Update Functions
User Computation



Scheduler

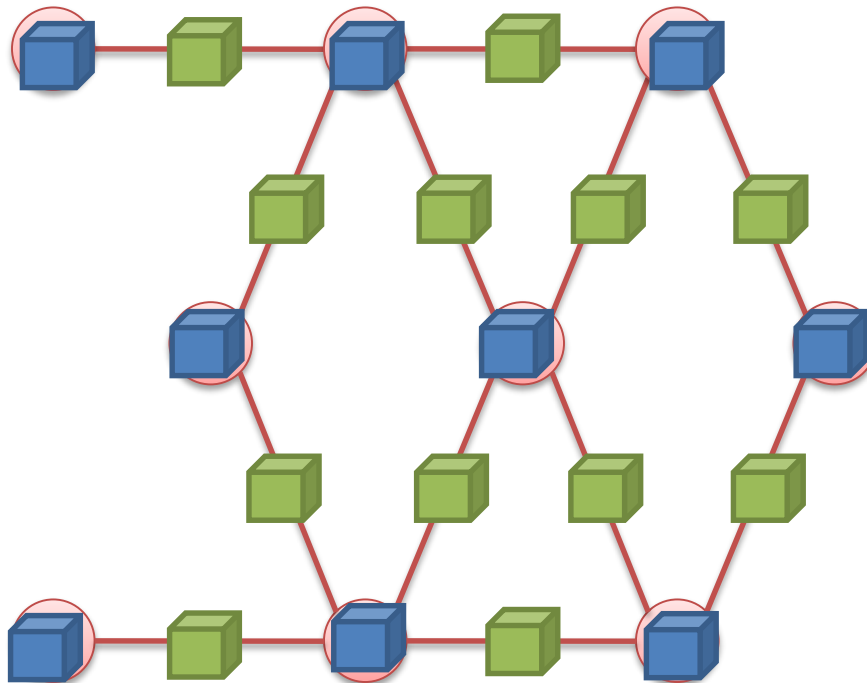


Consistency Model



Data Graph

A graph with arbitrary data (C++ *Objects*) associated with each vertex and edge



Graph: **Social Network**



Vertex Data: 

1. User profile text
2. Current interests estimates

Edge Data: 

1. Similarity weights

Implementation

All data and structure is stored in **memory**

- Supports fast random lookup needed for dynamic computation

Multicore Setting

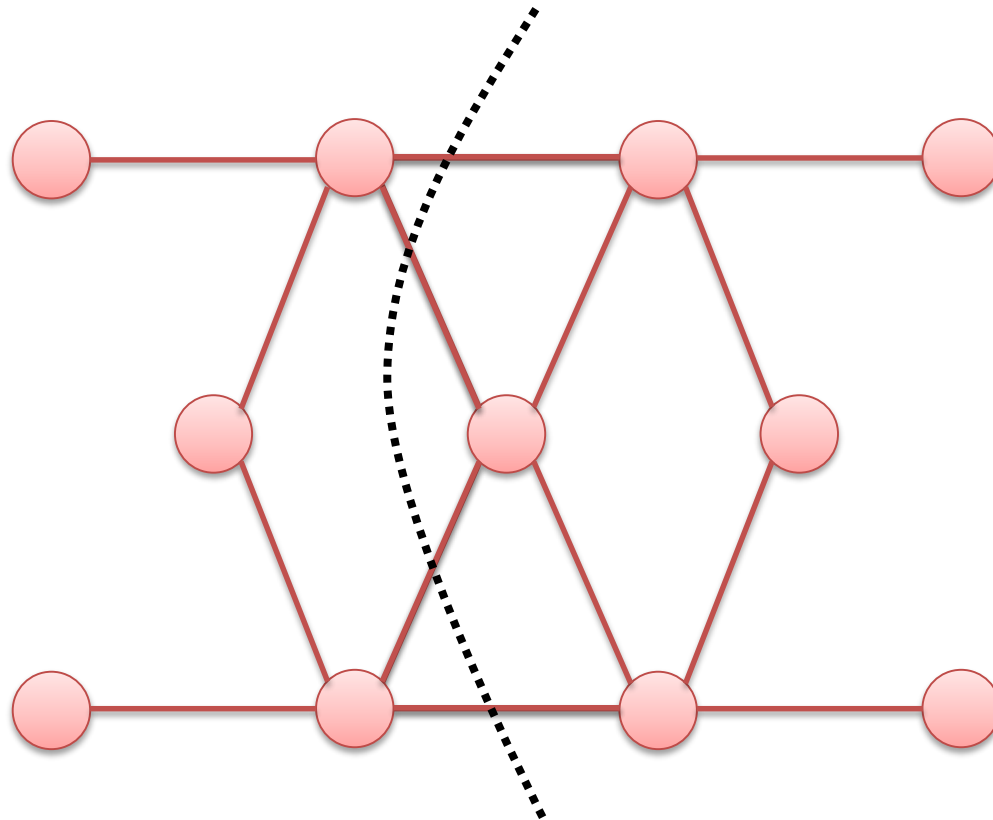
- Challenge: Fast lookup, low overhead
- Solution → dense data-structures (e.g., array)

Distributed Setting

- Challenge: Graph partitioning
- Solution → ParMetis and Random placement

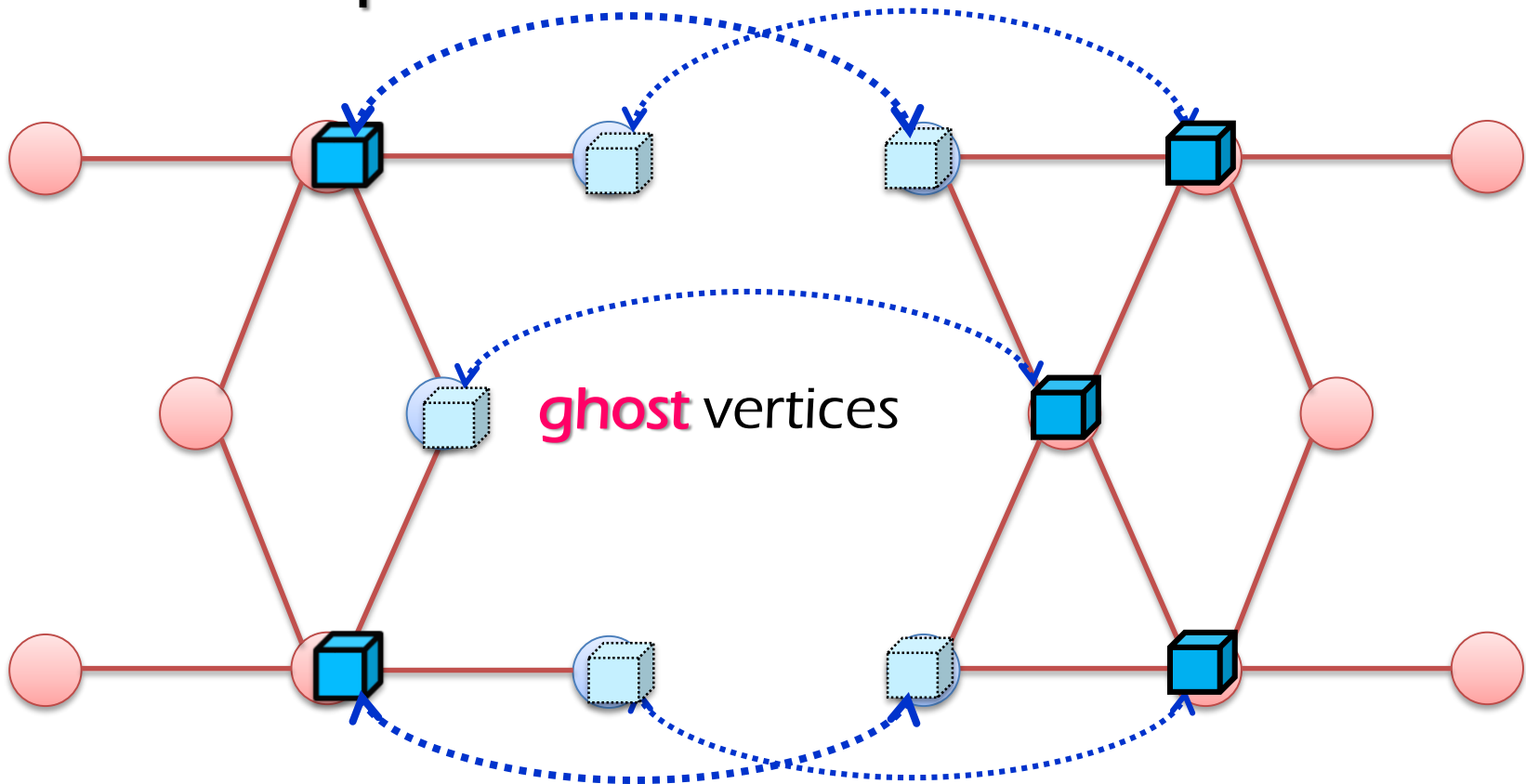
Distributed Graph

Partition the graph across multiple machines



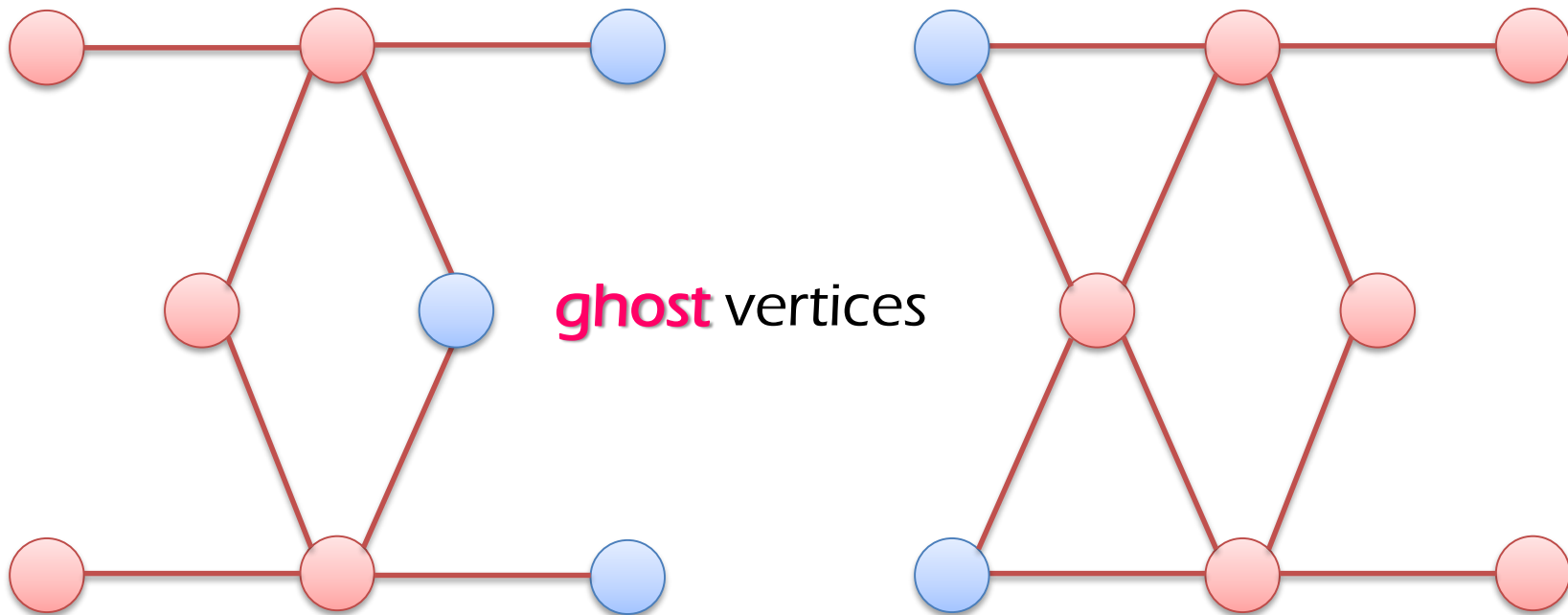
Distributed Graph

Ghost vertices maintain adjacency structure and replicate remote data



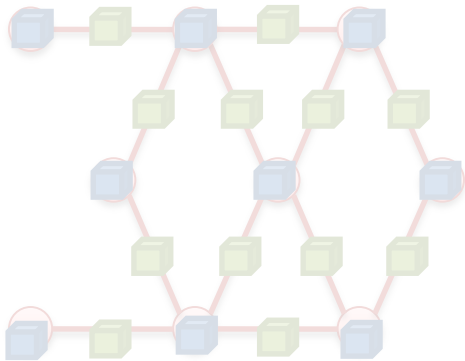
Distributed Graph

Cut efficiently using HPC Graph partitioning tools (e.g., ParMetis, ...)

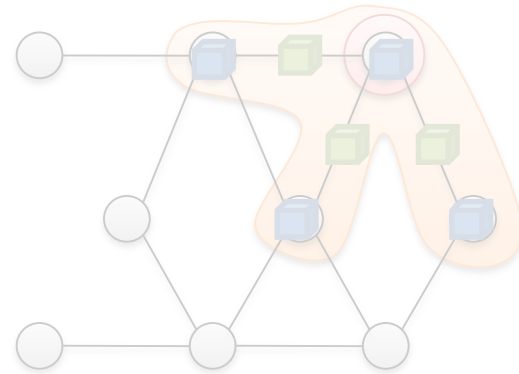


GraphLab Framework

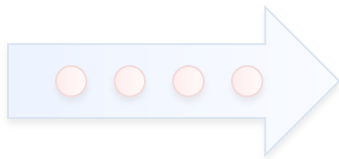
Graph Based
Data Representation



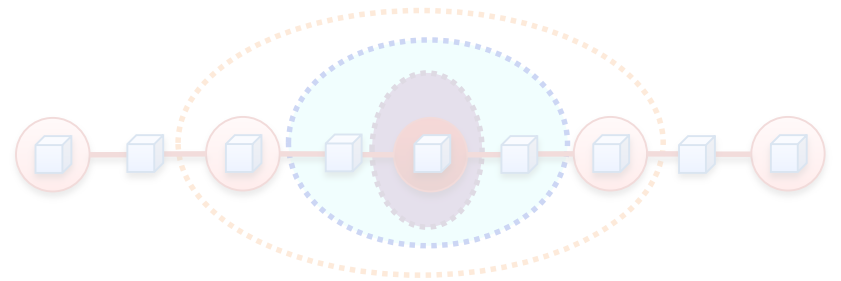
Update Functions
User Computation



Scheduler

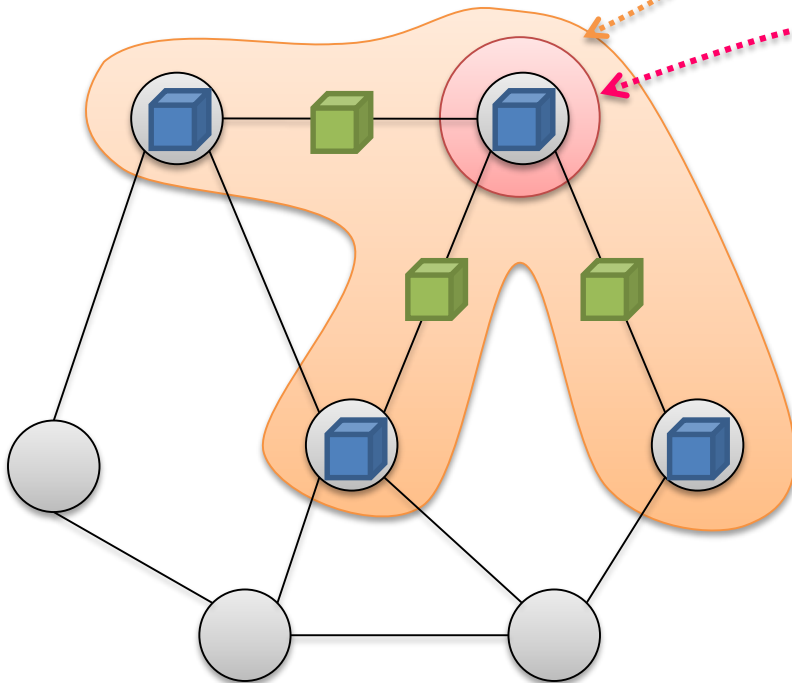


Consistency Model



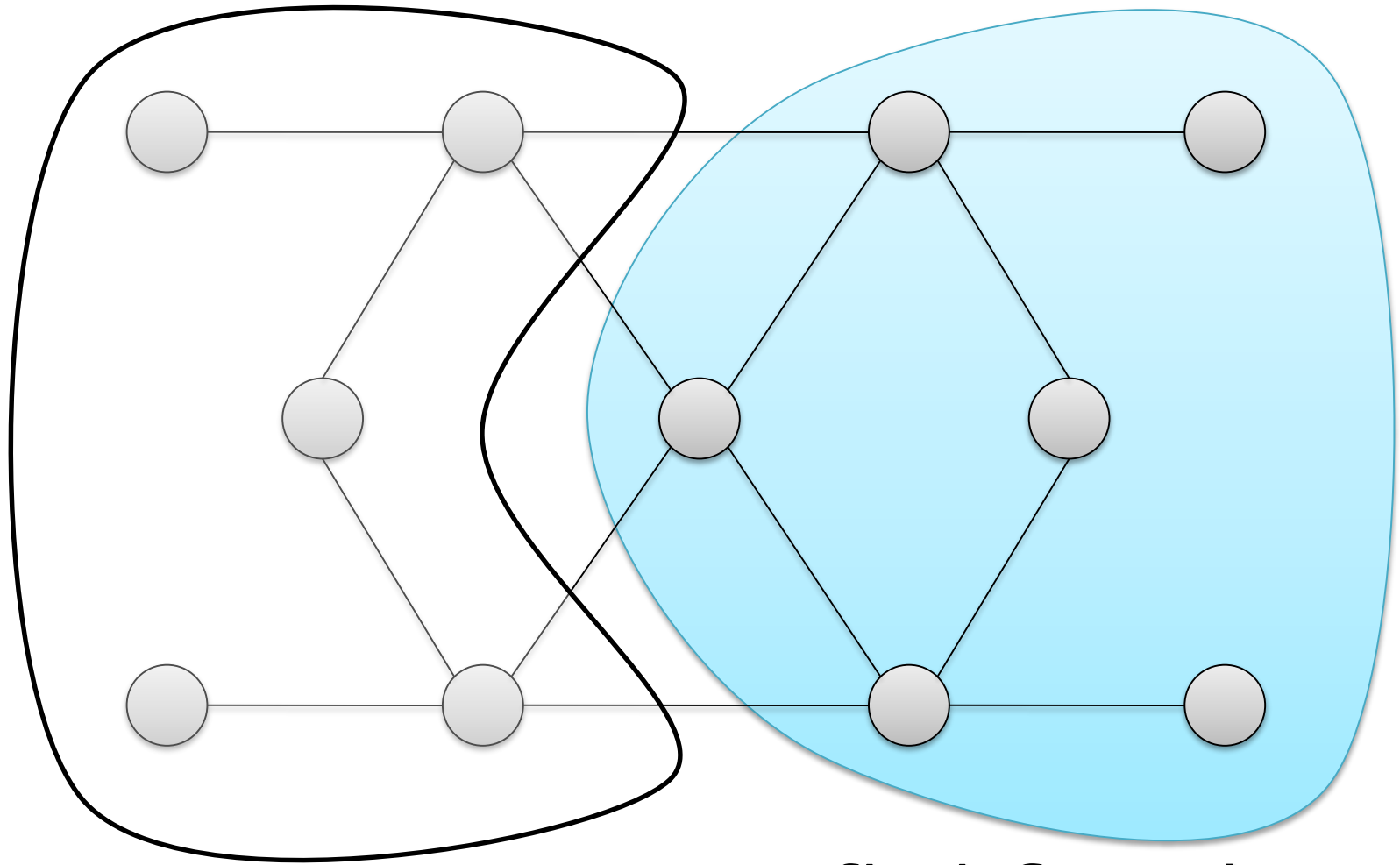
Update Function

update function: a user defined program which when applied to a **vertex** transforms the data in the **scope** of the vertex



```
void PageRank(scope) {  
    // Get Neighborhood data  
    float sum = 0, diff;  
    float last = this.val;  
    foreach (nbr in scope.in_nbrs)  
        sum += nbr.val/nbr.nout_nbrs;  
  
    // Update the vertex data  
    this.val = 0.15 + 0.85*sum;  
  
    // Reschedule Nbrs if needed  
    diff = abs(this.val - last);  
    if (diff > epsilon)  
        reschedule(this.out_nbrs);  
}
```

Dynamic Computation

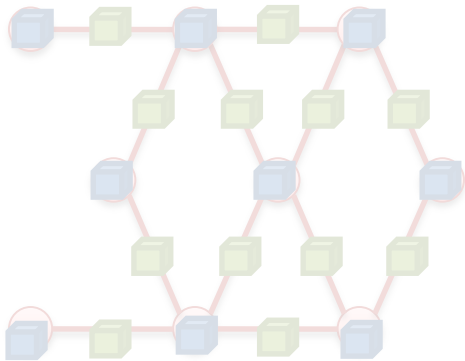


Converged

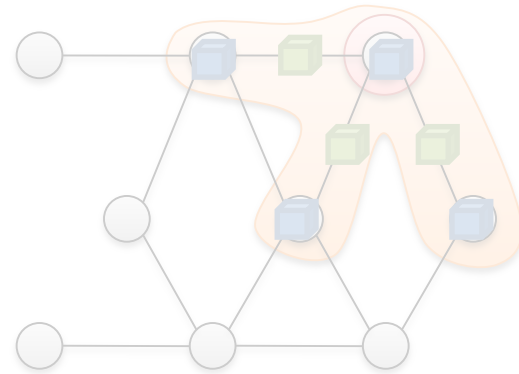
**Slowly Converging
Focus Effort**

GraphLab Framework

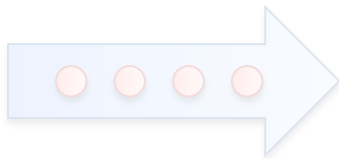
Graph Based
Data Representation



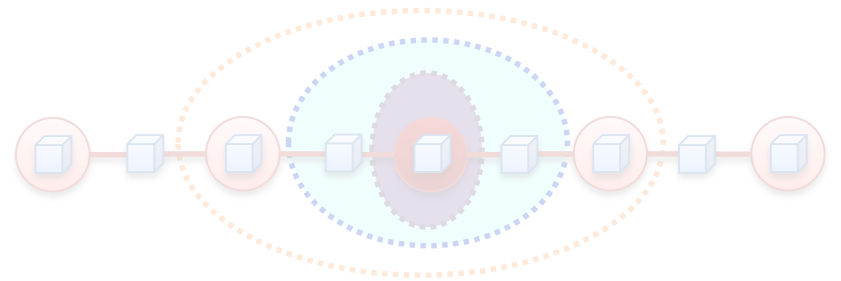
Update Functions
User Computation



Scheduler

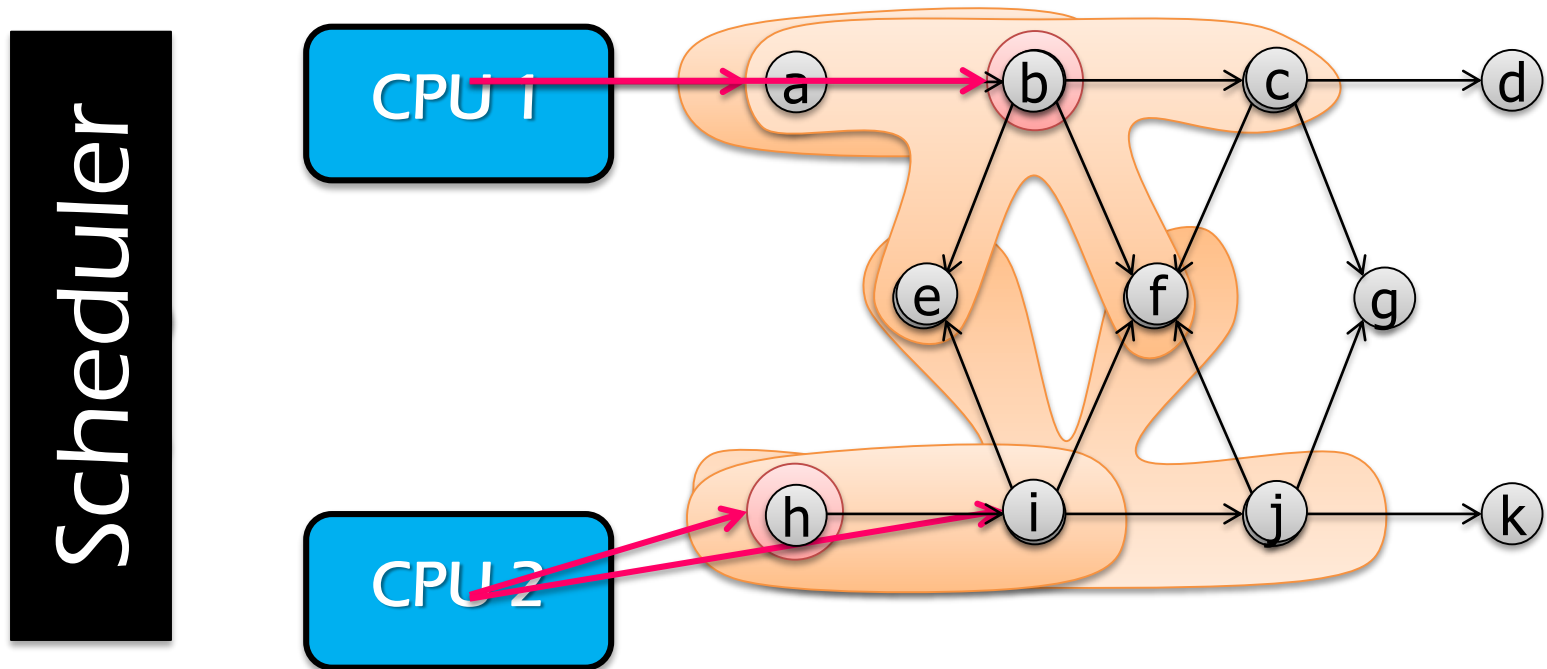


Consistency Model



GraphLab Scheduler

The scheduler determines the order that vertices are updated



The process repeats until the scheduler is empty

GraphLab Scheduler

The choice of schedule affects
the correctness and parallel performance
of the algorithm

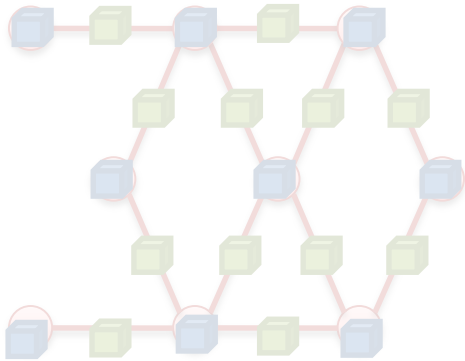
GraphLab provides several diff schedulers

- Vertices are updated

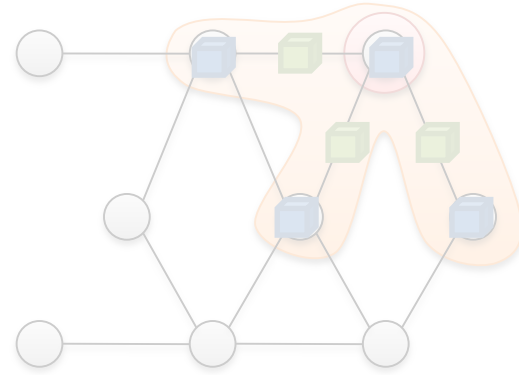
→ **Round Robin, FIFO, Priority**

GraphLab Framework

Graph Based
Data Representation



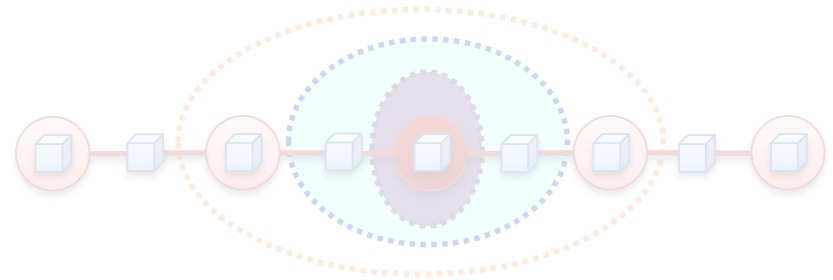
Update Functions
User Computation



Scheduler

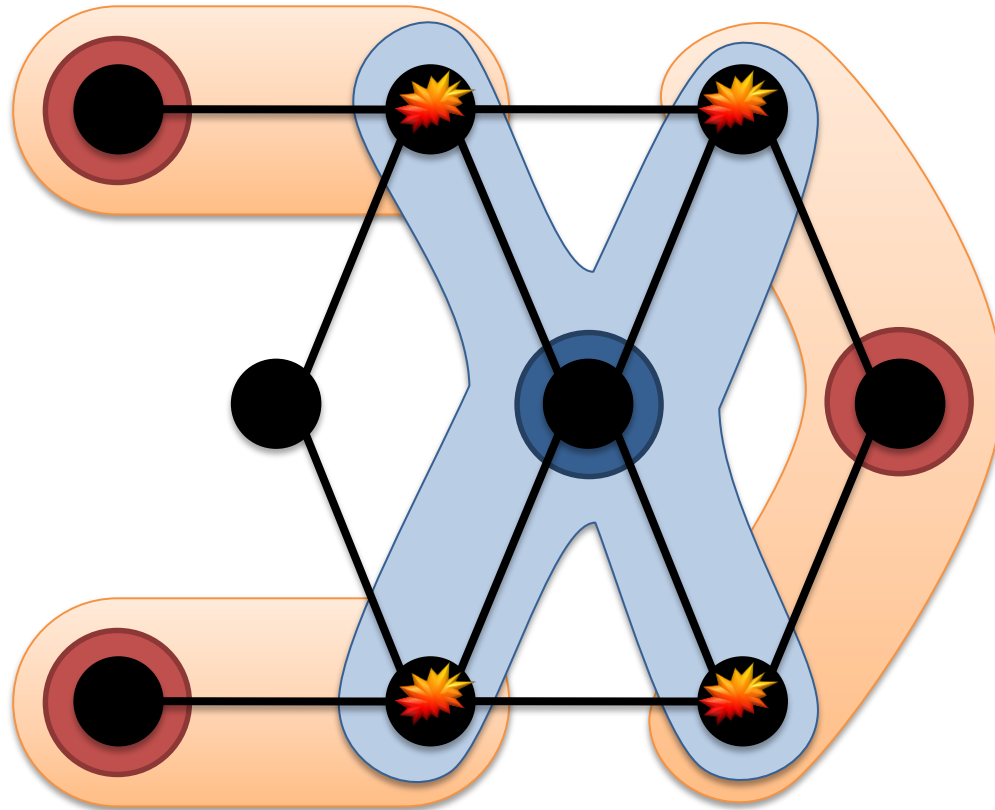


Consistency Model



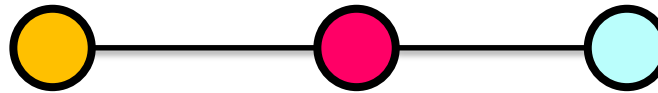
Race-free Execution

How much can computation overlap?



Sequential Consistency

For each parallel execution, there exists a sequential execution of update functions which produces the same result.



Parallel

CPU 1

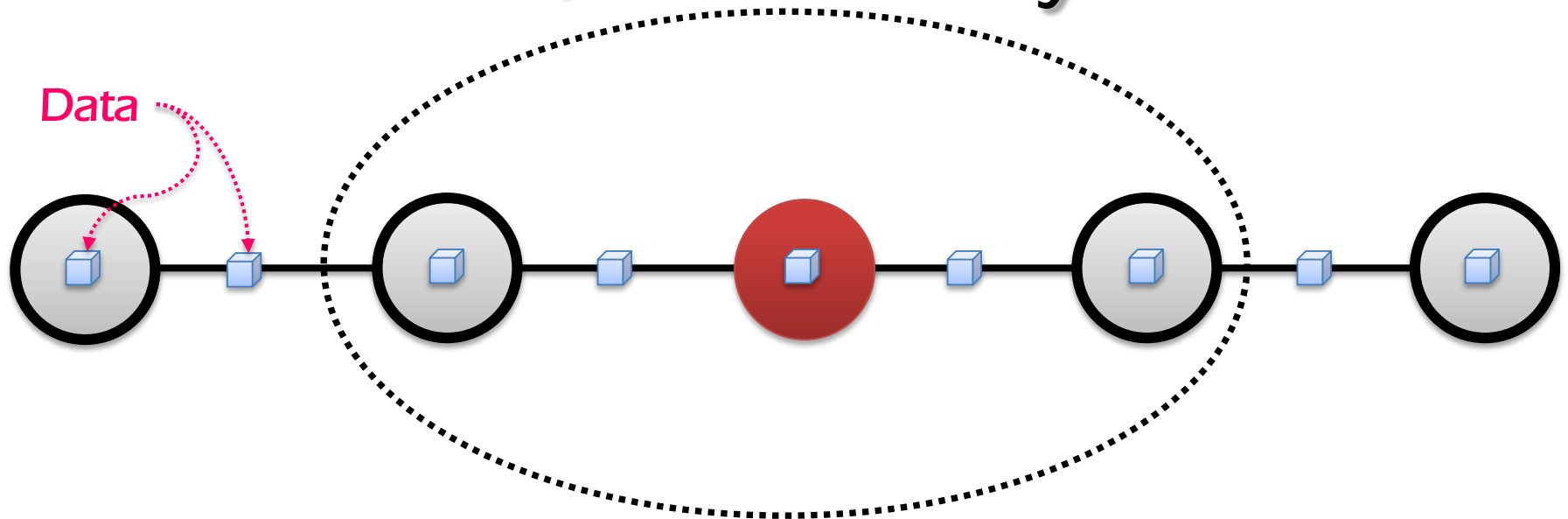
CPU 2

Sequential

Single
CPU

Consistency Rule

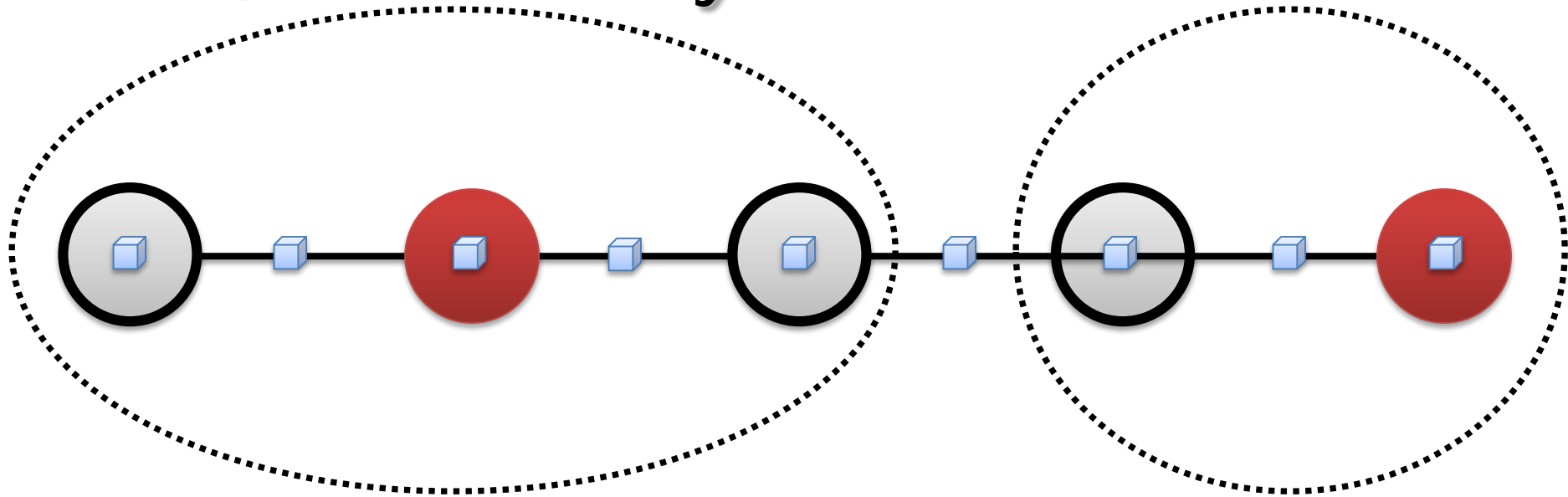
Full Consistency



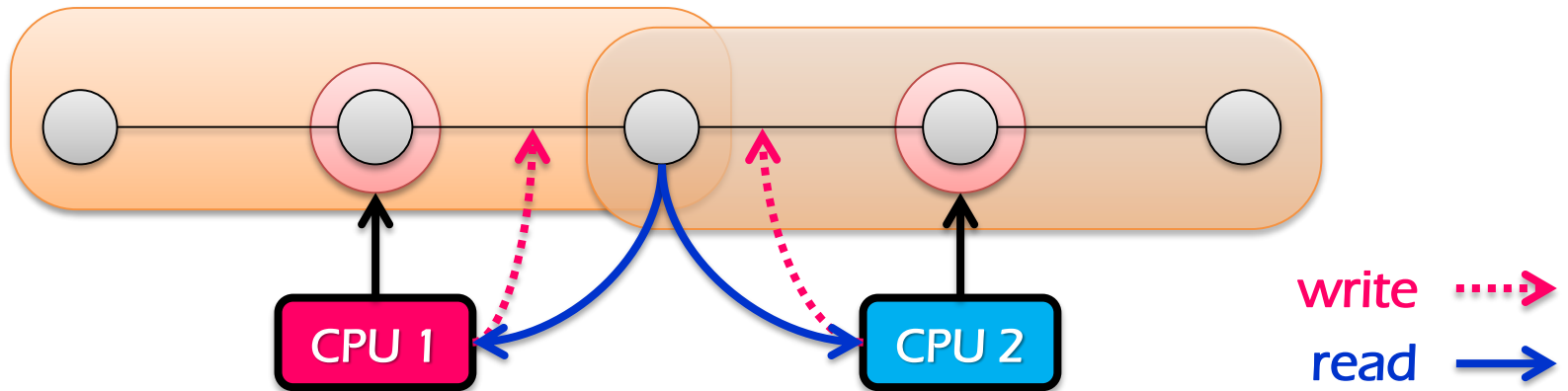
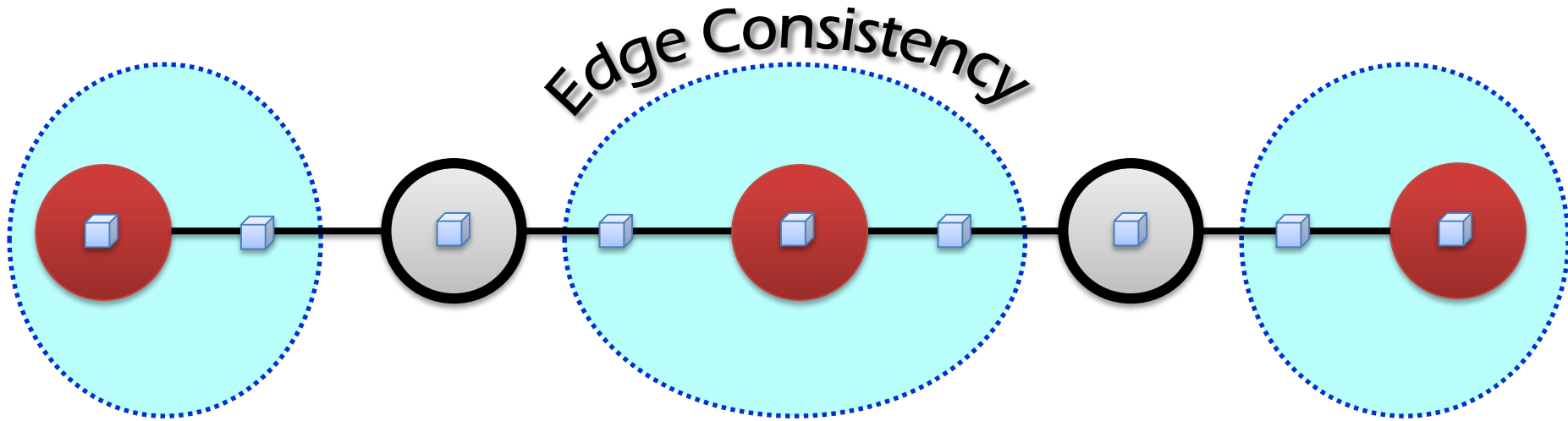
Guaranteed sequential consistency
for all update functions

Full Consistency

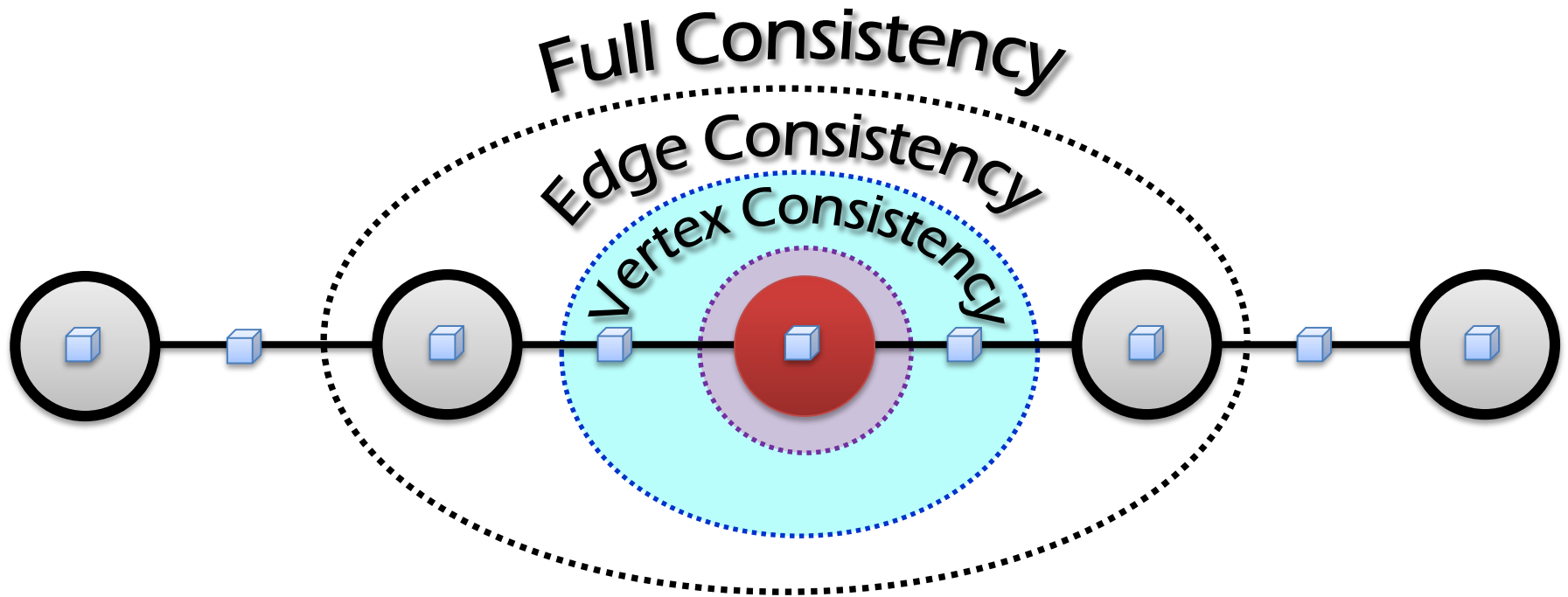
Full Consistency



Edge Consistency



More Parallelism



Consistency through Scheduling

Edge Consistency Model

- Two vertices can be updated **simultaneously**
→ they do not share an edge

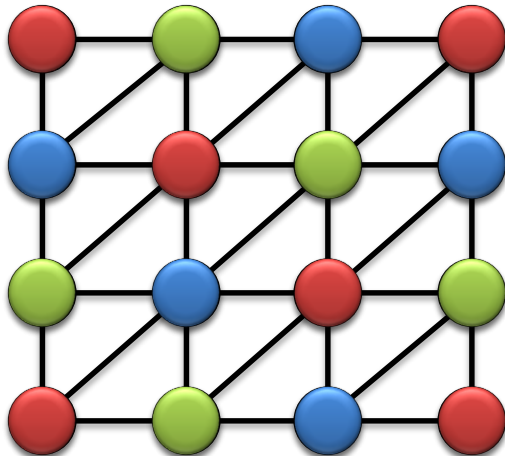
Consistency through Scheduling

Edge Consistency Model

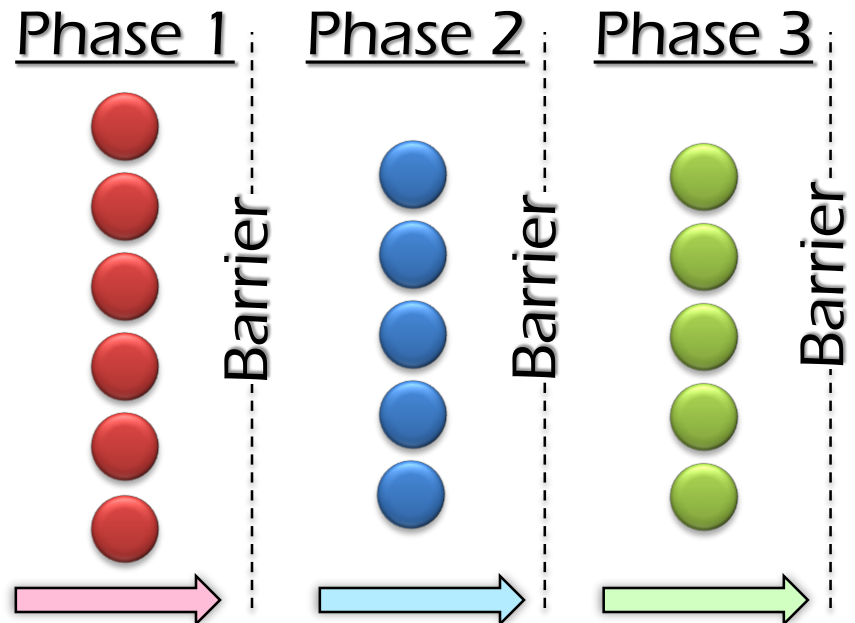
- Two vertices can be updated **simultaneously**
→ they do not share an edge

same color

Graph Coloring



Execute in Parallel
Synchronously



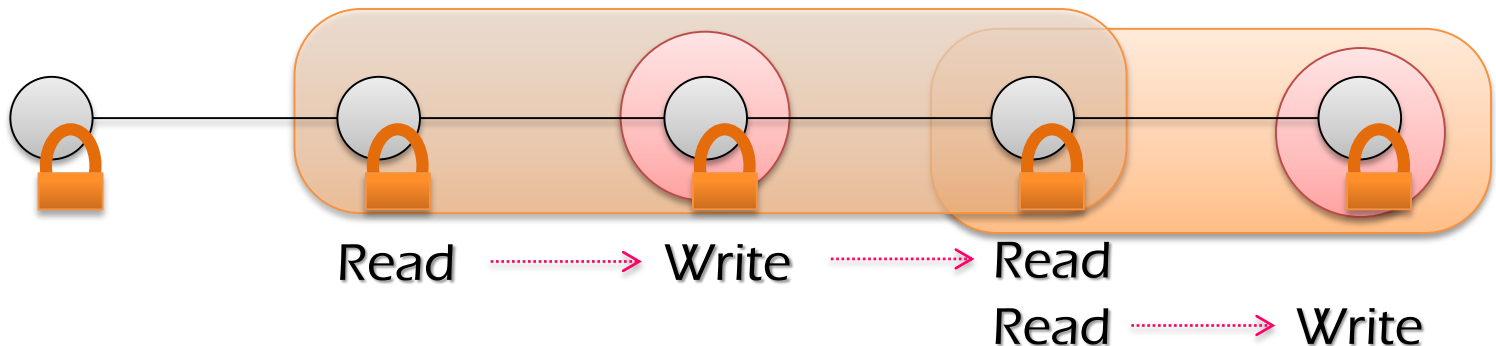
Consistency through R/W Locks

Multicore Setting: R/W Locks (Pthread)

- **Full** consistency



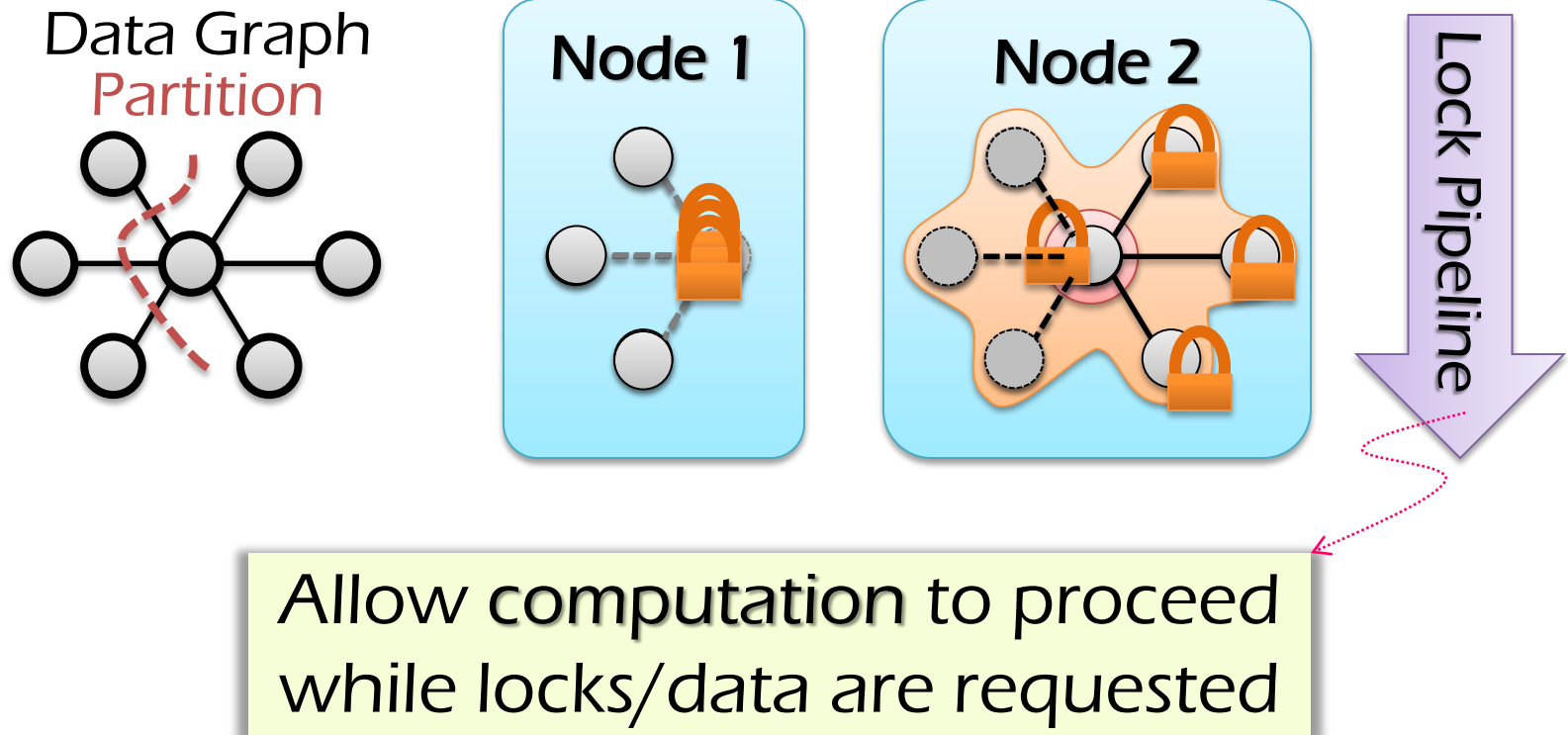
- **Edge** consistency



Consistency through **R/W Locks**

Distributed Setting: Distributed Locking

- Prefetch Locks and Data



Conclusion

An **abstraction** tailored to Machine Learning

A **distributed** and **parallel** framework
which compactly expresses

- Data/computational dependencies
- Iterative computation

Next Lecture

Topic: Graph-structure analytics (II)

Paper

Rong Chen et al., “**PowerLyra: Differentiated Graph Computation and Partitioning on Skewed Graphs**”. 10th ACM SIGOPS European Conference on Computer Systems (EuroSys), **2015**

THANKS