Automatic Scaling Iterative Computations

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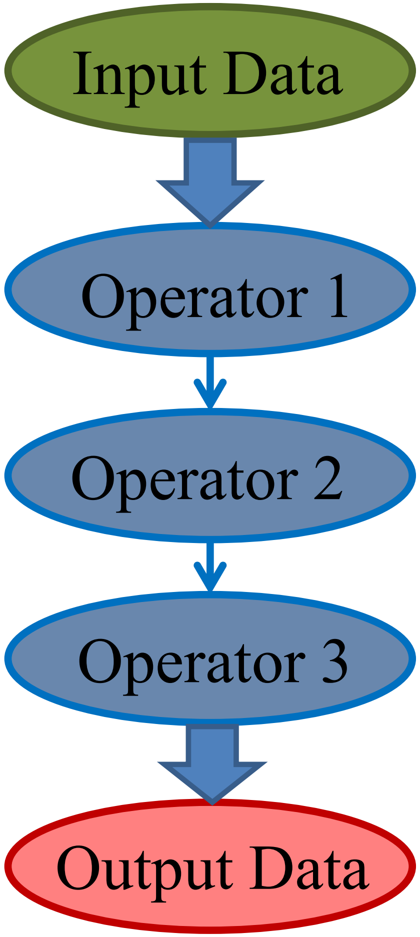
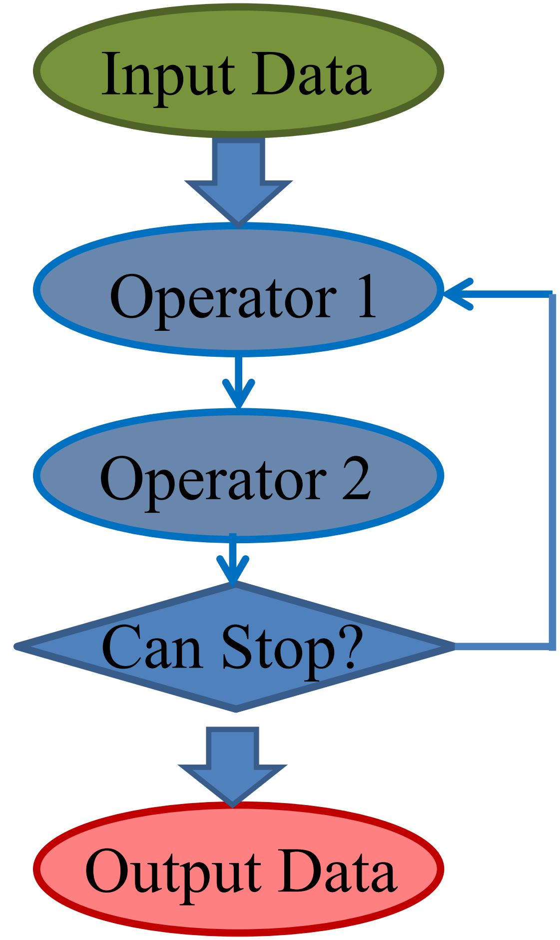
What are Non-Iterative Computations?

- Non-iterative computation flow
  - Directed Acyclic
- Examples
  - Batch style analytics
    - Aggregation
    - Sorting
  - Text parsing
    - Inverted index
  - etc..



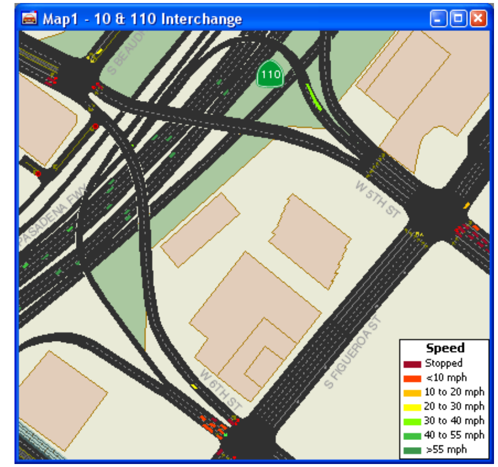
What are Iterative Computations?

- Iterative computation flow
  - Directed ***Cyclic***
- Examples
  - Scientific computation
    - Linear/differential systems
    - Least squares, eigenvalues
  - Machine learning
    - SVM, EM algorithms
    - Boosting, K-means
  - Computer Vision, Web Search, etc ..



Massive Datasets are Ubiquitous

- Traffic behavioral simulations
  - Micro-simulator cannot scale to NYC with millions of vehicles



- Social network analysis
  - Even computing graph radius on single machine takes a long time

- Similar scenarios in predicative analysis, anomaly detection, etc

Why Hadoop Not Good Enough?

- Re-shuffle/materialize data between operators
  - Increased overhead at each iteration
  - Result in bad performance

- Batch processing records within operators
  - Not every records need to be updated
  - Result in slow convergence

Talk Outline

- Motivation
- Fast Iterations: BRACE for Behavioral Simulations
- Fewer Iterations: GRACE for Graph Processing
- Future Work

Challenges of Behavioral Simulations

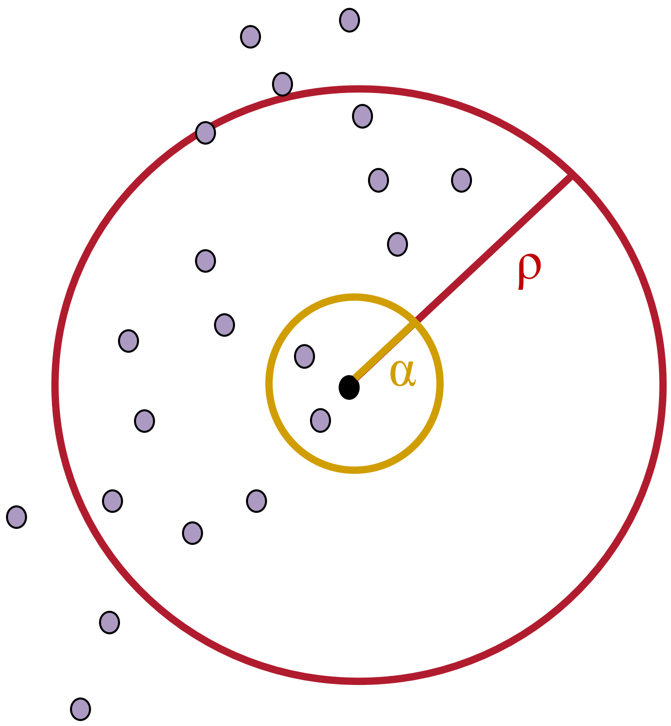
- ***Easy to program → not scalable***
  - Examples: Swarm, Mason
  - Typically one thread per agent, lots of contention
- ***Scalable → hard to program***
  - Examples: TRANSIMS, DynaMIT (traffic), GPU implementation of fish simulation (ecology)
  - Hard-coded models, compromise level of detail

What Do People Really Want?

- A new simulation platform that combines:
  - Ease of programming
    - Scripting language for domain scientists
  - Scalability
    - Efficient parallel execution runtime

A Running Example: Fish Schools

- Adapted from Couzin et al., Nature 2005
- Fish Behavior
  - Avoidance: if too close, repel other fish
  - Attraction: if seen within range, attract other fish
  - Spatial locality for both logics

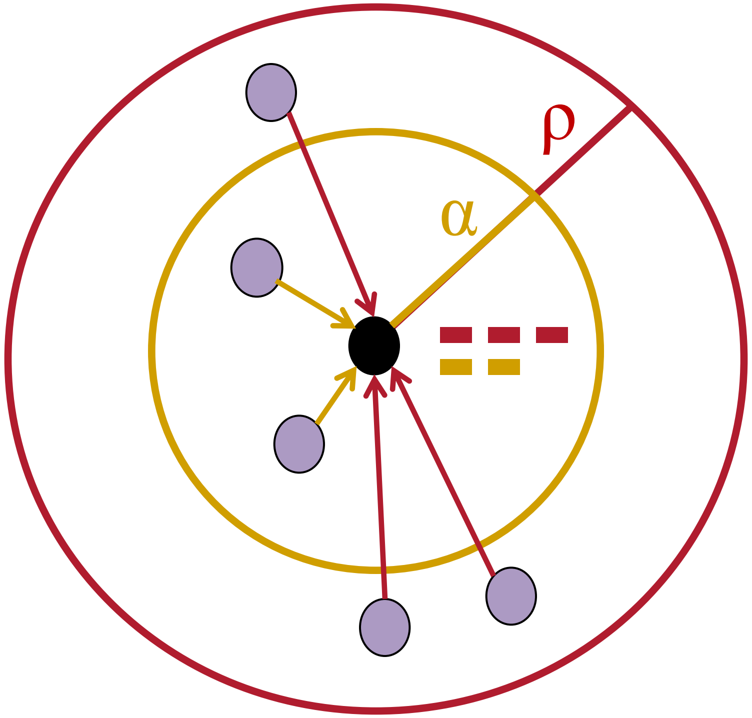


State-Effect Pattern

- Programming pattern to deal with concurrency
- Follows time-stepped model
- **Core Idea:** Make all actions inside of a tick *order-independent*

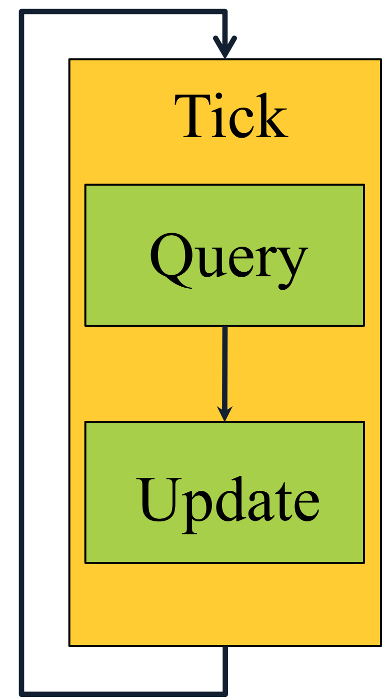
States and Effects

- States:
  - Snapshot of agents at the beginning of the tick
    - position, velocity vector
- Effects:
  - Intermediate results from interaction, used to calculate new states
    - sets of forces from other fish



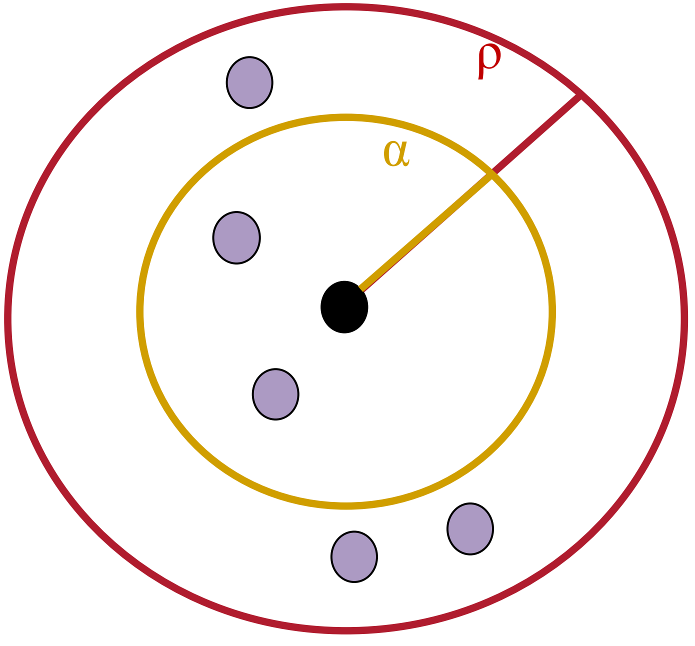
Two Phases of a Tick

- Query: capture agent interaction
  - Read states → write effects
  - Each effect set is associated with *combinator* function
  - Effect writes are *order-independent*
- Update: refresh world for next tick
  - Read effects → write states
  - Reads and writes are totally local
  - State writes are *order-independent*



A Tick in State-Effect

- Query
  - For fish f in visibility α:
    - Write repulsion to f's effects
  - For fish f in visibility ρ:
    - Write attraction to f's effects
- Update
  - new velocity = combined repulsion + combined attraction + old velocity
  - new position = old position + old velocity



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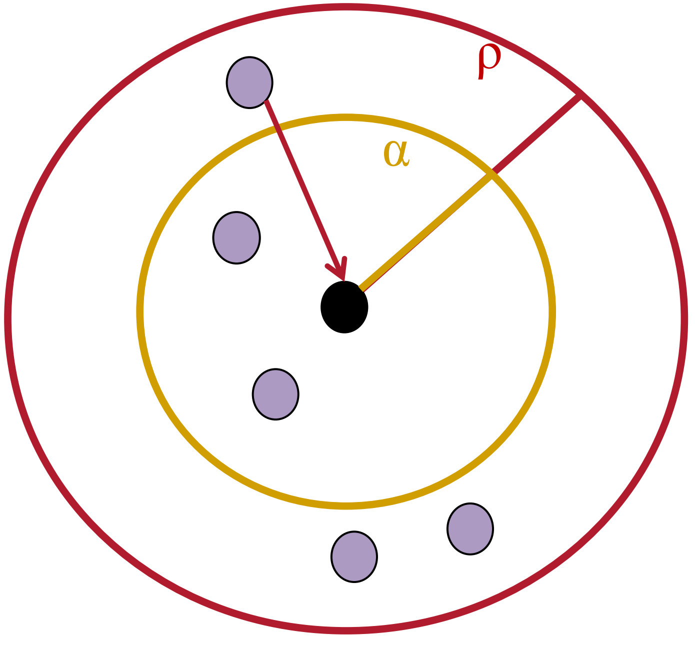

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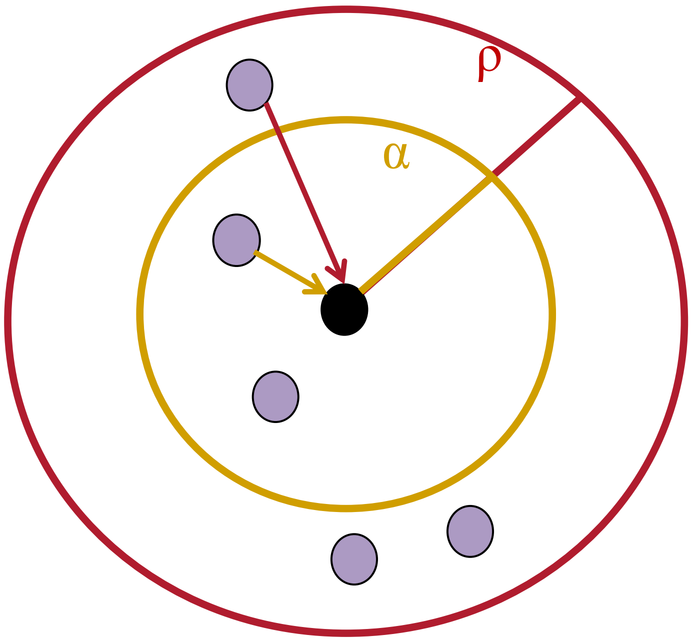

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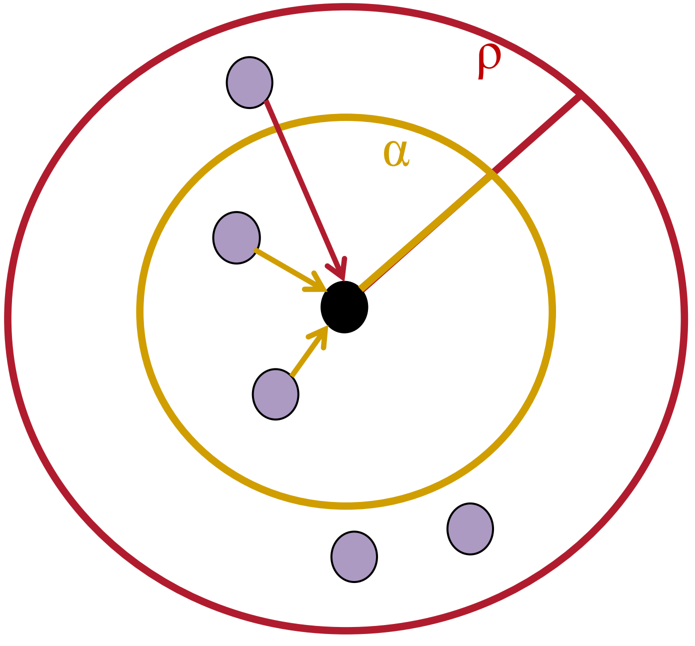

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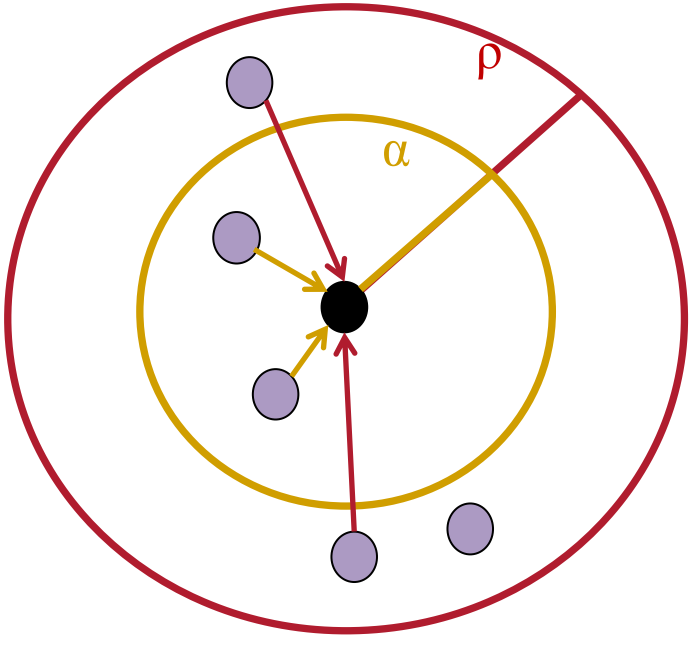

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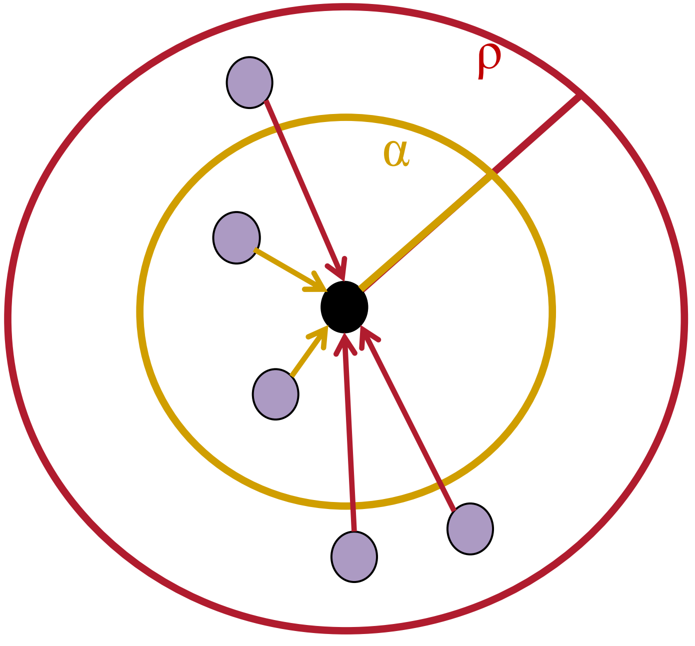

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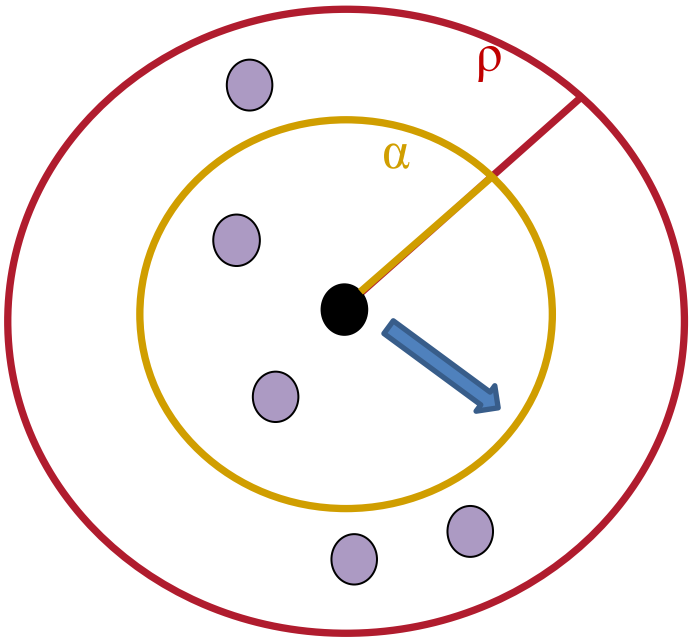

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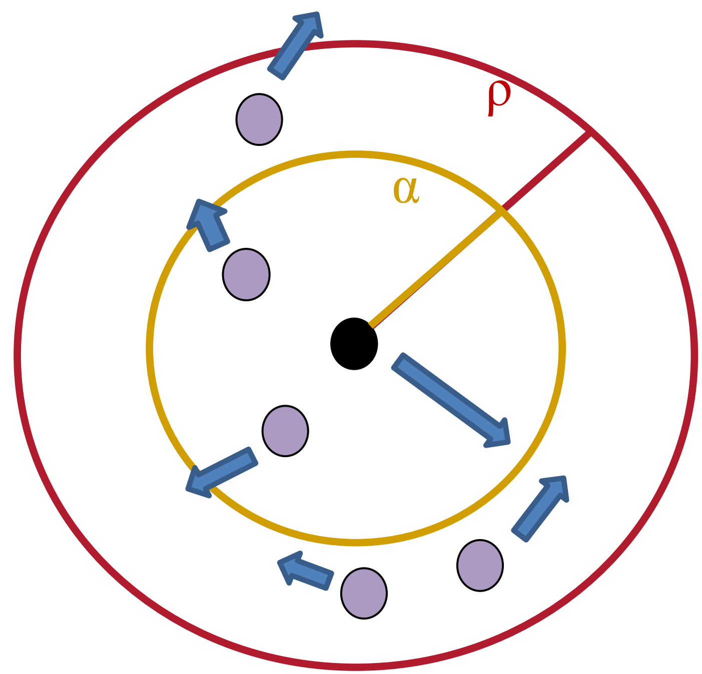
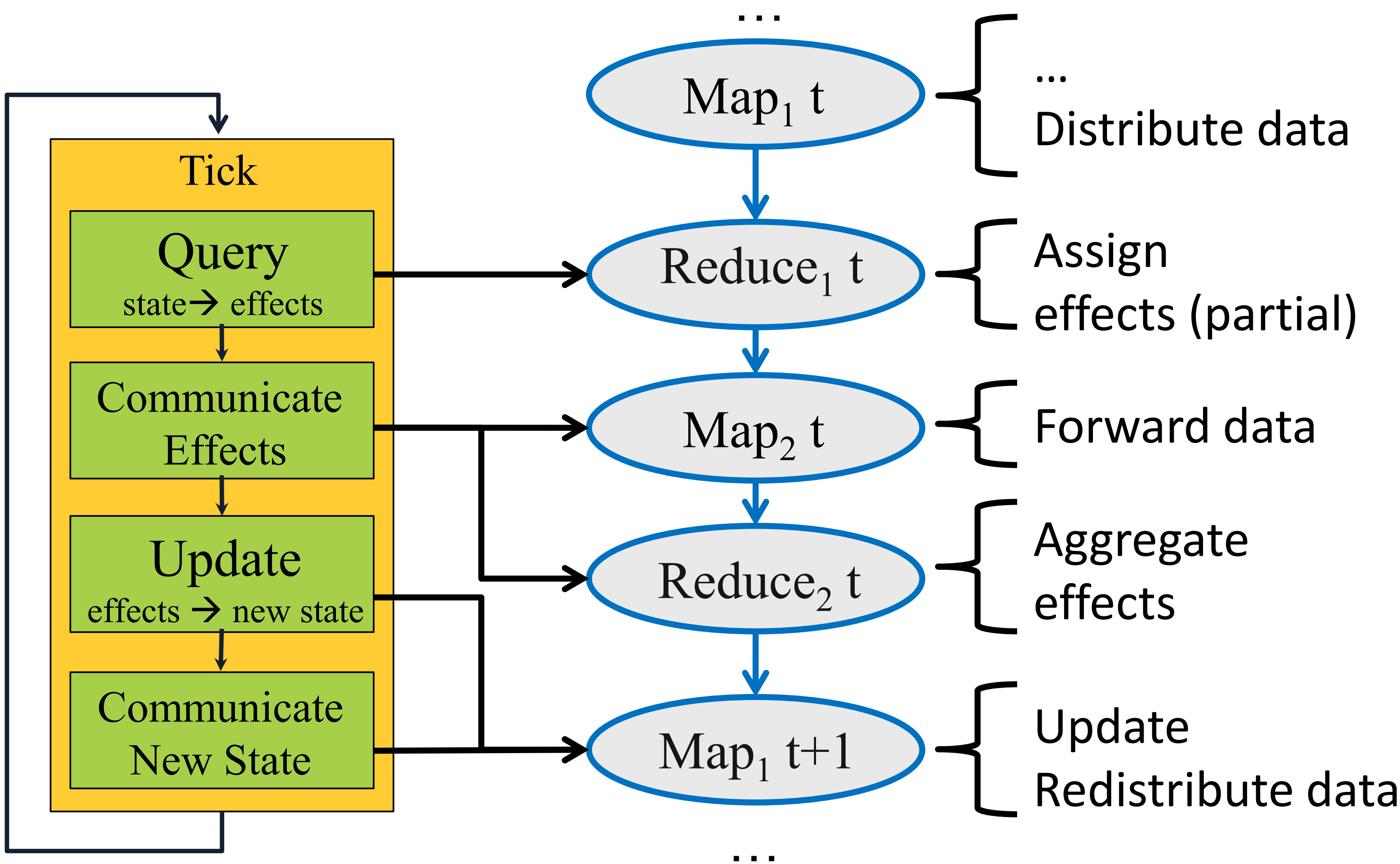


From State-Effect to Map-Reduce

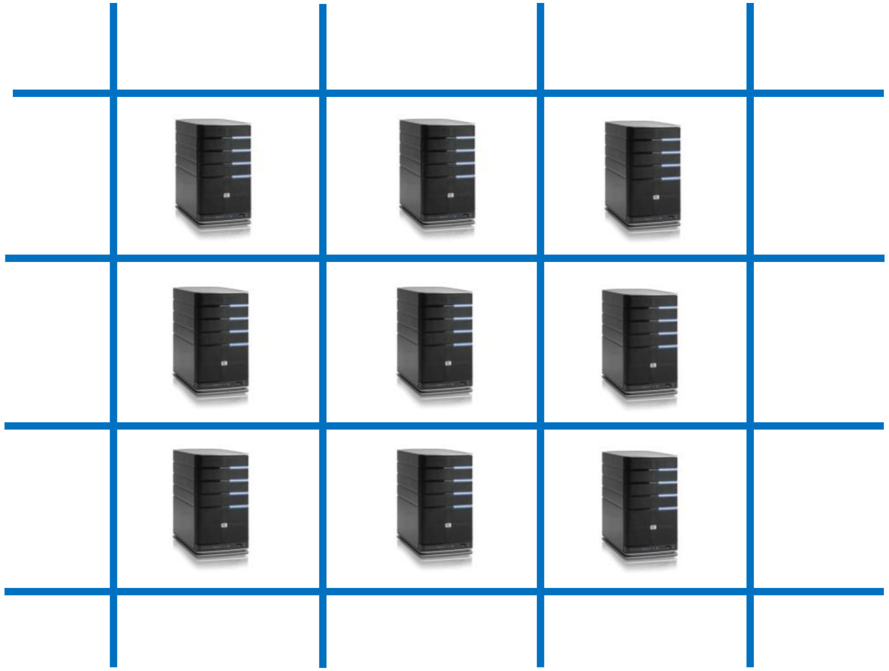


BRACE (**B**ig **R**ed **A**gent **C**omputation **E**ngine)

- BRASIL: High-level scripting language for domain scientists
  - Compiles to iterative MapReduce work flow
- Special-purpose MapReduce runtime for behavioral simulations
  - Basic Optimizations
  - Optimizations based on *Spatial Locality*

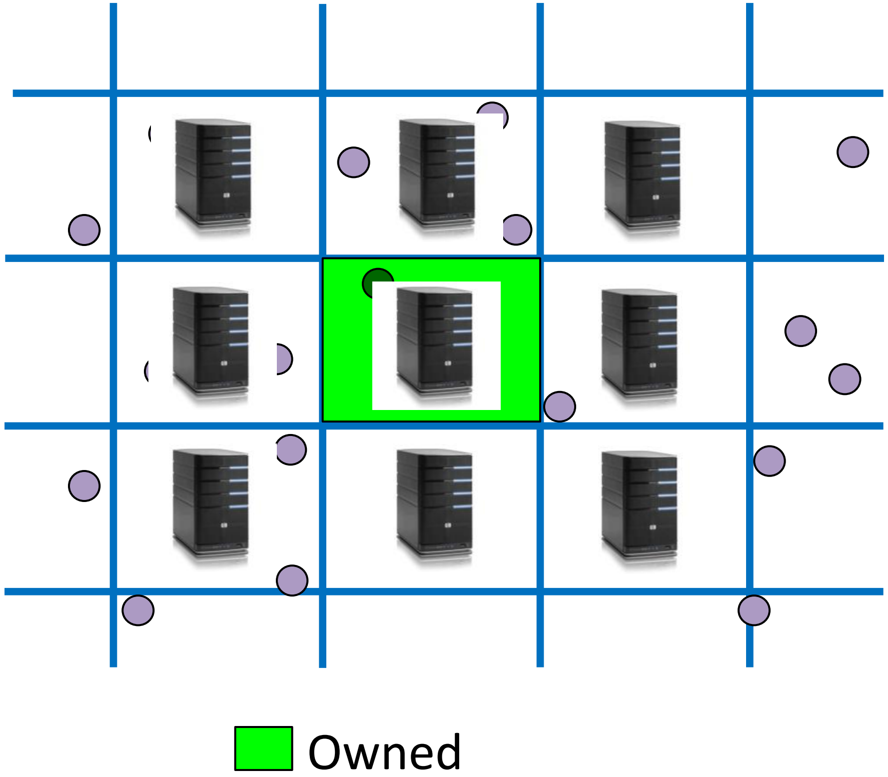
Spatial Partitioning

- Partition simulation space into regions, each handled by a separate node



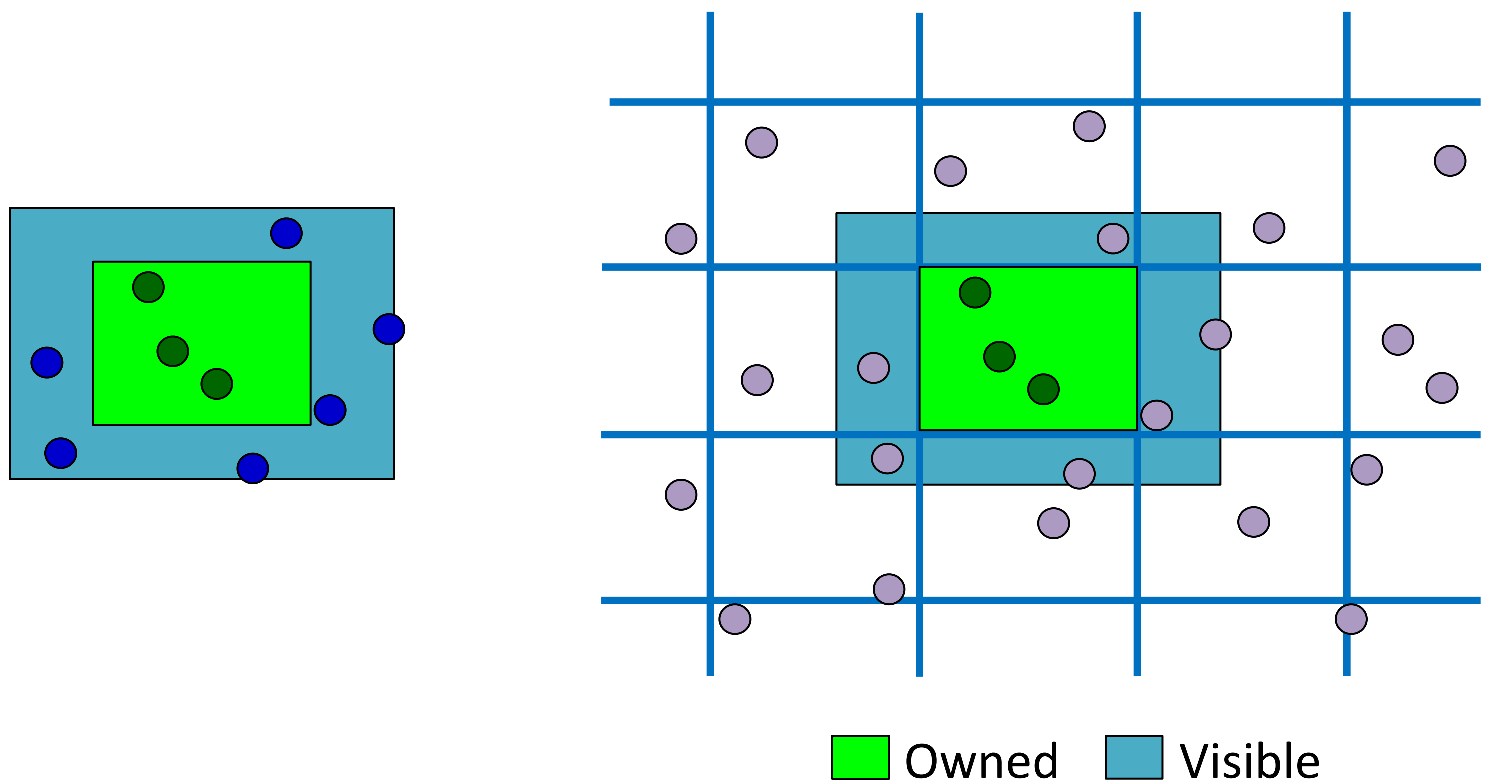
Communication Between Partitions

- *Owned Region*: agents in it are owned by the node



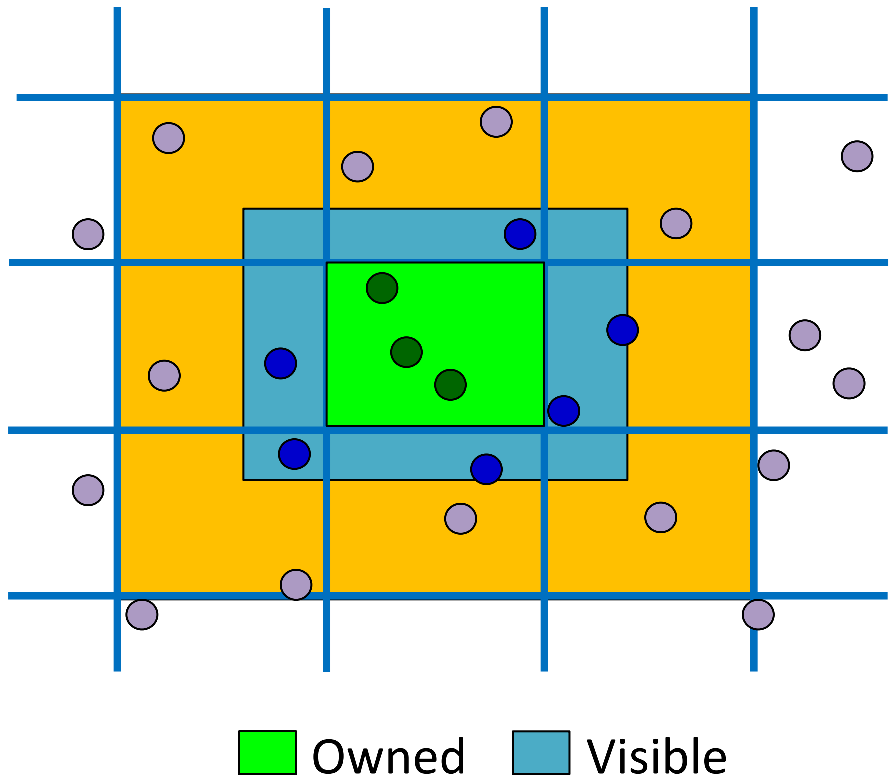
Communication Between Partitions

- *Visible Region*: agents in it are not owned, but need to be seen by the node



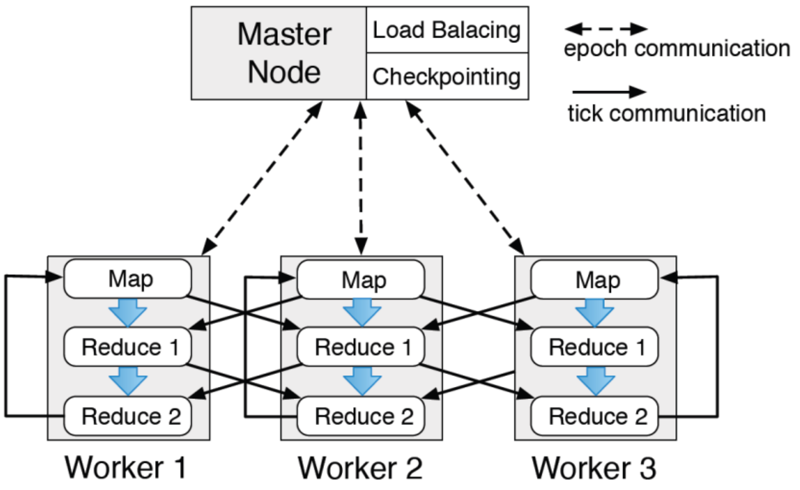
Communication Between Partitions

- *Visible Region*: agents in it are not owned, but need to be seen by the node
- Only need to communicate with neighbors to
  - refresh states
  - forward assigned effects



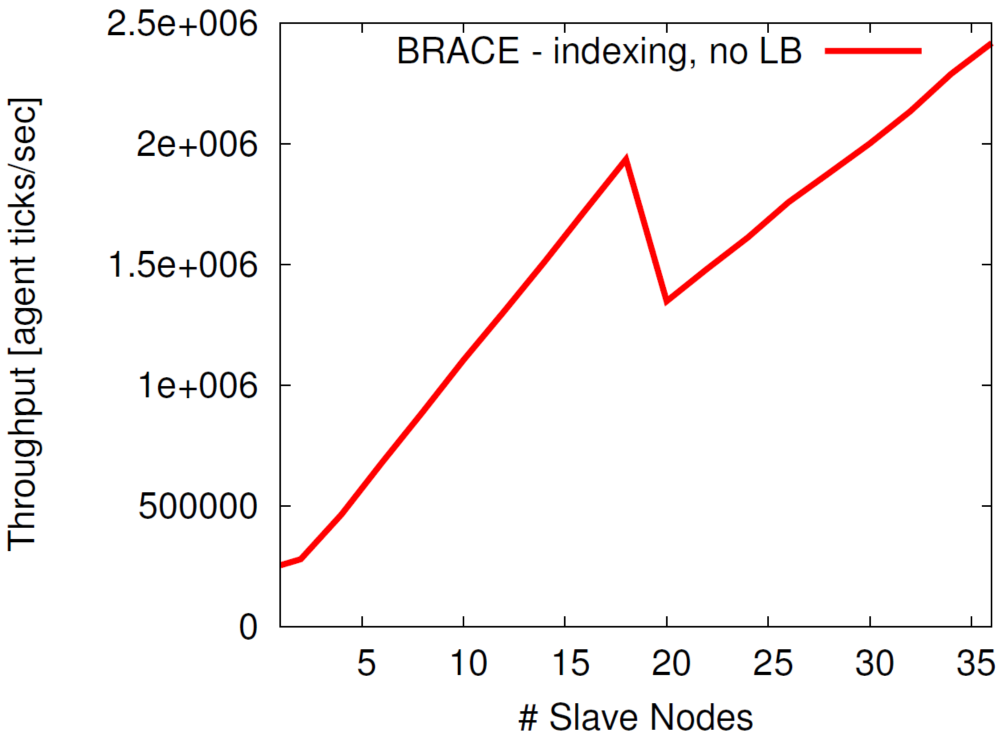
Experimental Setup

- BRACE prototype
  - Grid partitioning
  - KD-Tree spatial indexing
  - Basic load balancing



- Hardware: Cornell WebLab Cluster (60 nodes, 2xQuadCore Xeon 2.66GHz, 4MB cache, 16GB RAM)

Scalability: Traffic



- Scale up the size of the highway with the number of the nodes
- Notch consequence of multi-switch architecture

Talk Outline

- Motivation
- Fast Iterations: BRACE for Behavioral Simulations
- Fewer Iterations: GRACE for Graph Processing
- Conclusion

Large-scale Graph Processing

- Graph representations are everywhere
  - Web search, text analysis, image analysis, etc.

- Today's graphs have scaled to millions of edges/vertices

- Data parallelism of graph applications
  - Graph data updated *independently* (i.e. on a per-vertex basis)
  - Individual vertex updates only depend on connected neighbors

Synchronous v.s. Asynchronous

- Synchronous graph processing
  - Proceeds in batch-style “ticks”
  - Easy to program and scale, slow convergence
  - Pregel, PEGASUS, PrIter, etc
- Asynchronous processing
  - Updates with most recent data
  - Fast convergence but hard to program and scale
  - GraphLab, Galois, etc

What Do People Really Want?

- Sync. Implementation at first
  - Easy to think, program and debug

- Async. execution for better performance
  - Without re-implementing everything

GRACE (**GRA**ph **C**omputation **E**ngine)

- Iterative synchronous programming model
  - Update logic for individual vertex
  - Data dependency encoded in message passing

- Customizable bulk synchronous runtime
  - Enabling various async. features through relaxing data dependencies

Running Example: Belief Propagation

- Core procedure for many inference tasks in graphical models

- Upon update, each vertex first computes its new belief distribution according to its incoming messages: $b_u(x_u) \propto \phi_u(x_u) \prod_{e_{w,u} \in E} m_{w \to u}(x_u)$

- Then it will propagate its new belief to outgoing messages:

$$m_{u \to v}(x_v) \propto \sum_{x_u \in \Omega} \phi_{u,v}(x_u, x_v) \cdot \frac{b_u(x_u)}{m_{v \to u}(x_u)}$$

Sync. vs. Async. Algorithms

Algorithm 1: Original BP Algorithm

Initialize $b_u^{(0)}$ as ϕ_u for all $u \in V$;
Calculate the message $m_{u \to v}^{(0)}$ using $b_u^{(0)}$ according to Eq. 2 for all $u \to v \in E$;
Initialize $t = 0$;
repeat
    $t = t + 1$;
    foreach $u \in V$ **do**
        Calculate $b_u^{(t)}$ using $m_{w \to u}^{(t-1)}$ according to Eq. 1 ;
        foreach outgoing edge $e_{u,v}$ *of* u **do**
            Calculate $m_{u \to v}^{(t)}$ using $b_u^{(t)}$ according to Eq. 2 ;
        end
    end
until $\forall u \in V, ||b_u^{(t)} - b_u^{(t-1)}|| \leq \epsilon$;

Algorithm 2: Residual BP Algorithm

Initialize $b_u^{(new)}$ as ϕ_u and $b_u^{(old)}$ as uniform distribution for all $u \in V$;
Initialize $m_{u \to v}^{(old)}$ as uniform distribution for all $u \to v \in E$;
Calculate message $m_{u \to v}^{(new)}$ using $b_u^{(new)}$ according to Eq. 2 for all $u \to v \in E$;
repeat
    $u = \arg\max_v(\max_{(w,v) \in E} ||m_{w \to v}^{\text{new}} - m_{w \to v}^{\text{old}}||)$;
    Set $b_u^{(old)}$ to $b_u^{(new)}$;
    Calculate $b_u^{(new)}$ using $m_{w \to u}^{(new)}$ according to Eq. 1 ;
    foreach outgoing edge $e_{u,v}$ *of* u **do**
        Set $m_{u \to v}^{(old)}$ to $m_{u \to v}^{(new)}$;
        Calculate $m_{u \to v}^{(new)}$ using $b_u^{(new)}$ according to Eq. 2 ;
    end
until $\forall u \in V, ||b_u^{(new)} - b_u^{(old)}|| \leq \epsilon$;

- Update logic are actually the same: Eq 1 and 2
- Only differs in when/how to apply the update logic

Vertex Update Logic

```
List<Message> Proceed(List<Message> msgs)
```

- Read in one message from each of the incoming edge
- Update the vertex value
- Generate one message on each of the outgoing edge

Belief Propagation in Proceed

```
List<Msg> Proceed(List<Msg> msgs) {
  // Compute new belief from received messages
  Distribution newBelief = potent;
  for (Msg m in msgs) {
    newBelief = times(newBelief, m.belief);
  }
  // Compute and send out messages
  List<Msg> outMsgs(outDegree);
  for (Edge e in outgoingEdges) {
    Distribution msgBelief = divide(newBelief, Msg[e]);
    msgBelief = convolve(msgBelief, e.potent);
    msgBelief = normalize(msgBelief);
    outMsg[e] = new Msg(msgBelief);
  }
  // Vote to terminate upon convergence
  if (L1(newBelief, belief) < eps) voteHalt();
  return outMsgs;
}
```

- Consider fix point achieved when the new belief distribution does not change much

Customizable Execution Interface

- Each vertex is associated with a scheduling priority value
- Users can specify logic for:
  - Updating vertex priority upon receiving a message
  - Deciding vertex to be processed for each tick
  - Selecting messages to be used for Proceed
- We have implemented 4 different execution policies for users to directly choose from

Original Belief Propagation

```
void OnRecvMsg(Edge e, Message msg) {
  // Do nothing to update priority
  // since every vertex will be scheduled
}

Msg OnSelectMsg(Edge e) {
  return PrevRcvdMsg(e);
}

void OnPrepare(List<Vertex> vertices) {
  ScheduleAll(Everyone);
}
```

- Use last received message upon calling Proceed, and schedule all vertices to be processed for each tick

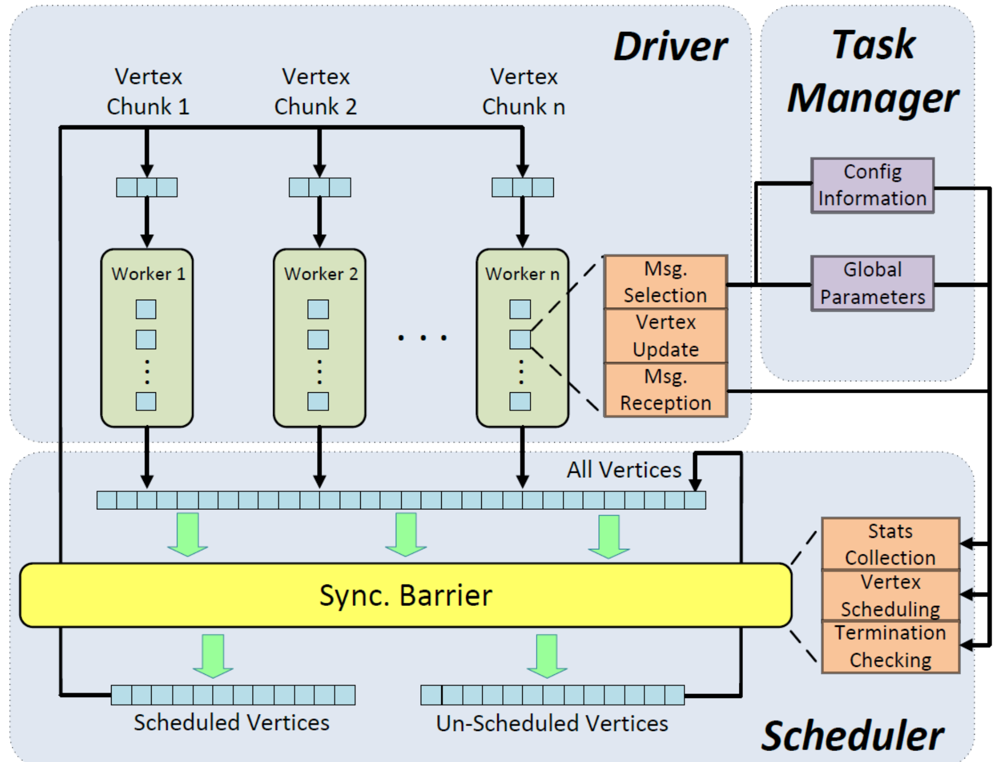
Residual Belief Propagation

```
void OnRecvMsg(Edge e, Message msg) {
  Distn lastBelief = LastUsedMsg(e).belief;
  float residual = L1(newBelief, msg.belief);
  UpdatePriority(residual, max);
}

Msg OnSelectMsg(Edge e) {
  return LastRcvdMsg(e);
}

void OnPrepare(List<Vertex> vertices) {
  Vertex selected = vertices[0];
  for (Vertex vtx in vertices) {
    if (vtx.priority > selected.priority)
      selected = vtx;
  }
  Schedule(selected);
}
```

- Use message residual as its “contribution” to vertex’s priority, and only update vertex with highest priority

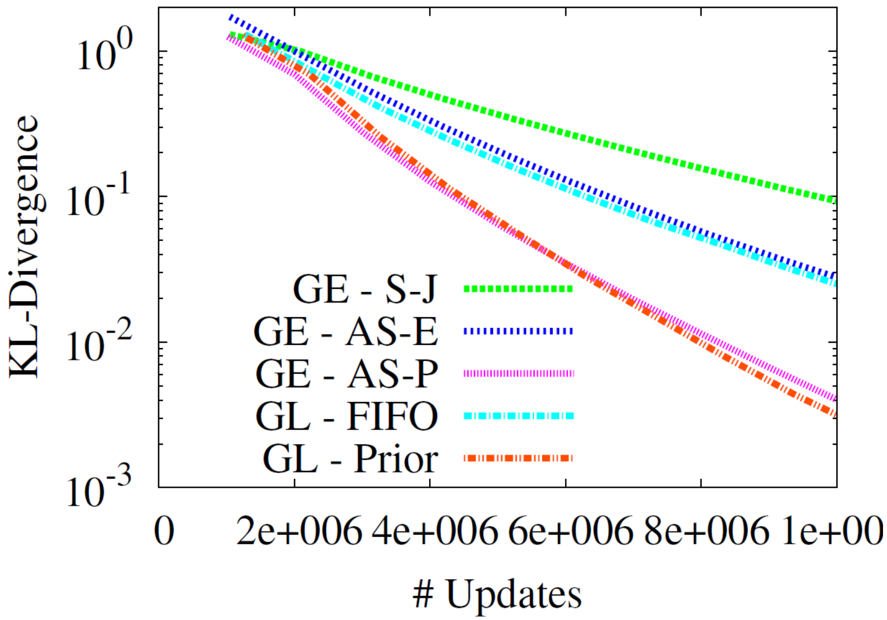
Experimental Setup

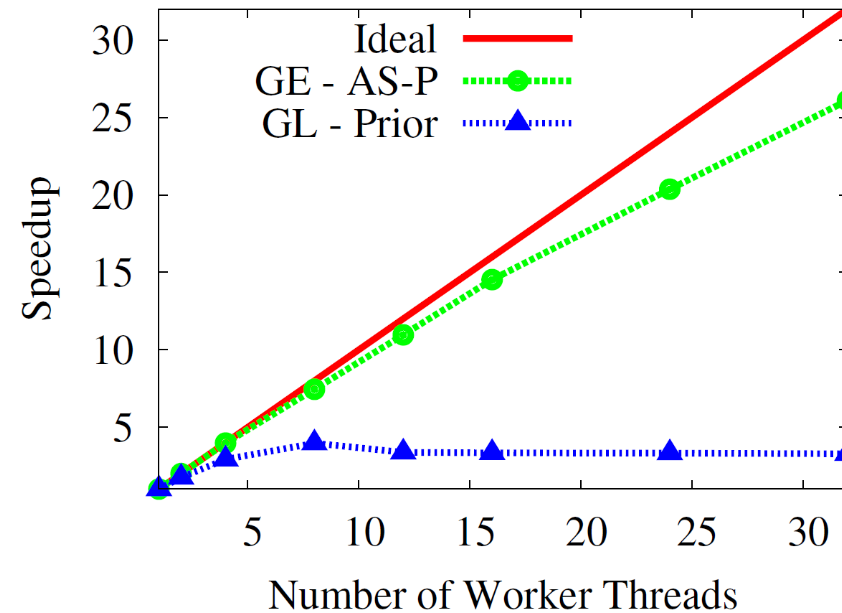
- GRACE prototype
  - Shared-memory
  - Policies
    - Jacobi
    - GaussSeidel
    - Eager
    - Prior



- Hardware: 32-core Computer with 8 quad-core processors and quad channel 128GB RAM.

Results: Image Restoration with BP





- GRACE’s prioritized policy achieve comparable convergence with GraphLab’s async scheduling, while achieve near linear speedup

Conclusions

Thank you!

- Iterative computations are common patterns in many applications
  - Requires programming simplicity and automatic scalability
  - Needs special care for performance
- Main-memory approach with various optimization techniques
  - Leverage data locality to minimize communication
  - Relax data dependency for fast convergence

Acknowledgements