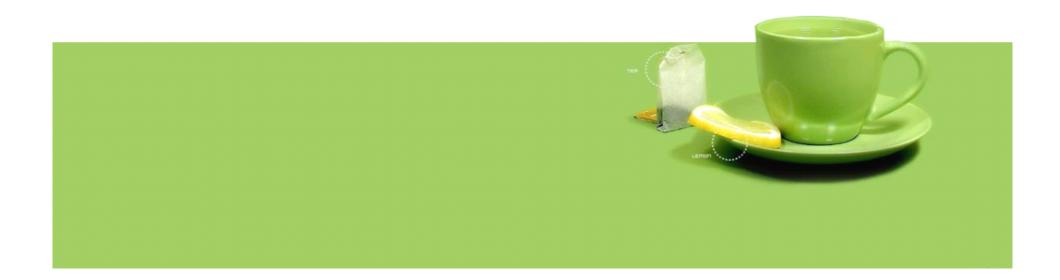
Behavioral Simulations in MapReduce

JingYu Yang Jan 25th,2011



Outline

Outline

- Motivation & Introduction
- Behavior Simulations In The State-Effect Pattern
- MapReduce For Simulations
- Programing Agent Behavior
- Experiments
- Conclusion



What is MapReduce?

- MapReduce is a framework for processing huge datasets on certain kinds of distributable problems using a large number of computers (nodes), collectively referred to as a cluster.
- "Map" step: The master node takes the input, chops it up into smaller sub-problems, and distributes those to worker nodes
- "Reduce" step: The master node takes the answers to all the sub-problems and combines them in some way to get the output



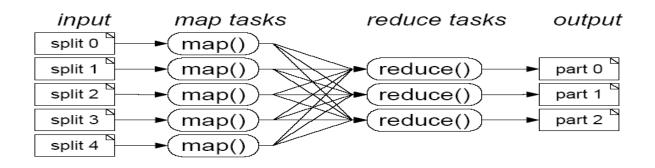
What is MapReduce?

• map : (k1;v1)->[(k2;v2)]

produces a set of intermediate key-value pairs

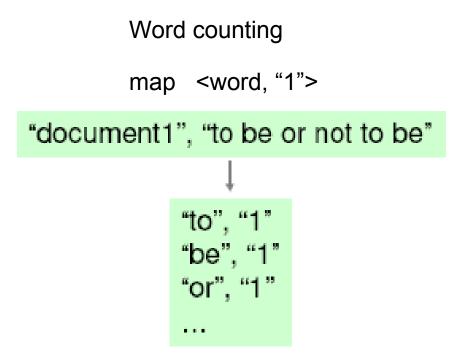
• reduce : (k2; [v2])->[v3]

collects all of the intermediate pairs with the same key and produces a value





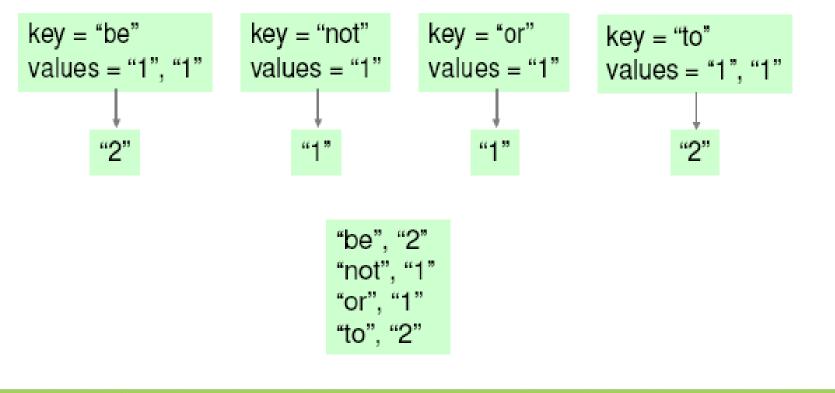
Small Example





Small Example







What are Behavioral Simulations?

- Also called agent-based simulations
- Understand large complex systems
- Tackling the ecological and infrastructure challenges of our society.
- Application Areas Traffic, Ecology, Sociology, etc.



Why Behavioral Simulations?



Ecology

Use behavioral simulations to model collective animal motion, such as that of locust swarms or fish schools
Crucial for they affect human food security

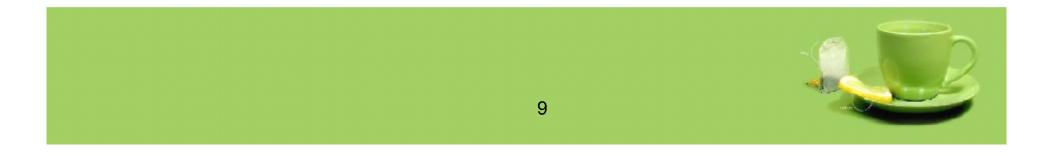
- Traffic
 - -Congestion cost \$87.2 billion in the U.S. in 2007
 - Evaluating proposed traffic management systems before implementing them





Challenges of Behavioral Simulations

- Easy to program \rightarrow not scalable
- Scalable \rightarrow hard to program
- Purpose: close the gap



Requirements for Simulation Platforms

- Support for Complex Agent Interaction
- Automatic Scalability
- High Performance
- Commodity Hardware
- Simple Programming Model



Contribution

- show how behavioral simulations can be abstracted in the state-effect pattern
- show how MapReduce can be used to scale behavioral simulations
- present a new scripting language for simulations
- perform an experimental evaluation with two real-world behavioral simulations



Outline

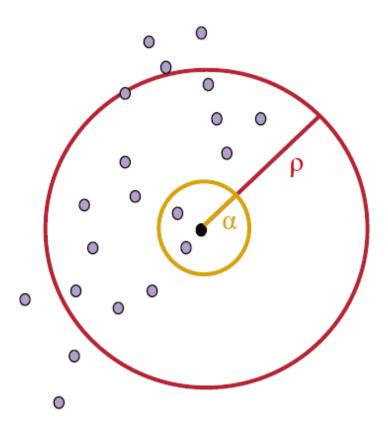
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A Running Example: Fish Schools

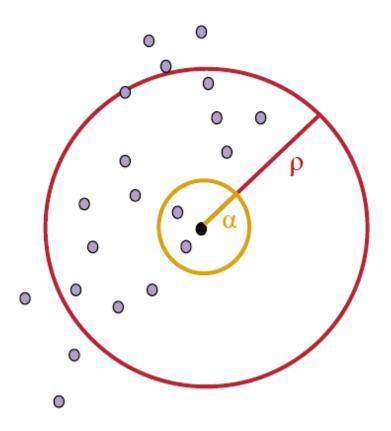
- Fish Behavior
- –Avoidance: if too close, repel other fish
- Attraction: if seen within range, attract other fish





A Running Example: Fish Schools

- Time-stepping: agents proceed in ticks
- Concurrency: agents are concurrent within a tick
- Interactions: agents
 continuously interact
- Spatial Locality: agents have limited visibility





Traditional Solutions for Concurrency

- Preempt conflicts
- Avoiding conflicts (Rollback in case of conflicts)
- Problems:
 - –Frequency of local interactions among agents \rightarrow many conflicts
 - -Poor scalability
 - due to either excessive synchronization or frequent rollbacks



- Programming pattern to deal with concurrency
- Time-stepped model ticks→represent the smallest time period of interest
- Events occur during same tick can be reordered or parallelized
- Basic Idea:separate read and write operation limit the synchronization necessary between agents



• States:

-public attributes that are updated only at tick boundaries

state attributes remain fixed during a tick

Only need to be synchronized at the end of each tick

• Effects:

-intermediate computations as agents interact to calculate new states

effect attribute has an associated decomposable and orderindependent combinator function for combining multiple assignments



States and Effects

• States:

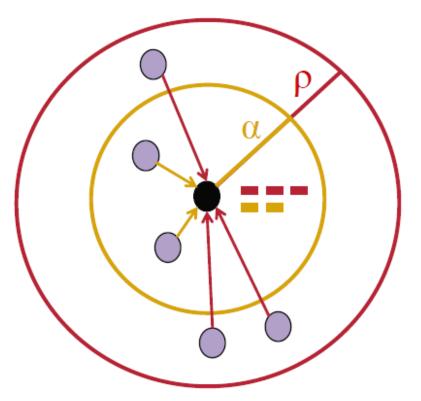
–Snapshot of agents at the beginning of the tick

position, velocity vector

• Effects:

–Intermediate results from interaction, used to calculate new states

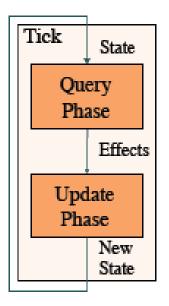
sets of forces from other fish





Two Phases of a Tick

- Query Phase: agents inspect their environment to compute effects
 - –Read states \rightarrow write effects
 - -Effect values combined using the appropriate combinator function
 - -Effect writes are order-independent
- Update Phase: agents update their own state
 - –Read effects →write states
 - -Reads and writes are totally local
 - -State writes are order-independent



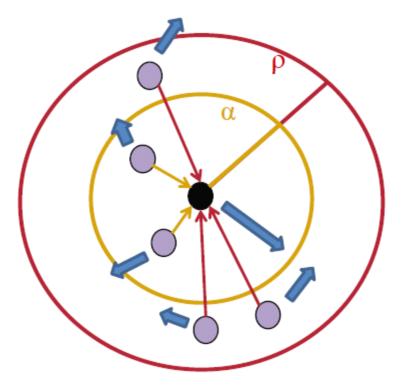


- Only way that agents can communicate is through effect assignments in the query phase
- local assignment agent updates one of its own effect attributes
- non-local assignment agent writes to an effect attribute of a different agent



A Tick in Fish Simulation

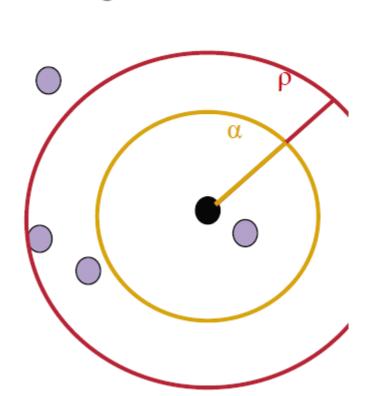
- Query
 - -For fish f in visibility α:
 •Write repulsion to f's effects
 -For fish f in visibility ρ:
 •Write attraction to f's effects
- Update
 - –new velocity = combined repulsion + combined attraction + old velocity
 - -new position = old position +
 old velocity





A Tick in Fish Simulation

- 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





The Neighborhood Property

- Synchronization at tick boundaries may still be very expensive
- Don't needs to query every other agent in the simulated world to compute its effects
- Most behavioral simulations are spatial, and simulated agents can only interact with other agents that are close according to a distance metric



The Neighborhood Property

- visibility
 - visible region
 - the region of space containing agents
 - that this agent can read from or assign effects to
- reachability
 - reachable region
 - the region that the agent can move to after the update phase.

(reachable region will be a subset of its visible region , is not required)



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Simulations as Iterated Spatial Joins

- Since agents only query other agents within their visible regions, processing a tick is similar to a spatial selfjoin
- Join each agent with the set of agents in its visible region and perform the query phase using only these agents
- Update phase:agents move to new positions within their reachable regions and we perform a new iteration of the join during the next tick



Iterated Spatial Joins in MapReduce

- Map task spatially partitioning agents into a number of disjoint regions
- Reduce task

join the agents using their visible regions

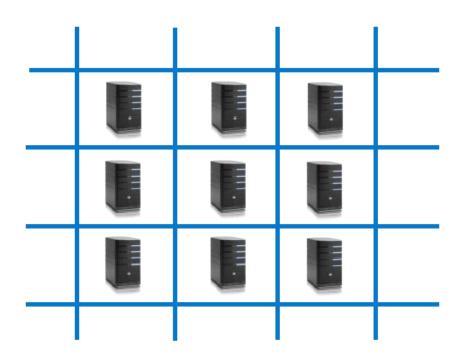
effects	map ₁	reduce ^t	map ^t	reduce ^t	map ₁ ^{t+1}
local	update ^{t-1} distribute ^t	queryt	_		update ^t distribute ^{t+1}
non- local	update ^{t-1} distribute ^t	non-local effect ^t		effect aggregation ^t	update ^t distribute ^{t+1}

 Table 1: The state-effect pattern in MapReduce



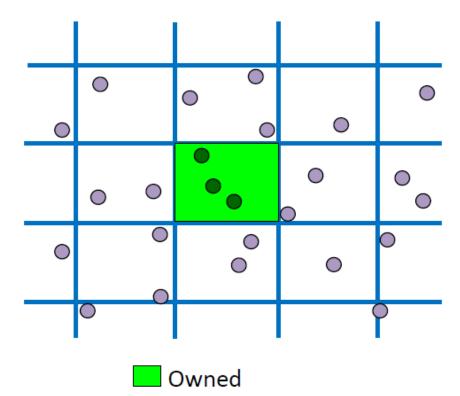
Spatial Partitioning

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



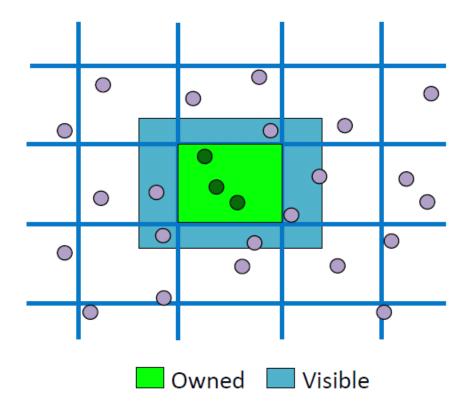


 Owned Region: agents in it are owned by the node





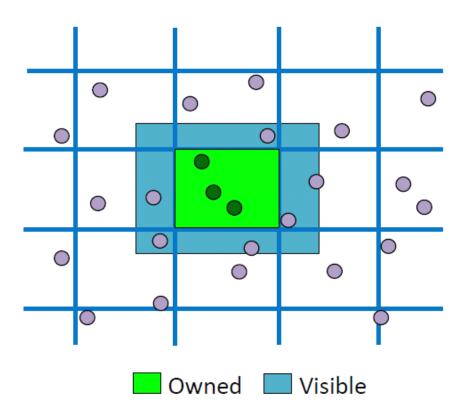
- Visible Region: agents in it are not owned, but need to be seen by the node
- The map task replicates each agent a to every partition that contains a in its visible region.





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

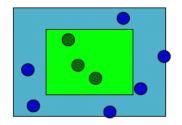
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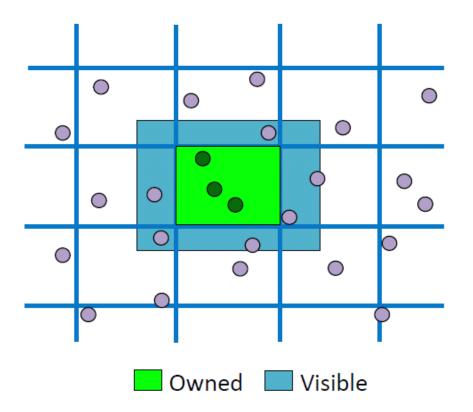




 Visible Region: agents in it are not owned, but need to be seen by the node

State Communication

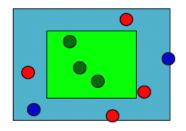


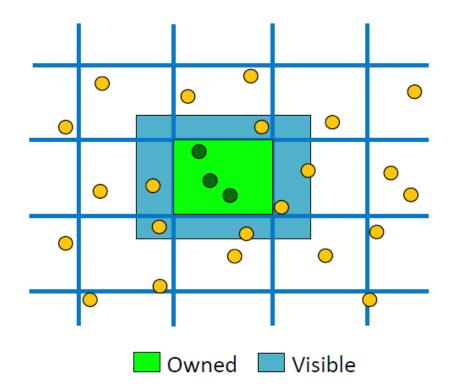




 Visible Region: agents in it are not owned, but need to be seen by the node

Query

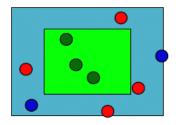


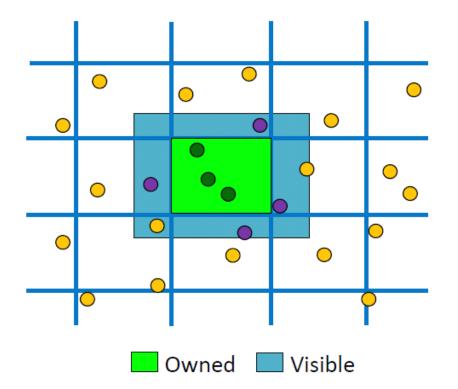


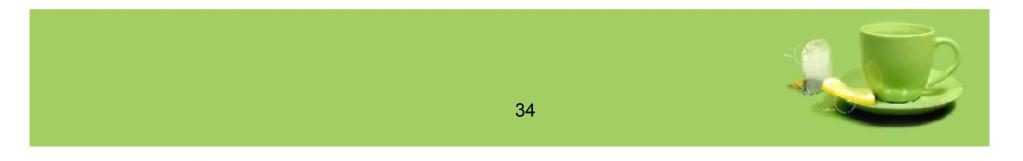


 Visible Region: agents in it are not owned, but need to be seen by the node

Effect communication

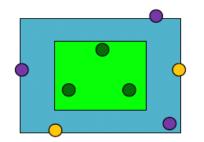


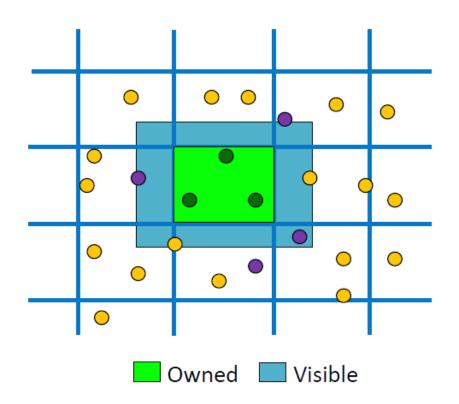




 Visible Region: agents in it are not owned, but need to be seen by the node

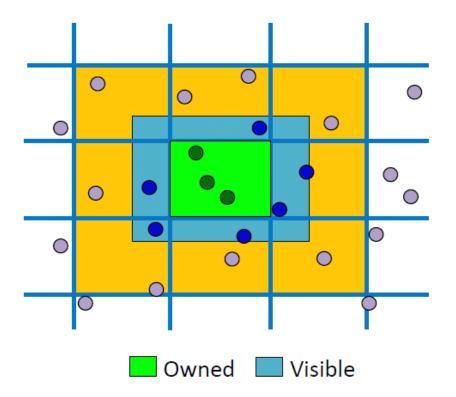
Update







- 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





Local Effects Assignment

•Map^t₁:tick t begins when the first map task, assigns each agent to a partition (distribute^t).

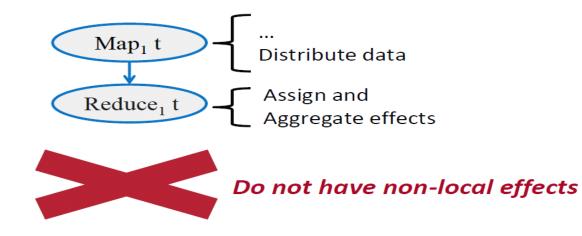
• Reduce^t₁:outputs a copy of each agent it owns after executing the query phase and updating the agent's effects.

•The tick ends when the next map task, map^{t+1}_1 , executes the update phase (update^t).

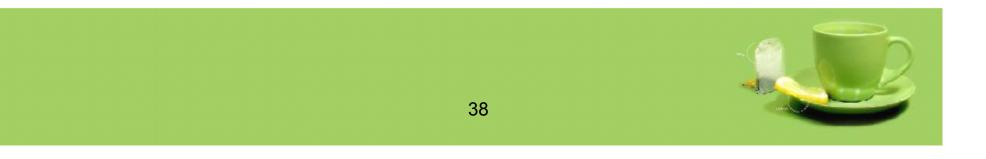
e	effects	map ₁	reduce ^t	map ^t	reduce ^t	$\operatorname{map}_1^{t+1}$
	local	update ^{t-1} distribute ^t	queryt	_	_	update ^t distribute ^{t+1}
	non- local	update ^{t-1} distribute ^t	non-local effect ^t		effect aggregation ^t	update ^t distribute ^{t+1}



Local Effects Assignment



effects	map ₁	reduce ^t	map_2^t	reduce ^t	map ₁ ^{t+1}
local	update ^{t-1} distribute ^t	query ^t			update ^t distribute ^{t+1}
non- local	update ^{t-1} distribute ^t	non-local effect ^t	_	effect aggregation ^t	update ^t distribute ^{t+1}



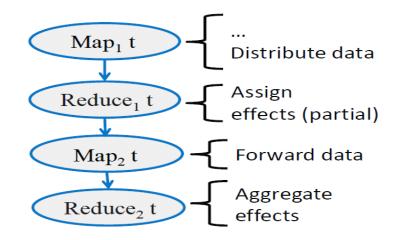
Non-Local Effects Assignment

- •Using two MapReduce passes
- •The first map task, $map_{1,}^{t}$ is the same
- •The first reduce task, reduce^t₁, performs non-local effect assignments to its replicas (non-local effect^t)
- •Second map task:only necessary for distribution,not perform any computation
- •reduce^t₂: computes the final value for each aggregate (effect aggregation^t)
- •Also called map-reduce-reduce model

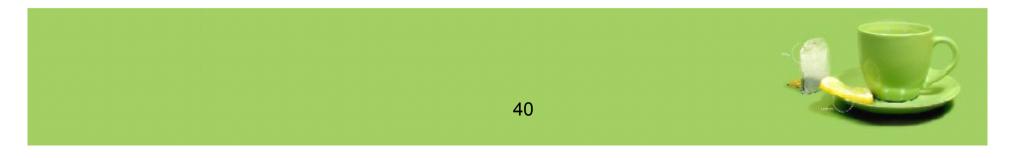
effects	map ₁	reduce ^t	map ^t	reduce ^t ₂	map ₁ ^{t+1}
local	update ^{t-1} distribute ^t	queryt			update ^t distribute ^{t+1}
non- local	update ^{t-1} distribute ^t	non-local effect ^t		effect aggregation ^t	update ^t distribute ^{t+1}

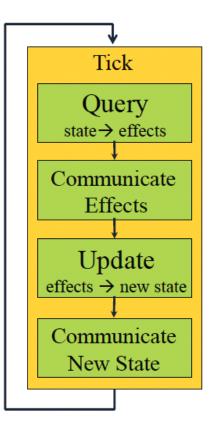


Non-Local Effects Assignment

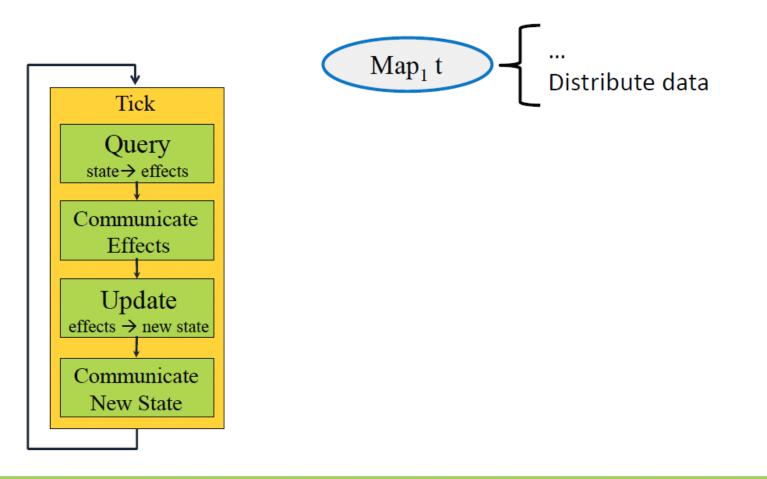


effects	map ₁	reduce ^t	map ₂ ^t	reduce ^t ₂	map_1^{t+1}
local	update ^{t-1} distribute ^t	query ^t			update ^t distribute ^{t+1}
non- local	update ^{t-1} distribute ^t	non-local effect ^t		effect aggregation ^t	update ^t distribute ^{t+1}

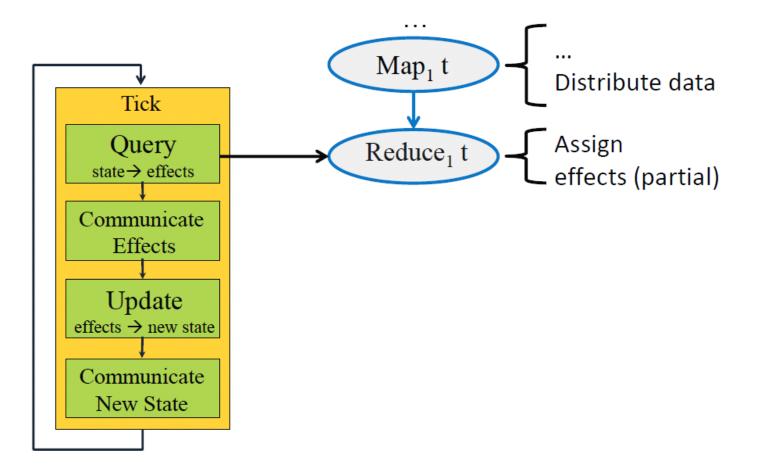


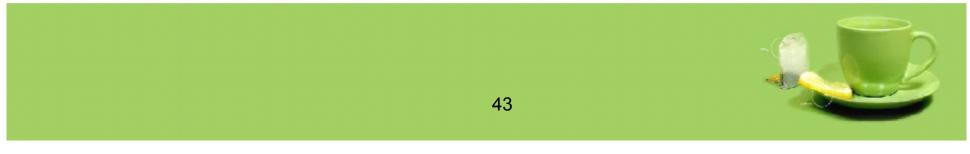


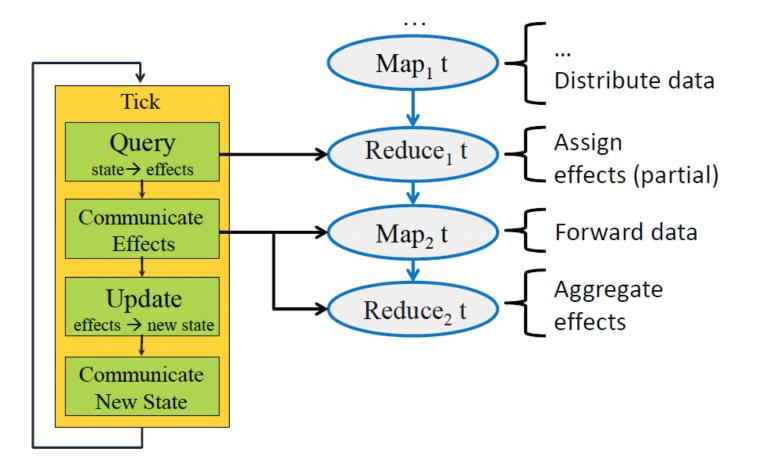


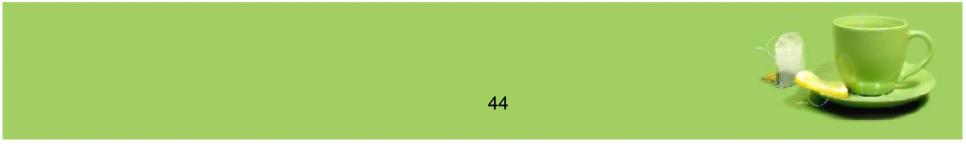


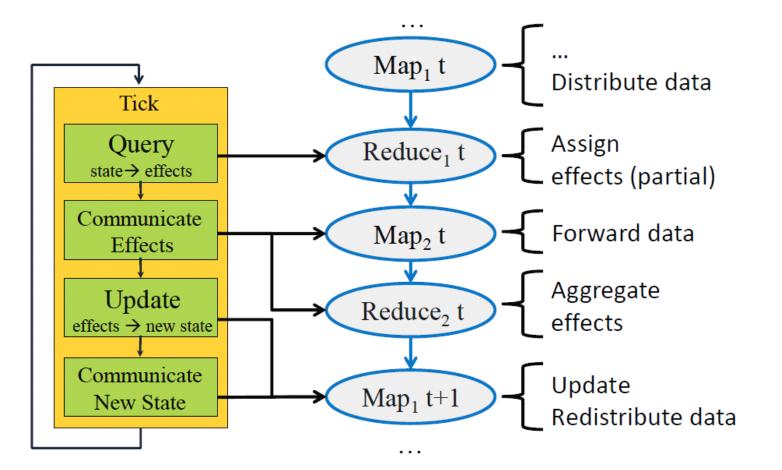


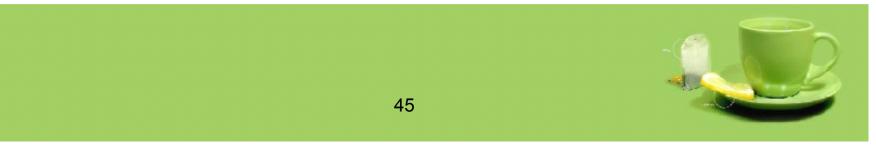








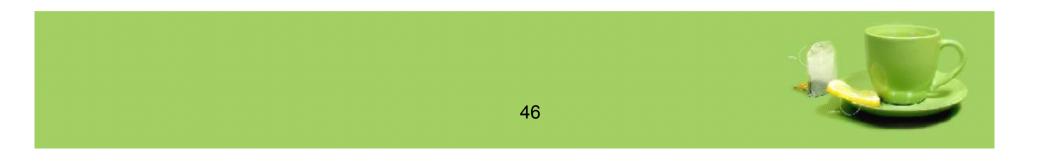




BRACE(Big Red Agent Computation Engine)

- Special-purpose MapReduce engine for behavioral simulations
- Goal of BRACE : process a very large number of ticks efficiently, and to avoid I/O or communication overhead
- Why introducing Brace?

behavioral simulations have considerably different characteristics than traditional MapReduce applications



BRACE(Big Red Agent Computation Engine)

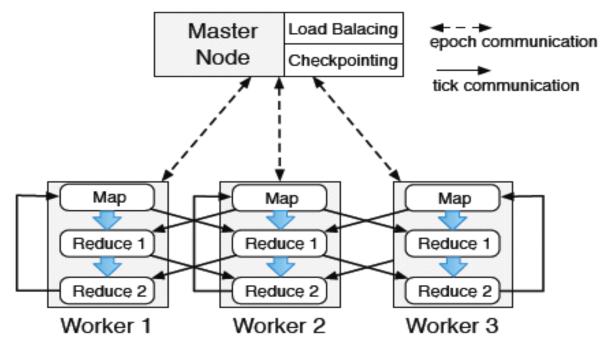
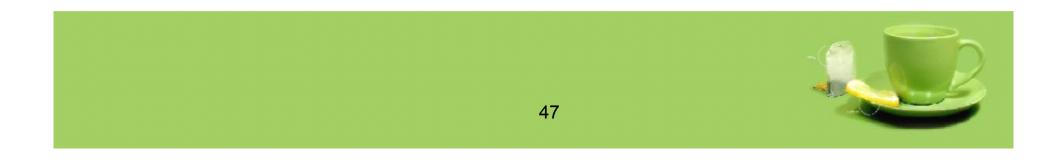
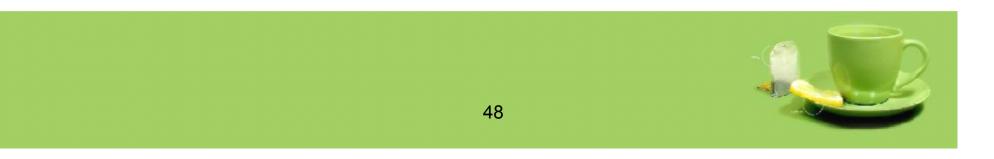


Figure 1: BRACE Architecture Overview



BRACE(Big Red Agent Computation Engine)

- Shared-Nothing, Main-Memory Architecture expect data volumes to be modest, so BRACE executes map and reduce tasks entirely in main memory
- Fault Tolerance
 - employ epoch synchronization with the master to trigger coordinated checkpoints
- Partitioning and Load Balancing
- Collocation of Tasks



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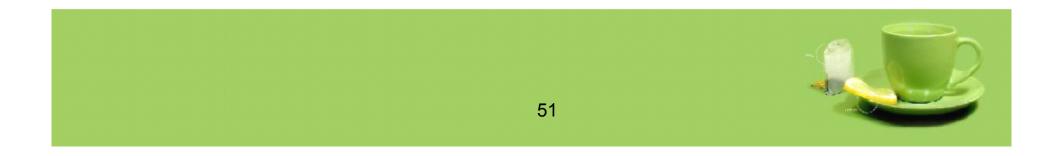
BRASIL(Big Red Agent SImulationLanguage)

- High-level language for domain scientists closer to the scientific models that describe agent behavior
- object-oriented language
- Programs specify behavior logic of individual agents

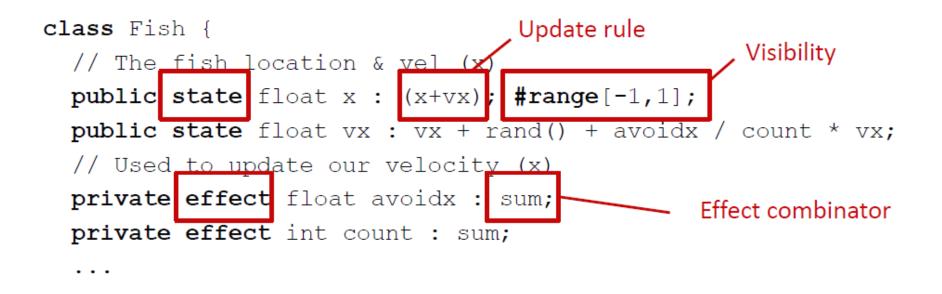


BRASIL(Big Red Agent SImulationLanguage)

- looks superficially like Java The programmer can specify fields, methods, and constructors
- each field in class must be tagged as either state or effect
- query phase expressed by run() method
- State fields are read-only
- Effect assignments are aggregated at the effect field
- Has some important restrictions



Fish in BRASIL





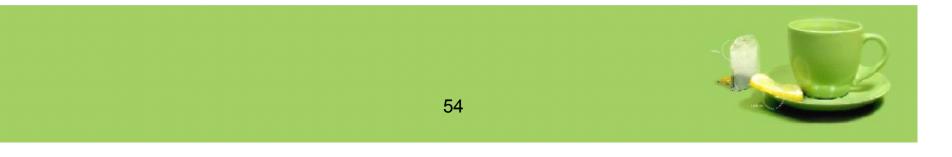
Fish in BRASIL

```
class Fish {
  // The fish location & vel (x)
  . . .
  /** The query-phase for this fish. */
 public void run() {
    // Use "forces" to repel fish too close
    foreach(Fish p : Extent<Fish>) {
       p.avoidx < -1 / abs(x - p.x);
                                               Effect assignment
       . . .
       p.count <- 1;
                              53
```

Effect Inversion

- An important optimization that is unique to our framework involves eliminating non-local effects.
- Rewritten expression does not change the results of the simulation, but only assigns effects locally.

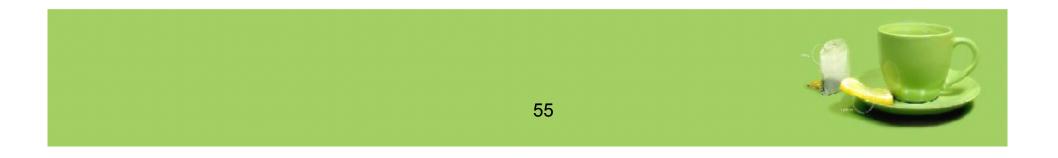
```
foreach(Fish p : Extent<Fish>) {
    avoidx <- 1 / abs(p.x - x);
    avoidy <- 1 / abs(p.y - y);
    count <- 1;
}</pre>
```



Effect Inversion

 Theorem: Every behavioral simulation written in BRASIL that uses non-local effects can be rewritten to an equivalent simulation that uses local effects only

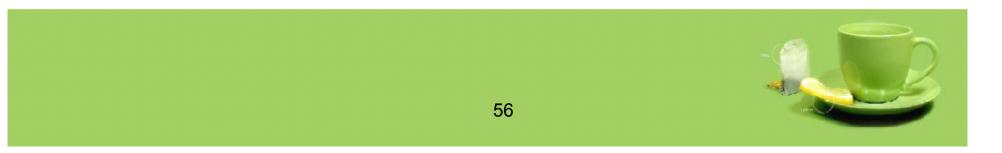
-Proof in the VLDB 2010 paper



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Experimental Setup

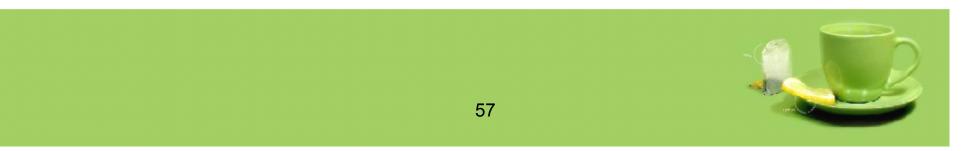
- Implementation
 - -BRACE MapReduce runtime implemented in C++ ,Our BRASIL compiler, written in Java and directly generates C++
 - -Grid partitioning

assigns each grid cell to a separate slave node

- -Include KD-Tree spatial indexing, rebuild every tick
- -Basic load balancing
- -Checkpointing is not yet integrated
- Simulation Workloads

implemented realistic traffic and fish school simulations

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



Traffic: Indexing vs. Seg. Length

- Compares the performance of MITSIM against BRACE using BRASIL
- Without spatial indexing: Brace's Performance Degrades quadratically with increasing segment length

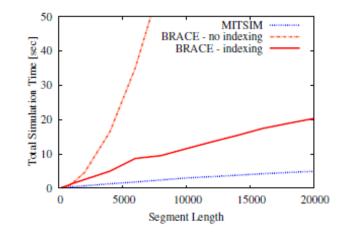
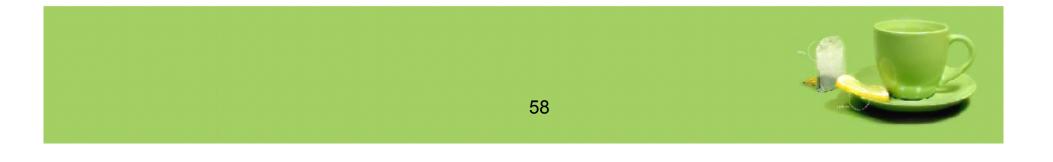


Figure 3: Traffic: Indexing vs. Seg. Length



Fish: Indexing vs. Visibility

increase the visibility range:

KD-tree indexing performance decreases

 indexing yields from two to three times improvement over a range of visibility values.

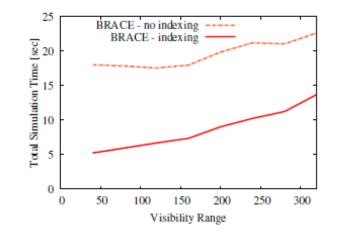
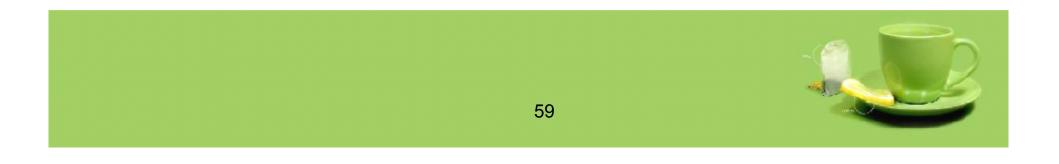


Figure 4: Fish: Indexing vs. Visibility



Predator: Effect Inversion

- Effect Inversion increases agent tick throughput
 - from 3.59 million (Idx-Only) to 4.36 million (Idx+Inv) with KD-tree indexing enabled
 - from 2.95 million (No-Opt) to 3.63 million (Inv-Only) with KD-tree indexing disabled

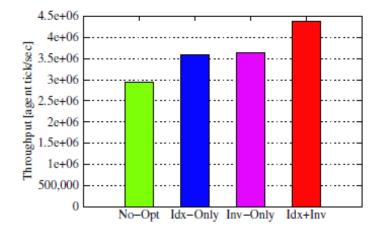


Figure 5: Predator: Effect Inversion



Traffic: Scalability

Nearly linear scalability

 Sudden drop is an artifact of IP routing in the multi-switch configuration

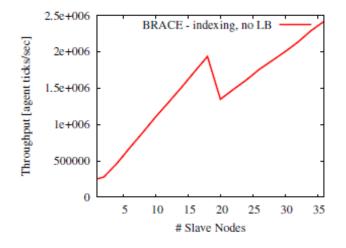
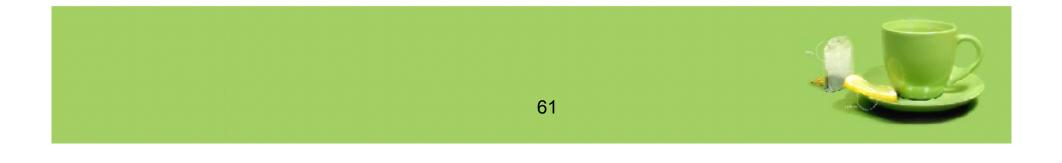


Figure 6: Traffic: Scalability



Fish: Scalability

- move in two different fixed directions
- Without load balancing:form in nodes at the extremes of simulated space,load at all other nodes falls to zero
- With load balancing:throughput increases linearly with the number of nodes

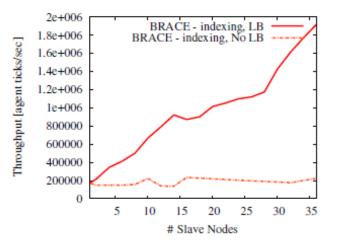
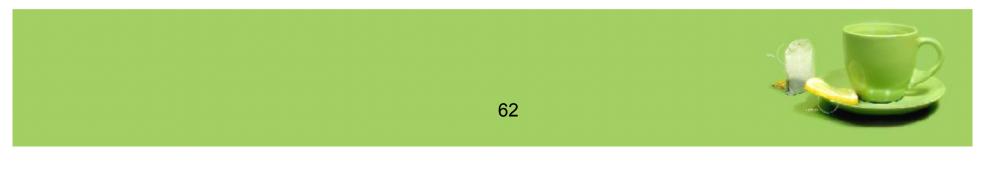


Figure 7: Fish: Scalability



Fish: Load Balancing

- With load balancing the time per simulation epoch is essentially flat
- With load balancing
 - the epoch time gradually increases
 - reflects all agents being simulated by only two nodes

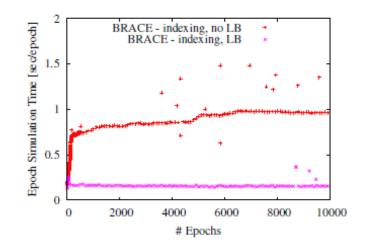
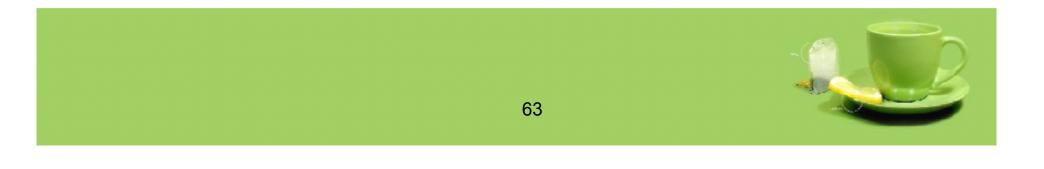


Figure 8: Fish: Load Balancing



- MapReduce can be used to scale behavioral simulations across clusters
- New programming environment for behavioral simulations
 - –Easy to program: Simulations in the state-effect pattern → BRASIL

-Hides all the complexities of modeling computations in MapReduce -parallel programming from domain scientists

–Scalable: State-effect pattern in special-purpose MapReduce Engine → BRACE

-shared-nothing, in-memory MapReduce framework

-exploits collocation of mappers and reducers to bound communication overhead



Thanks!

