Cluster Computing

Big Data Parallelism

- Huge data set
  - crawled documents, web request logs, etc.
- Natural parallelism:
  - can work on different parts of data independently
  - image processing, grep, indexing, many more

- What are the issues that we need to tackle in building big data analytics systems?

Challenges

- Parallelize application
  - Where to place input and output data?
  - Where to place computation?
  - How to communicate data? How to manage threads? How to avoid network bottleneck?
- Balance computations
- Handle failures of nodes during computation
- Scheduling several applications who want to share infrastructure

Goal of MapReduce

- To solve these distribution/fault-tolerance issues once in a reusable library
  - To shield the programmer from having to re-solve them for each program
- To obtain adequate throughput and scalability
- To provide the programmer with a conceptual framework for designing their parallel program

Map Reduce

- Overview:
  - Partition large data set into M splits
  - Run map on each partition, which produces R local partitions; using a partition function R
  - Run reduce on each intermediate partition, which produces R output files
  - Hidden intermediate shuffle phase

Details

- Input values: set of key-value pairs
  - Job will read chunks of key-value pairs
  - “key-value” pairs a good enough abstraction
- Map(key, value):
  - System will execute this function on each key-value pair
  - Generate a set of intermediate key-value pairs
- Reduce(key, values):
  - Intermediate key-value pairs are sorted
  - Reduce function is executed on these intermediate key-values

Count words in web-pages

```
Map(key, value) {
   // key is url
   // value is the content of the url
   For each word W in the content
      Generate(W, 1);
}


Reduce(key, values) {
   // key is word (W)
   // values are basically all 1s
   Sum = Sum all 1s in values

   // generate word-count pairs
   Generate (key, sum);
}
```

Reverse web-link graph

Go to google advanced search:
"find pages that link to the page:" cnn.com

```
Map(key, value) {
   // key = url
   // value = content
   For each url, linking to target
      Generate(output target, url);
}

Reduce(key, values) {
   // key = target url
   // values = all urls that point to the target url
   Generate(key, list of values);
}
```

- Question: how do we implement “join” in MapReduce?
  - Imagine you have a log table L and some other table R that contains say user information
  - Perform Join (L.uid == R.uid)
    - Say size of L >> size of R
    - Bonus: consider real world zipf distributions

Implementation

- Depends on the underlying hardware: shared memory, message passing, NUMA shared memory, etc.
- Inside Google:
  - commodity workstations
  - commodity networking hardware (1Gbps at node level and much smaller bisection bandwidth)
  - cluster = 100s or 1000s of machines
  - storage is through GFS

Implementation

- Partition input data into M splits
  - starts up many copies of the program on a cluster
  - one master and multiple slaves
  - Map function invoked on key-values
  - Output is buffered in memory and periodically logged to disk (local disk)
- Reduce invocations: partition the intermediate key space into R pieces (e.g., hash(key) % R)
- R and partition function is specified by user

Implementation

- Master keeps track of locations of intermediate keys
- Reducer accesses these values through RPCs
    - reducer sorts all keys assigned to it
    - iterates over each unique key and performs reduce over associated values
    - emits output values that are appended to a final output file for this reduce partition (in GFS)

Role of the Master

- Keeps state regarding the state of each worker machine (pings each machine)
- Reschedules work corresponding to failed machines
- Orchestrates the passing of locations to reduce functions

Discussion

- what are the performance limitations of map reduce?
- what are the constraints imposed on map and reduce functions?
- how would you like to expand the capability of map reduce?

Map Reduce Criticism

- “Giant step backwards” in programming model
- Sub-optimal implementation
- “Not novel at all”
- Missing most of the DB features
- Incompatible with all of the DB tools

Comparison to Databases

- Huge source of controversy; claims:
  - parallel databases have much more advanced data processing support that leads to much more efficiency
    - support an index; selection is accelerated
    - provides query optimization
  - parallel databases support a much richer semantic model
    - support a scheme; sharing across apps
    - support SQL, efficient joins, etc.

Where does MR win?

- Scaling
- Loading data into system
- Fault tolerance (partial restarts)
- Approachability

Piccolo

- MapReduce restrictions:
  - just two phases
  - map can see only its split
  - reduce sees just one key at a time
- Piccolo programming model:
  - any number of phases (determined by controller)
  - computation proceeds in rounds:
    - example: page rank
    - global key/value tables store intermediate data

Naive PageRank

```
curr = Table(key=PageID, value=double)
next = Table(key=PageID, value=double)
```

```
def pr_kernel(graph, curr, next):
  i = my_instance
  n = len(graph)/NUM_MACHINES
  for s in graph[(i-1)*n:i*n]
    for t in s.out:
      next[t] += curr[s.id] / len(s.out)
```

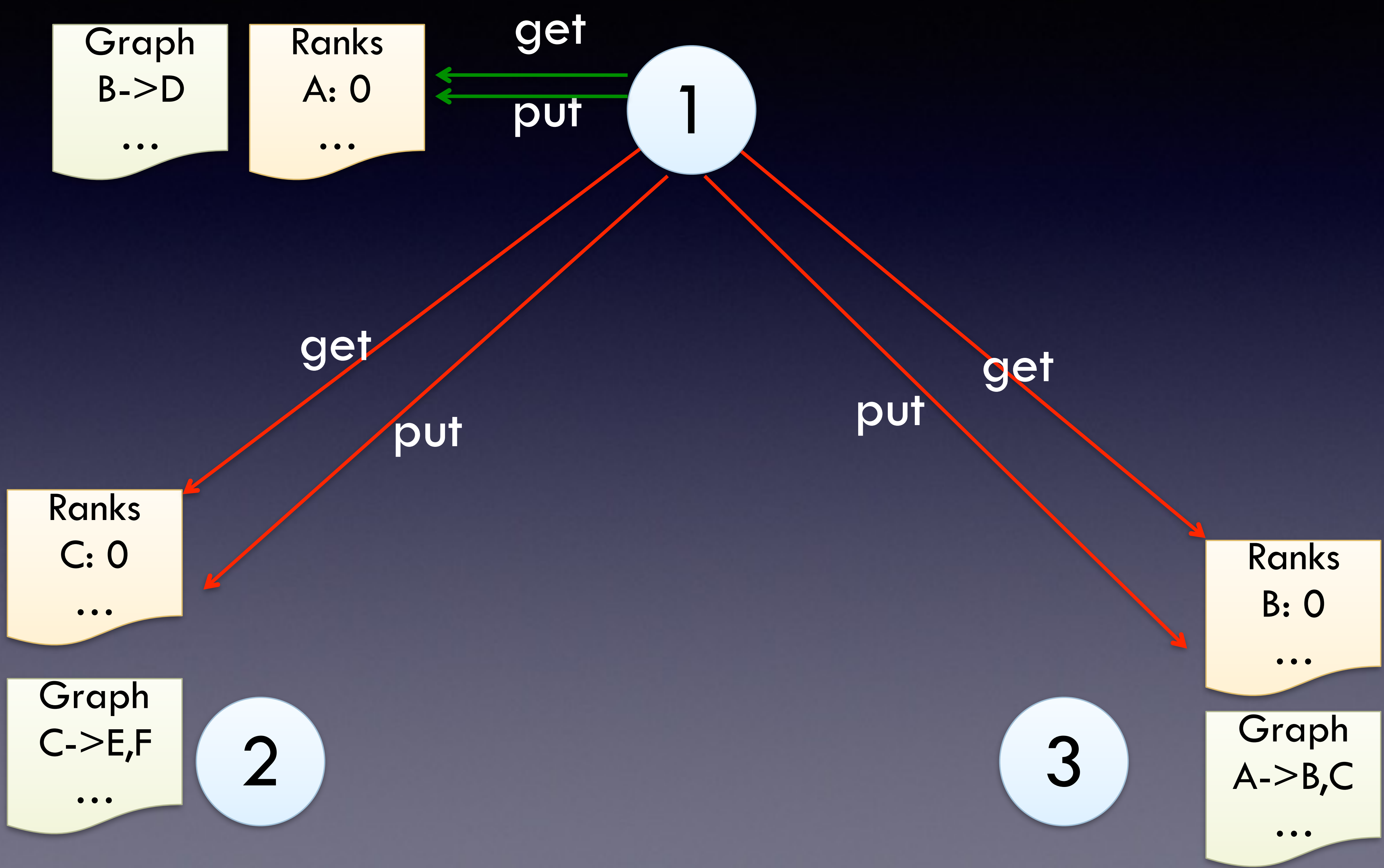
Jobs run by many machines

```
def main():
  for i in range(50):
    launch_jobs(NUM_MACHINES, pr_kernel,
                         graph, curr, next)
    swap(curr, next)
    next.clear()
```

Controller launches jobs in parallel

Run by a single controller

Naïve PageRank is Slow



PageRank: Locality

```
curr = Table(…,partitions=100,partition_by=site)
next = Table(…,partitions=100,partition_by=site)
group_tables(curr,next,graph)

def pr_kernel(graph, curr, next):
   for s in graph.get_iterator(my_instance)
      for t in s.out:
         next[t] += curr[s.id] / len(s.out)

def main():
   for i in range(50):
      launch_jobs(curr.num_partitions,
                  pr_kernel,
                  graph, curr, next,
                  locality=curr)
      swap(curr, next)
      next.clear()
```

Control table partitioning

Co-locate tables

Co-locate execution with table

PageRank: Synchronization

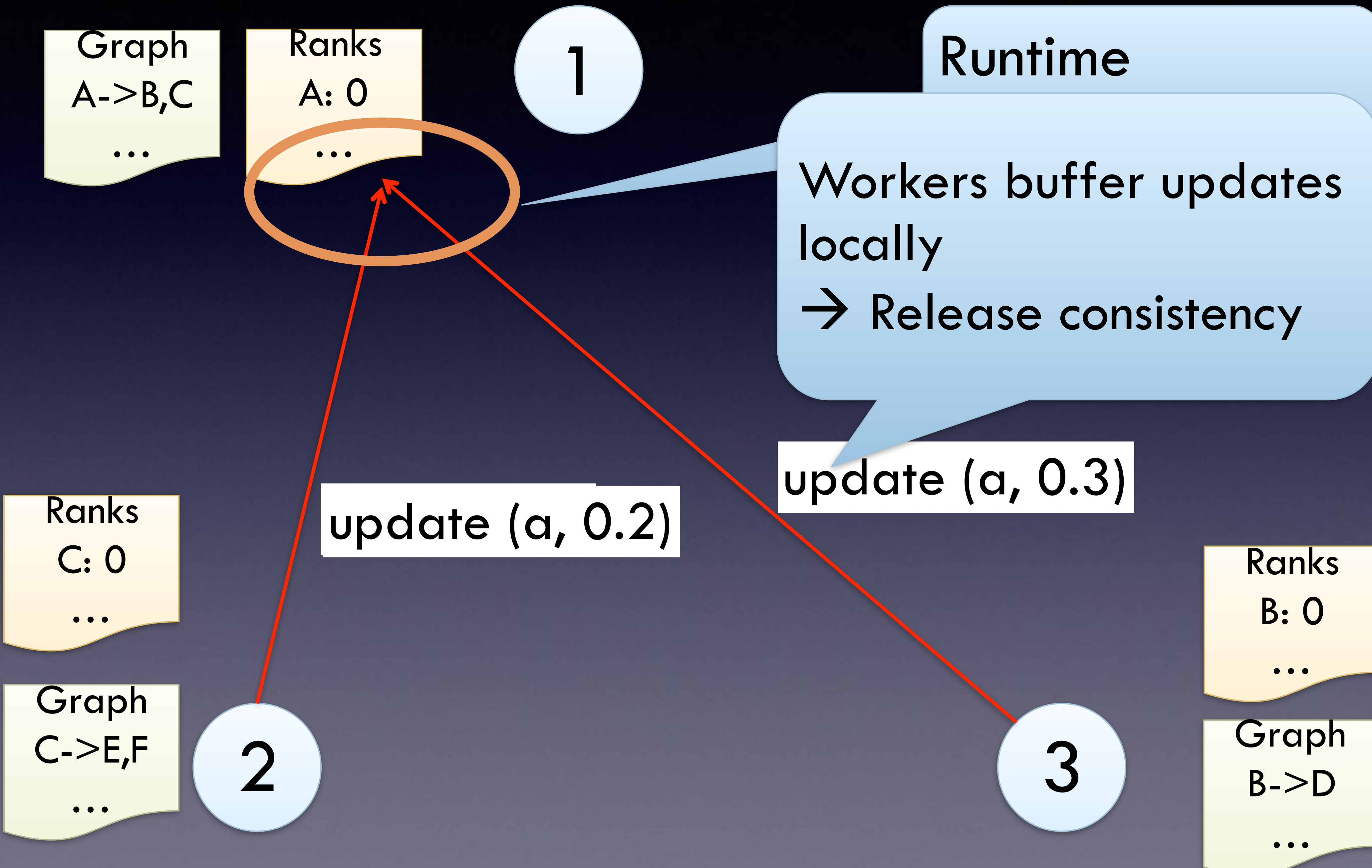
```
curr = Table(…,partition_by=site,accumulate=sum)
next = Table(…,partition_by=site,accumulate=sum)
group_tables(curr,next,graph)

def pr_kernel(graph, curr, next):
  for s in graph.get_iterator(my_instance)
    for t in s.out:
      next.update(t, curr.get(s.id)/len(s.out))

def main():
  for i in range(50):
    handle = launch_jobs(curr.num_partitions,
                         pr_kernel,
                         graph, curr, next,
                         locality=curr)
    barrier(handle)
    swap(curr, next)
    next.clear()
```

Accumulation via sum

Update invokes accumulation function

Explicitly wait between iterations

Efficient Synchronization



PageRank: Checkpointing

```
curr = Table(…,partition_by=site,accumulate=sum)
next = Table(…,partition_by=site,accumulate=sum)
group_tables(curr,next)
def pr_kernel(graph, curr, next):
   for node in graph.get_iterator(my_instance)
      for t in s.out:
         next.update(t,curr.get(s.id)/len(s.out))

def main():
   curr, userdata = restore()
   last = userdata.get('iter', 0)
   for i in range(last,50):
      handle = launch_jobs(curr.num_partitions, pr_kernel,
                           graph, curr, next,
                           locality=curr)
      cp_barrier(handle, tables=(next), userdata={'iter':i})
      swap(curr, next)
      next.clear()
```

Restore previous computation

User decides which tables to checkpoint and when

- How does Piccolo compare to MapReduce:
    - in terms of programmability
    - in terms of performance (stragglers, load balance, etc.)
    - in terms of fault tolerance