MapReduce and Hadoop

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Motivation

- Simple programming model for Big Data
  - Distributed, parallel – but hides this
- Established success at petabyte scale
  - Internet search indexes, analysis
  - Google, yahoo facebook
- Recently: 8000 nodes sort 10PB in 6.5 hours
- Open source frameworks with different goals
  - Hadoop, phoenix
- Lots of research in last 5 years
  - Adapt scientific computation algorithms to MapReduce, performance analysis

A programming model with some nice consequences

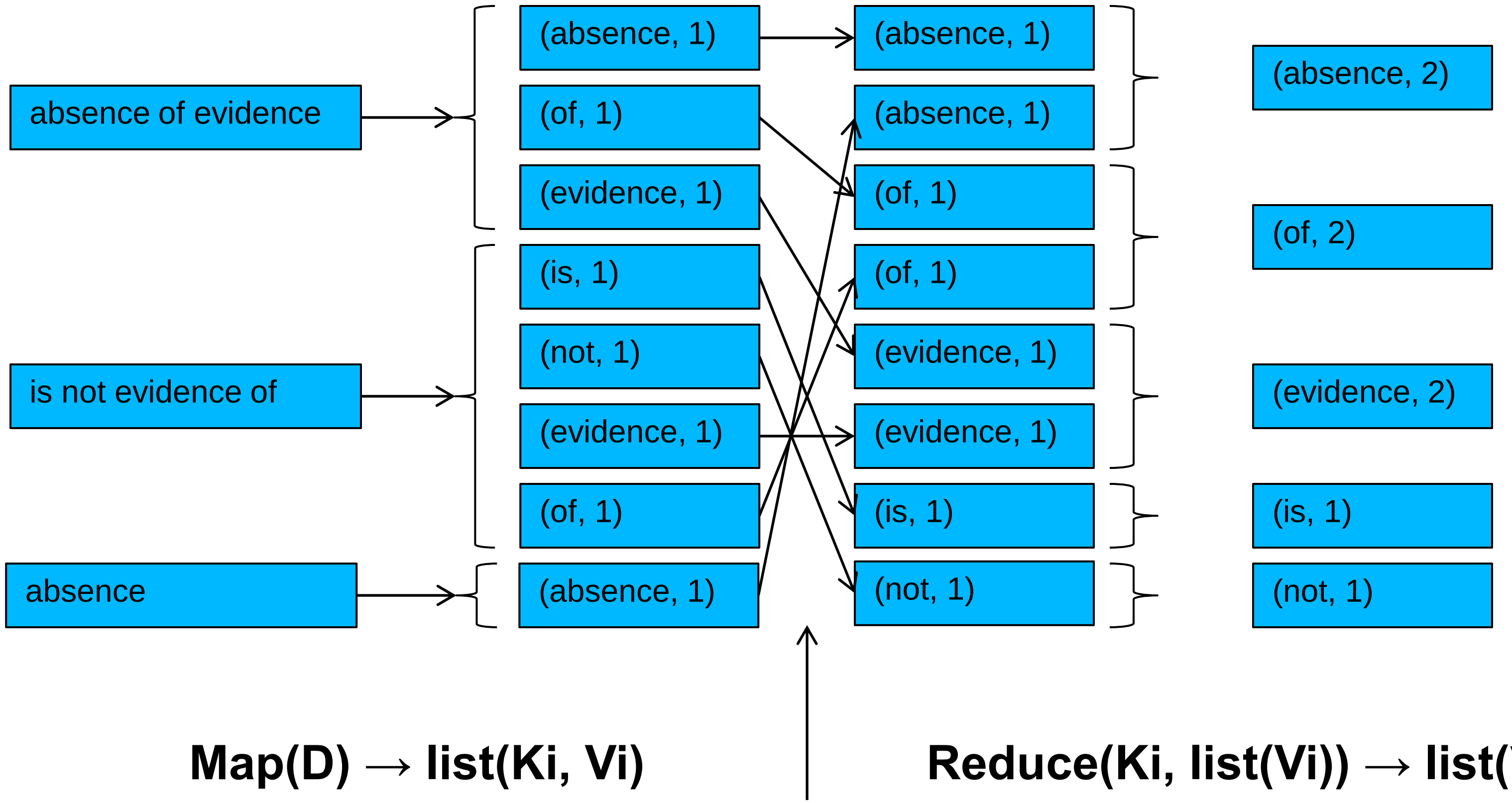
- Map(D) → list(Ki, Vi)
- Reduce(Ki, list(Vi)) → list(Vf)
- Map: "Apply a function to every member of dataset" to produce a list of key-value pairs
  - Dataset: set of values of uniform type D
    - Image blobs, lines of text, individual points, etc
  - Function: transforms each value into a list of zero or more key,value pairs of types Ki, Vi
- Reduce: Given a key and all associated values, do some processing to produce list of type Vf
- Execution over data is managed by a MapReduce framework

Canonical example: Word Count

- D = lines of text
- Ki = Single Words
- Vi = Numbers
- Vf = Word/count pairs
- Map(D) = Emit pairs containing each word and the number 1
- Reduce(Ki, list(Vi)) = Sum all the numbers in the list associated with the given word. Emit the word and the resulting count

Map(D) → list(Ki, Vi)
Reduce(Ki, list(Vi)) → list(Vf)

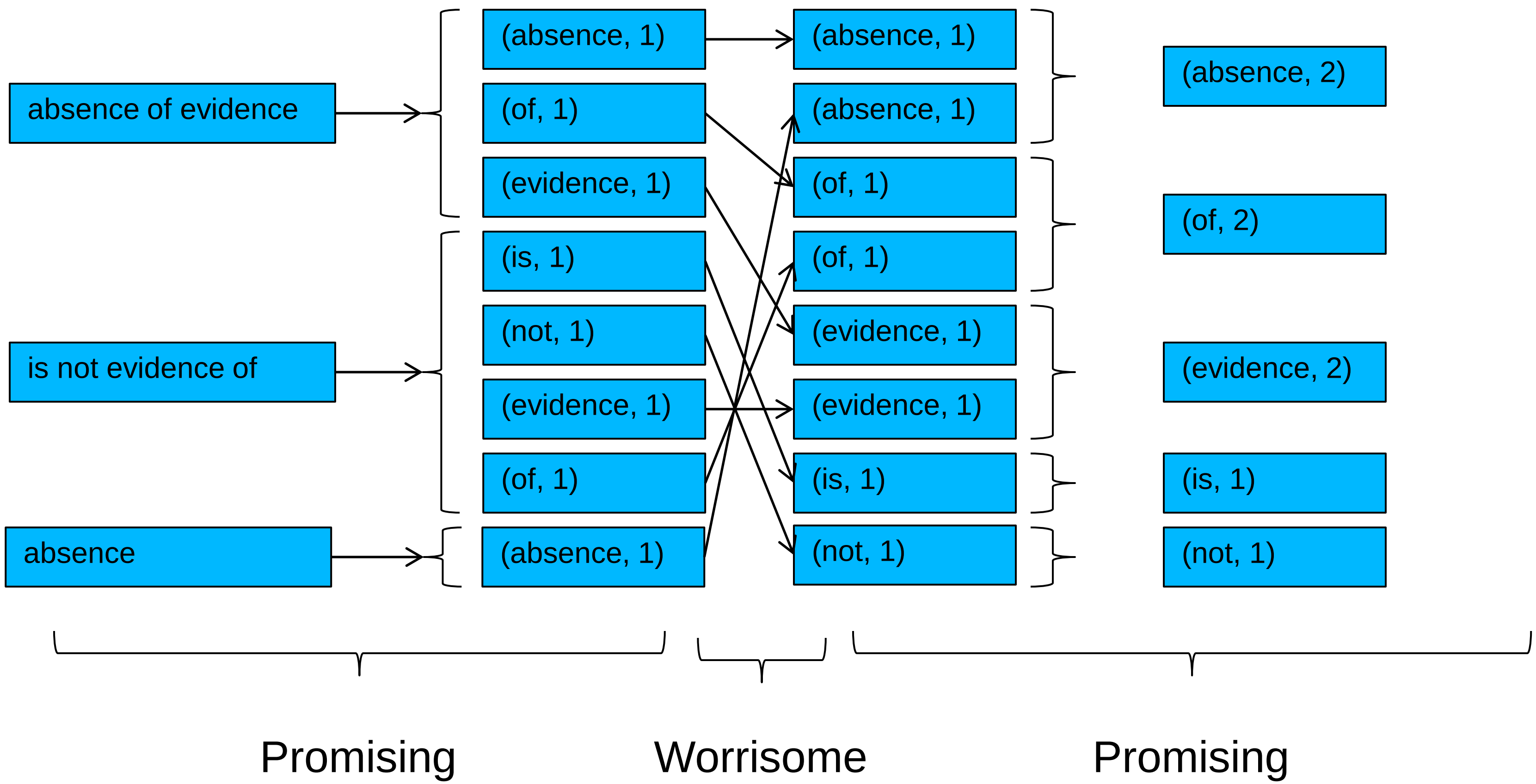
Canonical example: Word Count



Map(D) → list(Ki, Vi) **Reduce(Ki, list(Vi)) → list(Vf)**

Somehow need to group by keys so Reduce can be given all associated values!

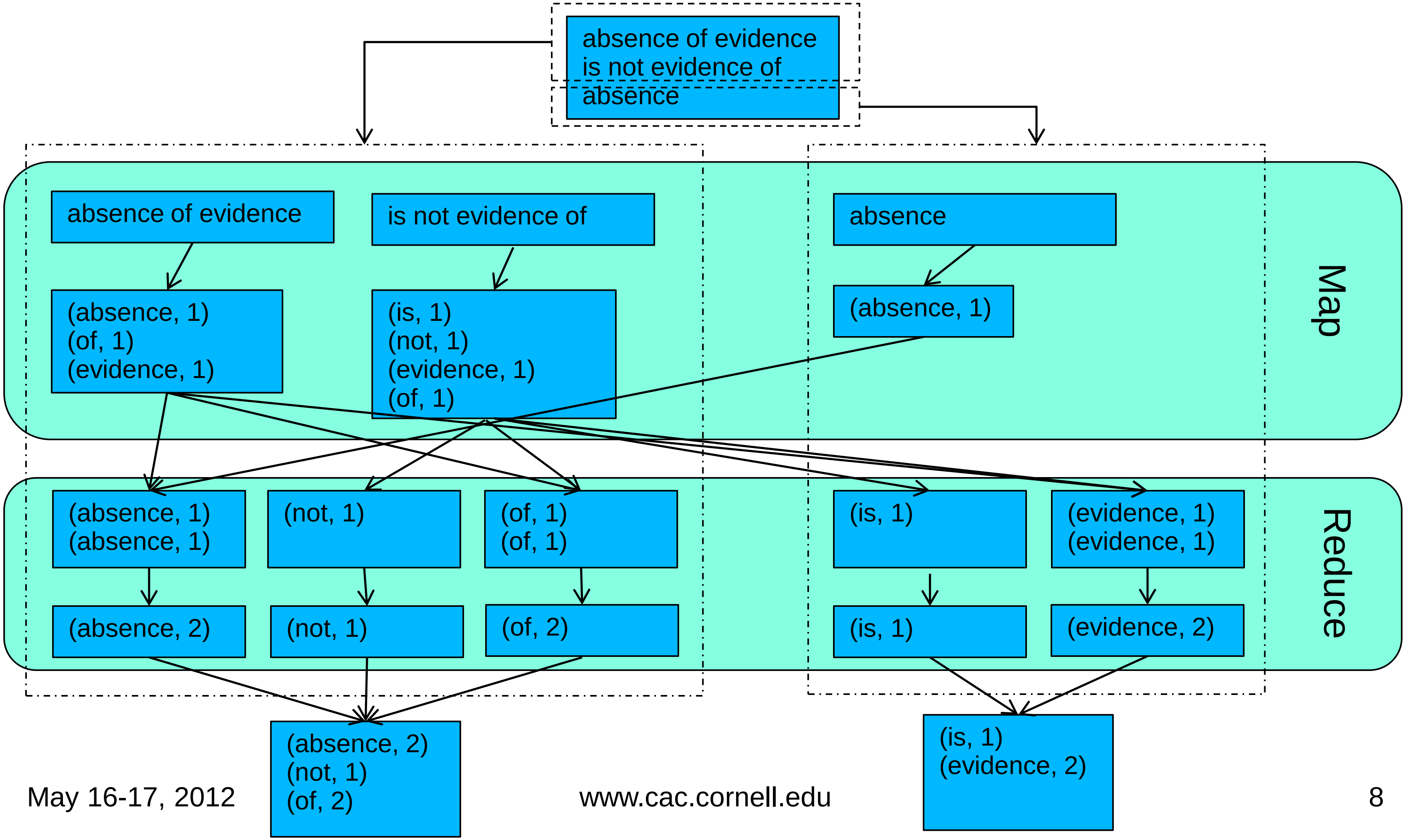
Opportunities for Parallelism?



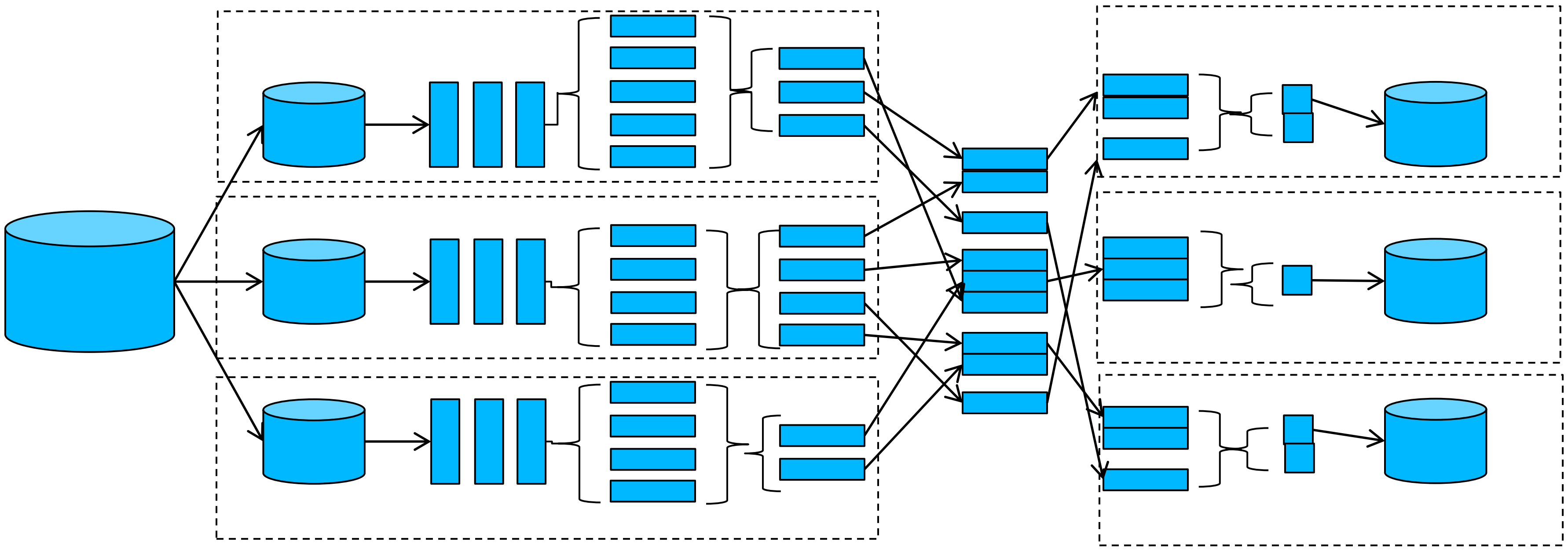
Opportunities for Parallelism

- Map and Reduce functions are independent
  - No explicit communication between them
  - Grouping phase between Map and Reduce is the only point of data exchange
- Individual Map, Reduce results depend only on input value.
  - Order of data, execution does not matter in the end.
- Input data read in parallel
- Output data written in parallel

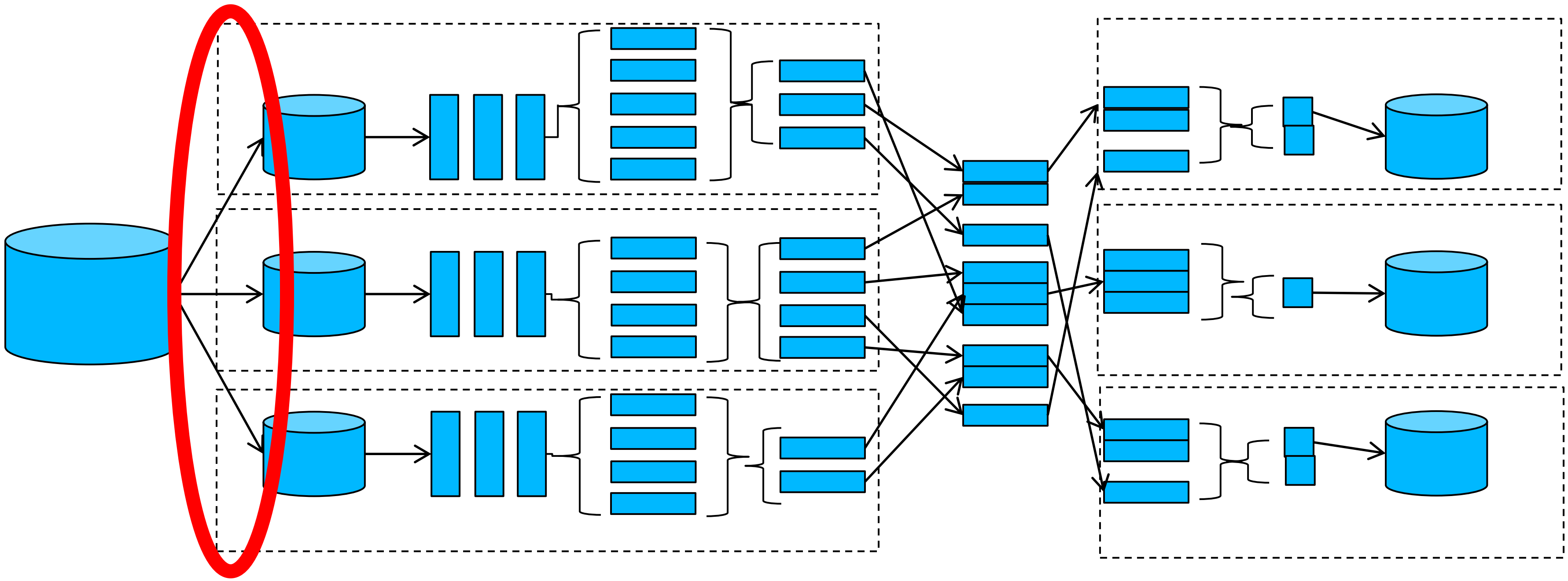
Parallel, Distributed execution



Full Parallel Pipeline



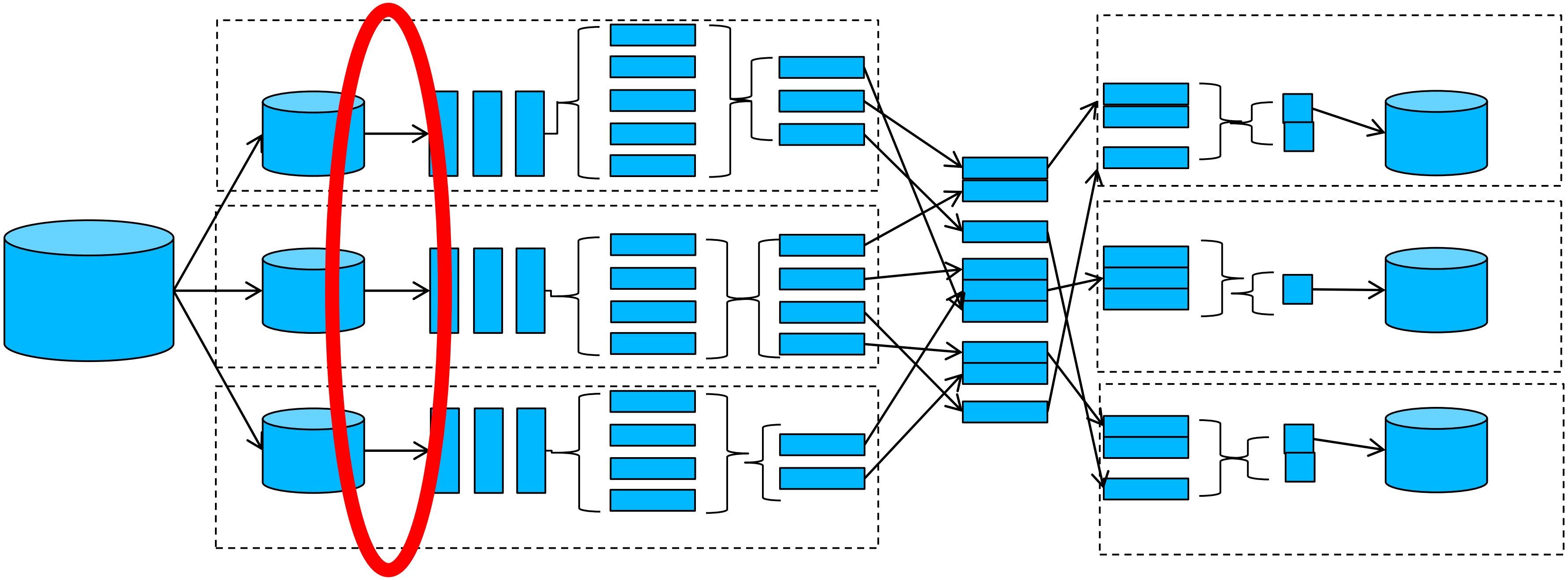
Full Parallel Pipeline



Split – Divide data into parallel streams

- Use features of underlying storage technology
    - File sharding, locality information, parallel data formats

Full Parallel Pipeline



Read – Chop data into iterable units

- Most common in MapReduce world – Lines of Text
- Can be arbitrary simple or complex –integer arrays, pdf documents, mesh fragments, etc.

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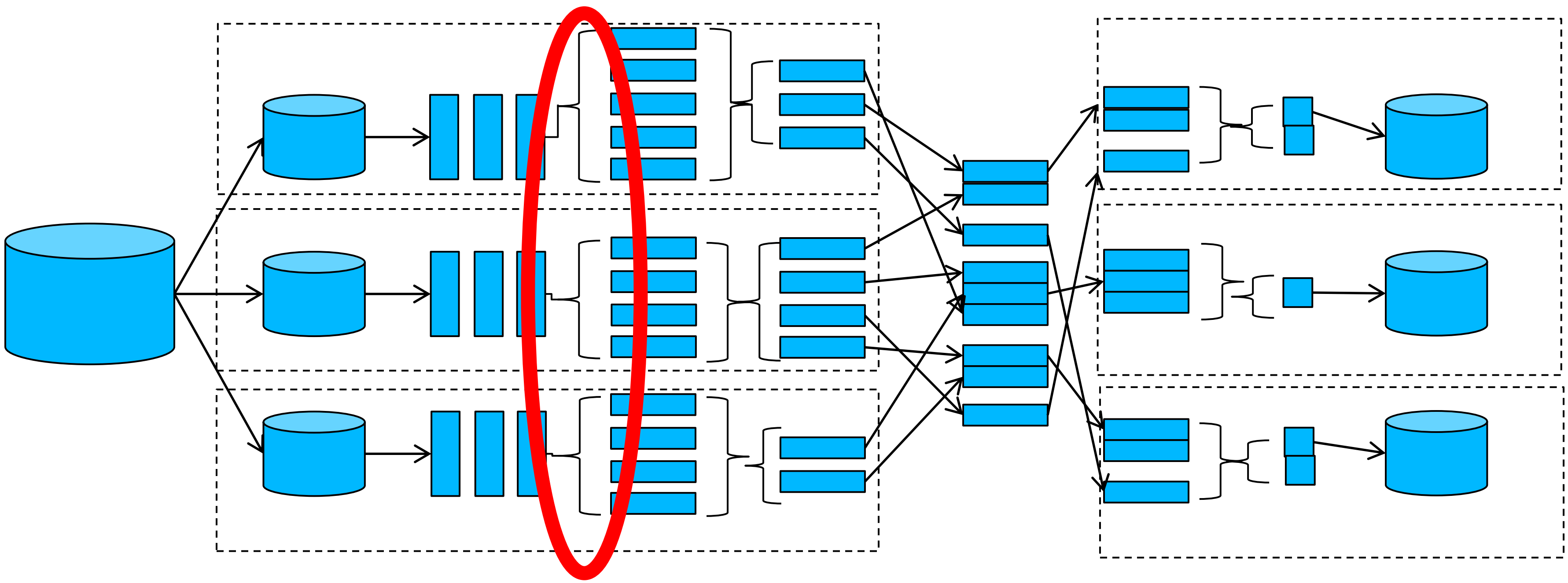
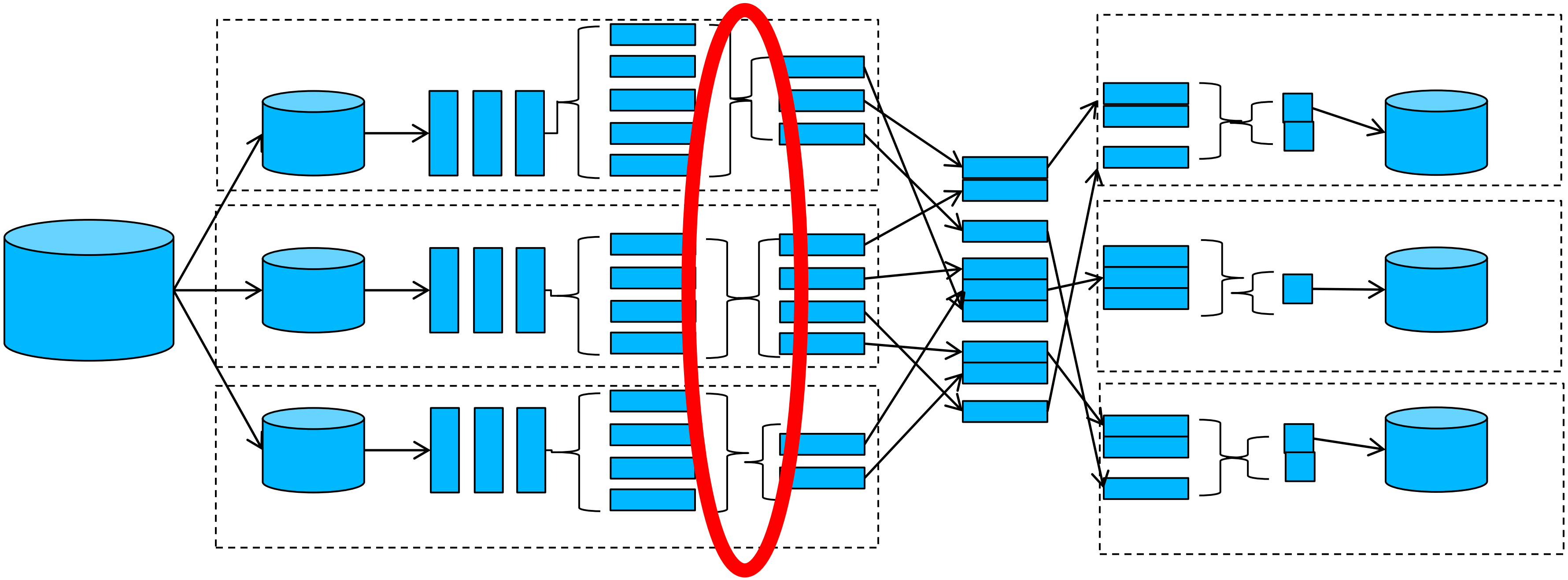
Full Parallel Pipeline



Map – Apply a function, return a list of keys/values

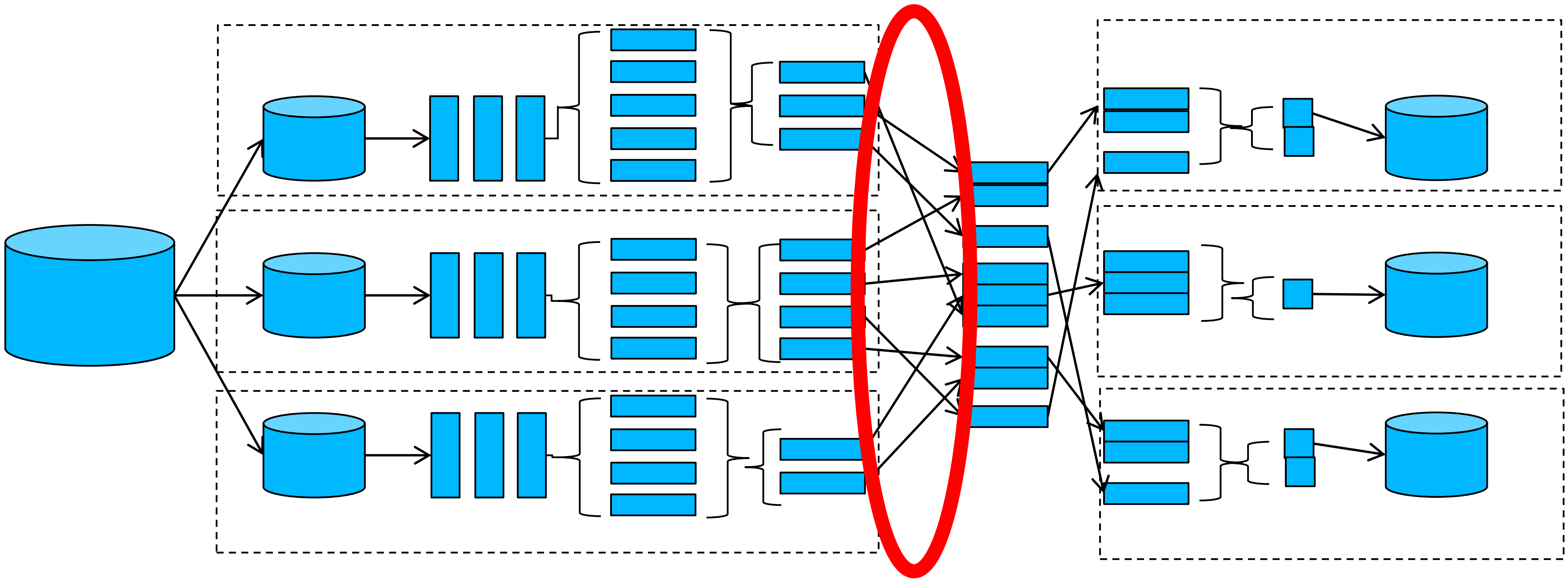
Full Parallel Pipeline



Combine – (optional) execute a “mini-reduce” on some set of map output

- For optimization purposes
- May not be possible for every algorithm

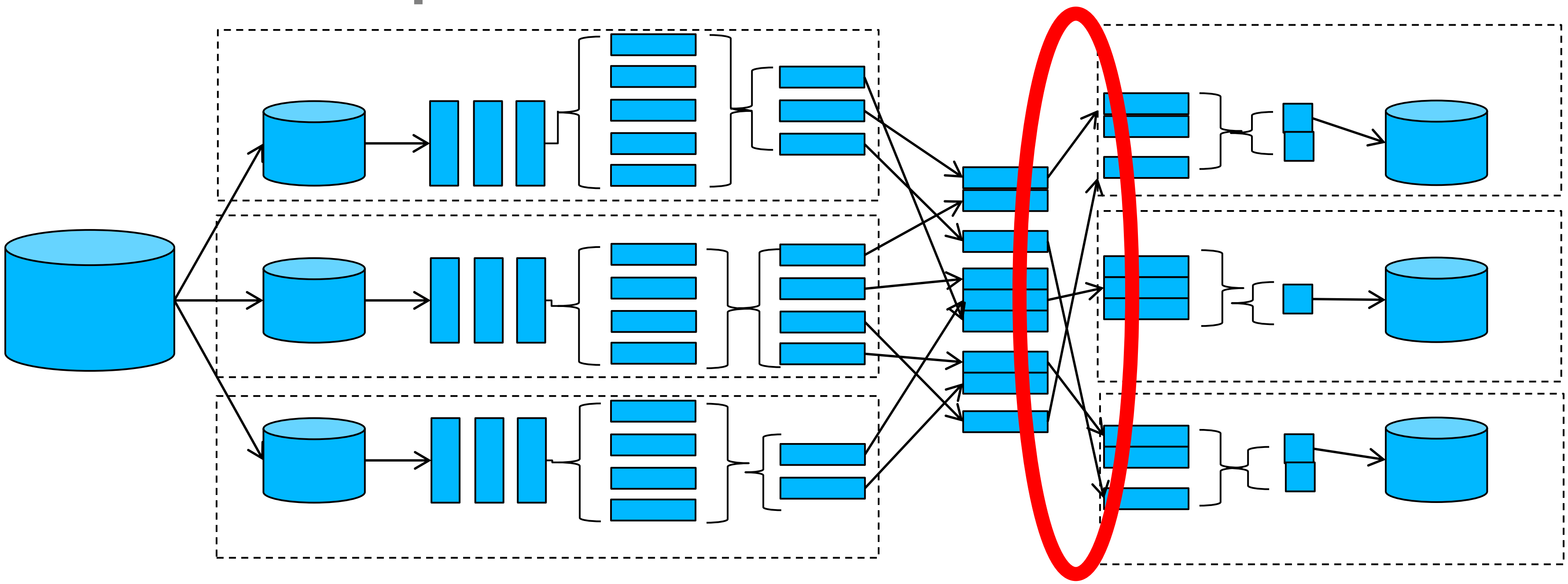
Full Parallel Pipeline



Group – Group all results by key, collapse into a list of values for each key

- Need **all** intermediate values before this can complete
- Automatically performed by MapReduce framework

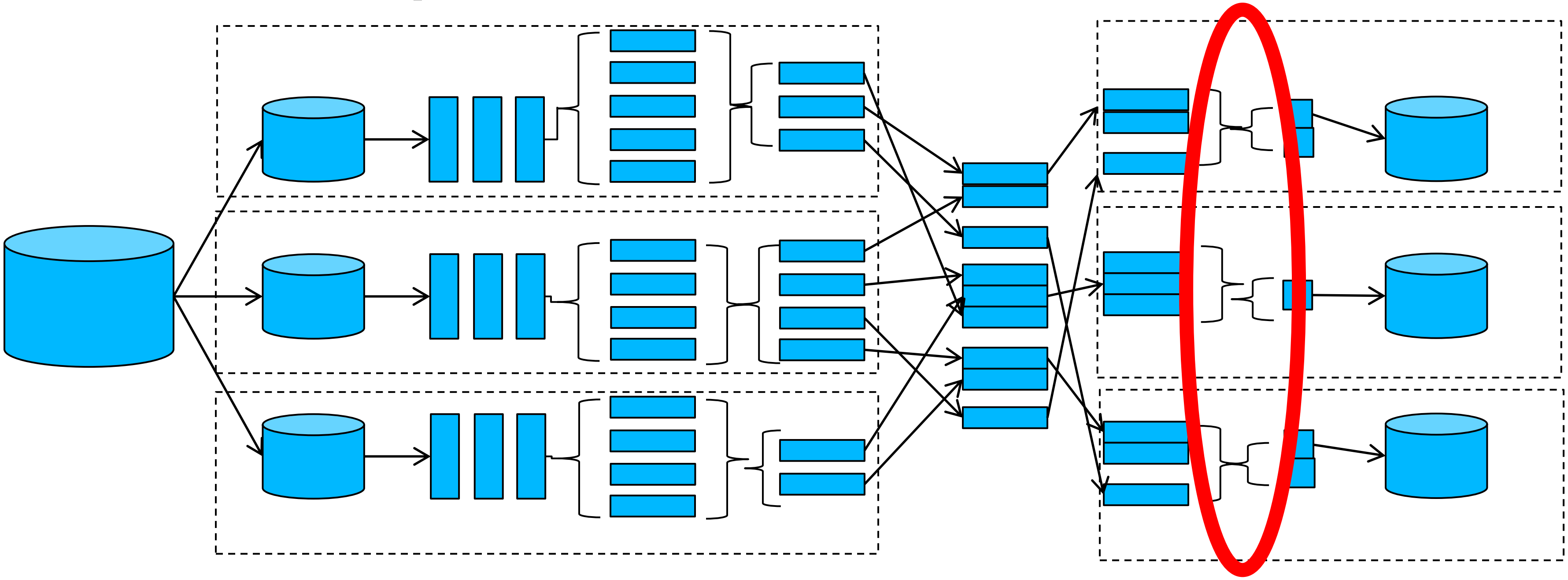
Full Parallel Pipeline



Partition – Send grouped data to reduce processes

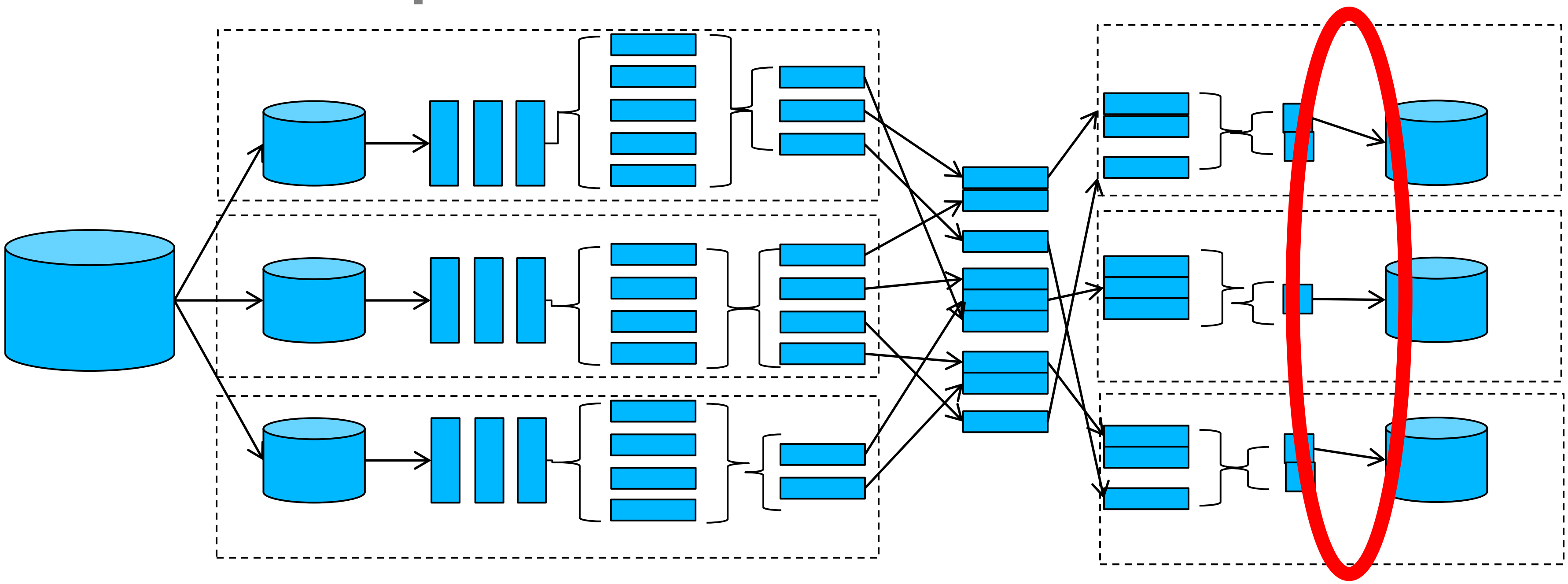
- Typically, just a dumb hash to evenly distribute
- Opportunities for balancing or other optimization.

Full Parallel Pipeline



Reduce – Run a computation over each aggregated result, produce a final list of values

Full Parallel Pipeline



Write – Move Reduce results to their final destination

- Could be storage, or another MapReduce process!

Programming considerations

You *must* provide:

- Map, Reduce functions

You *may* provide:

- Combine, if it helps
- Partition function, if it matters

Framework must provide:

- Grouping and data shuffling

Framework may provide:

- Read, Write
  - For simple data such as lines of text
- Split
  - For parallel storage or data formats it knows about

Benefits

- Presents an easy-to-use programming model
  - No synchronization, communication by individual components. Ugly details hidden by framework.
- Execution managed by a framework
  - Failure recovery (Maps/Reduces can always be re-run if necessary)
  - Speculative execution (Several processes operate on same data, whoever finishes first wins)
  - Load balancing
- Adapt and optimize for different storage paradigms

Drawbacks

- Grouping/partitioning is serial!
  - Need to wait for **all** map tasks to complete before **any** reduce tasks can be run
- Some algorithms may be hard to conceptualize in MapReduce.
- Some algorithms may be inefficient to express in terms of Map Reduce

Hadoop

- Open Source MapReduce framework in Java
  - Spinoff from Nuch web crawler project
- HDFS – Hadoop Distributed Filesystem
  - Distributed, fault-tolerant, sharding
- Many sub-projects
  - Pig: Data-flow and execution language. Scripting for MapReduce
  - Hive: SQL-like language for analyzing data
  - Mahout: Machine learning and data mining libraries
    - K-means clustering, Singular Value Decomposition, Bayesian classification

Hadoop

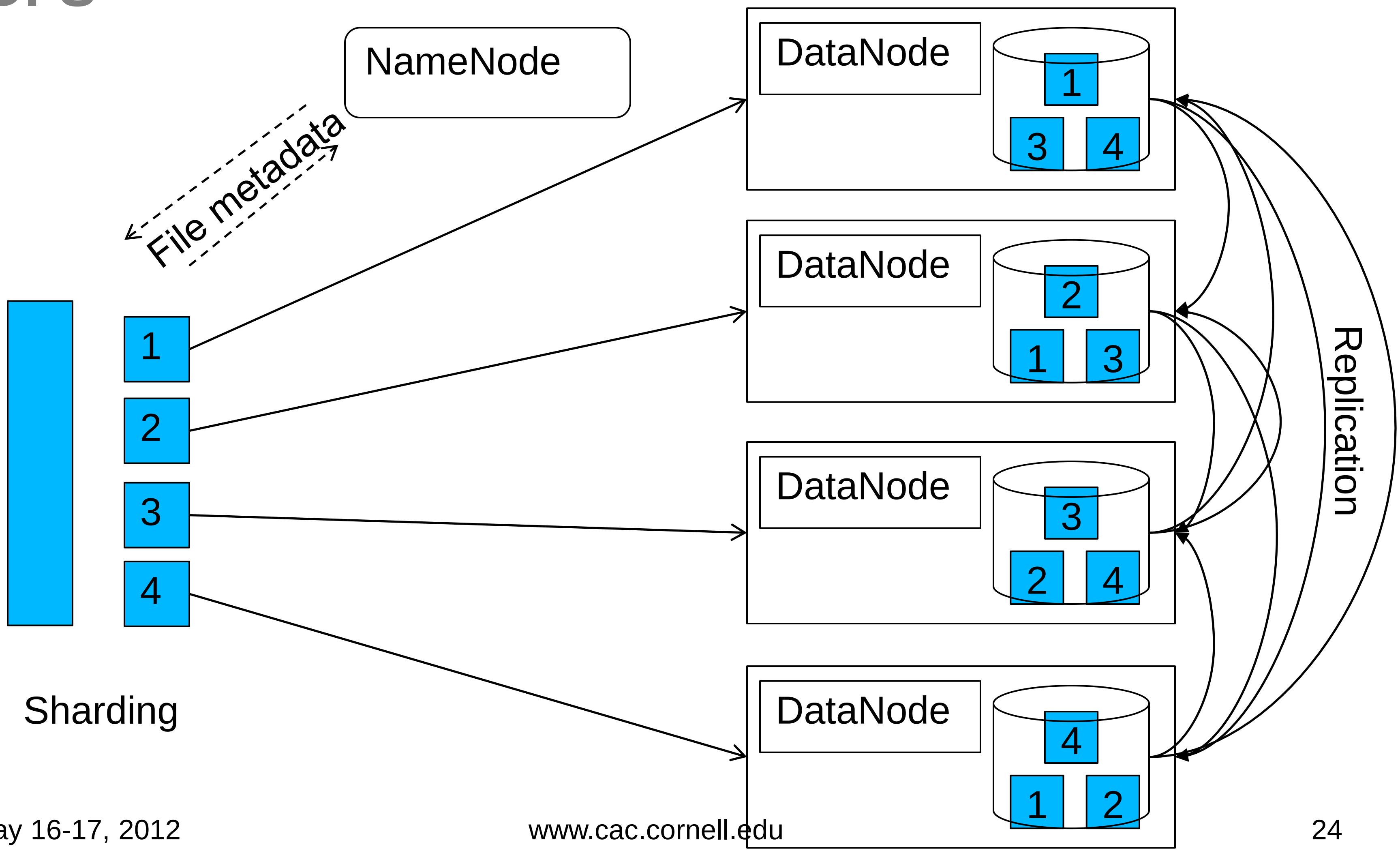
- User provides java classes for Map, Reduce functions
  - Can subclass or implement virtually every aspect of MapReduce pipeline or scheduling
- Streaming mode to STDIN, STDOUT of external map, reduce processes (can be implemented in any language)
  - Lots of scientific data that goes beyond lines of text
  - Lots of existing/legacy code that can be adapted/wrapped into a Map or Reduce stage.

```
stream -input /dataDir/dataFile
-file myMapper.sh -mapper "myMapper.sh"
-file myReducer.sh -reducer "myReducer.sh"
-output /dataDir/myResults
```

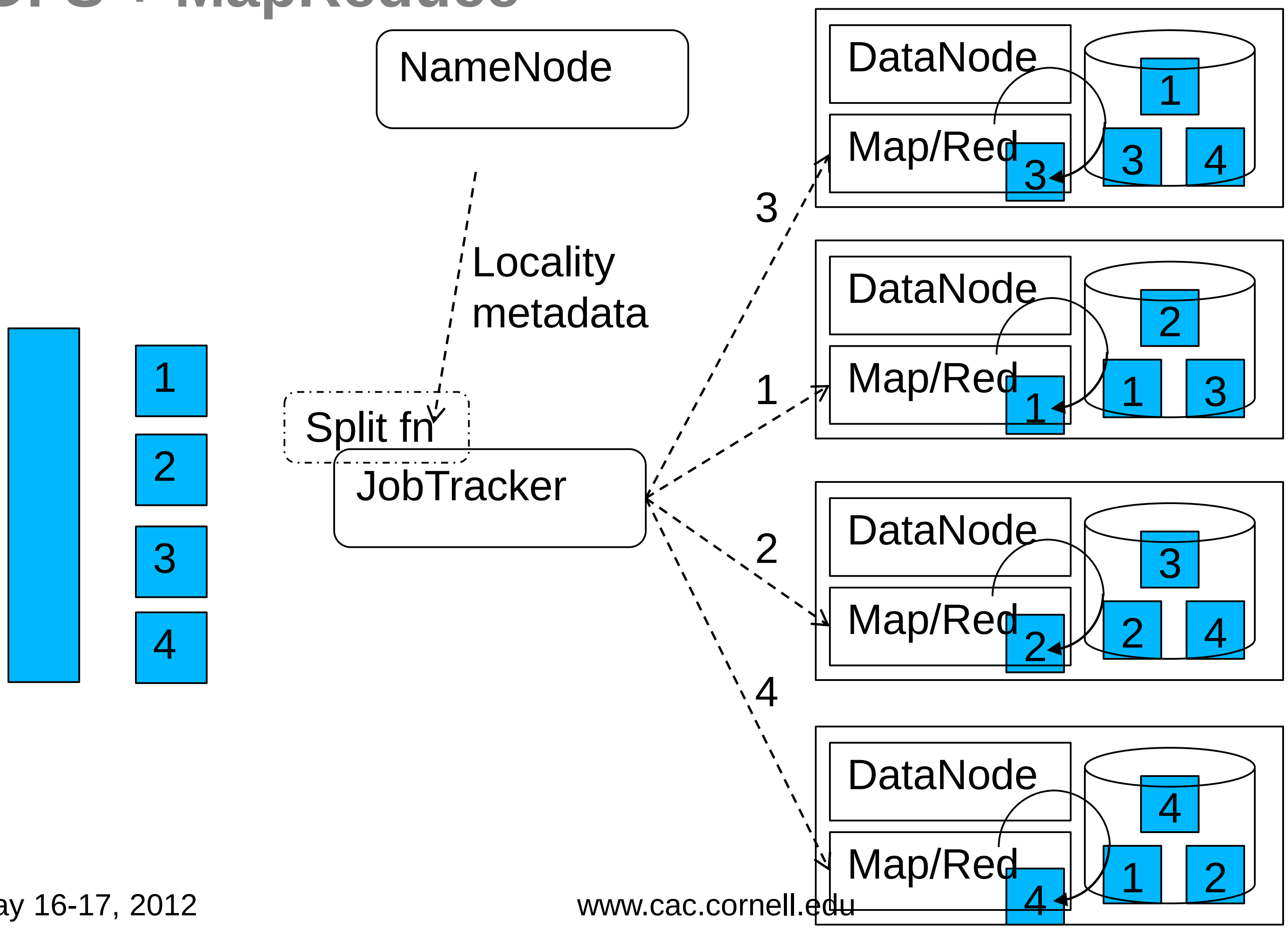
HDFS

- Data distributed among compute nodes
  - Sharding: 64MB chunks
  - Redundancy
- Small number of large files
- Not quite POSIX file semantics
  - No random write, append
- Write-once read many
- Favor throughput over latency
- Streaming/sequential access to files

HDFS


NameNode
File metadata
DataNode
1
3
4
DataNode
2
1
3
DataNode
3
2
4
DataNode
4
1
2
Replication
1
2
3
4
Sharding

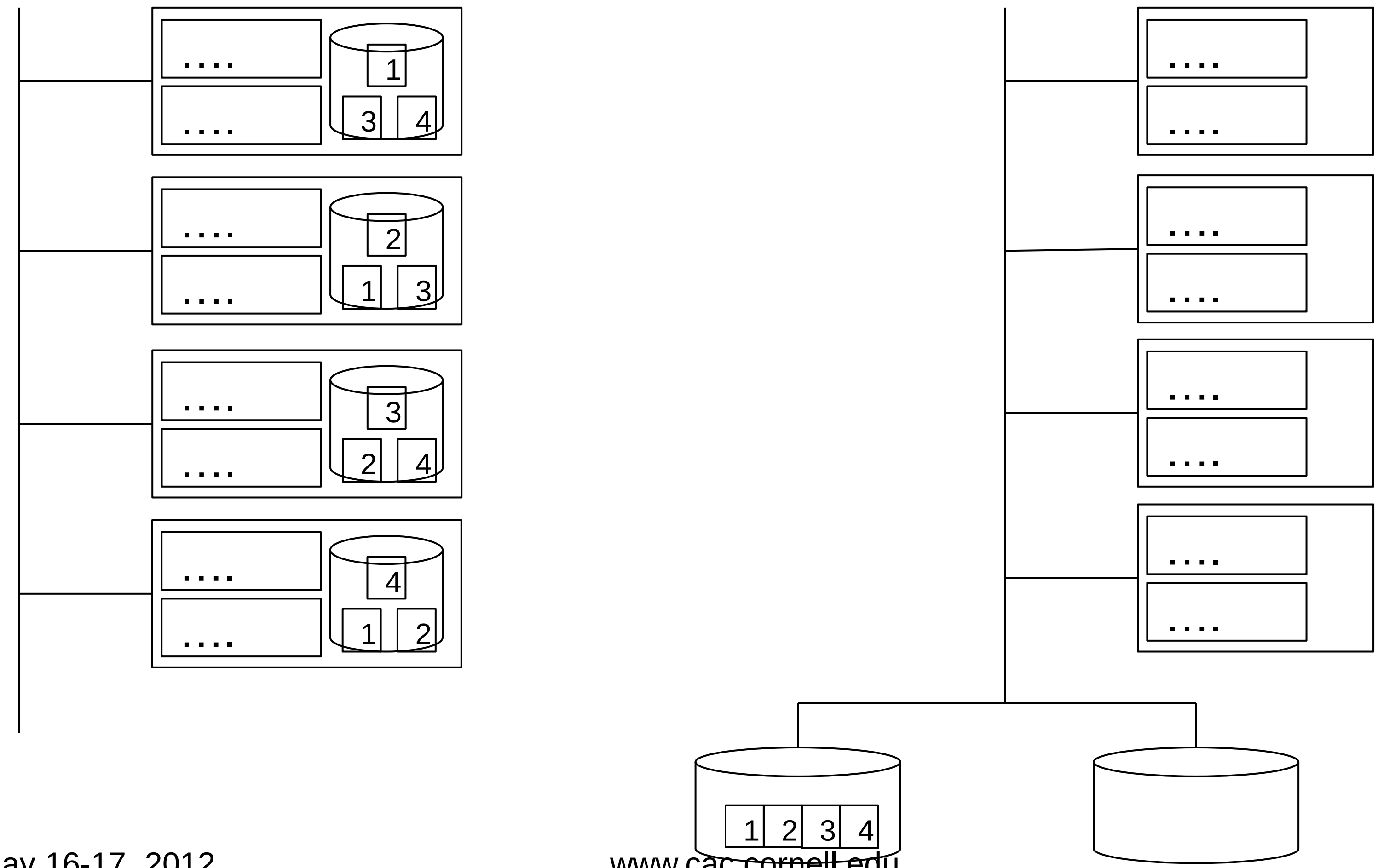
HDFS + MapReduce



HDFS + MapReduce

- Assume failure-prone nodes
  – Data and computation recovery through redundancy
- Move computation to data
  – Data is local to computation, direct-attached storage to each node
- Sequential reads on large blocks
- Minimal contention
  – Simultaneous maps/reduces on a node can be controlled by configuration

Hadoop + HDFS vs HPC



Hadoop in HPC environments

- Access to local storage can be problematic
  - Local storage may not be available at all
  - Even if so, long-term HDFS usually not possible
- HPC relies on global storage (e.g. Lustre) via high-speed interconnect.
  - What is meaning of “locality” in inherently non-local (but parallel) storage?

Hadoop @ TACC

- On *Longhorn* visualization cluster
- Special, local, persistent /hadoop filesystem on some machines
  - 48 nodes with 2TB HDFS storage/node
  - 16 nodes with 1TB HDFS storage/node, extra large memory (144GB memory)
- Modified hadoop distribution
  - Starts HDFS on allocated nodes
- Special Hadoop queue
- By request only
- Details at https://sites.google.com/site/tacchadoop

Still much to learn

- Most established patterns are from web and text processing (inverted indexes, ranking, clustering, etc)
- Scientific data and algorithms much more varied
  - Papers describing an existing problem applied to MapReduce are common
- When does HDFS provide benefit over traditional global shared FS?
  - Tends to do poorly for small tasks, can be a crossover point that needs to be found
- Lots of tuning parameters
  - Data skew and heterogeneity may lead to long, inefficient jobs.

Why Hadoop?

- If you find the programming model simple/easy
- If you have a data intensive workload
- If you need fault tolerance
- If you have dedicated nodes available
- If you like Java
- If you want to experiment.