Relaxed Synchronization and Eager Scheduling for Map-Reduce

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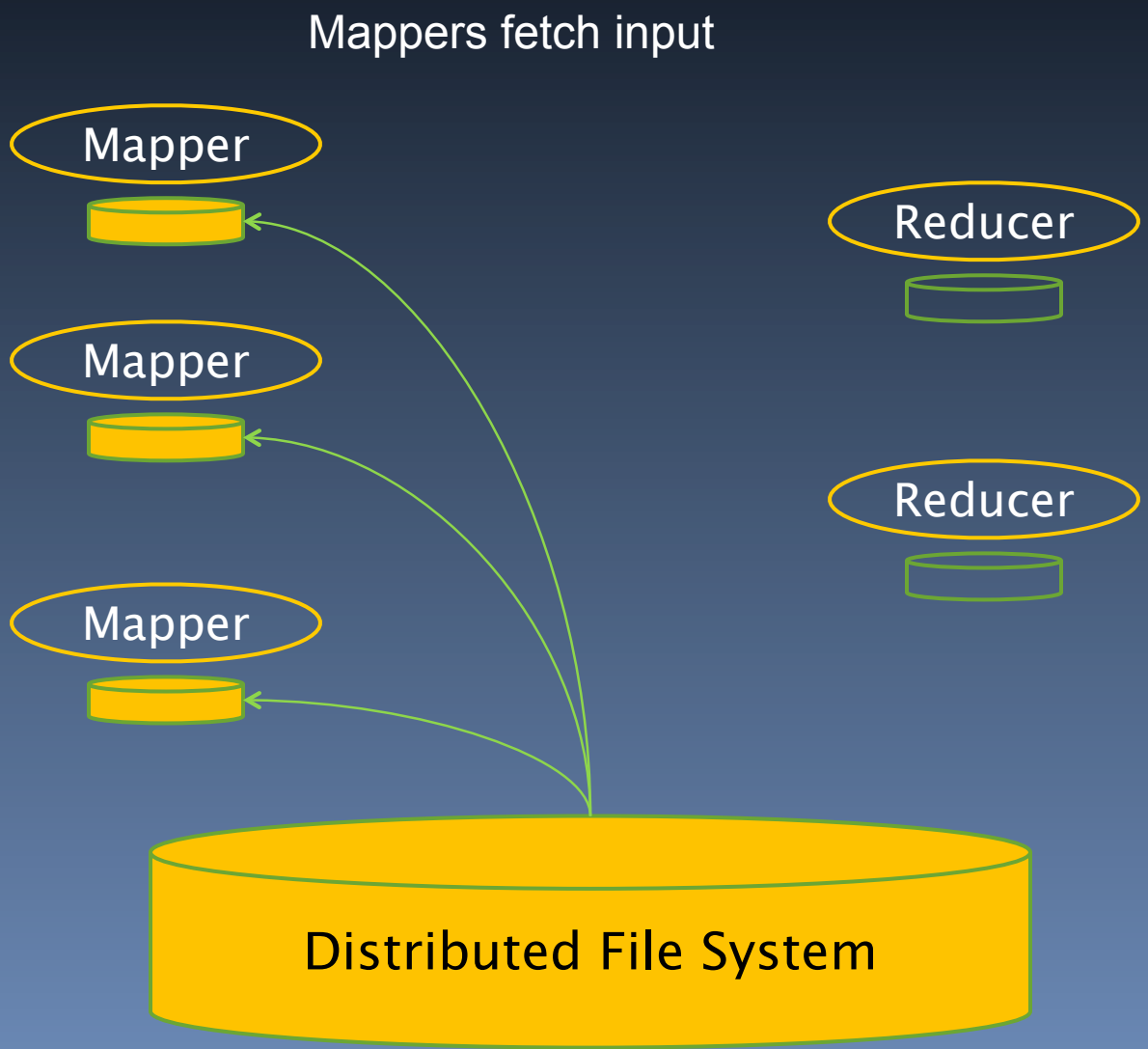
Goals of this project

- How can MapReduce be used to
  - support non-data parallel applications
  - specifically, **unstructured sparse graph algorithms**
    - social and biological networks
    - scientific datasets
- Enhancements to improve performance and scalability
  - without compromising
    - programmability
    - fault-tolerance

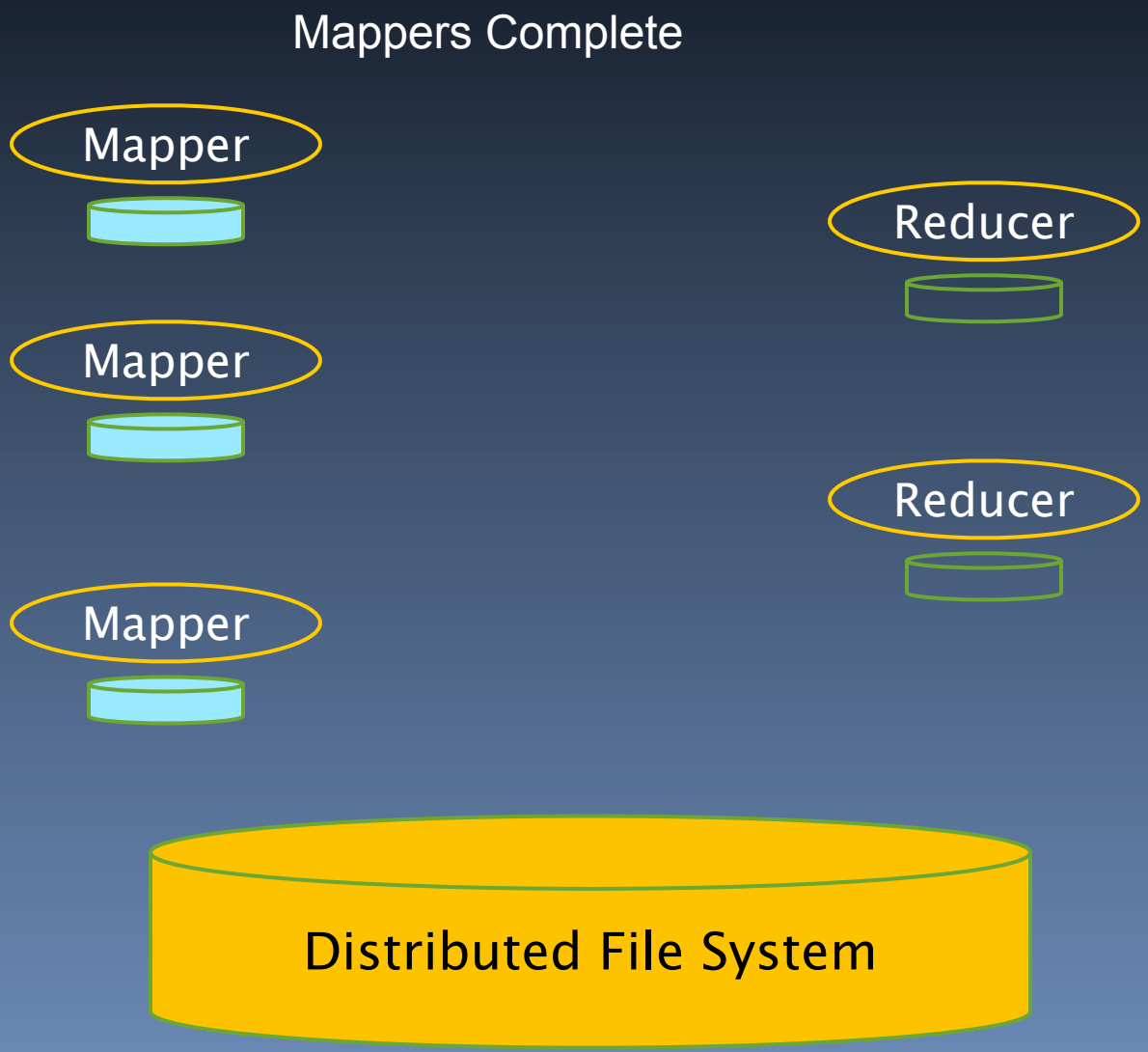
Observations

- Global reduction is a bottleneck for non-uniform algorithms
  - Often not necessary for correctness
- Tradeoff serial operation counts for partial reductions
  - locality enhancing mechanisms
    - natural graph partitioning
  - consistent with application semantics
- Show notable performance gains

MapReduce: Data Flow

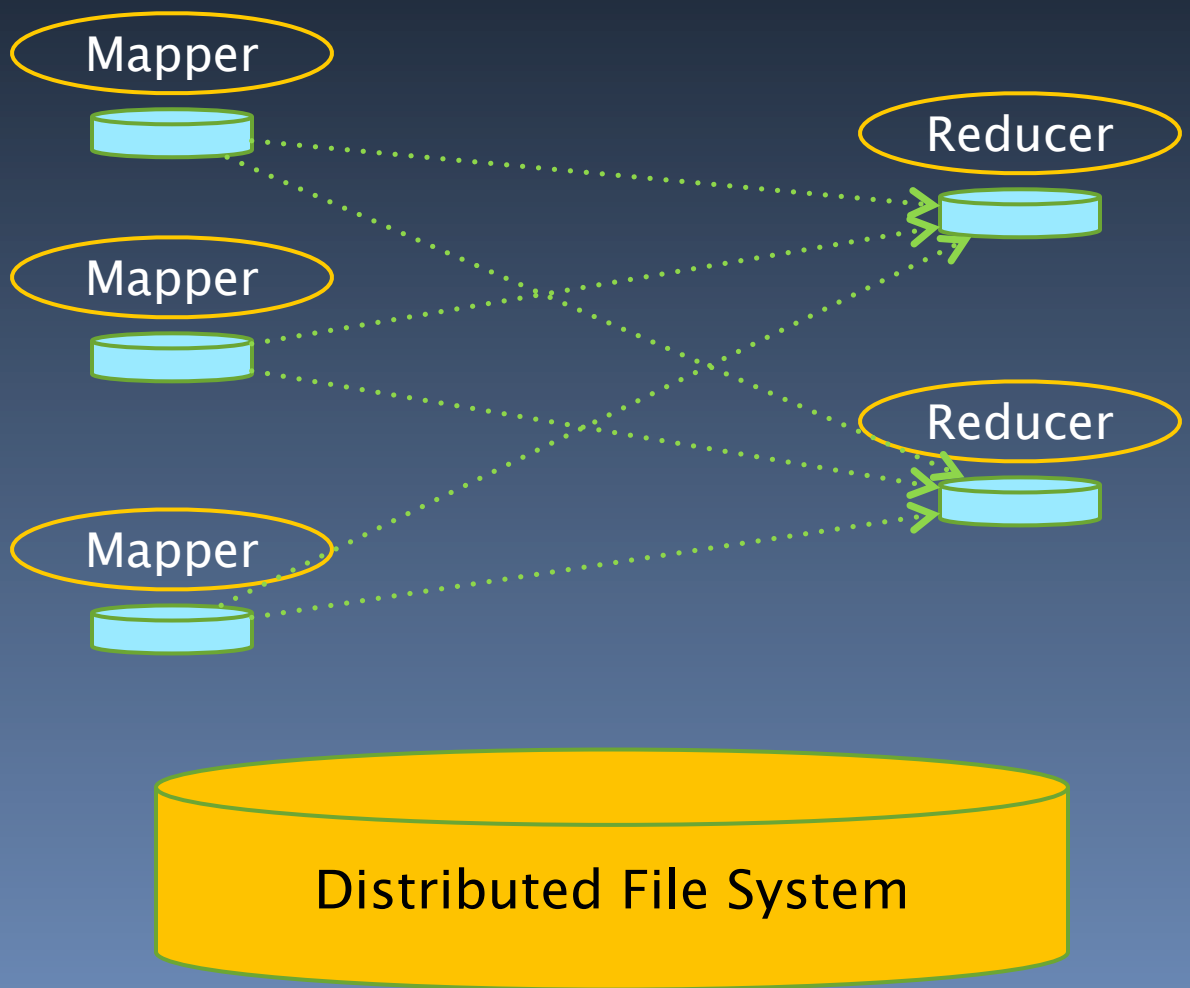


MapReduce: Data Flow

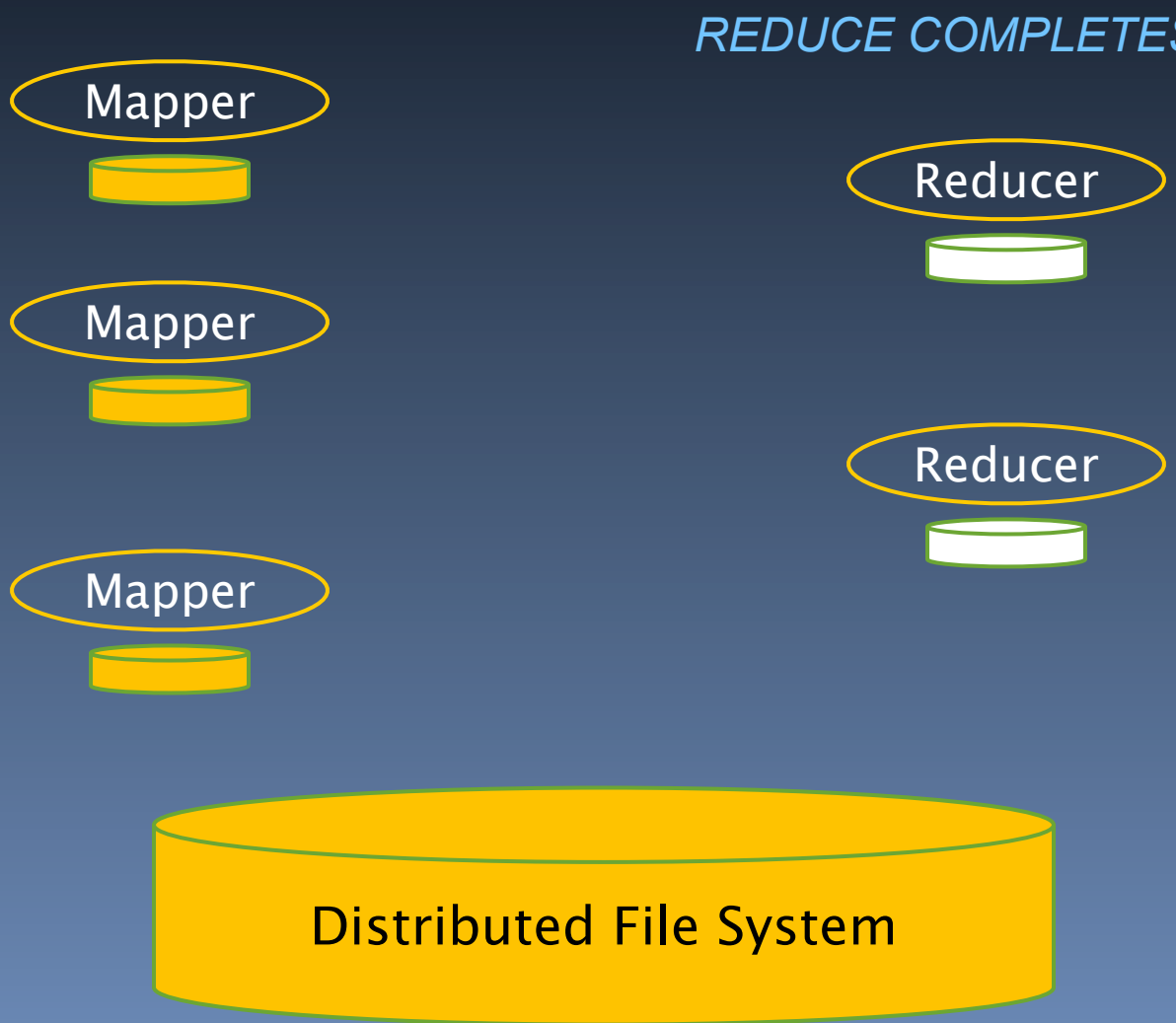


MapReduce: Data Flow

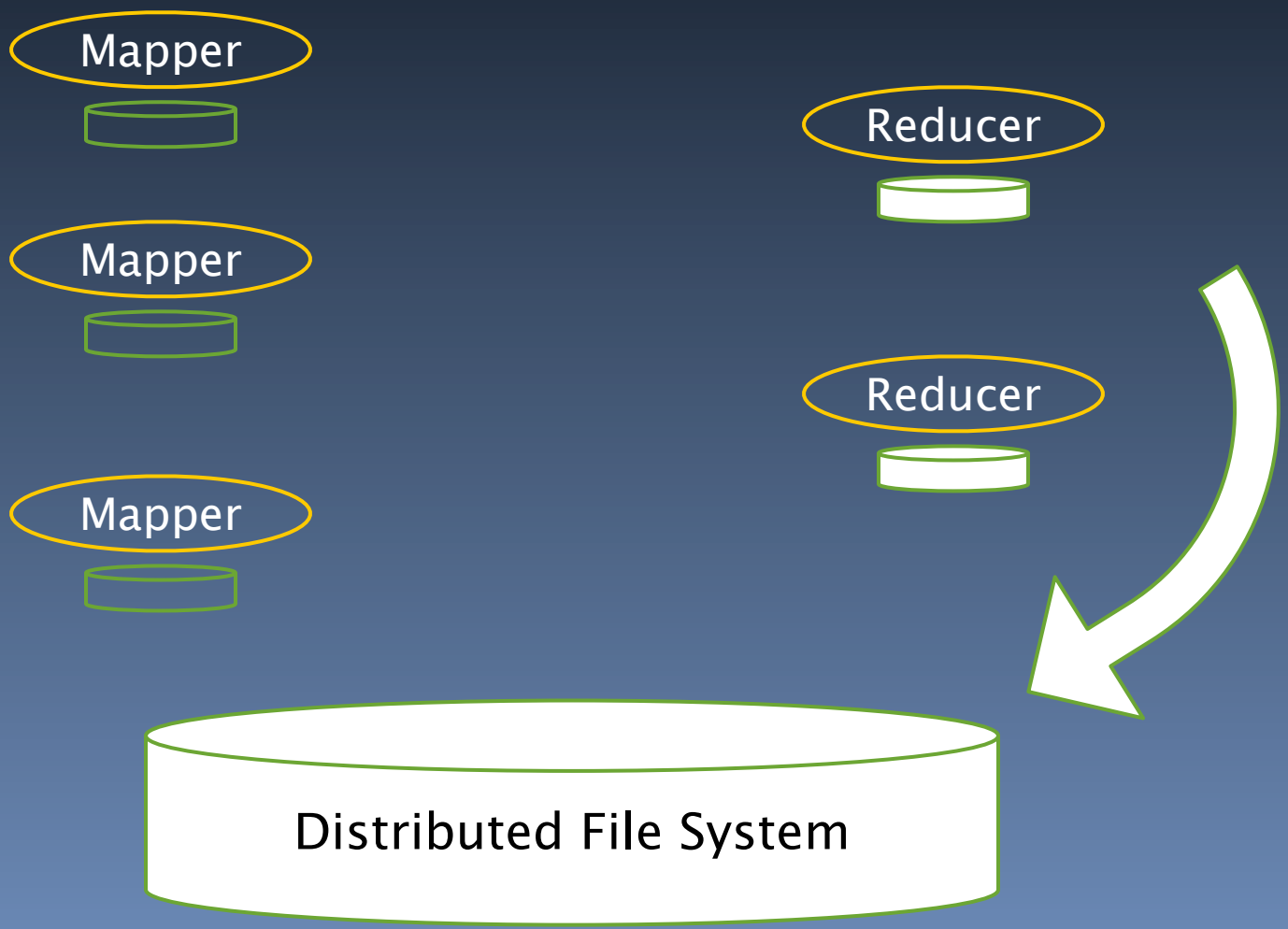
Reducers pull data from Mappers



MapReduce: Data Flow



MapReduce: Data Flow



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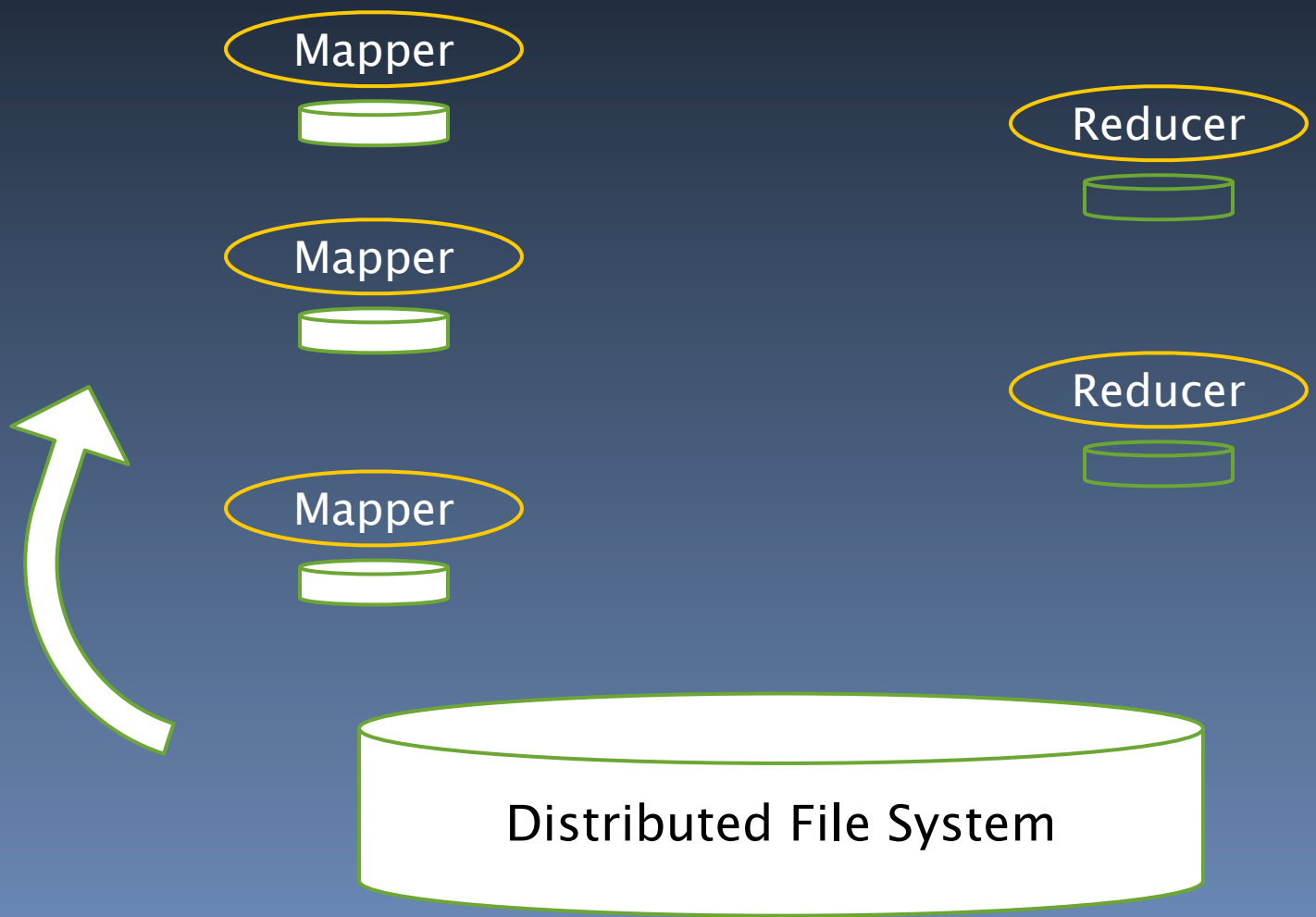


Characteristics

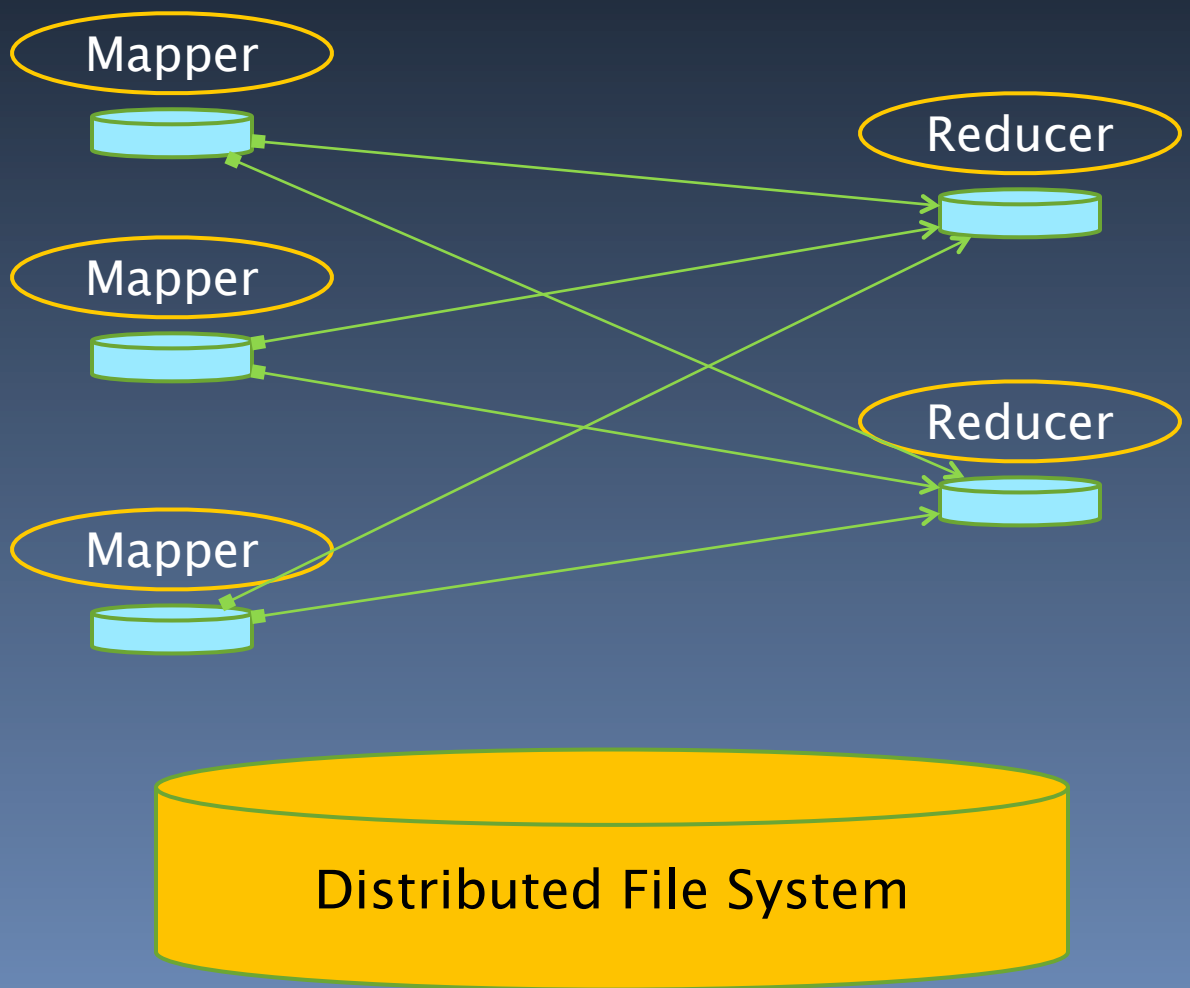
- Non data-parallel applications
  - E.g., search and prune, branch-and-bound
- Communication > Computation
  - Substantial non-local dataflow
  - More pronounced in iterative algorithms
    - how much does the input change across iterations?

Investigation

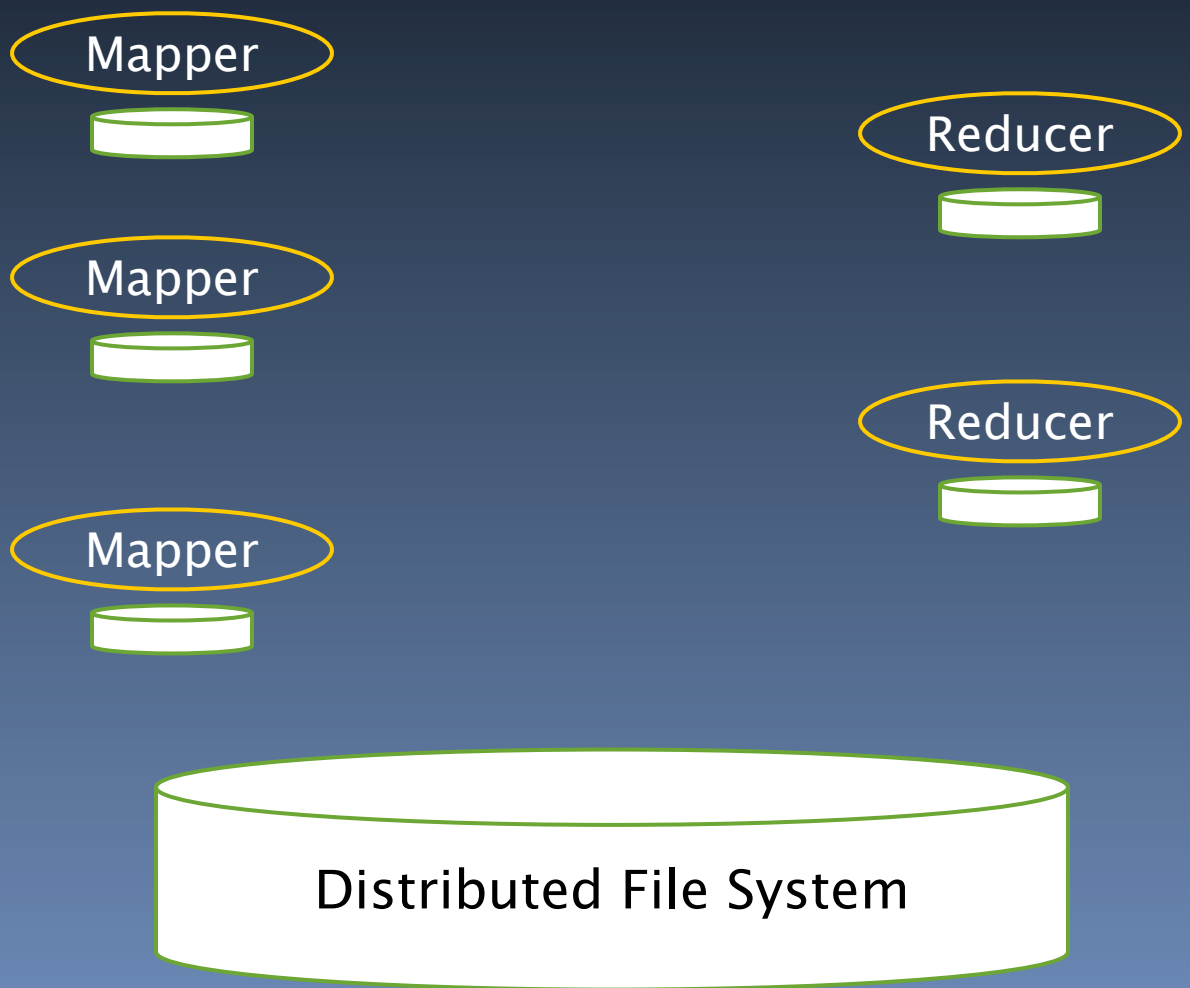
- Implemented sparse graph kernels/ apps
  - Matrix-matrix, matrix-vector products
  - Node accumulation, Similarity etc.
- Observation
  - Iterative structure
  - High synchronization costs under multiple iterations
    - Data shuffling, copying and hashing

Asynchronous data movement

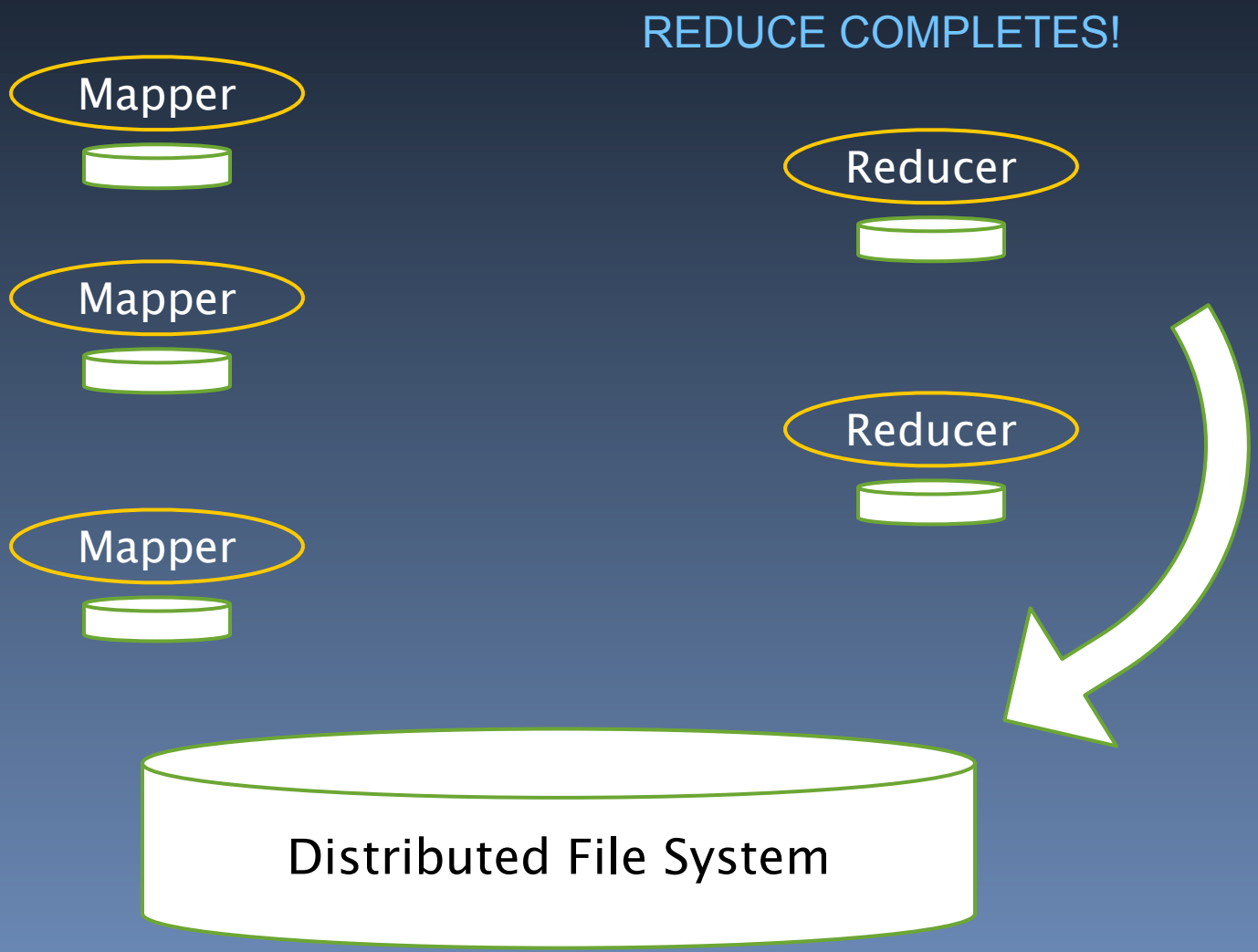
Mappers complete and asynchronously push data to reducers



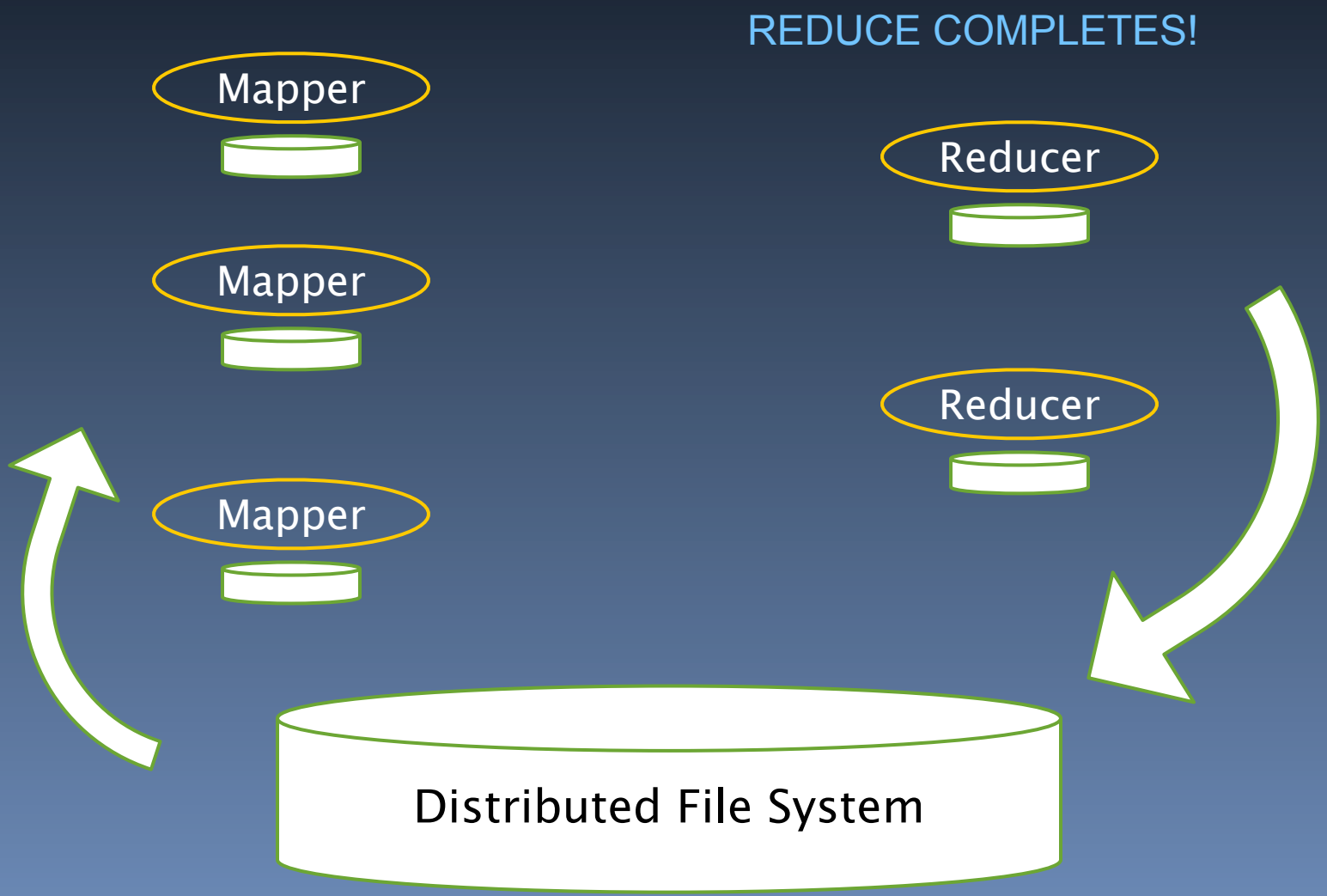
Asynchronous data movement



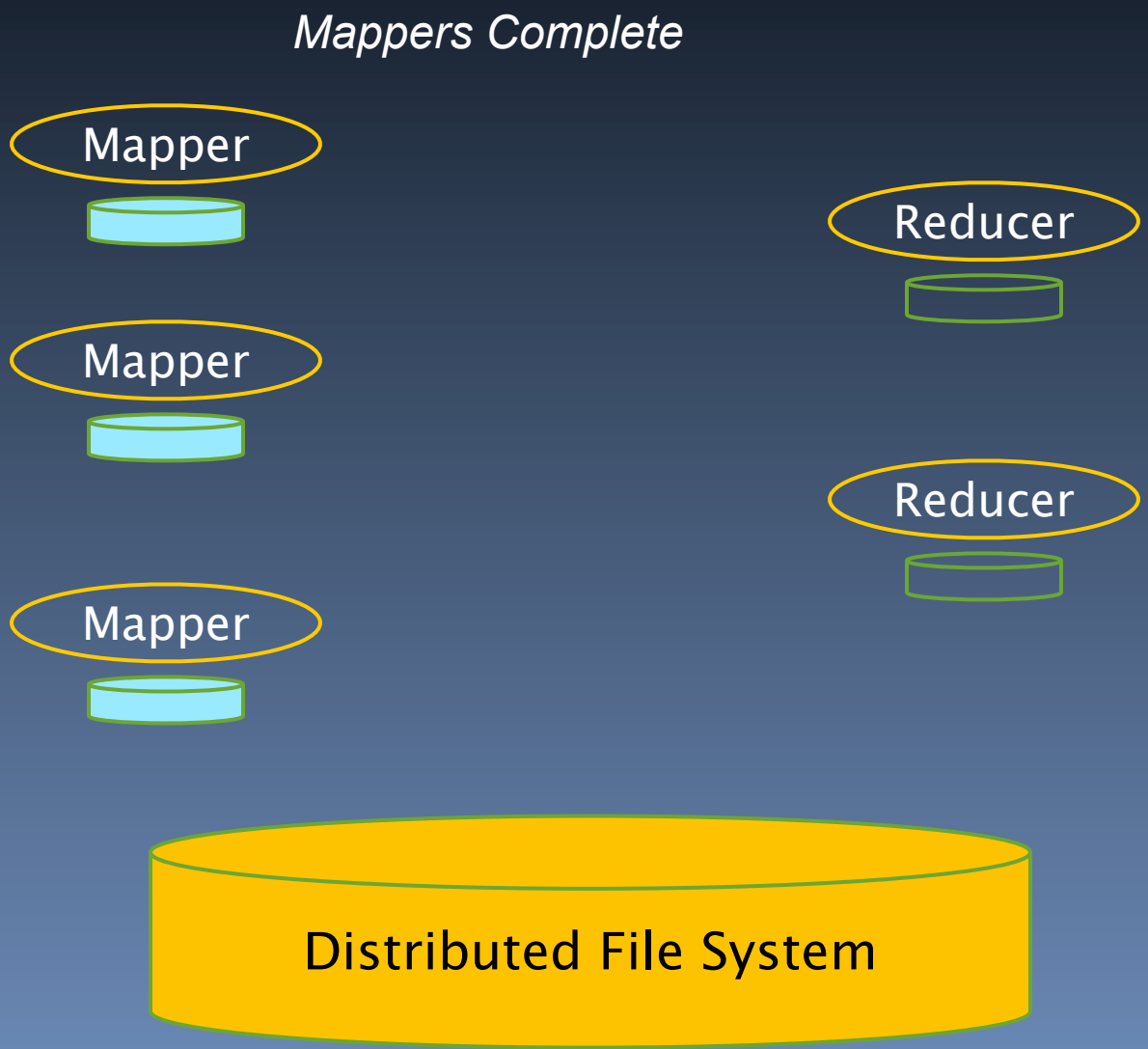
Asynchronous data movement



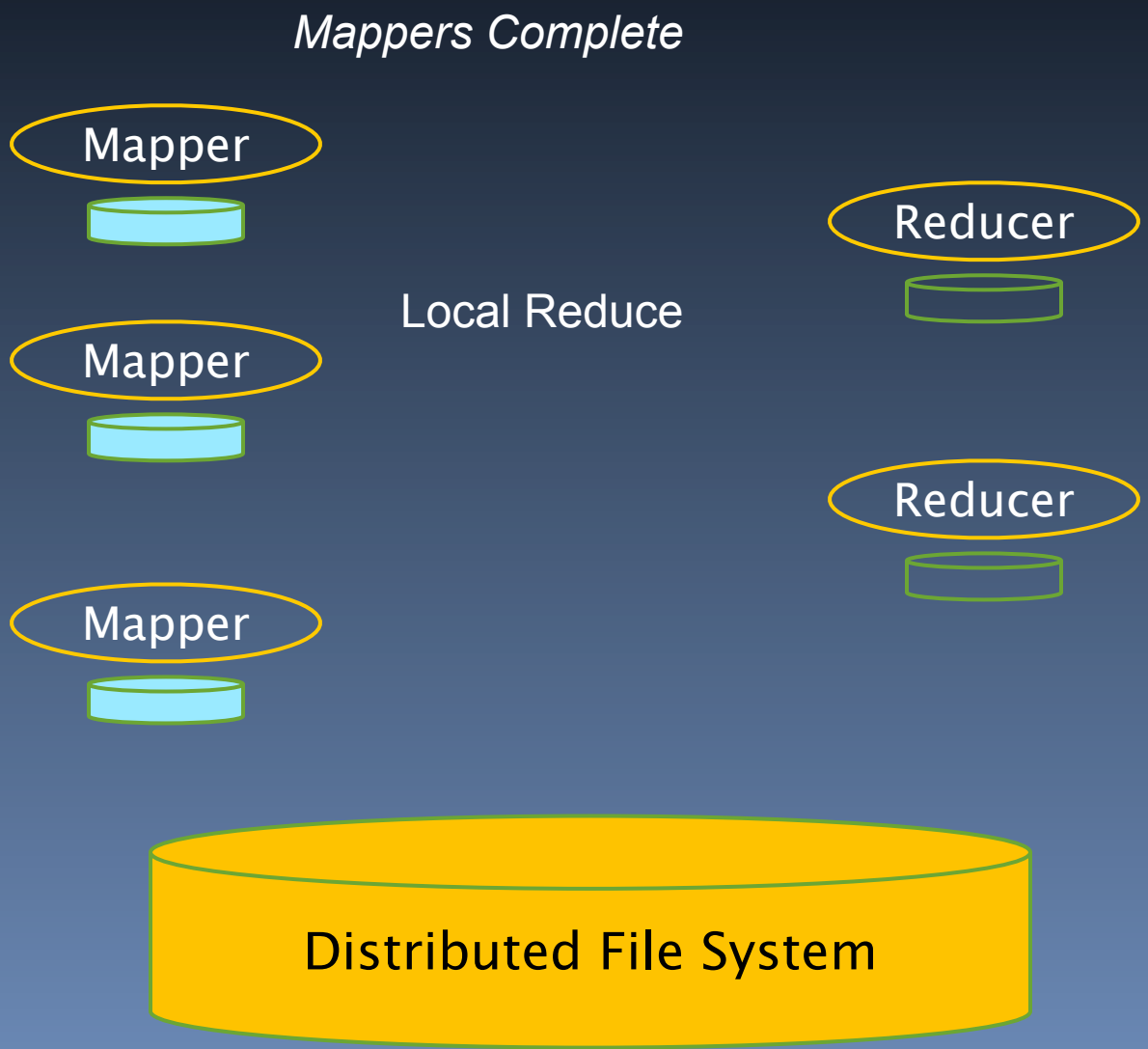
Asynchronous data movement



Relaxed Synchronization



Relaxed Synchronization



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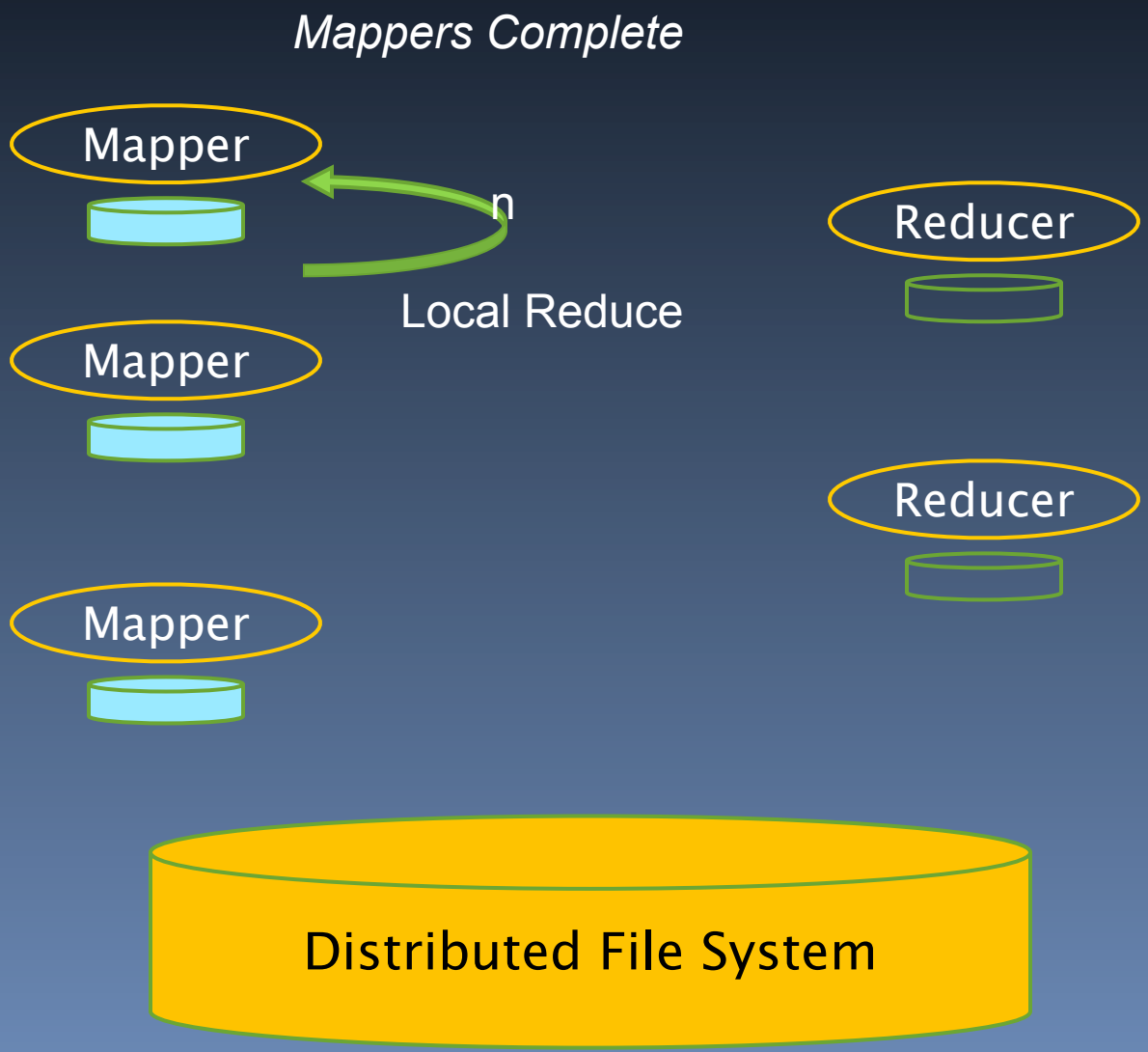

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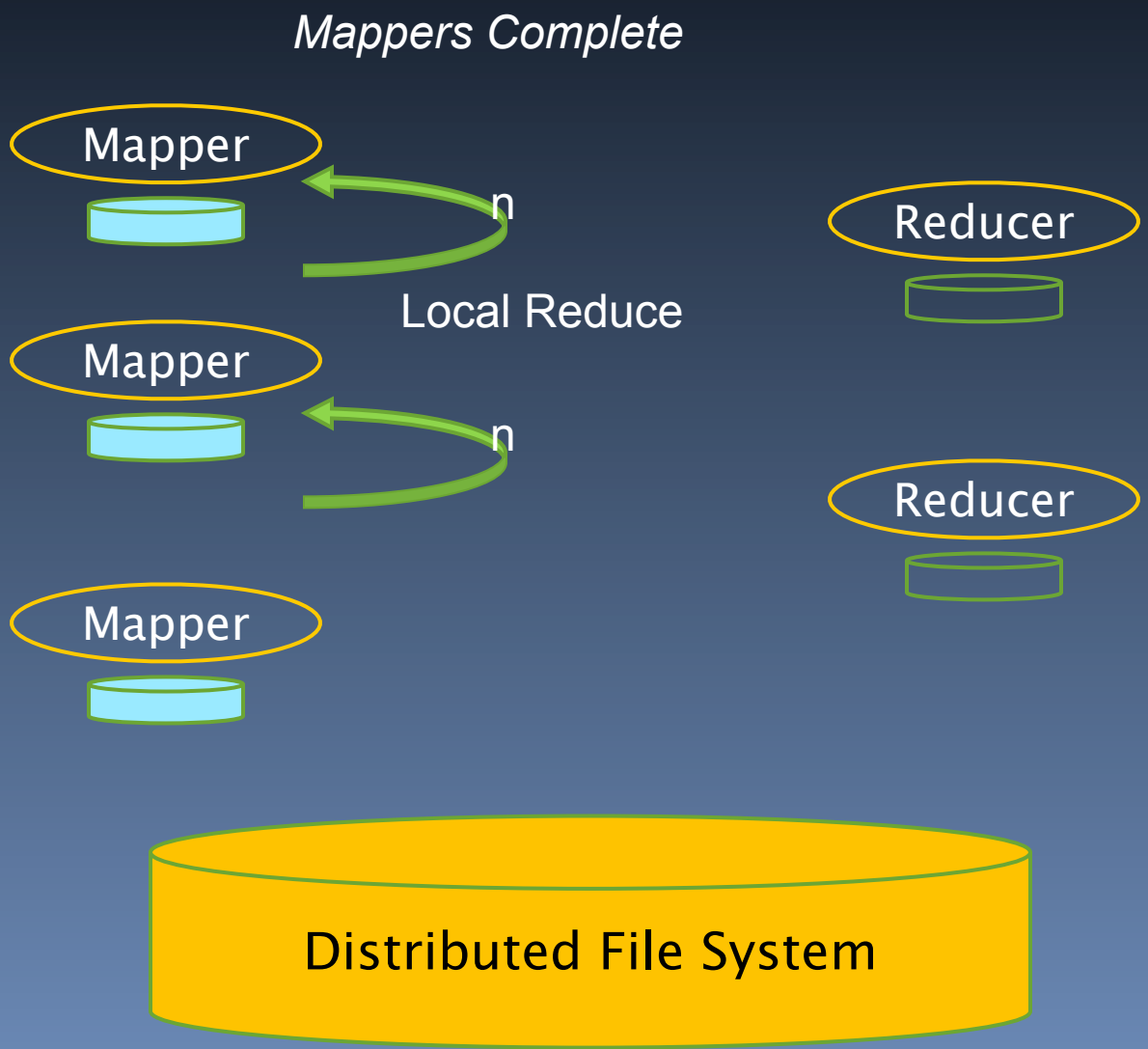

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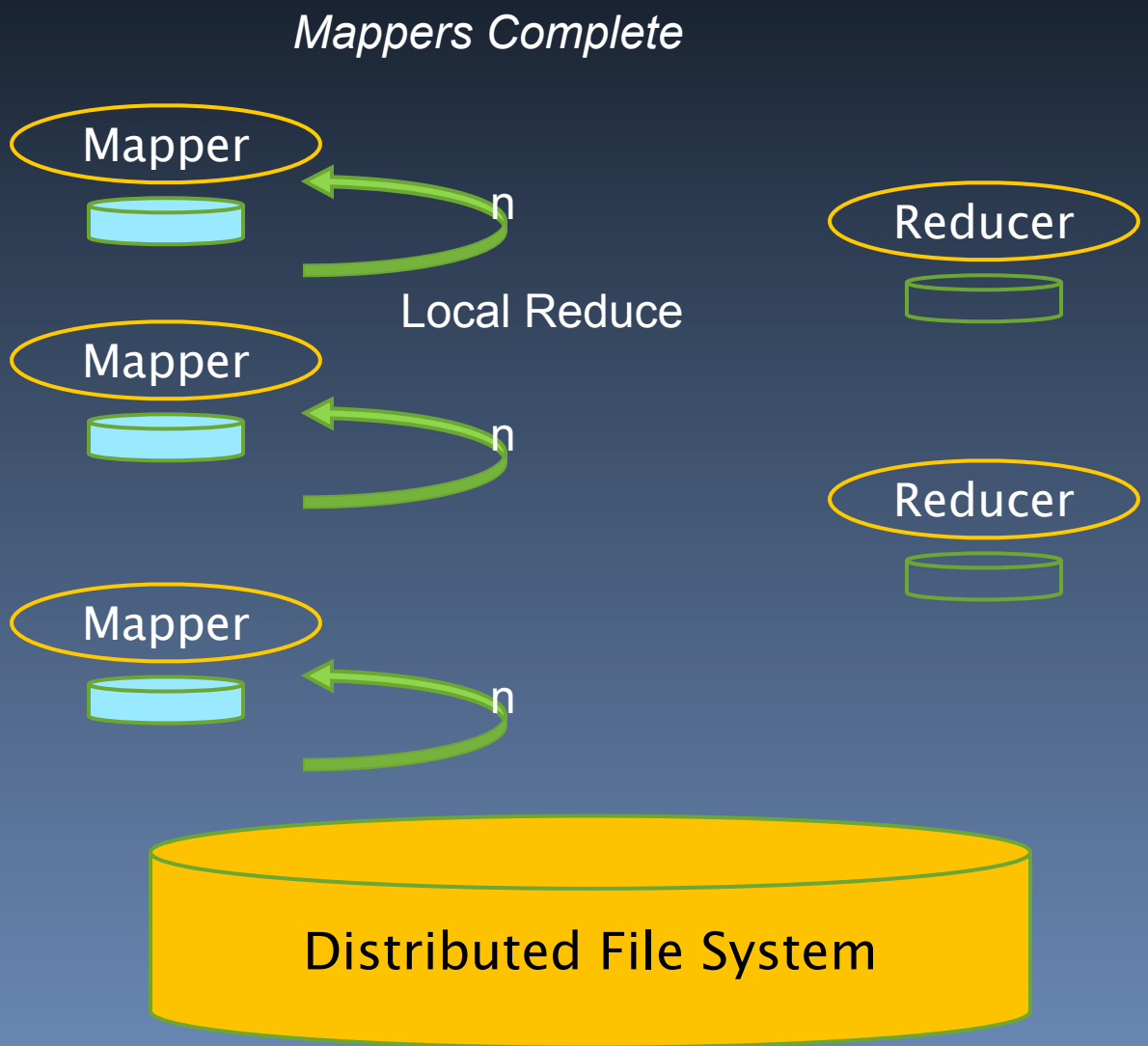
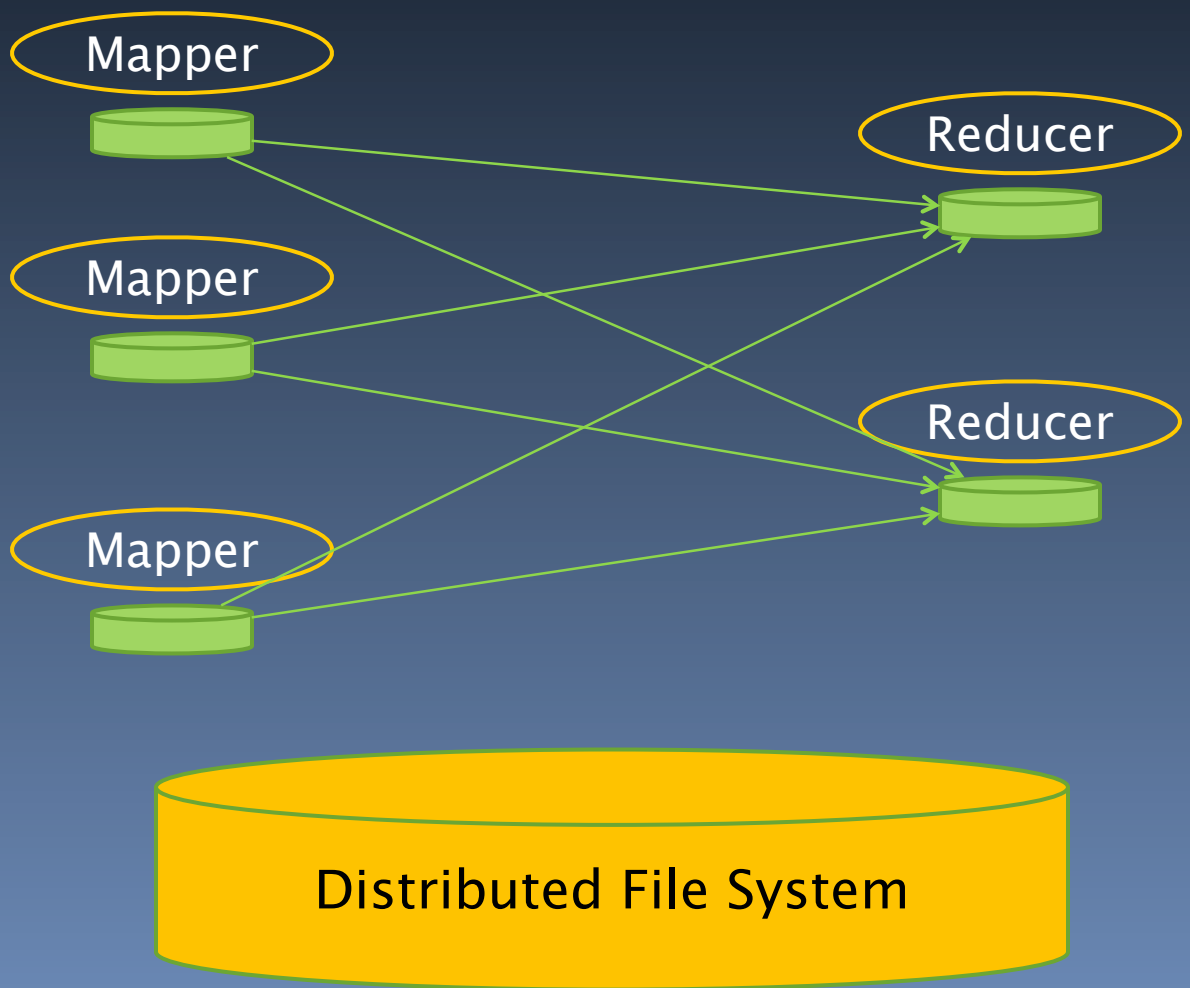


Relaxed Synchronization

Perform global synchronization after local convergence or iteration bound



Relaxed Synchronization – Applicability

- Asynchronous algorithms
  - Order of operations doesn't matter
  - Monotonicity, commutativity
- Desirable input partitioning properties
  - Fewer dependencies across partitions
- Examples
  - Pagerank, eigenspectra,
  - clustering (K-Means), etc.

Pagerank

- Algorithmic asynchrony
- Input
  - Hubs-and-spokes model
  - Densely-connected components
  - Minimal dependencies across components

Pagerank – MapReduce

- Map input
  - Key: Source
  - Value: Outlinks
- Map output
  - Key: Destination Node ID
  - Value: Contribution of Src towards Dst's Pagerank

Pagerank – MapReduce

- Reduce input
  - Key: Node ID
  - Value: All inlinks' Pagerank contributions
- Reduce output
  - Key: Node ID
  - Value: Pagerank

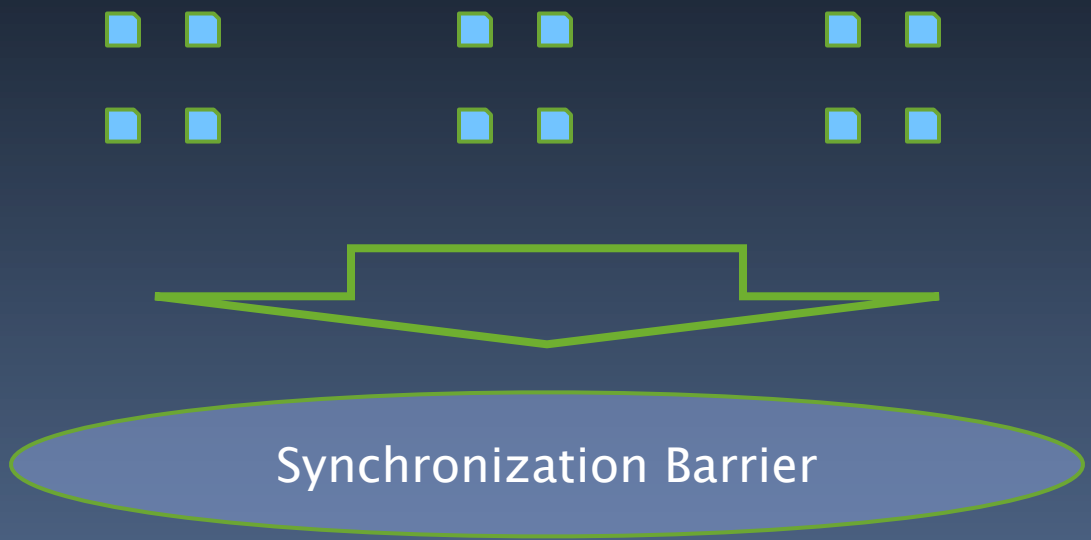
Pagerank - General

Pagerank – General

Maps

Pagerank – General

Maps



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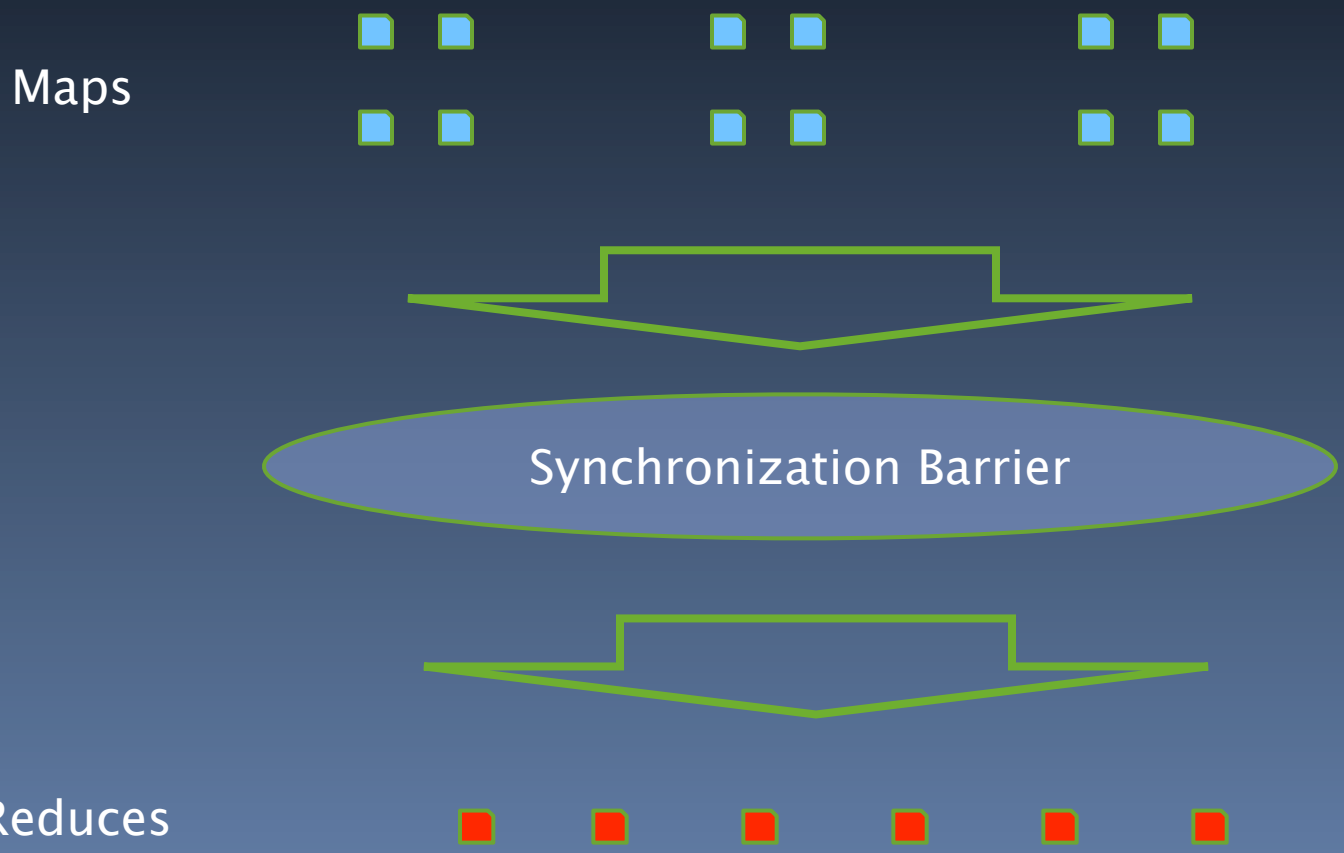

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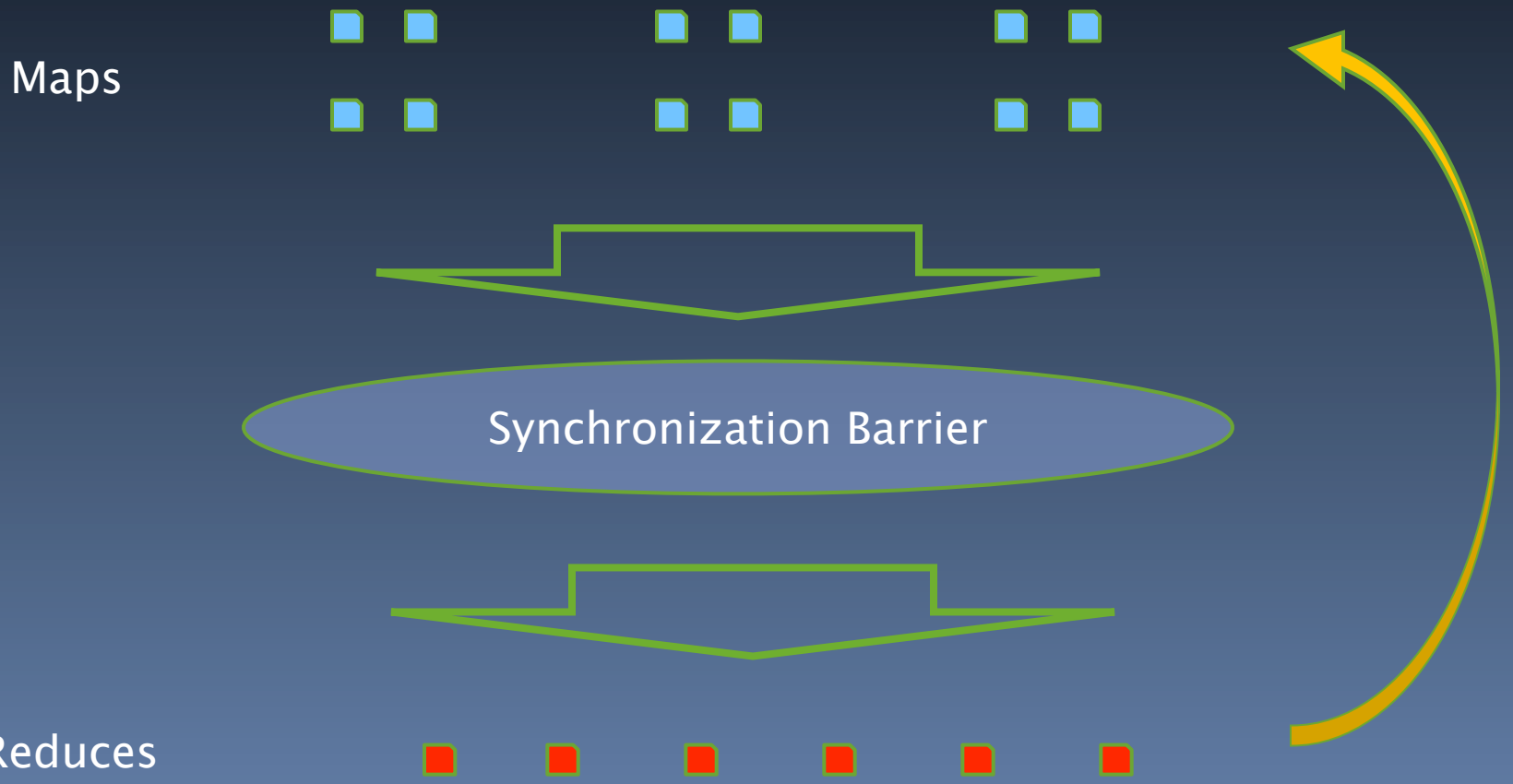
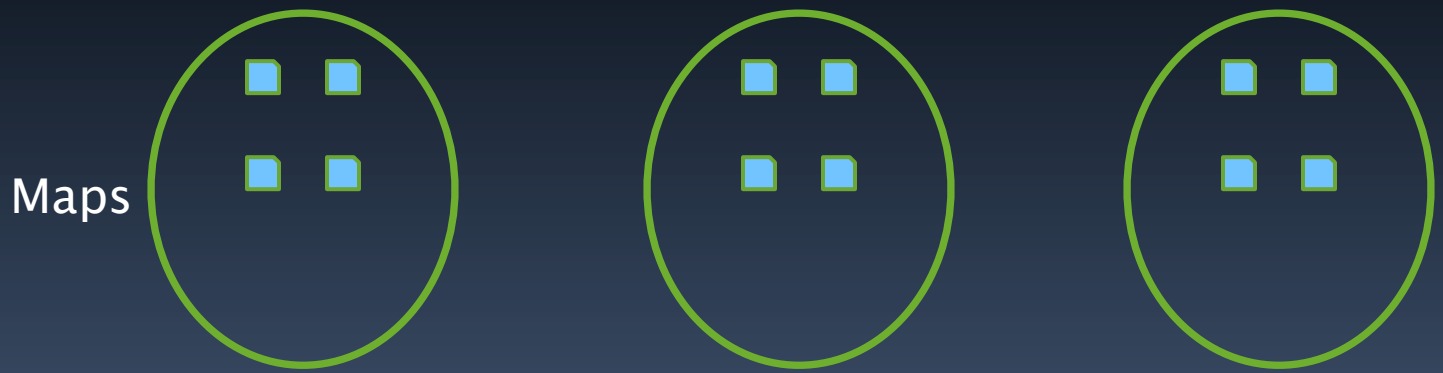


Pagerank - Relaxed Synch.

Maps

Pagerank – Relaxed Synch.



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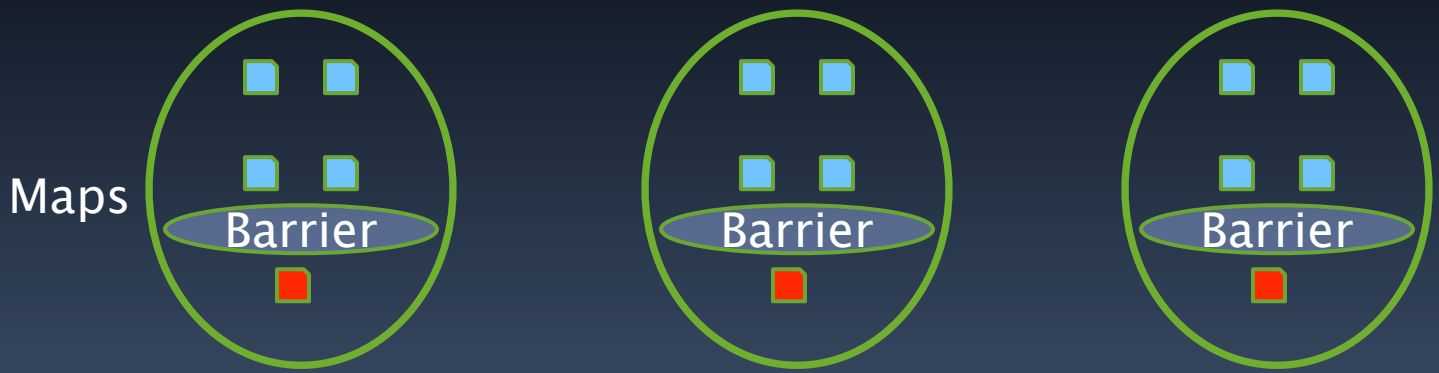

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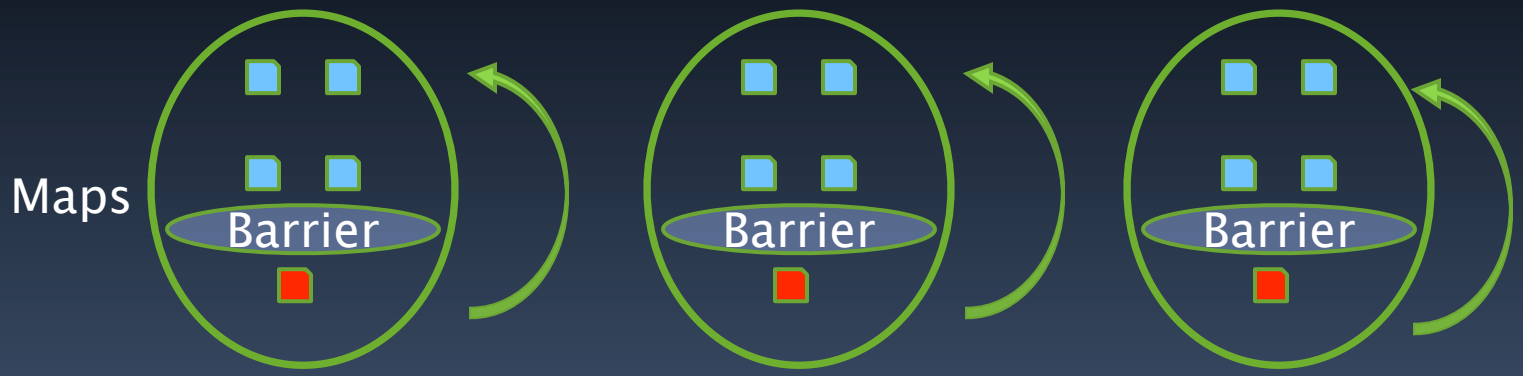

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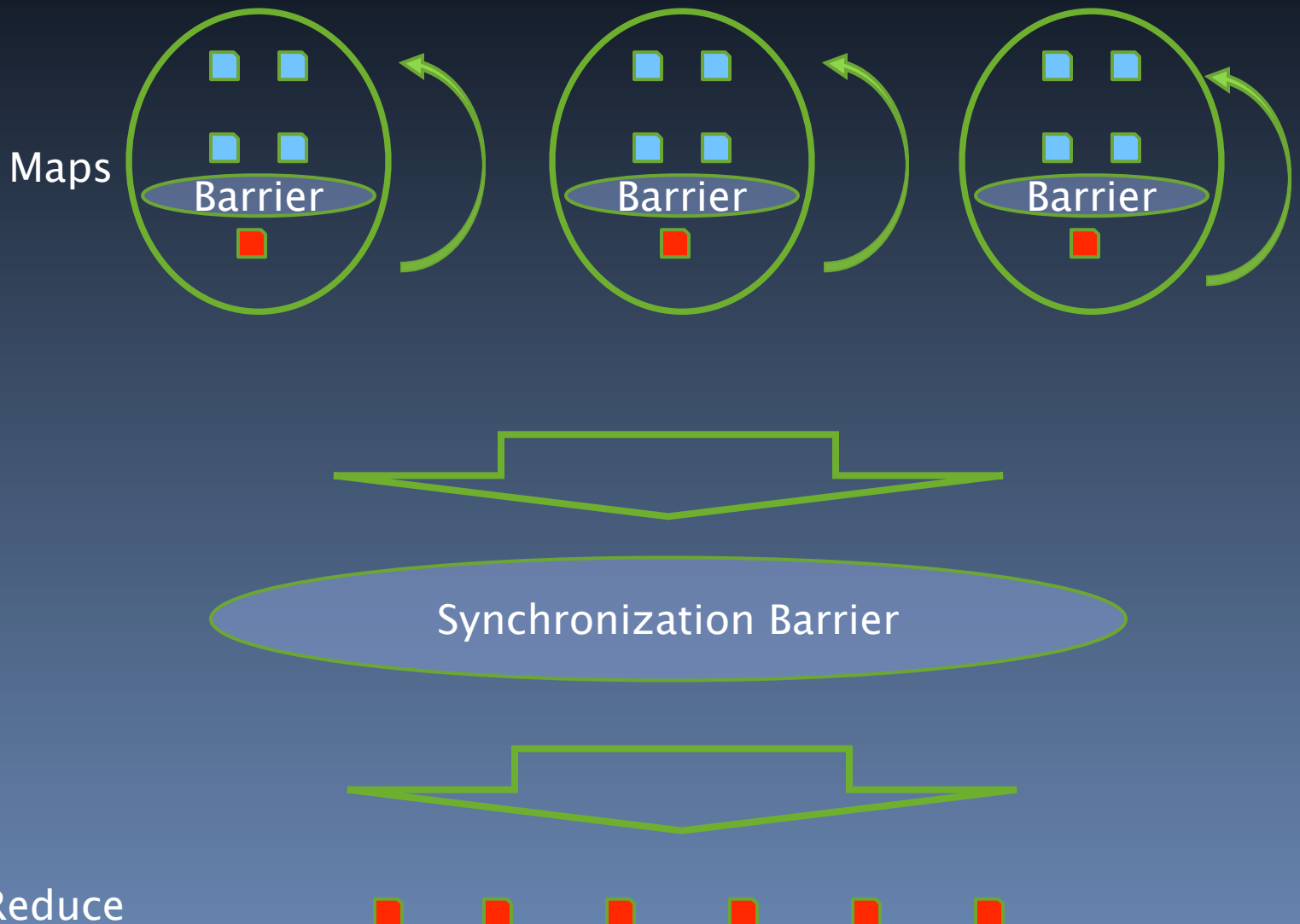

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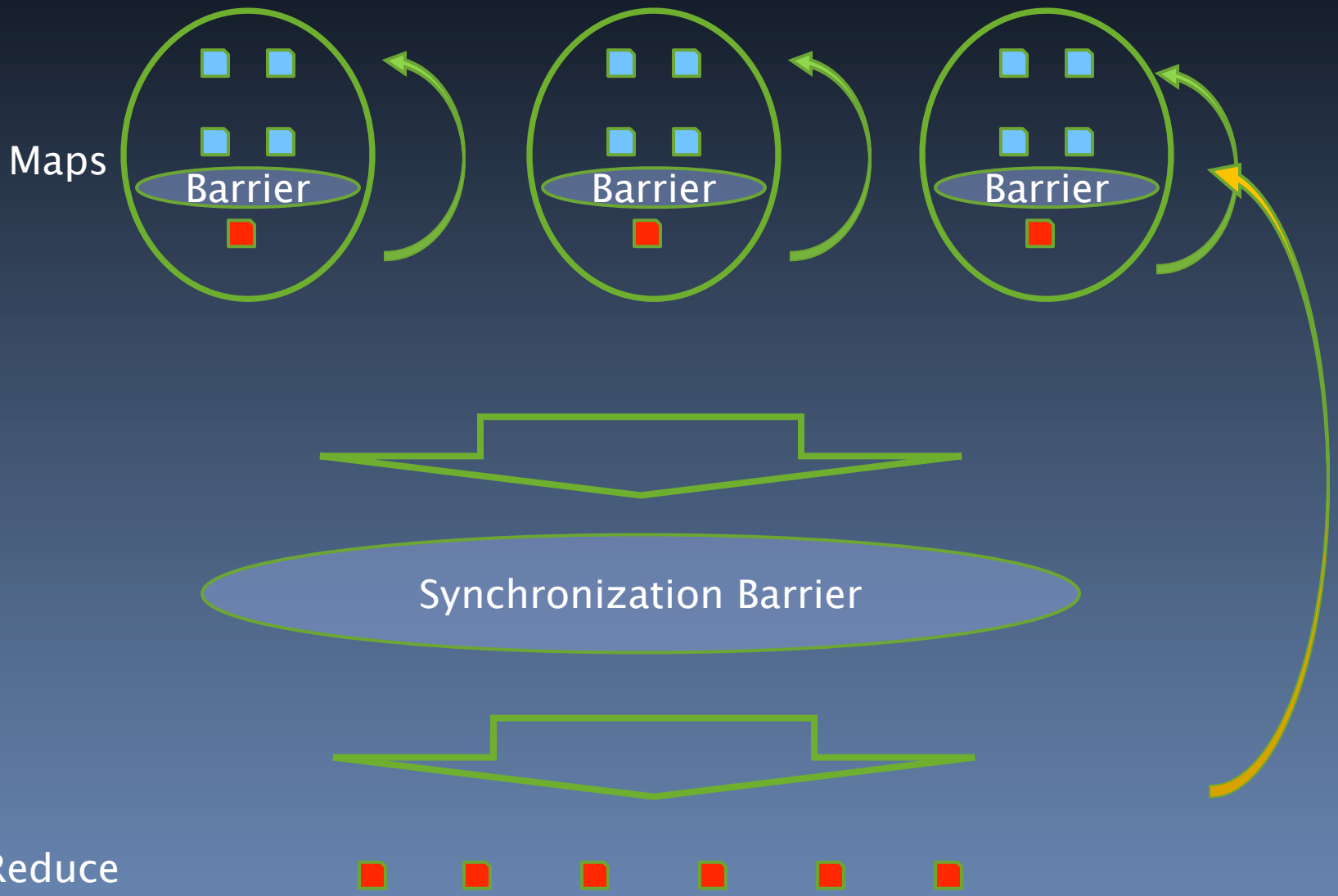


Evaluation

- Pagerank implementation
  - General – synchronization after every iteration
  - Eager
    - Each Map has local “MapReduce”, using a local hashtable for local Pageranks
    - Currently, each local map is implemented sequentially

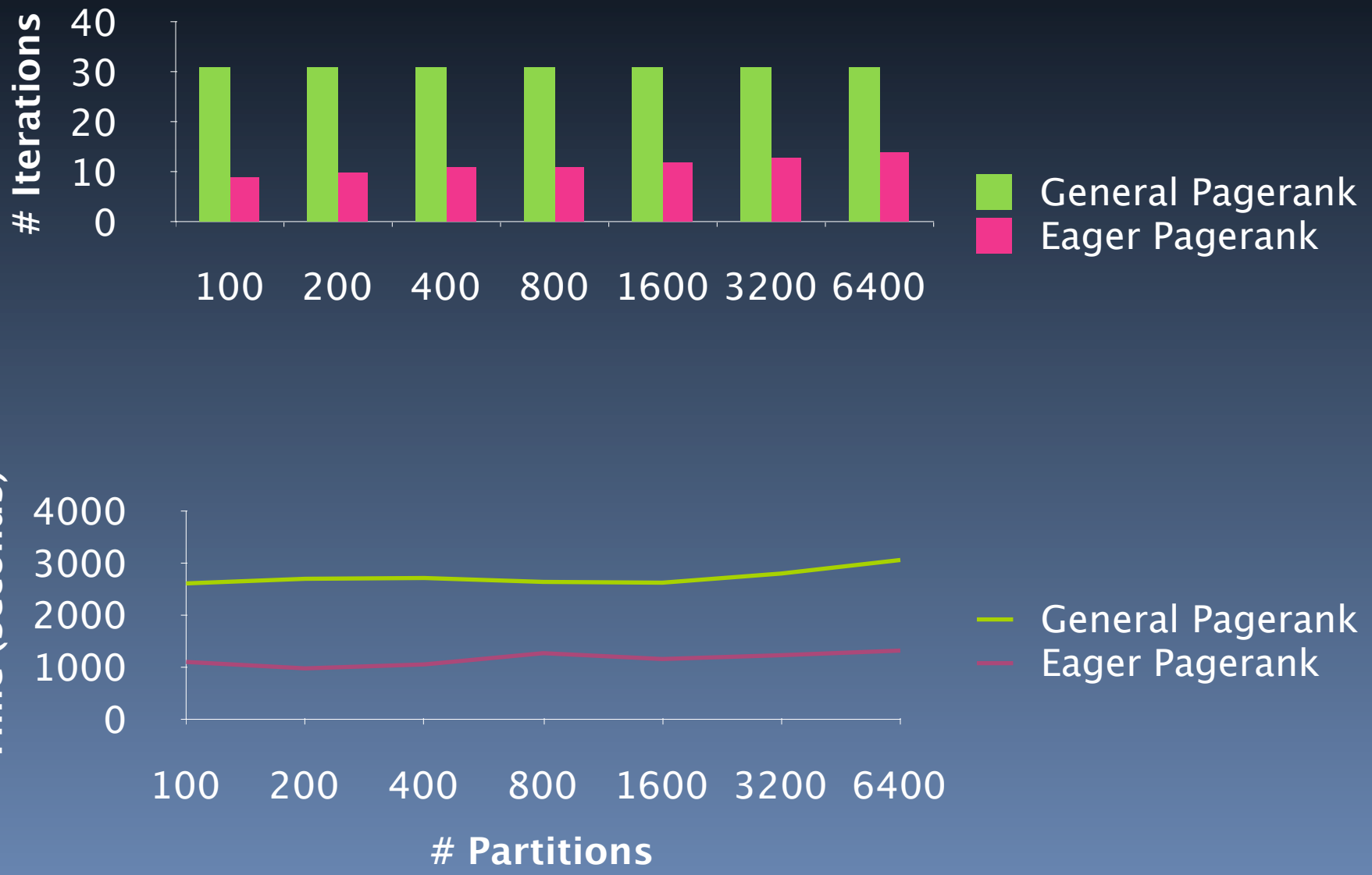
Test bed: CluE cluster

Machines	460
Physical resources	Intel® Xeon™ CPU 2.80 GHz 4 GB RAM, 2 x 400 GB hard drives
Virtual machines	1 per host
Software	Hadoop 0.17.2, Java 1.6
Heap space	1 GB per slave

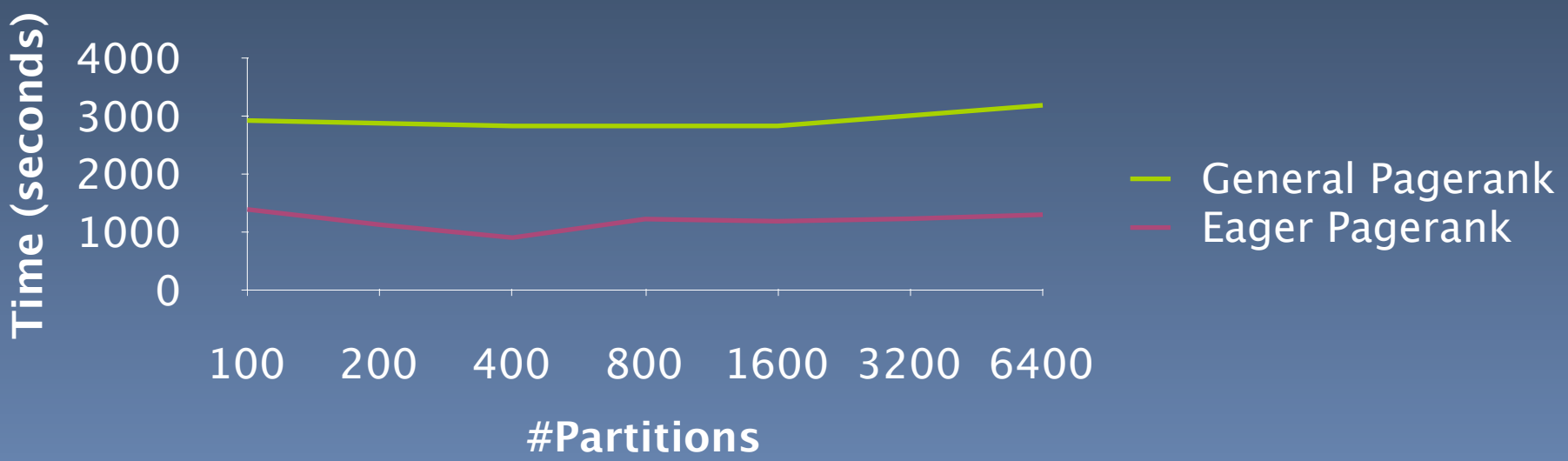
Input Graphs

- Synthetic power-law graph
  - Generate using preferential attachment
  - 100,000 nodes, 3 million edges
  - Damping factor: 0.85
- Stanford web graph
  - From Stanford WebBase project - 2002
  - 280,000 nodes, 3 million edges
  - Damping factor: 0.75
- Partition graphs using Metis
  - small cost (< 10 secs)

Performance: Synthetic power law graph

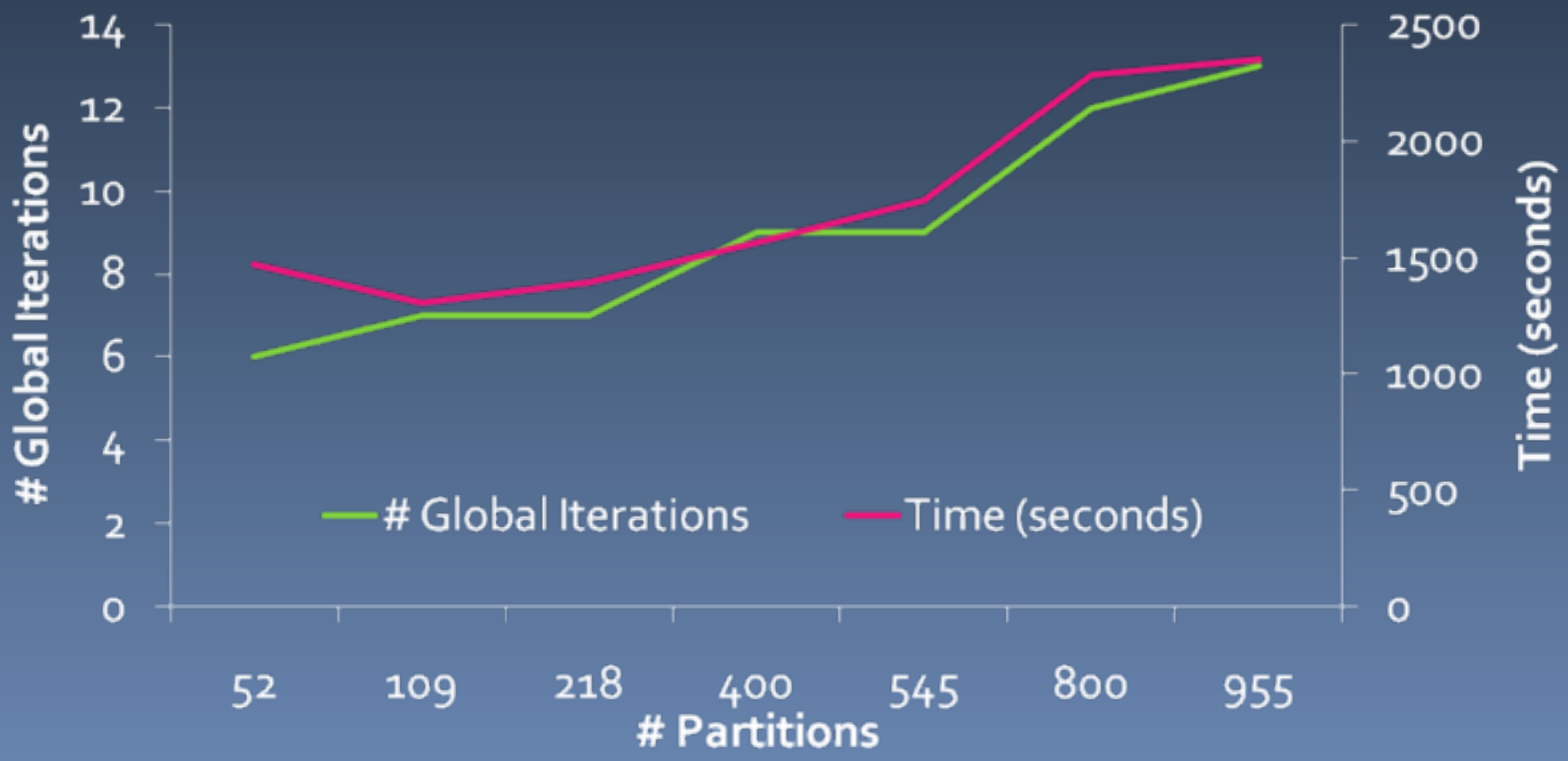


Performance: Stanford Web Graph

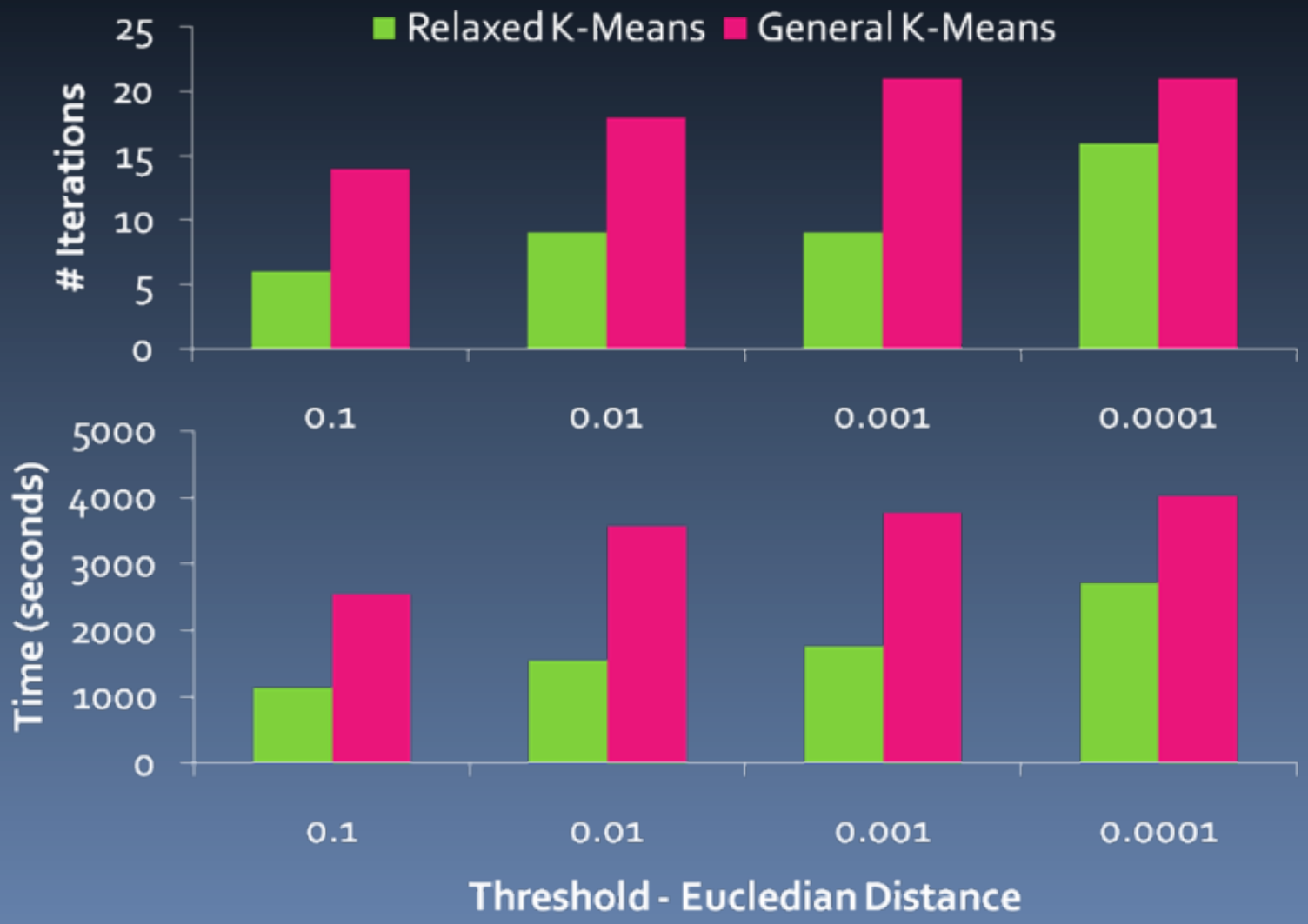


K-Means

- On US Census data (200K points, 68 dimensions)
  - Relaxed approach uses pairwise clustering
- General K-Means: 18 iterations
- Threshold: 0.01 for convergence



K-Means – threshold



Future Work

- Implement hierarchical relaxed synchronization
- Extracting operations from semantics
  - Pregel
- Validation on larger data sets
- Build a system with asynchronous data transfer – caches etc.
- Understand implications on fault-tolerance

Summary

- Can enhance scalability and performance MapReduce for
  - an interesting class of unstructured graph algorithms
- Key ideas
  - Relaxed synchronization
  - Algorithmic asynchrony
- Beneficial tradeoff between increased serial operation counts and reduced global synchronization

Questions?

Other details

- Additional overhead
  - Metis – graph partitioning
  - < 10 seconds
- Local iterations
  - Per-partition ~ 40 per one global iteration