Big Data Learning Systems

Tyson Condie

Cloud and Information Services Lab, Microsoft

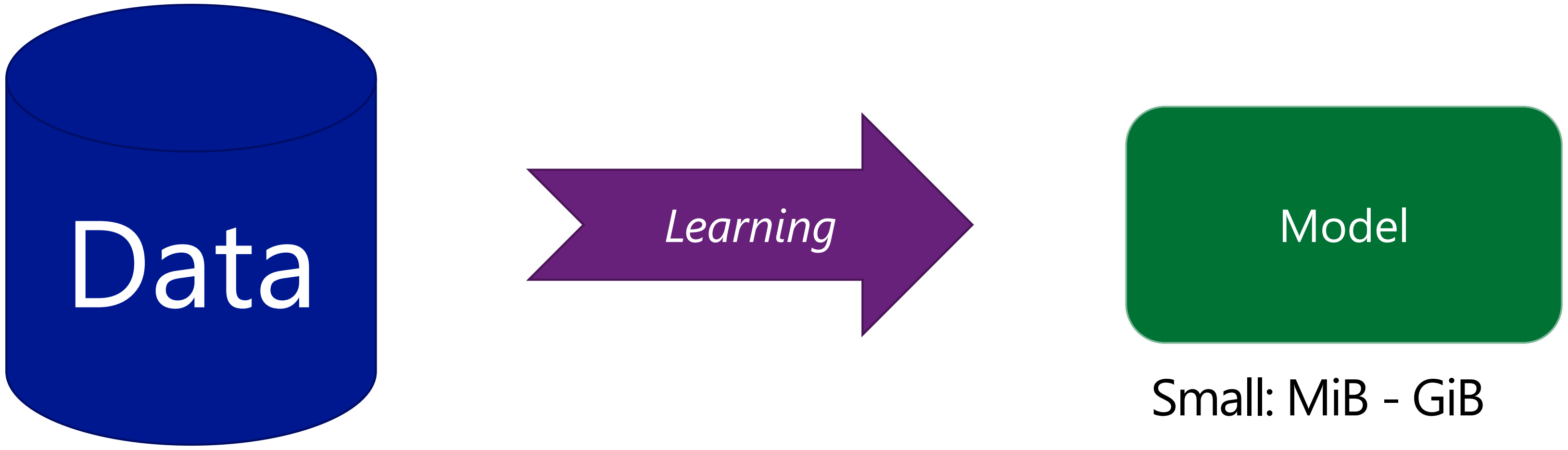
Collaborators: Markus Weimer, Rusty Sears, Byung-Gon Chun, Shravan Narayanamurthy, Sriram Rao, Carlo Curino, Raghu Ramakrishnan

“Machine Learning is Programming by Example”

Used when:

- Programming is hard (e.g. topic detection, bioinformatics)
- Program changes all the time (recommender systems, antispam)

Machine Learning



Big: TiB - PiB

Small: MiB - GiB

Supervised
- Classification
- Regression
- Recommender

Unsupervised
- Clustering
- Dimensionality reduction
- Topic modeling

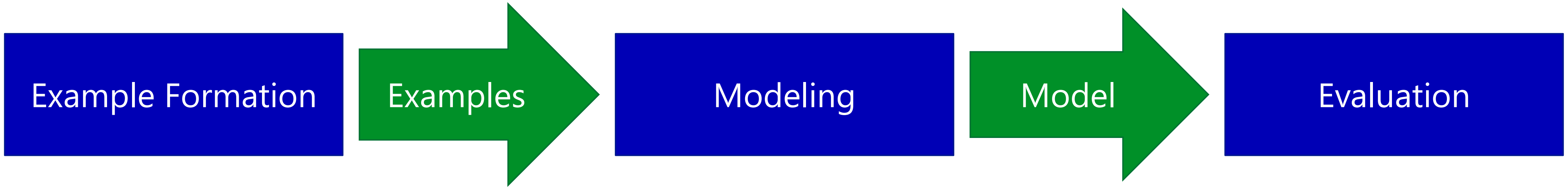
Machine Learning Workflow

Step I: Example Formation

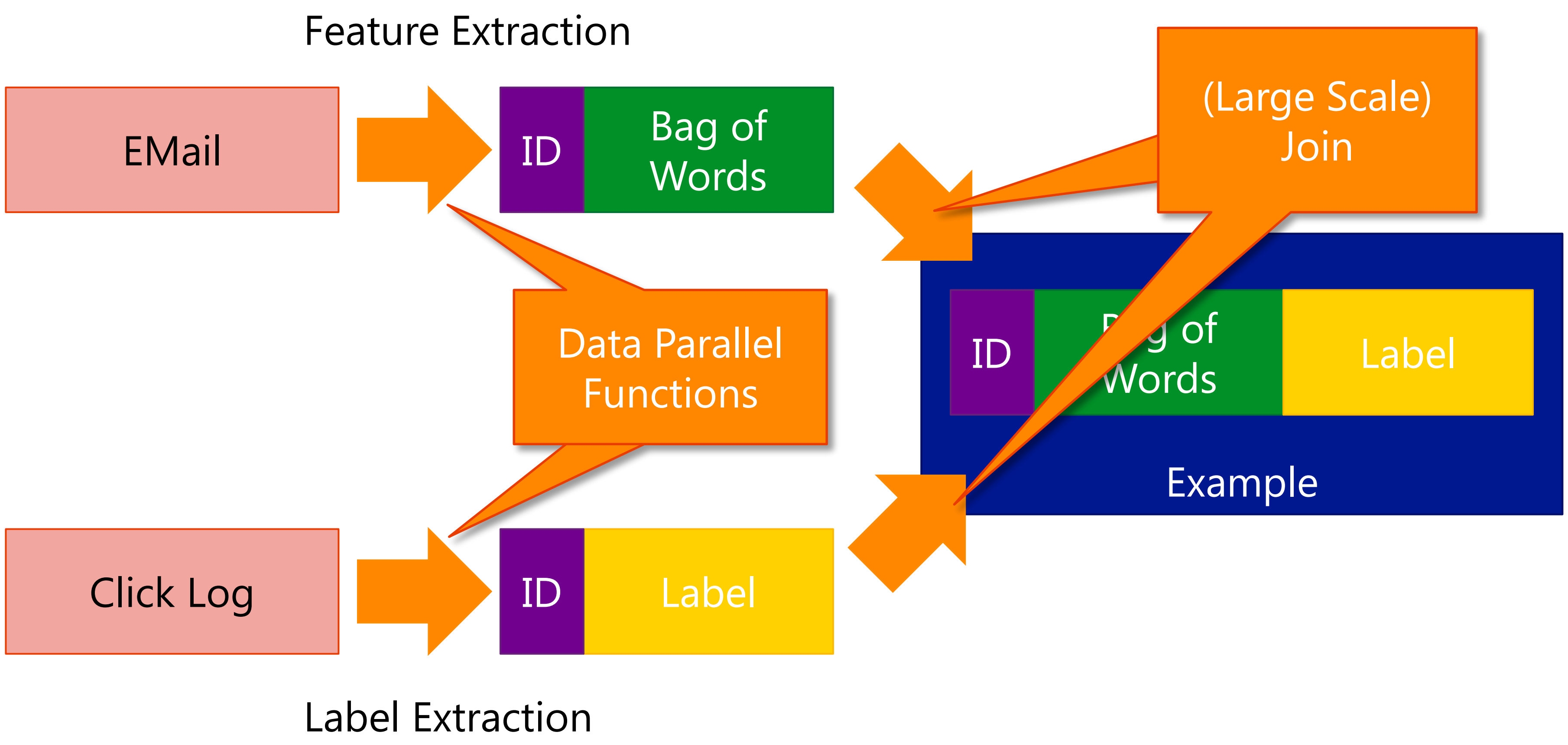
Feature and Label Extraction

Step II: Modeling

Step III: Evaluation (and eventually Deployment)



Example Formation at Scale



Machine Learning Workflow

Step I: Example Formation

Feature and Label Extraction

Step II: Modeling

Step III: Evaluation

Example Formation

Modeling

Evaluation

Machine Learning Workflow

Step I: Example Formation

Feature and Label Extraction

Step II: Modeling

Step III: Evaluation

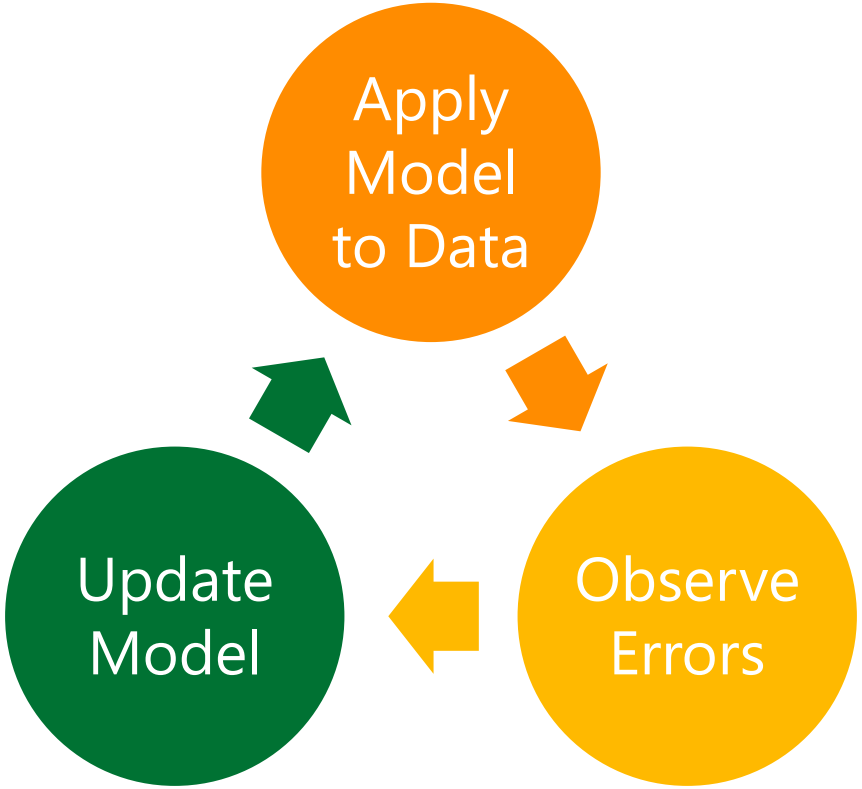
Example Formation

Modeling

Evaluation

Modeling (30,000ft)

Learning is Iterative



There isn't **one** computational model (yet)

Statistical Query Model: Algorithm operates on statistics of the dataset

Graphical Models: Heavy message passing, possibly asynchronous.

Many more: Custom solutions

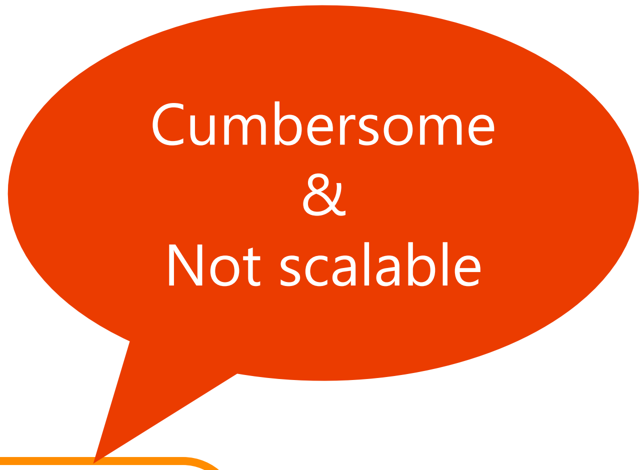
Machine Learning Workflow

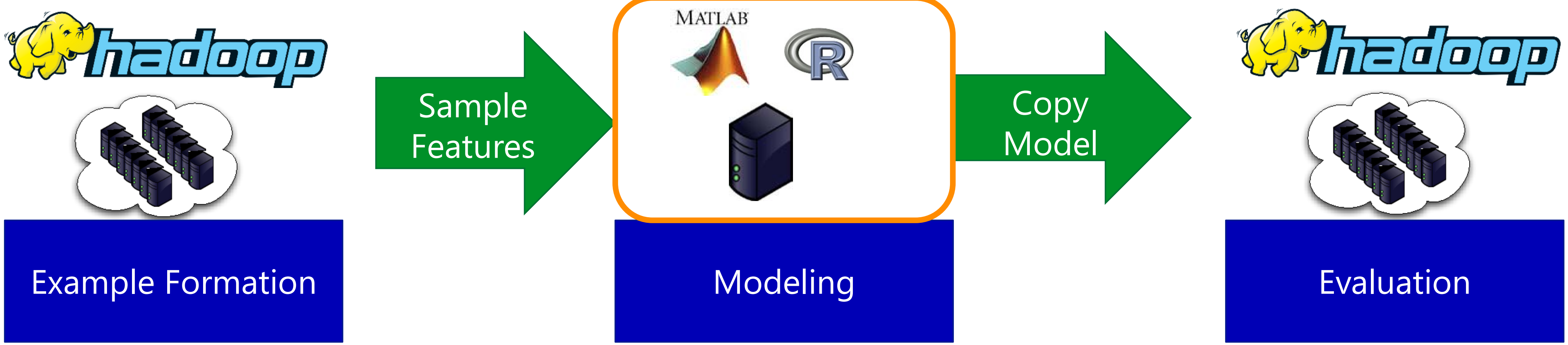
Step I: Example Formation

Feature and Label Extraction

Step II: Modeling

Step III: Evaluation





Distributed Learning

Machine Learning in MapReduce?

+ MapReduce model fits statistical query model learning

- Hadoop MR does not support iterations (30x slowdown compared to others)
- Hadoop MR does not match other forms of algorithms

"Solution": Map only jobs

1. Allocate a set of map tasks
2. Instantiate learning algorithm
3. Execute iterative algorithm until convergence
4. Release mappers

→ Hadoop Abuse

Hadoop Abusers 1: (All)Reduce and friends

Decision Trees on Hadoop

Jerry Ye et al.

Runs OpenMPI on a map only job

Uses HDFS for coordination/bootstrap

Vowpal Wabbit

John Langford et al.

AllReduce on a map-only job

Uses custom server for coordination/bootstrap

Constructs a binary aggregation tree

Optimizes node selection via redundant tasks

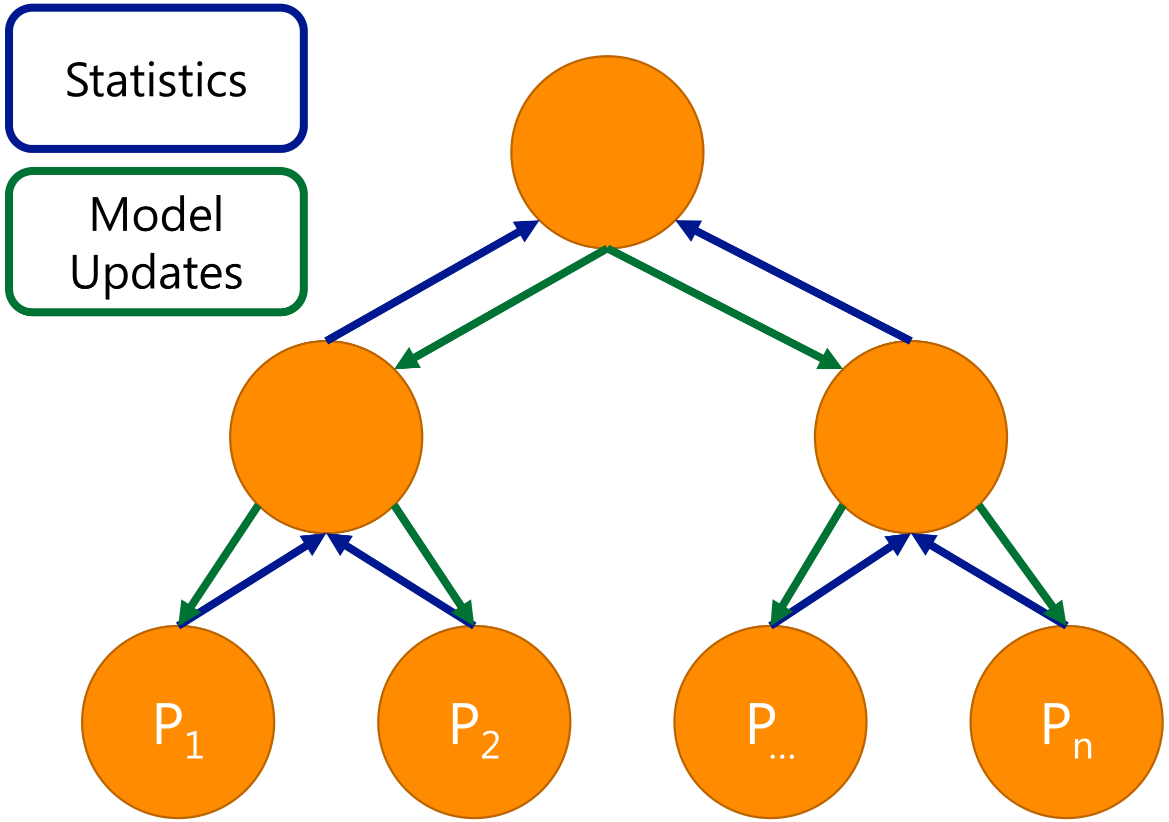
Worker/Aggregator Abstraction

Markus Weimer and Sriram Rao

Iterative Map-Reduce-Update on a map-only job

Uses Zookeeper for coordination/bootstrap

Custom communication between workers and aggregator



Hadoop Abusers 2: The Graph View

Apache Giraph

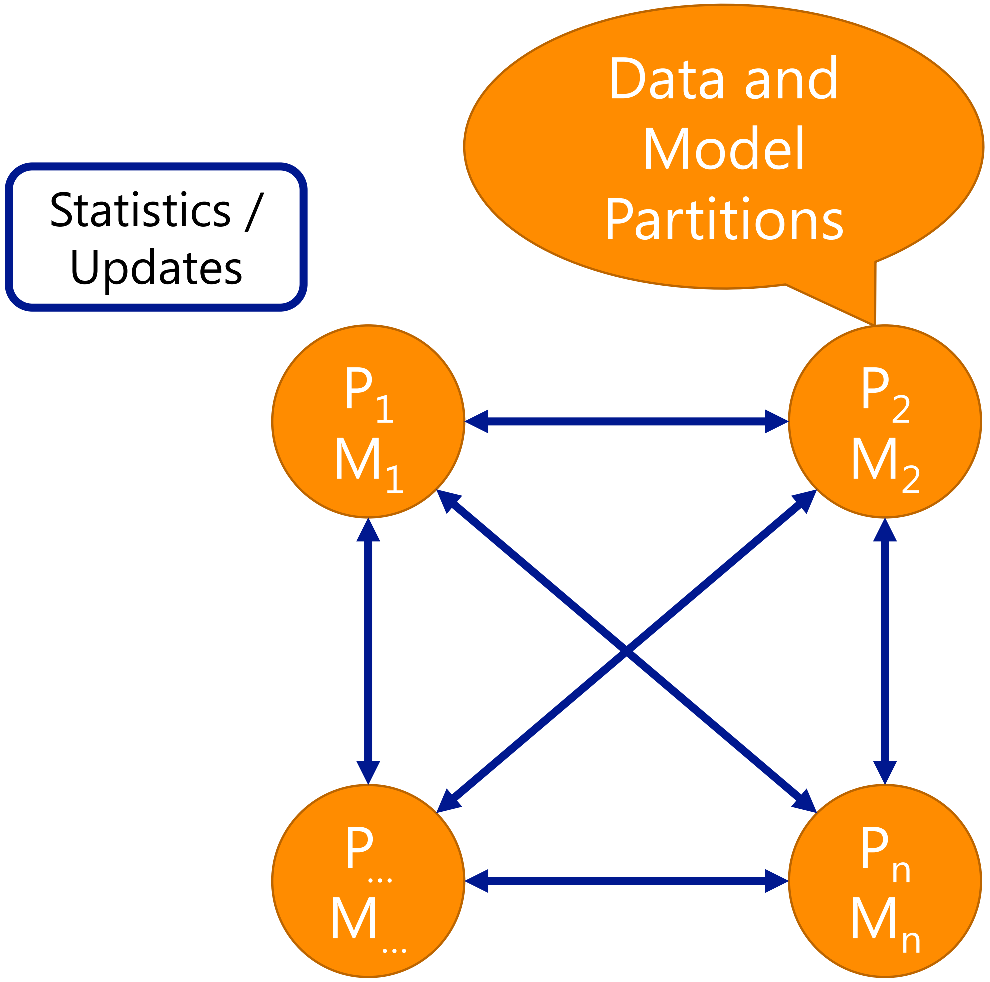
Avery Chen et al.

Open source implementation of Pregel on a map-only job
Uses Zookeeper for coordination/bootstrap
Graph computation using “think like a vertex” UDFs
Executes BSP message passing algorithm

Yahoo! LDA (YLDA)

Alex Smola and Shravan Narayanamurthy

Instantiate Graphical Model on a map-only job
Uses HDFS for coordination/bootstrap
Coordinate global parameters via shared memory
   Version 1: memcached. Version 2: ICE



Problems with this Approach

Problems for the Abusers

Fault Tolerance Mismatch

MapReduce fault tolerance actually gets in the way

Resource Model Mismatch

MapReduce's resource selection often suboptimal for the job at hand (data local vs. communication)

Cumbersome integration with M/R

Every Abuser has to implement ...

Networking

Cluster Membership

Bulk data transfers

...

Problems for the Cluster

Abusers Violate MapReduce assumptions

Network usage bursts in (All)Reduce

Local disk use in VW

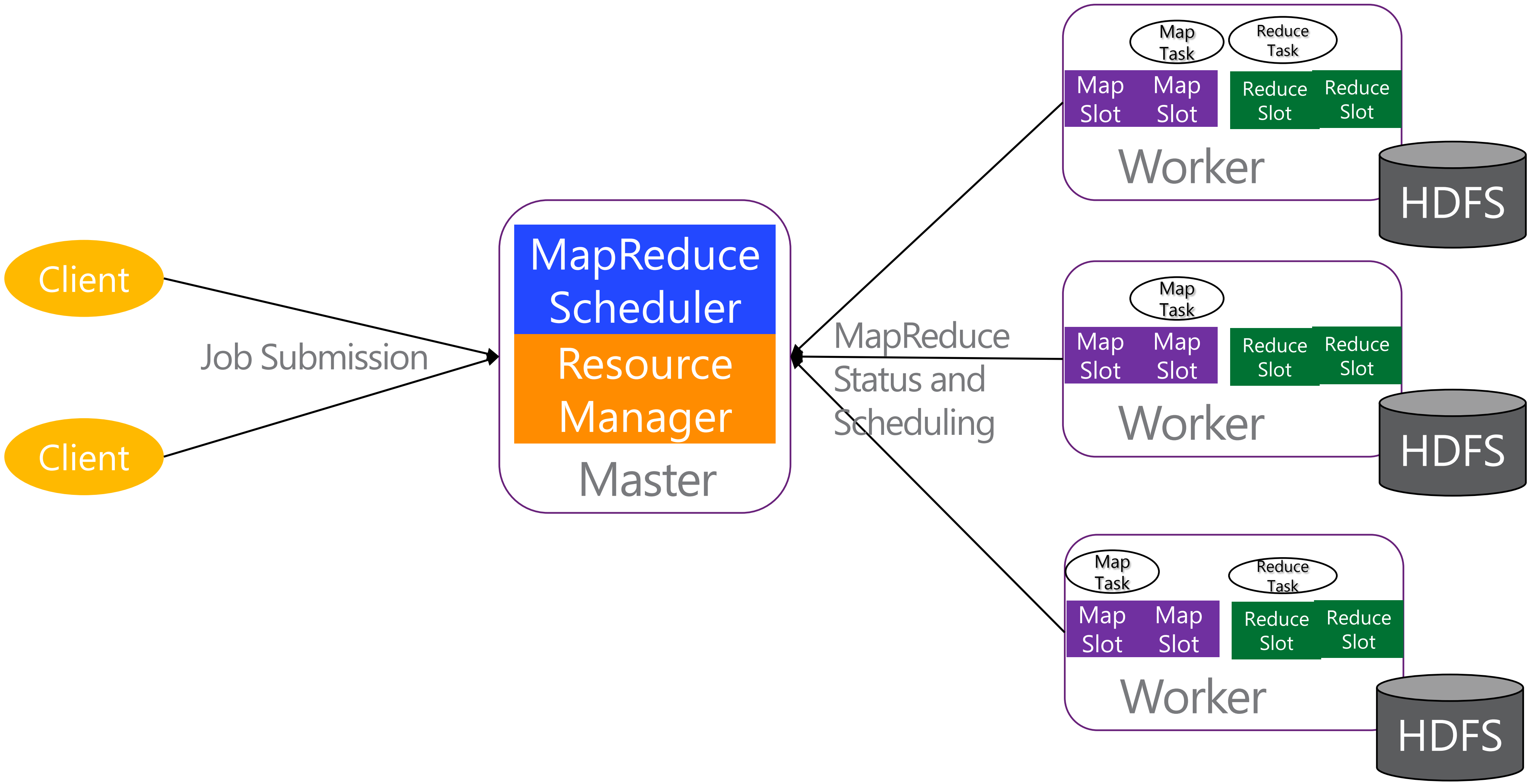
The Abusers are disrespectful of other users

e.g. production workflows

Hoarding of resources (even worse as Hadoop does not support preemption)

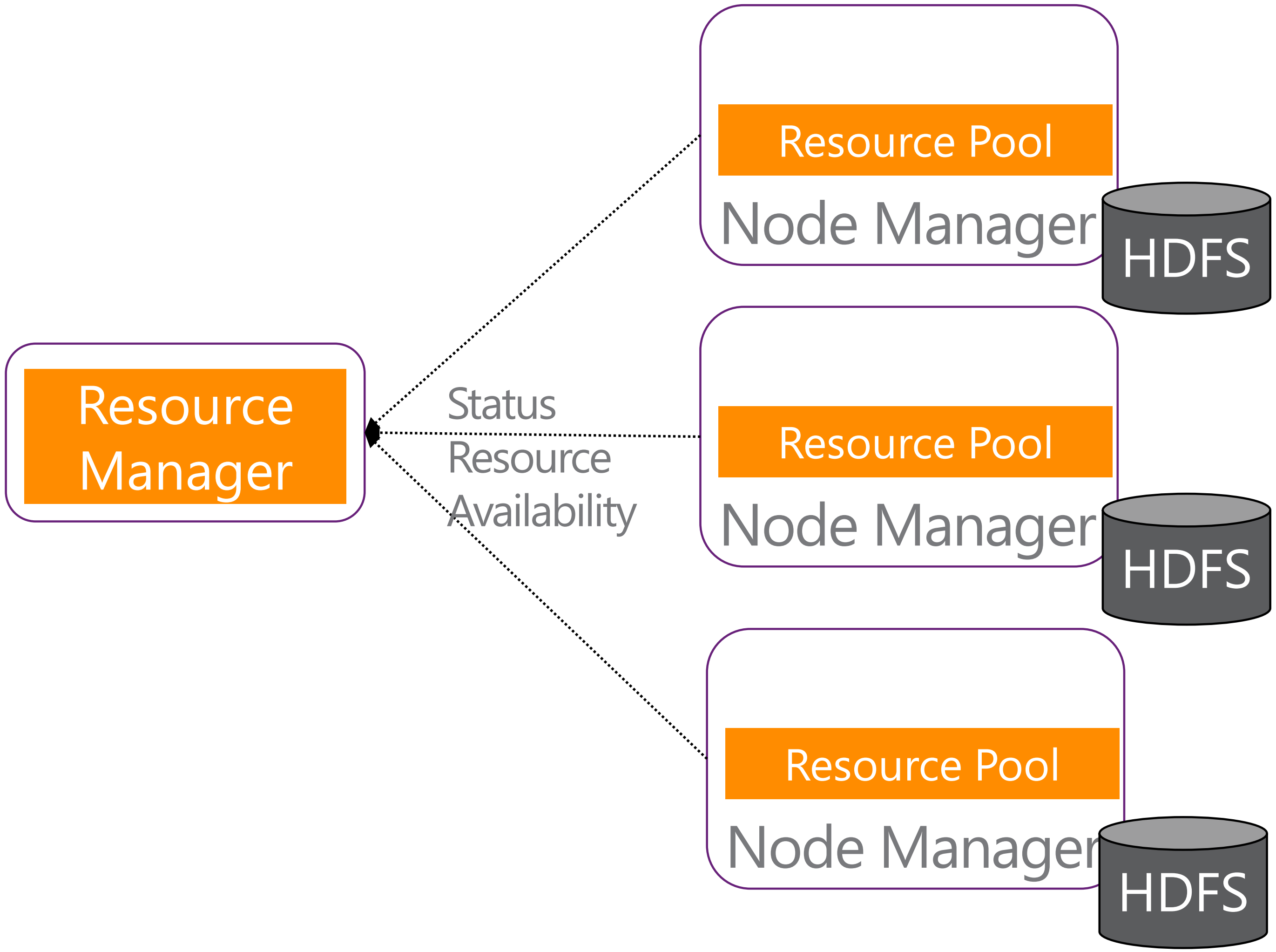
Rise of the Resource Managers

Hadoop v1



Client
Client
Job Submission
MapReduce Scheduler
Resource Manager
Master
MapReduce Status and Scheduling
Map Task
Reduce Task
Map Slot
Map Slot
Reduce Slot
Reduce Slot
Worker
HDFS
Map Task
Map Slot
Map Slot
Reduce Slot
Reduce Slot
Worker
HDFS
Map Task
Reduce Task
Map Slot
Map Slot
Reduce Slot
Reduce Slot
Worker
HDFS

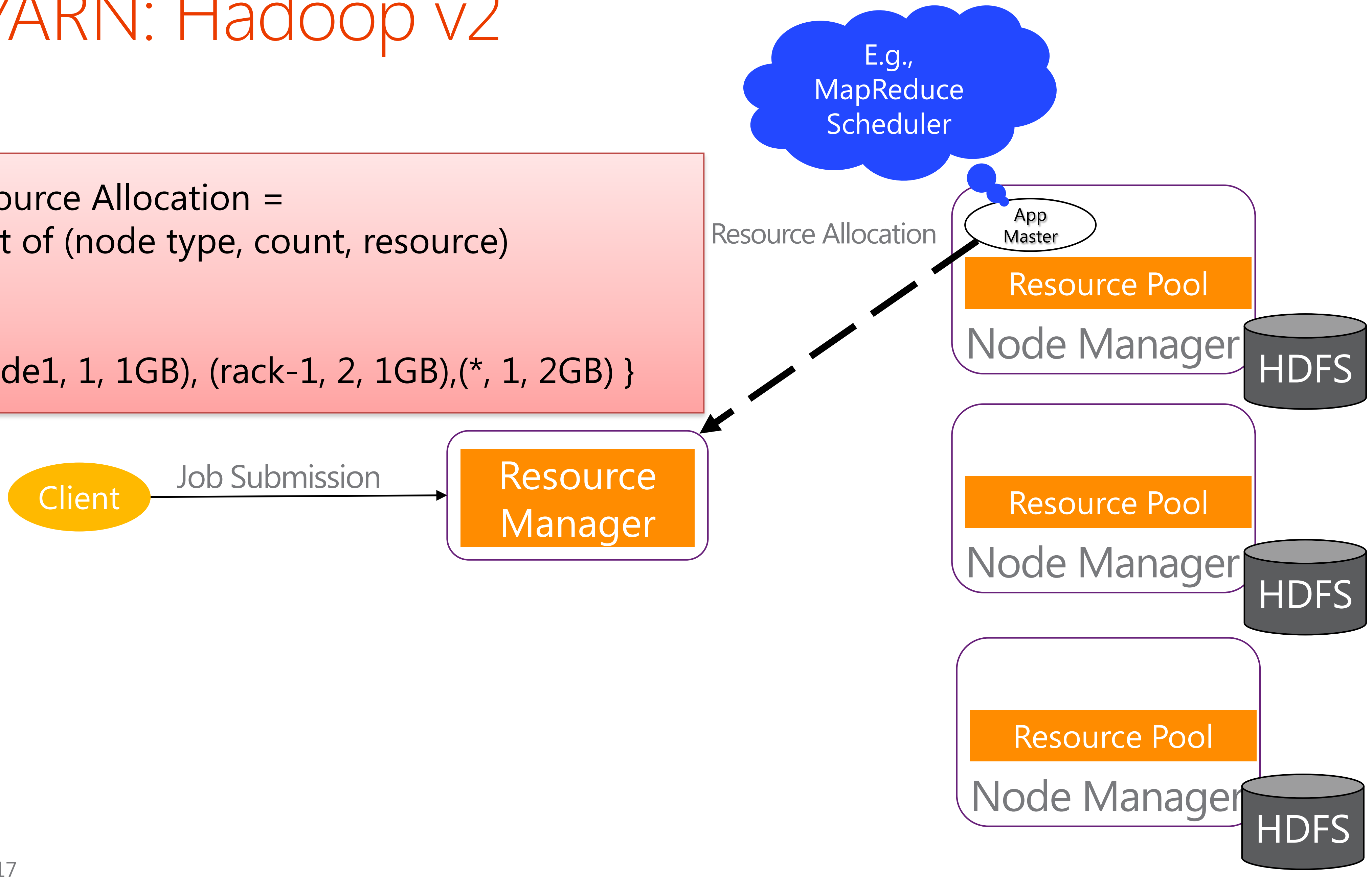
YARN: Hadoop v2



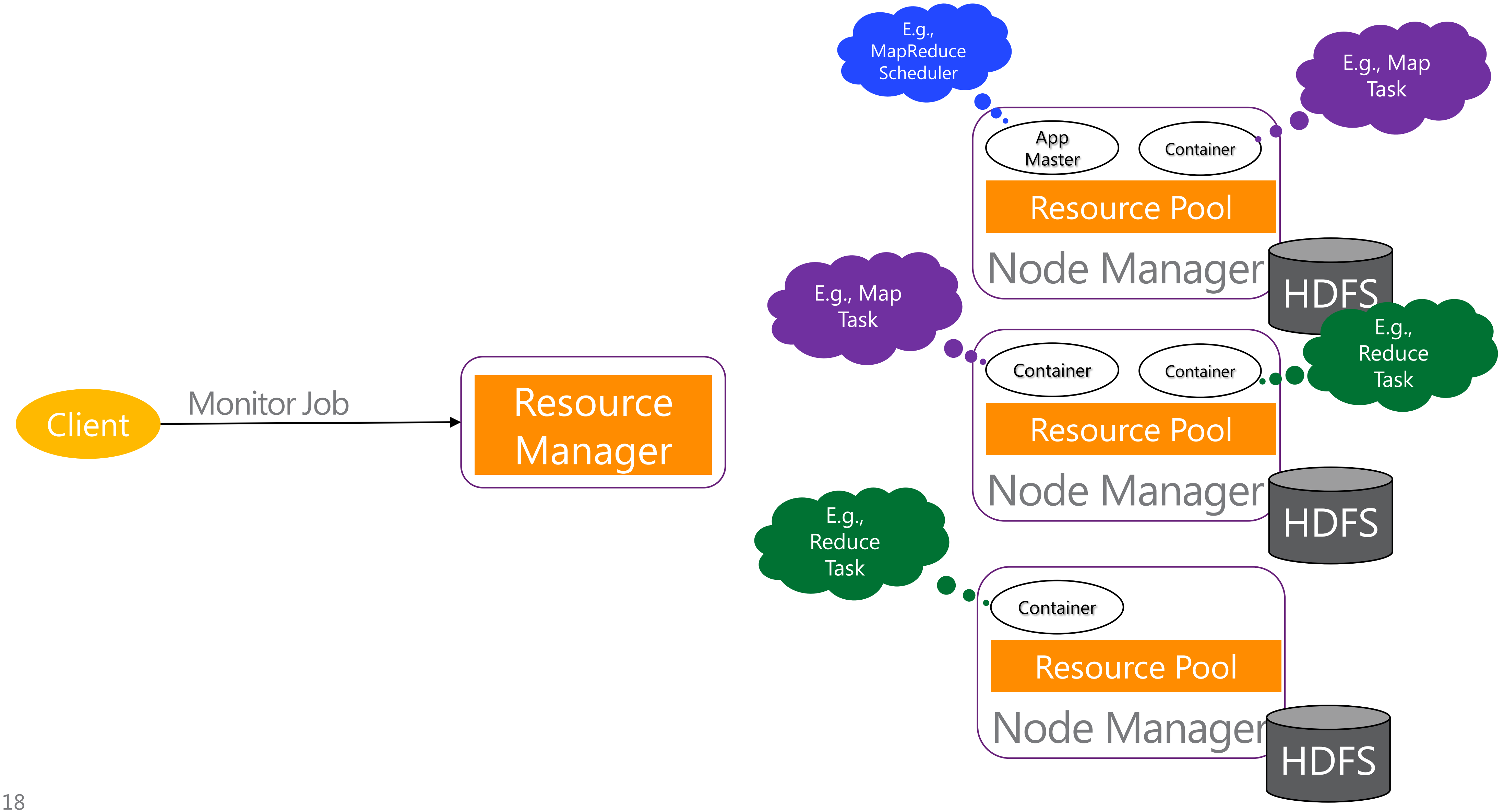
YARN: Hadoop v2

Resource Allocation =
list of (node type, count, resource)

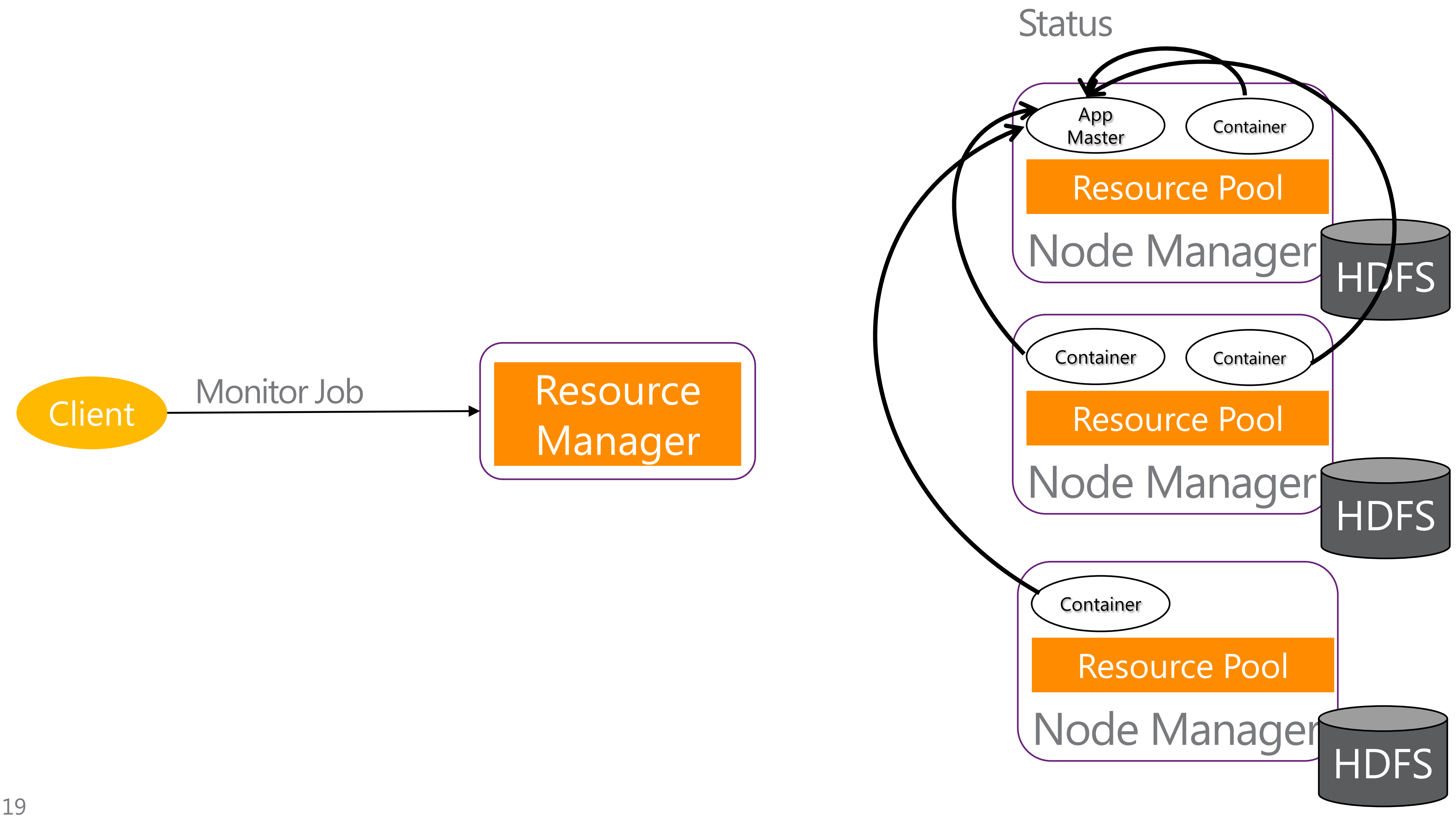
E.g.
{ (node1, 1, 1GB), (rack-1, 2, 1GB),(*, 1, 2GB) }



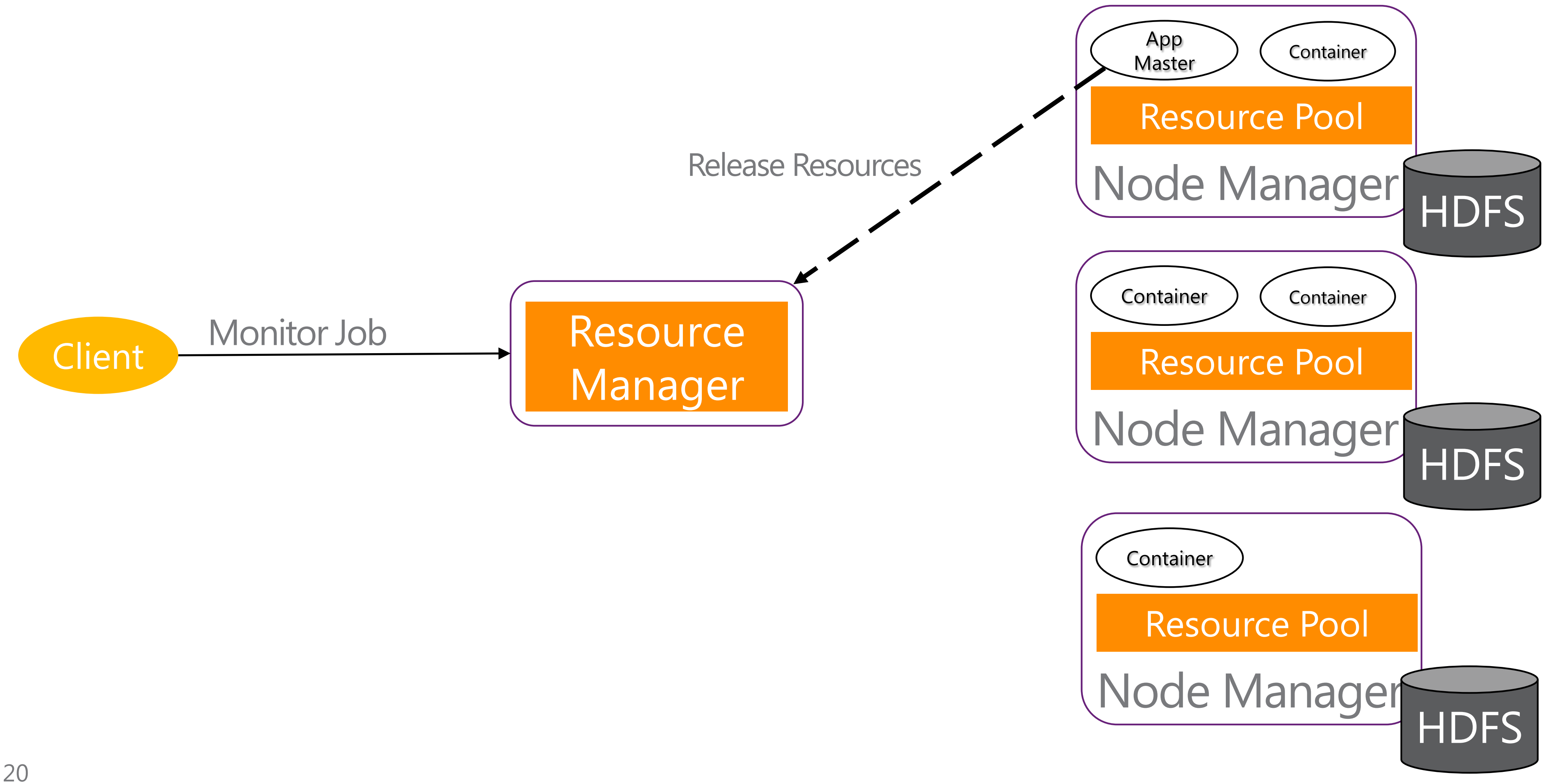
YARN: Hadoop v2



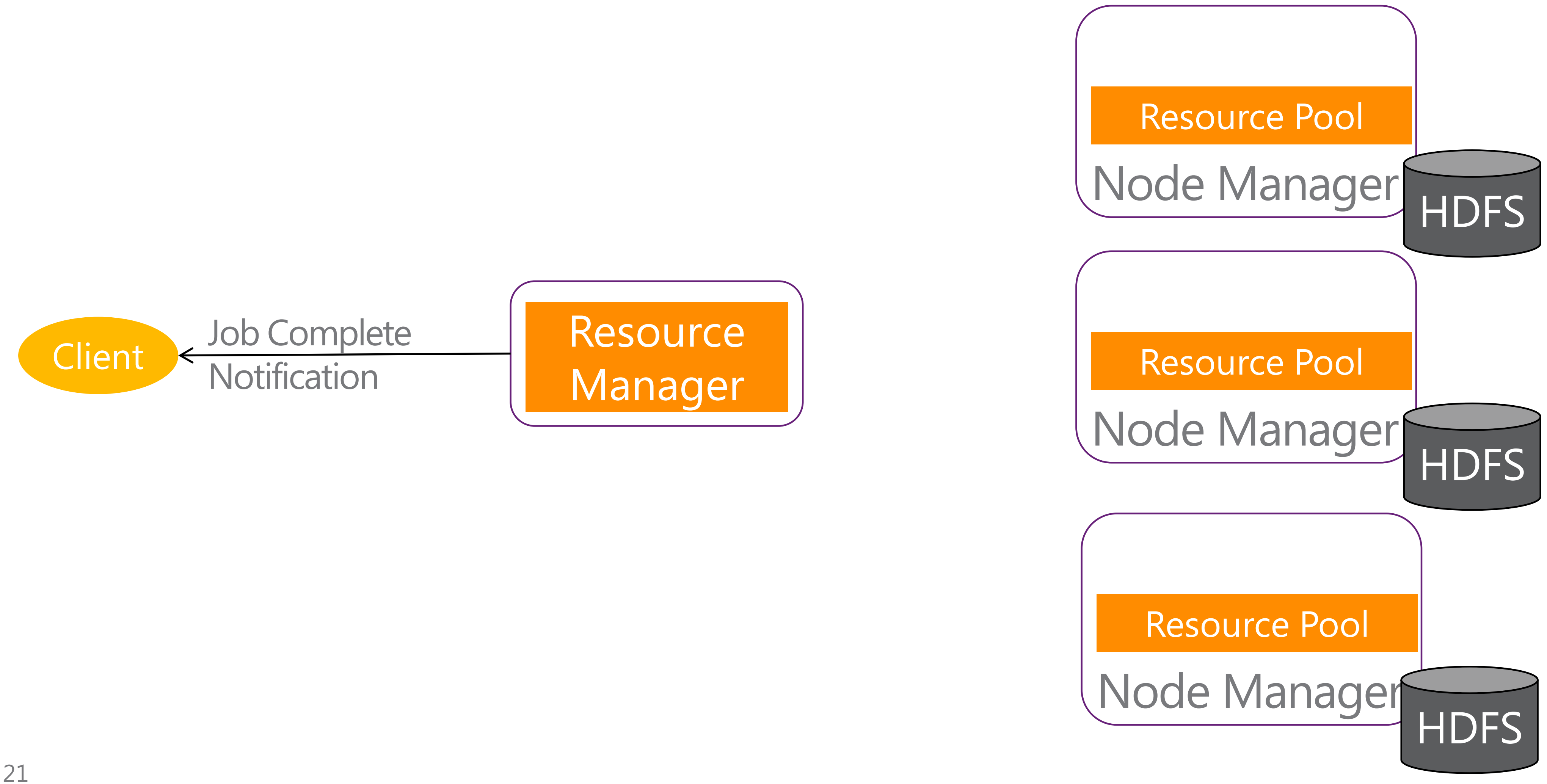
YARN: Hadoop v2



YARN: Hadoop v2



YARN: Hadoop v2



YARN: A step in the right direction

Disentangles resource allocation from the computational model

- YARN manages the cluster resource allocations
- Application masters manage computation on allocated resources

Low-level API

- Containers are empty processes (with resource limits)
- No assumed higher-level semantics

REEF: Retainable Evaluator Execution Framework

Goals for REEF

Ease development on resource managers (like YARN)

Cluster membership: Heartbeats, Failure notification, etc.

Networking: Naming, Message Passing, Group Communications, etc.

State management: Checkpointing, Storage, etc.

…

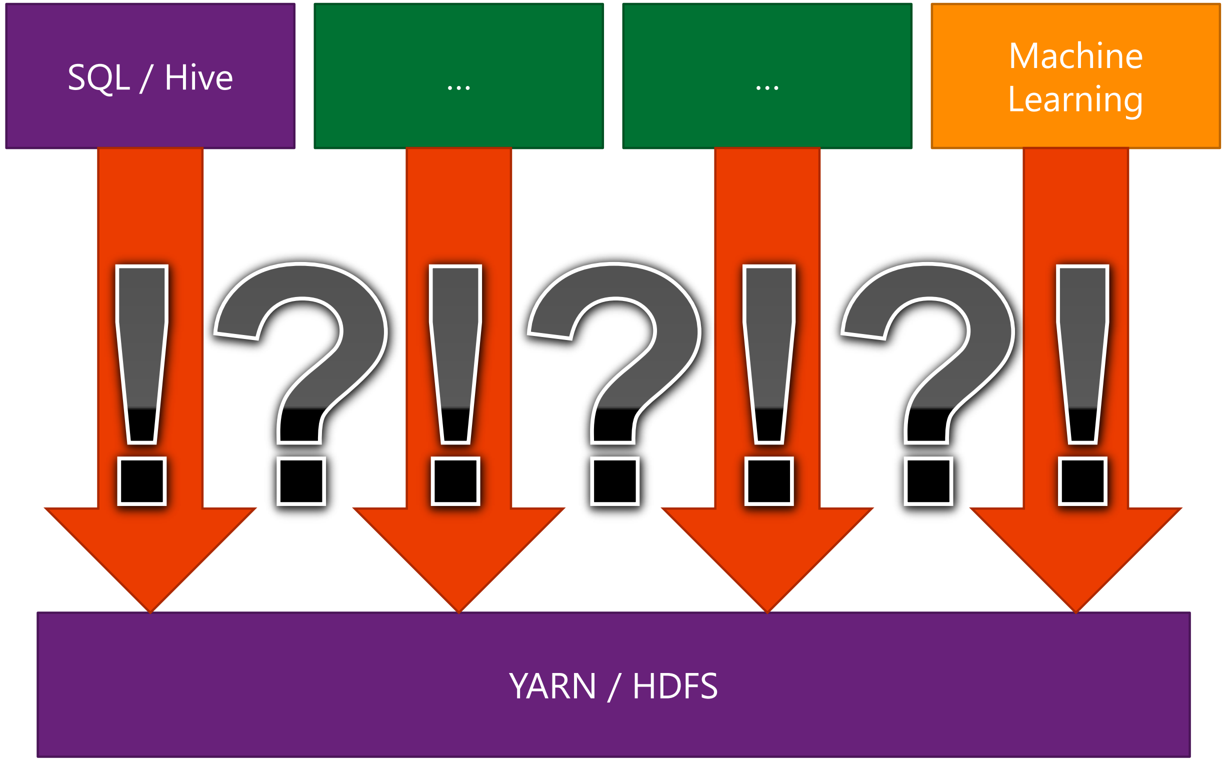
Unify different computations on a single runtime

e.g. Map/Reduce followed by MPI followed by stream processing

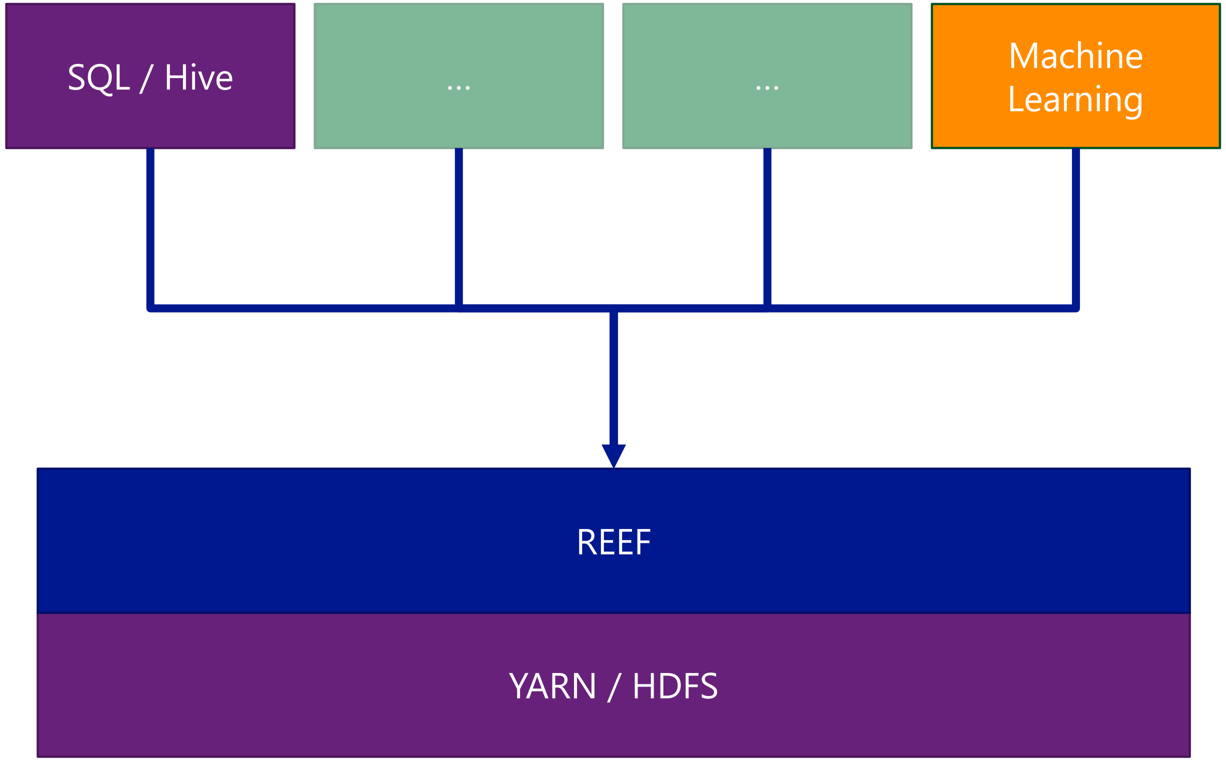
Hand-over of resources (containers on the machines)

Hand-over of data and state (ideally, in RAM)

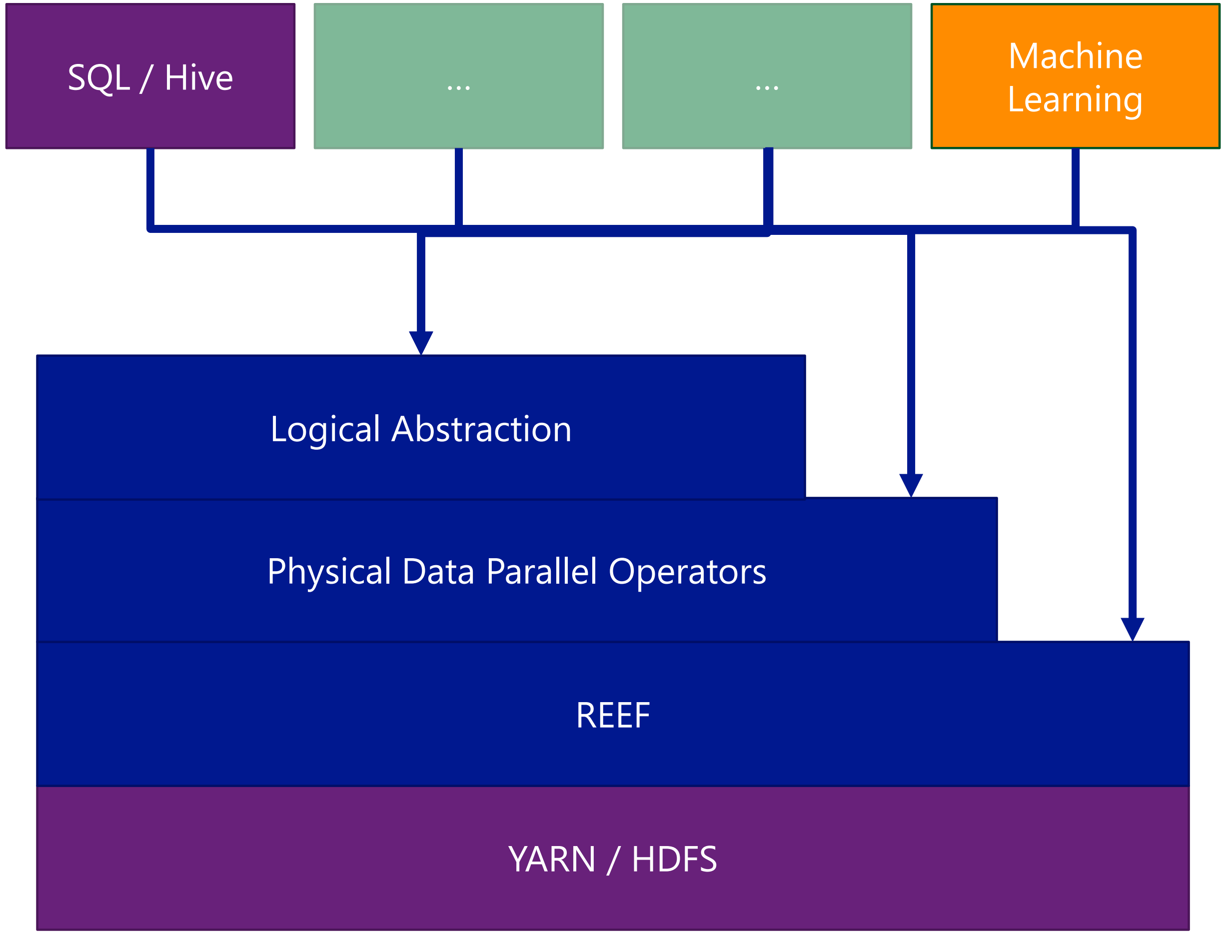
The Challenge



The Solution: add a layer of indirection



REEF in the Stack (Future)



REEF: Computation and Data Management

Extensible Control Flow

Job Driver — Control plane implementation. **User code** executed on YARN's Application Master

Activity — **User code** executed within an **Evaluator**.

Evaluator — Execution Environment for **Activities**. One **Evaluator** is bound to one YARN Container.

Data Management Services

Storage
- Abstractions: Map and Spool
- Local and Remote

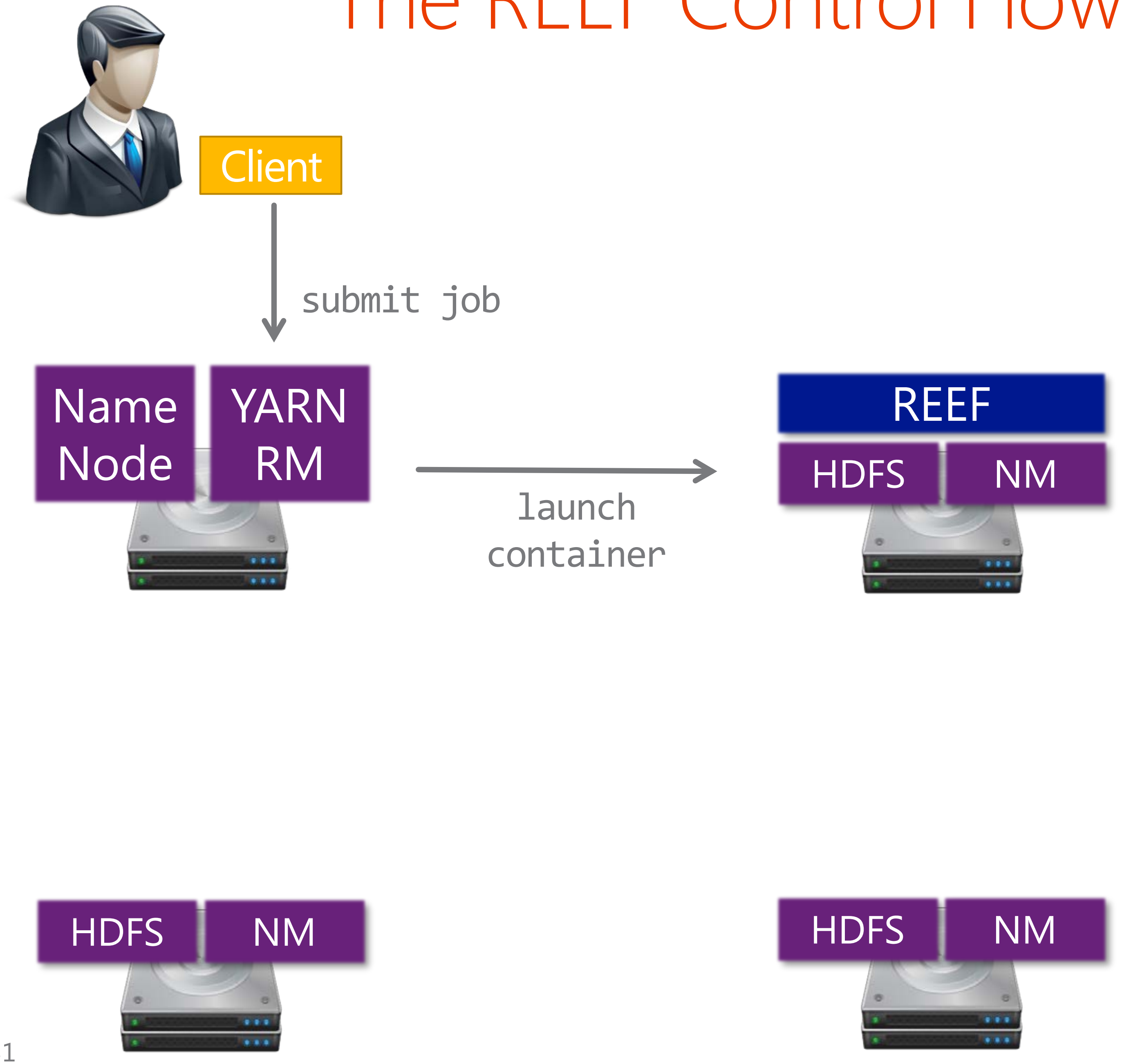
Network
- Message passing
- Bulk Transfers
- Collective Communications

State Management
- Fault Tolerance
- Checkpointing

REEF Control Flow

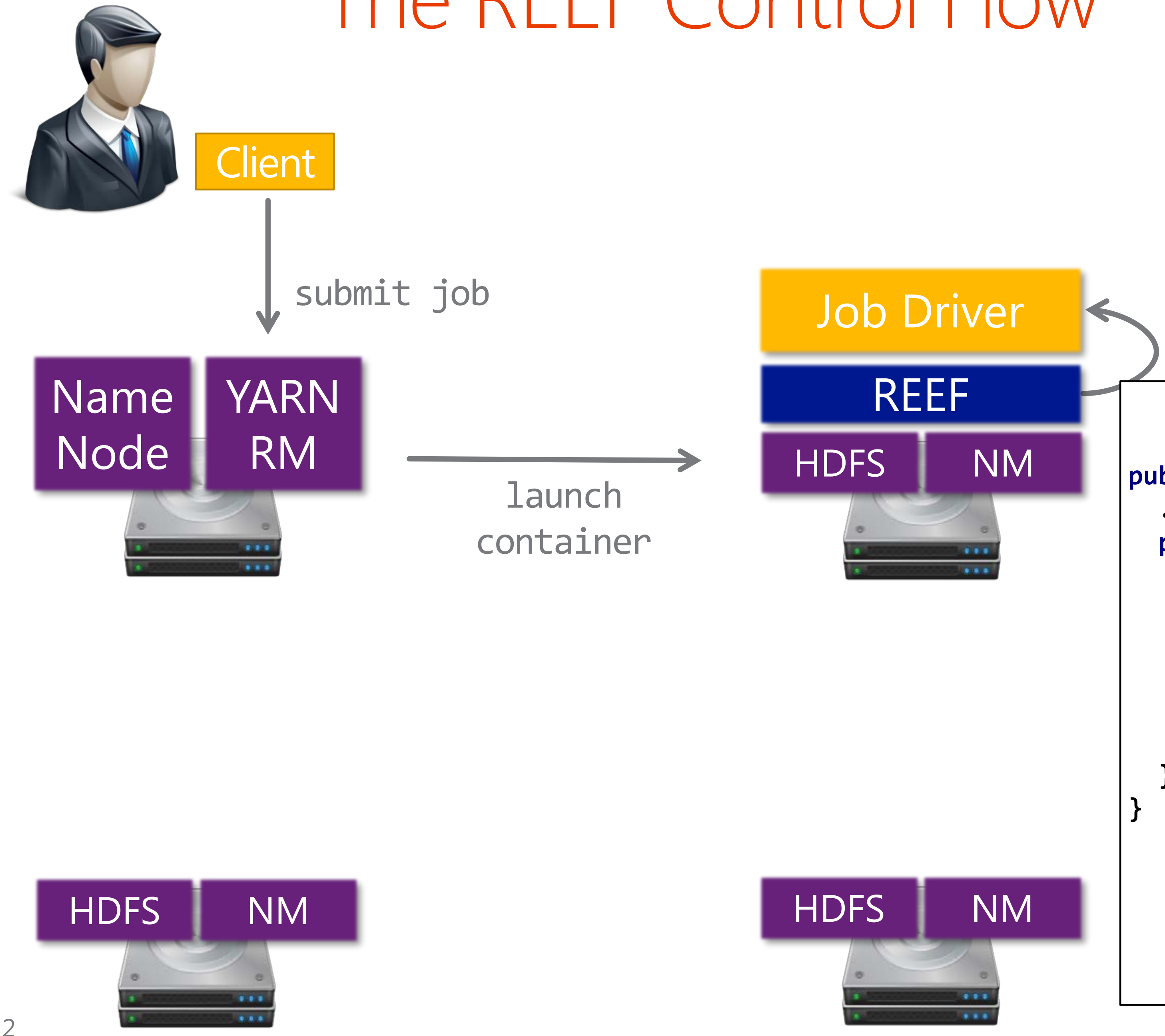
Running Example: Distributed Shell

The REEF Control Flow



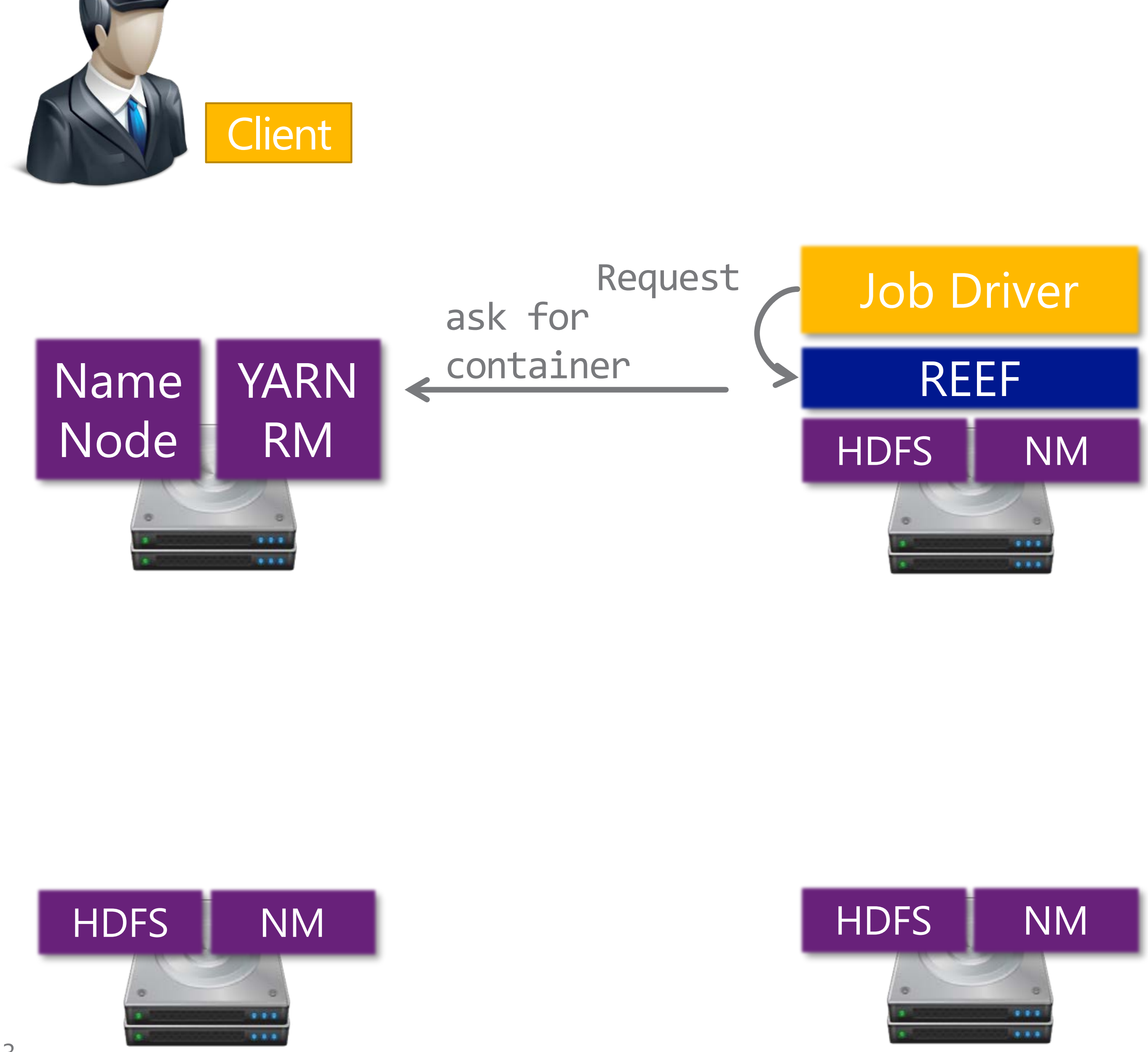

```
public class DistributedShell {
  ...
  public static void main(String[] args){
    ...
    Injector i = new Injector(yarnConfiguration);
    ...
    REEF reef = i.getInstance(REEF.class);
    ...
    reef.submit(driverConf);
  }
}
```

The REEF Control Flow



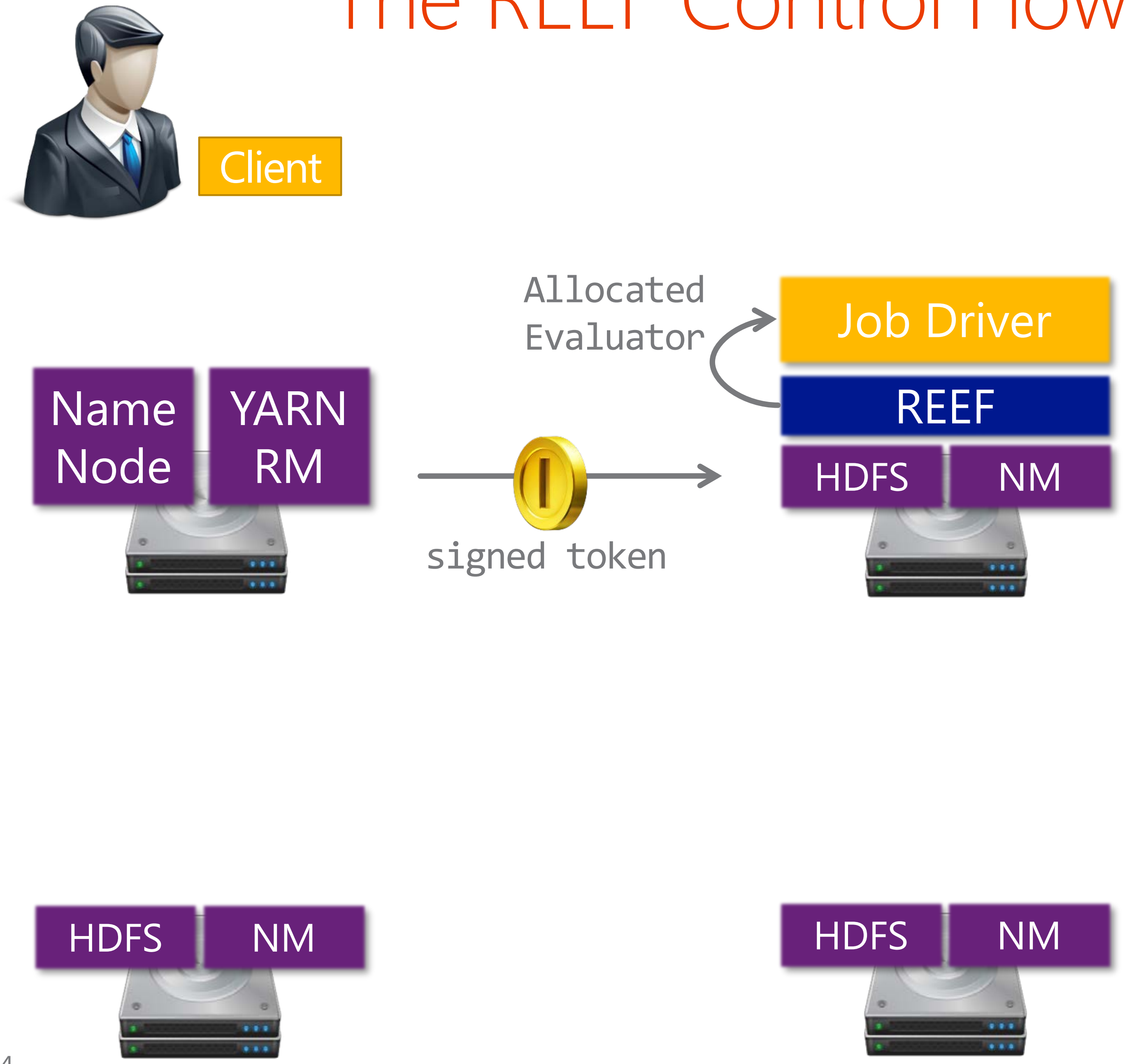

```java
public class DistributedShell {
  ...
  public static void main(String[] args){
    ...
    Injector i = new Injector(yarnConfiguration);
    ...
    REEF reef = i.getInstance(REEF.class);
    ...
    reef.submit(driverConf);
  }
}
```

The REEF Control Flow



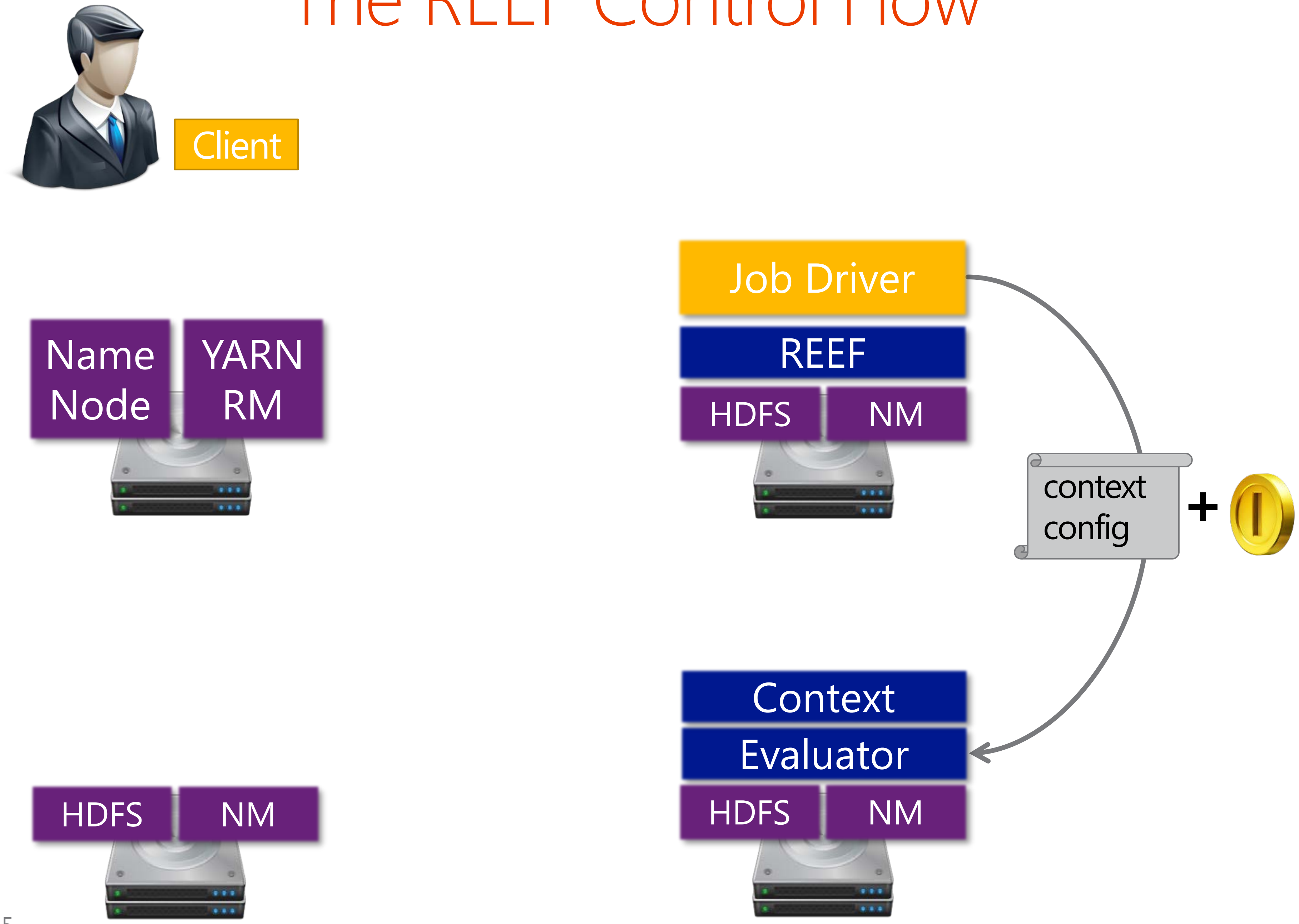

```java
public class DistributedShellJobDriver {
  private final EvaluatorRequestor requestor;
  ...

  public void onNext(StartTime time) {

    requestor.submit(EvaluatorRequest.Builder()
                          .setSize(SMALL).setNumber(2)
                          .build()
                          );

  }

  ...
}
```

The REEF Control Flow

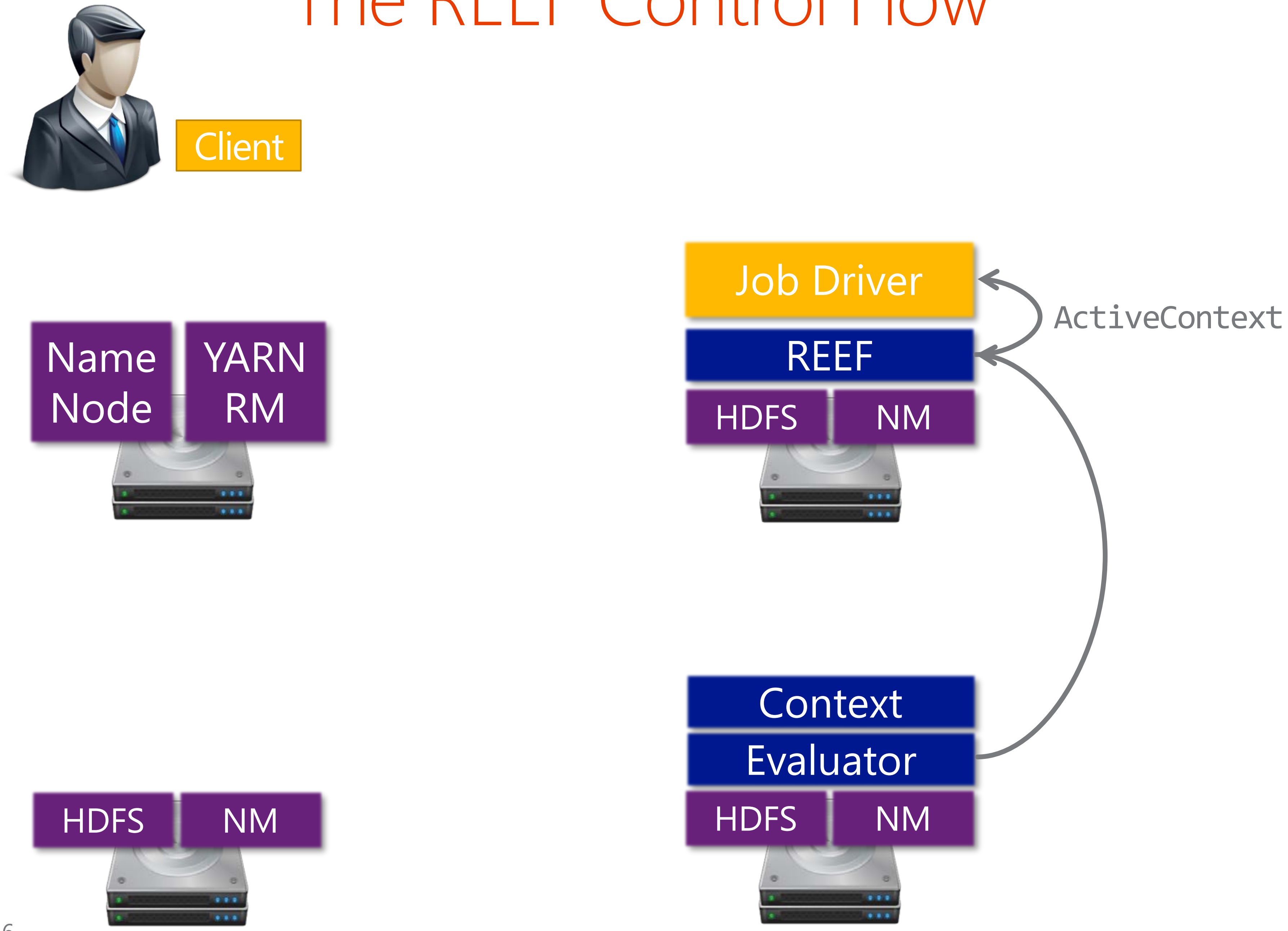



```java
public class DistributedShellJobDriver {
  private final EvaluatorRequestor requestor;
  ...

  public void onNext(AllocatedEvaluator eval) {
    Configuration contextConf = ...;
    eval.submitContext(contextConf)
  }

  ...
}
```

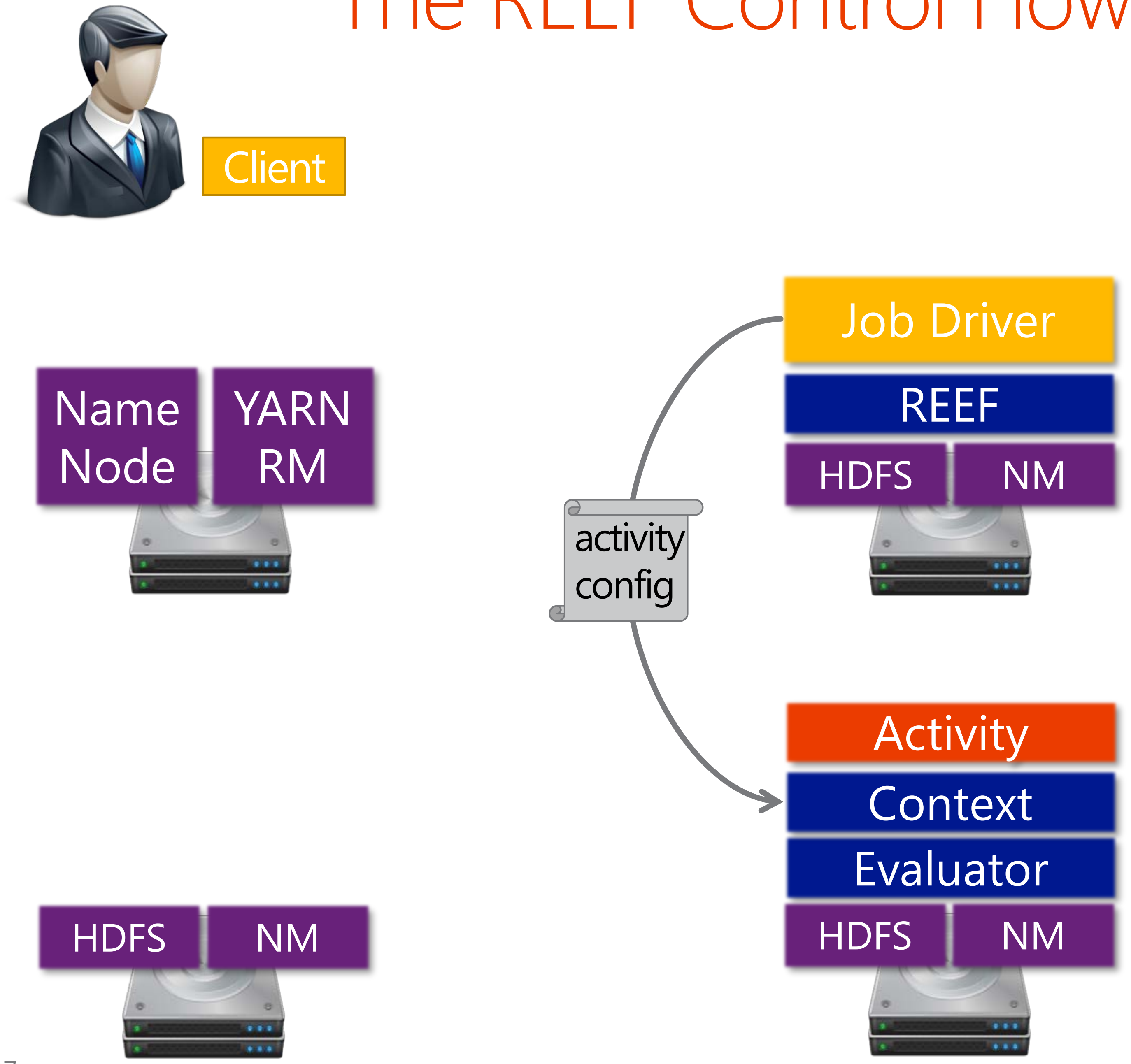
The REEF Control Flow



The REEF Control Flow

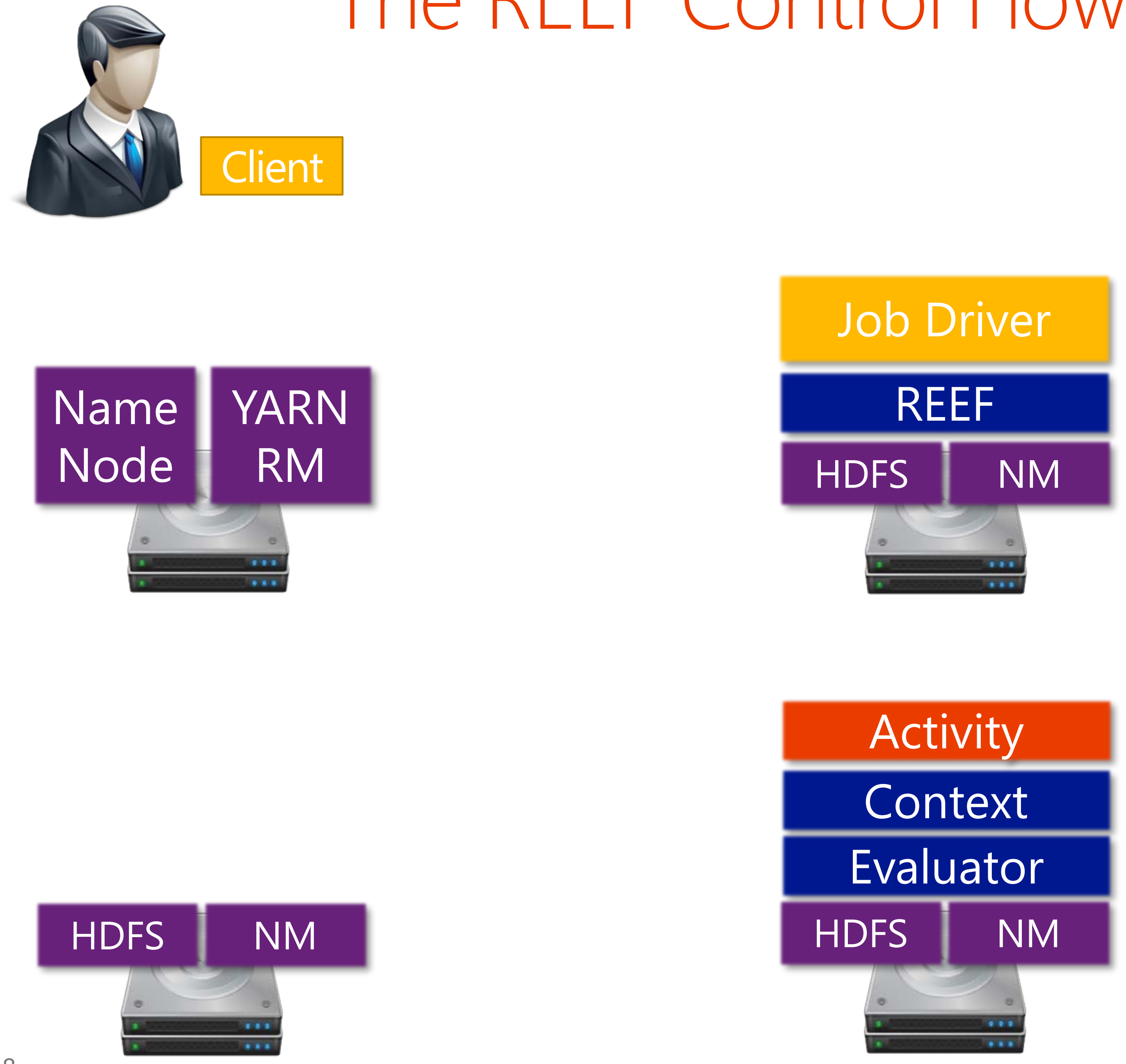


The REEF Control Flow



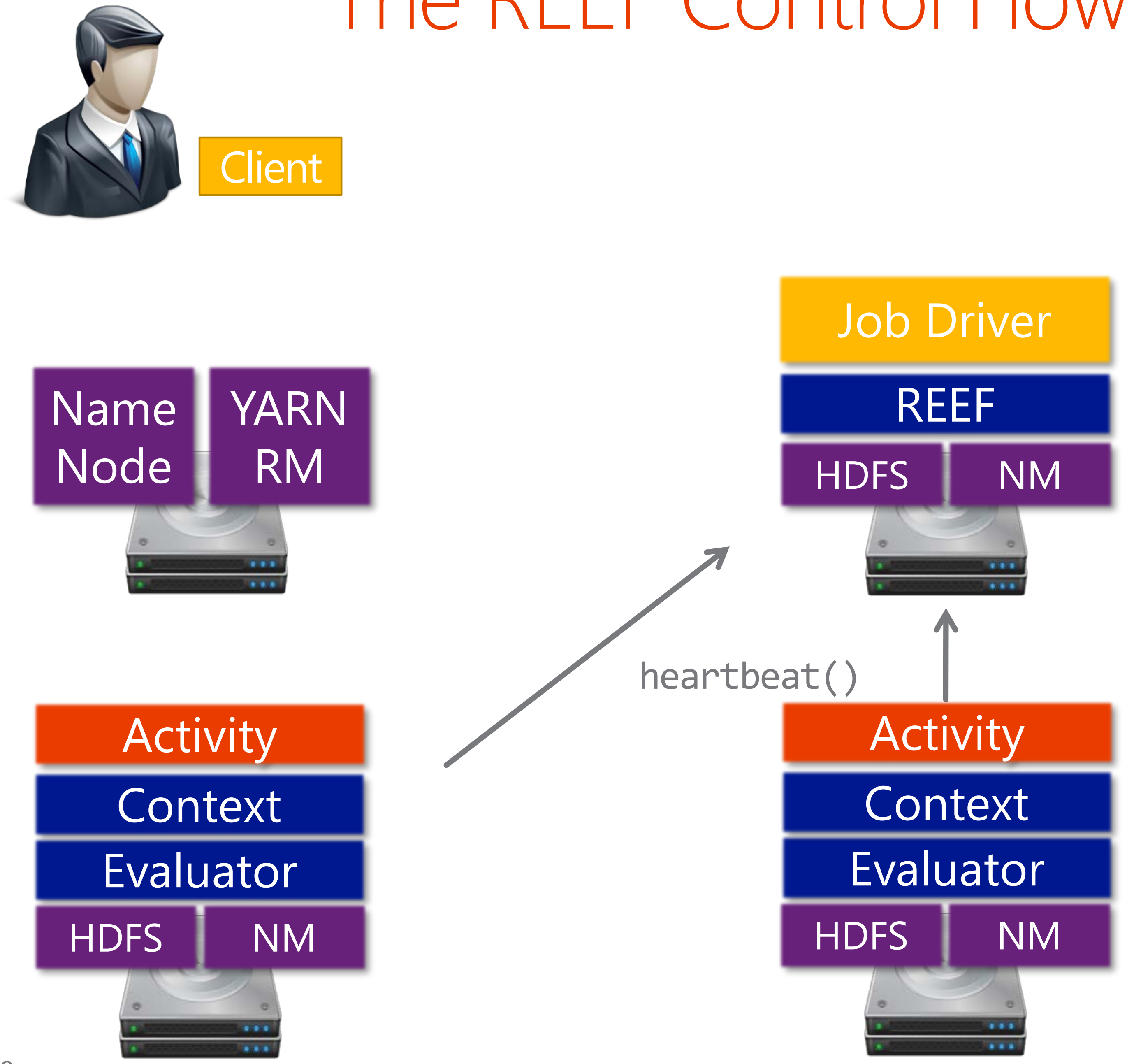

```java
public class DistributedShellJobDriver {
  private final String cmd = “ls”;

  [...]

  public void onNext(ActiveContext ctx) {
    final String activityId = [...];

    Configuration activityConf = Activity.CONF
            .set(IDENTIFIER, "ShellActivity")
            .set(ACTIVITY, ShellActivity.class)
            .set(COMMAND, this.cmd)
            .build();

    ctx.submitActivity(activityConf);
  }

  [...]

}
```

The REEF Control Flow

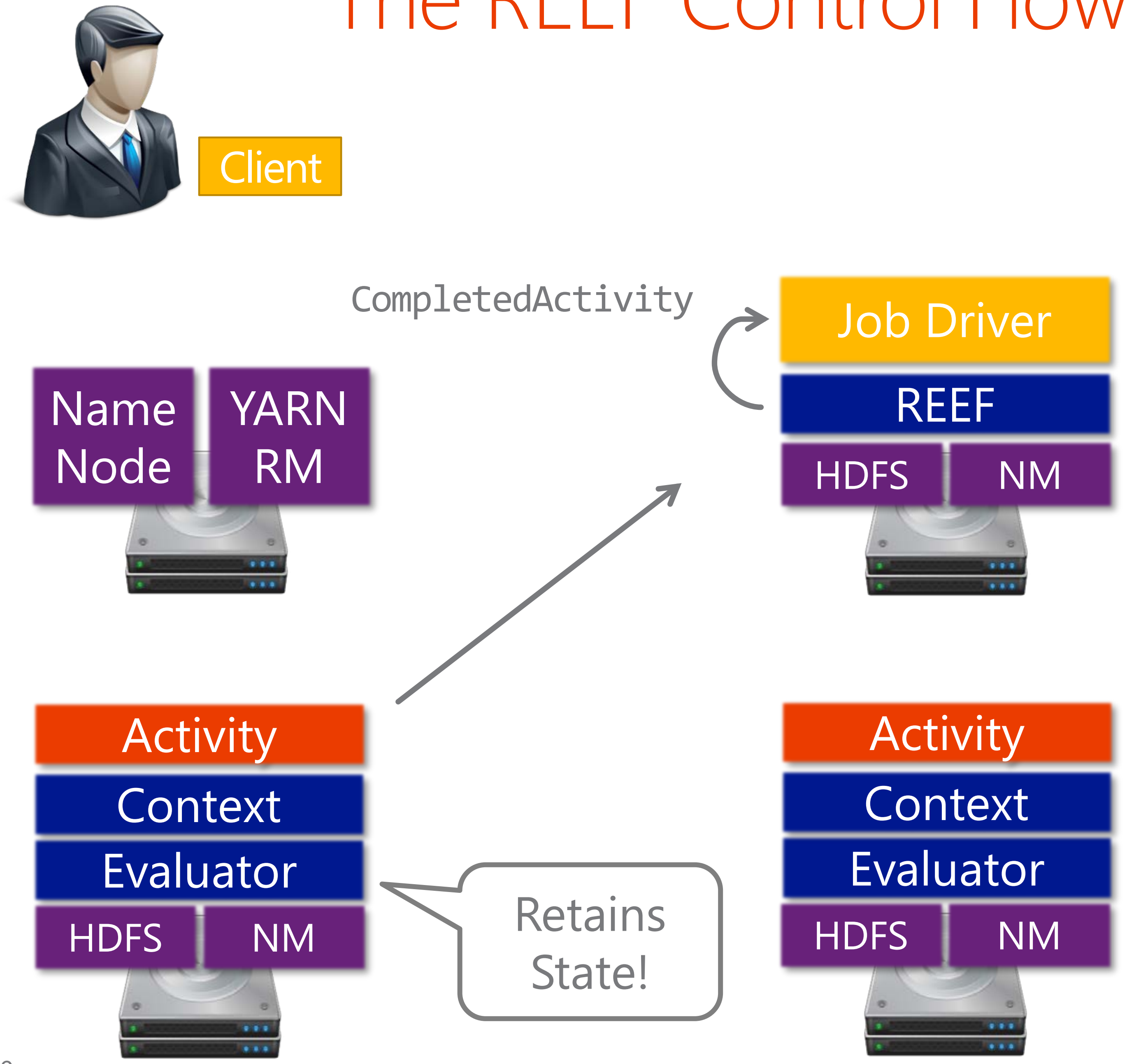



```java
class ShellActivity implements Activity {

  private final String command;

  @Inject
  ShellActivity(@Parameter(Command.class) String c) {
    this.command = c;
  }

  private String exec(final String command){
    ...
  }

  @Override
  public byte[] call(byte[] memento) {
    String s = exec(this.cmd);
    return s.getBytes();
  }

}
```

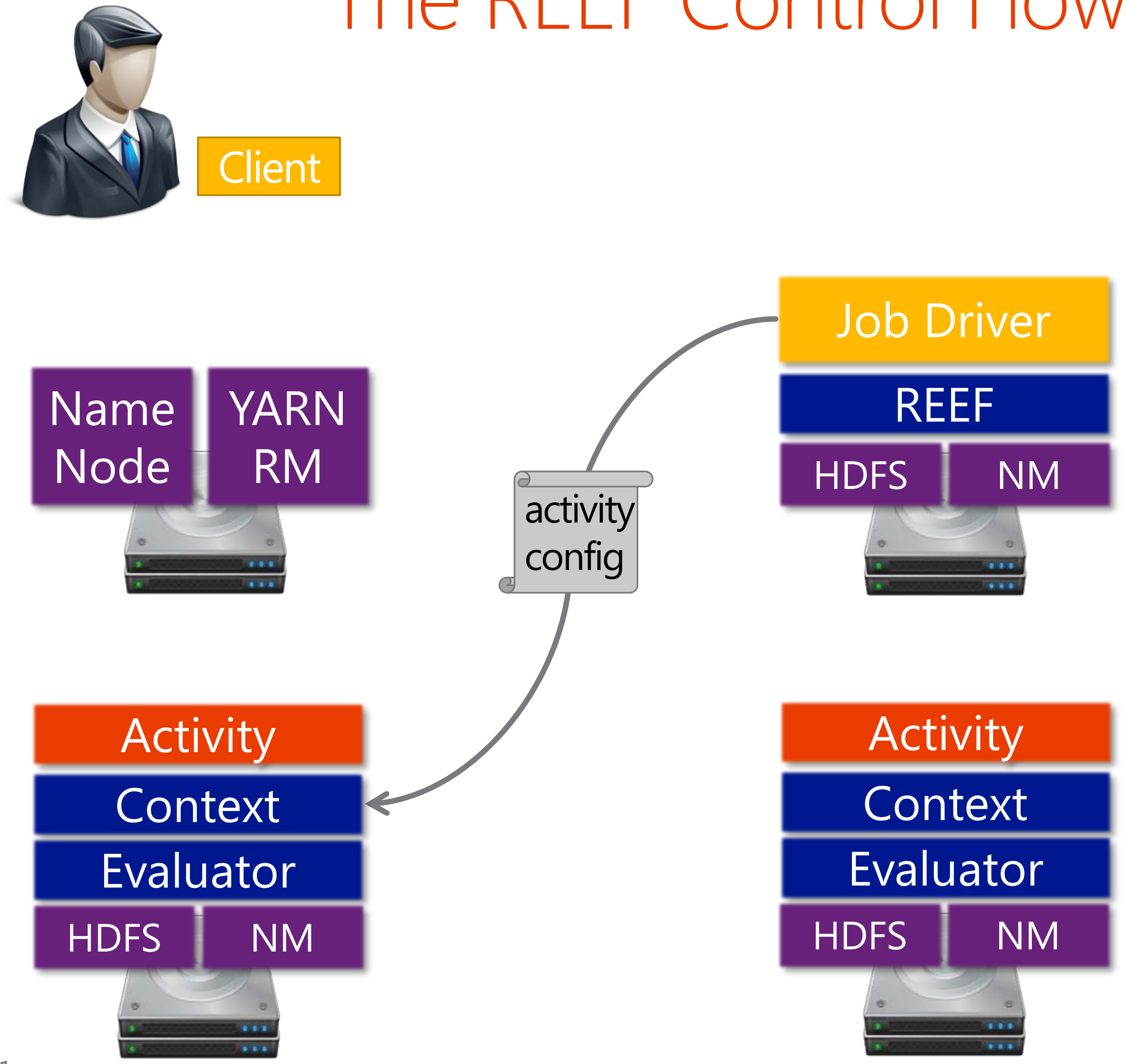
The REEF Control Flow



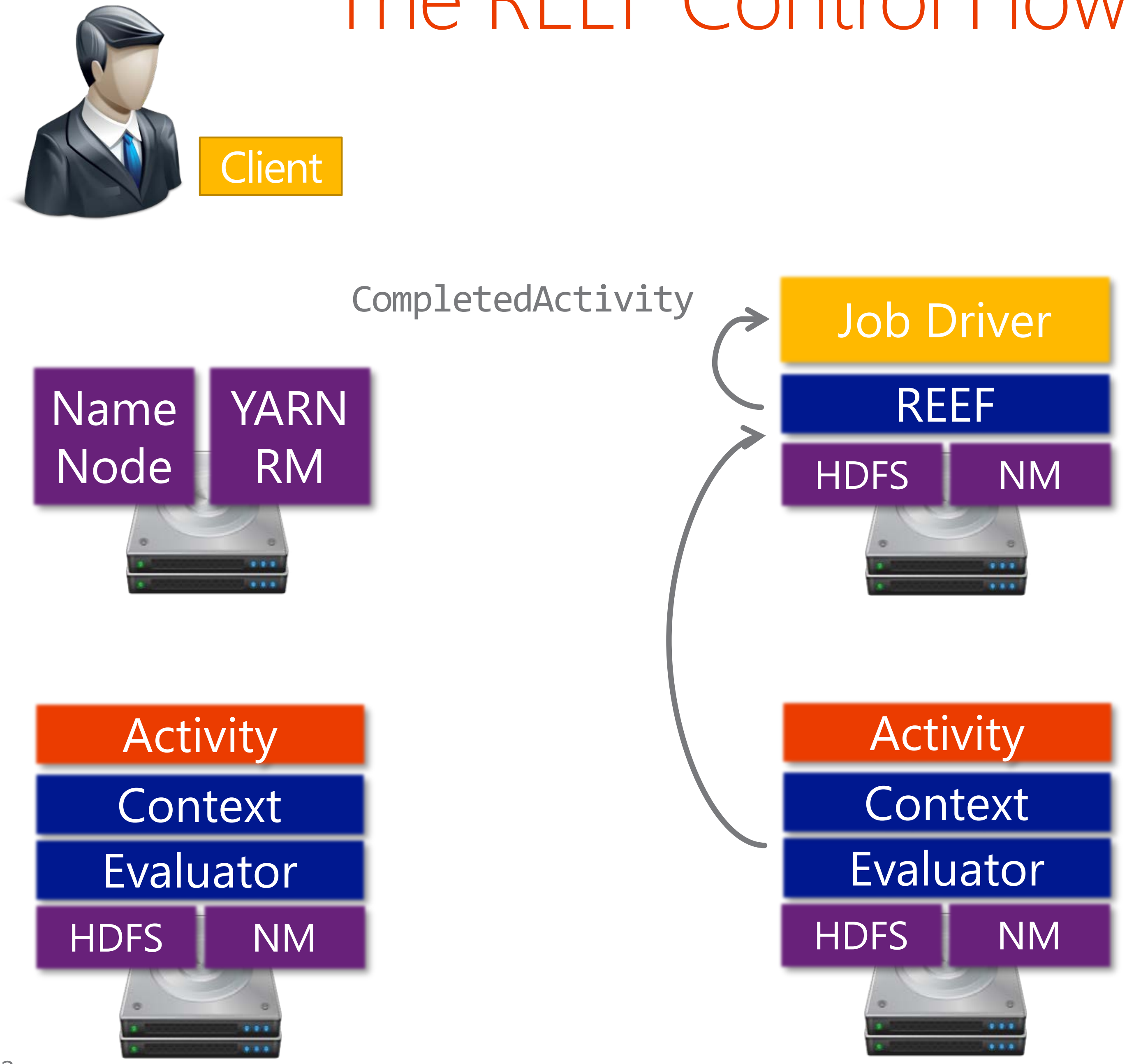
The REEF Control Flow



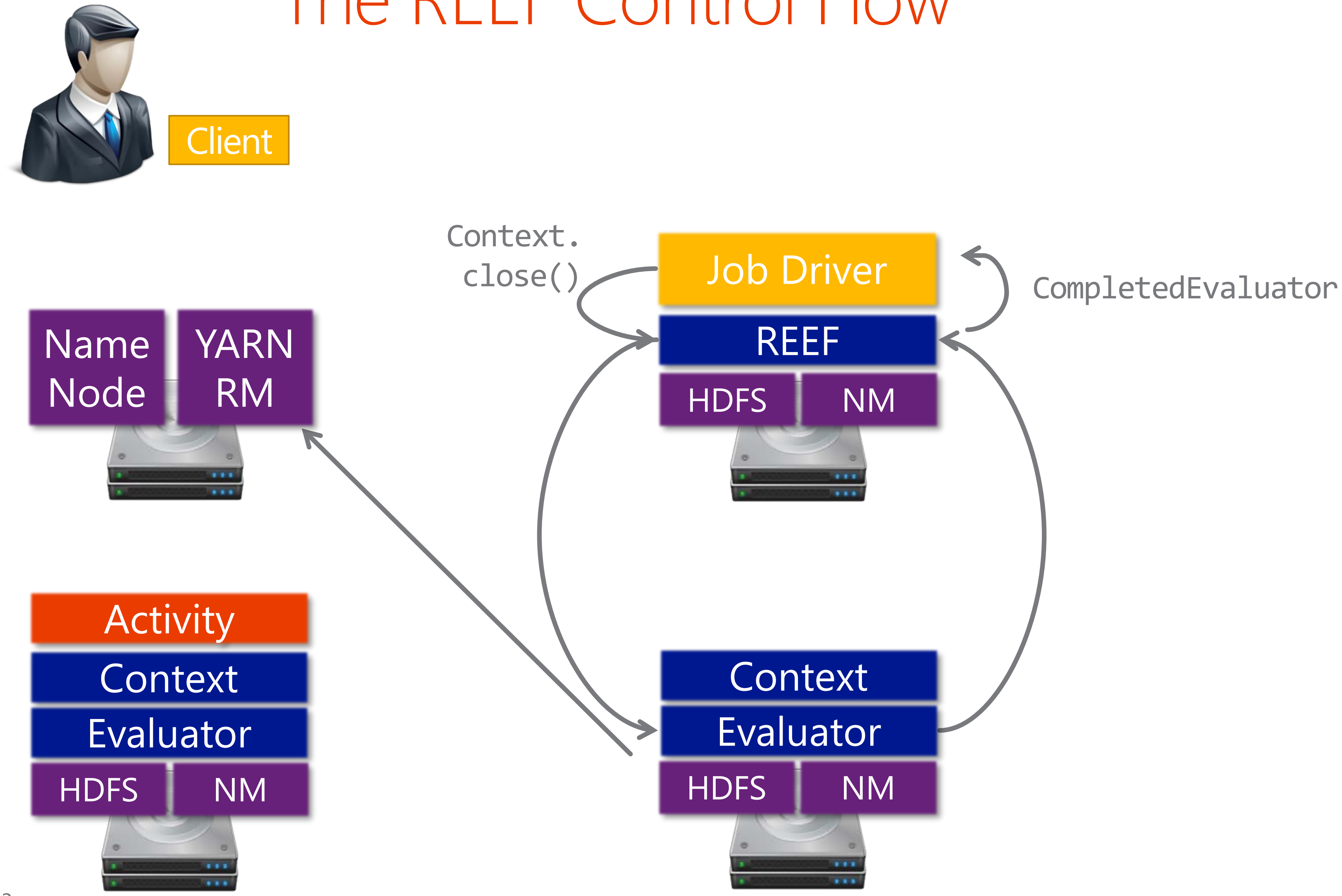
The REEF Control Flow



The REEF Control Flow



The REEF Control Flow



REEF Control Flow: Summary

Control Flow is centralized in the Driver

Evaluator allocation & configuration
Activity configuration & submission

Error Handling is centralized in the Driver

When an Activity throws an Exception, we ship & throw it at the Driver
When an Evaluator dies, we throw an Exception at the Driver

Easy to reason about and debug

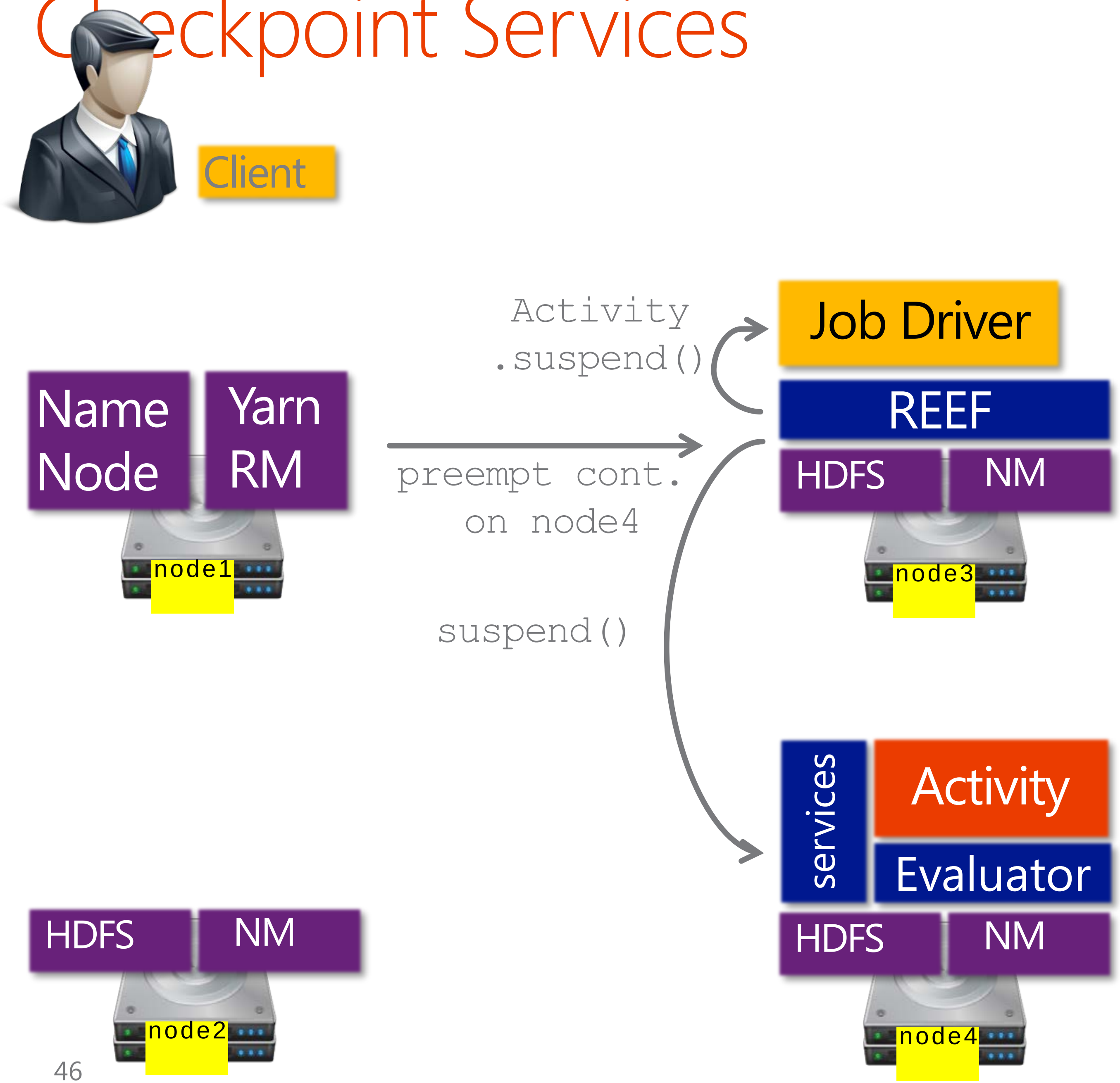
All APIs are asynchronous

Driver files requests via non-blocking API calls
REEF fires events at user (e.g. Evaluator availability, Exceptions, …)
Goal: REEF is stateless for fault-tolerant drivers

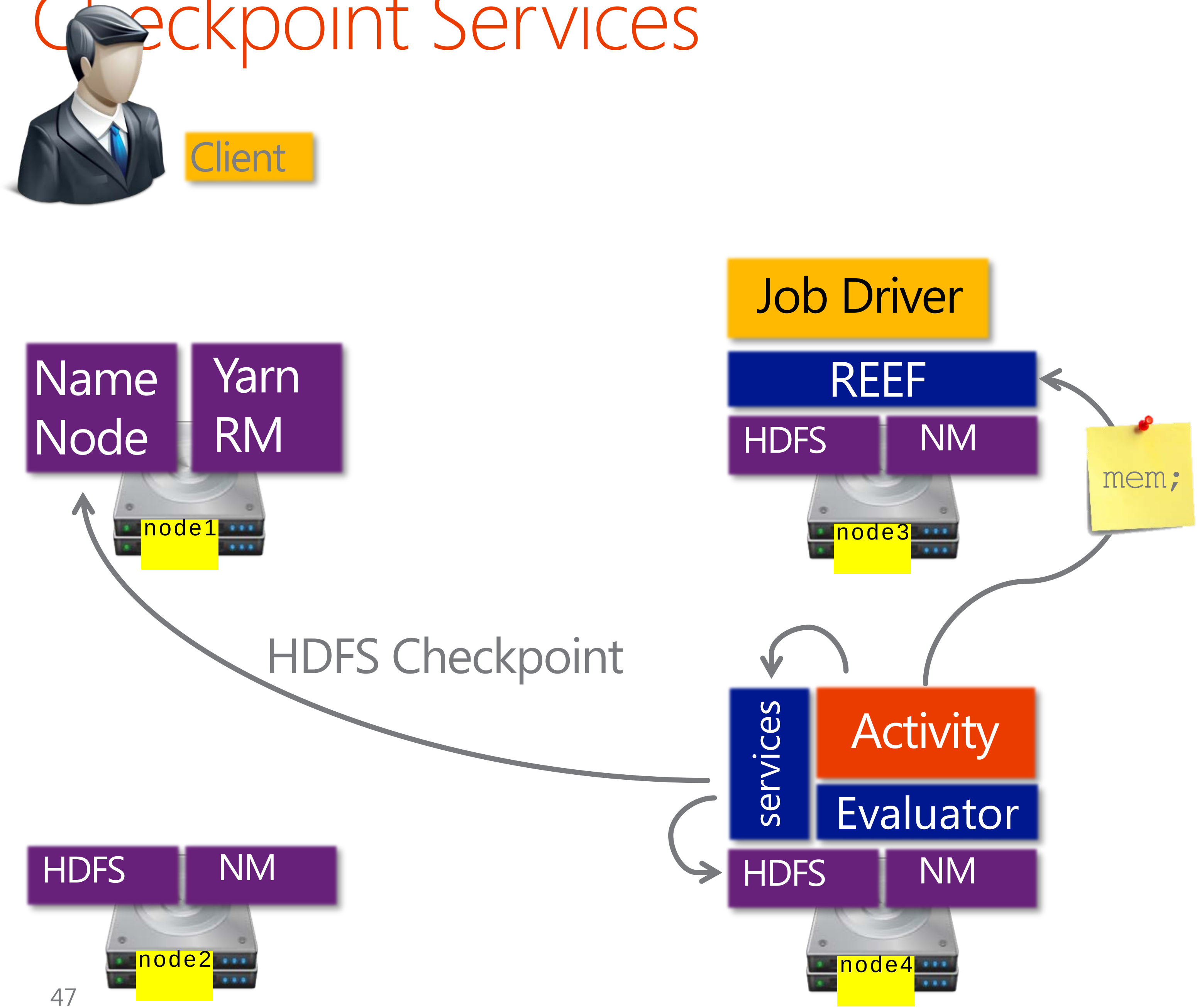
Scalable

Checkpoint Services

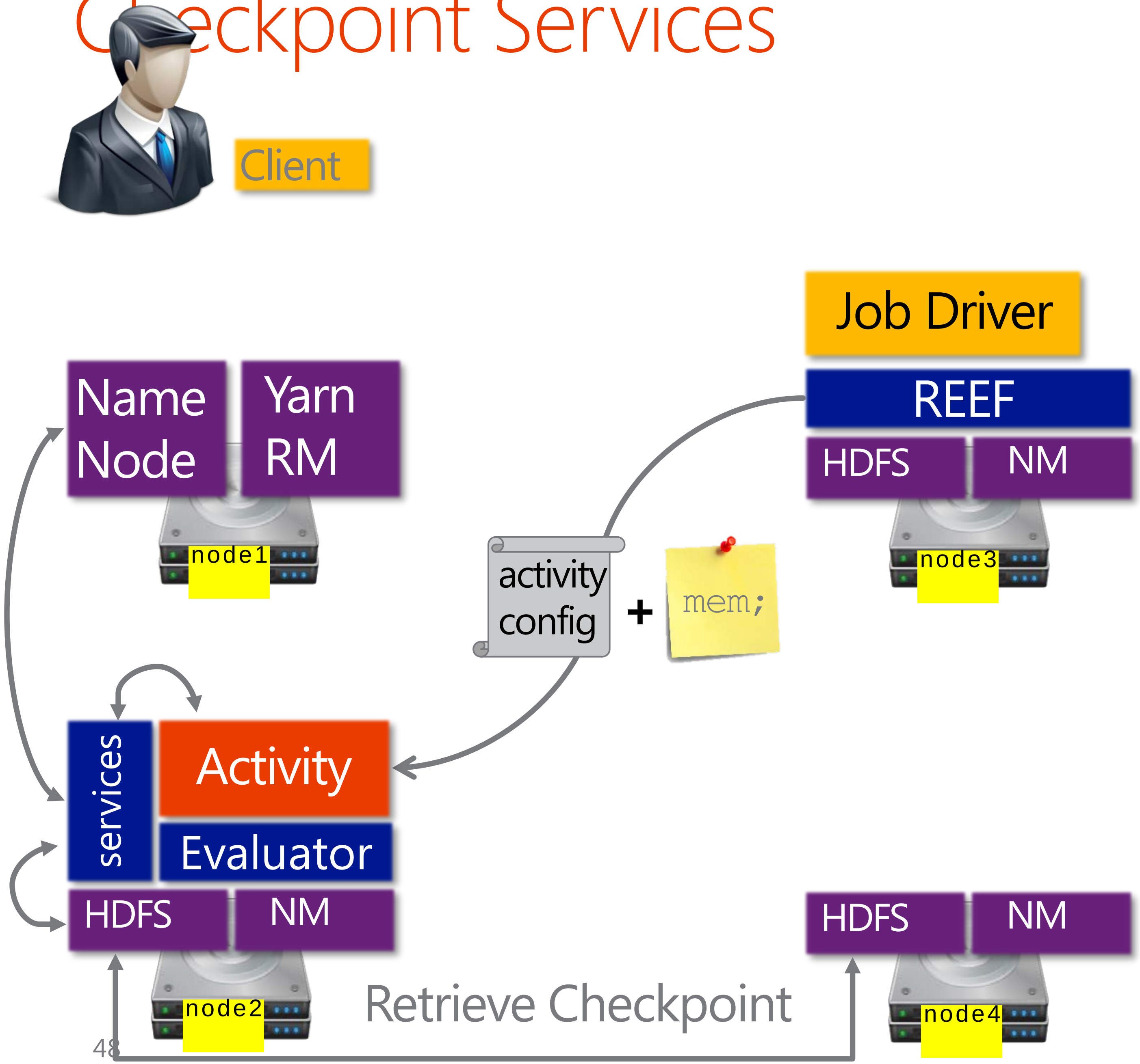
Checkpoint Services



Checkpoint Services

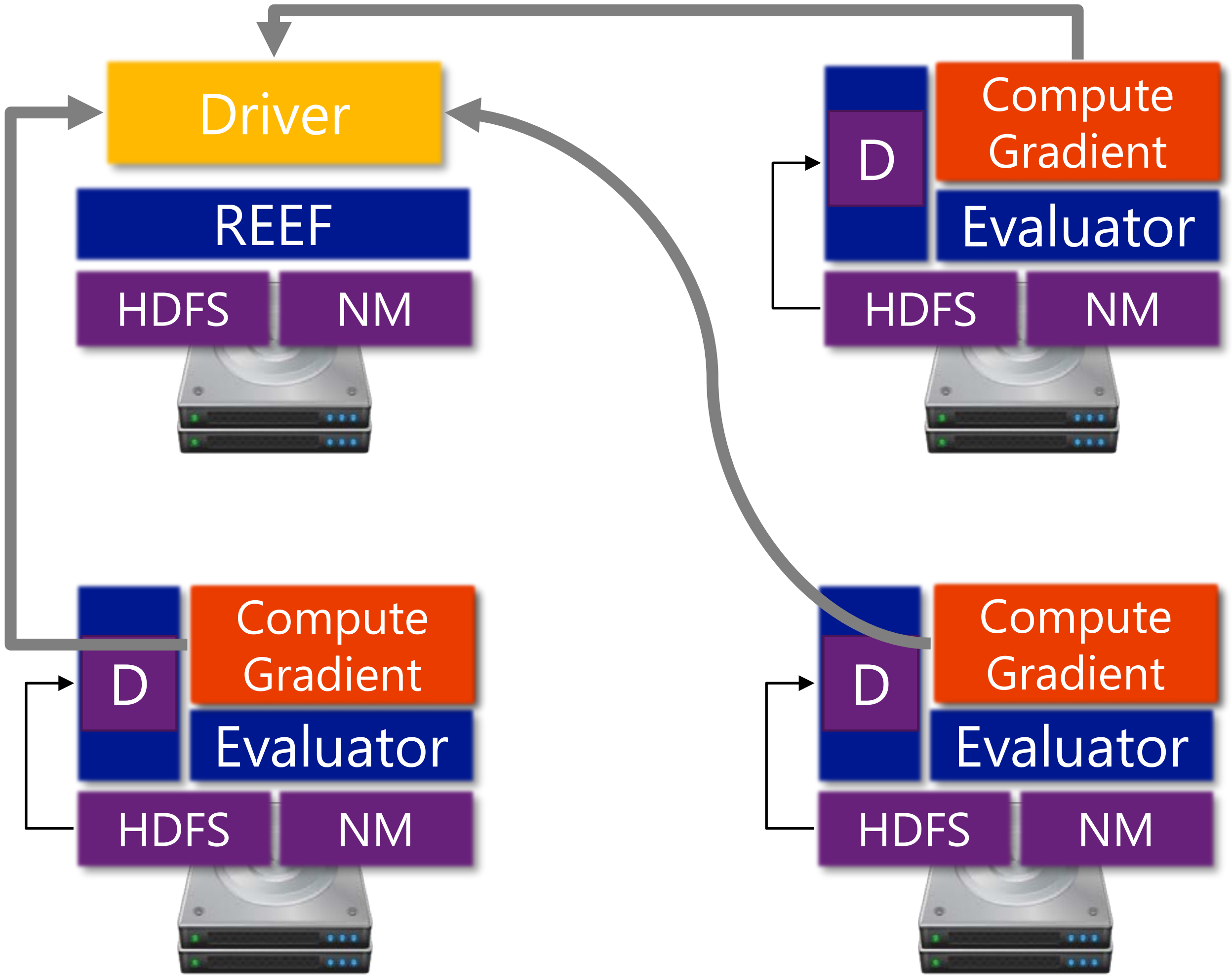


Checkpoint Services



Learning in REEF

Simple Batch Gradient Descent

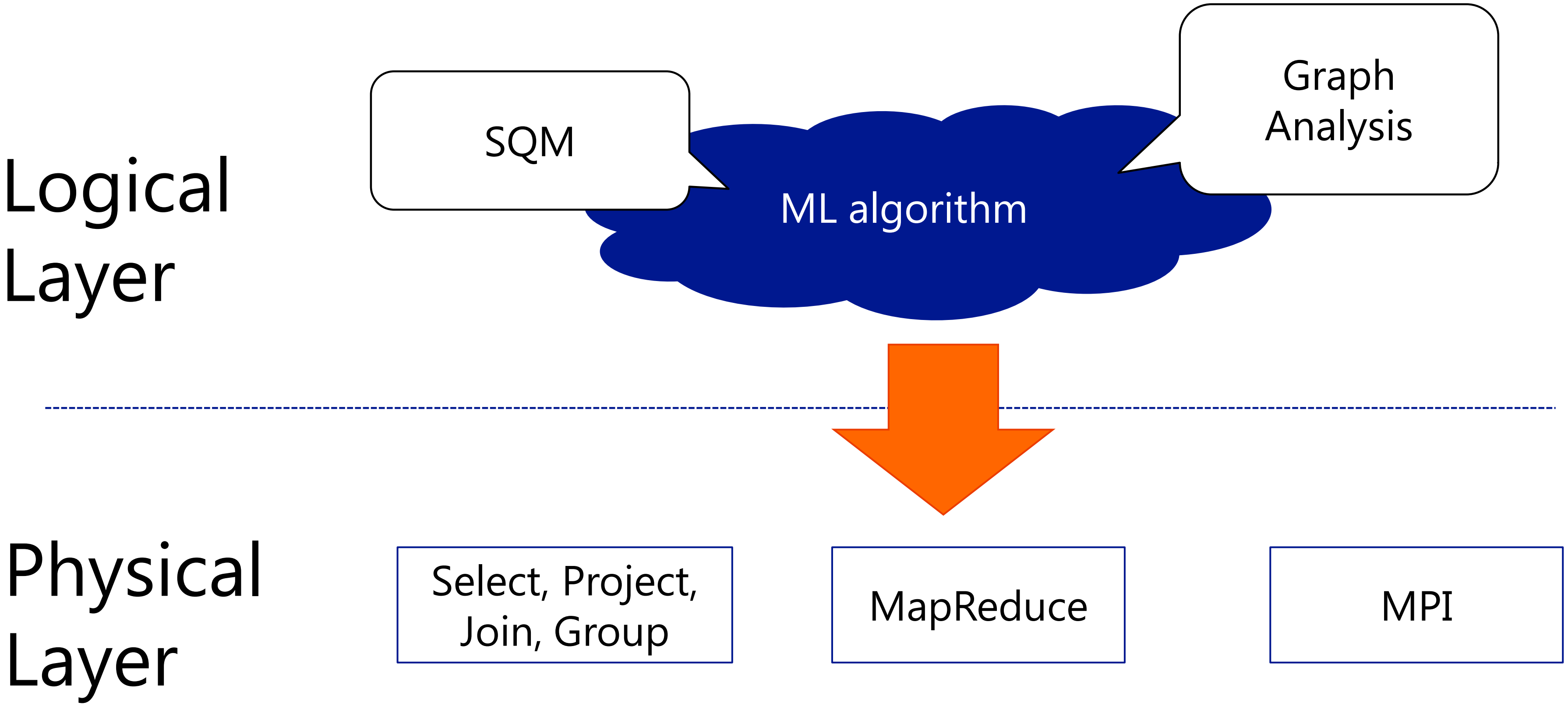


1. Driver Launches
2. Driver Launches Evaluators
3. Driver submits LoadActivity
4. Activity loads Data
5. Activity finishes

6. **Until Converged:**
   Driver submits ComputeGradient
   Gradient is shipped to the Driver

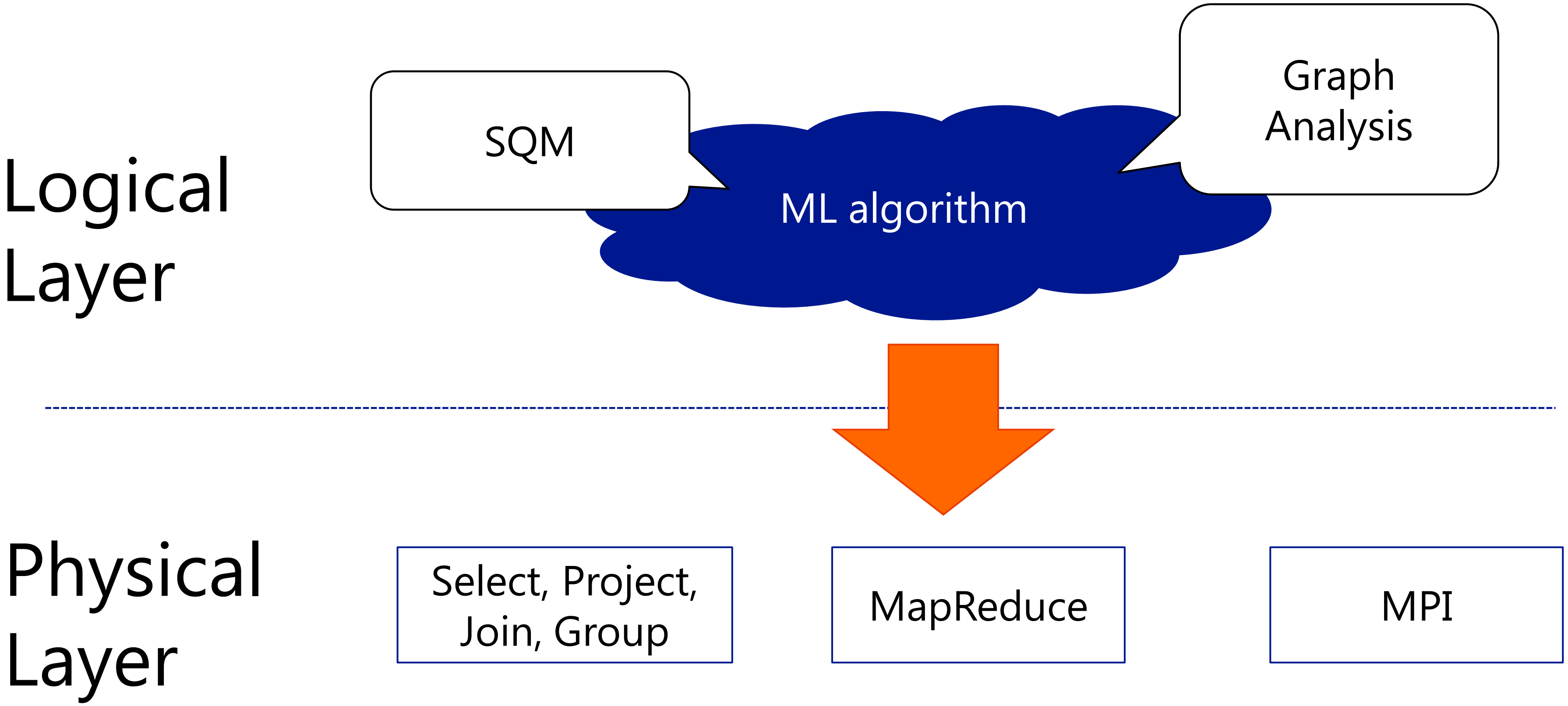
Conclusion

Logical/Physical Separation



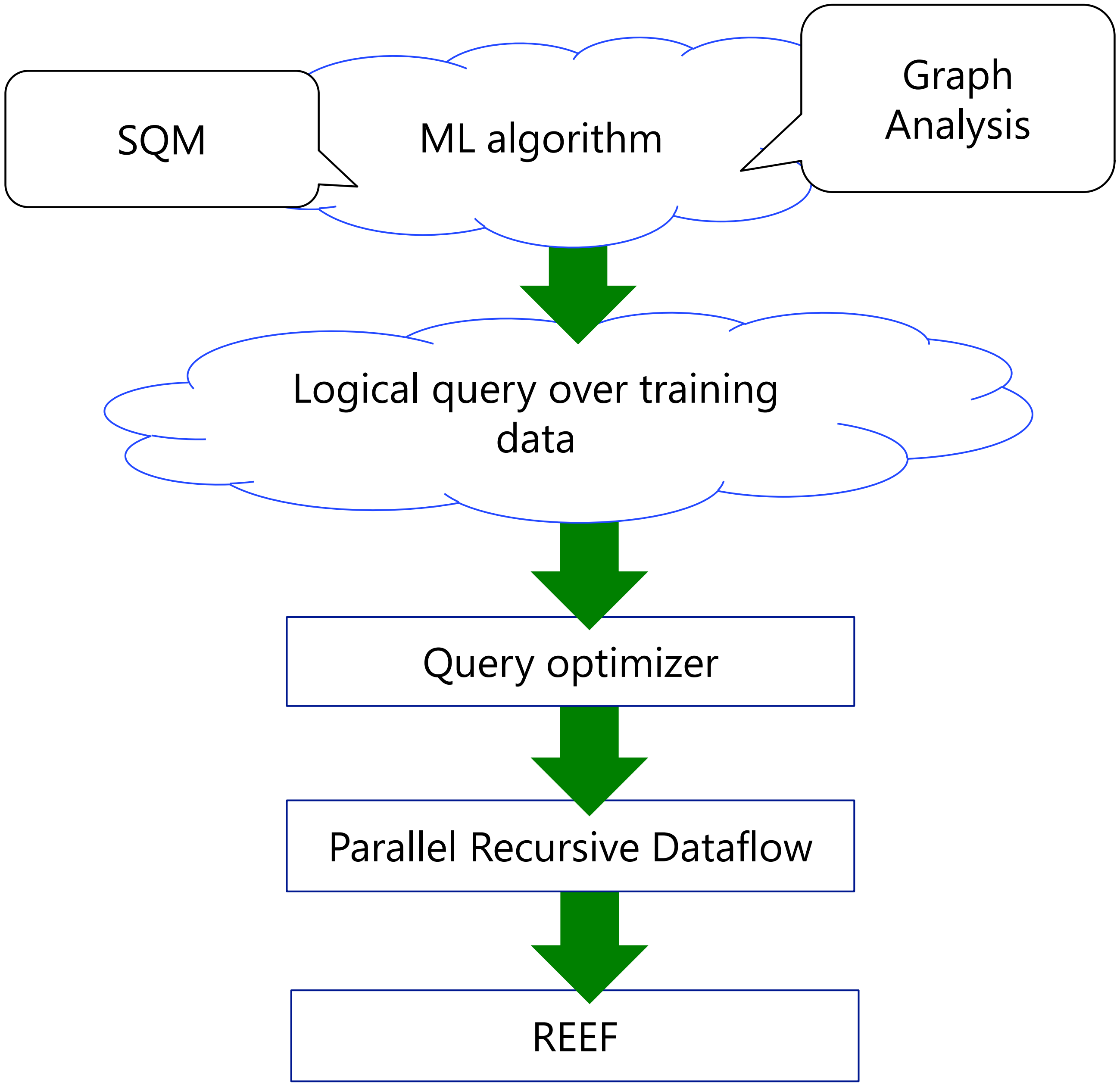
- Observation #1: Enables query optimization
- Can we automate this translation?

Logical/Physical Separation



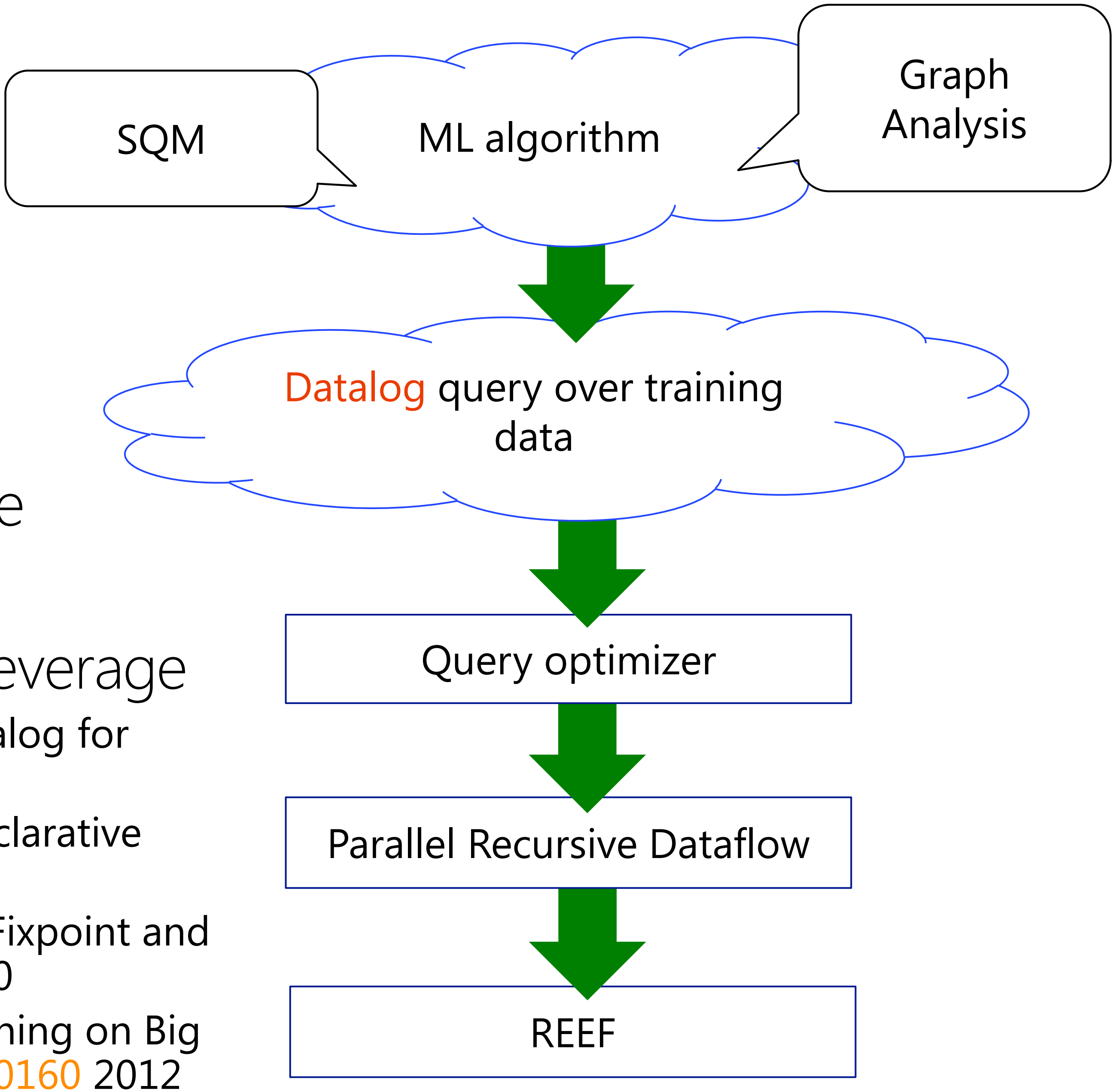
- Observation #2: Systems have to solve the same problems and adopt similar solutions
- Can we isolate these solutions in reusable modules?

A Unifying Design



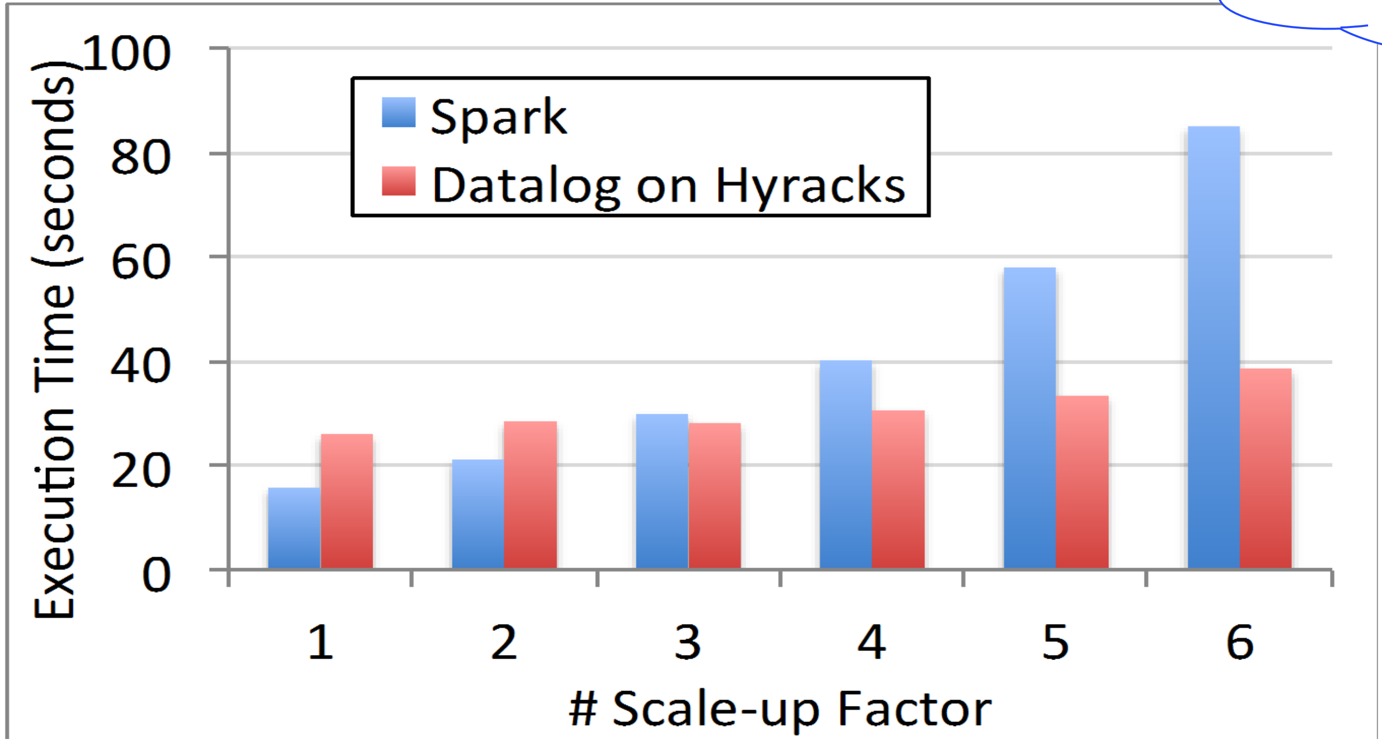
Datalog?

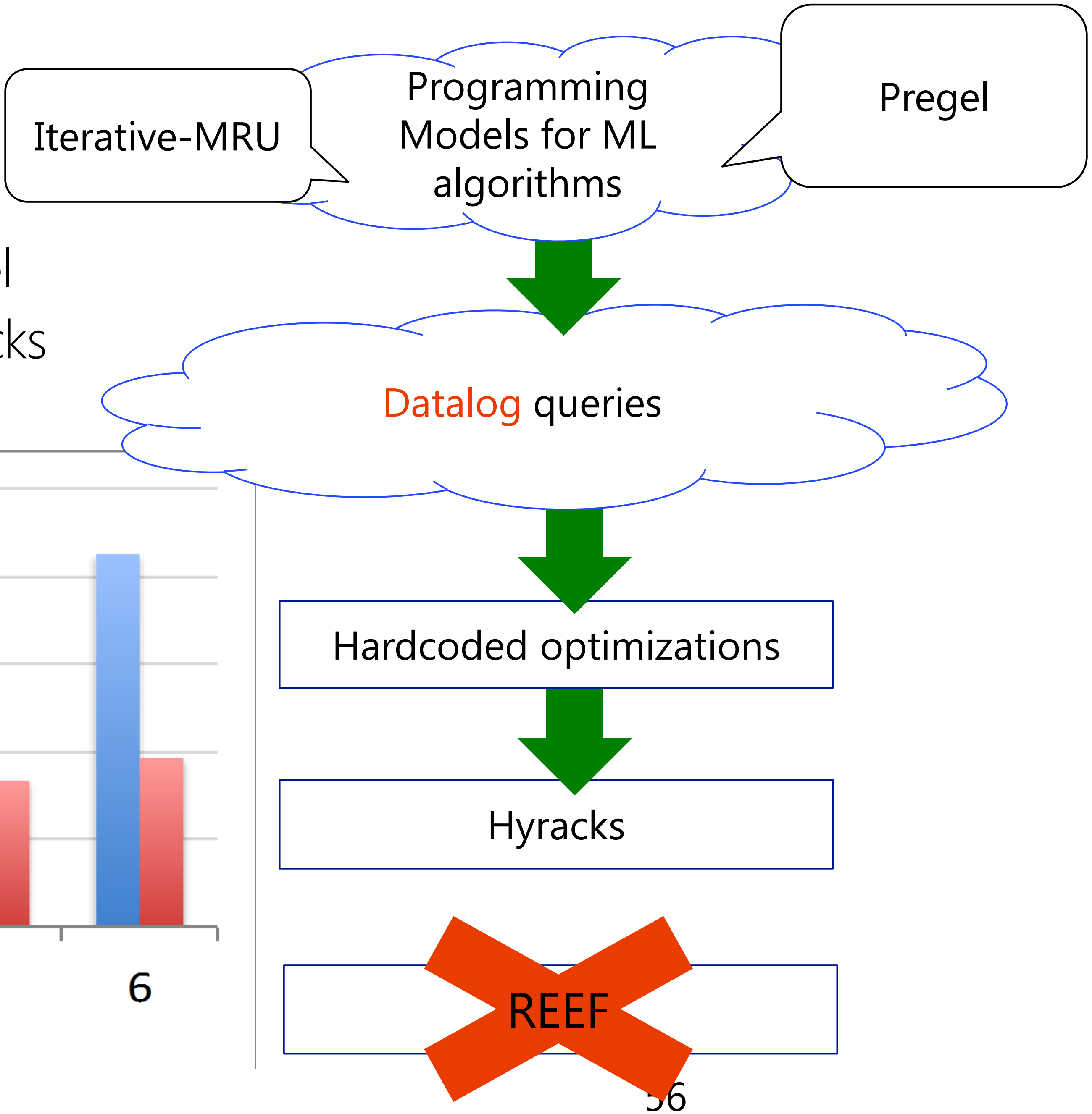
- Recursion is built into the language
- Amenable to optimizations
- Lots of existing work that we can leverage
  - J. Eisner and N. Filardo. Dyna: Extending datalog for modern AI. In Datalog '10
  - S. Funiak et al. Distributed inference with declarative overlay networks. EECS Tech Report 2008
  - D. Deutch, C. Koch, T. Milo. On Probabilistic Fixpoint and Markov Chain Query Languages. In PODS '10
  - Y. Bu et al. Scaling Datalog for Machine Learning on Big Data. Tech Report http://arxiv.org/abs/1203.0160 2012



Version 0.1

- Implementation over Hyracks
- Supports both Iterative-MRU and Pregel
- Standard optimizations + some new tricks



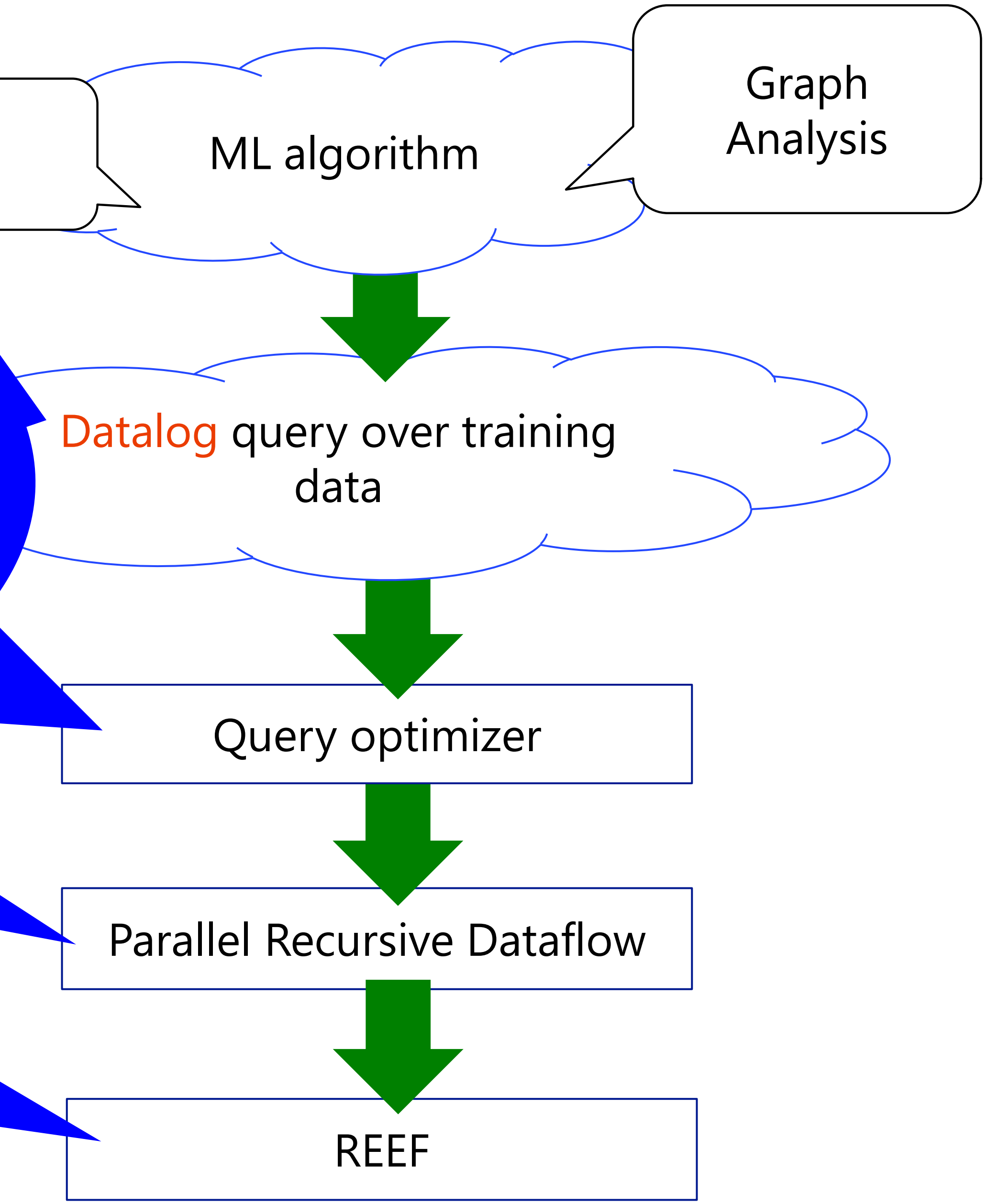


Ope

- Provenance for triage
  - "My model misbehaves - why?"
- Fault-awareness policies
- Incremental learning

Processing

- State Management
- Caching policies



Conclusion

- Open source release soon
  - Apache 2 license
  - MapReduce support (including Hive)

- Machine learning libraries supported
  - Iterative Map-Reduce-Update
  - MPI (Graphical Models)
  - Mahout compatibility?

- Contact: Tyson Condie
  - tcondie@microsoft.com
  - tcondie@cs.ucla.edu

Microsoft

UCLA Engineering
HENRY SAMUELI SCHOOL OF
ENGINEERING AND APPLIED SCIENCE
Birthplace of the Internet