Slides Credit: Matthias Boehm

SCIENCE
PASSION
TECHNOLOGY

Data Integration and Large Scale Analysis
08 Cloud Resource Management

Shafaq Siddiqi

Graz University of Technology, Austria

Last update: Dec 01, 2023

ISDS

Announcement

- Submissions are open in the TeachCenter
- Exam registration is open
- Course Evaluation is open

Course Outline Part B:
Large-Scale Data Management and Analysis

12 Distributed Stream Processing

13 Distributed Machine Learning Systems

Compute/ Storage

11 Distributed Data-Parallel Computation

10 Distributed Data Storage

Infra

09 Cloud Resource Management and Scheduling

08 Cloud Computing Fundamentals

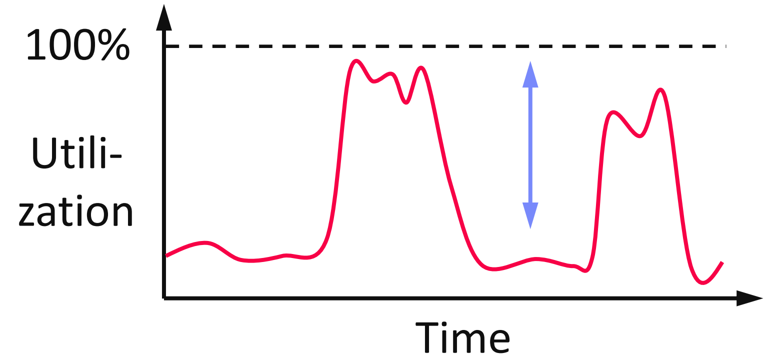
Agenda

- **Motivation, Terminology, and Fundamentals**
- **Resource Allocation, Isolation, and Monitoring**
- **Task Scheduling and Elasticity**

Motivation, Terminology, and Fundamentals

Recap: Motivation Cloud Computing, cont.

- **Argument #1: Pay as you go**
  - No upfront cost for infrastructure
  - Variable utilization ➔ over-provisioning
  - **Pay per use or acquired resources**



- **Argument #2: Economies of Scale**
  - Purchasing and managing IT infrastructure at scale ➔ **lower cost** (applies to both HW resources and IT infrastructure/system experts)
  - Focus on **scale-out on commodity HW** over scale-up ➔ **lower cost**

- **Argument #3: Elasticity**
  - Assuming perfect scalability, work done in **constant time * resources**
  - Given virtually unlimited resources allows to reduce time as necessary

100 days @ 1 node

≈

1 day @ 100 nodes

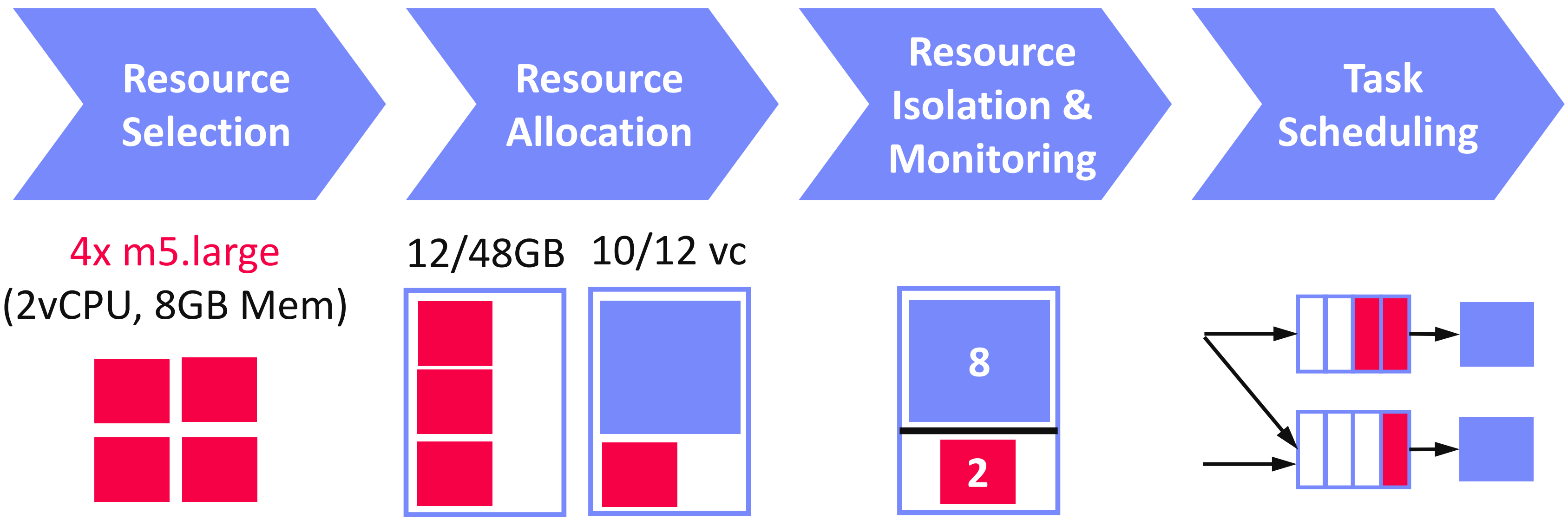
(but beware Amdahl's law: max speedup **sp = 1/s**)

Overview Resource Management & Scheduling

- **Resource Bundles**
  - Logical containers (aka nodes/instances) of different resources (**vcores**, **mem**)
  - Disk capacity, **disk** and **network** bandwidth
  - Accelerator devices (**GPUs**, FPGAs), etc

Scheduling is a fundamental computer science technique (at many different levels)

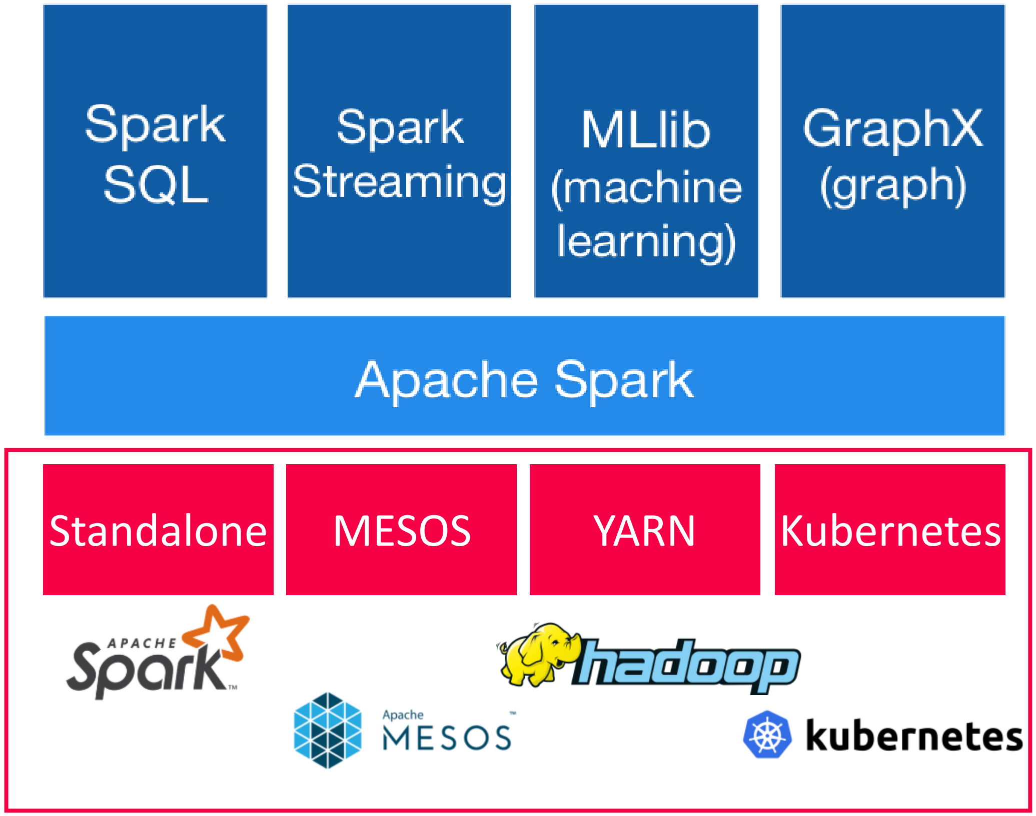
- **Resource Management**



Recap: Apache Spark History and Architecture

- **High-Level Architecture**
  - **Different language bindings**: Scala, Java, Python, R
  - **Different libraries**: SQL, ML, Stream, Graph
  - Spark core (incl RDDs)
  - Different file systems/ formats, and data sources: **HDFS**, **S3**, **DBs**, **NoSQL**
  - **Different cluster managers**: Standalone, Mesos, **Yarn**, **Kubernetes**

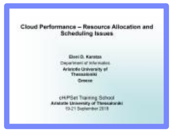
[https://spark.apache.org/]



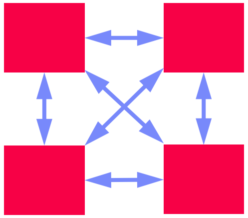
→ **Separation of concerns: resource allocation vs task scheduling**

Scheduling Problems

[Eleni D. Karatza: Cloud Performance Resource Allocation and Scheduling Issue, **Aristotle University of Thessaloniki 2018**]

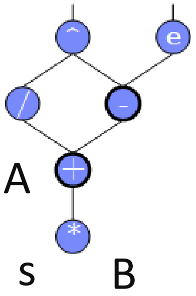


- **Bag-of-Tasks Scheduling**
  - Job of **independent** (embarrassingly parallel) tasks
  - **Examples:** EC2 instances, map tasks
- **Gang Scheduling**
  - Job of frequently **communicating** parallel tasks
  - **Examples:** MPI programs, parameter servers



- **DAG Scheduling**
  - Job of tasks with **precedence constraints** (e.g., data dependencies)
  - **Examples:** Op scheduling Spark, TensorFlow, SystemDS

$$\mathbf{C} = \mathbf{A} + s * \mathbf{B}$$
$$\mathbf{D} = (\mathbf{C}/2)\hat{}(\mathbf{C}\text{-}1)$$
$$\mathbf{E} = \exp(\mathbf{C}\text{-}1)$$



- **Real-Time Scheduling**
  - Job or task with associated deadline (soft/hard)
  - **Examples:** rendering, car control

Basic Scheduling Metrics and Algorithms

- **Common Metrics**
  - Mean time to completion (total runtime for job), and max-stretch (completion/work – relative slowdown)
  - Mean response time (job waiting time for resources)
  - Throughput (jobs per time unit)
- **#1 FIFO (first-in, first-out)**
  - Simple queueing and processing in order
  - **Problem:** Single long-running job can stall many short jobs
- **#2 SJF (shortest job first)**
  - Sort jobs by expected runtime and execute in order ascending
  - **Problem:** Starvation of long-running jobs
- **#3 Round-Robin (FAIR)**
  - Allocate similar time (tasks, time slices) to all jobs

Resource Allocation, Isolation, and Monitoring

Resource Selection

- **#1 Manual Selection**
  - Rule of thumb (I/O, mem, CPU characteristics of app)
  - Data characteristics, and framework configurations, experience

- **Example Spark Submit**

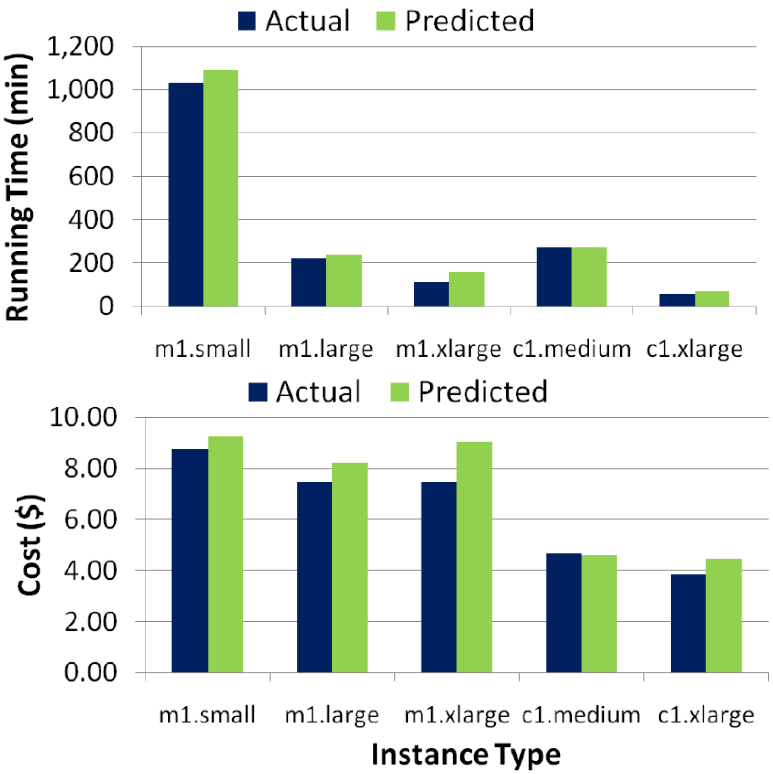
```
export HADOOP_CONF_DIR=/etc/hadoop/conf
SPARK_HOME=../spark-2.4.0-bin-hadoop2.7

$SPARK_HOME/bin/spark-submit \
  --master yarn --deploy-mode client \
  --driver-java-options "-server –Xms40g –Xmn4g" \
  --driver-memory 40g \
  --num-executors 10 \
  --executor-memory 100g \
  --executor-cores 32 \
  SystemDS.jar -f test.dml -stats -explain -args …
```

Resource Selection, cont.

- **#2 Application-Agnostic, Reactive**
  - Dynamic allocation based on workload characteristics
  - **Examples:** Spark dynamic allocation, Databricks AutoScaling
- **#3 Application-Aware, Proactive**
  - Estimate time/costs of job under different configurations (what-if)
  - Min $costs under time constraint
  - Min runtime under $cost constraint

[Herodotos Herodotou, Fei Dong, Shivnath Babu: No one (cluster) size fits all: automatic cluster sizing for data-intensive analytics. **SoCC 2011**]

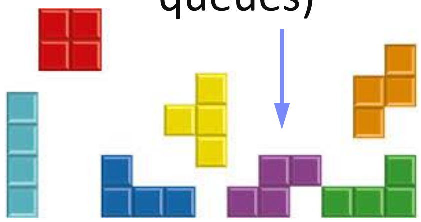
(fixed MR job w/ 6 nodes)



Resource Negotiation and Allocation

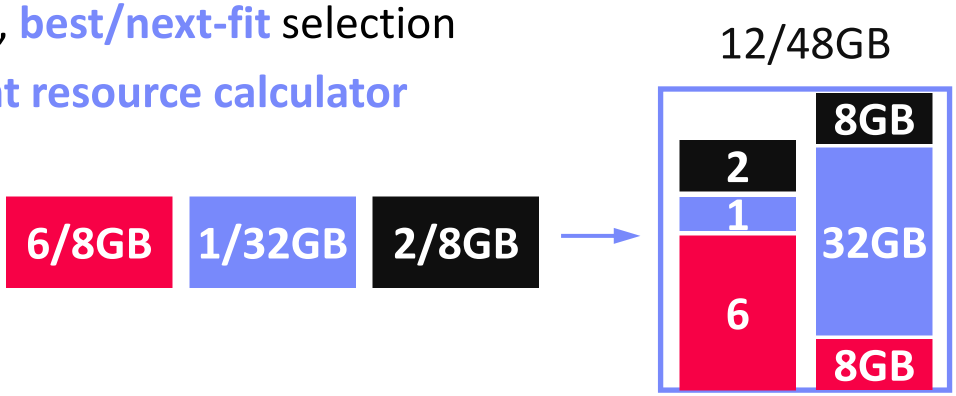
- **Problem Formulation**
  - N nodes with memory and CPU constraints
  - Stream of jobs with memory and CPU requirements
  - Assign jobs to nodes (or to minimal number of nodes)
  - ➔ **Knapsack problem** (**bin packing problem**)

"Tetris Analogy"
(w/ expiration and queues)



- **In Practice: Heuristics**
  - Major concern: **scheduling efficiency** (online, cluster bottleneck)
  - Approach: **Sample queues**, **best/next-fit** selection
  - Multiple metrics: **dominant resource calculator**

[https://blog.cloudera.com/managing-cpu-resources-in-your-hadoop-yarn-clusters/]



Slurm Workload Manager

- **Slurm Overview**
  - Simple Linux Utility for Resource Management (SLURM)
  - Heavily used in **HPC clusters** (e.g., MPI gang scheduling)

- **Scheduler Design**
  - Allocation/placement of requested resources
  - Considers nodes, sockets, cores, HW threads, memory, GPUs, file systems, SW licenses
  - Job submit options: **`sbatch`** (async job script), **`salloc`** (interactive), **`srun`** (sync job submission and scheduling)
  - **Configuration:** cluster, node count (ranges), task count, mem, etc
  - **Constraints via filters:** sockets-per-node, cores-per-socket, threads-per-core mem, mem-per-cpu, mincpus, tmp min-disk-space
  - Elasticity via re-queueing

[Don Lipari: The SLURM Scheduler Design, User Group Meeting, **2012**]

Background: Hadoop JobTracker (anno 2012)

- **Overview**
  - Hadoop cluster w/ fixed configuration of **n map** slots, **m reduce slots** (fixed number and fixed memory config map/reduce tasks)
  - JobTracker schedules map and reduce tasks to slots
  - FIFO and FAIR schedulers, account for data locality
- **Data Locality**
  - Levels: **data local**, **rack local**, **different rack**
  - **Delay scheduling** (with FAIR scheduler) wait 1-3s for data local slot

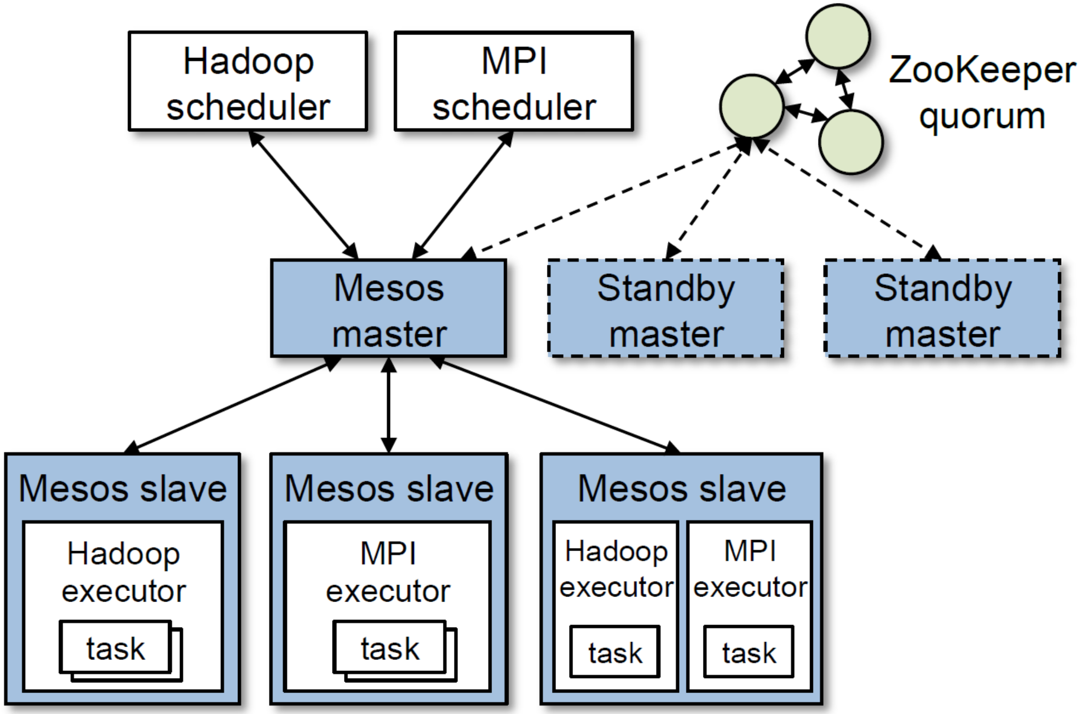
[Matei Zaharia et al: Delay scheduling: a simple technique for achieving locality and fairness in cluster scheduling. **EuroSys 2010**]

- **Problem**
  - Intermixes resource allocation and task scheduling → **Scalability problems in large clusters**
  - Forces every application into MapReduce programming model

Mesos Resource Management

[Benjamin Hindman et al: Mesos: A Platform for Fine-Grained Resource Sharing in the Data Center. **NSDI 2011**]

- **Overview Mesos**
  - Fine-grained, **multi-framework cluster sharing**
  - Scalable and efficient scheduling → **delegated to frameworks**
  - **Resource offers**

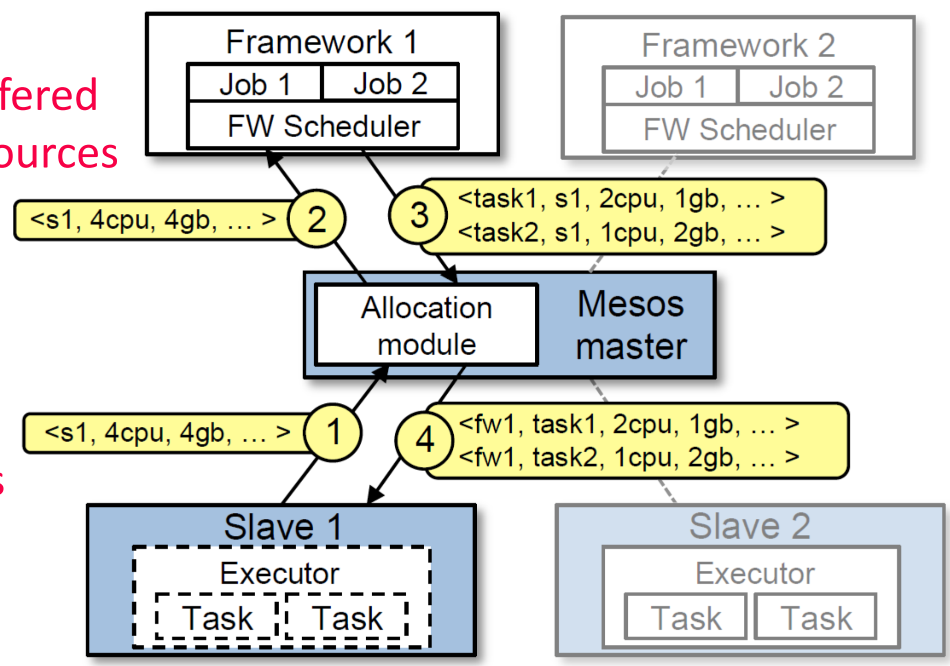


Mesos Resource Management, cont.

- **Resource Offers**
  - Mesos master decides how many resources to offer
  - Framework scheduler decides which offered resources to accept/reject
  - **Challenge:** long waiting times, lots of offers → **filter specification**

Offered resources

Reported available resources



Mesosphere Marathon: container orchestration (e.g., Docker)

YARN Resource Management

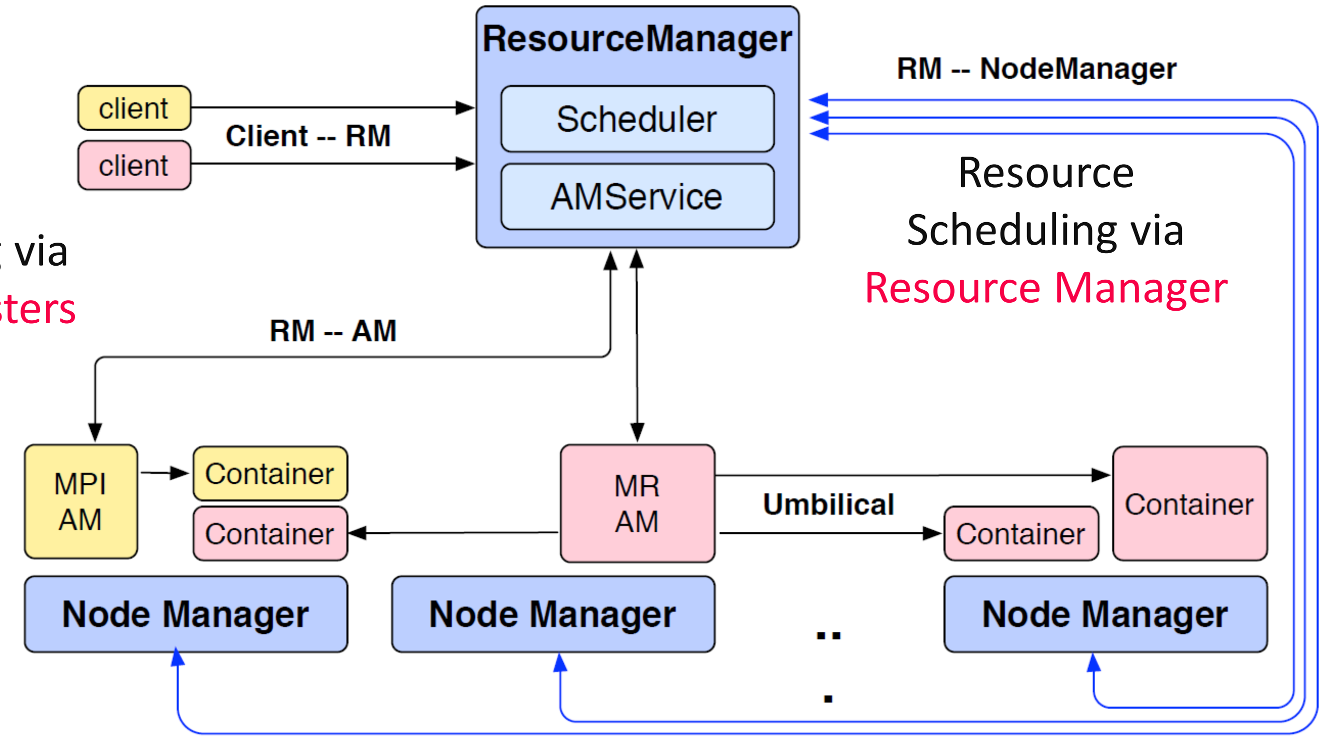
[Vinod Kumar Vavilapalli et al: Apache Hadoop YARN: yet another resource negotiator. **SoCC 2013**]

- **Overview YARN**
  - Hadoop 2 decoupled resource scheduler (negotiator)
  - Independent of programming model, **multi-framework cluster sharing**
  - **Resource Requests**

Task Scheduling via Application Masters (AMs)

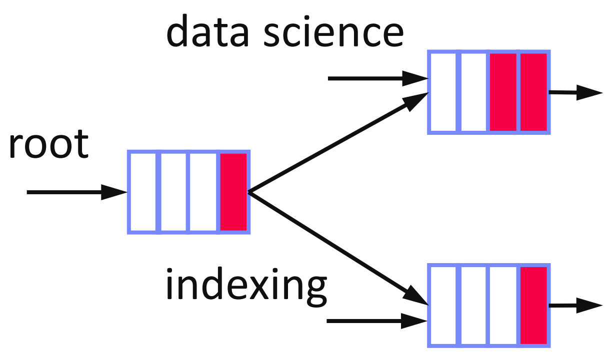
Resource Scheduling via Resource Manager

Resource Isolation via Node Managers



YARN Resource Management, cont.

- **Capacity Scheduler**
  - Hierarchy of queues w/ shared resource among sub queues
  - Soft (and optional hard) **[min, max]** constraints of max resources
  - Default queue-user mapping
  - No preemption during runtime (only redistribution over queues)



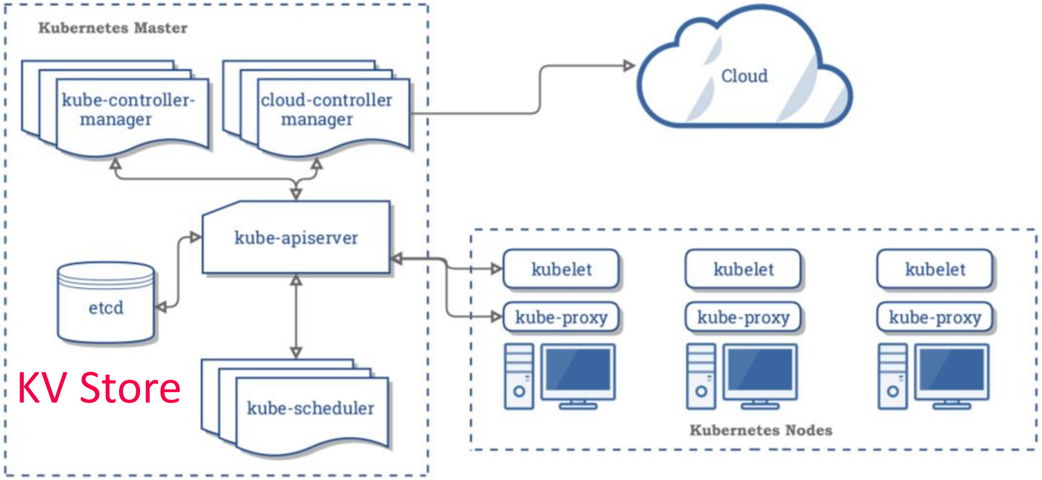
- **Fair Scheduler**
  - All applications get same resources over time
  - Fairness decisions on memory requirements, but dominant resource fairness possible too

Kubernetes Container Orchestration

- **Overview Kubernetes**
  - **Open-source** system for automating, deployment, and **management of containerized applications**
  - Container: resource isolation and application image

➔ **from machine- to application-oriented scheduling**

- **System Architecture**
  - **Pod:** 1 or more containers w/ individual IP
  - **Kubelet:** node manager
  - **Controller:** app master
  - **API Server** + **Scheduler**
  - Namespaces, quotas, access control, auth., logging & monitoring
  - Wide variety of applications



[https://kubernetes.io/docs/concepts/overview/components/]

Kubernetes Container Orchestration, cont.

- **Pod Scheduling (Placement)**
  - Default scheduler: **`kube-scheduler`**, custom schedulers possible
  - **#1 Filtering:** finding feasible nodes for pod
    (resources, free ports, node selector, requested volumes, mem/disk pressure)
  - **#2 Scoring:** score feasible nodes → select highest score
    (spread priority, inter-pod affinity, requested priority, image locality)
  - Tuning: # scored nodes: `max(50, percentageOfNodesToScore [1,100])`
    (sample taken round robin across zones)

  ➔ **Binding:** scheduler notifies API server

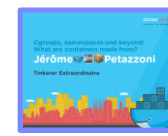
Resource Isolation

- **Overview Key Primitives**
  - Platform-dependent resource isolation primitives → container runtime
  - **Linux namespaces:** restricting visibility
  - **Linux cgroups:** restricting usage

Linux Containers
(e.g., basis of Docker)

- **Cgroups (Control Groups)**
  - Developed by Google engineers → Kernel 2.6.24 (2008)
  - **Resource metering and limiting** (memory, CPU, block I/O, network)
  - Each subsystem has a hierarchy (tree) with each node = group of processes
  - Soft and hard limits on groups
  - **Mem** hard limit → triggers OOM killer (physical, kernel, total)
  - **CPU** → set weights (time slices)/no limits, cpuset to pin groups to CPUs

[Jérôme Petazzoni: Cgroups, name-spaces and beyond: What are containers made from? DockerConEU 2015.]

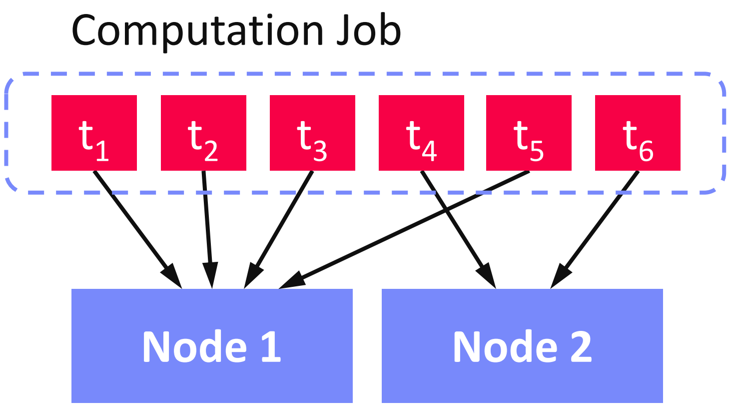


[https://www.youtube.com/watch?v=sK5i-N34im8&feature=youtu.be]

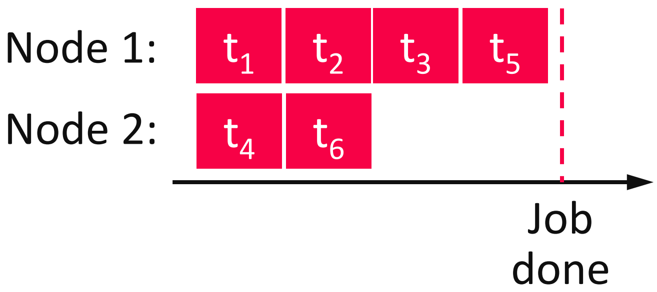
Task Scheduling and Elasticity

Task Scheduling Overview

- **Problem Formulation**
  - Given computation job and set of resources (servers, threads)
  - Distribute job in pieces across resources



- **#1 Job-Task Partitioning**
  - Split job into sequence of N tasks
- **#2 Task Placement / Execution**
  - Assign tasks to K resources for execution
- **Goal: Min Job Completion Time**
  - **Beware:** Max runtime per resource determines job completion time

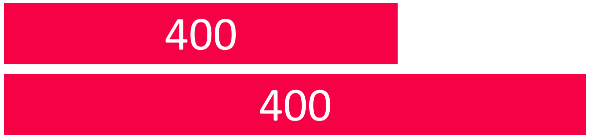


Task Scheduling – Partitioning

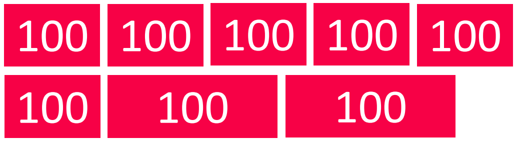
Example Hyper-param Tuning

```
parfor(i in 1:800)
  R[i,] = lm(X,y,reg[i])
```

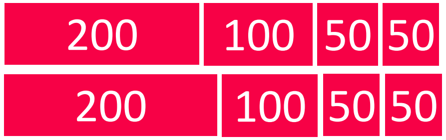
- **Static Partitioning**
  - M = K tasks, task size ceil(N/K)
  - Low overhead, poor load balance



- **Fixed Partitioning**
  - M = N/d tasks, task size d
  - E.g., # iterations, # tuples to process



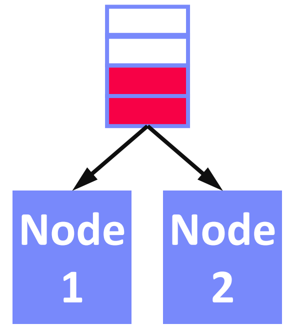
- **Self-Scheduling**
  - Exponentially decreasing task sizes d
    → M = log N tasks (w/ min task size)
  - Low overhead and good load balance at end
  - **Guided self scheduling**
  - **Factoring:** waves of task w/ equal size



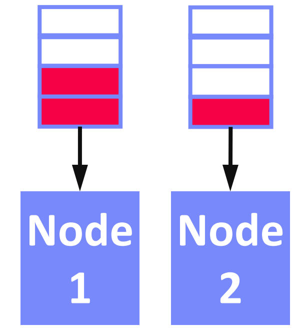
[Susan Flynn Hummel, Edith Schonberg, Lawrence E. Flynn: Factoring: a practical and robust method for scheduling parallel loops. **SC 1991**]

Task Scheduling – Placement

- **Task Queues**
  - Sequence of tasks in FIFO queue
  - **#1 Single Task Queue**
    (self-balancing, but contention)
  - **#2 Per-Worker Task Queue**
    (work separation, and preparation)



“Airport”



“Super Market”

- **Work Stealing**
  - On **empty worker queue**, probe other queues and **“steal”** tasks
  - More common in multi-threading, difficult in distributed systems

- **Excursus: Power of 2 Choices**
  - Choose d bins at random, task in least full bin
  - Reduce max load from $\frac{\log M}{\log \log M}$ to $\frac{\log \log M}{\log M}$

[Michael D. Mitzenmacher: The Power of Two Choices in Randomized Load Balancing, **PhD Thesis UC Berkeley 1996**]

Spark Task Scheduling, cont.

- **Fair Scheduler Configuration**
  - Pools with shares of cluster
  - Scheduling modes: FAIR, FIFO
  - **weight:** relative to equal share
  - **minShare:** min numCores

```
<allocations>
  <pool name="data_science">
    <schedulingMode>FAIR</schedulingMode>
    <weight>1</weight>
    <minShare>6</minShare>
  </pool>
  <pool name="indexing">
    <schedulingMode>FIFO</schedulingMode>
    <weight>2</weight>
    <minShare>8</minShare>
  </pool>
</allocations>
```

- **Spark on Kubernetes**
  - Run Spark in shared cluster with Docker container apps, Distributed TensorFlow, etc
  - Custom controller, and shuffle service (dynAlloc)

```
$SPARK_HOME/bin/spark-submit \
  --master k8s://https://<k8s-api>:<k8s-api-port> \
  --deploy-mode cluster
  --driver-java-options "-server -Xms40g -Xmn4g" \
  --driver-memory 40g \
  --num-executors 10 \
  --executor-memory 100g \
  --executor-cores 32 \
  --conf spark.kubernetes.container.image=<sparkimg> \
  SystemDS.jar -f test.dml -stats -explain -args …
```

Spark Dynamic Allocation

[https://spark.apache.org/docs/latest/job-scheduling.html]

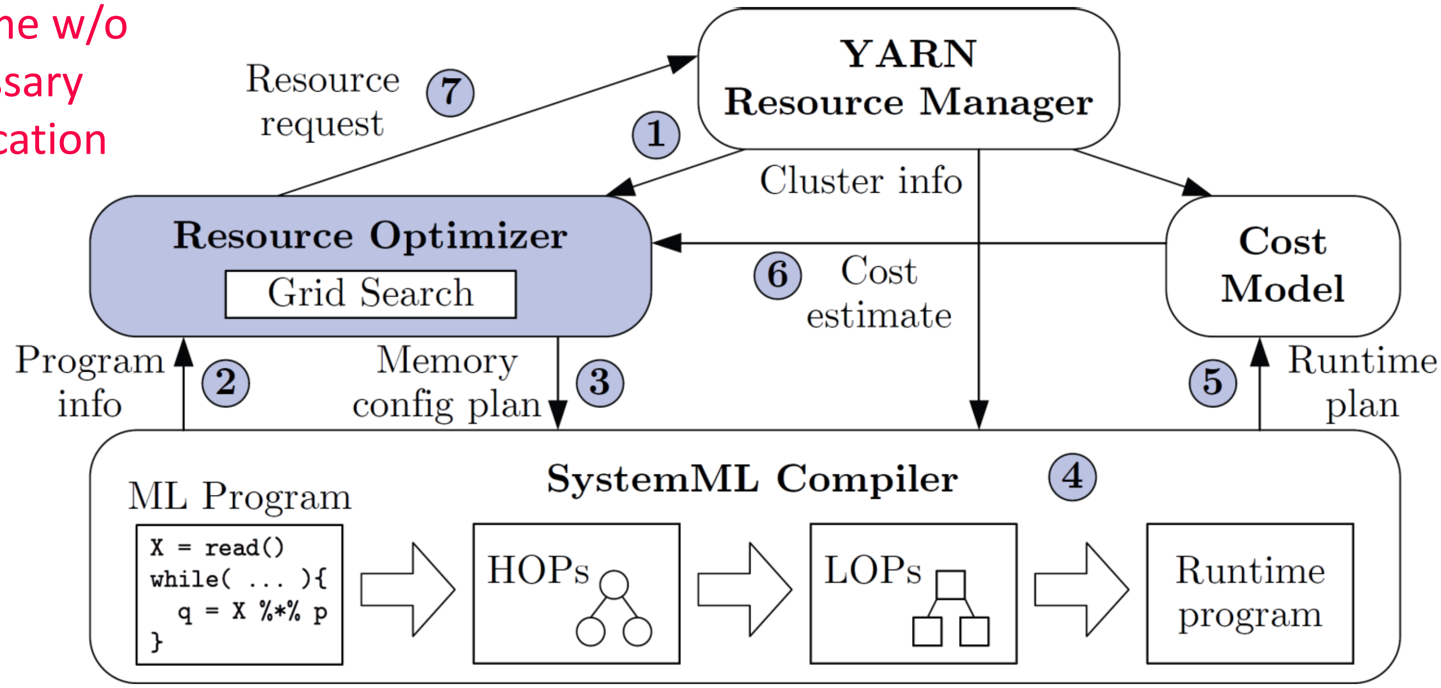
- **Configuration for YARN/Mesos**
  - Set `spark.dynamicAllocation.enabled = true`
  - Set `spark.shuffle.service.enabled = true` (robustness w/ stragglers)
- **Executor Addition/Removal**
  - **Approach:** look at task pressure (pending tasks / idle executors)
  - Increase exponentially (add **1**, **2**, **4**, **8**) if pending tasks for `spark.dynamicAllocation.schedulerBacklogTimeout`
  - Decrease executors they are idle for `spark.dynamicAllocation.executorIdleTimeout`

Resource Elasticity in SystemML

[Botong Huang et al.: Resource Elasticity for Large-Scale Machine Learning. **SIGMOD 2015**]

- **Basic Ideas**
  - Optimize ML program resource configurations via **online what-if analysis**
  - Generating and **costing runtime plans** for local/MR
  - **Program-aware** grid enumeration, pruning, and re-optimization techniques

Min runtime w/o unnecessary over-allocation



Summary and Q&A

- **Motivation, Terminology, and Fundamentals**
- **Resource Allocation, Isolation, and Monitoring**
- **Task Scheduling and Elasticity**

- **Next Lectures**
  - **10 Distributed Data Storage** [Dec 15]