Data Integration and Large-scale Analysis (DIA)
09 Cloud Resource Management and Scheduling

Prof. Dr. Matthias Boehm
Technische Universität Berlin
Berlin Institute for the Foundations of Learning and Data
Big Data Engineering (DAMS Lab)

Last update: Dec 12, 2024

Announcements / Administrative Items

- **#1 Video Recording**
  - Hybrid lectures: in-person H 0107, zoom live streaming, video recording
  - https://tu-berlin.zoom.us/j/9529634787?pwd=R1ZsN1M3SC9BOU1OcFdmem9zT202UT09

- **#2 Exercises/Projects**
  - **Reminder:** exercise/project submissions by **Jan 30** (no extensions)
  - Make use of **virtual** office hours **Wed 4.30pm-6pm**

- **#3 Course Evaluations**
  - DIA not part of this evaluation this semester

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

- **Definition Cloud Computing**
  - **On-demand, remote storage and compute resources, or services**
  - **User:** computing as a utility (similar to energy, water, internet services)
  - **Cloud provider:** computation in data centers / multi-tenancy

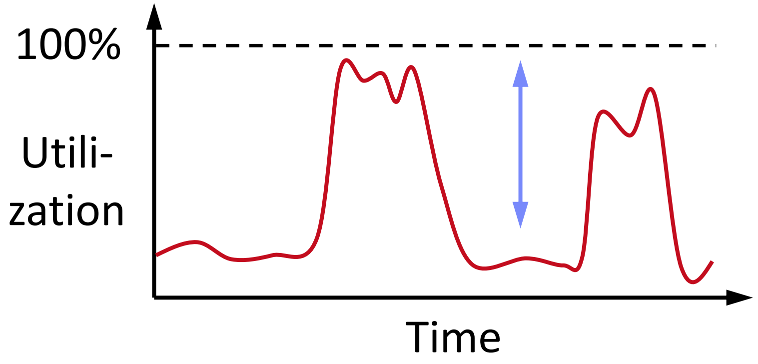
"Computing as a Utility"

- **Service Models**
  - **IaaS: Infrastructure as a service** (e.g., storage/compute nodes)
  - **PaaS: Platform as a service** (e.g., distributed systems/frameworks)
  - **SaaS: Software as a Service** (e.g., email, databases, office, github)

➔ **Transforming IT Industry/Landscape**
  - Since ~2010 increasing move from on-prem to cloud resources
  - System software licenses become increasingly irrelevant
  - Few cloud providers dominate IaaS/PaaS/SaaS markets (w/ 2018 revenue): **Microsoft Azure Cloud** ($ 32.2B), **Amazon AWS** ($ 25.7B), **Google Cloud** (N/A), **IBM Cloud** ($ 19.2B), **Oracle Cloud** ($ 5.3B), **Alibaba Cloud** ($ 2.1B)

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

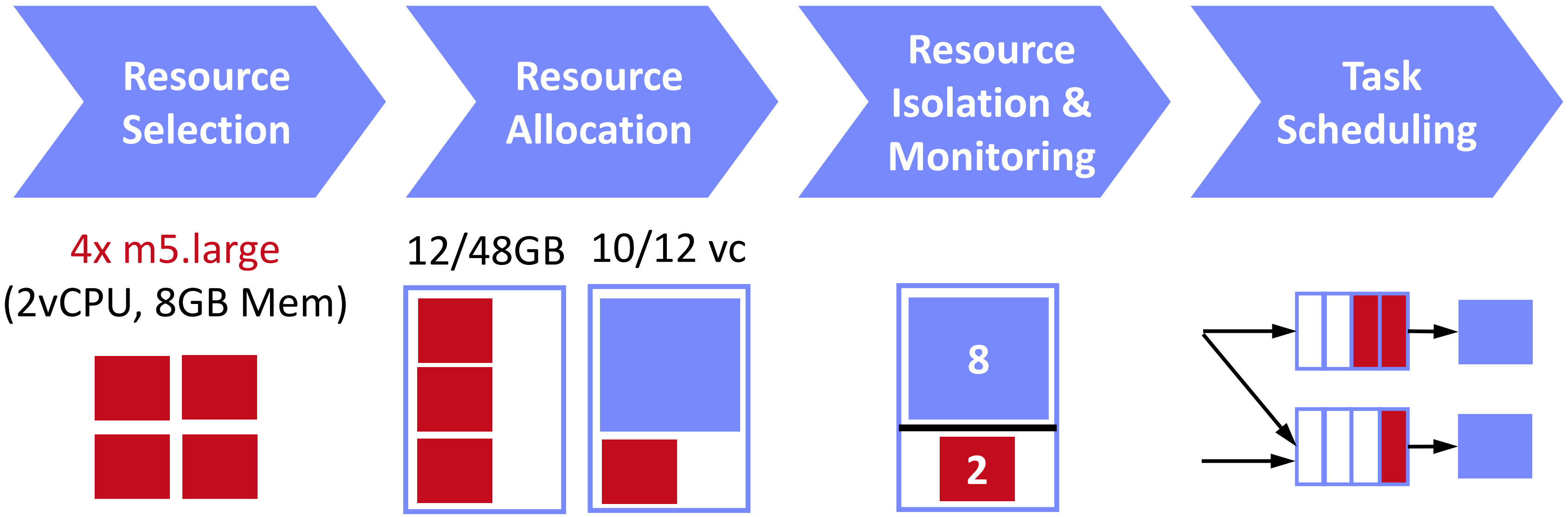
(but beware Amdahl's law: max speedup **sp = 1/s**)

Overview Resource Management & Scheduling

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

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

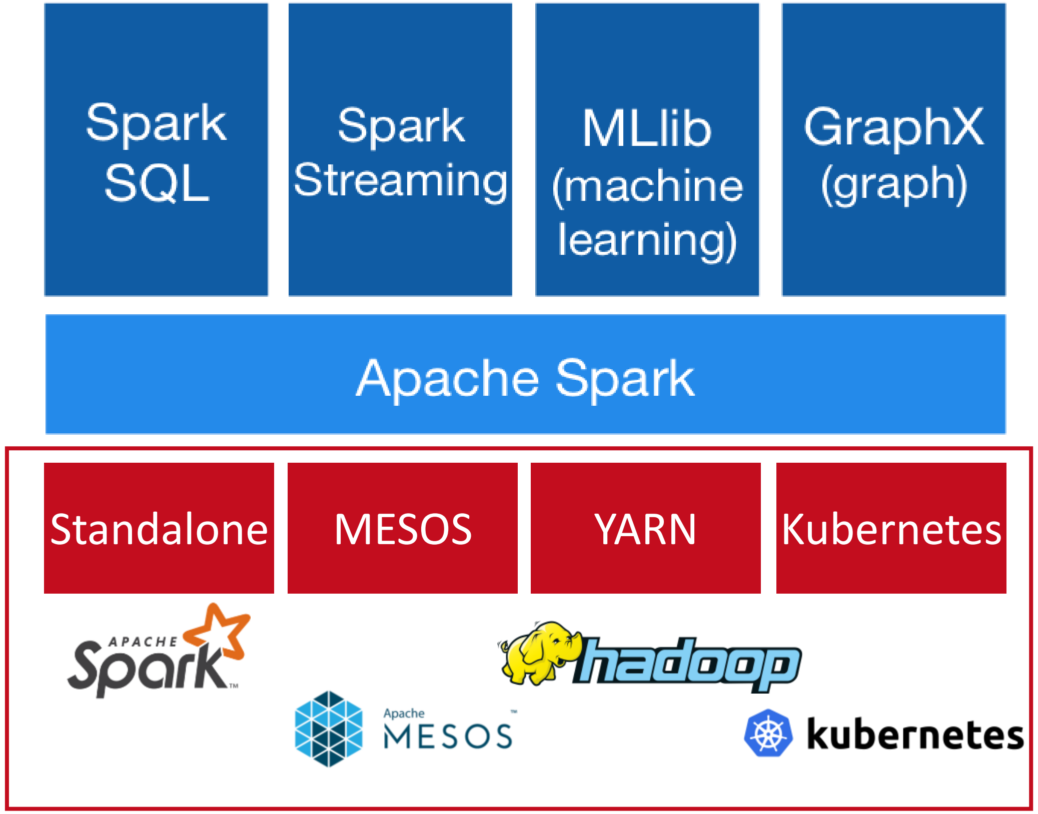
- **Resource Management**



Overview Resource Management & Scheduling, cont.

- **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**

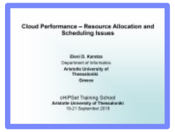
[https://spark.apache.org/]



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

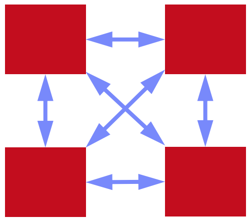
Scheduling Problems

[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

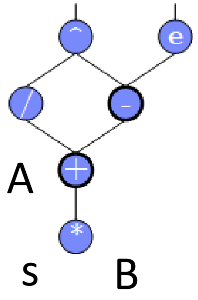


- **DAG Scheduling**
  - Job of tasks with **precedence constraints** (e.g., data dependencies)
  - **Examples:** Op scheduling Spark, TensorFlow, SystemDS

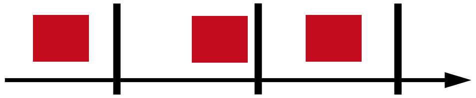
$C = A + s * B$

$D = (C/2)^\wedge(C\text{-}1)$

$E = \exp(C\text{-}1)$



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



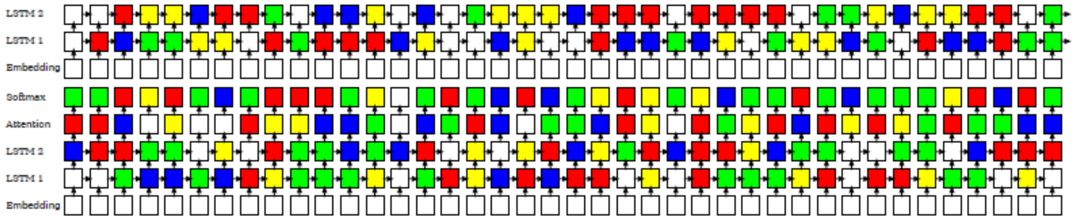
Scheduling Problems, cont.

- **Operator-Device Placement**
  - Given neural network, multiple devices → operator placement (parallelism, data transfer)
  - Sequence-to-sequence model to predict which operations should run on which device

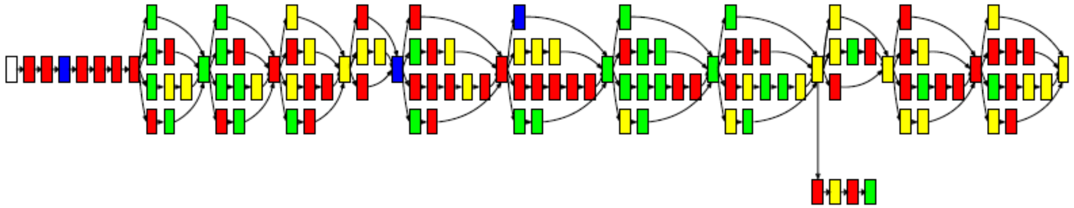
  - **Example: ML Workloads**
    - white: CPU; colors: different GPU devices

[Azalia Mirhoseini et al: Device Placement Optimization with Reinforcement Learning. **ICML 2017**]

Neural Machine Translation (RNN)



Inception V3 (CNN)



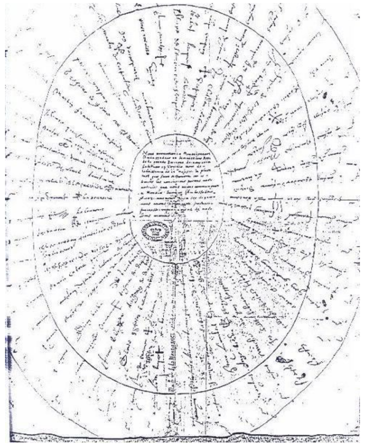
Basic Scheduling Metrics and Algorithms

- **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)
  - **Constraints / SLOs:** max monetary costs, max latency, deadline

Service Level Agreements (**SLA**)
→ Service Level Objectives (**SLO**)
→ Service Level Indicators (**SLI**)

- **#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

[**Credit:** https://en.wikipedia.org (French "ruban rond" – English round ribbon)]



Resource Allocation, Isolation, and Monitoring

Resource Selection → Resource Allocation → Resource Isolation & Monitoring → Task Scheduling

Resource Selection

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

- **Example Spark Submit**

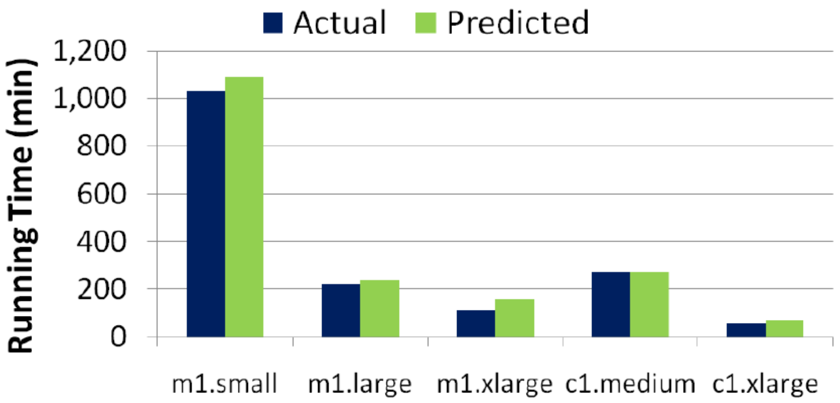
```
export HADOOP_CONF_DIR=/etc/hadoop/conf
SPARK_HOME=../spark-2.4.0-bin-hadoop2.7

$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 …
```

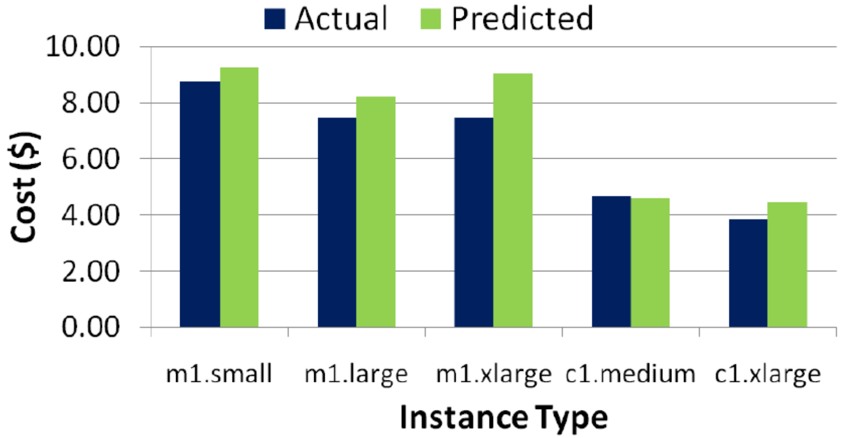
Resource Selection, cont.

- **#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 scenario analysis)
  - 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)

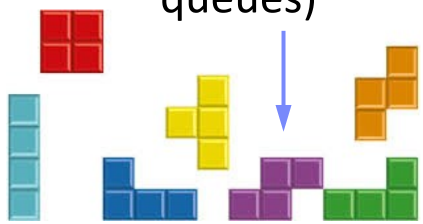




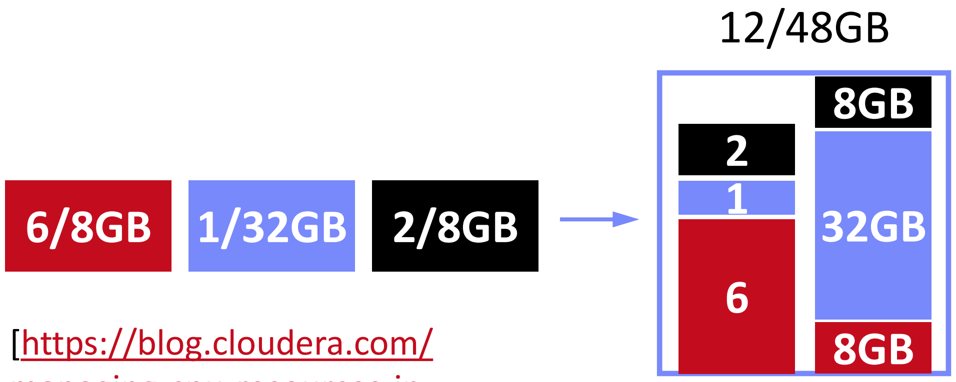
Resource Negotiation and Allocation

- **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

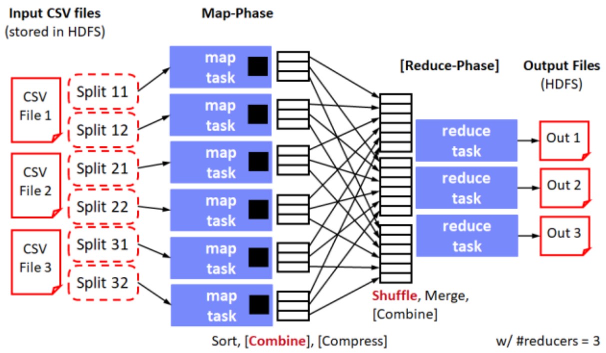
- **Slurm Overview**
  - Simple Linux Utility for Resource Management (SLURM)
  - Heavily used in **HPC clusters** (e.g., MPI gang scheduling)

- **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

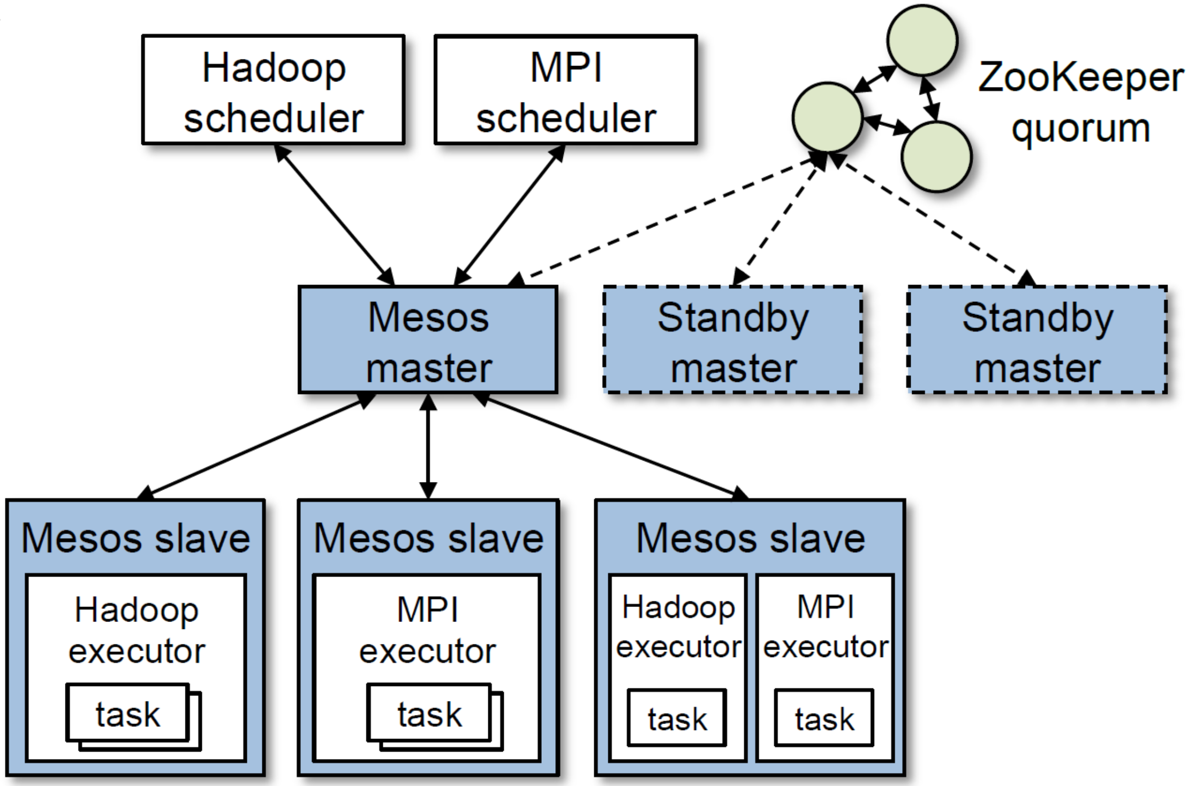
[Matei Zaharia et al: Delay scheduling: a simple technique for achieving locality and fairness in cluster scheduling. **EuroSys 2010**]

- **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**



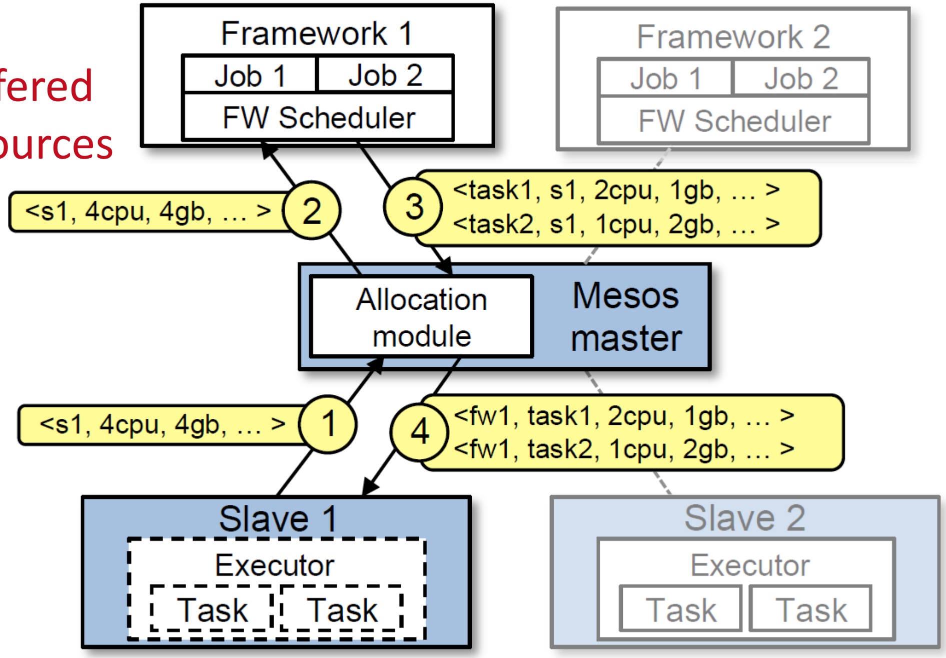
Mesos Resource Management, cont.

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

- **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)

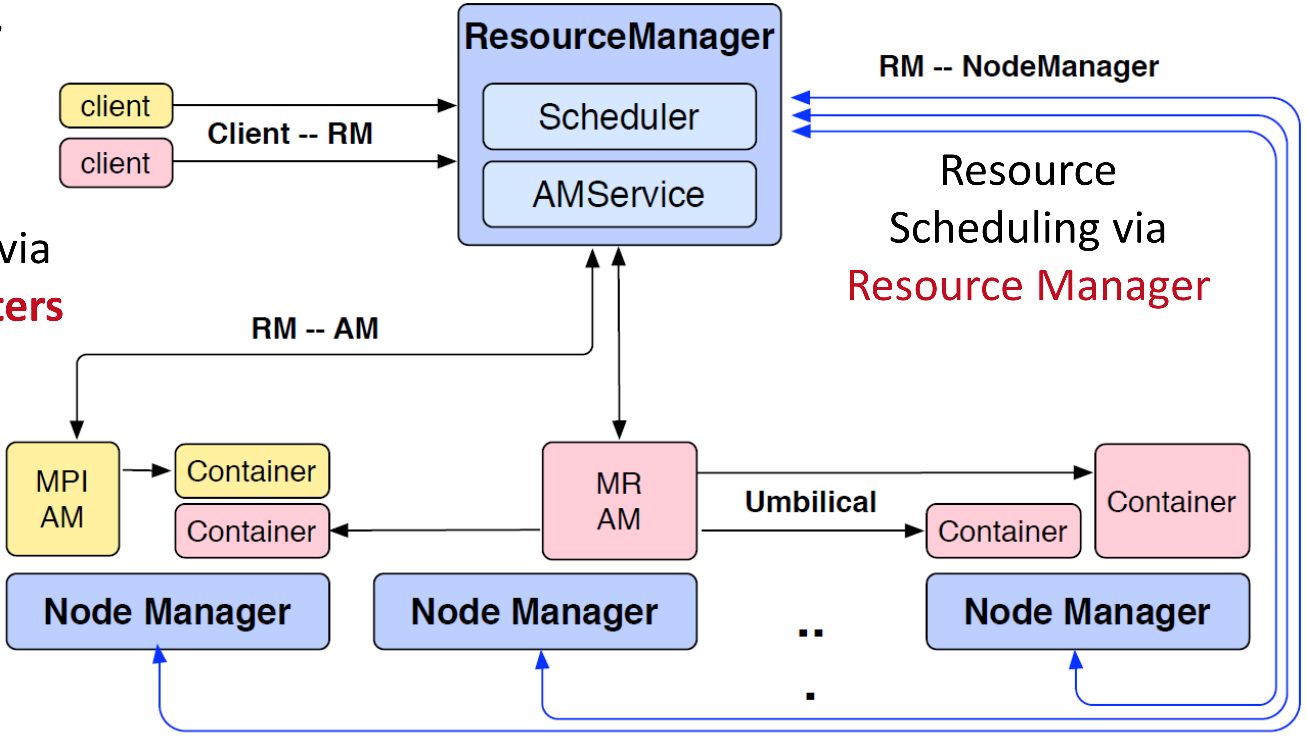
YARN Resource Management

[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 Isolation via **Node Managers**



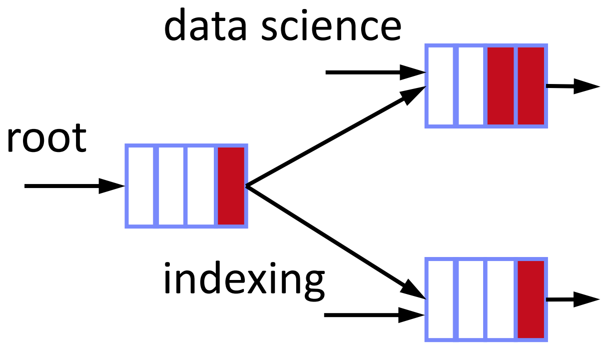
YARN Resource Management, cont.

- **Example Apache SystemML AM Submission** (anno 2014)

```
// Set up the container launch context for the application master
ContainerLaunchContext amContainer =
         Records.newRecord(ContainerLaunchContext.class);
amContainer.setCommands(Collections.singletonList(command));
amContainer.setLocalResources(constructLocalResourceMap(yconf));
amContainer.setEnvironment(constructEnvionmentMap(yconf));

// Set up resource type requirements for ApplicationMaster
Resource capability = Records.newRecord(Resource.class);
capability.setMemory((int)computeMemoryAllocation(memHeap));
capability.setVirtualCores(numCores);

// Finally, set-up ApplicationSubmissionContext for the application
String qname = _dmlConfig.getTextValue(DMLConfig.YARN_APPQUEUE);
appContext.setApplicationName(APPMASTER_NAME); // application name
appContext.setAMContainerSpec(amContainer);
appContext.setResource(capability);
appContext.setQueue(qname); // queue (w/ min/max capacity constraints)

// Submit application (non-blocking)
yarnClient.submitApplication(appContext);
```

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

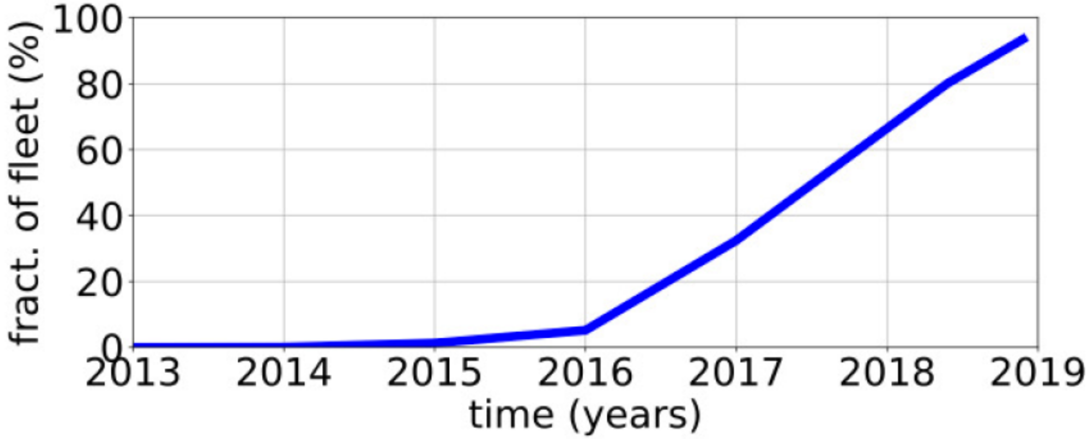
Hydra: Federated RM @ Microsoft

- **Overview Hydra**
  - Federated RM for internal MS big-data cluster
  - Leverage **sub-clusters w/ YARN RM + router**
  - AM-RM proxy (communication across sub clusters)
  - Global policy generator + state store for runtime adaptation

[Carlo Curino et al.: Hydra: a federated resource manager for data-center scale analytics. **NSDI 2019**]

[https://www.youtube.com/watch?v=kX13YamZXY&feature=emb_logo]

- **Deployment Statistics**



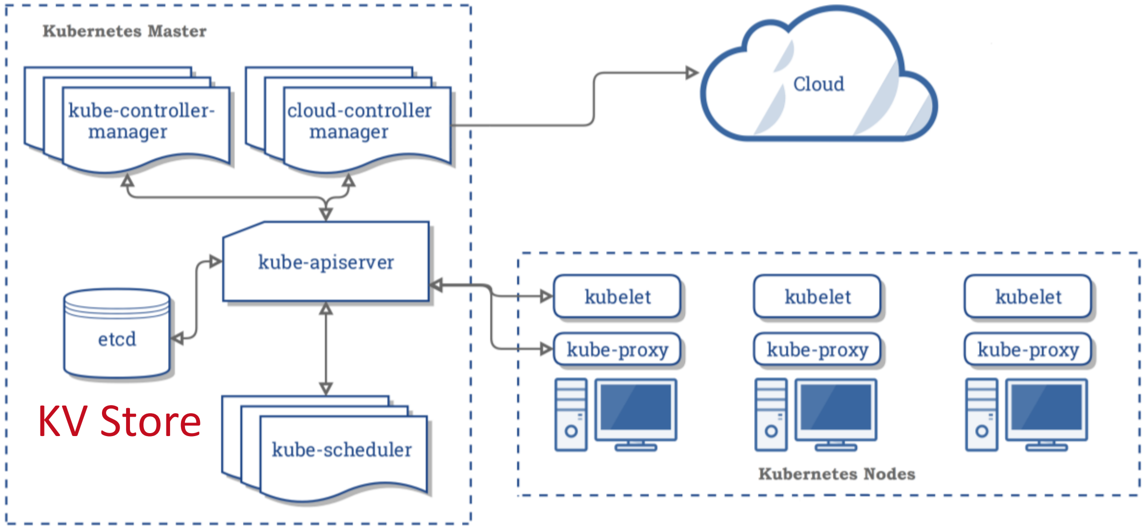
>250K servers
>500K daily jobs
>1 ZB data processed
>1T tasks scheduled
(~2G tasks daily)
>70K QPS (scheduling)
~60% avg CPU util

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)

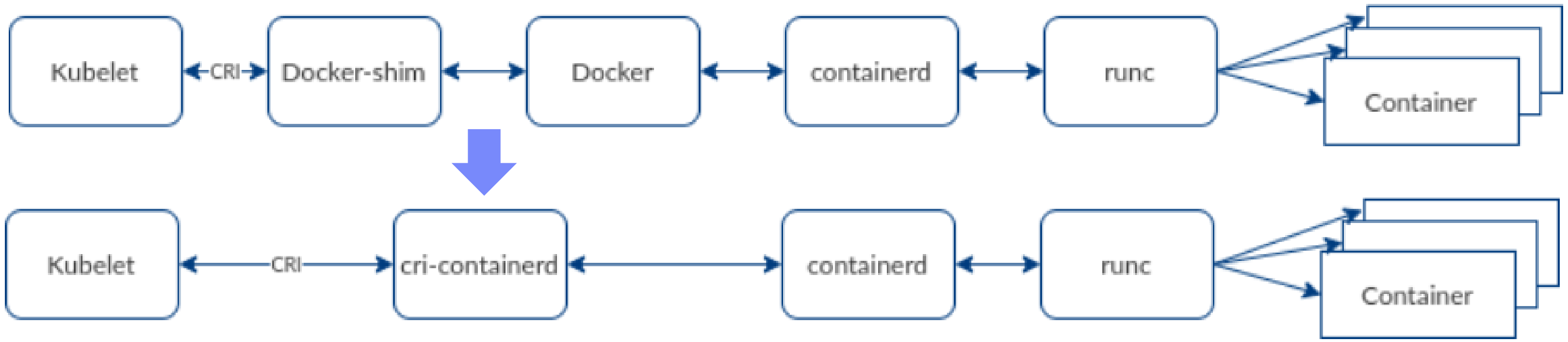
  → **Binding:** scheduler notifies API server

Container Runtime

- **Container Stack**
  - Docker as stack of development and runtime services
  - `containerd`: high-level daemon for image management
  - `runc`: low-level container runtime

[https://www.inovex.de/blog/containers-docker-containerd-nabla-kata-firecracker/]

[**Credit:** www.inovex.de]



- **Kubernetes deprecated Docker** (as of 12/2020)
  - Container Runtime Interface (CRI)
  - Integrate other runtimes: cri-containerd, cri-o (Open Container Initiative)

[https://kubernetes.io/blog/2016/12/container-runtime-interface-cri-in-kubernetes/]

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]

Resource Isolation, cont.

[https://developer.ibm.com/hadoop/2017/06/30/deep-dive-yarn-cgroups/]

- **Example YARN**
  - Set max CPU time per node manager
  - Container weights: cores/total cores
  - OOM killer if mem w/ overhead exceeded

```
<property>
  <name>yarn.nodemanager.resource.
   percentage-physical-cpu-limit<name>
  <value>60</value>
</property>
```

(hard → strict/soft)

- **Lesson Learned**
  - "The resource isolation provided by containers has enabled Google to drive utilization significantly higher than industry norms. [..] Borg uses containers to co-locate batch jobs with latency-sensitive, user-facing jobs on the same physical machines."
  - "The isolation is not perfect, though: containers cannot prevent interference in resources that the operating-system kernel doesn't manage, such as level 3 processor caches and memory bandwidth […]"

[Abhishek Verma et al. Large-scale cluster management at Google with Borg. **EuroSys 2015**]

[Malte Schwarzkopf et al.: Omega: flexible, scalable schedulers for large compute clusters. **EuroSys 2013**]

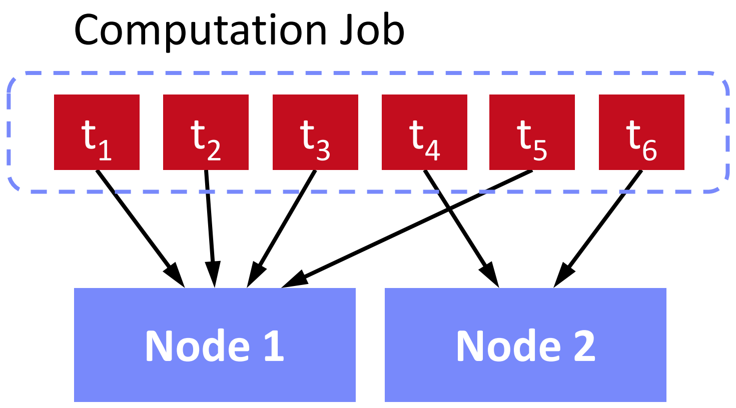
[Brendan Burns et al.: Borg, Omega, and Kubernetes. **ACM Queue 14(1): 10 (2016)**]

Task Scheduling and Elasticity

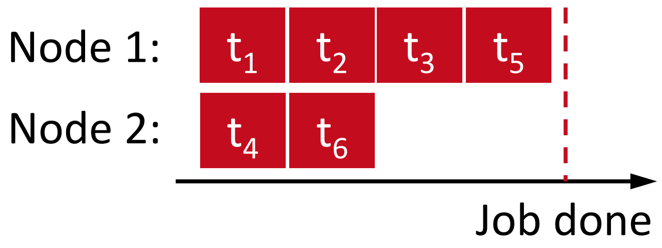
Resource Selection → Resource Allocation → Resource Isolation & Monitoring → **Task Scheduling**

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

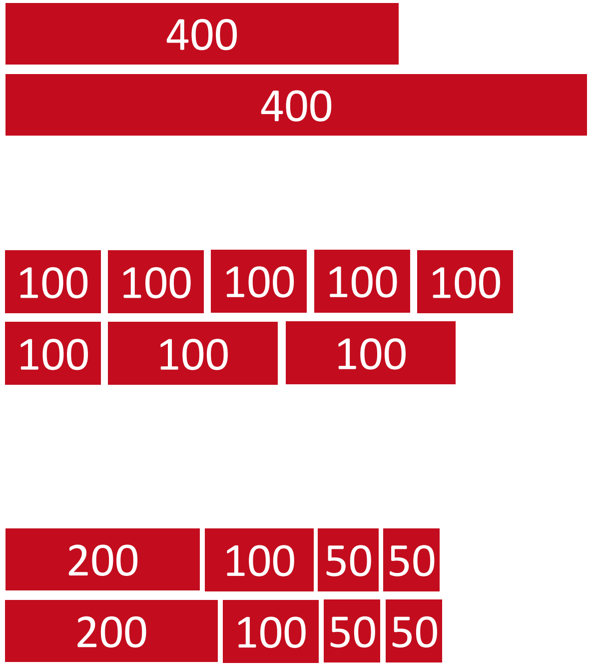


Task Scheduling – Partitioning

Example Hyper-param Tuning

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

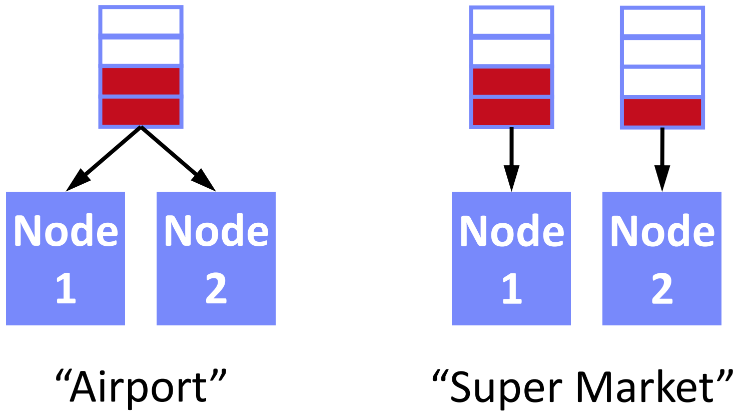
- **Static Partitioning**
  - M = K tasks, task size ceil(N/K)
  - Low overhead, poor load balance
- **Fixed Partitioning**
  - M = N/d tasks, task size d
  - E.g., # iterations, # tuples to process
- **Self-Scheduling**
  - Exponentially decreasing task sizes d
    → M = log N tasks (w/ min task size)
  - 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)



- **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

- **Overview**
  - Schedule job DAGs in stages (shuffle barriers)
  - Default task scheduler: **FIFO**; alternative: **FAIR**

SystemDS Example (80GB):

```
X = rand(rows=1e7,cols=1e3)
parfor(i in 1:4)
  for(j in 1:10000)
    print(sum(X)) #spark job
```

FIFO

Stage Id ▾	Description	Submitted	Duration	Tasks: Succeeded/Total	Input	Output	Shuffle Rea
37	fold at RDDAggregateUtils.java:150 +details (kill)	2019/12/12 23:48:07	Unknown	0/596			
36	fold at RDDAggregateUtils.java:150 +details (kill)	2019/12/12 23:48:06	0.7 s	391/596 (23 running)	48.9 GB		
35	fold at RDDAggregateUtils.java:150 +details (kill)	2019/12/12 23:48:05	1 s	424/596 (20 running)	53.0 GB		
34	fold at RDDAggregateUtils.java:150 +details (kill)	2019/12/12 23:48:05	2 s	504/596 (20 running)	63.0 GB		

FAIR

Fair Scheduler Pools (5)

Pool Name	Minimum Share	Pool Weight	Active Stages	Running Tasks	SchedulingMode
default	0	1	0	0	FIFO
parforPool2	0	1	1	38	FIFO
parforPool1	0	1	1	16	FIFO
parforPool3	0	1	1	3	FIFO
parforPool0	0	1	1	43	FIFO

Active Stages (4)

Stage Id ▾	Pool Name	Description	Submitted	Duration	Tasks: Succeeded/Total	Input	Output	Shuffle Rea
206	parforPool0	fold at RDDAggregateUtils.java:150 +details (kill)	2019/12/12 23:14:20	1.0 s	368/596 (67 running)	46.0 GB		
205	parforPool2	fold at RDDAggregateUtils.java:150 +details (kill)	2019/12/12 23:14:20	1 s	432/596 (43 running)	54.0 GB		
204	parforPool1	fold at RDDAggregateUtils.java:150 +details (kill)	2019/12/12 23:14:19	2 s	561/596 (11 running)	70.1 GB		
203	parforPool3	fold at RDDAggregateUtils.java:150 +details (kill)	2019/12/12 23:14:19	2 s	590/596 (6 running)	73.7 GB		

Spark Task Scheduling, cont.

- **FAIR scheduling w/ k=32 concurrent jobs and 200GB**

FAIR:
Share 320 cores among 32 concurrent jobs
→ ~10 tasks/job

Active Stages (32)

Stage Id	Pool Name	Description	Submitted	Duration	Tasks: Succeeded/Total	Input	Output	Shuffle Read	Shuffle Write
663	parforPool7	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:58	0.3 s	48/1490 (25 running)	6.0 GB			
662	parforPool9	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:57	0.7 s	186/1490 (25 running)	23.3 GB			
661	parforPool10	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:57	0.7 s	221/1490 (24 running)	27.6 GB			
660	parforPool11	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:57	0.8 s	327/1490 (25 running)	40.9 GB			
659	parforPool21	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:57	2 s	506/1490 (9 running)	63.3 GB			
658	parforPool6	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:56	2 s	518/1490 (9 running)	64.8 GB			
657	parforPool1	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:56	2 s	572/1490 (10 running)	71.5 GB			
656	parforPool24	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:56	3 s	603/1490 (9 running)	75.4 GB			
655	parforPool13	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:55	3 s	684/1490 (10 running)	85.5 GB			
654	parforPool20	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:54	4 s	736/1490 (10 running)	92.0 GB			
653	parforPool4	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:54	4 s	750/1490 (9 running)	93.8 GB			
652	parforPool23	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:54	5 s	797/1490 (7 running)	99.6 GB			
651	parforPool15	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:53	5 s	847/1490 (9 running)	105.9 GB			
650	parforPool29	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:53	5 s	808/1490 (9 running)	101.0 GB			
649	parforPool2	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:52	6 s	926/1490 (9 running)	115.8 GB			
648	parforPool26	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:52	6 s	917/1490 (9 running)	114.6 GB			
647	parforPool31	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:52	6 s	913/1490 (9 running)	114.1 GB			
646	parforPool19	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:51	7 s	1023/1490 (9 running)	127.9 GB			
645	parforPool5	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:51	7 s	1011/1490 (7 running)	126.4 GB			
644	parforPool30	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:50	8 s	1036/1490 (9 running)	129.5 GB			
643	parforPool3	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:49	9 s	1056/1490 (8 running)	132.0 GB			
642	parforPool17	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:49	9 s	1125/1490 (9 running)	140.6 GB			
641	parforPool16	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:49	9 s	1158/1490 (9 running)	144.7 GB			
640	parforPool18	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:49	9 s	1124/1490 (9 running)	140.5 GB			
639	parforPool0	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:48	10 s	1287/1490 (9 running)	160.9 GB			
638	parforPool28	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:48	10 s	1251/1490 (9 running)	156.4 GB			
637	parforPool12	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:48	11 s	1341/1490 (9 running)	167.6 GB			
636	parforPool27	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:47	12 s	1309/1490 (9 running)	163.6 GB			
635	parforPool8	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:47	12 s	1299/1490 (8 running)	162.4 GB			
634	parforPool14	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:46	12 s	1413/1490 (9 running)	176.6 GB			
633	parforPool25	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:46	12 s	1343/1490 (9 running)	167.9 GB			
632	parforPool22	fold at RDDAggregateUtils.java:148 +details (kill)	2021/11/27 15:51:46	12 s	1415/1490 (7 running)	176.9 GB			

Elapsed:
~40min

	RDD Blocks	Storage Memory	Disk Used	Cores	Active Tasks	Failed Tasks	Complete Tasks	Total Tasks	Task Time (GC Time)	Input	Shuffle Read	Shuffle Write	Blacklisted
Active(11)	1490	200 GB / 595.3 GB	0.0 B	320	329	0	8714054	8714383	218.4 h (57 min)	1.2 PB	0.0 B	0.0 B	0
Dead(0)	0	0.0 B / 0.0 B	0.0 B	0	0	0	0	0	0 ms (0 ms)	0.0 B	0.0 B	0.0 B	0
Total(11)	1490	200 GB / 595.3 GB	0.0 B	320	329	0	8714054	8714383	218.4 h (57 min)	1.2 PB	0.0 B	0.0 B	0

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]

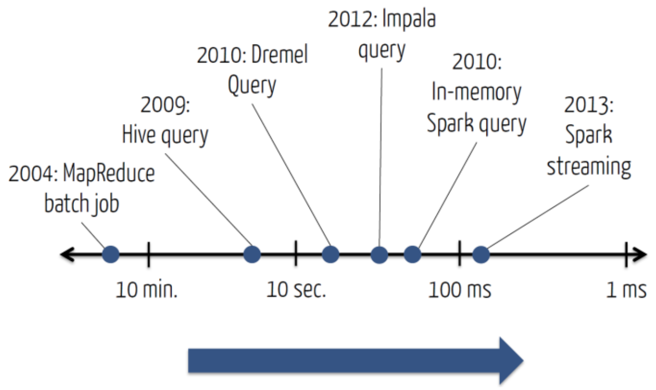
- **Configuration for YARN/Mesos**
  - Set `spark.dynamicAllocation.enabled = true`
  - Set `spark.shuffle.service.enabled = true` (robustness w/ stragglers)
- **Executor Addition/Removal**
  - **Approach:** look at task pressure (pending tasks / idle executors)
  - Increase exponentially (add **1**,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

```
spark-submit \
  --conf spark.shuffle.service.enabled=true \
  --conf spark.dynamicAllocation.enabled=true \
  --conf spark.dynamicAllocation.minExecutors=0 \
  --conf spark.dynamicAllocation.initialExecutors=1 \
  --conf spark.dynamicAllocation.maxExecutors=20
```

Sparrow Task Scheduling

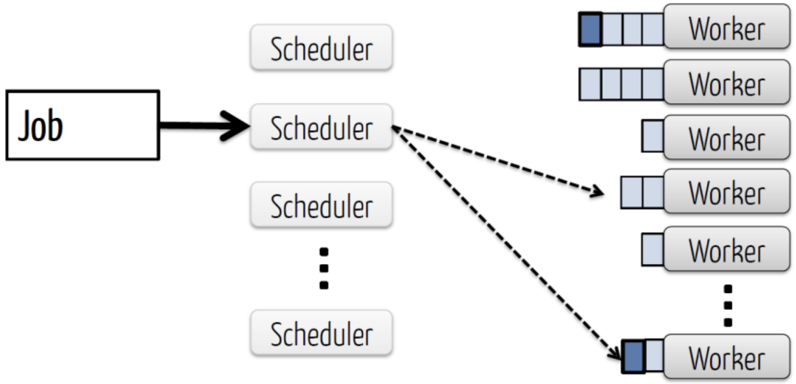
[Kay Ousterhout, Patrick Wendell, Matei Zaharia, Ion Stoica: Sparrow: distributed, low latency scheduling. **SOSP 2013**]

- **Sparrow Overview**
  - Decentralized, randomized task scheduling with constraints, fair sharing
  - **Problems:** **Low latency**, quality placement, fault tolerance, high throughput

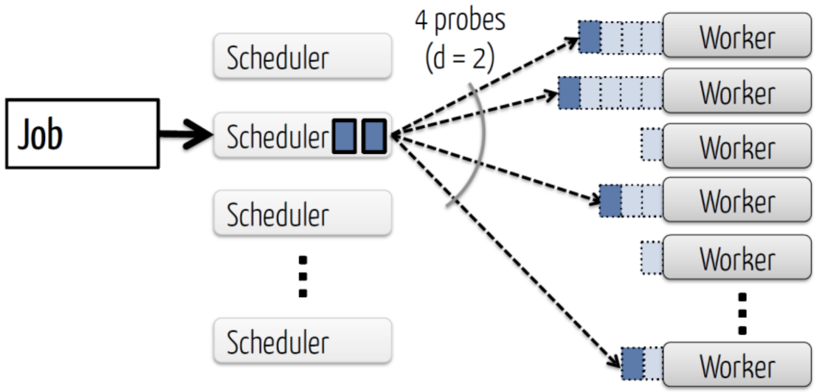


- **Approach**
  - **Baselines:** Random, Per-task (power of two choices)
  - New Techniques: **Batch Scheduling**, **Late Binding**

Baseline: Per-task sampling



Batch sampling w/ late binding

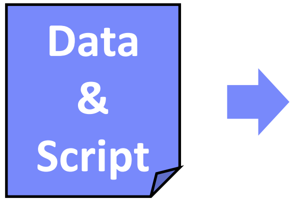


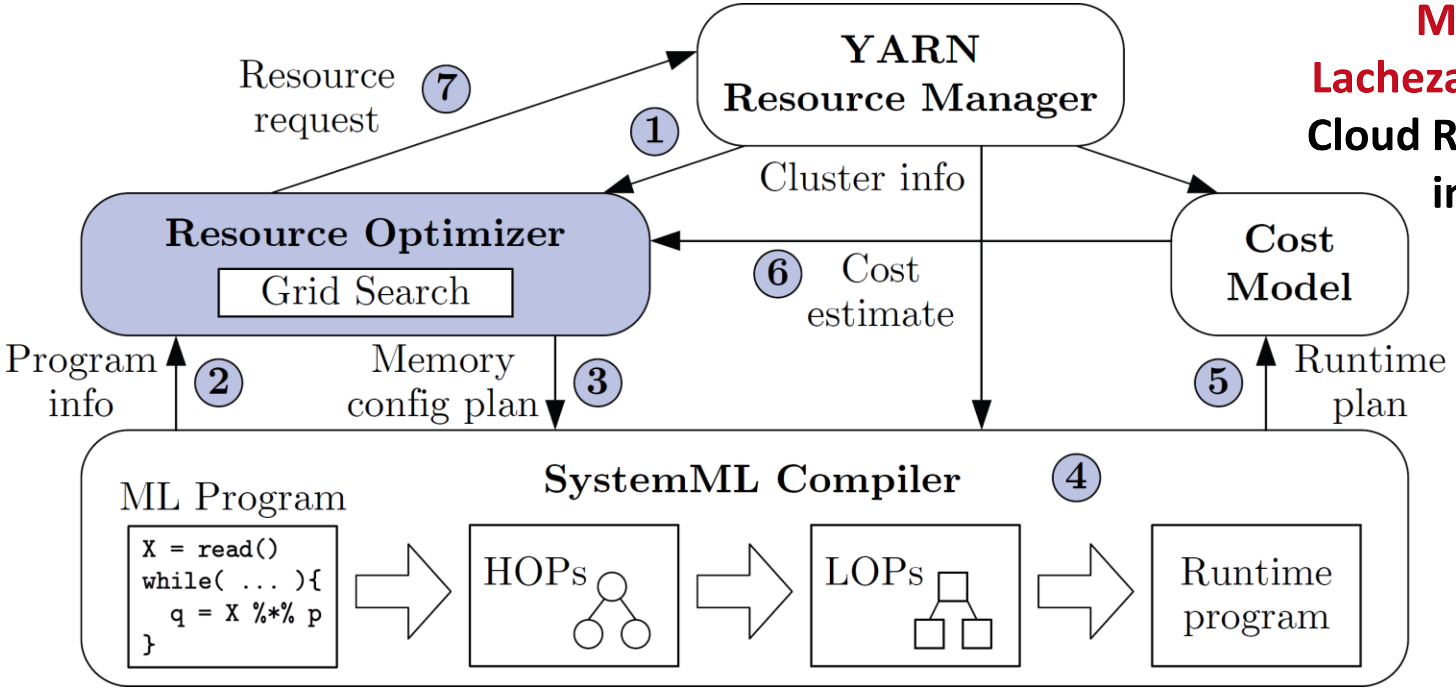
Resource Elasticity in SystemML

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

- **Resource Optimizer for ML Workloads**
  - Optimize ML program resource configurations via online **what-if analysis and plan generation**
  - **Minimize cost w/o unnecessary overprovisioning**, program-aware enumeration (e.g., mem estimates)
- **Deployment**
  - Initial Compilation
  - Dynamic Recompilation during Runtime

Master Thesis Lachezar Nikolov (2024): Cloud Resource Elasticity in SystemDS

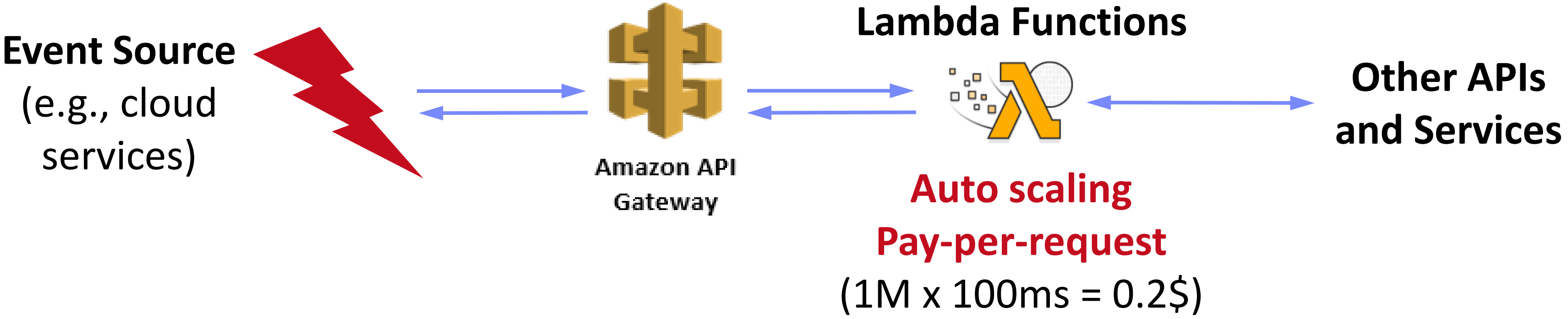




Serverless Computing (FaaS)

[Joseph M. Hellerstein et al: Serverless Computing: One Step Forward, Two Steps Back. **CIDR 2019**]

- **Definition Serverless**
  - **FaaS:** functions-as-a-service (event-driven, stateless input-output mapping)
  - Infrastructure for deployment and auto-scaling of APIs/functions
  - Examples: **Amazon Lambda**, **Microsoft Azure Functions**, etc



- **Example**

```java
import com.amazonaws.services.lambda.runtime.Context;
import com.amazonaws.services.lambda.runtime.RequestHandler;

public class MyHandler implements RequestHandler<Tuple, MyResponse> {
    @Override
    public MyResponse handleRequest(Tuple input, Context context) {
       return expensiveModelScoring(input); // with read-only model
    }
}
```

Summary and Q&A

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

- **Next Lectures (Large-scale Data Management and Analysis)**
  - **10 Distributed Data Storage** [Dec 19]
  - **Holidays**
  - **11 Distributed, Data-Parallel Computation** [Jan 09]
  - **12 Distributed Stream Processing** [Jan 16]
  - **13 Distributed Machine Learning Systems** [Jan 23]