Microsoft

Apollo

Scalable and Coordinated Scheduler for Cloud-Scale Computing

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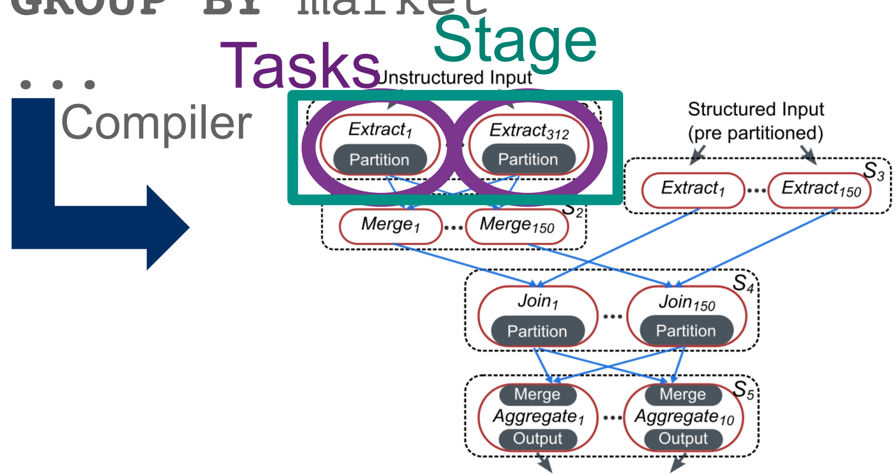
Cloud Scale Job

- High level SQL-Like language
- The job query plan is represented as a DAG
- **Tasks** are the basic unit of computation
- Tasks are grouped in **Stages**
- Execution is driven by a scheduler

Job sample: SCOPE (VLDBJ, 2012)

```
SELECT
AVG(DateTime.Parse(latency))
AS E2ELatency,
market
FROM
QueryLatencies
GROUP BY market
...
```



Scheduling at Cloud Scale

Minimize job latency while
maximizing cluster utilization

Challenges

1. Scale
2. Heterogeneous workload
3. Maximize utilization

Challenging Scale

Jobs process **gigabytes to petabytes** of data

and issue peaks of **100,000 scheduling requests/seconds**

Clusters run up to **170,000 tasks in parallel**

and each contains **over 20,000 servers**

Challenge: How to make optimal scheduling decisions at full production scale

Heterogeneous Load

Tasks runs from **seconds to hours**

Tasks can be **IO bound** or **CPU bound**

Tasks can require from 100MB to more than 10GB of memory

Short tasks are sensitive to **scheduling latency**

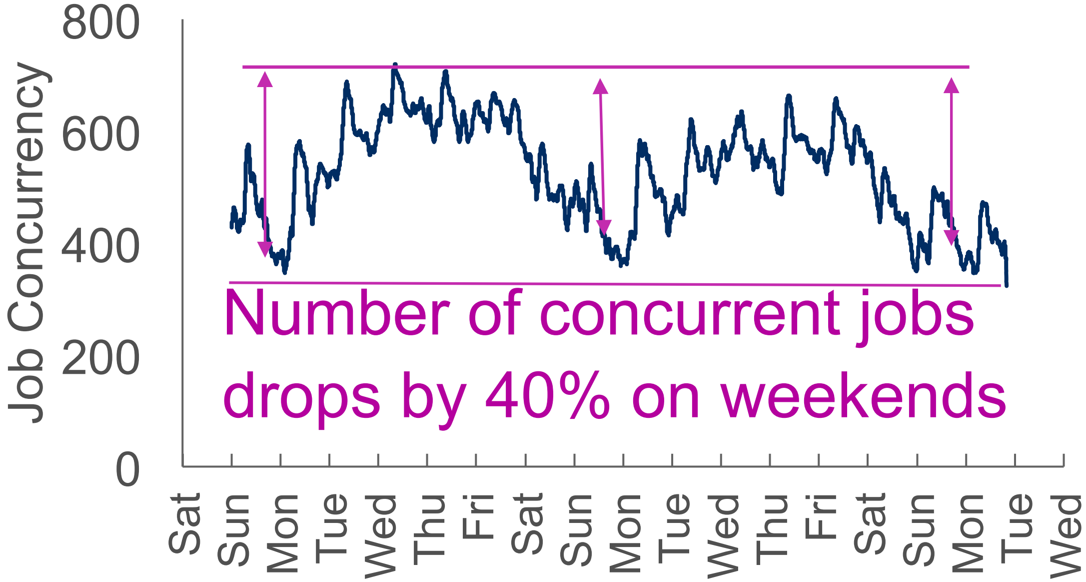
Long IO bound tasks are sensitive to **locality**

Challenge:

Make **optimal scheduling decisions** for a **complex workload**

Maximizing Utilization

We need to effectively use resources and
maintain performance guarantees
but the workload constantly fluctuates



Challenge: **Maximize utilization** while maintaining performance guarantees with a **dynamic workload**

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Background
Challenges
Overview
— Distributed and coordinated architecture
— Estimation-based scheduling
— Conflict resolution
— Opportunistic scheduling
Evaluation at scale
Related work
Conclusion

Distributed and Coordinated

To scale, Apollo adopts a distributed and coordinated architecture

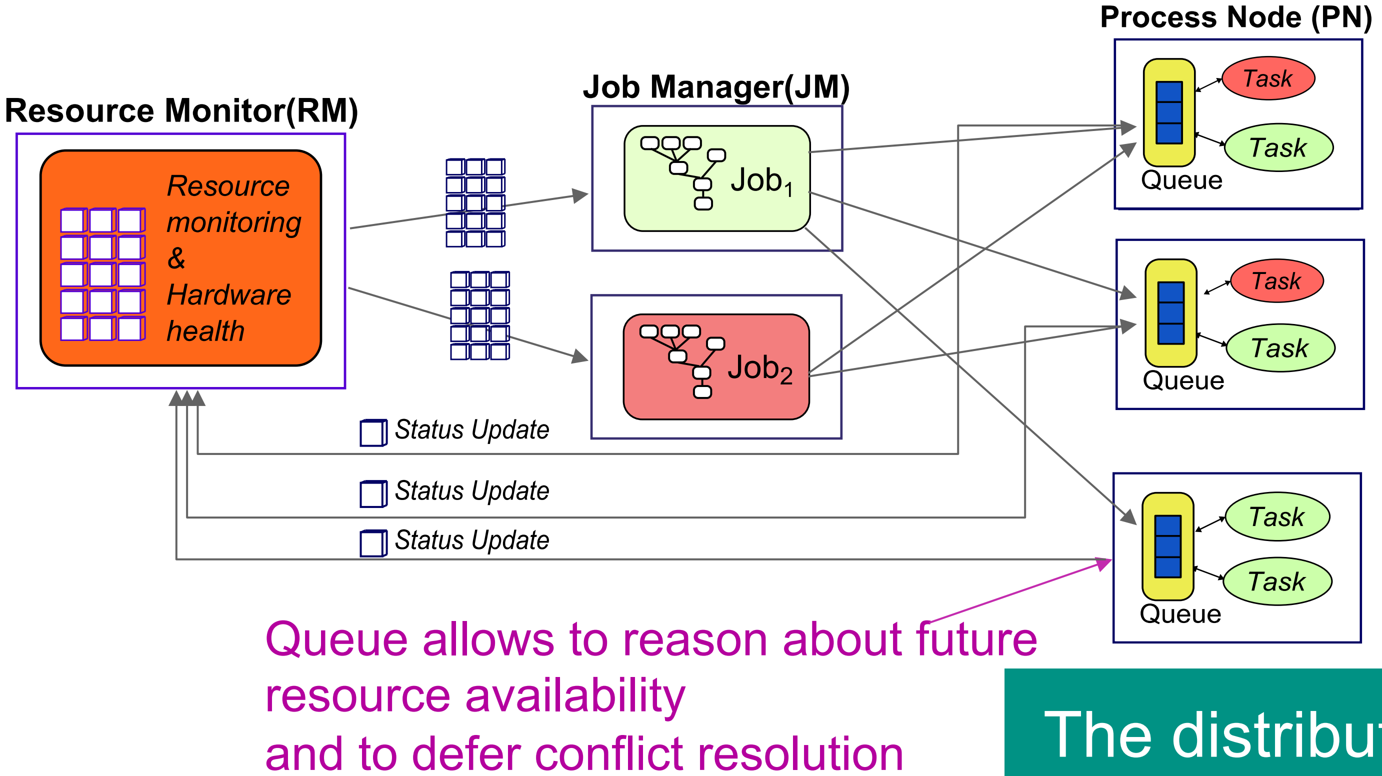
There is one scheduler per job

each making high quality decisions independently,

informed by global information

.

Distributed and Coordinated



The distributed architectures scales by allowing schedulers to **make independent decisions** with **global coordination**

Representing Load

The server load representation must

- Be hardware independent
- Be lightweight
- Supports heterogeneous workload

Apollo represents the load

- Using a wait-time matrix
- It represents the **expected wait time** to obtain resource of a certain size

→ *Memory*

↓ *CPU*

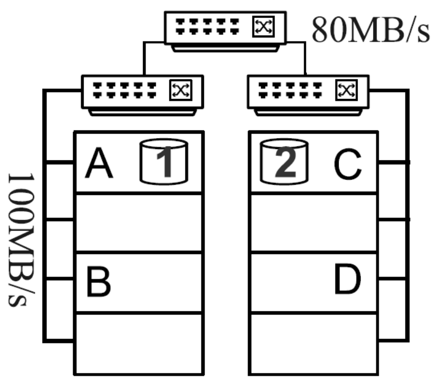
	4GB	8GB	12GB	16GB
2 core	0	10	10	16
4 core	0	10	10	16
6 core	5	10	10	16
8 core	10	15	15	25

Wait-time matrix (seconds)

Status Update

The wait time matrix allows to **reason about future resource availability**

Optimizing for various factors



Server	Wait	I/O	Wait+I/O
A	0s	63.13s	63.13s
B	0s	63.5s	63.5s
C	40s	32.50s	72.50s
D	5s	51.25s	

To optimize performance, the scheduler needs to simultaneously consider many conflicting factors

Estimation-Based Scheduling

Apollo minimizes the estimated task completion time

$$E = I + W + R$$

E:	Estimated task completion time
I:	Initialization time
W:	Wait time
R:	Runtime (including locality impact)

Apollo **minimize** the **task completion time** by considering relevant factors holistically

Correcting Conflicts

Cluster is dynamic

- Schedulers can have conflicts
- Apollo defers the correction of conflict

Apollo re-evaluates prior decisions

- Triggers a duplicate if the decision isn't optimal with up to date information

The correction mechanisms allows Apollo to **handle cluster dynamics**

Opportunistic scheduling

Maximize utilization

— Use the remaining capacity
— Dispatch more than the resource allocation
— Tasks only consume otherwise idle resources
— Tasks can be preempted or terminated
— Tasks can be upgraded

Opportunistic scheduling allows Apollo to **maximize utilization**

Additional techniques

— Limit capacity share of each job
— Random queuing

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How well does Apollo scale?

Apollo runs on Microsoft production clusters

— Incrementally rolled out from September to December 2013

— Each containing over **20,000 servers**

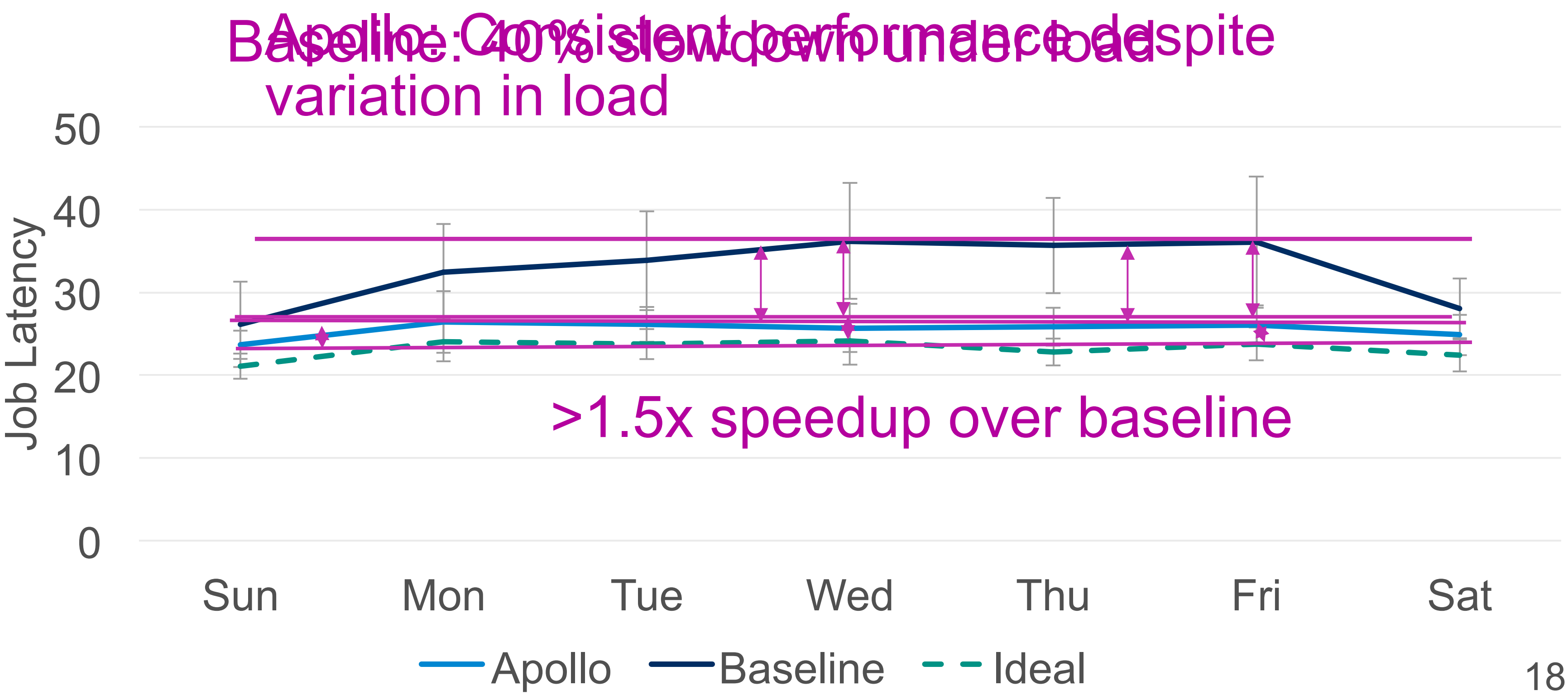
In one cluster, Apollo

— Runs **170,000 tasks** in parallel

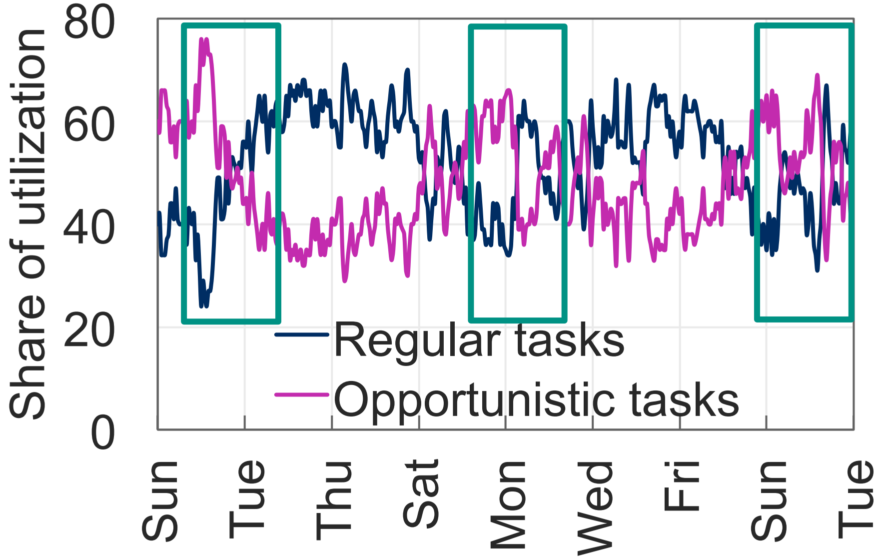
— Tracks **14,000,000 pending tasks**

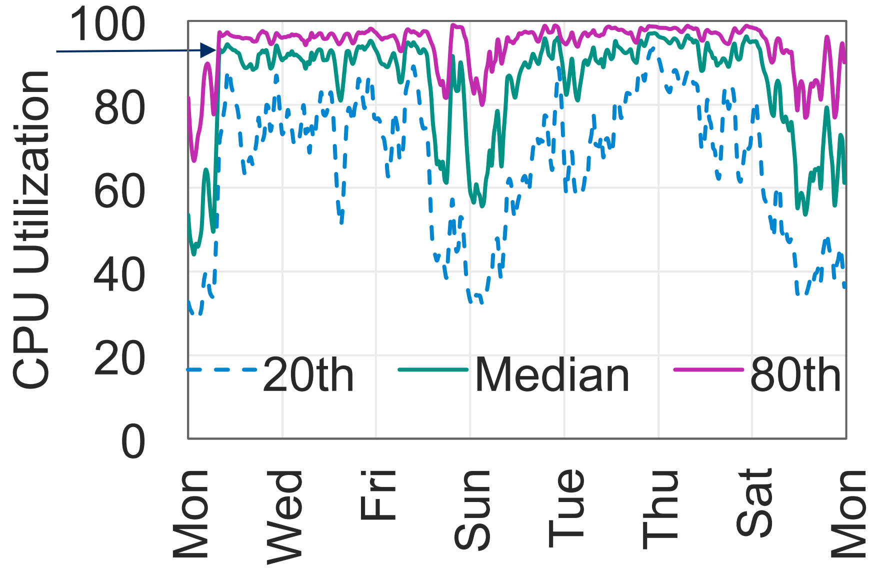
How does Apollo perform?

- **Baseline**: Previous production scheduler, lacking coordination and estimates
- **Ideal**: Trace-driven simulator with infinite capacity



Does Apollo use resources efficiently?





Opportunistic tasks increase their share of utilization on weekends

90% median CPU utilization under load

No impact to regular tasks

Regular tasks < 1 second queue time at the 95th percentile

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Related Work

Centralized Schedulers

Quincy

Delay Scheduler

Hierchical Schedulers

Mesos

Yarn

Corona

Decentralized Schedulers

Sparrow

Omega

Conclusion

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Loosely Coordinated Distributed architecture	High Quality Scheduling	Maximize resource utilization
Deployed to clusters with over 20,000 servers	Minimize task completion time Consistent performance	Opportunistic scheduling 90% median CPU utilization