Realizing value in shared compute infrastructures

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Carnegie Mellon Parallel Data Laboratory

Talk outline

- Shared cluster environments + thesis statement
- 2 case studies: specializing application frameworks
- 2 case studies: from perspective of cluster operators
- Conclusion

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nent eworks operators

Shared cluster environments

- Highly heterogeneous resources and applications
 - Many users from various groups and organizations
 - Time varying load
- Examples of shared cluster environments:
 - Public clouds (AWS, Azure, GCE)
 - Private clouds (MS Cosmos, Google Borg)



Example: Shared cluster environment



User goals in shared clusters

- **Users:** Run applications in shared environment ullet
 - Goal 1: Meet application business requirements
 - Goal 2: Minimize cost of meeting requirements
- Challenges:
 - Resource heterogeneity
 - Wide variety of pricing mechanisms



Cluster operator goals in shared clusters

- Cluster operators: Maximize profit & satisfy users
 - Goal 1: Prioritize resource allocation to applications -Using some notion of "user value"
 - Goal 2: Maximize "profit" = "value" achieved costs
- Challenges:
 - Resource heterogeneity and availability
 - Hidden user values and performance requirements
 - Cluster capacity + cost management

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Thesis statement

Value-realized in shared data environments can be improved both by value- and dependency-aware resource management systems from cluster operators and by costand heterogeneity-aware applications from users.

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Application-specific resource acquisition: Case studies

- 1. Elastic web services
 - Spot-dancing for elastic services with latency SLOs
 - Tributary [USENIX ATC 2018]
- 2. General containerized batch task scheduling
 - Cost-aware container scheduling in the public cloud
 - Stratus [ACM SoCC 2018] -Best student paper award

More background: Public clouds

- Public clouds offer a variety of resources
 - e.g., varying compute capacity, storage, HW accelerators
- Under different types of contracts
 - e.g., reliable, transient, and burst
- Difficult for users to choose resources cost-effectively!

Achieve user value through: Application-specific, cost-aware resource acquisition

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Adv: Often > 50% cheaper vs on-demand, *refund if revoked in 1st hr*





M4.10xlarge in us-east-1b

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M4.10xlarge

Availability Zone

- us-east-1a
- us-east-1b
- us-east-1c
- us-east-1d
- us-east-1e
- us-east-1f

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Elastic web services & spot instances

- Elastic web services
 - Manage a pool of VMs to serve client requests
 - Need to meet latency SLOs (e.g., request within X ms)
 - Stateless services (Tributary's focus) allow quick scaling
- Spot instances *cheaper but riskier* than on-demand:
 - Instances can be revoked, leading to missed SLOs

Tributary embraces risk associated w/ spot instances to achieve lower cost while meeting SLOs



Exploiting spot resources

- Naïve selection of spot \rightarrow bulk revocations
 - Large alloc of low cost \rightarrow low # of VMs left if price spikes
- Observation: Spot market prices not too correlated



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Tributary strategy

- Selects resources from multiple spot markets
 - Exploit pricing low or non-correlation
- Uses different bids within the same spot market
 - Higher/lower bid \rightarrow less risk/more partial-hours
- ML-based prob model \rightarrow extra resources acquired
 - Added benefit: soaks up unexpected spikes in requests
- Expected cost w.r.t. SLO
 - Cost offset by lower cost VMs and free partial hours

Tributary experimental setup

- 4 real world internet traces
 - Show Clarknet
- Compare vs 3 systems
 - AWS AutoScale shown
- AWS AutoScale:
 - Acquires lowest cost
 - Bid on-demand price ullet



Tributary experimental results

Tributary 40% lower cost, 60% less reqs violating SLO





Tributary experimental results

- Tributary 40% lower cost, 60% less reqs violating SLO
- AutoScale costs 60% more vs Tributary to match SLO attained



SLO SLO attained

Tributary takeaway

- Diversified resource pools mitigate revocation risk
 - Prob model \rightarrow diverse + extra resources \rightarrow SLO attained
 - Considering expected cost + partial-hours \rightarrow lower cost
- Reduces cost vs compared systems

on risk) attained

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Background and motivation

- Virtual cluster (VC) scheduling:
 - Schedule containerized batch tasks on to rented VMs
 - Different from traditional cluster scheduling:
 - -Add/remove VMs any time \rightarrow dynamically sized
 - -VC can be highly heterogeneous

Diverse offerings + VC elasticity to lower cost of executing batch workloads

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Stratus

- Stratus: Sched middleware that sizes VC + place tasks
- Goal: Lower cost of executing batch workloads
- Key: Wasted resource-time is wasted money
 - VMs should be highly utilized while rented
 - Use cost-efficient resources ullet

Runtime binning: Pack tasks of similar runtime on to VM



Aligning runtimes: Runtime binning

- Runtime bins: *Logical* groups of tasks and VMs lacksquare
- Idea: Tasks w/ similar predicted run times on same VM \bullet
 - Pluggable task run time predictor
 - VM highly utilized while rented \rightarrow high tasks per dollar

Aligning runtimes: Runtime binning

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Experimental setup

- Simulation-based experiments
 - Google and Two-Sigma cluster traces
- Focus on batch analytics jobs
- Spot market traces for dynamically priced VMs
 - Always bid on-demand price little to no preemptions
- Compare against Fleet: SpotFleet + ECS (AWS)
 - SpotFleet: Scaling based on policies
 - ECS: Packing containers on to VMs

/Ms emptions 5 (AWS)

Stratus vs Fleet

- Fleet: SpotFleet + ECS (Amazon offerings)
- Stratus reduces cost by 17% (Google) and 22% (TwoSigma)



Stratus takeaway

- Runtime binning → high VM utilization during rental
- Simultaneous consideration of scaling, packing, and cost-per-resource leads to reduced cost

g rental ing, and

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Cluster-operator resource management: Case studies

- 1. Scheduling to increase attained utility in cluster
 - Unearthing inter-job dependencies for better scheduling
 - Wing [USENIX OSDI 2020]
- 2. Load-shifting to reduce cluster operation costs
 - Reducing costs with dependency-informed load-shifting
 - Talon [Submission-prep]

Background: Cosmos

- Microsoft's internal data analytics platform
- Multiple multi-tenant clusters •
 - Tens of thousands of nodes each
 - Shared by many teams and orgs
 - Primarily SCOPE jobs
 - Batch analytics jobs similar to Spark/MapReduce
 - -80% resource-time

Background: Inter-job dependencies

- Inter-job dependencies:
 - Occur when job dep on output of earlier job as input
 - Pervade shared envs, but ignored in resource mgmt
- GDPR enables inter-job dependency analysis
 - Untapped opportunities
 - Wing (discussed later) first to analyze in large cluster – Forms basis of next two case studies



Shared data environments



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Shared data environments





Shared data environments



depends on **B** depends on **A**

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Data from a Cosmos cluster



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Millions of daily tasks

TBs of job + data prov logs daily

Data from a Cosmos cluster

100s of hierarchical queues (teams)

40k+ daily jobs

50k+ servers

160k+ daily inter-job dependencies

80% jobs depend 95% of queues inter-dependent on other jobs

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Millions of daily tasks

TBs of job + data prov logs daily

68% jobs recurring

Cluster-operator resource scheduling: Case studies

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Wing summary



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Wing summary



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Problems when not considering deps

Inter-job dependencies pervade data envs, but are ignored in resource management

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Problems when not considering deps

Inter-job dependencies pervade data envs, but are ignored in resource management

Missed deadlines, wasted resources, and untapped opportunities

We can fix this, with recurring and predictable inter-job dependencies

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Towards addressing inter-job deps

Wing

Discovers + analyzes inter-job dependencies from data provenance

Scheduling with Wing guidance

Scheduling that prioritizes the most value-impactful jobs, informed with historical recurring inter-job dependencies





Job value & inter-job dependencies

- Failing/finishing jobs late can impact downstream jobs
- Wing analyzes the aggregate value (impact) of jobs



m jobs jobs





Wing-Agg: Wing-guided scheduling

- Goal of value scheduling: Achieve most value given workload
- **Wing-Agg**: YARN's prio-based sched + Wing-guidance
 - Prioritize recurring jobs with high aggregate value efficiency



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Experimental setup

- Trace-driven simulations on real cluster traces
 - Preserves inter-job dependencies and properties
- Goal: Attain more value from the same workload \bullet
 - Value metric: Total file output downloads attained
- Experiments at various cluster sizes (capacities)
 - To simulate resource-constrained clusters

Value-attainment

• Wing-Agg: Prio as historical agg value / agg compute



% Cosmos cluster capacity

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Value-attainment

• Wing-Agg: Prio as historical agg value / agg compute



% Cosmos cluster capacity

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Default YARN

■ Wing-Agg

Wing takeaways

- Inter-job dependencies prevalent in real clusters
 - But, can be predictable with recurrence
- Inter-job dependencies need to be addressed lacksquare
 - To ensure jobs meet their deadlines, reduce resource wastage, and improve value attained in shared clusters

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Talon summary

- Talon: Workflow mgr that reduces cluster op cost by reducing expensive locked-in reserved capacity
 - Load-shift workload off-peak using inter-job deps 1.
 - Exploiting low-cost *transient resources* 2.
 - -Reduce preemption impact w/ load-shifting

Reduces reserved resources by 38% with minimal deadline violations



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(%)

cap

Reserved

Background

- Resource types common in shared clusters:
 - Reserved: Long-term committed
 - Expensive and inflexible (locked-in long-term)
 - On-prem/reserved instances/guaranteed cap in cluster
 - Transient: Low-priority, intermittently-available
 - -Lower cost, no lock in, but preemption/revocation risk
 - Spot instances/opportunistic cap in cluster
- Load-shift jobs: Change when job is run

) in cluster

Cosmos workload capacity planning

Capacity planning Cosmos workload peak



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Cosmos workload capacity planning

Capacity planning Cosmos workload peak



If only reserved, need this much cap (traditional approach)

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Cosmos workload + load-shifting

Capacity planning Cosmos workload peak



Scenario: yellow resource-time can be load-shifted off-peak

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Cosmos workload + load-shifting

Capacity planning Cosmos workload peak



Scenario: yellow resource-time can be load-shifted off-peak

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Cosmos workload + exploit transient

Capacity planning Cosmos workload peak



Scenario: Low-cost transient resources available

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Cosmos workload + exploit transient

Capacity planning Cosmos workload peak



Scenario: Low-cost transient resources available

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Talon: Reducing reserved lock-in

Capacity planning Cosmos workload peak



Talon:

- (1) Reduce reserved
 - resource cap + cost w/load-shifting and transient resources
- (2) Do so without more deadline violations

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Two ways to reduce reserved peak

1. Inter-job dependency-based load-shifting

2. Use transient resources

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Two modes of load-shifting

1. Delay: Run a job later, try not to violate job DL

- Output + run time preds both need to be accurate
- Little benefit (10% resource-time > 1 hr) + risk
- Talon does not delay jobs ullet
- 2. Advance: Run job earlier
 - Traditionally difficult, Talon uses inter-job deps





Advancing jobs: Opportunity analysis

- Job eligible to be advanced if:
 - All inputs ready and available
 - *Recurring* + *predictable* based on done jobs
- Predict recurring job arrival if dep on + follows completed upstream job w/ high prob
 - e.g., Job B dep on Job A > 90%
- Work with other WF Mgrs for advanceability

~24% resource-time advanceable > 1 hour

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15 min - 1 hr < 15 min</p> 1hr - 3 hr > 3 hr





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Transient resource risks

- Want to: Use transient resources to reduce reserved
- Risks: Intermittent availability, (bulk) preemption \bullet
 - Task replication can help w/ preemptions and DL violations, but
 - Aggressive usage \rightarrow retries \rightarrow queueing & more DL violations



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"Storm" of retries

Scheduling policy: Admission + placement

- Jobs eligible to start arrive at scheduling policy •
- Policy admit + place jobs on reserved/transient:
 - Based on run time, time load-shifted, resources, etc
 - ex 1: Queue adv'd if low resource avail to reduce reserved
 - ex 2: Urgent jobs run reliably (reserved or transient + reps)
- Key to min DL violations: handling (bulk) preemptions:
 - Do not use transient too aggressively
 - Adv'd jobs w/ long slack can run transient w/o replicas
Experimental setup

- Simulation experiments on Cosmos traces
- Transient resources: Scaled Harvest (Spot) VM traces
- Jobs wait for inputs to start
 - Different from in Wing, where jobs may fail if missing input
- Deadline: Time of first non-job output usage
- Compared approaches:
 - Traditional: Peak-provisioned, reserved only
 - GHDP: GreenHadoop, a green-energy scheduler
 - GHDP-R: Replicas on transient to reduce violations

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Experimental results

- GHDP (no rep) experience DL violations due to retries ullet
- Talon 38% reduction vs Traditional
- Talon achieves lowest num of deadline violations



(%) violations **8.0** 0.6 0.4 adlir 0.2

Talon takeaways

- Inter-job dependencies critical to exploit load-shifting •
 - 24% job resource-time can be advanced by > 1 hr
- Talon can effectively reduce reserved committed capacity using combination of load-shifting + transient resources
 - Up to 38% reserved capacity reduction vs traditional
 - Lowest # of deadline violations under diff scenarios

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Thesis contributions: App-specific resource acquisition

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