Improving Preemptive Scheduling with Application-Transparent Checkpointing in Shared Clusters

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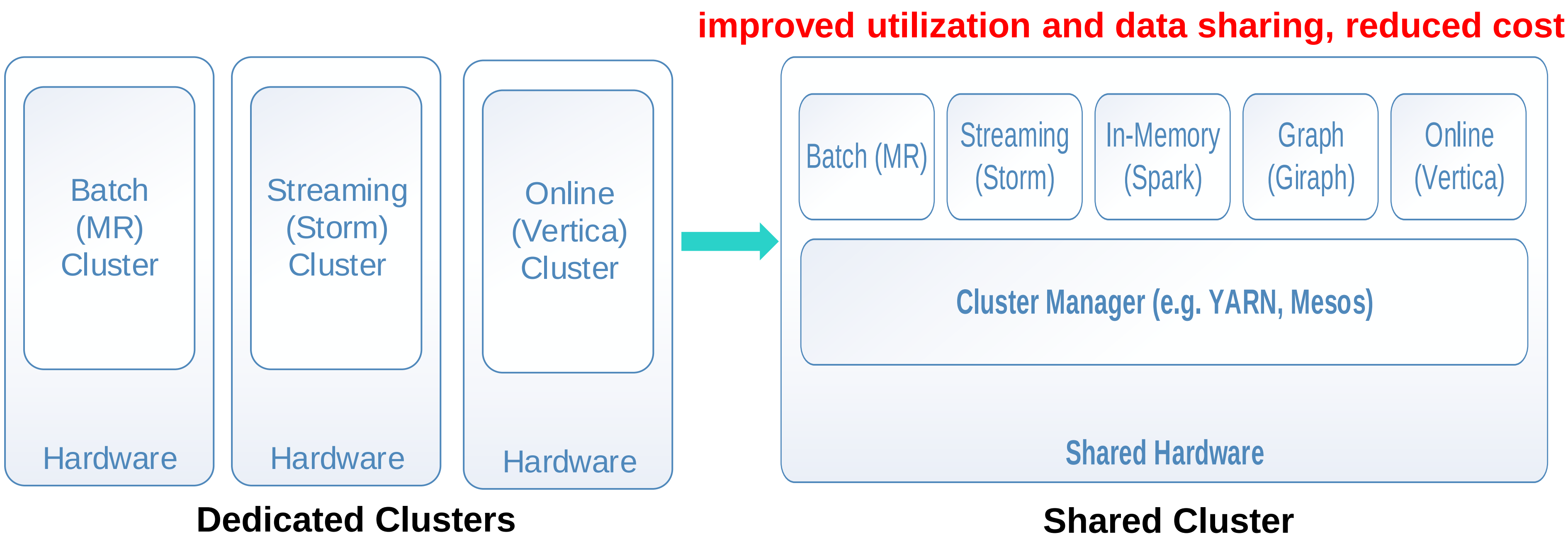
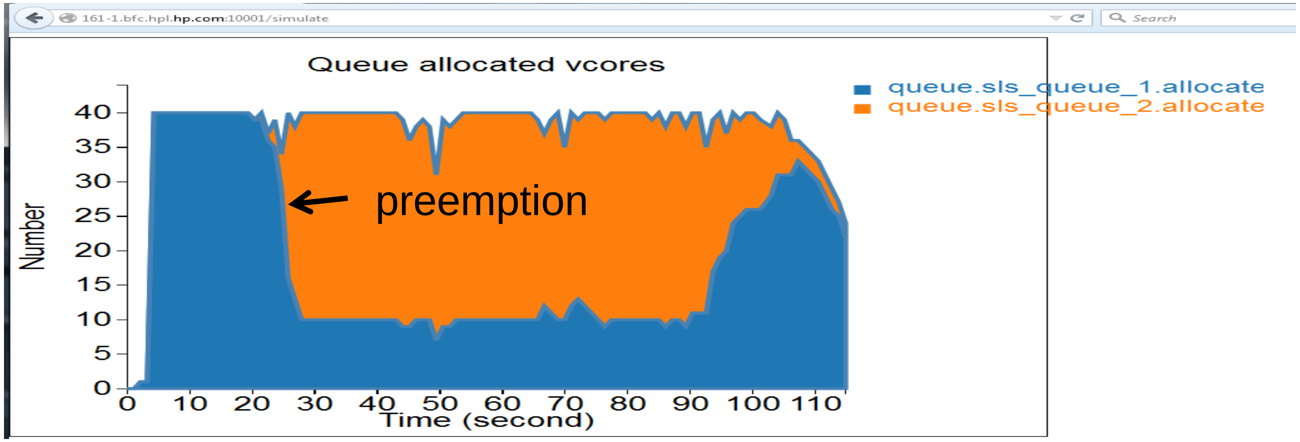
Shared Clusters for Big Data Systems

– Dynamic resource sharing across multiple frameworks, apps and users
  – Examples - Google cluster (Omega), Mesos, Hadoop YARN, Bing's Dryad



Preemption in Shared Clusters

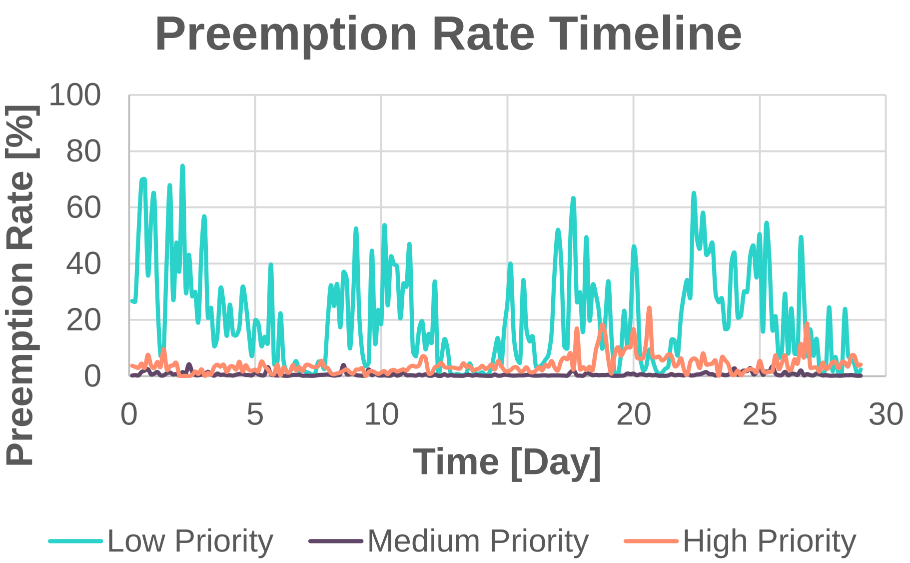
– **Coordinate resource sharing, guarantee QoS and enforce fairness**



– **Problem: preemption in shared clusters is expensive!**
  – Simply kill and restart jobs later
  – Significant resource waste
  – Delays completion time of long running or low priority jobs

Real World Examples

29-day trace from Google: 672,000 jobs on 12,500 machines



Task Priority	Num. of Tasks	Percent Evicted
Free (0-1)	28.4M	20.26%
Middle (2-8)	17.3M	0.55%
Production (9-11)	1.70M	1.02%

Many tasks preempted

Latency Sensitivity	Num. of Tasks	Percent Evicted
0 (lowest)	37.4M	11.76%
1	5.94M	18.87%
2	3.70M	8.14%
3 (highest)	0.28M	14.80%

Even latency-sensitive tasks are evicted

– Google Cluster: 12.4% of scheduled tasks preempted and up to 30k CPU-hours (35% of total capacity) wasted!

– Microsoft Dryad cluster[1]: ~21% jobs killed

– Facebook Hadoop cluster[2]: repeatedly kill and restart long running jobs

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[1] Scarlett: Coping with Skewed Popularity Content in MapReduce Clusters. Ananthanarayanan et. al. EuroSys 2011.
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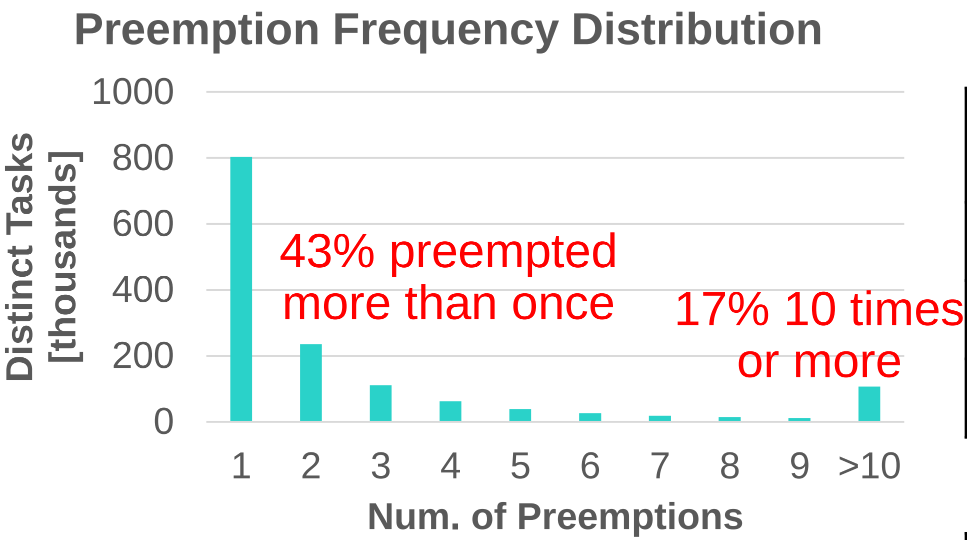

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Checkpointing-based Preemptive Scheduling

Our solution: use checkpoint/restore for preemption instead of kill/restart

Use system level, application-transparent checkpointing mechanism

– Linux CRIU (**C**heckpoint-**R**estore **I**n **U**serspace)

– Distributed and remote checkpoint/restart

Leverage fast storage such as NVM for efficient checkpointing

– Store checkpoints on NVM (NVMFS or NVRAM)

Adaptive preemption policies and optimization techniques

– Combine checkpoint and kill, local and remote checkpointing/resumption

– Incremental checkpointing with memory trackers

Application-transparent Suspend-Resume

Checkpointing using CRIU (Checkpoint/Restore In Userspace)

– Freeze a running program and suspend it in memory or output to disk
– Saves sockets, threads, namespaces, memory mappings, pipes

Dump

– Build process tree from /proc/$pid/task/$tid/children and seize them with ptrace
– Collect VMA areas, file descriptor numbers, registers, etc… of each process

Restore

– Read process tree from file and start saved processes with clone() call
– New memory map created filled with checkpointed data

Suspend-Resume with DFS and NVM

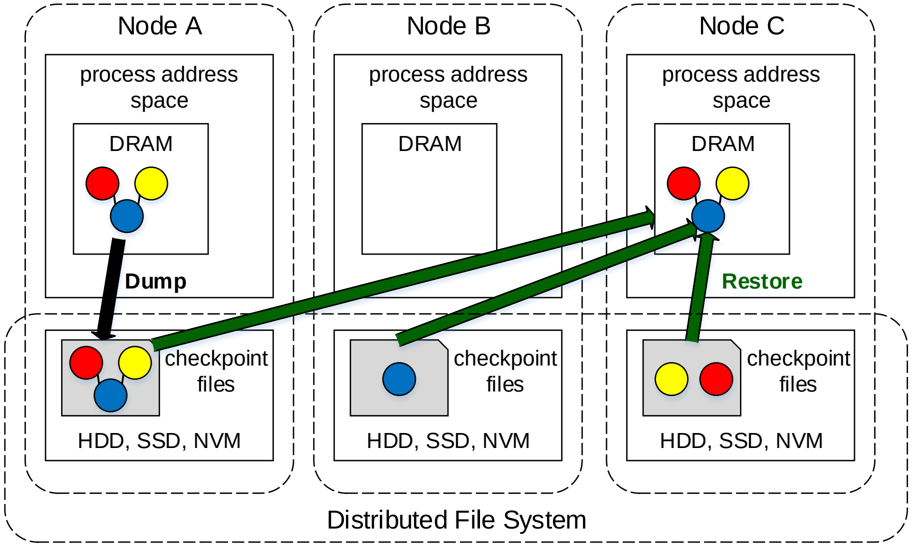
Support distributed and remote checkpoint-resume

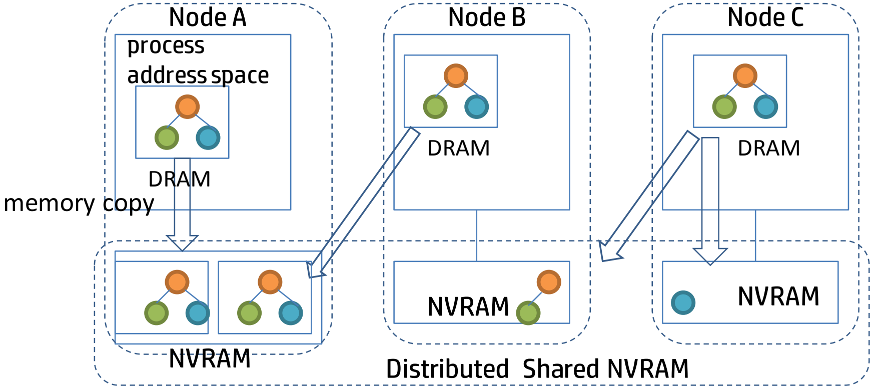
– Save checkpoints on HDFS

Checkpoint with NVM

– Use NVM as fast disk
  – Save CRIU checkpoints in NVM-based file systems (e.g, PMFS)
– Use NVM as virtual memory (NVRAM)
  – Copy checkpoints from DRAM to NVM using memory operations
  – Shadow buffer

Incremental checkpointing





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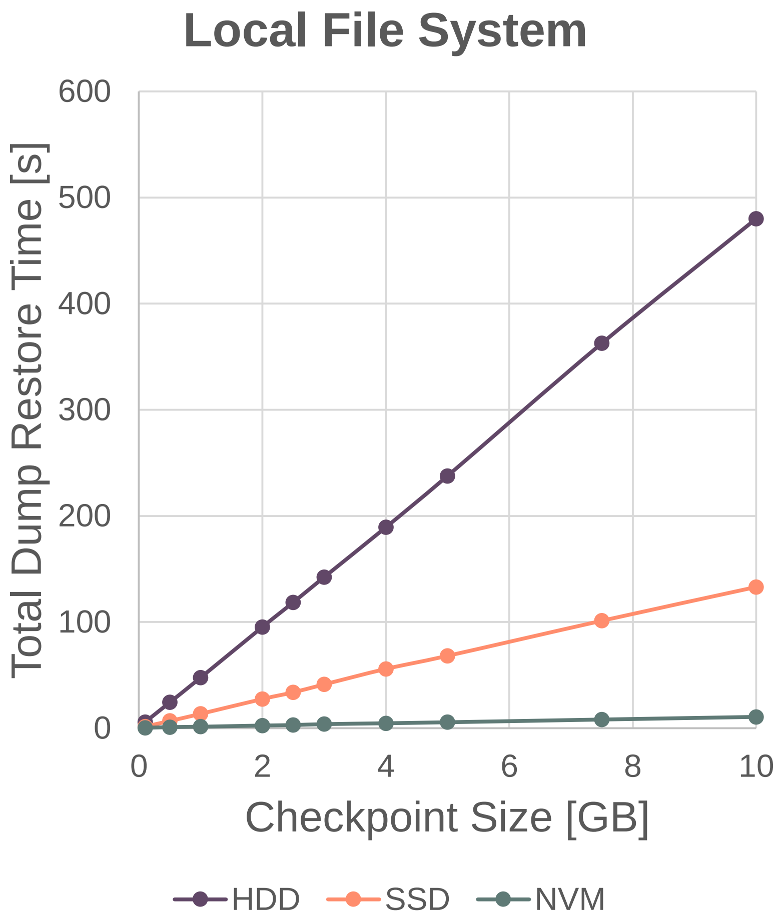
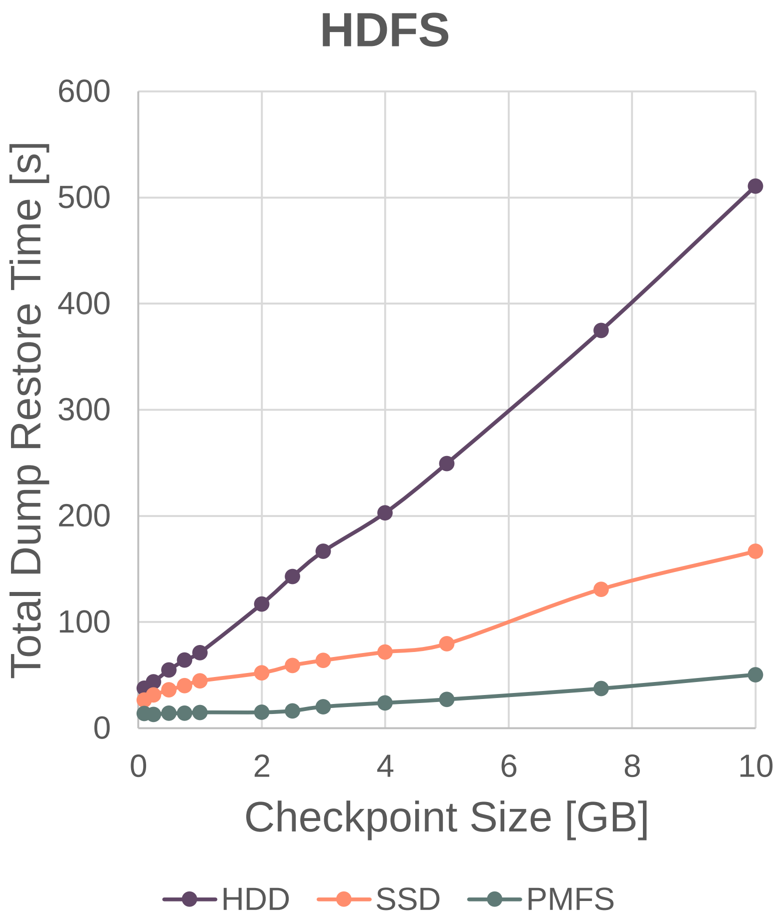
Suspend and Restore Performance





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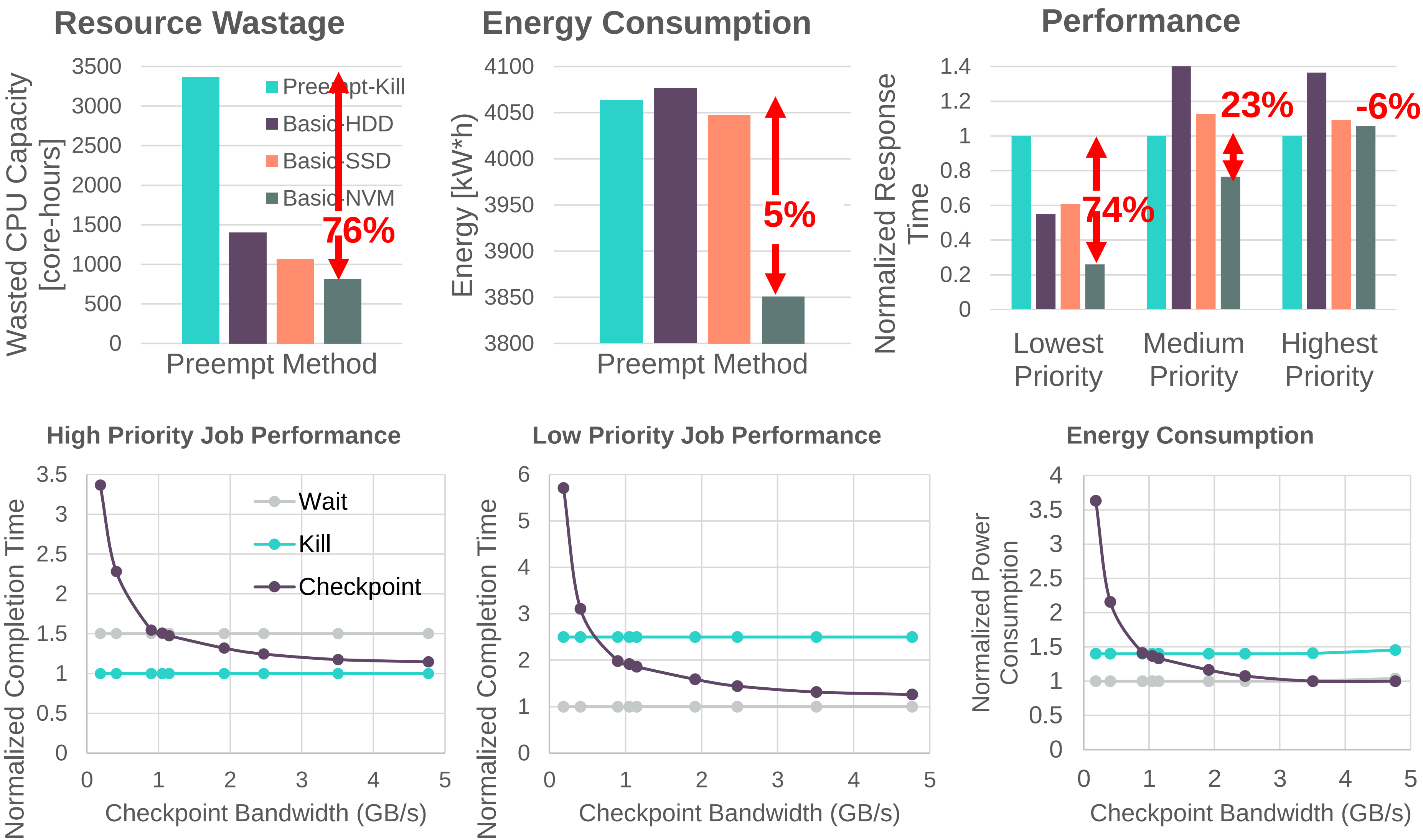
Benefits of Incremental Checkpointing

5GB initial dump size, change 10% of the memory and dump again

Storage	First Checkpoint	Second Checkpoint
HDD	169.18s	15.34s
SSD	43.73s	4.08s
PMFS	2.92s	0.28s

Google Trace-driven Simulation



Adaptive Policies and Optimization

Adaptive preemption dynamically selects victim tasks and preemption mechanisms (checkpoint or kill) based on the progress of each task and its checkpoint/restore overhead.

Adaptive resumption restores preempted jobs/tasks locally or remotely according to their overheads and available resources.

Incremental checkpointing with memory trackers

Adaptive Preemption Algorithms

Algorithm 1: Preemption Algorithm

$$overhead_{chkpt} = \frac{size}{bw_{write}} + \frac{size}{bw_{read}} + queue\_time_{dump}$$

```
candidate_victims = get_candidate_victims();
sort(candidate_victims);
for Task t in candidate_victims do
    if t.progress > t.checkpoint_overhead then
        if t.previous_checkpoint != null then
            do_incremental_checkpoint(t);
        else
            do_normal_checkpoint(t);
        end
    else
        kill(t);
    end
end
```

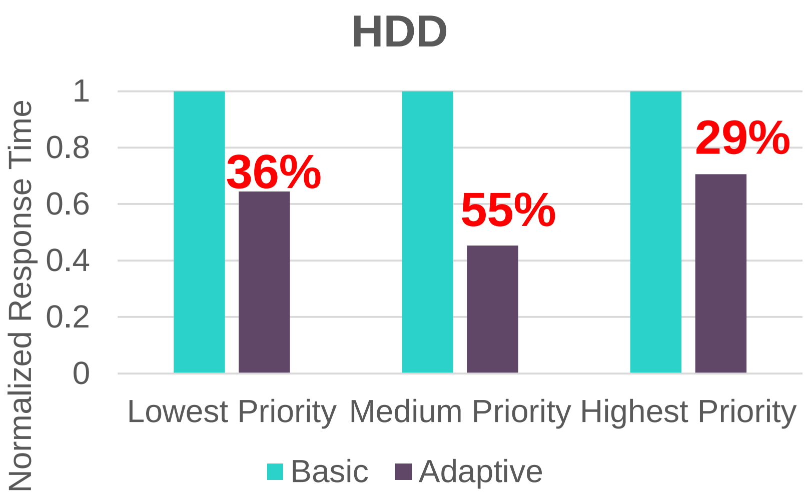
Algorithm 2: Resumption Algorithm

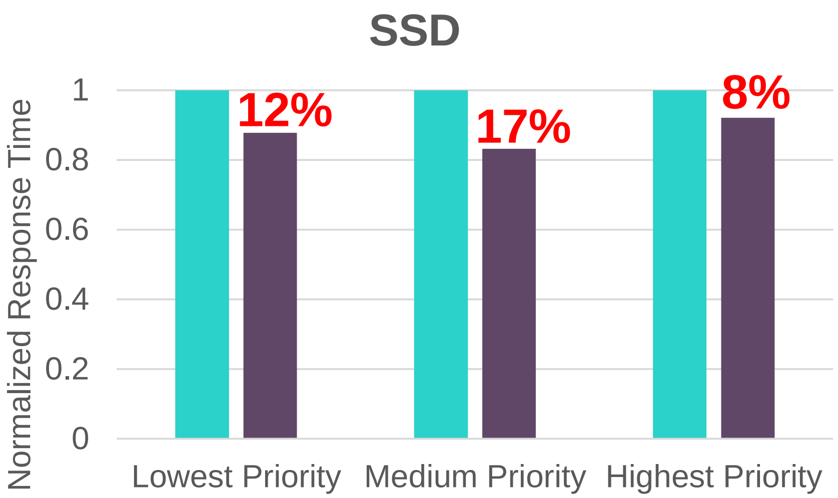
$$overhead_{local} = \frac{size}{bw_{read}} + queue\_time_{local}$$

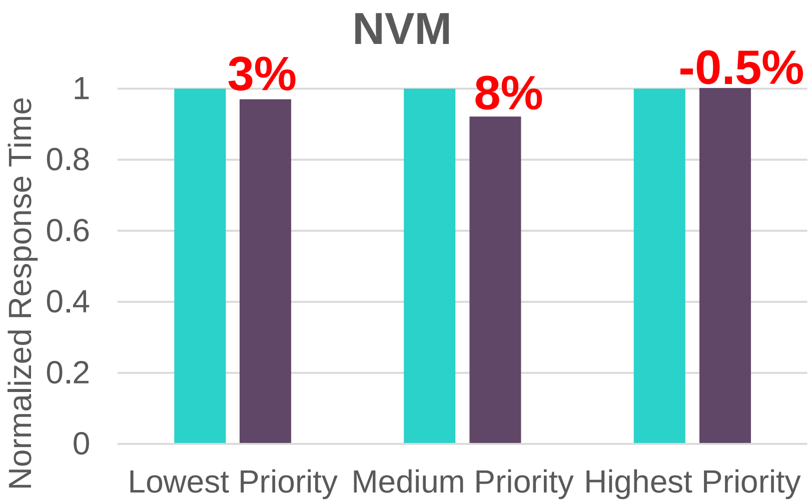
$$overhead_{remote} = \frac{size}{bw_{net}} + \frac{size}{bw_{read}} + queue\_time_{remote}$$

```
preempted_tasks = get_preempted_tasks();
for Task t in preempted_tasks do
    if t.previous_checkpoint == null then
        restart_task(t);
    else
        if t.local_resume_overhead <=
        t.remote_resume_overhead then
            do_local_resume(t);
        else
            do_remote_resume(t);
        end
    end
end
```

Performance Improvement with Adaptive Policies







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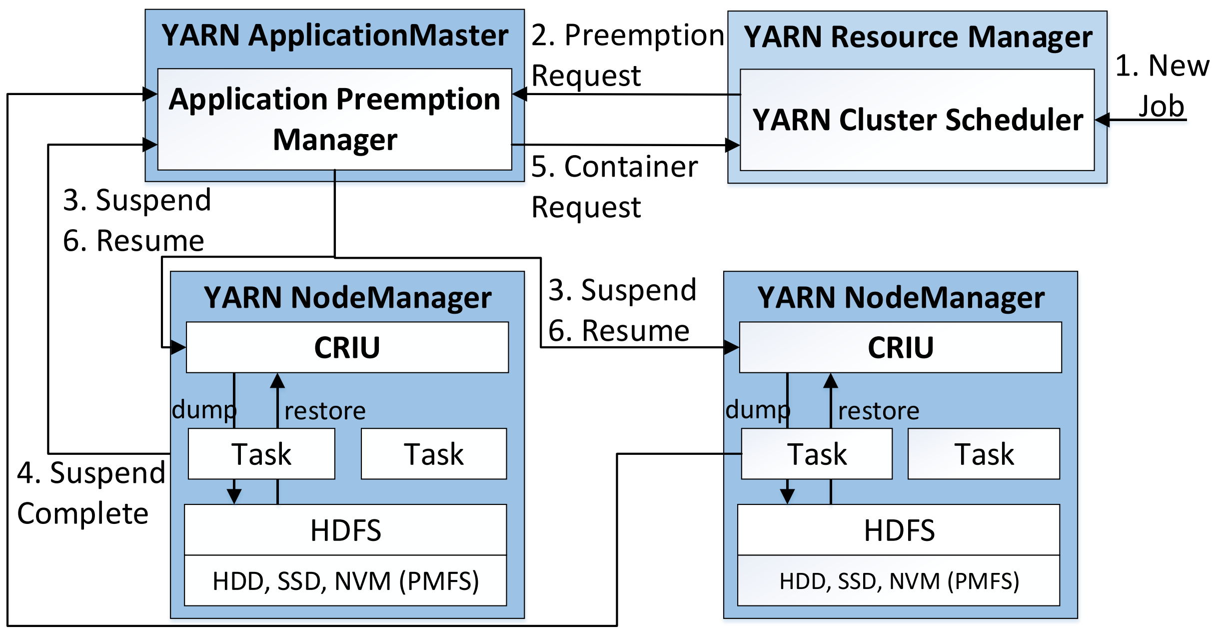
Implementation with Hadoop YARN

YARN – cluster resource manager

- Global resource scheduler (ResourceManager)
- Submit ApplicationMasters (jobs) to RM
- Supports capacity and fair scheduling

DistributedShell

- Comes standard with YARN
- Runs a shell command in a set of containers in a distributed and parallel manner



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Testbed and Experiment Setup

- 8 node Hadoop YARN cluster
  - Dual socket Xeon 5650 CPU (6 cores/each)
  - 96GB memory (48GB emulated NVM using PMFS)
  - 500GB HDD (un-optimized)
  - 120GB SSD
  - 24 concurrent containers (1 CPU/2 GB memory)

- Workload
  - Modeled after Facebook workload[1]
  - Mix of high/low priority jobs (7,000+ tasks)

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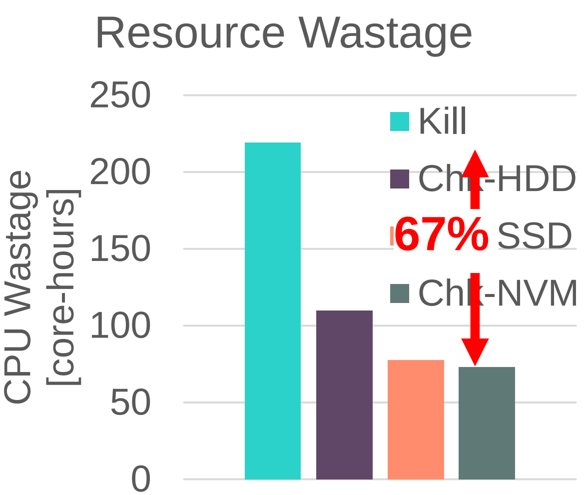
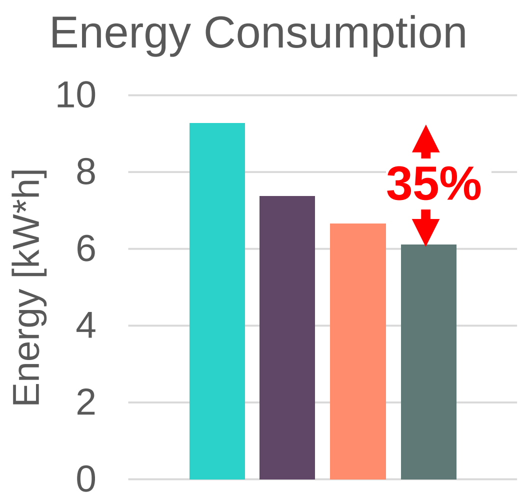
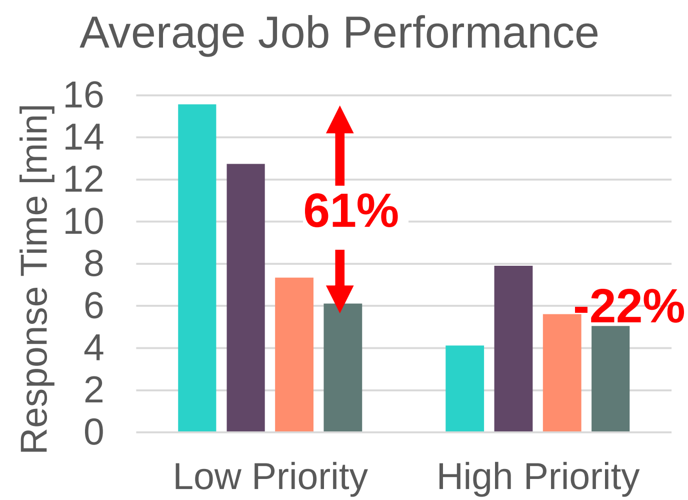
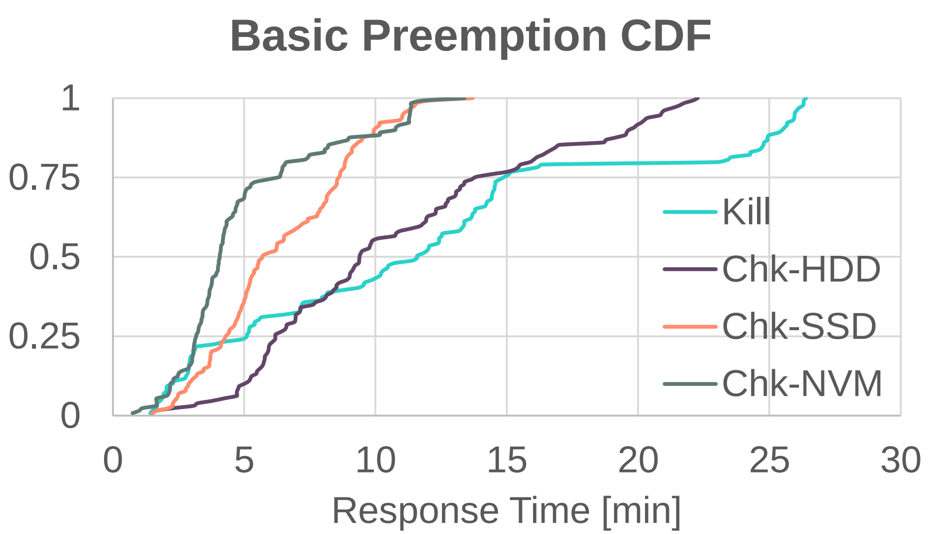
Comparison of Different Preemption Policies on YARN

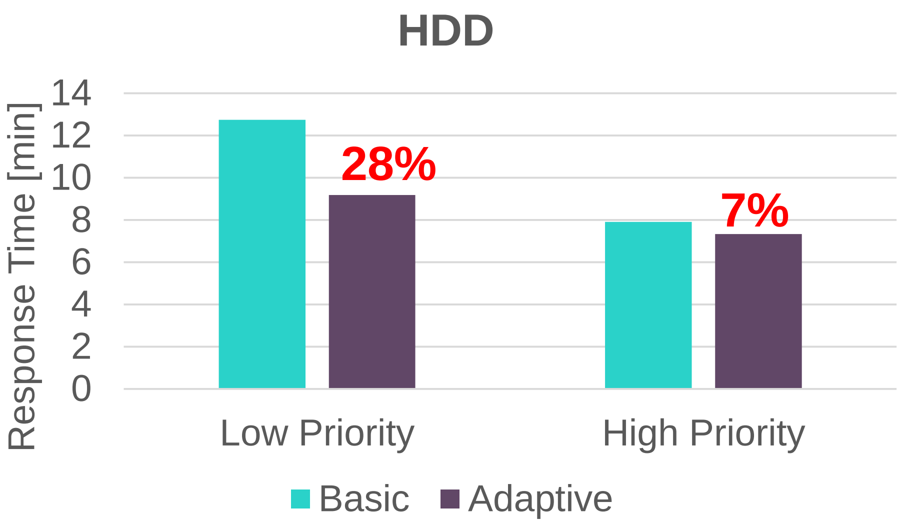


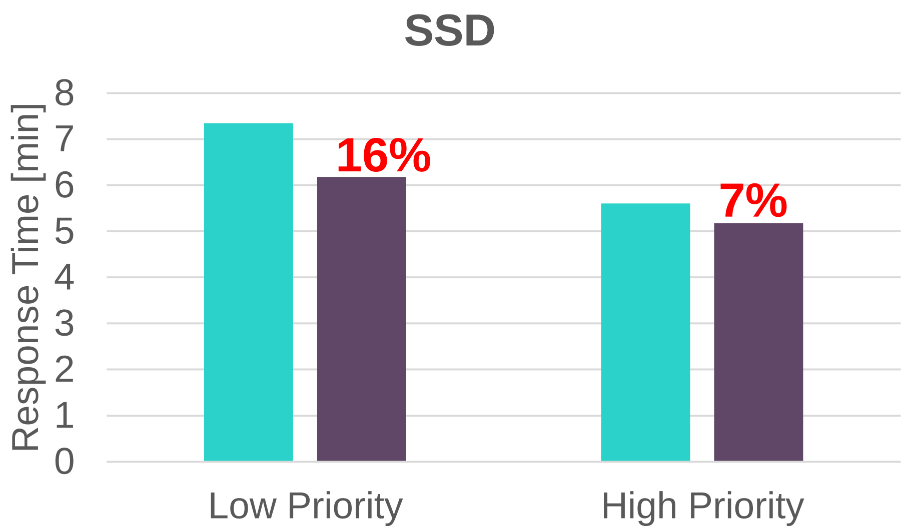


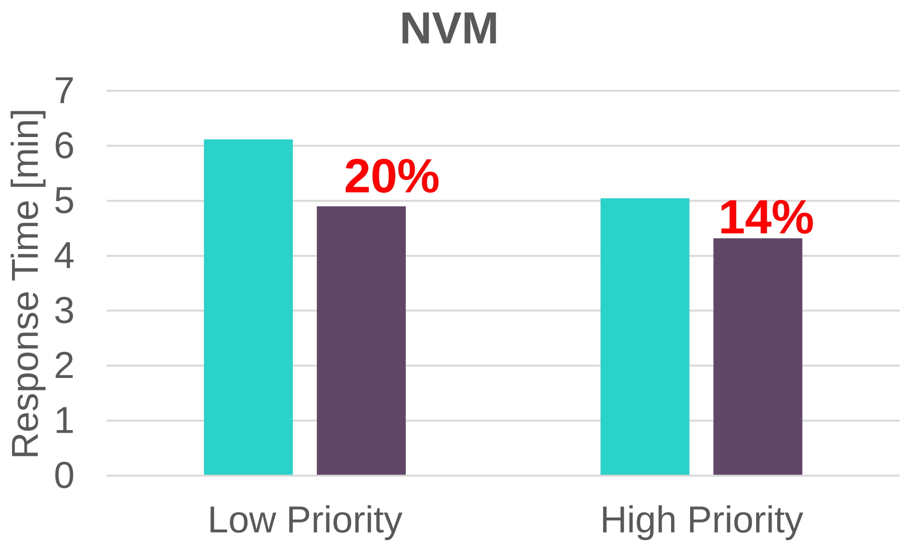




Benefits of Adaptive Preemption







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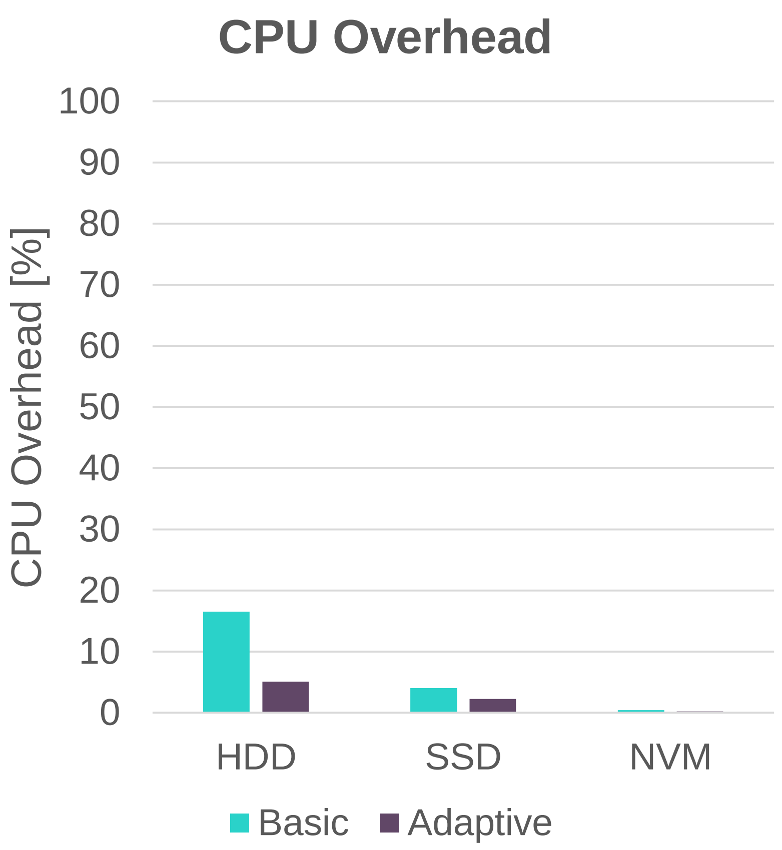
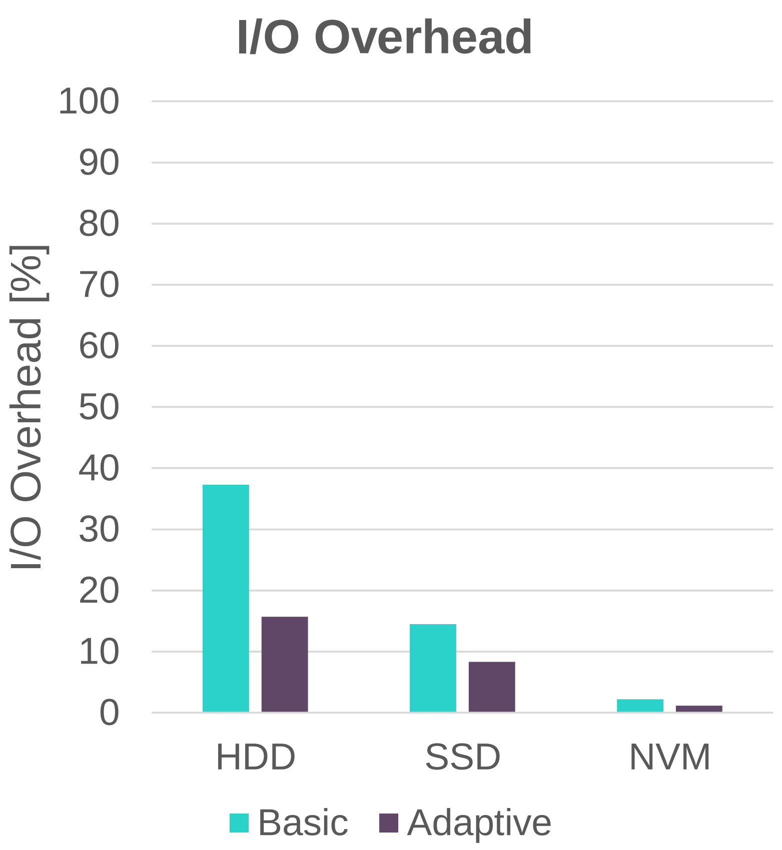
Overhead of Checkpoint-based Preemption

CPU overhead is negligible, but I/O overhead is significant on slow storage





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Conclusion and Future Work

- Preemption in shared clusters is expensive and preemption using application-transparent checkpointing is able to improve resource efficiency and overall application performance.
- Adaptive preemption that combines checkpoint and kill can further improve the performance and reduce the preemption cost.
- By leveraging emerging fast storage technologies such as NVM, even more savings can be achieved.

Future Work

- A wide range of applications
- Checkpointing with NVRAM
- Integration with other cluster scheduling policies

Thank you

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