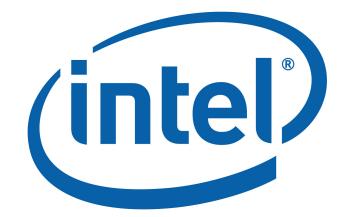
Progress on Efficient Integration of Lustre* and Hadoop/YARN



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* Some name and brands may be claimed as the property of others.

MapReduce

- A simple data processing model to process big data
- Designed for commodity off-the-shelf hardware components.
- Strong merits for big data analytics
 - **Scalability**: increase throughput by increasing # of nodes
 - Fault-tolerance (quick and low cost recovery of the failures of tasks)
- YARN, the next generation of Hadoop MapReduce
 Implementation







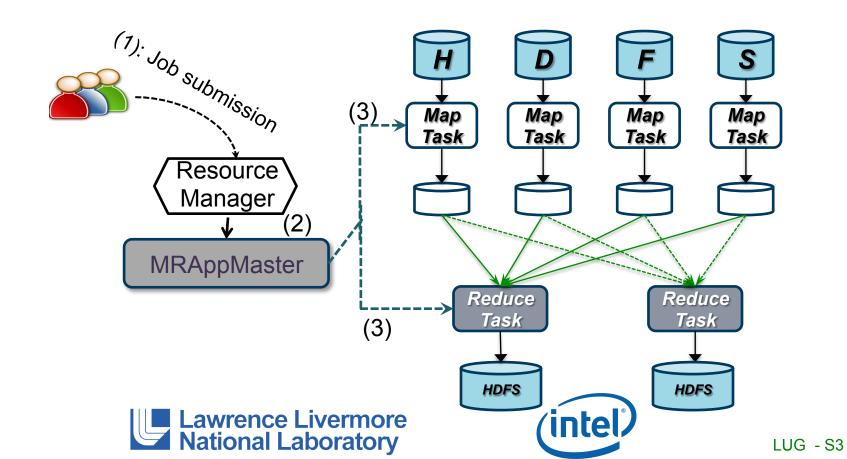
High-Level Overview of YARN

- Consists of HDFS and MapReduce frameworks.
- Exposes *map* and *reduce* interfaces.

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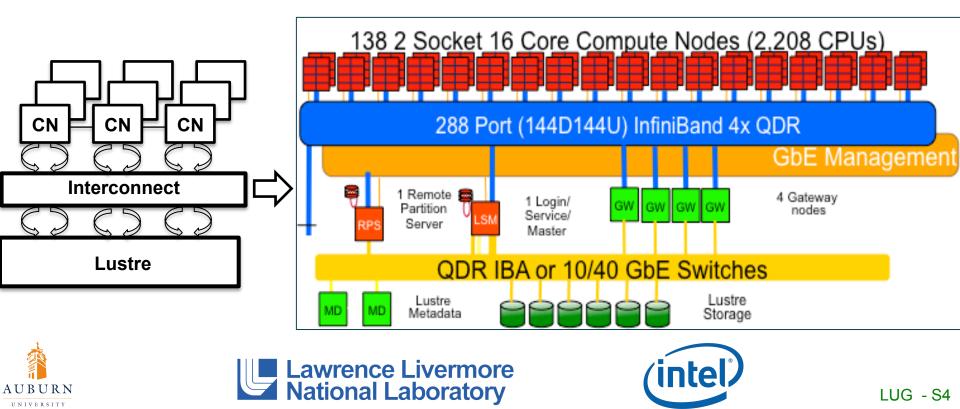
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- ResourceManager and NodeManagers
- MRAppMaster, MapTask, and ReduceTask.



Supercomputers and Lustre*

- Lustre popularly deployed on supercomputers
- A vast number of computer nodes (CN) for computation
- A parallel pool of back-end storage servers, composed a large pool of storage nodes



Lustre for MapReduce-based Analytics?

Desire

- Integration of Lustre as a storage solution
- Understand the requirements of MapReduce on data organization, task placement, and data movement, and their implications to Lustre
- Approach:
 - Mitigate the impact of centralized data store at Lustre
 - Reduce repetitive data movement from computer nodes and storage nodes
 - Cater to the preference of task scheduling and data locality





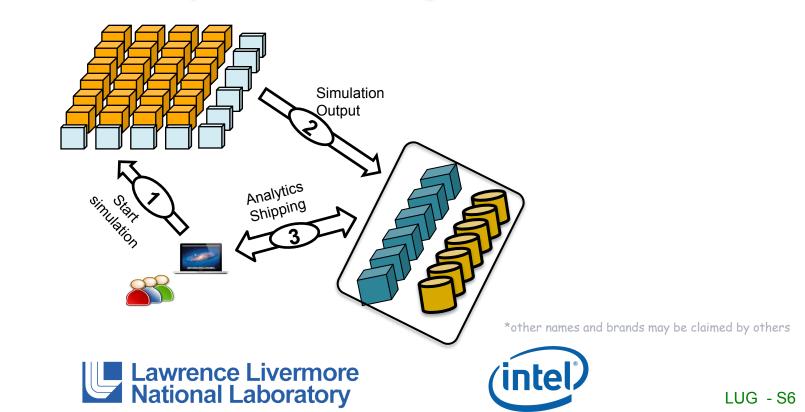


Overarching Goal

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- Enable analytics shipping on Lustre* storage servers
 - Users ship their analytics jobs to SNs on-demand
- Retain the default I/O model for scientific applications, storing data to Lustre
- Enable *in-situ* analytics at the storage nodes



Technical Objectives

- Segregate analytics and storage functionalities within the same storage nodes
 - Mitigate interference between YARN and Lustre*
- Develop a coordinated data placement and task scheduling between Lustre and YARN
 - Enable and exploit data and task locality
- Improve Intermediate Data Organization for Efficient Shuffling on Lustre

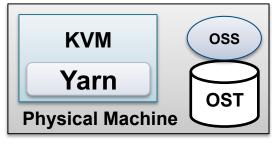






YARN and Lustre* Integration with Performance Segregation

- Leverage KVM to create VM (virtual machine) instances on SNs
- Create Lustre storage servers on the physical machines (PMs)
- Run YARN programs and Lustre clients on the VMs
- Placement of YARN Intermediate data
 - On Lustre or local disks?



A Total of 8 OSTs

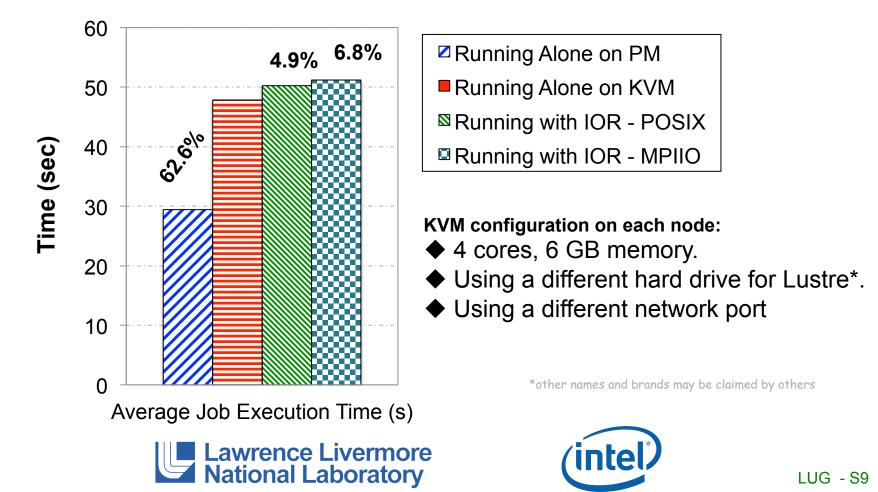






Running Hadoop/YARN on KVM

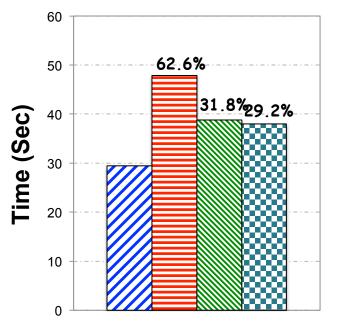
- 50 TeraSort jobs, 1GB input each. One job submitted every 3 seconds,
- There is a huge overhead caused by running YARN on KVM.
- Running IOR on 6 other machines. The impact is not very significant.





KVM Overhead

- 4 cores are not enough for YARN jobs
- 6 cores help improve the performance of YARN
- Increasing memory size from 4GB to 6GB has little effects when number of cores is the bottleneck



Average Job Excution Time (s)



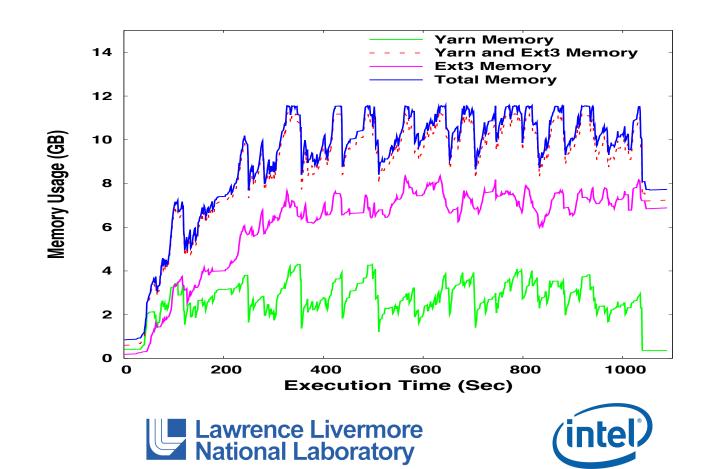




Running on PM
Running on KVM (4 Cores, 6GB Memory)
Running on KVM (6 Cores, 4GB Memory)
Running on KVM (6 Cores, 6GB Memory)

YARN Memory Utilization

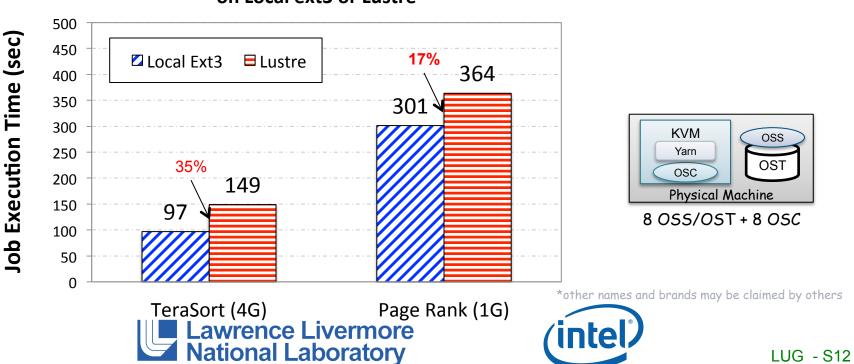
- Running Yarn on the physical machines alone.
- NodeManager is given 8GB memory, 1GB per container, 1GB heap per task.
- HDFS with local ext3 disks. Intensive writes to HDFS (via local ext3)





Intermediate Data on Local Disk or Lustre*

- Place intermediate data on local ext3 file system or Lustre, which is mapped to KVM (yarn.nodemanager.local-dirs).
- Yarn and Lustre Clients are placed on the KVM, OSS/OST on the Physical Machine
- Terasort (4G) and PageRank (1G) benchmarks have been measured

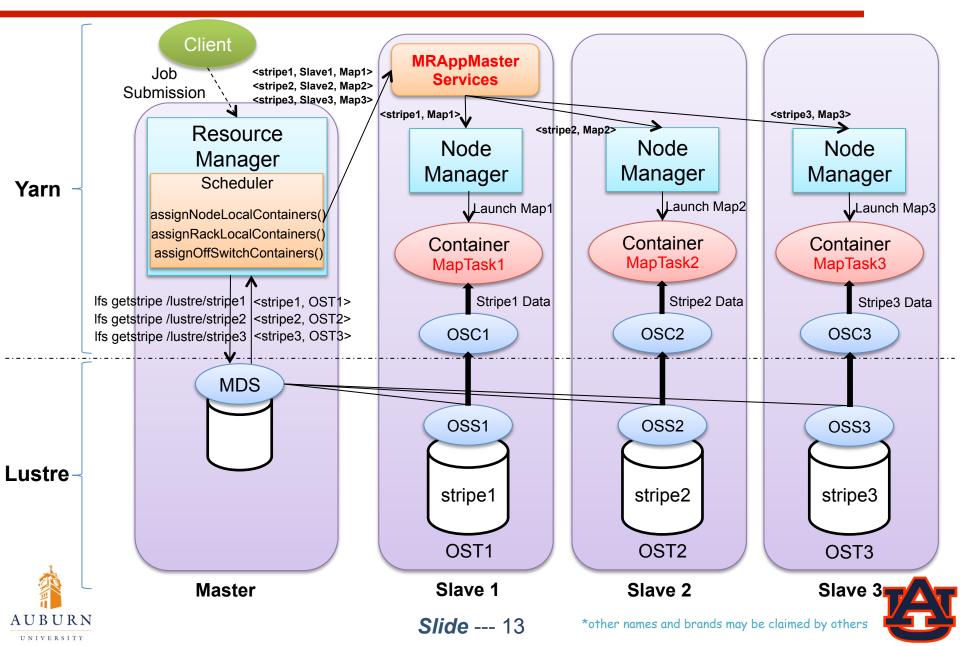


Configuring Yarn's intermediate data directory on Local ext3 or Lustre

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Data Locality for YARN on Lustre*



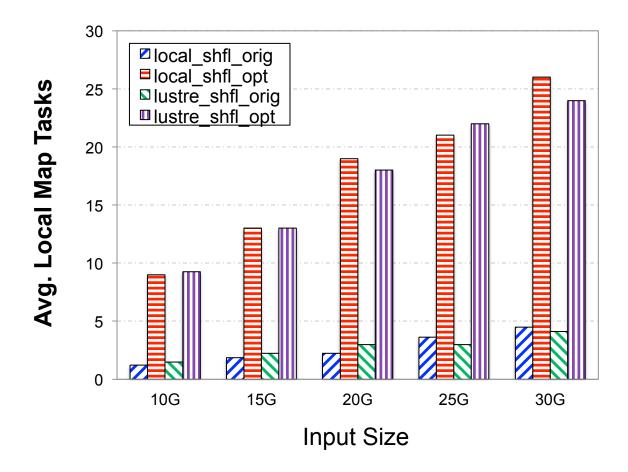
Background of TeraSort Test

- Four cases being compared
 - Intermediate Data on Lustre* or Local disks
 - Scheduling Map tasks with or without data locality
 - lustre_shfl_opt: (on lustre, with locality)
 - lustre_shfl_orig: (on lustre, without locality)
 - local_shfl_opt: (on local disks, with locality)
 - local_shfl_orig: (on local disks, without locality)
- Test environments
 - -- Lustre 2.5 with dataset from 10GB to 30GB and 128MB stripe size and block size





Average Number of Local Map Tasks



- local_shfl_opt and lustre_shfl_opt achieve high locality
- The other two have low locality.

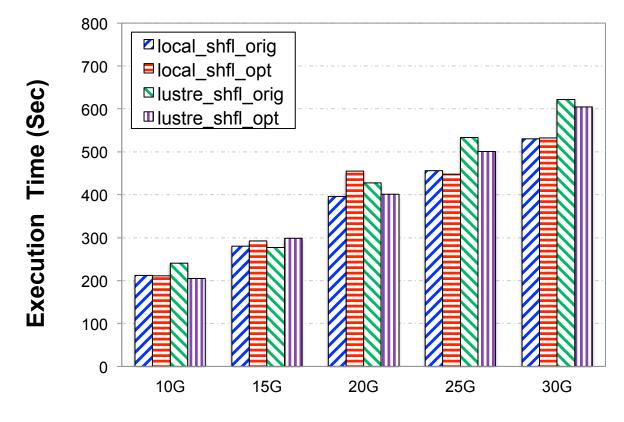
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Terasort under Lustre* 2.5



Input Size

- On average, local_shfl_orig has best performance
- lustre_shfl_opt is in the middle of best case and worst case;



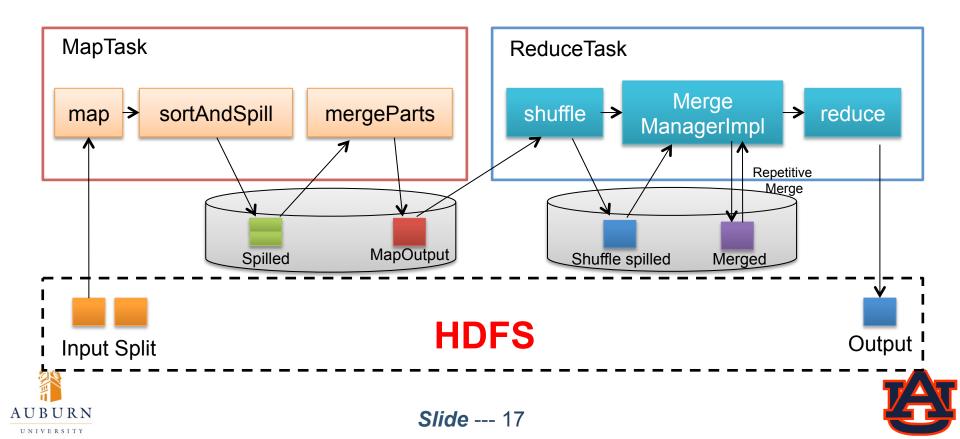
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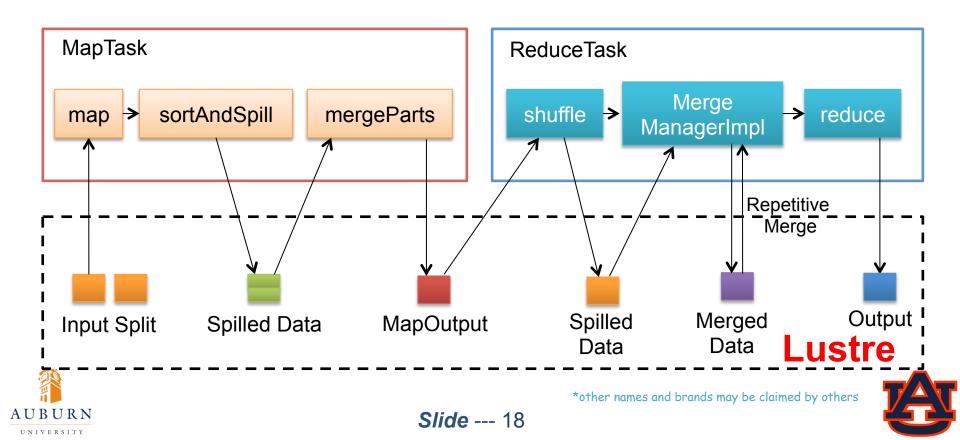
Data Flow in Original YARN over HDFS

- This figure shows all of the Disk I/O in original Hadoop
- Map Task: Input Split, Spilled Data, MapOutput
- Reduce Task: Shuffled Data, Merged Data, Output Data



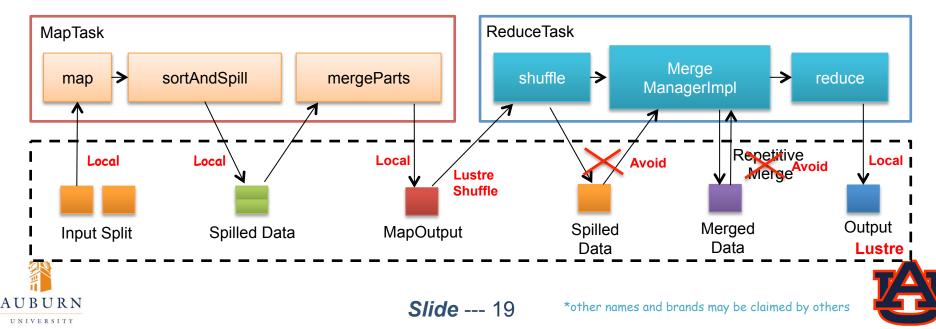
Data Flow in YARN over Lustre*

- This figure shows all of the Disk I/O of YARN over Lustre
- Avoid as much Disk I/O as possible
- Speed up Reading Input data and Writing Output data



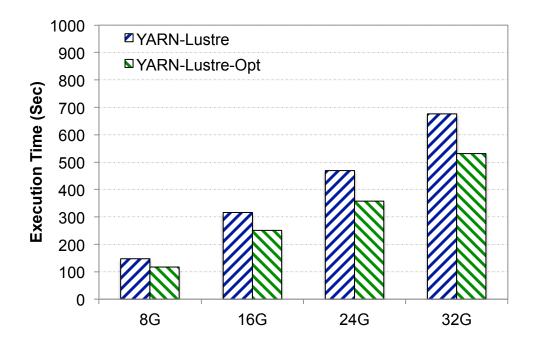
New Implementation Design Review

- Improve I/O performance
 - Read/Write from/to local OST
 - Avoid unnecessary shuffle spill and repetitive merge
 - After all MapOutput has been written, launch reduce task to read data
 - Avoid Lustre* write/read lock issues?
 - Reduce Lustre write/read contention?
- Reduce network contention
 - Most of data is written/read from local OST through virtio bridged network
 - Reserve more network bandwidth for Lustre Shuffle



Evaluation Results

- SATA Disk for OST, 10G Networking, Lustre* 2.5
- Running Terasort Benchmark, 1 master node, 8 slave nodes
- Optimized YARN performs on 21% better than the original YARN on average









Summary

- Explore the design of an Analytics Shipping Framework by integrating Lustre* and YARN
- Provided End-to-End optimizations on data organization, movement and task scheduling for efficient integration of Lustre and YARN
- Demonstrated its performance benefits to analytics applications







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