

Characterizing the Performance of Analytics Workloads on the Cray XC40 Cray: Michael Ringenburg, Shuxia Zhang, Kristyn Maschhoff, Bill Sparks NERSC: Evan Racah, Prabhat

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Agenda

- Last year at CUG: Showed how to run common open source analytics frameworks on XC systems
- Today: How do we understand, monitor, tune performance on XC40?
 - Focus on Apache Spark framework more flexibility, better performace, increasing adoption relative to Hadoop
 - SyncSort Survey: 70% Spark interest vs 55% Hadoop.

• Look at a couple use cases/techniques, plus a networking analysis

- Bottom-up: mining system metrics data from HiBench with collect1
- Top down: application log analysis of CX matrix decompositon in Spark
- TCP networking performance on XC

• In the paper: additional details, plus suggested optimizations

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Spark Background: Execution Model

- Driver is the "master": execute main, distribute work , collect results
- Executors are the "workers": execute parallel work across partitions of the data
- Computations lazily evaluated nothing happens until result required at driver:

```
val lens = file.map(l => (l.length,l))
val sorted = lens.sortByKey()
sorted.collect() // execution starts HERE
```

• Jobs, Stages, and Tasks:

- Job: Computation that returns a result to driver
- Stage: Unit of work that can be executed without communication. Jobs with internode communication requirements have multiple stages.
- Between job stages: barrier, global all-to-all shuffle
- Task: The computation of a stage on a single partition



= Java Virtual Machine Instance

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Spark Background: Shuffle

- Communication between executors implemented via shuffles
 - Senders send data to block managers; block managers write to disks, tell scheduler how much destined for each receiver
 - Barrier until all senders
 complete shuffle writes
 - Receivers request data; block managers read and send



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Shuffle on the XC40

- Spark assumes distributed cluster, with local persistent storage on each node for shuffle files (also for spilling RDDs).
- Not present on XC systems. Options:
 - Global Lustre file system: Many small files, and file opens/closes = high metadata overheads that dominate performance of shuffles.
 - DRAM-based tmpfs: Much faster, but storage limited to 50% of memory on node. Works for many workloads, but can run into memory bottlenecks.
 - Hybrid: Use both. Better performance than pure Lustre.
 - Loopback filesystems (see earlier presentation in Session 7A): Each node create a filesystem within a single Lustre file. Managed locally. Eliminates MDS overheads, coherency issues.

Our Analysis Approaches

• Collectl

- Commonly used for collecting compute node system metrics for HPC jobs
- Used a 1 second sampling rate
 - Negligible overheads next to overheads of analytics frameworks found to have no impact on completion time of our workloads
 - Accurate: tested by comparing aggregated Lustre metrics with input and output data set sizes, saw less than 1% variation
- Used R+pdbMPI to analyze, plot results

Spark event logs

- Track start and end times of jobs, tasks, stages
- Collect application level metrics for each task (GC time, serialization time, shuffle read/write, etc)
- Can view in Spark History Server, or parse with scripts

• TCP network performance analysis with iperf3, tcpdump

- Similar performace on Kmeans, PageRank, Sleep
- XC40 faster Sort, TeraSort, Wordcount, Bayes
- Let's examine...

Intel HiBench

- Originally MapReduce, Spark added in version 4 We selected common Spark workloads without Hive dependencies
- **Compared performance with** Urika XA system
 - XA: FDR Infiniband, XC40: Aries
 - Both: 32 core Haswell nodes
 - XA: 128 GB/node, XC40: 256 GB/node (problems fit in memory on both)



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Collectl: Examining Memory Usage



- PageRank much larger variation between executors in memory usage
 - Points to variation in data set/# links per page
- Wordcount much higher OS file cache usage
 - Spark uses file system for spills and shuffle data

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Collectl Example: Understanding Memory Usage



- Examing TCP traffic points to reason for larger OS cache usage: Larger shuffles
- Variability of PageRank indicates bottleneck due to stragglers/imbalance
- Wordcount has larger shuffles, and much less variability, indicating potential bottleneck in data movement
 - Takes better advantage of interconnect

Benefits of Collectl-Based Profiling

- Spark event log/history server can't give this level of detail
 - Only shows static size of persisted RDDs/DataFrames
 - Only shows application memory usage (no OS)
 - Only shows total shuffle traffic per stage
 - Etc...
- Collectl-based analysis allows you to view all system metrics, and how they change over time

Case Study 2: CX for MSI

- CX matrix decomposition applied to mass spectrometry data from bioimaging (Spark implementation from NERSC and AMPLab)
 - Analysis of 1 TB Mass Spectrometry (MSI) dataset
 - Matrix with columns for each spatial location
 - Method: dimensionality reductions via CX factorization
 - Approximately factors *m* x *n* matrix A into *m* x *k* matrix C and *k* x *n* matrix X, where the *k* columns of C are drawn from A. The "rank" k is typically much less than n
 - Goal is to select the *k* columns of A such that CX is as close as possible to A.
 - These columns best "explain" the data in the matrix

• These types of matrix decomposition operations are also common in Machine Learning applications

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Comparison Platforms

Platform	Total Cores (Haswell)	Core Frequency	Interconnect	DRAM	SSDs/ node	Platform	Total Runtime
Amazon EC2 r3.8xlarge	960 (30 nodes x 32 per-node)	2.5 GHz	10 Gigabit Ethernet	256 GB	2 x 320 GB	Amazon EC2	24.0 min
						XC40 w/ tmpfs &	23.1 min
Cray XC40	960 (30 nodes x 32 per-node)	2.3 GHz	Aries	256 GB	None	Lustre	
						XC40 w/ tmpfs	18.1 min
Athena early prototype	960 (40 nodes x 24 per-node)	2.5 GHx	Aries	128 GB	1 x 800 GB	Athena early prototype	15.2 min

Two options for XC40 scratch space: DRAM tmpfs, or tmpfs & Lustre blend

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Performance Analysis via Event Logs

Platform	Total Runtime	Load Time	Time per iteration	Average Local Task	Average Aggregation Task	Average Network Wait
Amazon EC2	24.0 min	92 sec	161 sec	4.4 sec	27.1 sec	21.7 sec
Cray XC40 w/ tmpfs & Lustre	23.1 min	139 sec	125 sec	3.5 sec (max: 12!)	6.8 sec	1.1 sec
Cray XC40 w/ tmpfs	18.1 min	137 sec	94 sec	3.0 sec	7.3 sec	1.5 sec
Athena prototype	15.2 min	53 sec	92 sec	2.8 sec	9.9 sec	2.7 sec

• Workload: Load MSI dataset; 5 iterations, each with local stage (compute local sums) and aggregation stage

• Observations:

- Load times faster on machines with local SSD storage
- Aggregation stage tasks (shuffle read) much faster on Aries-based systems
- Network wait on XC40 was lower than Athena, due to better peak TCP bandwidth
- All tmpfs, or fast local SSDs sped up local task time (shuffle write)
- Mixing Lustre and tmpfs adds long tail to shuffle write time distribution, creating stragglers that slow iterations

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Advantages of Log Analysis

Application level view

- What tasks are bottlenecks
- Where applications are spending their time (e.g., garbage collection, serialization, compression, waiting at barriers, etc)

Tools integrated with the Spark/Hadoop/etc ecosystem

- WebUI
- Visualizations that have application-level information (stages, operations, etc)
- User familiarity

Analysis of TCP Bandwidth w/ iperf3



Message length (bytes)

- Communication in open source analytics frameworks is typically over TCP (for portability)
- Aries performs well, especially with new kernel. Peak performance hit at ~ 8K-16K.



- Picked two shuffle senstive applications CX and GraphX PageRank
 - CX is more uniform (sending matrix columns) than PageRank (variable sized edge lists)
 - Both have a number of large data packets
 - CX: 58% at least 21KB
 - PageRank: 46% at least 16KB

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- System metrics data from collect1
- Application log analysis
- Network performance (TCP)
- Looked at two benchmarks
 - HiBench suite
 - CX (NERSC implementation)

Paper discusses performance improvement possibilities

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