# Experiences Running and Optimizing the Berkeley Data Analytics Stack on Cray Platforms

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**Cray Inc.**

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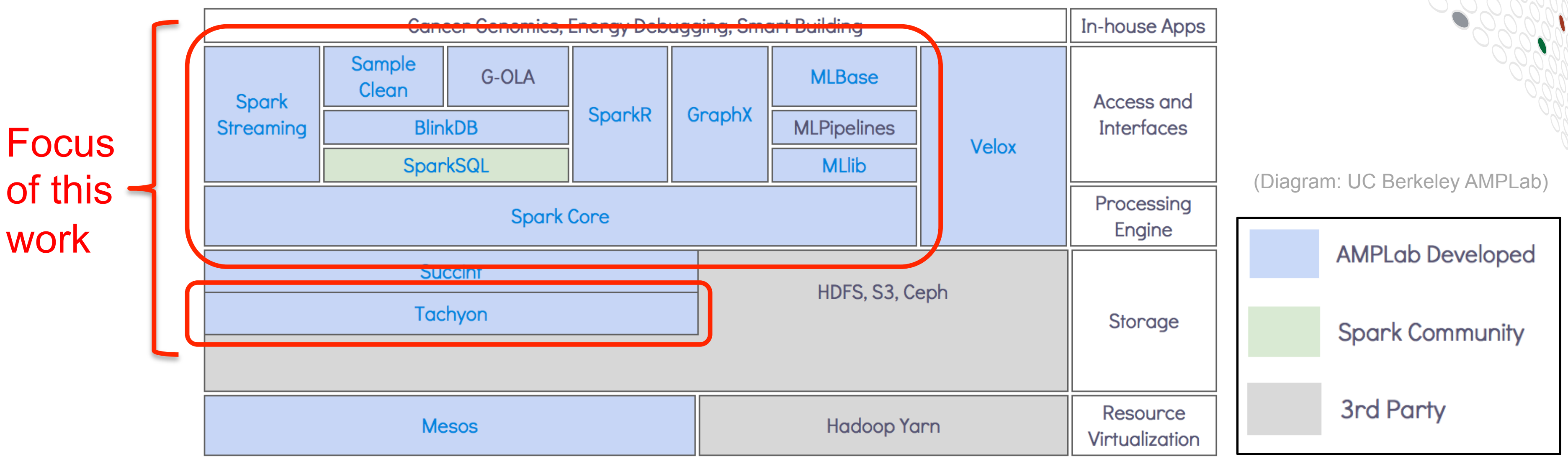
# Berkeley Data Analytics Stack (BDAS)

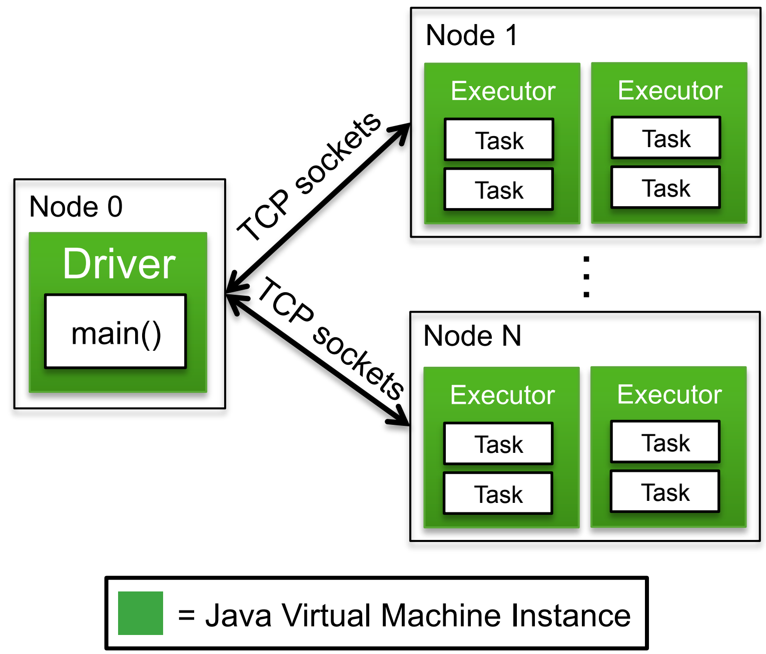



(Diagram: UC Berkeley AMPLab)

- **Spark in-memory analytics framework**
  - Includes modules for graph analysis, SQL, machine learning, and streaming
- **Tachyon distributed in-memory file system**
- **Mesos cluster manager**

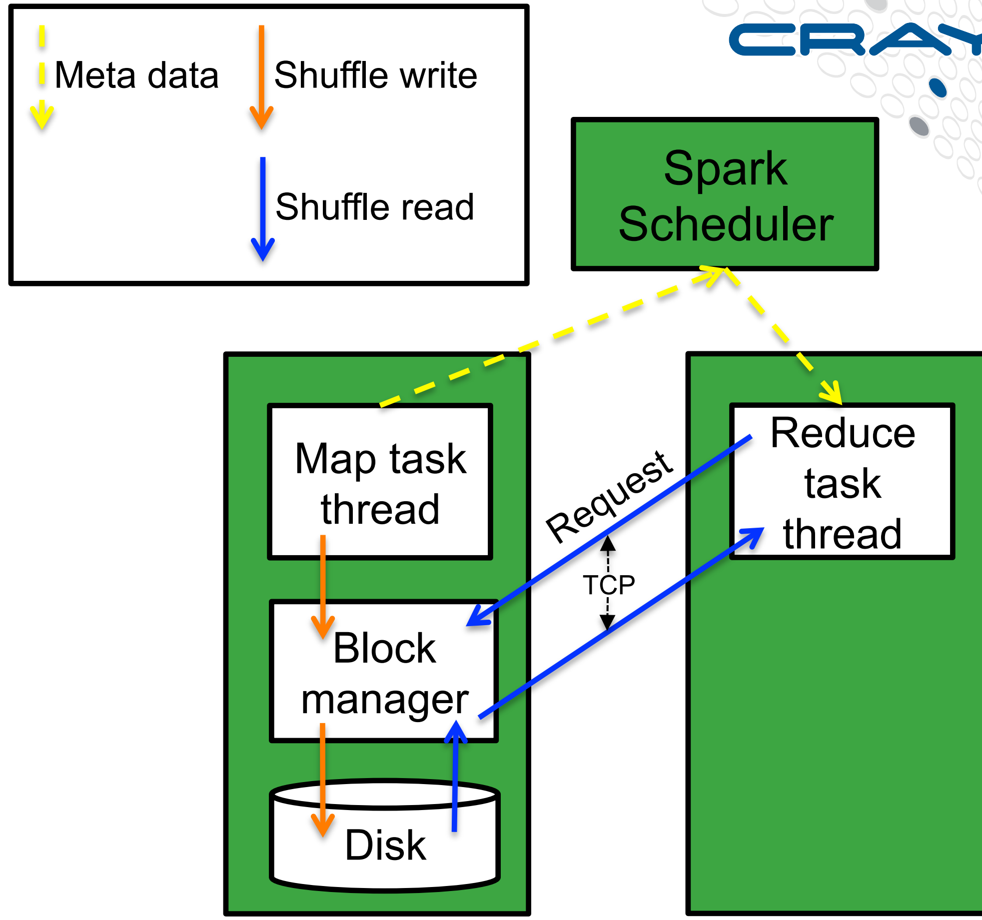
# Spark Execution Model

- **Master-slave parallelism**
- **Driver (master)**
  - Executes main
  - Distributes RDDs & tasks to executors
- **Resilient Distributed Dataset (RDD)**
  - Spark's primary data abstraction
  - Partitioned amongst executors
  - Fault-tolerant via lineage
- **Executors (slaves)**
  - Lazily execute tasks (operations on partitions of the RDD)
  - Global all-to-all shuffles for data exchange



# Spark Shuffle

- **All data exchanges between executors implemented via *shuffle***
  - Senders ("mappers") send data to block managers; block managers write to disks, tell scheduler *how much* destined for each reducer
  - Barrier until all mappers complete shuffle writes
  - Receivers ("reducers") request data from block managers *that have data for them*; block managers read and send



# Spark Programming Model: Example

Create array of {1, 2, …, 1,000,000}

Partition array into a 40-partition RDD distributed across executor nodes.

(Can also create from file.)

Spark *transformation* (modify data in RDDs)

Spark *action* (return result to driver)

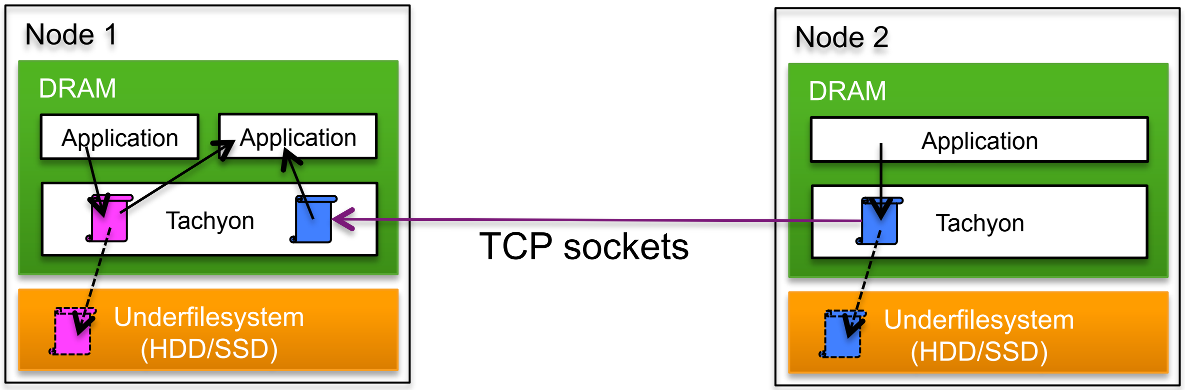
```
val arr1M = Array.range(1,1000001)
val rdd1M = sc.parallelize(arr1M, 40)
val evens = rdd1M.filter(
              a => (a%2) == 0
            )
evens.take(5)

>>> Array[Int] = Array(2, 4, 6, 8, 10)
```

compute

Lazy Evaluation: No computation until result requested

# Tachyon




- **Distributed in-memory filesystem**
  - HDD/SSD I/O replaced with DRAM loads and stores
- **Fault tolerance via:**
  - Asynchronous checkpoints to (persistent) underfilesystem
  - Persistent *lineage* tracking

# Spark and Tachyon on Cray Systems

- **This paper reports our experiences running and optimizing BDAS on three Cray systems**
  - Urika-XA Exterme Analytics Platform
    - 48 dual socket nodes, 16-core Haswell, FDR Infiniband, 800 GB SSD and 1TB HDD on every node, 128 GB DRAM/node
    - Cloudera Distribution of Hadoop 5.3, w/ Spark 1.2
  - Prototype Aries-based system with node-local SSDs
    - 43 dual socket nodes, 12-core Haswell, Cray Aries, 800 GB SSD and 1TB HDD on every node, 128 GB DRAM/node
    - Spark 1.3 and Tachyon 0.6.1 on top of CentOS 6.4
  - XC 40
    - Used 43 nodes, dual 16-core Haswell, Cray Aries interconnect, 128 GB DRAM/node
    - Spark 1.3 in Cluster Compatibility Mode (CCM)

# Configuring Spark for Cray Systems

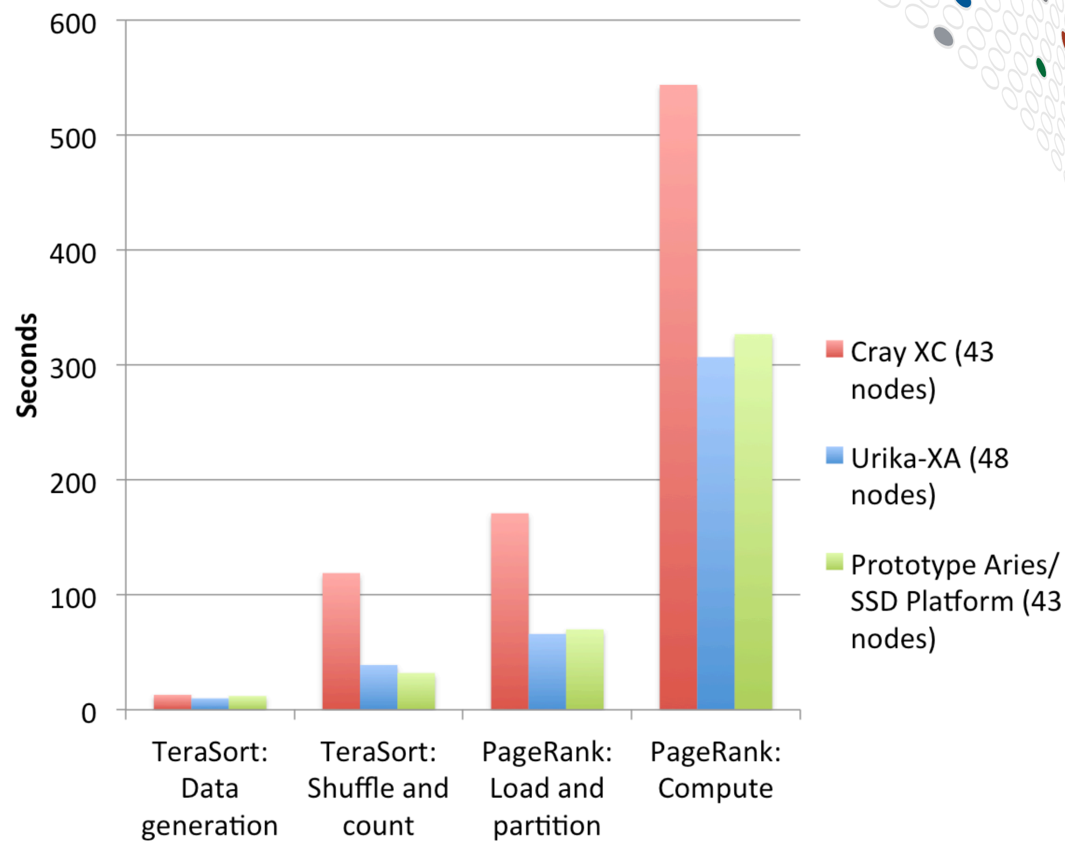
- **Spark Shuffle: responsible for data movement between executors**
  - File I/O is often shuffle bottleneck
  - **Sort-based shuffle**: consolidates intermediate files; friendlier to OS cache
  - **Urika-XA, Prototype Aries system**: moved shuffle files to local SSDs
  - **XC systems**: placed shuffle files in local RAM disk
    - Has tendency to fill RAM, so allocated secondary shuffle directory on Lustre
- **Studying additional configs related to network capabilities**
  - Default parameters tuned for commodity interconnects: willing to spend a lot of compute time to save on network traffic
  - Does this make sense with a more capable interconnect?
  - Recent research (Ousterhout et al, NSDI '15 in May) indicates network tuning may have gone to far – compute now the bottleneck…

# Configuring Spark Memory Usage

- **Need to balance memory usage between Spark, Virtual Machines/Interpreters, OS file buffer**
  - Extra executor memory minimizes spills to disk
  - Leaving "slack" in Java heap => less garbage collection overhead
  - Extra memory not used by applications => larger OS file buffer (improves shuffle performance)
  - On XC, more RAM disk space improves shuffles
  - Best performance in our tests: typically ~50% of total memory to executors

# Spark Results

- **Local SSDs provide large benefit**
  - Aries prototype and Urika-XA SSDs vs XC RAM disk
  - Preventing RAM disk exhaustion requires backing with Lustre
- **Recent results (post-paper) show we can cut another 25% by eliminating compresssion**



# Tachyon Results

| Dataset | Size | Lustre to GraphRDD | Tachyon to GraphRDD | Tachyon Load Speedup |
|---|---|---|---|---|
| LiveJournal | 1.0 GB | 13.8 seconds | 5.4 seconds | 2.6x |
| Twitter | 24.3 GB | 41.1 seconds | 19.4 seconds | 2.1x |

- **Compared loading GraphX edgelist file from Lustre vs Tachyon**
  - Flushed OS file caches between runs
- **At least 2x speedup from Tachyon**

# Potential Future Optimizations

- **Replace TCP sockets with native Aries communication**
  - **High-performance Big Data project at Ohio State**: Hadoop, HDFS, and Spark via RDMA over Infiniband
  - **Unstructured Data Acellerator (UDA) plugin (Mellanox, Auburn University)**: Hadoop MapReduce Shuffle over Infiniband
- **Explore causes of RAM disk exhaustion on XC**
  - Appears to fill up quicker than should
  - Currently round robin betweek RAM/Lustre … bias towards RAM?
  - Investigating Spark code w/ AMPLab assistance
  - Or, move shuffle files to DataWarp

# Potential Future Optimizations

- **Integrate optimized libraries and engines**
  - Linear algebra common in MLLib (Spark machine learning) – AMPLab sped up perfomance by swapping in optimized linear algebra libraries
  - Cray Graph Engine (see CUG paper, talk earlier this week) outperforms GraphX algorithms by 10x
  - Investigate calling Cray libraries and integerating with CGE
- **Continue investigation of Compute/Network configuration tradeoffs**
  - Compression
  - Locality wait
  - Speculation
  - Max MB in flight

# Summary

- **Paper describes our experiences running Spark and Tachyon across a variety of Cray platforms**
- **Investigated configurations, tuning, and potential optimizations**
  - Network/compute tradeoffs
  - Shuffle improvements
  - Tigher integration of Cray libraries, engines
- **Questions? Contact the authors (mikeri@cray.com, kristyn@cray.com), or Venkat Krishnamurthy <venkat@cray.com>.**