Sunrise or Sunset: Exploring the Design Space of Big Data Software Stacks

Panel Presentation at HPBDC ‘17

by

Dhabaleswar K. (DK) Panda
The Ohio State University
E-mail: panda@cse.ohio-state.edu

http://www.cse.ohio-state.edu/~panda
Q1: Are Big Data Software Stacks Mature or Not?

• Big Data software stacks like Hadoop, Spark and Memcached have been there for multiple years
  – Hadoop – 11 years (Apache Hadoop 0.1.0 released on April, 2006)
  – Spark – 5 years (Apache Spark 0.5.1 released on June, 2012)
  – Memcached – 14 years (Initial release of Memcached on May 22, 2003)

• Increasingly being used in production environments

• Optimized for commodity clusters with Ethernet and TCP/IP interface

• Not yet able to take full advantage of modern cluster and/or HPC technologies
Data Management and Processing on Modern Clusters

- Substantial impact on designing and utilizing data management and processing systems in multiple tiers
  - Front-end data accessing and serving (Online)
    - Memcached + DB (e.g. MySQL), HBase
  - Back-end data analytics (Offline)
    - HDFS, MapReduce, Spark
Who Are Using Hadoop?

- Focuses on large data and data analysis
- Hadoop (e.g. HDFS, MapReduce, RPC, HBase) environment is gaining a lot of momentum
- [http://wiki.apache.org/hadoop/PoweredBy](http://wiki.apache.org/hadoop/PoweredBy)
Spark Ecosystem

- Generalize MapReduce to support new apps in same engine
- Two Key Observations
  - General task support with DAG
  - Multi-stage and interactive apps require faster data sharing across parallel jobs

Spark Ecosystem:

- BlinkDB
- Spark Streaming (real-time)
- GraphX (graph)
- MLlib (Machine Learning)
- Caffe, TensorFlow, BigDL, etc. (Deep Learning)

Spark ecosystem components:

- Spark
- Standalone
- Apache Mesos
- YARN
Who Are Using Spark?

• Focuses on large data and data analysis with in-memory techniques
• Apache Spark is gaining a lot of momentum
• http://spark.apache.org/powered-by.html
Q2: What are the Main Driving forces for New-generation Big Data Software Stacks?
Increasing Usage of HPC, Big Data and Deep Learning

Convergence of HPC, Big Data, and Deep Learning!!!
How Can HPC Clusters with High-Performance Interconnect and Storage Architectures Benefit Big Data and Deep Learning Applications?

- Can the bottlenecks be alleviated with new designs by taking advantage of HPC technologies?
- What are the major bottlenecks in current Big Data processing and Deep Learning middleware (e.g. Hadoop, Spark)?
- Can RDMA-enabled high-performance interconnects benefit Big Data processing and Deep Learning?
- Can HPC Clusters with high-performance storage systems (e.g. SSD, parallel file systems) benefit Big Data and Deep Learning applications?
- How much performance benefits can be achieved through enhanced designs?
- How to design benchmarks for evaluating the performance of Big Data and Deep Learning middleware on HPC clusters?

Bring HPC, Big Data processing, and Deep Learning into a “convergent trajectory”!
Can We Run Big Data and Deep Learning Jobs on Existing HPC Infrastructure?
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Q3: What Chances are Provided for the Academia Communities in Exploring the Design Spaces of Big Data Software Stacks?
Designing Communication and I/O Libraries for Big Data Systems: Challenges

Applications

Big Data Middleware (HDFS, MapReduce, HBase, Spark, gRPC/TensorFlow, and Memcached)

Benchmarks

Programming Models (Sockets)

RDMA Protocols

Communication and I/O Library

Point-to-Point Communication

Threaded Models and Synchronization

Virtualization (SR-IOV)

I/O and File Systems

QoS & Fault Tolerance

Performance Tuning

Networking Technologies (InfiniBand, 1/10/40/100 GigE and Intelligent NICs)

Commodity Computing System Architectures (Multi- and Many-core architectures and accelerators)

Storage Technologies (HDD, SSD, NVM, and NVMe-SSD)
The High-Performance Big Data (HiBD) Project

- RDMA for Apache Spark
- RDMA for Apache Hadoop 2.x (RDMA-Hadoop-2.x)
  - Plugins for Apache, Hortonworks (HDP) and Cloudera (CDH) Hadoop distributions
- RDMA for Apache HBase
- RDMA for Memcached (RDMA-Memcached)
- RDMA for Apache Hadoop 1.x (RDMA-Hadoop)
- OSU HiBD-Benchmarks (OHB)
  - HDFS, Memcached, HBase, and Spark Micro-benchmarks
- [http://hibd.cse.ohio-state.edu](http://hibd.cse.ohio-state.edu)
- Users Base: 230 organizations from 30 countries
- More than 21,800 downloads from the project site

Available for InfiniBand and RoCE
Also run on Ethernet

Network Based Computing Laboratory

High-Performance Big Data

The Ohio State University
RDMA for Apache Hadoop 2.x Distribution

- High-Performance Design of Hadoop over RDMA-enabled Interconnects
  - High performance RDMA-enhanced design with native InfiniBand and RoCE support at the verbs-level for HDFS, MapReduce, and RPC components
  - Enhanced HDFS with in-memory and heterogeneous storage
  - High performance design of MapReduce over Lustre
  - Memcached-based burst buffer for MapReduce over Lustre-integrated HDFS (HHH-L-BB mode)
  - Plugin-based architecture supporting RDMA-based designs for Apache Hadoop, CDH and HDP
  - Easily configurable for different running modes (HHH, HHH-M, HHH-L, HHH-L-BB, and MapReduce over Lustre) and different protocols (native InfiniBand, RoCE, and IPoIB)

- Current release: 1.1.0
  - Based on Apache Hadoop 2.7.3
  - Compliant with Apache Hadoop 2.7.1, HDP 2.5.0.3 and CDH 5.8.2 APIs and applications
  - Tested with
    - Mellanox InfiniBand adapters (DDR, QDR, FDR, and EDR)
    - RoCE support with Mellanox adapters
    - Various multi-core platforms
    - Different file systems with disks and SSDs and Lustre

http://hibd.cse.ohio-state.edu
Different Modes of RDMA for Apache Hadoop 2.x

- **HHH**: Heterogeneous storage devices with hybrid replication schemes are supported in this mode of operation to have better fault-tolerance as well as performance. This mode is enabled by default in the package.
- **HHH-M**: A high-performance in-memory based setup has been introduced in this package that can be utilized to perform all I/O operations in-memory and obtain as much performance benefit as possible.
- **HHH-L**: With parallel file systems integrated, HHH-L mode can take advantage of the Lustre available in the cluster.
- **HHH-L-BB**: This mode deploys a Memcached-based burst buffer system to reduce the bandwidth bottleneck of shared file system access. The burst buffer design is hosted by Memcached servers, each of which has a local SSD.
- **MapReduce over Lustre, with/without local disks**: Besides, HDFS based solutions, this package also provides support to run MapReduce jobs on top of Lustre alone. Here, two different modes are introduced: with local disks and without local disks.
- **Running with Slurm and PBS**: Supports deploying RDMA for Apache Hadoop 2.x with Slurm and PBS in different running modes (HHH, HHH-M, HHH-L, and MapReduce over Lustre).
RDMA for Apache Spark Distribution

• High-Performance Design of Spark over RDMA-enabled Interconnects
  – High performance RDMA-enhanced design with native InfiniBand and RoCE support at the verbs-level for Spark
  – RDMA-based data shuffle and SEDA-based shuffle architecture
  – Support pre-connection, on-demand connection, and connection sharing
  – Non-blocking and chunk-based data transfer
  – Off-JVM-heap buffer management
  – Easily configurable for different protocols (native InfiniBand, RoCE, and IPoIB)

• Current release: 0.9.4
  – Based on Apache Spark 2.1.0
  – Tested with
    • Mellanox InfiniBand adapters (DDR, QDR, FDR, and EDR)
    • RoCE support with Mellanox adapters
    • Various multi-core platforms
    • RAM disks, SSDs, and HDD
  – http://hibd.cse.ohio-state.edu
HiBD Packages on SDSC Comet and Chameleon Cloud

- RDMA for Apache Hadoop 2.x and RDMA for Apache Spark are installed and available on SDSC Comet.
  - Examples for various modes of usage are available in:
    - RDMA for Apache Hadoop 2.x: /share/apps/examples/HADOOP
    - RDMA for Apache Spark: /share/apps/examples/SPARK/
  - Please email help@xsede.org (reference Comet as the machine, and SDSC as the site) if you have any further questions about usage and configuration.

- RDMA for Apache Hadoop is also available on Chameleon Cloud as an appliance
  - https://www.chameleонcloud.org/appliances/17/

M. Tatineni, X. Lu, D. J. Choi, A. Majumdar, and D. K. Panda, Experiences and Benefits of Running RDMA Hadoop and Spark on SDSC Comet, XSEDE’16, July 2016
Performance Numbers of RDMA for Apache Hadoop 2.x – RandomWriter & TeraGen in OSU-RI2 (EDR)

Cluster with 8 Nodes with a total of 64 maps

- **RandomWriter**
  - **3x** improvement over IPoIB for 80-160 GB file size

- **TeraGen**
  - **4x** improvement over IPoIB for 80-240 GB file size
Performance Numbers of RDMA for Apache Hadoop 2.x – Sort & TeraSort in OSU-RI2 (EDR)

- **Sort**
  - 61% improvement over IPoIB for 80-160 GB data

- **TeraSort**
  - 18% improvement over IPoIB for 80-240 GB data

Cluster with 8 Nodes with a total of 64 maps and 14 reduces

Cluster with 8 Nodes with a total of 64 maps and 32 reduces
Design Overview of Spark with RDMA

• Design Features
  – RDMA based shuffle plugin
  – SEDA-based architecture
  – Dynamic connection management and sharing
  – Non-blocking data transfer
  – Off-JVM-heap buffer management
  – InfiniBand/RoCE support

• Enables high performance RDMA communication, while supporting traditional socket interface
• JNI Layer bridges Scala based Spark with communication library written in native code


Performance Evaluation on SDSC Comet – SortBy/GroupBy

- InfiniBand FDR, SSD, 64 Worker Nodes, 1536 Cores, (1536M 1536R)
- RDMA vs. IPoIB with 1536 concurrent tasks, single SSD per node.
  - SortBy: Total time reduced by up to 80% over IPoIB (56Gbps)
  - GroupBy: Total time reduced by up to 74% over IPoIB (56Gbps)
Performance Evaluation on SDSC Comet – HiBench PageRank

32 Worker Nodes, 768 cores, PageRank Total Time

64 Worker Nodes, 1536 cores, PageRank Total Time

- InfiniBand FDR, SSD, 32/64 Worker Nodes, 768/1536 Cores, (768/1536M 768/1536R)
- RDMA vs. IPoIB with 768/1536 concurrent tasks, single SSD per node.
  - 32 nodes/768 cores: Total time reduced by 37% over IPoIB (56Gbps)
  - 64 nodes/1536 cores: Total time reduced by 43% over IPoIB (56Gbps)
Evaluation with BigDL on RDMA-Spark

- VGG training model on the CIFAR-10 dataset
- Evaluated on SDSC Comet supercomputer
- Initial Results: RDMA-based Spark outperforms default Spark over IPoIB by a factor of 4.58x
Design Overview of NVM and RDMA-aware HDFS (NVFS)

- **Design Features**
  - RDMA over NVM
  - HDFS I/O with NVM
    - Block Access
    - Memory Access
  - Hybrid design
    - NVM with SSD as a hybrid storage for HDFS I/O
  - Co-Design with Spark and HBase
    - Cost-effectiveness
    - Use-case

Evaluation with Hadoop MapReduce

- TestDFSIO on SDSC Comet (32 nodes)
  - Write: NVFS-MemIO gains by $4x$ over HDFS
  - Read: NVFS-MemIO gains by $1.2x$ over HDFS

- TestDFSIO on OSU Nowlab (4 nodes)
  - Write: NVFS-MemIO gains by $4x$ over HDFS
  - Read: NVFS-MemIO gains by $2x$ over HDFS
Overview of RDMA-Hadoop-Virt Architecture

- Virtualization-aware modules in all the four main Hadoop components:
  - **HDFS**: Virtualization-aware Block Management to improve fault-tolerance
  - **YARN**: Extensions to Container Allocation Policy to reduce network traffic
  - **MapReduce**: Extensions to Map Task Scheduling Policy to reduce network traffic
  - **Hadoop Common**: Topology Detection Module for automatic topology detection

- Communications in HDFS, MapReduce, and RPC go through RDMA-based designs over SR-IOV enabled InfiniBand

Evaluation with Applications

- 14% and 24% improvement with Default Mode for CloudBurst and Self-Join
- 30% and 55% improvement with Distributed Mode for CloudBurst and Self-Join
Deep Learning: New Challenges for MPI Runtimes

- Deep Learning frameworks are a different game altogether
  - Unusually large message sizes (order of megabytes)
  - Most communication based on GPU buffers
- How to address these newer requirements?
  - GPU-specific Communication Libraries (NCCL)
    - NVidia’s NCCL library provides inter-GPU communication
  - CUDA-Aware MPI (MVAPICH2-GDR)
    - Provides support for GPU-based communication
- Can we exploit CUDA-Aware MPI and NCCL to support Deep Learning applications?
Efficient Broadcast: MVAPICH2-GDR and NCCL

- NCCL has some limitations
  - Only works for a single node, thus, no scale-out on multiple nodes
  - Degradation across IOH (socket) for scale-up (within a node)
- We propose optimized MPI_Bcast
  - Communication of very large GPU buffers (order of megabytes)
  - Scale-out on large number of dense multi-GPU nodes
- Hierarchical Communication that efficiently exploits:
  - CUDA-Aware MPI_Bcast in MV2-GDR
  - NCCL Broadcast primitive

Large Message Optimized Collectives for Deep Learning

- MV2-GDR provides optimized collectives for large message sizes
- Optimized Reduce, Allreduce, and Bcast
- Good scaling with large number of GPUs
- Available with MVAPICH2-GDR 2.2GA
OSU-Caffe: Scalable Deep Learning

- Benefits and Weaknesses
  - Multi-GPU Training within a single node
  - Performance degradation for GPUs across different sockets
  - Limited Scale-out
- OSU-Caffe: MPI-based Parallel Training
  - Enable Scale-up (within a node) and Scale-out (across multi-GPU nodes)
  - Network on ImageNet dataset


OSU-Caffe is publicly available from: http://hidl.cse.ohio-state.edu

![Graph showing training time for GoogLeNet (ImageNet) on 128 GPUs]
Open Challenges in Designing Communication and I/O Middleware for High-Performance Big Data Processing

- High-Performance designs for Big Data middleware
  - NVM-aware communication and I/O schemes for Big Data
  - SATA-/PCIe-/NVMe-SSD support
  - High-Bandwidth Memory support
  - Threaded Models and Synchronization
  - Locality-aware designs

- Fault-tolerance/resiliency
  - Migration support with virtual machines
  - Data replication

- Efficient data access and placement policies

- Efficient task scheduling

- Fast deployment and automatic configurations on Clouds

- Optimization for Deep Learning applications
Sunrise or Sunset of Big Data Software?

Assuming 6:00 am as sunrise and 6:00 pm as sunset, We are at 8:00 am.
Thank You!

panda@cse.ohio-state.edu

http://www.cse.ohio-state.edu/~panda

Network-Based Computing Laboratory
http://nowlab.cse.ohio-state.edu/

The High-Performance Big Data Project
http://hibd.cse.ohio-state.edu/