



15th ANNUAL WORKSHOP 2019

HPNL: A HIGH-PERFORMANCE LIGHT WEIGHTED NETWORK LIBRARY FOR BIGDATA APPLICATION

Haodong Tang, Jian Zhang, Fred Zhang
{haodong.tang, jian.zhang, fred.zhang} @intel.com

Intel

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- Configurations: see performance benchmark test configurations.

AGENDA

- **Background and motivation**
- **RDMA enabling in bigdata software ecosystem**
- **Transportation agnostic messenger proposals – HPNL**
- **Optimizing Spark shuffle with HPNL and Persistent Memory**
- **Summary & Next steps**



BACKGROUND AND MOTIVATION

BACKGROUND AND MOTIVATIONS

■ Bigdata analytics software stack requires RDMA for higher performance

- Spark is expected to achieve high throughput & ultra-low latency for different workloads like ad-hoc query, real-time streaming, and machine learning
- There are bottlenecks to be improved in shuffle phase
- While RDMA networking can lead to orders of magnitude improvement, using VERB interface is a challenge for application development and porting

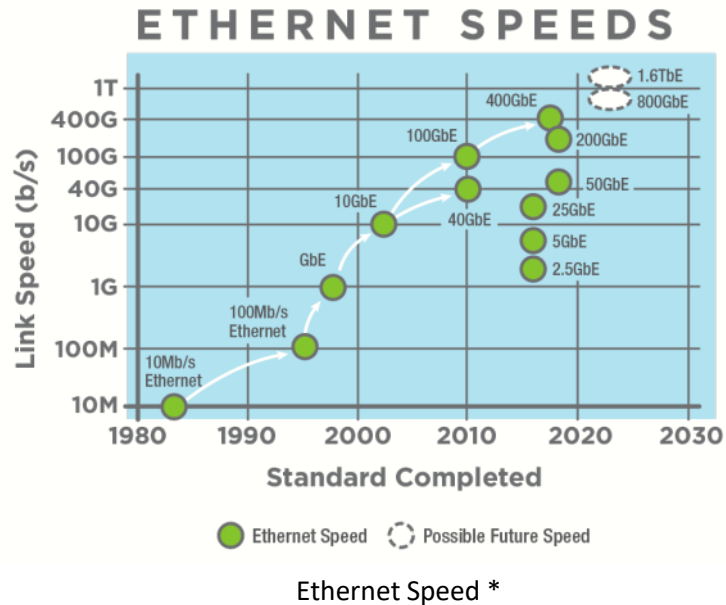
■ Motivations

- A light-weight network library built on Libfabric
- Protocol-independent networking framework that can easily run on all transportation protocols: TCP, RDMA, IB, OPA etc.
- Flexible interfaces & abstractions: C/JAVA API and high-level abstraction to let developer easily replace other TCP/IP based network library, like ASIO or Netty

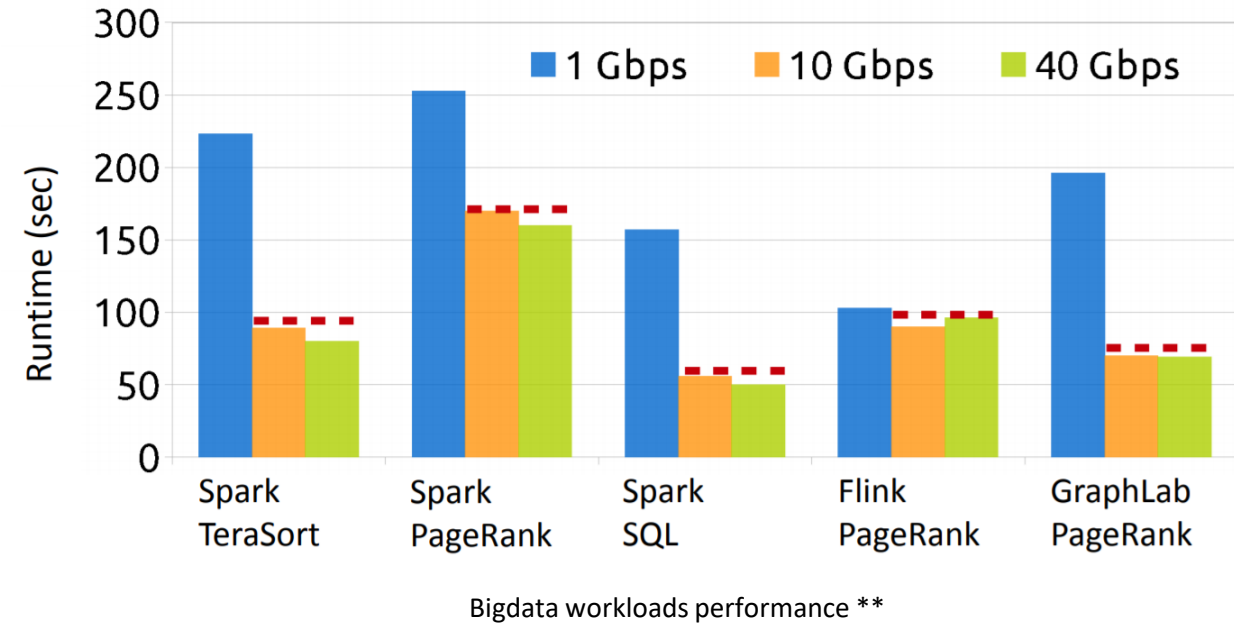
BIGDATA APPLICATION MEETS MODERN NETWORK TECHNOLOGY

■ Network interconnects have evolved

- Bandwidth from 1Gbps to 100Gbps
- Message RTT latency reduced by an order of magnitude



- BigData Application cannot benefit from new HW
- Network consecutive evolving doesn't result in application consecutive speedup.



Source

*: <https://ethernetalliance.org/the-2018-ethernet-roadmap>

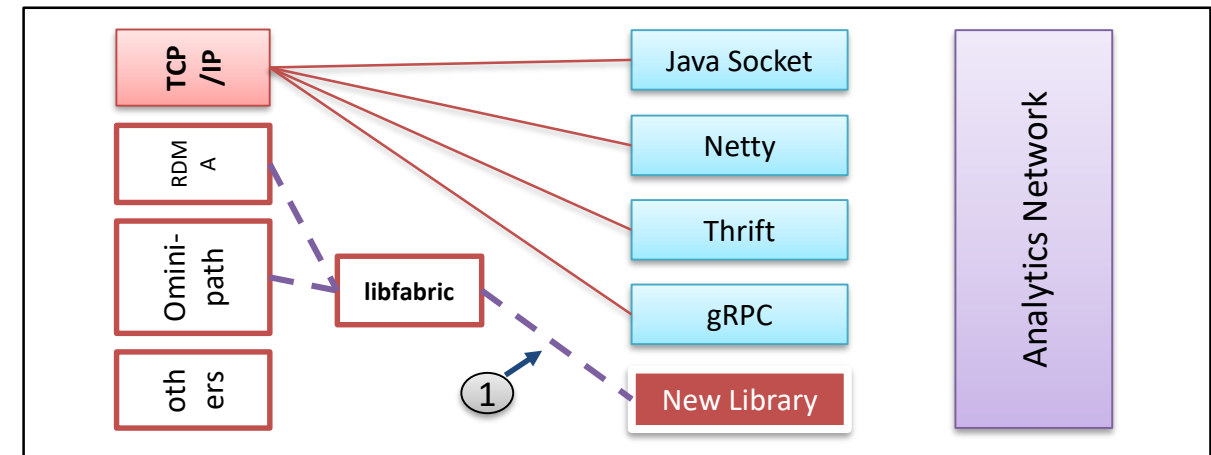
** : https://www.openfabrics.org/images/eventpresos/2017presentations/109_Crail_BMetzler.pdf



RDMA ENABLING IN BIGDATA ECOSYSTEM

APPROACH 1 – INTEGRATE LIBFABRIC INTO BIGDATA APP CASE BY CASE

- Existing projects for BigData w/ RDMA
 - SparkRDMA.
 - TeraSort benchmark shows **x2.63** overall reduced in execution time.*
 - HiDB project from OSU.
 - HiBench PageRank total time reduced by **37%-43%** over IPoIB.**
- Pros
 - Easy to integrate to one BigData application
- Cons
 - Hard to benefit all the BigData App, need to integrate case by case.
 - Can't enable cross-stack optimization.

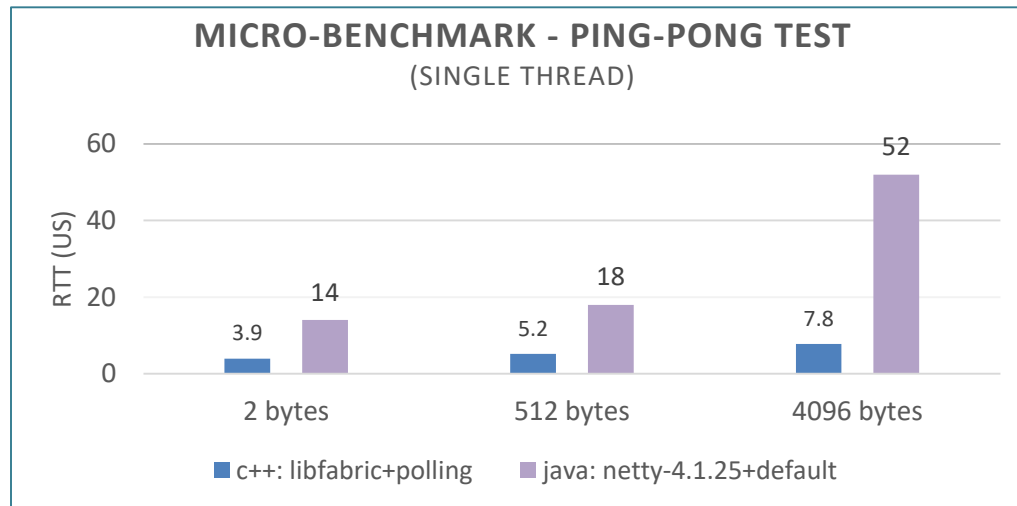


* <https://github.com/Mellanox/SparkRDMA>

** <http://hibd.cse.ohio-state.edu/performance/pagerank/>

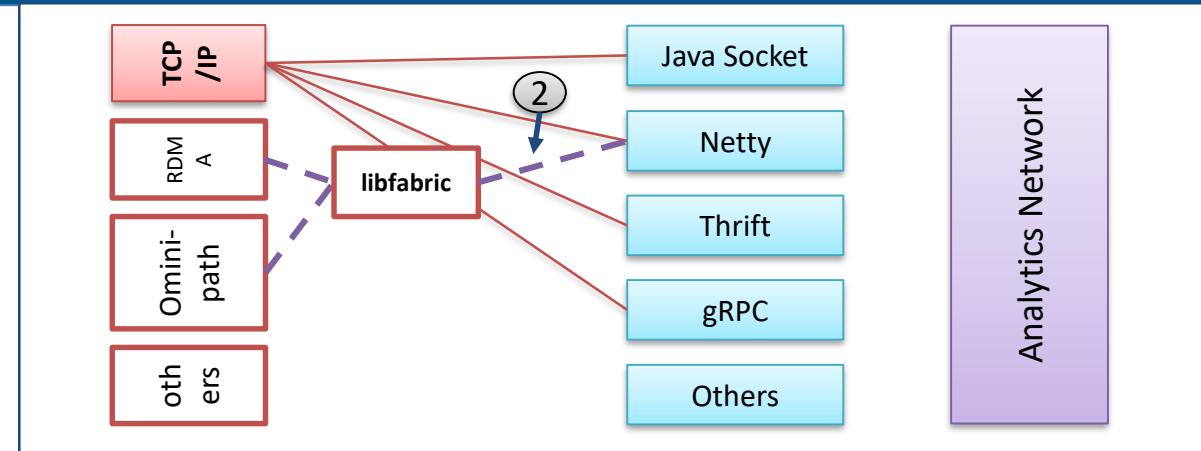
APPROACH 2 – INTEGRATE LIBFABRIC INTO EXISTING LIB

- **Netty*** is widely used in BigData application.
- **However, message transfer is more expensive than RDMA.**
 - Message RTT time is higher.
 - Consumes more CPU.



* <https://netty.io/index.html>

****** <https://netty.io/wiki/adopters.html>



Pros

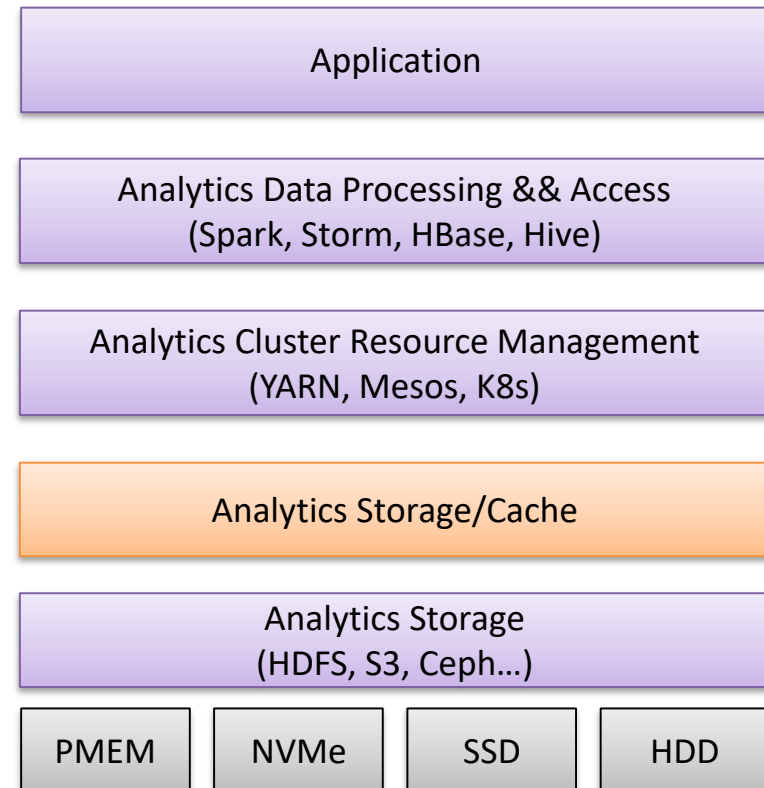
- When Netty supports RDMA & Omni-Path, all the BigData App based on Netty will benefit directly.

Cons

- Hard to implement all the interface in Netty transport layer.
- Can't enable cross-stack optimization.

APPROACH 3 – FULL STACK OPTIMIZATION FOR DATA STORAGE

- **Existing projects for BigData by this way.**
 - Crail from IBM.
 - [FlashNet](#): Flash/Network Stack Co-Design
 - [Octopus](#): An RDMA-enabled Distributed Persistent Memory File System
- **Pros**
 - Co-designed storage/network stack optimized to reduce cross-stack overhead between network and flash IO.

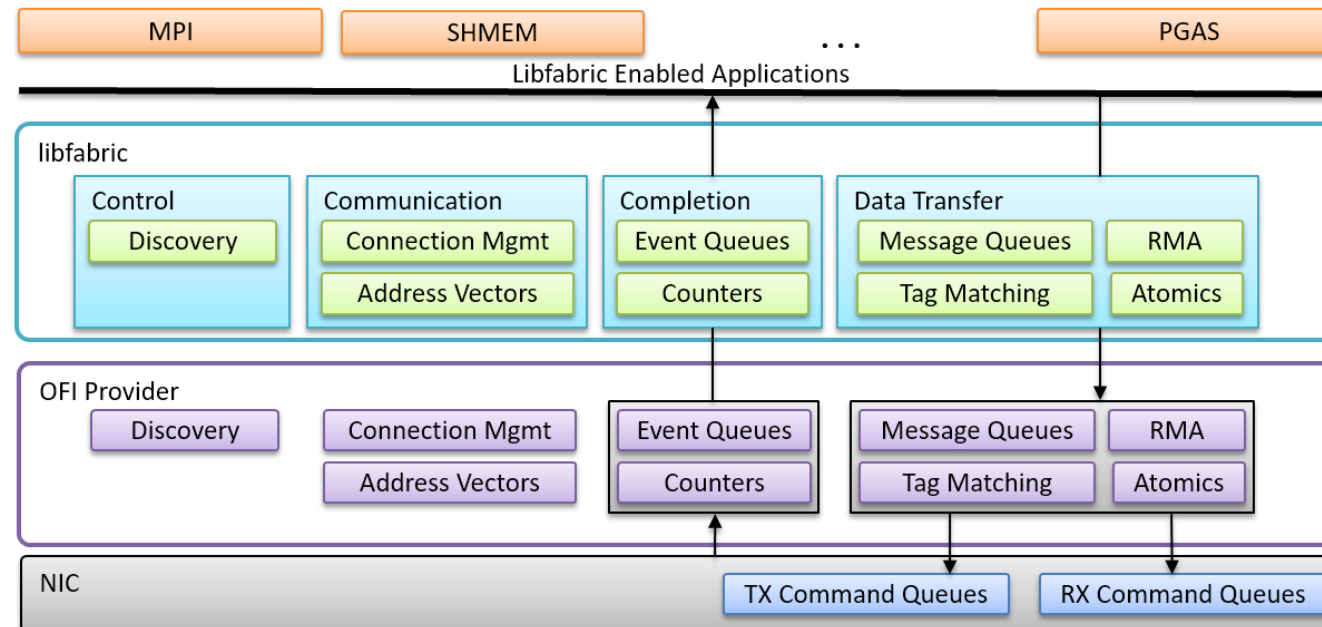




TRANSPORTATION AGNOSTIC MESSENGER– HIGH PERFORMANCE NETWORK LIBRARY (HPNL)

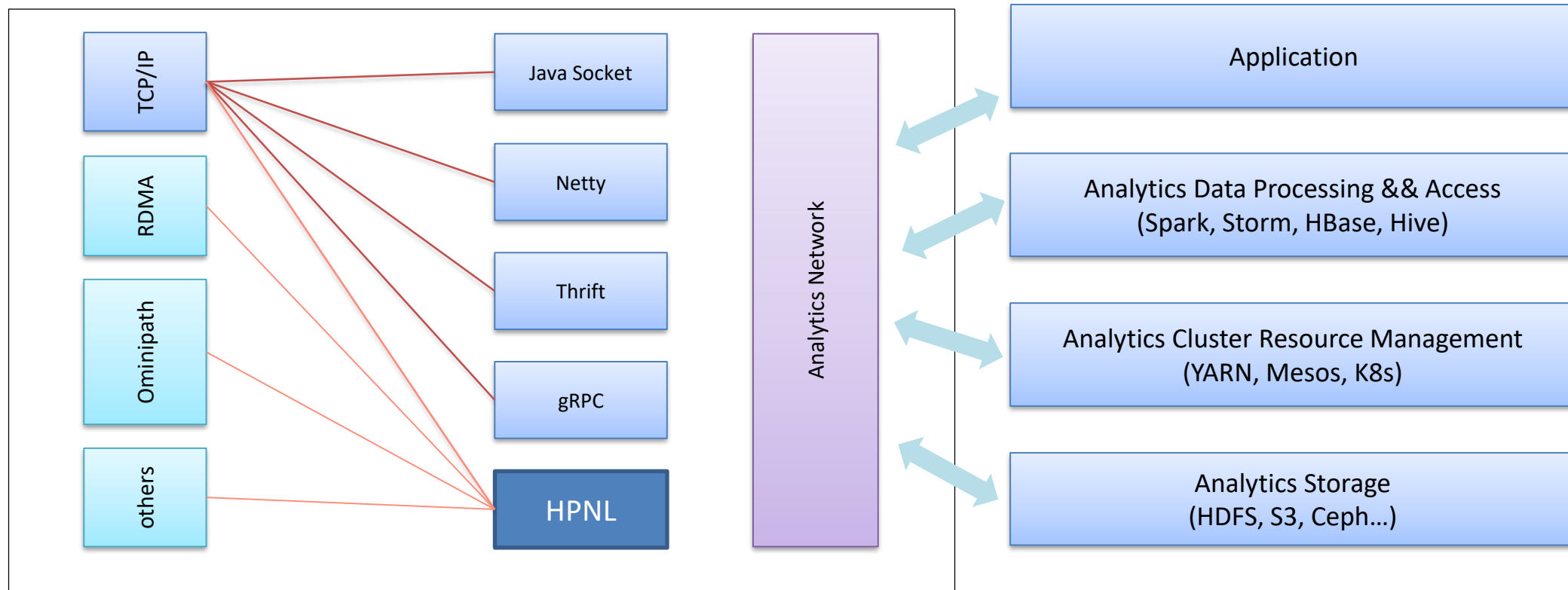
WHY LIBFABRIC?

- Libfabric is developed by the OFI Working Group, a subgroup of [OFA](https://ofiwg.github.io).
- Goals: to define interfaces that enable a tight semantic map between application and underlying fabric services.
- **Libfabric is friendly to application developers, transportation protocol agnostic, easy to port and migrate to new hardware.**



*source: <https://ofiwg.github.io/libfabric/>

WHERE DOES HPNL FIT IN THE BIGDATA STACK?



- **HPNL is a general-purpose network library and a appropriated choice to accelerate BigData application with HPC network technology.**

PREVIOUS WORK: RDMA IN CEPH

■ XIO Messenger.

- Based on Accelio, seamlessly supporting RDMA.
- Scalability issue.
- Merged to Ceph master three years ago, no support for now.

■ Async Messenger.

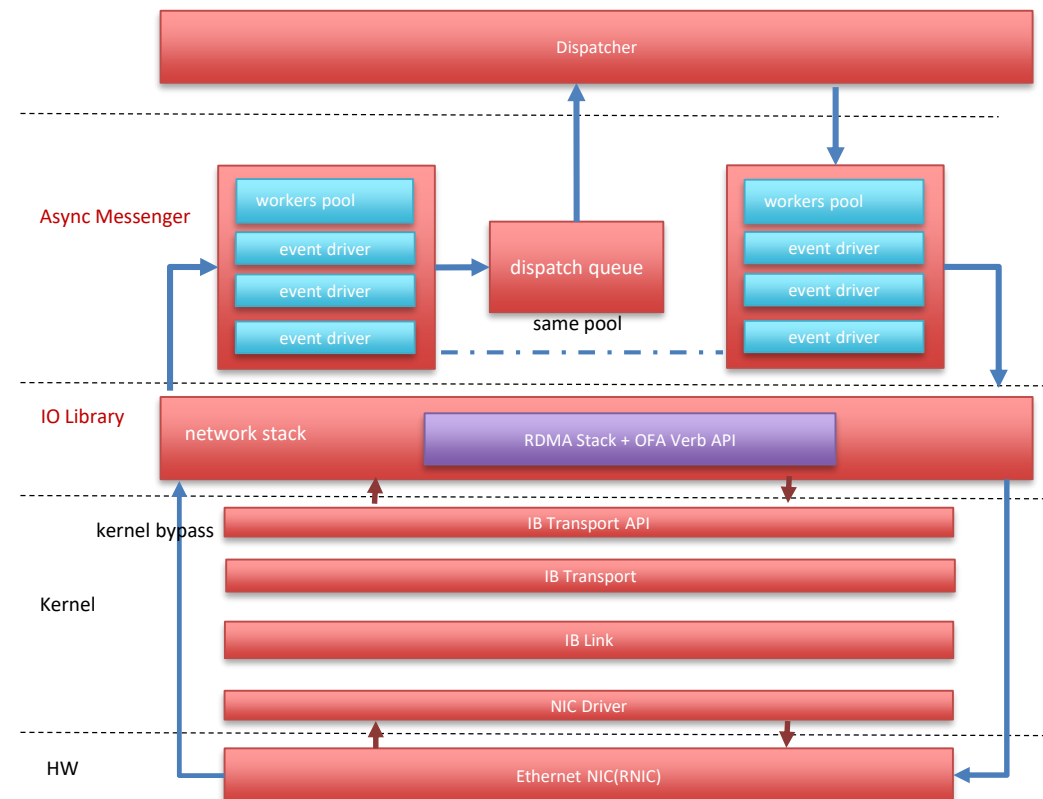
- Async Messenger is compatible with different network protocol, like Posix, RDMA and DPDK.
- Current RDMA implementation supports IB protocol.

■ We implemented iwrap based RDMA for Ceph and pushed to upstream *

- Showed 17% performance improvement for 4K random write compared with TCP/IP
- Connection management: RDMA-CM based RDMA connection management
- Queue pairs: centralized memory pool for recv queue (RQ)

■ Extended the work, build a developer friendly library for bigdata applications

* [Accelerating Ceph with RDMA and NVMe-OF: OFA 2018](#)



HPNL ARCHITECTURE

■ Zero-copy approach

- The HPNL buffer allowed to be directly used by application without copying data between HPNL buffer and application buffer.
- Thanks to RDMA, it supporting user-space to kernel-space zero-copy.

■ Threading model

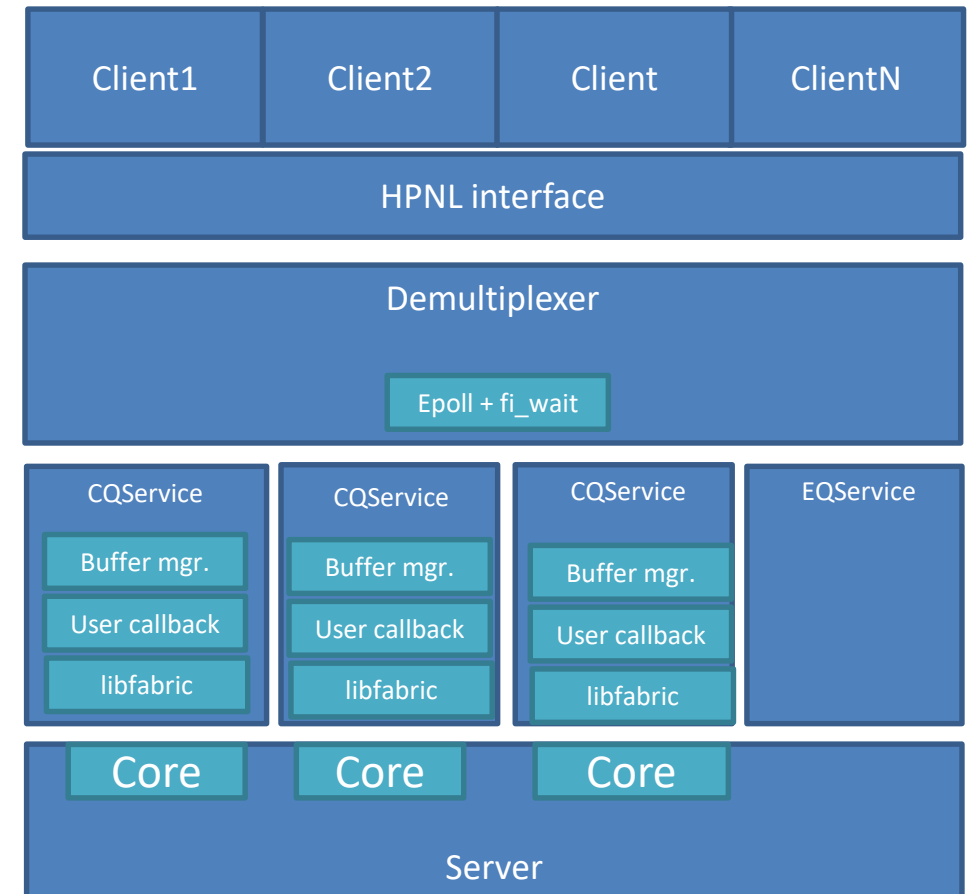
- Implements the Proactor model.
- Interrupt + polling approach to optimize HPNL thread.
- Supports thread binding to specific core.

■ HPNL interface

- C/C++ and Java interface.
- Supports send, receive, remote read, remote write semantics.
- Pluggable buffer management interface.
- Capable of using Persistent memory as RDMA buffer.

■ Open Source

- HPNL is Under internal opensource process, expected to be opensourced in Q2.



MICROBENCHMARK CONFIGURATION

■ Hardware

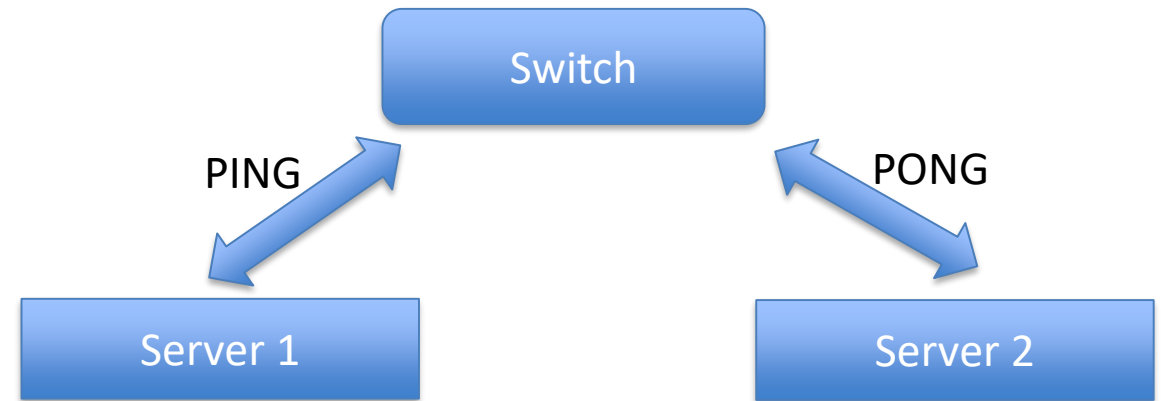
- Intel(R) Xeon(R) CPU E5-2699 v4 @ 2.20GHz
- Mellanox ConnectX-4 – RoCE V2
- Arista 7060 CX2-32S

■ Software

- HPNL Java interface with libfabric v1.6.0
- OFED
- CentOS 7

■ Micro benchmark Methodology

- Send/receive based Ping-pong test
- 1million times transfer of 4K sized message



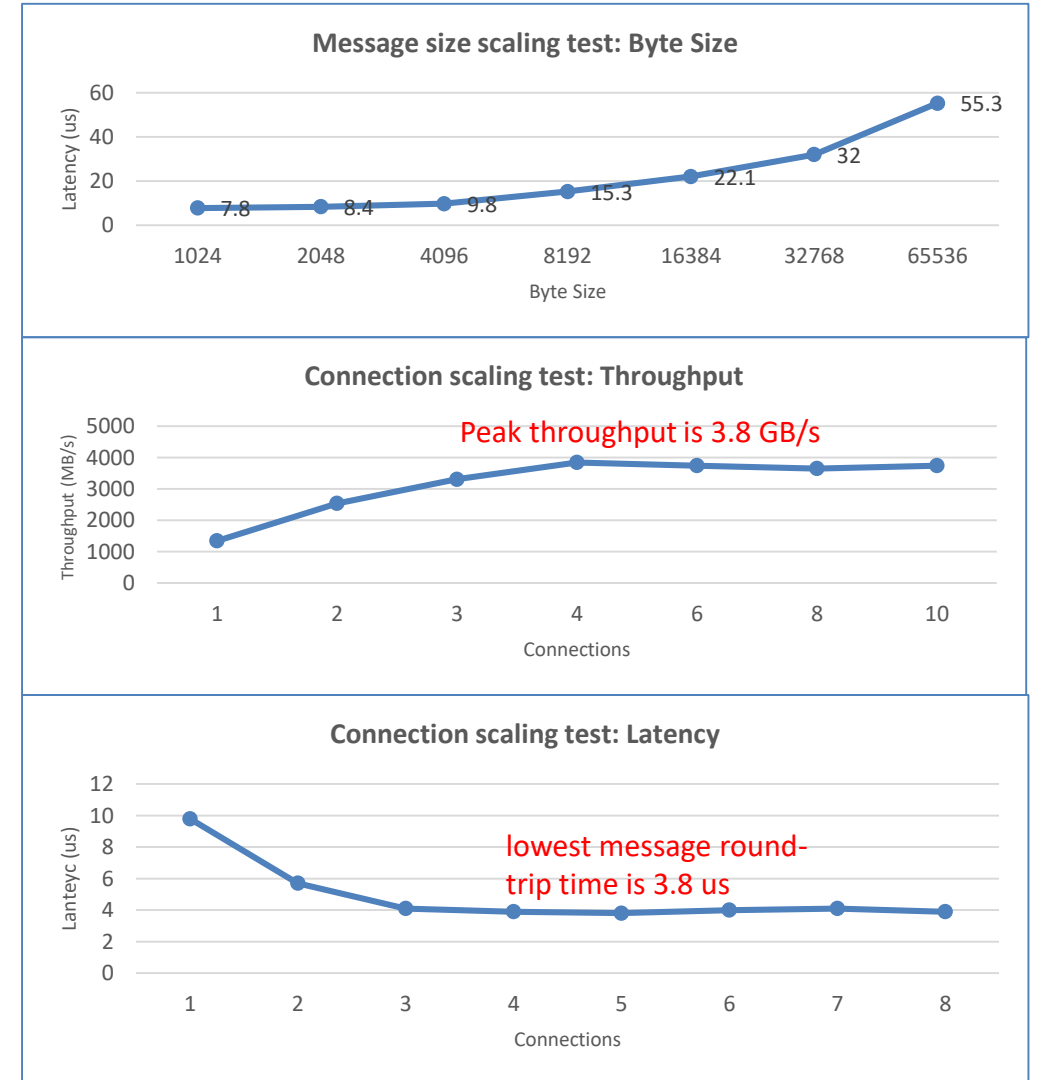
MICRO WORKLOADS PERFORMANCE

■ Test 1: message size scaling test, single thread

- Shows better performance than Netty or ASIO.

■ Test 2: Connection scaling test

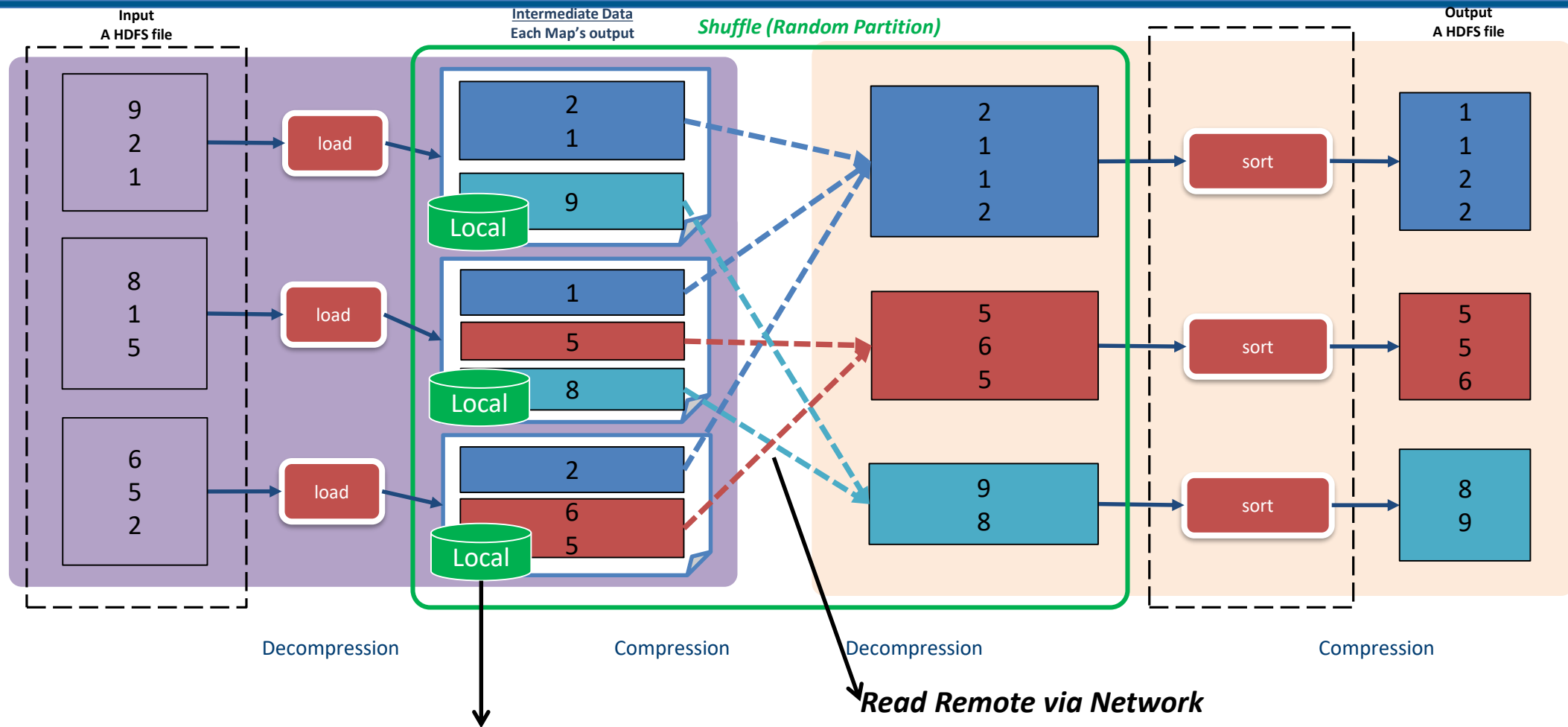
- Message size: 65536
 - Hits bandwidth limitation.
- Message size: 4096
 - Send/recv based interface shows round-trip time less than 4 us.





OPTIMIZING SPARK SHUFFLE WITH HPNL AND PERSISTENT MEMORY

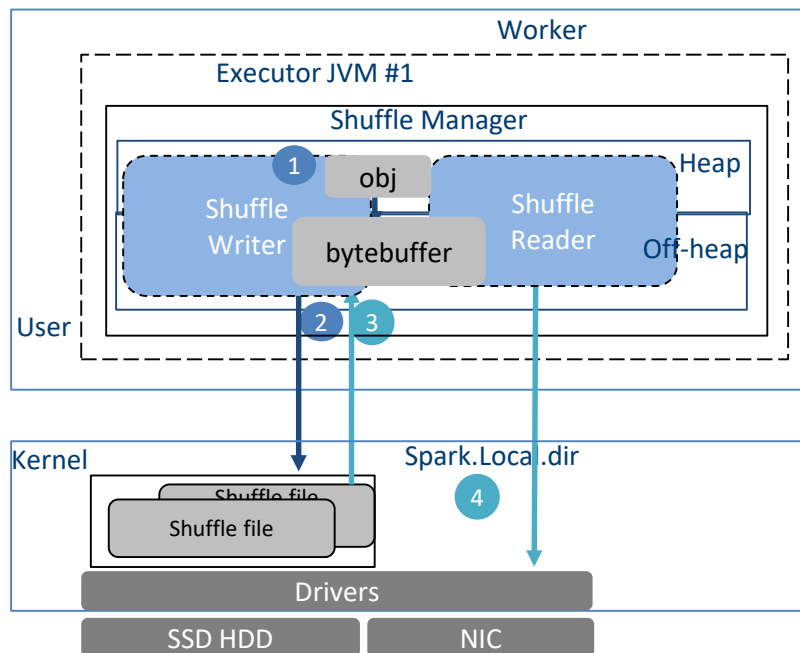
SPARK SHUFFLE



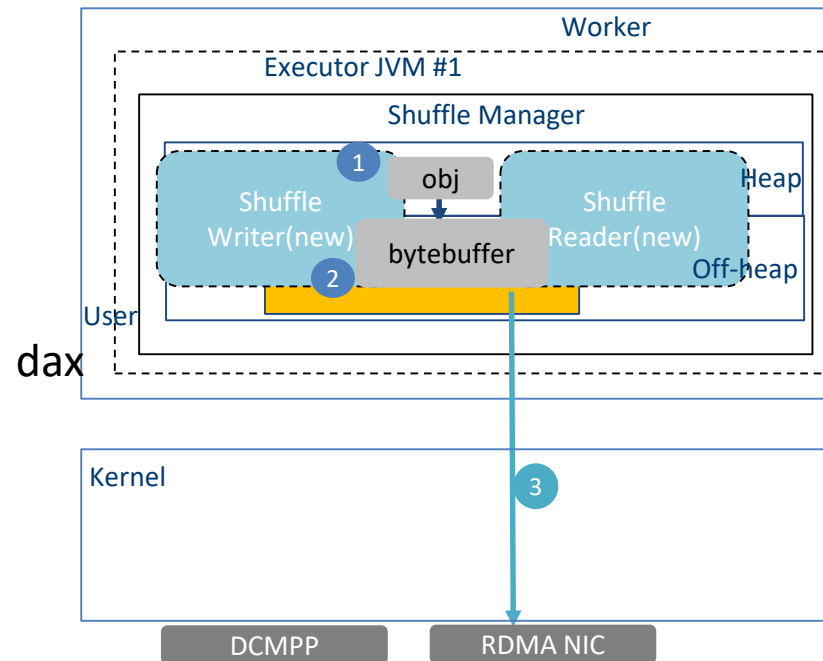
Write Local, can use shuffle service to cache the data.

<https://github.com/intel-hadoop/HiBench/blob/master/sparkbench/micro/src/main/scala/com/intel/sparkbench/micro/ScalaSort.scala>

SPARK-PMOF CO-DESIGN



1. Serialize obj to off-heap memory
2. Write to local shuffle dir
3. Read from local shuffle dir
4. Send to remote reader through TCP-IP
 - Lots of context switch
 - POSIX buffered read/write on shuffle disk
 - TCP/IP based socket send for remote shuffle read



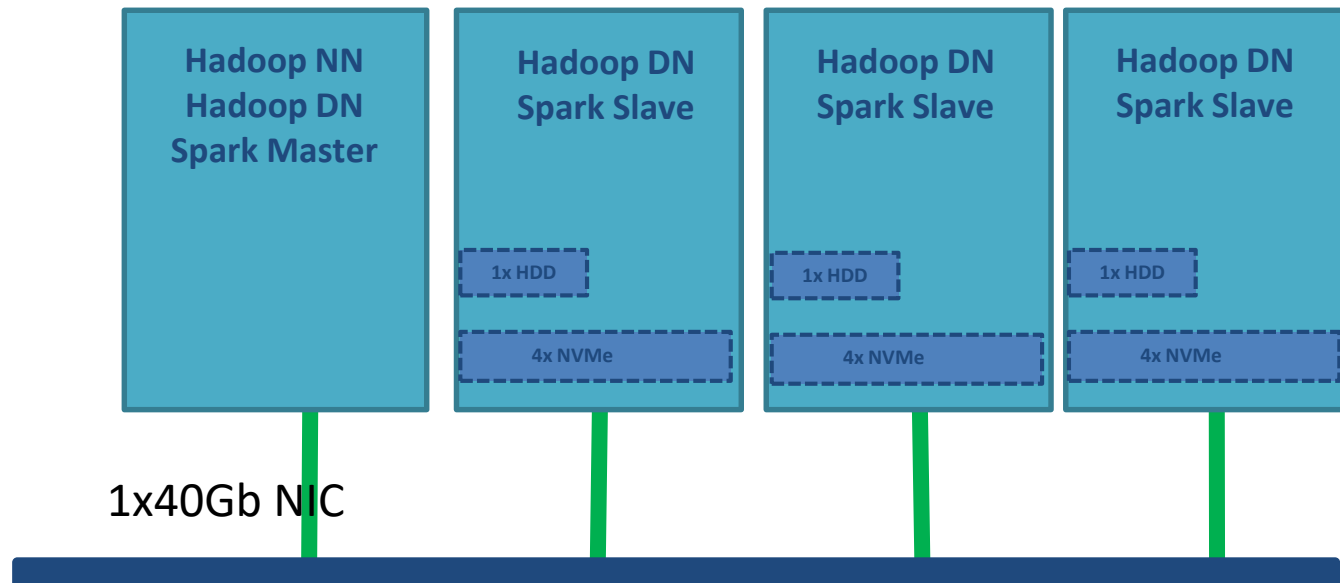
1. Serialize obj to off-heap memory
2. Persistent to DCMPP (pmem_memcpy_persistent)
3. Read from remote DCMPP through RDMA, DCMPP is used as RDMA memory buffer
 - No context switch
 - Efficient read/write on DCMPP
 - RDMA read for remote shuffle read

Shuffle write

Shuffle read

DCMPP

SYSTEM CONFIGURATION



3 Node cluster

Hardware:

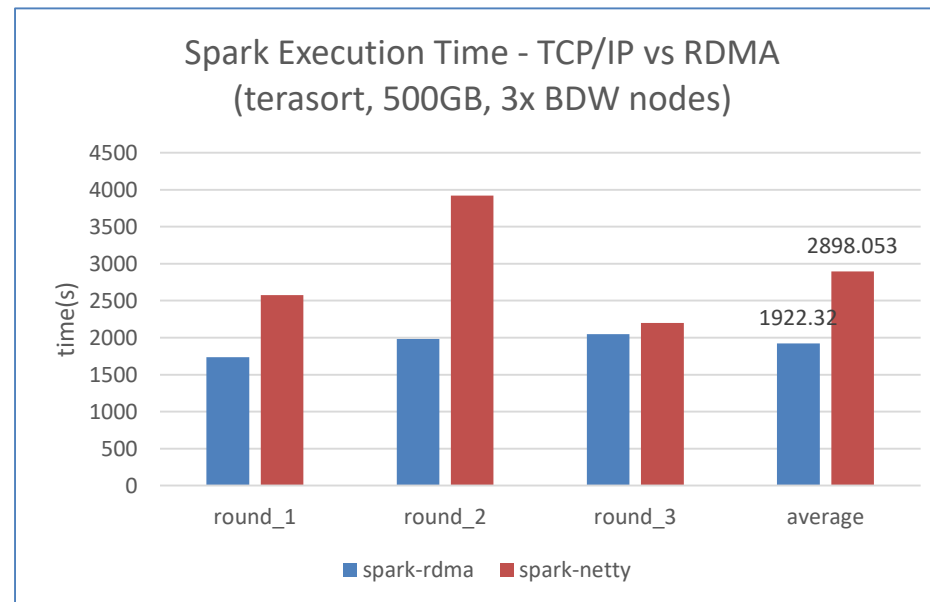
- Intel® Xeon™ processor E5 2699V4 @ 2.2GHz, 558GB Memory
- 1x Mellanox ConnectX-4 40Gb NIC
- 1x 1TB HDD for spark-shuffle
- 4x NVMe for HDFS

Software:

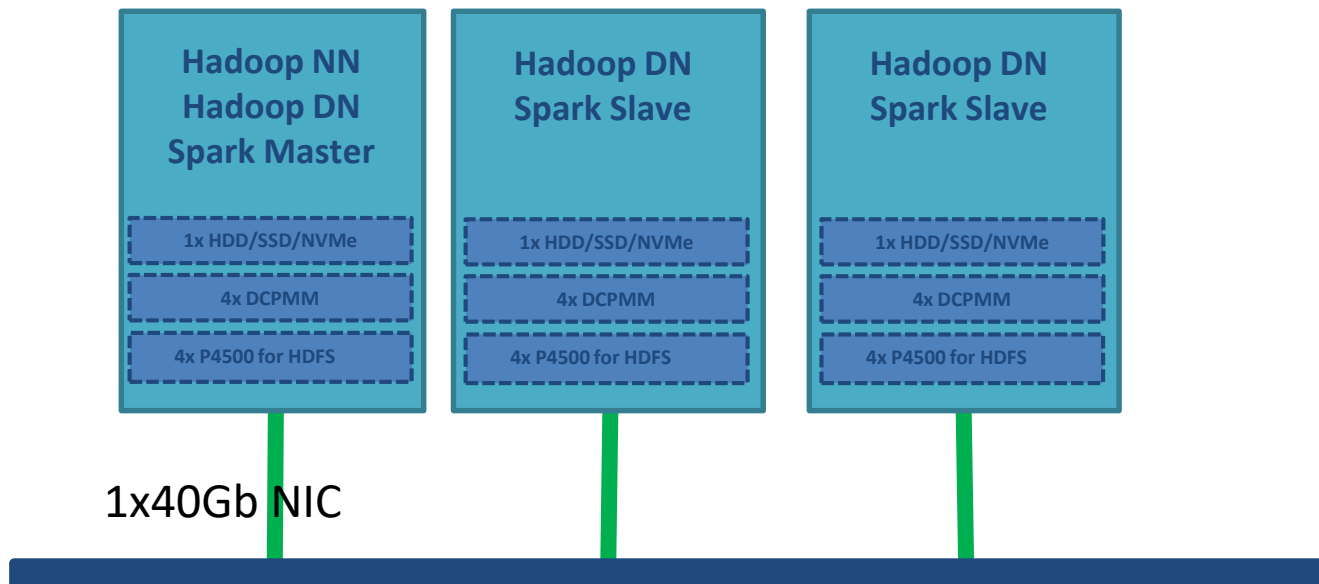
- Hadoop 2.7
- Spark 2.3
- CentOS 7
- HiBench TeraSort 500GB

RDMA PERFORMANCE BENEFITS FOR SPARK SHUFFLE

- **1.5x performance improvement**
 - And much stable!
 - Page cache impact on spark-netty performance



SYSTEM CONFIGURATION



3 Node cluster

Hardware:

- Intel(R) Xeon(R) Gold 6140 CPU @ 2.30GHz
- 1x Mellanox ConnectX-4 40Gb for shuffle
- 384 G MEM
- 1 x X722 for Hadoop
- 4x P4500 for HDFS
- 4x 256GB DCPMM
- 1x HDD/SSD (1x 400Gb DC S3700)/NVMe (1x P4500)/(4x 256GB) DCPMP for Shuffle

Software:

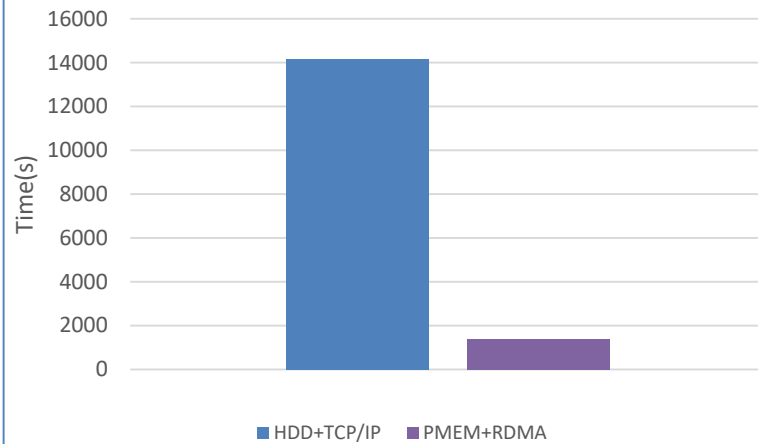
- Fedora 27
- Kernal 4.18.19-100.fc27.x86_64
- Hadoop 2.7
- Spark 2.3
- Libfabric 1.6.2
- MLNX_OFED_LINUX-4.5-1.0.1.0-fc27-x86_64

Workloads:

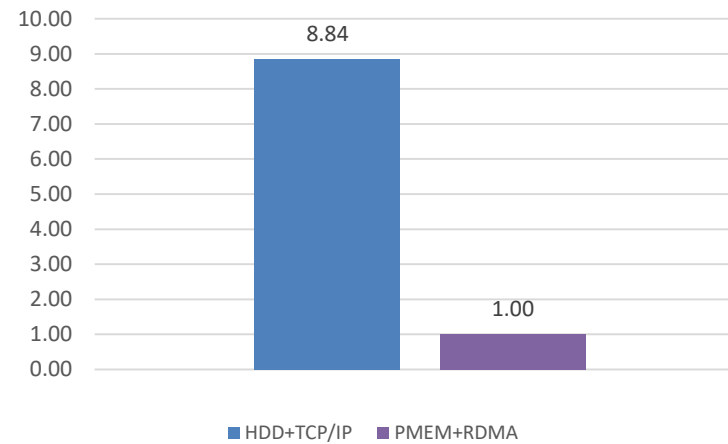
- Hibench terasort 1TB

PERFORMANCE SUMMARY

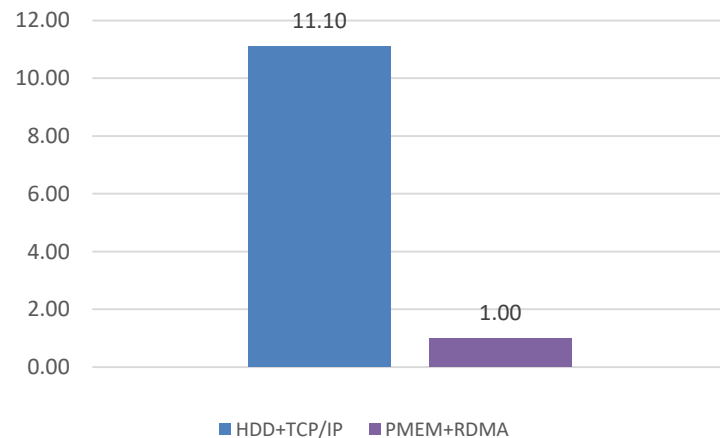
Spark TeraSort End-to-end Time



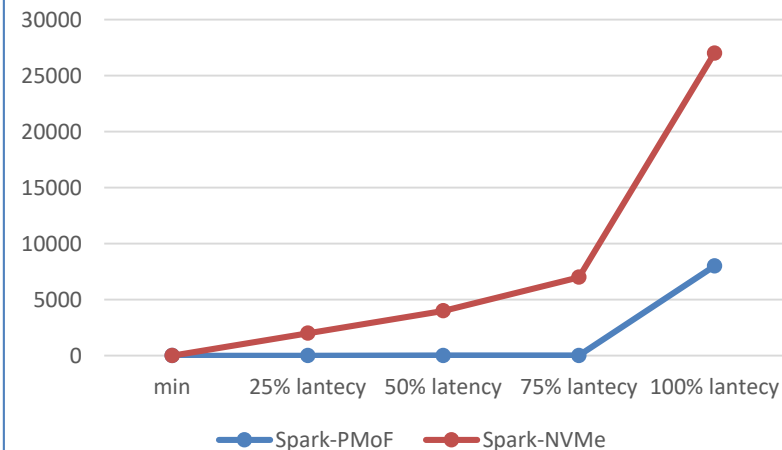
Terasort Stage 1 (Normalized)



Terasort Stage 2 (Normalized)



Read block time (ms)



■ PMoF vs. HDD

- PMEM and PMEM+RDMA are 9.17x and 9.10x faster than HDD respectively.
- However, the benefit over NVMe+TCP/IP is not very big
- Other opportunities:
 - Lower CPU utilization
 - Latency sensitive workloads – streaming

STAGE 2 PERFORMANCE BREAKDOWN (HDD+TCP/IP)

Summary Metrics for 1000 Completed Tasks

Metric	Min	25th percentile	Median	75th percentile	Max
Duration	3.7 min	11 min	13 min	14 min	22 min
Scheduler Delay	0 ms	0 ms	2 ms	3 ms	23 ms
Task Deserialization Time	2 ms	3 ms	3 ms	4 ms	1.0 s
GC Time	4 s	8 s	9 s	11 s	21 s
Result Serialization Time	0 ms	0 ms	0 ms	0 ms	2 ms
Getting Result Time	0 ms	0 ms	0 ms	0 ms	0 ms
Peak Execution Memory	0.0 B	0.0 B	0.0 B	0.0 B	0.0 B
Output Size / Records	632.9 MB / 6636259	874.1 MB / 9166014	951.7 MB / 9979334	1035.6 MB / 10858719	1329.5 MB / 13940317
Shuffle Read Blocked Time	2.5 min	8.5 min	9.7 min	11 min	15 min
Shuffle Read Size / Records	670.9 MB / 6636259	926.6 MB / 9166014	1008.8 MB / 9979334	1097.7 MB / 10858719	1409.2 MB / 13940317
Shuffle Remote Reads	596.7 MB	823.5 MB	896.0 MB	976.8 MB	1253.5 MB

STAGE 2 PERFORMANCE BREAKDOWN (PMEM+RDMA)

Summary Metrics for 1000 Completed Tasks

Metric	Min	25th percentile	Median	75th percentile	Max
Duration	36 s	1.0 min	1.1 min	1.3 min	1.7 min
Scheduler Delay	0 ms	3 ms	3 ms	4 ms	0.2 s
Task Deserialization Time	2 ms	4 ms	5 ms	6 ms	0.1 s
GC Time	2 s	9 s	11 s	13 s	26 s
Result Serialization Time	0 ms	0 ms	0 ms	0 ms	38 ms
Getting Result Time	0 ms	0 ms	0 ms	0 ms	0 ms
Peak Execution Memory	0.0 B	0.0 B	0.0 B	0.0 B	0.0 B
Output Size / Records	632.9 MB / 6636259	874.1 MB / 9166014	951.7 MB / 9979334	1035.6 MB / 10858719	1329.5 MB / 13940317
Shuffle Read Blocked Time	0 ms	2 ms	3 ms	5 ms	8 s
Shuffle Read Size / Records	670.9 MB / 6636259	926.6 MB / 9166014	1008.8 MB / 9979334	1097.7 MB / 10858719	1409.2 MB / 13940317
Shuffle Remote Reads	598.3 MB	820.3 MB	895.6 MB	976.8 MB	1256.8 MB

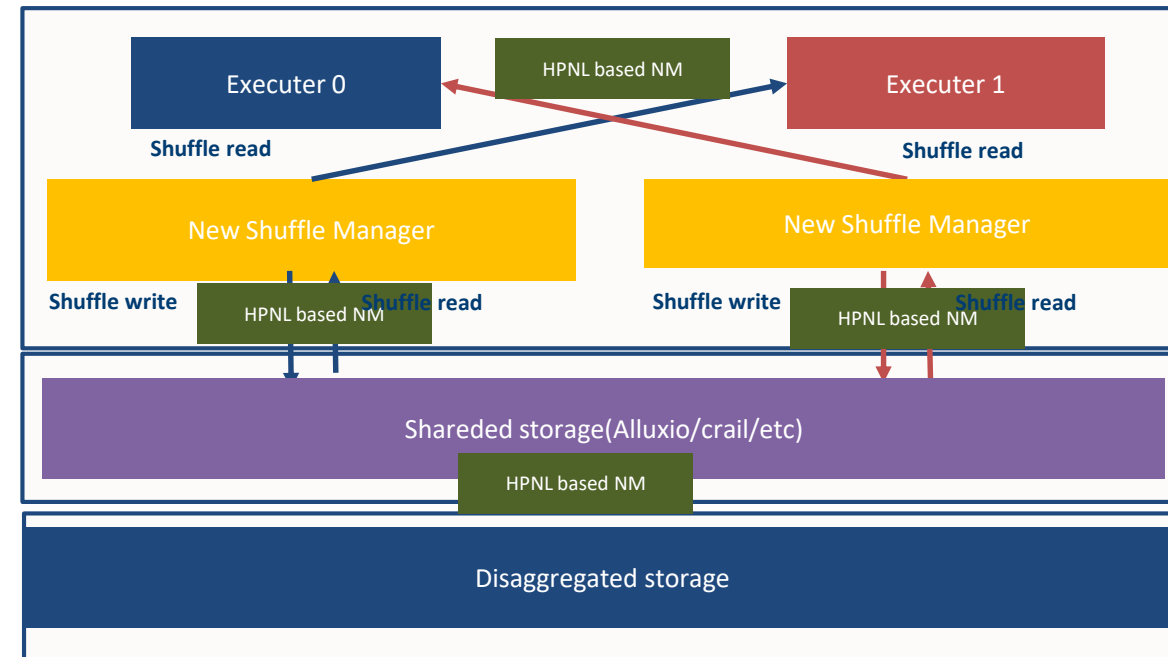
NEXT: HPNL INTEGRATION WITH EXTERNAL SHUFFLE CLUSTER

▪ Elastic Deployment with compute and storage disaggregation requires independent shuffle solution

- Shuffle I/O are decoupled from a specific network/storage.
- Shuffle read and write can be implemented using configurable network transports and backend storage

▪ External shuffle cluster

- Lots of on-going efforts making HCFS as shuffle: [[Spark-1529](#), [Spark-3685](#), [SPARK-25299](#)]
- And lots of customized solutions
- Independent HPNL library can be integrated with customized solutions
- Opensource version reference design based on HCFS shuffle manager and HDFS will come out soon





SUMMARY

SUMMARY & NEXT STEP

■ Summary

- Traditional TCP/IP stack can't benefit more and more Real-time BigData processing even with modern network hardware while RDMA has been proved as an effective way to speedup BigData workload from existing projects.
- HPNL is a transportation Agnostic high performance network library based on libfabric
- HPNL demonstrated significant performance advantage over TCP/IP for bigdata applications
 - 1.5x over TCP/IP for spark terasort
- Spark shuffle with HPNL and pmem delivers up to 9x performance improvement over traditional shuffle solution based on TCP/IP and HDD
- Persistent memory over fabrics with HPNL and pmem enables new workloads and new storage solutions
 - Latency sensitive workloads and external/remote shuffle cluster

■ Next step

- RPC with HPNL
- RDMA in external shuffle cluster



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THANK YOU

Haodong Tang, Jian Zhang, Fred Zhang

haodong.tang@intel.com, jian.zhang@intel.com, fred.zhang@intel.com

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[March, 2019]





BACKUP

BACKUP – SPARK PMOF TEST CONFIGURATIONS

■ Terasort 1TB:

- `hibench.spark.master yarn-client`
- `hibench.yarn.executor.num 12`
- `yarn.executor.num 12`
- `hibench.yarn.executor.cores 8`
- `yarn.executor.cores 8`
- `spark.shuffle.compress false`
- `spark.shuffle.spill.compress false`
- `spark.executor.memory 60g`
- `spark.executor.memoryoverhead 10G`
- `spark.driver.memory 80g`
- `spark.eventLog.compress = false`
- `spark.executor.extraJavaOptions=-XX:+UseG1GC`
- `spark.hadoop.yarn.timeline-service.enabled false`
- `spark.serializer org.apache.spark.serializer.KryoSerializer`
- `hibench.default.map.parallelism 200`
- `hibench.default.shuffle.parallelism 1000`