OPENFABRICS ALLIANCE

15th ANNUAL WORKSHOP 2019

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

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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

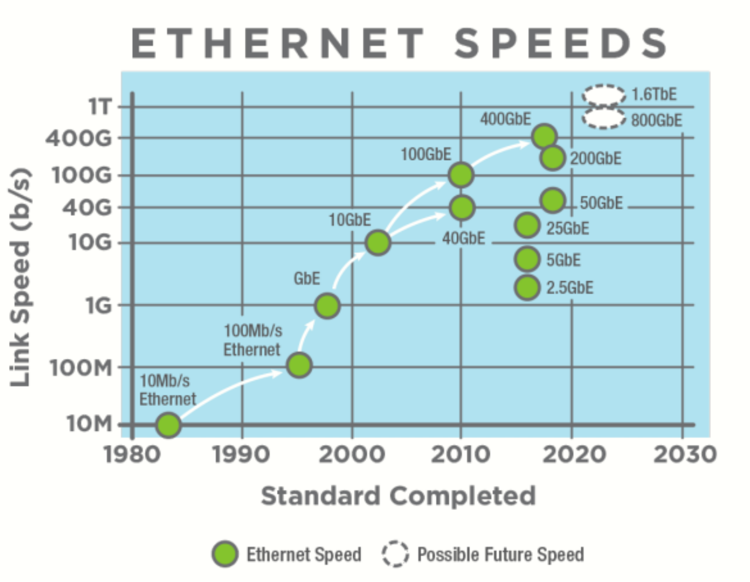
BACKGROUND AND MOTIVATION

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 leads 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

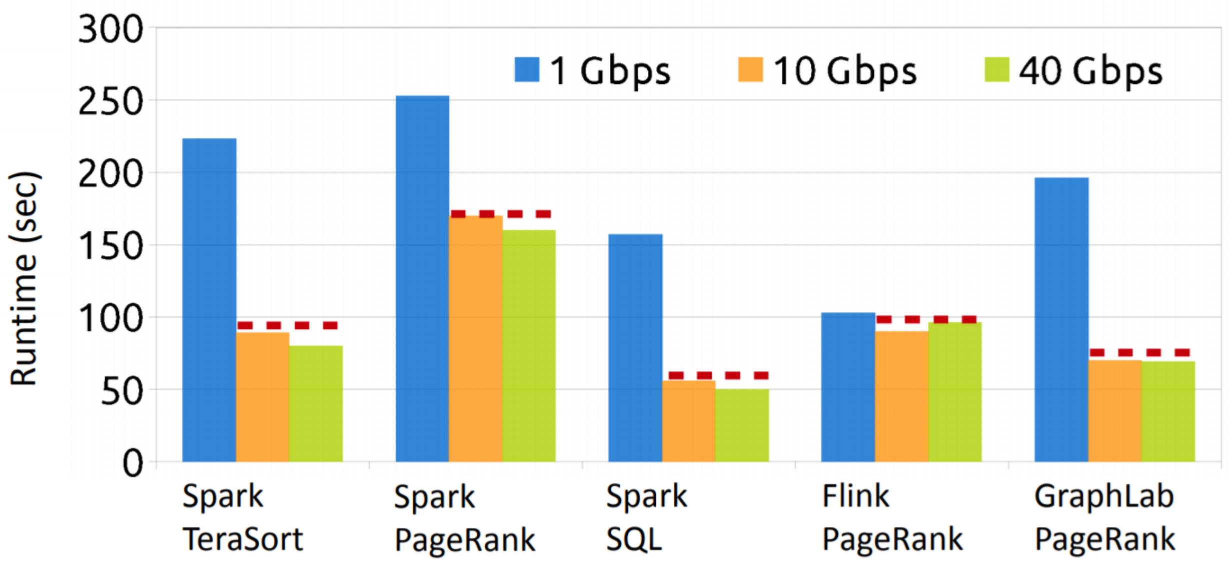
BIGDATA APPLICATION MEETS MODERN NETWORK TECHNOLOGY

- **Network interconnects have evolved**
  - Bandwidth from 1Gbps to 100Gbps
  - Message RTT latency reduced by an order of magnitude



Ethernet Speed *

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



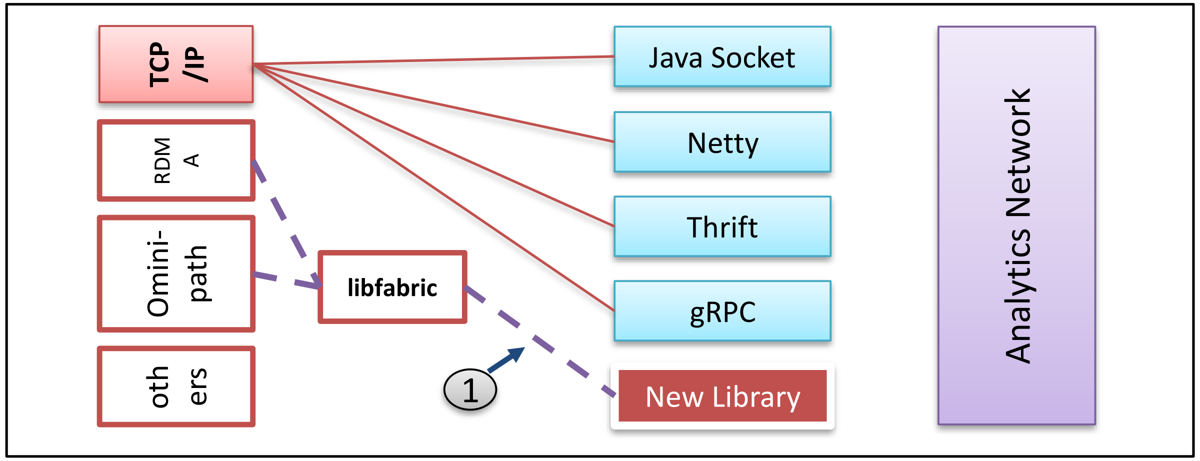
Bigdata workloads performance **

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

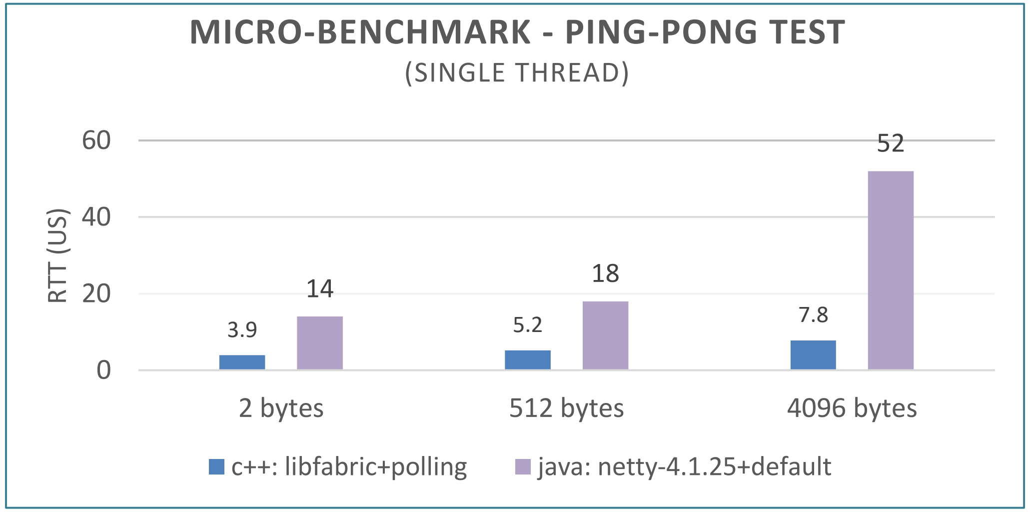
- **Existing projects for BigData w/ RDMA**
  - SparkRDMA.
    - TeraSort benchmark shows 2.63x overall reduced in execution time.*
  - HiDB project from OSU.
    - HiBench PageRank total time reduced by 37%-43% over IPoIB.**
- **Pros**
  - Easy to integrate to one BigData application
- **Cons**
  - Hard to benefit all the BigData App, need to integrate case by case.
  - Can't enable cross-stack optimization.



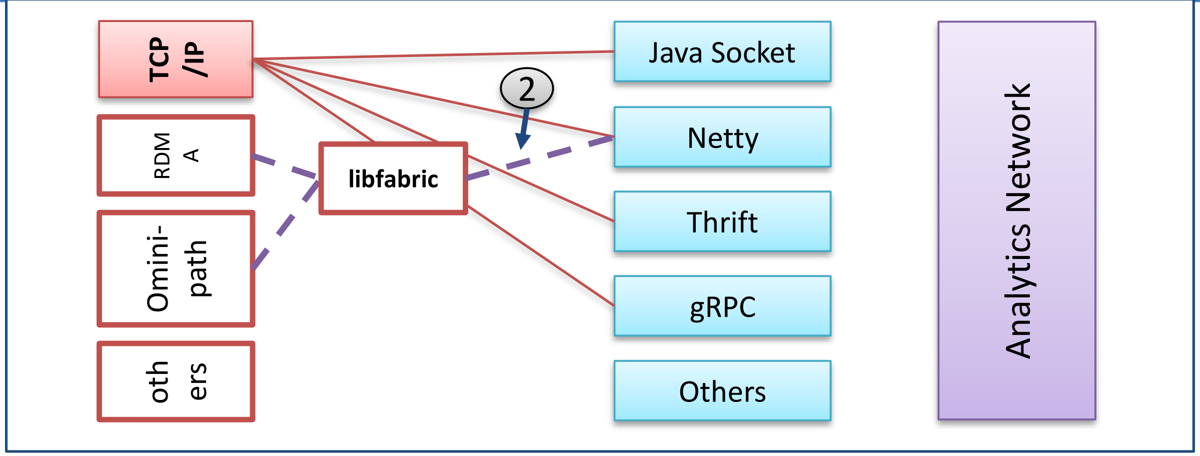
* https://github.com/Mellanox/SparkRDMA
** http://hibd.cse.ohio-state.edu/performance/pagerank/

APPROACH 2 – INTEGRATE LIBFABRIC INTO EXISTING LIB

- **Netty* is [widely](https://netty.io/wiki/adopters.html)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

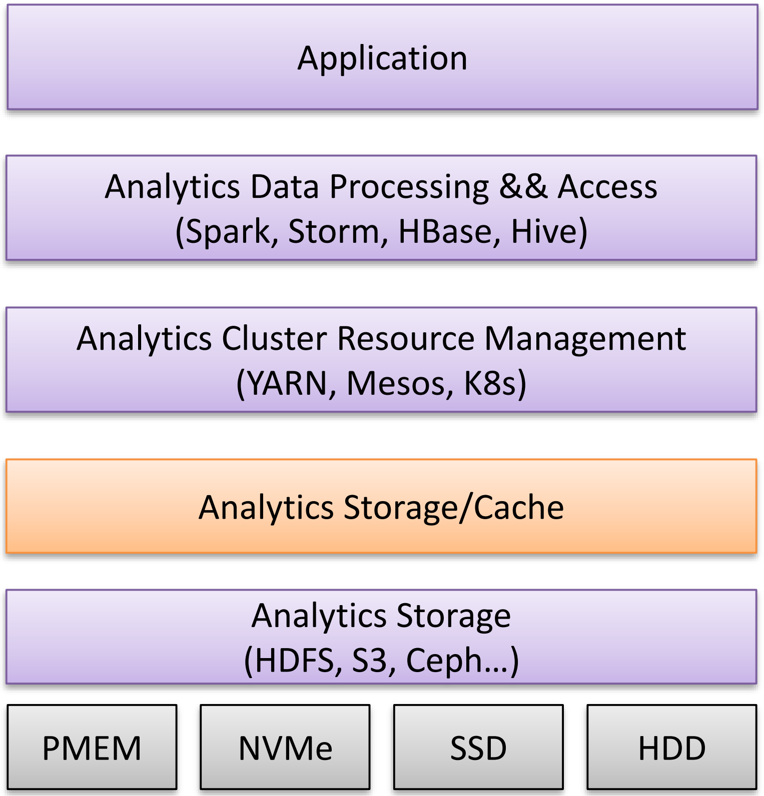
- When Netty supports RDMA & Omni-Path, all the BigData App based on Netty will benefit directly.

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

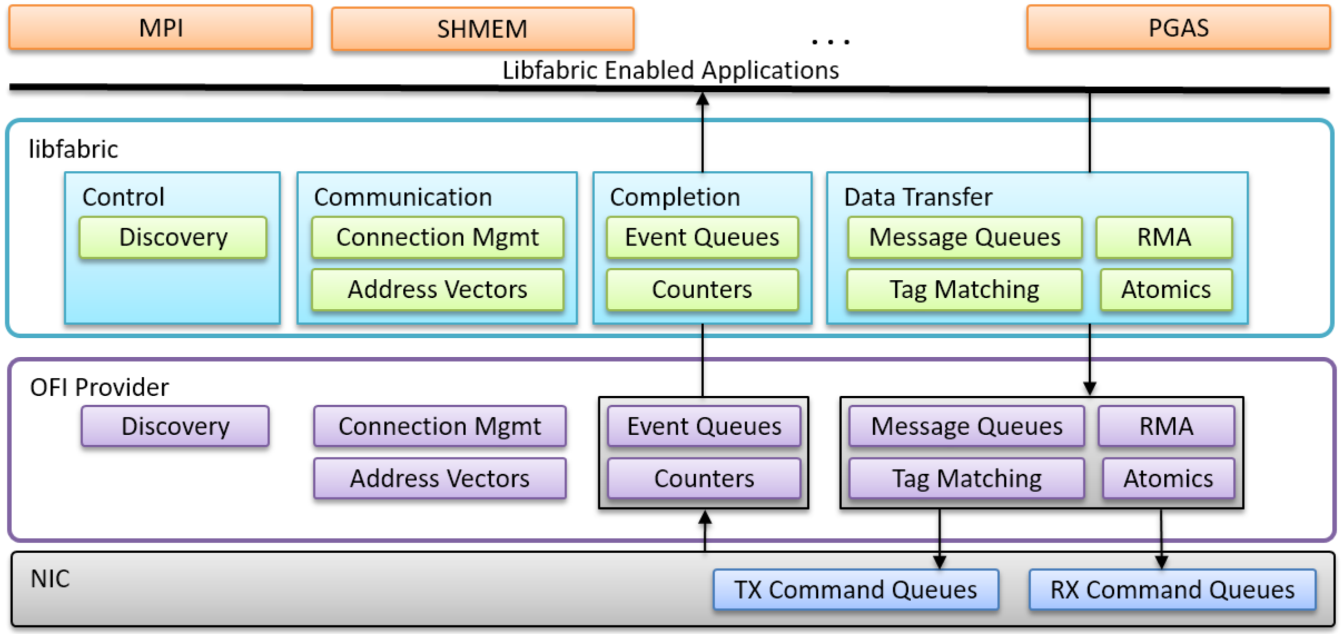
- **Existing projects for BigData by this way.**
  - Crail from IBM.
  - FlashNet: Flash/Network Stack Co-Design
  - Octopus: An RDMA-enabled Distributed Persistent Memory File System
- **Pros**
  - Co-designed storage/network stack optimized to reduce cross-stack overhead between network and flash IO.



TRANSPORTATION AGNOSTIC MESSENGER– HIGH PERFORMANCE NETWORK LIBRARY (HPNL)

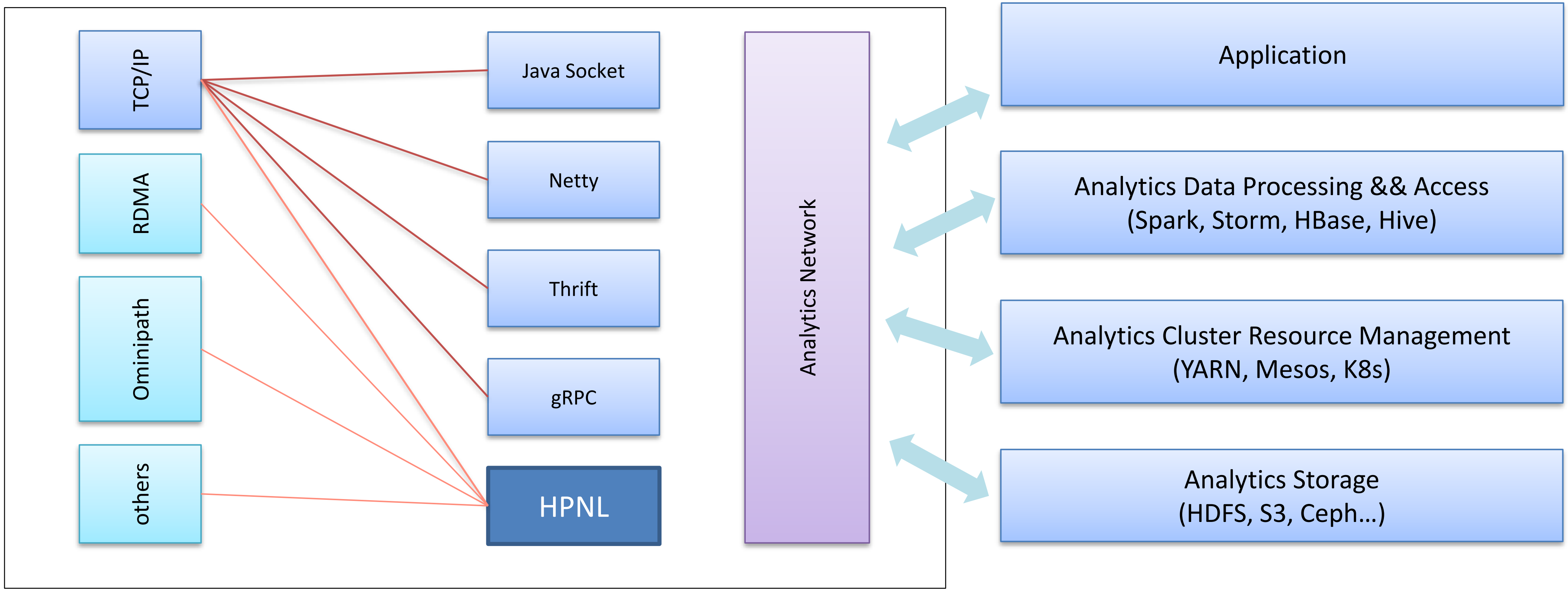
WHY LIBFABRIC?

- Libfabric is developed by the OFI Working Group, a subgroup of OFA.
- Goals: to define interfaces that enable a tight sematic 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/

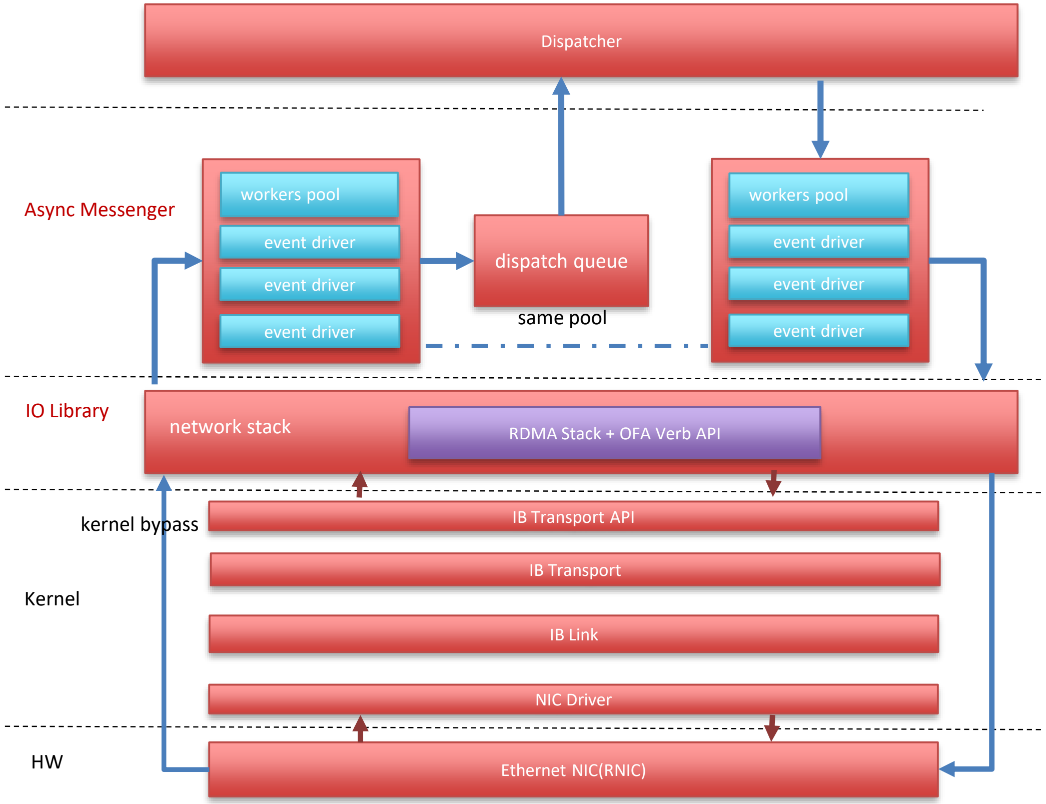
WHERE DOES HPNL FIT IN THE BIGDATA STACK?



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

PREVIOUS WORK: RDMA IN CEPH

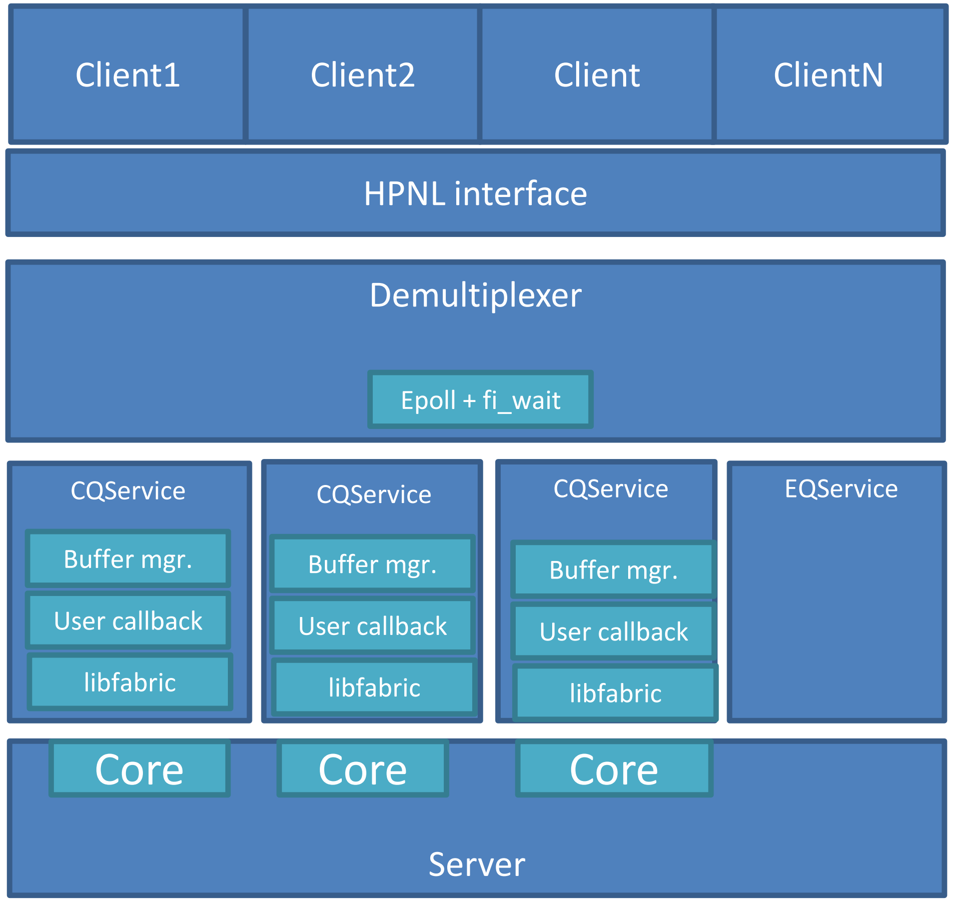
- **XIO Messenger.**
  - Based on Accelio, seamlessly supporting RDMA.
  - Scalability issue.
  - Merged to Ceph master three years ago, no support for now.
- **Async Messenger.**
  - Async Messenger is compatible with different network protocol, like Posix, RDMA and DPDK.
  - Current RDMA implementation 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

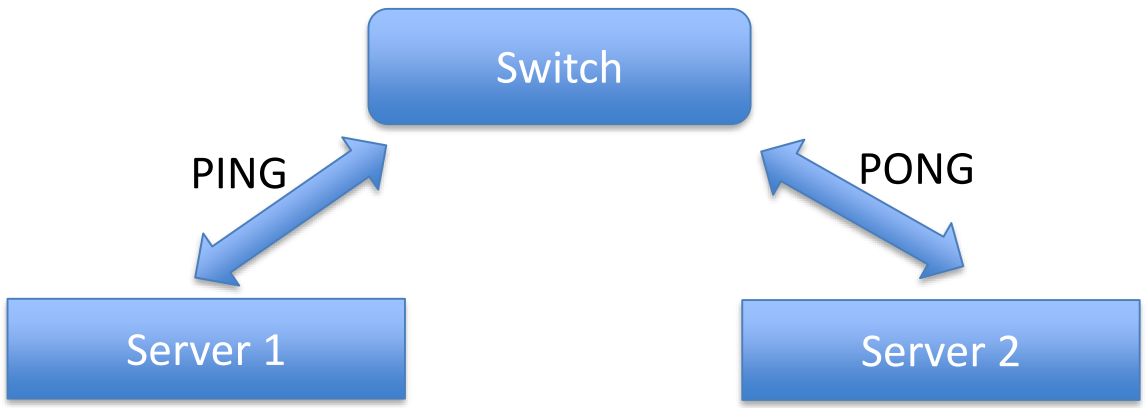
HPNL ARCHITECTURE

- **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.



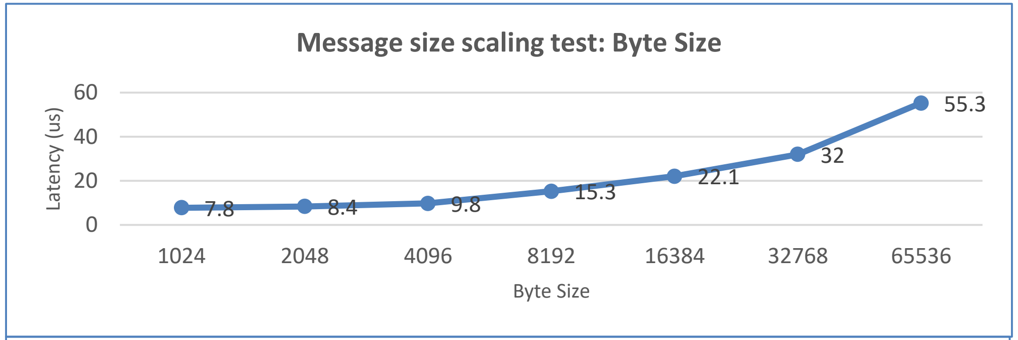
MICROBENCHMARK CONFIGURATION

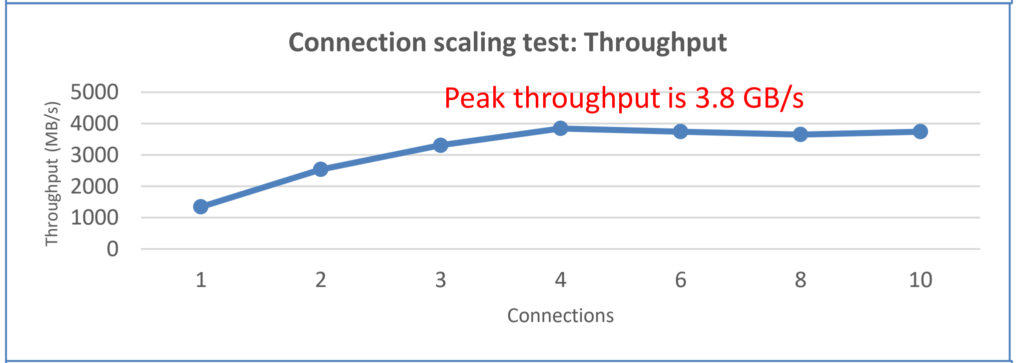
- **Hardware**
  - Intel(R) Xeon(R) CPU E5-2699 v4 @ 2.20GHz
  - Mellanox ConnectX-4 – RoCE V2
  - Arista 7060 CX2-32S
- **Software**
  - HPNL Java interface with libfabric v1.6.0
  - OFED
  - CentOS 7
- **Micro benchmark Methodology**
  - Send/receive based Ping-pong test
  - 1million times transfer of 4K sized message

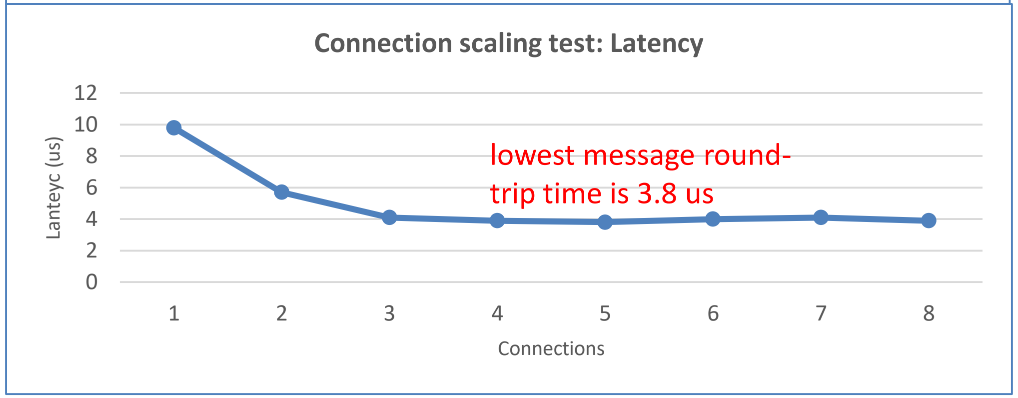


MICRO WORKLOADS PERFORMANCE

- **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.

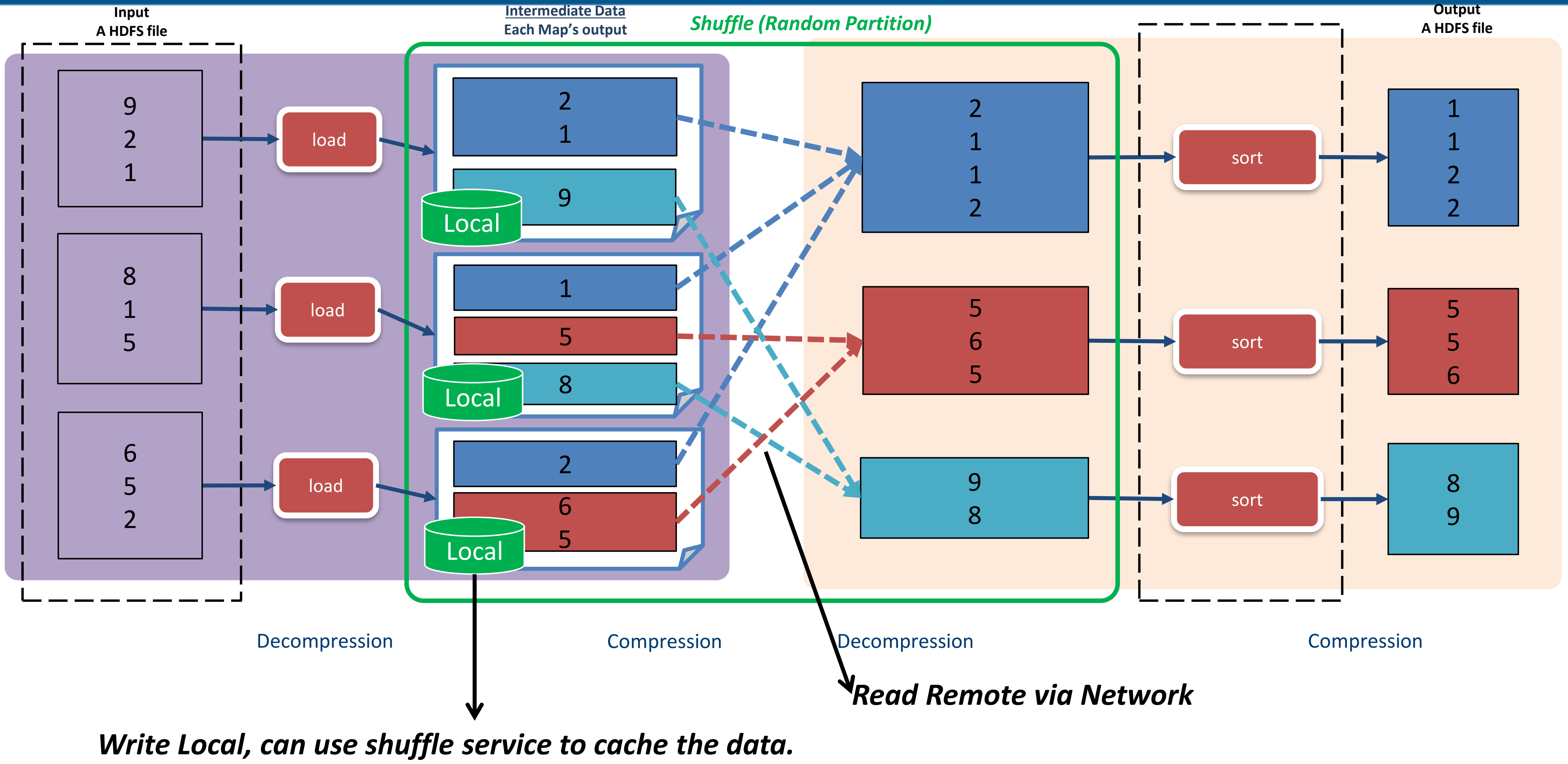






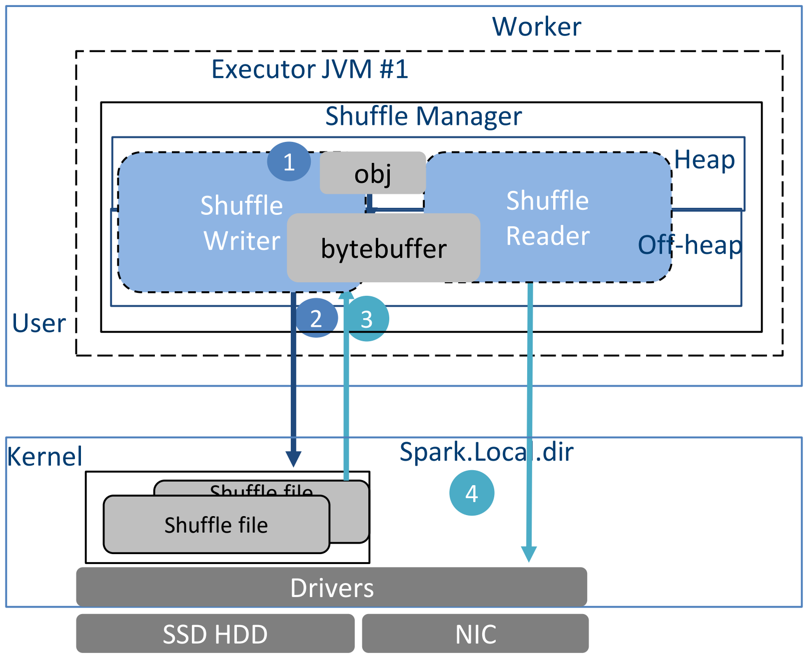
OPTIMIZING SPARK SHUFFLE WITH HPNL AND PERSISTENT MEMORY

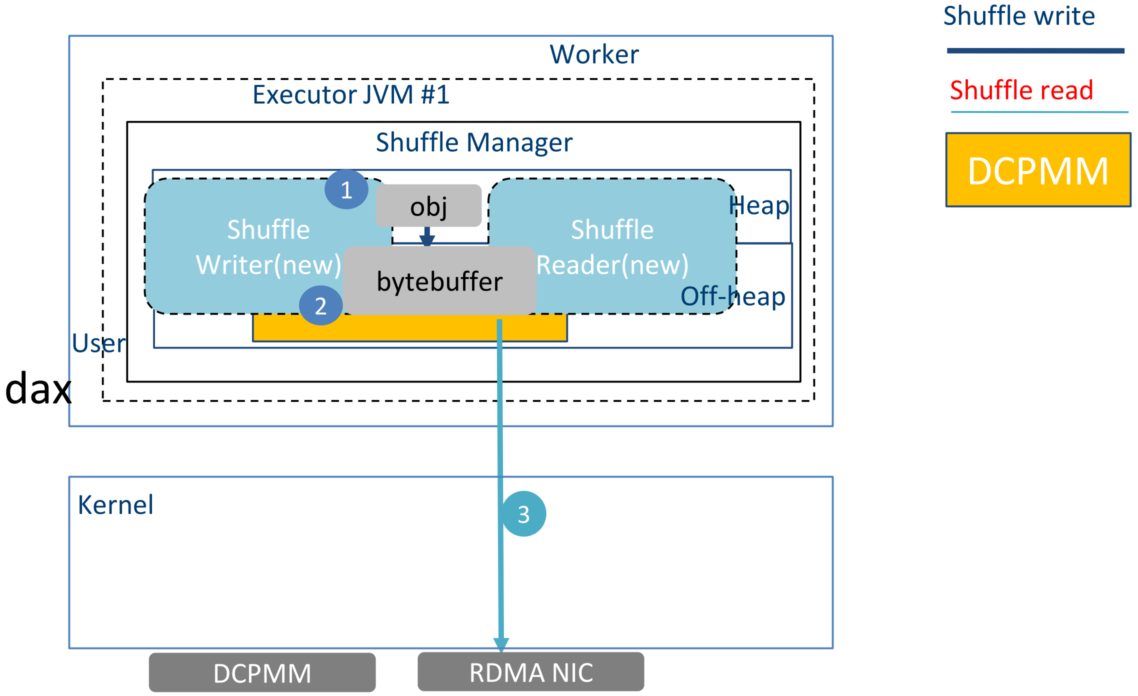
SPARK SHUFFLE



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

SPARK-PMOF CO-DESIGN





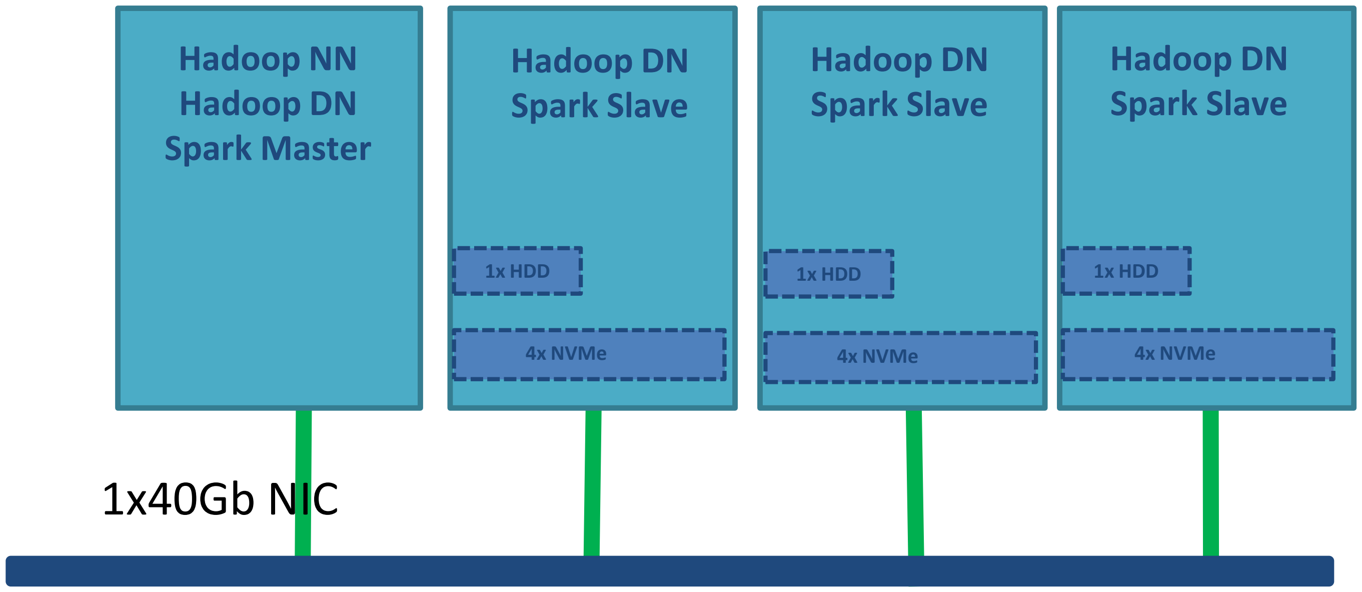
1. Serialize obj to off-heap memory
2. Write to local shuffle dir
3. Read from local shuffle dir
4. Send to remote reader through TCP-IP

- ➢ 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 DCPMM (pmem_memcpy_persistent)
3. Read from remote DCPMM through RDMA, DCPMM is used as RDMA memory buffer

- ➢ No context switch
- ➢ Efficient read/write on DCPMM
- ➢ RDMA read for remote shuffle read

SYSTEM CONFIGURATION



3 Node cluster

Hardware:

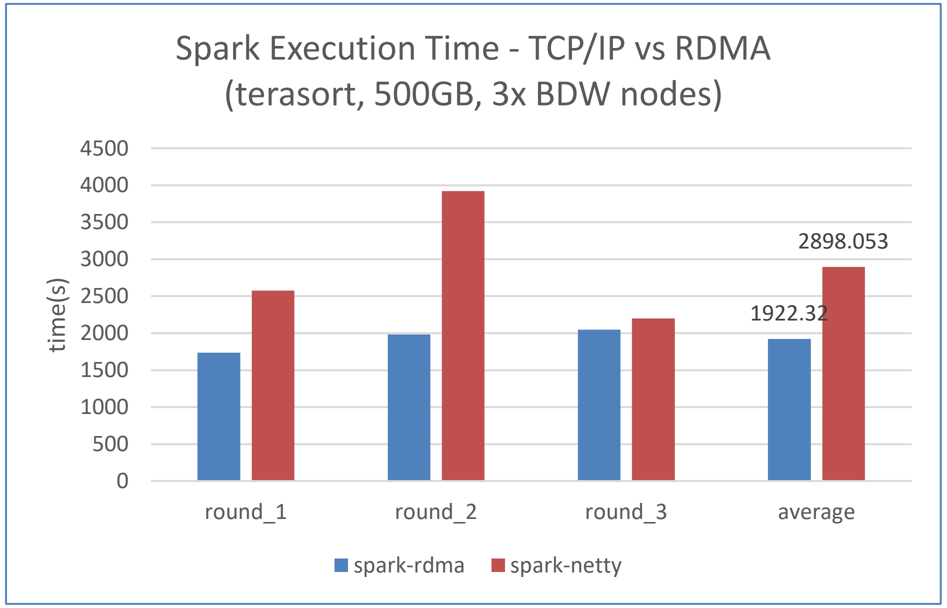
- Intel® Xeon™ processor E5 2699V4 @ 2.2GHz, 558GB Memory
- 1x Mellanox ConnectX-4 40Gb NIC
- 1x 1TB HDD for spark-shuffle
- 4x NVMe for HDFS

Software:

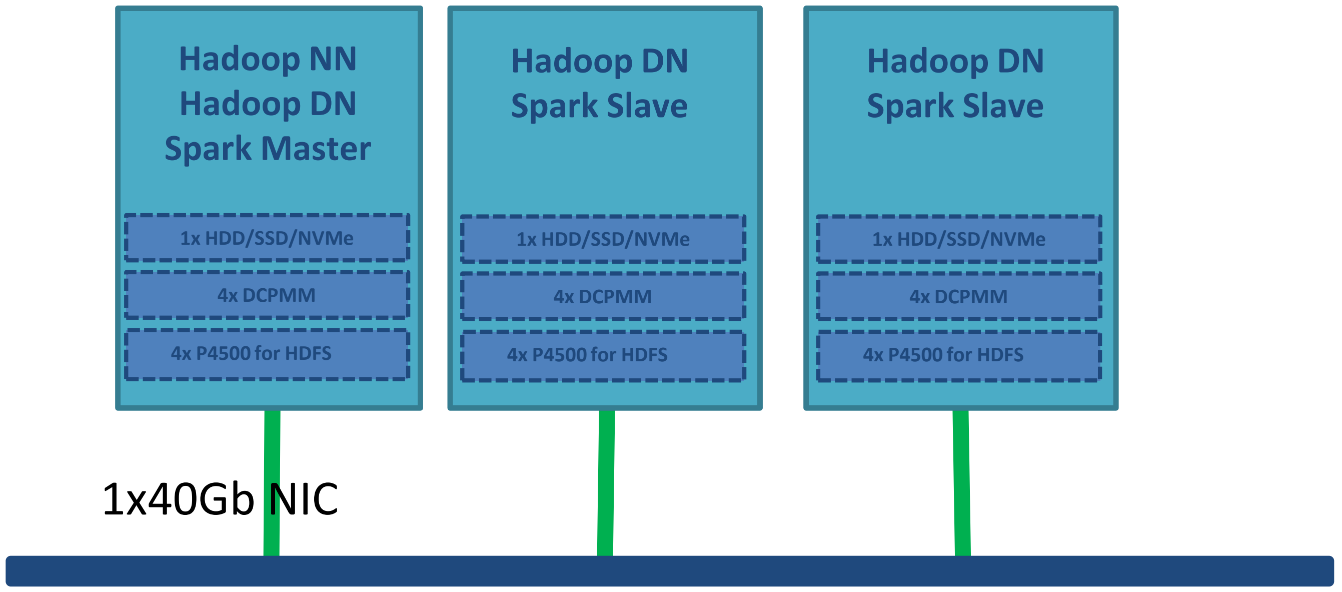
- Hadoop 2.7
- Spark 2.3
- CentOS 7
- HiBench TeraSort 500GB

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) DCPMM for Shuffle

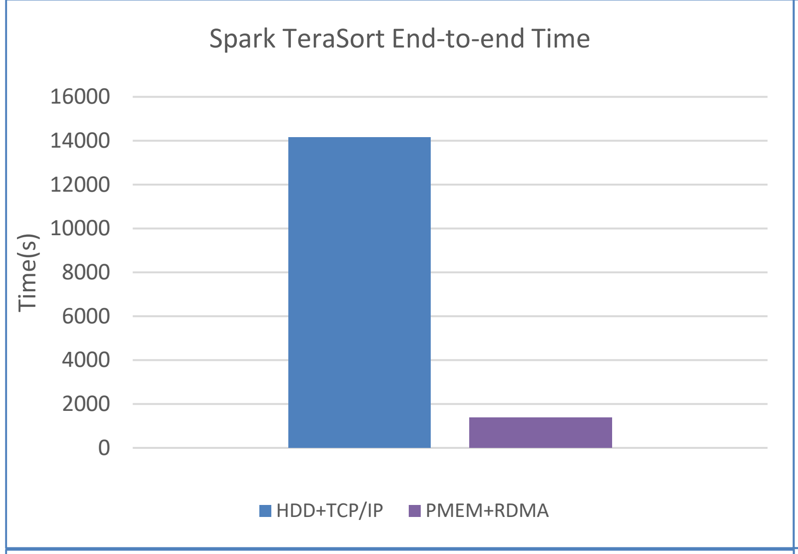
Software:

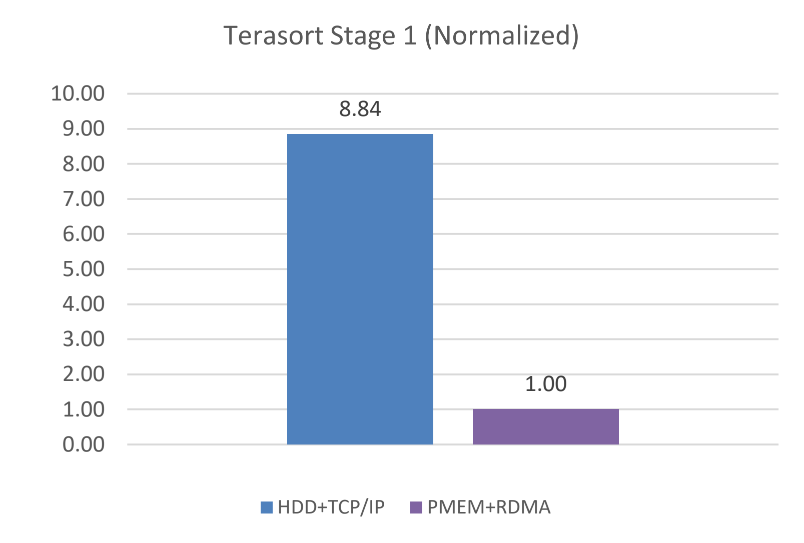
- Fedora 27
- Kernal 4.18.19-100.fc27.x86_64
- Hadoop 2.7
- Spark 2.3
- Libfabric 1.6.2
- MLNX_OFED_LINUX-4.5-1.0.1.0-fc27-x86_64

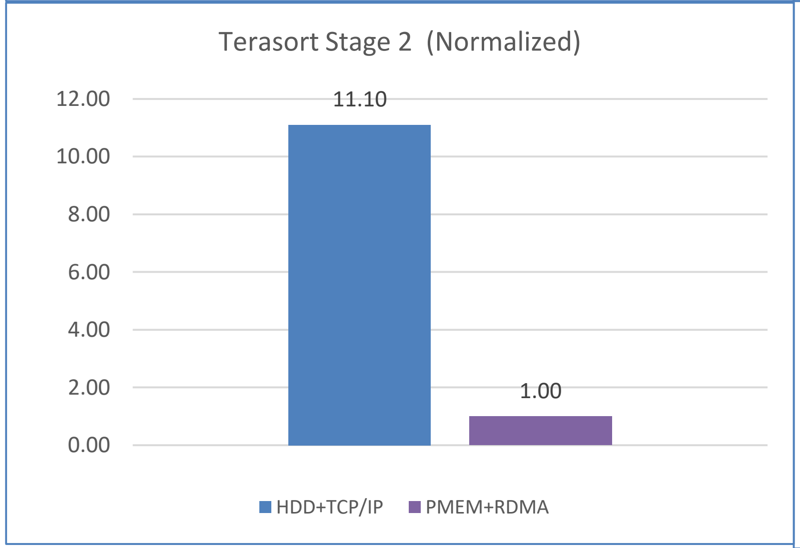
Workloads:

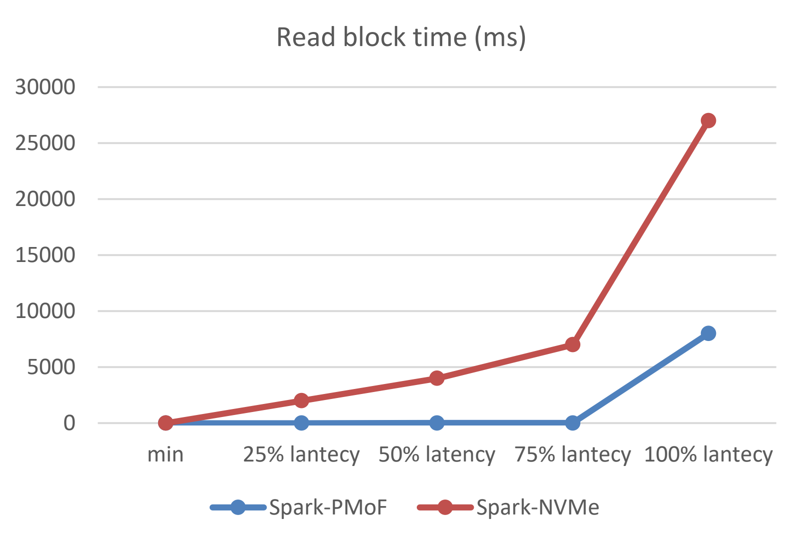
- Hibench terasort 1TB

PERFORMANCE SUMMARY









- **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

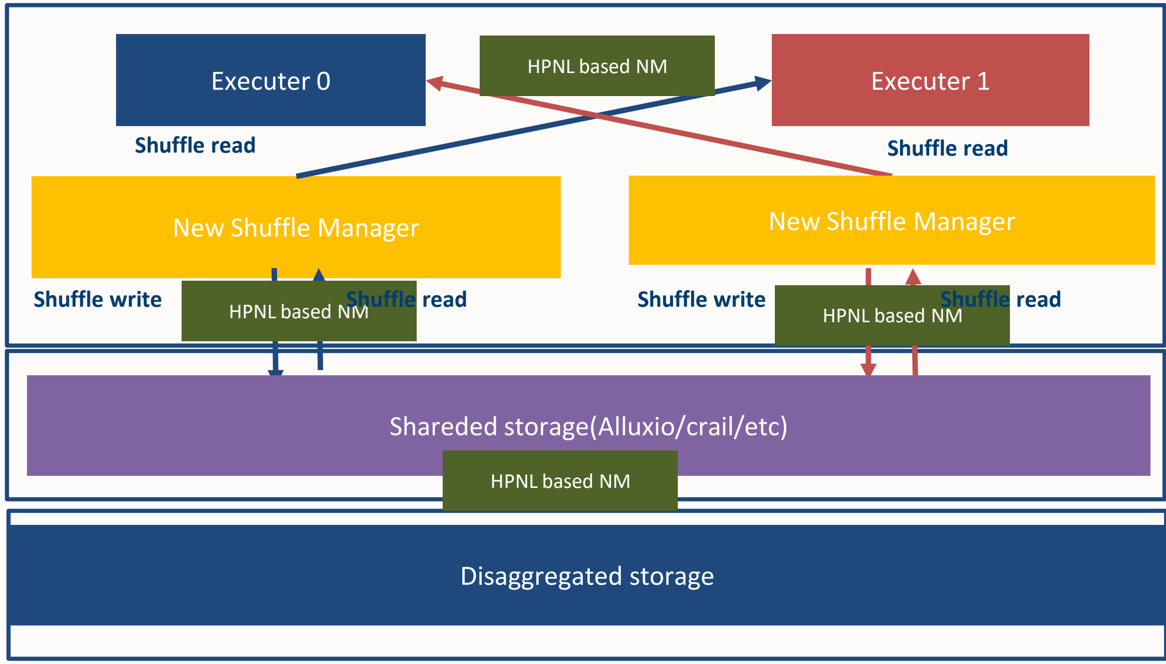
STAGE 2 PERFORMANCE BREAKDOWN (PMEM+RDMA)

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

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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