

# Running Spark on a High-Performance Cluster using RDMA Networking and NVMe Flash

Patrick Stuedi, IBM Research

#### **Hardware Trends**

community target

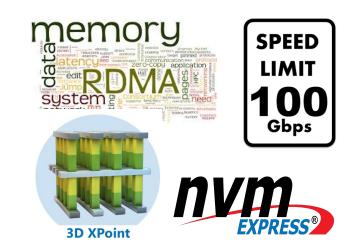
	2010	2017	
Storage	100 MB/s 100ms	1000 MB/s 200us	
Network	1Gbps 50us	10Gbps 20us	
CPU	~3GHz	~3GHz	



#### **Hardware Trends**

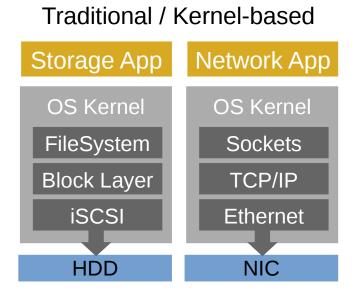
community our target target

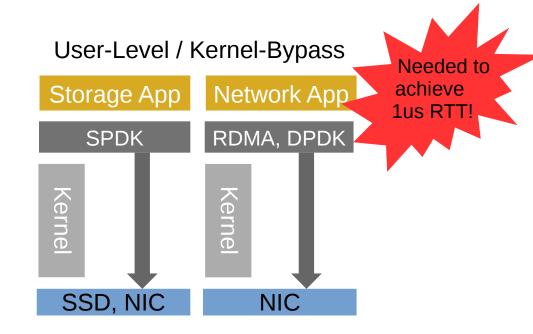
	2010	2017	2017
Storage	100 MB/s	1000 MB/s	10 GB/s
	100ms	200us	50us
Network	1Gbps	10Gbps	100Gbps
	50us	20us	1us
CPU	~3GHz	~3GHz	





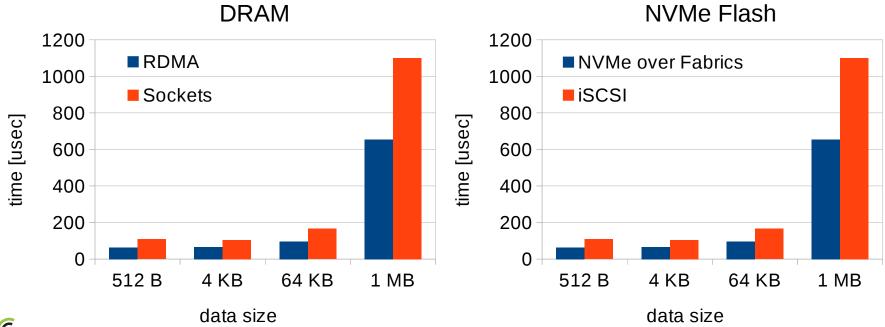
#### **User-Level APIs**





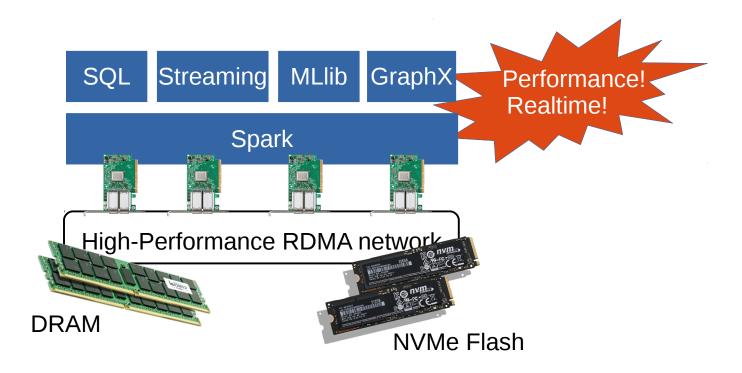


#### **Remote Data Access**



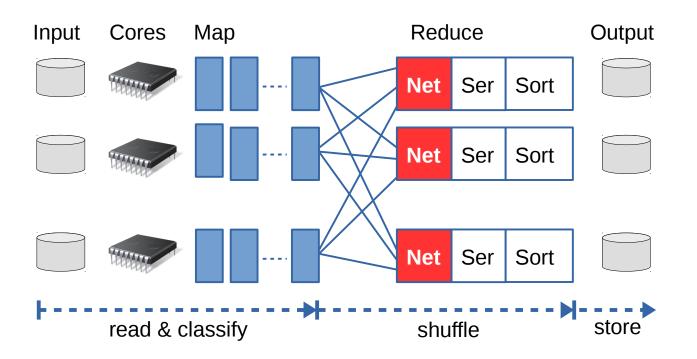


#### Let's Use it!





## Case Study: Sorting in Spark





#### **Experiment Setup**

- Total data size: 12.8 TB
- Cluster size: 128 nodes
- Cluster hardware:
  - DRAM: 512 GB DDR 4
  - Storage: 4x 1.2 TB NVMe SSD
  - Network: 100GbE Mellanox RDMA

Flash bandwidth per node matches network bandwidth

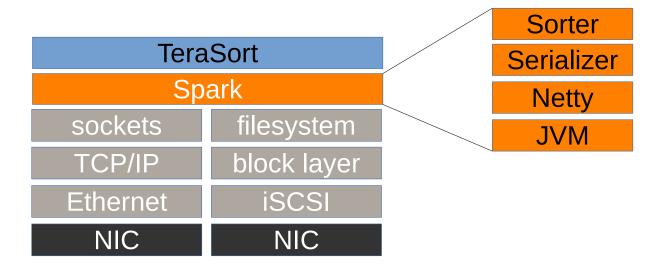


#### **How is the Network Used?**





#### What is the Problem?



- Spark uses legacy networking and storage APIs: no kernel-bypass
- Spark itself introduces additional I/O layers: Netty, serializer, sorter, etc.

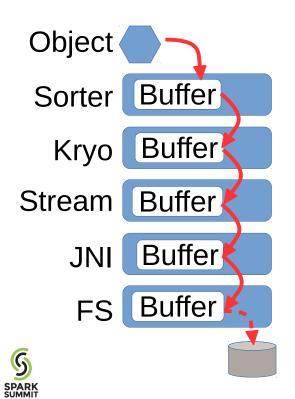


## **Example: Shuffle (Map)**





## **Example: Shuffle (Map)**



## Example: Shuffle (Map+Reduce)



## Example: Shuffle (Map+Reduce)



#### How can we fix this...

- Not just for shuffle
  - Also for broadcast, RDD transport, inter-job sharing, etc.
- Not just for RDMA and NVMe hardware
  - But for any possible future high-performance I/O hardware
- Not just for co-located compute/storage
  - Also for resource disaggregation, heterogeneous resource distribution, etc.
- Not just improve things
  - Make it perform at the hardware limit



## The CRAIL Approach



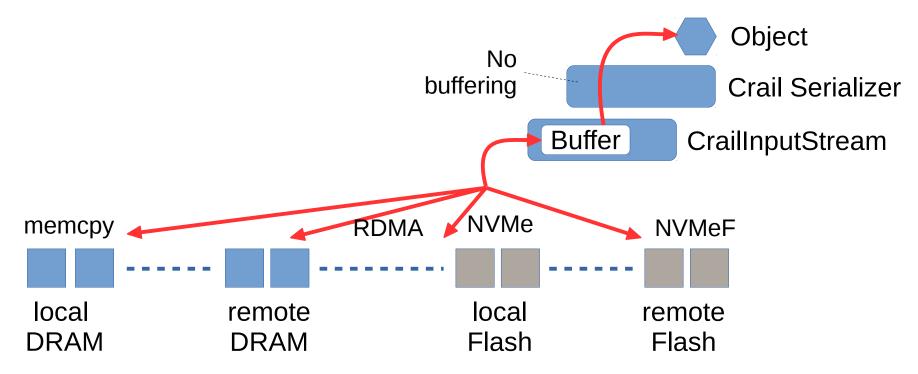


#### **Example: Crail Shuffle (Map)**



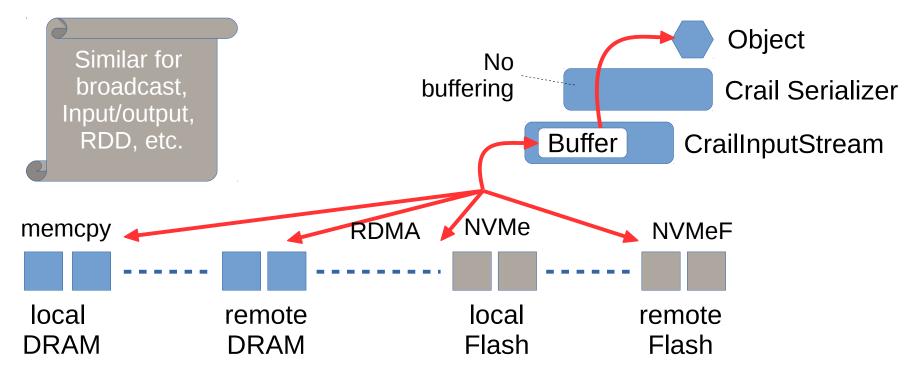


## **Example: Crail Shuffle (Reduce)**





## **Example: Crail Shuffle (Reduce)**



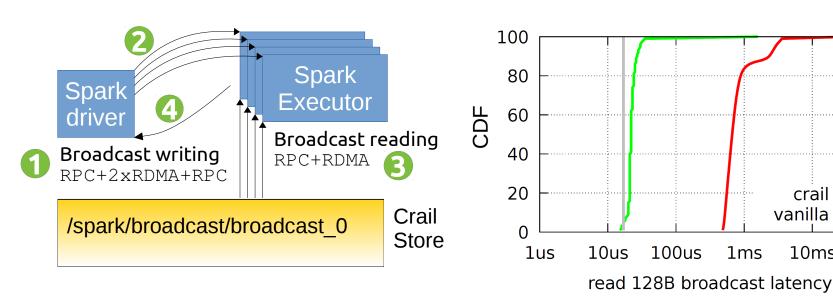


#### **Performance: Configuration**

- Experiments
  - Performance: Broadcast, GroupBy, Sorting, SQL (memory)
  - Disaggregation, tiering: Sorting (memory/flash)
- Cluster size: 8 nodes, except TeraSort: 128 nodes
- Cluster hardware:
  - DRAM: 512 GB DDR 4
  - Storage: 4x 1.2 TB NVMe SSD
  - Network: 100GbE Mellanox RDMA



## **Spark Broadcast**



```
val bcVar = sc.Broadcast(new Array[Byte](128))
sc.parallelize(1 to tasks, tasks).map(_ => {
 bcVar.value.length
  .count
```

crail

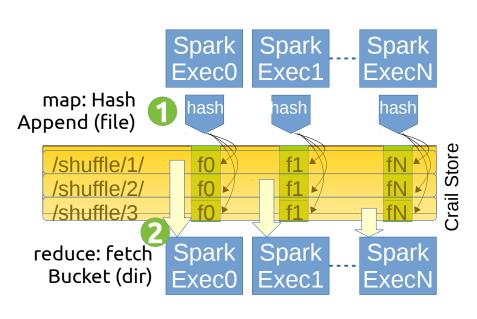
10ms

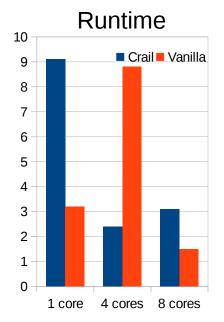
100ms

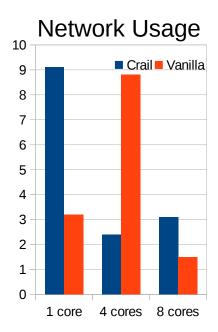
vanilla

1ms

## **Spark GroupBy**

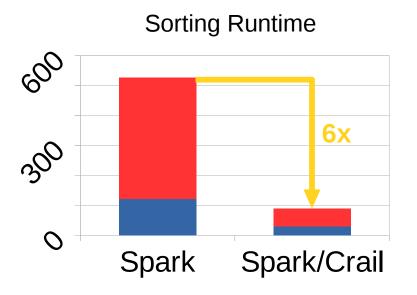




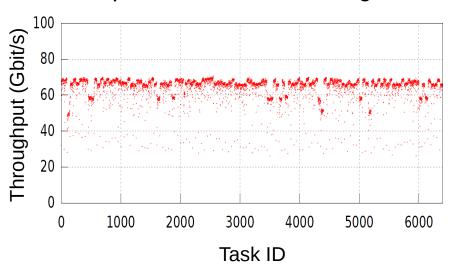


```
val pairs = sc.parallelize(1 to tasks, tasks).flatmap(_ => {
   var values = new array[(Long,Array[Byte])](numKeys)
   values = initValues(values)
}).cache().groupByKey().map(v => v._1).count()
```

#### Sorting 12.8 TB on 128 nodes



#### Spark/Crail Network Usage





#### How fast is this?

Spark

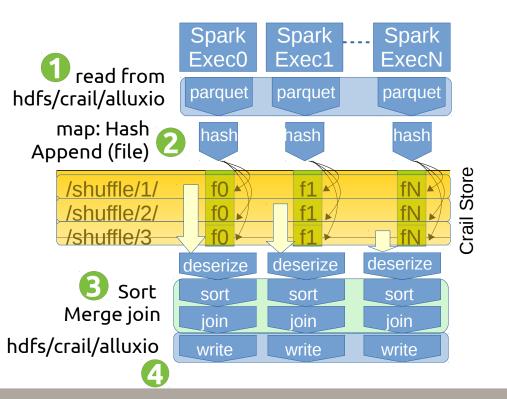
Native C distributed sorting benchmark

#### www.sortingbenchmark.org

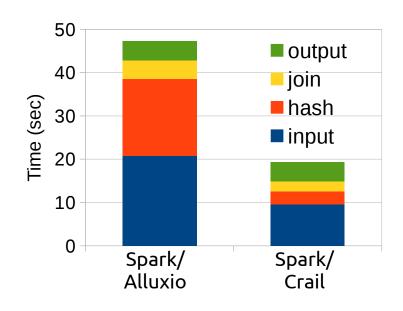
	Spark/Crail	Winner 2014	Winner 2016
Size (TB)	12.8	100	100
Time (sec)	98	1406	98.6
Total cores	2560	6592	10240
Network HW (Gbit/s)	100	10	100
Rate/core (GB/min)	3.13	0.66	4.4

Sorting rate of Crail/Spark only 27% slower than rate of Winner 2016



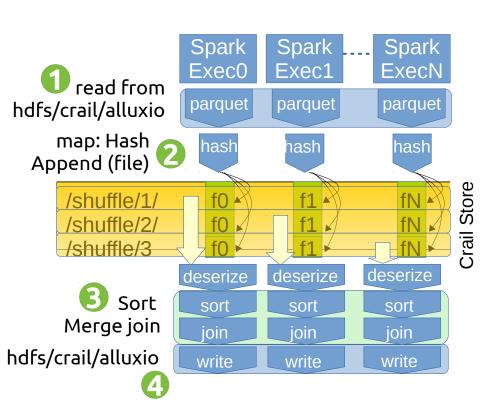


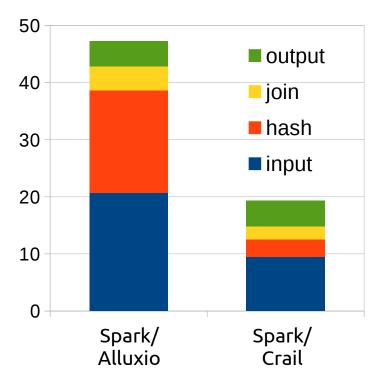
## **Spark SQL Join**



```
val ds1 = spSess.read.parquet("...")
val ds2 = spSess.read.parquet("...")
val resultDS = ds1.joinWith(ds1, ds1(key) === ds2(key))
resultDS.write.format("parquet").mode(SaveMode.Overwrite).save("...")
```

## Spark SQL Join (Broadcast)





#### Conclusions

- Effectively using high-performance I/O hardware in Spark is challenging
- Crail is an attempt to re-think how Spark should interact with network and storage hardware
  - User-level I/O, storage disaggregation, memory/flash convergence



#### Crail for Spark is Open Source

- www.crail.io
- github.com/zrlio/spark-io
- github.com/zrlio/crail
- github.com/zrlio/parquetgenerator
- github.com/zrlio/crail-terasort



## Thank You.

## The CRAIL Approach

