11. In-storage Processing

Special Topics in Computer Systems:

Modern Storage Systems (IC820-01)

Instructor:

Prof. Sungjin Lee (sungjin.lee@dgist.ac.kr)

Outline

- Why In-storage Processing?
- Case Studies
 - BlueDBM: Big-data Analytic Platform with In-storage Processing
 - BlueCache: Hardware-accelerated Key-value Store
 - Biscuit: User-programmable In-storage Processing Framework
 - IESSD: Inference-Enabled SSDs

near - data processing storage

In-storage Computing

NDP: data source

Extension of near-data processing (NDP) for storage devices

- The idea of NDPL: computation is performed right at the data source
 - e.g., *Processing in Memory (PIM)*: the integration of a processor with RAM

Efficient when the cost of moving data is very high

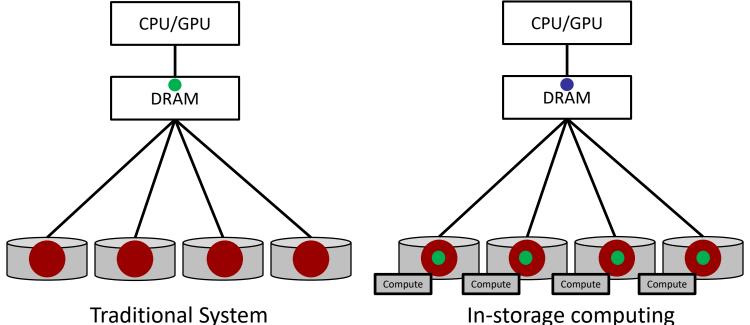
Example: All-flash array

- 가 . 가 bottleneck.
- PCIe bandwidth is about 64 GB/s, but a single SSD offers 5~10 GB/s
- Modern storage servers are composed of many SSDs (10~250 SSDs)
- The PCIe bus is bottleneck!

All - flash array , SSD가 PCIe bandwidth가 bottleneck SSD .

In-storage Computing (Cont.)

- Transferring large amounts of data to DRAM is time and energy consuming
 - PCIe bus / network are becoming a bottleneck
- In-storage acceleration (or near-data process) is one of emerging solutions
 - Offload computation logics into storage side; return only results to host side
 - Better performance, lower energy consumption, and higher scalability



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BlueDBM Project

- The BlueDBM project started around early 2013 with the aim of accelerating big data analytics on NAND flash clusters
- Various companies, including Quanta, Samsung, Hynix, and Lincoln Lab, supported or are supporting this project
- Now, it becomes an excellent playground for flash research
 - and is evolving now



Big Bata Analytics

- Analysis of previously unimaginable amount of data can provide deep insight
 - Google has predicted flu outbreaks a week earlier than the Center for Disease Control (CDC)
 - Analyzing personal genome can determine predisposition to diseases
 - Social network chatter analysis can identify political revolutions before newspapers
 - Scientific datasets can be mined to extract accurate models

A Currently Popular Solution: RAM Cloud

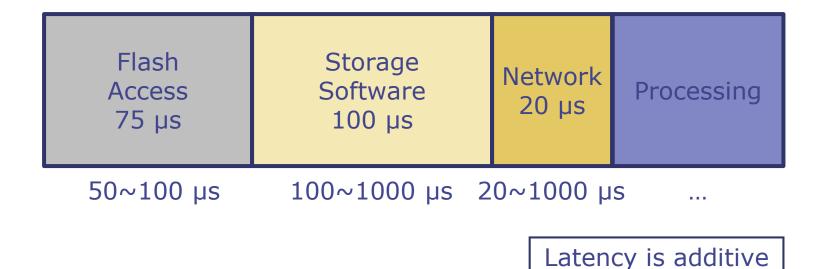
- Cluster of machines with large DRAM capacity and fast interconnect
 - + Fastest as long as data fits in DRAM
 - Power hungry and expensive
 - Performance drops when data doesn't fit in DRAM

What if enough DRAM isn't affordable?

- Flash-based solutions may be a better alternative
 - + Faster than Disk, cheaper than DRAM
 - + Lower power consumption than both
 - Legacy storage access interface is burdening
 - Slower than DRAM

Latency Profile of Distributed Flash-based Analytics

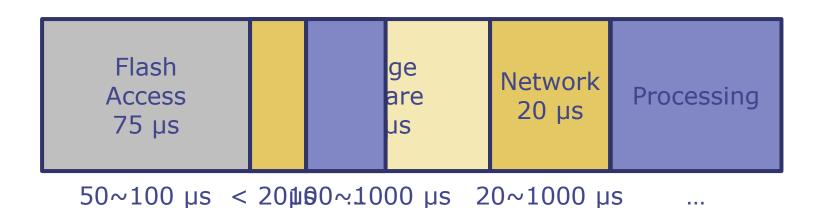
- Distributed processing involves many system components
 - Flash device access
 - Storage software (OS, FTL, ...)
 - Network interface (10gE, Infiniband, ...)
 - Actual processing



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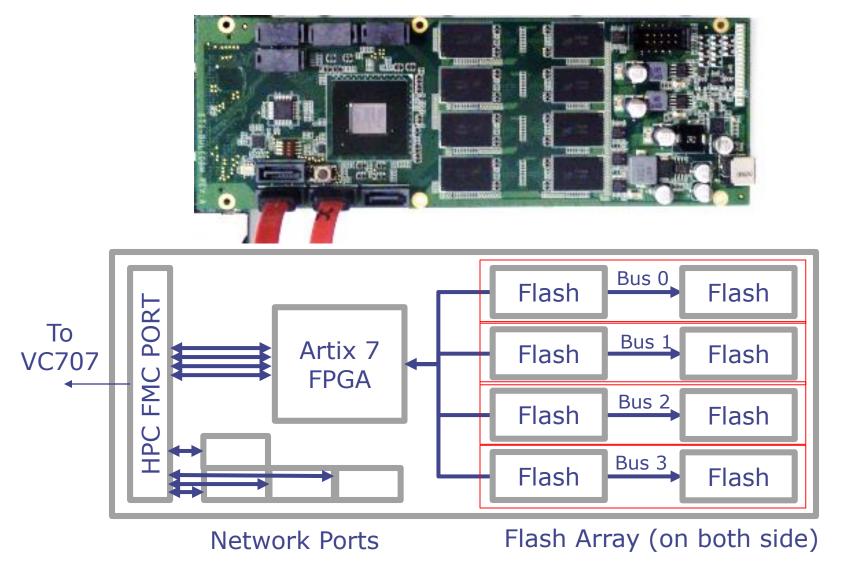
Latency Profile of Distributed Flash-based Analytics

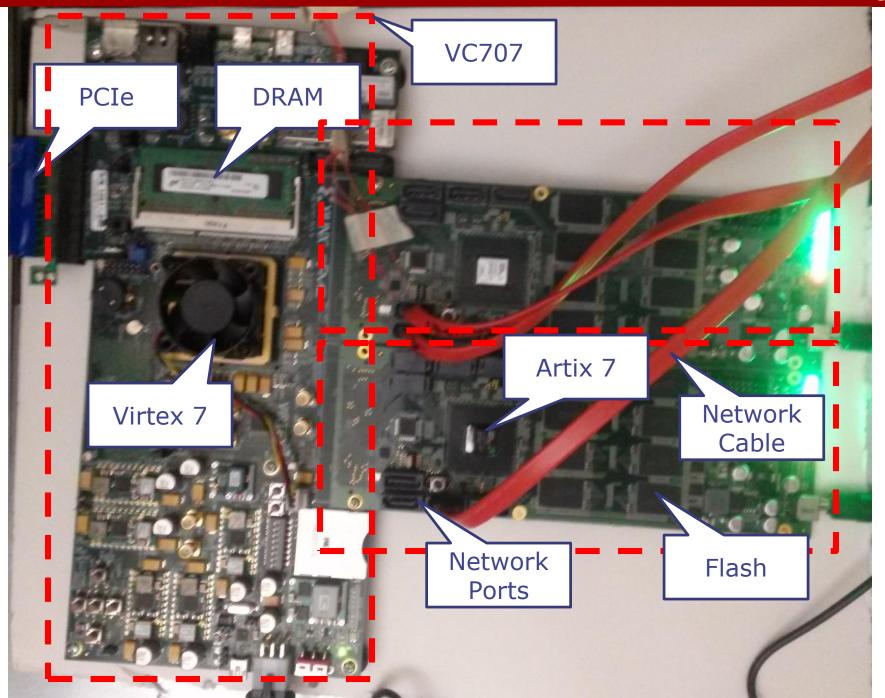
- Architectural modifications can remove unnecessary overhead
 - Near-storage processing
 - Cross-layer optimization of flash management software*
 - Dedicated storage area network
 - Accelerator



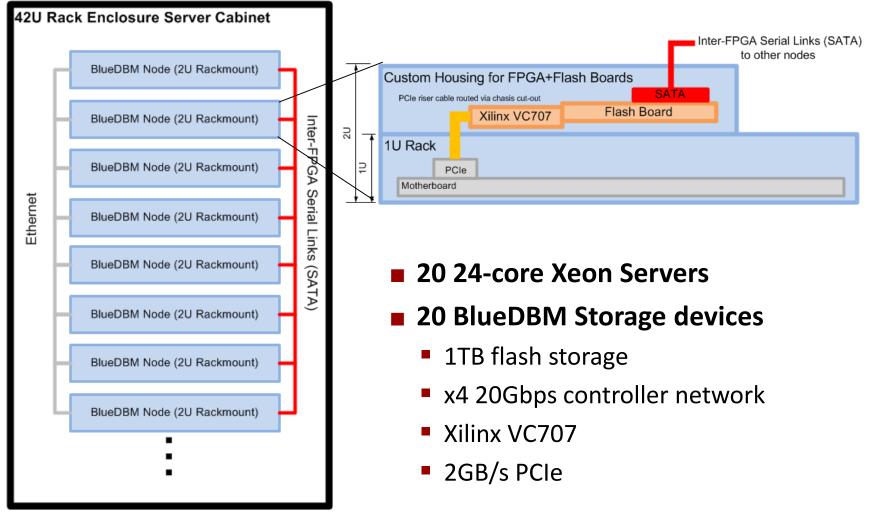
Difficult to explore using flash packaged as off-the-shelf SSDs

Custom Flash Card Had to be Built





BlueDBM: Platform with In-storage Processing and Inter-controller Networks



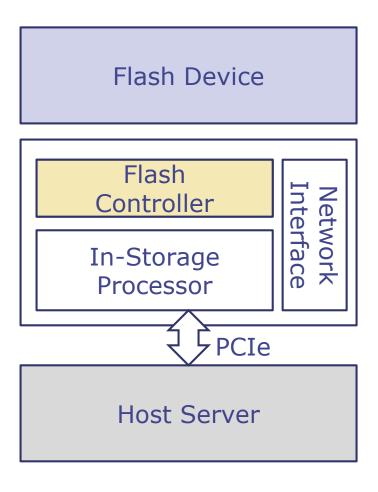
BlueDBM: Platform with In-storage Processing and Inter-controller Networks





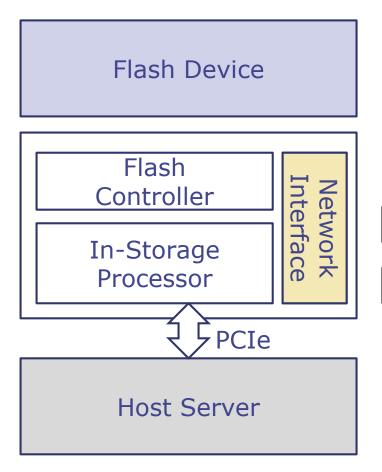
- 20 24-core Xeon Servers
- 20 BlueDBM Storage devices
 - 1TB flash storage
 - x4 20Gbps controller network
 - Xilinx VC707
 - 2GB/s PCle

BlueDBM Node Architecture

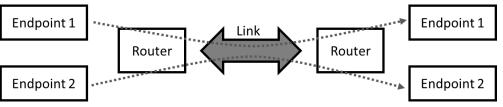


- Lightweight flash management with very low overhead
 - Adds almost no latency
 - ECC support

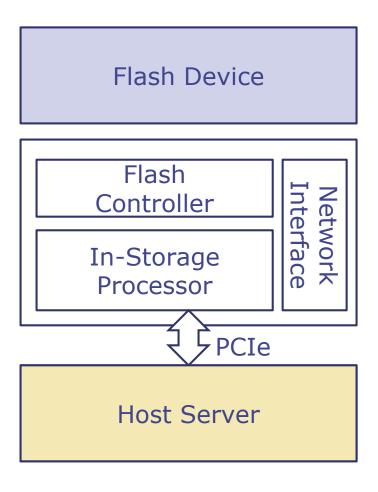
BlueDBM Node Architecture



- Custom network protocol with low latency/high bandwidth
 - x4 20Gbps links at 0.5us latency
 - Virtual channels with flow control



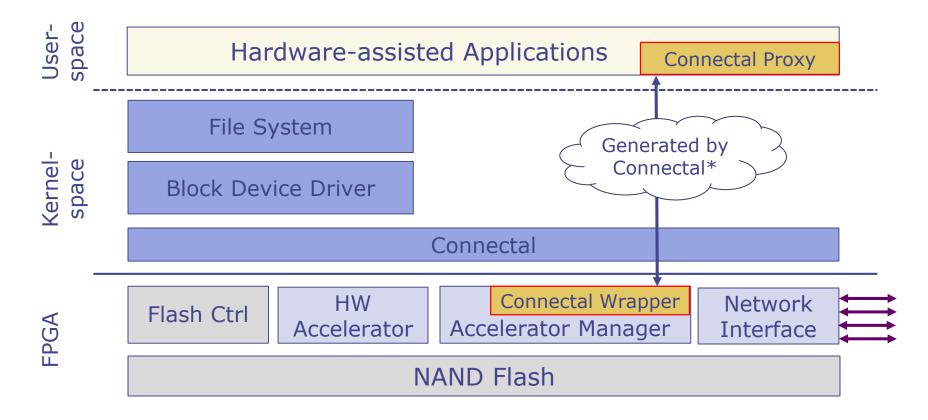
BlueDBM Node Architecture



Software has very low level access to flash storage

- High level information can be used for low level management
- FTL implemented inside file system

BlueDBM Software View



 BlueDBM provides a generic file system interface as well as an accelerator-specific interface (Aided by Connectal)

Power Consumption is Low

Component	Power (Watts)
VC707	30
Flash Board (x2)	10
Storage Device Total	40

Storage device power consumption is a very conservative estimate

Component	Power (Watts)
Storage Device	40
Xeon Server	200+
Node Total	240+

GPU-based accelerator will double the power

BlueDBM Applications

Content-based image search

Faster flash with accelerators as replacement for DRAM-based systems

Graph analytics

 Benefits of lower latency access into distributed flash for computation on large graphs

Content-based Image Retrieval

- Takes a query image and returns similar images in a dataset of tens of million pictures
- Image similarity is determined by measuring the distance between histograms of each image
 - Histogram is generated using RGB, HSV, "edgeness", etc.
 - Better algorithms are available!

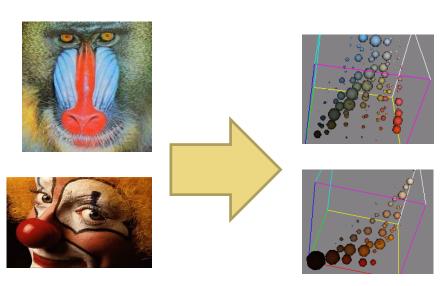


Image Search Accelerator

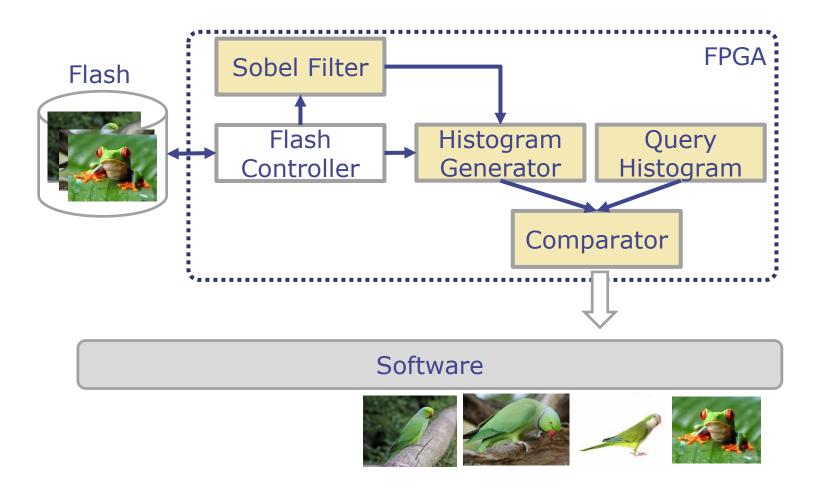
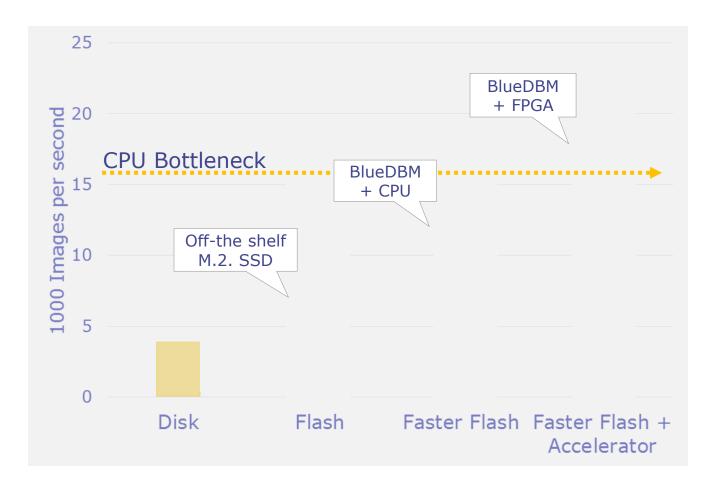


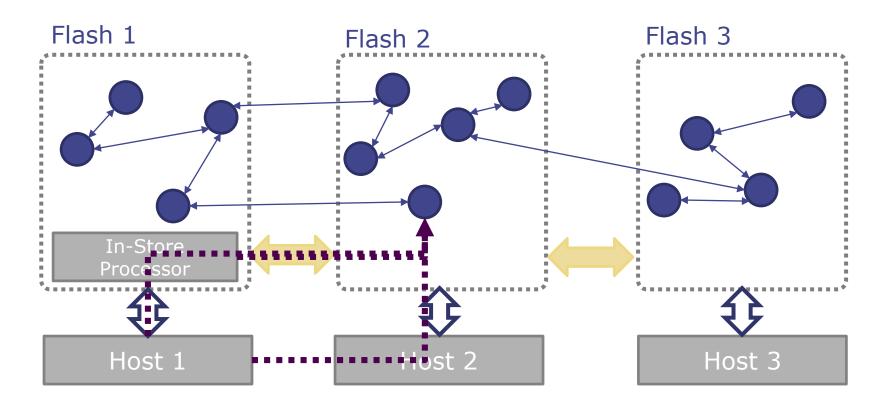
Image Query Performance



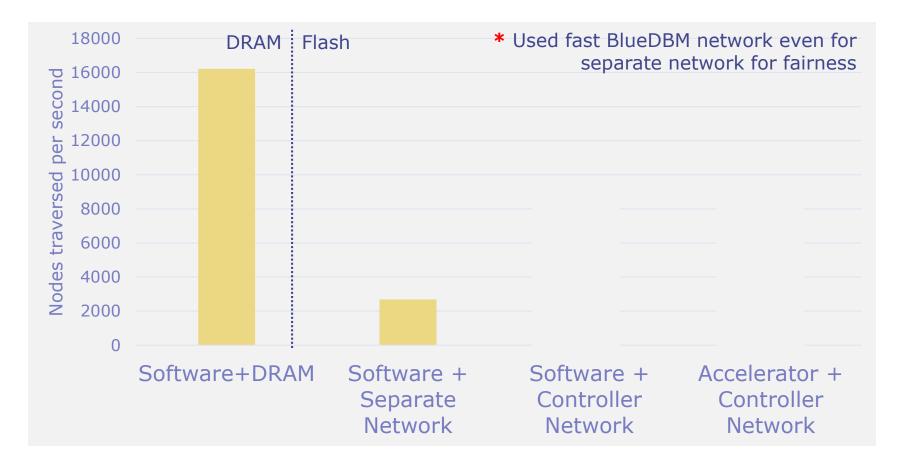
Faster flash with acceleration can perform at DRAM speed

Graph Traversal

- Very latency-bound problem, because often cannot predict the next node to visit
 - Beneficial to reduce latency by moving computation closer to data



Graph Traversal Performance



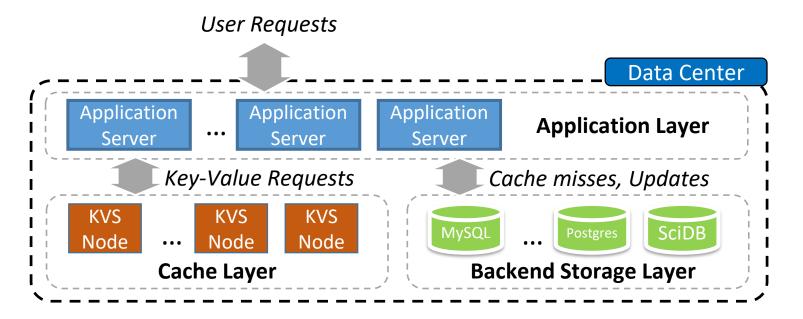
■ Flash based system can achieve comparable performance with a much smaller cluster

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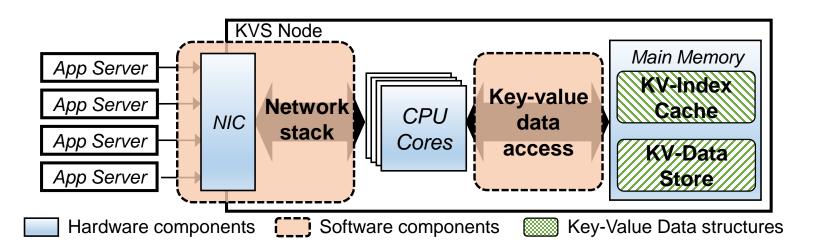
KVS Cache in Data Center

- Application servers transforms a user read-request into multiple GET requests
 - A cache miss requires 1) backend queries and 2) cache refill by a SET request
- Write-request deletes relevant KV pairs and updates the backend
 - Subsequent read-request is a miss and automatically refill the cache



X86-based KVS Architecture

- Application servers communicate with the KVS server via NIC
- x86 processors processes key-value requests stored in memory
 - KV-Index Cache only keeps the pointers to the objects
 - KV-Data Store keeps the object data



OOO Processors Efficient for KVS?

- State-of-the-art KVSs (>120+ MRPS)
 - Direct packet injection from NIC to LLC (Intel DDIO)
 - MICA[ISCA'15], Mega-KV[VLDB'15]
- Higher throughput needs more hardware
 - MICA uses 24 cores and 12 10GbE to produce 120MRPS
 - Mega-KV uses 2 GTX 780 GPUs to produce 160MRPS
 - 399.2W for MICA, and 899.2W for Mega-KV

Hardware accelerators can efficiently process KVS queries with low power

KVS cache's Performance Depends on Aggregate Memory Size

■ Popular Solution: Add more DRAMs

- + Cache capacity increase with no performance loss
- expensive and power hungry
- limited by ~ 256GB/server
- performance drops dramatically if data does not fit in DRAM

working set memcached miss

Alternative solution: Use flash memory

- + More cache capacity, 10X cheaper than DRAM
- + 10-100X lower power consumption than DRAM
- + 100X higher storage density than DRAM
- Slower than DRAM

Existing Flash-based Solution

- SSDs as a simple swap device for DRAM is undesirable for KVS
 - Small random writes leads to poor performance
- A better solution is to move KV-Data Store to flash
 - KV-Index Cache keeps abbreviated keys and data pointers in DRAM
 - KV-Data Store keeps both keys and values as a log on flash
 - Keys need to be compared to produces a hit
 - FlashStore[VLDB'10], Twitter's Fatcache, ...

FTL is Burdensome

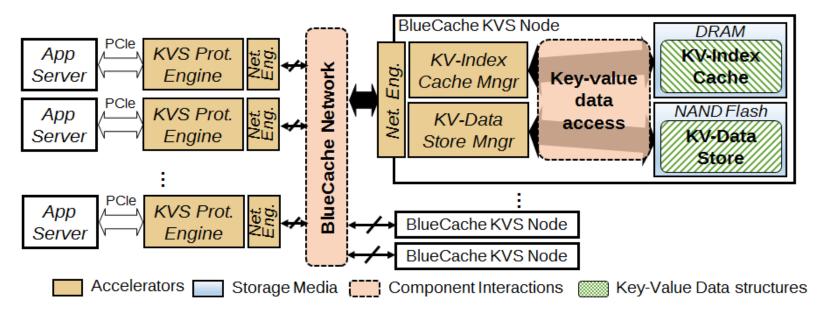
- Flash translation layer is deployed in SSDs to provide harddrive-like behaviors
 - Manages wear-leveling, bad block management, address mapping and garbage collection
 - Uses significant hardware (multi-core ARM with a large DRAM)
- Benefits have been shown for no-FTL flash-based file systems, such as SDF [ASPLOS'15], AMF [FAST'16]

A KVS design that eliminates FTL, and *directly* manages raw NAND flash chips can harness the full device performance

BlueCache Architecture

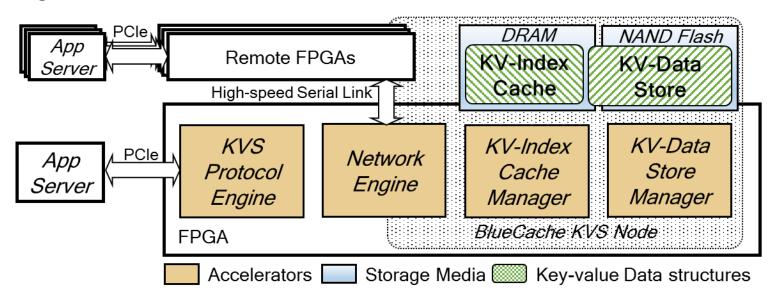
A Distributed NoFTL flash-based KVS with HW accelerators

- Application servers uses KVS Protocol Engine via PCIe to communicate with KVS nodes
- KVS node uses hardware accelerators which directly manage KV pairs on NAND-flash array of chips



BlueCache Architecture (Cont.)

- BlueCache implements hardware accelerators on a single FPGA board on BlueDBM
 - KVS Protocol Engine auto-batches KVS requests
 - In-storage Network Engines with dynamic allocation of virtual channels per application
 - 4-way set-associative KV-index cache
 - Log-structured KV-Data Store without FTL

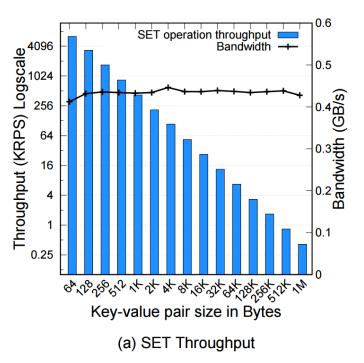


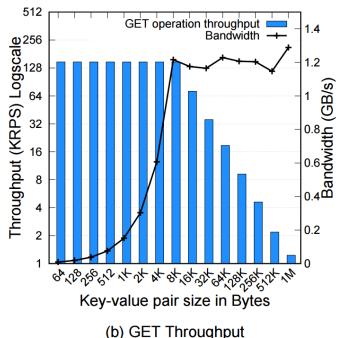
Software Interface

- Provides a multi-thread C++ library to applications
 - Provides three synchronous C++ functions of SET, GET, DELETE
 - Accessible to JAVA applications via JNI
 - Multiple threads needed to saturate BlueCache node bandwidth (>128 threads)

Single-node Performance

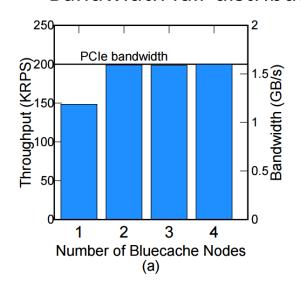
- SETs saturate flash chip write bandwidth (430MB/s)
- GETs saturate flash chip random read bandwidth
 - For KV Size < 8KB, operation throughput is 148 KRPS
 - For KV size >= 8KB, operation throughput limited by flash read bandwidth (1.2GB/s)

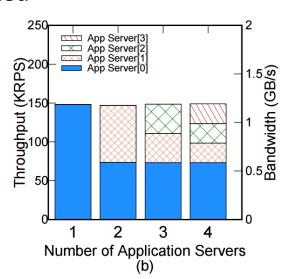


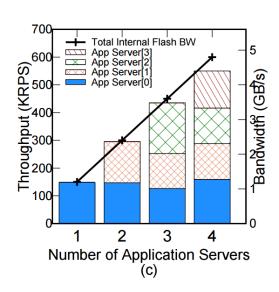


Multi-node Performance

- Single application server, multiple Bluecache nodes
 - Limited by PCIe bandwidth
- Multiple application servers, single BlueCache node
 - Limited by flash bandwidth
 - Favors application server where KVS is attached
- Multiple application servers, multiple BlueCache nodes
 - Bandwidth fair distributed







BlueCache is Low Power

- A BlueCache node uses 40 Watts at peak
- 20-node system consumes 800 Watts and provides 20TB storage
- > 25X lower GB/Watt than x86-based systems

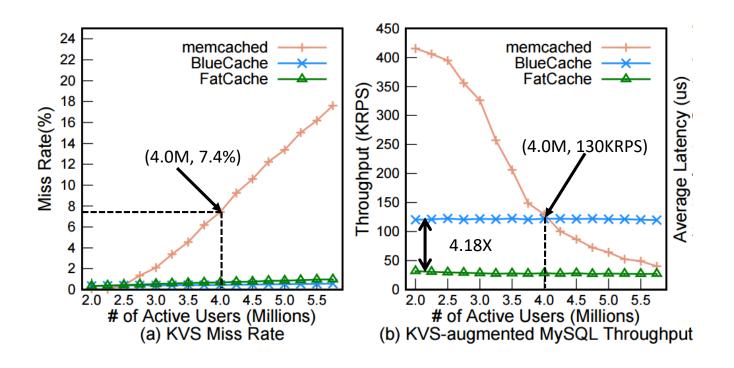
Platforms	Capacity (GB)	Power (Watt)	Capacity/Power (GB/Watt)
BlueCache	20,000	800	25.00
FlashStore [VLDB'10]	80	83.5	0.96
MICA [ISCA'15]	128	399.2	0.32
Mega-KV [VLDB'15]	128	899.2	0.14

A Social Networking Example

- We ran BG [CIDR'13], a social networking benchmark, to evaluate the efficacy of BlueCache against other KVS systems
 - Transforms facebook-like social actions into MySQL queries
 - Uses KVS to cache MySQL queries
 - Open source code

Key Result

- BlueCache can outperform in-memory KVS when the latter has more than 7.4% misses
- BlueCache is 4.18X faster than x86-based KVS with flash memory of similar performance



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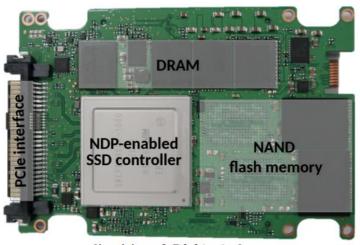
Biscuit

- A user-programmable in-storage processing framework for SSDs and data-intensive applications
 - C++ language support (C++ standard library)
 - Dynamic loading of user programs
 - Mutithreading, multi-core support



SSD Hardware

Use dedicated MPU for in-storage processing



[Inside of PM1725]

Item	Description	
Host interface	PCIe Gen.3 ×4 (3.2 GB/s)	
Protocol	NVMe 1.1	
Device density	1 TB	
SSD architecture	Multiple channels/ways/cores	
Storage medium	Multi-bit NAND flash memory	
Compute resources	Two ARM Cortex R7 cores	
for Biscuit	@750MHz with MPU	
On-chip SRAM	< 1 MiB	
DRAM	≥ 1 GiB	

- Limitations: Low compute power, no cache coherence, a small amount of fast memory, no MMU, and restrictive synchronization primitives
- How to run in-storage software logics inside Biscuit?

Biscuit Runtime

Cooperative multithreading

- A limited form of multithreading (fiber as a scheduling unit)
- Less context switching overhead
- Safe resource sharing without locking

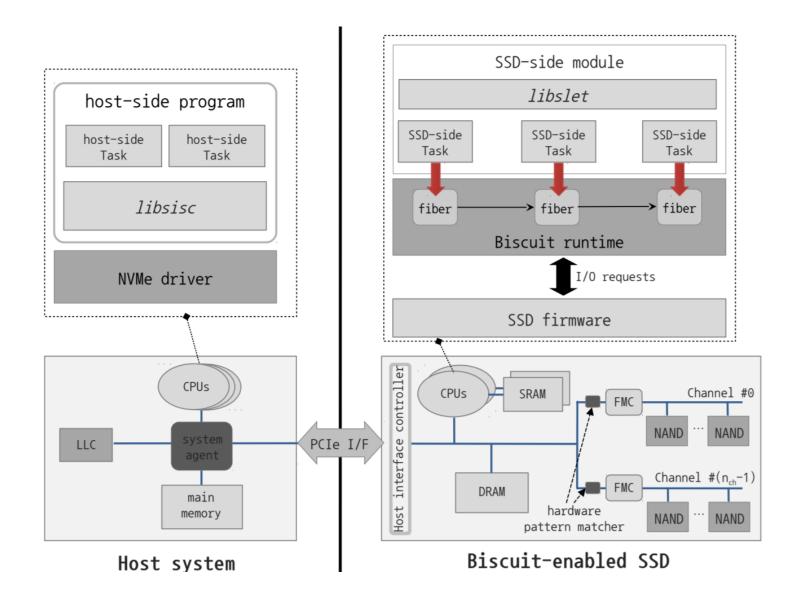
Shared nothing architecture

- Enforced by the programming model and APIs
- C++11 move semantics supported

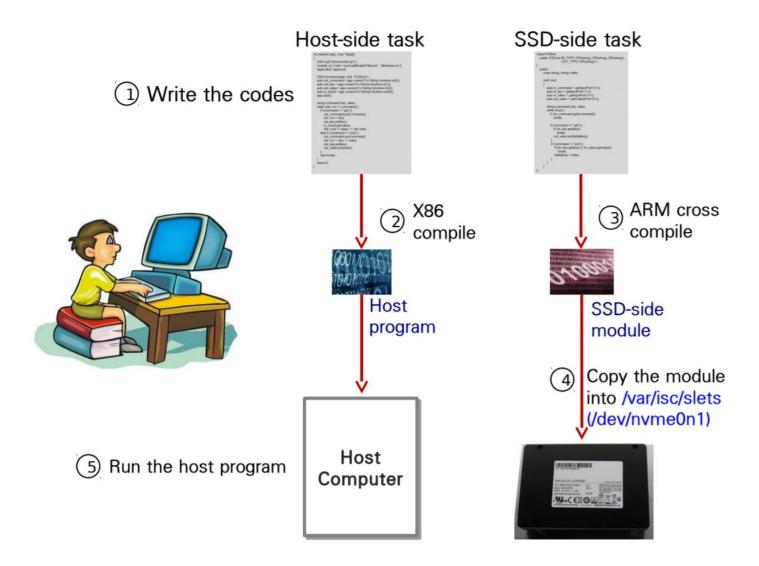
Dynamic loader for user programs

- User program as position-independent code (PIC)
- Symbol relocation to locate each program in a separate address space

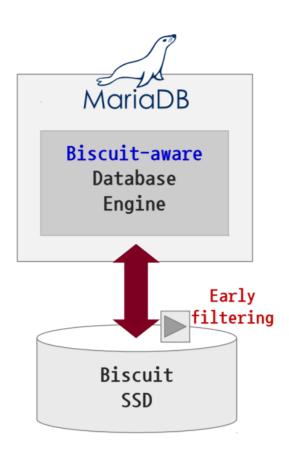
Biscuit System Architecture



Development Process



Application Level Results



Data analytics with a real DB engine

- MariaDB 5.5.42
 - TPC-H dataset at a scale factor of 100 (160 GiB)
- Modified the query planner to
 - Identify a candidate table amenable for offloading;
 - Estimate its selectivity1 using a sampling method;
 - Determine whether the table is indeed a good target (based on a selectivity threshold);
 - and finally offload the identified filter to the SSD.

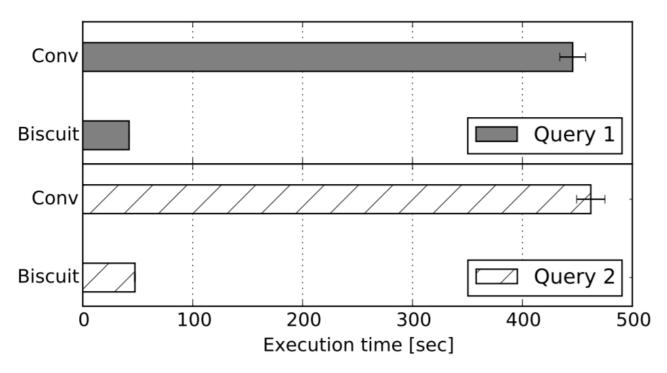
Sample Queries

Query 1 (single filter predicate, selectivity for shipdate: 0.02)

```
SELECT l_orderkey, l_shipdate, l_linenumber FROM lineitem
WHERE l_shipdate = '1995-1-17'
```

Query 2 (more complex WHERE clause, selectivity for shipdate: 0.04)

Experimental Results



- Biscuit achieves speed-ups of about 11× and 10×
 - Large internal bandwidth of Biscuit
 - Rapid scanning of the dataset by the hardware pattern matcher
- Execution times on Biscuit were very consistent

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IESSD: Inference-Enabled SSD

■ IESSD is in capable of performing DNN operations inside an SSD, avoiding frequent data movements between application servers and data storage

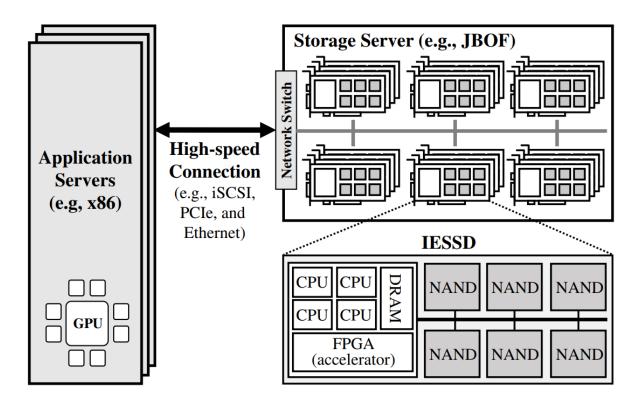
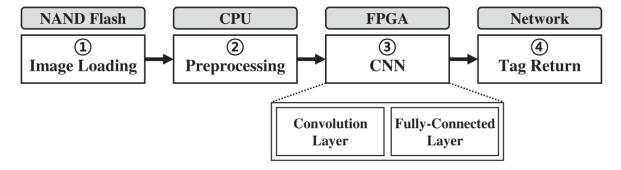


Fig. 1. Overall architecture of Al acceleration system with IESSDs

Image Classification with DNN

Image loading - > Preprocessing - > CNN - > Tag Return

Four main steps of the image tagging process and entities that perform at each step in the baseline IESSD design



■ Latency of each step of image classification

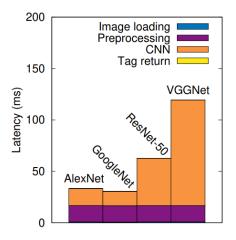


Fig. 3. Latency of each step

Optimization

 To maximally exploit HW resources available in an SSD, we employ three optimization techniques

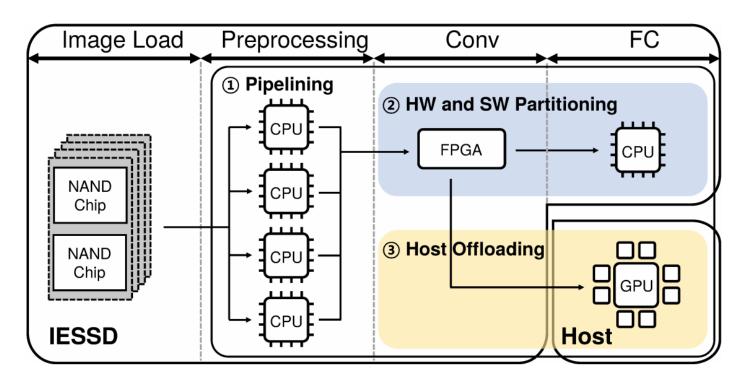
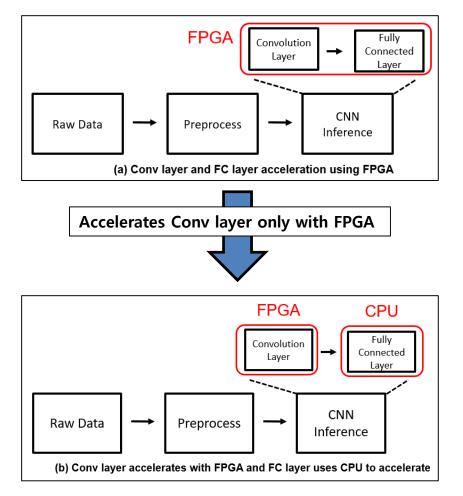


Fig. 4. Three optimization techniques in IESSD

HW-SW Partitioning

■ Run the convolution layer in FPGA and the fully connected layer in CPU → Better utilize FPGA

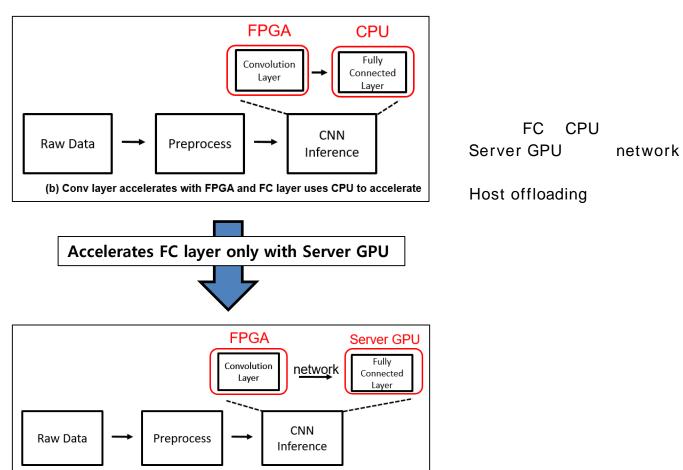


[HW - SW Partitioning] conv layer **FPGA** FC CPU **FPGA**

Host Offloading

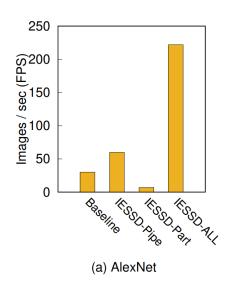
Split the layers and offload the fully connected layer to the host GPU

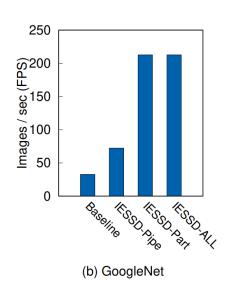
(b) Conv layer accelerates with FPGA and FC layer uses Server GPU to accelerate

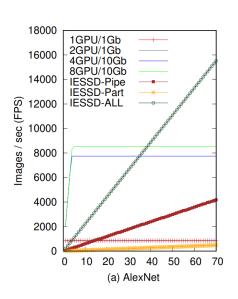


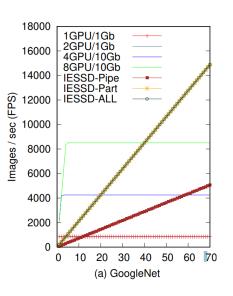
Experimental Results

- IESSD-ALL exhibited the best performance, achieving 221.9 and 212.7 throughput (images/sec) for AlextNet and GoogleNet
- IESSD-ALL outperformed 8 GPU/10 GbE when more than 39 IESSDs were employed in AFA
- IESSD consumes 1.78x and 5.31x less power than 8 GPUs at the cross points where IESSD overtakes 8 GPU/10 GbE









Single IESSD performance

Multiple IESSD performance

End of Chapter 11