Cloud Storage 2

15-719/18-709: Advanced Cloud Computing

Greg Ganger George Amvrosiadis Majd Sakr

Feb 11, 2019

15-719/18-709: Advanced Cloud Computing

Agenda: Cloud-scale storage

 Scalable storage: essential for scalable cloud systems

Covered Approach 1: extend familiar distributed file systems

- Basic design tradeoffs: statelessness, caching, etc.
- NASD: scaling the data transfer path
- Haystack: optimize for specific workload
- GFS: fault-tolerance, targeted consistency model
- TableFS: efficiency for small files too

Approach 2: abandon traditional file system model

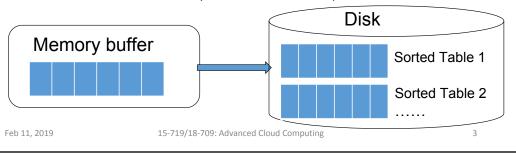
• Examples: AWS S3, AWS EBS, Docker

Feb 11, 2019

15-719/18-709: Advanced Cloud Computing

Log Structured Merge (LSM) Trees

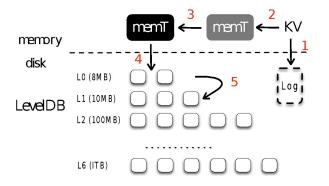
- Insert / Updates
 - Buffer and sort recent inserts/updates in memory
 - · Write-out sorted buffers into local file system sequentially
 - · Less random disk writes than traditional B-Tree
- Lookup / Scan
 - · Search sorted tables one by one from the disk
 - · Compaction is merge sort into new files, deleting old (cleaning)
 - Bloom-filter and in-memory index to reduce lookups



Write Optimized like LFS (cleaning = compaction)

LSM-trees: Insertion

1. Write sequentially 2. Sort data for quick lookups 3. Sorting and garbage collection are coupled



Clean so there is no overlap in SSTables in each level after 0

- (Cacheable) index per SSTable
- Lists 1st & last key per SSTable

[Lanyue Lu, FAST16]

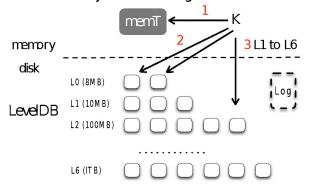
Feb 11, 2019

15-719/18-709: Advanced Cloud Computing

O(log size) lookup like B-tree

LSM-trees: Lookup

- 1. Random reads
- 2. Travel many levels for a large LSM-tree



- (Cacheable) Bloom filter per SSTable
- Skip ~99% unneeded lookups

[Lanyue Lu, FAST16]

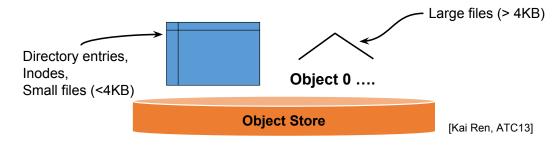
Feb 11, 2019

15-719/18-709: Advanced Cloud Computing

5

TableFS: metadata in LSM Trees

- Small objects embedded in LSM tree (tabular structure)
 - E.g. directory entries, inodes, small files
 - Turn many small files into one large object (~ 2MB)
- Larger files stored in object store indexed by TableFS-assigned IDs



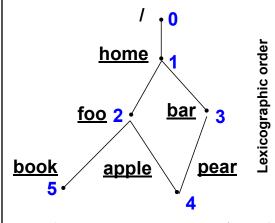
Feb 11, 2019

15-719/18-709: Advanced Cloud Computing

Table Schema

- Key: <Parent inode number, hash(filename)>
 - Inodes with multiple hard links: <inode number, null>
- Value: filename, inode attrs, inlined file data (or symlink to large object)

 [Kai Ren, ATC13]



| Кеу | Value |
|------------------------|---|
| <0,hash(home)> | 1, "home", struct stat |
| <1,hash(foo)> | 2, "foo", struct stat |
| <1,hash(<i>bar</i>)> | 3, "bar", struct stat |
| <2,hash(apple)> | 4, "apple", hard link |
| <2,hash(book)> | 5, "book", struct <i>stat</i> , inline small file |
| <3,hash(pear)> | 4, "pear", hard link |
| <4,null> | 4, struct <i>stat</i> , large file pointer |

Feb 11, 2019

15-719/18-709: Advanced Cloud Computing

Table Schema (cont)

- Advantages:
 - Fewer random lookups by co-locating dir entries with inode attrs, small files
 - "readdir" performs sequential scan on the table

| Entries | in |
|----------------|----|
| the sam | e |
| director | 'n |
| | • |
| | |

| | Key | Value |
|---|-------------------------|---|
| | <0,hash(home)> | 1, "home", struct stat |
| • | <1,hash(foo)> | 2, "foo", struct stat |
| | <1,hash(<i>bar</i>)> | 3, "bar", struct stat |
| | <2,hash(apple)> | 4, "apple", hard link |
| | <2,hash(<i>book</i>)> | 5, "book", struct <i>stat</i> , inline small file |
| | <3,hash(pear)> | 4, "pear", hard link |
| | <4,null> | 4, struct <i>stat</i> , large file pointer |

[Kai Ren, ATC13]

Feb 11, 2019

15-719/18-709: Advanced Cloud Computing

Popular cloud storage options

- 1. Provide a "traditional" filesystem
 - The OS running in each VM mounts file service
 - · just like any client would in client-server distributed FS
 - E.g., NFS, AFS, Google file system, HDFS
 - Discussed on Monday
- 2. Provide block stores (virtual disks)
- 3. Provide a "union" filesystem on each client
- 4. Provide an "object store"

9

2. Provide block stores (virtual disks)

- A common option in VM-based environments
 - Guest OS running in a VM has code for FSs on disks
 - · assumes that it has private access to disk capacity
 - So, give it a "disk" to use
 - · but, giving it a physical disk isn't VM/cloud style
- Virtual disk looks to guest OS just like real disk
 - Same interface
 - · read/write of fixed-size blocks, ID'd by block number
 - Guest OS can format it, implement an FS atop it, etc.
 - · VMM makes guest OS disk operations access the right content
- Most cloud infrastructures have this option
 - E.g., AWS Elastic Block Store (EBS), OpenStack Cinder

Virtual Disk (VD) implementation

- Client OSs think that they are using a real disk
 - So, they use disk-like block interfaces
 - e.g., SCSI rather than NFS
 - Guest OS may or may not know virtual disk is local
 - Non-local interface: network-disk interface (iSCSI)
 - Local interface: VMM translates to other protocol as needed
- VDs often implemented as files
 - A file is a sequence of bytes
 - So, a file can hold a sequence of fixed-sized blocks
 - So, a file server can be used for VDs
 - E.g., each VD is a file
 - May be accessed by block protocol or file protocol
 - E.g., via non-local or local from above,

More Virtual Disk (VD) stuff

- Thin provisioning
 - Promise more space that you have
 - E.g., tell 20 VMs they each get 1TB, but only have 10TB
 - Allocate physical space only for blocks that get written
 - · Most devices are not used to full capacity
 - Benefits from TRIM and other storage class stuff ©
- Performance interference
 - Each VM may have a virtual disk
 - OS in VM assumes it will behave like a real disk
 - Including performance behavior!
 - We expect time-sharing to have fairness / QoS
 - Need it for storage too
 - · But, it's very difficult
 - Interference in caches, on-disk placement, metadata,

One aggressive demonstration of Quality of Storage

IOFlow: a Software-Defined Storage Architecture.

Eno Thereska, Hitesh Ballani, Greg O'Shea, Thomas Karagiannis, Antony Rowstron, Tom Talpey, Richard Black, Timothy Zhu. SOSP 2013, Farmington PA, Nov 2013.

- SDN "forwarding rules" replaced with "request queue ordering"
- Flows are abstraction of SLO, service binding, data & requests
 - Used for bandwidth allocation & sharing, content checking, prioritization for latency

Feb 11, 2019

15-719/18-709: Advanced Cloud Computing

13

3. Provide "union" filesystems

- A common option in container-based environments
 - Container runs atop OS
 - Container is given access to (part of) file system
 - usually thinks it has entire FS (via chroot)
 - Needs some "system-wide" and some "private" files
 - so, we want to give it both
- Make a single FS view from multiple FSs
 - Show contents of a directory as merge of several
 - · With a sorted order when there are name conflicts
 - Implemented by a layer atop the individual FSs
 - Each operation accesses "unioned" FSs as appropriate

4. Provide "object" store

- A common option in large clouds
 - A simplified, generic "file" storage system
 - · Like files, objects are sequences of bytes
 - · Unlike FSs, usually just numerical object IDs
 - Example: AWS S3
 - Some (e.g., box or iCloud) provide simple directories too
- Usually limited interface and semantics
 - E.g., CRUD API: Create, Read (get), Update (put), Delete
 - No open/close, rename, links, locks, etc.
 - Often assumes single writer, sequential (or all-at-once)
 - No promises re: sharing/concurrency, interrupted writes, etc.

15

Next

- Cool Saurabh talk about analytics storage atop S3
- Next
 - Wednesday: tail latency
 - Next week: frameworks-2 and key-value stores

A Case for Packing and Indexing in Cloud File Systems

Saurabh Kadekodi **Bin** Fan*, Adit Madan*, Garth Gibson

PARALLEL DATA
LABORATORY
Carnegie Mellon University

, *Alluxio Inc.

Carnegie Mellon Parallel Data Laboratory

17

Workload

- Spark job processing all data in memory and producing 3.2 million 8KB files
- Packing tiny files improves throughput and reduces cost

18

• By how much?

Carnegie Mellon Parallel Data Laboratory

Improved Throughput Guess?

- 10x
- 25x
- 50x

61x more

- 100x
- more

Carnegie Mellon

Parallel Data Laboratory

ntto://www.policemuredu

Saurabh Kadekodi © February 18

Reduced Experiment Price?

- 10x
- 25x
- 50x

25000x less

- 100x
- more

Carnegie Mellon Parallel Data Laboratory

nttp://www.pal.emu.eau

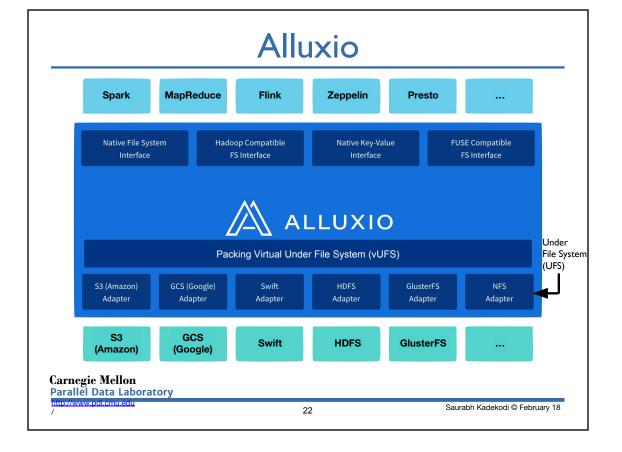
Problem Statement

- To augment a cloud file system's write-back cache with a packing and indexing layer that coalesces small files or segments of slow-growing files to transform arbitrary user workload(s) to a write pattern more ideal for cloud storage in terms of — transfer sizes, number of objects and price.
- tl;dr Batch cloud writes and make large transfers.

21

 Invariant: Never write small files to backing cloud stores.

Carnegie Mellon
Parallel Data Laboratory







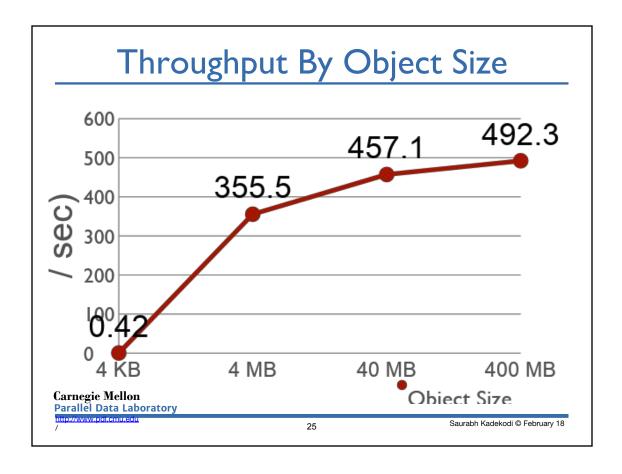
Carnegie Mellon Parallel Data Laboratory

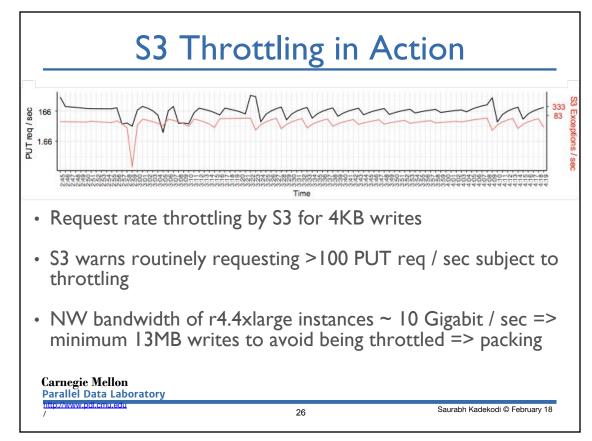
Saurabh Kadekodi © February 18

Performance Motivation

- r4.4xlarge EC2 instances
- 4 Alluxio workers
- I Alluxio masters
- ~I3 GB data
- Increasing file sizes (4KB 400MB)
 - 3.2M files of size 4KB (smallest)
 - 32 files of 400 MB (largest)

Carnegie Mellon Parallel Data Laboratory









Carnegie Mellon Parallel Data Laboratory

ntto://www.policemuredu

Saurabh Kadekodi © February 18

Price Motivation

27

| S3 Pricing | PUT, COPY, | GET | Data Retrieval |
|-------------|------------------|------------------|-------------------|
| Model | POST | | Cost |
| Standard | \$0.05 / | \$0.04 / | Free |
| | 10000 req, | 100000 req, | (for certain data |
| | same for retries | same for retries | center locations) |
| Standard w/ | \$0.1 / | \$0.1 / | \$0.01 / GB |
| Infrequent | 10000 req, | 100000 req, | |
| Access | no retries | no retries | |

- For just one million files, the put cost = \$5
- Packing can reduce cost by at least the packing factor

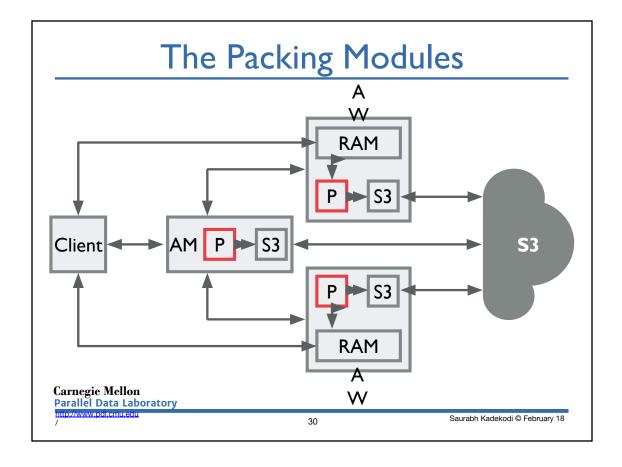
Carnegie Mellon Parallel Data Laboratory

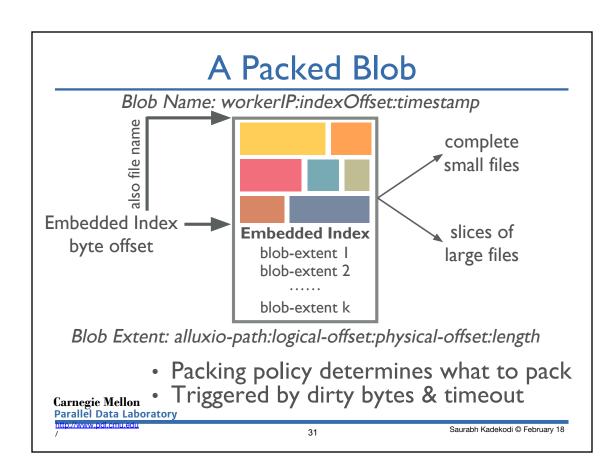
ttto://www.pdi.cmu.edu

Design

29

Carnegie Mellon Parallel Data Laboratory





Blob Descriptor Table - BDT (Index)

- Maps Alluxio files Current Location
- Implemented as LevelDB to bound memory usage
- Global BDT in centralized location
- Each worker has BDT as optimization

Carnegie Mellon
Parallel Data Laboratory

Evaluation

Carnegie Mellon Parallel Data Laboratory

http://www.pdi.cmu.edu

Saurabh Kadekodi © February 18

Configuration

- Experiment Small file concurrent create (avg of 2 runs)
 - I AlluxioMaster (i.e. I PackingMaster)
 - 4 AlluxioWorkers (i.e. 4 PackingWorkers)
 - 32 concurrent clients (workload generators) 8 per AW
 - 100K files (each 8KB) per client ~ totally 3.2M files
 - · Total workload size: 24.4 GB

Carnegie Mellon Parallel Data Laboratory

/www.pdl.cmu.edu

Packing Configuration

Max blob size: I GB

• Packing interval: 5 sec

• # Packing threads: 16

• # Master threads: 16

Backup interval: I min

Carnegie Mellon

Parallel Data Laboratory

ntto://www.proincemune.oiu

35

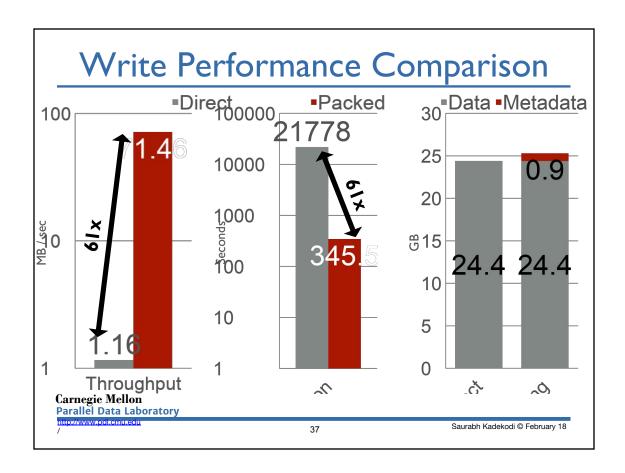
Saurabh Kadekodi © February 18

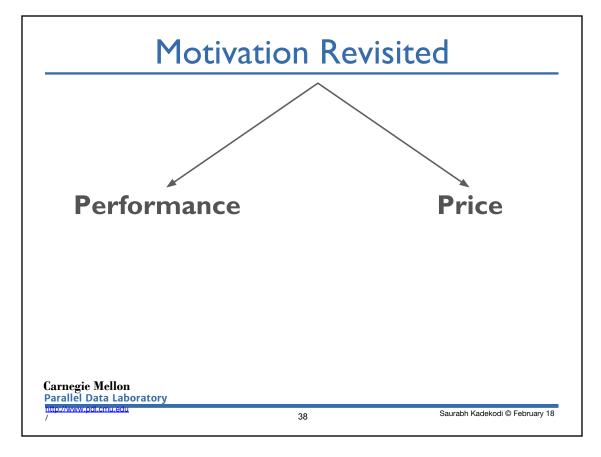
Motivation Revisited



Carnegie Mellon Parallel Data Laboratory

nttox//www.policemu.edi





Cloud Storage Price

| S3 Pricing | PUT, COPY, | GET | Data Retrieval |
|-------------|------------------|------------------|-------------------|
| Model | POST | | Cost |
| Standard | \$0.05 / | \$0.04 / | Free |
| | 10000 req, | 100000 req, | (for certain data |
| | same for retries | same for retries | center locations) |
| Standard w/ | \$0.1 / | \$0.1 / | \$0.01 / GB |
| Infrequent | 10000 req, | 100000 req, | |
| Access | no retries | no retries | |

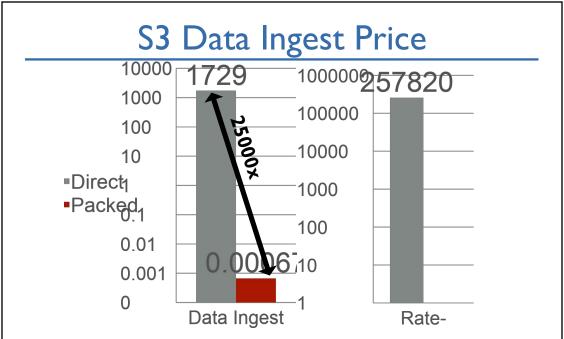
39

Carnegie Mellon

Parallel Data Laboratory

http://www.odi.cmu.edu

Saurabh Kadekodi © February 18



Request rate is throttled much more than data rate

40

Carnegie Mellon Parallel Data Laboratory

Conclusion

- S3 prefers large objects
- S3 rate limits ops / sec to their buckets
- · Packing eliminates this problem by:
 - Reducing ops made to S3 by at least 1000x
 - · Making much more infrequent accesses

Carnegie Mellon

Parallel Data Laboratory

ntto://www.pdi.emu.edu

41

Saurabh Kadekodi © February 18

Questions?

Thank You!

Carnegie Mellon Parallel Data Laboratory

ww.pdr.cmu.edu A2 Saurabh Kadekodi © February 18

