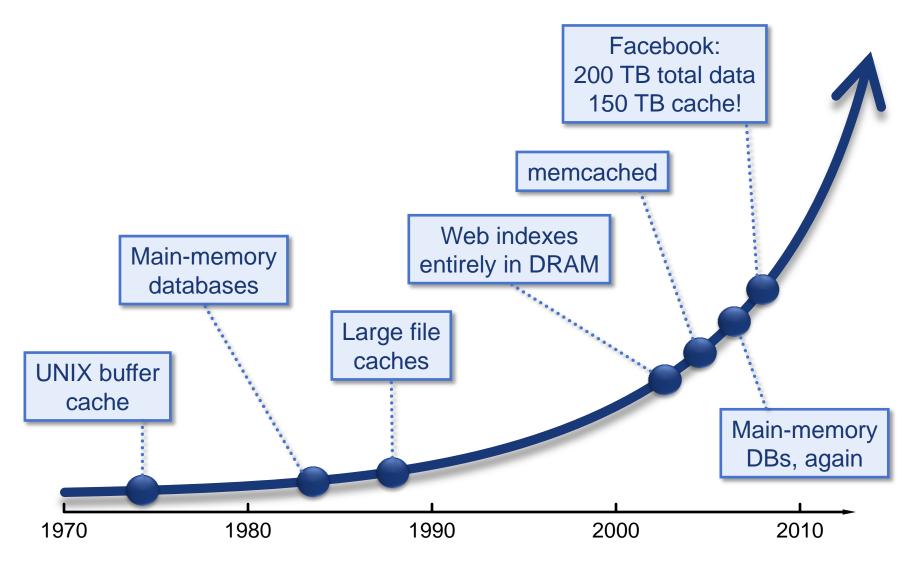
A Compilation of RAMCloud Slides (through Oct. 2012)

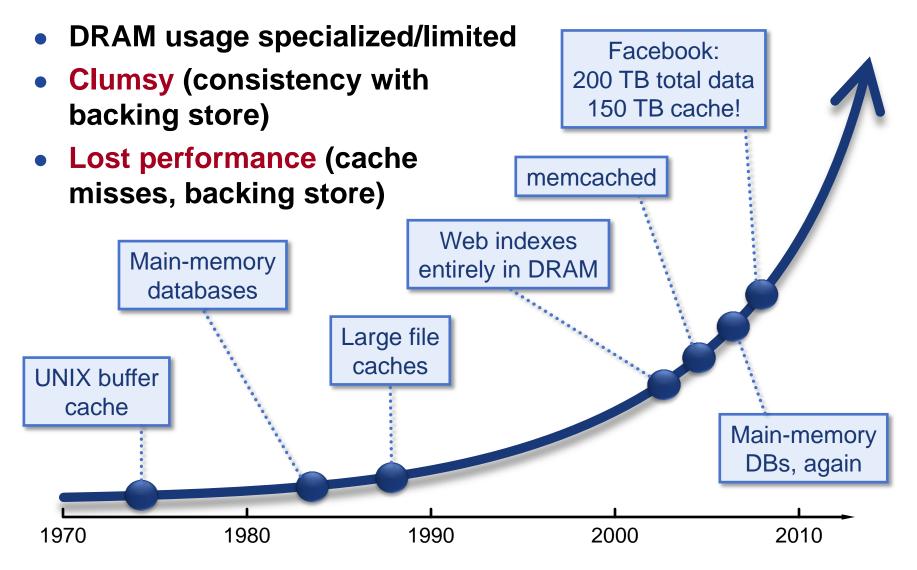
John Ousterhout Stanford University



DRAM in Storage Systems



DRAM in Storage Systems



RAMCloud

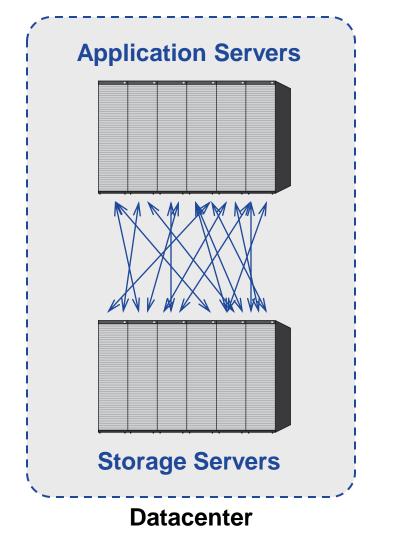
Harness full performance potential of large-scale DRAM storage:

- General-purpose storage system
- All data always in DRAM (no cache misses)
- Durable and available
- **Scale**: 1000+ servers, 100+ TB
- Low latency: 5-10µs remote access

Potential impact: enable new class of applications

RAMCloud Overview

- Storage for datacenters
- 1000-10000 commodity servers
- 32-64 GB DRAM/server
- All data always in RAM
- Durable and available
- Performance goals:
 - High throughput: 1M ops/sec/server
 - Low-latency access: 5-10µs RPC



Example Configurations

	2010	2015-2020
# servers	2000	4000
GB/server	24GB	256GB
Total capacity	48TB	1PB
Total server cost	\$3.1M	\$6M
\$/GB	\$65	\$6

For \$100-200K today:

- One year of Amazon customer orders
- One year of United flight reservations

Why Does Latency Matter?

Traditional Application Web Application Ul Image: Application in the second second

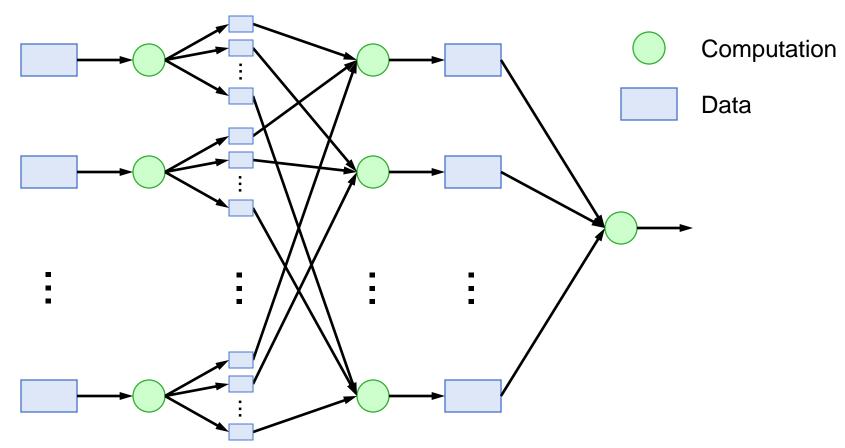
<< 1µs latency

0.5-10ms latency

Large-scale apps struggle with high latency

- Random access data rate has not scaled!
- Facebook: can only make 100-150 internal requests per page

MapReduce



- \checkmark Sequential data access \rightarrow high data access rate
- Not all applications fit this model
- × Offline

October 2, 2012

Goal: Scale and Latency

Traditional Application Web Application Application Servers Storage UI UI App. App. Servers ogic _ogic Data Structures Single machine Datacenter 0.5-10ms latency << 1µs latency

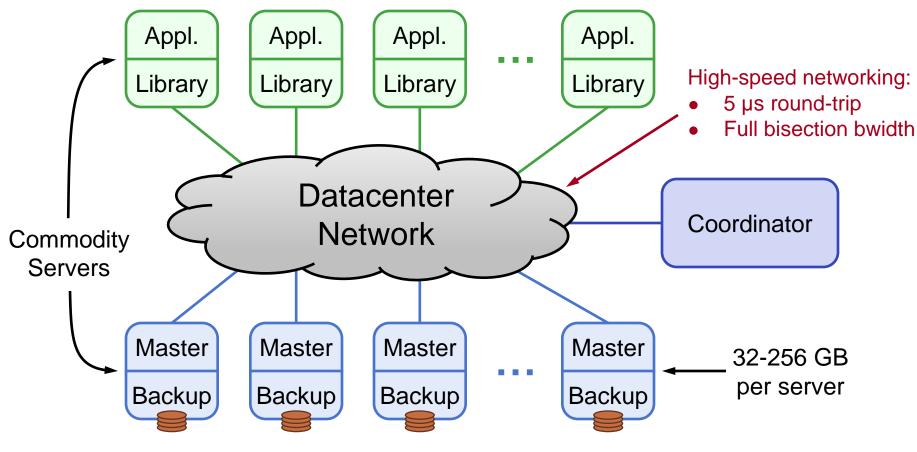
5-10µs

Enable new class of applications:

- Crowd-level collaboration
- Large-scale graph algorithms
- Real-time information-intensive applications

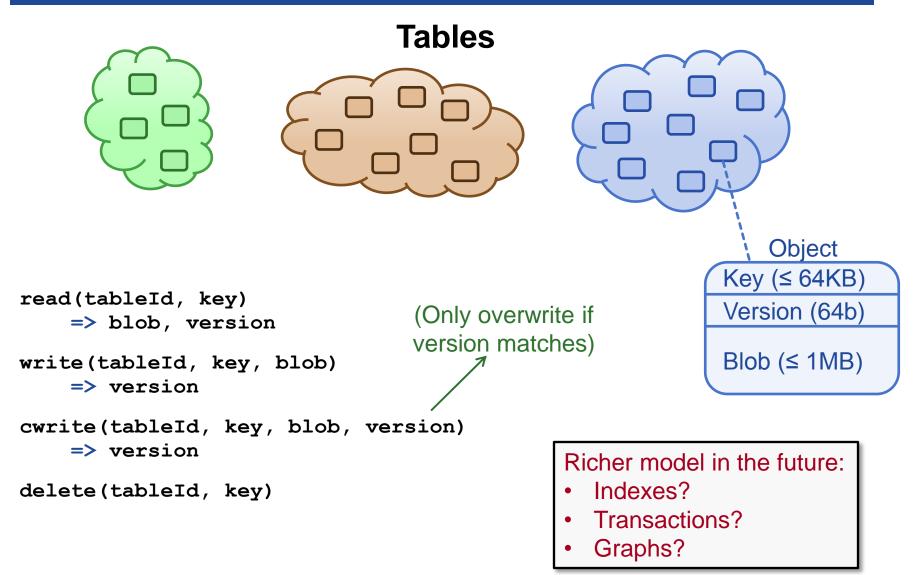
RAMCloud Architecture

1000 – 100,000 Application Servers



1000 – 10,000 Storage Servers

Data Model



Research Issues

- Durability and availability
- Fast communication (RPC)
- Data model
- Concurrency, consistency, transactions
- Data distribution, scaling
- Multi-tenancy
- Client-server functional distribution
- Node architecture

Research Areas

- Data models for low latency and large scale
- Storage systems: replication, logging to make DRAM-based storage durable

• Performance:

- Serve requests in < 10 cache misses
- Recover from crashes in 1-2 seconds
- Networking: new protocols for low latency, datacenters

• Large-scale systems:

- Coordinate 1000's of machines
- Automatic reconfiguration

Durability and Availability

• Goals:

- No impact on performance
- Minimum cost, energy

• Keep replicas in DRAM of other servers?

- 3x system cost, energy
- Still have to handle power failures

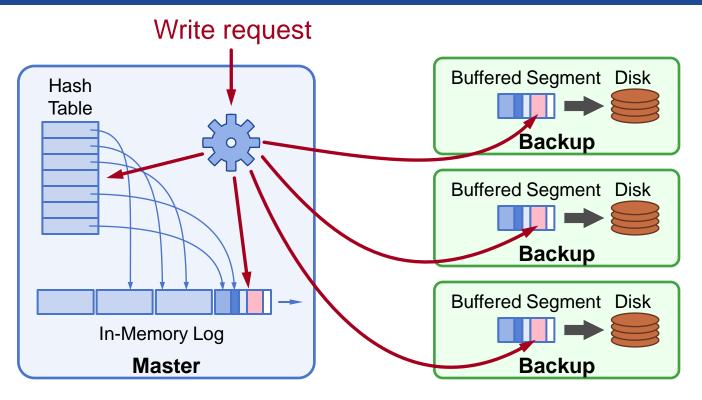
• **RAMCloud** approach:

- 1 copy in DRAM
- Backup copies on disk/flash: durability ~ free!

Issues to resolve:

- Synchronous disk I/O's during writes??
- Data unavailable after crashes??

Buffered Logging



- No disk I/O during write requests
- Log-structured: backup disk and master's memory
- Log cleaning ~ generational garbage collection

Crash Recovery

 Power failures: backups must guarantee durability of buffered data:

- Per-server battery backups?
- DIMMs with built-in flash backup?
- Caches on enterprise disk controllers?

• Server crashes:

- Must replay log to reconstruct data
- Meanwhile, data is unavailable
- Solution: fast crash recovery (1-2 seconds)
- If fast enough, failures will not be noticed

• Key to fast recovery: use system scale

Recovery, First Try

• Master chooses backups statically

Each backup mirrors entire log for master

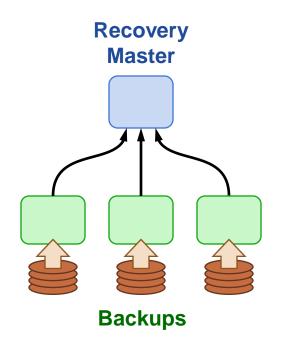
• Crash recovery:

- Choose recovery master
- Backups read log info from disk
- Transfer logs to recovery master
- Recovery master replays log

• First bottleneck: disk bandwidth:

64 GB / 3 backups / 100 MB/sec/disk
 ≈ 210 seconds

Solution: more disks (and backups)



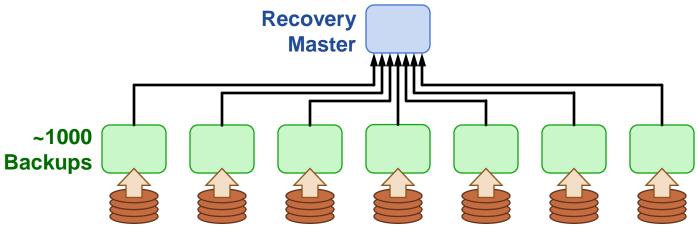
Recovery, Second Try

• Scatter logs:

- Each log divided into 8MB segments
- Master chooses different backups for each segment (randomly)
- Segments scattered across all servers in the cluster

• Crash recovery:

- All backups read from disk in parallel
- Transmit data over network to recovery master



Scattered Logs, cont'd

• Disk no longer a bottleneck:

- 64 GB / 8 MB/segment / 1000 backups ≈ 8 segments/backup
- 100ms/segment to read from disk
- 0.8 second to read all segments in parallel

• Second bottleneck: NIC on recovery master

- 64 GB / 10 Gbits/second ≈ 60 seconds
- Recovery master CPU is also a bottleneck

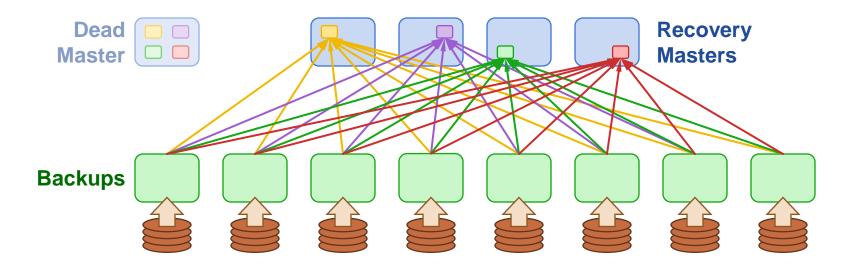
• Solution: more recovery masters

- Spread work over 100 recovery masters
- 64 GB / 10 Gbits/second / 100 masters ≈ 0.6 second

Recovery, Third Try

• Divide each master's data into partitions

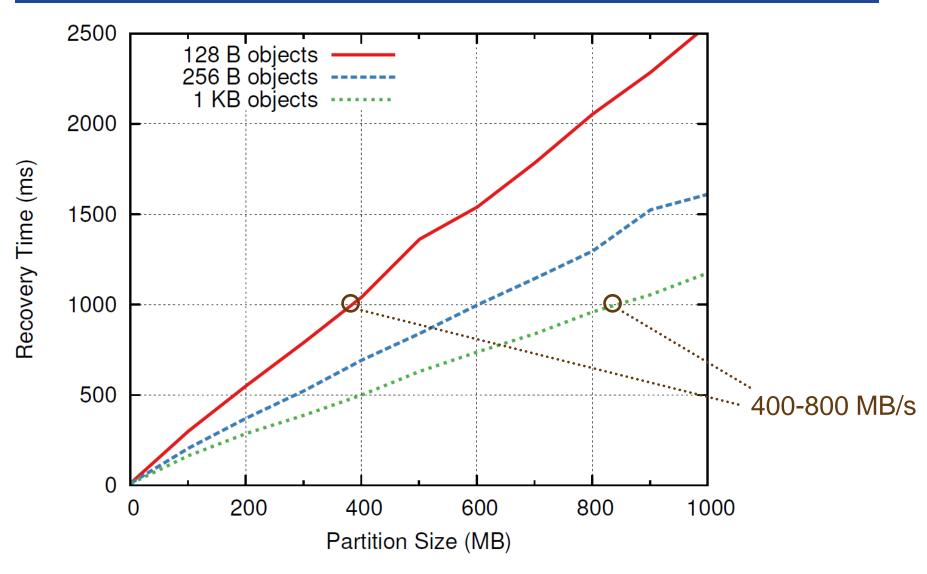
- Recover each partition on a separate recovery master
- Partitions based on tables & key ranges, not log segment
- Each backup divides its log data among recovery masters



Project Status

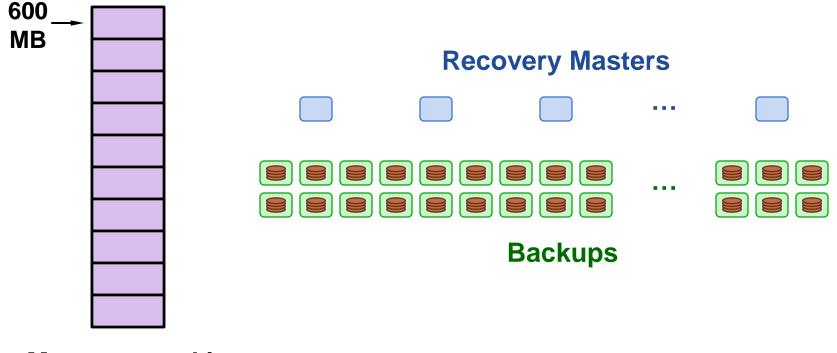
- Goal: build production-quality implementation
- Started coding Spring 2010
- Major pieces working:
 - RPC subsystem (supports multiple networking technologies)
 - Basic operations, log cleaning
 - Fast recovery
 - Prototype cluster coordinator
- Nearing 1.0-level release
- Performance (80-node cluster):
 - Read small object: 5.3µs
 - Throughput: 850K small reads/second/server

Single Recovery Master



Evaluating Scalability

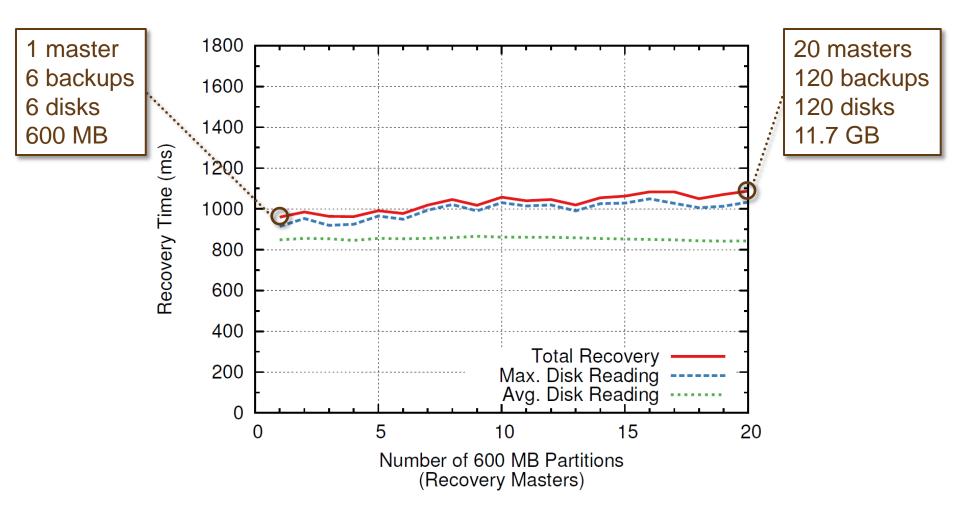
Recovery time should stay constant as system scales



Memory used in crashed master

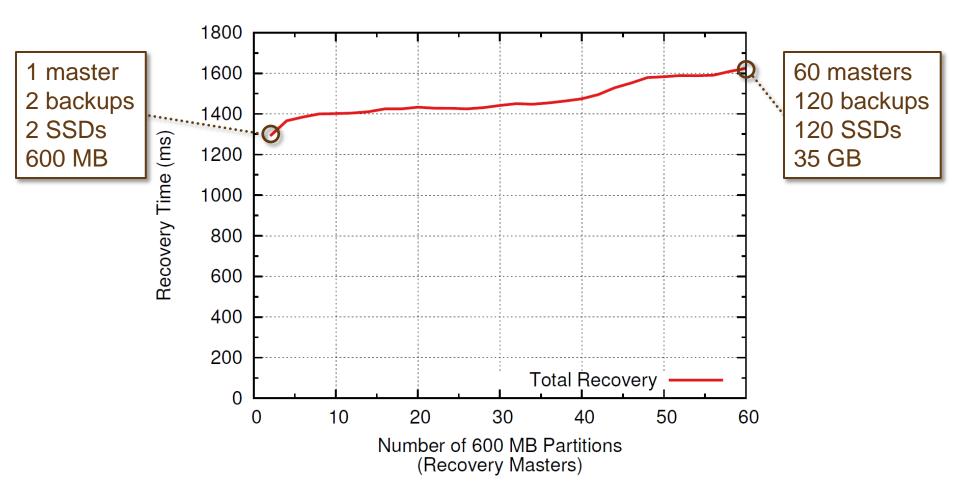
October 2, 2012

Recovery Scalability



Scalability (Flash)

2 flash drives (250MB/s) per partition:



Conclusion

- Achieved low latency (at small scale)
- Not yet at large scale (but scalability encouraging)
- Fast recovery:
 - < 2 seconds for memory sizes up to 35GB</p>
 - Scalability looks good
 - Durable and available DRAM storage for the cost of volatile cache

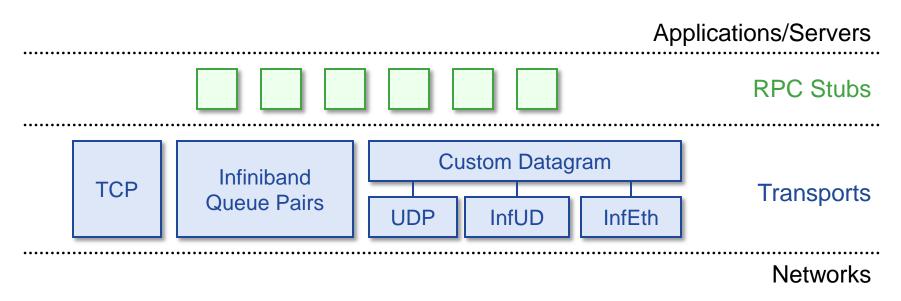
• Many interesting problems left

- Goals:
 - Harness full performance potential of DRAM-based storage
 - Enable new applications: intensive manipulation of large-scale data

RPC Transport Architecture

Transport API: Reliable request/response	ClientSend(rec wait()		-		rvers eqBuf, respBuf)
InfRcTransport	TcpTrans	port	Fa	astTransport	
Infiniband verbs Reliable queue pairs Kernel bypass Mellanox NICs	Kernel TC	P/IP UdpDrive	r	InfUdDriver	InfEthDriver
Driver API: Unreliable o	datagrams	Kernel UDP		Infiniband unreliable datagrams	10GigE packets via Mellanox NIC

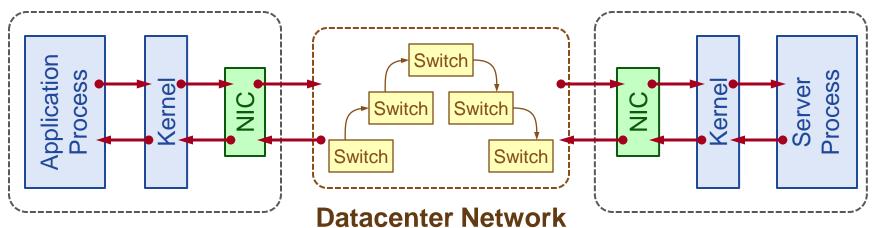
RAMCloud RPC



- Transport layer enables experimentation with different networking protocols/technologies
- Basic Infiniband performance (one switch):
 - 100-byte reads: 5.3 μs
 - 100-byte writes (3x replication):
 - Read throughput (100 bytes, 1 server): 800 Kops/sec

16.1 µs

Datacenter Latency Today



Application Machine

Server Machine

Component	Delay	Round-trip
Network switch	10-30µs	100-300µs
OS protocol stack	15µs	60µs
Network interface controller (NIC)	2.5-32µs	10-128µs
Propagation delay	0.2-0.4µs	0.4-0.8µs

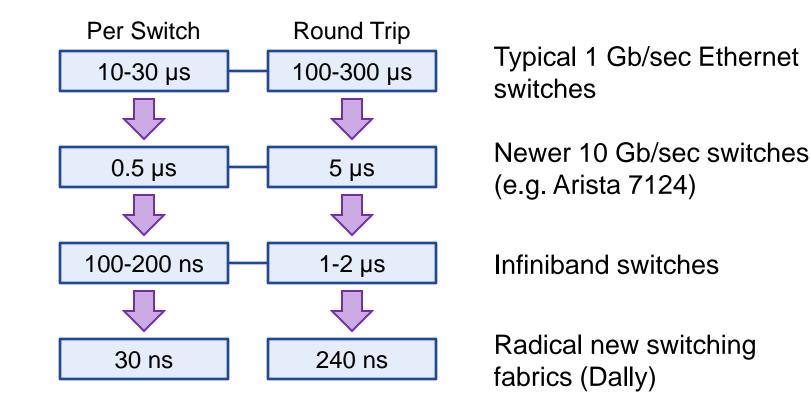
RAMCloud goal: 5-10µs

Typical today: 200-400µs

Faster RPC: Switches

Overall: must focus on latency, not bandwidth

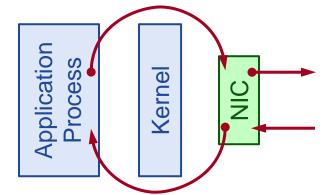
• Step 1: faster switching fabrics

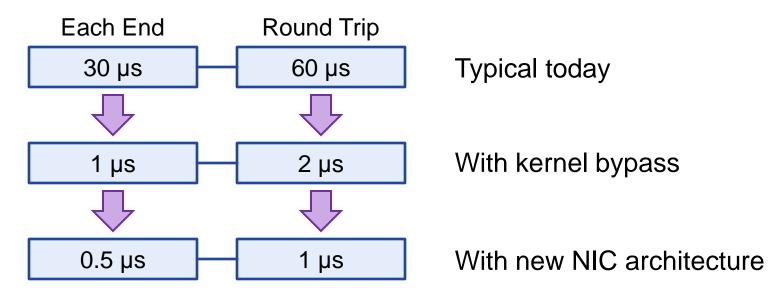


Faster RPC: Software

• Step 2: new software architecture:

- Packets cannot pass through OS
 - Direct user-level access to NIC
- Polling instead of interrupts
- New network protocol





Faster RPC: NICs

• Traditional NICs focus on throughput, not latency

• E.g. defer interrupts for 32 µs to enable coalescing

• CPU-NIC interactions are expensive:

- Data must pass through memory
- High-latency interconnects (Northbridge, PCIe, etc.)
- Interrupts

• Best-case today:

- 0.75 µs per NIC traversal
- 3 µs round-trip delay

• Example: Mellanox Infiniband NICs (kernel bypass)

Total Round-Trip Delay

Component	Today	3-5 Years	10 Years
Switching fabric	100-300µs	5µs	0.2µs
Software	60µs	2µs	2µs
NIC	8-128µs	3µs	3µs
Propagation delay	1µs	1µs	1µs
Total	200-400µs	11µs	6.2µs

• In 10 years, 2/3 of round-trip delay due to NIC!!

- 3µs directly from NIC
- 1µs indirectly from software (communication, cache misses)

New NIC Architecture?

Must integrate NIC tightly into CPU cores:

- Bits pass directly between L1 cache and the network
- Direct access from user space
- Will require architectural changes:
 - New instructions for network communication
 - Some packet buffering in hardware
 - Hardware tables to give OS control
 - Analogous to page tables
 - Take ideas from OpenFlow?
 - Ideally: CPU architecture designed in conjunction with switching fabric
 - E.g. minimize buffering

Round-Trip Delay, Revisited

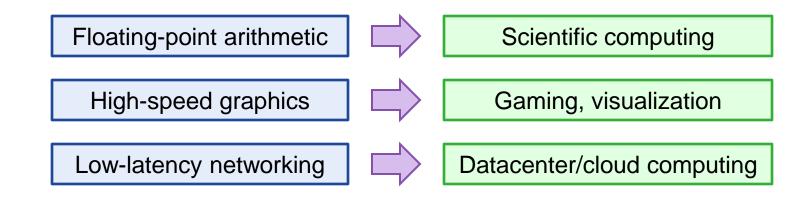
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Software	60µs	2µs	1µs
NIC	8-128µs	3µs	0.2µs
Propagation delay	1µs	1µs	1µs
Total	200-400µs	11µs	2.4µs

• Biggest remaining hurdles:

- Software
- Speed of light

Other Arguments

Integrated functionality drives applications & markets:



 As # cores increases, on-chip networks will become essential: solve the off-chip problem at the same time!

Using Cores

• Goal: service RPC request in 1µs:

- < 10 L2 cache misses!</p>
- Cross-chip synchronization cost: ~1 L2 cache miss

• Using multiple cores/threads:

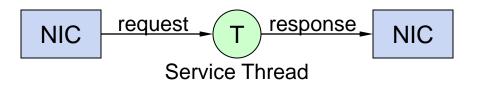
- Synchronization overhead will increase latency
- Concurrency may improve throughput

• Questions:

- What is the best way to use multiple cores?
- Does using multiple cores help performance?
- Can a single core saturate the network?

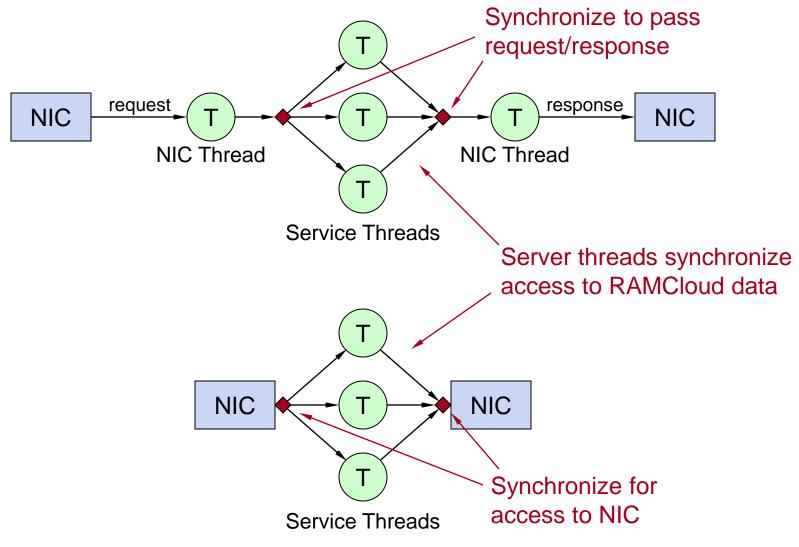
Baseline

• 1 core, 1 thread:



- Poll NIC, process request, send response
- No synchronization overhead
- **×** No concurrency

Multi-Thread Choices



Other Thoughts

• If all threads/cores in a single package:

- No external memory references for synchronization
- Does this make synchronization significantly faster?

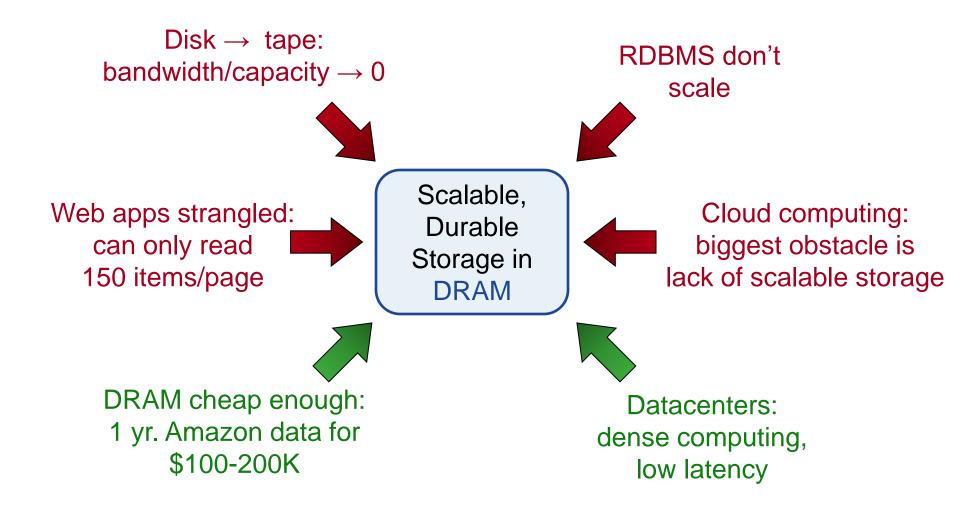
• Why not integrated NIC?

- Transfer incoming packets directly to L2 cache (*which* L2 cache?....)
- Eliminate cache misses to read packets

• Plan:

- Implement a couple of different approaches
- Compare latency and bandwidth

Winds of Change



Research Areas

- Data models for low latency and large scale
- Storage systems: replication, logging to make DRAM-based storage durable

• Performance:

- Serve requests in < 10 cache misses
- Recover from crashes in 1-2 seconds
- Networking: new protocols for low latency, datacenters

• Large-scale systems:

- Coordinate 1000's of machines
- Automatic reconfiguration

Why not a Caching Approach?

• Lost performance:

• 1% misses \rightarrow 10x performance degradation

• Won't save much money:

- Already have to keep information in memory
- Example: Facebook caches ~75% of data size

• Availability gaps after crashes:

- System performance intolerable until cache refills
- Facebook example: 2.5 hours to refill caches!

Why not Flash Memory?

• DRAM enables lowest latency today:

5-10x faster than flash

• Many candidate technologies besides DRAM

- Flash (NAND, NOR)
- PC RAM
- • •
- Most RAMCloud techniques will apply to other technologies

RAMCloud Motivation: Technology

Disk access rate not keeping up with capacity:

	Mid-1980's	2009	Change
Disk capacity	30 MB	500 GB	16667x
Max. transfer rate	2 MB/s	100 MB/s	50x
Latency (seek & rotate)	20 ms	10 ms	2x
Capacity/bandwidth (large blocks)	15 s	5000 s	333x
Capacity/bandwidth (1KB blocks)	600 s	58 days	8333x

- Disks must become more archival
- More information must move to memory

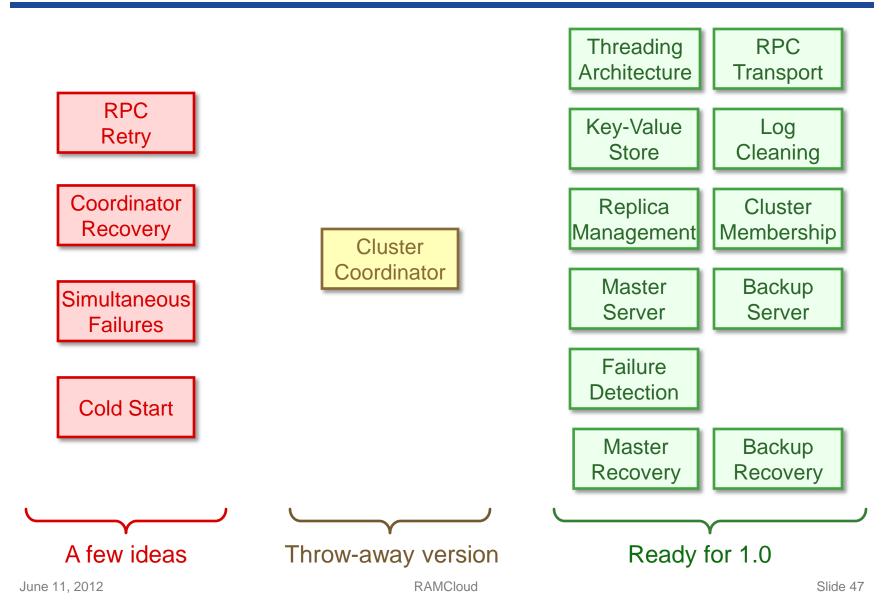
RAMCloud Motivation: Technology

Disk access rate not keeping up with capacity:

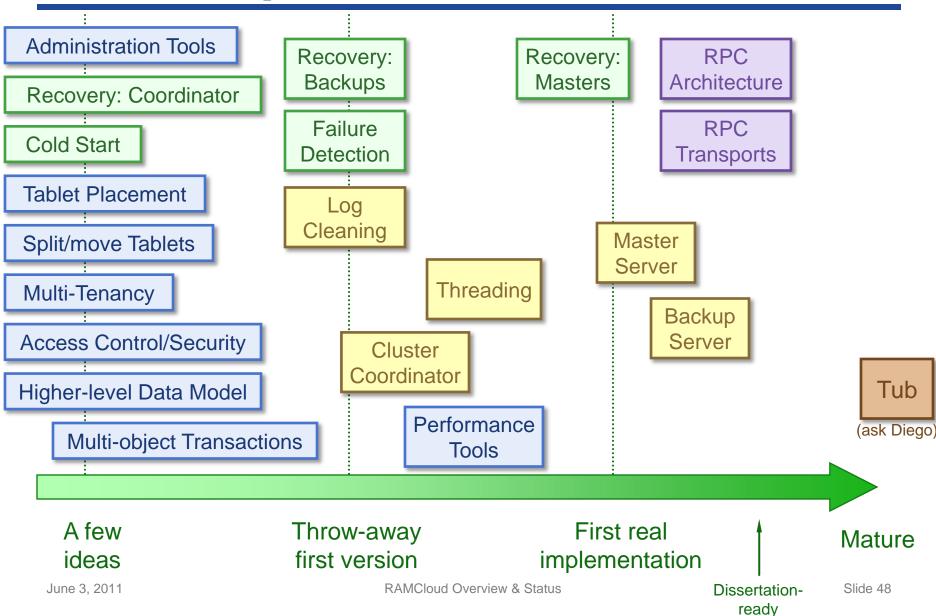
	Mid-1980's	2009	Change
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Capacity/bandwidth (large blocks)	15 s	5000 s	333x
Capacity/bandwidth (1KB blocks)	600 s	58 days	8333x
Jim Gray's rule	5 min	30 hours	360x

- Disks must become more archival
- More information must move to memory

Implementation Status



Implementation Status



RAMCloud Code Size

Code	36,900 lines
Unit tests	16,500 lines
Total	53,400 lines

Selected Performance Metrics

• Latency for 100-byte reads (1 switch):

InfRc	4.9 µs
TCP (1GigE)	92 µs
TCP (Infiniband)	47 µs
Fast + UDP (1GigE)	91 µs
Fast + UDP (Infiniband)	44 µs
Fast + InfUd	4.9 µs

- Server throughput (InfRc, 100-byte reads, one core):
 1.05 × 10⁶ requests/sec
- Recovery time (6.6GB data, 11 recovery masters, 66 backups)

1.15 sec

Lessons/Conclusions (so far)

- Fast RPC is within reach
- NIC is biggest long-term bottleneck: must integrate with CPU
- Can recover fast enough that replication isn't needed for availability
- Randomized approaches are key to scalable distributed decision-making

The Datacenter Opportunity

• Exciting combination of features for research:

- Concentrated compute power (~100,000 machines)
- Large amounts of storage:
 - 1 Pbyte DRAM
 - 100 Pbytes disk
- Potential for fast communication:
 - Low latency (speed-of-light delay < 1µs)
 - High bandwidth
- Homogeneous

• Controlled environment enables experimentation:

• E.g. new network protocols

• Huge Petri dish for innovation over next decade

How Many Datacenters?

- Suppose we capitalize IT at the same level as other infrastructure (power, water, highways, telecom):
 - \$1-10K per person?
 - 1-10 datacenter servers/person?

	U.S.	World
Servers	0.3-3B	7-70B
Datacenters	3000-30,000	70,000-700,000

(assumes 100,000 servers/datacenter)

• Computing in 10 years:

- Devices provide user interfaces
- Most general-purpose computing (i.e. Intel processors) will be in datacenters

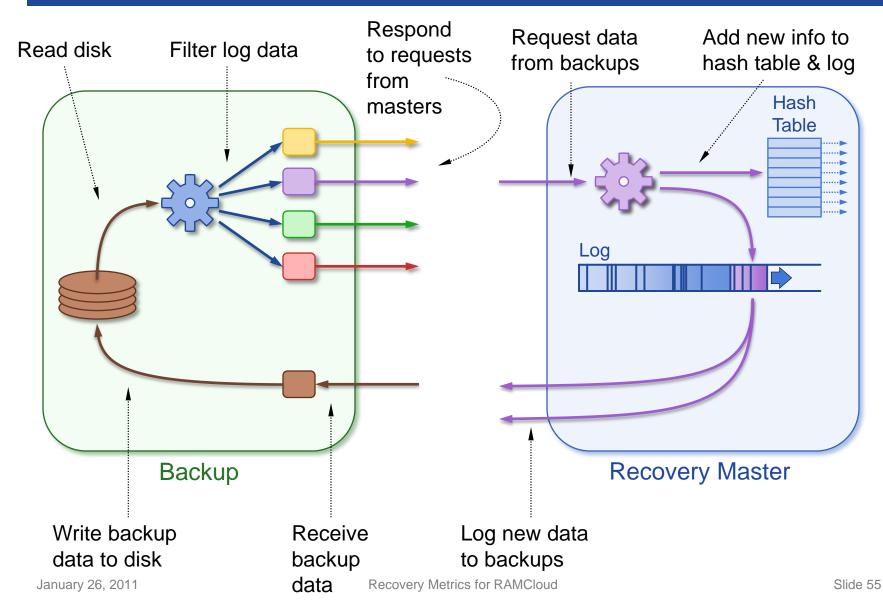
Logging/Recovery Basics

• All data/changes appended to a log:

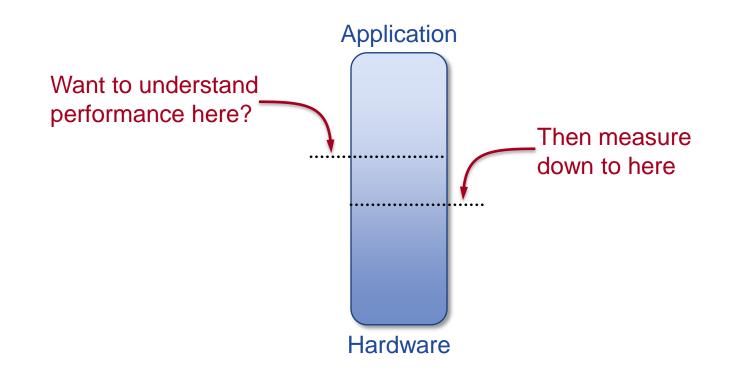


- One log for each master (kept in DRAM)
- Log data is replicated on disk on 2+ backups
- During recovery:
 - Read data from disks on backups
 - Replay log to recreate data on master
- Recovery must be fast: 1-2 seconds!
 - Only one copy of data in DRAM
 - Data unavailable until recovery completes

Parallelism in Recovery



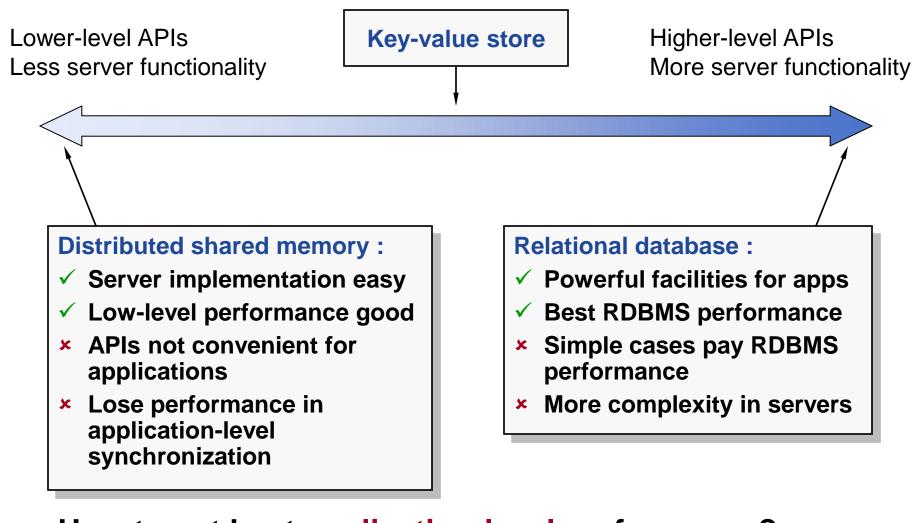
Measure Deeper



- Performance measurements often wrong/counterintuitive
- Measure components of performance
- Understand why performance is what it is

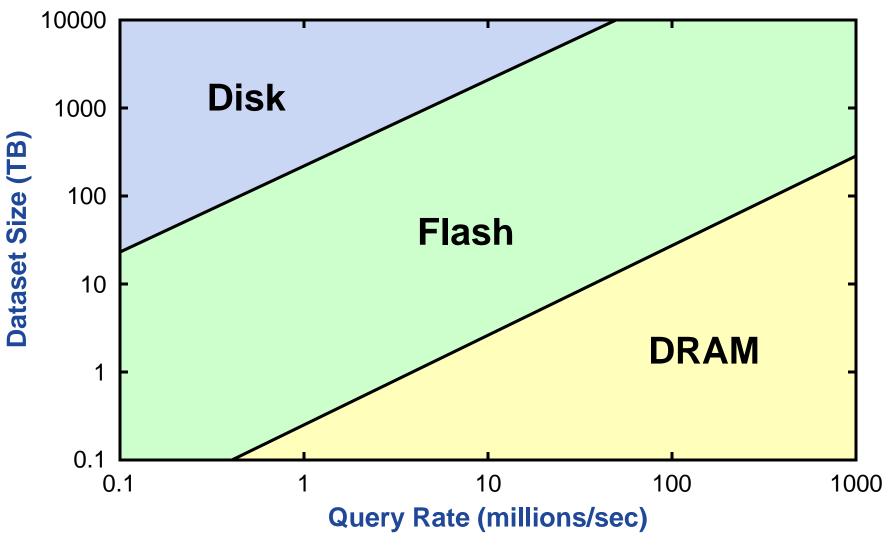
January 26, 2011

Data Model Rationale



How to get best application-level performance?

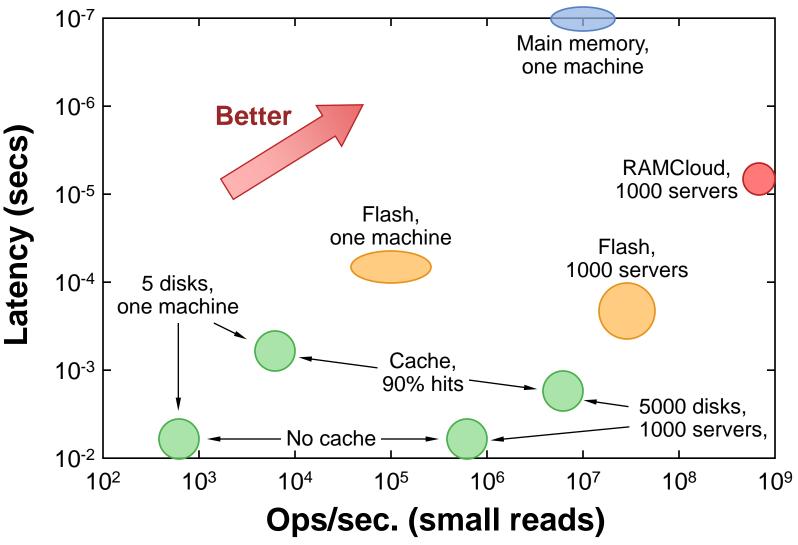
Lowest TCO



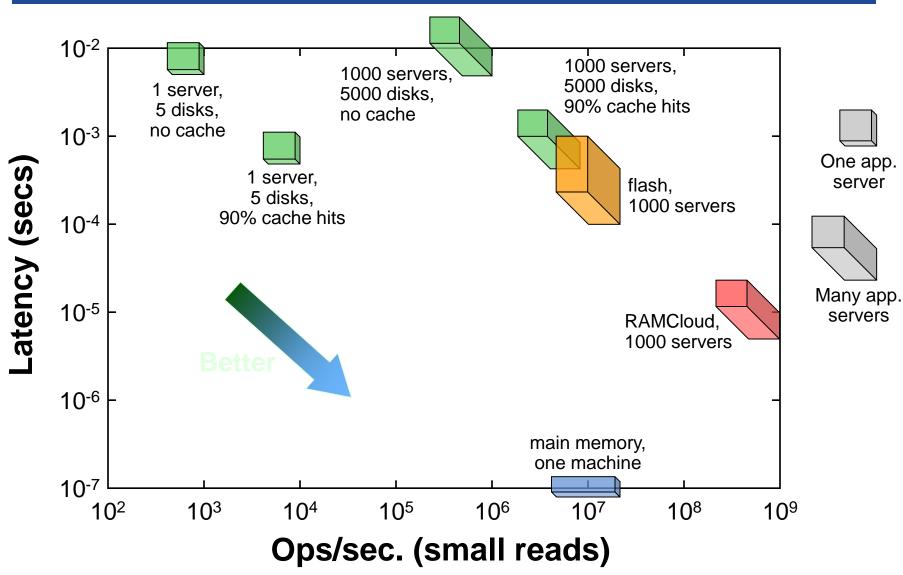
August 9, 2010

from "Andersen et al., "FAWN: A Fast Array of Wimpy Nodes", Proc. 22nd Symposium on Operating System Principles, 2009, pp. 1-14.

Latency vs. Ops/sec



Latency vs. Ops/sec



Latency vs. Ops/Sec.

What We Have Learned From RAMCloud

John Ousterhout Stanford University

(with Asaf Cidon, Ankita Kejriwal, Diego Ongaro, Mendel Rosenblum, Stephen Rumble, Ryan Stutsman, and Stephen Yang)



Introduction

A collection of broad conclusions we have reached during the RAMCloud project:

- Randomization plays a fundamental role in large-scale systems
- Need new paradigms for distributed, concurrent, fault-tolerant software
- Exciting opportunities in low-latency datacenter networking
- Layering conflicts with latency
- Don't count on locality
- Scale can be your friend

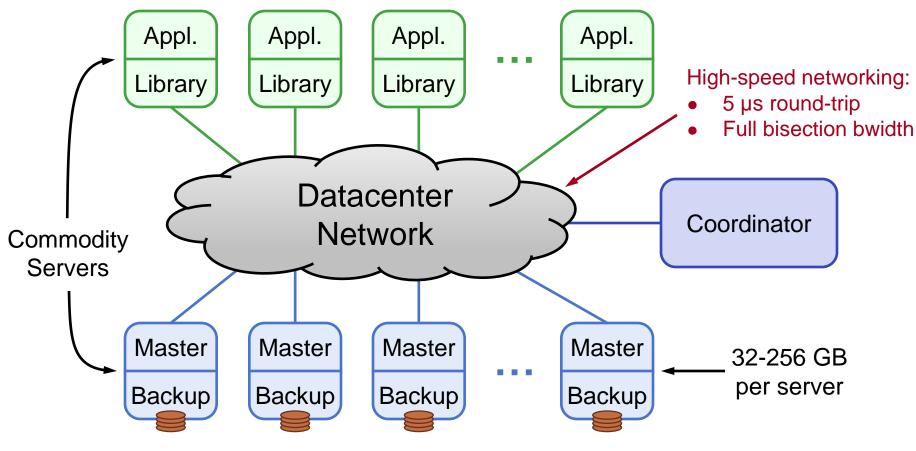
Harness full performance potential of large-scale DRAM storage:

- General-purpose key-value storage system
- All data always in DRAM (no cache misses)
- Durable and available
- **Scale**: 1000+ servers, 100+ TB
- Low latency: 5-10µs remote access

Potential impact: enable new class of applications

RAMCloud Architecture

1000 – 100,000 Application Servers

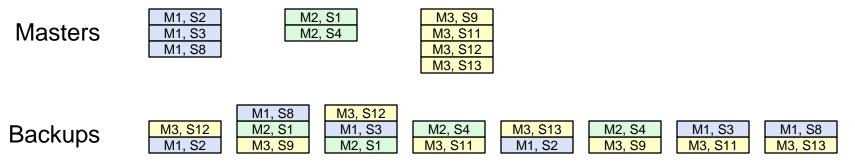


1000 – 10,000 Storage Servers

Randomization

Randomization plays a fundamental role in large-scale systems

- Enables decentralized decision-making
- Example: load balancing of segment replicas. Goals:
 - Each master decides where to replicate its own segments: no central authority
 - Distribute each master's replicas uniformly across cluster
 - Uniform usage of secondary storage on backups



Randomization, cont'd

• Choose backup for each replica at random?

Uneven distribution: worst-case = 3-5x average

• Use Mitzenmacher's approach:

- Probe several randomly selected backups
- Choose most attractive
- Result: almost uniform distribution

Sometimes Randomization is Bad!

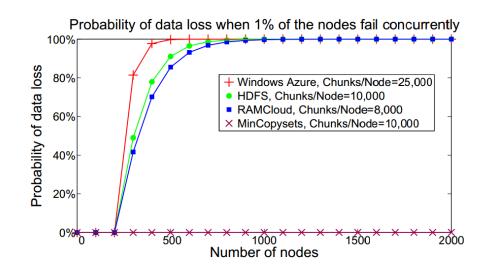
• Select 3 backups for segment at random?

• Problem:

- In large-scale system, any 3 machine failures results in data loss
- After power outage, ~1% of servers don't restart
- Every power outage loses data!

• Solution: derandomize backup selection

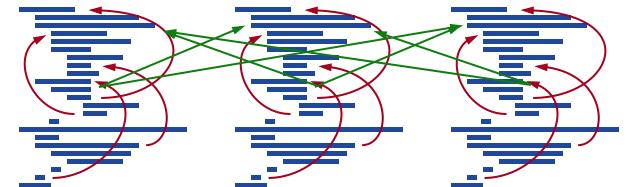
- Pick first backup at random (for load balancing)
- Other backups deterministic (replication groups)
- Result: data safe for hundreds of years
- (but, lose more data in each loss)



DCFT Code is Hard

 RAMCloud often requires code that is distributed, concurrent, and fault tolerant:

- Replicate segment to 3 backups
- Coordinate 100 masters working together to recover failed server
- Concurrently read segments from ~1000 backups, replay log entries, re-replicate to other backups
- Traditional imperative programming doesn't work

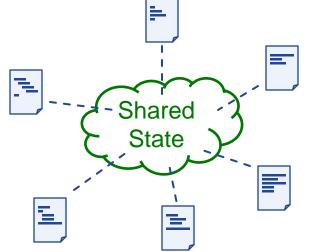


Must "go back" after failures

Result: spaghetti code, brittle, buggy

DCFT Code: Need New Pattern

Experimenting with new approach: more like a state machine



• Code divided into smaller units

- Each unit handles one invariant or transition
- Event driven (sort of)
- Serialized access to shared state

These ideas are still evolving

Low-Latency Networking

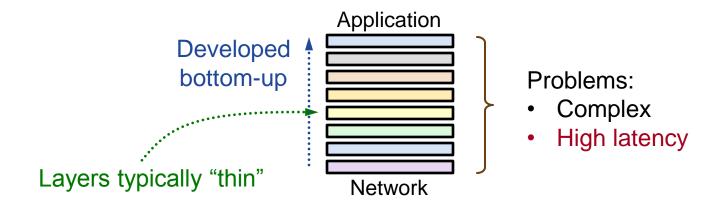
- Datacenter evolution, phase #1: scale
- Datacenter evolution, phase #2: latency

Typical round-trip in 2010:	300µs
Feasible today:	5-10µs
Ultimate limit:	< 2µs

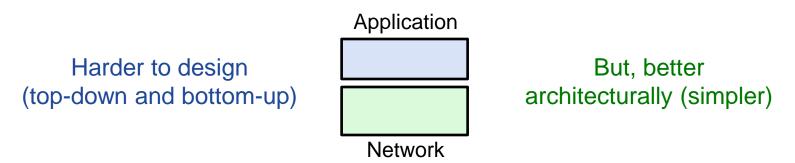
- No fundamental technological obstacles, but need new architectures:
 - Must bypass OS kernel
 - New integration of NIC into CPU
 - New datacenter network architectures (no buffers!)
 - New network/RPC protocols: user-level, scale, latency (1M clients/server?)

Layering Conflicts With Latency

Most obvious way to build software: lots of layers



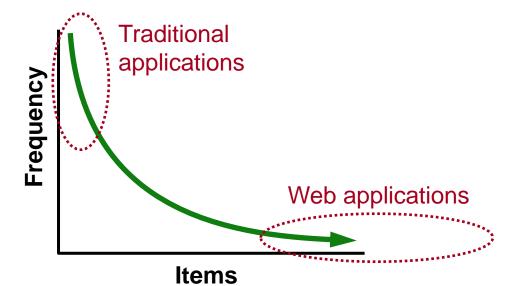
For low latency, must rearchitect with fewer layers



Don't Count On Locality

 Greatest drivers for software and hardware systems over last 30 years:

- Moore's Law
- Locality (caching, de-dup, rack organization, etc. etc.)
- Large-scale Web applications have huge datasets but less locality
 - Long tail
 - Highly interconnected (social graphs)



Make Scale Your Friend

• Large-scale systems create many problems:

- Manual management doesn't work
- Reliability is much harder to achieve
- "Rare" corner cases happen frequently

• However, scale can be friend as well as enemy:

- RAMCloud fast crash recovery
 - Use 1000's of servers to recover failed masters quickly
 - Since crash recovery is fast, "promote" all errors to server crashes
- Windows error reporting (Microsoft)
 - Automated bug reporting
 - Statistics identify most important bugs
 - Correlations identify buggy device drivers

Conclusion

Build big => learn big

• My pet peeve: too much "summer project research"

- 2-3 month projects
- Motivated by conference paper deadlines
- Superficial, not much deep learning

• Trying to build a large system that really works is hard, but intellectually rewarding:

- Exposes interesting side issues
- Important problems identify themselves (recurrences)
- Deeper evaluation (real use cases)
- Shared goal creates teamwork, intellectual exchange
- Overall, deep learning