Server Benchmarking w/

Team: Ali Ansari, Shanqing Lin, Rafael Pizarro Solar, Ayan Chakraborty, Bugra Eryilmaz, Babak Falsafi, Michael Ferdman ASPLOS'23, Vancouver









DATACENTER GROWTH





■Data → fuel for digital economy

- Exponential demand for digital services (e.g., search, media streaming)
- Many apps (e.g., AI) with higher exponential demand

*CAGR: Cumulated Annual Growth Rate

DATACENTERS ARE BACKBONE OF CLOUD



- It are a server of a server
- Centralized to exploit economies of scale
- Network fabric w/ µ-second connectivity
- Often limited by
 - Electricity
 - Network
 - Cooling



350MW, Boydton

DATACENTERS NOT GETTING DENSER





End of Moore's Law (of Silicon)

- Five decades of doubling density
- Recent slowdown in density
- Chip density limited by physics

Growth means building more
41%/year → 28x in ten years
At 15%/year → 7x more DCs

IT ELECTRICITY IN TWH





SCALE-OUT DATACENTERS



Cost is the primary metric Online services hosted in memory Consolidated w/ analytics & containers Design server for low cost, scale out



TODAY'S SERVERS



- Today's platforms are PC's of the 80's
 - CPU "owns" and manages memory
 - OS moves data back/forth from peripherals
 - Legacy interfaces connecting the CPU/mem to outside
 - Legacy POSIX abstractions
- Fragmented logic/memory:
 - Manycore network cards w/ own memory
 - Flash controllers with embedded cores and memory
 - Discrete accelerators with own memory

80'S DESKTOP





- 33 MHz 386 CPU, 250ns DRAM
- OS: Windows, Unix BSD (or various flavors)
- Focus: multi-programmed in-memory compute

TODAY'S SERVER vs 80'S DESKTOP





- Dual 2GHz CPU's, 50ns DRAM
- OS: Linux (and various distributions)

DESKTOP WORKLOADS

SPECint

- CPU integer performance
- SPECfp
 - CPU floating-point performance

PARSEC

- Multicore/manycore (parallel) CPU performance
- Renaissance
 - Java performance





spec[®]

SERVER WORKLOADS



- Independent requests/tasks
- Diverse workloads
- Deep software stacks
- Huge datasets
- Large instruction working sets
- Spend time in the OS
- Strict response-time constraints
- Various programming env.Python, JAVA, Scala, Rust, C/C++, etc.



SERVER != DESKTOP WORKLOADS





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DATACENTER SERVICES



"First-party" workloads (e.g., search, retail, media)

- 1. Online services
- 2. Analytics
- A few tier monoliths (CloudSuite)
- µServices (DeathStarBench)

"Third-party" workloads (cloud)

- 3. Virtualized
- Container instances (run any suite)
- Serverless (vHive)

CloudSuite



- Represents first-party cloud services
 - Two classes of workloads: analytics and online services
- Based on state-of-the-art open-source software stacks
- Containerized for use
- Various performance metrics
 - Throughput: requests per seconds (RPS)
 - Completion time for analytics workloads
 - Tail latency for online services
 - µArch characteristics

CloudSuite 1.0



- Introduced in Clearing the Clouds [Ferdman, ASPLOS'12]
 - Best paper award
 - IEEE Micro Top Picks
- Highlighted the characteristics of Cloud workloads
 - Instruction supply bottleneck
 - Low instruction- and memory-level parallelism
 - Data working sets beyond the on-chip cache capacities
 - Memory bandwidth overprovisioned

Mismatch between the Cloud workloads and the server CPUs

SERVICES STUCK IN MEMORY [ASPLOS'12]





Cache overprovisioned

Instruction supply bottlenecked

SCALE-OUT PROCESSORS [ISCA'12]





General-purpose CPU
X Logic 60% of silicon
X 6x bigger cores



FIRST GEN. CLOUD-NATIVE CPU





Case for Workload Optimized Processors For Next Generation Data Center & Cloud

Gopal Hegde VP/GM, Data Center Processing Group

Thunder X

- Based on SOP blueprint
- Designed to serve data
- 7x more core than cache
- Optimizes instruction supply
- Ran stock software
- 10x throughput over Xeon



APPLICATION vs. OS CYCLES



Application 📒 OS

Unlike SPEC, server workloads spend more execution time in the OS

INSTRUCTION MPKI





Unlike SPEC, server workloads suffer from instruction cache misses at L1-I and L2

HISTORY OF CloudSuite



CloudSuite 1.0: the first release, presented at ASPLOS'12

- CloudSuite 2.0: Data Caching added, published at TOCS'12
- CloudSuite 3.0: Workloads are revisited and offered as Docker containers (Tutorials at EuroSys'16 and DATE'17)
- And now, CloudSuite 4.0 ...



OUTLINE



Part 1: Why CloudSuite?

- Server workloads' benchmarking
- Introducing CloudSuite 4.0

Part 2: Hands-on experience

- CloudSuite on a real machine
 - Tuning the workload
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- CloudSuite in a full-system emulator (QEMU)
 - Cache hierarchy simulation

CloudSuite 4.0





NEW IN CloudSuite 4.0

- Multi-arch support
 - All workloads run on x86 and ARMv8
 - 4 workloads also run on RISC-V
- Software stack updates
 - Ubuntu 22.04
 - OpenJDK 17
 - Iatest releases of application software
- Ease of use
 - Enhanced docs
 - Useful tuning parameters







TARGET AUDIENCE



System designers

Assess & compare systems' performance for cloud workloads

Computer architects

Derive insights for future server design

Cloud service providers

Measure performance and sustainability

CloudSuite 4.0





ANALYTICS



- Usually a machine learning algorithm running over large datasets
- No tail latency metric
- Performance metrics
 - Completion time (for a given input size)
 - Throughput (metric is benchmark-/algorithm-specific)



DATA ANALYTICS



Extract useful information from massive amounts of data (Big Data)

- Predict user preferences, opinions, behavior
- Benefit from information (e.g., business, security)
- MapReduce execution model
 Mapupage cossing appall parts
 - Map: processing small parts
 - Reduce: aggregating the results
- Several examples
 - Song recommendation (Spotify)Spyware detection (Facebook)



DATA ANALYTICS (cont.)



- Application: Text classification based on naïve Bayes classifier
 - Classes: Art, History, Economics, Health, Technology, etc.
- Software: Apache Hadoop and Apache Mahout
- Dataset: Wikipedia English page articles
- Performance metric: # pages classified per unit of time, completion time
 MAHOUT Workers



CloudSuite 4.0







Parallel distributed graph processing
Data mining on graphs
Graph examples

Social networks (Facebook, Twitter)

Web graph

Microservices in a datacenter



GRAPH ANALYTICS (cont.)

Application: PageRank
 Measures influence of Twit

- Measures influence of Twitter users
- How much attention followers pay to a user
- Software: Apache Spark, GraphXParallel framework for graph processing

Dataset: Twitter user graph





GRAPH ANALYTICS (cont.)



- Distributes the graph across nodes
- Iterative computation with adjacent vertices
- Communication across machines for adjacent vertices
- Performance metric: completion time



CloudSuite 4.0





IN-MEMORY ANALYTICS

In-memory processing of human-generated data

Extract useful information from users' data
 Predict users' preferences, rates

Several examples

- Movie recommendation (Netflix)
- Item recommendation (Amazon)
- Song recommendation (Spotify)
- Recommending new friends (Social networks)





IN-MEMORY ANALYTICS (cont.)



- Application: Alternating Least Squares (ALS), used in recommendation systems
- Software: Apache Spark, MLlib
- Dataset: Movielens video dataset



Item
IN-MEMORY ANALYTICS (cont.)



- Trains a recommendation model with the ALS matrix factorization algorithm
- Master partitions user rating matrix and sends them to workers
- Workers perform local matrix factorization and send results to master
- Performance metric: completion time for factorizing the rating matrix



CloudSuite 4.0





ONLINE SERVICES



Operate on large datasets

Throughput is important, but also need high service quality
Tail latency of requests is critical for service quality
Goal: Maximizing throughput under Service-Level Objective (SLO)

Performance metrics

- Throughput (metric is benchmark-specific)
- Latency (expressed in terms of the N-th percentile tail latency)



Online services target finding the maximum throughput under SLO

TAIL LATENCY



- Slowest response times affect the end-to-end QoS [Dean, CACM'13]
- Tail latency is usually 95, 99, or 99.9 percentile of the requests' latency



Performance hiccups have to be rare in large-scale distributed systems



- Online services are often latency-sensitive
- Fetching data from disk is slow
- Data is cached in memory for fast data access
 - General-purpose, in-memory key-value store
 - Caches data for other apps, another tier before back-end

DATA CACHING (cont.)



Application: Memcached

- High throughput objects retrieval
- Free & open-source, high-performance, distributed object caching system
- Dataset: Twitter object popularity dataset
 - Keys' distribution and their values' sizes
 - Configurable size of the dataset

Performance metric: # req/s, under SLO (e.g., 1ms)





CloudSuite 4.0





DATA SERVING



- Global-scale online services rely on NoSQL databases
 - Inherently scalable
 - Suitable for unpredictable schema changes
- Scale out to meet service requirements
 - Accommodate fast data generation rate



DATA SERVING (cont.)





DATA SERVING (cont.)



- Application: Apache Cassandra
 - A popular NoSQL database: many use cases (e.g., Expedia, eBay, Netflix)
- Performance metric: # R/W ops/s under SLO (e.g., ~10ms)



DATA SERVING (cont.)



- Database: generated and populated by YCSB
 - Defines number & size of fields, and total entries
- Predefined mixes of read/write operations
- Popularity of access distributions (e.g., Zipfian)



CloudSuite 4.0





MEDIA STREAMING



- Media streaming expected to dominate internet traffic
 - Around 80% of global web traffic [globenewswire]
- Increasing popularity of media streaming services
 - Video sharing sites, movie streaming services, podcasts, etc.
- Fast and low latency Internet access
 - High quality media streaming even on affordable devices



MEDIA STREAMING (cont.)





MEDIA STREAMING (cont.)



- Application: Nginx server with TLSv1.3 enabled
- Dataset: mix of pre-encoded videos
 - Configurable dataset size
 - Four video resolutions (240p, 360p, 480p, 720p)
 - Zipfian popularity distribution

Performance metrics: utilized bandwidth (Kbps) without connection timeout



MEDIA STREAMING (cont.)



- Imitates real video streaming users' behavior
 - Requests for video chunks with delay
 - Different video lengths and resolutions
- Implements HTTPS connection with TLSv1.3
- Uses the videoperf client, based on the httperf traffic generator



CloudSuite 4.0





WEB SEARCH



Crucial feature for online services
High volume of queries
Quick response time (< 1s)
Accurate results

 Embedded search appears in almost all websites
 Service's profit and users' experience







Frontend



Index Serving Node (ISN)



Query Term	Document
Benchmark	1, 6, 19,
CloudSuite	5, 40,
Datacenter	6, 10, 13, 20,
EPFL	5, 10, 23,
PerfKit	3, 6, 10, 20,











- Application: Apache Solr search engine for ISNs
- Dataset: Inverted index & snippets
 - Crawled with Apache Nutch
 - Indexed with Apache Lucene
- Performance metric: # queries/sec under SLO (e.g., 200ms)

User

 Frontend





PARALLEL SYSTEM ARCHITECTURE LA

- Faban traffic generator
- Flexible request mixes
 - # terms per request from published surveys
 - Terms extracted from the crawled dataset



Frontend



Index Serving Node (ISN)





CloudSuite 4.0







WEB SERVING

Key to all internet-based services

All services are accessed through web servers
 APACHE NGLINE
 APACHE NGLINE

Various technologies construct web content





ebay





amazon



WEB SERVING (cont.)





Database Server





Application: Elgg, a social network engine running with PHP

• Web server: Nginx with TLSv1.3



WEB SERVING (cont.)



- Database: MariaDB
 - 100 K users with friends, messages, posts, etc.
- Cache server: Memcached
- Performance metric: # pages/s under SLO (e.g., 1s)



WEB SERVING (cont.)



- Faban traffic generator
- Pre-configured page transition matrix for around 30 request types
 - Friend request, posting a blog, status update, sending private messages, etc.



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CloudSuite in a full-system emulator (QEMU)

Cache hierarchy simulation



- Download the `CloudSuite-ASPLOS2023.pem` from <u>cloudsuite.ch/asplos23-tutorial/</u>
- Connect to the entry point:
 chmod 0400 CloudSuite-ASPLOS2023.pem
 ssh -i CloudSuite-ASPLOS2023.pem ubuntu@<ip address given in tutorial>
 Connect to your personal node:
 - ./connect.sh <my_number>
 - Run `tmux`
- Check that both folders part01 and part02 are available



We have provided AWS EC2 nodes for Part 2. Please make sure everyone is connected to their node.

See you in a bit...



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METHODOLOGY



AWS Machine

- Xeon Platinum 8124M processor
- Missing PMUs
- Release year: 2017
- Skylake µArch 36 cores, 1-socket
 - 32 KB L1-I, 48 KB L1-D
 - 1 MB L2
 - 24.8 MB LLC
- Ubuntu 22.04
- Perf Tool 5.15.0-1031-aws

PARSA Machine

- Xeon Gold 6338N processor
- All PMUs
- Release year: 2021
- Ice Lake µArch 64-cores, 2-sockets
 - 32 KB L1-I, 48 KB L1-D
 - 1.25 MB L2
 - 48 MB LLC
- Ubuntu 22.04
- Perf Tool 5.19.0-35-generic



Online services target finding the maximum throughput under SLO
RUNNING THE DATA CACHING WORKLOAD



- Pull server image and start server container
- Pull client image and start client container
- Scale dataset from base Twitter dataset
 - Consider a 10 GB dataset in memory [Shao, CASCON'05]
- Warm up server
 - The client brings the dataset to server's memory
- Load server
 - Set request per second (RPS) parameter and measure throughput and latency
- Run `./01-data-caching-launch.sh`

WARMED UP



	Warmed up	10 GB	dataset					
	1	1						
Outstar	ncing requests per w	ork <mark>er:</mark>						
6963 61	L <mark>96 7074 7543 736</mark> 3 6:	154 7152	7454					
You are	e warmed up, sir							
			– DONE					
ubuntu@	ip-172-31-30-253:~/	part01-r	ealsystem\$					
ubuntu@	pip-172-31-30-253:~/	bart01-r	ealsystem\$	free	-h			
	total	used	free		shared	buff/cache	available	
Mem:	68Gi	10Gi	48Gi		1.0Mi	9.5Gi	57Gi	
Swap:	0B	0B	0B					

TUNING (cont.)



AWS Skylake same socket

Load (RPS)	Throughput (RPS)	99th %tile (ms)	CPU util.	Queueing (req. per worker)
20K				
40K				
100K				
142K				
170K				
372K				
1'000K				

TUNING

- Run `ctrl-b` then `>` then `v`; then open `htop`
- SLO ~= 1 ms
- Run `./02-data-caching-tune.sh`

Queuing	Throu	ughput							āil Lat	ency	
unix_ts, timeDiff, L679063339, 5.000005, Jutstanding requests per	rps, 171983.2, WOIKEL	requests, 859917,	gets, 687987,	sets, 171930,	hits, 687987,	misses, 0,	avg_lat, 0.398698,	90th, 0.679100,	95th, 0.777100,	99th, 1.100000,	std, 0.217527,
10 22 10 7 10 13 3 14 univ_totimeDiff 1679063344, 5.000005, Dutstanding requests per 7 5 8 16 10 5 16 4	rps, 171970.6, worker:	requests, 859854,	gets, 687887,	sets, 171967,	hits, 687887,	misses, 0,	avg_lat, 0.387853,	90th, 0.659100,	95th, 0.753000,	99th, 0.963100,	std, 0.208296,
unix_ts, timeDiff, 1679063349, 5.000005, Dutstanding requests per 12 2 3 2 5 3 10 4	rps, 172275.6, worker:	requests, 861379,	gets, 689222,	sets, 172157,	hits, 689222,	misses, 0,	avg_lat, 0.395049,	90th, 0.677000,	95th, 0.775100,	99th, 0.986100,	std, 0.214206,



TUNING AWS EC2 RESULTS



AWS Skylake same socket

Load (RPS)	Throughput (RPS)	99th %tile (ms)	CPU util.	Queueing (req. per worker)
20K	20K	0.04	20%	0
40K	40K	0.05	40%	0
100K	100K	0.17	92%	0
142K	142K	~1	100%	10
170K	170K	1.7	100%	20
372K	372K	13	100%	450
1'000K	380K	infinite	100%	infinite

THROUGHPUT vs. LATENCY RESULTS



Throughput
 99th %tile (ms)



Online services target finding the maximum throughput under SLO

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Cache hierarchy simulation

µArch CHARACTERISTICS



- Load the machine at maximum throughput under SLO
- Run `./03-data-caching-loadrps.sh`
- Run `Ctrl-b` then `>` then `v` to open a new vertical tmux panel
 Change panels with `ctrl-b` then arrow keys

unix_ts,	timeDiff,	rps, 144055 9	requests, 720280	gets, 576470	sets, 143810	hits, 576470	misses, ø	avg_lat, 0 389770	90th, 0 644100	95th, 0 724100	99th, a 908100	std, 0 196837	min, a a11000	max, a	avgGetSize
Outstanding	requests per	worker:	,20200,	0,04,01	140010,	5754757	0,	0.0077707	0.044100,	0.724100,	0.700100,	0.170007,	0.011000,	1.070000,	1001.0000/0
648248	13														
unix_ts, 1679737996,	timeDiff, 5.000005,	rps, 144171.7,	requests, 720859,	gets, 577088,	sets, 143771,	hits, 577088,	misses, 0,	avg_lat, 0.389451,	90th, 0.643100,	95th, 0.726100,	99th, 0.919100,	std, 0.198711,	min, 0.011000,	max, a 2.187000,	avgGetSize 1081.577193
Outstanding	requests per	worker:													
10 9 9 6 4 6 unix_ts, 1679738001, Outstanding 2 6 5 4 5 1	5 3 timeDiff, 5.000005 requests per 5 6	rps, 144099.7, WOINGI.	requests, 720499,	gets, 576301,	sets, 144198,	hits, 576301,	misses, 0,	avg_lat, 0.393499,	90th, 0.653100,	95th, 0.735100,	99th, 0.928100,	std, 0.201349,	min, 0.012000,	max, 3 1.745000,	avgGetSize 1081.573364
ubuntu@ip-17	2-31-39-192:	~/part01-real	system\$												



- Out-of-Order processors are designed to maximize IPC
- IPC: Instructions Per Cycle
- Run `./04-perf-uarch-ipc.sh`

[ubuntu@ip-172-31-39-192:~/part01-realsystem\$ \
[> cat 04-perf-uarch-ipc.sh
perf stat -C 2 -M IPC -- sleep 5
ubuntu@ip-172-31-39-192:~/part01-realsystem\$



Perf shows that Data Caching has low IPC

ubuntu@ip-172-31-39-192:~/part01-realsystem\$ perf stat -C 2 -M IPC -- sleep 5

Performance counter stats for 'CPU(s) 2':

14010328857inst_retired.any#0.83 IPC16839319312cpu_clk_unhalted.thread

5.000979643 seconds time elapsed

Why can the CPU not execute more instructions?



- Cloud workloads have huge datasets
- MPKI = Misses Per Kilo Instructions
- LnMPKI measures only data misses
- Run `./05-perf-uarch-dcache.sh`

[ubuntu@ip-172-31-39-192:~/part01-realsystem\$ \
[> cat 05-perf-uarch-dcache.sh
perf stat -C 2 -M L1MPKI,L2MPKI --- sleep 10
perf stat -C 2 -M L3MPKI --- sleep 10
ubuntu@ip-172-31-39-192:~/part01-realsystem\$



L1-D MPKI is high, 9.2

~25% of L1-D misses also miss in the L2

~80% of L2 data misses also miss in the LLC

ecparsa@ecocloud-exp02:~/asplos_tutorial\$ perf stat -C 2 -M L1MPKI,L2MPKI,L3MPKI -- sleep 5

Performance counter stats for 'CPU(s) 2':

13,269,444,240	INST_RETIRED.ANY	#	1.95 L3MPK
25,858,737	MEM_LOAD_RETIRED.L3_MISS		
13,269,444,132	INST_RETIRED.ANY	#	2.66 L2MPK
35,355,458	MEM_LOAD_RETIRED.L2_MISS		
13,269,444,024	INST_RETIRED.ANY	#	9.32 L1MPK
123,733,994	MEM LOAD RETIRED.L1 MISS		

5.002211089 seconds time elapsed



- Server workloads have large instruction working sets
- Frontend supplies instructions
- L1-I misses are on the critical path
- Run `./06-perf-uarch-icache`

[ubuntu@ip-172-31-39-192:~/part01-realsystem\$ \

[> cat 06-perf-uarch-icache.sh
perf stat -C 2 -e frontend_retired.l1i_miss,instructions -- sleep 5
ubuntu@ip-172-31-39-192:~/part01-realsystem\$



- L1-I MPKI is around 20
- Back of the envelope calculation
 - (250M/13.3B)*1000 ~= 20 MPKI
 - L2 access latency ~= 10 cycles
 - 20*10 stall cycles = 200 stall cycles PKI
 - 200 stall cycles out of 1000 total cycles
 - 20% performance drop due to L1-I misses

ecparsa@ecocloud-exp02:~/asplos_tutorial\$ perf stat -C 2 -e frontend_retired.l1i_miss,instructions -- sleep 5

Performance counter stats for 'CPU(s) 2':

251,857,093 frontend_retired.l1i_miss 13,289,567,102 instructions

5.002147902 seconds time elapsed

TOP-DOWN METHODOLOGY [Yasin, ISPASS'14]





Top-Down is a powerful technique to identify the bottlenecks



- Top-Down indicates Data Caching is mostly backend bound
- Frontend bound is also noticeable
 - Instruction supply is a bottleneck
- Only 18% of pipeline slots are useful

ecparsa@ecocloud-exp0	<pre>2:~/asplos_tutorial\$ perf</pre>	stat –C 2 ·	topdown	sleep 5	
Performance counter	stats for 'CPU(s) 2':				
retiring 18.0%	bad speculation 2.7%	frontend	bound 20.0%	backend	bound 59.2%
5.002252470 se	conds time elapsed				

Fix the backend problem to improve performance of Data Caching

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Cache hierarchy simulation





- QEMU is a free and open-source full-system emulator
 - Supports various hardware platforms including x86, ARM, and RISC-V
- Running CloudSuite requires full-system support
 - QEMU can emulate network, disk, memory allocation, etc.
- Emulating CloudSuite requires emulating billions of instructions
 QEMU emulates 400 Millions of Instructions Per Second (MIPS) per core



SIMULATION SLOWDOWN

Simulation slowdown per core

- Real machine:
- QEMU:
- Functional simulation:
- Simple CPU Model:
- OoO CPU Model:

- ~ 2 GIPS ~ 400 MIPS
- $\sim 1 \text{ MIPS}$
- ~ 100 KIPS
- ~ 10 KIPS

5 s 30 min 5 h 2.3 days

1 s

For more details about simulation challenges and techniques, please check [SMARTS, ISCA'03]



QEMU LIMITATIONS



QEMU does not support multi-node execution
 Clients and servers must be run on the same QEMU machine

- Time distortion
 - QEMU emulation is 10x slower than the real machine
 - Slowdown affects system behavior like timeouts and tail latencies
 - Solutions like enabling icount mitigate the problem

METHODOLOGY



- QEMU 7.0 (2022)
 - AARCH64
 - Ubuntu 22.04 LTS server
 - 4 cores, 8 GB of memory
 - icount enabled
- Data Caching
 - Snapshot `running`
 - Dataset ~= 1 GB dataset
 - RPS = 500; 99th %tile ~80 ms
 - Server on core 2
 - Clients on cores 1,3

- Cache Sim plugin
 - L1-D
 - 32 KB, 8-way set associative
 - L1-I
 - 32 KB, 8-way set associative
 - L2 private, inclusive
 - I MB, 16-way set associative

QEMU HANDS-ON EXERCISE



Run `03-run-sim-qemu.sh`

deno_bino/dend	• • • • •
IMAGE_DIR=\$PWD/images	icount for
	time distortion
<pre>\$QEMU_DIR/build/aarch64-softmmu/gemu-system-aarch64 \</pre>	
cpu max -machine virt,gic-version=3 -smp 4 -m 16G \	
-rtc clock=vm \	
<pre>-drive file=\$IMAGE_DIR/qemu-efi.img,format=raw,if=pflash,readonly=on \</pre>	
<pre>-drive file=\$IMAGE_DIR/varstore.gcow2,format=gcow2,if=pflash,readonly=on \</pre>	
<pre>-drive file=\$IMAGE_DIR/jammy-server-cloudimg-arm64.qcow2_format=qcow2,if=virtio \</pre>	plugin for
-object rng-random,filename=/dev/urandom,id=rng0	
<pre>-device virtio-rng-pci, rng=rng0</pre>	cache sim.
-device virtio-net, netdev=net0	
<pre>-netdev user.id=net0.hostfwd=tcp::8022-:22</pre>	
<pre>-icount shift=0,sleep=on,align=off </pre>	
-D ./cache-sim-log -d plugin	
-plugin \$QEMU_DIR/contrib/plugins/libcache-inclusive.so	snapshot with
-loadvm running	
-nographic	running bench.

CACHE SIMULATION RESULTS



- L1-I MPKI is very high
 - No prefetchers
- L1-D and L2 data MPKI corroborates previous results
 - Dataset is only 1 GB

core #	Instructions	L1-D	MPKI L2	dMPKI L1-I	MPKI L2	iMPKI L2	MPKI
0	0	i -	–nan	–nan İ	–nan İ	-nan	–nan
kernel	0	1	–nan	–nan	–nan	-nan	–nan
user	0	 -	-nan	-nan	-nan	-nan	–nan
1	0	1	-nan	-nan	-nan	-nan	–nan
kernel	0		-nan	-nan	-nan	-nan	–nan
user	0	1	-nan	-nan	-nan	-nan	–nan
2	10000000		12.5	4.0	51.5	1.9	5.9
kernel	7076409		14.4	4.5	64.1	1.9	6.4
user	2923591		7.9	3.0	20.9	1.8	4.7
3	0		-nan	-nan	-nan	-nan	–nan
kernel	0		-nan	-nan	-nan	-nan	–nan
user	0		-nan	-nan	-nan	-nan	-nan
sum	10000000		12.5	4.0	51.5	1.9	5.9
kernel	7076409		14.4	4.5	64.1	1.9	6.4
user	2923591		7.9	3.0	20.9	1.8	4.7

FUTURE WORK



- New benchmarks
 - Database workloads
 - Django and Node.js web applications
- Better support for RISC-V
 - Now, only 4 workloads run on RISC-V
- Updating QFlex
 - Full-system simulation by integrating CloudSuite, QEMU, and QFlex













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Backup Slides

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SUMMARY OF CHANGES



	CloudSuite 3.0	CloudSuite 4.0
Platforms	×86	x86, ARM, (partial support for RISC-V)
OS	Debian buster	Ubuntu 22.04
Data Analytics	Hadoop 2.7.4 (2017)	Hadoop 2.10.2 (2022)
Graph Analytics	Spark 2.1.0 (2016) Scala 2.10.4 (2017)	Spark 3.3.2 (2023) Scala 2.13.10 (2022)
In-memory Analytics	Spark 2.1.0 (2016) Scala 2.10.4 (2017)	Spark 3.3.2 (2023) Scala 2.13.10 (2022)

SUMMARY OF CHANGES (cont.)



	CloudSuite 3.0	CloudSuite 4.0		
Data Caching	Memcached 1.4.24 (2015)	Memcached 1.6.15 (2022)		
Data Serving	Cassandra 2.1.12 (2015) YCSB 0.3.0 (2015)	Cassandra 4.1 (2022) YCSB 0.14.0 (2018)		
Media Streaming	raw plain text files no encryption	real videos TLSv1.3 encryption		
Web Search	Solr 5.2.1 (2015)	Solr 9.1 (2022)		
Web Serving	Elgg 1.9.3 (2014) PHP 5 (2016) MySQL 5.5.62 (2018) Memcached 1.4.14 (2012)	Elgg 4.3 (2022) PHP 8.1 (2022) MariaDB 10.6 (2021) Memcached 1.6.15 (2022)		

QEMU EMULATION ENGINE



- Translation phase from guest code to Translation Blocks (TB)
- Execution phase of the Translation Blocks



QEMU INSTRUMENTATION



- Plugin system since QEMU 5.0 release (2020)
 - Allows for easy hooks to key phases of QEMU execution
 - Inserts callbacks on instruction and data access

```
static void vcpu_tb_trans(qemu_plugin_id_t id, struct qemu_plugin_tb *tb)
    size_t n_insns; size_t i; InsnData *data;
    n_insns = qemu_plugin_tb_n_insns(tb);
    for (i = 0; i < n_insns; i++) {</pre>
        struct gemu_plugin_insn *insn = gemu_plugin_tb_get_insn(tb, i);
        qemu_plugin_register_vcpu_mem_cb(insn, vcpu_mem_access,
                                          QEMU_PLUGIN_CB_NO_REGS,
                                          rw, data);
        qemu_plugin_register_vcpu_insn_exec_cb(insn, vcpu_insn_exec,
                                                QEMU_PLUGIN_CB_NO_REGS, data);
```

QEMU EXECUTION ENGINE



- Insert callbacks for instruction execution
- Insert callback for memory accesses

