



PIMCLOUD: QOS-AWARE RESOURCE MANAGEMENT OF LATENCY-CRITICAL APPLICATIONS IN CLOUDS WITH PROCESSING-IN-MEMORY

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Cornell University *Currently with Shuhai Lab at Huawei Cloud





Motivation · Characterization · PIMCloud · Evaluation · Conclusions







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Besteffort

- Throughput-oriented
- No latency constraint







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Besteffort

GraphLab





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- Throughput-oriented
- No latency constraint







Google Translate





GraphLab





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- Throughput-oriented
- No latency constraint

- Tail latency
- Strict QoS constraint



Google Maps





Google Translate





Motivation · Characterization · PIMCloud · Evaluation · Conclusions







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• More LC applications



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• More LC applications



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• LC microservices

• More LC applications

• Colocation of LC applications on the same node



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Heterogeneous computation



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HARDWARE TRENDS IN CLOUDS









Heterogeneous computation



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Heterogeneous computation

Heterogenous **memory accesses**



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PIM-ENABLED CLOUD SERVER





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PIM-ENABLED CLOUD SERVER



- Low memory latency
- Shallow memory hierarchy

- Wimpy core type
- Varying core count



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Hardware Trend Emerging PIM Platforms

+ Software Trend Latency-Critical(LC) Cloud Applications



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PIMCLOUD



Hardware Trend Emerging PIM Platforms

+ **Software Trend** Latency-Critical(LC) Cloud Applications

How can LC applications leverage PIM?



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Hardware Trend Emerging PIM Platforms + Software Trend Latency-Critical(LC) Cloud Applications



- First study to explore PIM for latency-critical (LC) cloud applications
- Characterization
 - To understand the implications of the PIM architecture to LC applications
- PIMCloud: A QoS-aware resource manager for multiple LC applications in PIMenabled systems
 - Manages PIM-introduced resources





Hardware Trend Emerging PIM Platforms + Software Trend Latency-Critical(LC) Cloud Applications



- The first to explore PIM for latency-critical (LC) cloud applications
- Characterization
 - *To understand the implications of the PIM architecture to LC applications*
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LC APPLICATIONS



Application	Silo Masstree		ImgDNN	Xapian	Moses	Sphinx
Domain	In-memory Database	Key-value store	Image recognition	Web search	Real-time translation	Speech recognition
Target QoS	1 ms	1 ms	7 ms	10 ms	10 ms	6 s
Per-core IPC	1.18	1.09	1.07	1.38	0.99	0.55
LLC MPKI	1.50	6.02	16.78	3.66	23.17	10.40
LLC Miss Rate	2%	12%	45%	37%	77%	47%
Memory Bandwidth (GB/s)	0.32	3.40	7.83	2.58	10.29	2.57
Memory Capacity (GB)	1.8	9.3	0.3	5.6	2.5	1.4

Six diverse LC applications from Tailbench [IISWC'16]



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Motivation · Characterization · PIMCloud · Evaluation · Conclusions







Motivation · Characterization · PIMCloud · Evaluation · Conclusions





- Which PIM stack to place each memory page?
- Local VS remote memory access for PIM cores
 - 20ns VS 35ns (VS 62ns from a CPU core)





Characterized ArchitectureIDMemLatCoreMemHie #Cores1HighBrawnyDeep4

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		Charact	terized A	Architectu	ire
	ID	MemLat	Core	MemHie	#Cores
	1	High	Brawny	Deep	4
CPU-	2	High	Brawny	Shallow	
centric	3	High	Wimpy	Deep	
	4	High	Wimpy	Shallow	
Un-	5	Low	Brawny	Deep	
realistic	6	Low	Brawny	Shallow	
PIM-	7	Low	Wimpy	Deep	
centric	8	Low	Wimpy	Shallow	



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realistic	6	Low	Brawny	Shallow	6								
PIM-	7	Low	Wimpy	Deep	10								
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- PIM-centric architectures are able to meet QoS at low load





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		Characterized Architecture					ormalized	Max Loa	d (Max	RPS u	nder Q	oS)
	ID	MemLat	Core	MemHie	#Cores	Silo	Masstree	ImgDNN	Xapian	Moses	Sphinx	AVG
	1	High	Brawny	Deep	4	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CPU-	2	High	Brawny	Shallow	6	0.89	0.85	1.17	1.33	1.41	1.25	1.15
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		Charact	terized A	Architectu	ıre	No	Normalized Max Load (Max RPS under Qo									
	ID	MemLat	Core	MemHie	#Cores	Silo	Masstree	ImgDNN	Xapian	Moses	Sphinx	AVG				
	1	High	Brawny	Deep	4	1.00	1.00	1.00	1.00	1.00	1.00	1.00				
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On average, PIM-centric architectures outperform CPU-centric ones

- •Up to 52% gain from low memory latency
- •Up to 44% gain from shallow memory hierarchy
- •Up to 5% gain from many wimpy cores





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Individual applications have different preferences over CPU and PIM



Implications of PIM – Data Placement







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Implications of PIM – Data Placement







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Implications of PIM – Data Placement





 Dynamic page manipulation (page migration+replication) is essential to achieve the best performance.



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LC applications have varying preference to PIM

- At runtime, it is critical to be aware of the heterogeneity, and allocate the right type of resources to each application
- Dynamic data placement is critical to achieve the best performance



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Hardware Trend Emerging PIM Platforms + Software Trend Latency-Critical(LC) Cloud Applications



- The first to explore PIM for latency-critical (LC) cloud applications
- Characterization
 - To understand the implications of the PIM architecture to LC applications
- PIMCloud: A QoS-aware resource manager for multiple LC applications in PIMenabled systems
 - Manages PIM-introduced resources









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• The same feedback-control loops as PARTIES [ASPLOS'19]





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• The same feedback-control loops as PARTIES [ASPLOS'19]



• Upsize/Downsize handles resource adjustment

- Core allocation
 - Core type
 - Core count
- Data placement
 - Pages to migrate/replicate at runtime





PIMCloud – Core Allocation





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PIMCloud – Core Allocation



• Main challenge: reduce the allocation space



(a) Preference-oblivious managers: mixed cores for each app.



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- Main challenge: reduce the allocation space
- Pre-sorting offline
 - A quick offline profiling to obtain each application's preference
 - Sort applications in decreasing preference to PIM



(a) Preference-oblivious managers: mixed cores for each app.





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(a) Preference-oblivious managers: mixed cores for each app.



(b) Preference-aware PIMCloud: reduced allocation space, and more saving in cores under the same performance.





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 - Sort applications in decreasing preference to PIM
- At runtime
 - Applications are allocated in order
 - The allocation space is the same as a homogeneous setting



(a) Preference-oblivious managers: mixed cores for each app.



(b) Preference-aware PIMCloud: reduced allocation space, and more saving in cores under the same performance.



(c) PIMCloud at runtime when App2's input load increases: the preference order is maintained.





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 - A quick offline profiling to obtain each application's preference
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PIMCloud – Data Placement



- Main challenge: reduce the number of migrated/replicated pages
- Only the hottest pages are manipulated at runtime



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Simulator: ZSim

- CPU: 4 Haswell-like cores, 2.4 GHz, 32KB L1, 256KB L2, 8MB L3
- PIM: 8 ARM Cortex-A57-like cores per memory stack, 2 GHz, 32KB L1
- Extend the memory model to HBM

»16 vaults, 160GB/s peak memory bandwidth

Applications: Tailbench

- 20 threads
- 20s warmup, 10s execution (about 72 billion cycles)
- Run on 8 Haswell-like cores by default

Baselines:

- **Default**: relying on the OS to manage resources
- AMS [MICRO'18]: a scheduler for batch jobs in PIM systems
- Octopus-Man [HPCA'15]: a scheduler for LC apps in systems with heterogeneous cores







Colocation of Xapian, ImgDNN and Masstree at various input loads.

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Colocation of Xapian, ImgDNN and Masstree at various input loads.

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	(a) Default) AN	ΛS		(c)	Oct	ορι	ıs-N	lan	(0	d) P	IMC	lou	d			

PIMCloud outperforms all the baselines

- Core isolation: better than *Default*
- Adjust core count based on load: better than AMS
- Preference-aware: better than Octopus-Man
- Manage data placement: better than all the baselines



Evaluation - Scalability







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Evaluation - Scalability





Convergence time doesn't increase exponentially with more apps / larger systems
Worst case convergence time is 20s

• Convergence time is less than 10s more than 70% of the time.



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- Colocation of 2 LC apps at various input load
- Colocation of 2 LC apps and a BE job at various input load
- Decomposition of PIMCloud
- Dynamic load



SUMMARY



Motivation

- Increasingly important LC applications that will be colocated on the same node
- Increasingly heterogeneous cloud platforms
 - Especially PIM that brings heterogeneity to computation and memory at the same time

PIMCloud

- Characterization of LC applications on PIM
 - More than half of the LC applications perform better on PIM than on CPU
- A QoS-aware and PIM-aware resource manager for LC applications in PIM-enabled systems
 - Leverages preference to reduce the allocation space down to a homogeneous setting
 - Manipulates only hot pages at runtime







PIMCLOUD: QOS-AWARE RESOURCE MANAGEMENT OF LATENCY-CRITICAL APPLICATIONS IN CLOUDS WITH PROCESSING-IN-MEMORY

Thanks! Q & A

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