

PULP PLATFORM Open Source Hardware, the way it should be!



Open source HW solutions for EdgeAI PULP platform in action

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Parallel Ultra Low Power project in a nutshell

Started in 2013, after Luca join Zürich

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We wanted to design energy puting systems

Joule

- wide pr Equally efficient for IoT and H
- Key points
 - Parallel processing
 - Near threshold
 - ore Efficient swit
 - Making best
 - Heterogeneous a celeration
 - And open source using a period sive license

Who is behind PULP?



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Al: where GOPS are needed for better results



The more we can do on the EDGE the better

Less energy used for communication

Major contribution to energy is the communication overhead.

Latency / independence

Communication to cloud brings issues in getting responses in time, What happens if communication is disturbed?

More privacy & security

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Acquiring and consuming private data locally reduces attack surface

Question is how much can we afford to do on EDGE



This is how we get more out of PULP

AI related optimizations

Energy efficient RISC-V core (20 pJ/op - 8 bit)

(1-2 pJ/op - 8 bit)

(50-100 fJ/op - 4 bit)

(5-10 fJ/op – ternary)

- ISA extensions for DSP
- Configurable datapath

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- Fully specialized datapath
 And there is more
- Efficient parallelization, Smart wakeup, Better I/O

Numbers using GF22FDX, Near Threshold @0.6V, High core utilization, minimal I/O & overhead

XPULP

RBE, NE

XNE



RI5CY* – An Open MCU-class RISC-V Core for EE-AI *Now called CV32E40P by OpenHW group





RISC-V ISA is extensible by construction (great!)

- V1 Baseline RV32IMC (not so good for ML) HW loops
- V2 Post modified Load/Store
 - MAC operations
 - SIMD 2/4 + Dot Product + Shuffling
- V3 Bit manipulation unit Lightweight fixed-point support

M. Gautschi et al., "Near-Threshold RISC-V Core With DSP Extensions for Scalable IoT Endpoint Devices," in IEEE Transactions on Very Large Scale Integration (VLSI) Systems, vol. 25, no. 10, pp. 2700-2713, Oct. 2017, doi: 10.1109/TVLSI.2017.2654506.



RISC-V

Ν

Convolution

8-bit

PULP-NN: Xpulp ISA exploitation RV32IMCXpulp

N/4

RV32IMC

addi a0,a0,1 addi t1,t1,1 addi t3,t3,1 addi t4,t4,1 lbu a7, -1(a0)a6, -1(t4)1bu lbu a5,-1(t3) 1bu t5,-1(t1) mul s1,a7,a6 a7,a7,a5 mul add s0, s0, s1 mul a6,a6,t5 add t0.t0.a7 a5,a5,t5 mul t2,t2,a6 add t6,t6,a5 add s5,a0,1c000bc bne

 $P \uparrow T \downarrow \downarrow \downarrow$ so, E=P×T $\downarrow \downarrow$ Nice! But what about the GOPS? Faster + Superscalar is not efficient!

lp.setup p.lw w1, 4(a0!) p.lw w2, 4(a1!) x1, 4(a2!) p.lw x2, 4(a3!) p.lw pv.sdotsp.b s1, w1, x1 pv.sdotsp.b s2, w1, x2 pv.sdotsp.b s3, w2, x1 pv.sdotsp.b s4, w2, x2 end



M7: 5.01 CoreMark/MHz - 58.5 µW/MHz M4: 3.42 CoreMark/MHz - 12.26 µW/MHz

9x less

instructions

than RV32IMC

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ML, Parallel, Near-threshold: a Marriage Made in Heaven

- As VDD decreases. operating speed decreases
- However efficiency increases \rightarrow more work done per Joule
- Until leakage effects start to dominate zürich
 - Put more units in parallel to get performance up and keep them busy with a parallel workload

ML is massively parallel and scales well $(P/S \uparrow with NN size)$



D. Rossi et al., "Energy-Efficient Near-Threshold Parallel Computing: The PULPv2 Cluster," in IEEE Micro, vol. 37, no. 5, pp. 20-31, Sep/Oct 2017, doi: 10.1109/MM.2017.3711645.

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Multiple RI5CY Cores (1-16) in one cluster







CLUSTER

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Low-Latency Shared TCDM



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DMA for data transfers from/to L2



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Shared instruction cache with private "loop buffer"



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Results: RV32IMCXpulp vs RV32IMC

- 8-bit convolution
 - Open source DNN library
- 10x through xPULP
 - Extensions bring real speedup
- Near-linear speedup
 - Scales well for regular workloads
- 75x overall gain

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- Sub-byte: x2 x4 better
- Mixed precision supported (more later)



Garofalo et al. "PULP-NN: Accelerating Quantized Neural Networks on Parallel Ultra-Low-Power RISC-V Processors arxiv.org:1908.11263 [cs.NE]

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An additional I/O controller is used for IO

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Deploying DNNs on PULP

QuantLab

- Quantization Laboratory
- NEMO
 - NEural Minimization for pytOrch

DORY

- Deployment Oriented to memoRY
- PULP-NN
 - PULP Neural Network backend

Burrello et al. "DORY: Automatic End-to-End Deployment of Real-World DNNs on Low-Cost IoT MCUs" arxiv.org:2008.07127 [cs.DC]

What's next? Sub-pJ/OP Accelerators

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Tightly-coupled HW Compute Engine

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A. D. Mauro, F. Conti, P. D. Schiavone, D. Rossi and L. Benini, "Always-On 674µ W@4GOP/s Error Resilient Binary Neural Networks With Aggressive SRAM Voltage Scaling on a 22-nm loT End-Node," in IEEE Transactions on Circuits and Systems I: Regular Papers, vol. 67, no. 11, pp. 3905-3918, Nov. 2020, doi: 10.1109/TCSI.2020.3012576.

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But how to achieve sub-mW average power?

1mW average power with 10mW active power (10GOPS @ 1pJ/OP) → sub mW sleep

Duty cycling not acceptable when input events are asynchronous → watchful Sleep

Log(P)

Detect & Compress → 1-10mW

Stream \rightarrow 100mW

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Watchful sleep \rightarrow <1mW

HD-Based smart Wake-Up Module - Hypnos

		Design	
Ext. Mem	Men Con	Technology	GF22 UHT
	12	Area	670 kGE
	Men	Max. Frequency	3 MHz
	RISC	SCM-Memory	32 kBit
f _{clk}		32 kHz	200 kHz
max. sampling rate		150 SPS/Channel	1'000 SPS/Channel
P _{SWU, dynamic}		0.99 µW	6.21 µW
P _{SWU, leakage}		0.70 µW	0.70 µW
P _{SPI, dynamic}		1.28 μW	8.00 µW
P _{SWU, total} Measured		2.97 μW	14.9 μW
		(51)	Unit
🔘 githu	o.com/pul	lp-platform/hvpnos	

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_ Eggiman et al. "A 5 μW Standard Cell Memory-based Configurable Hyperdimensional Computing Accelerator for Always-on Smart Sensing" arxiv:2102.02758 [eess.SP]

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VEGA: Extreme Edge IoT Processor

- RISC-V cluster (8cores +1)
 614GOPS/W @ 7.6GOPS (8bit DNNs), 79GFLOPS/W @
 1GFLOP (32bit FP appl)
- Multi-precision HWCE(4b/8b/16b) 3×3×3 MACs with normalization / activation: 32.2GOPS and 1.3TOPS/W (8bit)
- 1.7 µW cognitive unit for autonomous wake-up from retentive sleep mode

D. Rossi et al., "4.4 A 1.3TOPS/W @ 32GOPS Fully Integrated 10-Core SoC for IoT End-Nodes with 1.7µW Cognitive Wake-Up From MRAM-Based State-Retentive Sleep Mode," 2021 IEEE International Solid- State Circuits Conference (ISSCC), 2021, pp. 60-62, doi: 10.1109/ISSCC42613.2021.9365939.

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- 1.7 µW cognitive unit for autonomous wake-up from retentive sleep mode
- Fully-on chip DNN inference with 4MB MRAM

	Technology	22nm FDSOI			
	Chip Area	12mm ²			
	SRAM	1.7 MB			
1001	MRAM	4 MB			
	VDD range	0.5V - 0.8V			
	VBB range	0V - 1.1V			
	Fr. Range	32 kHz - 450 MHz			
	Pow. Range	1.7 µW - 49.4 mW			

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PULP is an Open Platform

- For science ... fundamental "research infrastructure"
 - Reduce "getting up to speed" overhead for partners
 - Enables fair and well controlled benchmarking
- For Business ... it is truly disruptive
 - Reduces the NRE , faster innovation path for startups
 - New business models (for profit and non-for profit)

Heterogeneous & Flexible

- 1-3 orders of magnitude improvement (wrt to efficient RV) by acceleration
 - Achieved through efficient implementation, ISA extensions, heterogeneous accelerator combinations
- To achieve true system-level sub pj/Op operation, everything little thing counts
 - Efficient I/O, 3D integration, sleep modes, power conversion

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