



# Energy Efficiency in Computing (2)

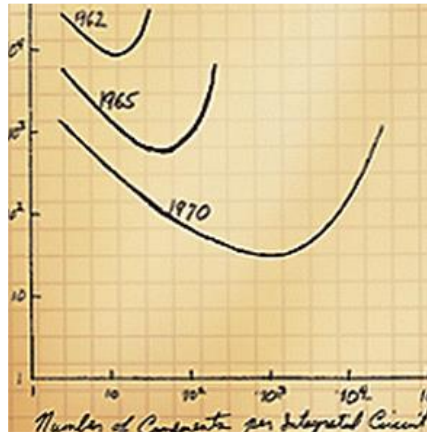
CERN Academic Training – May 2016

Andrzej Nowak

<http://tik.services>

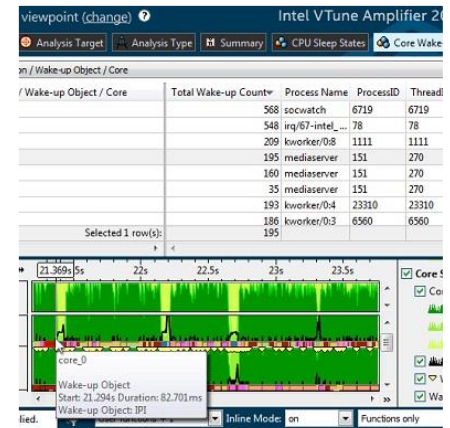
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innovation  
knowledge

# Outline



## Day 1: Silicon, hardware

## Day 2: Datacenters, software, future technologies



# Energy-efficient Datacenters

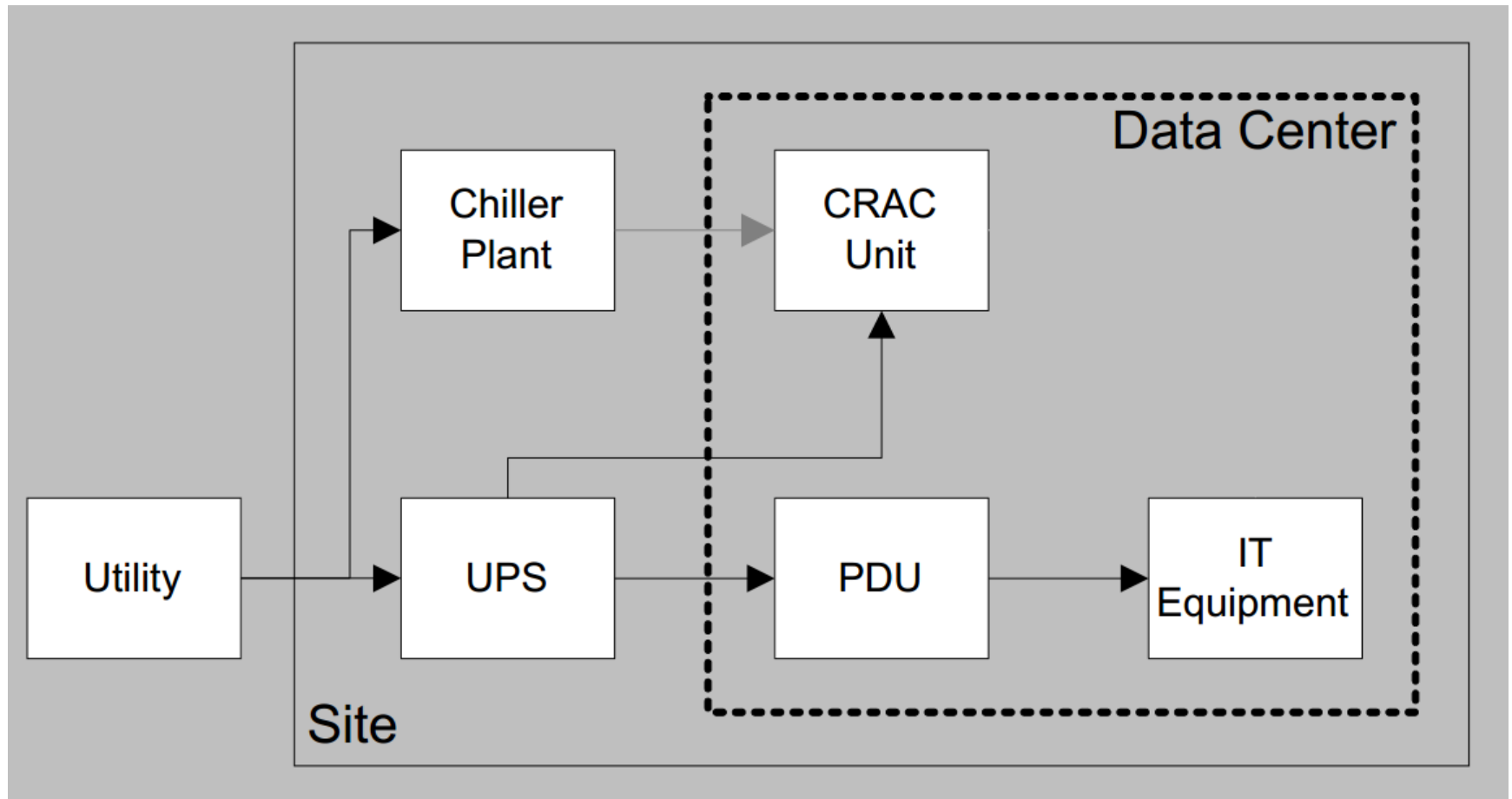
# Top500 power efficiency

## MOST POWER EFFICIENT ARCHITECTURES

Computer	Rmax/Power
<a href="#">Tsubame KFC/DL</a> , NEC, Xeon 6C 2.1GHz, IB FDR, <b>NVIDIA K80</b>	4,856
<a href="#">Sugon Cluster W780I</a> , Xeon 8C 2.6GHz, IB QDR, <b>NVIDIA K80</b>	4,778
<a href="#">Inspur TS10000 HPC Server</a> , Xeon 6C 2.4GHz, 10GE, <b>NVIDIA K40</b> (Multiple)	4,497 (best)
<a href="#">Suiren</a> , Xeon 10C 2.2GHz, IB FDR <b>PEZY-SC</b>	4,044
<b>Taurus GPUs</b> , Bull R400, Xeon 12C 2.5GHz, IB FDR, <b>NVIDIA K80</b>	3,277
<a href="#">Sango</a> , <a href="#">Supermicro</a> , Xeon 12C 2.5GHz, IB FDR, <b>Intel Phi</b>	3,223
<a href="#">XingGui</a> , Dell, Xeon 10C/8C 2/2.6GHz, IB FDR, <b>NVIDIA K40m/K20m</b>	3,187
<b>Romeo</b> , Bull Cluster, Xeon 8C 2.6GHz, IB FDR, <b>NVIDIA K20x</b>	3,131
<a href="#">Sekirei-ACC</a> , SGI ICE XA, 12C 2.5GHz, IB FDR, <b>NVIDIA K40</b>	3,045
<b>HA-PACS TCA</b> , Cray Cluster, Xeon 10C 2.8GHz, QDR, <b>NVIDIA K20x</b>	2,980
<b>SANAM</b> , <a href="#">Adtech</a> , ASUS, Xeon 8C 2.0GHz, IB FDR, <b>AMD FirePro</b>	2,973

**[Mflops/Watt]**

# Datacenters



# Datacenters

## Metrics that matter

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Power Usage Effectiveness

$$PUE = \frac{\textit{Total Power}}{\textit{IT Power}}$$

Server-PUE

$$ITUE = \frac{\textit{Infrastructure Burden} + \textit{Compute}}{\textit{Compute}}$$

Total Usage Effectiveness

$$TUE = PUE \times ITUE$$

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# Datacenter choices

## From M.K. Patterson/Intel

- Air or liquid cooling? What kind? Where does it come from?
- Hot- or cold-aisle?
- What kind of floor, is it raised?
- Modular or not?
- What kind of UPS?
- What kind of rack density?
- Material vs. TCO cost



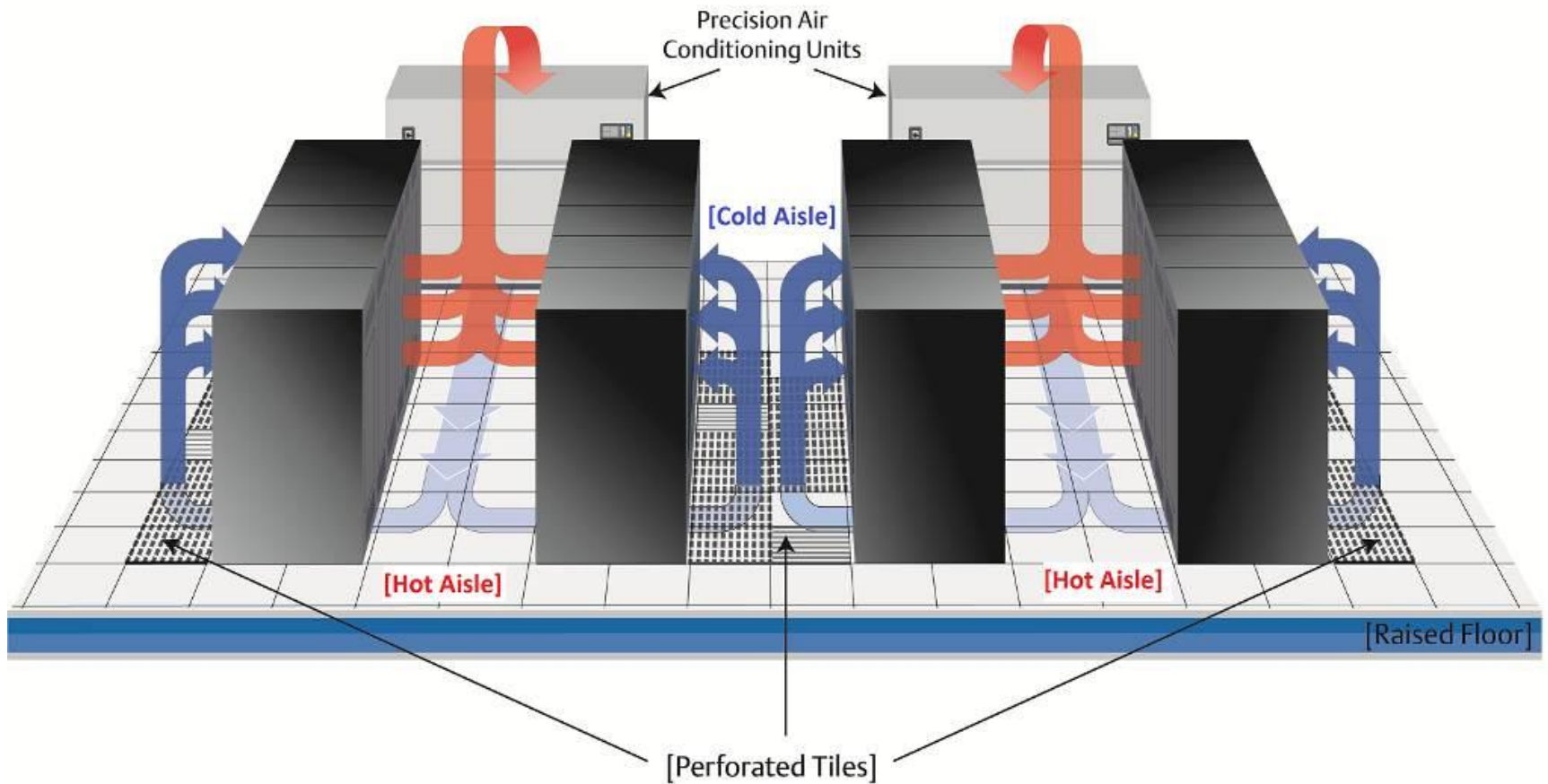
Image: CERN

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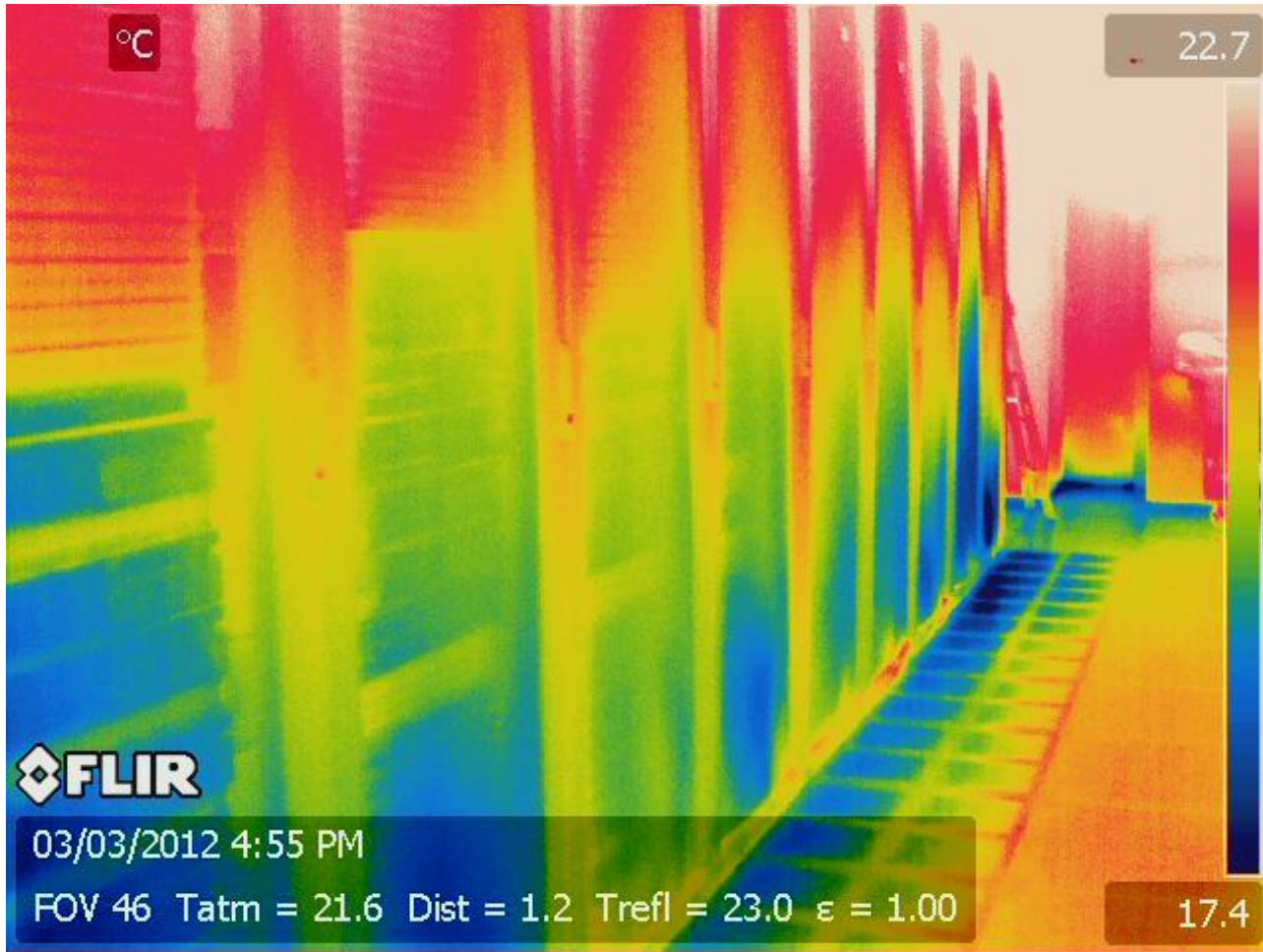


# Thermal control

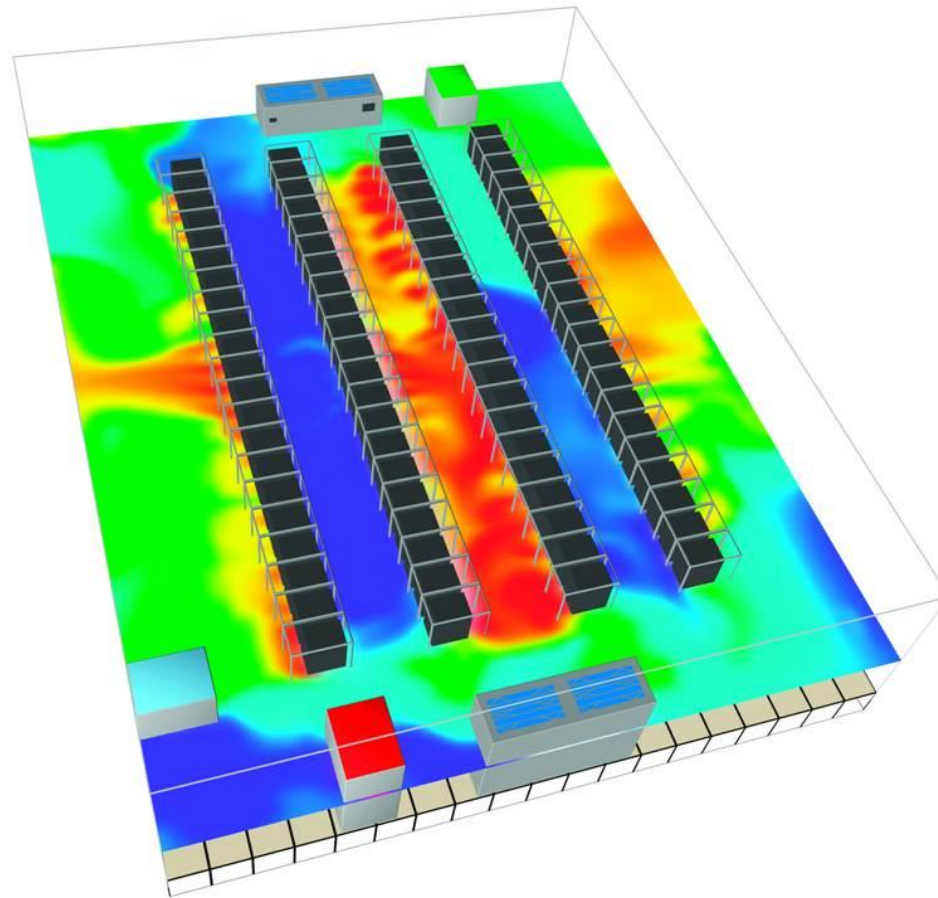
## Hot Aisle/ Cold Aisle Approach



# Thermal debugging



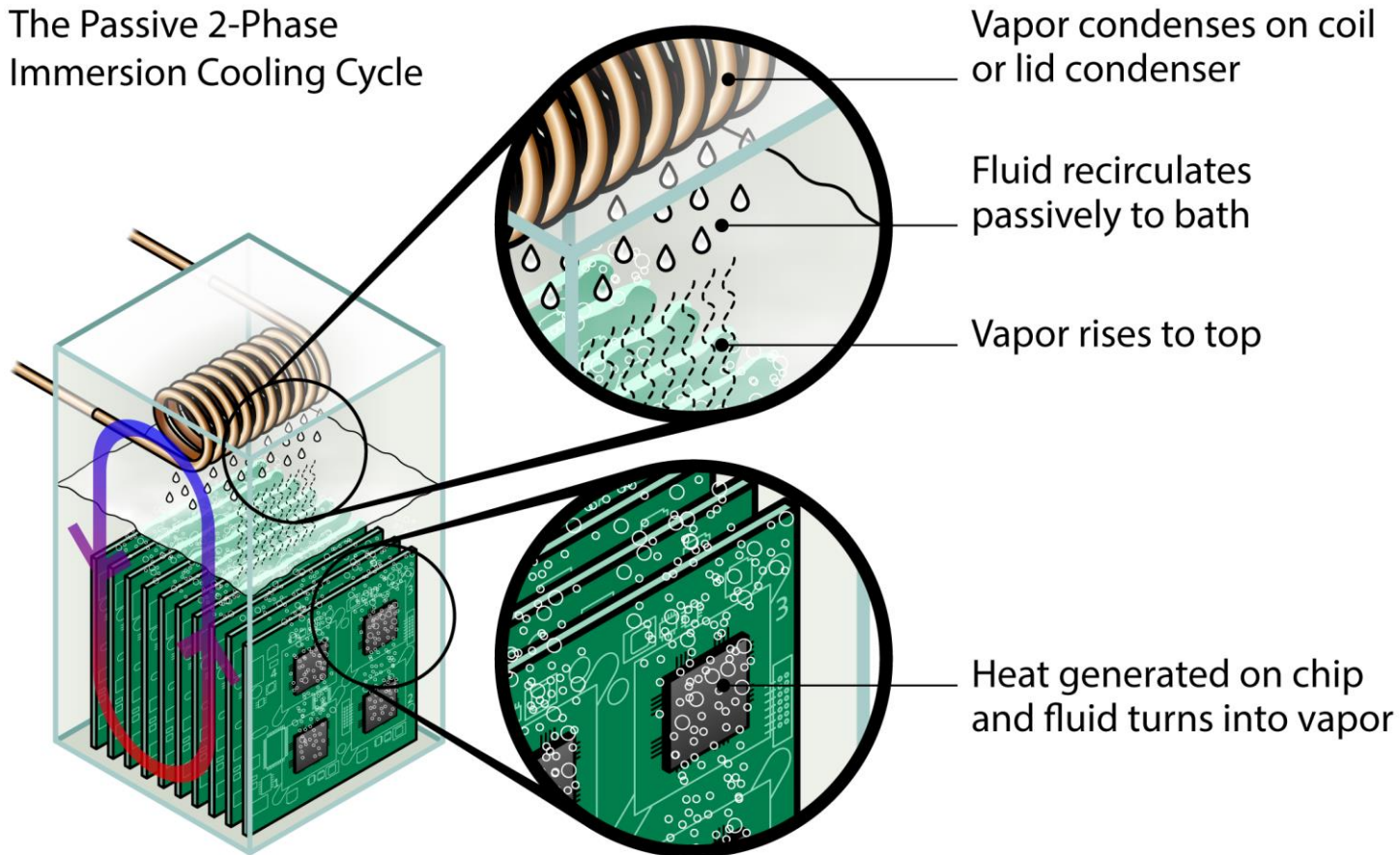
# Thermal debugging



# Creative solutions for datacenters

## Submersion cooling

The Passive 2-Phase  
Immersion Cooling Cycle

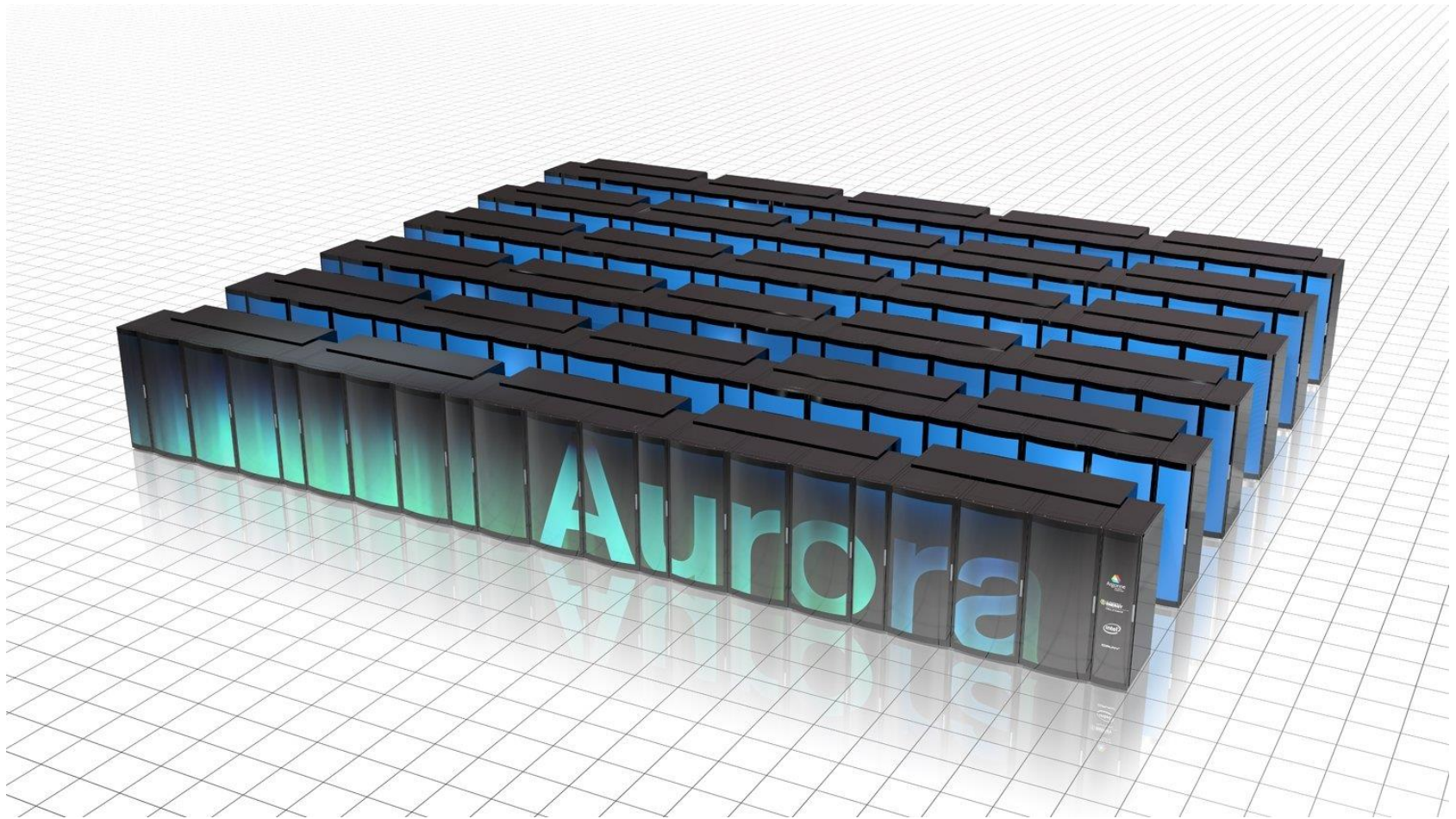


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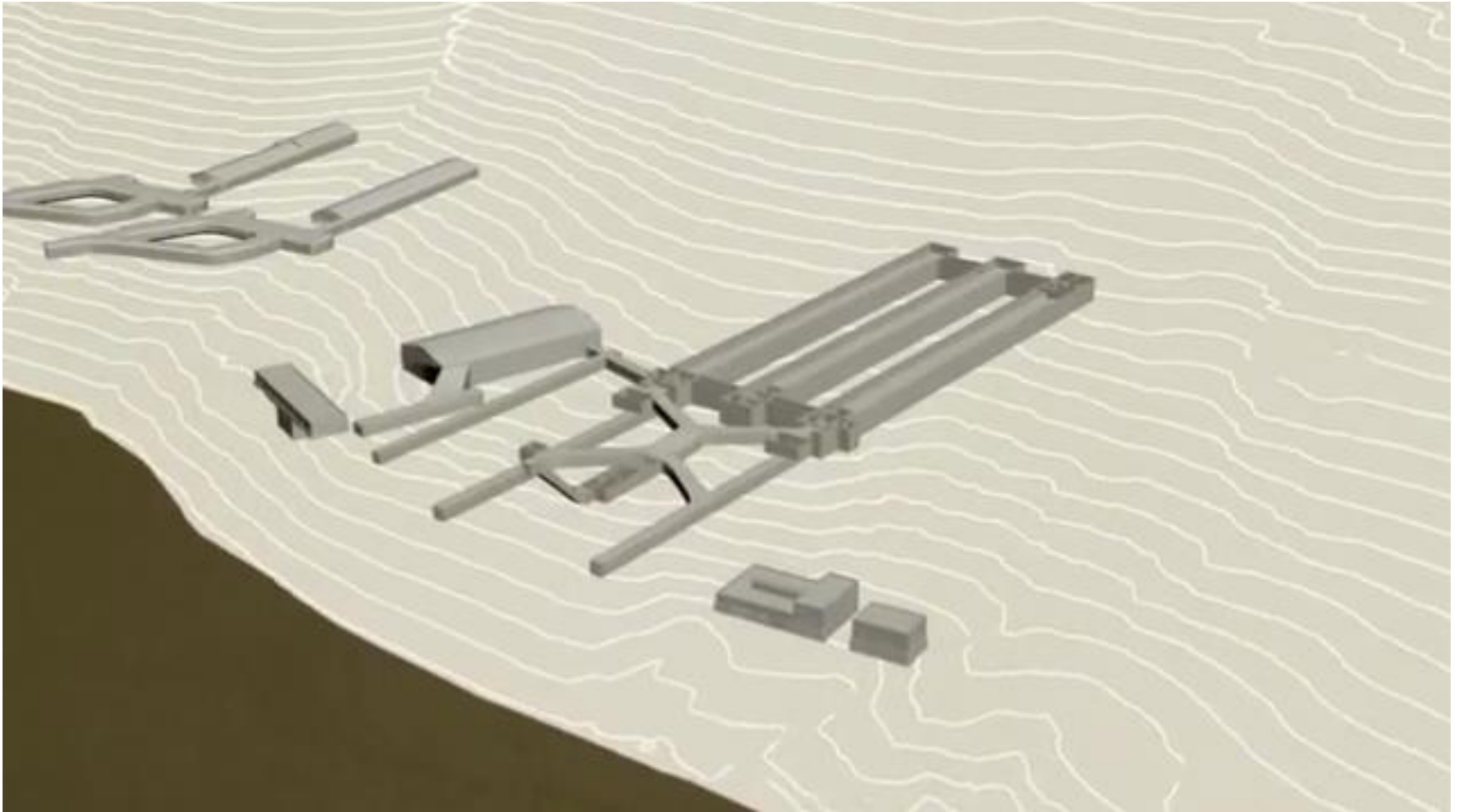
# Creative solutions for datacenters

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# Creative solutions for datacenters

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# Not-so-creative solutions?

- Ultimately - density:
  - In-package memory, stacked (2.5D or 3D)
  - Integrated fabric/networking
  - Higher package integration
  - Switching closer to compute
  - Si-Ph – cost benefits, but power performance a question
- As well as:
  - Metrics and research
  - Power
  - Cooling optimization

# Energy-efficient Software



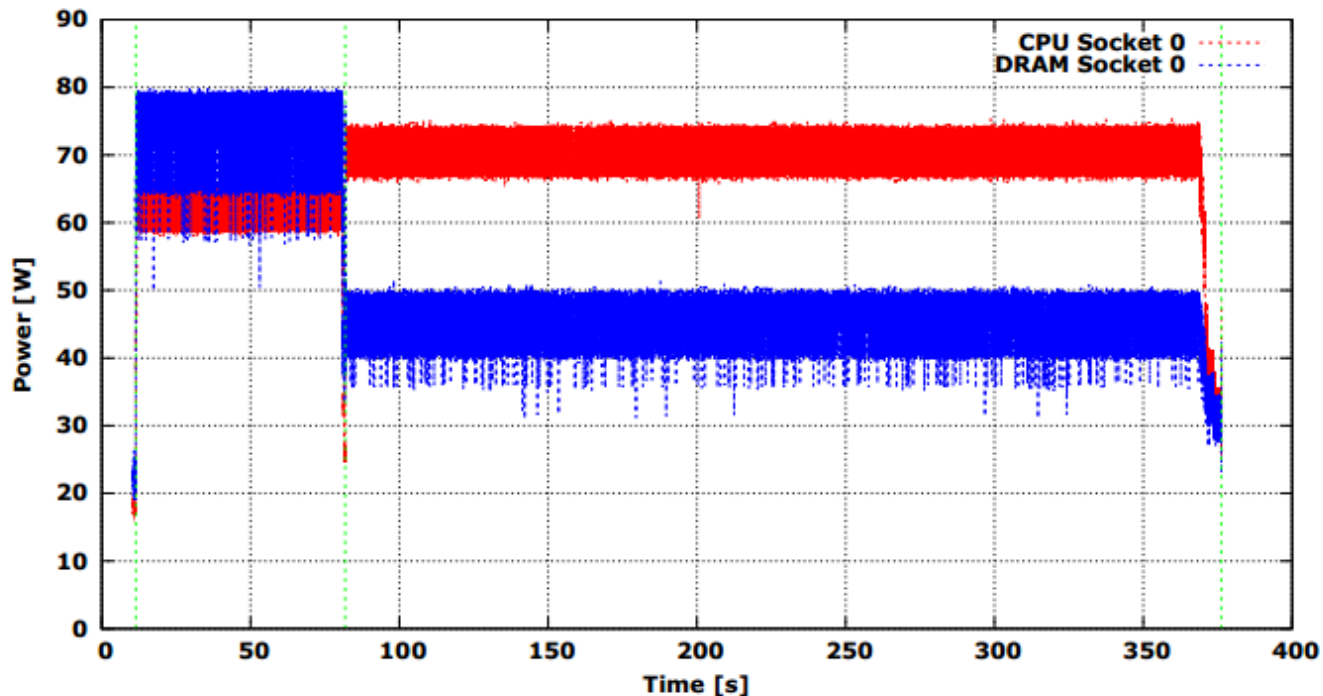
# Energy and code



Image: E. Calore / INFN / COLA

# Energy and code

## Acquired data example using RAPL counters



Intel Haswell CPU energy counters acquired at 100Hz and converted in Watt; acquisition performed with a custom developed wrapper to the PAPI library.

# Energy per instruction?

## Example study

Instruction	Cortex-A7		Cortex-A15	
	min EPI	max EPI	min EPI	max EPI
Simple Integer	50	80	200	450
Simple Float/Double	90	200	250	1500
Multiplication	80	340	360	1730
Division	150	1200	1270	1960
Load (L1 hit)	150	195	450	450
Store (L1 hit)	185	195	680	750
Store (L1 miss)	200		700	
Load (L1 miss)	270		1000	

**Table 7.1:** Minimum (w/o RAW) and maximum (w/ RAW) Energy per Instruction (pJ) at 1GHz

# Energy per instruction?

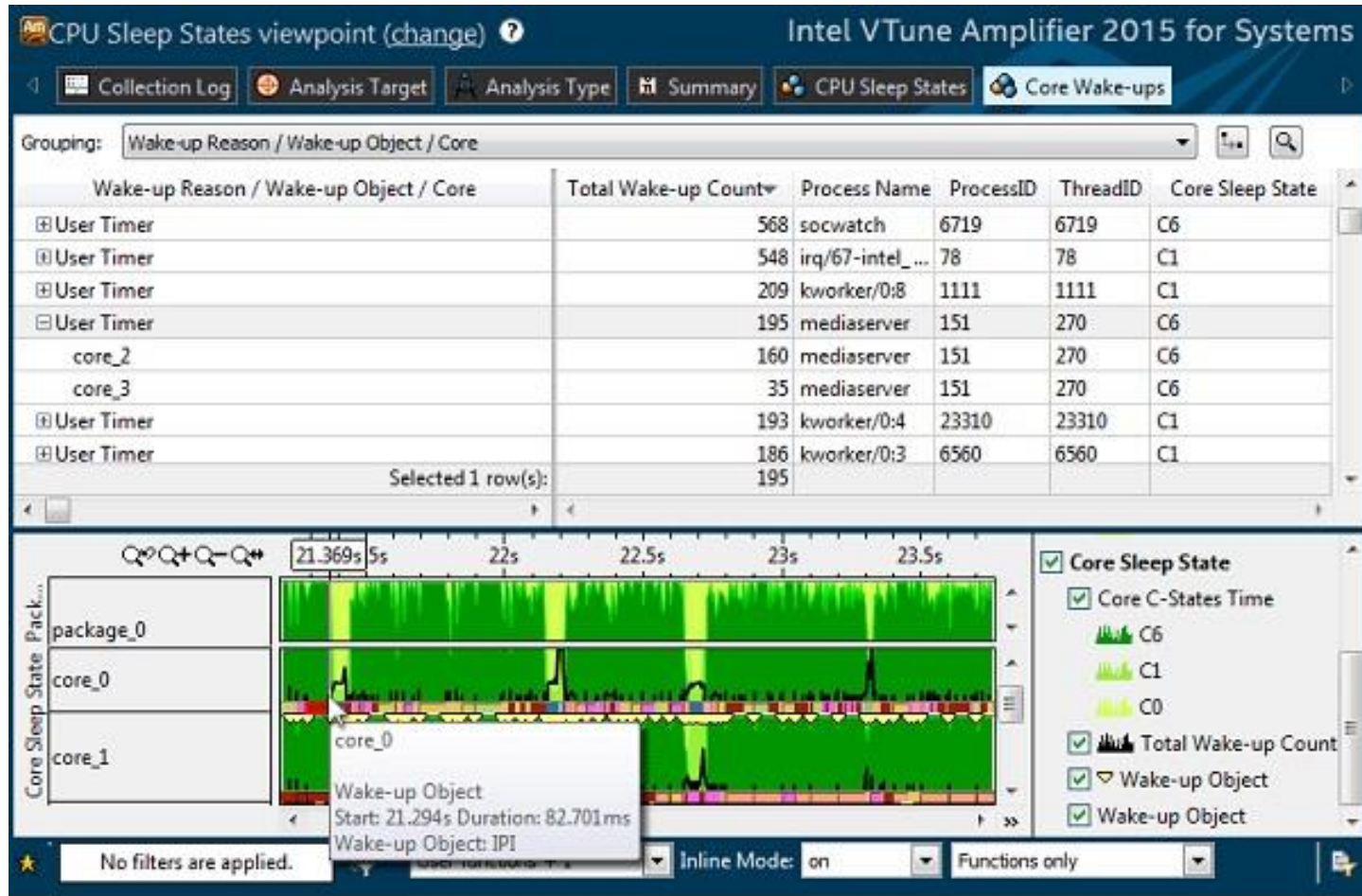
## Example study

Cortex-A7 Energy Per Instruction (pJ)

Freq. MHz \ Instr.	500	600	700	800	900	1000	1100	1200
add	63	62	61	64	72	82	94	105
and	54	53	52	54	61	69	79	89
eor	55	55	54	56	63	72	81	92
mul	116	114	112	116	128	146	166	189
orr	55	55	54	56	63	72	81	92
rsb	63	62	62	65	72	83	93	105
sub	64	63	62	65	73	83	94	105
div	178	174	170	177	195	221	251	286

**Table 7.4:** Integer logic and arithmetic instructions with 3 register operands with RAW dependencies

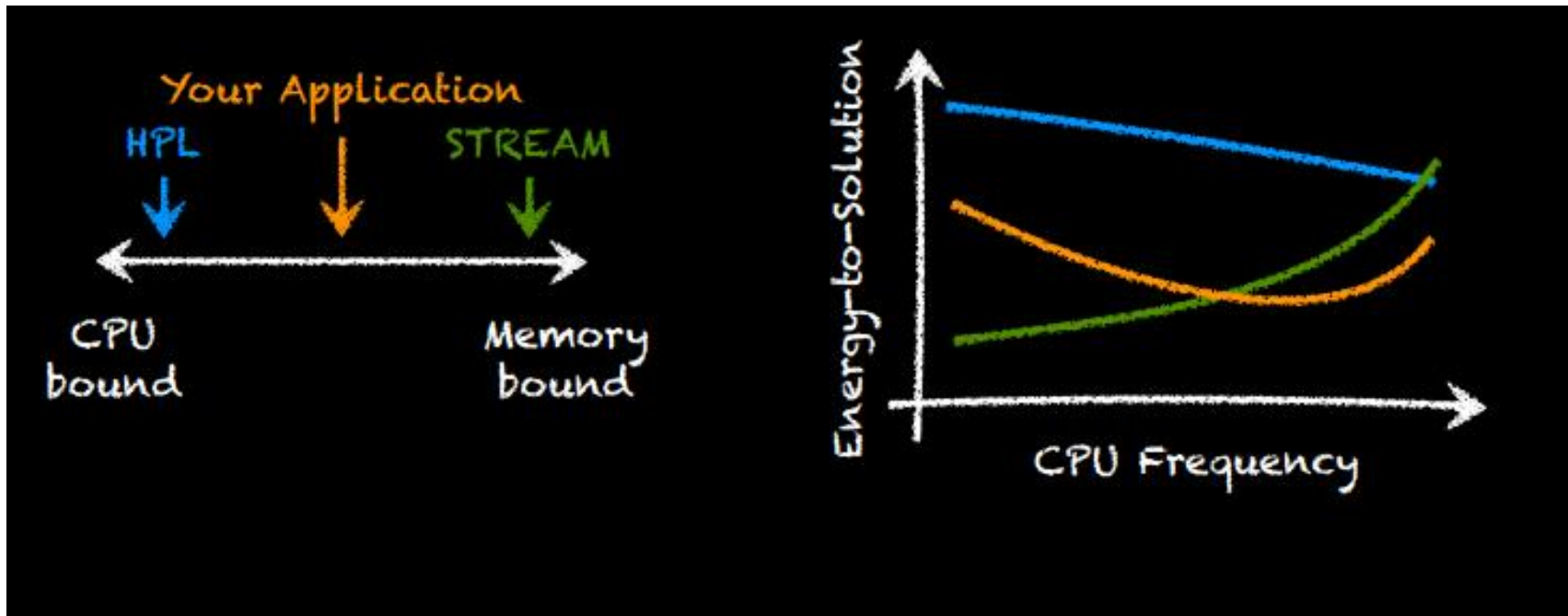
# Energy profiling





# Energy-aware scheduling

“Energy to solution”



# Energy-aware scheduling

“Energy to solution”

## Conclusion

- LRZ Policy on SuperMUC is now:
  - No application tag: run @ default frequency (2.3 GHz)
  - With application tag:
    - Execute at 2.4 GHz if performance gain > 2.5%
    - Execute at 2.5 GHz if performance gain > 5%
    - Execute at 2.6 GHz if performance gain > 8.5%
    - Execute at 2.7 GHz if performance gain > 12%
- Applies to all jobs on SuperMUC
- Estimated energy savings ~5 %
- Big incentive for scientists to improve their codes!

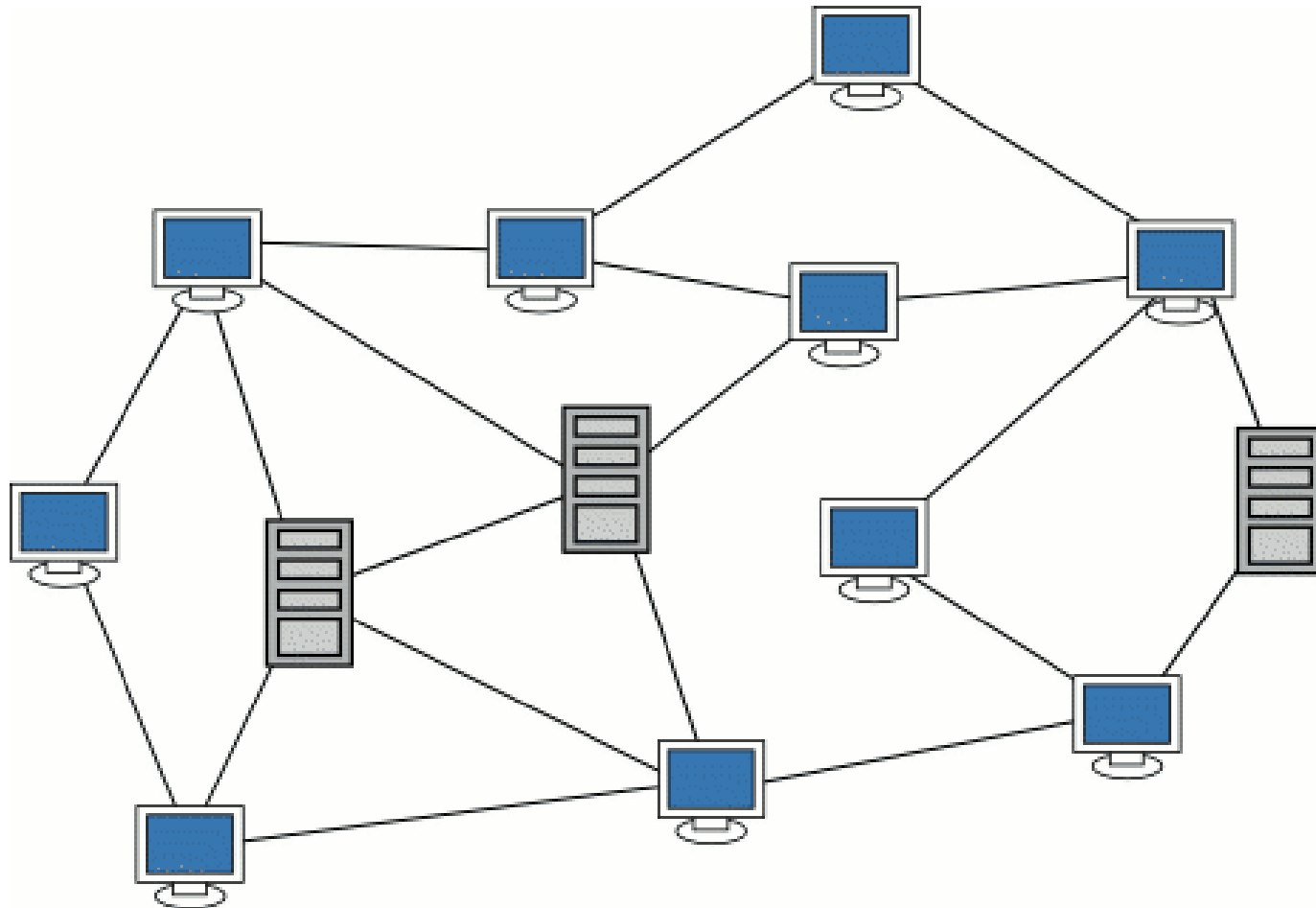
# Future technologies, applications

From mainstream to exotic





# Mesh networking/computing



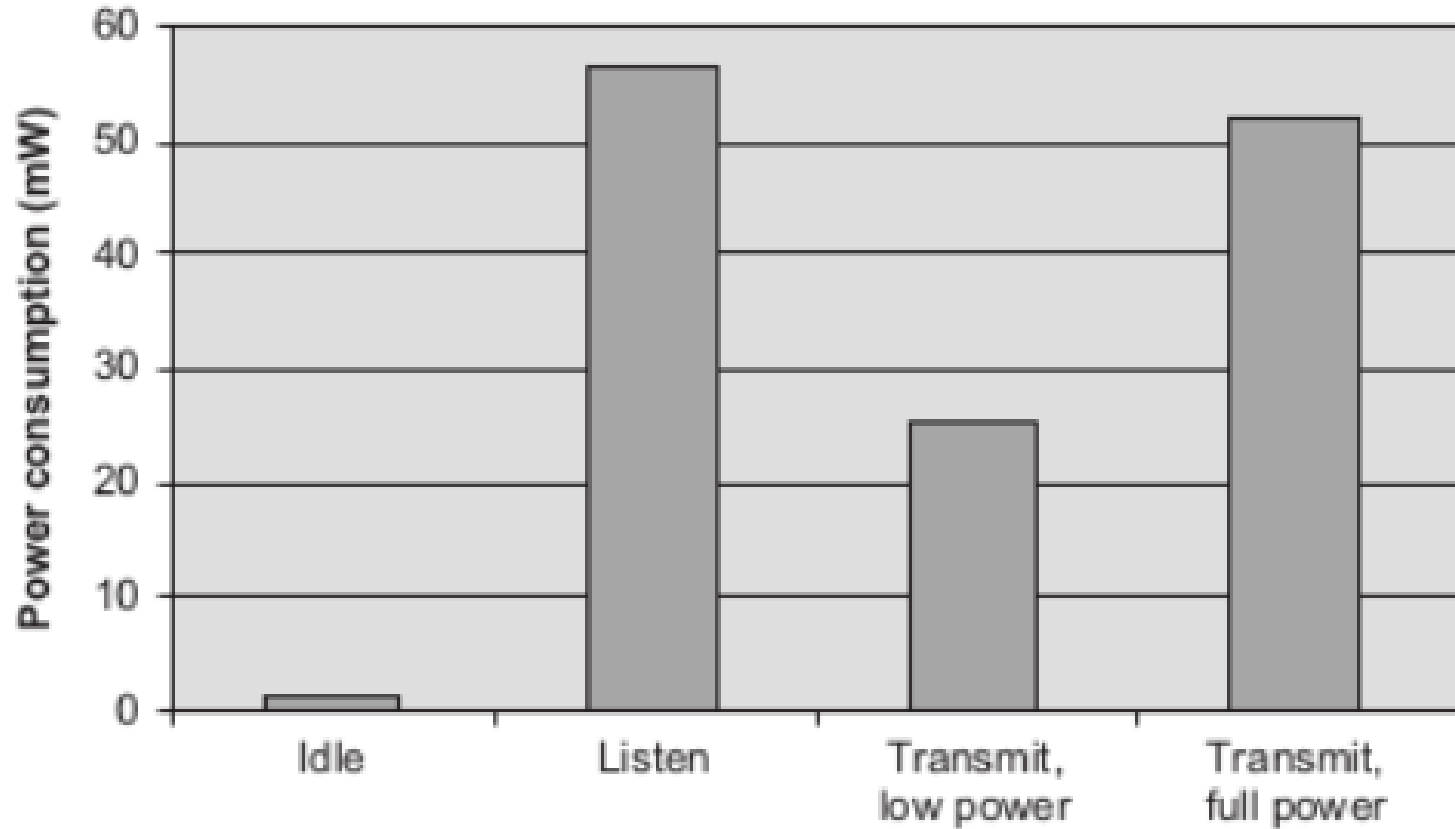
# “The Internet of Things”

## Communication and energy

	Wi-Fi	Zigbee	Bluetooth Low Energy
Sleep	10 $\mu$ W	4 $\mu$ W	8 $\mu$ W
Receive (Rx) Power	90 mW	84 mW	28.5 mW
Transmit (Tx) Power	350 mW	72 mW	26.5 mW
Average Power for 10 Messages Per Day	500 $\mu$ W	414 $\mu$ W	50 $\mu$ W

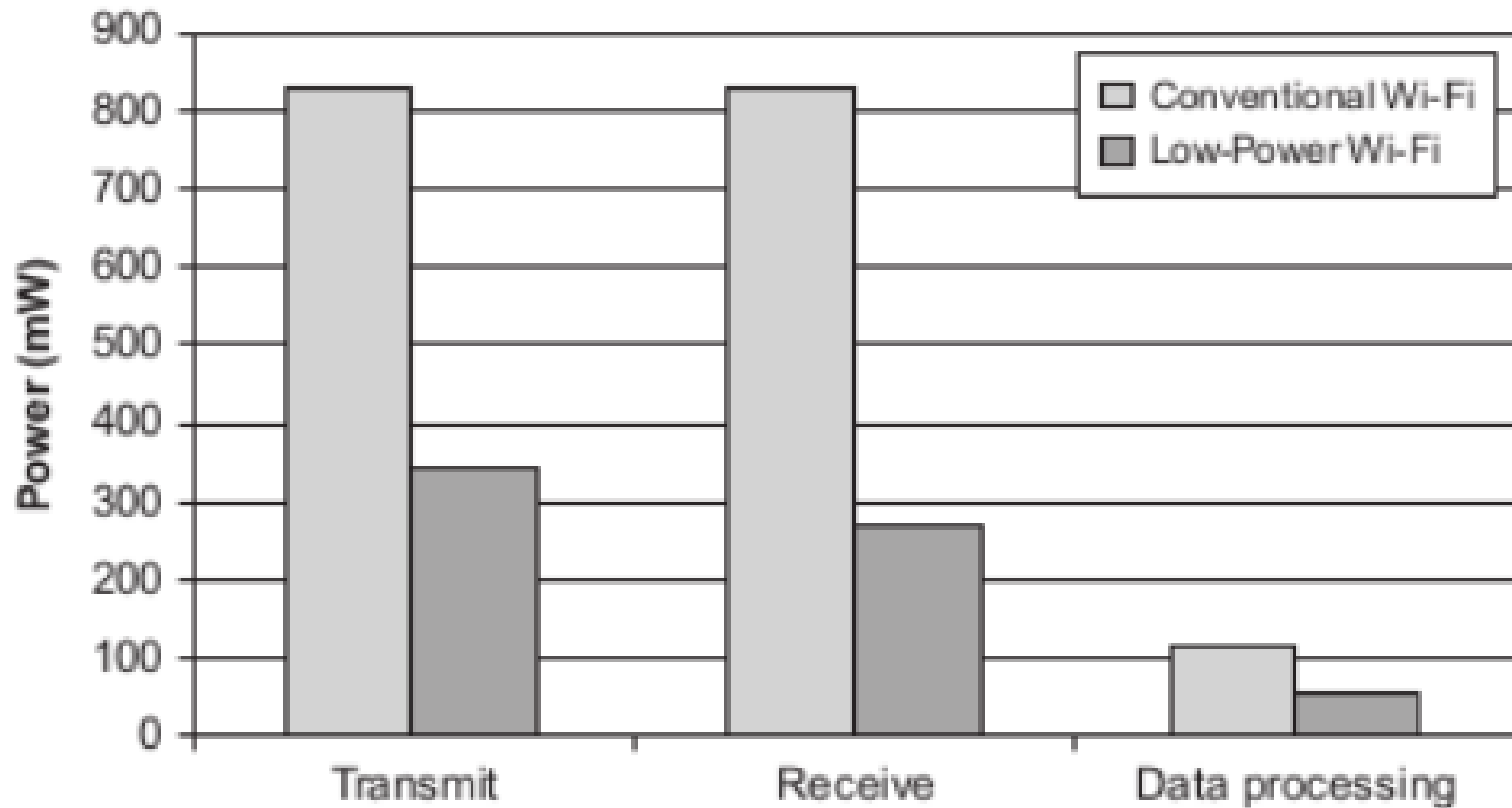
# “The Internet of Things”

802.15.4 example



# “The Internet of Things”

## Wi-Fi example

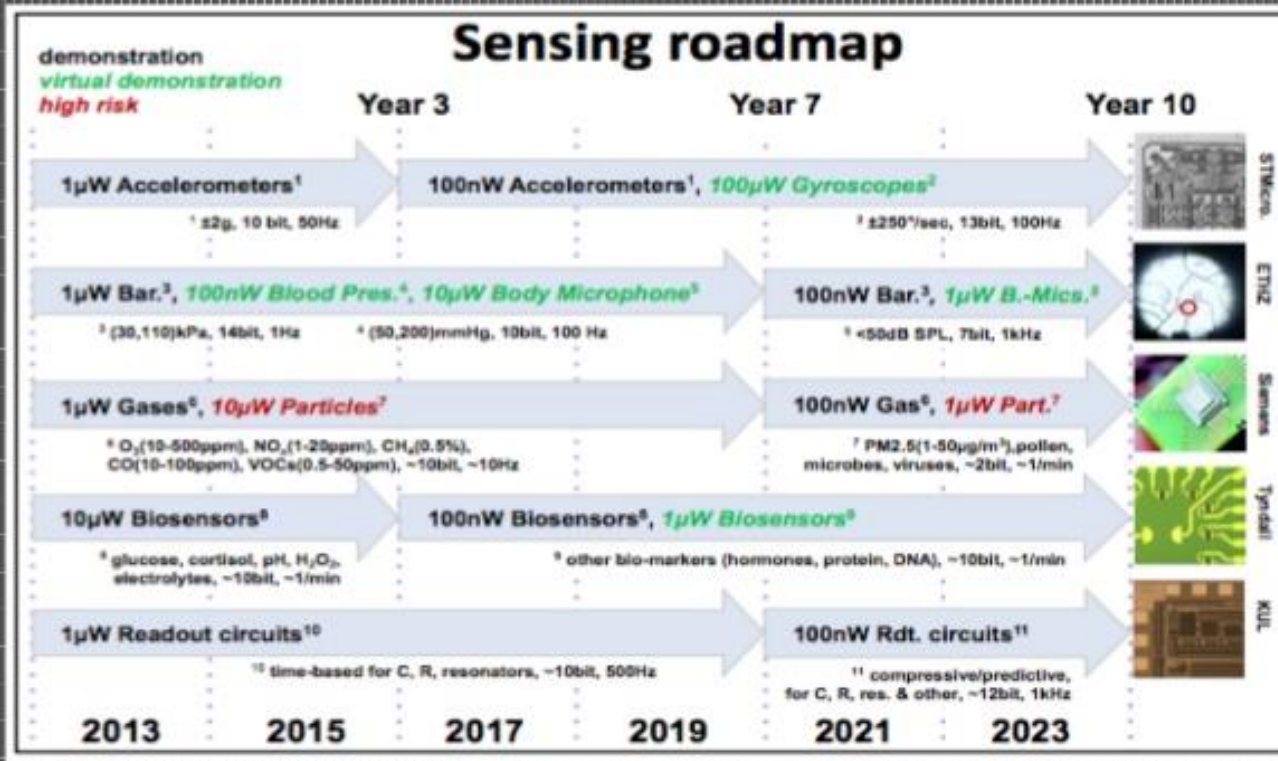


# “The Internet of Things”

BLE example – standard 600mAh battery

		Broadcasting power		
		-30 dBm [low]	-4 dBm	+4 dBm [high]
Advertising interval	2000 ms [long]	3.3 years	3 years	2.3 years
	1000 ms	1.9 years	1.7 years	1.3 years
	600 ms	1.2 years	1 year	300 days
	200 ms	160 days	140 days	104 days
	50 ms [short]	40 days	35 days	26 days

## SENSORS ROADMAP – POWER REDUCTION IN IoT CURRENT SOA EH TECHNOLOGIES (10µW to 15mW) MEETING DEMAND OF IoT SENSORS



Reduce the power consumption per transducer below 100 nW; while meeting resolution, bandwidth and measurement range constraints

# “The Internet of Things” recapped

## Energy harvesting

Source	Energy source	Source power	Harvested power
<b>Photovoltaic</b>			
Indoor	Energy Harvester at office environment	0.1mW/cm <sup>2</sup>	10uW/cm <sup>2</sup>
Outdoor	Energy Harvester outside in a sunny day at noon	100mW/cm <sup>2</sup>	10mW/cm <sup>2</sup>
<b>Vibration</b>	Human walking with harvester in their shoes	0.5+1m/s@1+50Hz	4uW/cm <sup>2</sup>
<b>Thermal</b>	Human body at ambient air	20mW/cm <sup>2</sup>	25uW/cm <sup>2</sup>
<b>RF</b>			
GSM 900MHz	RF harvester at a city restaurant	0.3 to 0.03uW/cm <sup>2</sup>	0.1uW/cm <sup>2</sup>
GSM 1800MHz		0.1 to 0.01uW/cm <sup>2</sup>	



# Accelerators

## According to Intel

### KNL Performance



Significant performance improvement for compute and bandwidth sensitive workloads, while still providing good general purpose throughput performance.

1. Projected KNL Performance (1 socket, 200W CPU TDP) vs. 2 Socket Intel® Xeon® processor E5-2697v3 (2x145W CPU TDP)

# Accelerators

## According to NVIDIA

Tesla Model	K10	K20	K20X	K40	K80	M4	M40
GPU	2 * GK104	GK110	GK110	GK110B	2 * GK210B	GM206	GM200
CUDA Cores	2 * 1,536	2,496	2,688	2,880	4,992	1,024	3,072
Base Core Clock Speed	745 MHz	706 MHz	732 MHz	745 MHz	560 MHz	872 MHz	948 MHz
GPU Boost Clock Speed	-	-	-	875 MHz	875 MHz	1,072 MHz	1,114 MHz
SMXs or SMMs	2 * 8	13	14	15	2 * 13	8	24
Base SP, Teraflops	4.58	3.52	3.95	4.29	5.6	*	*
Peak SP, Teraflops	4.58	3.52	3.95	5.0	8.74	2.2	7.0
Base DP, Teraflops	0.19	1.17	1.31	1.43	1.87	*	*
Peak DP, Teraflops	0.19	1.17	1.31	1.66	2.91	0.06	0.20
GDDR5 Memory	8 GB	5 GB	6 GB	12 GB	24 GB	4 GB	12 GB
Memory Clock Speed	2.5 GHz	2.6 GHz	2.6 GHz	3.0 GHz	2.5 GHz	2.75 GHz	3.0 GHz
Memory Bandwidth	320 GB/sec	208 GB/sec	250 GB/sec	288 GB/sec	480 GB/sec	88 GB/sec	288 GB/sec
Power Draw	225 W	225 W	235 W	235 W	300 W	50 W - 75 W	250 W
SP Efficiency (Gigaflops/Watt)	20.4	15.6	16.8	21.3	29.1	29.3	28.0
* Base SP and DP teraflops unknown							

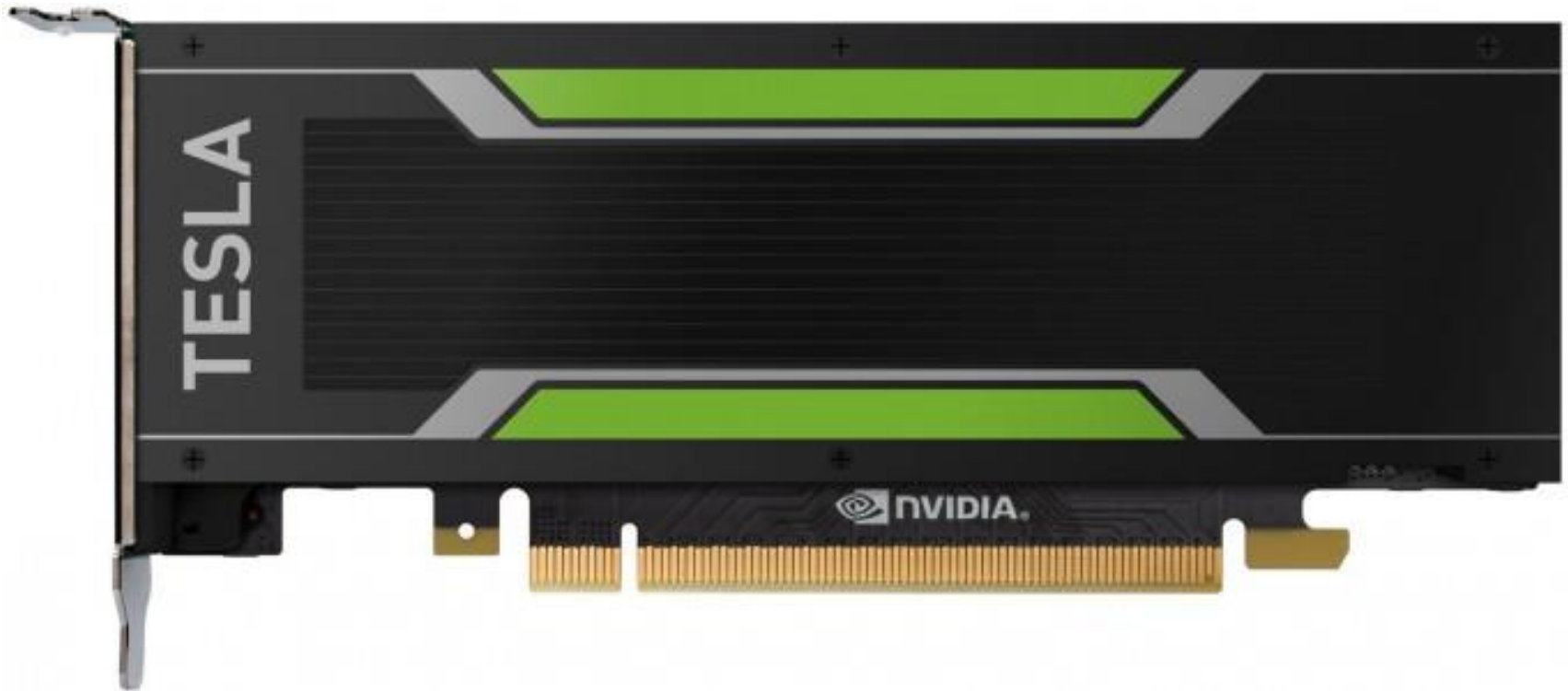
Table: NVIDIA

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# “Mini-accelerators”

## NVIDIA M4

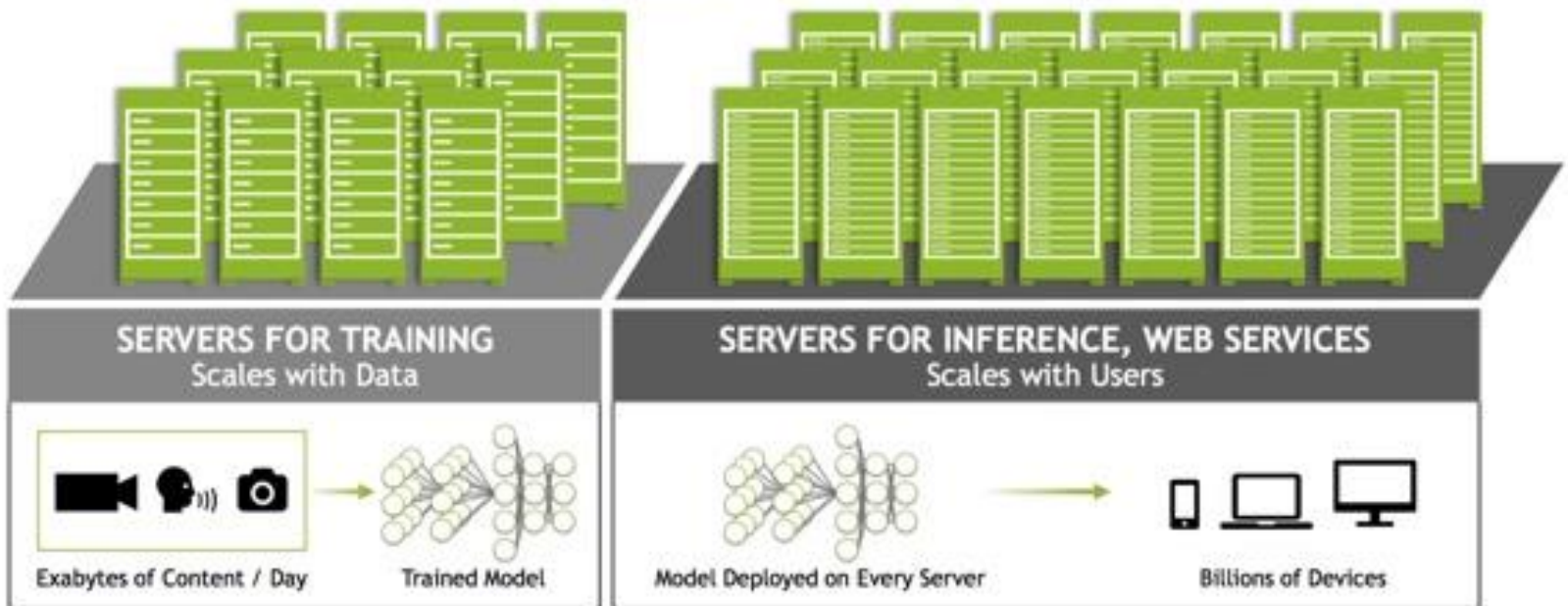
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# Heterogeneous... accelerators

## HYPERSCALE DATACENTER NOW ACCELERATED

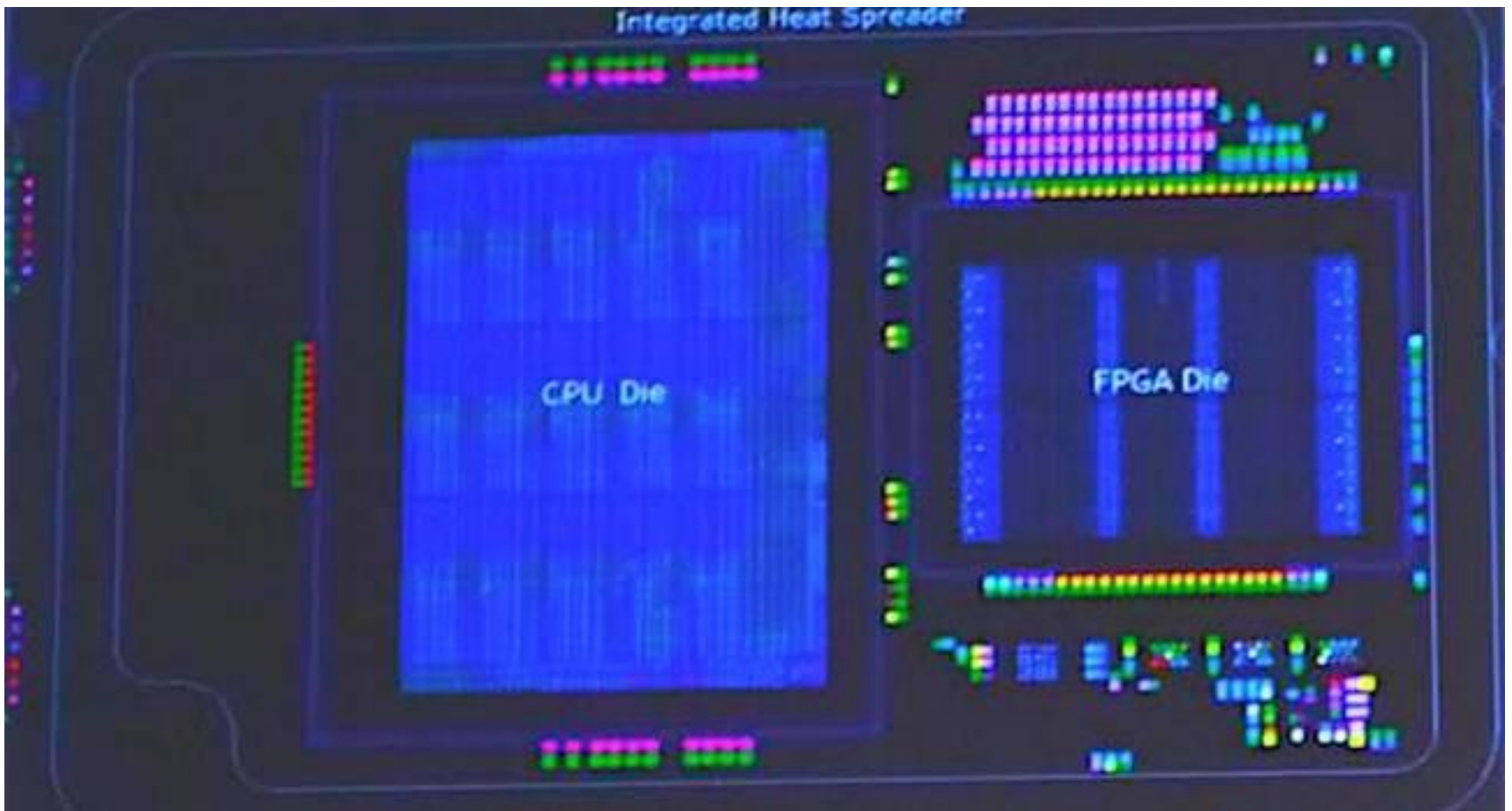
Tesla Platform



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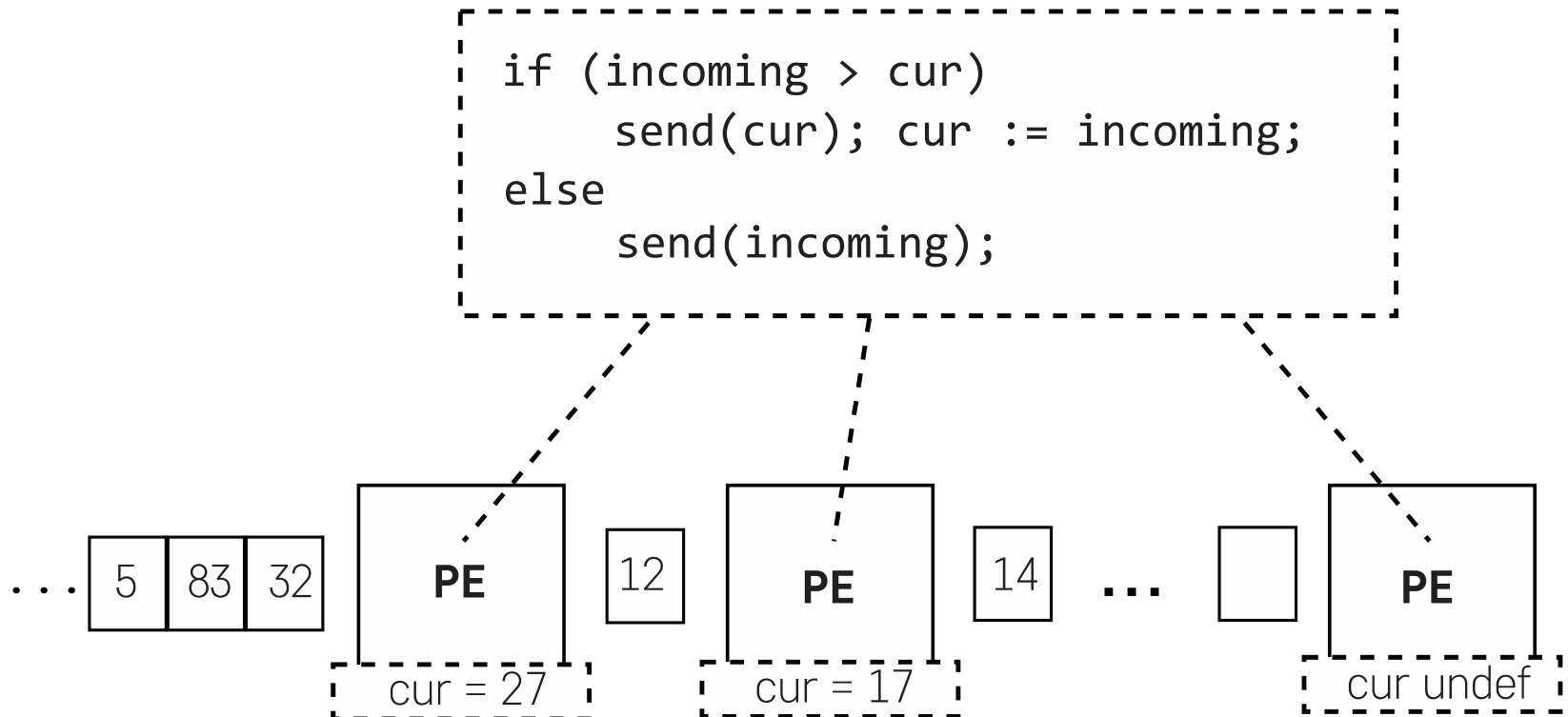


# Combos

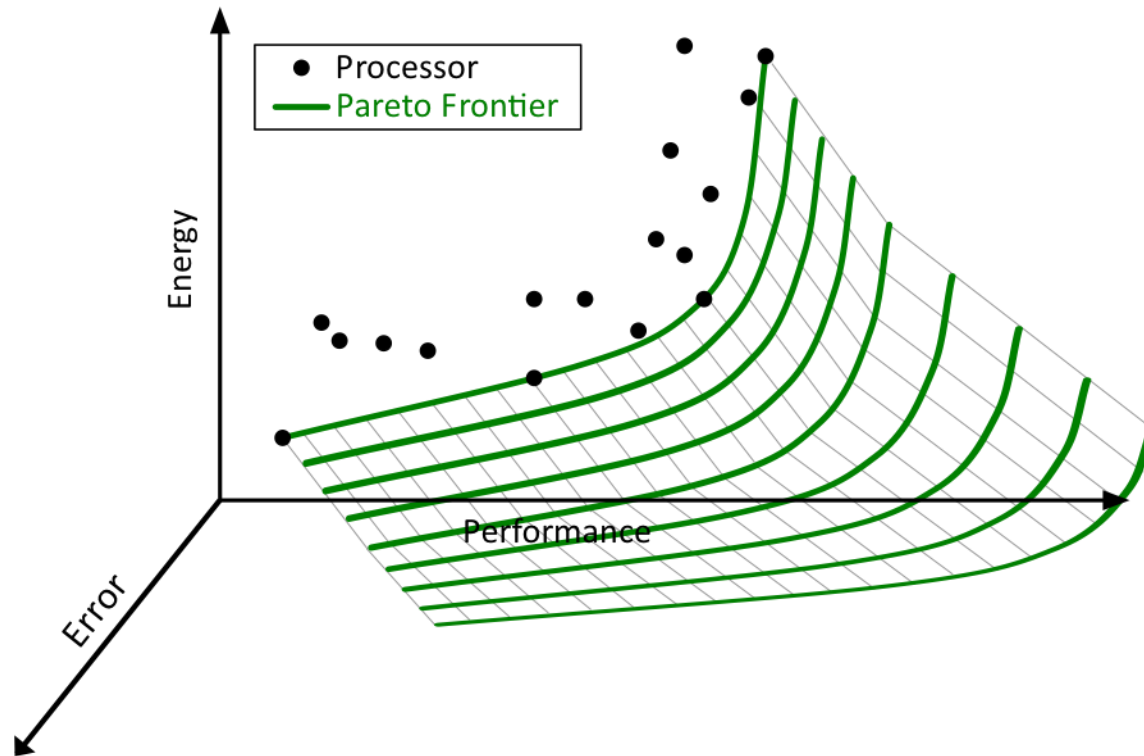


# Spatial architectures

## Triggered instructions



# Approximate computing



# “Imprecise” computing



Computing

## Why a Chip That’s Bad at Math Can Help Computers Tackle Harder Problems

DARPA funded the development of a new computer chip that’s hardwired to make simple mistakes but can help computers understand the world.

by Tom Simonite April 14, 2016

**Your math teacher lied to you. Sometimes getting your sums wrong is a good thing.**

So says Joseph Bates, cofounder and CEO of Singular Computing, a company whose computer chips are hardwired to be incapable of performing mathematical calculations correctly. Ask it to add 1 and 1 and you will get answers like 2.01 or 1.98.

The Pentagon research agency DARPA funded the creation of Singular’s chip because that fuzziness can be an asset when it comes to some of the hardest problems for computers, such as making sense of video or other messy real-world data. “Just because the hardware is sucky doesn’t mean the software’s result has to be,” says Bates.

A chip that can’t guarantee that every calculation is perfect can still get good results on many problems but needs fewer circuits and burns less energy, he says.

Bates has worked with Sandia National Lab, Carnegie Mellon University, the Office of Naval Research, and MIT on tests that used simulations to show how the S1 chip’s inexact operations might make certain tricky computing tasks more efficient. Problems with data that comes with built-in noise from the real world, or where some



# Approximate computing ctd.

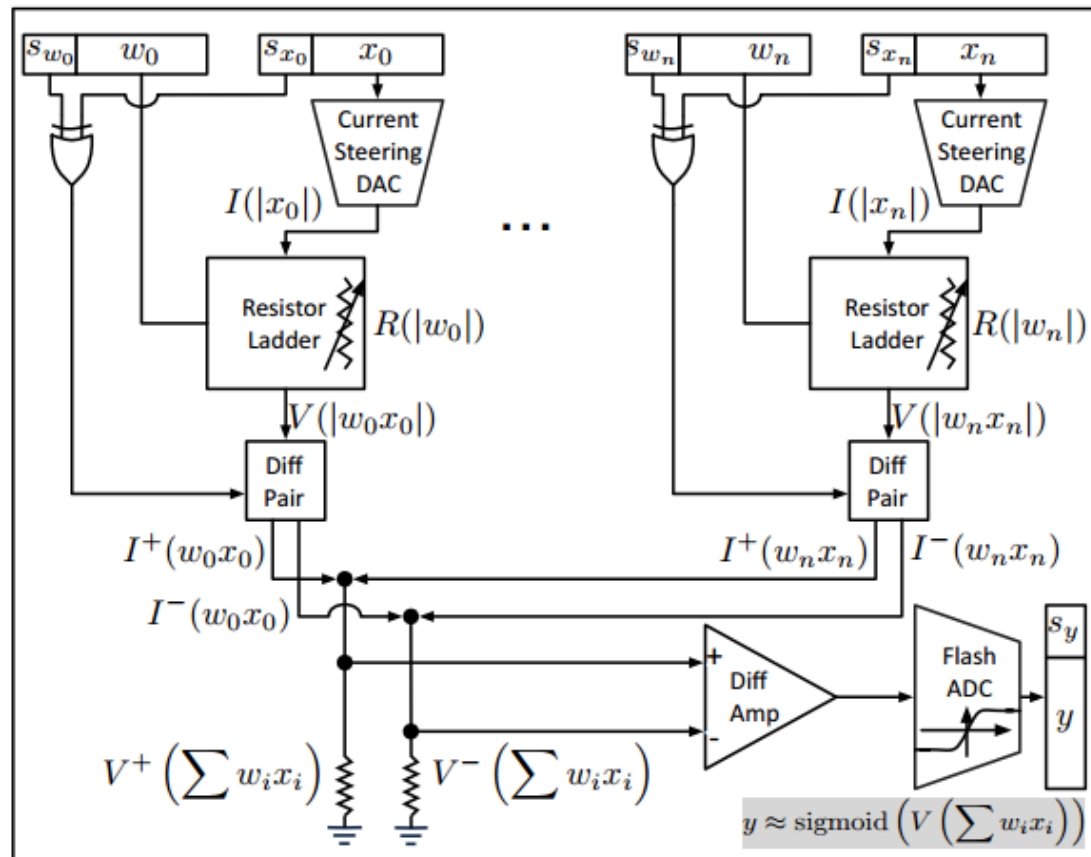
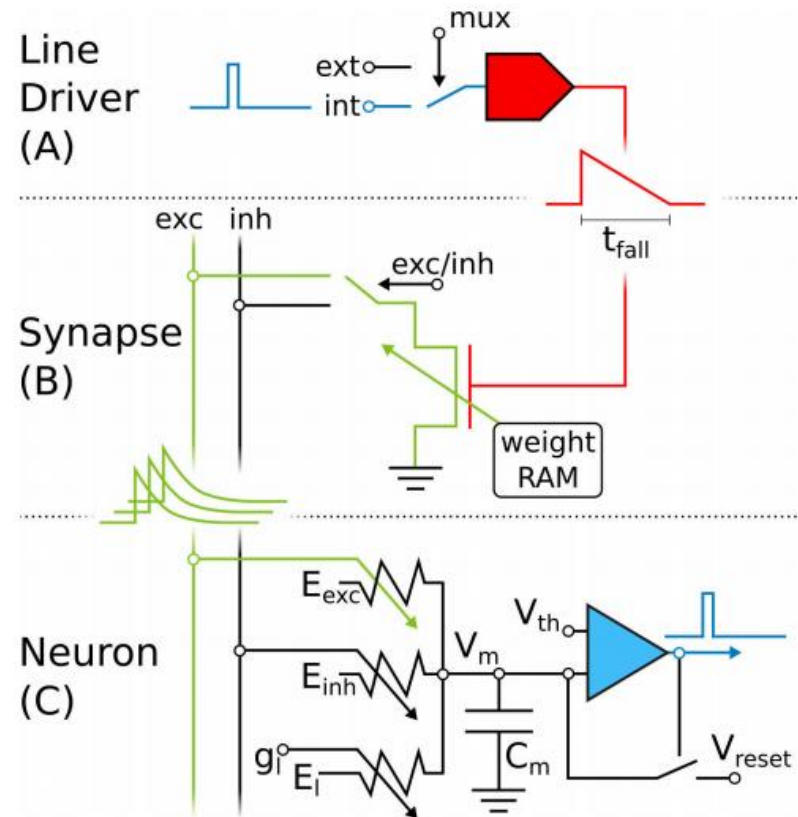


Figure 3: A single analog neuron (ANU).

# Neuromorphic computing (1)

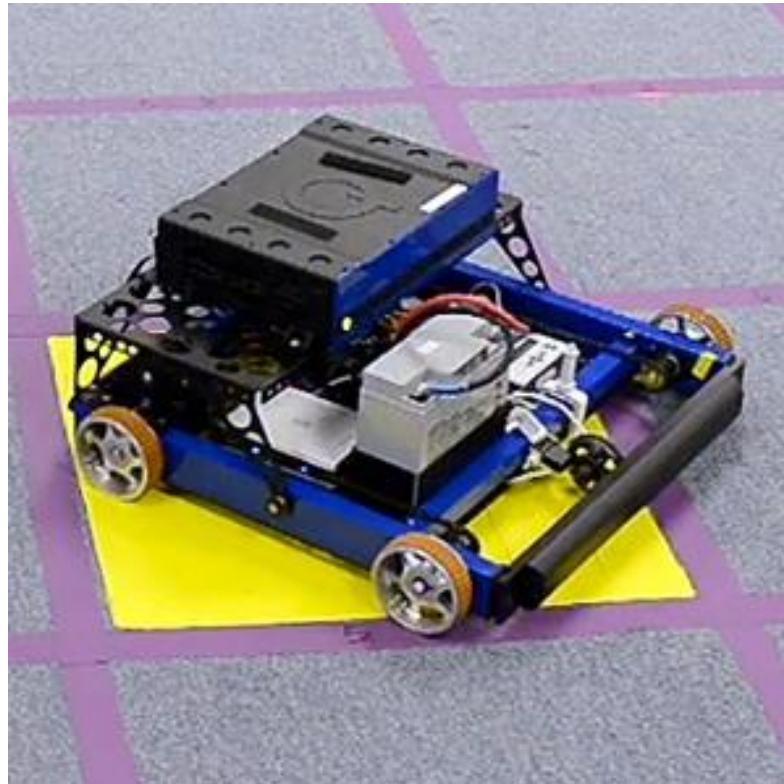
- Pattern detection, probabilistic inference
- Massive parallelism
- Storage and computation coupled and distributed
- Built on simple blocks (neurons)
- Analog operation – spiking networks



# Neuromorphic computing (2)

## Qualcomm

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# Neuromorphic computing (3)

## Qualcomm

### Replicating the brain architecture

Developing complex neuron models that can be implemented in hardware



Real neuron

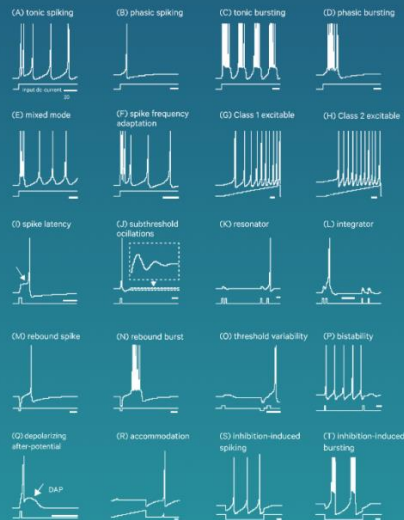
Electrical measurement

$$v' = 0.04v^2 + 5v + 140 - u + I$$

$$u' = a(bv - u)$$

if  $v = 30$  mV, then  $v \leftarrow c$ ,  $u \leftarrow u + d$

**Individual neuron modeling**

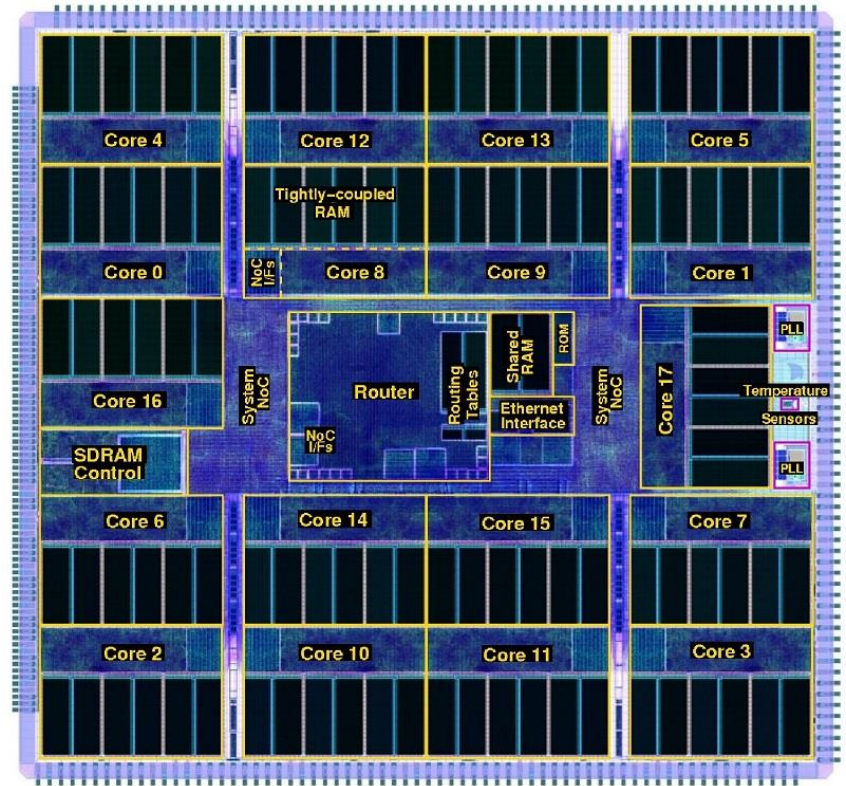
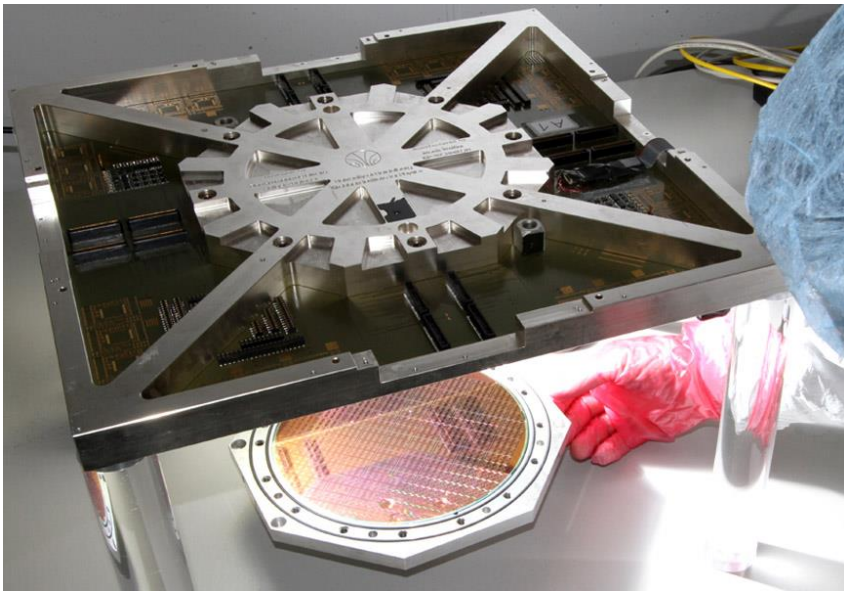


**Family of models**



**Tools and simulation in software or FPGA\* hardware**

\* Field-programmable gate array





# Neuromorphic computing (5)

## Processing Powers

	What they do well	What they're good for
<b>Neuromorphic chips</b>	Detect and predict patterns in complex data, using relatively little electricity	Applications that are rich in visual or auditory data and that require a machine to adjust its behavior as it interacts with the world
<b>Traditional chips (von Neumann architecture)</b>	Reliably make precise calculations	Anything that can be reduced to a numerical problem, although more complex problems require substantial amounts of power

MIT Technology Review

# Energy efficiency – bottom line

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## Infrastructure and casing

- Minimum power overheads

## Hardware

- Optimized for performance/Watt

## Operating system

- Energy aware, actively optimizing

## Software

- Energy aware



# Thank you

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