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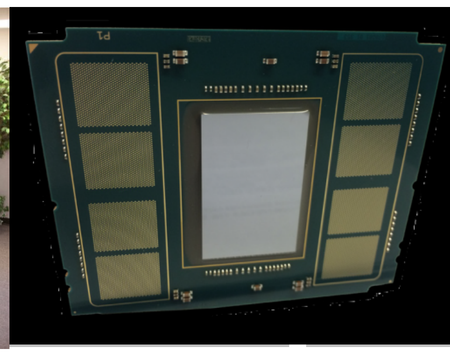
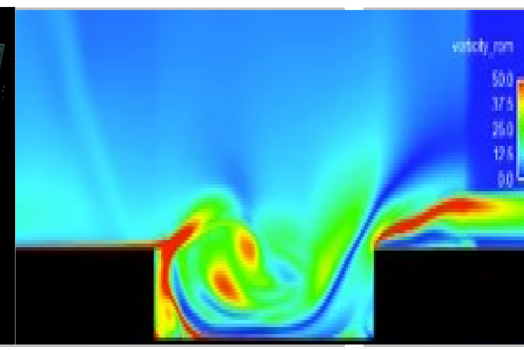
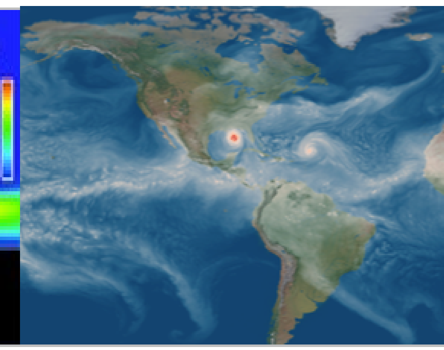

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Roadmapping and the Future of Computing

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Vision

R&D programs and roadmaps

- What new idea will spawn the next Google/Facebook?
- My guess: An application in AI and robotics/mobility
- However, the software will be too compute-intensive for CMOS + von Neumann
- Answer: Driver is a killer app not identified yet that will drive R&D requirements in architecture and devices

Future technology

- Quantum computing
  - good idea if it works someday
- Neural networks
  - novel in displacing programmers not just computers
- CMOS, 3D, architecture, new applications
  - there is a lot of future here
- Reversible and other exotic
  - Next-next generation

Categorization by Limits

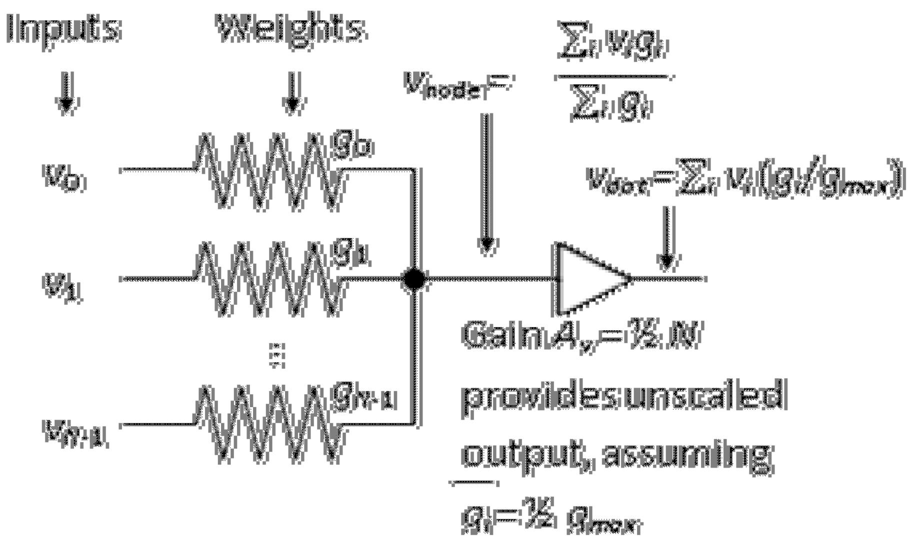
Name of approach	Performance limit or other capability	Investment to date
Neural networks (irrespective of implementation)	Learning and maybe intelligence[1]	Billions
Quantum computing (superconducting electronics)	Quantum speedup	Billions
Neuromorphic computing, i. e. implementations of neural networks	Thermodynamic (*kT*)[1]	Billions
Novel devices: Spintronics, Carbon Nanotubes, Josephson Junctions, new memories, etc.	Thermodynamic (*kT*)[2]	Millions (each)
Analog computing	Thermodynamic (*kT*)[3]	Millions
"3D+architecture," i. e. continuation of Moore's law	Thermodynamic (*kT*)[4]	Trillion
Reversible computing	Arbitrarily low energy/op	Millions

[1] DeBenedictis, Erik P. "Rebooting Computers as Learning Machines." *Computer* 49.6 (2016): 84-87.
[2] DeBenedictis, Erik P. "The Boolean Logic Tax." *Computer* 49.4 (2016): 79-82.
[3] DeBenedictis, Erik P. "Computational Complexity and New Computing Approaches." *Computer* 49.12 (2016): 76-79.
[4] DeBenedictis, Erik P. "It's Time to Redefine Moore's Law Again." *Computer* 50.2 (2017): 40-43 (still in print)

Comparing Architectures – as broadly defined

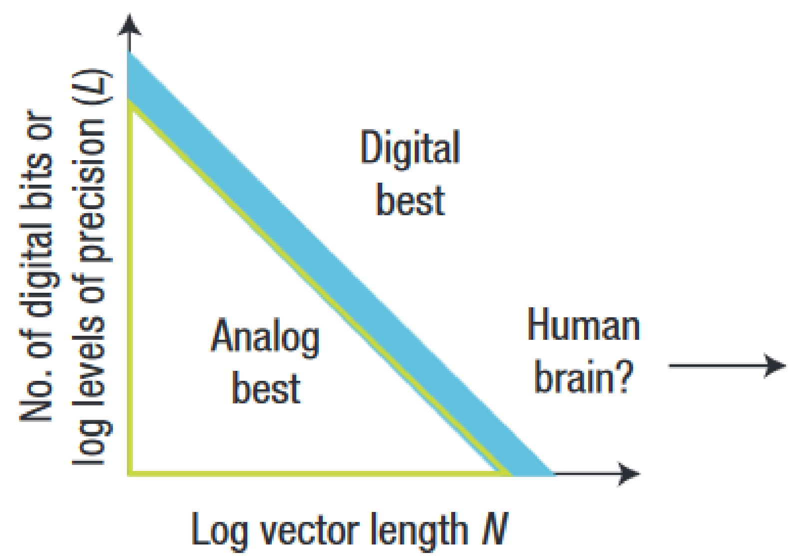
Example analog circuit

- Inputs v and $w = 1/g$



Which is better?

- We can rigorously say “it depends”



Circuit analysis (computational complexity)

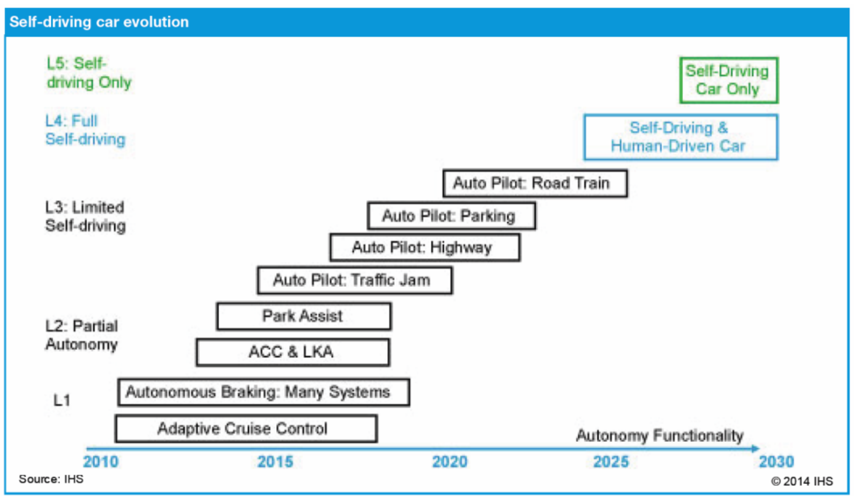
$$E_{digital} = \sim 24 \ \ln(1/p_{error}) \log_2^2(L)\ N\ kT$$
$$E_{analog}^{(B)} = \sim 1/24 \ \ln(1/p_{error})\ L^2\ N^2\ kT$$

Application Functionality Roadmap

SAE now US DOT Levels of Automation

0. None, 1. Driver Assist, 2. Partial, 3. Conditional, 4. High, 5. Full

(from [1])



General application areas and Moonshots (from [2])

- Big Data Analytics
- AI, such as robotics, human-computer interaction
- Manufacturing
- Biotechnology
- Supercomputers
- Spacecraft

[1]http://1.bp.blogspot.com/-68WQ4LKWiTg/VltzSFdmibI/AAAAAAABEwI/jvUXiYz1dyY/s1600/levelsofautonomy.png
[2]PCAST, Ensuring Long-Term U.S. Leadership in Semiconductors

Roadmapping in the Future

AI Milestone	Task Description	Technology / Architecture	Power / Ops	Year
Driver assist	Identify cars in other land when driver activates turn signal	CPU	$\frac{50\ W}{10^x}$	2000-2009
Full Self-drive	Drive car from sensors and visual cues	GPU	$\frac{50\ W}{10^y}$	20yy (safely)
Fully autonomous mini-robot	Plan, move, and carry out missions	Neuro-morphic?	$\frac{50\ mW}{10^z}$	20zz

Summary

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Thank You

See my Rebooting Computing Column in IEEE Computer

- April ‘16 Boolean Logic Tax
- June ’16 Learning Machines
- August ’16 Search for Secretariat
- October ’16: Help Wanted Turing
- December ’16 (see first page) →
- February ’17 Redefine Moore’s Law
- April ’17 Architecture’s Role

REBOOTING COMPUTING

Computational Complexity and New Computing Approaches

Erik P. DeBenedictis, Sandia National Laboratories

Computational complexity analysis allows us to quantify energy-efficiency scaling potential—an important task for assessing research options.

As we search for new ways to increase both computer performance and energy efficiency, it would be helpful to be able to predict long-term potential in advance. Here, I’ll show how computational complexity theory can quantify the energy efficiency potential of analog computing. The method could be applied to other computing approaches.

Analog computers are one option to restore growth in the computer industry. Such growth requires families of computers that can solve problems more cost-effectively over time, which today means improving energy efficiency. The improvement rate for the energy efficiency of digital computers has slowed, raising the question of whether analog computers could overtake them.

If analog and digital are viewed broadly as alternative computer implementations, then they should be subject to the same general principles. However, a specific digital computer’s effectiveness depends on its architecture and the algorithms running on it. These correspond to the circuitry of an analog computer.

Here, I’ll analyze digital and analog “neuromorphic” calculations using a computational complexity theory first developed for digital computer algorithms. The analysis doesn’t find a winner but provides new insights into which approach has more potential.

COMPARING A COMMON FUNCTION

Meaningful comparison of analog and digital requires a computing task amenable to both approaches. I’ll focus on artificial neural networks, where the comparison is between a digital implementation such as deep learning[1] and an analog neuromorphic implementation such as the ohmic weave circuit based on memristors.[2]

Biological neurons, which fill a role similar to *N*-input logic gates, mathematically evaluate the computational primitive called dot or inner product. *N* “presynaptic” neurons generate signals that become inputs of the *N*-input neuron under consideration. Each of the *N* signals v_i is multiplied by a synapse weight w_i and the products added to become the neuron’s output. A digital implementation