



Using Neuromorphic Computing Methods for General Computer Performance Growth

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Executive summary

- Moore's Law
 - To Moore, scaling looked like it could proceed for a long time (1965)
 - Landauer's kT reasoning was unimaginably far away (1961)
- Today
 - Leakage current troubles due to subthreshold slope $\ln 10 kT/q$
 - Landauer's reasoning now a limit at $kT \ln 2/\text{binary op/clock}$ (wrong)
 - Neuromorphic computing is cited as rejuvenating Moore's Law
- Key question
 - What about "neuromorphic" excepts it from thermodynamic limits?
- Answer
 - Nothing; theory has been misinterpreted
 - If we can understand the theory, maybe we can understand the scaling for neuromorphic systems.

kT is at the root of multiple problems

- Clock rate is not scaling anymore
 - Reason: excessive energy consumption
- Density continues to scale
 - Memory density scales just fine
 - Logic density could scale except for excess heat dissipation due to leakage current
- Leakage current is due to kT/q subthreshold slope limiting reduction in power supply voltage
- Beyond CMOS transistors are research topics
 - TFETs, piezotronic transistors, etc.
 - Benefit: Lower power supply voltage without leakage
 - Limit: thermal errors with probability $p_{\text{error}} = \exp(-e_{\text{signal}} / kT)$
- Hence kT limits speed, density, supply voltage, and reliability

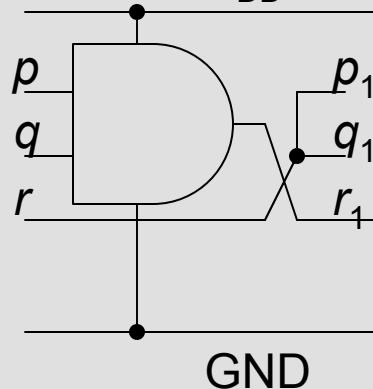
History of kT limits

- 1961: Landauer states “on the order of kT ” per operation
 - Exactly what the operation is is subject to debate
 - Furthermore, critics believe it is not a tight “limit”
- 1970s: Landauer, Neyman, Keyes, etc. try to figure out whether $\sim kT$ can be realized
 - This leads to Landauer-Shannon limit $p_{\text{error}} = \exp(-E_{\text{signal}} / kT)$, implying 30-100 kT is the lowest energy that can satisfy common reliability
- 1973: Bennett proposes reversible logic
 - Which goes much below kT , but uses a different operations
- 1980s, 90s, 00s, 10s: Popular usage is that Landauer’s operation is use of a logic gate
- 2016: We have to straighten it out

Erik says it is impossible to move information faster than twice the speed of light. Critics would not deny this limit but would say it is impossible to move information faster than one times the speed of light.

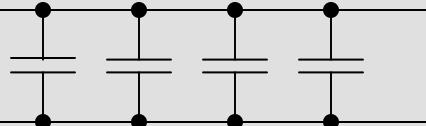
Models of computer energy dissipation

Machine: V_{DD}

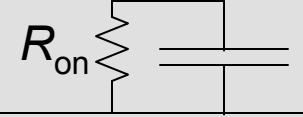


A. CV^2 model:

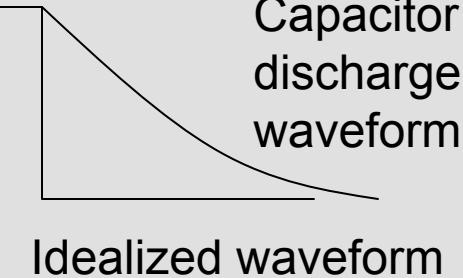
wire with capacitance per unit length



$$E_{gate-op} = \alpha^{1/2} C V_{DD}^2$$



Discharge circuit and waveform:



B. Information erasure model [Landauer 61]:

Irreversibility and Heat Generation in the Computing Process

Abstract: It is argued that computing machines inevitably involve devices which perform logical functions that do not have a single-valued inverse. This logical irreversibility is associated with physical irreversibility and requires a minimal heat generation, per machine cycle, typically of the order of kT for each irreversible function. This dissipation serves the purpose of standardizing signals and making them independent of their exact logical history. Two simple, but representative, models of bistable devices are subjected to a more detailed analysis of switching kinetics to yield the relationship between speed and energy dissipation, and to estimate the effects of errors induced by thermal fluctuations.

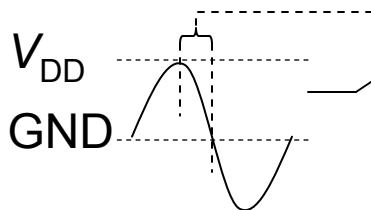
BEFORE CYCLE	AFTER CYCLE			FINAL STATE				
	p	q	r	p ₁	q ₁	r ₁		
1	1	1	1	→	1	1	1	α
1	1	0	0	→	0	0	1	β
1	0	1	0	→	1	1	0	γ
1	0	0	0	→	0	0	0	δ
0	1	1	0	→	1	1	0	γ
0	1	0	0	→	0	0	0	δ
0	0	1	0	→	1	1	0	γ
0	0	0	0	→	0	0	0	δ

...typically of the order of kT for each irreversible function

[Landauer 61] Landauer, Rolf. "Irreversibility and heat generation in the computing process." *IBM journal of research and development* 5.3 (1961): 183-191.

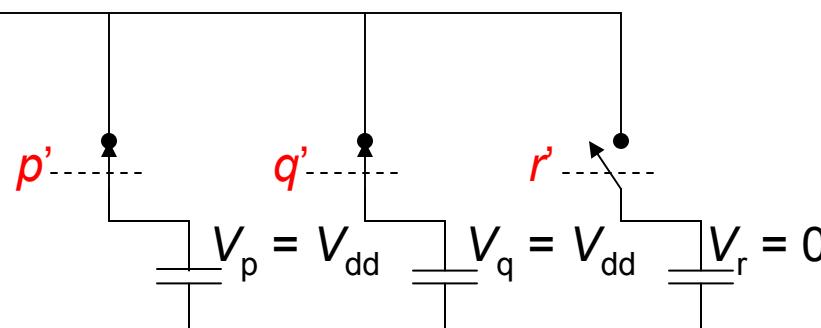
See also <http://rebootingcomputing.ieee.org/images/files/pdf/RCS4DeBenedictisposter.pdf>

Background on erasure model

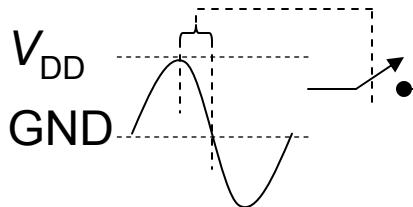


Close switch on downward cycle

A. Discharge a known-charged capacitor

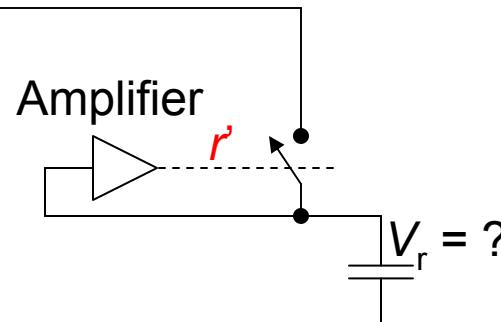


Works, but we need copies $p' = p$, $q' = q$, and $r' = r$ to set the switches, which prevents erasure of last copy of a signal



Close switch on downward cycle

B. Recover energy when state unknown



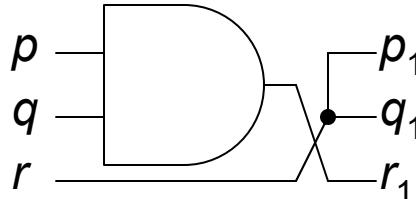
Works, but only until energy on capacitor is on the order of kT . Below this level, the amplifier can't decide whether to charge or discharge

Agenda for next several slides (speaker flip back and forth if you can)

- Look at Landauer's paper, paying attention to the message in
 - Title + abstract + diagrams
 - Body of article
- Go through example in the 1961 paper
 - An AND gate yields limit of 0.82 kT , which is $O(\text{kT})$
 - This is the "Landauer Limit" per popular usage
- Go through a modern example of neuromorphic synapse
 - Synapse yields limit of 0.0058 kT , which is not $O(\text{kT})$ so to speak
 - This is consistent with body of paper but not popular usage
- Why?

Landauer's method from the paper's example

System:



prob	p	q	r		p1	q1	r1	Si (k's)	State	Sf (k's)
0.125	1	1	1	→	1	1	1	0.25993	α	0.25993
0.125	1	1	0	→	0	0	1	0.25993	β	0.25993
0.125	1	0	1	→	1	1	0	0.25993	γ	0.367811
0.125	1	0	0	→	0	0	0	0.25993	δ	0.367811
0.125	0	1	1	→	1	1	0	0.25993	γ	0
0.125	0	1	0	→	0	0	0	0.25993	δ	0
0.125	0	0	1	→	1	1	0	0.25993	γ	0
0.125	0	0	0	→	0	0	0	0.25993	δ	0
								2.079442	Sf (k's)	1.255482
									Si-Sf (k's)	0.823959

Typically of the order of kT
for each irreversible function

From source:

Irreversibility and Heat Generation in the Computing Process

Abstract: It is argued that computing machines inevitably involve devices which perform logical functions that do not have a single-valued inverse. This logical irreversibility is associated with physical irreversibility and requires a minimal heat generation, per machine cycle, typically of the order of kT for each irreversible function. This dissipation serves the purpose of standardizing signals and making them independent of their exact logical history. Two simple, but representative, models of bistable devices are subjected to a more detailed analysis of switching kinetics to yield the relationship between speed and energy dissipation, and to estimate the effects of errors induced by thermal fluctuations.

BEFORE CYCLE			AFTER CYCLE			FINAL STATE
p	q	r	p ₁	q ₁	r ₁	
1	1	1	→	1	1	α
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1	0	1	→	1	1	γ
1	0	0	→	0	0	δ
0	1	1	→	1	1	γ
0	1	0	→	0	0	δ
0	0	1	→	1	1	γ
0	0	0	→	0	0	δ

...typically of the order of kT for each irreversible function

Backup: Details

- Each input combination gets a row
 - Each input combination k has probability p_k , p_k 's summing to 1
 - S_i (i for input) is the sum of all $p_k \log p_k$'s
- Each unique output combination is analyzed
 - Rows merge if the machine produces the same output
 - Each output combination k has probability p_k , p_k 's summing to 1
 - S_f (f for final) is the sum of all $p_k \log p_k$'s
- Minimum energy is $S_i - S_f$
- Notes
 - Inputs states that don't merge do not raise minimum energy
 - Inputs that merge raise minimum energy based on their probability
 - Assumption: All input combinations equally probable

Example: a learning machine

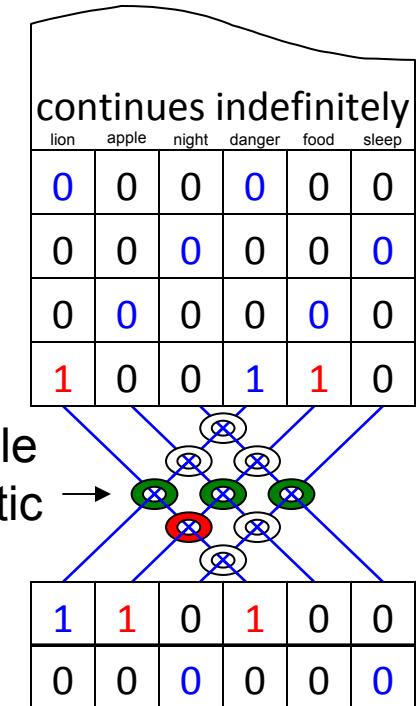
This “learning machine” example exceeds energy efficiency limits of Boolean logic. The learning machine monitors the environment for knowledge, yet **usually just verifies that it has learned what it needs to know**. Say “causes” (lion, apple, and night) and “effects” (danger, food, and sleep) have value 1.

Example input:

{lion, danger } {apple, food } {night, sleep } {lion, danger } {apple, food } {night, sleep } {lion, danger } {apple, food } {night, sleep } {lion, danger, food } {apple, food } {night, sleep } {lion, danger } {lion, danger }

Functional example:

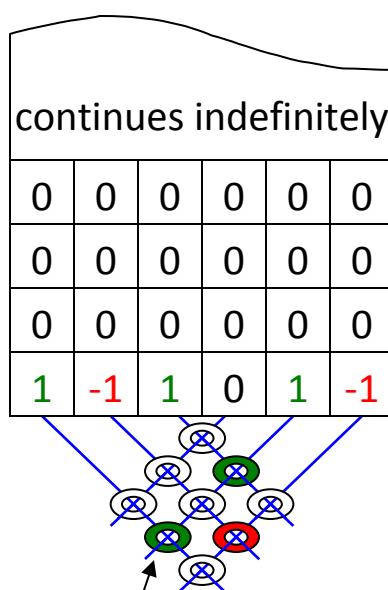
Machine continuously monitors environment for $\{1, 1\}$ or $\{-1, -1\}$ pairs and remembers them in state of a magnetic core. Theoretically, there is no need for energy consumption unless state changes.



Signals create currents;
core flips a ± 1.5

Analysis of one synapse in the learning machine

Boolean logic
equivalent system:



Old-style
magnetic core

	left wire	right wire	field dir.		left wire	right wire	field dir.	Si (k's)	State	Sf (k's)
0.062438	-1	-1	-1	→	-1	-1	-1	0.173176	A	0
0.062438	-1	0	-1	→	-1	0	-1	0.173176	B1	0.173176
0.062438	-1	1	-1	→	-1	1	-1	0.173176	C1	0.173176
0.062438	0	-1	-1	→	0	-1	-1	0.173176	D1	0.173176
0.062438	0	0	-1	→	0	0	-1	0.173176	E1	0.173176
0.062438	0	1	-1	→	0	1	-1	0.173176	F2	0.173176
0.062438	1	-1	-1	→	1	-1	-1	0.173176	G1	0.173176
0.062438	1	0	-1	→	1	0	-1	0.173176	H1	0.173176
0.0005	1	1	-1	→	1	1	1	0.0038	I	0.174061
0.0005	-1	-1	1	→	-1	-1	-1	0.0038	A	0.174061
0.062438	-1	0	1	→	-1	0	1	0.173176	B2	0.173176
0.062438	-1	1	1	→	-1	1	1	0.173176	C2	0.173176
0.062438	0	-1	1	→	0	-1	1	0.173176	D2	0.173176
0.062438	0	0	1	→	0	0	1	0.173176	E2	0.173176
0.062438	0	1	1	→	0	1	1	0.173176	F2	0.173176
0.062438	1	-1	1	→	1	-1	1	0.173176	G2	0.173176
0.062438	1	0	1	→	1	0	1	0.173176	H2	0.173176
0.062438	1	1	1	→	1	1	1	0.173176	I	0
probability of a learning event:								0.001	Si-Sf (k's)	0.005831
								2.778417	Sf (k's)	2.772585

Why is the “limit” so low? (I)

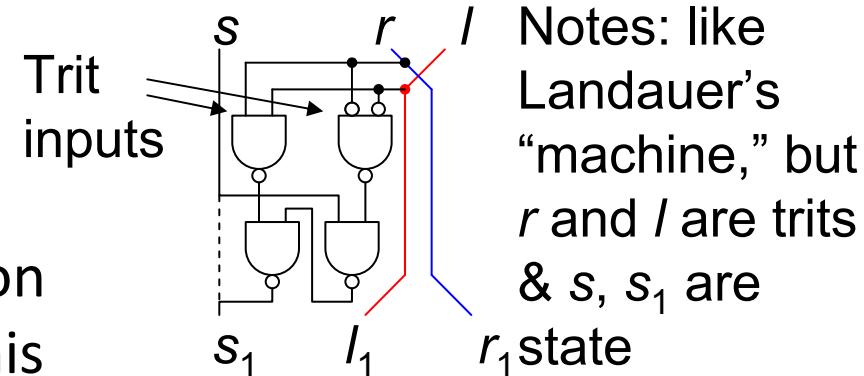
Probabilities

- The “limit” depends where you look in Landauer’s article
 - Word “limit” does not appear in the article (but “limitation”)
 - “on the order of kT ” (abstract) $kT \ln 2$ per bit erased (body)
 - 0.82 kT or 1.18 kT (he made a math error) in the example
- Actually, the “limit” assumes
 - The system is in thermodynamic equilibrium ($p = .125$)
 - Input bits have a full bit of information, $p_0 = p_1 = 0.5$
- However, the body of the paper very clearly talks about the probabilities of input states (or combinations)
- The example exploits the fact that synapses usually verify that they have learned what the need to know and actually change state with low probability

Why is the “limit” so low? (II)

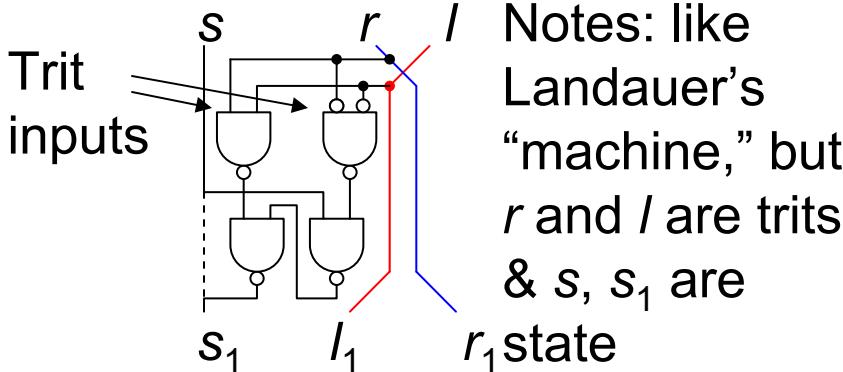
Aggregation principle

- The Landauer’s minimum energy stays the same or rises when a function is broken up into pieces – it cannot decrease
 - If splitting into pieces produces intermediate variables that have to be erased, minimum energy will increase
 - If the pieces digitally restore signals, they can’t be aggregated
- A single magnetic core implements the 4-gate sub circuit →
- The magnetic core application was engineered to exploit this aggregation
 - Ask a question if you want details

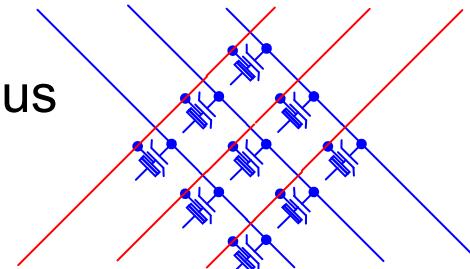


Comparison to CMOS and a modern nanotechnology implementation

CMOS implementation:

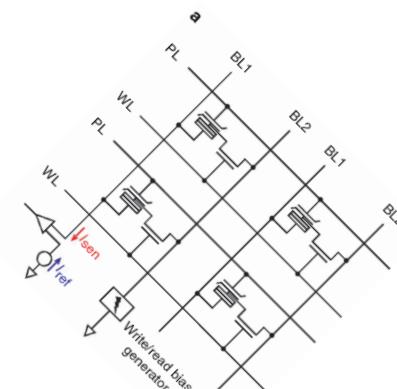


Notes: like Landauer's "machine," but r and l are trits & s, s_1 are trit inputs



Possible MeRAM implementation:

Magnetoelectric RAM is based on a device where voltage exceeding a threshold causes a nanomagnet to flip. Losses are negligible in absence of state change.

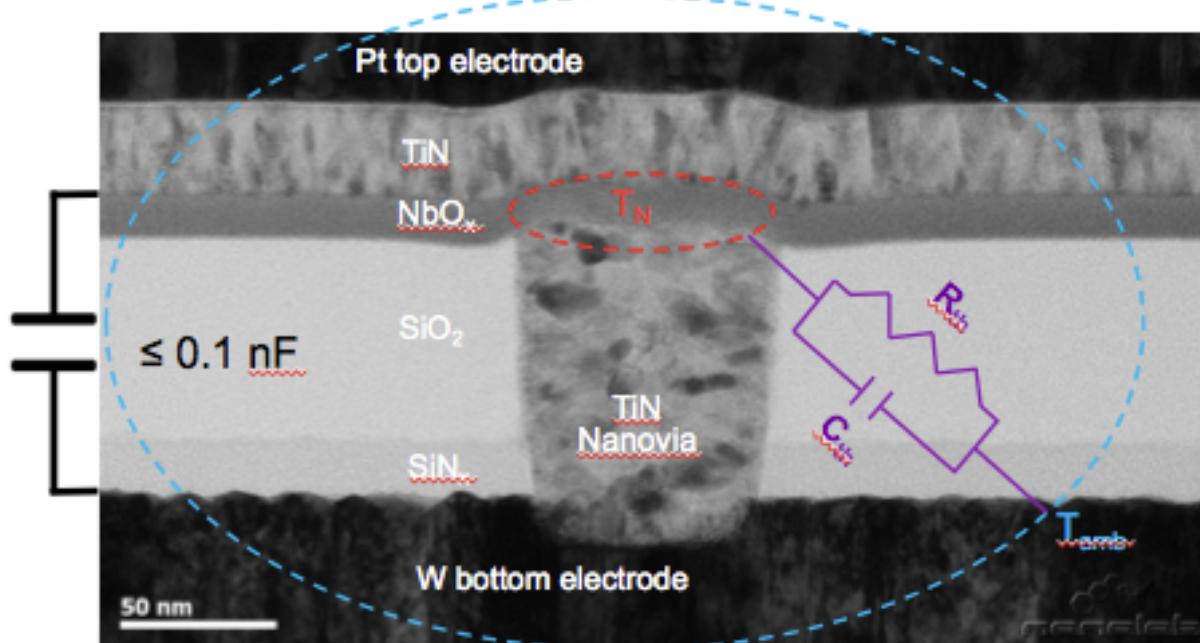


Jia-mian Hu, et al. "High-density magnetoresistive random access memory operating at ultralow voltage at room temperature." *Nature communications* 2 (2011): 553

Memristor-class device

- Late-breaking public info (you'll hear about this from Stan)

Integrated Mott memristor/capacitor – thermoelectric design



$R_{th} C_{th} \leq 0.1 \text{ ns}$
 $R_{th} \geq 10^6 \text{ K/W}$
 $C_{th} \leq 10^{-16} \text{ J/K}$

5000x faster
0.1% energy
of a neuron

Replaces 100's
of transistors

Dark field cross-sectional TEM image of NbO_x memristor. The heated region is thermally connected to T_{amb} through the effective thermal resistance, R_{th} , and thermal capacitance,

Why is the “limit” so low? (III)

Logic-memory integration

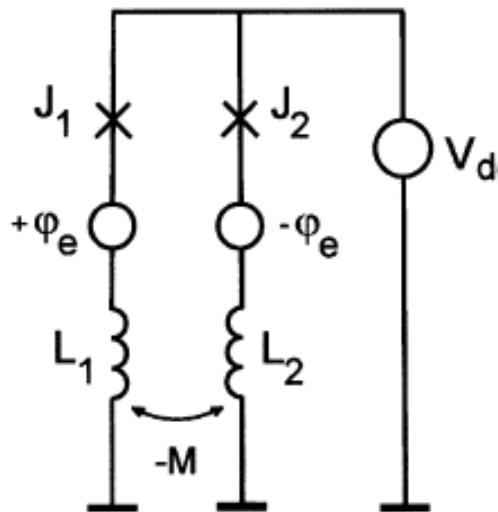
- The preceding methods won't help very much for the processor component of the von Neumann architecture
- A logic design is considered inefficient if the inputs to a large number of gates are nearly always 0 or 1. The design can be improved irrespective of anything in this slide deck.
- However, it is not poor design for a state-containing device (memory cell) to be idle most of the time – because it is serving the useful purpose of storing information
- While the preceding methods are independent of architecture, they give the biggest energy efficiency boost for processor-in-memory and neuromorphic

Can we find a device or circuit that might be able to reach the limit described?

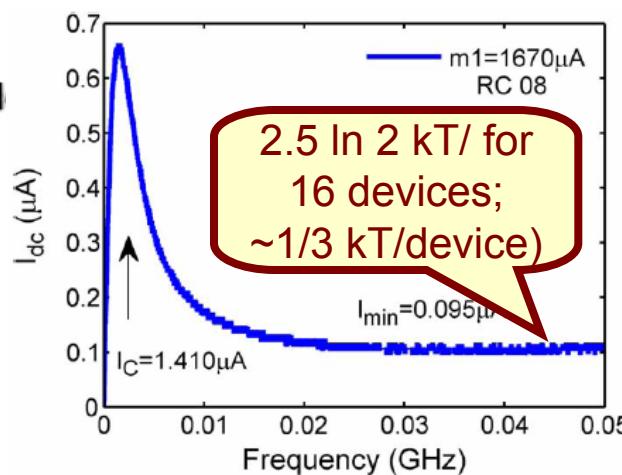
- Requirements
 - Row, column addressable (i. e. the array)
 - Addressed cell can be set to 1 or -1; all other cells unchanged
 - Zero dissipation if cell unaddressed or value already correct
 - Minimum energy ($T\Delta S$) if cell changes state
- Literature
 - P. Zulkowski and M. DeWeese, “Optimal finite-time erasure of a classical bit,” *Physical Review E* 89.5 (2014): 052140.
 - Uses a protocol for raising/lowering barriers and tilt
 - Dissipation $-T\Delta S + O(1/t_f)$, Landauer’s minimum as time limit $t_f \rightarrow \infty$
 - we can have a lot of discussion on this if you like
- Is there a circuit that does this?

Semenov's nSQUID circuit

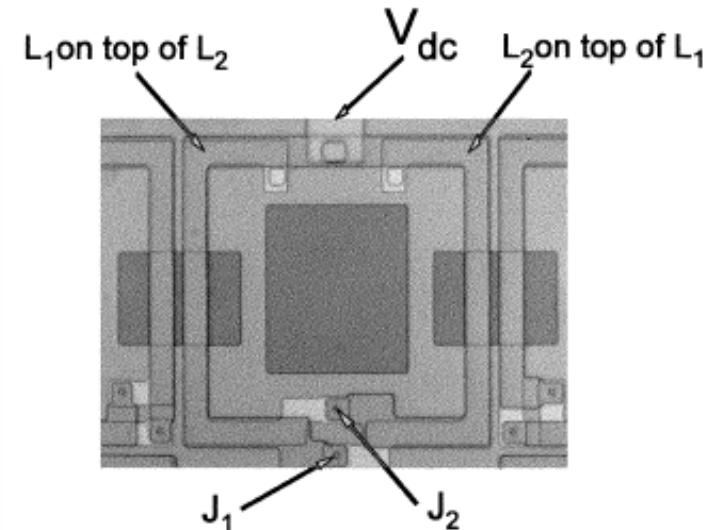
A. Circuit



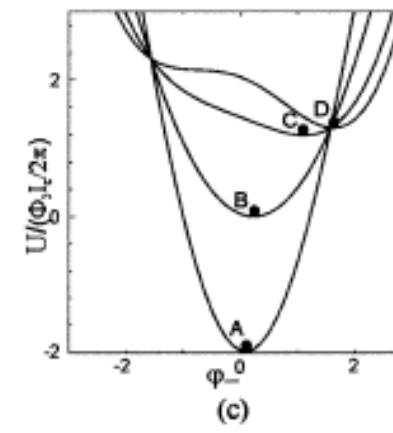
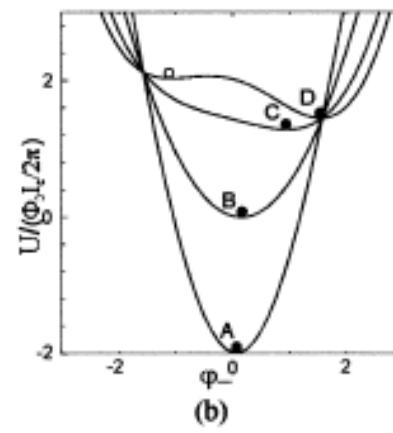
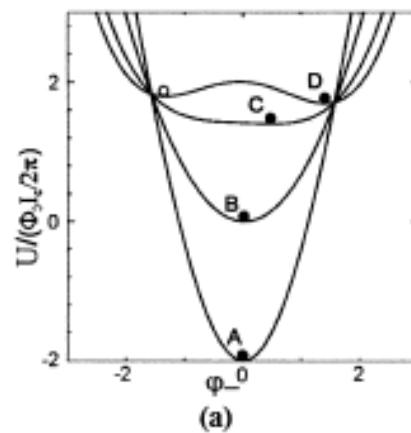
B. Measurements



C. Micrograph

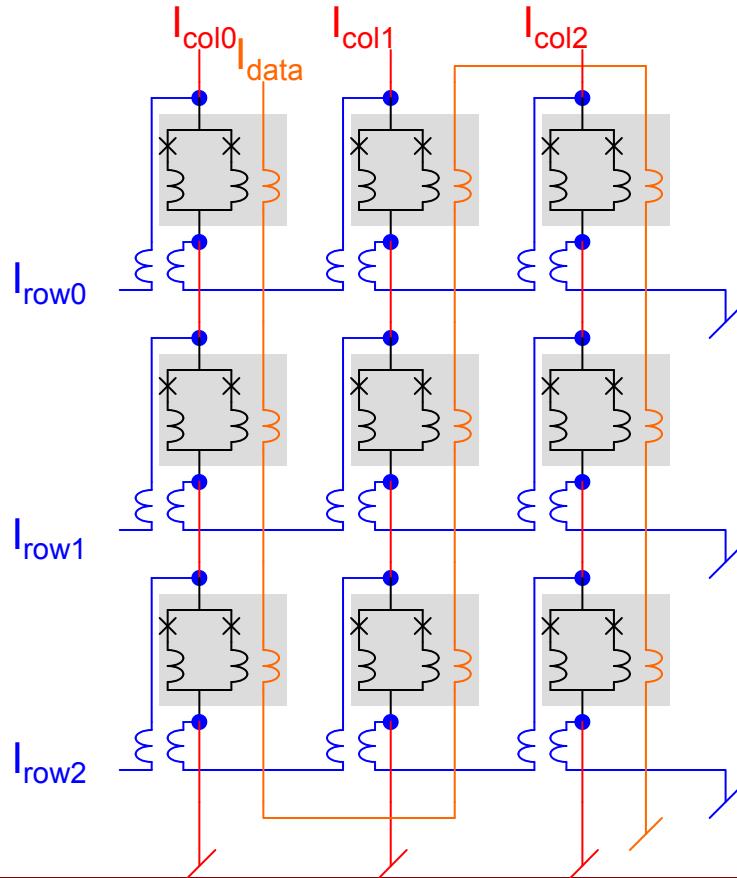


D. Behavior



Addition of addressing

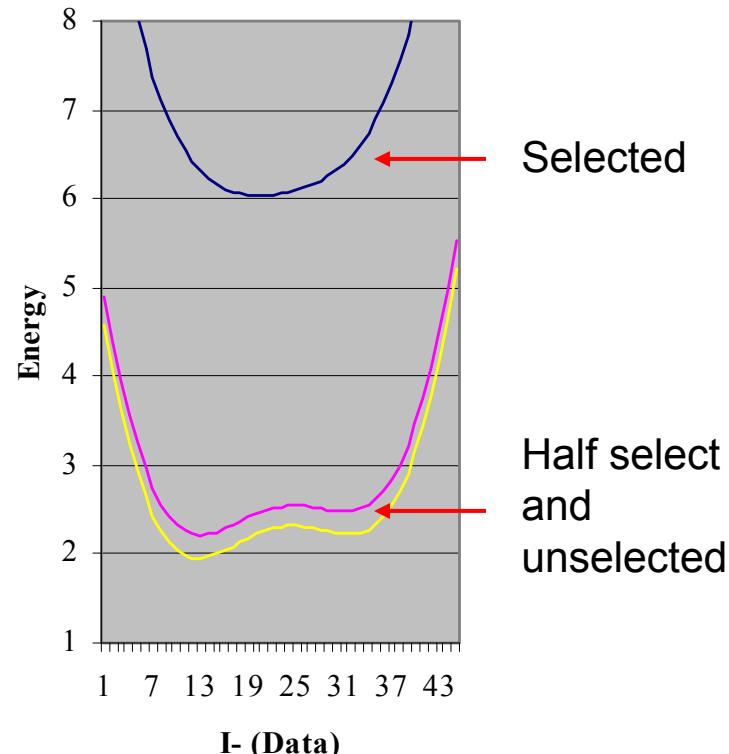
- Author proposes addressing, which was not present in Semenov's work



- Excel spreadsheet of wells

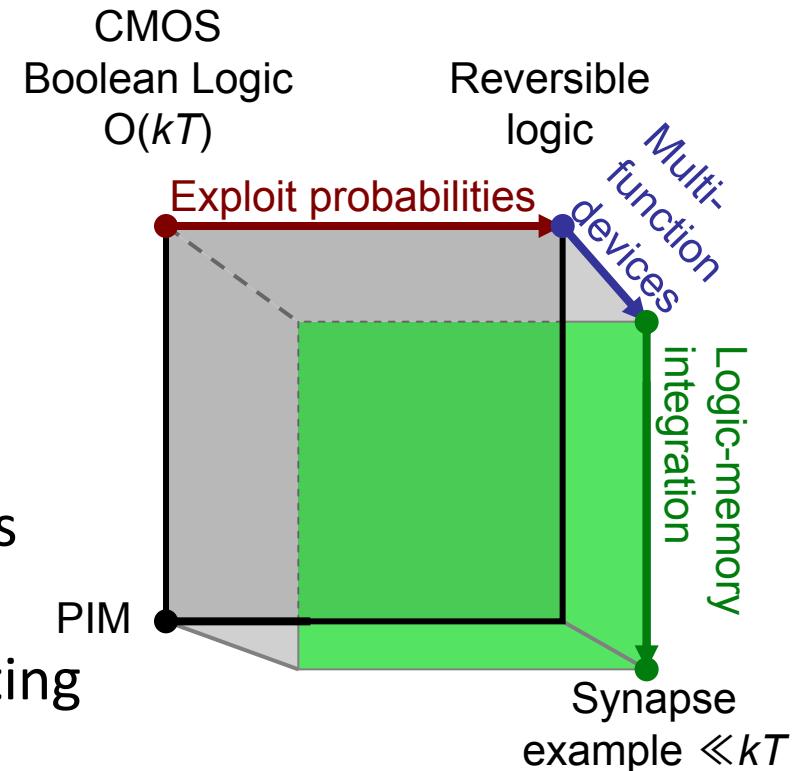
- Top: addressed
- Lower: Un- and half-addressed

A. Array addressing



Roadmap and agenda/Conclusions

- The cube forms a research agenda
- Each dimension can be explored separately
- Most of the vertices form recognized computer classes
- The lower-right corner represents a way to integrate neuromorphic computing into a general computing agenda
- Author have an ICRC paper with a guide to a roadmap based on E_r , the parasitic overhead energy of a gate



Conclusions

- Public believes “Moore’s law is ending” due to imminent approach to (improperly interpreted) “ kT ” limits; we show the limits are further out than commonly believed
- However, pushing out “limits” requires new approaches to computing as well as new devices. Approaches:
 - Optimize for probabilities in input data and intermediate variables
 - Find devices with higher level functions but the same dissipation
 - Use memory-intensive architectures (e. g. neural networks)
- This is a bridge between the brain and computing
- We don’t have a complete working example, but Semenov may have constructed and tested a suitable circuit in a different context and measured $1/3 kT$

Clarification: The limits we know of are leakage current, kT , $O(kT)$, $kT \ln 2$, $p_{\text{error}} = \exp(-e_{\text{signal}} / kT)$, $100 kT$. We’ll call these kT limits that differ by constant factors.