

Artificial synapses based on electrochemical lithium insertion into metal oxides for neuromorphic computing

PRESENTED BY

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Artificial neural networks and deep learning

Computers are fast and efficient at executing instructions

$$\frac{dx}{dt} = x^2$$

```
x=1;
dt = 0.01;
for i = 1:1000 {
    dxdt = x.^2;
    xnew = dt*dxdt;
    x = xnew; }
end
```

Computers struggle when there are no clear instructions for the task

Which one of these images is a cat?

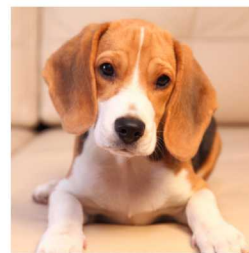
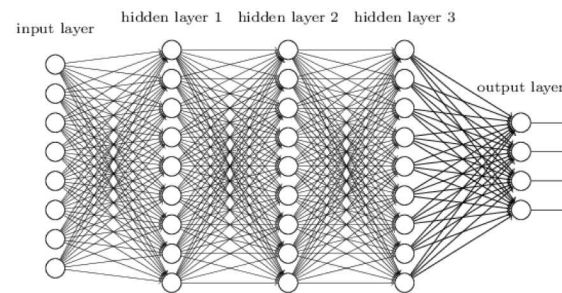


Image recognition
Autonomous driving
Natural language processing

Artificial neural networks: use training examples and error backpropagation to find the matrix weights that correctly maps the input $\mathbf{x}$ onto the desired output $\mathbf{y}$

$$\begin{bmatrix} y_1 \\ \vdots \\ y_m \end{bmatrix} = \begin{bmatrix} w_{1,1} & \cdots & w_{1,n} \\ \vdots & \ddots & \vdots \\ w_{m,1} & \cdots & w_{m,n} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$$

Inference and training are very energy expensive

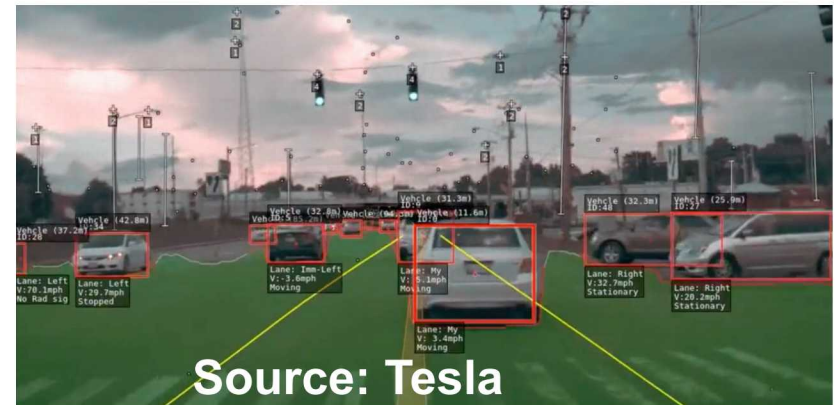




Energy in autonomous driving



Chevy Bolt

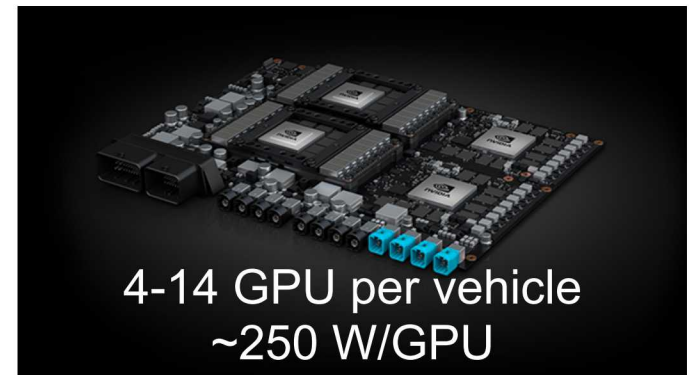


~100 GB/sec

Human brain: 10 Watt



Computing: 1-4 kW



4-14 GPU per vehicle
~250 W/GPU

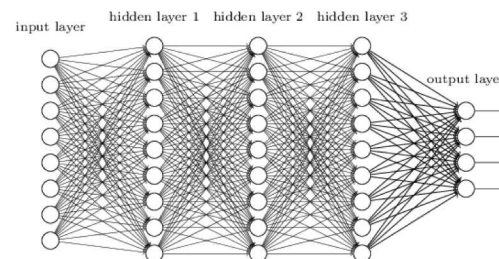
Nvidia



Digital and analog implementations of neural networks

$$\begin{bmatrix} y_1 \\ \vdots \\ y_m \end{bmatrix} = \begin{bmatrix} w_{1,1} & \cdots & w_{1,n} \\ \vdots & \ddots & \vdots \\ w_{m,1} & \cdots & w_{m,n} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$$

$n, m > 1000$

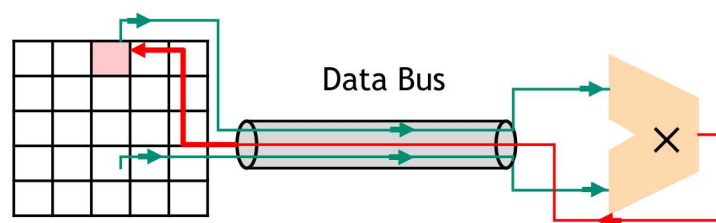


Von Neumann Digital

Separate logic and memory structures

SRAM to store the weights

Arithmetic logic unit for multiplication



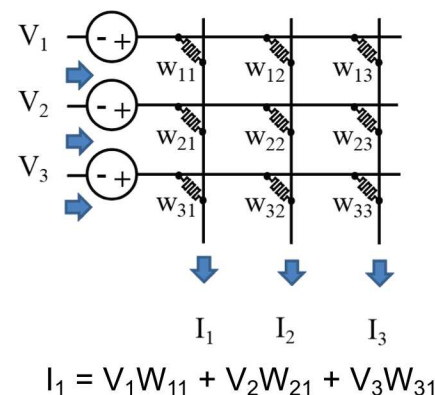
Uses established CMOS technology
Data bus results in latency and power

In-memory Parallel Analog

Use non-volatile memory

Crossbar for matrix multiplication

Conductance of each element can be changed in a predictable manner

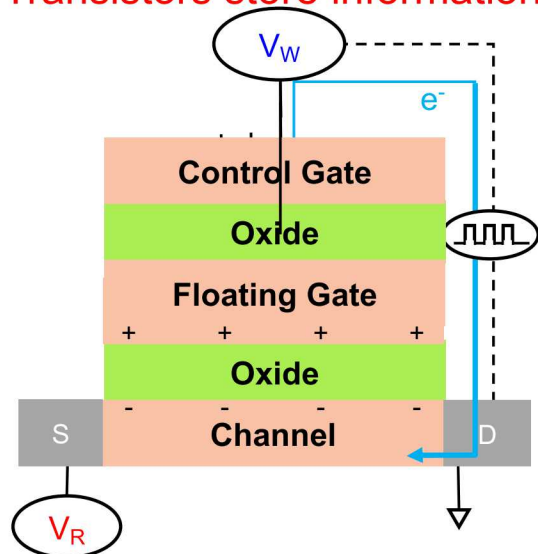


Simultaneous logic and memory
3 orders of magnitude less power



Three-terminal memory

Transistors store information by moving charge between the gate and the channel



$$\tau_{\text{retention}} = C_{\text{gate}} R_{\text{OFF}}$$

$$C_{\text{gate}} = \epsilon_0 \epsilon_r \frac{A}{t_{\text{ox}}} \approx 10^{-6} \text{ F cm}^{-2} = 10^{-16} \text{ F} \quad (A = 100 \text{ nm}^2)$$

Option 1: transistor switch: $R_{\text{OFF}} \sim 10^{15} \Omega$

$\tau_{\text{retention}} < 1 \text{ s}$ (Resistive Processing Unit, dynamic RAM)

S. Ambrogio, G. Burr, et al. *Nature*, **558**, 60 (2018)

Option 2: floating gate oxide switch, $R_{\text{OFF}} \sim \infty$

$\tau_{\text{retention}} > 10 \text{ yr}$ (Flash memory)

10V, high power, limited endurance (10^5)

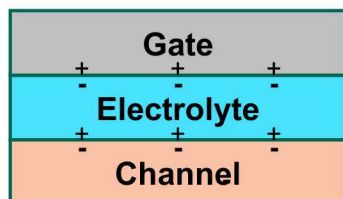
Improving retention by increasing C_{gate} ? $C = \frac{\Delta Q}{\Delta V}$

Electrochemical double-layer transistors

Electrons stored at the **interface**

$$C_{\text{gate}} \sim 10^{-4} \text{ F cm}^{-2}$$

$$t_{\text{ox}} < 1 \text{ nm}$$



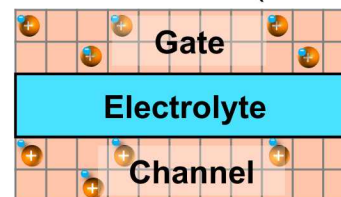
P. Gkoupidenis, G. Malliaras, *Adv Mater*, **27**, 7176 (2015)

Redox transistors

Electrons (and ions) are stored in the **bulk** of the material (battery)

Electron/ion neutral ambipolar pair enables ΔQ without electrostatic charging

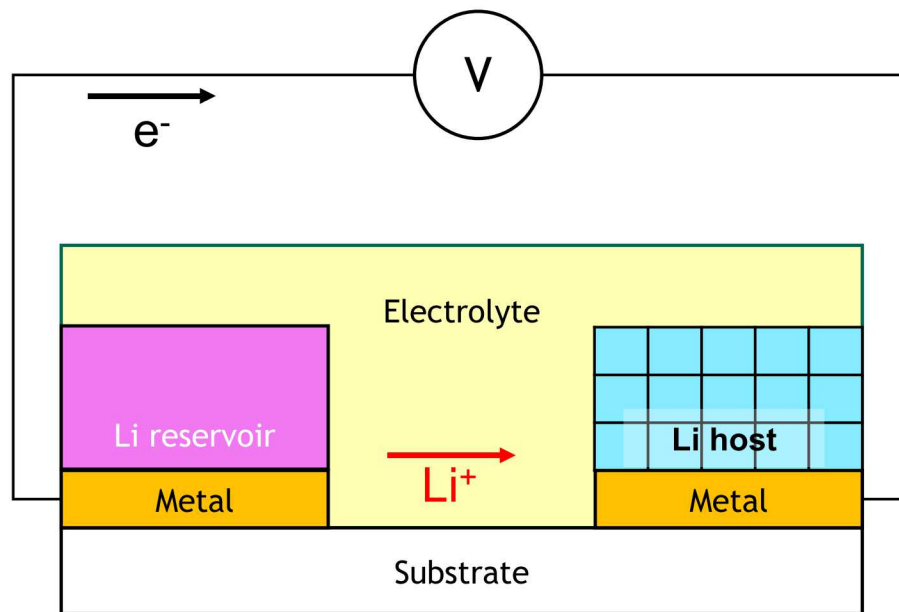
$$C_{\text{gate}} \sim 10^{-1} \text{ F cm}^{-2} \text{ (100-nm film)}$$



E. Fuller, *Adv Mater*, **29**, 1604310 (2017)
Y. van de Burgt, *Nat. Mater.*, **16**, 414 (2017)



Electrochemical ion insertion

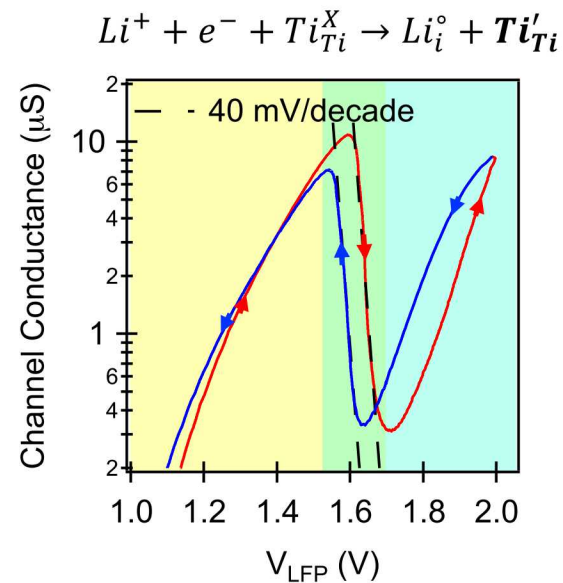
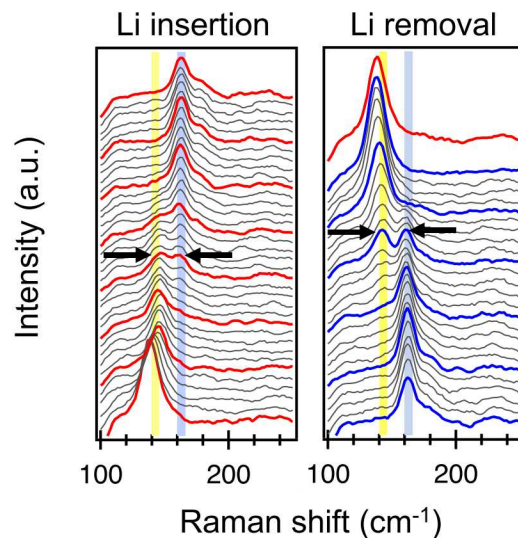
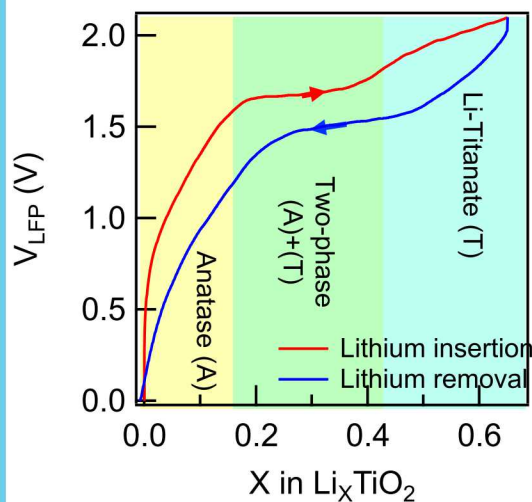
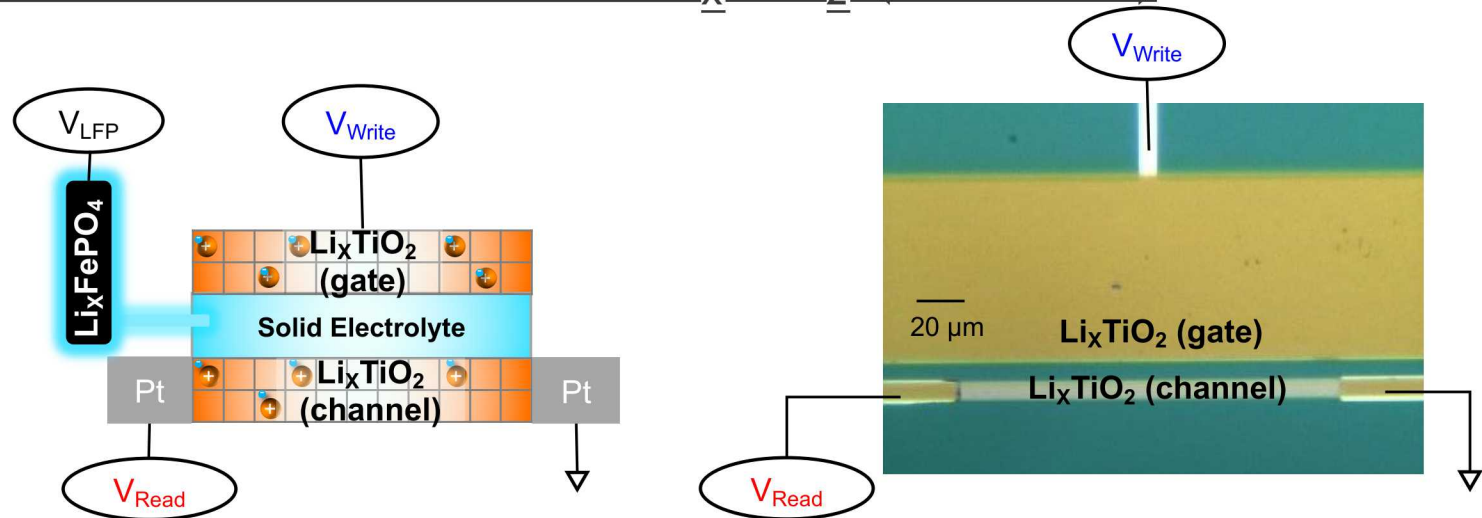


Charge storage with *minimal* electrostatic charging

In batteries, intercalation provides a high density of energy storage;
In redox transistors, intercalation provides a high density of information storage

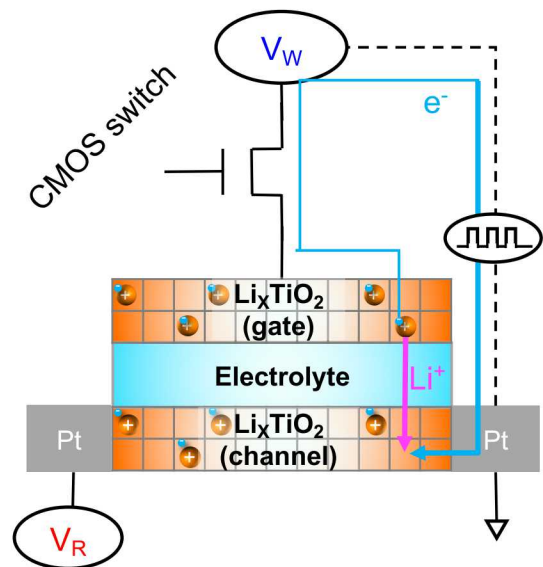


Lithium insertion into Li_xTiO_2 (anatase)

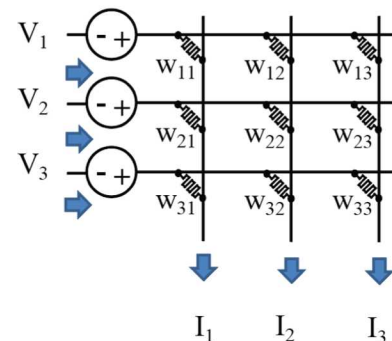
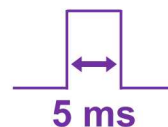




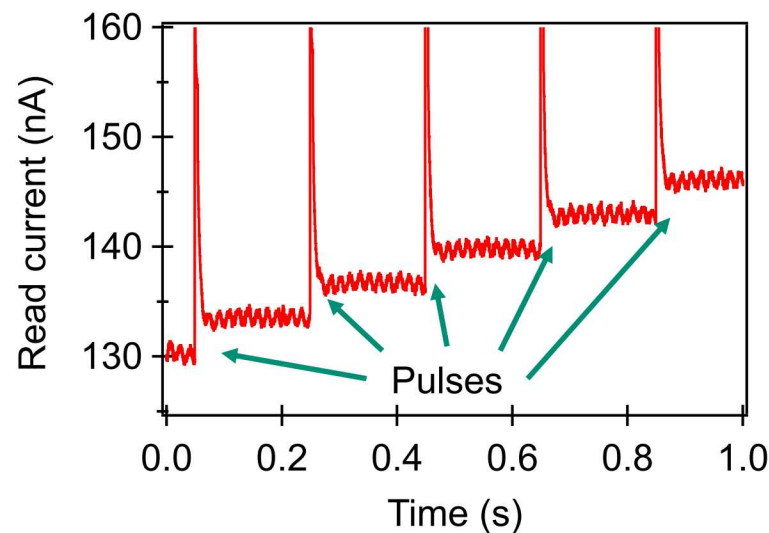
Redox transistor using Li_xTiO_2 (anatase)



$$V_W = \pm 150 \text{ mV}$$

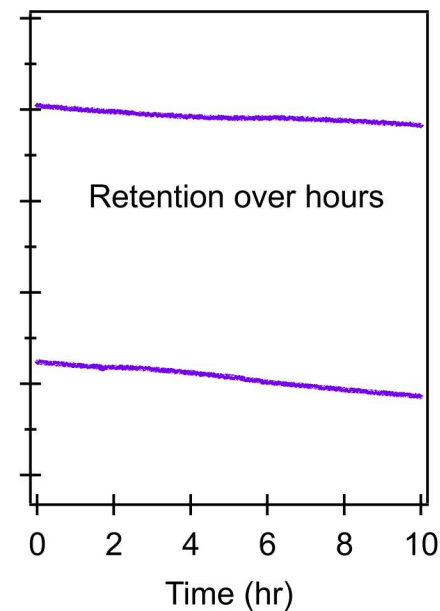
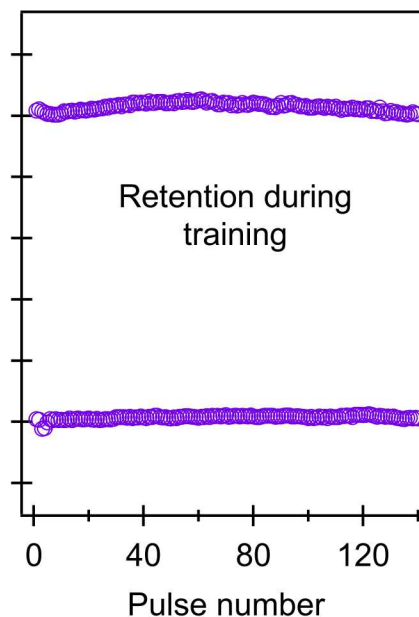
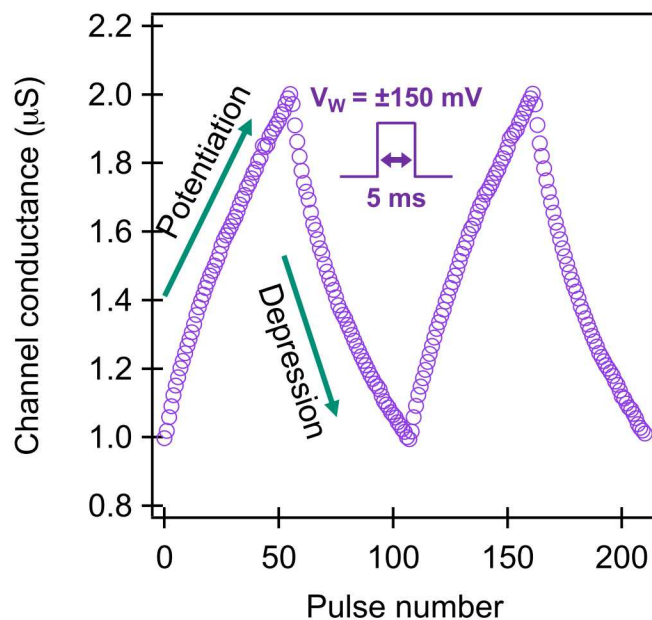


- Linear and symmetric programming
 - 150-mV write pulses
 - Analog, non-volatile states





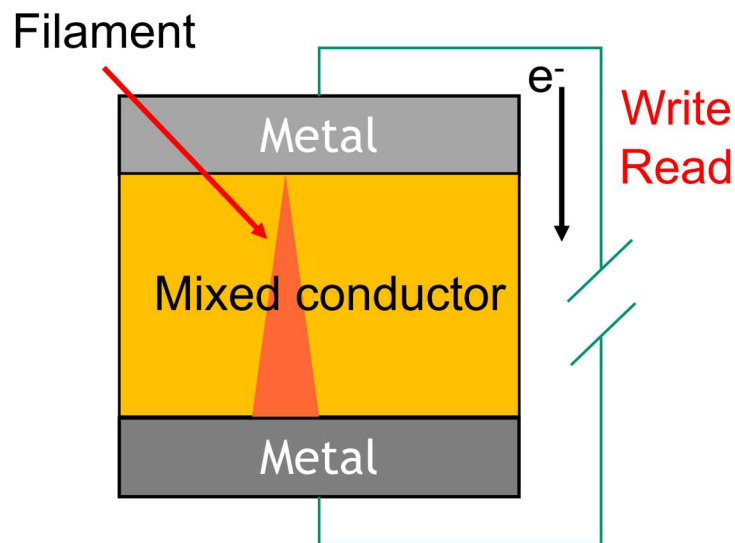
Redox transistor using Li_xTiO_2 (anatase)





Two-terminal vs three-terminal synaptic memory

Memristor

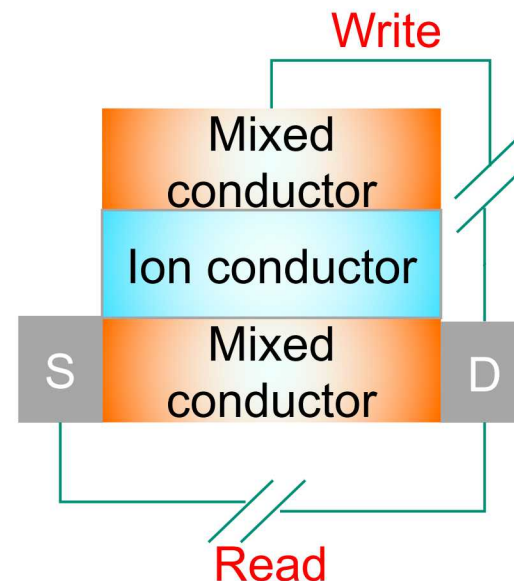


Electron current dominates write

$$I_{electron}^{write} \gg I_{ion}^{write}$$

Large joule heating
Unpredictable weight updates

Redox transistor



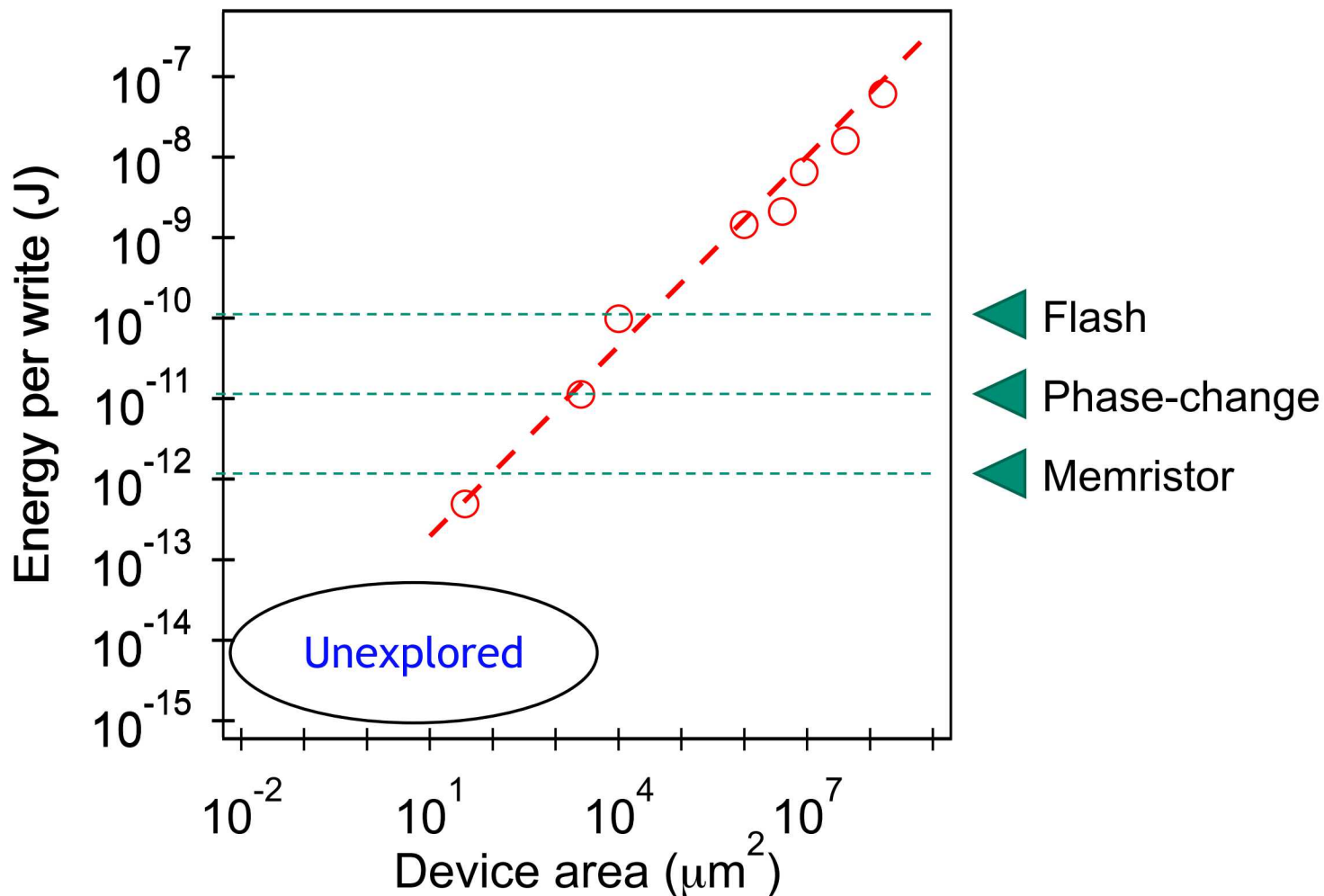
Electrolyte blocks electrons

$$I_{electron}^{write} = I_{ion}^{write}$$

Low write energy
Predictable /linear weight updates



Exceptional low-energy consumption

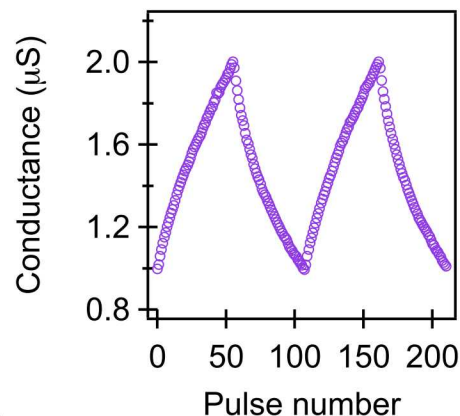


Y. Van de Burgt, *Nat Mater*, 16, 414(2017)
M. Sharbati *Adv. Mater.* 30, 1802353 (2018)
J. Yang et al. *Nat. Nano.* 8, 13(2012)

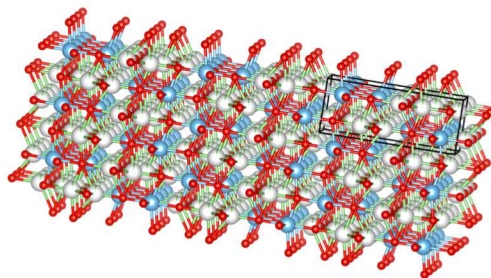


Linear programming and high accuracy

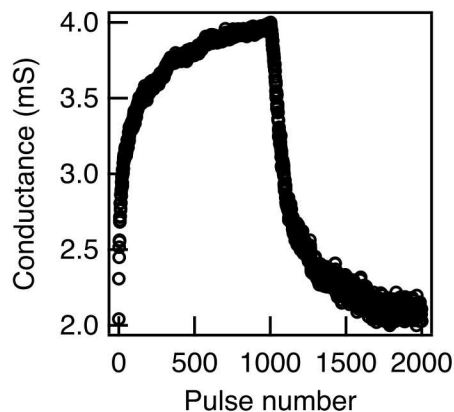
Li_xTiO_2 transistor
Voltage: ± 0.15 V



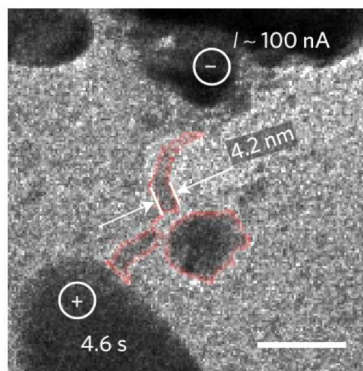
Redox transistors store information continuously as dopants in a crystal



TaO_x Memristor
Voltage: ± 1 V



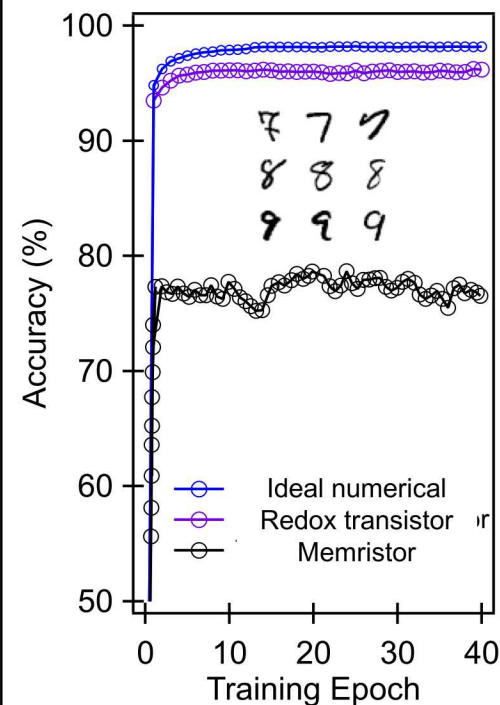
Memristors store information at filaments



R. Jacobs-Gedrim et al. *ICRC*, 2017

Wang et al. *Nat Mater.* 2017

Linearity is essential to train an accurate neural network



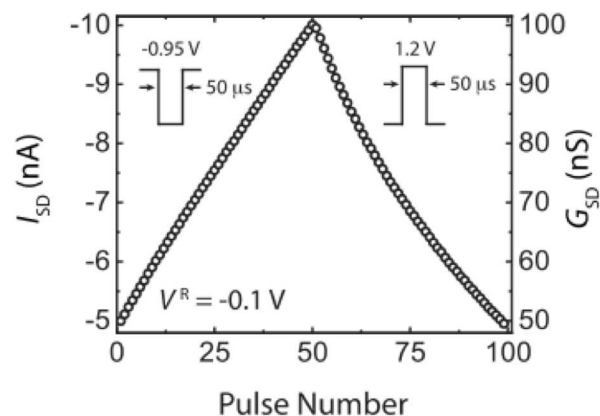
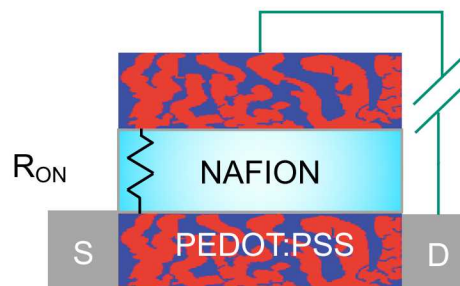
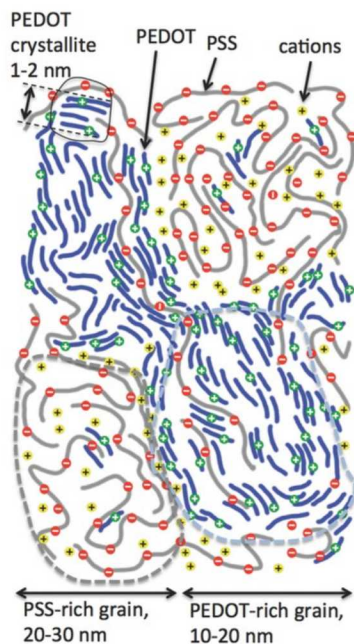
Crossbar Simulator



Polymer-based “super-capacitive” redox transistors

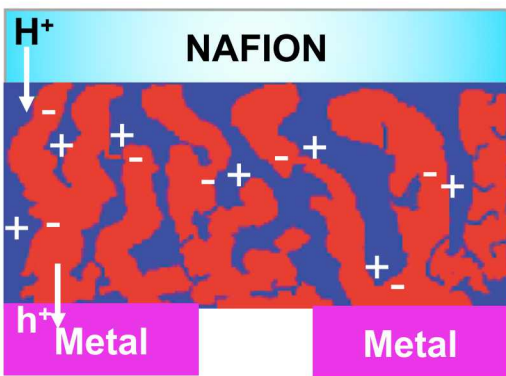
Alberto Salleo, Stanford University

PEDOT (hole conductor)
PSS (proton conductor)





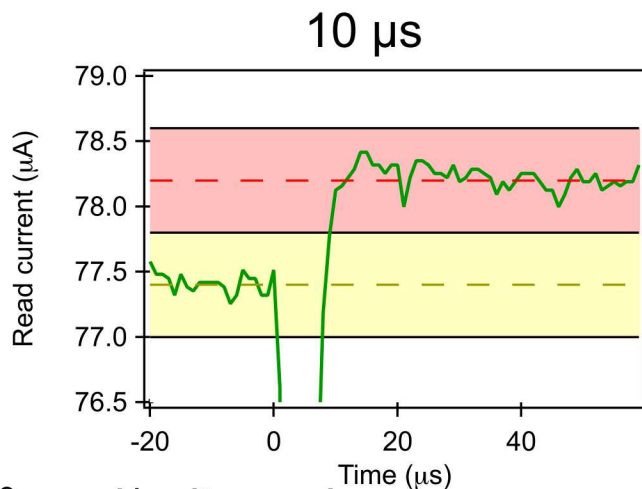
Super-capacitative vs intercalation redox transistor



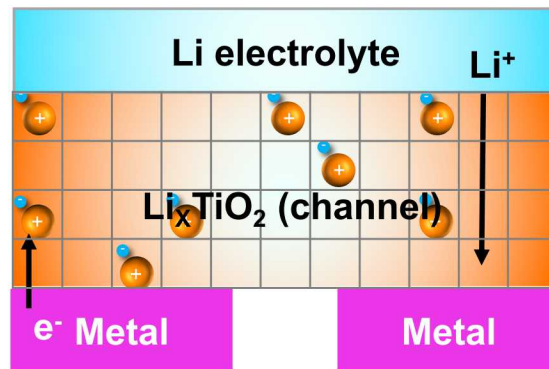
H^+ : proton; h^+ : hole

PEDOT:PSS

No charge transfer;
Fast single-specie diffusion
Low capacitance: 40 F cm^{-3}



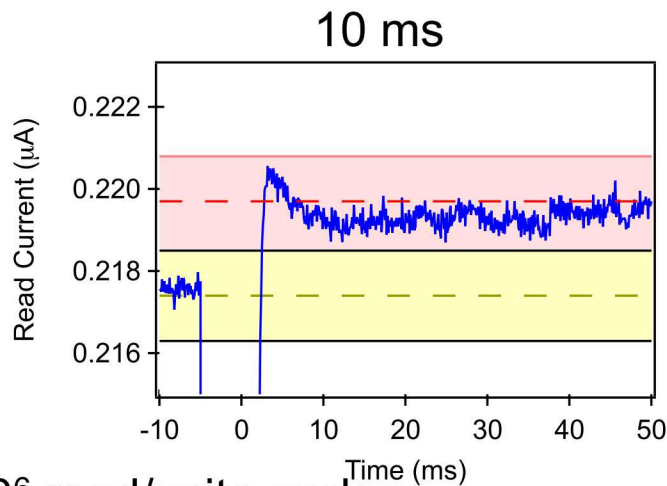
10^9 read/write cycles



Interfacial charge transfer

Slow chemical diffusion

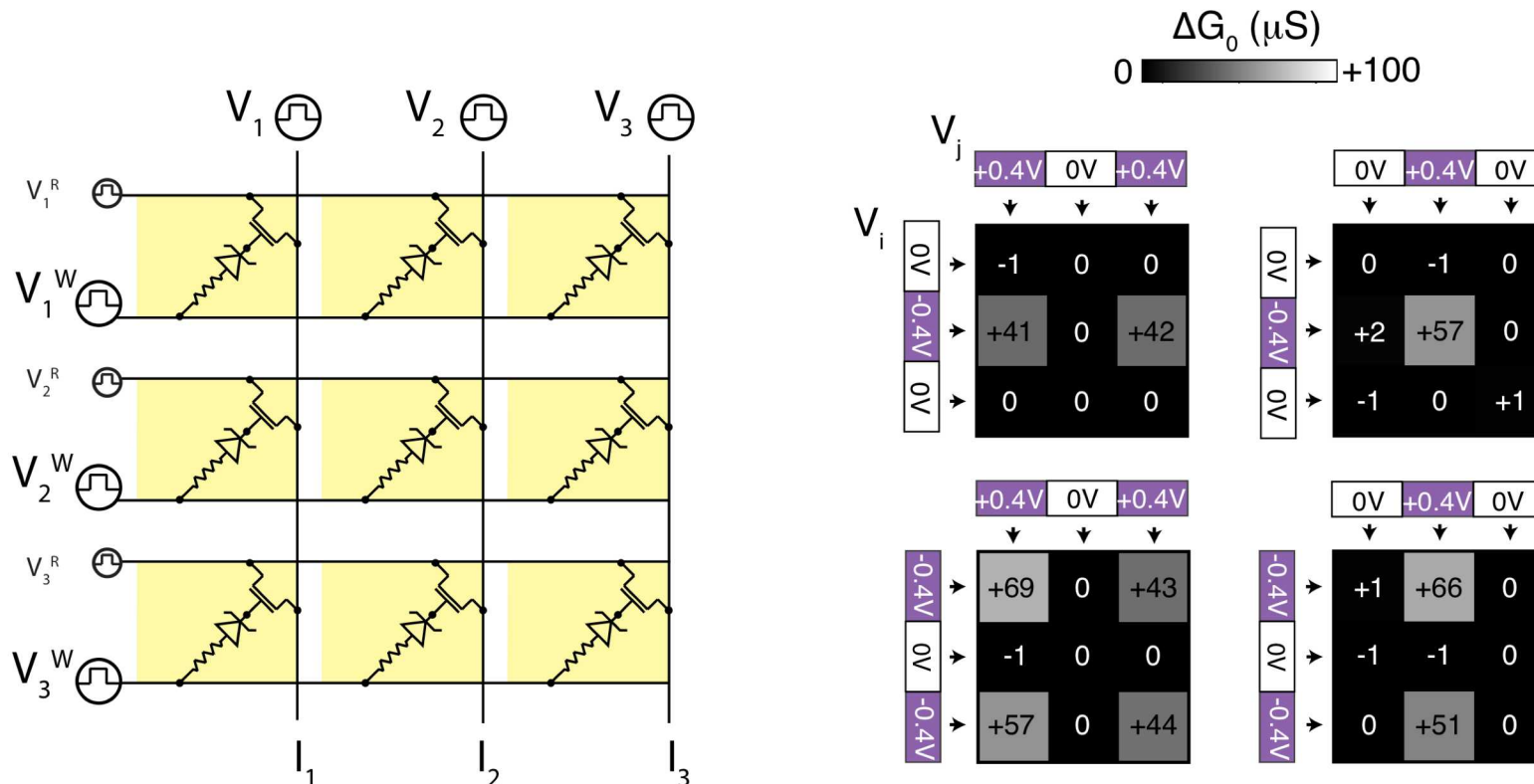
High capacitance: 5000 F cm^{-3}



10^6 read/write cycles



Parallel weight updates in crossbar arrays

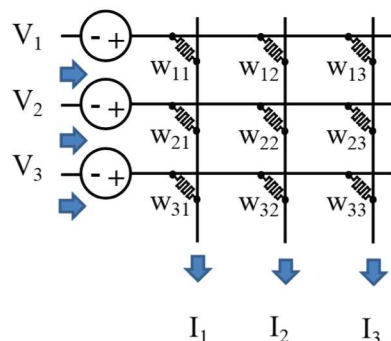


We can select the rows and columns in this crossbar to update the weights of many synapses in a highly parallel fashion in accordance with an outer product update

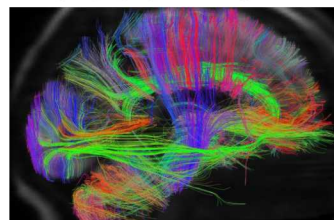


Redox transistors for neuromorphic computing

Analog neuromorphic computing provides lower energy and more parallelism compared to digital computing.

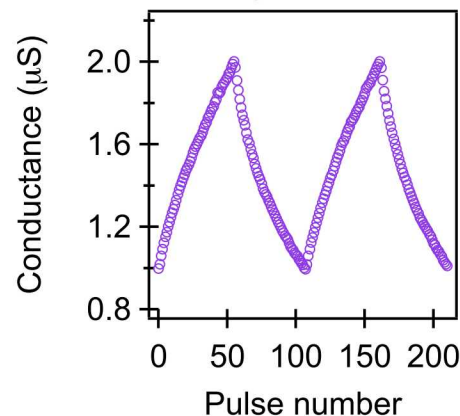
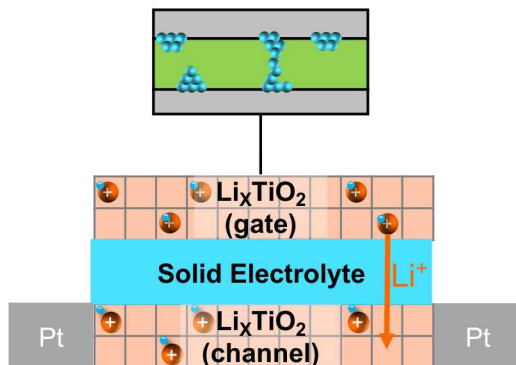


the brain ~10 Hz



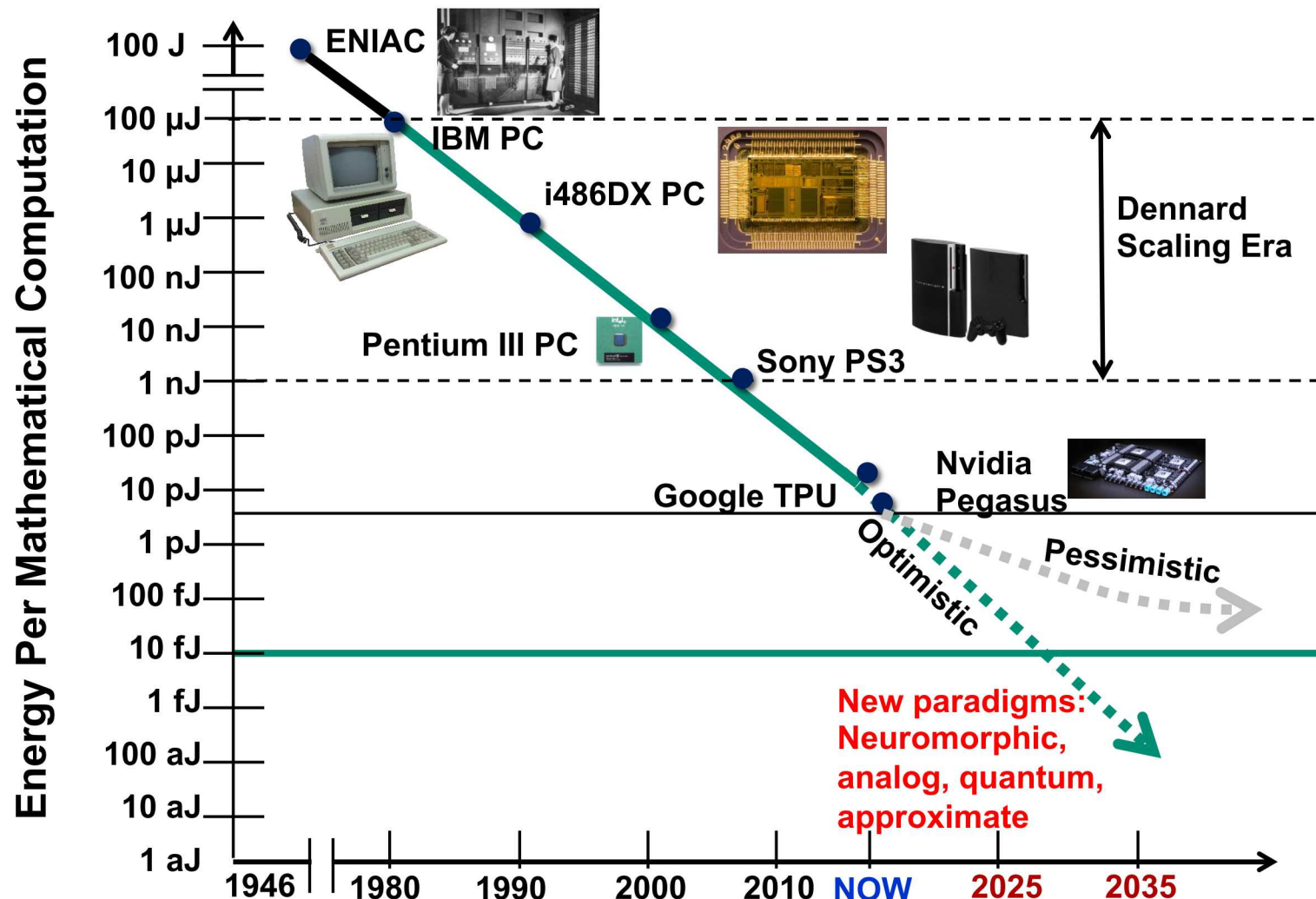
100 billion neurons
100 trillion synapses

Electrochemical ion insertion can be used to create highly linear, low voltage non-volatile analog transistors





Evolution of Computing Machinery





Acknowledgements

Sandia National Laboratories

Zhiyong Li, Francois Leonard, David Heredia, Maria Pilar Prieto,
Tomochika Kurita, Erik Isele

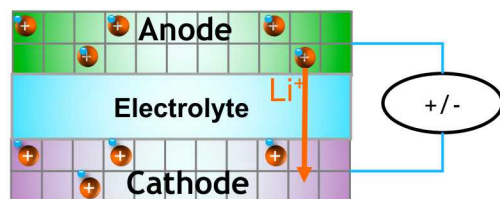


This work is supported by the Sandia National Laboratories Truman Fellowship Program, which is funded by the Laboratory Directed Research and Development (LDRD) Program. Sandia National Laboratories is a multi-mission laboratory managed and operated by National Technology and Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA-0003525.

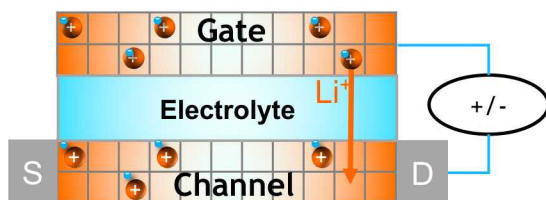


From batteries to redox transistors

Batteries: Maximize open-circuit voltage to store energy

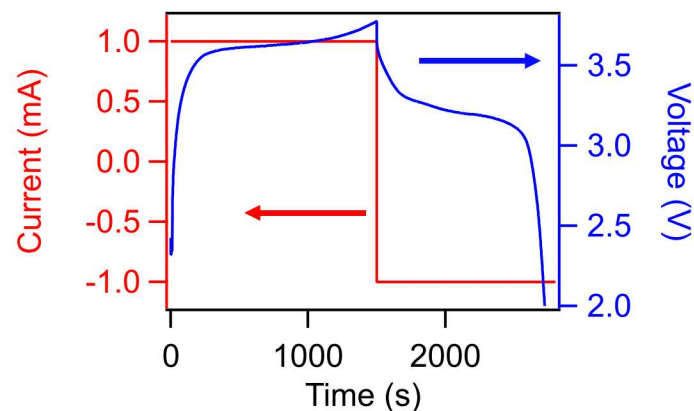


Redox transistors: Minimize open-circuit voltage for array integration

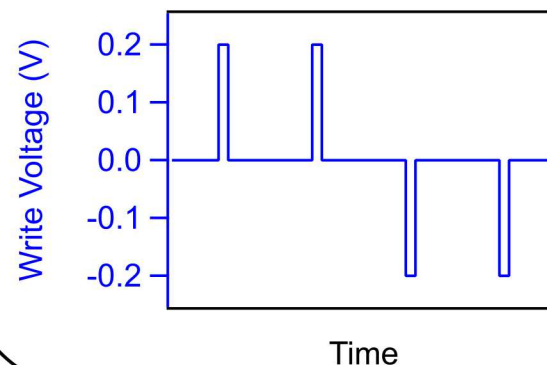


Materials should have a significant change in conductance with a minimal change in write voltage

Batteries: Current control

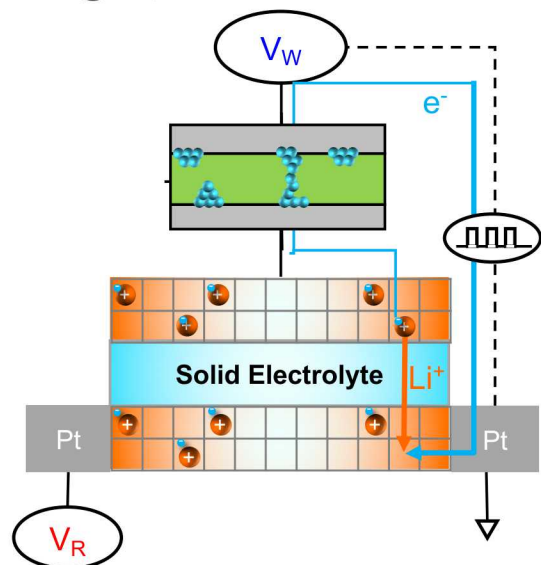


Redox transistors: Voltage control





Low-voltage, Si-free electrochemical memory



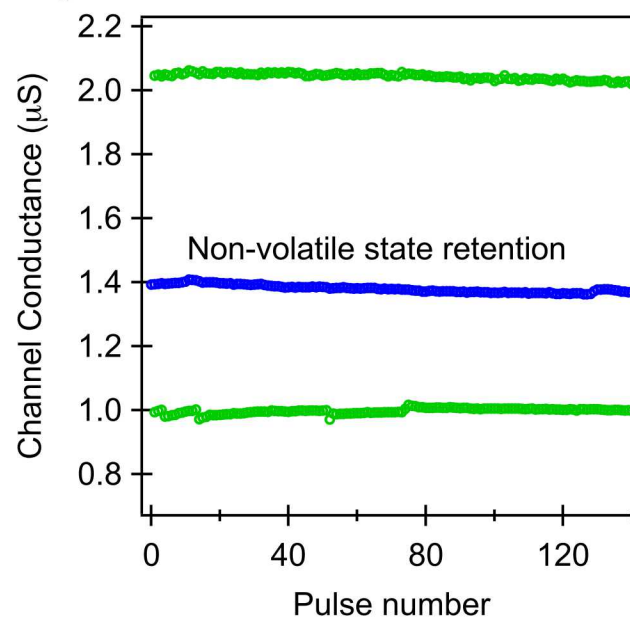
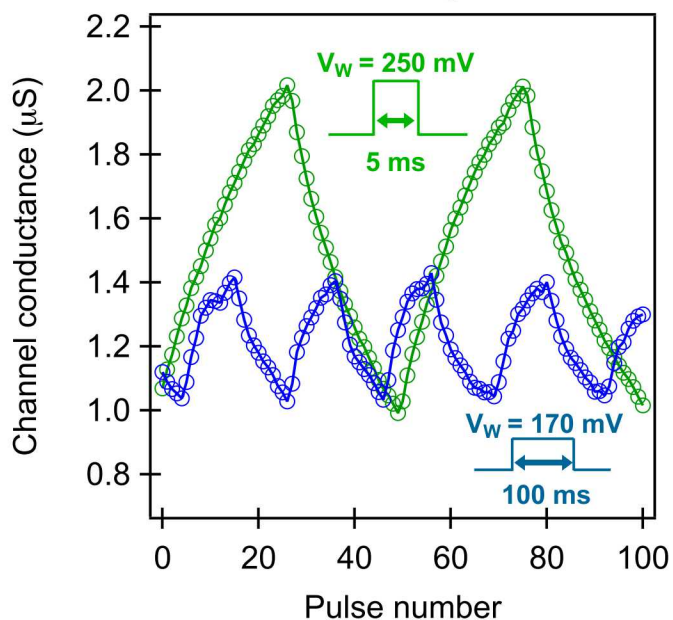
Diffusive memristor (Ag in SiO_x): high ON/OFF ratio

Redox transistor: high charge density via bulk storage

Both: Low switching voltages

Wang et al. Nat. Mater. 2017

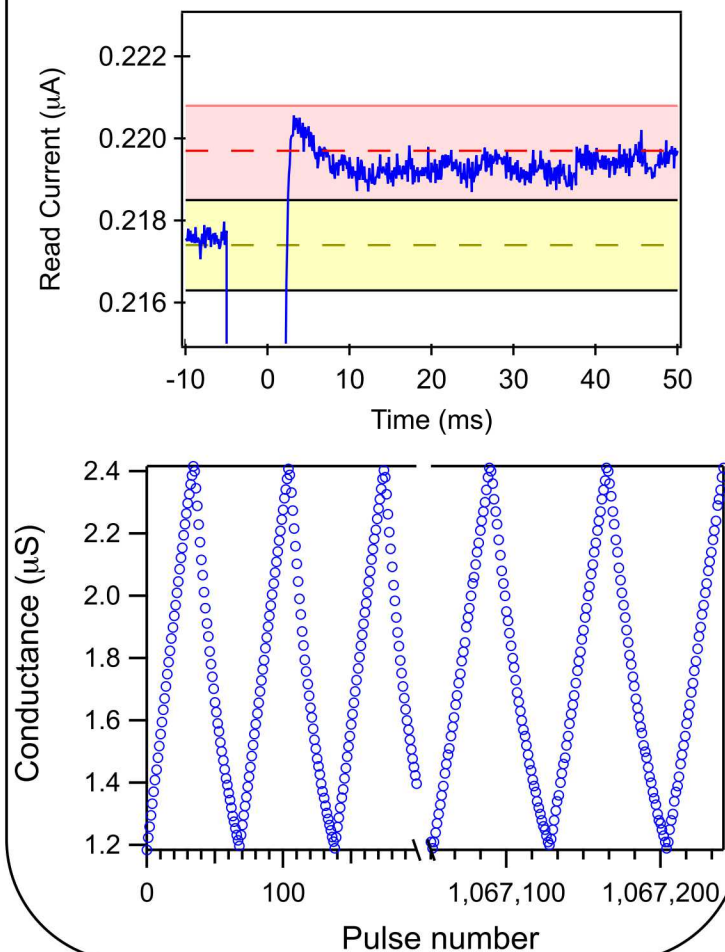
Non-volatile memory that switches at just 6 times the thermal voltage



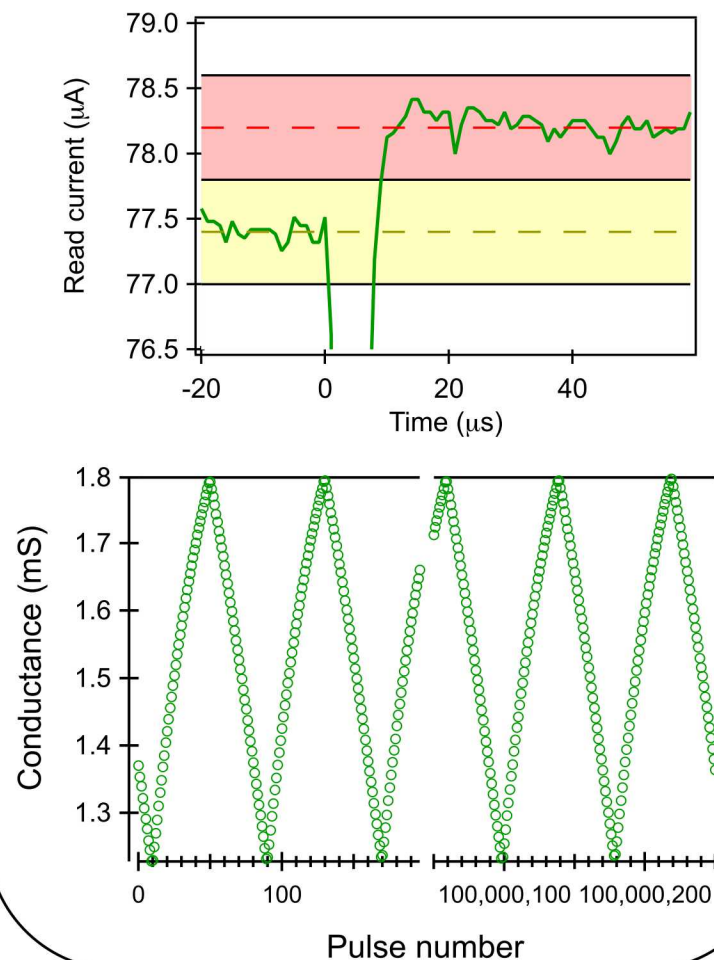


Switching speed and endurance

Intercalation Li_xTiO_2 ~5 ms,
 10^6 read/write cycles



Super-capacitive PEDOT ~10 μs
 10^8 read/write cycles





Scaling of energy, speed, and retention

ΔQ : amount of charge moved per weight update

$$\Delta Q \sim Volume \sim Area$$

$$Energy = V_{write} \Delta Q$$

$$Energy \sim Area$$

$$\tau_{write} = \frac{\Delta Q}{I} = \frac{\Delta Q}{V_{write}/R_{ON}} = \frac{R_{ON}\Delta Q}{V_{write}}$$

$$R_{ON} \sim 1/Area$$

Write time is independent of size in this geometry

$$\tau_{retain} = \frac{\Delta Q}{I_{leak}} = \frac{\Delta Q}{V_{gate-channel}/R_{OFF}} \sim C_{volumetric} R_{off}$$

Retention time is inversely proportional to the capacitance and the device area

