

# Ferroelectric Hafnia Superlattices for Bio-Inspired Computing.

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## Acknowledgements:

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- The authors acknowledge the *Binnig and Rohrer Nanotechnology Center (BRNC)*



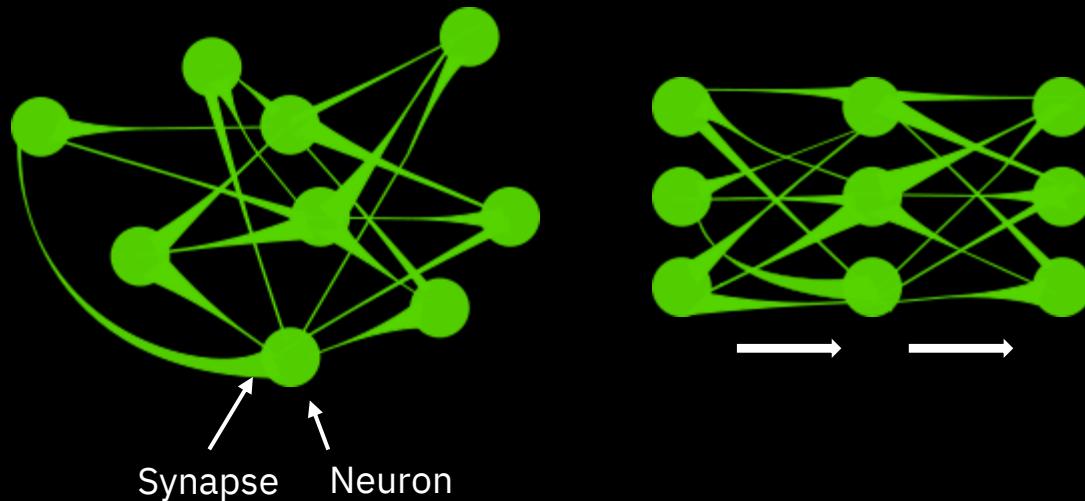
## 1. Motivation:

- a. Analog resistive switching in  $\text{HfZrO}_4$  devices for Artificial Neural Networks hardware
- b.  $\text{HfO}_2$  /  $\text{ZrO}_2$  superlattices for lower crystallization T.

## 2. Results:

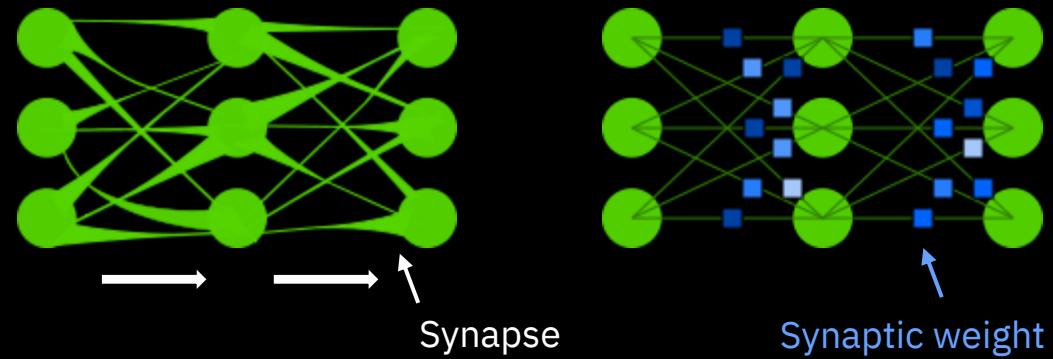
- a.  $5 \times (0.5 \text{ nm } \text{HfO}_2 / 0.5 \text{ nm } \text{ZrO}_2) / \text{WO}_x // \text{Si}$
- b. Co-integration of FTJ to CMOS in the BEOL

Bio Inspired Computing: Mimicking the brain, “Deep-Learning” algorithms are structured into layers of interconnected neurons.



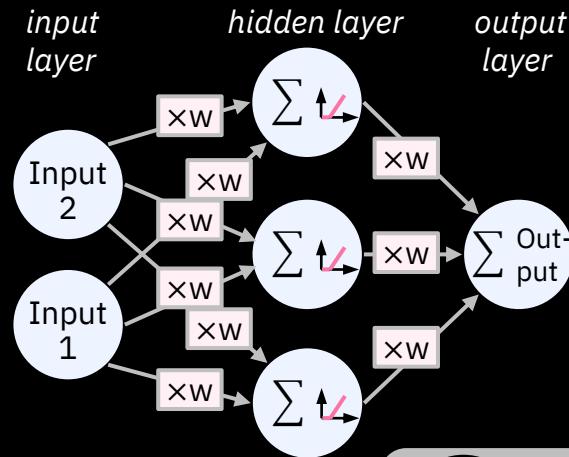
At each layer, a matrix vector multiplication is performed.  
“Learning” is achieved by adjusting the **matrix elements**,  
by analogy: the **synaptic weights**

$$\begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \cdot \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} ax + by + cz \\ dx + ey + fz \\ gx + hy + iz \end{bmatrix}$$

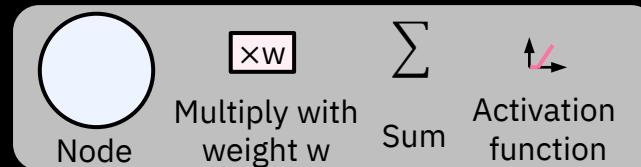
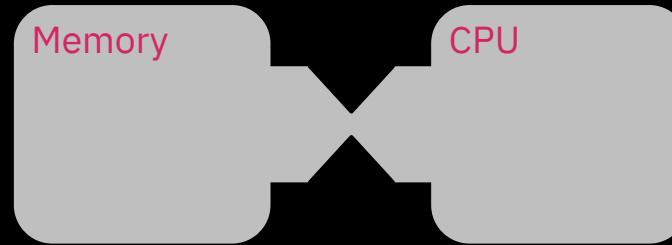


# Artificial Neural Network: Solving the Von Neumann bottleneck with In-Memory Computing

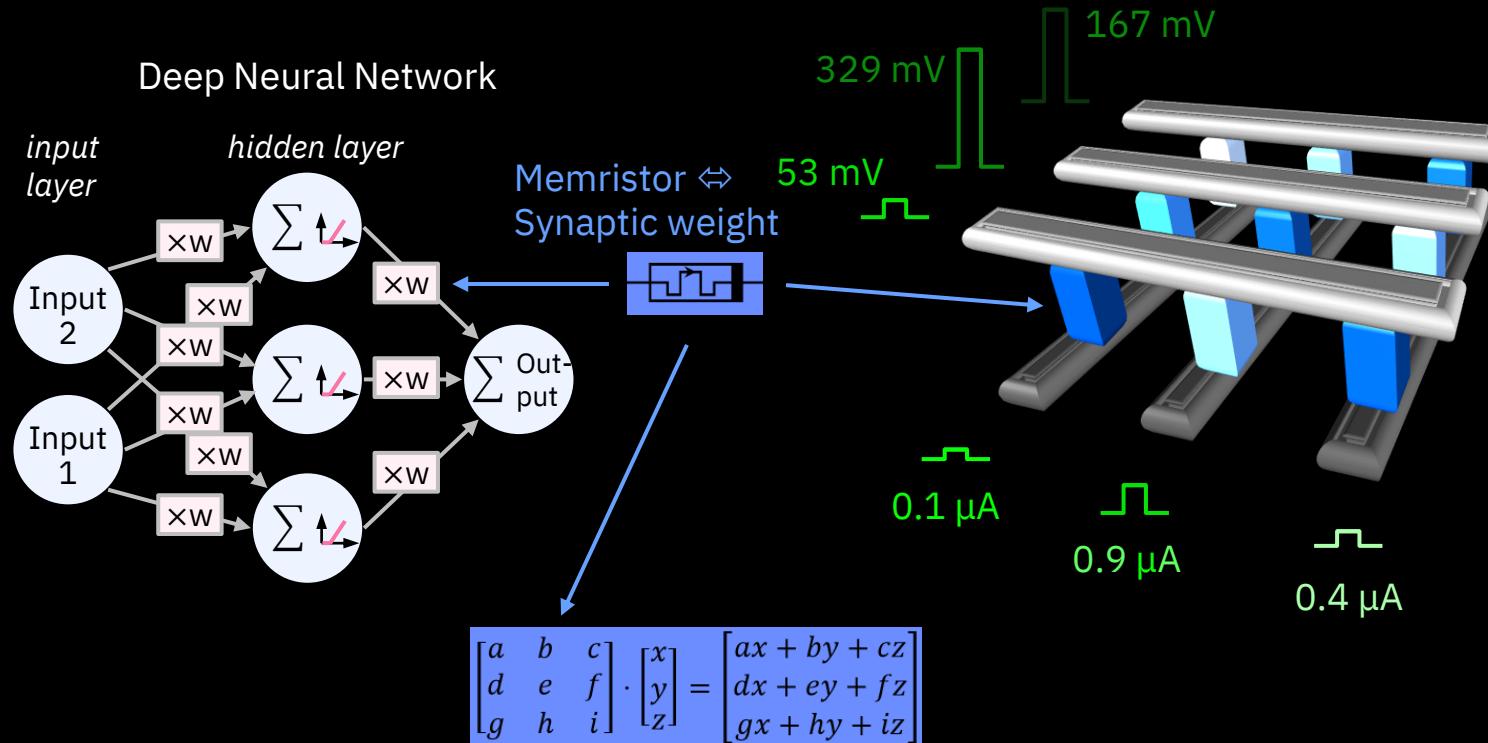
Deep Neural Network



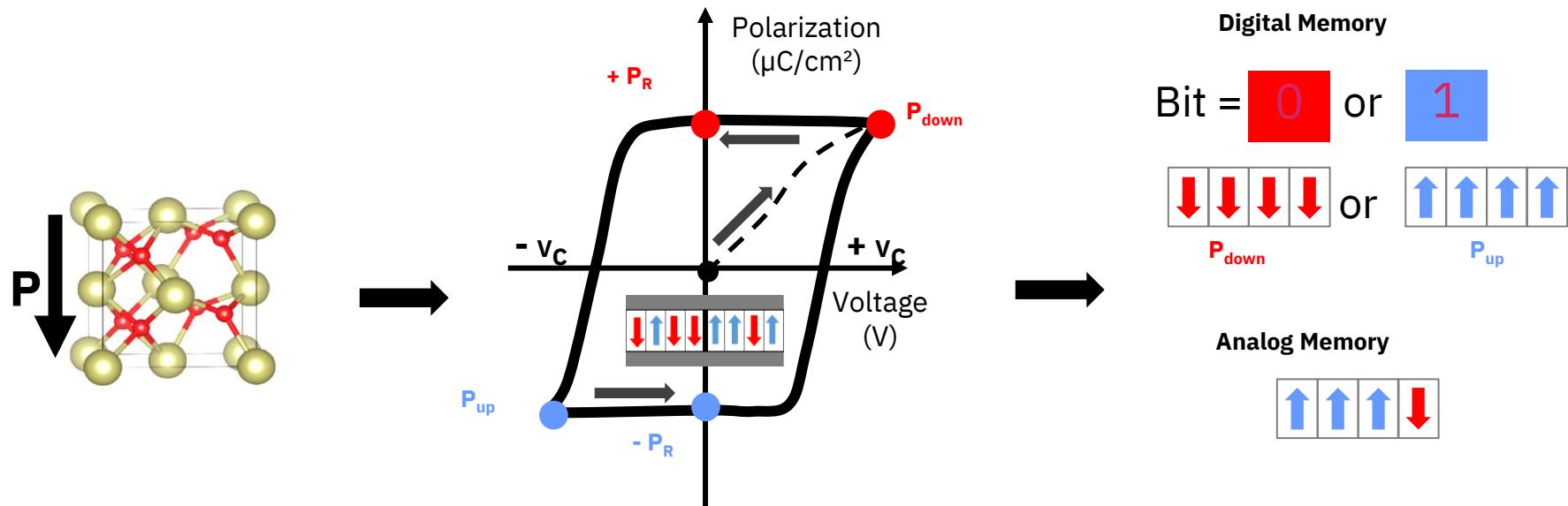
Von Neumann bottleneck



# Analog multiplication in an Artificial Neural Network: Parallel voltage drop through a cross-bar arrays of Memristors



# Ferroelectricity



- ❑ **Ferroelectricity** → asymmetric orthorhombic cell → dipoles (=Polarization)
- ❑ **Hysteresis** → Polarization switchable by an electric field
- ❑ **Coercive field,  $E_C$**   $\stackrel{\text{def}}{=}$  field to switch from one polarization state to the other
- ❑ **Remnant Polarization,  $P_R$**   $\stackrel{\text{def}}{=}$  polarization still available at null electric field

# “Passive” crossbars arrays

Halter et al., Crossbar operation of BiFeO<sub>3</sub>/Ce–CaMnO<sub>3</sub> ferroelectric tunnel junctions: From materials to integration, JMR 2023

Passive crossbar operation enabled by the sharp coercive field in BiFeO<sub>3</sub> ferroelectric.

*Problem:* difficult to industrialize (Pulsed Laser Deposition of single crystal thin films)

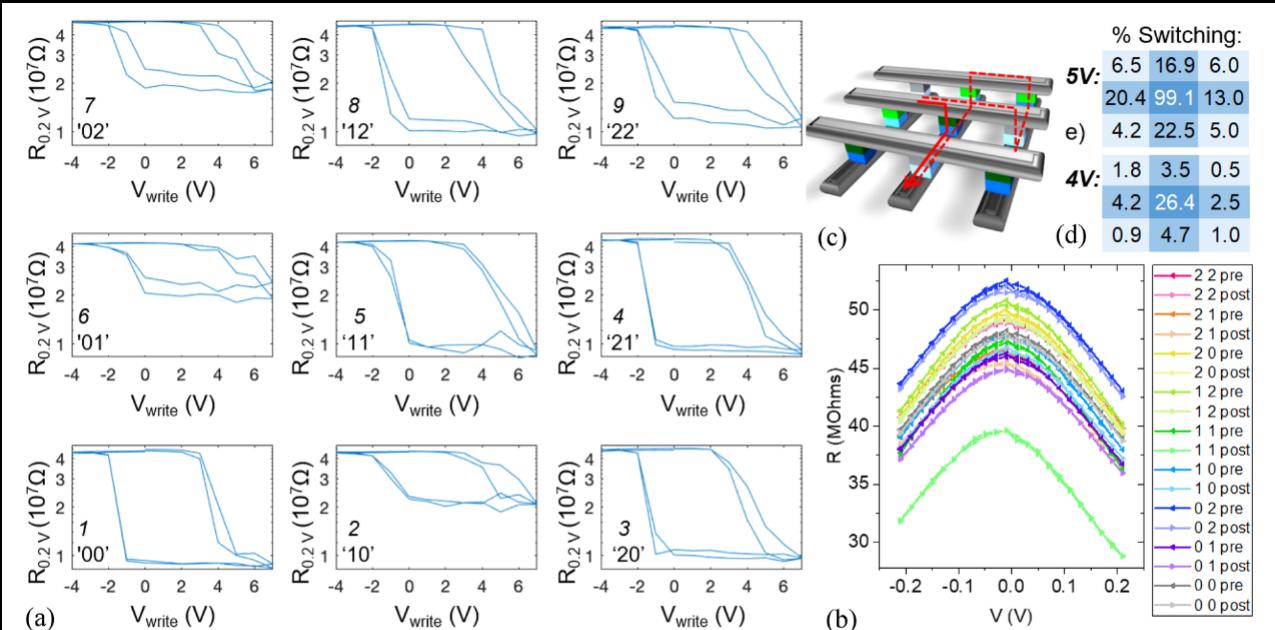
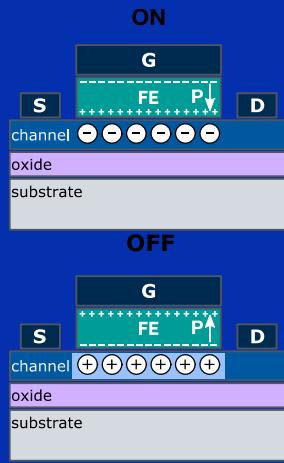


Figure 6: (a) Electro-resistance loops for nine FTJs in a 3×3 crossbar, numbered, ‘i, j’ with i, j in [0; 1; 2]. Consecutively: ‘00’, ‘10’, ‘20’, ‘21’, ‘11’, ‘01’, ‘02’, ‘12’, ‘22’. (b) R-V read sweeps before (-pre) and after (-post) applying 4 V to the element [1 1]: for this moderate programming voltage, the effect of sneak paths (c) is weak: as reported in the table in (d), neighboring elements have switched by  $dR_{ij}=2\text{--}5\%$  of the dynamic range measured in (a), and corner elements by 0–2%. (e) In contrast, for a programming voltage of 5 V to the central element [1 1], neighboring elements have switched by 13–22% of the dynamic range, and corner elements by 4–6%.

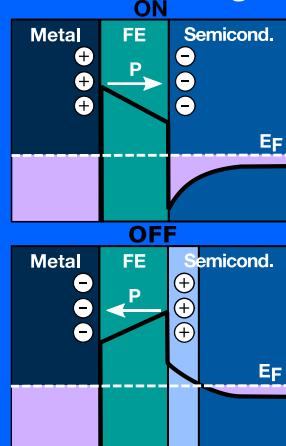
**Invited Feature Paper**  
DOI:10.1557/s43578-023-01158-8

# CMOS compatible memristive devices at ZRL: IBM-ETH Exploratory clean room fabrication capability ~ 950 m<sup>2</sup>, class 100-10000

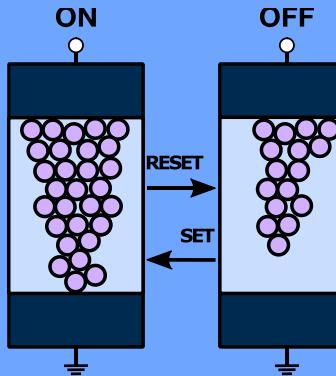
Ferroelectric Field Effect Transistor



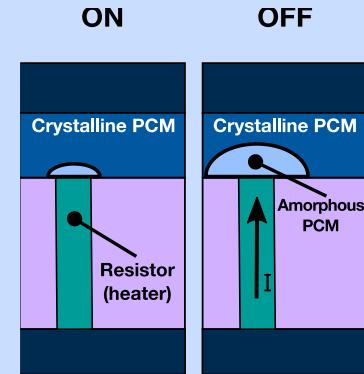
Ferroelectric Tunnelling Junction



Filamentary Resistive RAM



Phase Change Memory



Binnig and Rohrer  
Nanotechnology Center

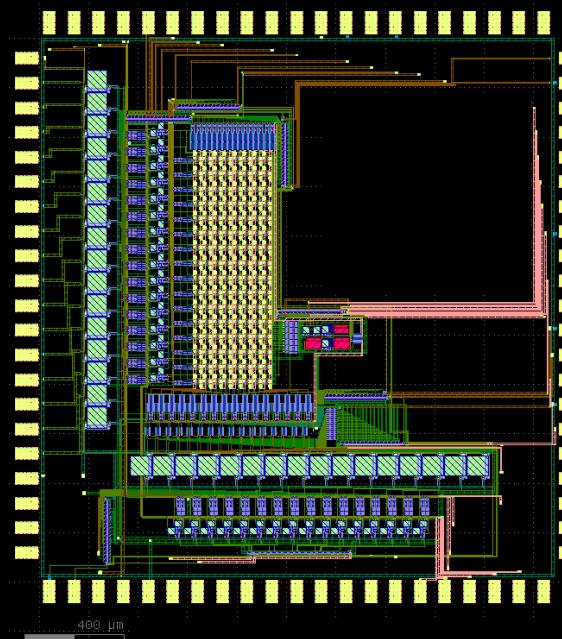
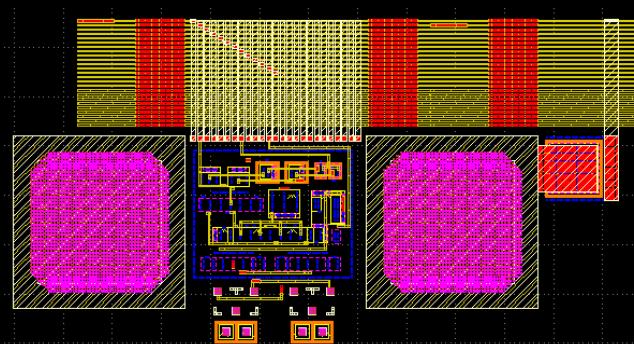


# Neuromorphic chips:

UNICO: ANR-19-CHR3-0006

**Voltage-Dependent Synaptic Plasticity (VDSP):  
Unsupervised probabilistic Hebbian plasticity rule  
based on neurons membrane potential**

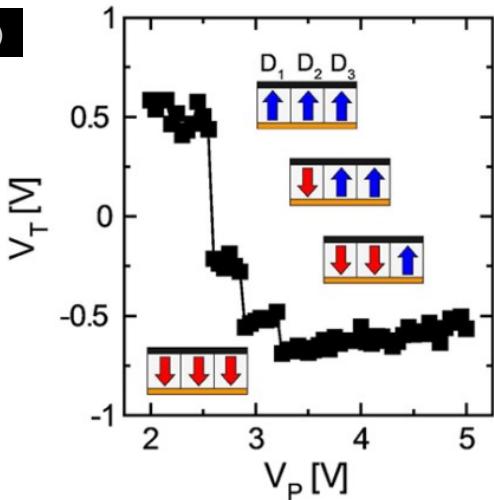
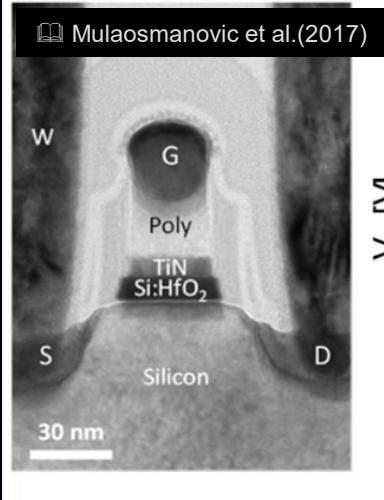
Nikhil Garg (CNRS, University of Sherbrooke)  
[DOI: 10.3389/fnins.2022.983950](https://doi.org/10.3389/fnins.2022.983950)



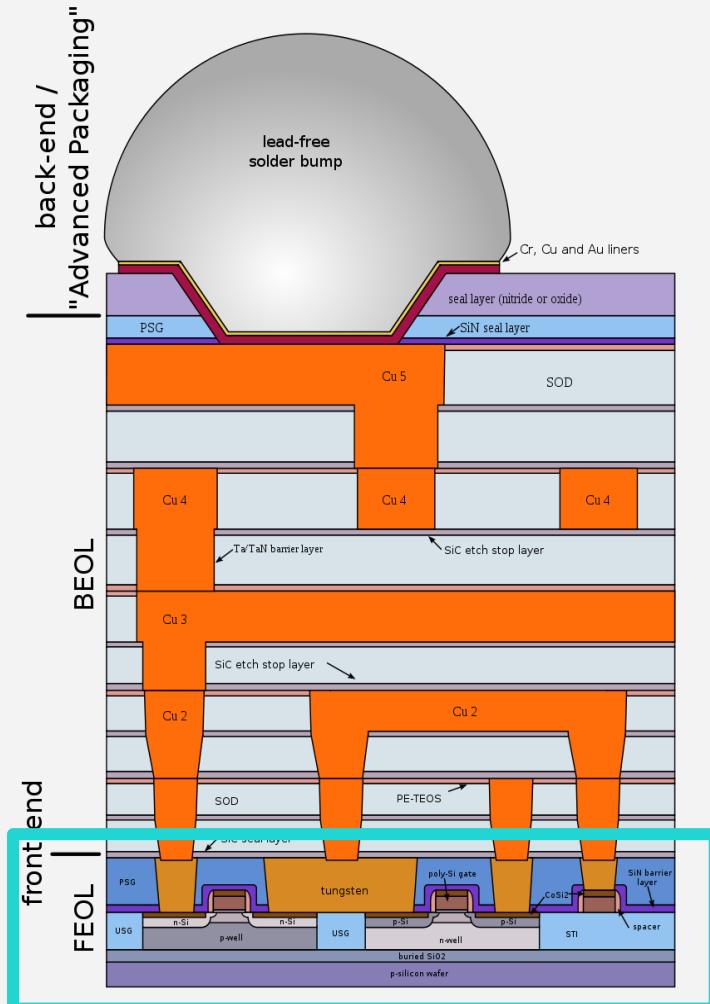
*BeFerroSynaptic: H2020-ICT-2019-2*

**BEOL technology platform based on ferroelectric synaptic devices  
for advanced neuromorphic processors**  
Institute of Neuroinformatics (UZH), NaMLab, University of Groningen  
<https://beferosynaptic.eu/publications>

# Integration of $\text{HfO}_2$ in the Front-End-Of-Line

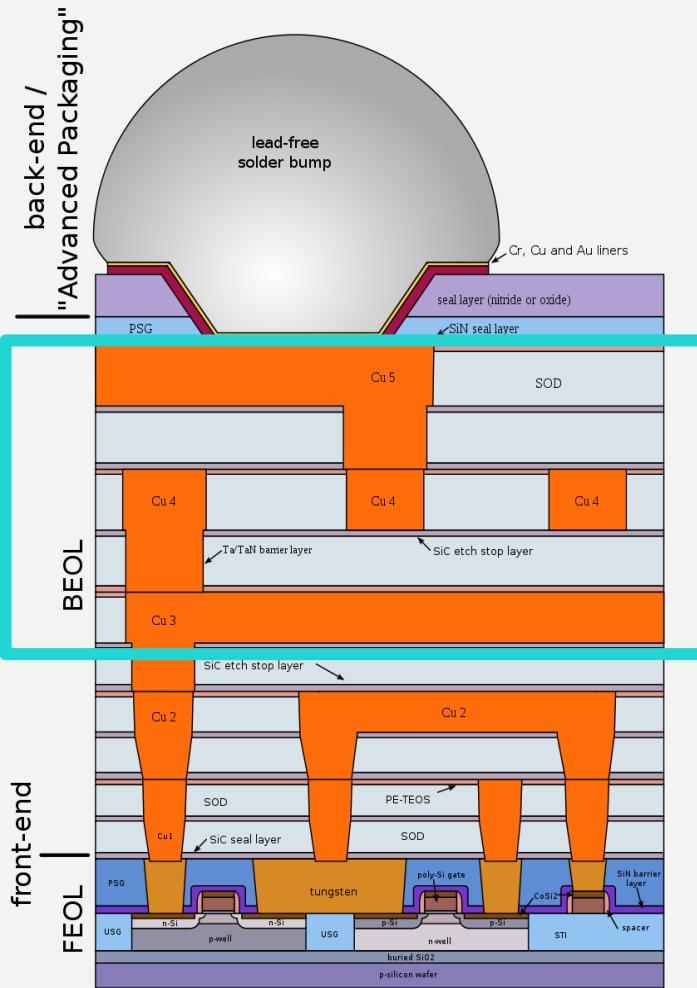
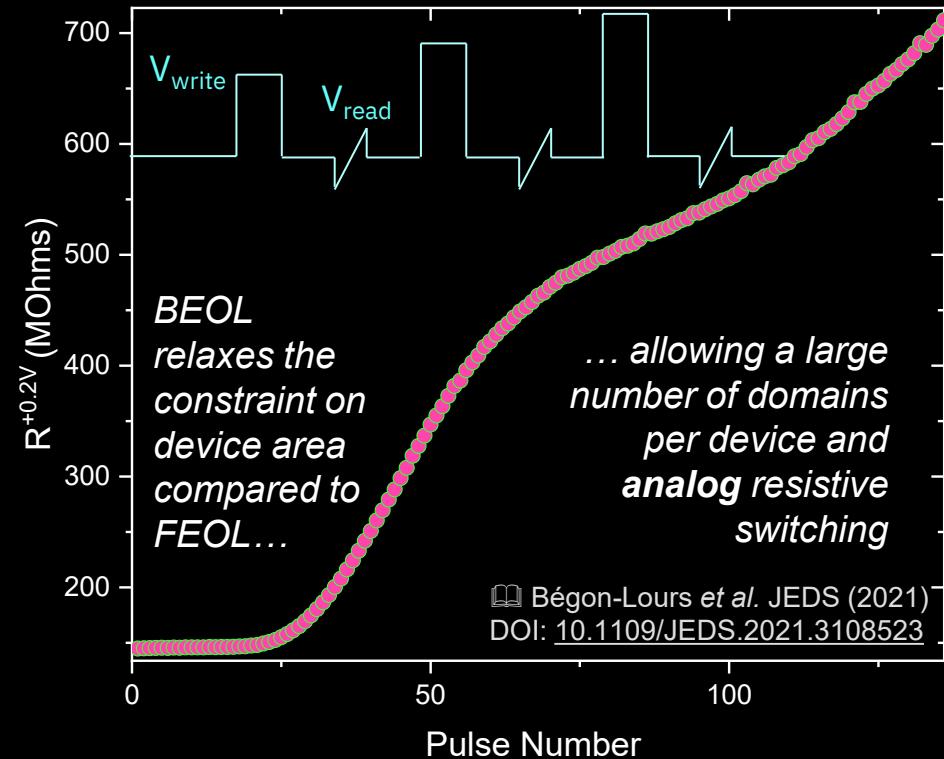


- Crystalline grains switch without sub-domains.
- In scaled devices, the number of grains is discrete



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<https://commons.wikimedia.org/w/index.php?curid=144544>

# Integration of $\text{HfZrO}_4$ in the Back-End-Of-Line



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# Oxide Interfaces

## *Example of the Ferroelectric Tunnel Junction*

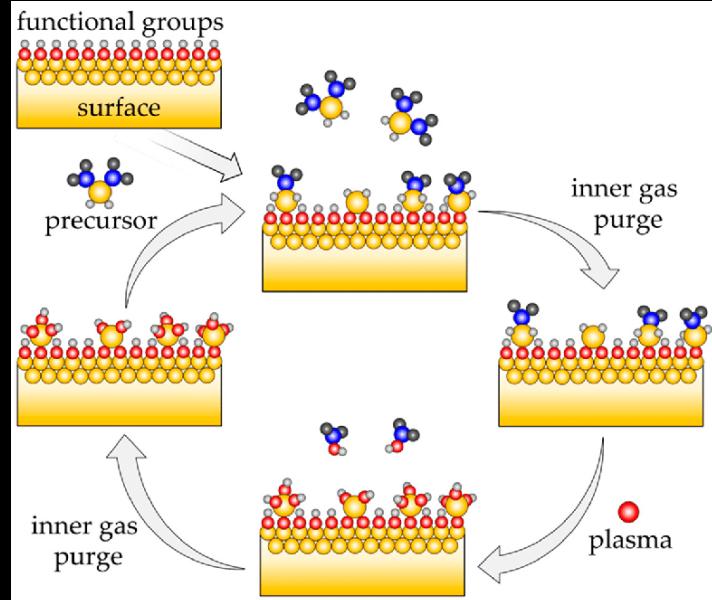
HZO deposition:  
**O<sub>2</sub> plasma** at 300C. TiNO<sub>x</sub> is expected:  
M/FE/DE/M stack.



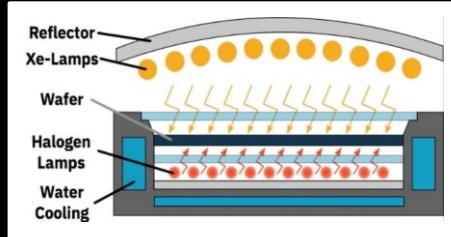
**Charge-trapping** in this layer might be detrimental to the **endurance**



TiNO<sub>x</sub> will also form, but **not** enhanced by O<sub>2</sub> plasma.  
M/FE/MO<sub>x</sub>/M stack, no charge-trapping.



# Ferroelectric tunnel junctions at IBM: HfZrO<sub>4</sub>/WO<sub>x</sub> bilayers



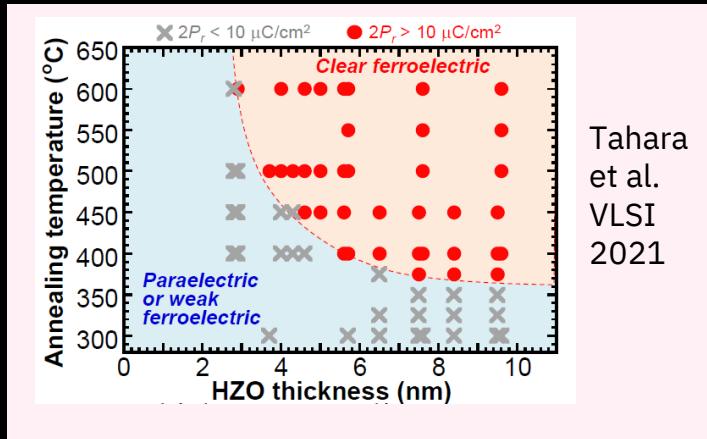
- Atomic Layer Deposition of TiN / HfZrO<sub>4</sub> / WO<sub>x</sub> / TiN
- Crystallisation by millisecond Flash Lamp Annealing  
    *É. O'Connor et al. (2018)*
- Device definition by Reactive Ion Etching & Ion Beam Etching



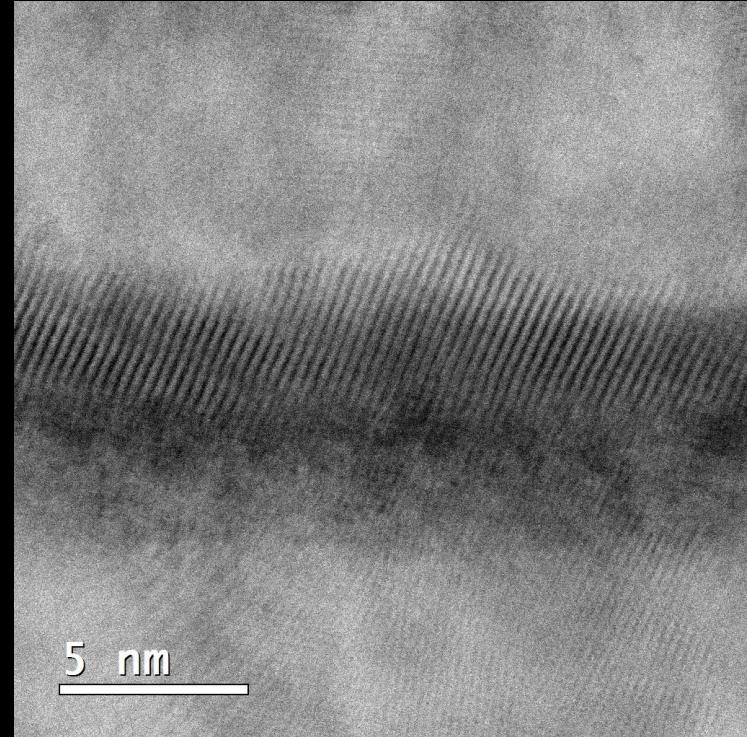
Back-End-Of-Line integration:  
constraint on the thermal  
budget (<400C)

Neuromorphic chips design:  
constraint on the device footprint  
(< (10μm)<sup>2</sup>) +  
constraint on I<sub>OFF</sub> & I<sub>ON</sub>

# Ultra-thin HZO (<3 nm): meet footprint + $I_{OFF}$ requirement, but crystallises above 400°C.

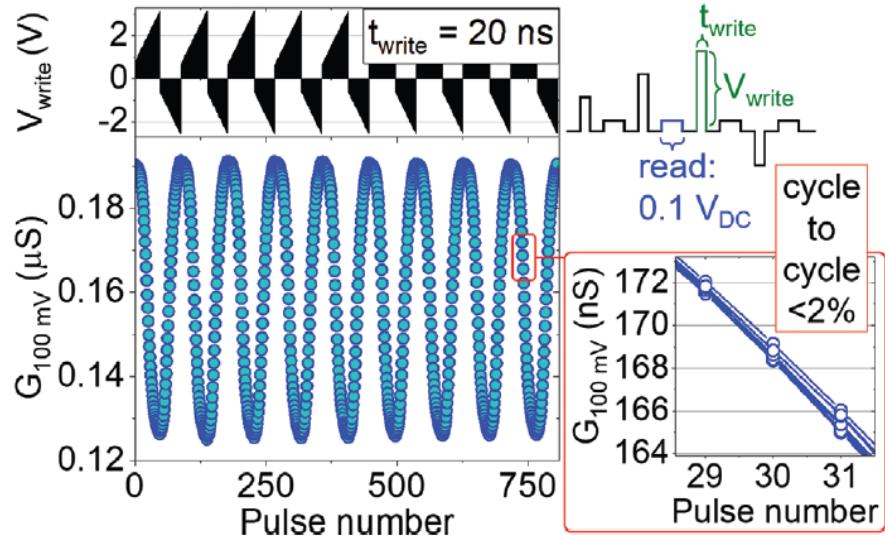


Tahara  
et al.  
VLSI  
2021

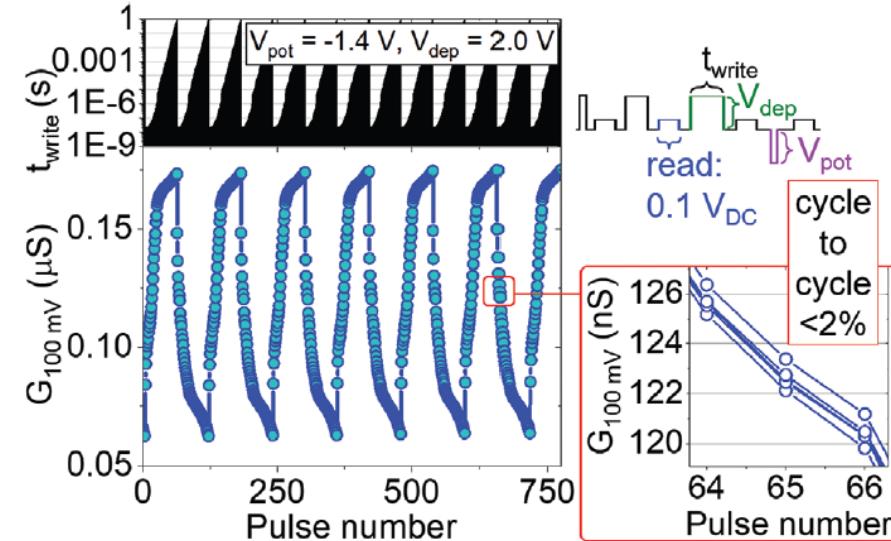


Bégon-Lours *et al.* Neuromorphic Computing and Engineering (2022)  
<https://doi.org/10.1088/2634-4386/ac5b2d>

# TiN / HZO 4nm / WO<sub>x</sub> / TiN / SiO<sub>2</sub> // Si junctions: Meet all the requirements for synaptic weights in the BEOL

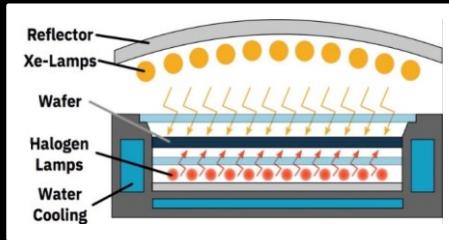
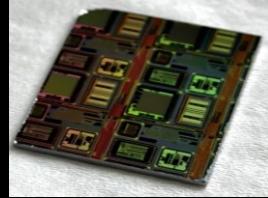


**Figure 4.** Synaptic potentiation and depression with pulses of increasing amplitude. The pulse amplitude  $V_{\text{write}}$  and the pulse duration  $t_{\text{write}}$  are defined as in the measurement scheme (top right). The inset shows the cycle-to-cycle variation.



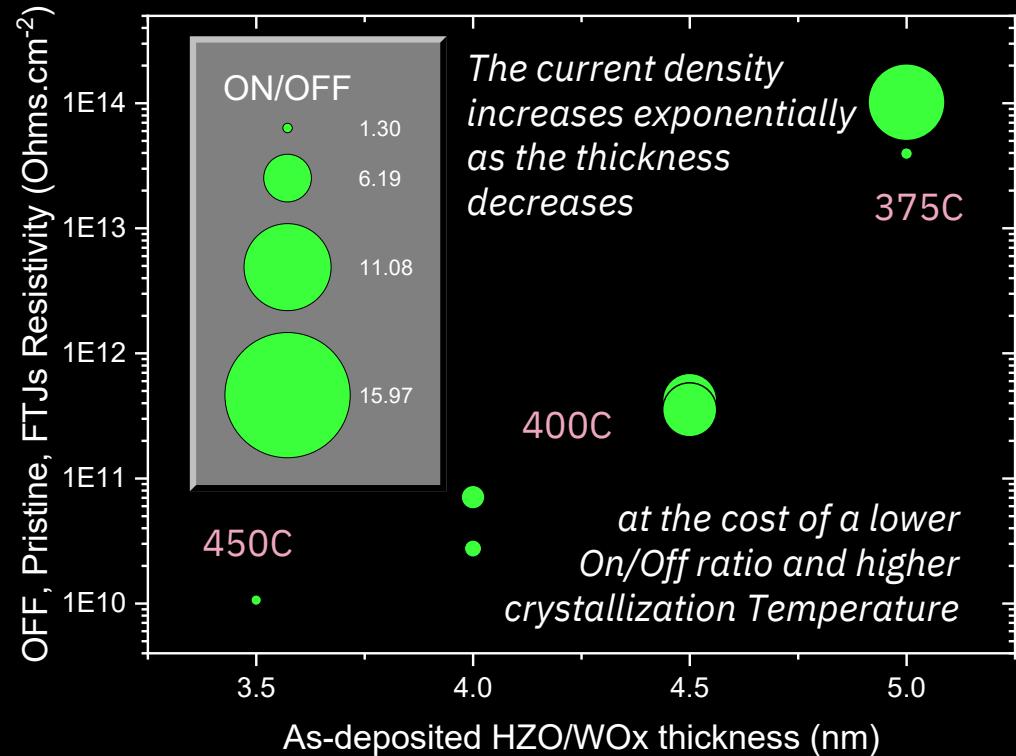
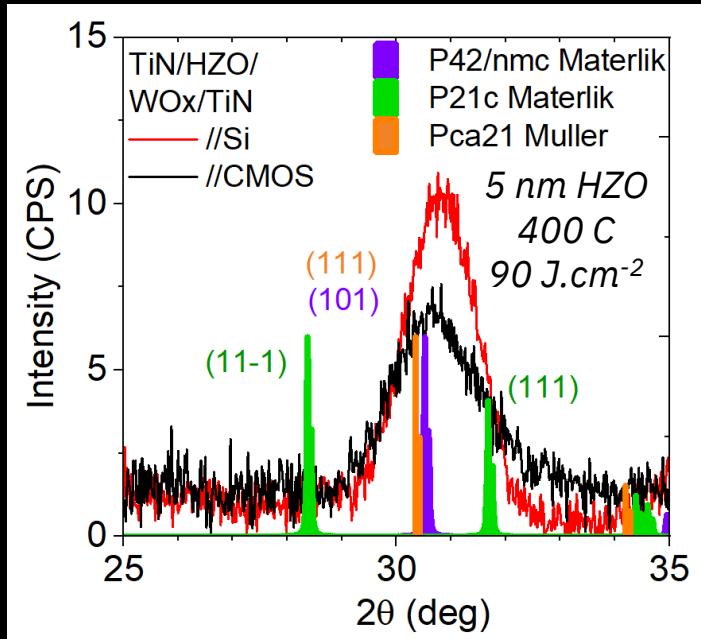
**Figure 5.** Long-term potentiation and depression for pulses with constant amplitudes  $V_{\text{pot}}$  and  $V_{\text{dep}}$  (as defined in the measurement scheme) and increasing duration  $t_{\text{width}}$ . The inset shows the cycle-to-cycle variation.

# Back-End-Of-Line integration of TiN / HZO 4 nm / WO<sub>x</sub> / TiN ferroelectric synaptic weights:

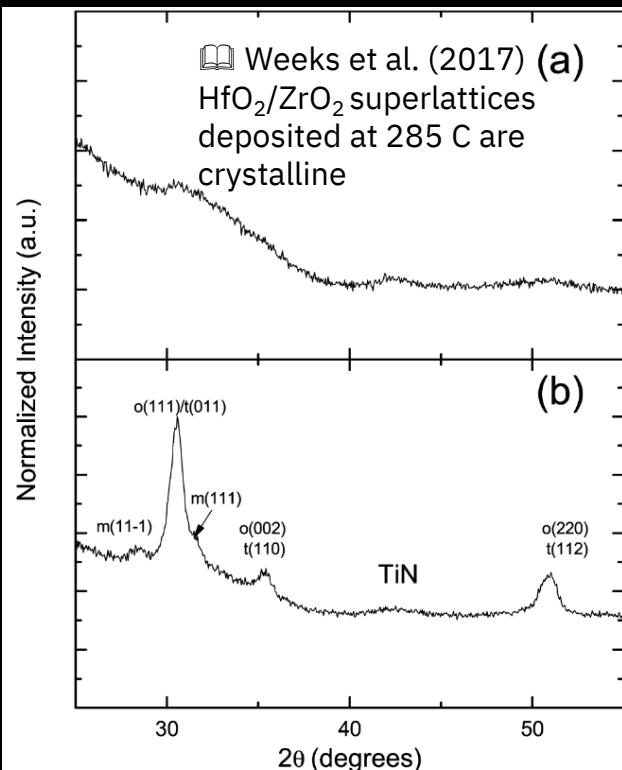


At 400C, crystallization of TiN / HZO 4 nm / WO<sub>x</sub> / TiN / SiO<sub>2</sub> // Si using a millisecond flash lamp annealing (90 J/cm<sup>2</sup>), but not on the CMOS substrate.

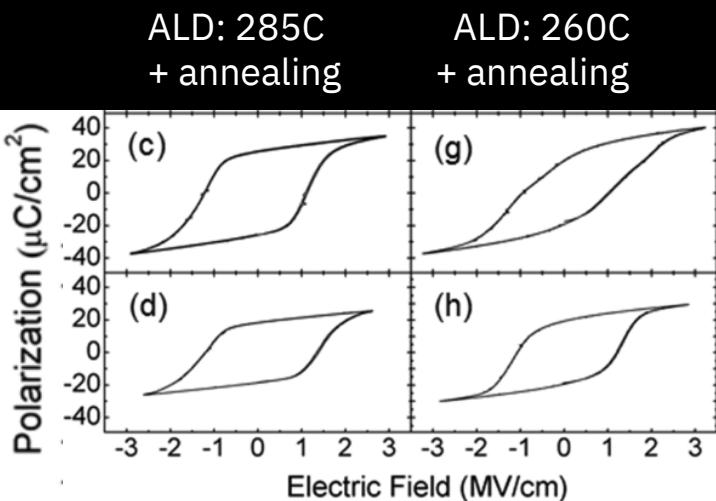
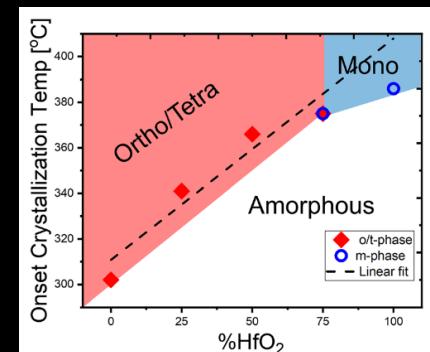
TiN / HZO 5 nm / WO<sub>x</sub> / TiN partially crystallises on the CMOS, but doesn't meet the footprint / I<sub>OFF</sub> requirements.



# Could ZrO<sub>2</sub> inclusion favor a lower crystallization temperature ?



Hsain et al. (2020):  
ZrO<sub>2</sub> has a lower  
crystallization temperature  
than HfO<sub>2</sub>.



(1 nm HfO<sub>2</sub> / 1nm ZrO<sub>2</sub>) $\times$ 4

HfZrO<sub>4</sub>

Figure 6. GIXRD scans of (1 nm HfO<sub>2</sub>/1 nm ZrO<sub>2</sub>)  $\times$  8 nanolaminates grown at (a) 260 °C and (b) 285 °C collected before any postdeposition annealing.

## 1. Motivation:

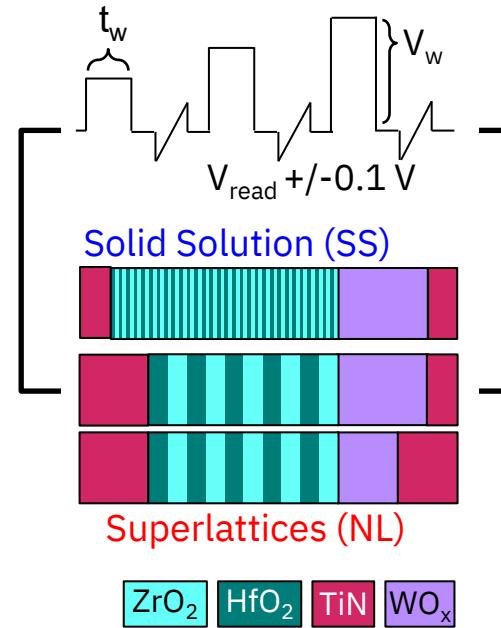
- a. Analog resistive switching in  $\text{HfZrO}_4$  devices for Artificial Neural Networks hardware
- b.  $\text{HfO}_2$  /  $\text{ZrO}_2$  superlattices for lower crystallization T.

## 2. Results:

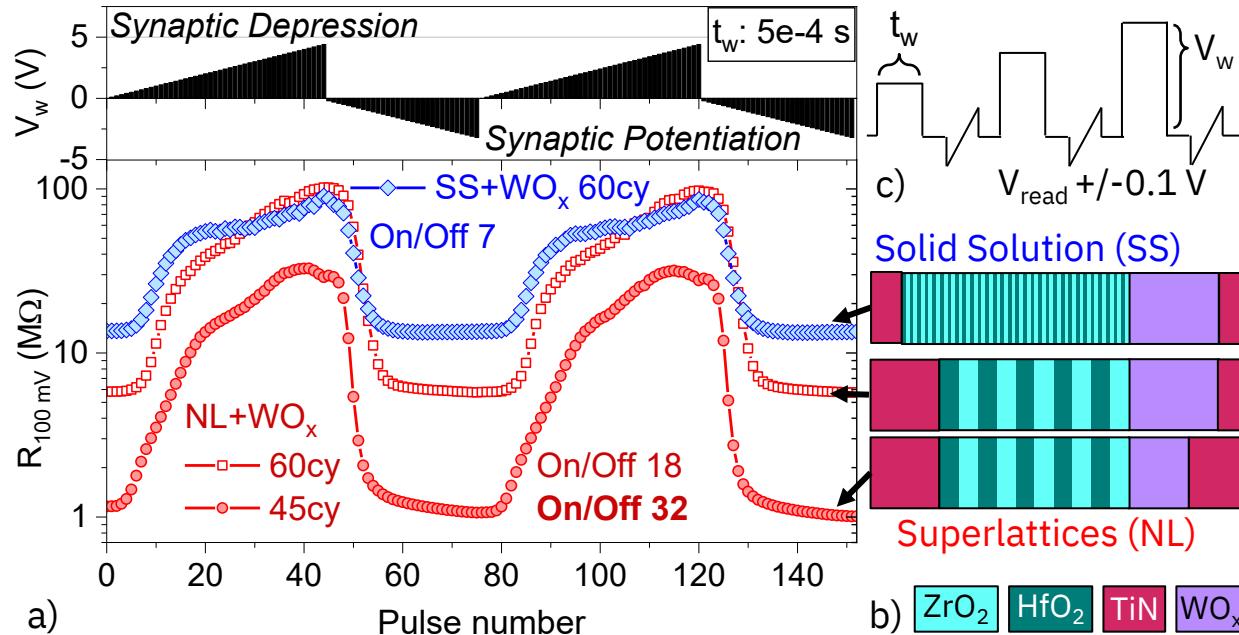
- a.  $5 \times (0.5 \text{ nm } \text{HfO}_2 / 0.5 \text{ nm } \text{ZrO}_2) / \text{WO}_x // \text{Si}$
- b. Co-integration of FTJ to CMOS in the BEOL

# HfO<sub>2</sub> / ZrO<sub>2</sub> superlattices by Atomic Layer Deposition

- 5 repetitions instead of 1 repetition in each supercycle.
- Millisecond flash lamp annealing at 400C for superlattices (4 nm) & solid solution (5 nm)
- Functionality test:
  - Writing: pulses of increasing amplitude and constant duration,
  - Reading: IV Sweep



# HfO<sub>2</sub> / ZrO<sub>2</sub> superlattices by Atomic Layer Deposition

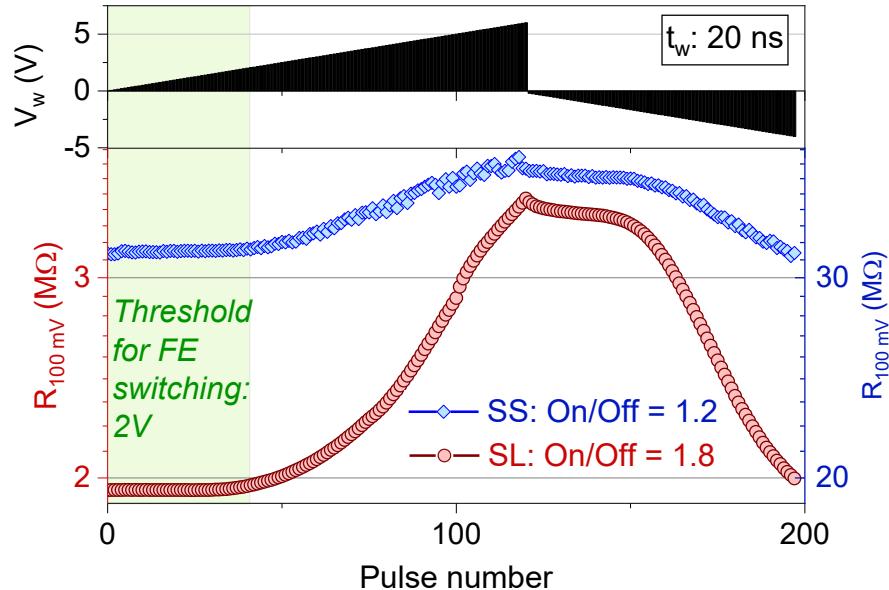


- HZO-SS  $\rightarrow$  HZO-SL. For equal  $I_{\text{Off}}$ ,  $I_{\text{on}}$  increases + increase of the On/Off ratio from 7 to 18.
- Optimization of the WO<sub>x</sub> interlayer thickness: a 50% thinner WO<sub>x</sub> layer further decreased the RON, the ROFF and **increased the On/Off ratio to 32**

# Ultra-fast switching (20 ns programming pulses)

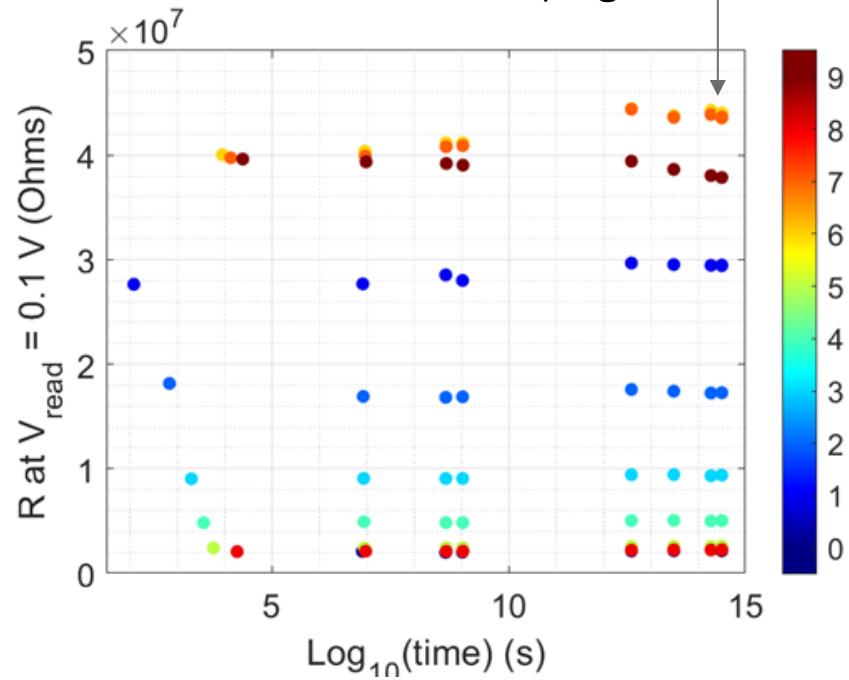
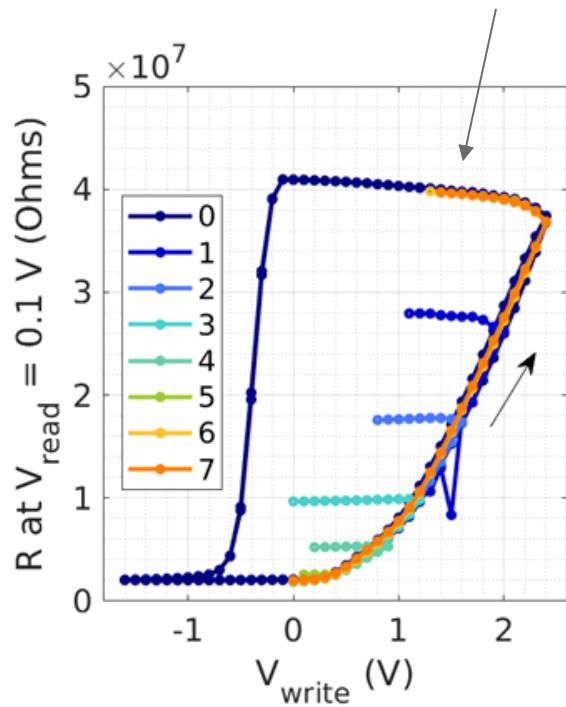
HZO-SS and HZO-SL synaptic weights on Si are operated under the increasing amplitude scheme (+6V/-4V, step size: 50 mV) with a **pulse width of 20 ns**.

Also in this ultra-fast regime, it is one order of magnitude smaller for the SL compared to the SS, while exhibiting a larger On/Off.

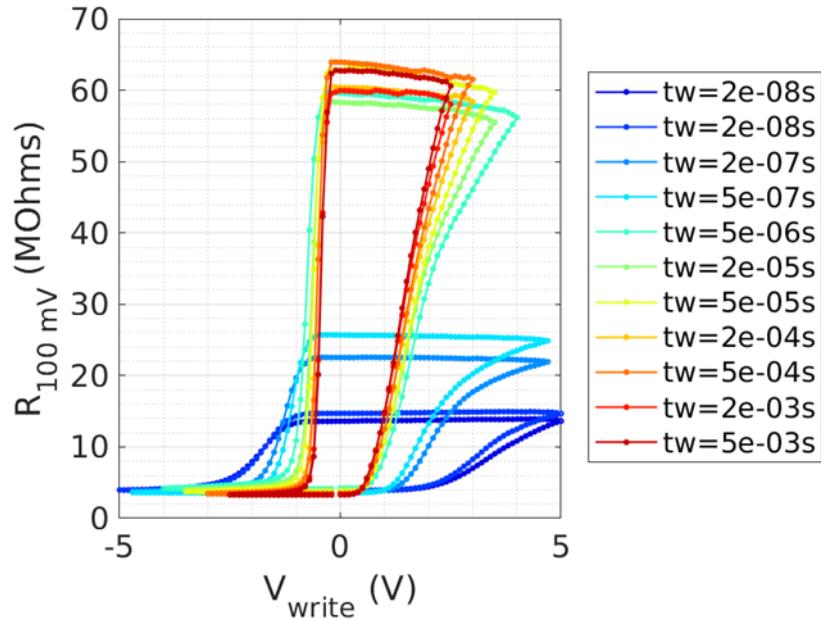


# Retention of the programmed states

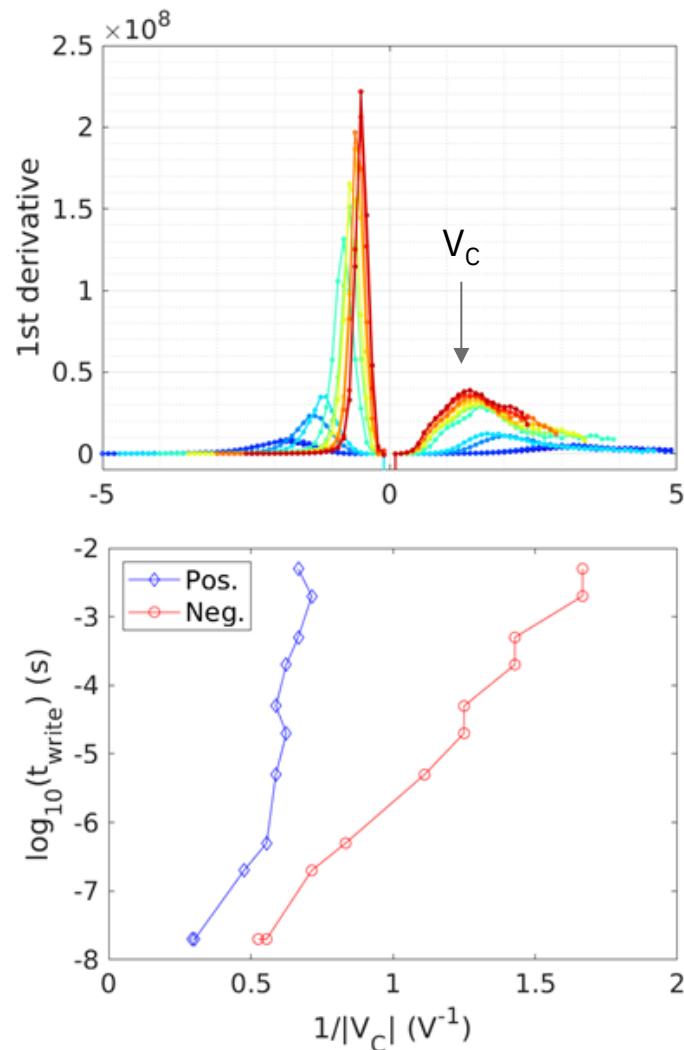
Resistance increases upon pulses of decreasing amplitude: else than ferroelectricity ?



# Merz law in ferroelectrics:

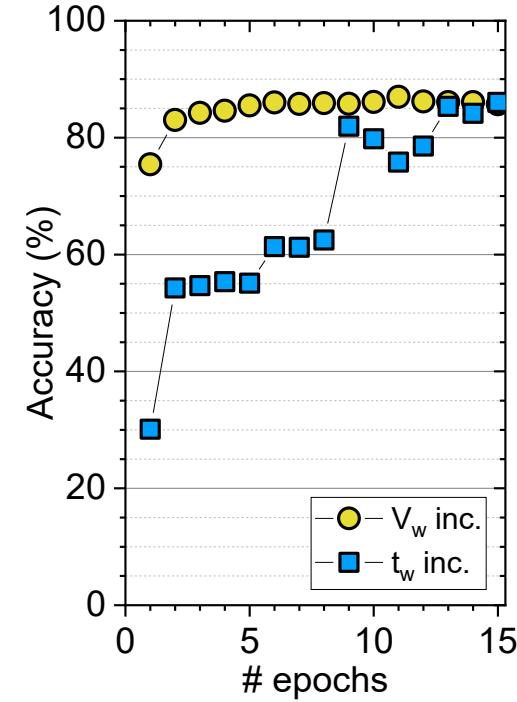
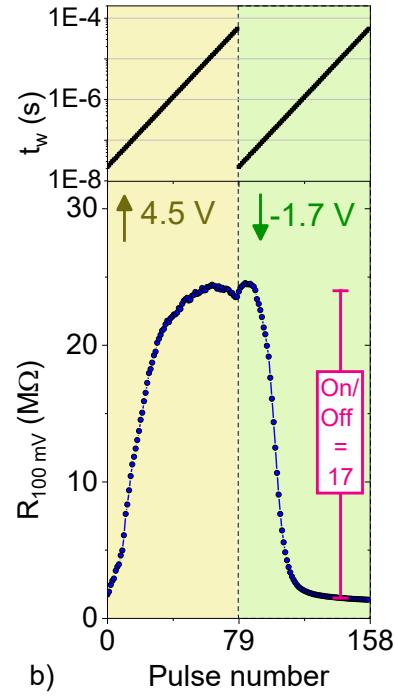
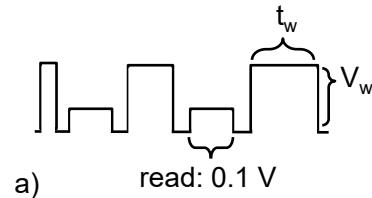


The coercive field depends on the programming pulse duration, but asymmetrically.

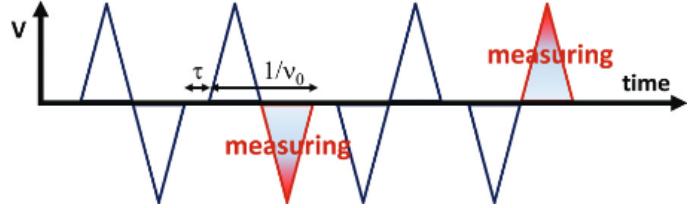


# Increasing pulse width scheme: slower convergence than increasing amplitude scheme, same accuracy.

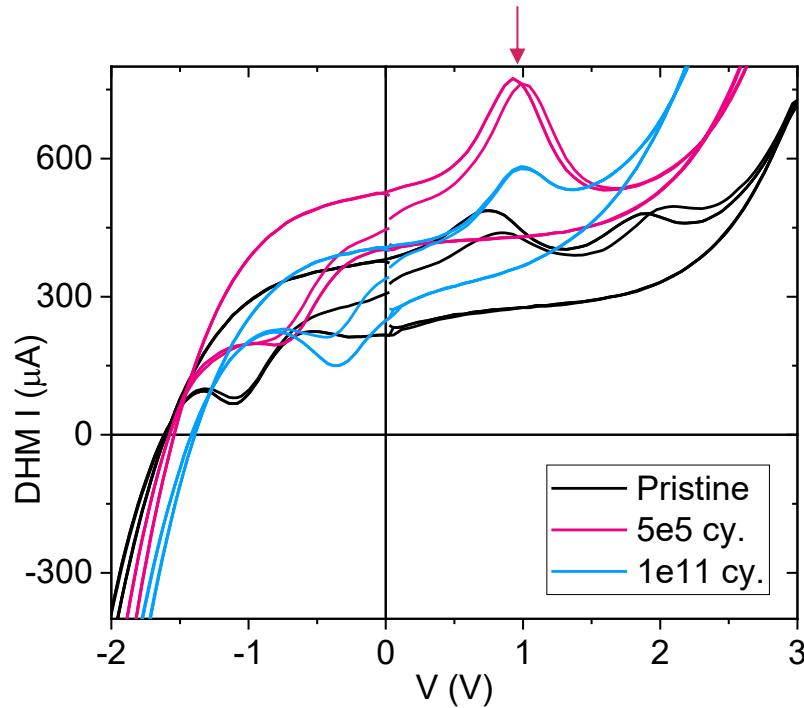
NeurosimMLP+V3.0 simulation framework (Luo 2019)  
Estimated accuracy of a ANN with 400, 100 and 10 neurons in the input, hidden and output layers (MNIST dataset).



# Ferroelectric characterization: Dynamic Hysteresis Mode & 3V endurance up to $10^{11}$ cycles.



Switching peak observed at 1V, but no saturation in the electroresistance loop: indicates non-ferroelectric contributions.



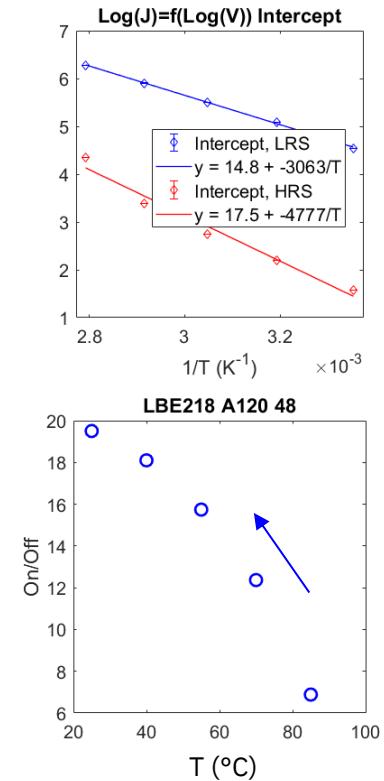
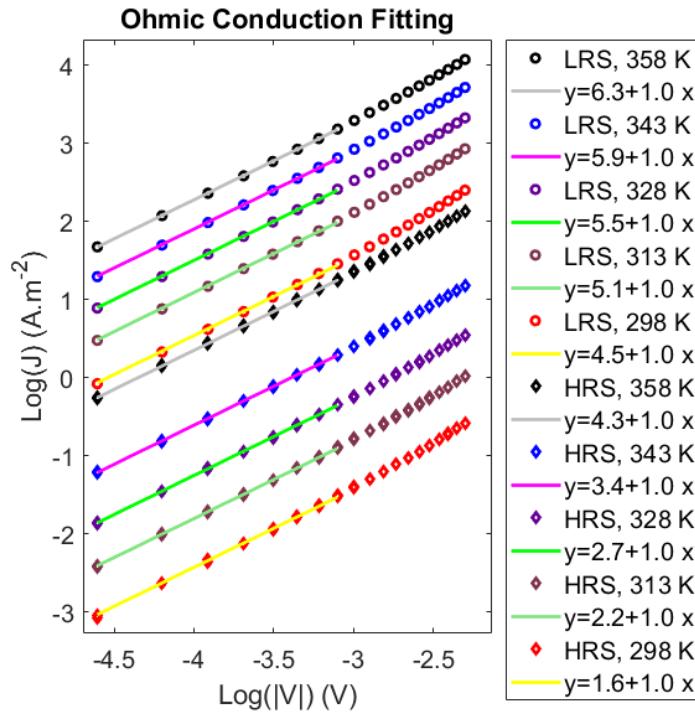
# Linear weight read for analog computing

**Linear** (Ohmic) conduction, ideal for implementing vector-matrix multiplications.

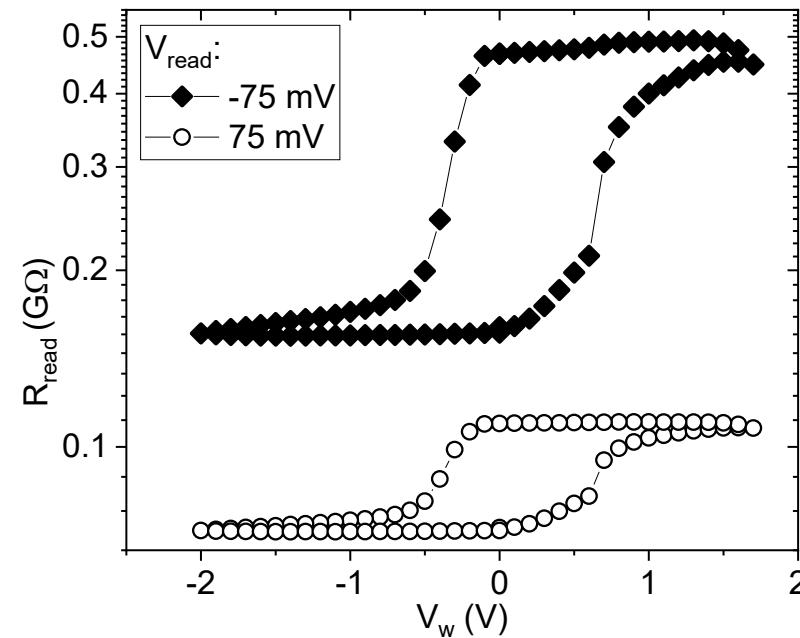
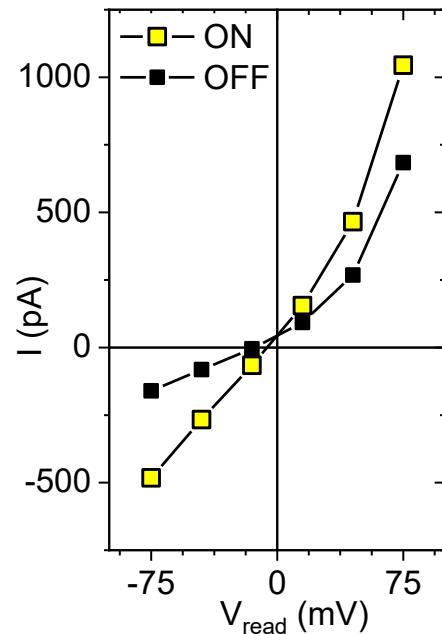
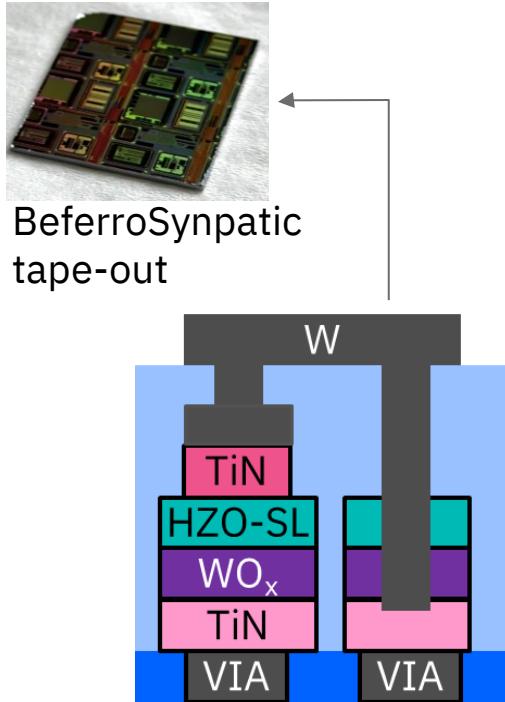
$$J = q\mu N_C \exp(-(E_C - E_F)/kT) E$$

Temperature dependent measurement in the On and Off states:

**Cumulated contributions** of a change in the energy barrier (**0.26 / 0.41 eV**) and a change in the carrier concentration \* mobility product (**8.7e14 / 1.2e16 (cm.V.s)<sup>-1</sup>** at RT).

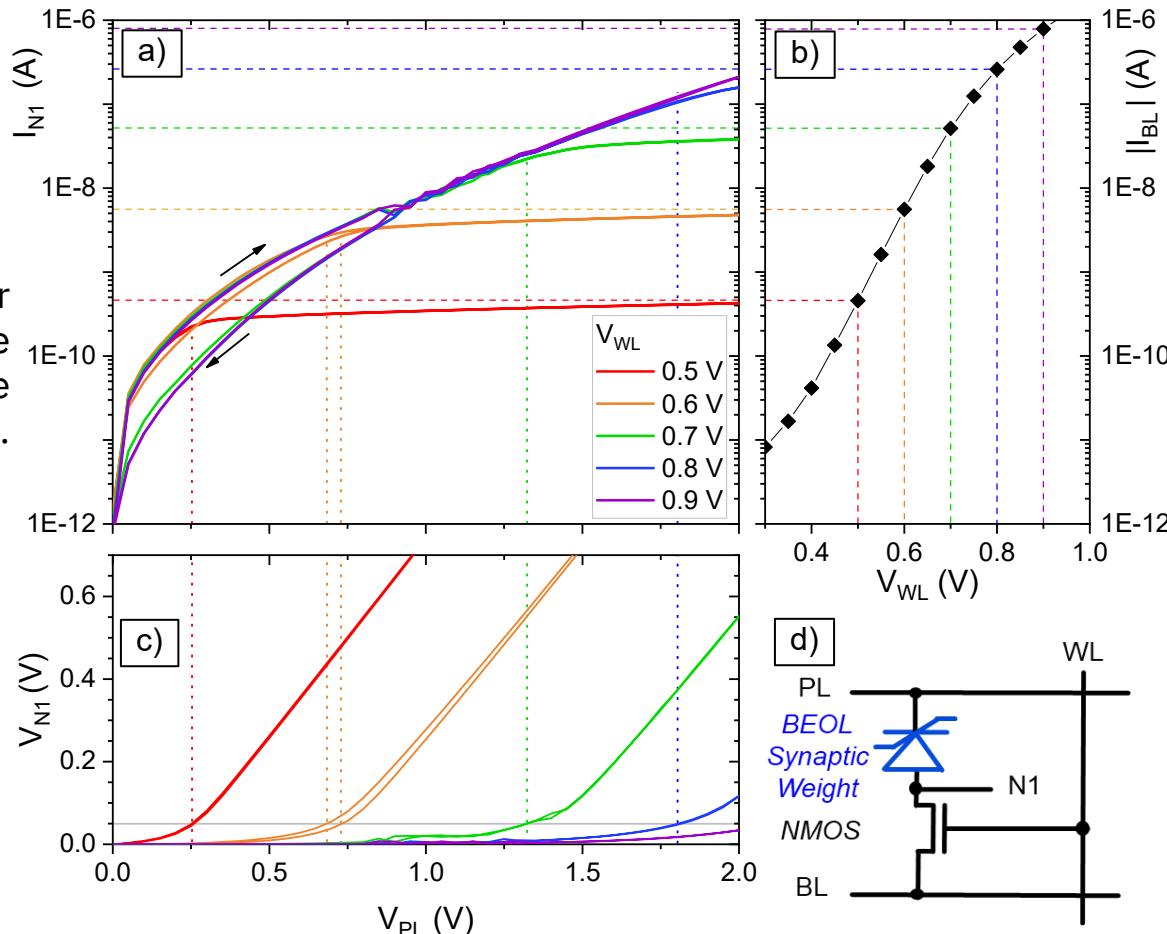


# Successful co-integration of HZO-SL synaptic weights to XFAB 180 nm CMOS: analog resistive switching



# Multi-level, 1T-1R operation.

$I_{N1} = f(V_{PL})$ , for various gate voltage  $V_{WL}$  on the NMOS transistor.



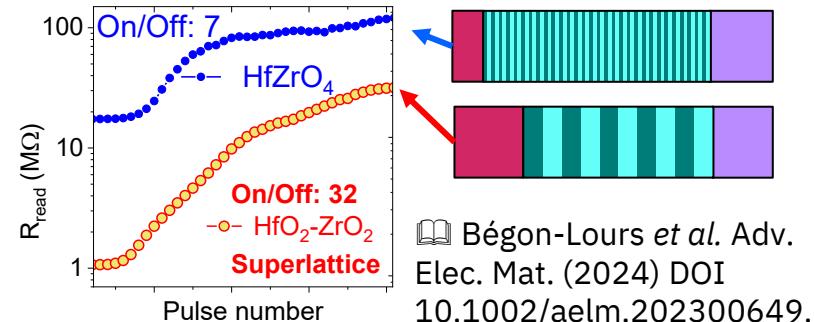
NMOS  
 $Id-Vg$ : the compliance observed in a) originates from the NMOS

The compliance gives rise to a potential  $V_{N1}$  at the source of the NMOS.

Bégon-Lours et al., under review in Adv. Elec Materials

# Summary: ultra-thin HfO<sub>2</sub>-ZrO<sub>2</sub> nanolayers

- CMOS integration of HZO was compromised by the temperature / footprint /  $I_{OFF}$  constraints.
- The novel HfO<sub>2</sub>/ZrO<sub>2</sub> superlattice synaptic weights exhibit:
  - Large On/Off up to 32
  - x8 improve in scalability,
  - Ultra-fast switching (20 ns),
  - Linear read out (in On and Off states),
  - High endurance ( $10^{11}$  full switching cycles).
- The cointegration of HZO-Superlattice to CMOS was successful:
  - Analog Resistive Switching
  - Multi-Level 1T-1R operation
- Outlook: hardware for artificial neural networks, supporting bio-inspired computing.



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