Scalable Algorithms for Neuromorphic In-Memory Computing with N-ary Spintronic Crossbar Arrays

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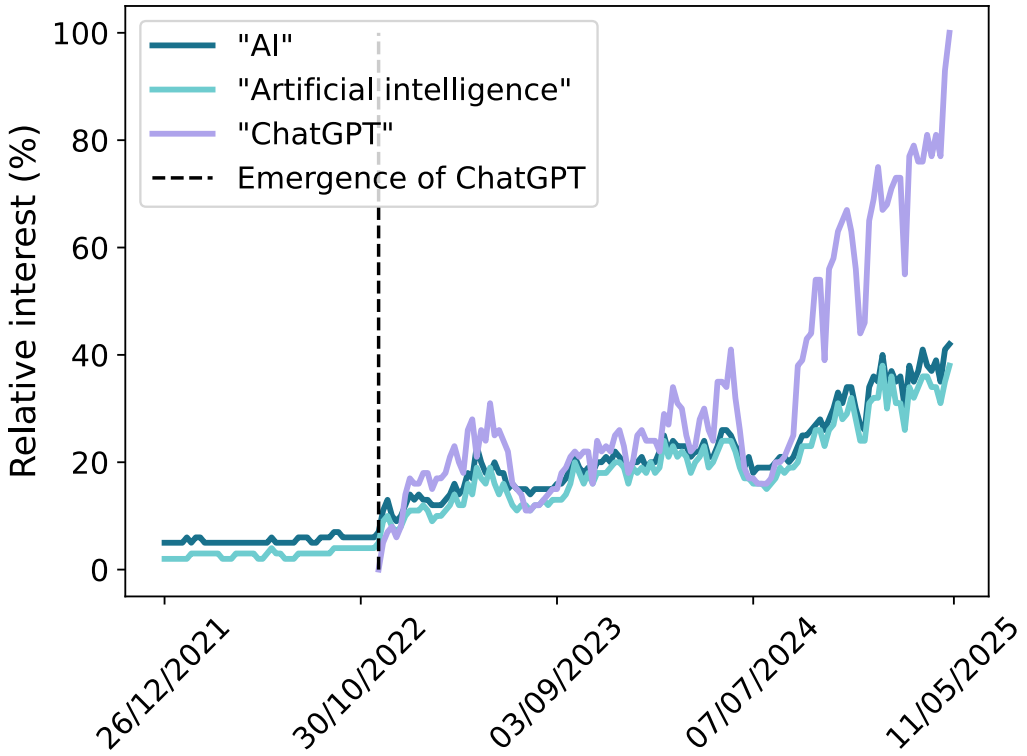
SPIE. OPTICS+ PHOTONICS

Strasbourg (France) | April 13, 2026

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FREEDOM TO RESEARCH

Artificial Intelligence from 2022

Growing interest on the Internet



AI chatbots that feel human…

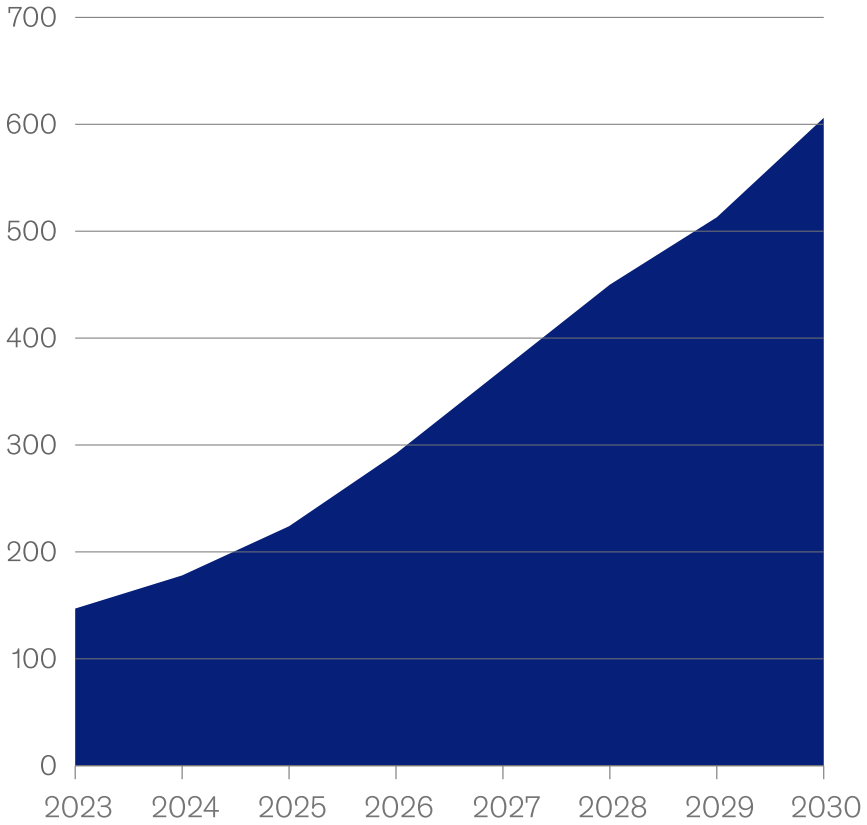


Google Trends (2025); *Global Energy Perspective 2023*, McKinsey, Oct 18, 2023; McKinsey analysis

Artificial Intelligence from 2022

Growing energy demand

Projected US datacenter energy consumption (TWh)



AI chatbots that feel human…

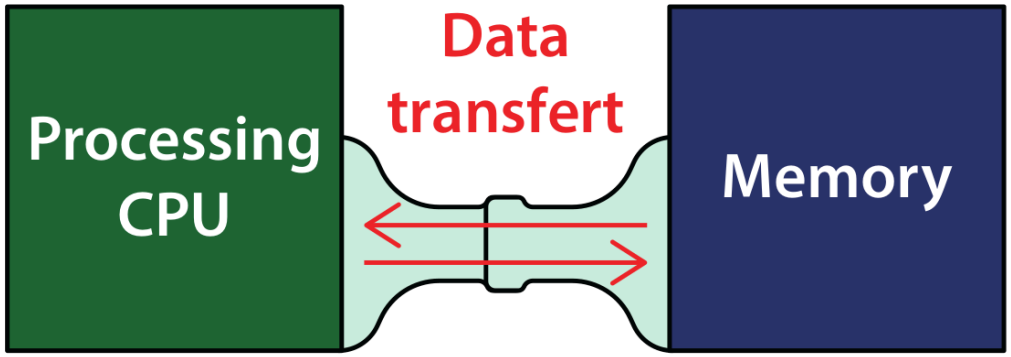
but are far less power-efficient than humans



Google Trends (2025); *Global Energy Perspective 2023*, McKinsey, Oct 18, 2023; McKinsey analysis

Digital computing systems are not flawless

von Neumann bottleneck

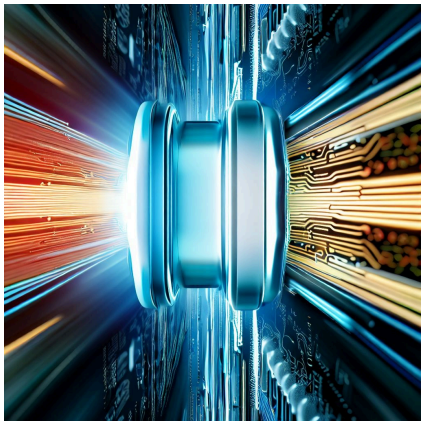


Time and energy consuming !

AI = Huge amount of simple operations…

…performed with high-precision hardware

DALL-E 3 prompt:
"A bottleneck representing limitations due to the separation between the CPU and the RAM"



130 kW !

⇒ slow and energy-hungry !

Digital computing systems



- **High-precision**
- **Separate from memory**
- **Limited parallelization**

VS

Mammalian brain



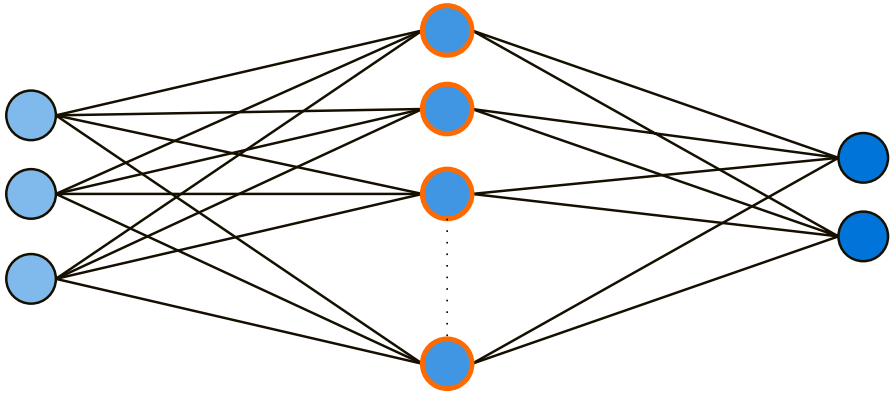
- **Low-precision**
- **Processing (neurons) and memory (synapses) intertwined**
- **Highly parallel**

Neuromorphic computing: Low power, analog, brain-inspired computing systems.

Neuromorphic spintronics: Neuromorphic computing systems based on **spintronic (nano)devices and phenomena**

Neural networks in a nutshell

Nonlinearity

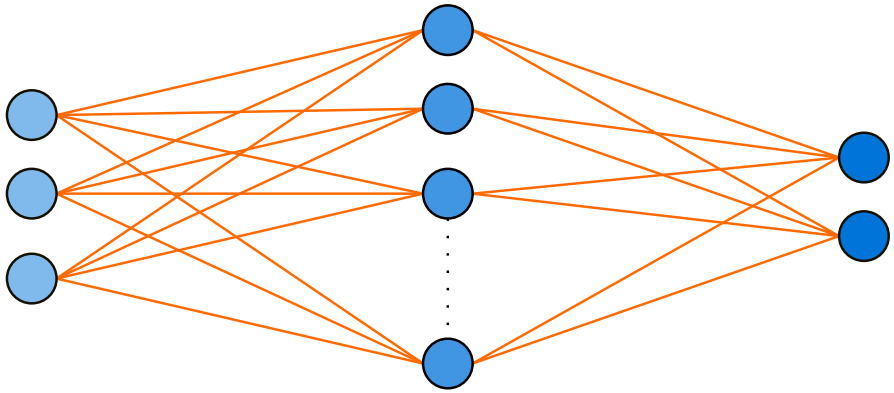


Nonlinear transformation of the input x in the neurons

$$y_{i,h} = \sigma\left(x_{i,h}\right)$$

ex: $\sigma \equiv$ sigmoid, tanh, reLU, …

Weighted sums



Weighted summation of the neurons output for computing the input of the next neurons.

The weights are learned during training.

$$x_{i,h} = \sum_{j} w_{ij} y_{j,(h-1)}$$

The Multiply-and-Accumulate (MAC) operation

The **MAC operation** is a **matrix-vector multiplication** written as

$$\boldsymbol{Ax} = \boldsymbol{b}$$

with:

- $\boldsymbol{A}$: $(m \times n)$ matrix
- $\boldsymbol{x}$: vector of length (n) corresponding to the **input**
- $\boldsymbol{b}$: vector of length (m) corresponding to the **ouput**

Each element b_i is the result of the weighted sum:

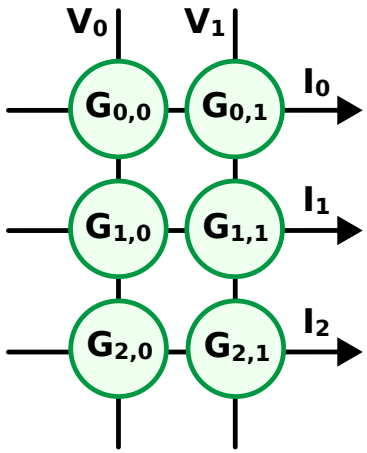
$$b_i = \sum_j A_{ij} x_j$$

Ex: $$\begin{pmatrix} b_0 \\ b_1 \\ b_2 \end{pmatrix} = \begin{pmatrix} A_{00} & A_{01} & A_{02} \\ A_{10} & A_{11} & A_{12} \\ A_{20} & A_{21} & A_{22} \end{pmatrix} \begin{pmatrix} x_0 \\ x_1 \\ x_2 \end{pmatrix}$$

$$b_1 = A_{10}x_0 + A_{11}x_1 + A_{12}x_2$$

Hardware binary MAC implementation

Physical implementation



Multiplication
Ohm's law

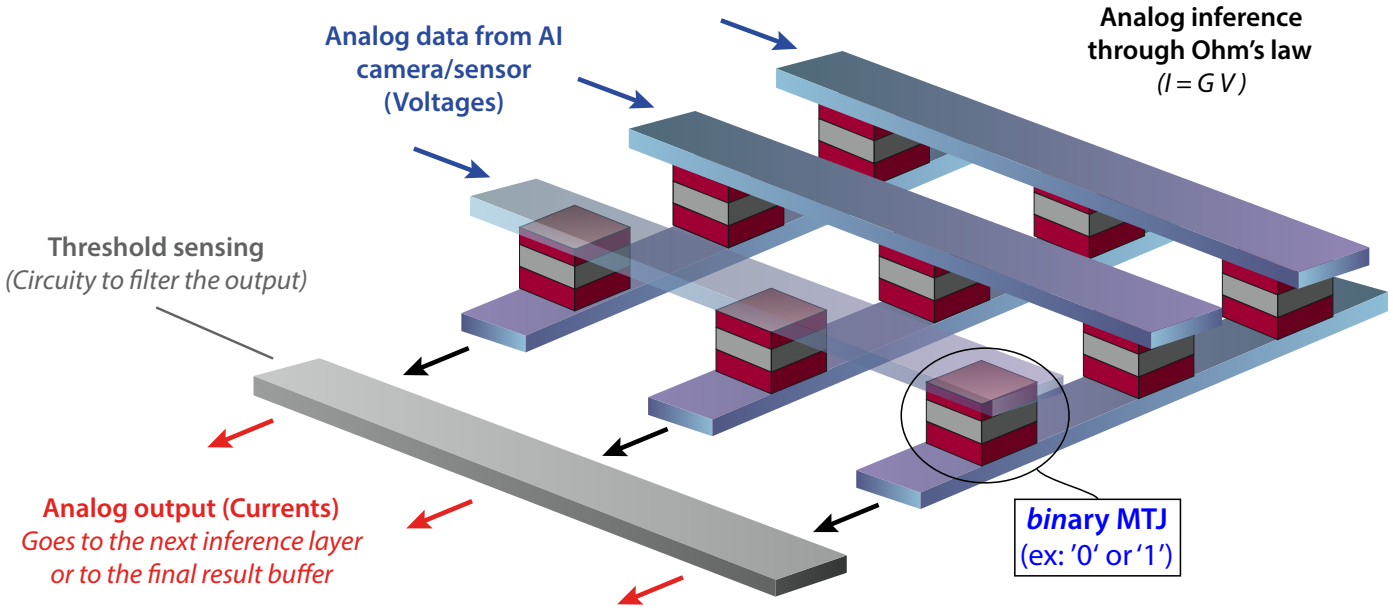
Accumulation
Kirchhoff's law

Input: Voltage V_j

Output: Current I_i

Weights: Conductances G_{ij}

Spintronics crossbar architecture (MRAM compatible):
Neural weights (cell conductance)

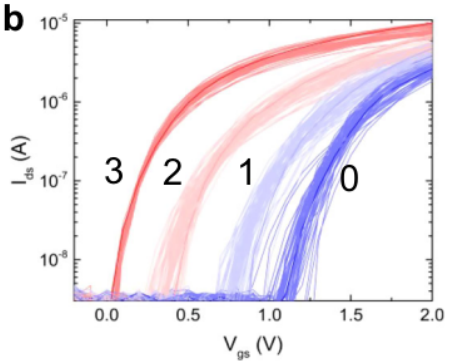


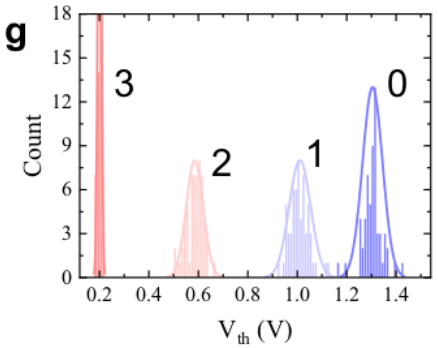
$$I_i = \sum_j I_{ij} = \sum_j G_{ij} V_j \iff \underline{I} = \underline{\underline{G}} \cdot \underline{V}$$

S. Jung *et al.*, *Nature* **601**, 211-216 (2022).

Hardware *n*-ary MAC operations

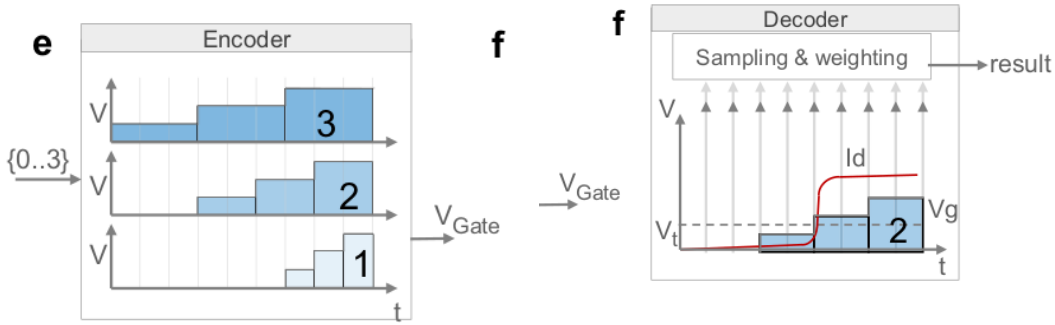
4 weights encoded in the V_{th} of the FET





Higher weight ⇒ FET triggering is faster

4 input levels in a **gate voltage** signal V_g



Higher input ⇒ V_g increases sooner

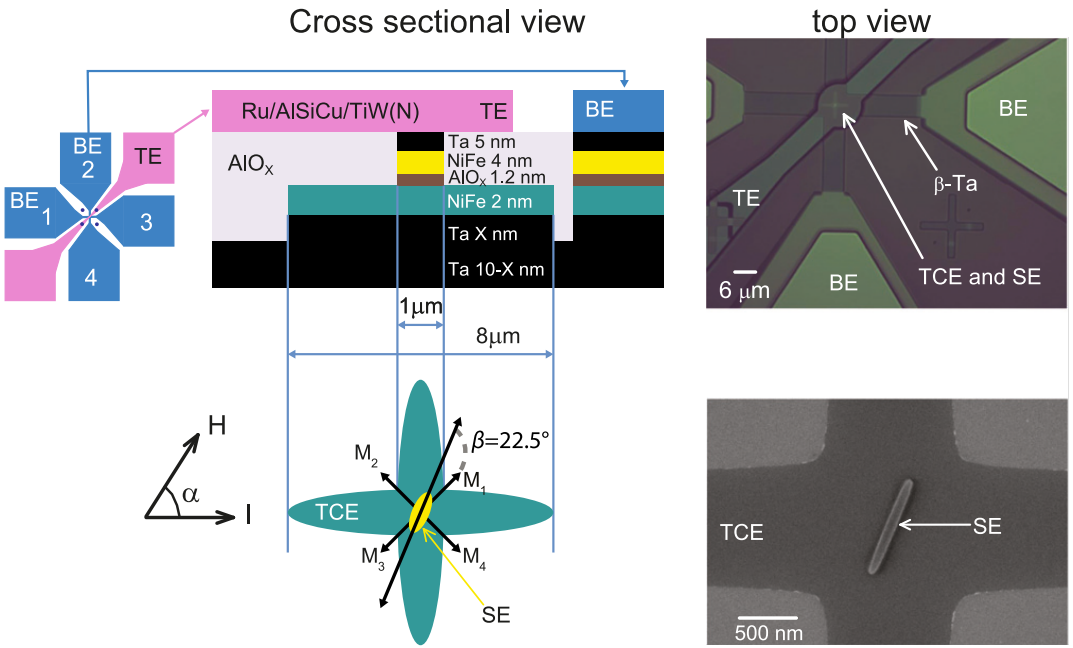
- **Multiplication**: time needed FET to trigger
- **Accumulation**: **capacitor** charged by the drains currents **along each line**

+ Overcomes computational limitations of binary crossbar

- Slower readout due to time needed to charge capacitor

T. Soliman *et al.*, *Nature Communications* **14**, 6348 (2023).

M^2TJs as multistate memristive cells



Key points:

- Use **four states** (*or more*) states for encoding the weights
- **M^2TJs versatility**: large range of different implementations (*current/resistance summation, encoding method, etc*)

⇒ **Improved computing power**

Conductance/resistance of the cell is tuned via the free layer magnetization

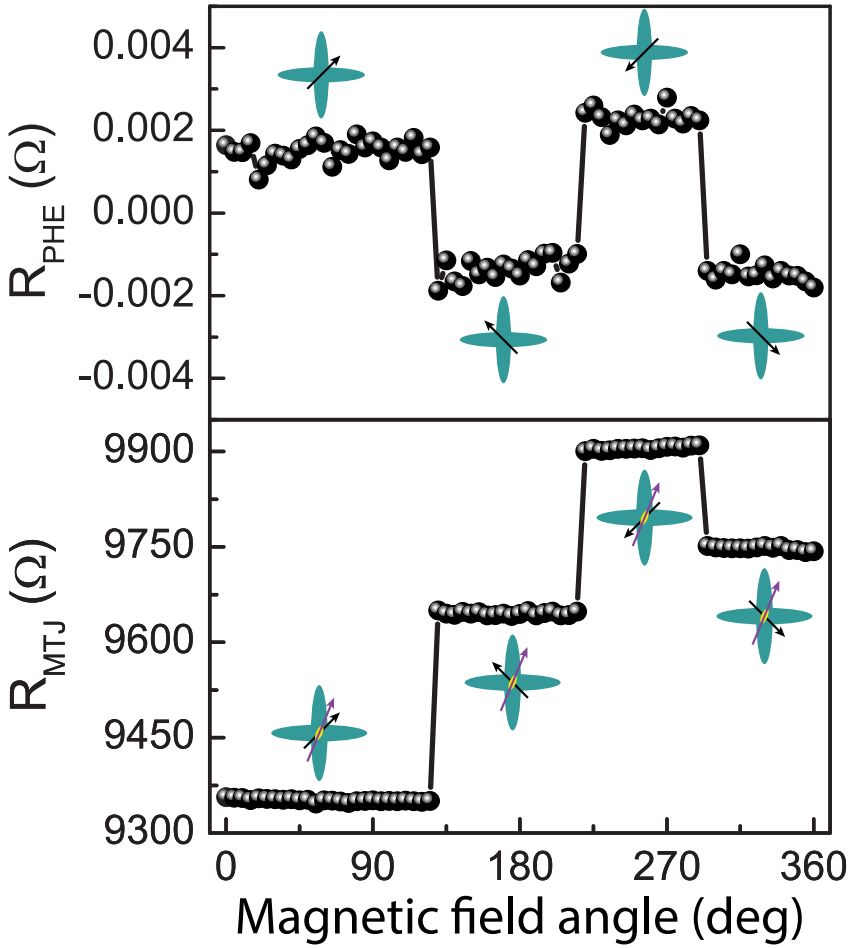
The references made here to S. Das *et al.* belong to our partners from BIU & INESC MN.

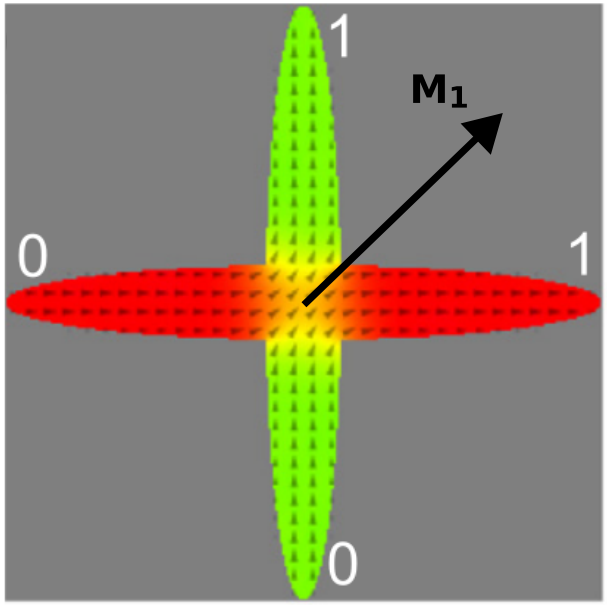
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Bar-Ilan University

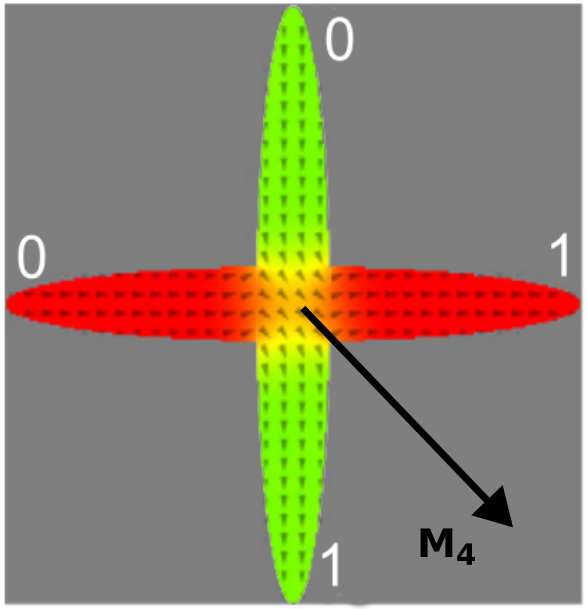
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S. Das *et al.*, *Applied Physics Letters* **116**, 26 (2020). | S. Das *et al.*, *Applied Physics Letters* **117**, 7 (2020).

M^2TJs as multistate memristive cells: writing the states







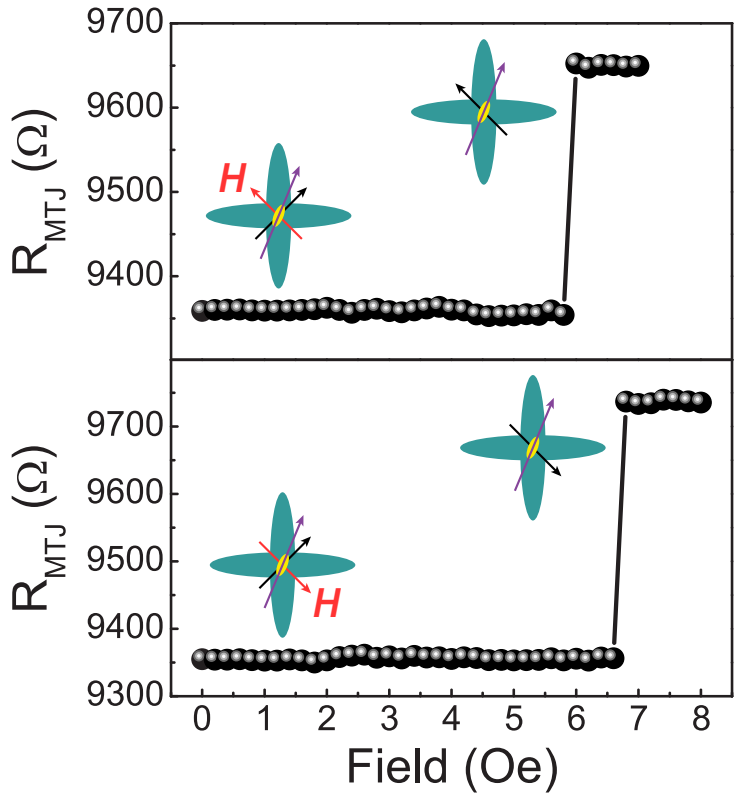
External magnetic field selects a magnetization state *M* in the free layer, hence controlling the misalignment with the magnetization of the fixed layer.

$$G_{ij}(\text{state}) = \frac{1}{R_{ij}(\text{state})} = \frac{1}{R_{ij}(\text{angle}, \text{noise})}$$

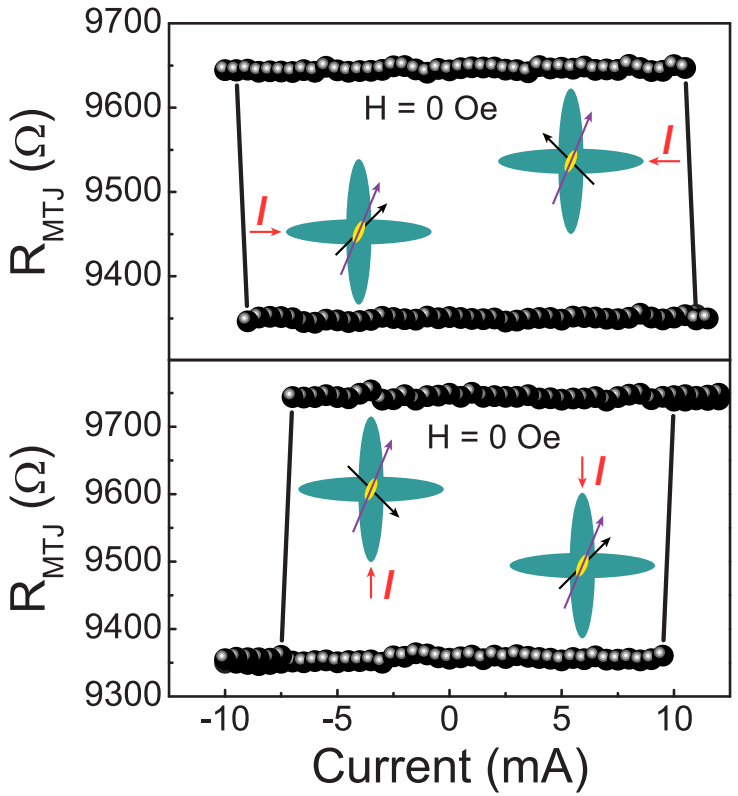
S. Das *et al.*, *Applied Physics Letters* **116**, 26 (2020). | S. Das *et al.*, *Applied Physics Letters* **117**, 7 (2020).

M^2TJs as multistate memristive cells: writing the states

Magnetic field switching



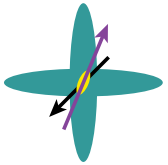
Spin-orbit torque (SOT) switching

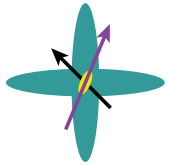


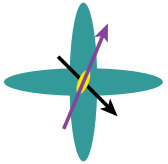
S. Das *et al.*, *Applied Physics Letters* **116**, 26 (2020). | S. Das *et al.*, *Applied Physics Letters* **117**, 7 (2020).

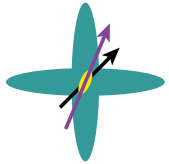
Encoding 4 states (2 bits)

⇒ 4-states junctions: R_{MTJ} =


~101.01 μS (state 1)


~103.41 μS (state 3)

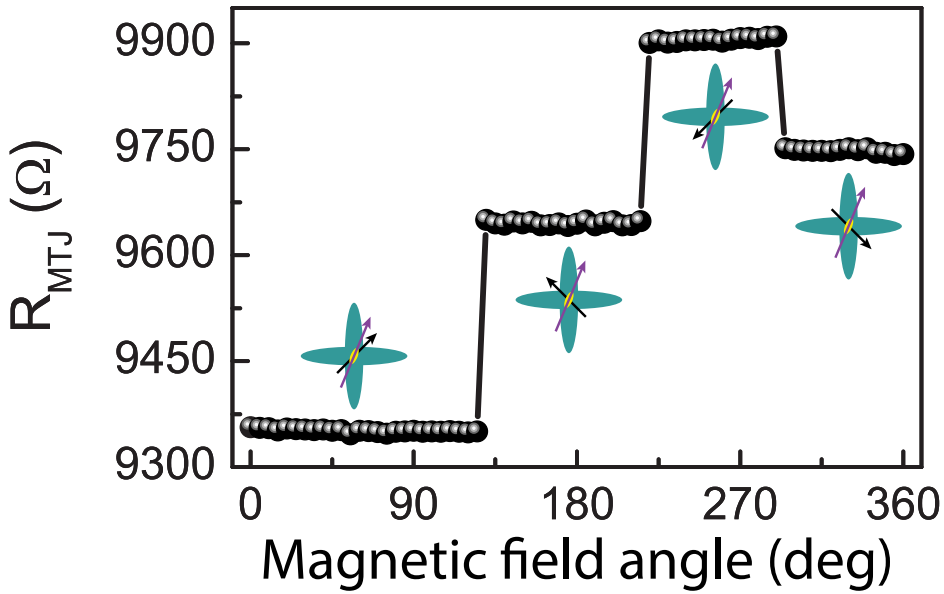

~102.56 μS (state 2)


~106.72 μS (state 4)

Magnetic field switching

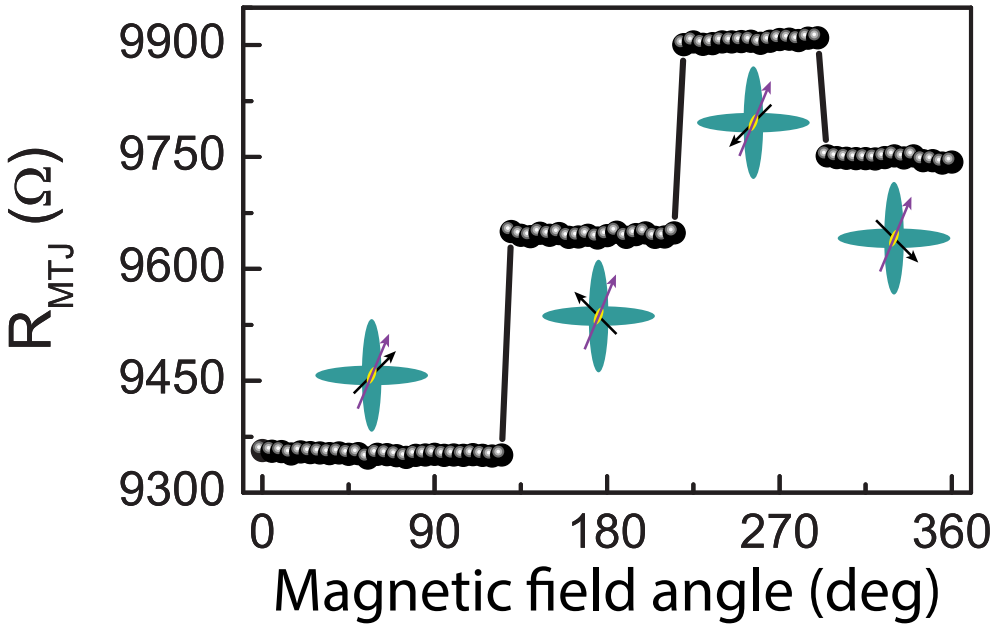
or

Spin-orbit torque switching



S. Das *et al.*, *Applied Physics Letters* **116**, 26 (2020). | S. Das *et al.*, *Applied Physics Letters* **117**, 7 (2020).

M²TJs non-idealities



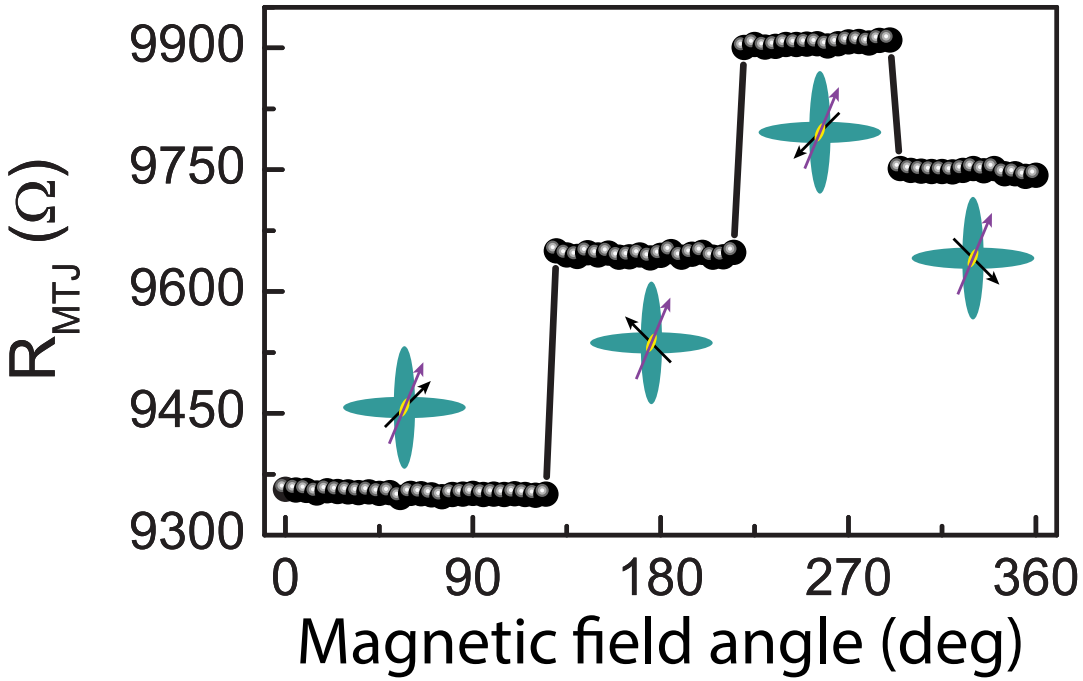
2 Challenges:

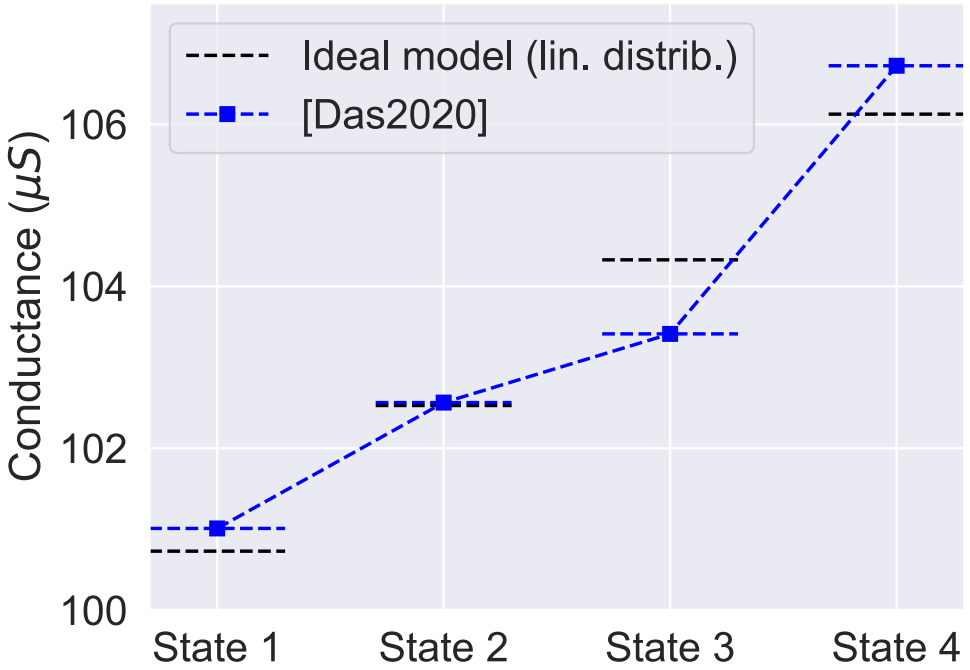
1. States are not increasingly ordered
2. States are not equidistant (not linearly distributed)

S. Das *et al.*, *Applied Physics Letters* **116**, 26 (2020). | S. Das *et al.*, *Applied Physics Letters* **117**, 7 (2020).

Linear approximation of the conductance states distribution

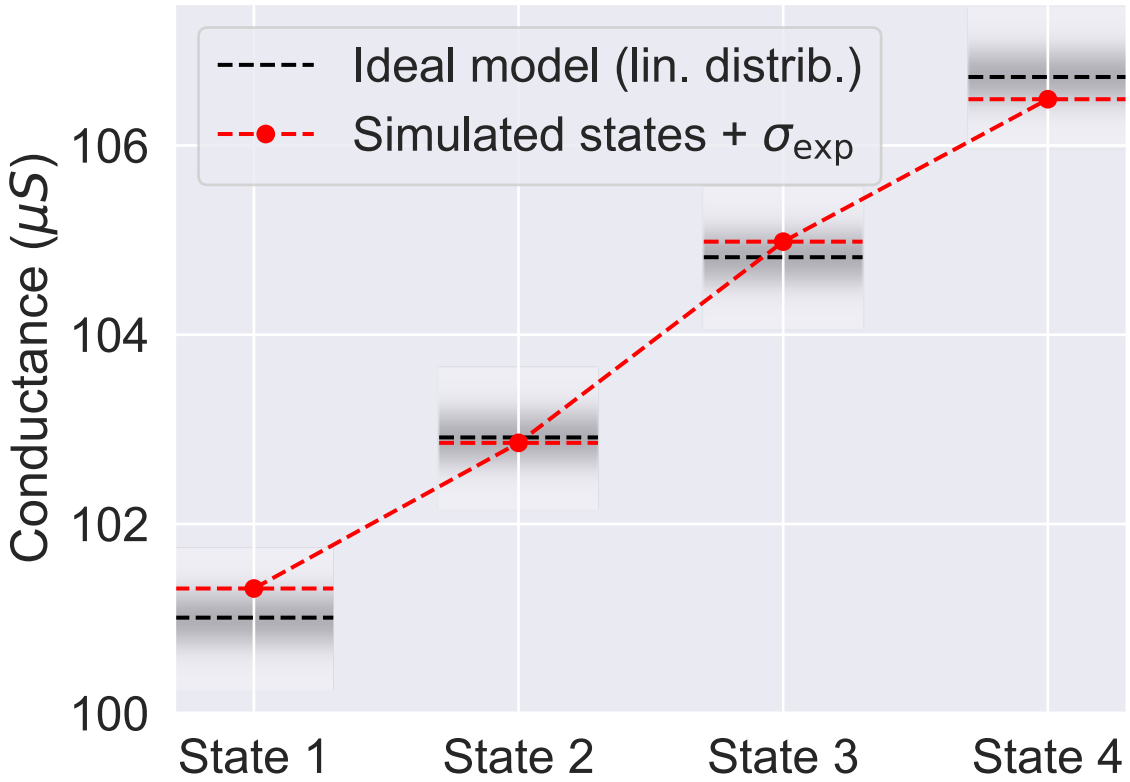
- The states of the **full crossbar** are modeled with a **linear regression**.
- 4 (generalized to ***n***) theoretical and **ideal states** are obtained.
- **Normally distributed** variabilities tend to vanish for large crossbar.
- **Cell-to-cell variability** and **measurement noise** can be included.





S. Das *et al.*, *Applied Physics Letters* **116**, 26 (2020). ; S. Das *et al.*, *Applied Physics Letters* **117**, 7 (2020).

Experimental (measurement) noise



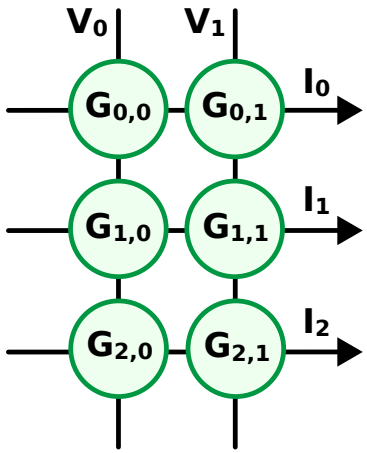
Example when $\sigma_{exp} = 0.25\mu$ S

In the **linear distribution** case:

- Assessment of **noise** affecting the **measurement of the current**
- Additive **Gaussian white noise** ($\mu = 0$ and $\sigma = \sigma_{exp}$)

Hardware *n*-ary MAC implementation

Physical implementation



Multiplication
Ohm's law

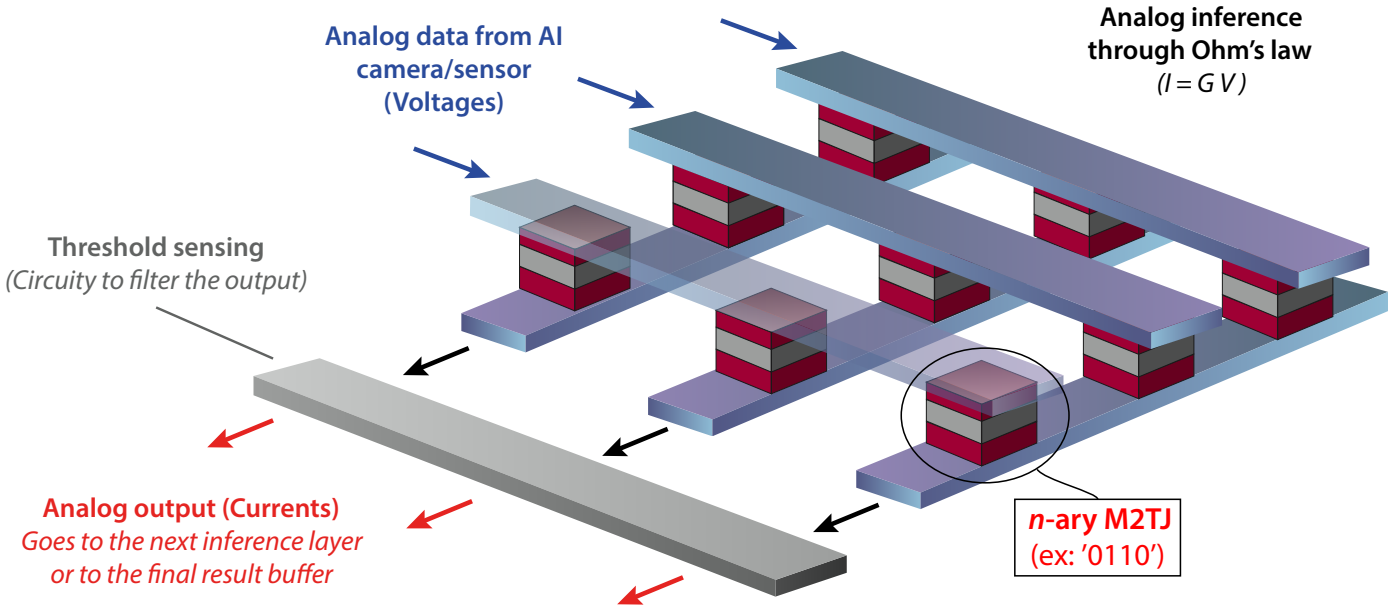
Accumulation
Kirchhoff's law

Input: Voltage V_j

Output: Current I_i

Weights: Conductances G_{ij}

Spintronics crossbar architecture (MRAM compatible):
Neural weights (cell conductance)



$$I_i = \sum_j I_{ij} = \sum_j G_{ij} V_j \iff \underline{I} = \underline{\underline{G}} \cdot \underline{V}$$

S. Jung *et al.*, *Nature* **601**, 211-216 (2022).

IMC and multistate implementation

Presentation of the **multistate IMC algorithm**:

- assumptions

$$\boldsymbol{I} = a_I \boldsymbol{x} + b_I \qquad R_{mn} = a_R A_{mn} + b_R$$

- **output signal to MVM result conversion**

$$\tilde{\boldsymbol{y}} = \frac{\boldsymbol{V} - b_R\left(nb_I + a_I\left(\boldsymbol{x}^T \cdot \boldsymbol{1}\right)\right)\boldsymbol{1} - a_R b_I(\boldsymbol{A}\cdot\boldsymbol{1})}{a_R a_I}$$

- weights quantization

$$\underset{A}{\operatorname{argmin}} \sum_{i=1}^{N} \sum_{w \in A_i} |w - A_i|^2 \quad \text{with} \quad A_i - A_{i-1} = d$$

Validation on the XOR approximation task

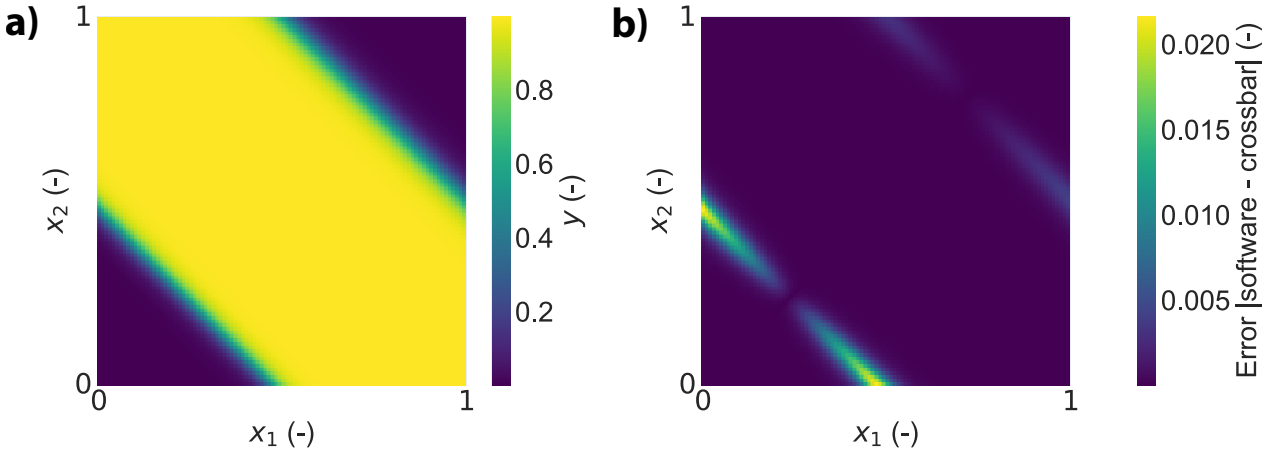
- In **noiseless conditions**, the crossbar MVM result is very close to the software MVM result:

x_1	x_2	y	$\hat{y}_{CPU}$	$\hat{y}_{crossbar}$
0	0	0	0.	7.726×10^{-6}
0	1	1	1.	9.998×10^{-1}
1	0	1	1.	9.998×10^{-1}
1	1	0	0.	1.021×10^{-3}

- Only error due to a small **shift of the weights** from quantization:

$$\boldsymbol{W}: \begin{pmatrix} 11.97 & 12.06 \\ 8.57 & 8.58 \end{pmatrix} \rightarrow \boldsymbol{A}: \begin{pmatrix} 12.01 & 12.01 \\ 8.58 & 8.58 \end{pmatrix}$$

- In **noiseless conditions**, the error is localized on the decision boundaries (best case):



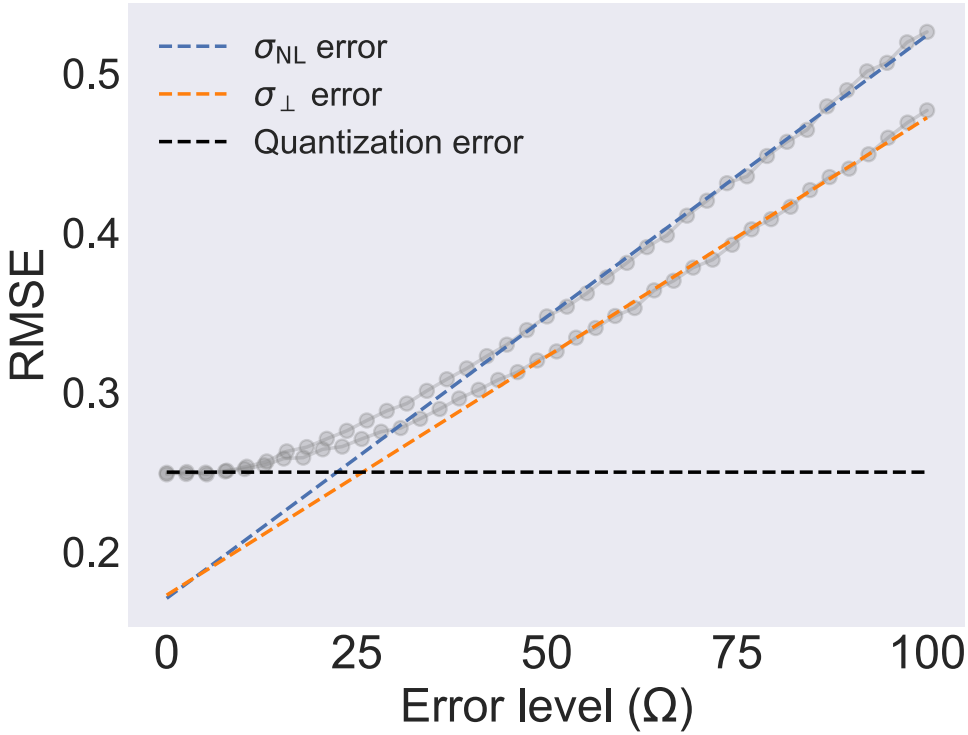
Validation on the MNIST classfication task (noiseless)

Need a more complex task to validate the method: MNIST classification with a simple ANN architecture (784-128-10) on a (4 x 4) crossbar array with 4 states

- **Software accuracy: 97.56%**
  Crossbar accuracy: 94.48% (3.08% drop)
  Requires 6272 sub-operations per inference !
- PCA dimensionality reduction: Input dimension 784 → 87 while keeping 90% of the data variance
  Software accuracy: 98.03% due less noise in the data
  Crossbar accuracy: 95.24% (2.79% drop) due to less noise in the data and simpler architecture
  Requires "only" 704 sub-operations per inference

Systematic and cell-specific errors assessment

- **Systematic nonidealities**: nonlinearly distributed states (shared by all the devices) (σ_{NL})
- **Cell-specific nonidealities**: resistance noise and device-to-device variations ($\sigma_{\perp}$)



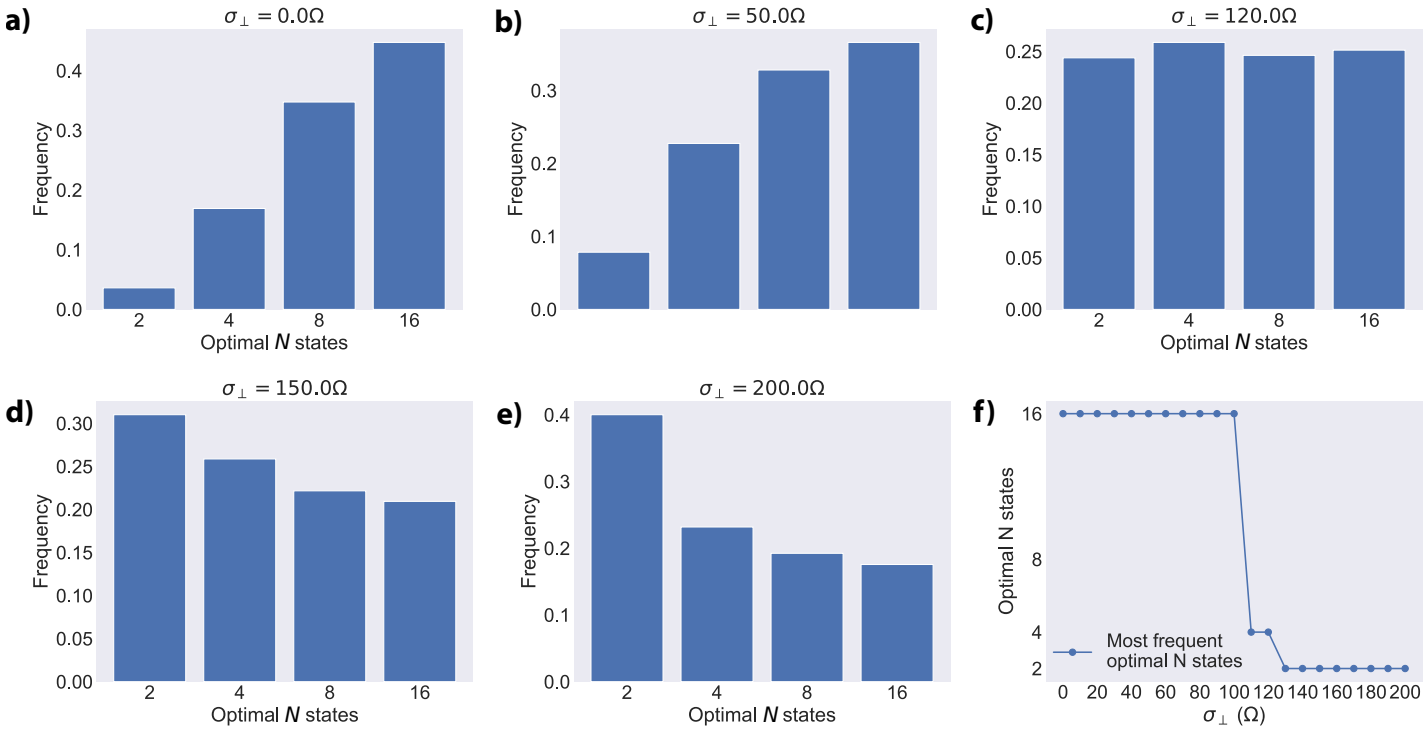
At low nonideality levels, the error is dominated by quantization (1/N).

For higher nonideality levels, the error is dominated by the nonidealities and becomes independent of N.

Error due to cell-specific nonidealities is less constraining than error due to systematic nonidealities, thanks to averaging over the array.

Optimal number of states

There is a trade-off between the gain of increasing the number of states (**decrease the quantization error**) and the increase of the error due to nonidealities (**loss of resolution**).



Theoretically, we have

$$N_{\text{opt}} \propto \left\lfloor \frac{R_{\text{max}} - R_{\text{min}}}{\sqrt{\sigma_{\text{NL}}^2 + \sigma_\perp^2}} \right\rfloor$$

but the curve on f) is "truncated step" looking due to constraining the N values to [2, 4, 8, 16].

Conclusion & take-home message

- The **deviation from perfectly linearly distributed states** induces an **intrinsic error** in the MAC operation.
- The **SNR however increases** when the **number of columns in the matrix** increases. Hence the array is optimized for multiplying vectors and **wide matrices**.
- The SNR should also increase with the number of columns when considering the **measurement noise**.
- We developed a framework for **dealing with the non-idealities** of M^2TJs crossbar arrays for performing the MAC operation.
- The framework allows to assess the **impact of experimental noise and device non-idealities** on the quality of the MAC operation.
- Simulated M^2TJs crossbar arrays were successfully used to **solve the XOR problem** using a simple neural network.

Aknowledgements

Neuromorphic Engineering Group @ UCLouvain



Prof. Flavio ABREU ARAUJO
Group leader



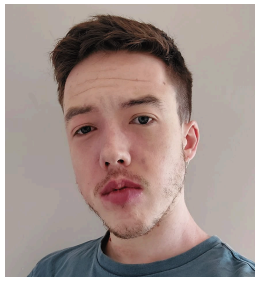
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Dr. Simon DE WERGIFOSSE
Post-doctoral researcher
(soon @ SPINTEC, FR)



Anatole MOUREAUX
Doctoral researcher



Anthony LOPES TEMPORAO
Doctoral researcher



Colin DUCARME
Doctoral researcher



Thomas COPPÉE
Doctoral researcher

MULTISPIN.AI
AI Co-Processor Research Project

Funded by the European Union

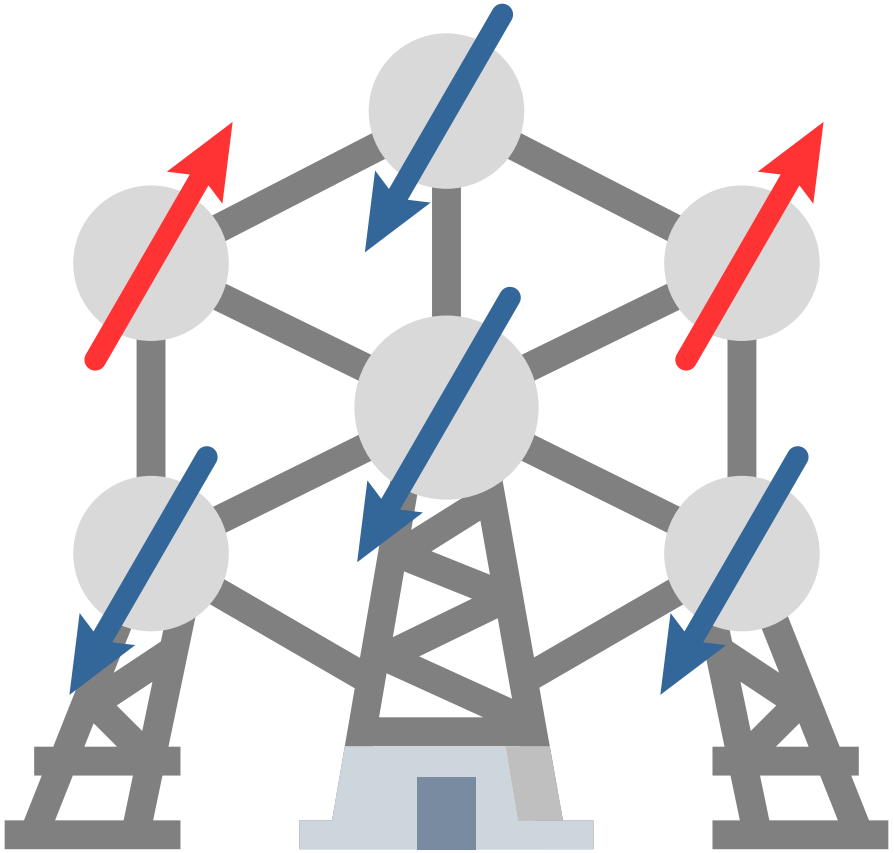
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FREEDOM TO RESEARCH

23rd Louis Néel Colloquium (CLN2026) — Save the date!



- **Date:** 8–11 September 2026
- **Location:** UCLouvain, Louvain-la-Neuve, Belgium
- **Topics:**
  - Nanomagnetism & magnetic materials
  - Spintronics & spin transport
  - Domain walls & spintronic devices
  - Molecular & low-dimensional magnetism
  - Emerging topics (AI, neuromorphic computing…)
  - Special PEPR SPIN session
- **Format:** 200 participants, 6 oral sessions, 2 poster sessions, keynote lecture, gala dinner
- **Abstract submission:** April 17 – May 15, 2026
- **Website:** cln2026.sciencesconf.org
- **Contact:** flavio.abreuaraujo@uclouvain.be