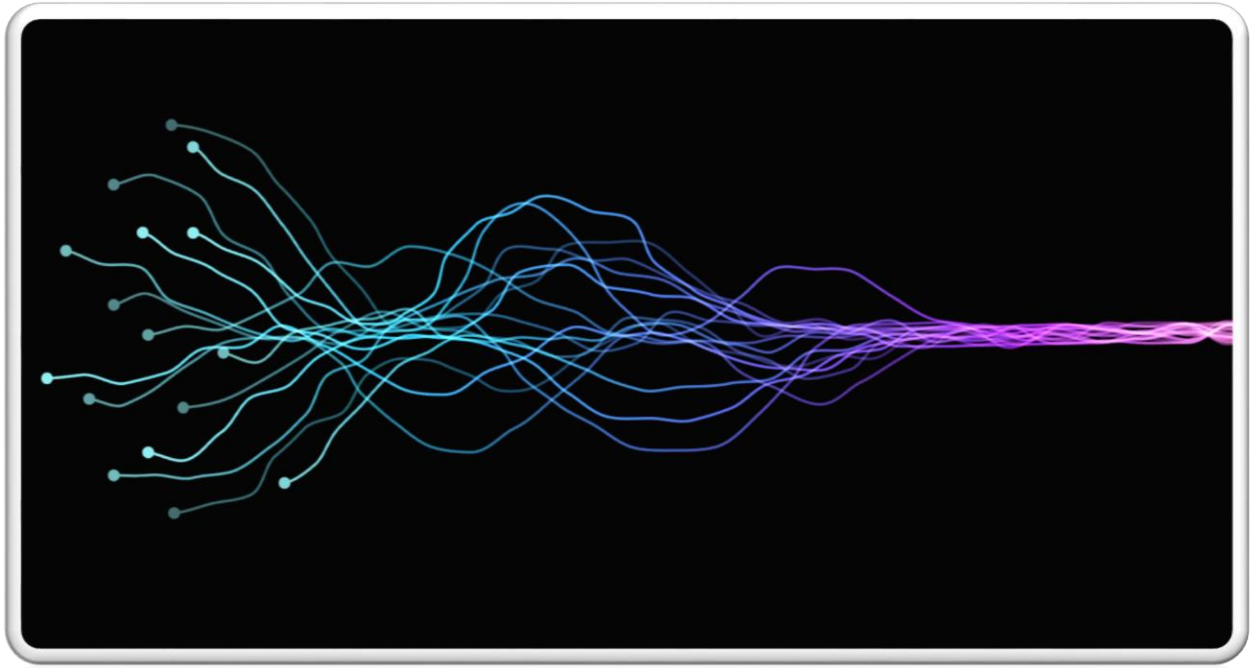
Edge AI
How to bring AI at the edge of the physical world

Benoît Miramond / LEAT



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Outline

- LEAT research lab
- Edge AI
- Different Edge lines
  - Edge lines and properties
  - Some examples studied at LEAT
- Smart sensors: When AI touches the physical world
  - A matter of energy
- The bio-inspired approach
- Conclusion

LABORATOIRE D'ELECTRONIQUE
ANTENNES ET TELECOMMUNICATIONS

Laboratoire d'Electronique, Antennes et Télécommunications

Unité Mixte de Recherche UMR7248
Université Côte d'Azur et CNRS

cnrs advancing the frontiers

cremant

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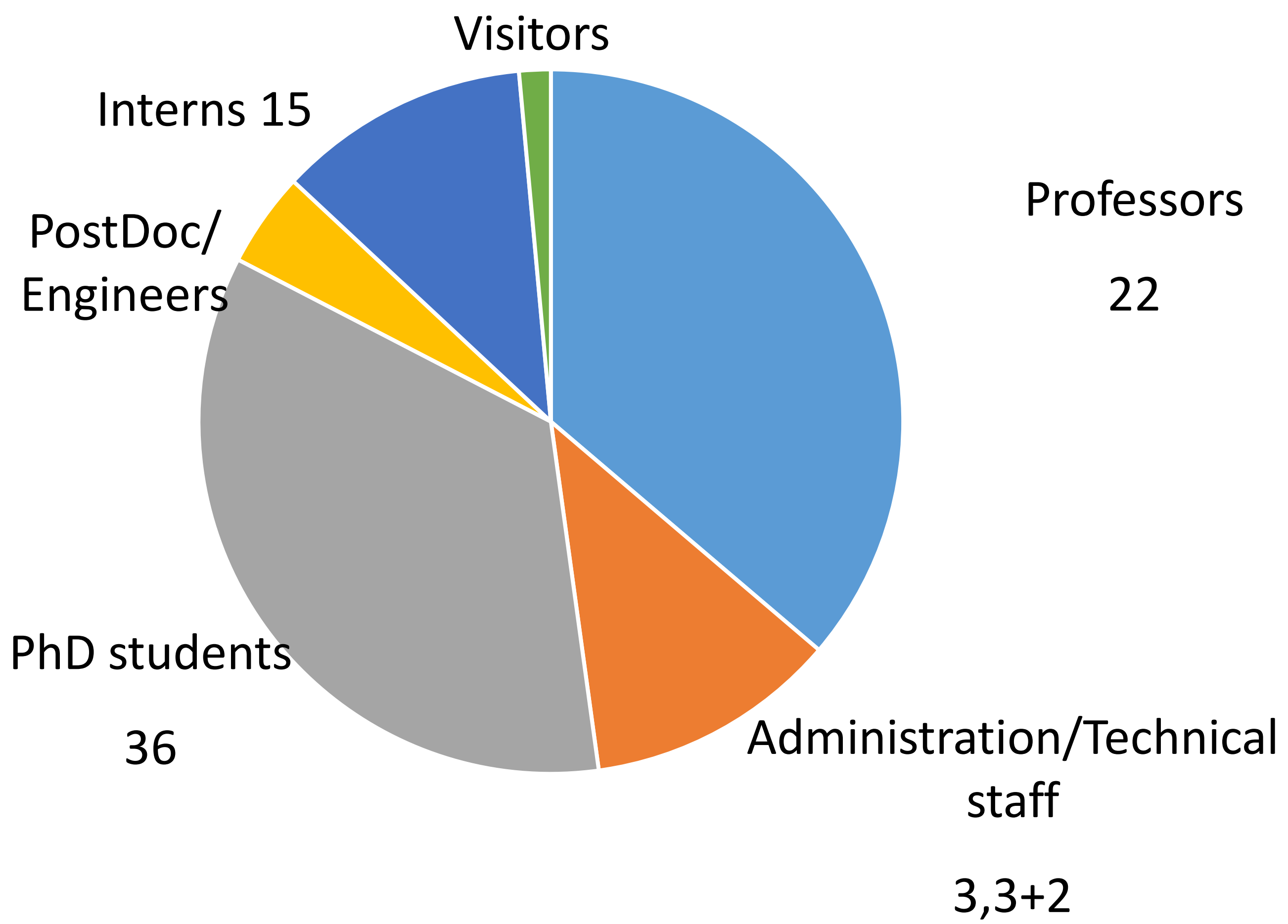
Location

Campus SophiaTech

Composition of the laboratory

Members : ~80 (June 2022)



Activities

Publications / Conferences

Patents / R&D

3 teams

Electronics/ Computer Sciences

Lab. Com. UCA/CNRS-Orange Labs

cremant

- Co-directors : Ph. Ratajczak (Orange Labs)
  F. Ferrero (UCA-CNRS)

- Joint research center
  - Orange Labs :
    Unité de recherche ANT: Antennes (Orange Labs Sophia)
    Unité de recherche WAVE: Interactions Ondes-corps humain(Orange Labs Paris)

- 2012-2022 Subjects of research
  - Integrated Antennas
  - Communications from 60 to 120 GHz
  - Sensors and sensor networks
  - New materials, electromagnetic modeling and applications

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Academic Collaborations

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BOWEN

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eDF

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NXP

GROUPE RENAULT

synopsys®

THALES

menta

Atos Bull

WIKA

Valeo

intel®

PROPHESEE
METAVISION FOR MACHINES

Research Teams

- **ISA**: **I**maging and **A**ssociated **A**ntennas **S**ystems
  Imagerie microondes et **S**ystèmes d'**A**ntennes

- **CMA**: **A**ntenna **D**esign and **M**odeling
  Conception et **M**odélisation d'**A**ntennes

- **EDGE**: **E**dge computing & **DiG**ital syst**E**ms
  Systèmes **N**umériques et **C**alcul embarqué

EDGE Team

Edge computing & **D**i**G**ital **E**lectronics

EDGE research axis

1. **eBrain** - **e**mbedded **B**io-inspi**R**ed **A**rtificial **I**ntelligence and **N**euromorphic Architectures

2. **eWISE** - **e**nergy-aware **WI**reless **S**ensor n**E**tworks

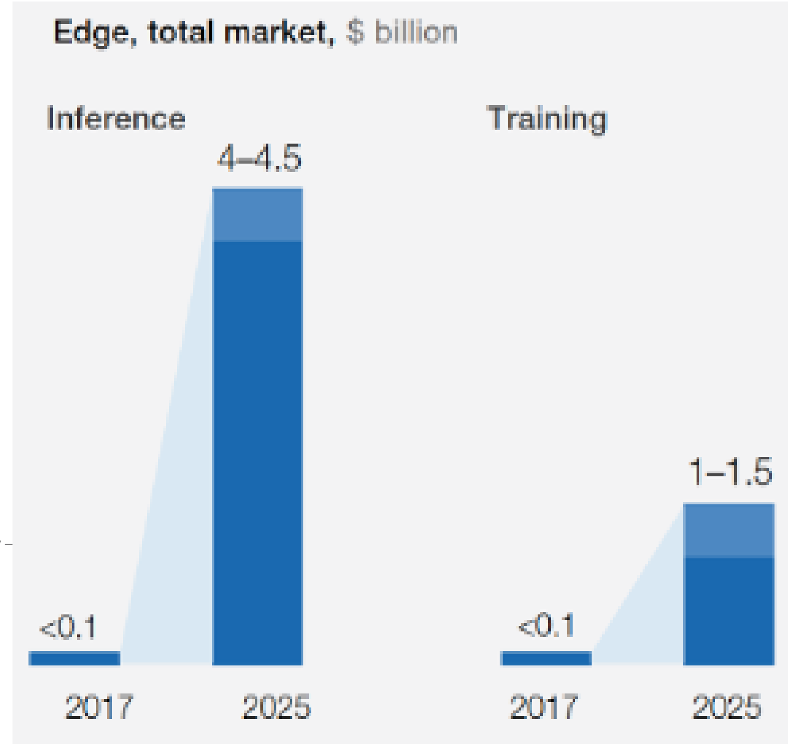
3. **eSoC** - **e**nergy efficiency of **SoC**

E-Health, Smart City

IoT, wearables

Autonomous cars

From embedded systems to Edge Intelligence



(1) McKinsey –

Data volume explodes with AI, 5G, IoT

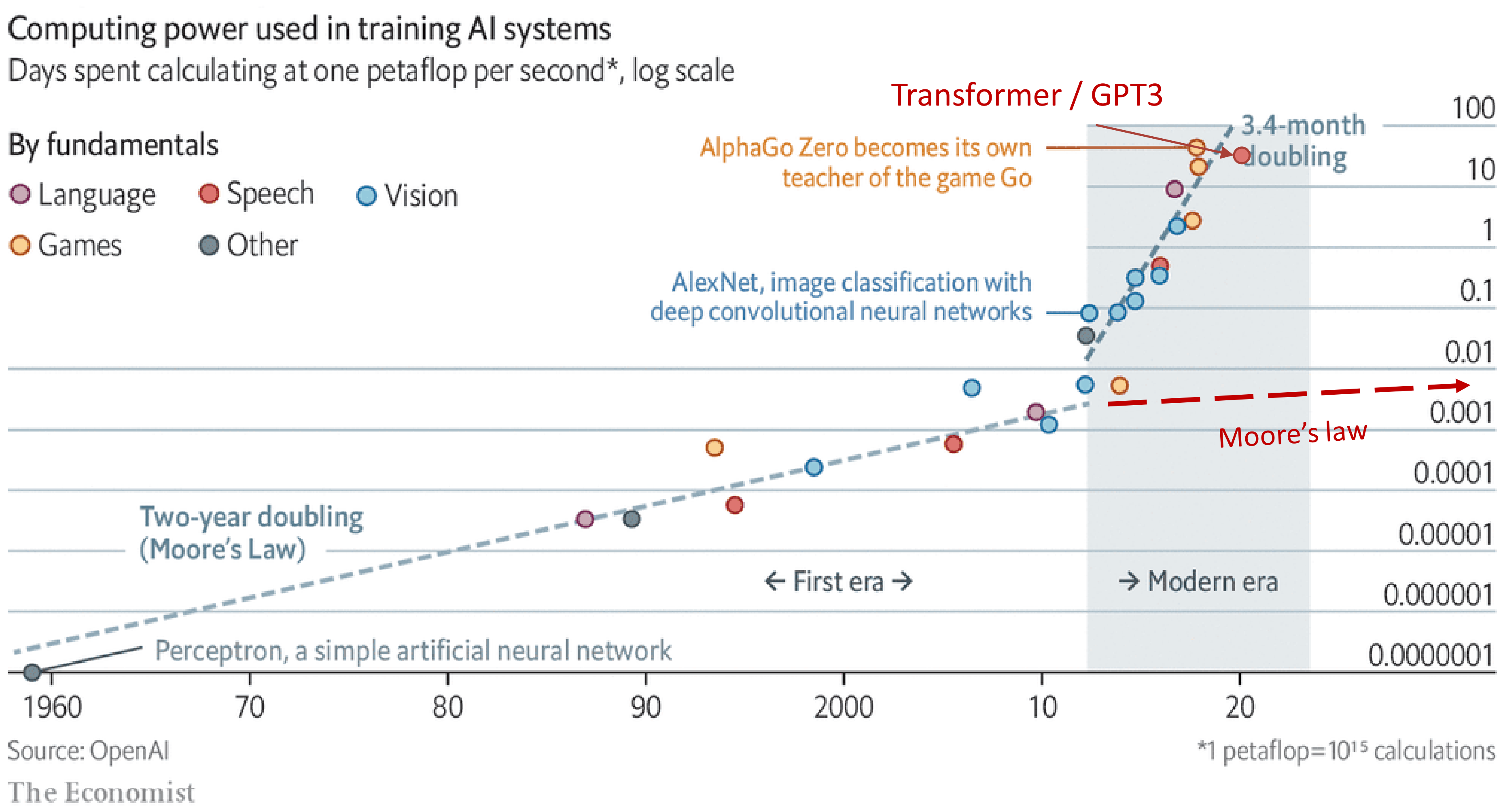
- ONLY 25% of usable data reach a datacenter
- 75% of data must be analyzed on site immediately

The impact in France and Europe will be immense in Aerospace, Automotive, Defense, Telecom,...

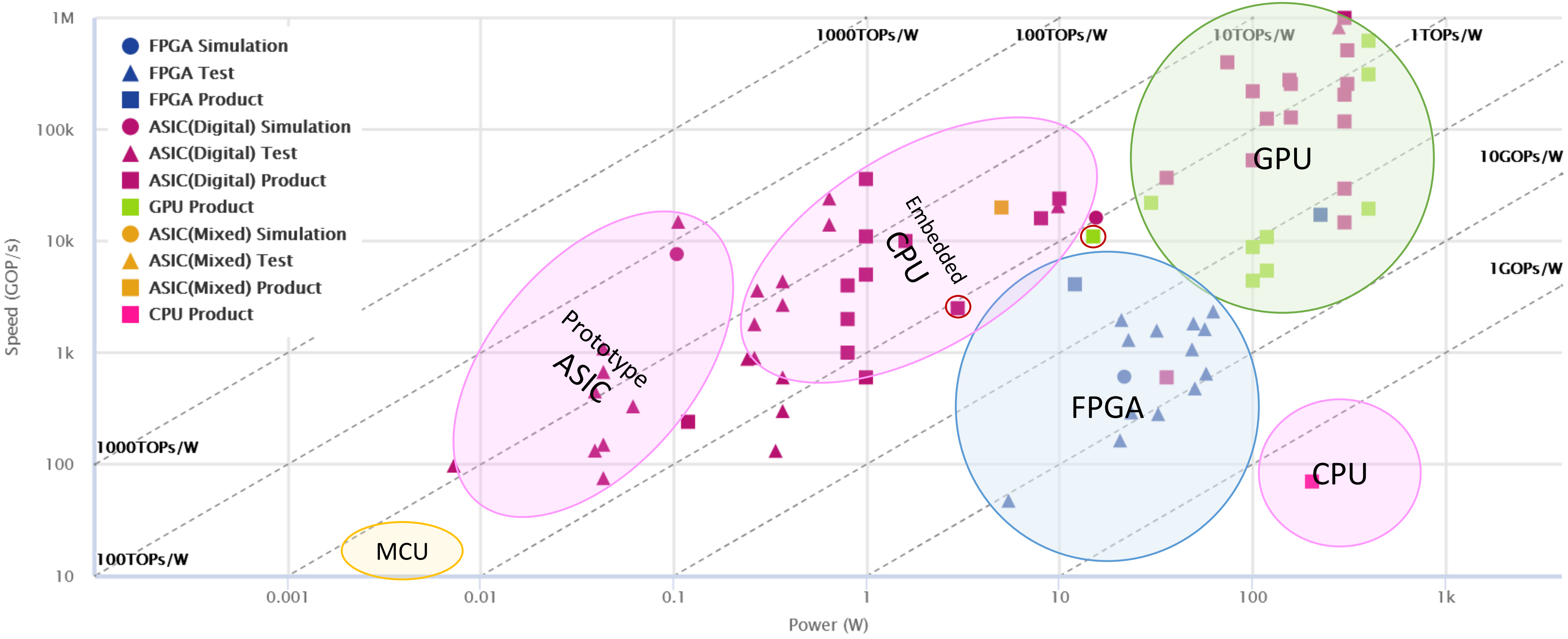
AI / Edge processors market has important growth
GPUs and FPGAs should not dominate this market.

1 Application-specific integrated circuit.
2 Central processing unit.
3 Field programmable gate array.
4 Graphics-processing unit.

A contrasted picture on Cloud Artificial Intelligence

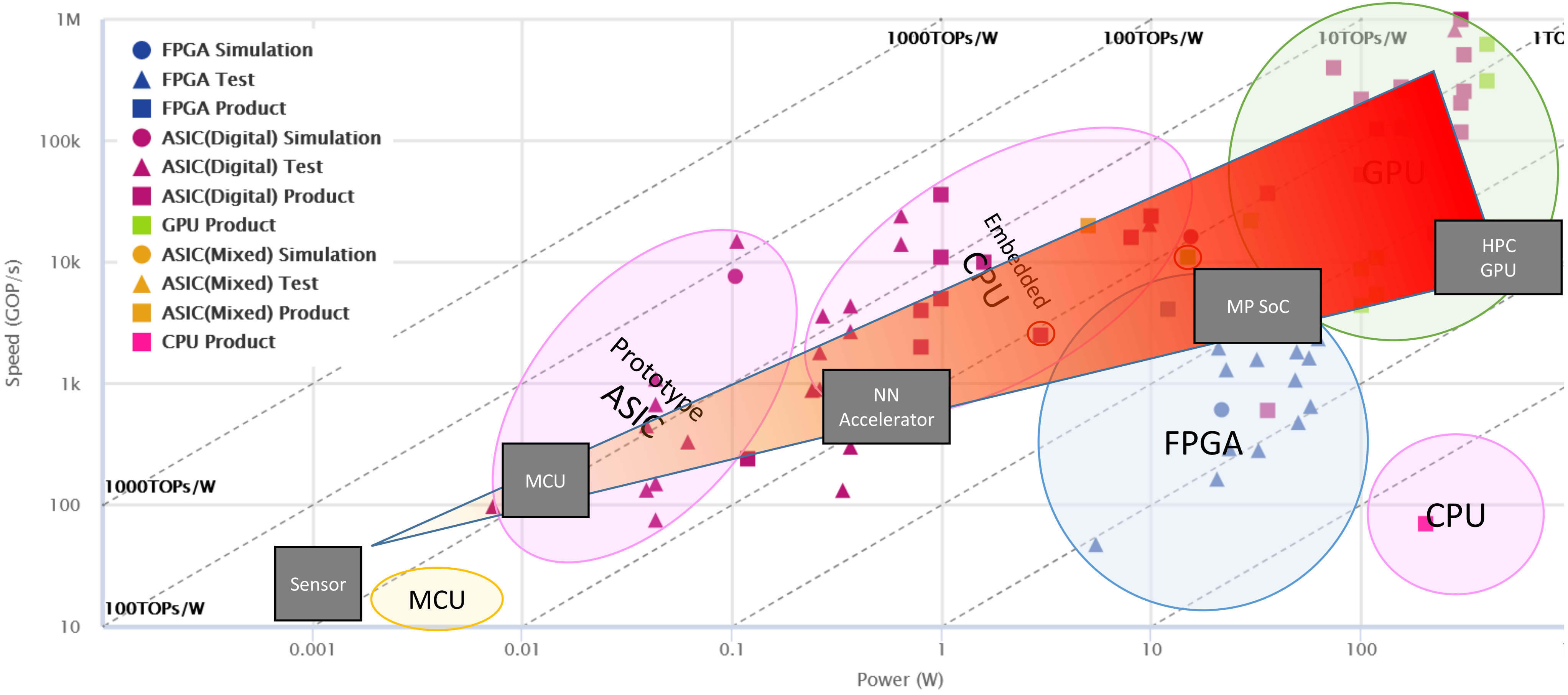


Digital Neural Network Accelerators



https://nicsefc.ee.tsinghua.edu.cn/projects/neural-network-accelerator/

Digital Neural Network Accelerators

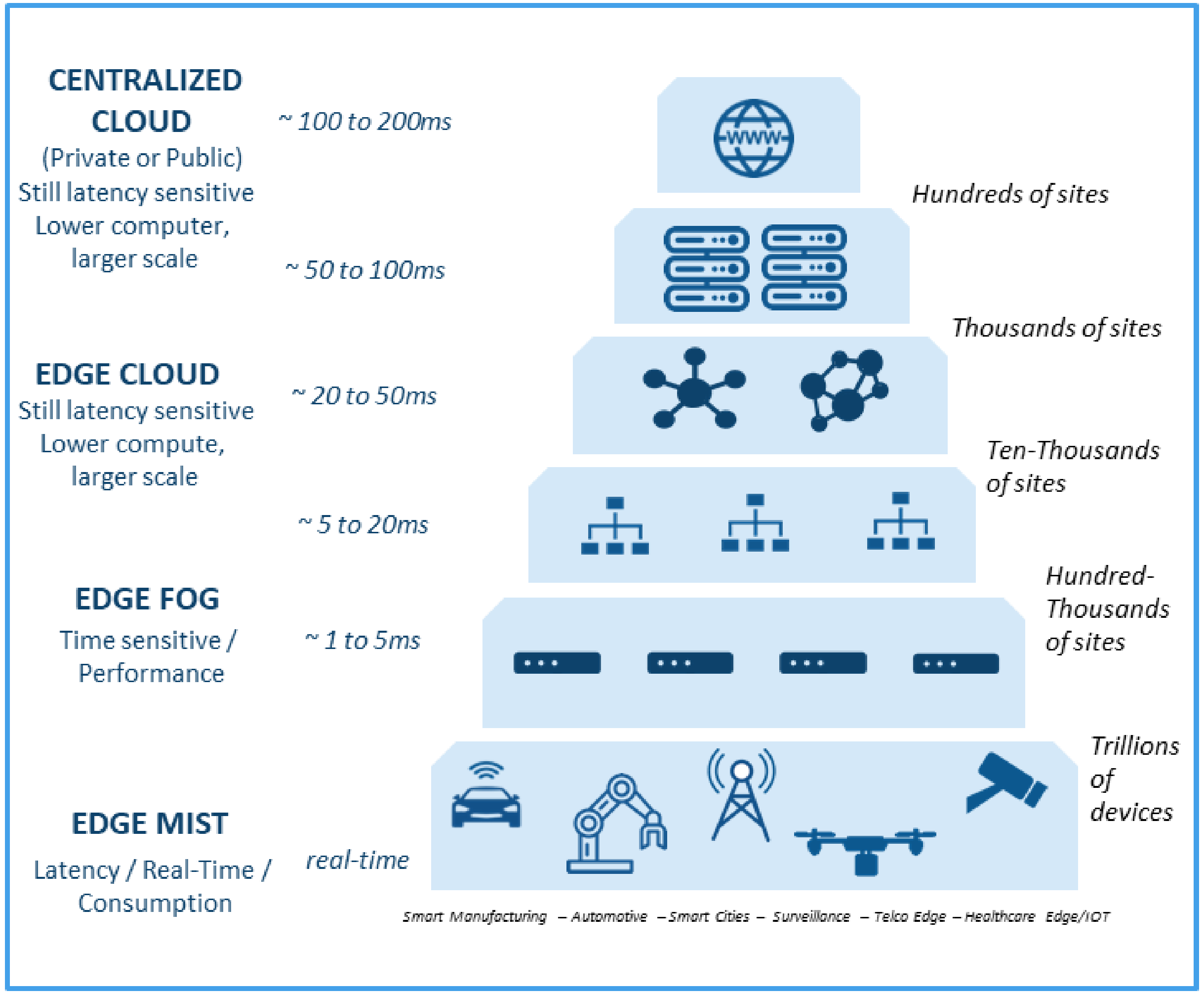


https://nicsefc.ee.tsinghua.edu.cn/projects/neural-network-accelerator/

- Specialized chips for AI calculation in the cloud
  - Nvidia GPU, US
  - Google TPU, US
  - Baidu Kunlun, CH
  - GraphCore, EN
  - Intel Movidius, US
  - Cerebras, US => 300.000 cores per wafer, 15kW
- At the Edge
  - NVIDIA Jetson can provide 11 T FLOPs, dissipating up to 15 W
  - Myriad X 4TOPS dissipating up to 1,5 W
  - Google Coral = 4 TOPS for 2W
  - …

Edge Lines

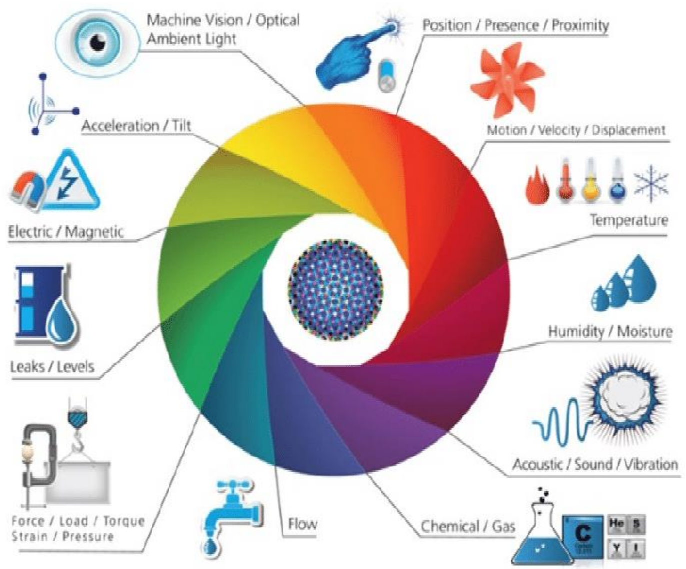
Edge Lines and their specific constraints



	Memory	Computation	Power	Efficiency
Edge Servers	GB	1 Tops	100 W	10 Gops/W
Gateway	MB	100 Gops	1 W	100 Gops/W
IoT Nodes	Hundreds of kB	1 Gops	1 mW	1 000 Gops/W

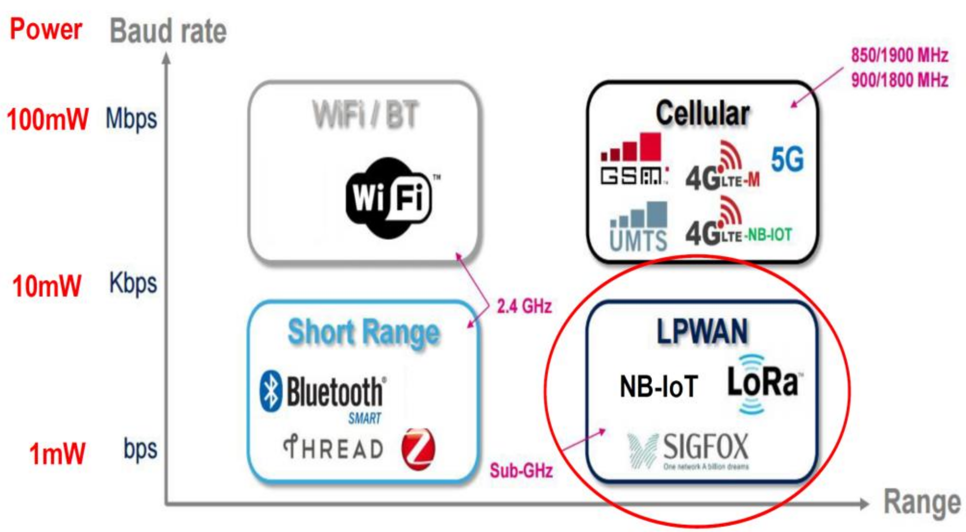
Key elements of IoT sensors

Sensors



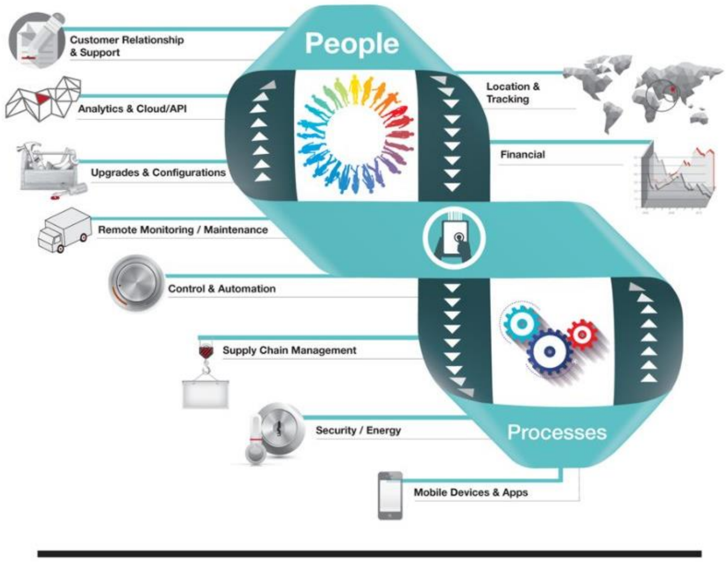
Captures a discrete representation of the dynamics of the physical world

Connectivity



Transmits the sensors data through wireless communication

Persons & process



Provides the information to people or process the raw data into more abstract information

When EdgeAI enables smart sensing

Fusion of AI, embedded sensors and connectivity

Smart sensors

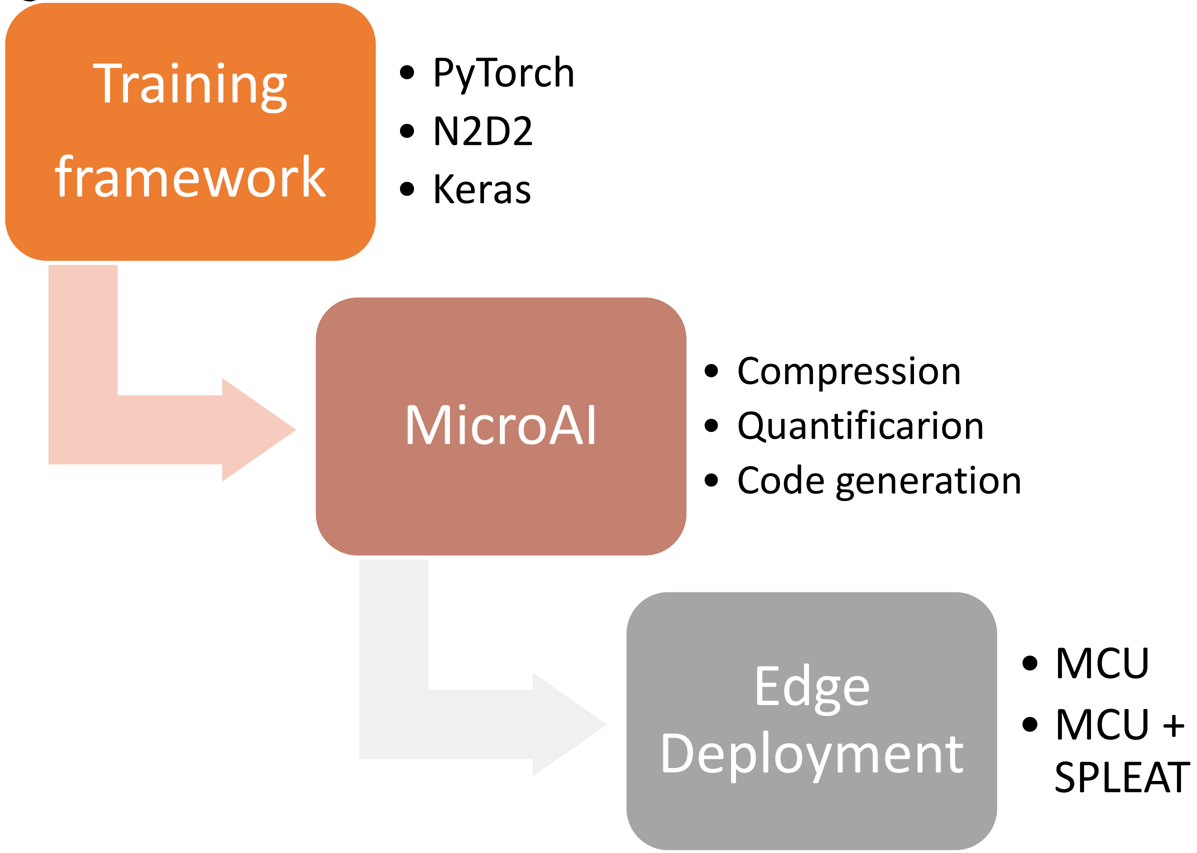
- Edge AI also offers the possibility to embed near-sensor processing

- **By bringing AI closer to the sensor, the goal is**
  - **To reduce the amount of data to communicate**
  - **To lower the global energy consumption of the digital infrastructure**
  - **To reduce latency for decising making (close or open loop)**

- Integrating AI into (near to) the sensor needs to specifically work at different scales
  - Algorithm/training: explore neural architecture that reduce parameters/computation
  - Embedded preparation: compression, quantization of the network
  - Electronic hardware: design and optimize the electronic architecture to support the neural network => Hw/Sw Codesign

The LEAT codesign flow for Edge AI

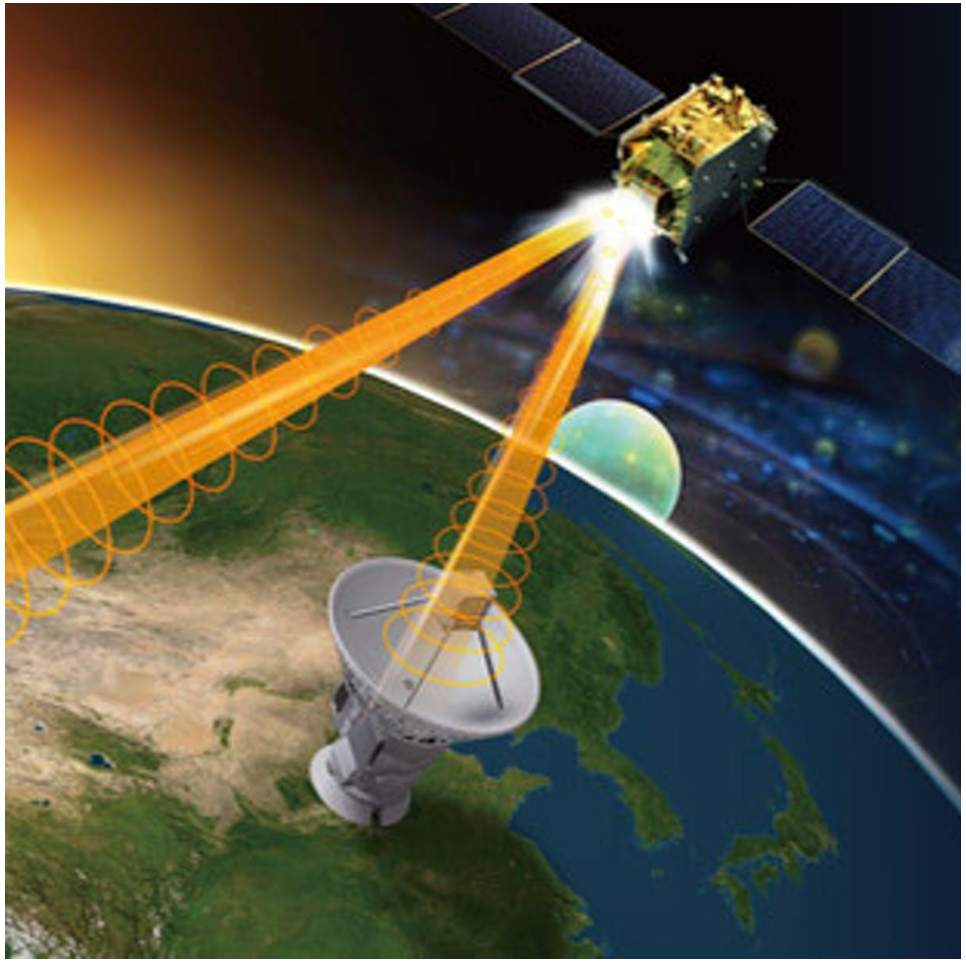
- Complete Solution*: from Training to Edge*
- Training of networks (frameworks PyTorch, Keras, N2D2)
- Embedded preparation of ANN with MicroAI
  - Quantification des SNN
  - Automatic code generation
  - Open-source: https://bitbucket.org/edge-team-leat/microai_public
- Hardware accelerator: next gen AI
  - Convolutionnal networks
  - Reprogrammable Architecture
  - Signal and Image processing applications



Quantization and deployment of deep neural networks on microcontrollers, PE Novac, GB Hacene, A Pegatoquet, B Miramond, V Gripon, Sensors 21 (9), 2984, 2021
SPLEAT: SPiking Low-power Event-based ArchiTecture for in-orbit processing of satellite imagery,, N. Abderrahmane B. Miramond, IJCNN 2022

Example of near-sensor classification

CIAR



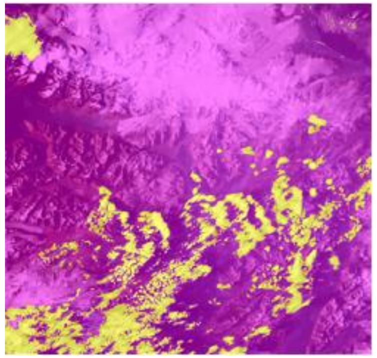
Send the entire image

1

VS.

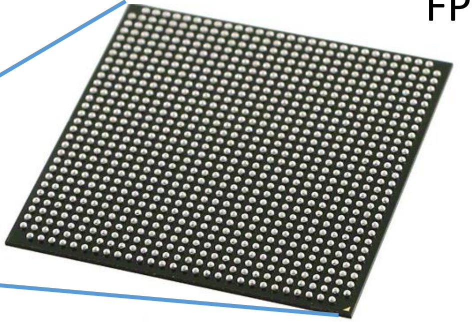
Send only the images without clouds, fire, …

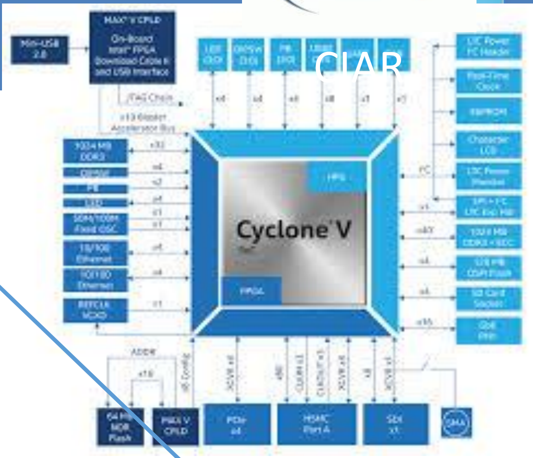
2



What is the on-board scientific experience ?

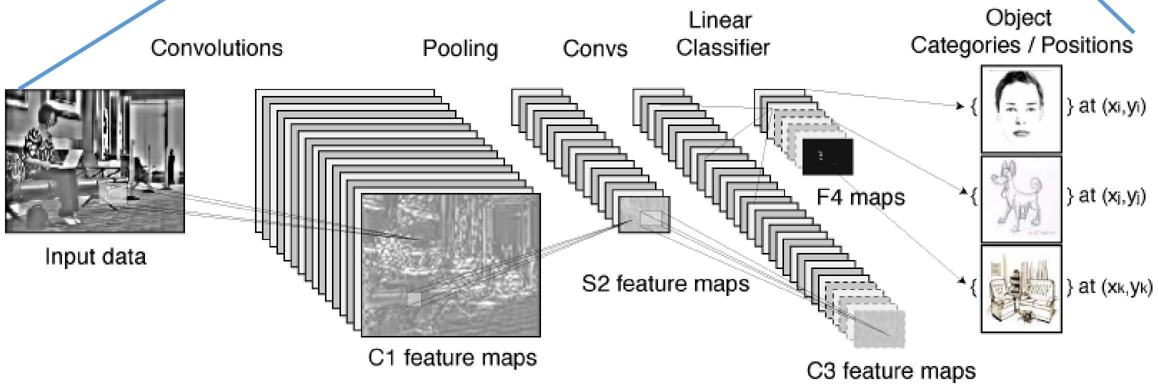
FPGA Electronic device



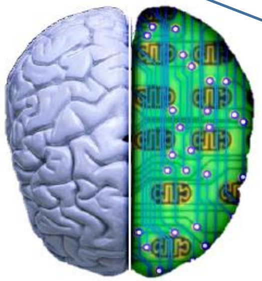


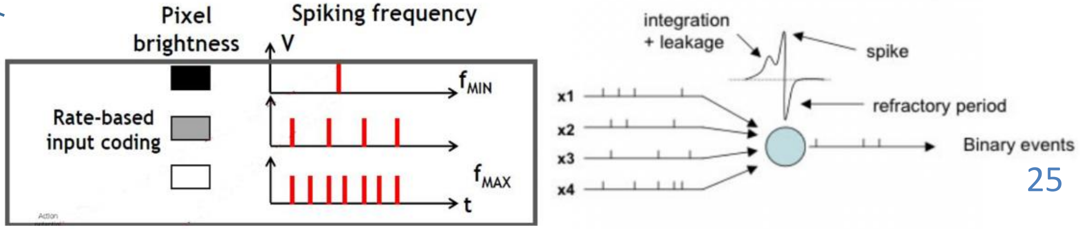
More details in the publication:
"An Hybrid Neural Network on FPGA for Embedded Satellite Image Classification", Edgar Lemaire et al., *IEEE International Symposium on Circuits and Systems (**ISCAS**), 2020*

1. Artificial Neural Network



2. Bio-inspired **Spiking Neural Network**



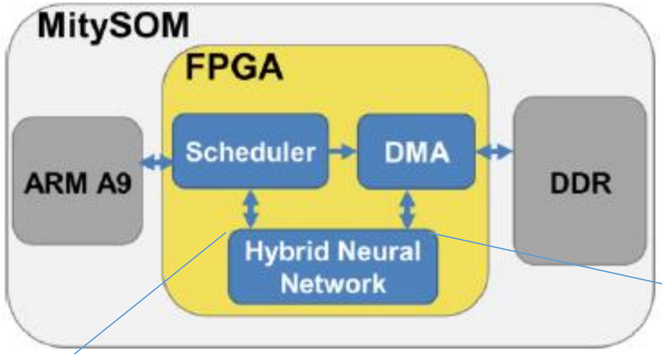


From Spiking Neural Networks to bio-inspired machine-learning

THALES

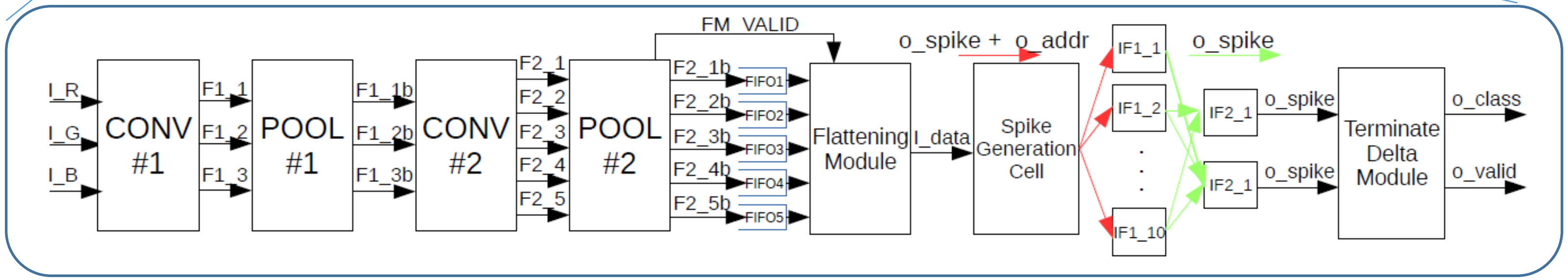
CIAR

Rate coding + CNN to SNN Conversion



MitySOM FPGA board

OPS-SAT: an ESA CubeSat



	Formal CNN	Hybrid CNN
Logic Cells occupation (%)	71%	59%
Working clock Frequency (MHz)	100	100
Recognition rate (%)	88	87
Average latency per image (μs)	25	43
LUTs in classif. stage (#)	9292	1572
Registers in classif. stage (#)	4320	1134
Block Memory Bits in classification stage (#)	0	3120
Power dissipation (mW)	1248.44	1192.66

Next step: full spike architecture with SPLEAT (SPiking Low-energy Event-based ArchiTecture) 1k -> 500k synapses

E Lemaire, M Moretti, L Daniel, B Miramond, P Millet, An FPGA-based Hybrid Neural Network accelerator for embedded satellite image classification, IEEE International Symposium on Circuits and Systems 2020

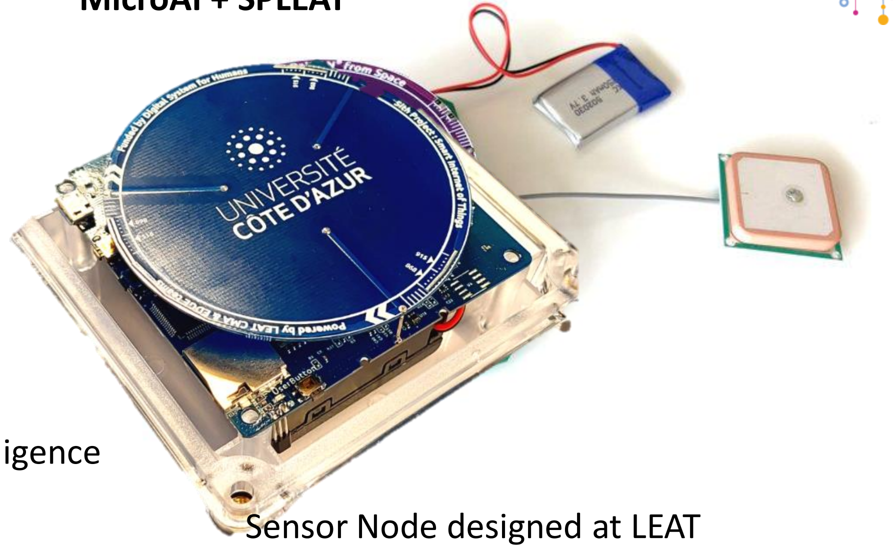
[L. Khacef, N. Abderrahmane and B. Miramond. Confronting machine-learning with neuroscience for neuromorphic architectures design. In International Joint Conference on Neural Networks (IJCNN). 2018]

Example of distributed AI with Satellite IoT

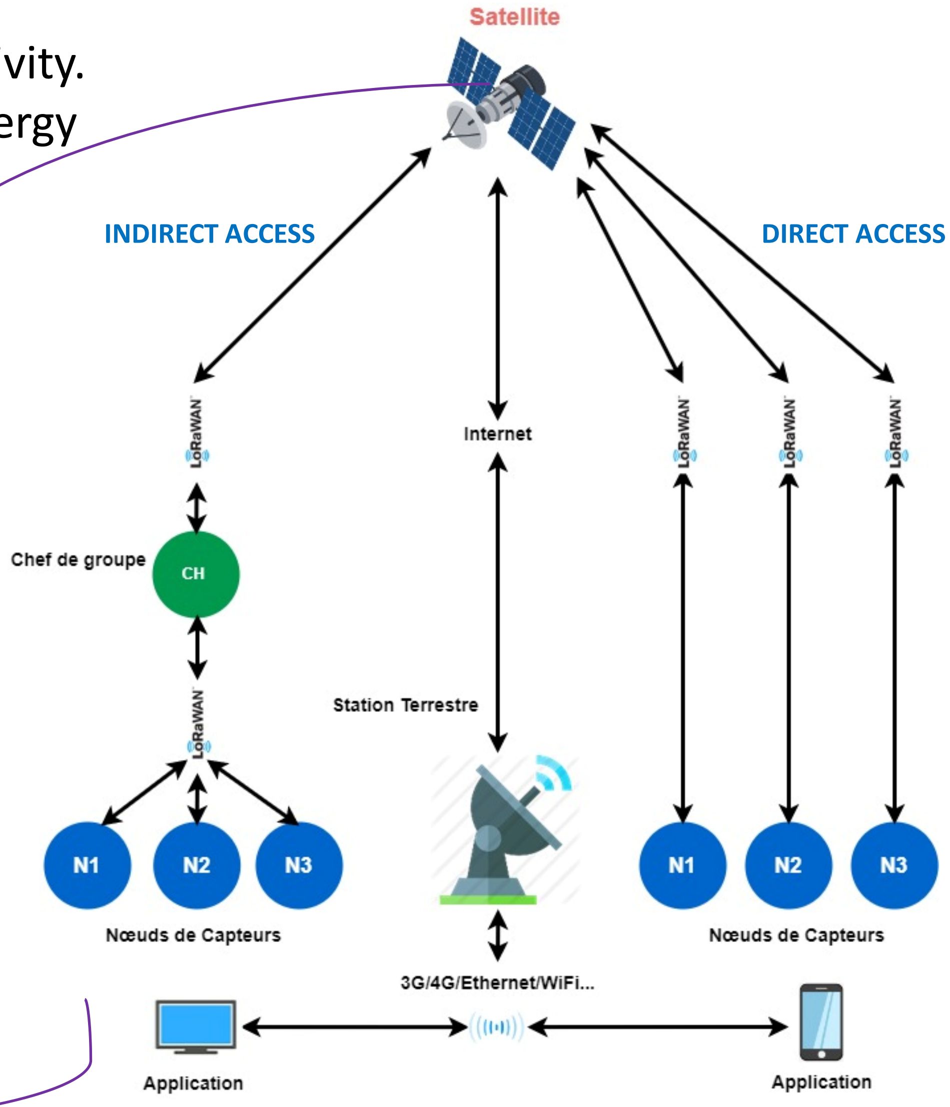
Ground sensors connected to a satellite.
End nodes embed sensors, MCU, battery and LoRA connectivity.
Each node embeds EdgeAI and has to be autonomous in energy

MicroAI + SPLEAT

Satellite LoRa Gateway
Embedded AI



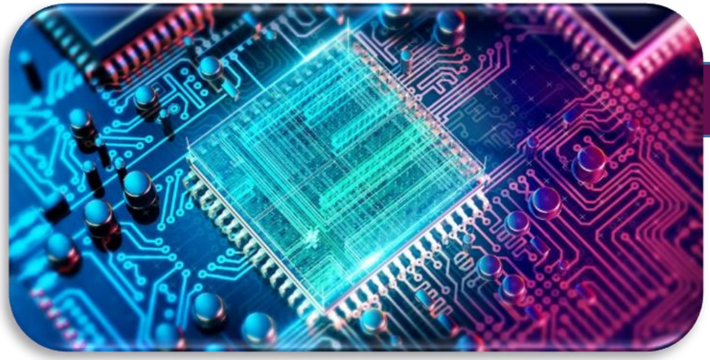
Sensor Node designed at LEAT



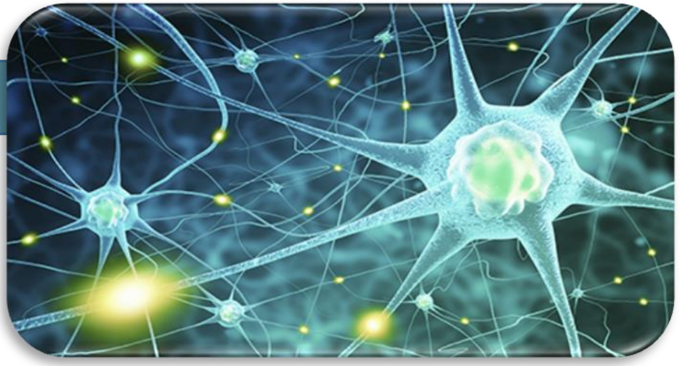
Ns: Nodes
CH: Cluster Head
AI: Artificial Intelligence

I. Abdoulaye, L. Rodriguez, C. Beleudy, B. Miramond, Embedded Artificial Neural Network for Data Prediction in Efficient Wireless Sensors Networks, ASPAI 2022

The bio-inspired approach at LEAT



Electronics



Cognitive Neurosciences

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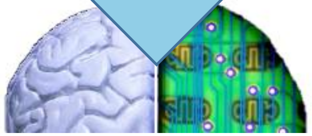
- Neuromorphic
- Embedded AI
- Smart IoT

Bio-inspired Artificial Intelligence

- Spiking Networks
- Brain plasticity
- Self-Organization



ebrAIn

Embedded Bio-inspiRed Artificial Intelligence and Neuromorphic systems

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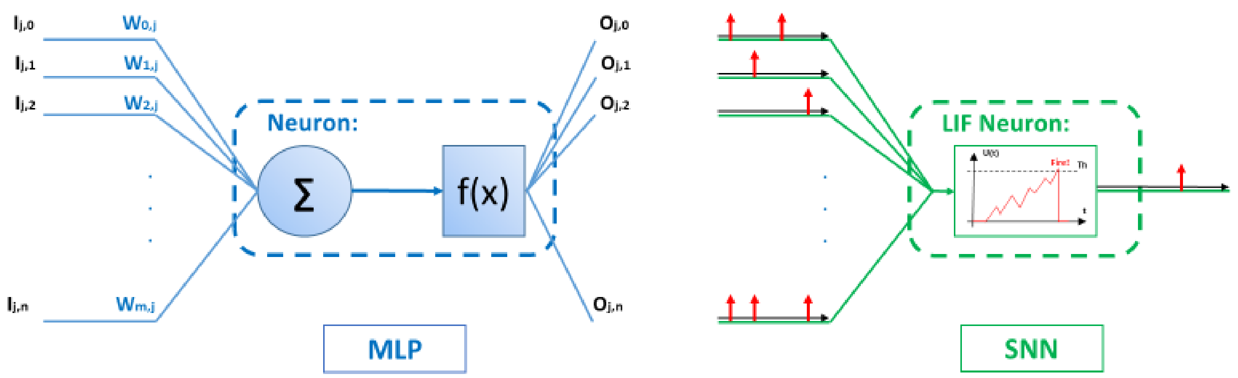
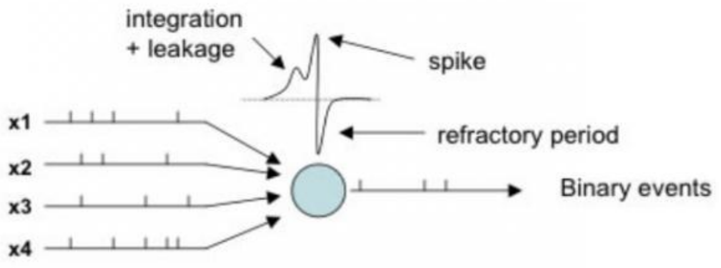
Bio-inspired computing with Spiking Neural Networks

- Spiking neural networks are the main subject of exploration in the domain of bio-inspired computing.
- **Main technical reasons:**
  - Impulsion coding
  - Temporal integration operations
  - Asynchronous behaviour
  - Decentralized learning rules
  - Bio-mimetic approach

CNN vs SNN with Leaky Integrate and Fire neurons

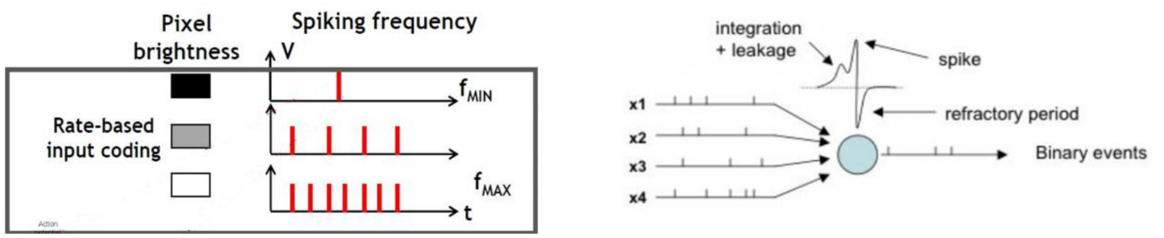


- **Main scientific questions**:
  1. How to code efficiently information in spikes ?
  2. Define new neural models: How to train those networks ?
  3. How to capture event-based data ?

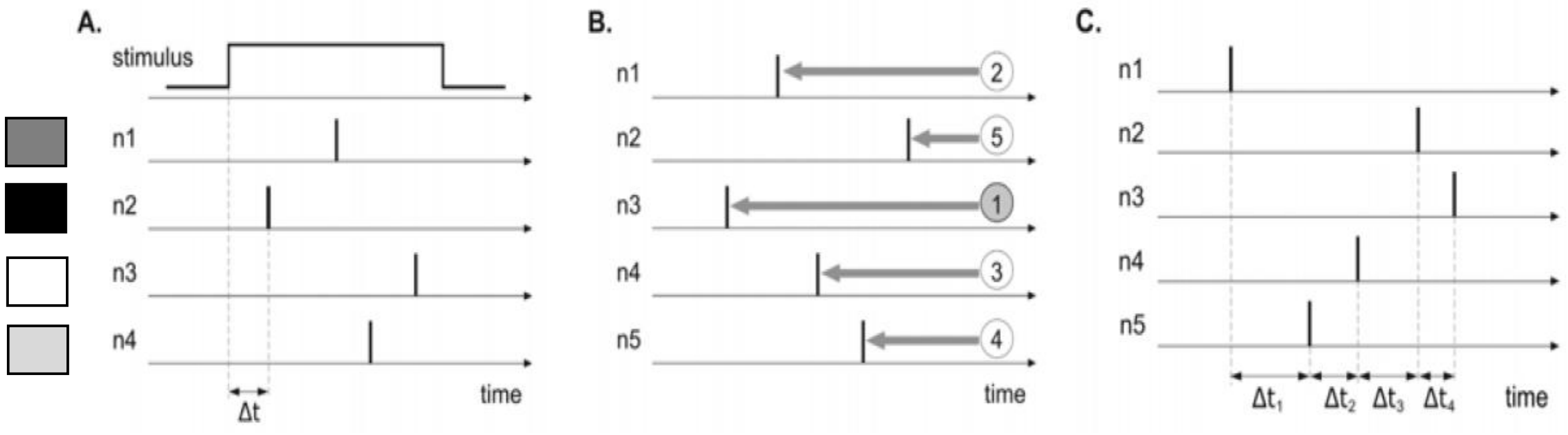


Question 1: Spike coding

- Rate coding
  - Rate coding find the average spiking frequency of a neuron over a certain timeframe



- Time coding
  - the neuron output is encoded in the temporal information of individual spikes.
    - time to first spike – TTFS (A),
    - rank order coding – ROC (B),
    - latency coding (C)



Ponulak, Filip & Kasiński, Andrzej. (2011). Introduction to spiking neural networks: Information processing, learning and applications. Acta neurobiologiae experimentalis. 71. 409-33.

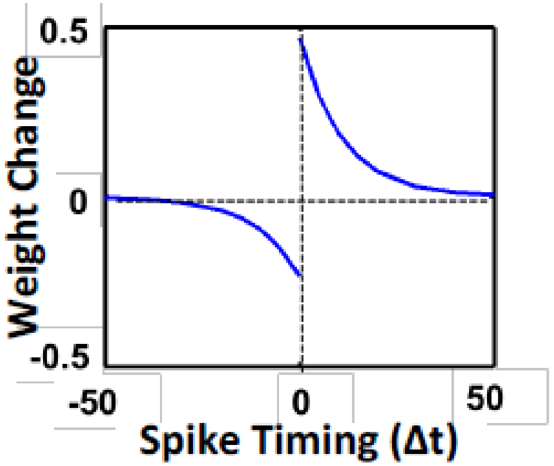
Question 2: Training spiking neural networks

1
STDP

2
Conversion

3
Spike
Backprop

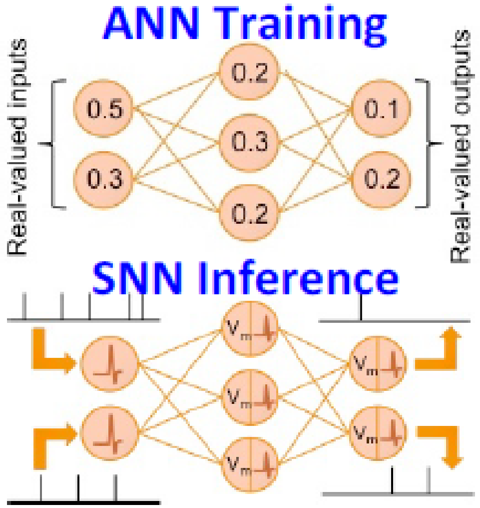
STDP Learning



Pros: Unsupervised local learning

Cons: Limited accuracy and shallow networks

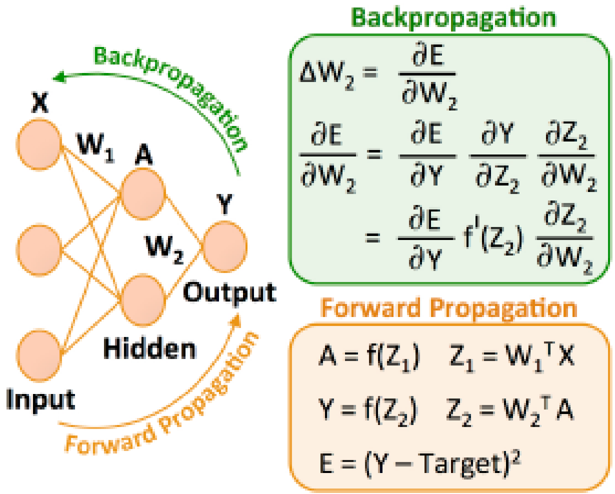
ANN-SNN Conversion



Pros: Takes advantage of standard ANN training

Cons: Incurs higher inference latency

Backpropagation



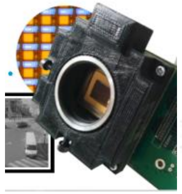
Pros: Competitive accuracy and lower inference latency

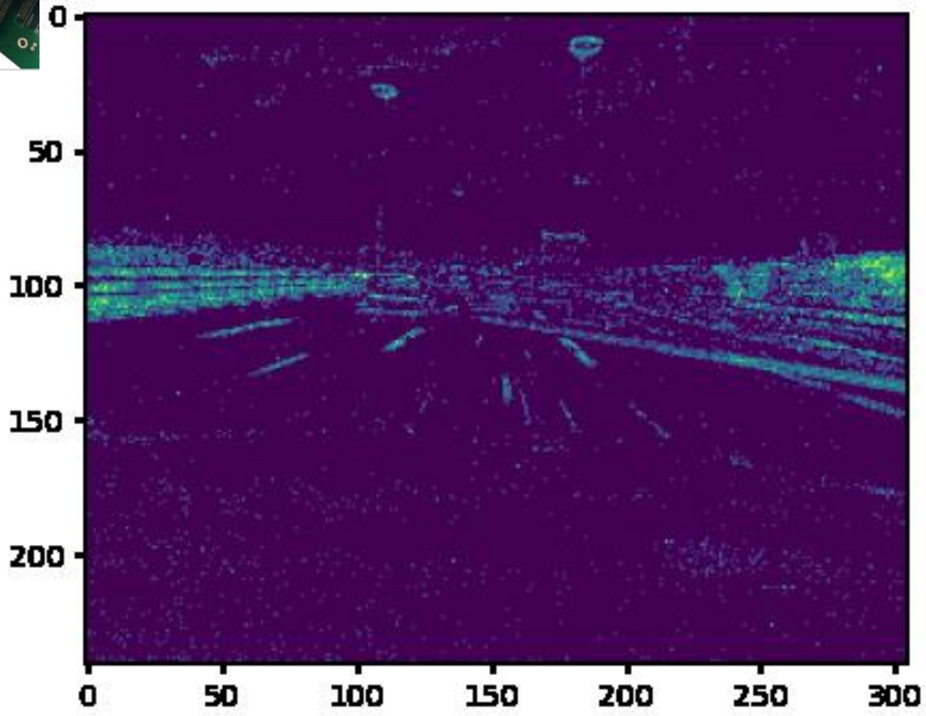
Cons: Higher training effort

G. Srinivasa, et. Al, TRAINING DEEP SPIKING NEURAL NETWORKS FOR ENERGY-EFFICIENT NEUROMORPHIC COMPUTING, ICASSP, 2020

Question 3. How to capture event-based data

DeepSee: industrial ANR Project





Event-based cameras (EBC)

Main technical reasons

- Event-based representation
- Sparse inputs
- High temporal sensibility (µs)
- High Dynamic Range (HDR)

Main scientific questions

- How to train SNN from event-based data ?
- How to take advantage of input sparsity ?

Application in image processing

Classification / Object Detection / Optical flow …

Main scientific results

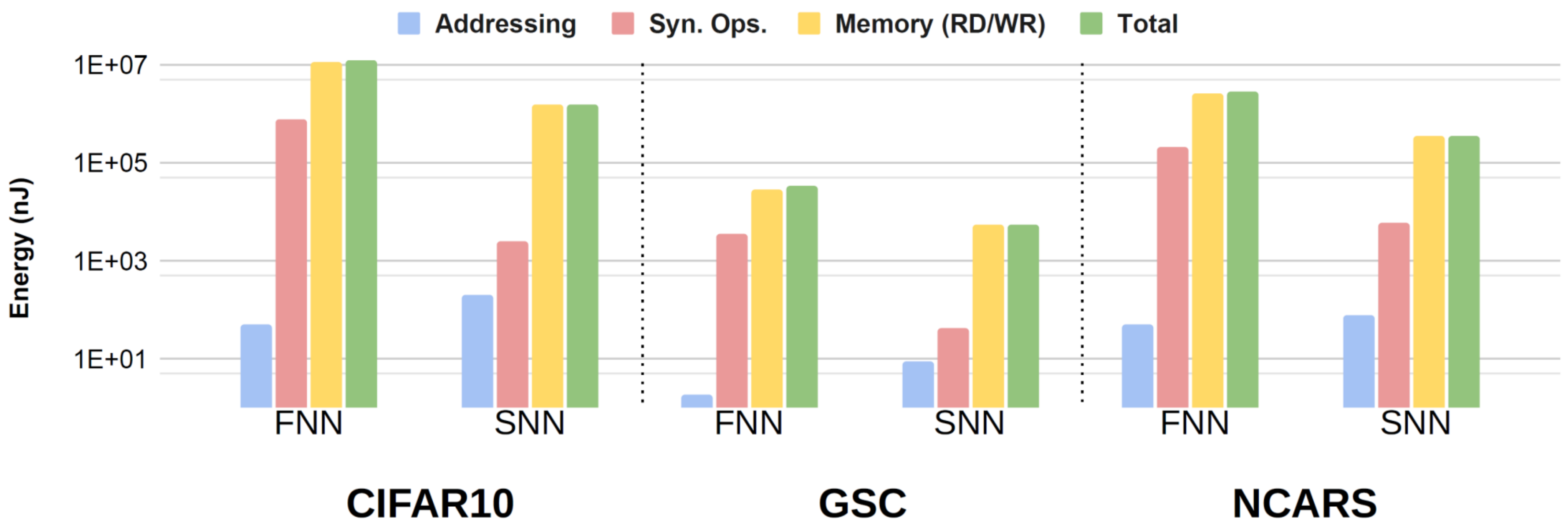
SNN with sparse convolutions [2]

First Spiking network for Object Detection on EBC [3]

[2] Learning from event cameras with sparse spiking convolutional networks, Loïc CORDONE, Sonia FERRANTE, Benoît Miramond; IJCNN 2021

[3] Object Detection with Spiking Neural Networks on Automotive Event Data, Loïc CORDONE, Benoît Miramond; IJCNN 2022

Comparison between CNN and SNN



	CIFAR 10	GSC	NCARS
Energy consumption reduction (ASIC 45 nm)	7.85 x	6.25 x	8.02 x
Spike Rate (vs. CNN)	0.1	0.14	0.08

An Analytical Estimation of Spiking Neural Networks Energy Efficiency , Edgar Lemaire, Loïc Cordone, Andrea Castagnetti, Pierre-Emmanuel Novac, Jonathan Courtois and Benoît Miramond, 29th International Conference on Neural Information Processing (ICONIP 2022)

Conclusion

Conclusion

- The combination of Edge AI and sensors
  - makes AI to the contact of the physics of the real world
  - Addresses the question of the energy consuption reduction of AI

- **By bringing AI closer to the sensor, the goal is**
  - **To reduce the amount of data to communicate**
  - **To lower the global energy consumption of the digital infrastructure**
  - **To reduce latency for decising making (close or open loop)**

- Original approach and promising results on bio-inspired AI thanks to
  - Greater sparsity
  - Event-based processing (specific neuromorphic hardware)
  - Reduced power consumption
  - And a large amount of unexplored features in the brain

- Remaining challenges for
  - EdgeAI training
  - Neuromorphic architectures
  - Realistic application demonstrations

EdgeAI, let’s play !

The field of possibilities is only limited by your imagination

Plug

Train

Embed

Play

Repeat …

IDEX <u>**Sith**</u> project, F. Ferrero, L. Rodriguez, B. Miramond

« l'organisation, la chose organisée, l'action d'organiser, et le résultat sont inséparables ».

Paul Valéry

Questions ?

[LEAT Lab, eBrain group: https://leat.univ-cotedazur.fr/ebrain/](https://leat.univ-cotedazur.fr/ebrain/)