Ultra Low Power Ambient Artificial Intelligence

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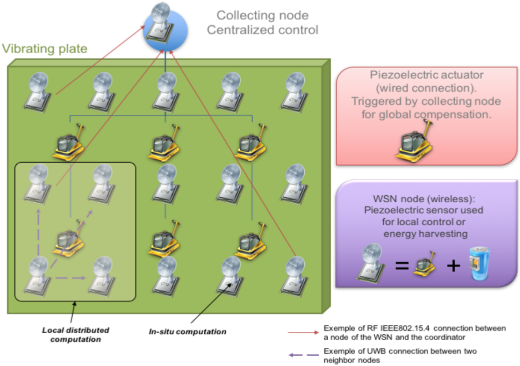
JRAF - Grenoble - Nov. 2022

Outline

Ampere's active control platform



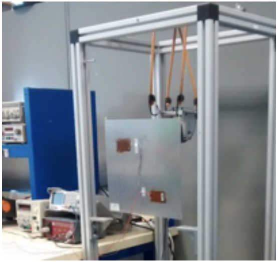


Figure 1: Ampere's vibrating bench

- Issues
  - Vibration Reduction
  - Energy Harvesting

CITI's Cortex Lab

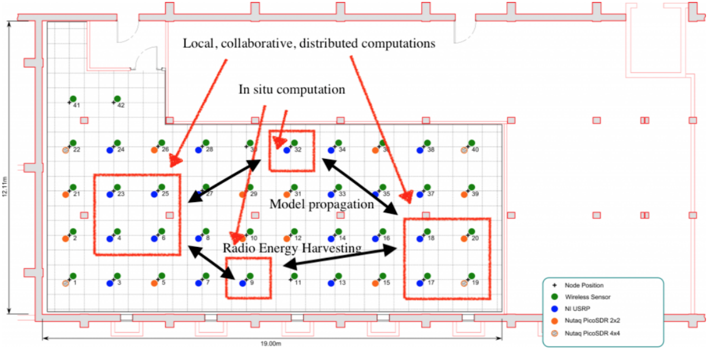


Figure 2: Nodes and activation example in Cortex Lab platform

- Issues
  - reallocate / power off antennas
  - max covering / bandwidth / homogeneity
  - min interferences

Ambient / Frugal AI

- Ambient Intelligence (AmI)[1]
  - embedded
  - context-aware
  - adaptive
  - anticipatory

- Frugal Artificial Intelligence (Frugal AI)[2]
  - input : less data
  - learning process : less computational resources
  - model : less memory
  - ★ reduced energy consumption

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[1] E. Aarts [Jan. 2004]. "Ambient intelligence: a multimedia perspective". In: *IEEE Multimedia*. DOI: 10.1109/MMUL.2004.1261101.

[2] Mikhail Evchenko et al. [Nov. 2021]. *Frugal Machine Learning*. DOI: 10.48550/arXiv.2111.03731.

Thesis Subject : Ultra Low Power Ambient Artificial Intelligence

- Started last month : $\sim$ 20 papers selected
- Goals
  - Deployment of a WSN as a monitoring and adaptive action solution
  - Minimal footprint energy aiming for autonomy
  - Exploiting networking AI to improve and maintain itself

★ Energy efficiency as a cross-cutting topic

- Focus on Time Series data (reduced feature set and samples)

Outline : State of the Art

SoA On-Device Learning : Resources constrained learning

- Target : WSN Nodes $\longrightarrow$ IoT low-end devices [Ojo et al. 2018]

MCU Arch	Clock speed	On-Board Storage	RAM	Current
16 or 32 bit	$\leq 50\ MHz$	$\leq 512\ KB$	$\leq 64\ KB$	$\leq 10\ mA$

- Memory constraints $\rightarrow$ Compressed Models [Profentzas et al. 2022]
  - Pruning
  - Quantization
  - Encoding
- Computation constraints $\rightarrow$ Preprocessed Models [Lin et al. 2022]
  - Transfer Learning
  - Fine Tuning

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Use 2-3 $\times$ more RAM

- Computation constraints $\rightarrow$ Preprocessed Models [Lin et al. 2022]
  - Transfer Learning
  - Fine Tuning

Tested on IoT middle-end device
No energy consumption evaluation

SoA Intermittent Learning : Duty cycling

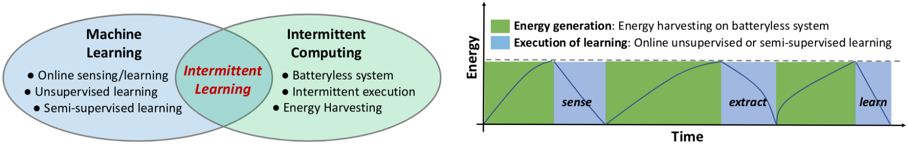


Figure 3: Intermittent Learner duty [Lee et al. 2019]

- Energy Harvesting → Extreme power scarcity
  - checkpointing approaches
  - task-based approaches [Lee et al. 2019]
- Changes in energy availability → Energy-aware reconfiguration [Bakar et al. 2021]
  - peripheral selection / sensor sampling
  - communication pattern

SoA Intermittent Learning : Duty cycling

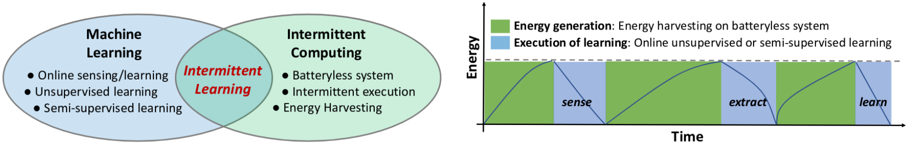


Figure 3: Intermittent Learner duty [Lee et al. 2019]

- Energy Harvesting → Extreme power scarcity
  - checkpointing approaches
  - task-based approaches [Lee et al. 2019]

  Do not consider powering off by itself
- Changes in energy availability → Energy-aware reconfiguration [Bakar et al. 2021]
  - peripheral selection / sensor sampling
  - communication pattern

  Use tiny machine learning model instead of heuristics

SoA Federated Learning : Bypass computational weaknesses

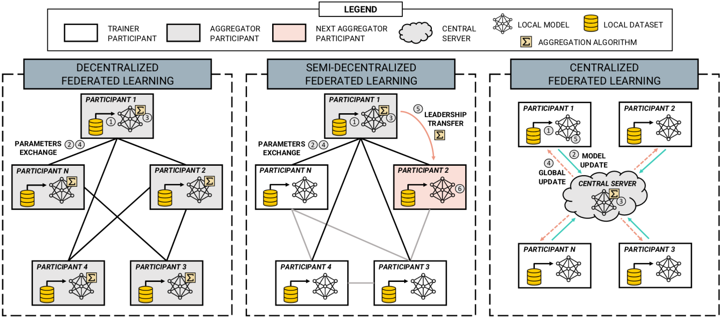


Figure 4: DFL architectures [Beltrán et al. 2022]

- Learning in a spatially correlated group → Adaptive Neighbor Matching [Z. Li et al. 2022]
- Costly communication → reduce shared weights [C. Li et al. 2021]

SoA Federated Learning : Bypass computational weaknesses

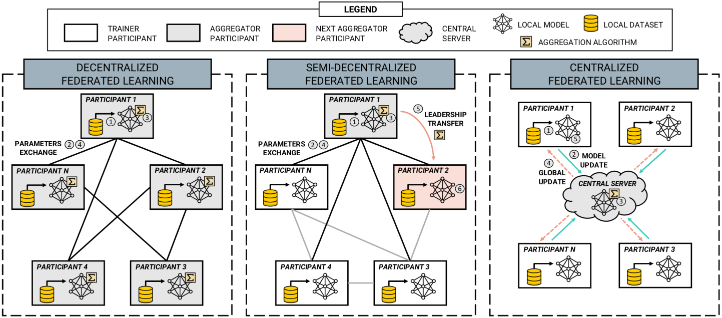


Figure 4: DFL architectures [Beltrán et al. 2022]

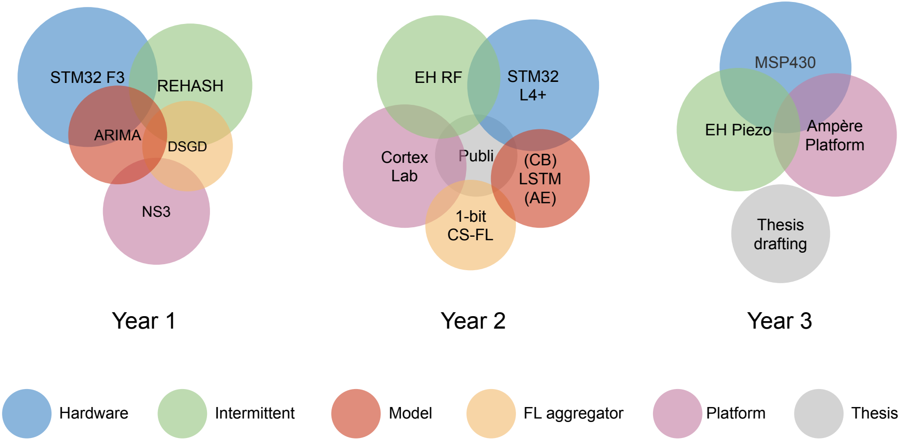
Do not evolve with changes & resource-consuming

- Learning in a spatially correlated group → Adaptive Neighbor Matching [Z. Li et al. 2022]
- Costly communication → reduce shared weights [C. Li et al. 2021]

Use a centralized FL Algorithm

Outline

Work plan … will most likely age poorly



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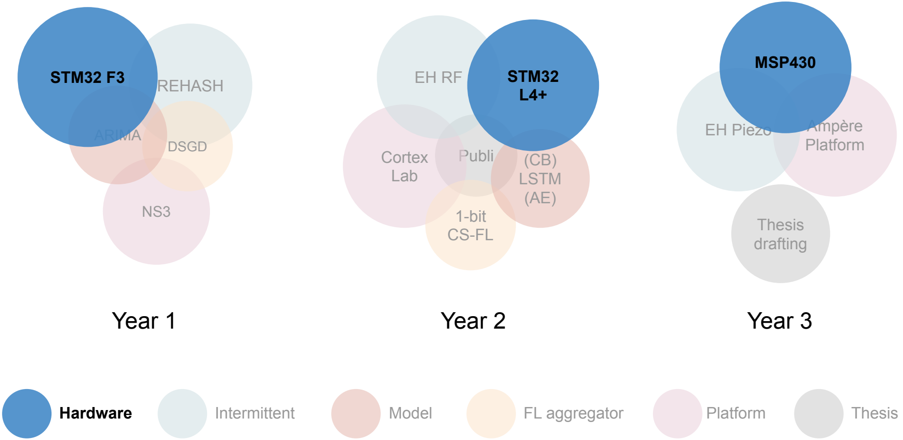

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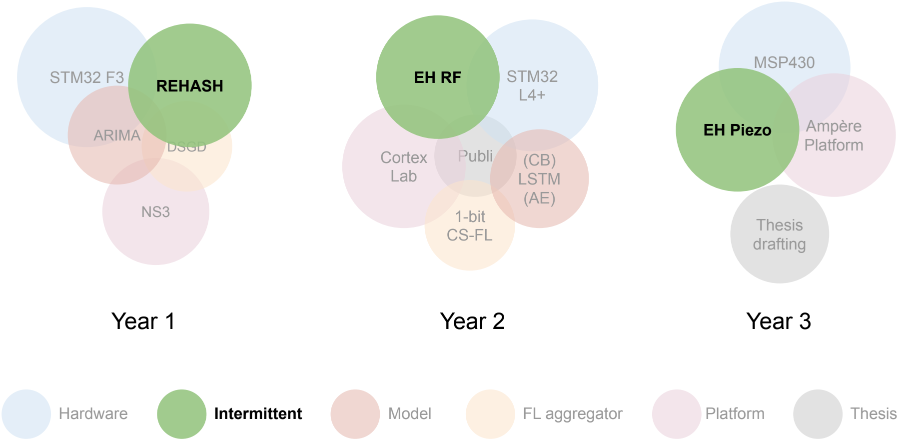

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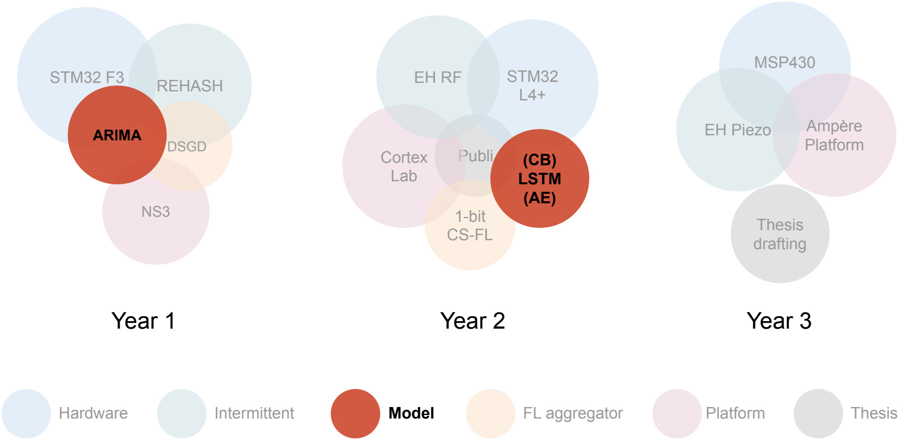

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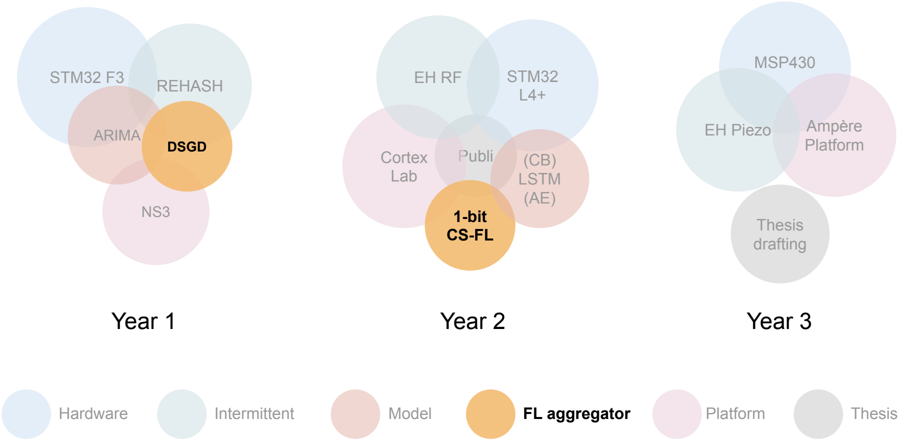

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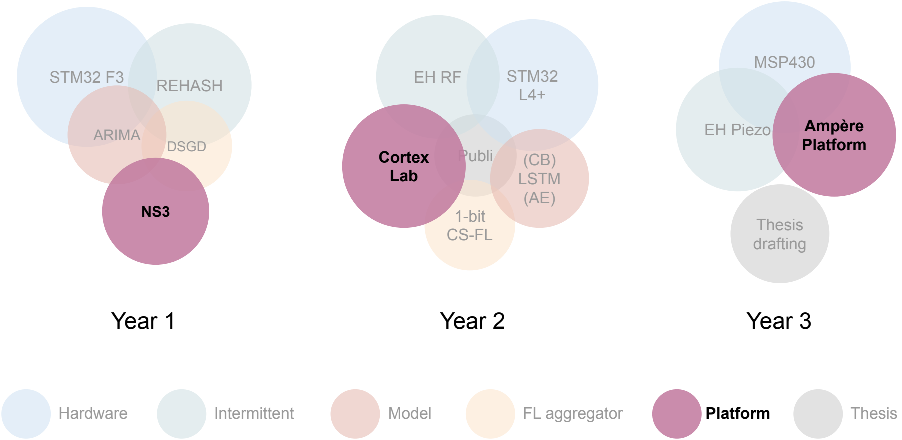

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