Investigating the benefits of Deep Learning for particle pulse-shape discrimination in a space-borne silicon detector

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M-MATISSE Mission

- ❑ Mars - Magnetosphere ATmosphere Ionosphere and Space-weather SciencE
- ❑ ESA M7 (PI : Beatriz Sanchez-Cano, U. Leicester, Co-PI : Francois Leblanc, LATMOS)
- ❑ Caracterization of the Magnetosphere-Ionosphere-Thermosphere coupling of Mars

- ❑ Two orbiters : Henri and Marguerite

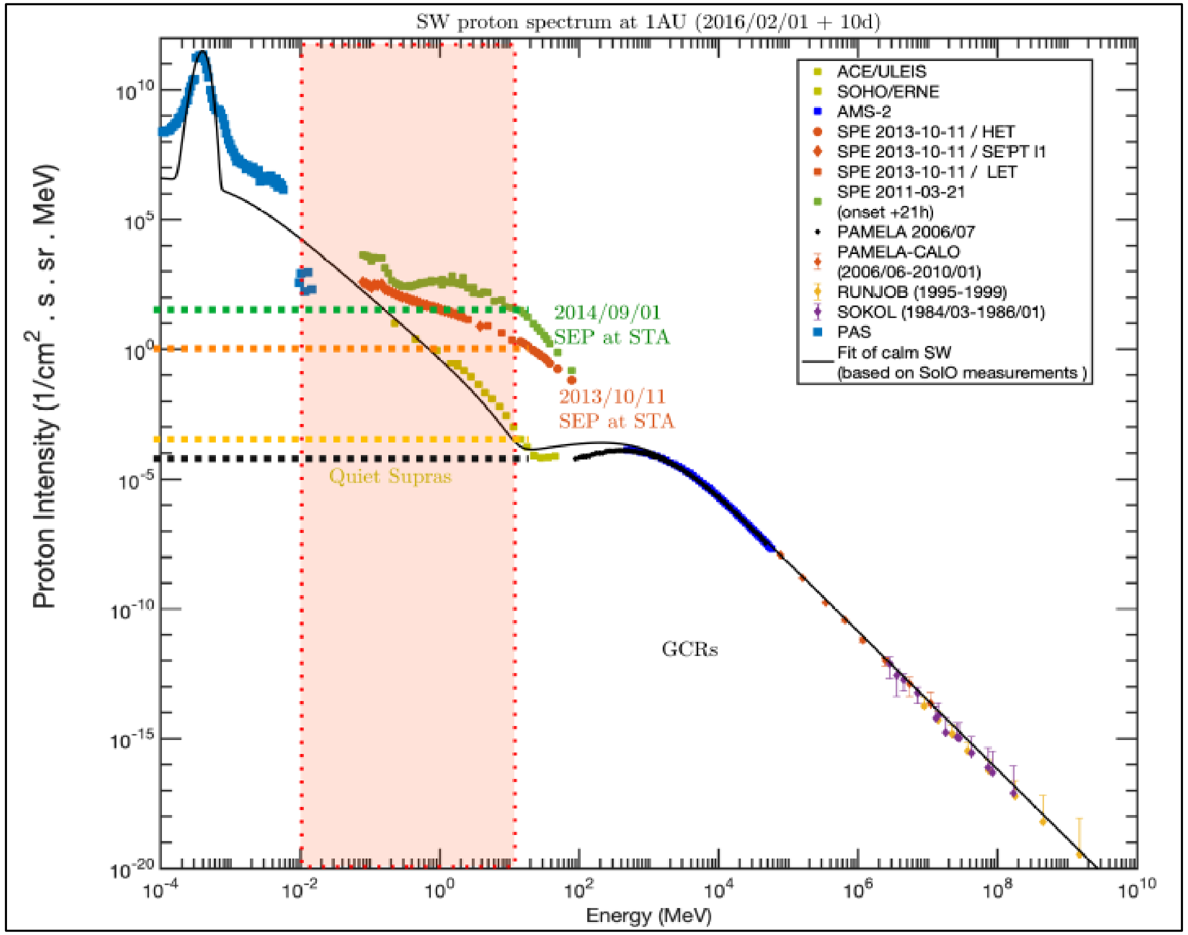
- ❑ Selected for competitive Phase A in Nov 2023
- ❑ Mission selection June 2026
- ❑ Mission Adoption Nov 2028

Science objectives

- ❑ SP@M : Solar Particles @ Mars

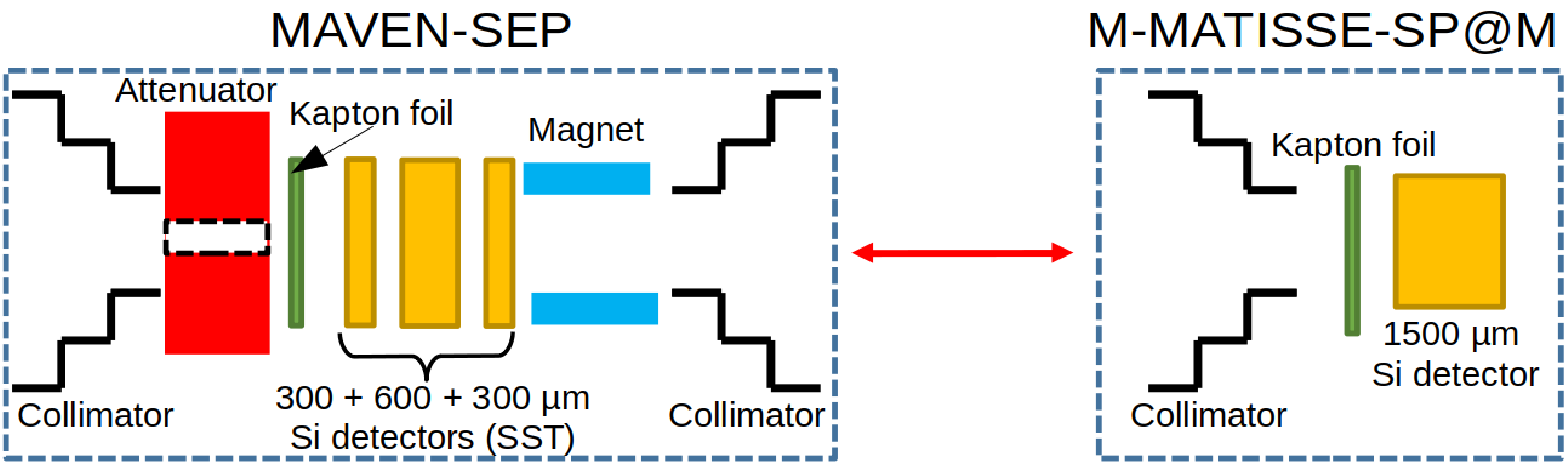
- ❑ Energy range :
  - ❑ Electrons from 30 keV to 1 MeV
  - ❑ Ions from 30 keV to 10 MeV

- ❑ Scientific goals :
  - ❑ Characterizing atmospheric escape
  - ❑ Understanding SEP-induced aurorae
  - ❑ Anticipating radar blackouts
  - ❑ Estimating radiation risk for future robotic and human missions



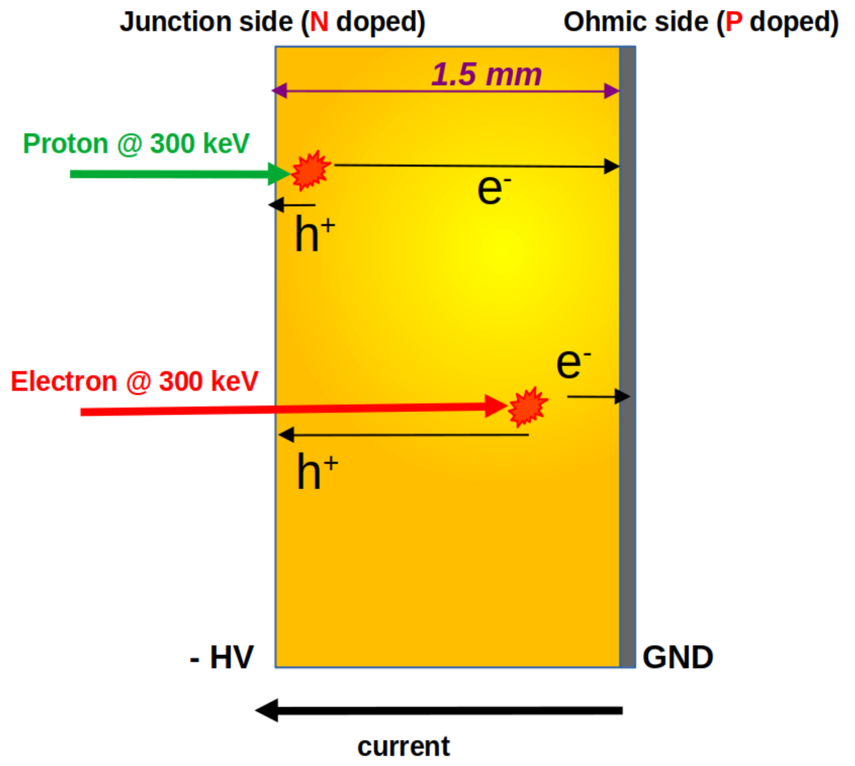
Solar proton flux intensity as a function of energy. SPAM's energy measurement range is highlighted in the red insert. <u>Credit:</u> Illya Plotnikov (IRAP).

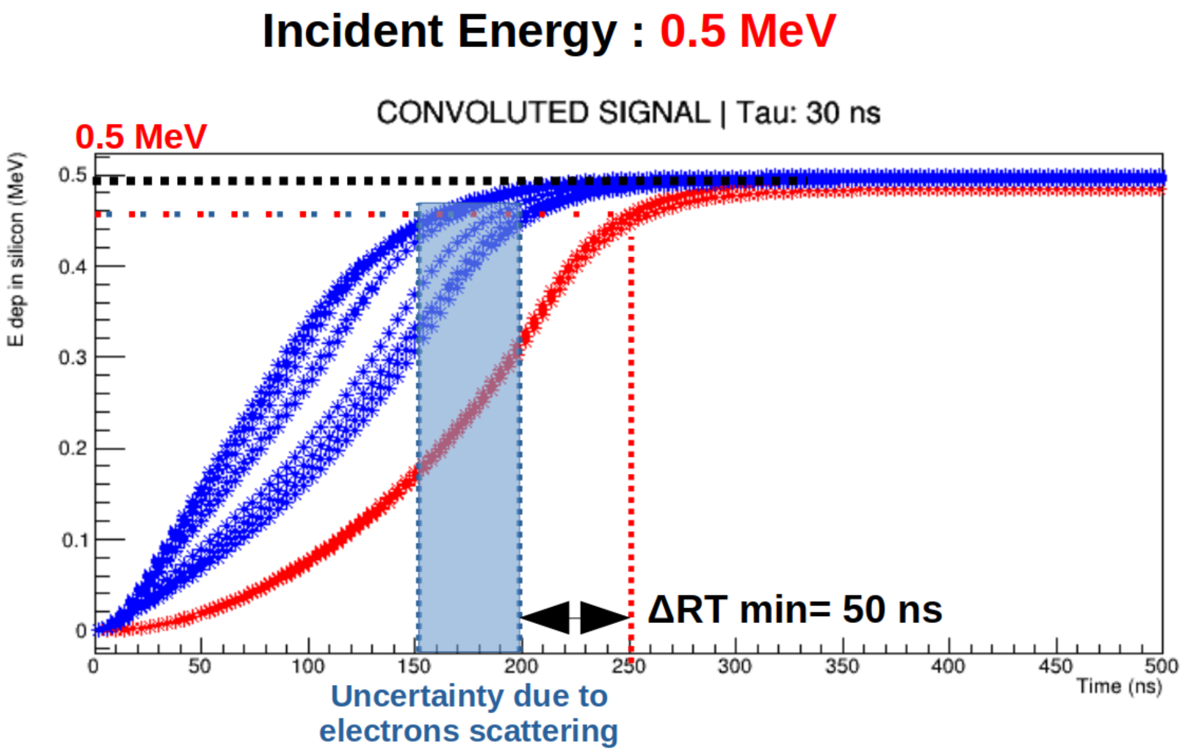
SP@M instrument design



- ❑ Replace Solid State Telescope (SST) with a single thick silicon detector
- ❑ Proton-electron discrimination by pulse shape analysis

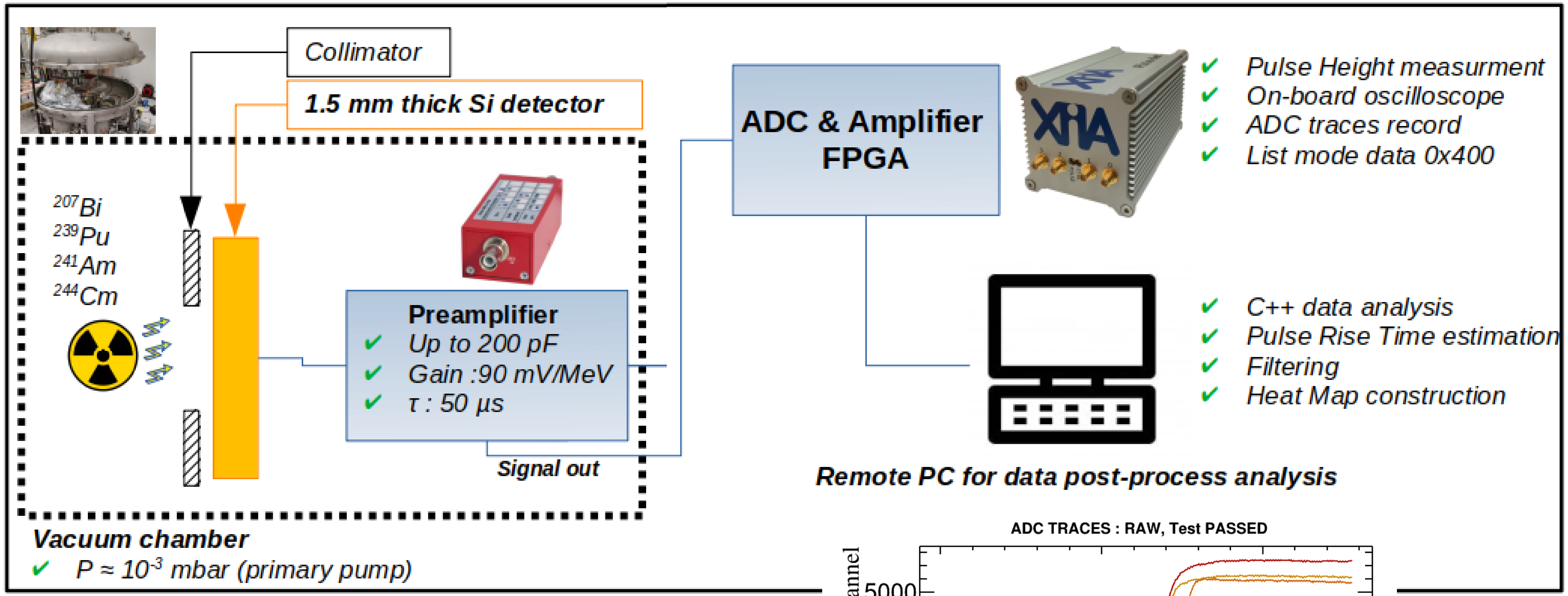
Discrimination method

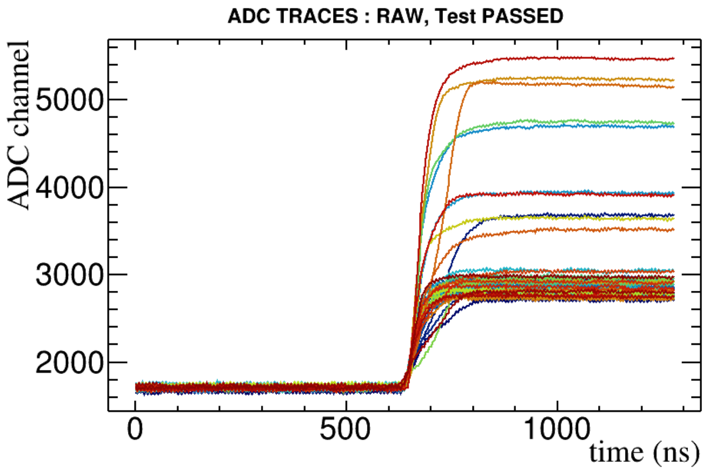




- ❑ Electrons are far more penetrating than protons and alphas.
- ❑ Depth of penetration proportional to the particle's incident energy
- ❑ Signal collection time (rise time) longer for protons

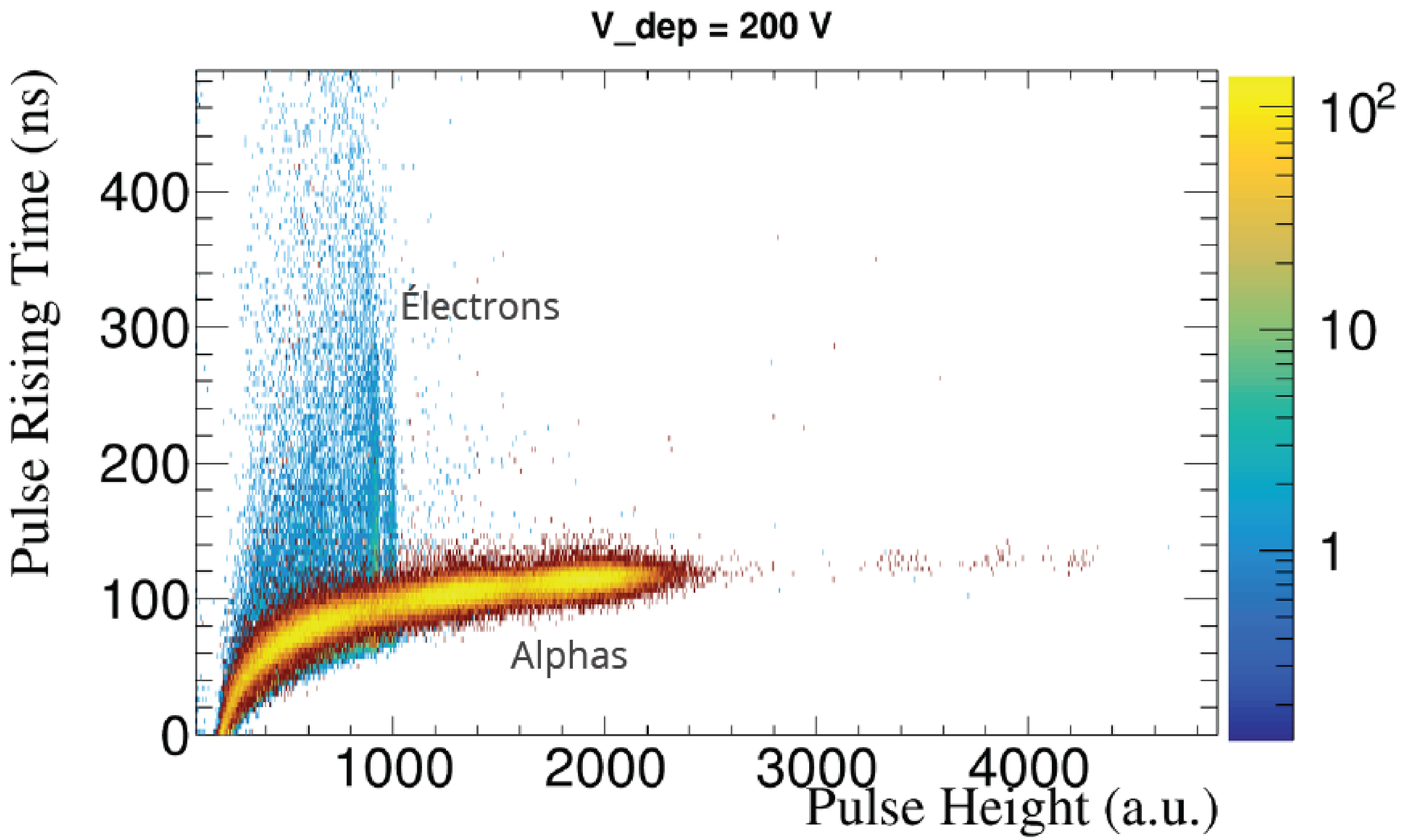
Signal acquisition

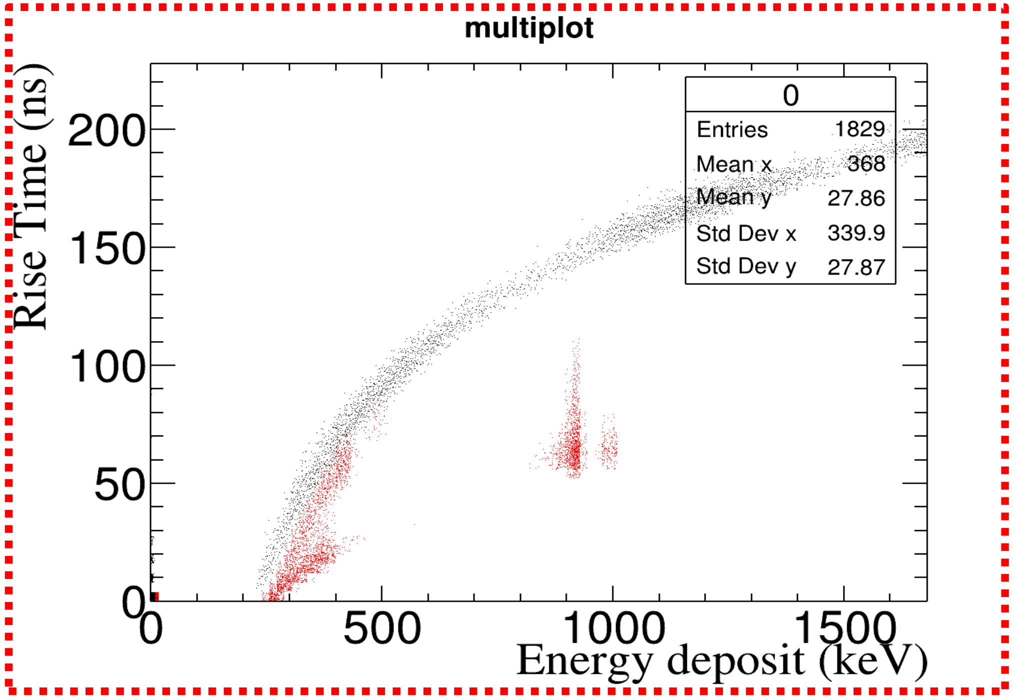




- ❑ Test bench developed at IRAP
- ❑ Irradiation with electrons and alphas
- ❑ Allows to record raw preamplifier output

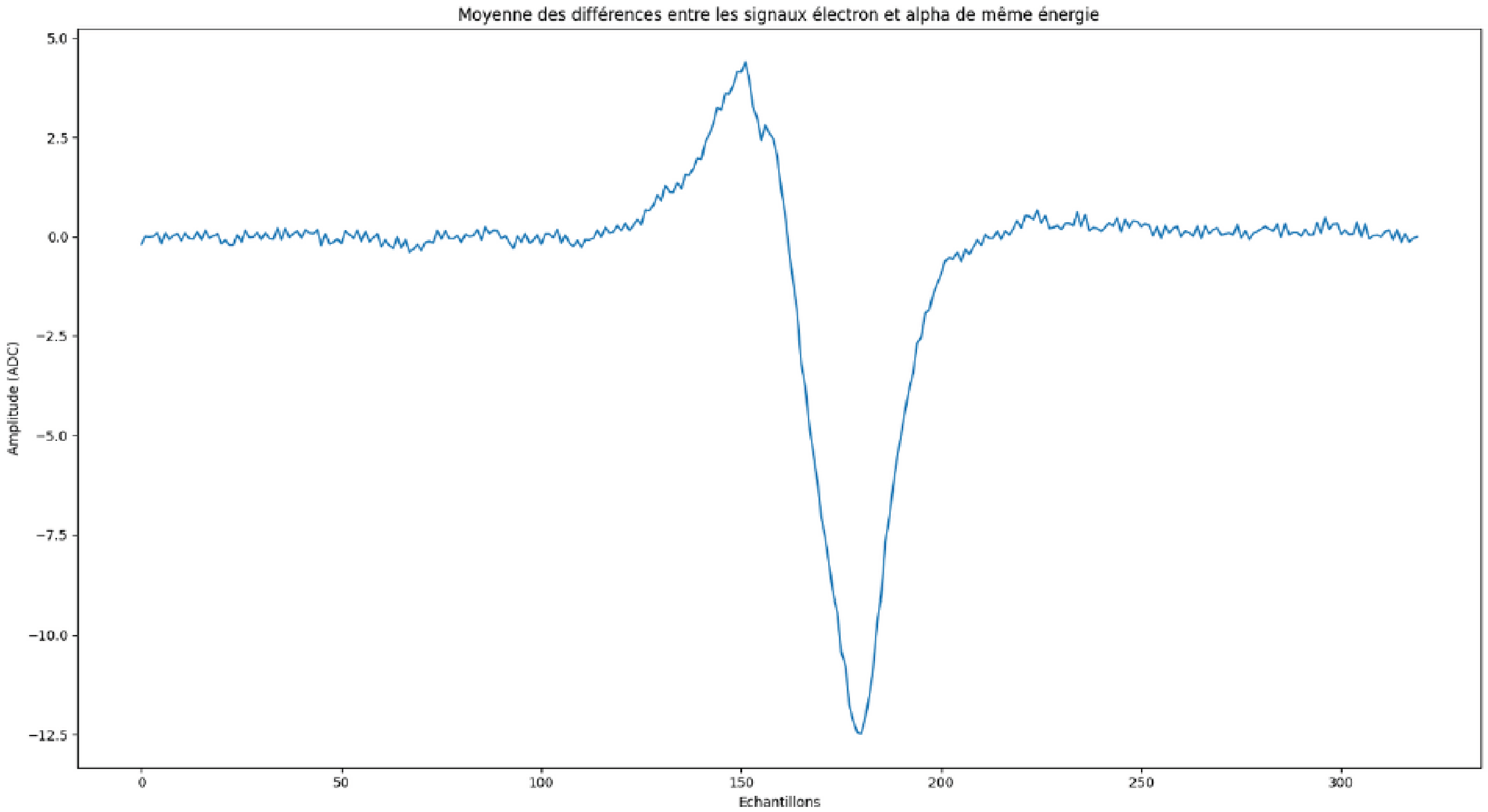
Energy-risetime heatmaps





- ❑ Confusion zone below ~500 keV
- ❑ Is machine learning a solution?

Pulse shape discrimination



- ❑ Difference in the pulse shape for same energy electrons and alphas
- ❑ Should allow discrimination

Machine learning

- Machine learning algorithms investigated :
  - Auto encoder
  - Convolutional neural network
  - Random forest

- Classification
  - Electron/alpha discrimination

- Regression
  - Determination of the energy and the rise time

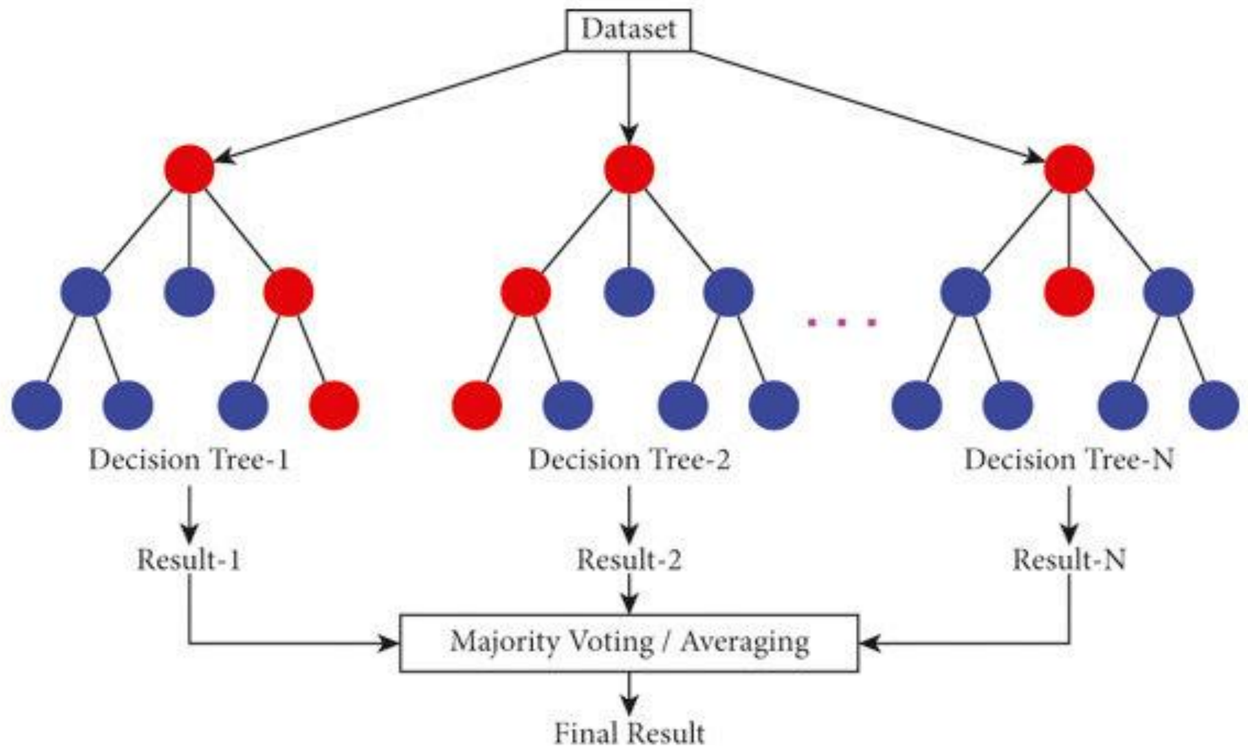
- Potential implementation in the instrument FPGA

Models efficencies

Model	Classification efficiency	Regression efficiency	Numerical weight
Auto-encoder	97%	Regression not possible	Light
CNN	99%	~ 23%	Heavy
Random Forest	99%	95-99%	Depends on the training data

- ❑ Random forest is the most promising model

Random forest



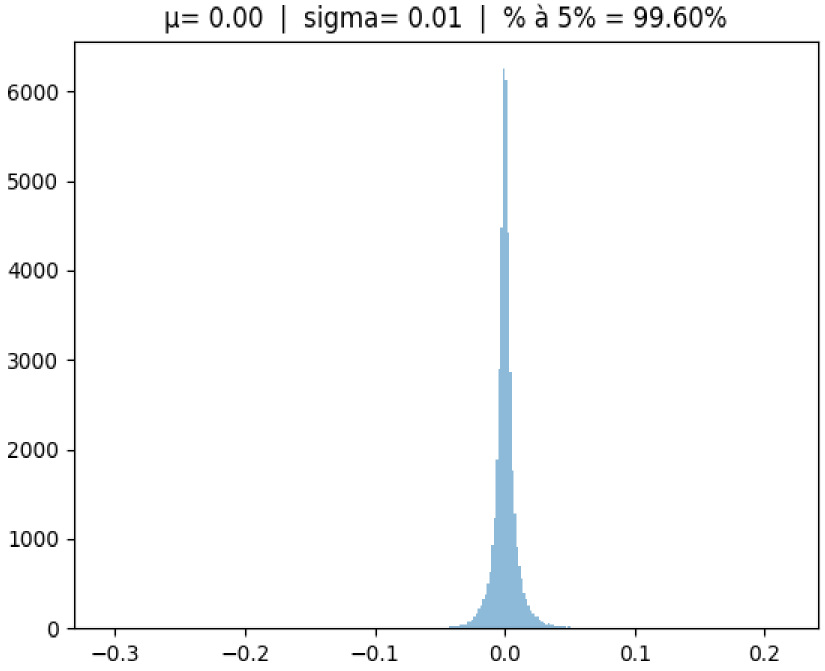
- ❑ Decision trees are formed through training, each using only a sample of the signal
- ❑ For a classifier, each tree returns a class (= a particle type) and the model's response is decided by majority vote
- ❑ For a regressor, each tree returns a value, and the model's response is decided by averaging the responses.

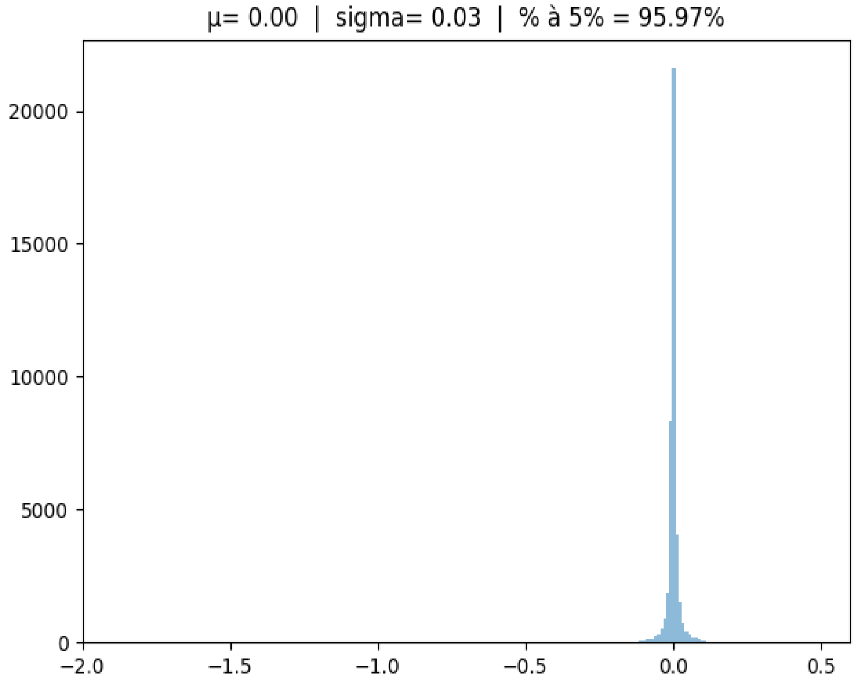
Random forest discrimination

RF Particle ID - 1.8e4 signals			
Reel / Prediction	Alpha	Electron	SUM
Alpha	988 49.40%	10 0.50%	998 99.00% 1.00%
Electron	12 0.60%	990 49.50%	1002 98.80% 1.20%
SUM	1000 98.80% 1.20%	1000 99.00% 1.00%	1978 / 2000 98.90% 1.10%

- ❑ Good results
- ❑ No bias in favor of one or the other class

Random forest regression





- ❑ 99% regression efficiency for Energy
- ❑ 95% regression efficiency for Rise time
- ❑ Efficiency increases with training (but memory needed as well)

Conclusions

- Very promising results for particle discrimination and regression of physical values
- Several factors not yet taken into account for “real life” use
  - Lower sampling frequency
  - Fixed point encoding
  - Protons instead of alphas
  - Zero classification (noise, GCRs…)
- “Black box” effect to be adressed
- Complexity of implementation on FPGA to be evaluated
- Test with protons in a particle accelerator will be performed