Реконструкция на сигнали в електромагнитния калориметър на експеримента PADME чрез машинно обучение

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СВ. КЛИМЕНТ ОХРИДСКИ

ФОНД НАУЧНИ ИЗСЛЕДВАНИЯ
МИНИСТЕРСТВО НА ОБРАЗОВАНИЕТО И НАУКАТА

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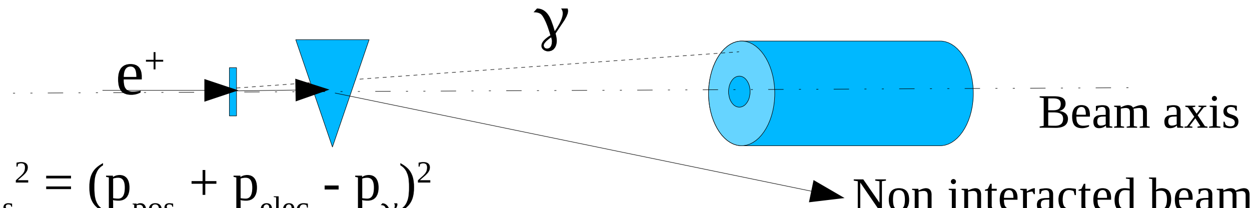
Outline

- The PADME Experiment: detectors and data taking
- Machine learning methods, developed for the PADME data reconstruction
  - Data simulation, neural networks and performance
- Applying the trained models on real experiment data
- Explainability investigation

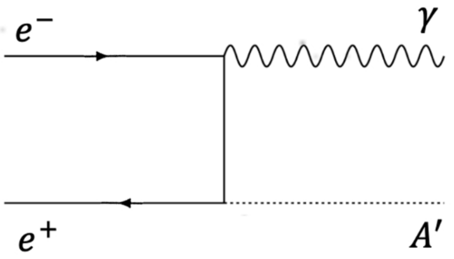
The PADME Experiment

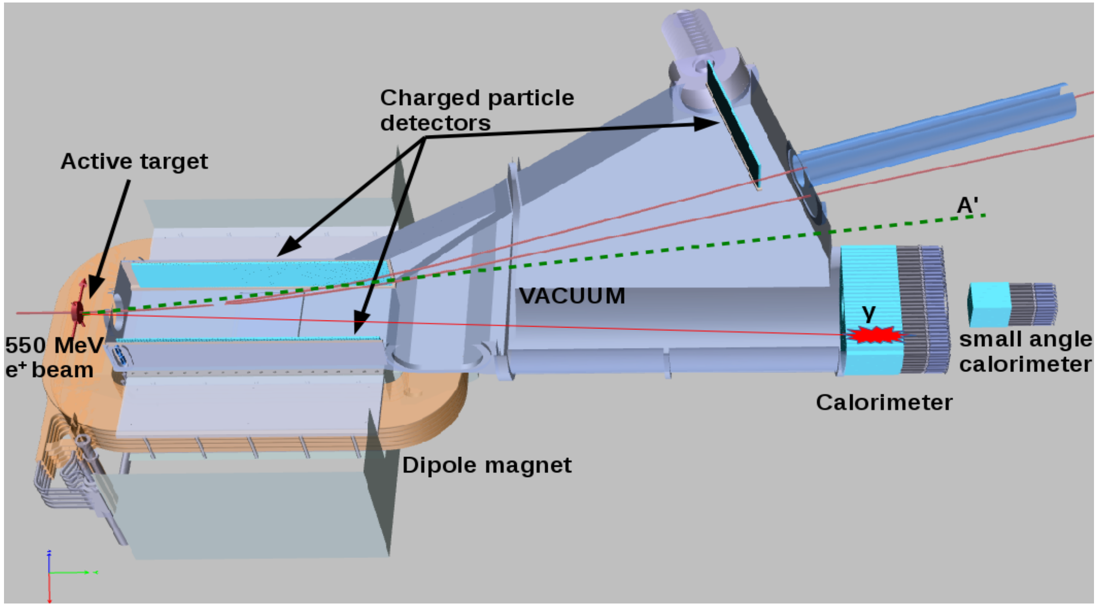
Positron Annihilation into Dark Matter Experiment



$$M_{miss}^2 = (p_{pos} + p_{elec} - p_\gamma)^2$$

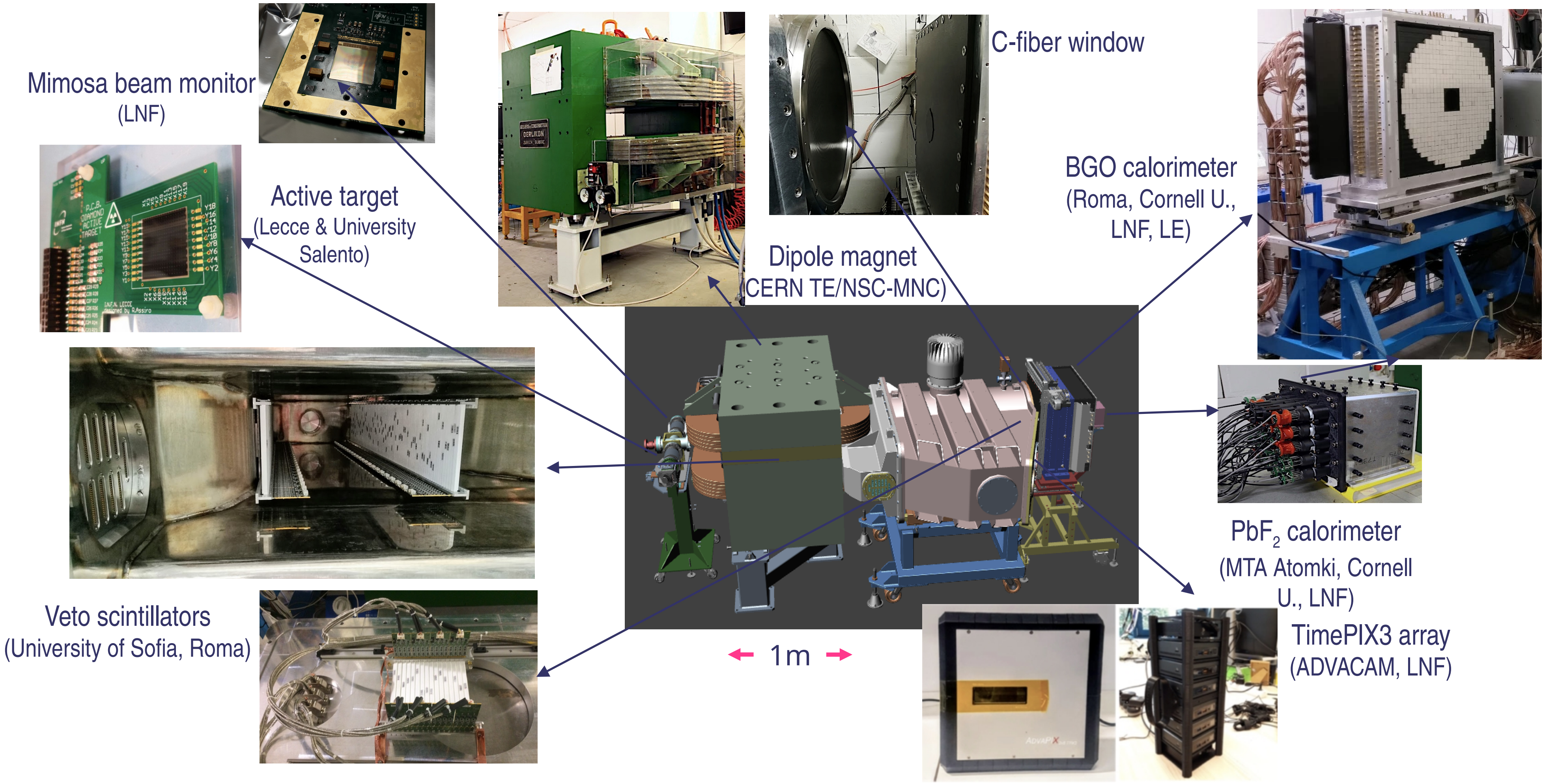
Associated production:
$e^+e^- \rightarrow A'\gamma$



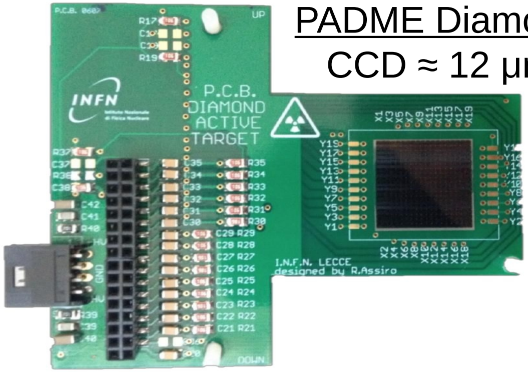


- Small scale fixed target experiment
  - e^+ @ Frascati Beam Test Facility
  - Accelerated e+ interacting in a thin diamond active target
  - Final states: e+, e-, photons
  - Charged particles detectors
  - Calorimeter
  - Beam monitoring system

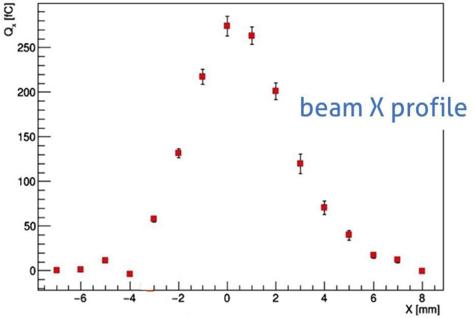
PADME Experiment

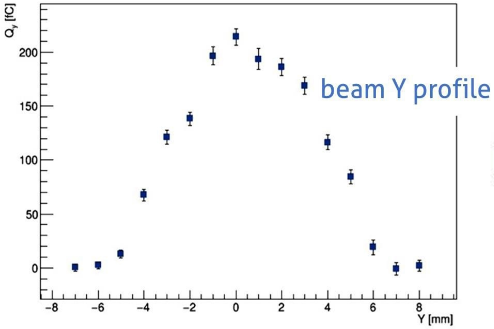


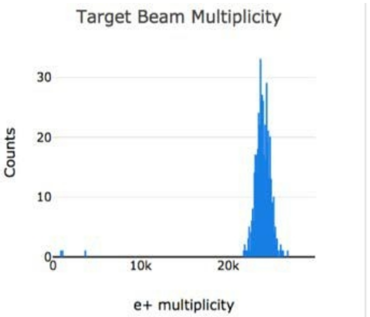
Active target

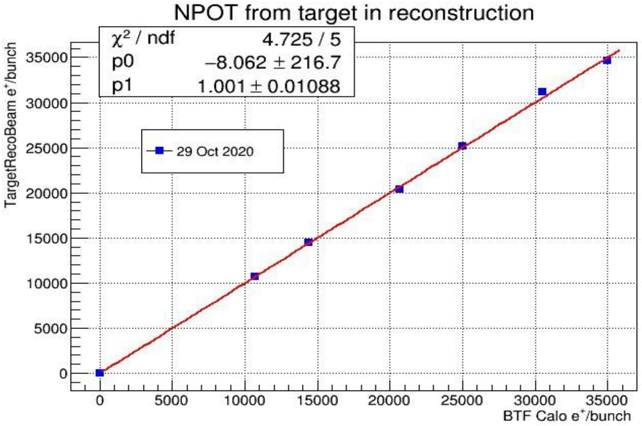


PADME Diamond
CCD ≈ 12 μm

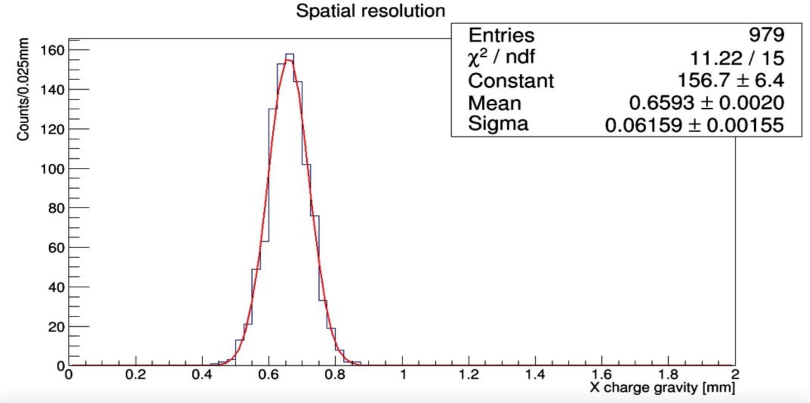






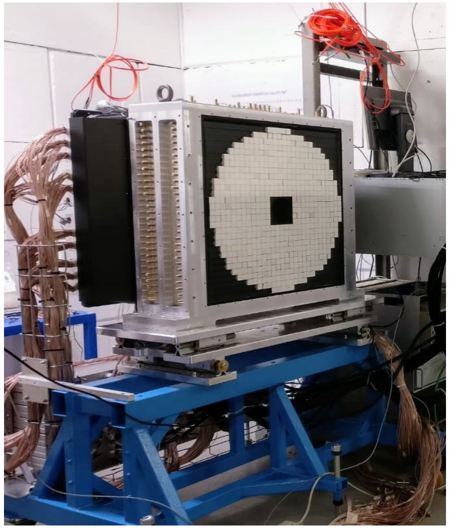


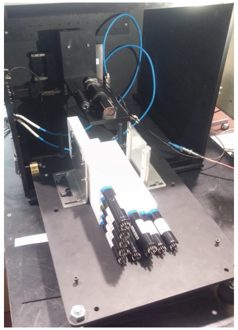
- **Polycrystalline diamond**
- 100 μm thickness:
- 16 × 1 mm strip and X-Y readout in a single detector
- Graphite electrodes using excimer laser



- *JINST* 12 (2017) 02, C02036

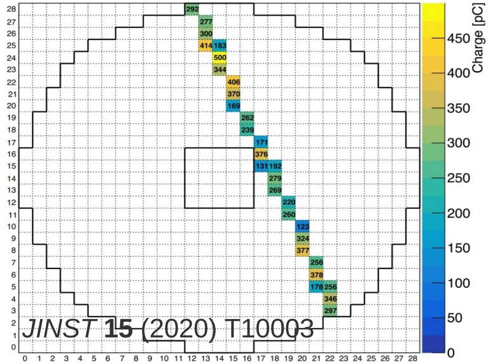
Calorimeters





ECAL: The heart of PADME

- 616 BGO crystals, 2.1 x 2.1 x 23 cm^3
- BGO covered with diffuse reflective TiO_2 paint
  - additional optical isolation: 50 – 100 µm black tedlar foils



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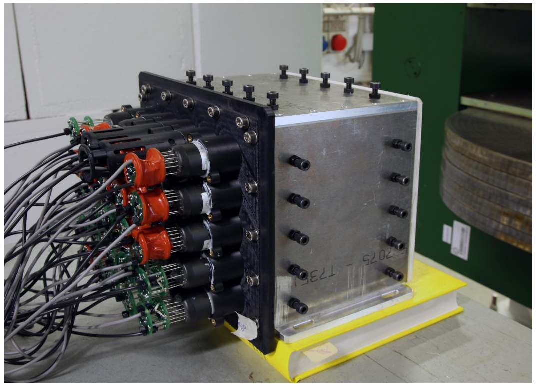
Calibration at several stages:

- BGO + PMT equalization with ^{22}Na source before construction
- Cosmic rays calibration using the MPV of the spectrum
- Temperature monitoring

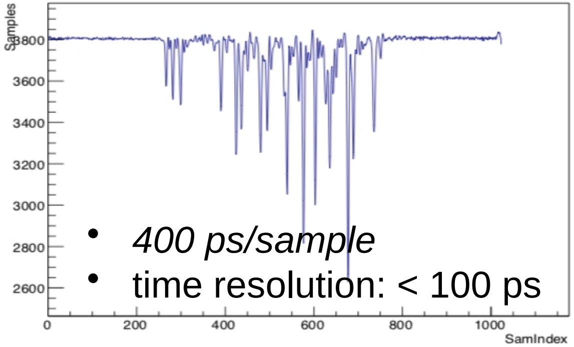


Nucl.Instrum.Meth.A 919 (2019) 89-97

Small Angle Calorimeter (SAC)

- 25 crystals - 5 x 5 matrix, Cherenkov PbF_2
- Dimensions of each crystal: 3 × 3 × 14 cm^3
- 50 cm behind ECal
- PMT readout: Hamamatsu R13478UV with custom dividers
- Angular acceptance: [0,19] mrad

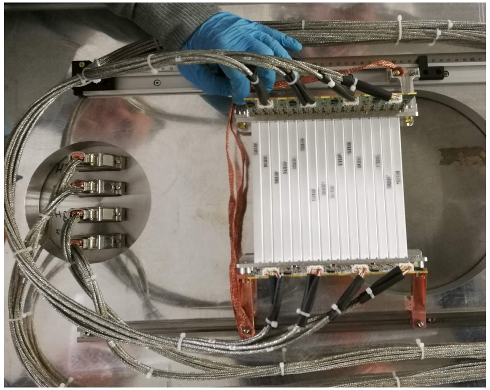
Recorded bunch



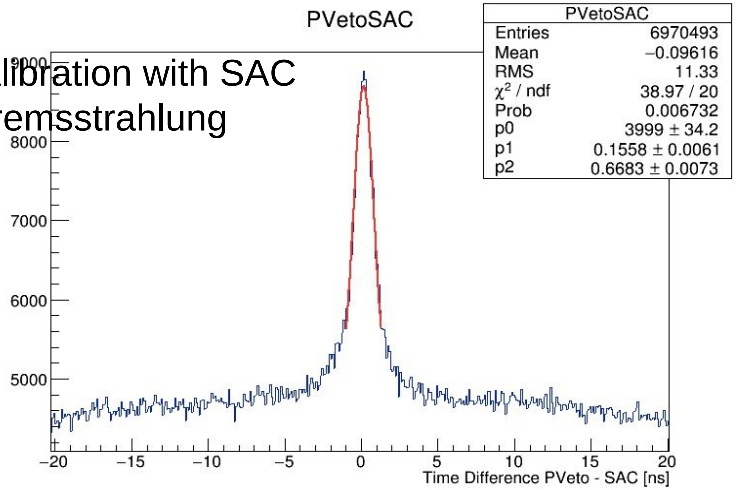
- *400 ps/sample*
- time resolution: < 100 ps

Charged particle detectors

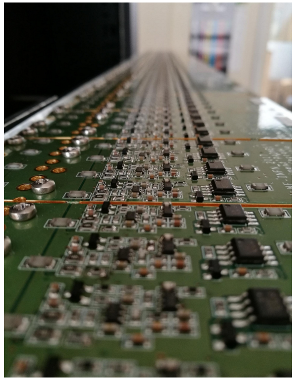
- Three sets of detectors detect the charged particles from the PADME target (at E_{beam} = 550 MeV):
  - **PVeto**: positrons with 50 MeV < p_{e+} < 450 MeV
  - **HEPVeto**: positrons with 450 MeV < p_{e+} < 500 MeV
  - **EVeto**: electrons with 50 MeV < p_{e+} < 450 MeV
- 96 + 96 (90) + 16 (x2) scintillator-WLS-SiPM RO channels
- Segmentation provides momentum measurement down to ~ 5 MeV resolution



Time calibration with SAC using Bremsstrahlung events



- Custom SiPM electronics, Hamamatsu S13360 3 mm, 25µm pixel SiPM
- Differential signals to the controllers, HV, thermal and current monitoring



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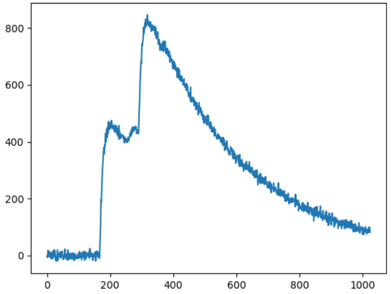
- Online time resolution: ~ 2 ns
- Offline time resolution after fine T_0 calculation – better than 1 ns

The machine learning approach to PADME data: a summary

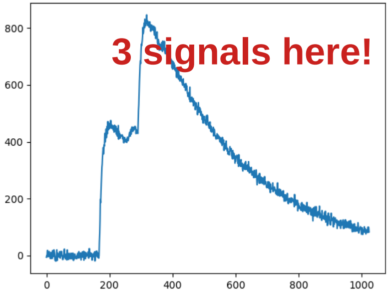
Signal simulation → Simple CNN for counting → Autoencoder → Modified autoencoder

Signal simulation



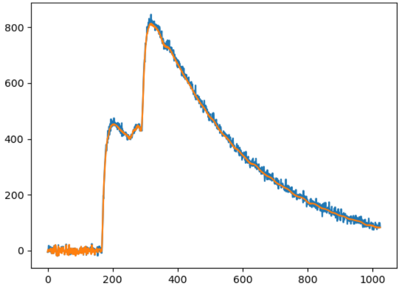
- Generation of noise + several waveforms
- Predefined signal shape
  - Difference between two exponents
  - Calorimeter response function
  - Fixed rise and fall time
- Random number of signals (between 0 and 4)
- Random amplitude and arrival time for each signal

Simple CNN for counting



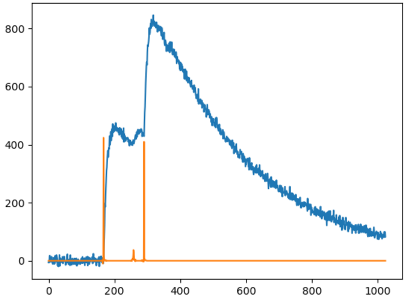
- Classification task to identify the number of pulses in a waveform
- Trained on 100 000 events
- 100% signal discrimination above 50 ns difference, 90% above 30 ns

Autoencoder



- Convolutional autoencoder for signal and noise description
- Unsupervised learning – both input and desired output are the waveform arrays
- The waveforms are successfully replicated with the noise in the signal regions significantly suppressed

Modified autoencoder

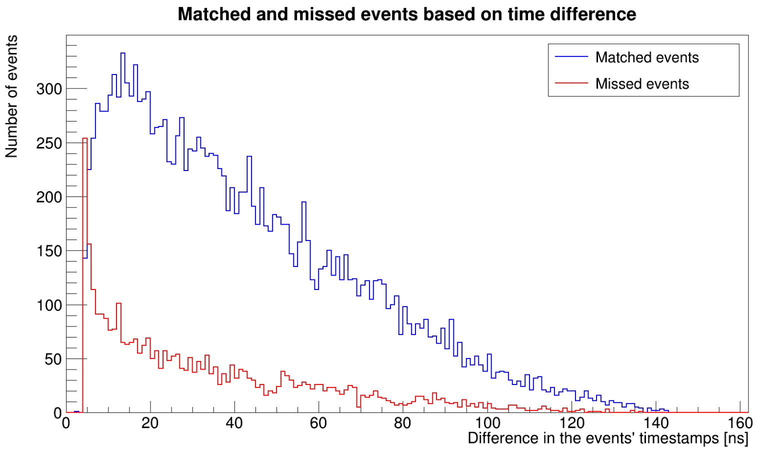


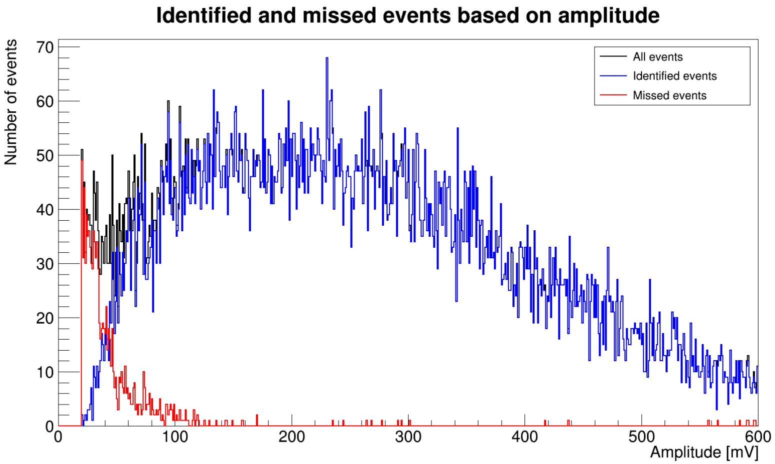
- Same architecture as autoencoder network
- Supervised learning –desired output contains information about the time and amplitude
- Efficiency for time and amplitude thoroughly investigated:
  - Excellent arrival time determination
  - Problems with amplitude reconstruction

Main properties of the modified autoencoder reconstruction

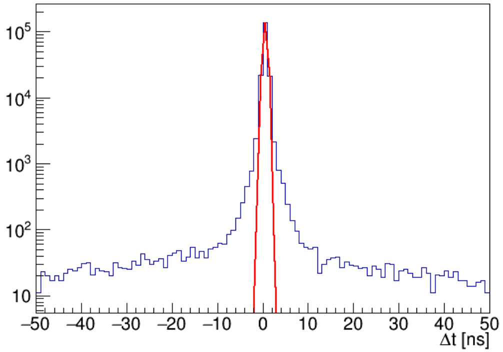
Pulse identification

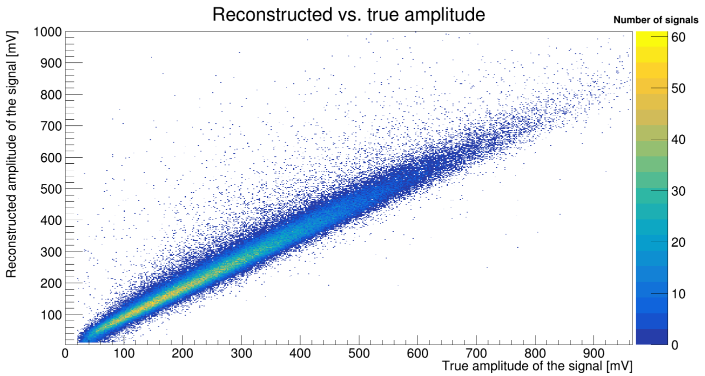
- Efficiency for lower numbers of signals are higher because of unrecognized signals from events with higher numbers
- For closely located signals: Most of the missed events are with dt < 10 ns
- Most of the events with amplitudes < 50mV are not identified





Arrival time and amplitude determination

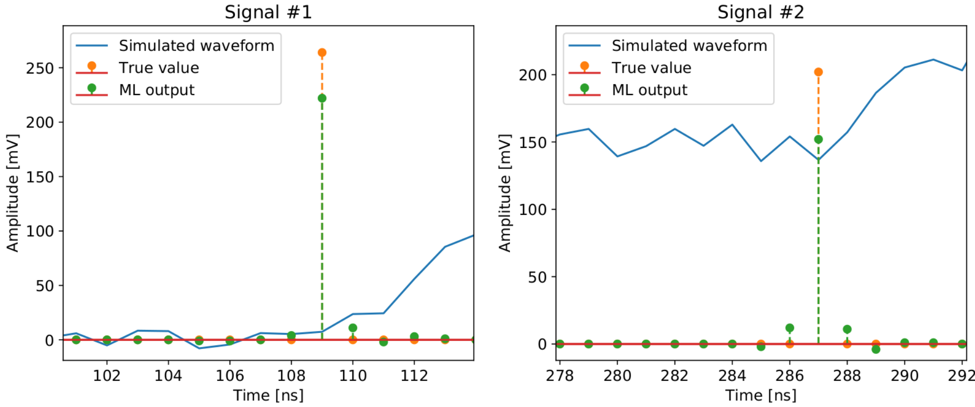


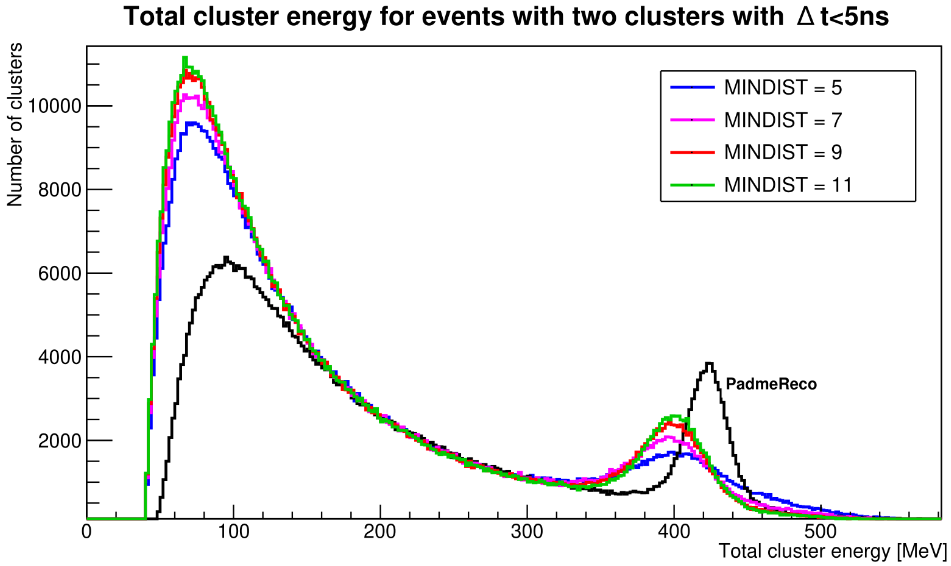


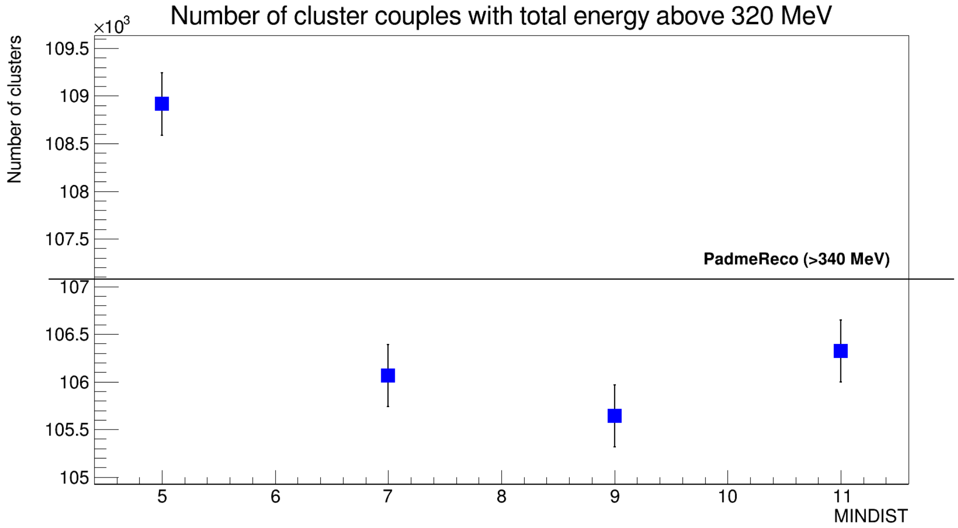
- Δt distribution is symmetric, non-gaussian tails exist
- σ ~ 520 ps, RMS ~ 3.2 ns
- Strong correlation between real and reconstructed amplitude
- Worse reconstruction for the small amplitudes

Application on real data and the effect of the merging window width using e+e-→γγ events

The merging window is the amount of neighboring position values added to the main signal amplitude when constructing the ML results

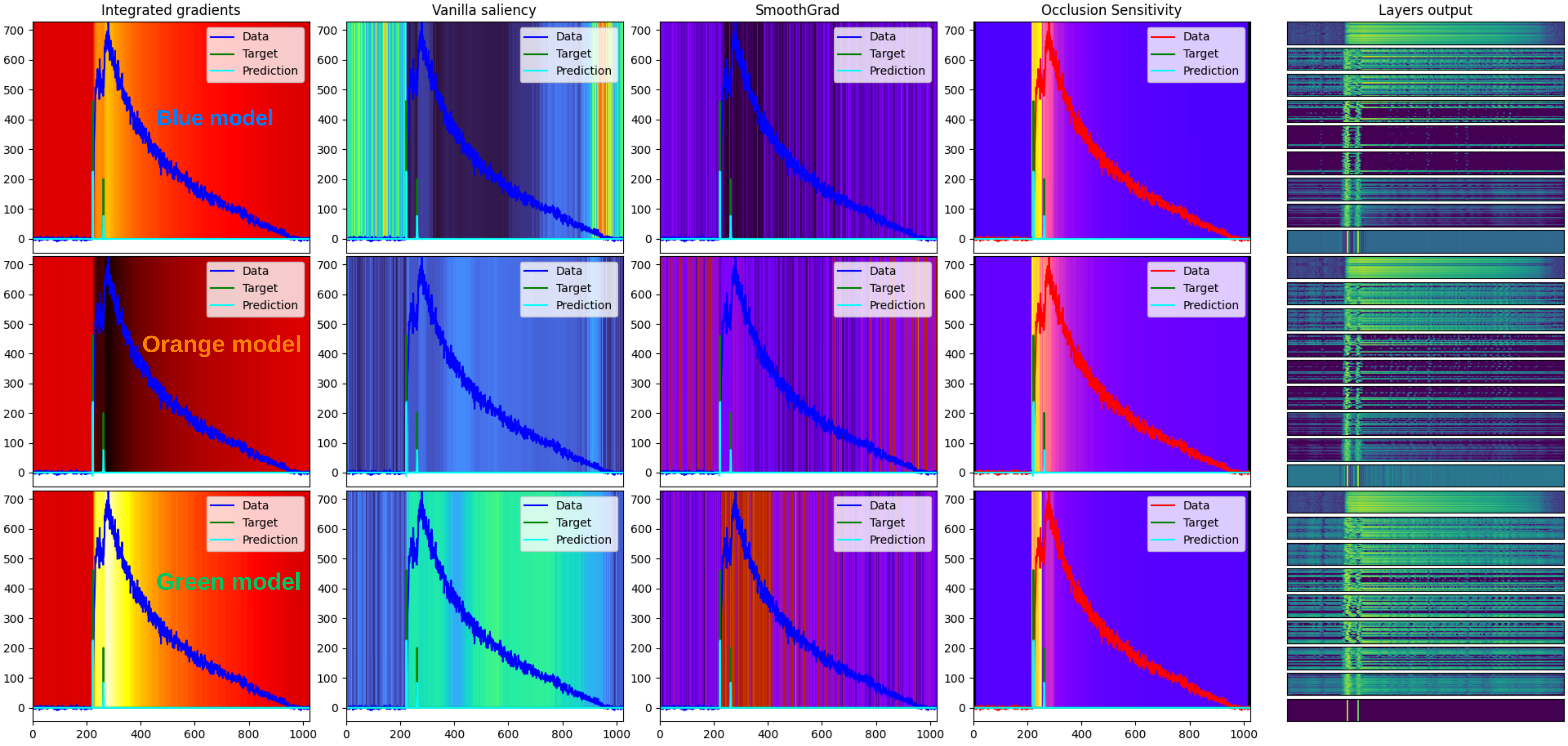






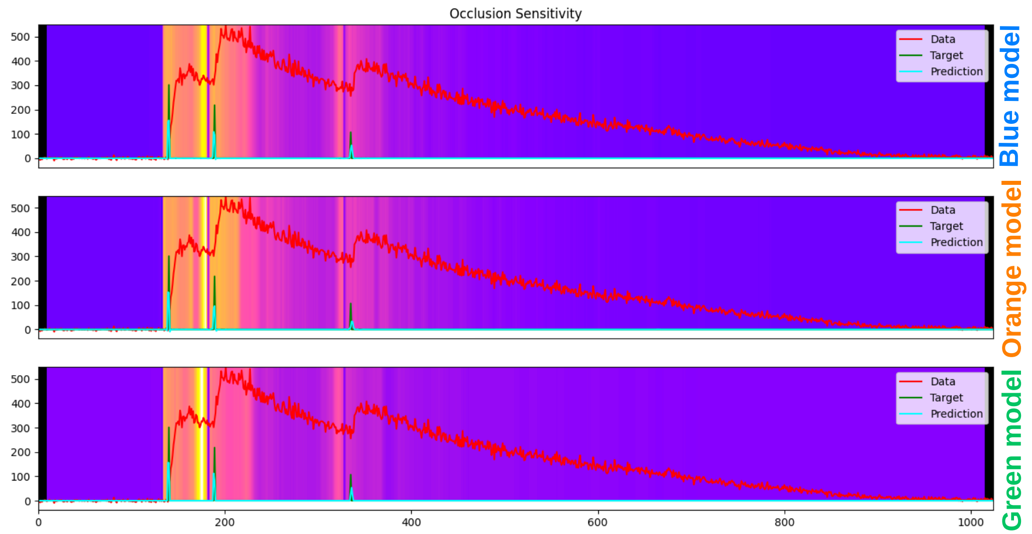
- **The total number of clusters for the original reconstruction and for the various ML cases is similar** despite the wider peak
- Solution is adjusting the ML reco peaks through introducing additional calibration

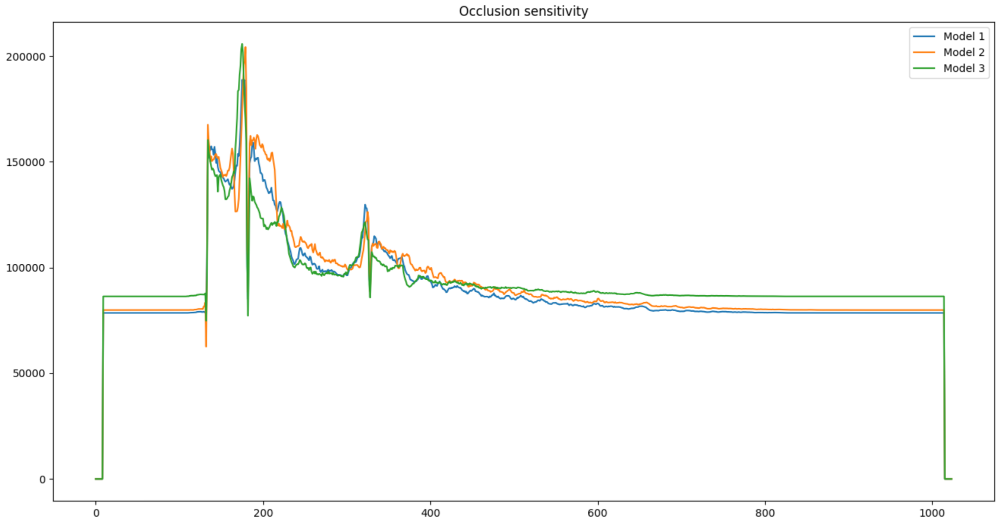
Development of explainability methods



Occlusion sensitivity investigation

- See predictions for certain cases of mask position
- First idea:
  - See what happens if we **mask the region right before the signal rise** → would the signal be misplaced, predicted earlier and with a higher amplitude?
  - See what happens if we leave only the signal rise and **mask the region before and after it** → would the signal be found at all?





Blue model: filter 18, linear activation
Orange model: filter 14, linear activation
Green model: filter 18, ReLu activation

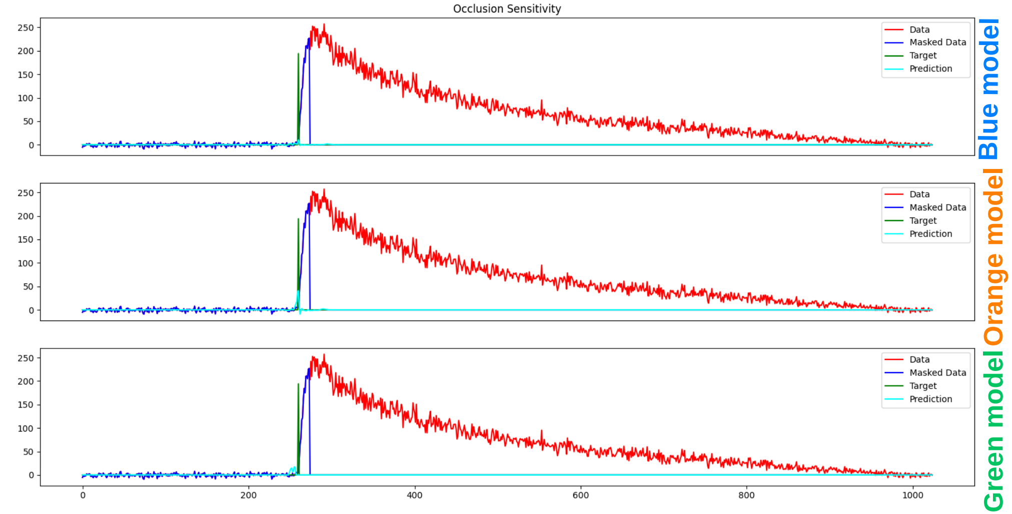
Gradually unmasking the signal

- After 3 unmasked values: signal starts to appear (at a wrong place)

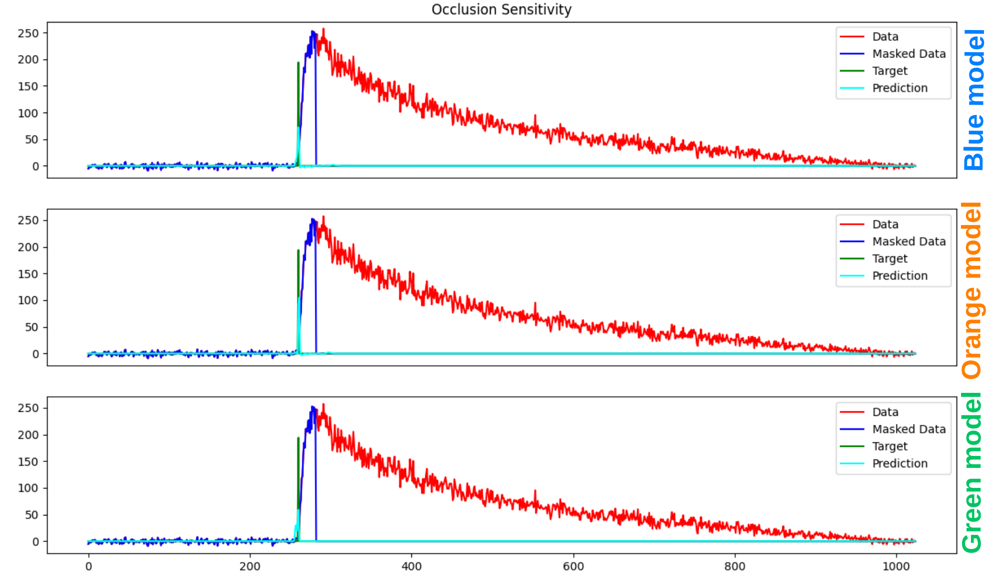
- After 12 unmasked values: arrival time is found

- After 15 unmasked values: amplitude rises

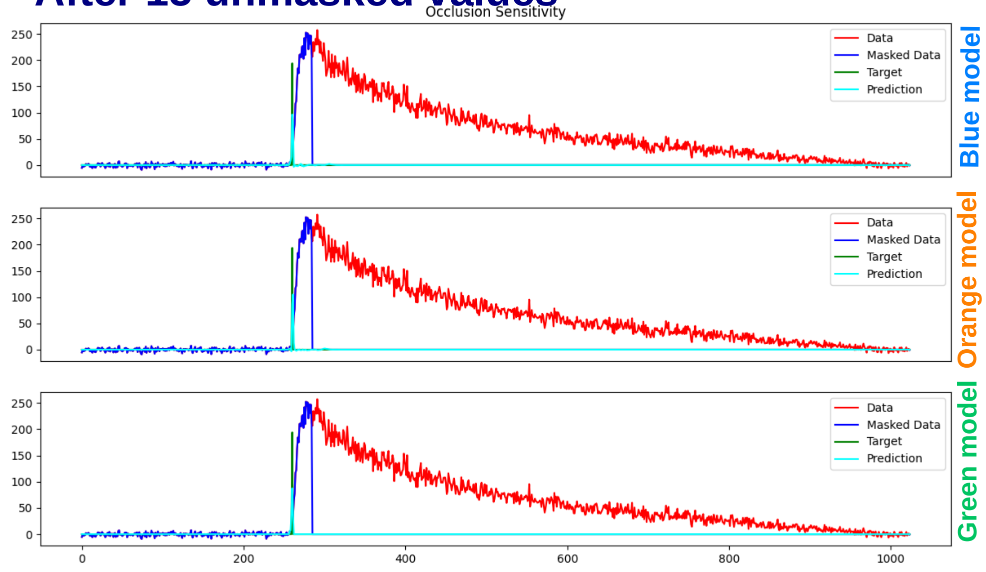
After 3 unmasked values



After 12 unmasked values



After 15 unmasked values

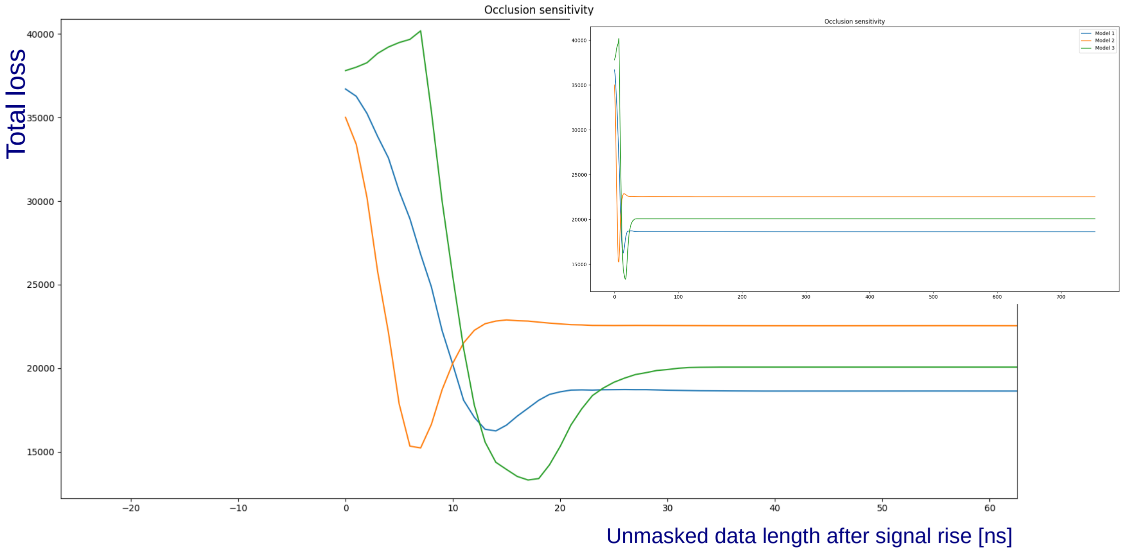


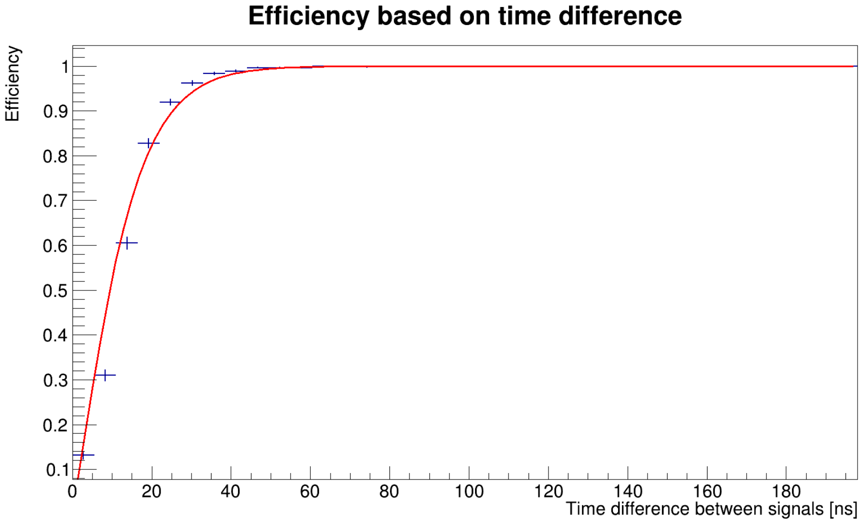
Gradually unmasking the signal

Blue model: filter 18, linear activation
Orange model: filter 14, linear activation
Green model: filter 18, ReLu activation

Total loss as a function of the number of unmasked values after the signal rise

- Initially very high – no signal found
- Lowers with unmasking more signals, reaches a minimum and returns to a constant
- Minimum for the green model is deepest (best model?) and is at 18 unmasked values after the signal rise – same as the last filter size
- Signal rise time + minimum value is what is needed to find a signal → explains the minimum distance between two signals for them to be separated? (30 ns from analysis)
  - “worse” models reach a minimum at fewer unmasked values → could they be better for double pulse separation

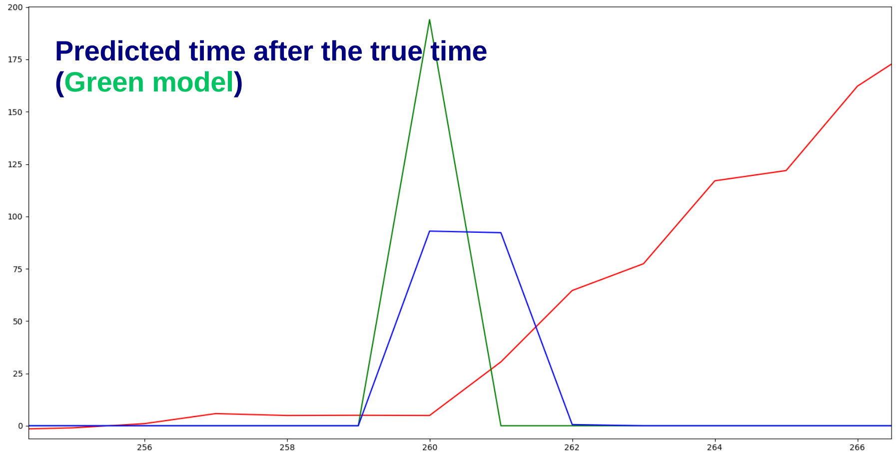


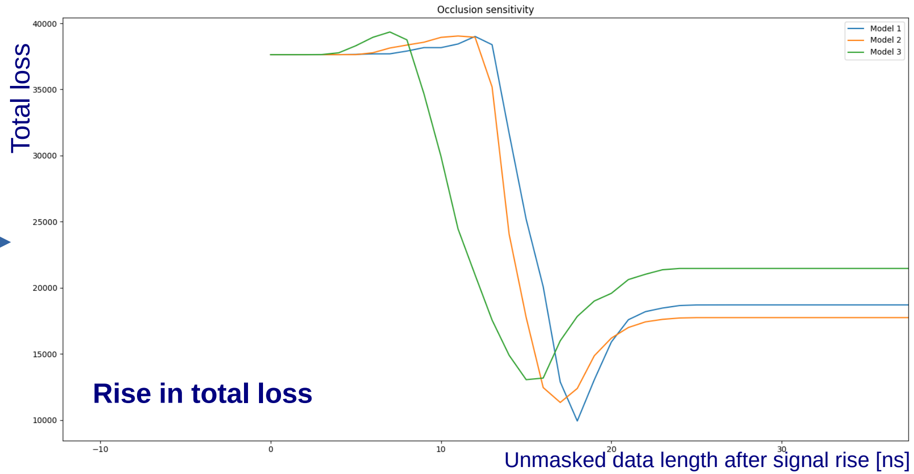


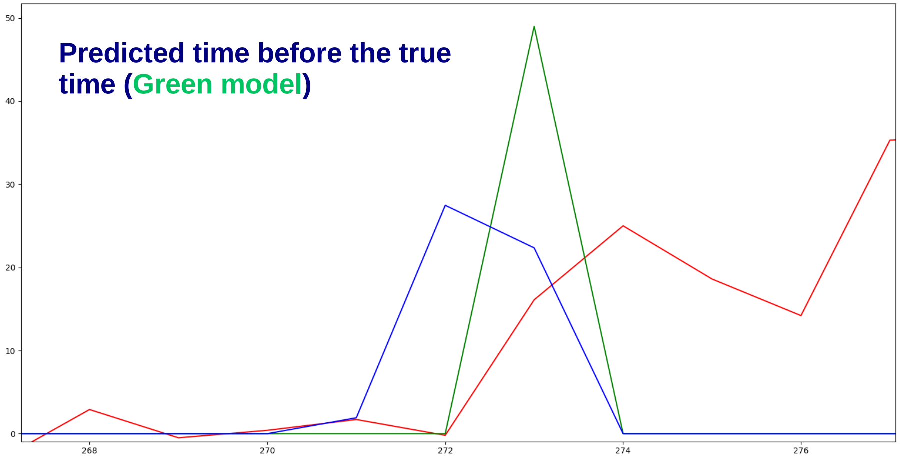
Weighted arrival time value

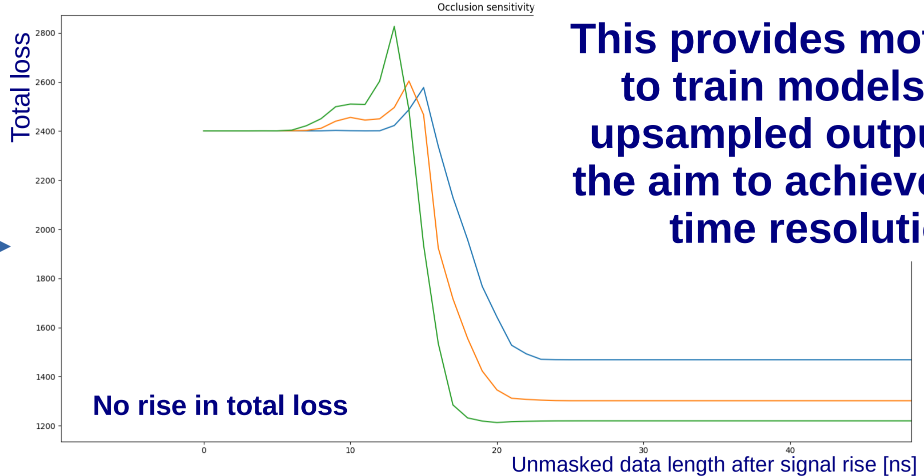
$$t_{arrival} = \frac{\sum_{i=t_{max}-\tau}^{t_{max}+\tau} t_i A_i}{\sum_{i=t_{max}-\tau}^{t_{max}+\tau} A_i}$$

The arrival time is no longer taken as the time of the maximum prediction (integer) but as the weighted average of all positions with non-zero predictions









This provides motivation to train models with upsampled output with the aim to achieve better time resolution

Conclusions

- PADME calorimetric system has to provide reliable energy reconstruction and shower separation

- Different ML topologies for signal reconstruction tested
  - Classification → number of signals
  - Autoencoder → noise filtration
  - Modified autoencoder → signal parameters estimation

- First successful physics events reconstruction: $e^+e^- \rightarrow \gamma\gamma$ events

- The occlusion sensitivity method was applied for investigation of the output of the neural networks.
  - Two distinct ways the loss behaves point to the importance of using the weighted average for the arrival time instead of simply the maximum position