What Machine Learning Can Do for Focusing Aerogel Detectors

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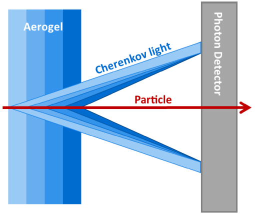
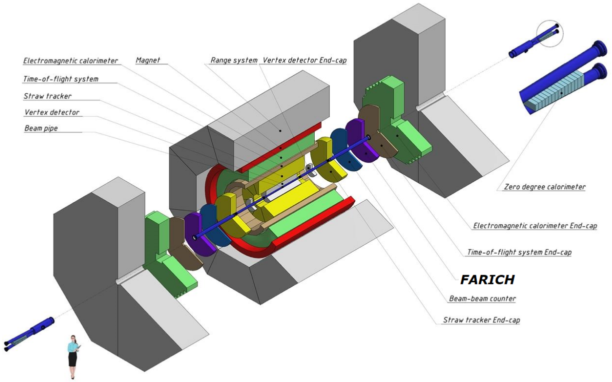
FARICH for SPD

Compact particle ID detector

- trade off between resolution and number of Cherenkov photons
- improve resolution with discrete focusing capability





https://nica.jinr.ru/projects/spd.php

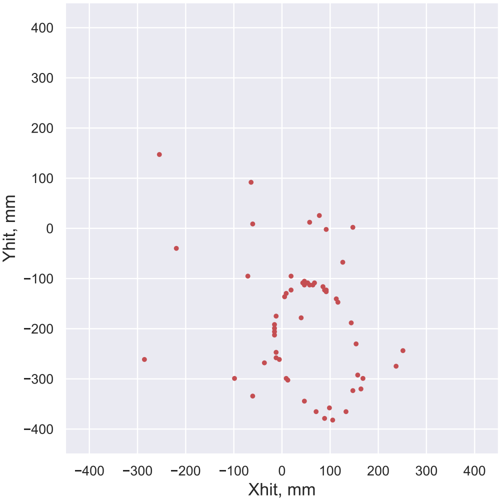
Data: "Simple" FARICH GEANT4 Simulation

- photodetector
  - 30×30 matrix of SiPM ($57600 = 30 \times 30 \cdot 8 \times 8$ total channels);
  - 3.16×3.16 mm^2 pixels;
  - 1 mm gap between matrices.
- radiator
  - 4 layers, $n_{\mathrm{max}} = 1.05$;
  - 35 mm total depth;
  - 200 mm in front of the photo detector.
- π^- with varying angles $[0^\circ, \dots, 45^\circ]$ and velocities $[0.957; 0.999]$

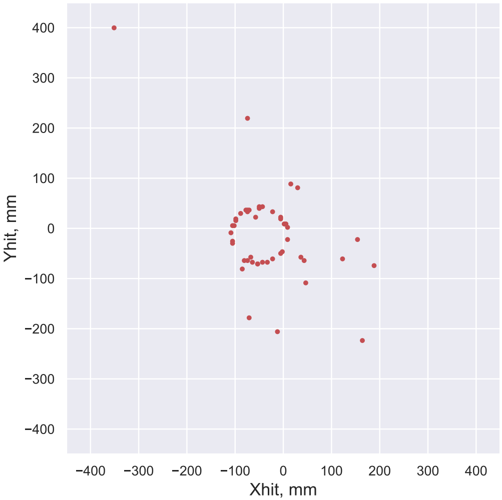
1.2M events

- photon hit coordinates
- hit times
- flat random noise is dynamically applied on top of the events

Data

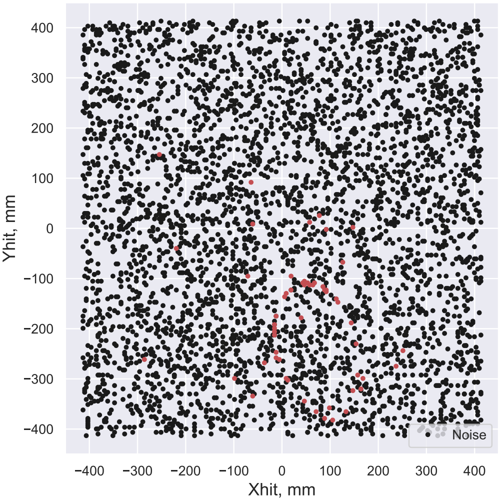


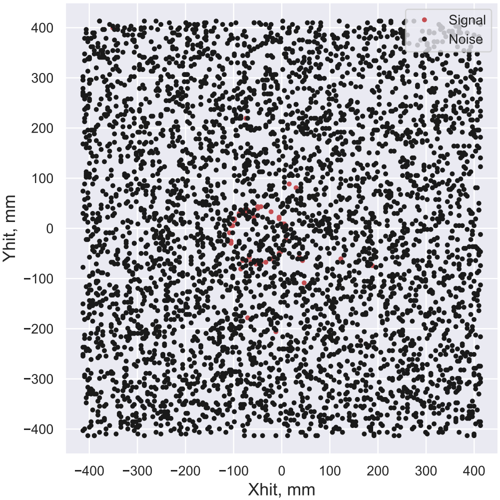
400
300
200
100
0
−100
−200
−300
−400
Yhit, mm
−400 −300 −200 −100 0 100 200 300 400
Xhit, mm



400
300
200
100
0
−100
−200
−300
−400
Yhit, mm
−400 −300 −200 −100 0 100 200 300 400
Xhit, mm

Data (Noise 1MHz/mm^2)





Online Data Filtering

Goals

- no info about particle track
- noise up to $1\text{MHz}/\text{mm}^2$
- efficiency $\geqslant 95\%$
- maximum possible noise suppression (orders of magnitude)

Online Data Filtering

Approach 1: Classification

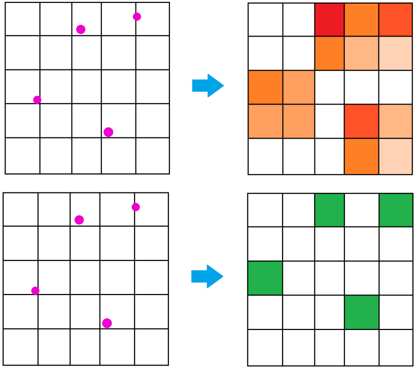
- create a dataset of events with / without signal (positive event $\geqslant 10$ signal photons)
- train Convolutional Neural Network (CNN) to perform binary classification

Metrics:

- Efficiency (events) $= \text{TPR} = \frac{\text{TP}}{\text{TP}+\text{FN}}$
- Noise Events Reduction $= \text{FPR} = \frac{\text{FP}}{\text{TN}+\text{FP}}$

Procedures: Data

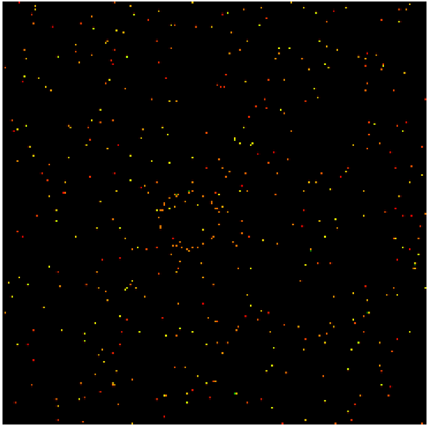
- irregular matrix structure due to gaps between SiPM
    - project hits (times) to a regular grid



Red — hits, green — times

Procedures: Data

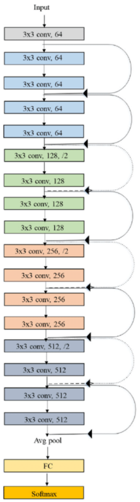
- irregular matrix structure due to gaps between SiPM
  - project hits (times) to a regular grid



Input image example

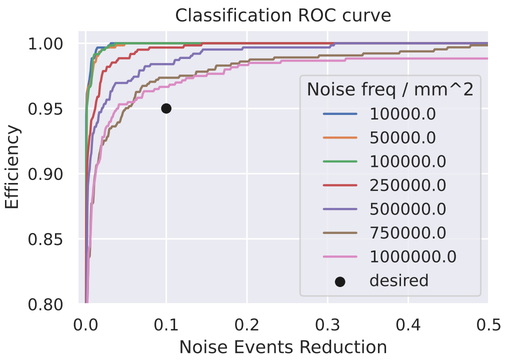
Procedures: Learning

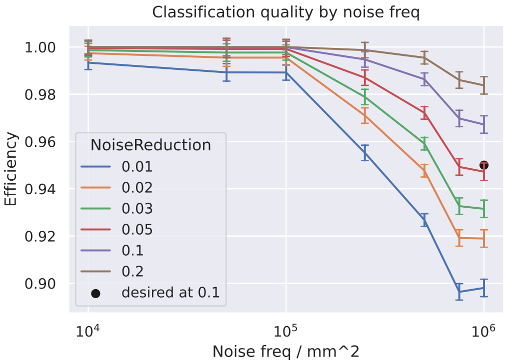
- use ResNet-18[1] CNN architecture
  - tune first and last layers to accommodate input and output data formats



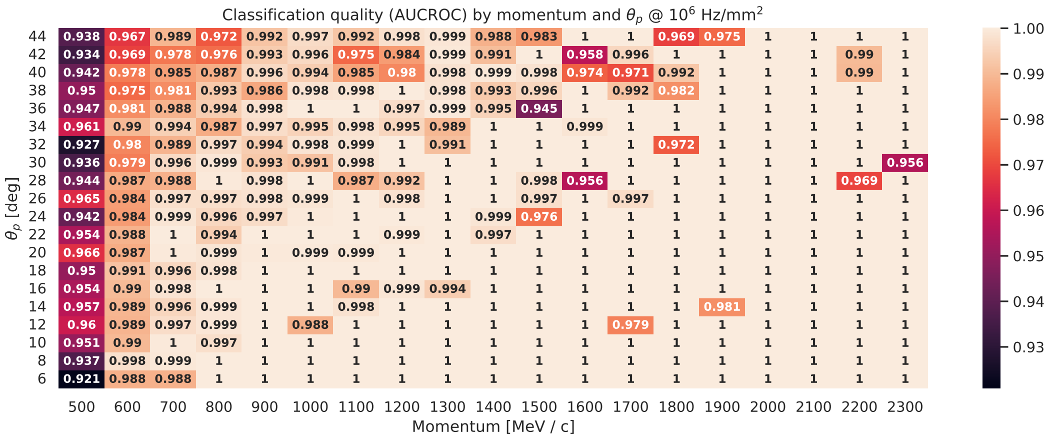
[1] He et al. Deep Residual Learning for Image Recognition. In CVPR 2016.

Experiment: Classification



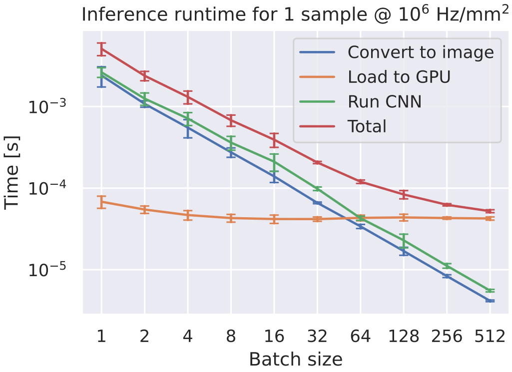


Experiment: Classification



θ_p [deg]	500	600	700	800	900	1000	1100	1200	1300	1400	1500	1600	1700	1800	1900	2000	2100	2200	2300
44	0.938	0.967	0.989	0.972	0.992	0.997	0.992	0.998	0.999	0.988	0.983	1	1	0.969	0.975	1	1	1	1
42	0.934	0.969	0.978	0.976	0.993	0.996	0.975	0.984	0.999	0.991	1	0.958	0.996	1	1	1	1	0.99	1
40	0.942	0.978	0.985	0.987	0.996	0.994	0.985	0.98	0.998	0.999	0.998	0.974	0.971	0.992	1	1	1	0.99	1
38	0.95	0.975	0.981	0.993	0.986	0.998	0.998	1	0.998	0.993	0.996	1	0.992	0.982	1	1	1	1	1
36	0.947	0.981	0.988	0.994	0.998	1	1	0.997	0.999	0.995	0.945	1	1	1	1	1	1	1	1
34	0.961	0.99	0.994	0.987	0.997	0.995	0.998	0.995	0.989	1	1	0.999	1	1	1	1	1	1	1
32	0.927	0.98	0.989	0.997	0.994	0.998	0.999	1	0.991	1	1	1	1	0.972	1	1	1	1	1
30	0.936	0.979	0.996	0.999	0.993	0.991	0.998	1	1	1	1	1	1	1	1	1	1	1	0.956
28	0.944	0.987	0.988	1	0.998	1	0.987	0.992	1	1	0.998	0.956	1	1	1	1	1	0.969	1
26	0.965	0.984	0.997	0.997	0.998	0.999	1	0.998	1	1	0.997	1	0.997	1	1	1	1	1	1
24	0.942	0.984	0.999	0.996	0.997	1	1	1	1	0.999	0.976	1	1	1	1	1	1	1	1
22	0.954	0.988	1	0.994	1	1	1	0.999	1	0.997	1	1	1	1	1	1	1	1	1
20	0.966	0.987	1	0.999	1	0.999	0.999	1	1	1	1	1	1	1	1	1	1	1	1
18	0.95	0.991	0.996	0.998	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
16	0.954	0.99	0.998	1	1	1	0.99	0.999	0.994	1	1	1	1	1	1	1	1	1	1
14	0.957	0.989	0.996	0.999	1	1	0.998	1	1	1	1	1	1	1	0.981	1	1	1	1
12	0.96	0.989	0.997	0.999	1	0.988	1	1	1	1	1	1	0.979	1	1	1	1	1	1
10	0.951	0.99	1	0.997	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
8	0.937	0.998	0.999	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
6	0.921	0.988	0.988	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Experiment: Classification



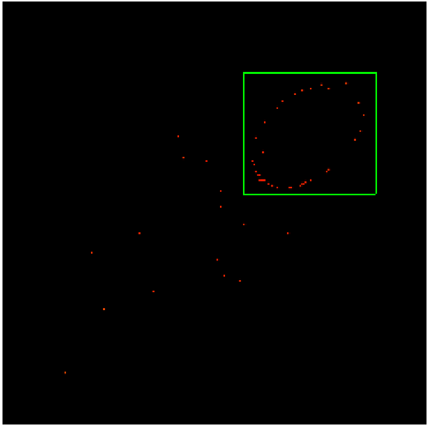
Online Data Filtering

Approach 2: Bounding box (bbox) regression

- compute ground truth bboxes for signal ellipses
- train CNN to extract bbox coordinates

Metrics:

- Efficiency (area) $= \frac{|B \cap B^{\mathrm{gt}}|}{|B^{\mathrm{gt}}|}$
- Reduction (area) $= \frac{|B|}{|B_{\mathrm{max}}|}$



Ground truth bbox example

Bbox regression objective

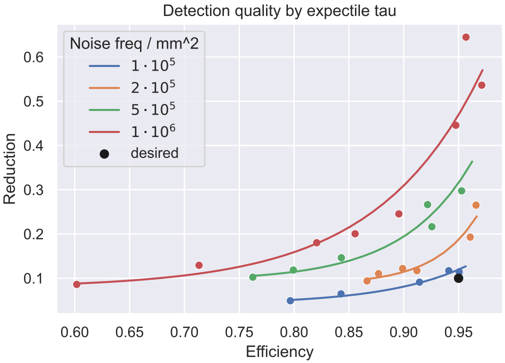
- with simple MSE many signal hits are lost
- use asymmetric version: **expectile loss** [2]

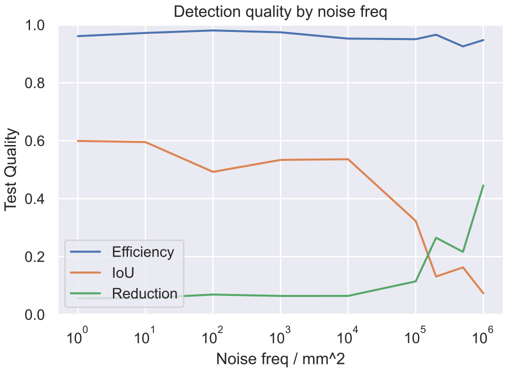
$$\text{quantile: } \operatorname{argmin}\left\{\sum_{i=1}^{n} \omega_\tau^q (y_i - q_i)|y_i - q_i|\right\},$$

$$\text{expectile: } \operatorname{argmin}\left\{\sum_{i=1}^{n} \omega_\tau^e (y_i - q_i)(y_i - q_i)^2\right\},$$

$$\text{where } \omega_\tau^q(\varepsilon) = \omega_\tau^e(\varepsilon) = \begin{cases} 1-\tau, & \varepsilon \leqslant 0 \\ \tau, & \varepsilon > 0 \end{cases}$$

Experiment: Bbox regression





Offline Reconstruction (RECO)

- train CNN regressor to predict $\beta = v/c$
- compare with statistical baseline (maximum likelihood)

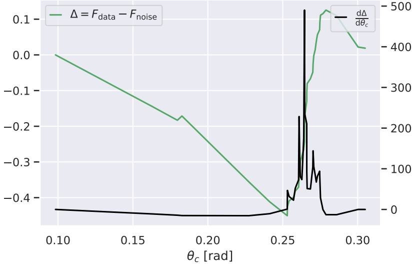
Configs:

- **ResNet:** no track prior
- **ResNet Centered:** center image using track info
- **ResNet Circular:** project hits to circular conic section, drop unphysical velocities, center
- **ResNet Fourier:** same as previous with added Fourier features

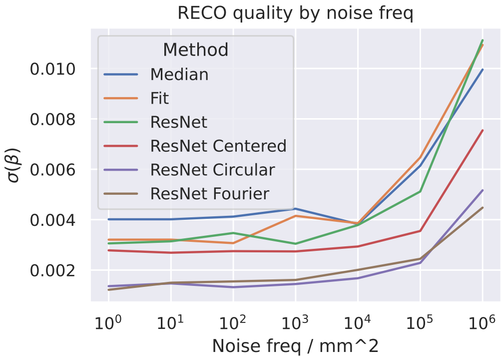
RECO: Statistical Baseline

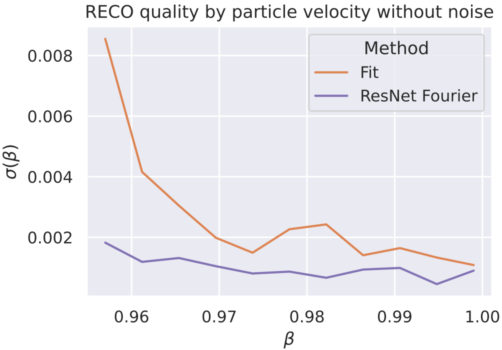
“Fit” algorithm:

- Compute Cherenkov angles θ_c
- Drop unphysical velocities $\beta = v/c \geqslant 1$
- Construct eCDF F_{data}
- Subtract pure noise CDF F_{noise}
- Take a numerical derivative and find its peak $\hat{\theta}_c = \arccos(1/n\hat{\beta})$

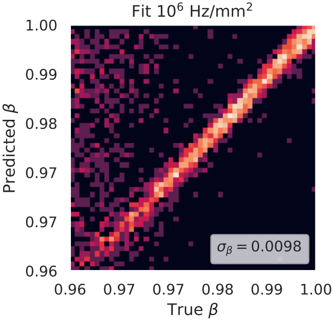


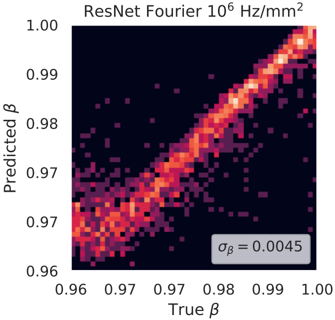
Experiment: RECO





Experiment: RECO





Conclusions

Online filtering:

- ResNet-18 CNN provides a significant level of denoising with high efficiency
- It is possible to achieve even higher noise reduction by performing bounding box regression on signal ellipses for positive events
- Real time performance is possible with optimizations

RECO:

- ResNet with track prior significantly outperforms stat models by β RMSE
- ResNet is more accurate on hard samples (low $\beta, \mathbf{p}$), where statistical models struggle the most because of random peaks in θ_c

References

[1] He et al. Deep Residual Learning for Image Recognition. In CVPR 2016.

[2] Arthur Charpentier. Quantile and Expectile Regresions. Erasmus School of Economics, May 2017.