What Machine Learning Can Do for a Focusing Aerogel Detectors

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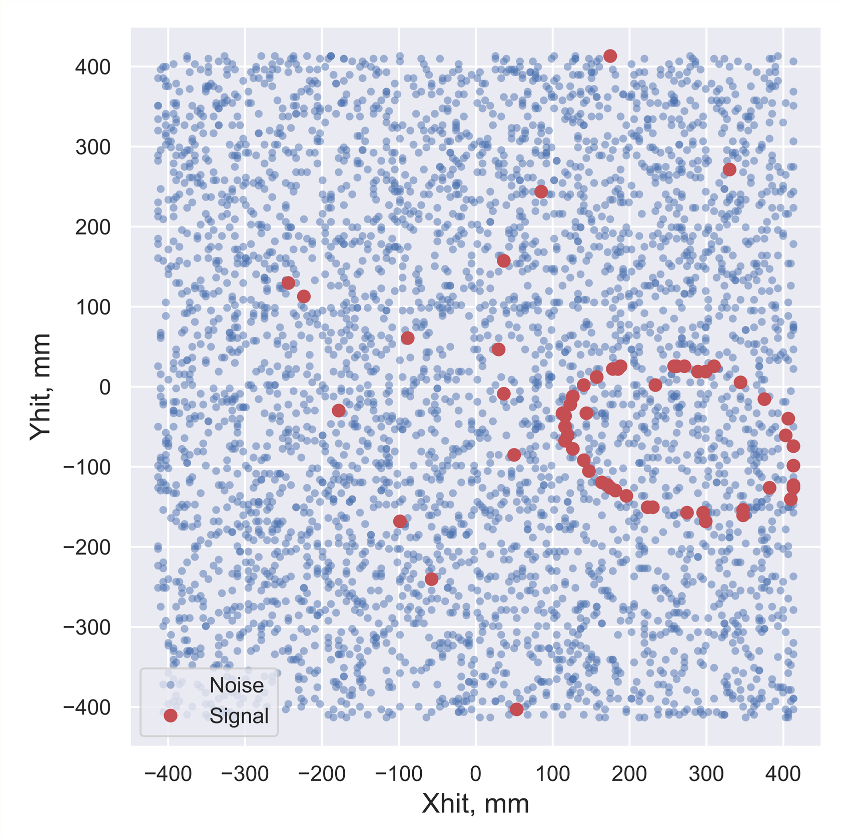
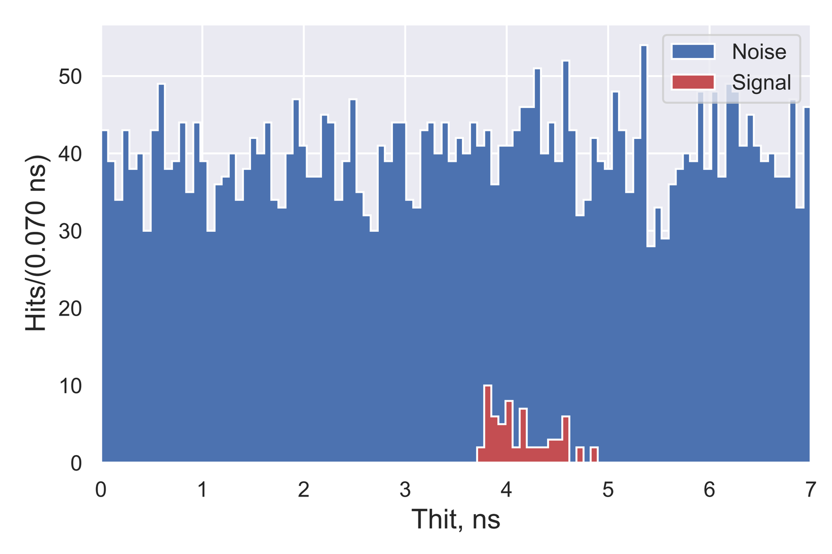
Problem: gathering data from the detector requires handling $\sim 10^8$ events/s. As the detector captures a great amount of noise, a fast and lightweight on-line noise filtering algorithm is needed to mitigate it. The off-line reconstruction task on noisy data should be addressed as well.

Solution: use Machine Learning tools to estimate the location of signal hits / the speed of the particle.

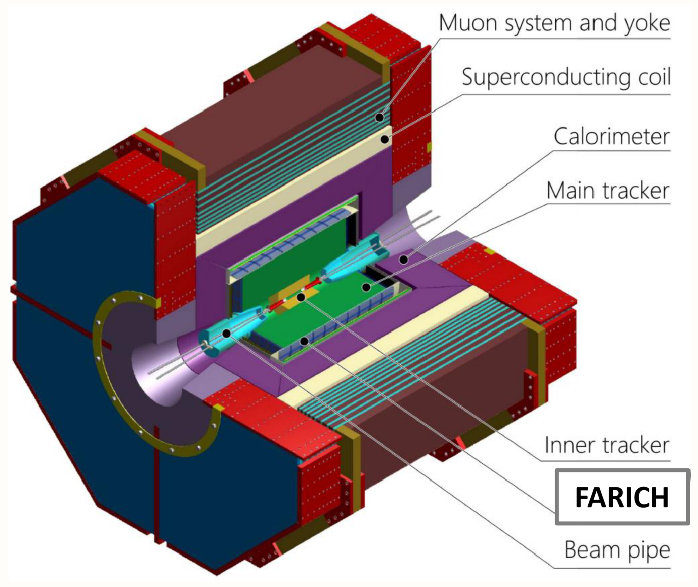
Data sample

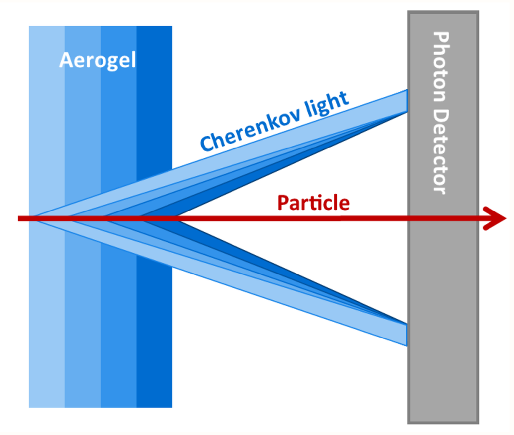
- Maximum operating noise intensity 1MHz/mm^2
- Noise / signal ratio ≈ 70





Setup





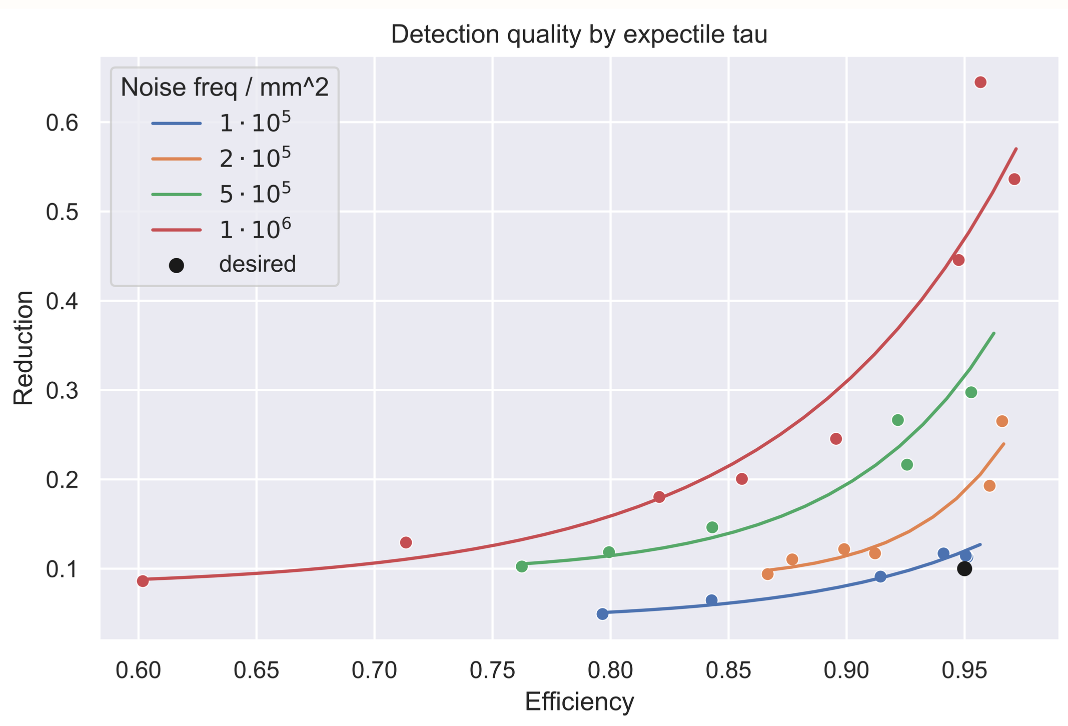
Noise filtering

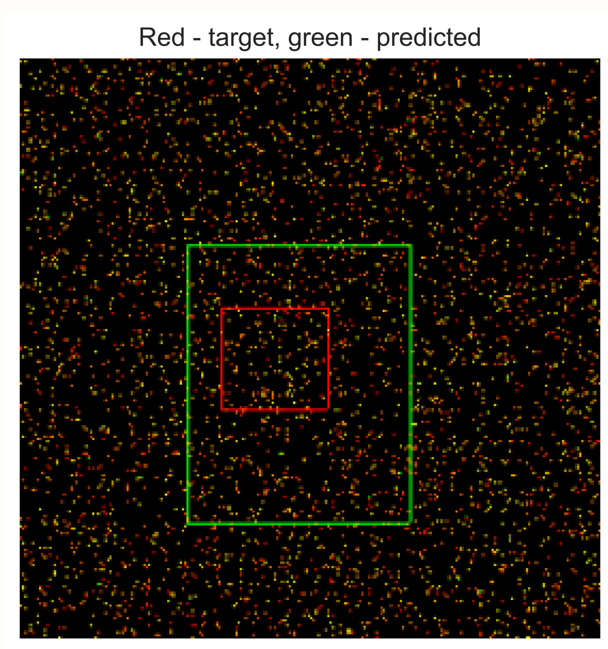
- Not regular matrix structure due to gaps between SiPM
  - project hits (times) to a regular grid
  1. 2-channel tensor: hits $\{0,1\}$ + times $[0;t_{\max}]$
  2. C-channel tensor: $t_0 \in [0,dt),\ t_1 \in [dt,2dt),\ \ldots \quad dt = t_{max}/C$
- Train ResNet-18 CNN to extract bounding box coordinates
- Objective: expectile loss (asymmetric MSE), penalizes cropping true data

$$\operatorname{argmin}\left\{\sum_{i=1}^{n}\omega_\tau^e(y_i-q_i)(y_i-q_i)^2\right\},\ \text{where}\ \omega_\tau^q(\varepsilon)=\omega_\tau^e(\varepsilon)=\begin{cases}1-\tau, & \varepsilon\leqslant 0\\ \tau, & \varepsilon>0\end{cases} \tag{1}$$

Metrics

- Efficiency $= \frac{|B \cap B^{gt}|}{|B^{gt}|}$, filtration efficiency
- Reduction $= \frac{|B|}{|B_{\max}|}$, noise suppression





Expectile τ	Efficiency↑	Reduction↓
0.924	0.856	**0.200**
0.939	0.896	0.245
0.950	0.947	0.447
0.960	**0.971**	0.536

Num channels C	Efficiency↑	Reduction↓
10	0.909	**0.369**
32	0.922	0.370
hits+times	0.947	0.447
64	**0.998**	0.892

Summary

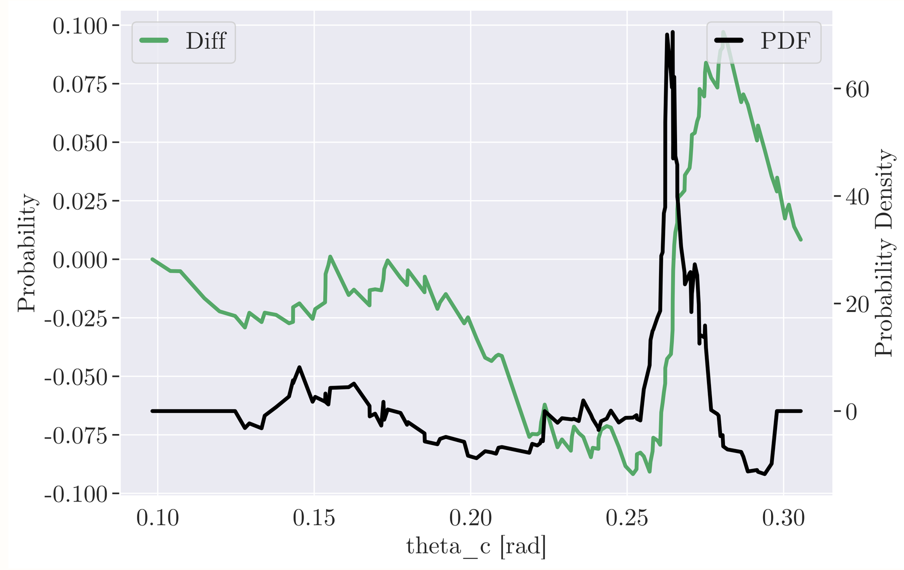
- ResNet-18 CNN provides a significant level of denoising with high efficiency:
  - Reduction ~ 0.4, Efficiency $\geqslant 0.95$ with 1MHz/mm^2 noise
  - Reduction ~ 0.1, Efficiency $\geqslant 0.95$ with 100KHz/mm^2 noise
- τ and C introduce a trade off between noise suppression and efficiency (see tables)
- An object detection pipeline built upon the model can be utilized for trigger mode
- Further optimization is needed to ensure real time performance

Reconstruction

Stat RECO

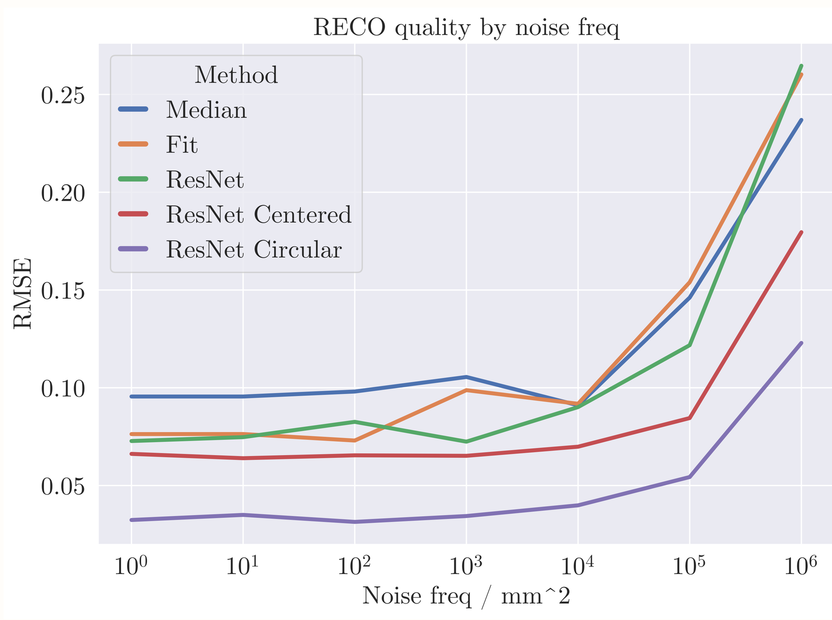
"Fit" algorithm:

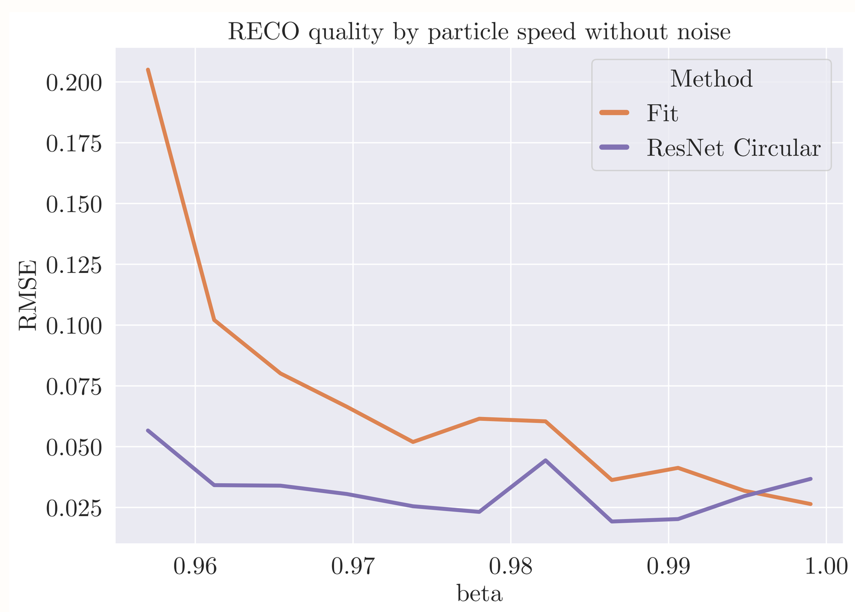
- Calculate Cherenkov angles θ_c before last layer refraction
- Drop physically impossible values corresponding to $\beta = v/c \geqslant 1$
- Subtract the pure noise CDF
- Take a numerical derivative and obtain the peak angle $\hat{\theta}_c$

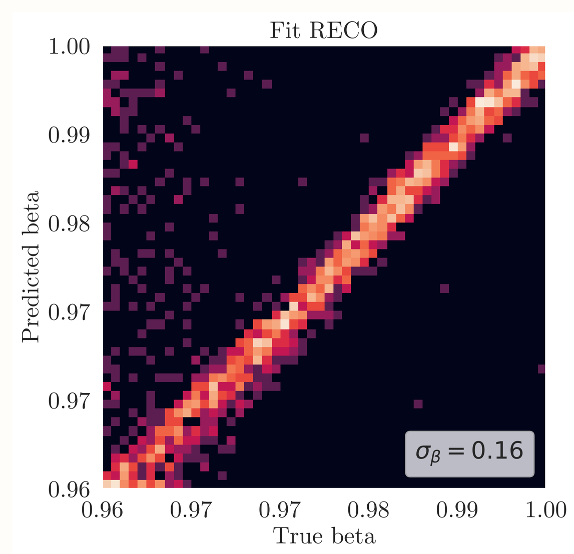


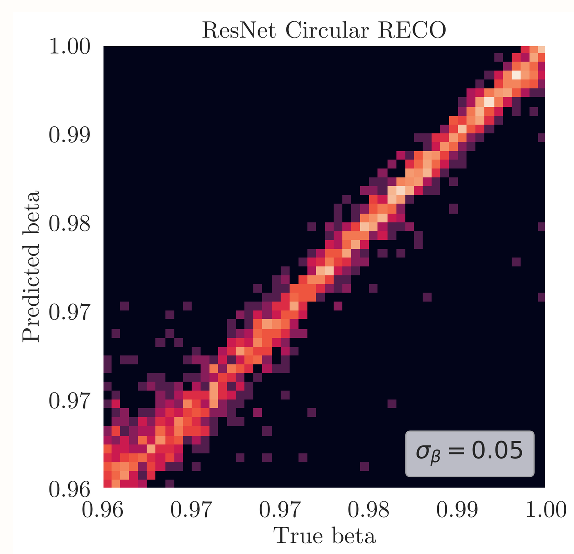
ML RECO

- Train ResNet-18 CNN to predict β with MSE objective
- Configurations:
  - no track prior
  - center image using track info
  - project hits to circular conic section, drop impossible, center









Summary

- ResNet without track prior is similar to stat models (top left figure)
- ResNet with track prior outperforms stat models by β RMSE on all tested noise intensities (top left figure)
- ResNet produces more accurate results for hard samples (low β & impulse), does not generate outliers (top right figure, bottom row)
- ML-based RECO performs favorably comparing with a statistically based RECO

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