What Machine Learning Can Do for Focusing Aerogel Detectors (FARICH)

F.Shipilov[1], A.Barnyakov[2,3], V.Bobrovnikov[2], S.Kononov[2,4], F.Ratnikov[1]

[1]HSE University, Moscow, Russia

[2]Budker Institute of Nuclear Physics of Siberian Branch Russian Academy of Sciences, Novosibirsk, Russia

[3]Novosibirsk State Technical University, Novosibirsk, Russia

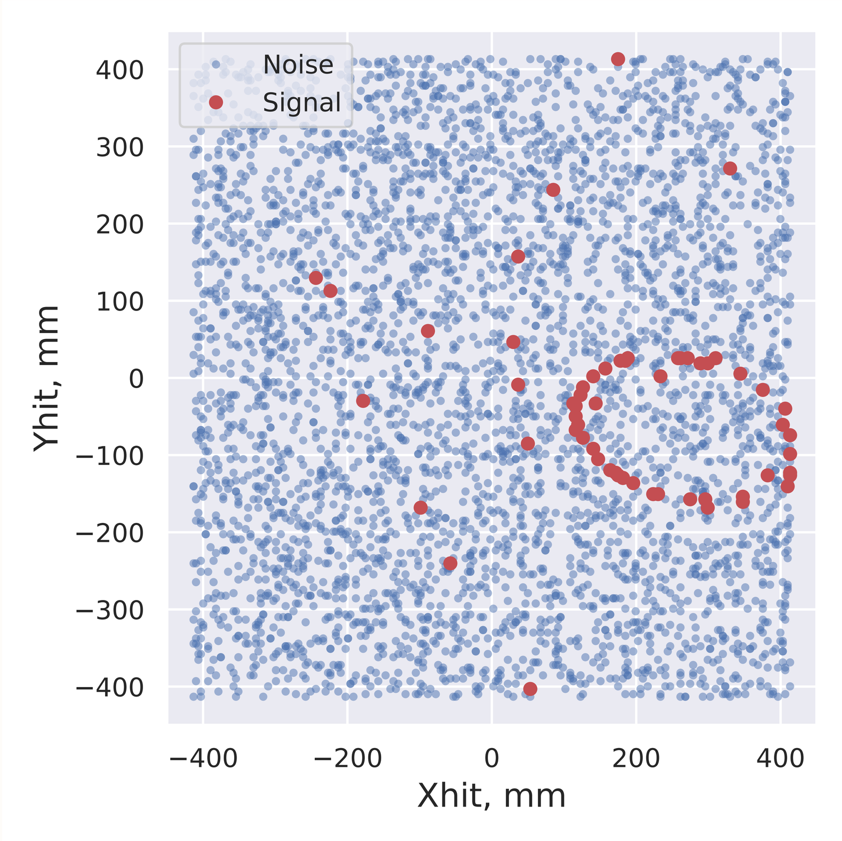
[4]Novosibirsk State University, Novosibirsk, Russia

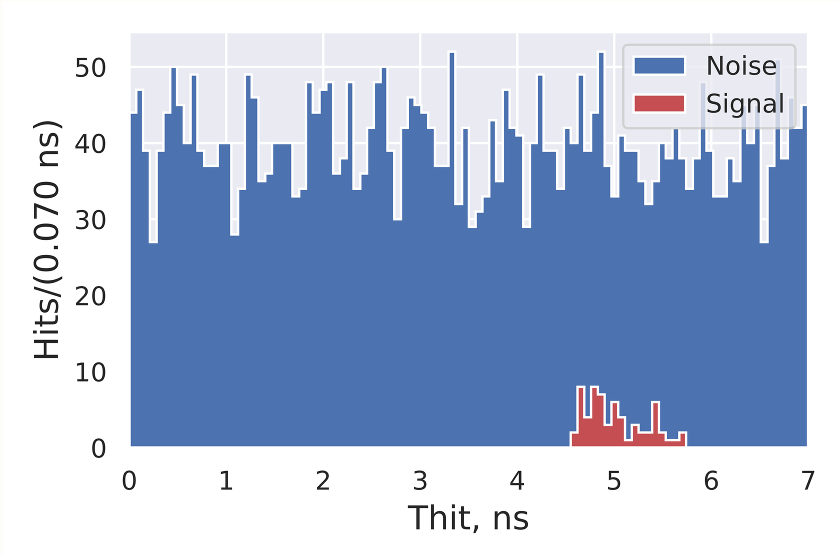
Problem: processing data flow from aerogel detector requires handling 10^{12} Hz hit rate. To reduce this number, a fast and lightweight on-line noise filtering algorithm is needed. The off-line reconstruction task should be addressed as well.

Solution: use Deep Learning tools to classify events / estimate velocity of the particle.

Data sample

- Maximum operating noise intensity 10^6 Hz/mm^2



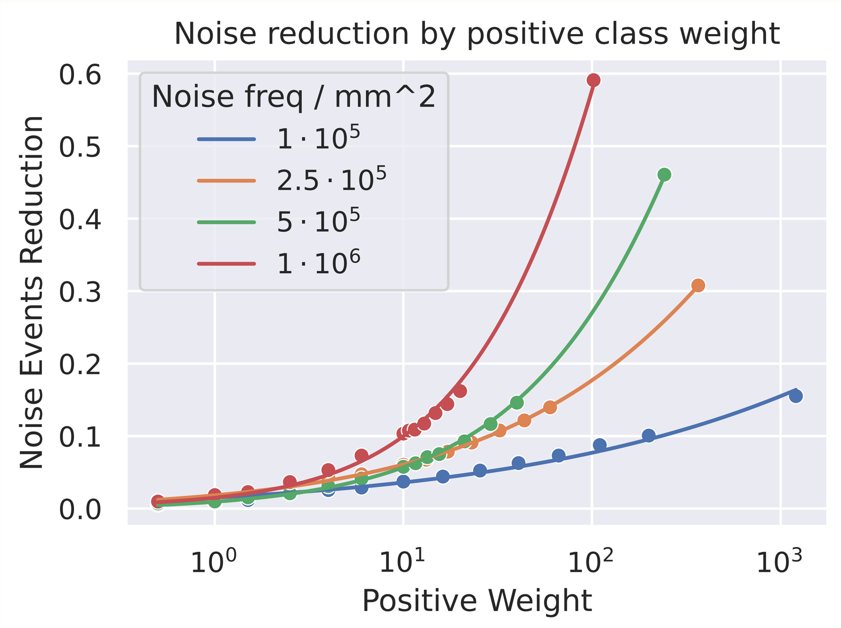


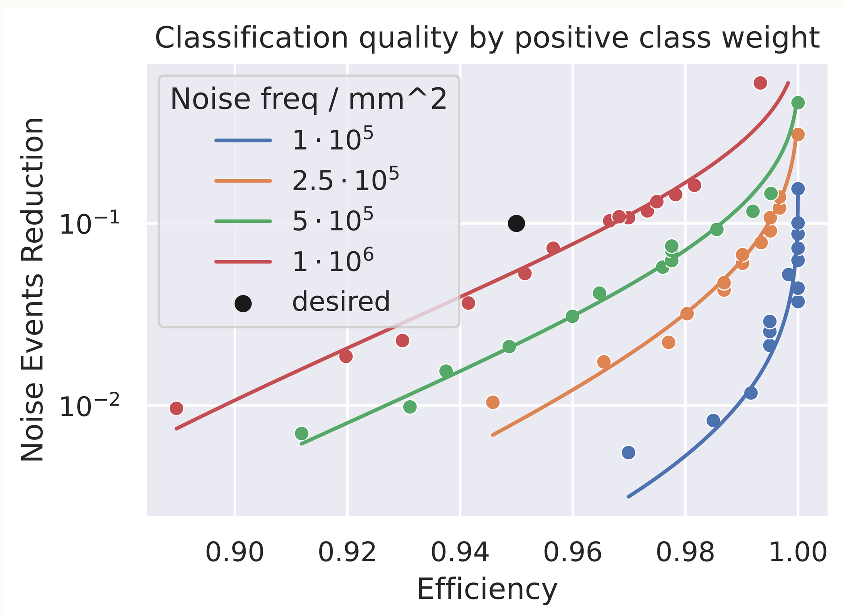
Noise Filtering

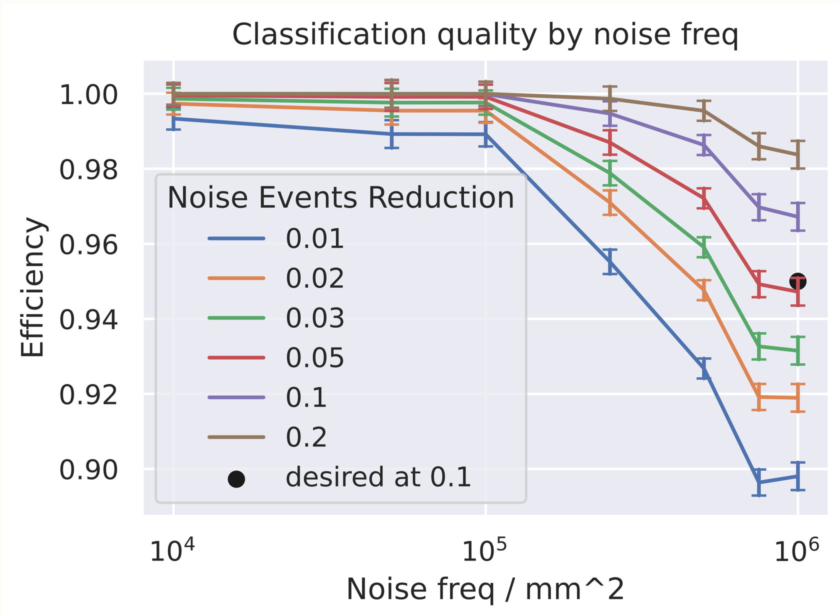
- Not regular matrix structure due to gaps between SiPM
  - project hits (times) to a regular grid
  - 2-channel tensor: hits $\{0,1\}$ + times $[0;t_{\max}]$
- Create a dataset of events with / without signal
  - random translation and time window on signal hits
  - positive event $\geqslant 10$ signal hits
  - 3/7 class ratio
- Train ResNet-18 CNN to perform weighted binary classification with positive class weight parameter
- Use pretrained weights from the reconstruction task to speed up learning process

Event classification metrics:

- Efficiency $= \frac{\text{TP}}{\text{TP+FN}}$
- Noise Events Reduction $= \frac{\text{FP}}{\text{TN+FP}}$



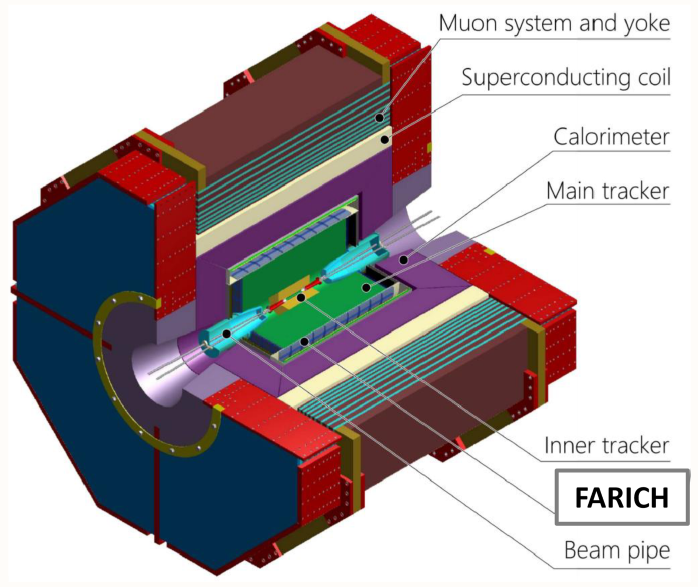


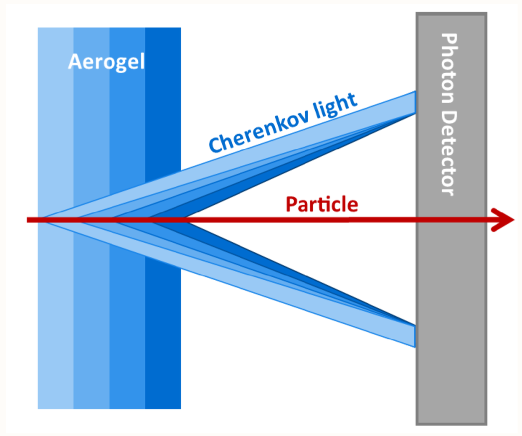


Filtering Summary

- ResNet-18 CNN provides a significant level of denoising with high efficiency:
  - Noise Events Reduction ~ 0.1, Efficiency $\geqslant 0.95$ @ 10^6 Hz/mm^2 noise
  - Noise Events Reduction ~ 0.01, Efficiency $\geqslant 0.97$ @ 10^5 Hz/mm^2 noise
- Positive class weight introduces a trade off between noise reduction and efficiency
- It is possible to achieve even higher noise reduction by performing bounding box regression on signal ellipses for positive events
- Further optimization is needed to ensure real time performance

Setup

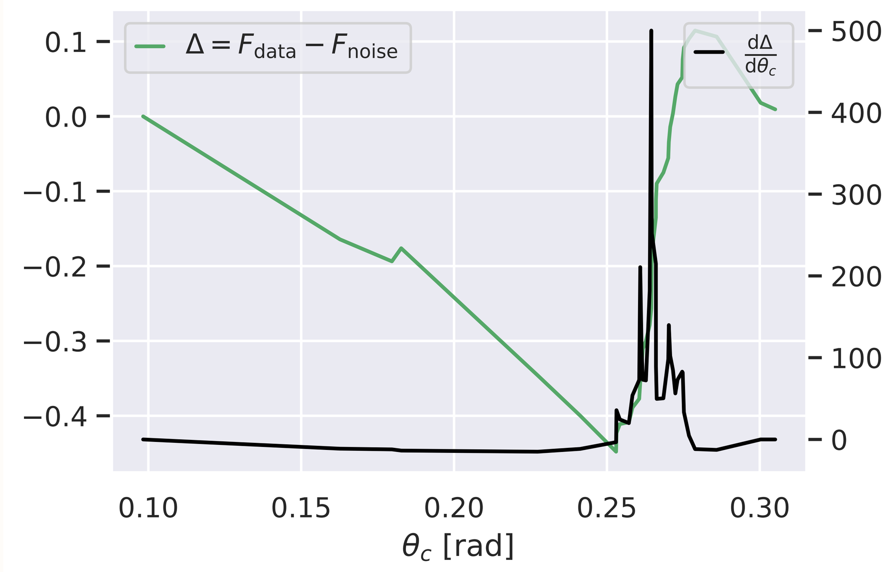




Reconstruction

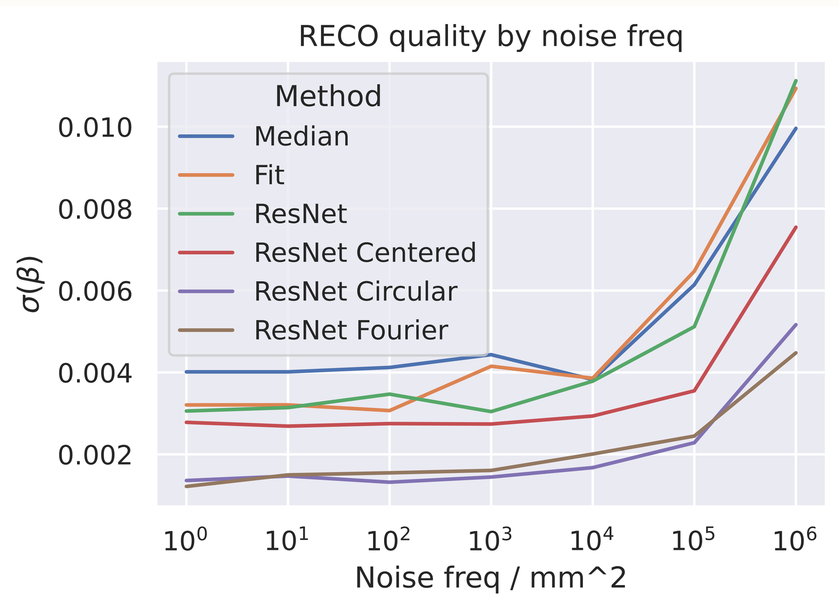
Stat RECO

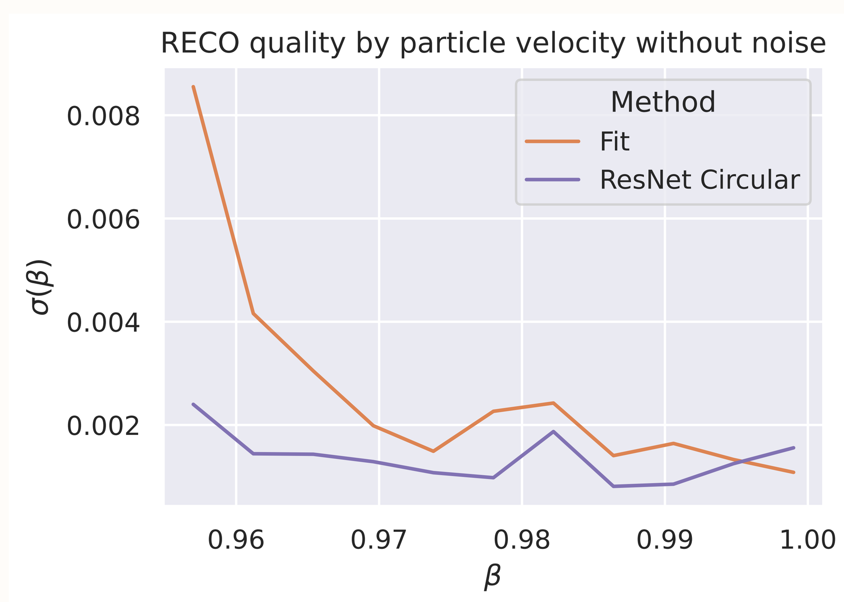
- **Median:** take a median of Cherenkov angle θ_c
- **Fit:**
  - Compute θ_c for each hit
  - Drop unphysical velocities $\beta = v/c \geqslant 1$
  - Construct eCDF F_{data}
  - Subtract pure noise CDF F_{noise}
  - Take a numerical derivative and find its peak $\hat{\theta}_c = \arccos(1/n\hat{\beta})$

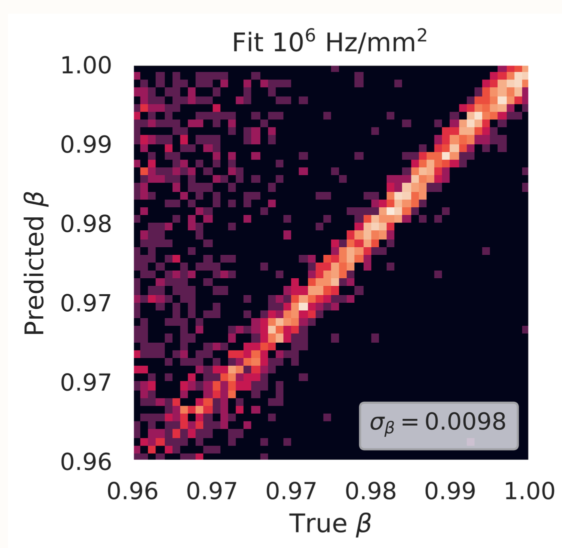


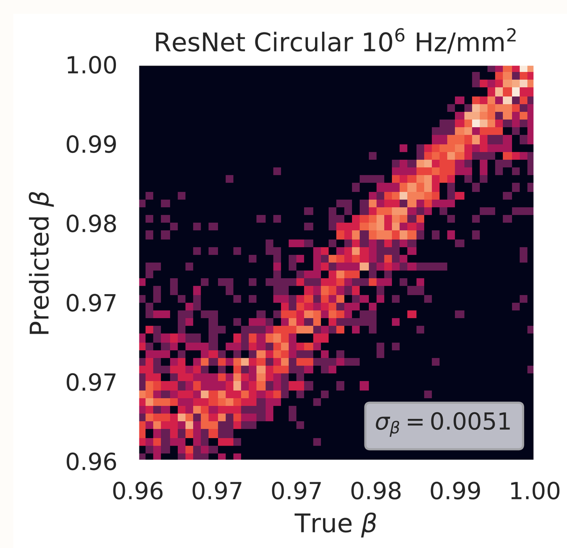
ML RECO

- Train ResNet-18 CNN to predict β with MSE objective
- Configurations:
  - **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 Summary

- ResNet without track prior is similar to stat models
- 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