ML-based fast simulation of FARICH responses

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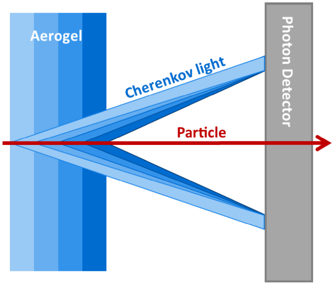
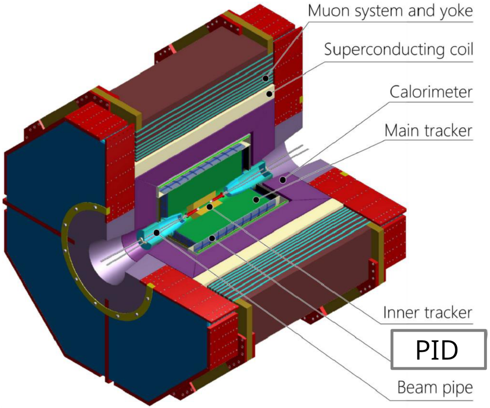
Introduction: FARICH

Focusing Aerogel Ring Imaging Cherenkov

Compact particle ID detector

- Trade off between resolution and number of Cherenkov photons
- Improve resolution by using layers of aerogel with varying refractive index

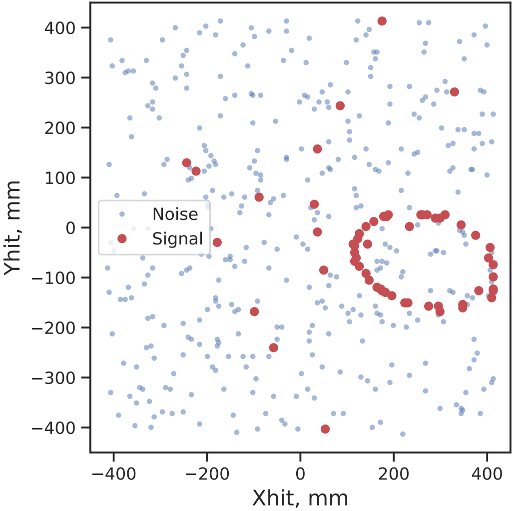




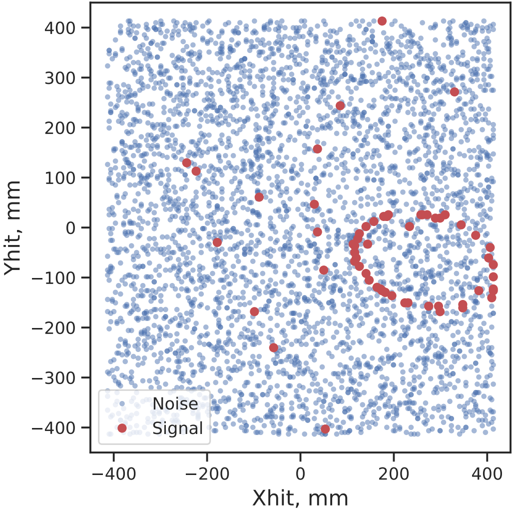
Barnyakov et al., NIM A553 (2005) 70.

Example Event

Optimistic DCR 100 kHz/mm^2



Pessimistic DCR 1 MHz/mm^2



Online Noise Filtering

Online Noise Filtering

Motivation

- SiPMs are noisy with insufficient cooling
- DAQ cannot handle capturing and storing all hits
- **Solution:** Software trigger to reduce data rate
- Drop background hits, preserve signal hits

Requirements

- Online mode: no tracker info
- Do not introduce any bias in RECO hypothesis
- Efficiency $\geqslant 95\%$
- At least 10x noise reduction

Approach 1

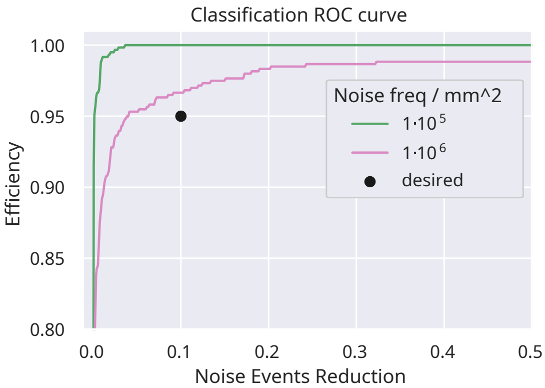
Classification

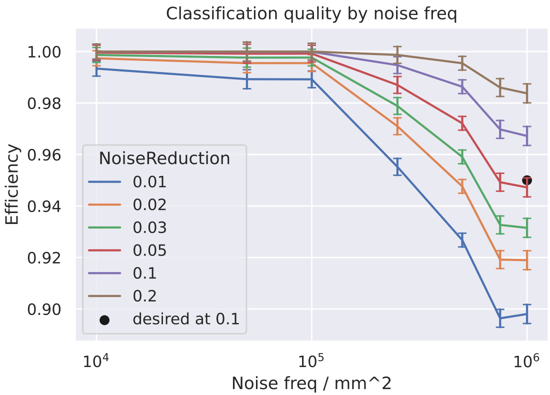
- create a dataset of events with / without signal (positive event $\geqslant 10$ signal photons)
- train Convolutional Neural Network (CNN) to perform binary classification

Metrics:

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

Results: Classification





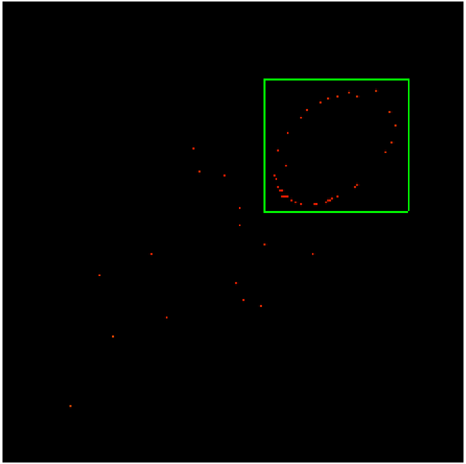
Approach 2

Bounding box (BBox) regression

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

Metrics:

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



Ground truth bbox example

BBox Regression Objective

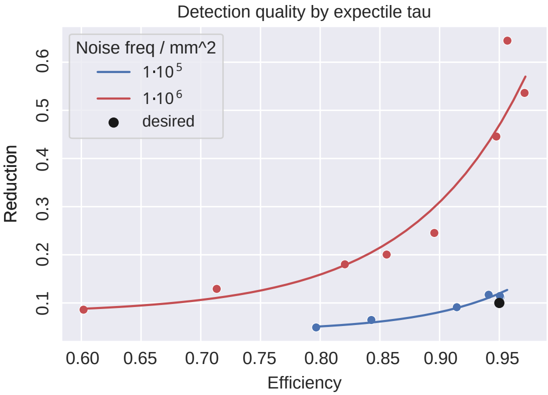
- Simple MSE tends to throw out signal hits
- Solution: use weighted version **Expectile Loss** [1]

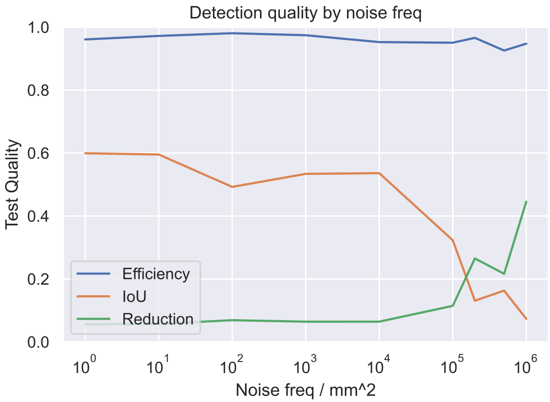
$$\text{quantile:} \quad \operatorname{argmin} \left\{ \sum_{i=1}^{n} w(y_i - q_i, \tau) \cdot |y_i - q_i| \right\},$$

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

$$\text{where } w(x, \tau) = \begin{cases} 1 - \tau, & x \leqslant 0 \\ \tau, & x > 0 \end{cases}$$

Results: BBox Regression





Summary: Online Noise 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

Part 2

Fast Simulation

Fast Simulation

- Detector simulation: the goal is to speed up event generation by means of a surrogate model, avoiding Monte-Carlo simulation
- Given particle rest mass m_0, momentum p and other parameters, obtain realistic samples of Cherenkov angles θ_c and polar angles ϕ_c

$$\cos\theta_c = \frac{1}{n\beta}, \quad p = \frac{m_0\beta}{\sqrt{1-\beta^2}} \tag{1}$$

- Generative adversarial networks can bypass the low-level photon generation while preserving the necessary fine details
- Can be made sufficiently fast and light-weight; easy to parallelize

Objectives: develop a generative neural network to reproduce raw detector responses, evaluate on a synthetic dataset, analyze and compare with the baseline

Assumptions:

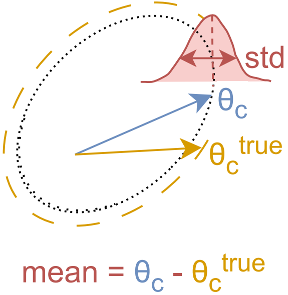
- Cherenkov angle θ_c is independent of azimuth ϕ_c (after accounting for refraction), ϕ_p (particle direction isotropy)

Learning:

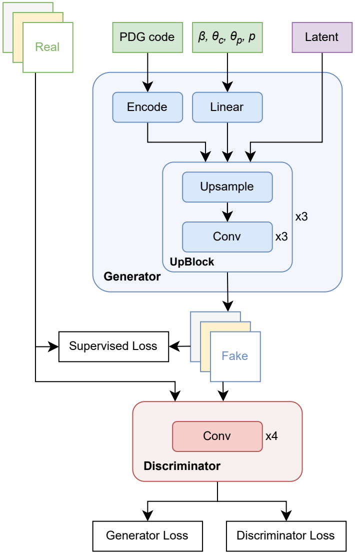
- fit a linear model to predict mean and std from particle parameters: $\beta^{\text{true}}, \theta_c^{\text{true}}, \theta_p^{\text{true}}, p^{\text{true}}$ and engineered features

Inference:

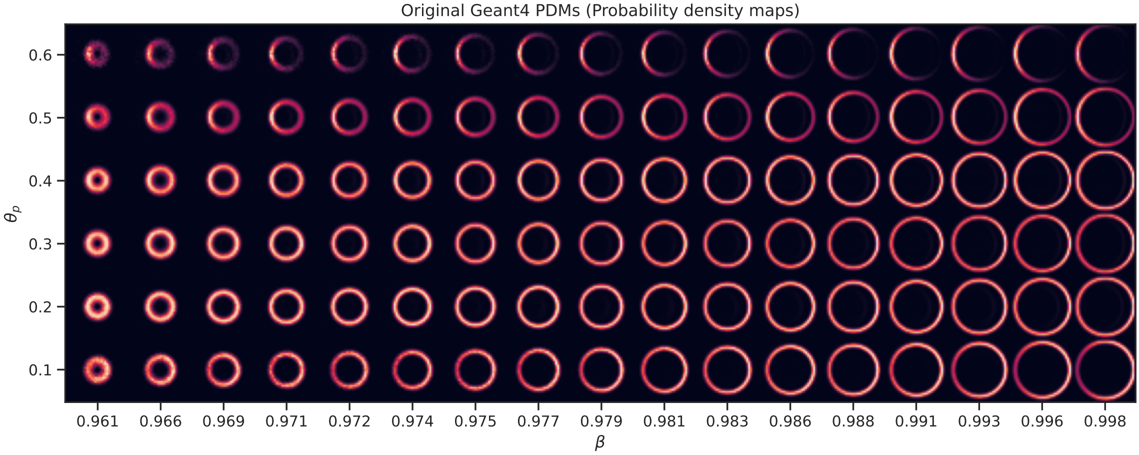
- sample θ_c from a normal distribution with mean, std
- sample ϕ_c from a uniform distribution



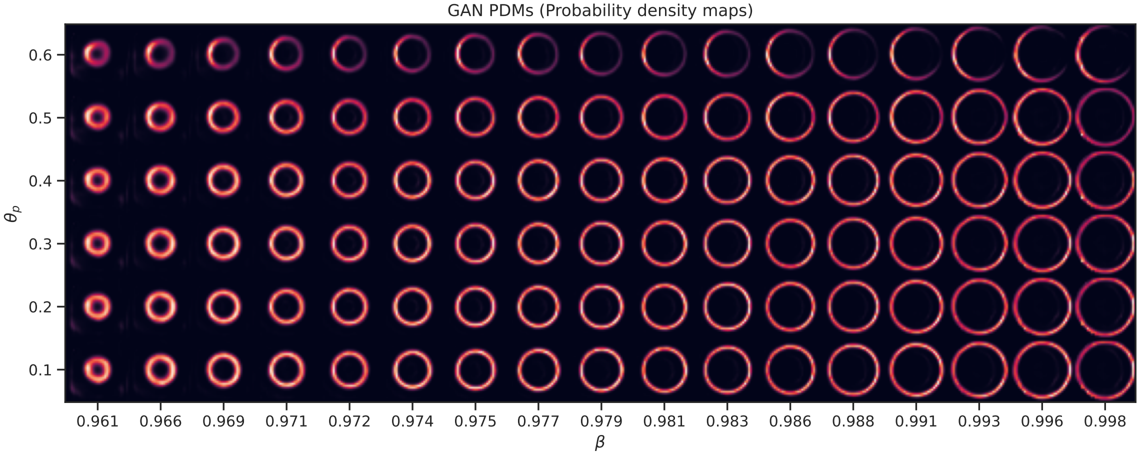
- GANs provide a sample-level mapping from a latent distribution to a complex real-world distribution
- A conditional GAN (cGAN) model is perfect for this task [2]
- **Input condition**: particle parameters $\beta^{\text{true}}, \theta_c^{\text{true}}, \theta_p^{\text{true}}, p^{\text{true}}$
- **Output**: is a projection of the detector response into a circle with refraction factored out
- Lightweight CNN architecture, 184k parameters



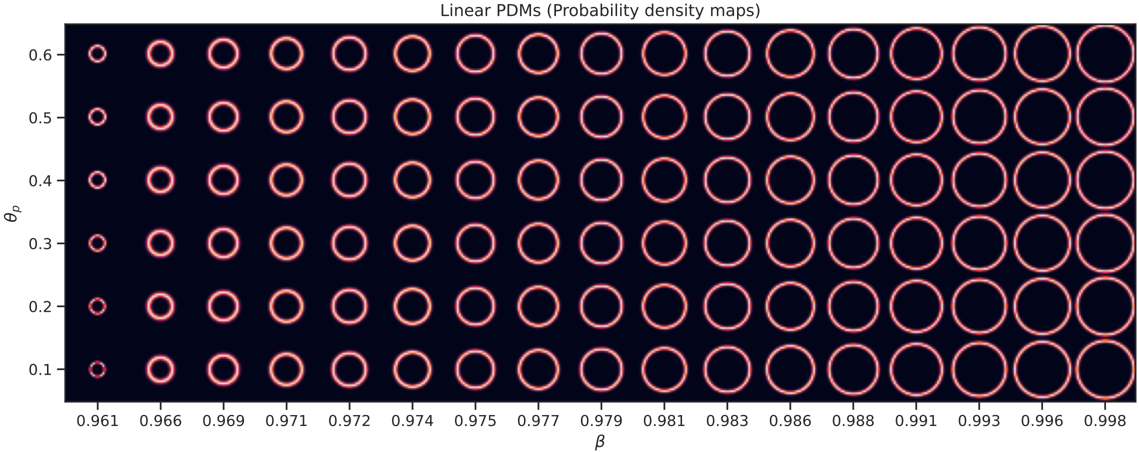
Original Geant4 data



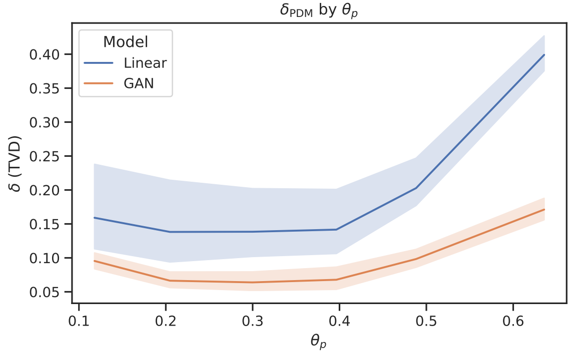
GAN simulation

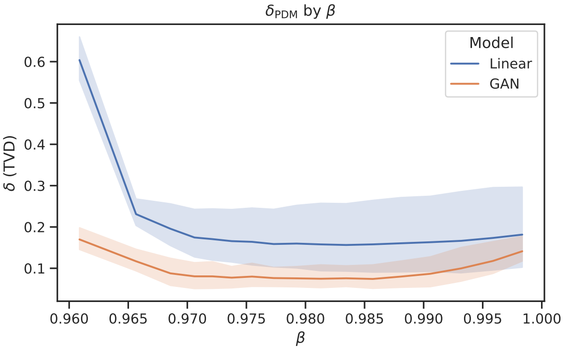


Linear simulation



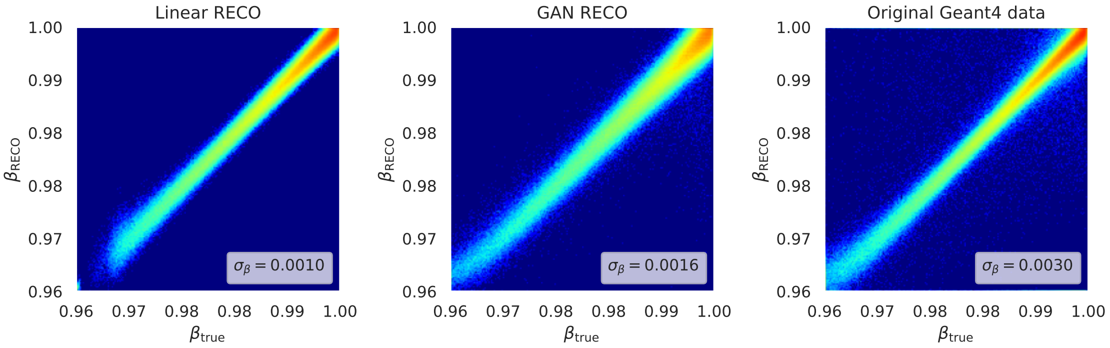
Results: Fast Simulation



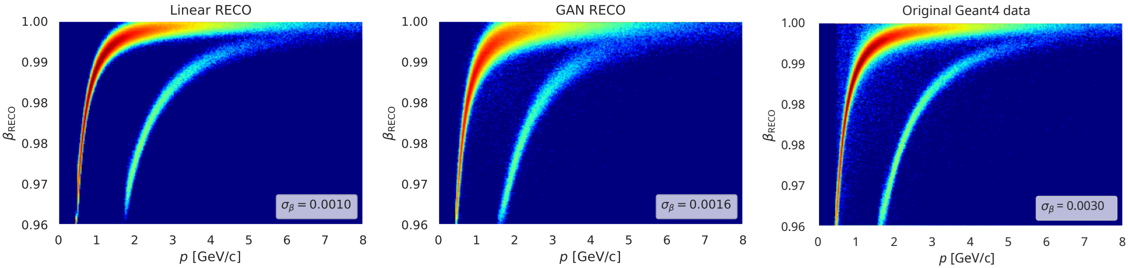


Method	$\delta_{\text{PDM}} \downarrow$
Linear	0.146 ± 0.001
cGAN	$\mathbf{0.105 \pm 0.001}$

Results: Fast Simulation



Results: Fast Simulation



Method	$\delta_{\text{RECO}} \downarrow$
Linear	0.29 ± 0.01
cGAN	$\mathbf{0.18 \pm 0.01}$

Simulation Summary

- cGAN outperforms the baseline by Total Variation Distance $\delta(P_{\text{Fake}}, P_{\text{Geant}})$ for PDMs and reconstructed β distributions. In particular, GAN is more accurate for low momenta
- Generator neural network is very lightweight. A *significant* speed up is achieved compared to Monte-Carlo

Problems/Difficulties

- projected PDMs should be converted to raw detector responses
  - PDM quantization is performed anyway, probably no significant performance penalty
  - another option is tweaking GAN to generate ellipses directly
- GAN underestimates distribution tails
  - incentivize outlier event generation via an additional loss component

Acknowledgements

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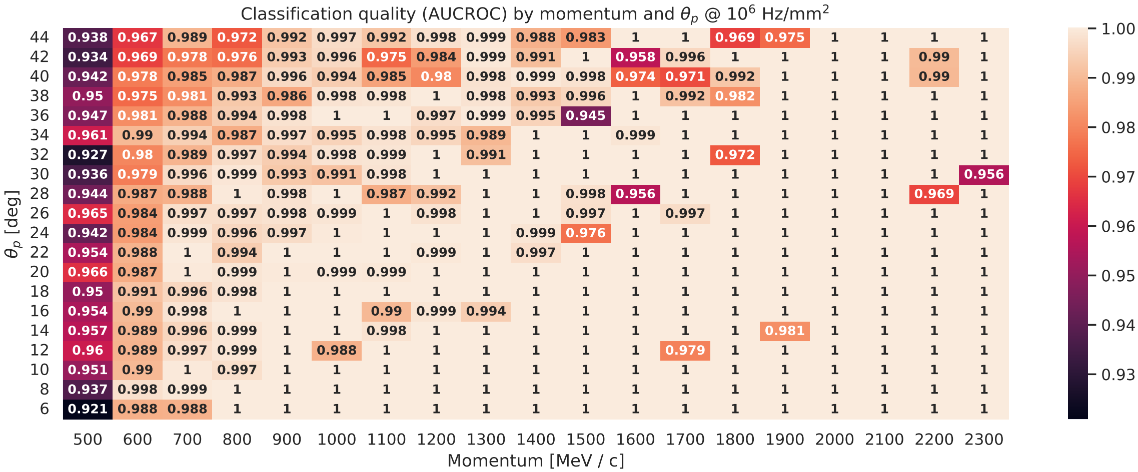
References

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

[2] Mehdi Mirza and Simon Osindero. Conditional Generative Adversarial Nets. In CoRR 2014.


Classification quality (AUCROC) by momentum and θ_p @ 10^6 Hz/mm^2
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
θ_p [deg]
500 600 700 800 900 1000 1100 1200 1300 1400 1500 1600 1700 1800 1900 2000 2100 2200 2300
Momentum [MeV / c]
1.00 0.99 0.98 0.97 0.96 0.95 0.94 0.93

Backup: Detailed Fast Simulation

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