Machine Learning for Fast Simulation of FARICH Detector

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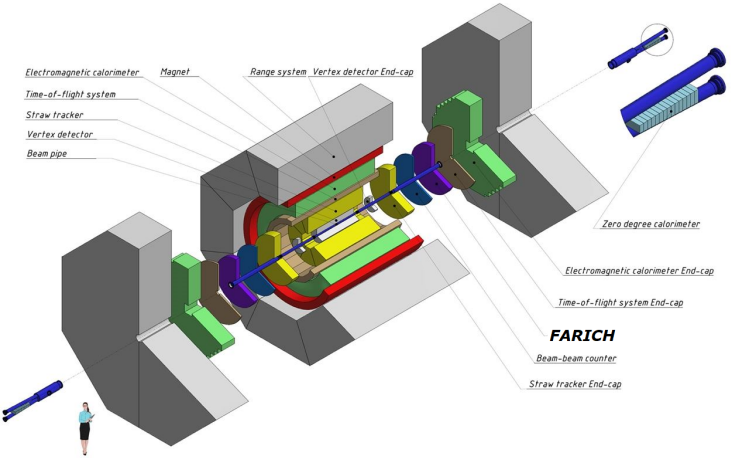
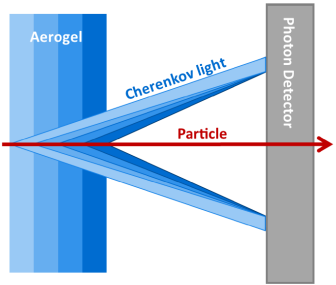
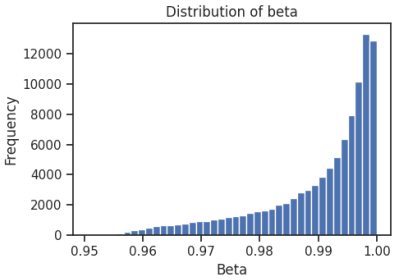
FARICH

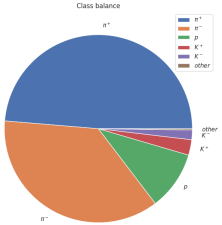

Electromagnetic calorimeter
Magnet
Range system
Vertex detector End-cap
Time-of-flight system
Straw tracker
Vertex detector
Beam pipe
Zero degree calorimeter
Electromagnetic calorimeter End-cap
Time-of-flight system End-cap
FARICH
Beam-beam counter
Straw tracker End-cap

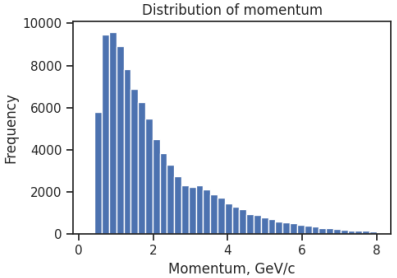

Aerogel
Cherenkov light
Particle
Photon Detector

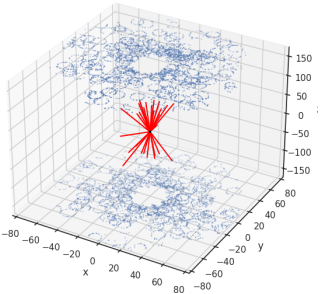
Dataset

- Geant4 “Production” sample
- 24 993 893 $\pi^{\pm}/K^{\pm}$ events
- split 97% training / 3% test samples
- Raw detector responses are projected into a circular shape (64×64 images) to factor out geometric and optical effects



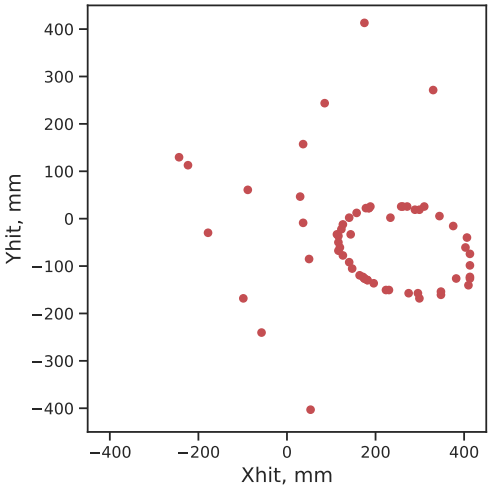




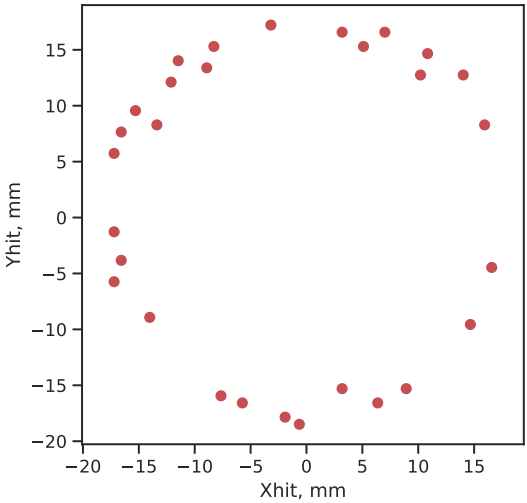


Example Event

Raw detector response



Projected into a circular shape



Refraction Removal

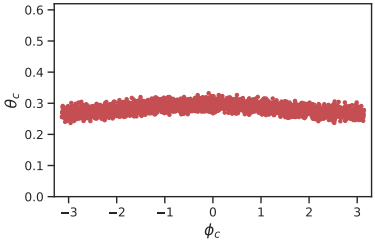
First order approximation

$$\alpha \approx \beta - (n-1)\tan\beta \tag{1}$$

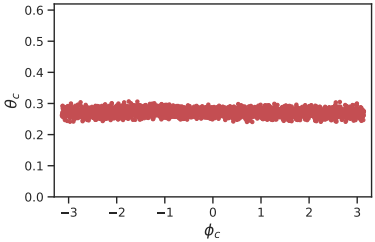
Or fixed-point iteration

$$\sin\alpha_{k+1} = \left(n\sqrt{1+\left(\frac{d}{r - h\tan\alpha_k}\right)^2} \right)^{-1} \tag{2}$$

θ_c before



θ_c after



Fast Simulation

Objectives:

- Bypass low-level photon generation
- Simulate raw detector responses
- Conditional generation from particle & track parameters
- Reproduce correct RECO statistics

Solution:
Convolutional Neural Network (CNN) outputting 2D images – detector responses

Linear Baseline

Assumptions:

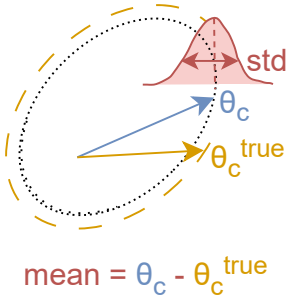
- Cherenkov angle θ_c is independent of azimuth ϕ_c (after accounting for refraction), ϕ_p (particle direction isotropy)

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



CNN Aprroach

Input:

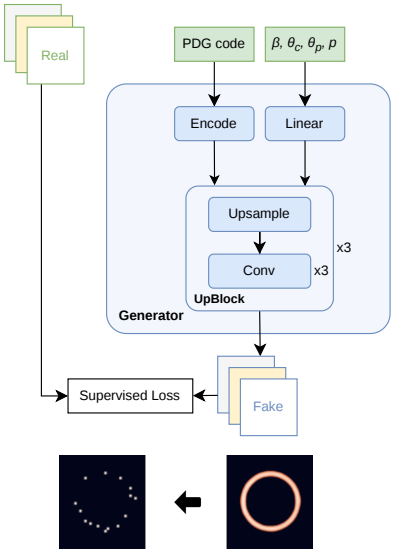
- Particle parameters $\beta^{\text{true}}, \theta_c^{\text{true}}, \theta_p^{\text{true}}, p^{\text{true}}$

Output:

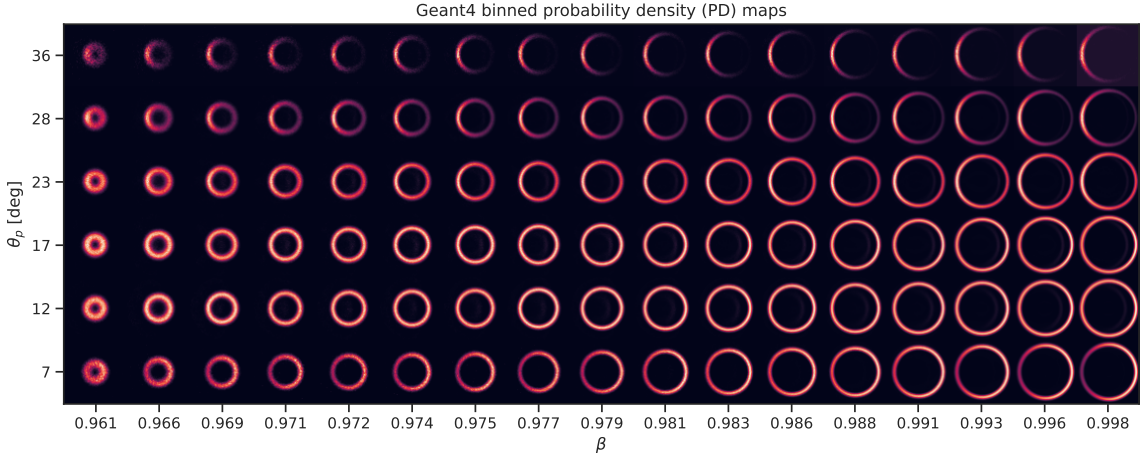
- Neural networks are smooth estimators and have difficulties reproducing binary detector response
- CNN outputs a smooth probability density (PD) map
- Discrete photon hits are randomly sampled from PD

Workflows:

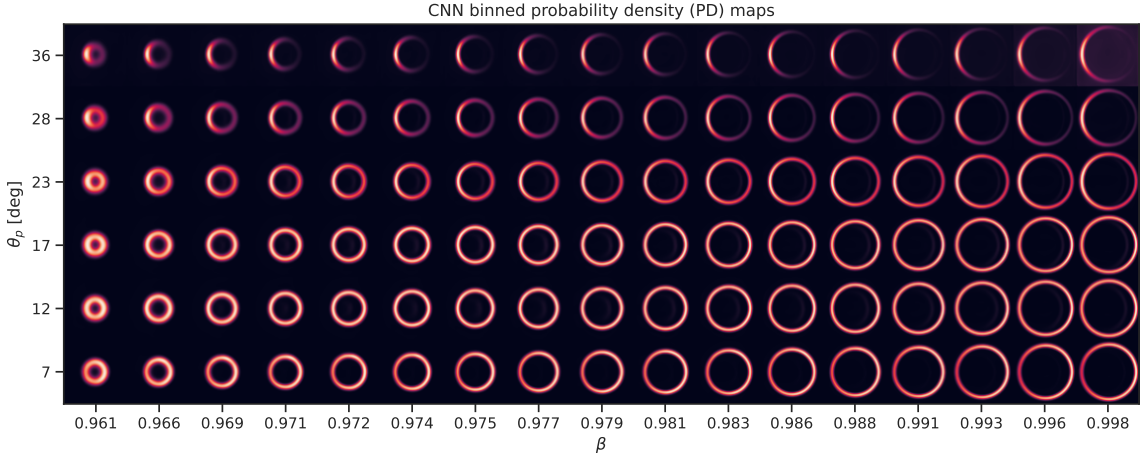
- **CNN BCE**: pixels are independent binary outputs, train with log-loss, sample from Bernoulli
- **CNN CE**: whole image is a categorical distribution of hit coordinates, train with multiclass cross entropy, sample from categorical distribution



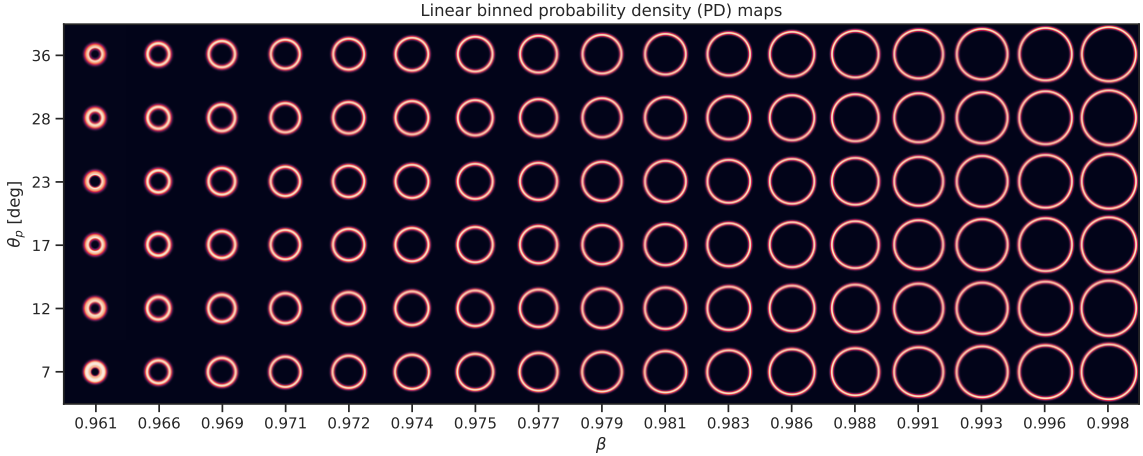
Original Geant4 data



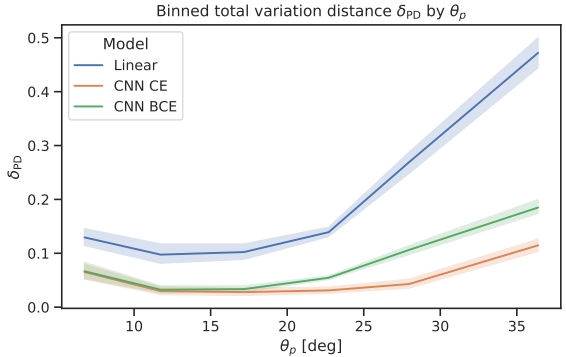
CNN simulation

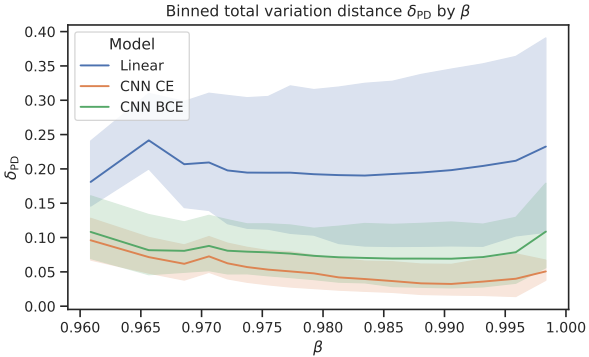


Linear simulation



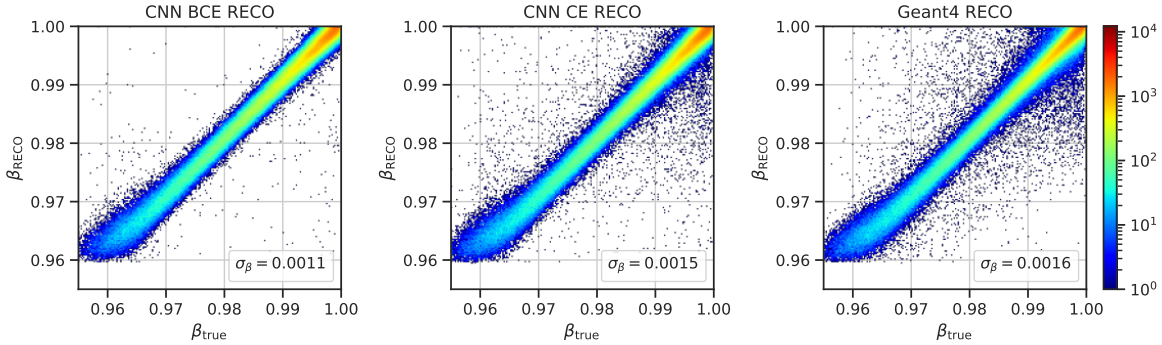
Results: Fast Simulation





Method	$\delta_{PD} \downarrow$
Linear	0.163 ± 0.001
CNN BCE	0.107 ± 0.001
CNN CE	$\mathbf{0.098 \pm 0.001}$

Results: Fast Simulation



Method	$\delta_{\text{RECO}} \downarrow$
Linear	0.27 ± 0.01
CNN BCE	0.07 ± 0.01
CNN CE	$\mathbf{0.06 \pm 0.01}$

Simulation Summary

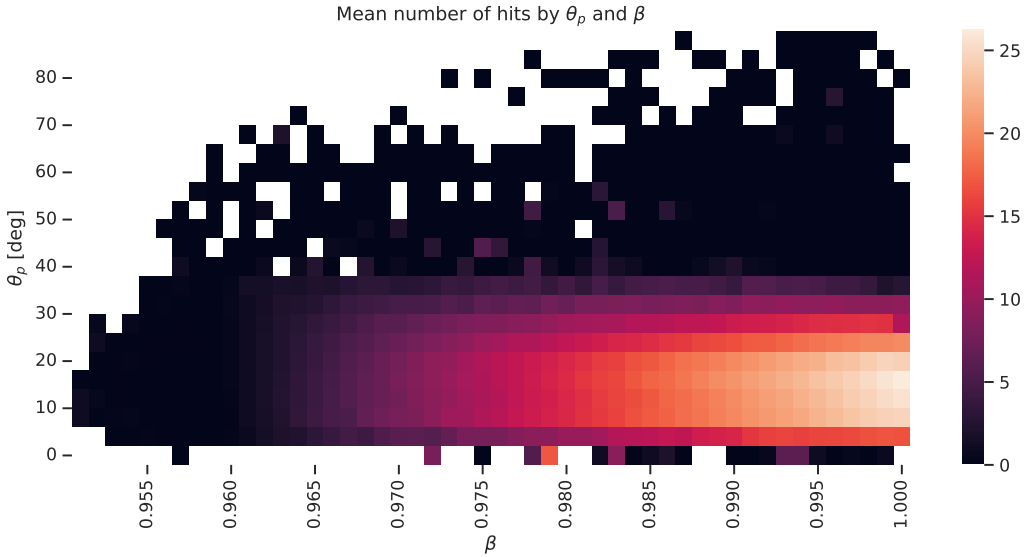
Outcomes:

- Reconstructed β shows good visual and σ_β agreement between CNN surrogate model and Geant4;
- CNN events can reconstructed by arbitrary method, no dependence on a particular RECO;
- Generator neural network is very lightweight. A significant speed up can be achieved compared to Monte-Carlo.

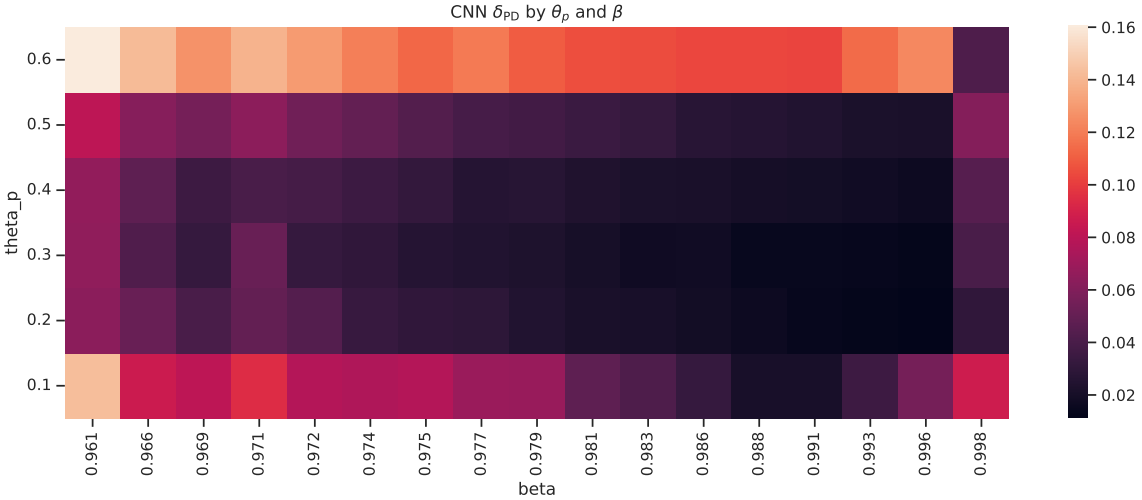
Problems/Difficulties:

- CNN outputs PD projections, not raw responses
  - Should not impact performance because of the 2 stage generation
  - Inverse projection is lossless up to pixel grid quantization error

Backup: Detailed N Hits



Backup: Detailed Fast Simulation



Backup: Detailed Fast Simulation

