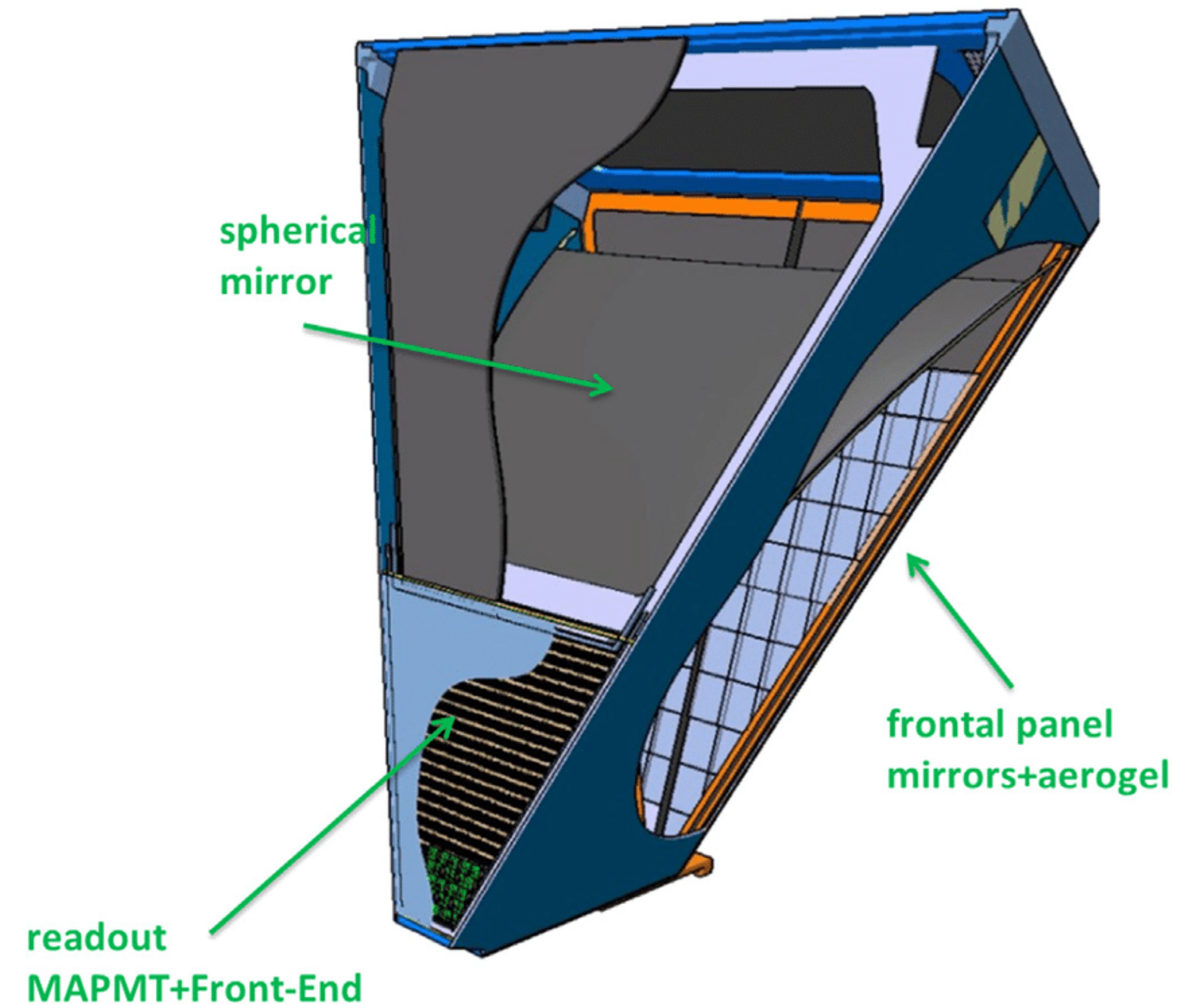


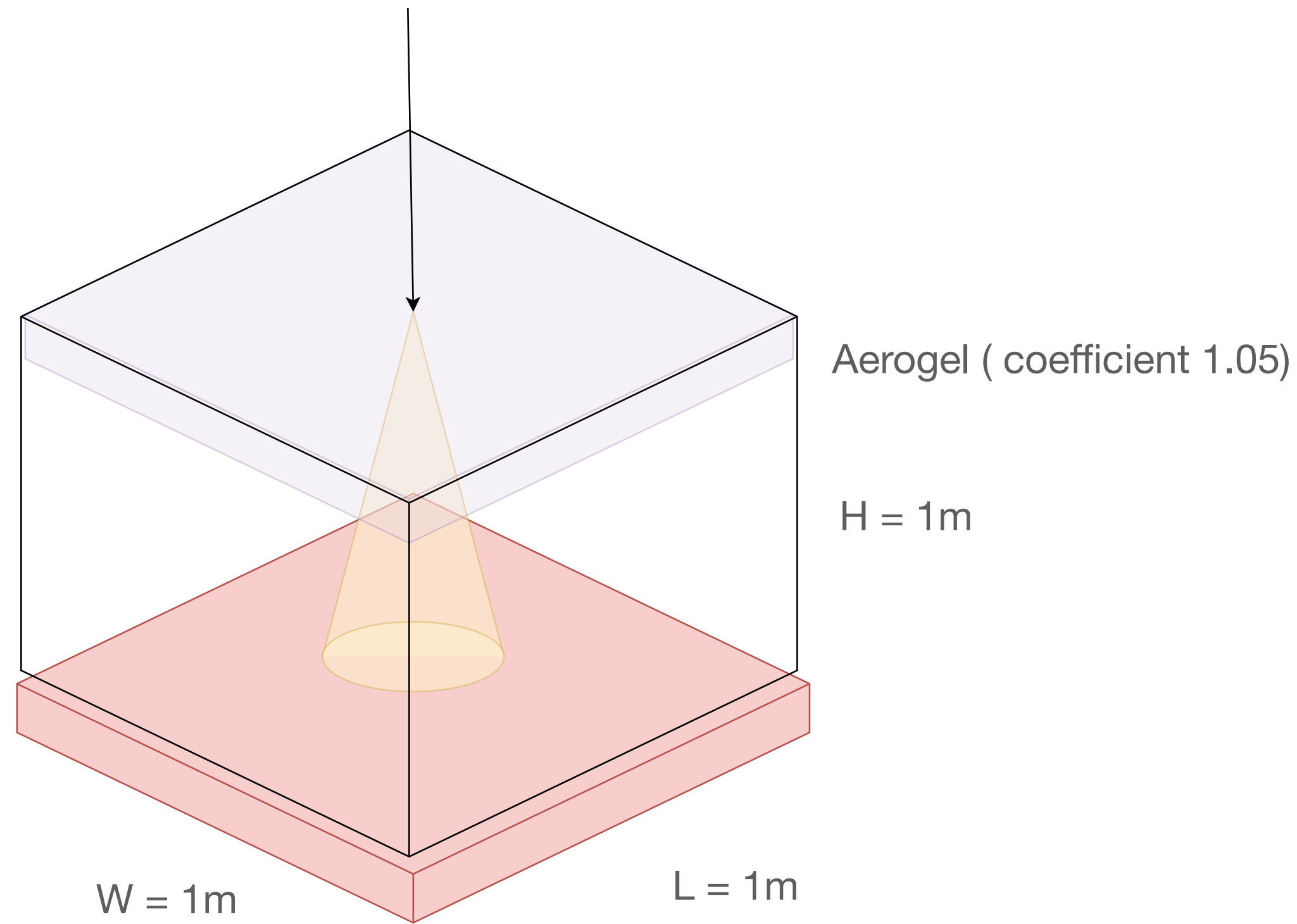
Machine Learning for RICH

Gagik Gavalian (Jefferson Lab)

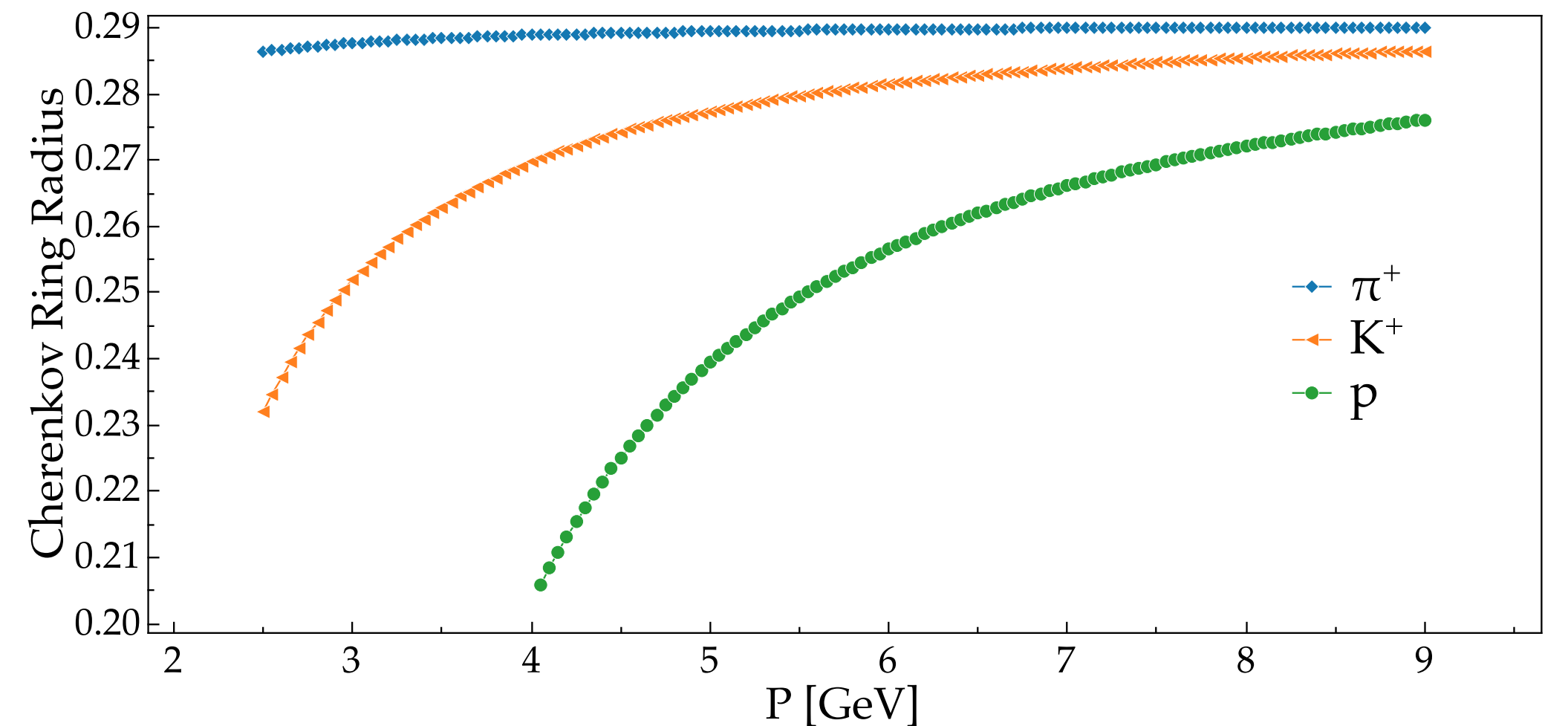
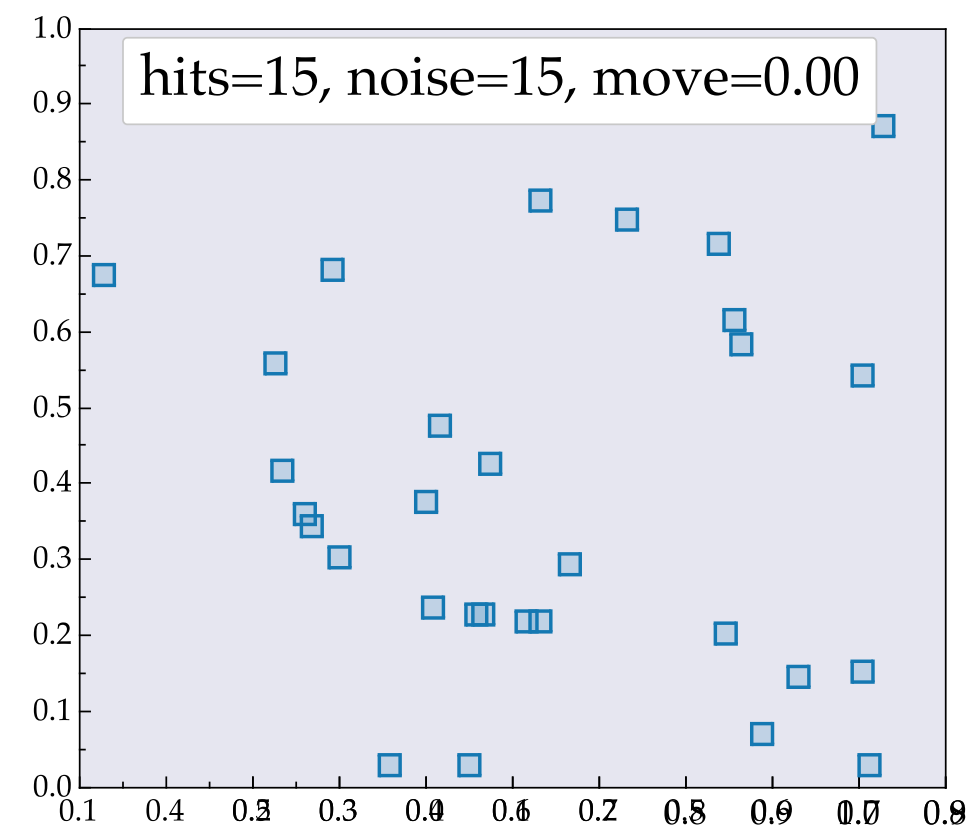
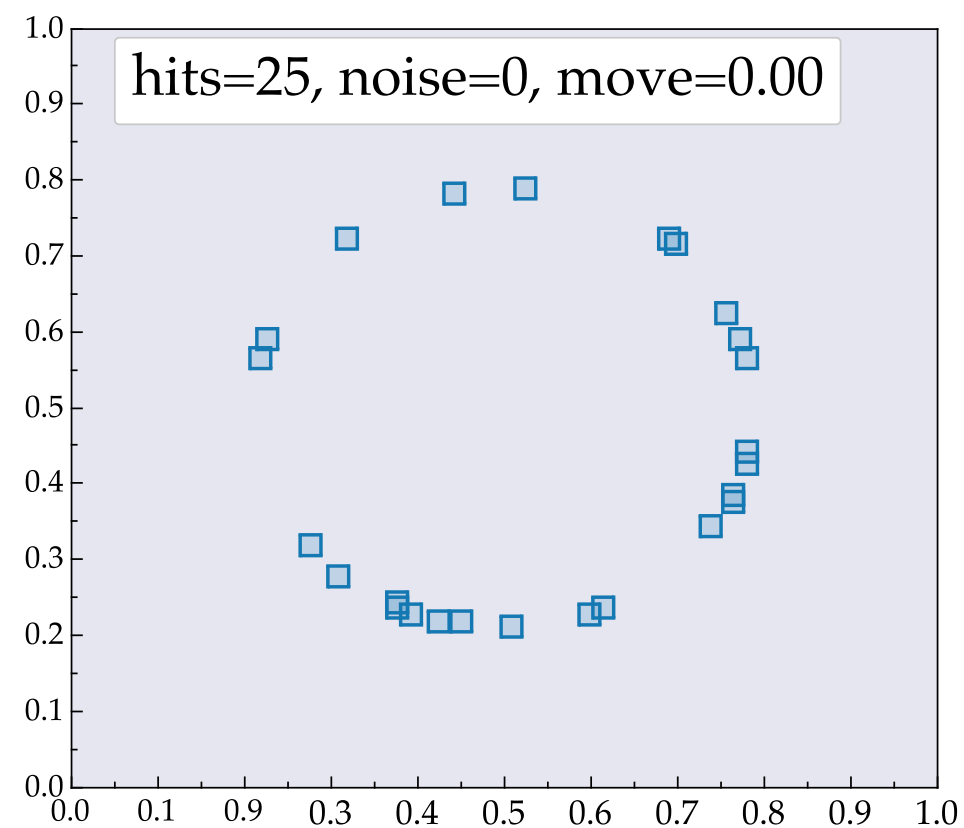
Mini Workshop for Kaon Physics (December 16, 2022)

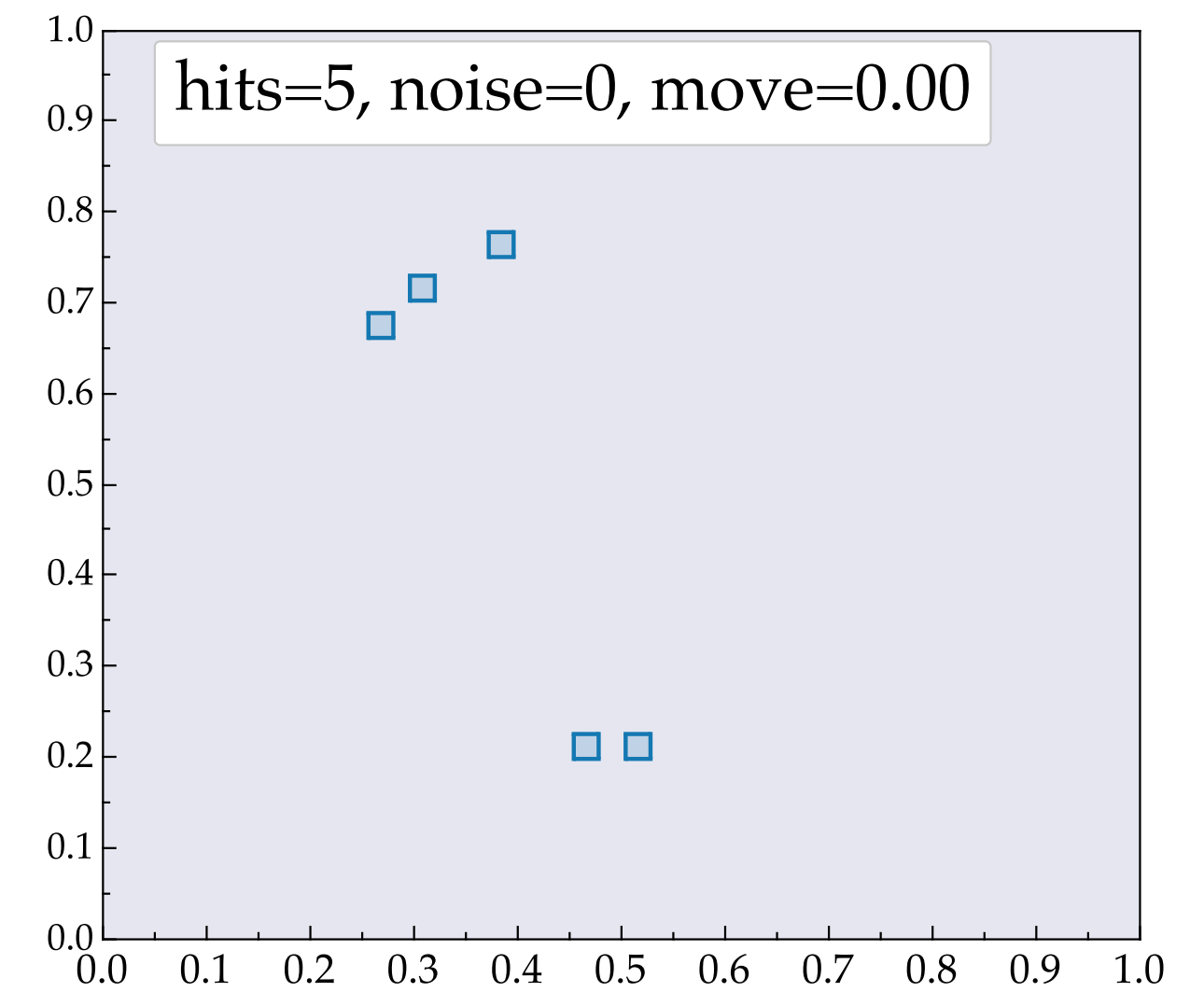
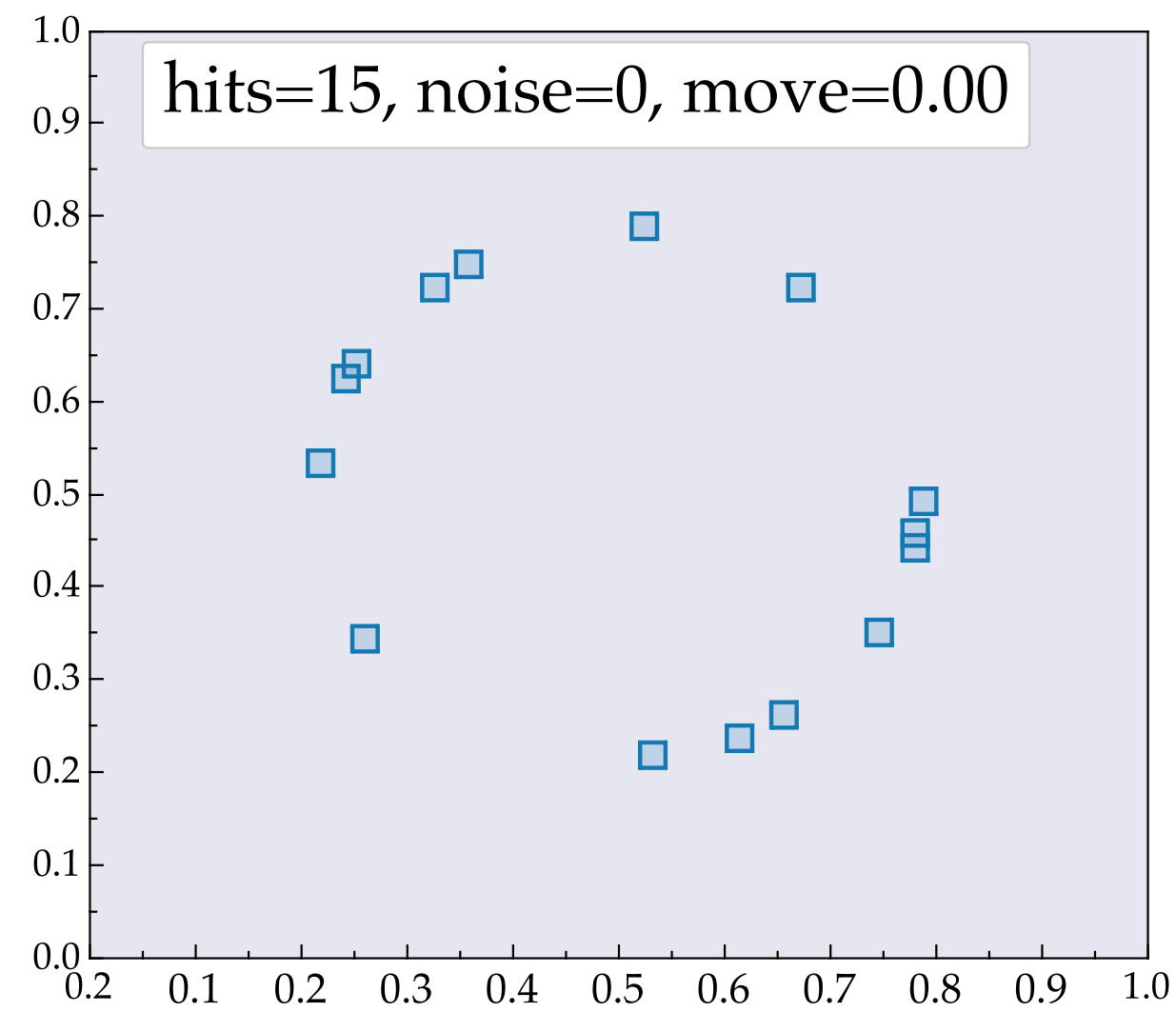
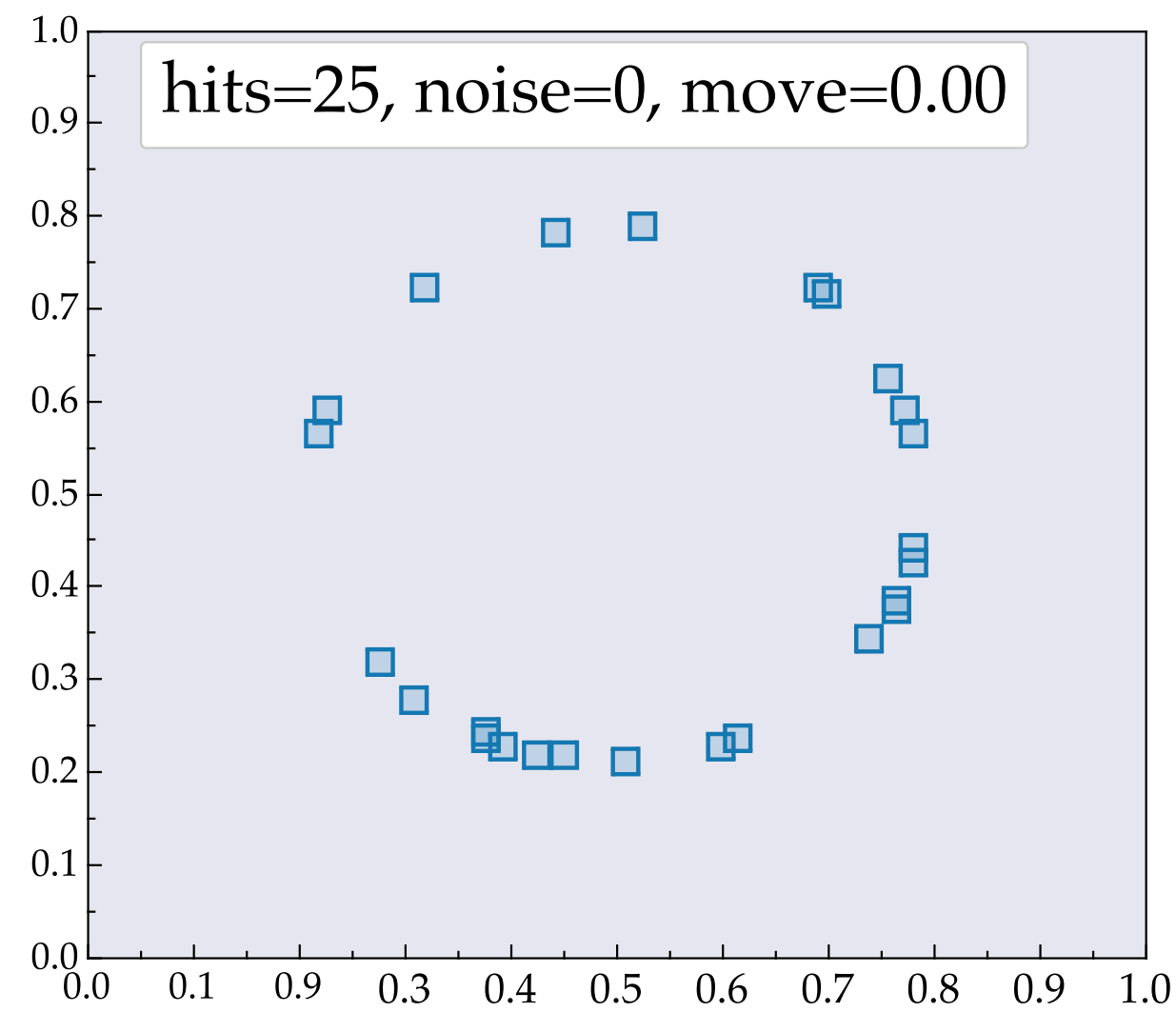
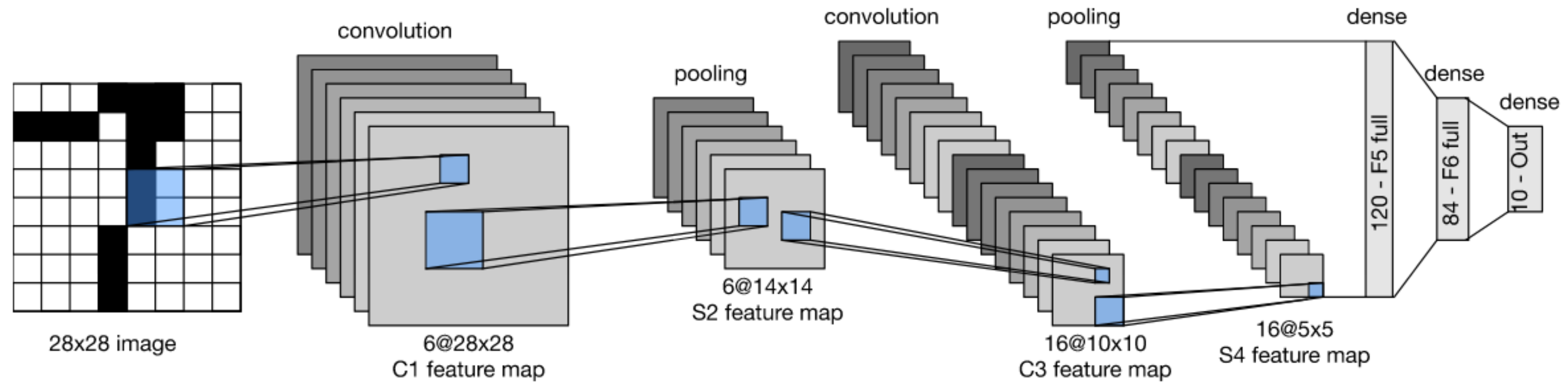
- ▶ Preliminary studies
- ▶ Neural Network Architecture
- ▶ Computational Graph
- ▶ Generative Adversarial Networks (GANs)
- ▶ Future Plans

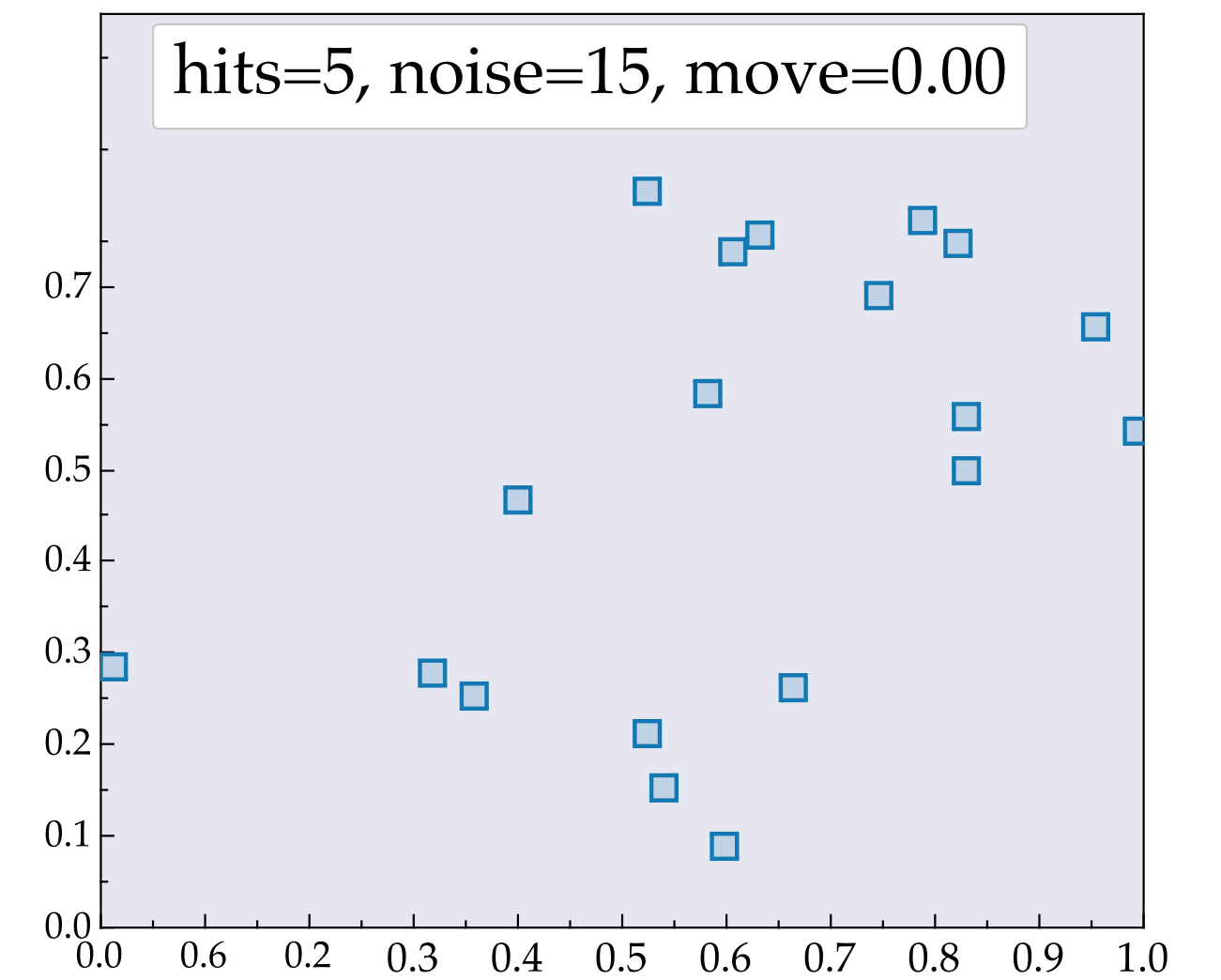
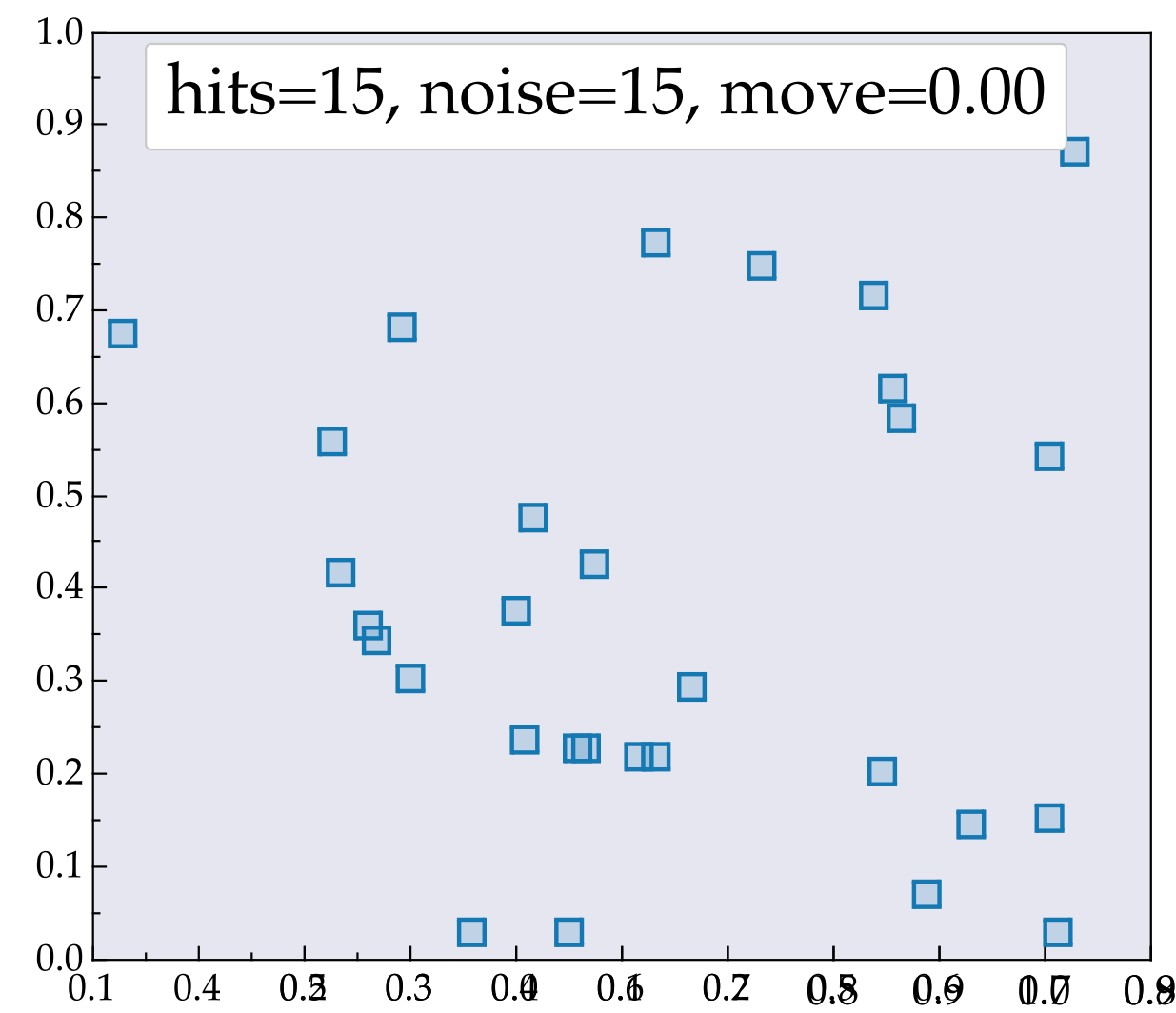
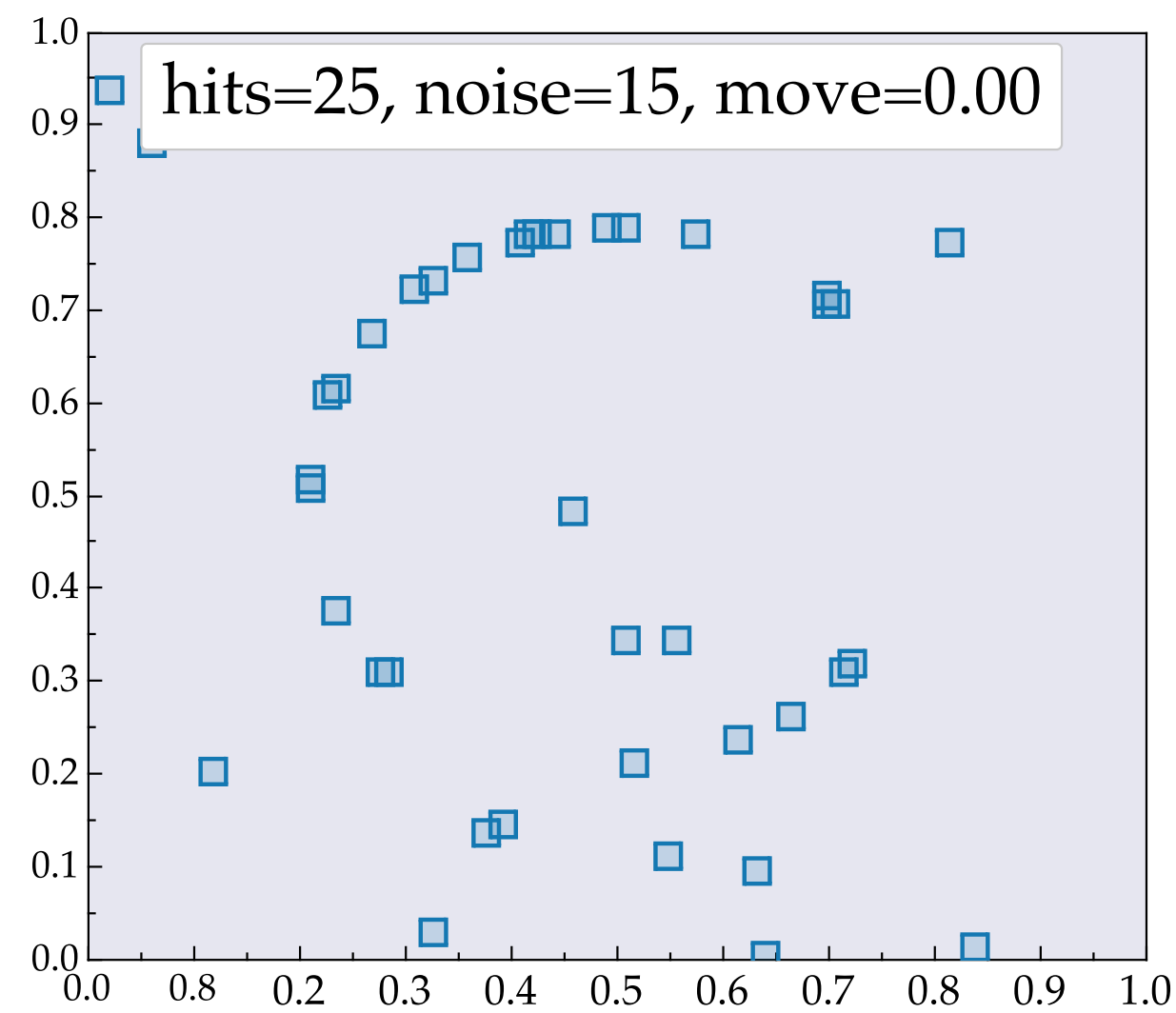
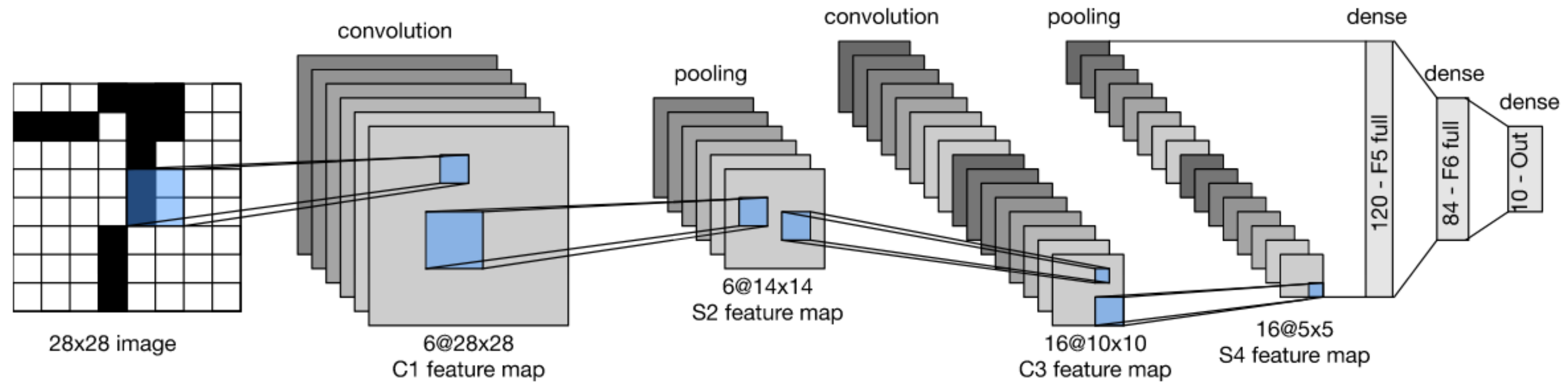




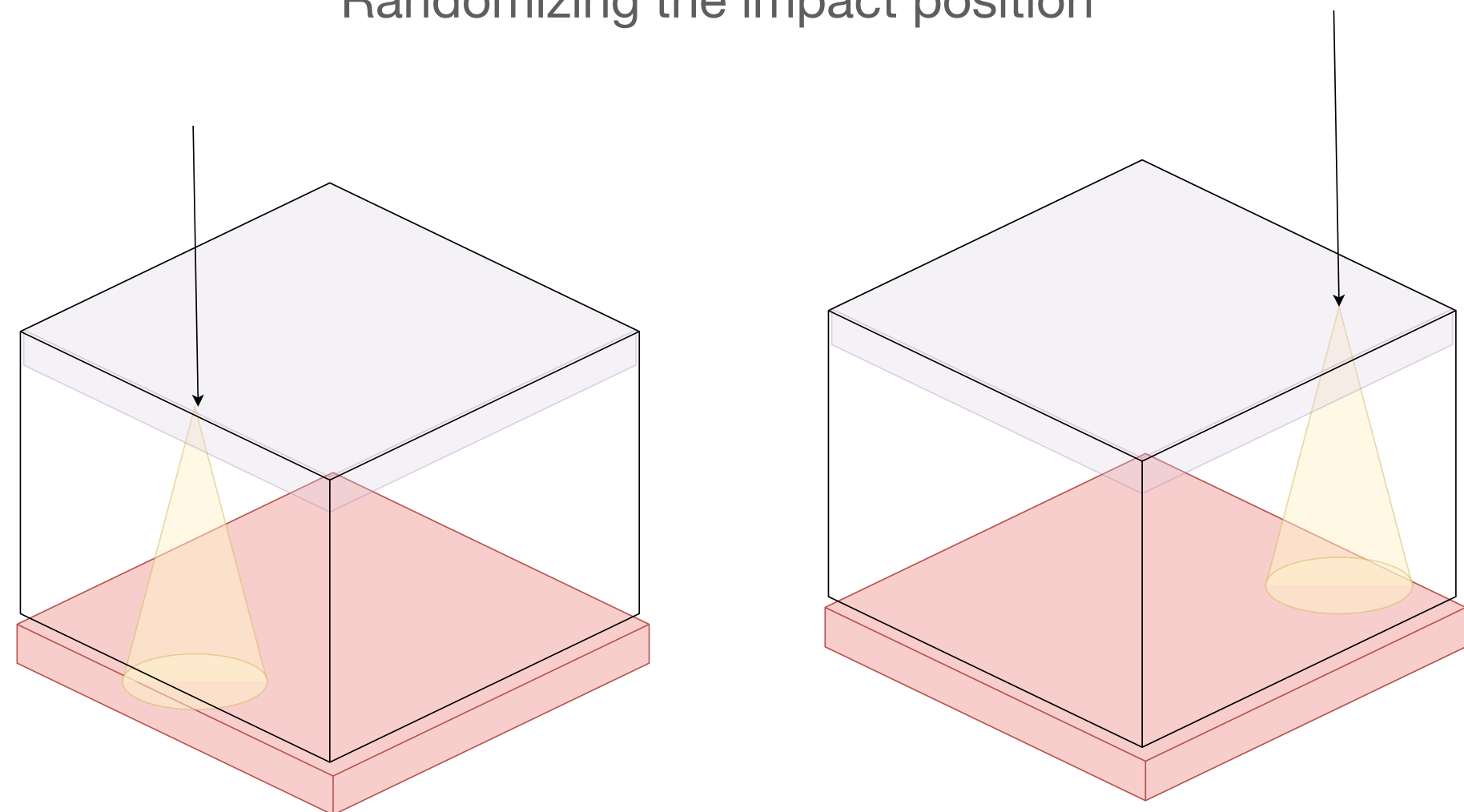
- ▶ **Simulation:** Simplified simulation with a square box with aerogel (refraction coefficient 1.05)
- ▶ **Photo-electrons:** Generating the Cherenkov ring with a various number of photo-electrons randomly distributed.
- ▶ **Noise:** Random levels of noise hits are added to the sample to evaluate network performance
- ▶ **Network Architecture:** Convolutional neural network trained on detector images to identify signal from kaon and pion.



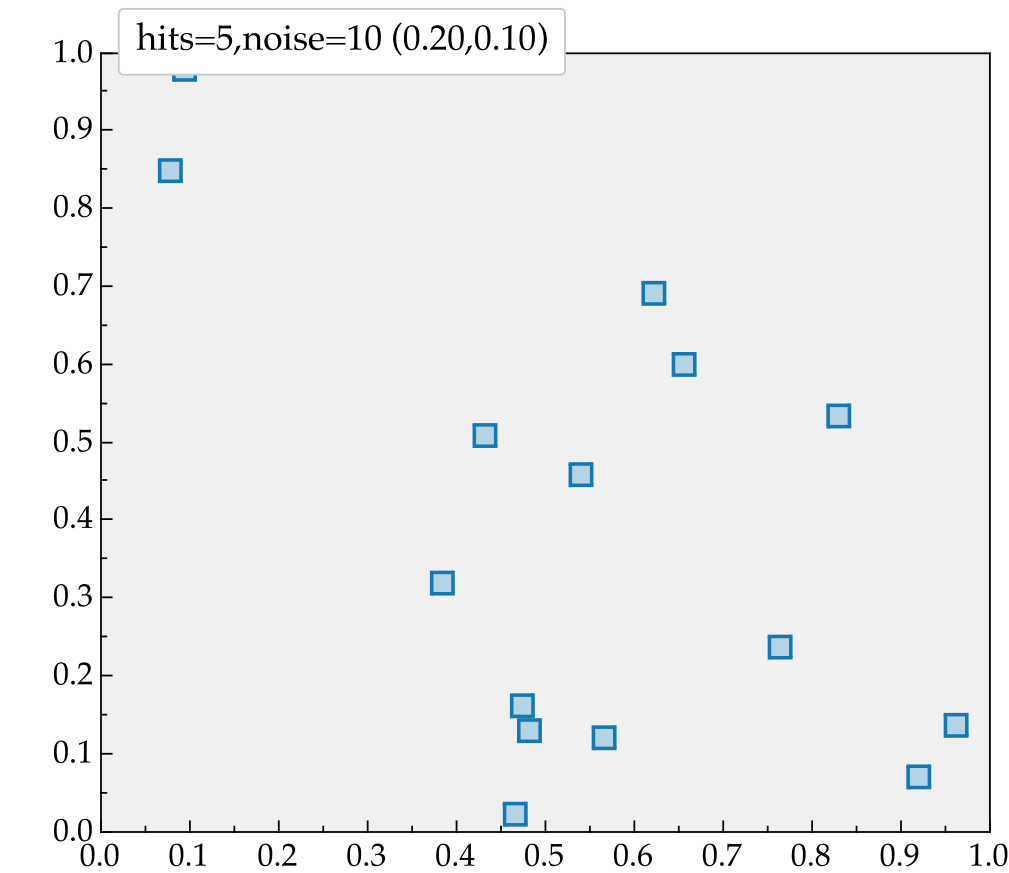
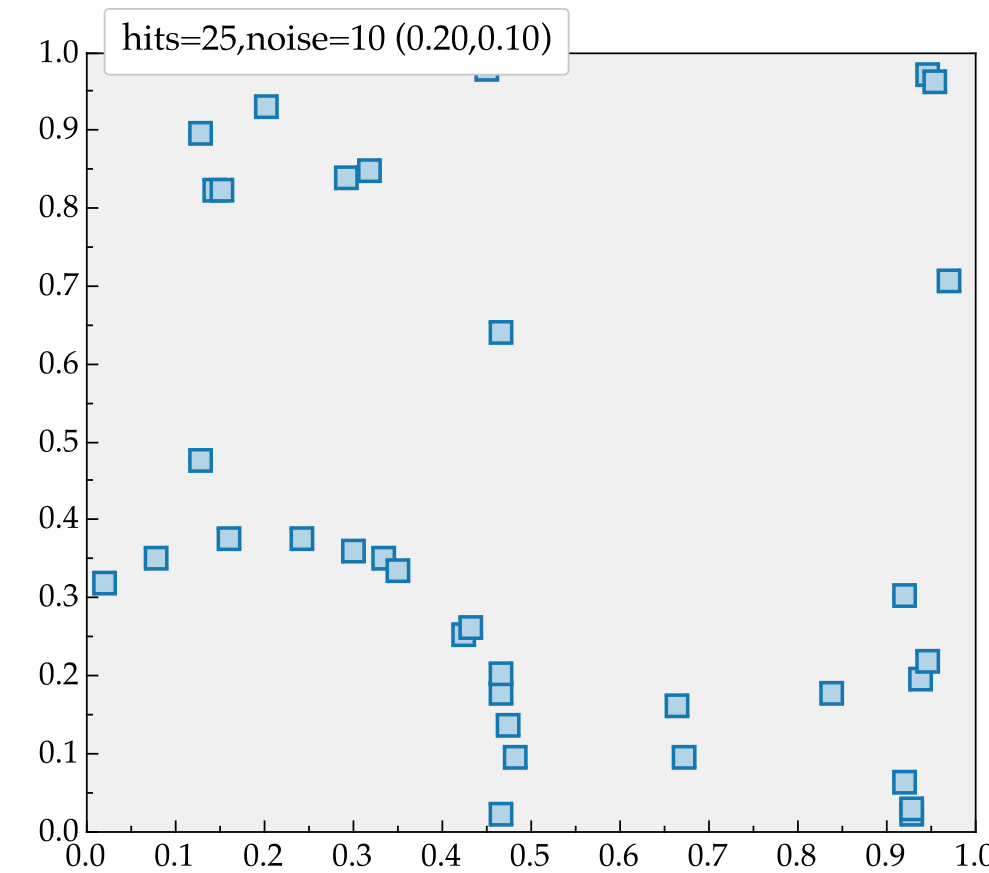
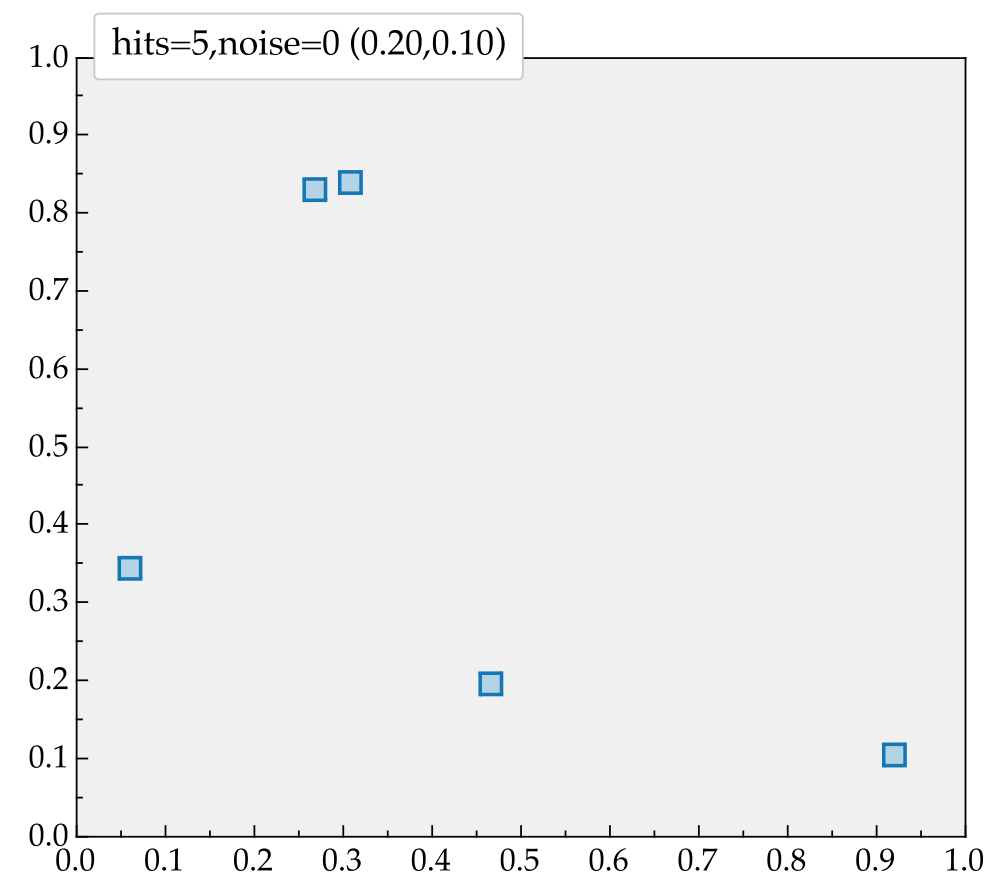
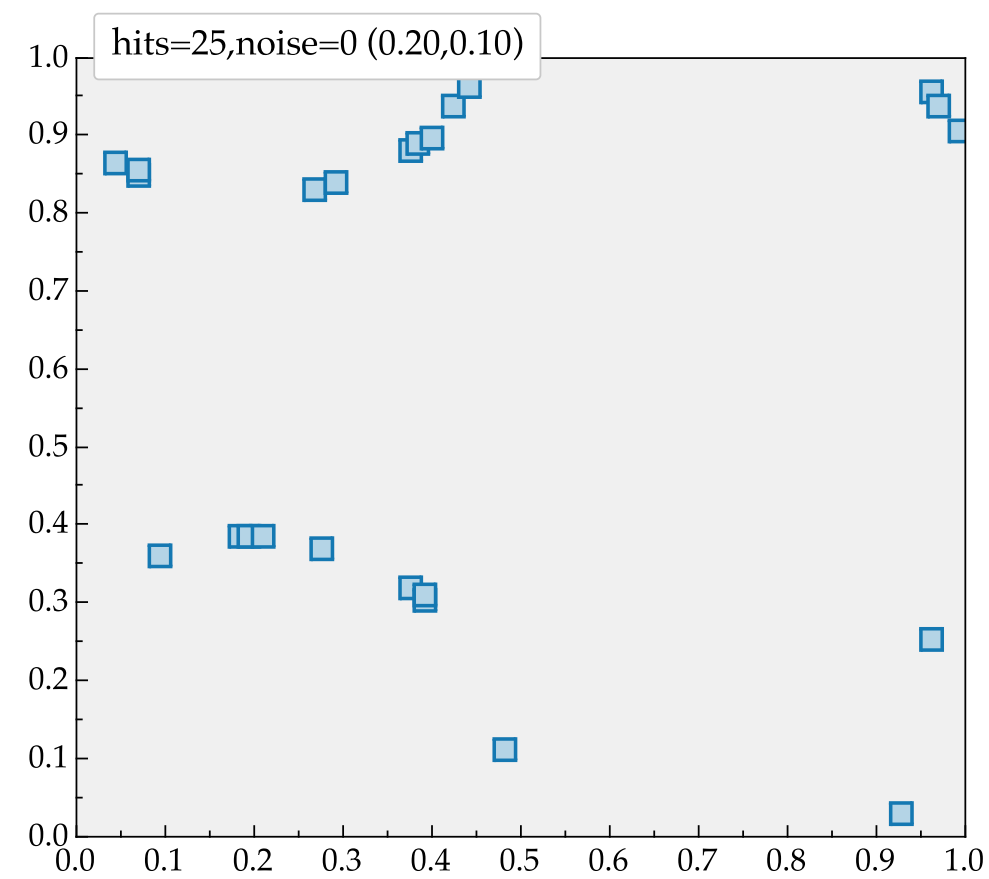




Randomizing the impact position



- ▶ **Simulation:** Simplified simulation with a square box with aerogel (refraction coefficient 1.05)
- ▶ **Photo-electrons:** Generating the Cherenkov ring with a various number of photo-electrons randomly distributed.
- ▶ **Noise:** Random levels of noise hits are added to the sample to evaluate network performance
- ▶ **Random impact position:** Randomizing the impact position of the particle on the box. Center = $(0.5,0.5) + \text{RNDM}(-0.4:0.4,-0.4:0.4)$
- ▶ **Network Architecture:** Convolutional neural network trained on detector images to identify signal from kaon and pion.



No Noise
Center (0,0)

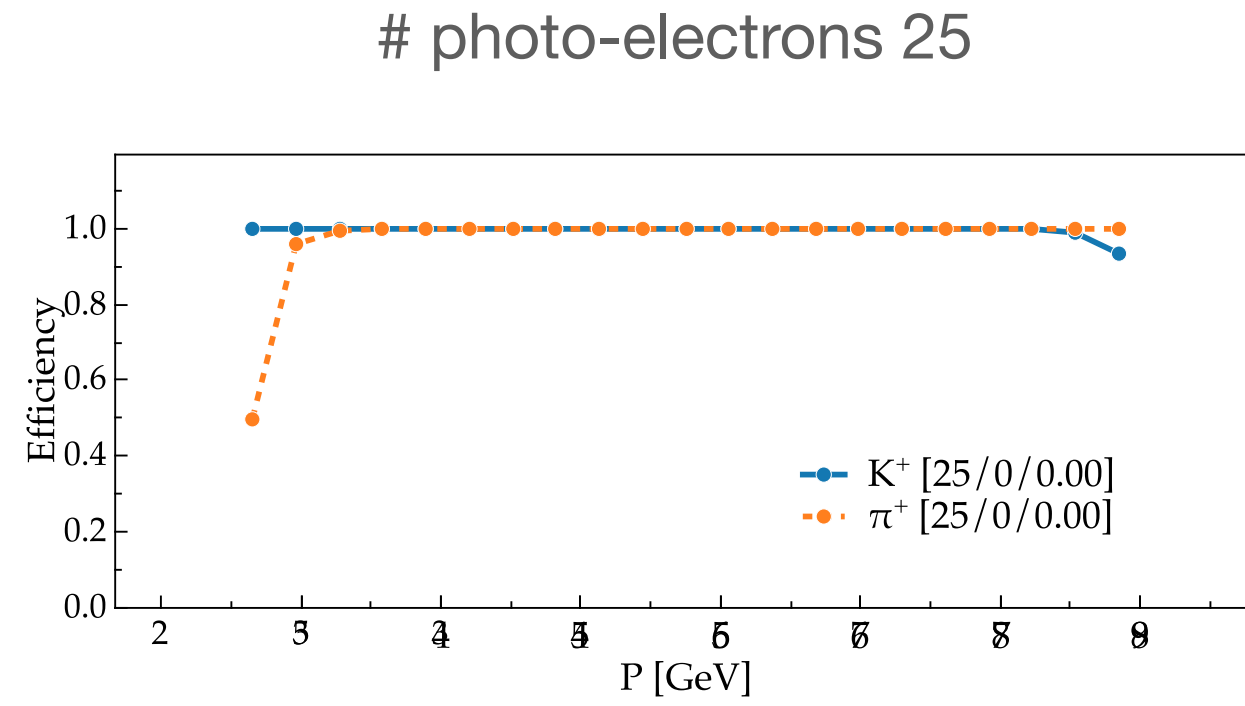


photo-electrons 15

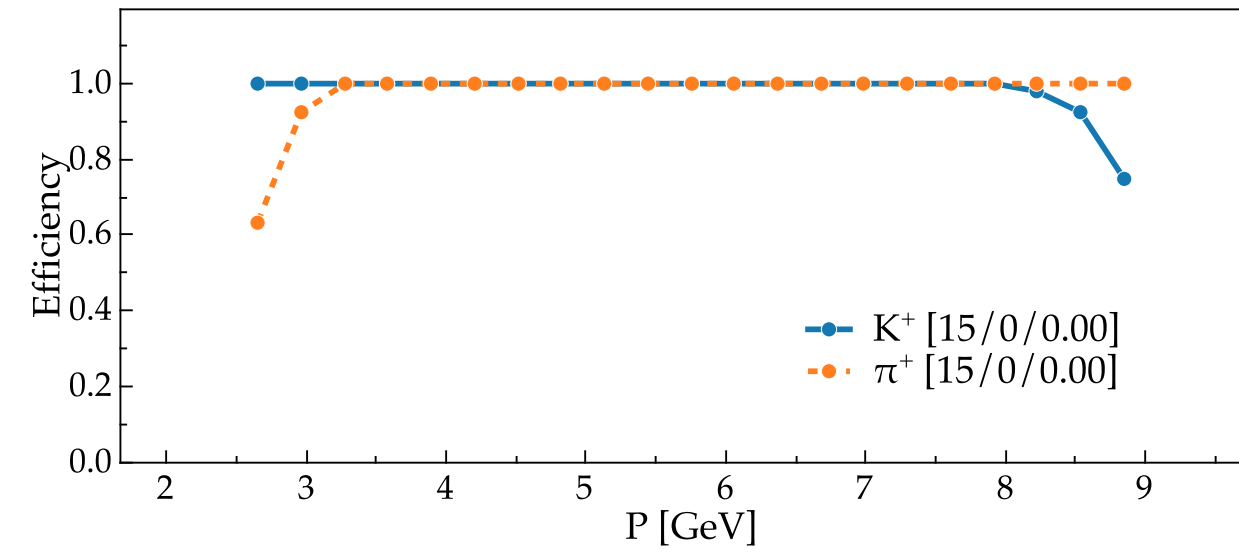
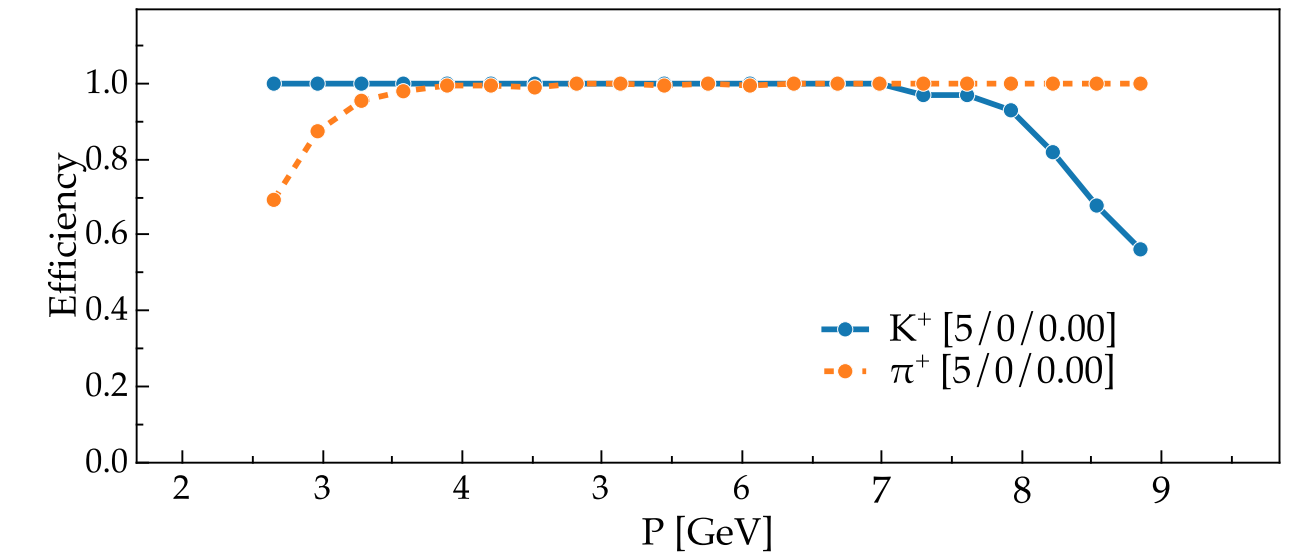
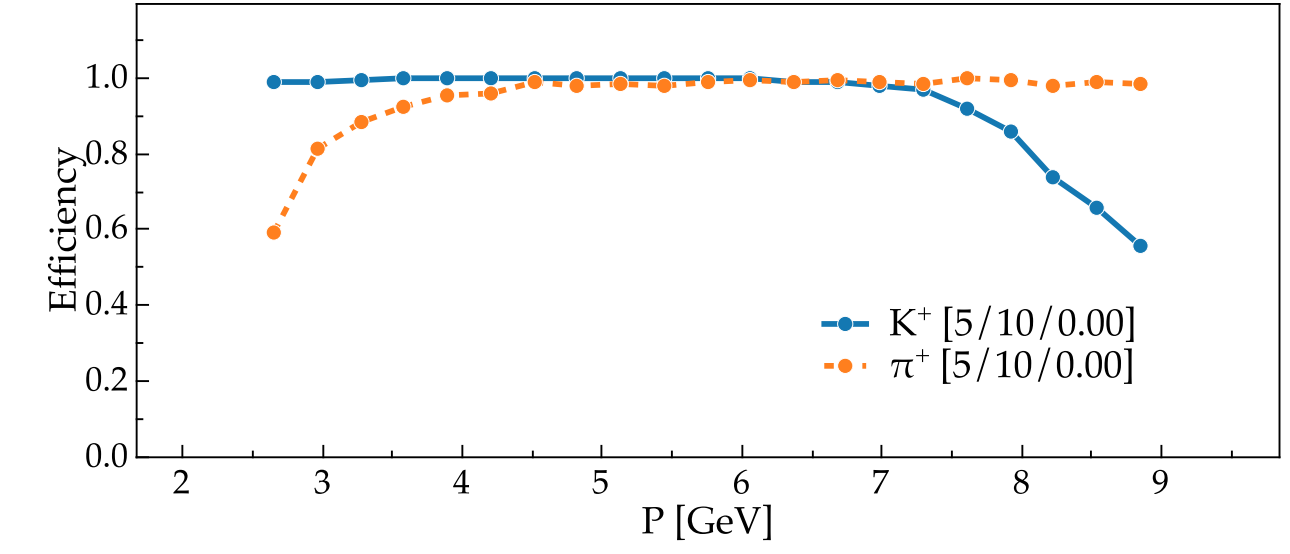
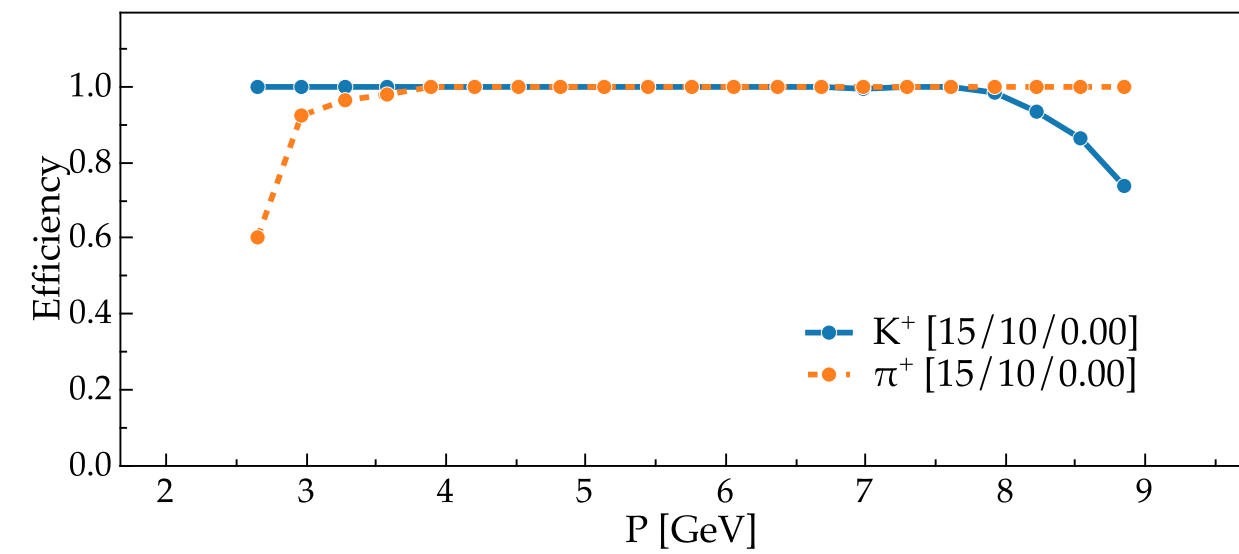
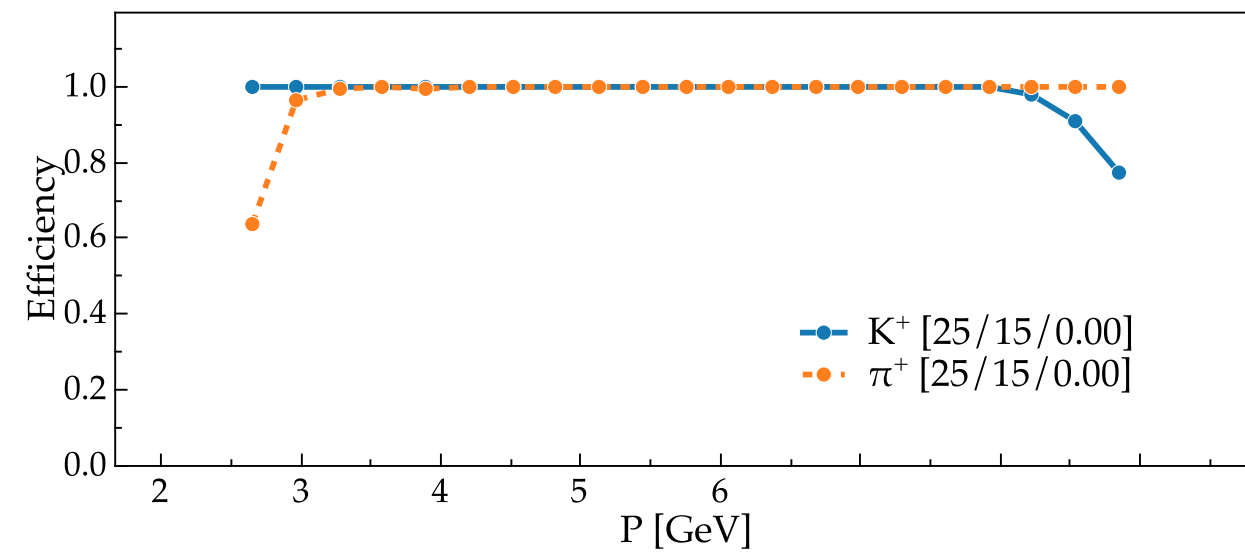


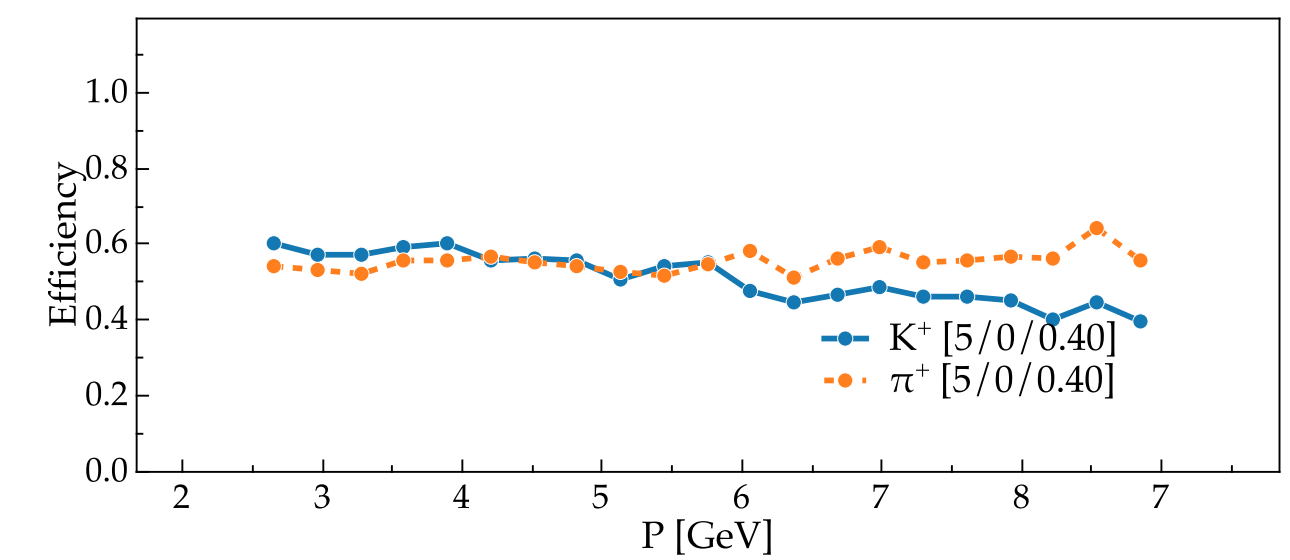
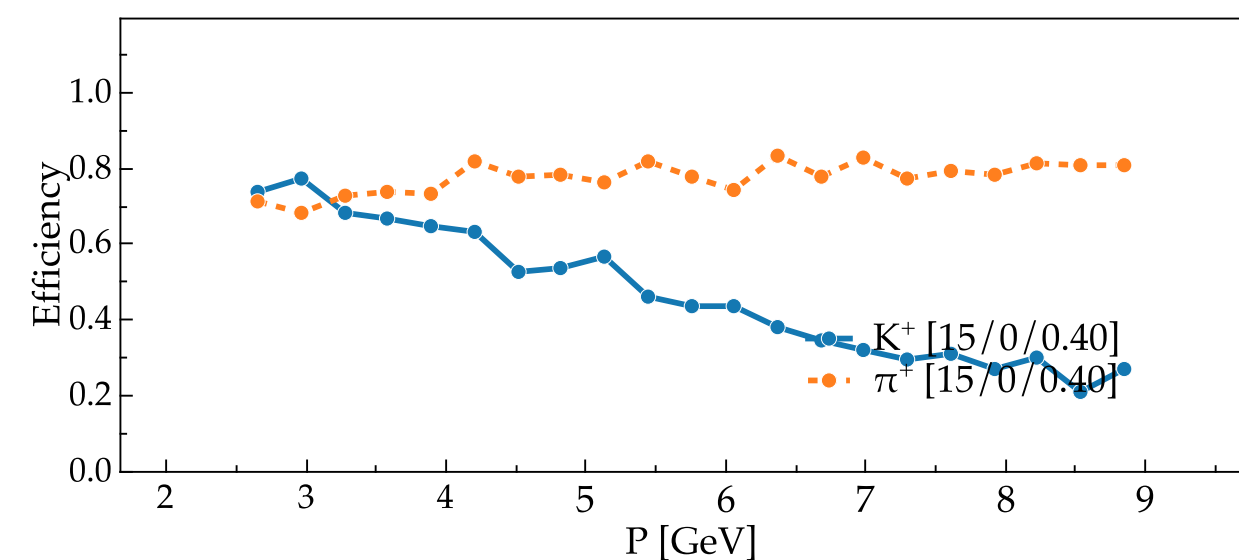
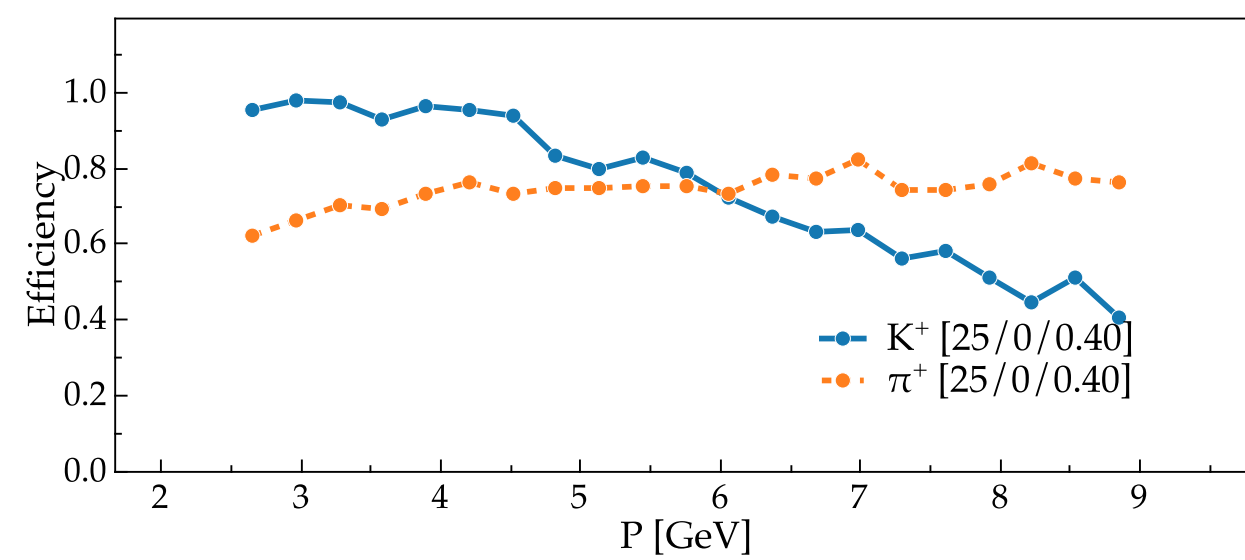
photo-electrons 5



Added Noise
Center (0,0)

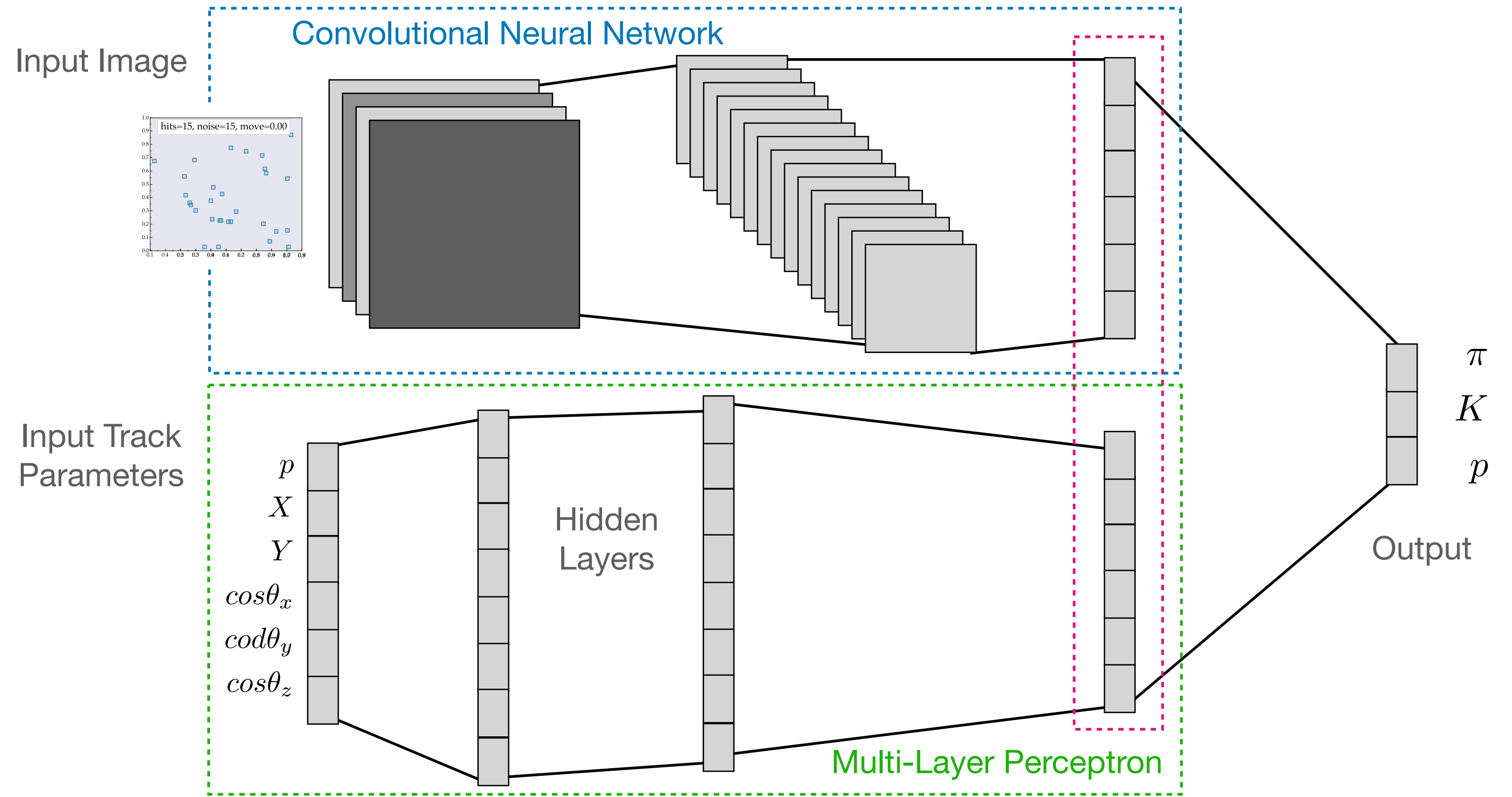
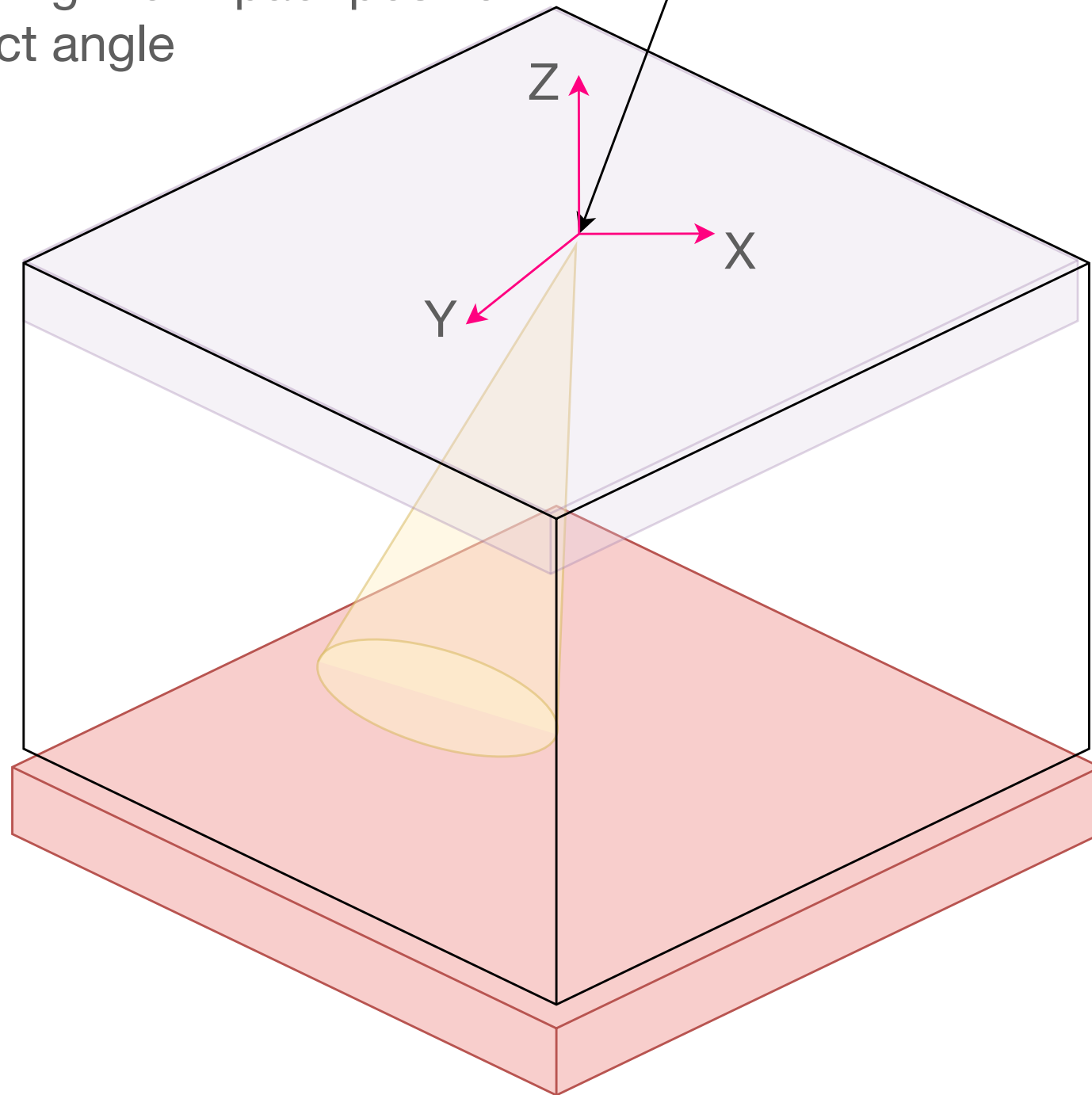


No Noise
Center
Random
(0,0) +/- 0.4



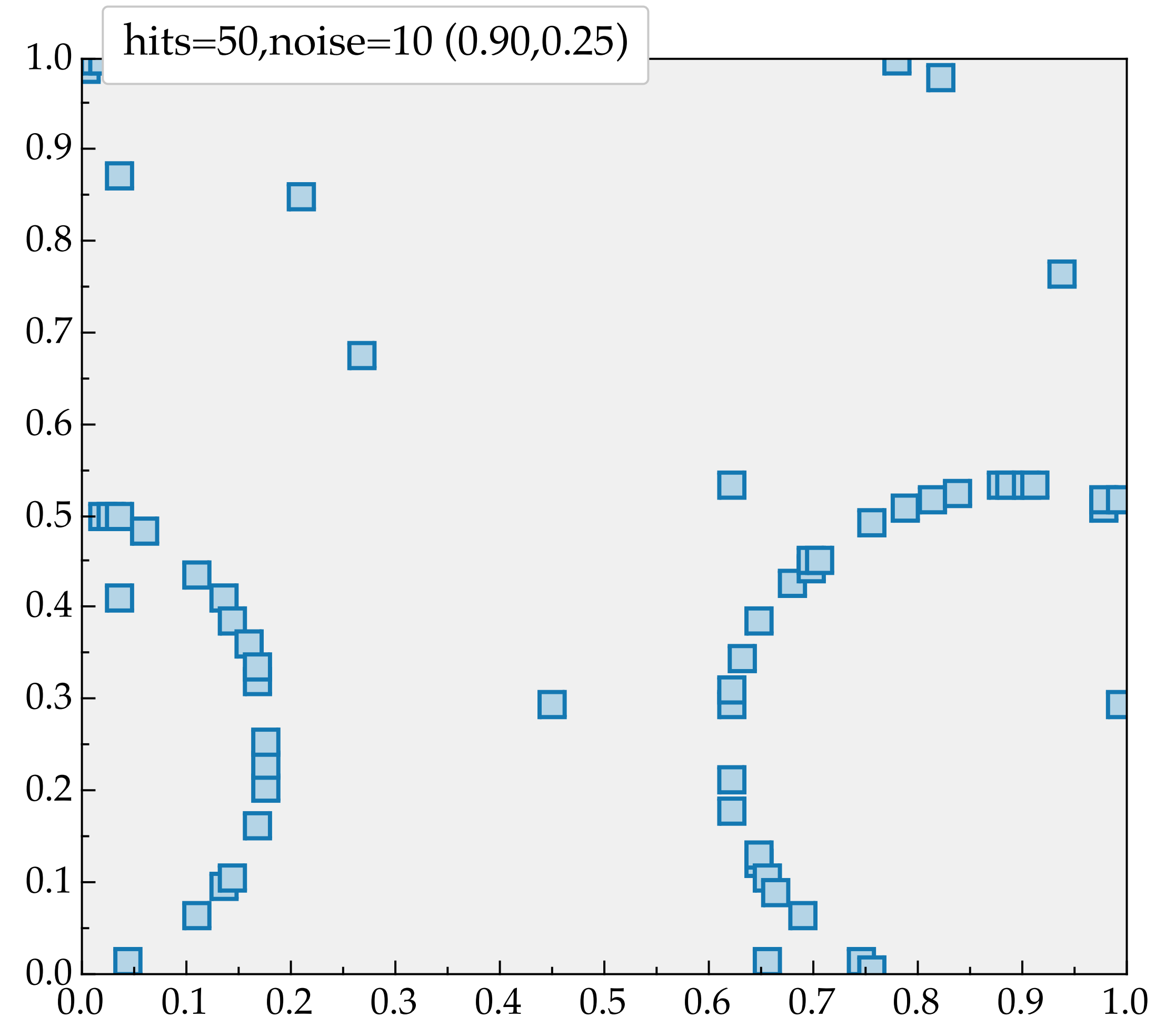
Input to Graph Computation Network
 $X[P, X, Y, \cos(\theta_x), \cos(\theta_y), \cos(\theta_z)]$

Randomizing the impact position and impact angle

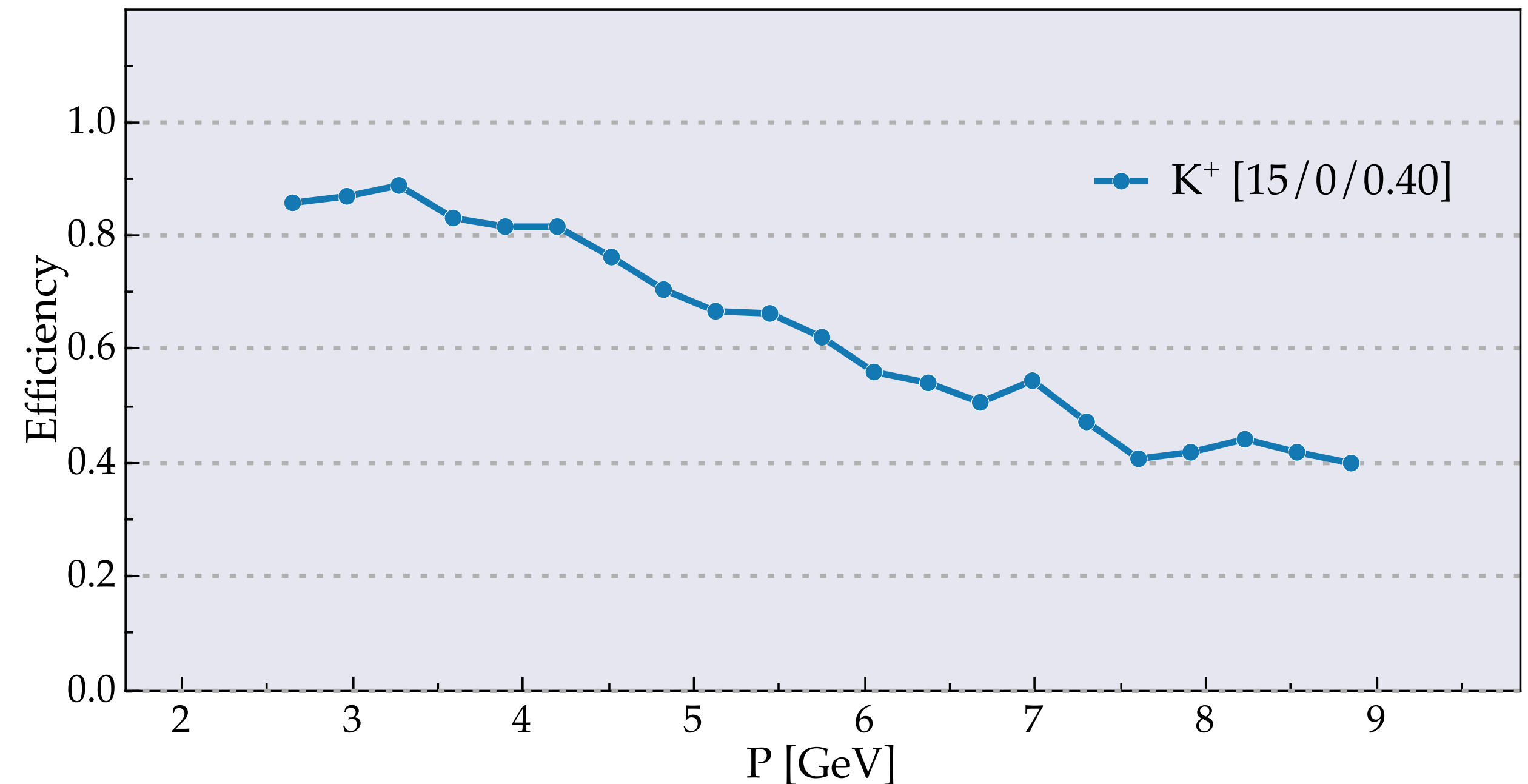


- ▶ **Computation Graph:** Consists of two different neural network architectures joined together to produce a classification output.
- ▶ **CNN:** Convolutional neural network analyzes the image of the ring from RICH detector
- ▶ **MLP:** Multilayer Perceptron provides input parameters for track producing the Cherenkov light.
- ▶ **Together** they provide classification for the particle.

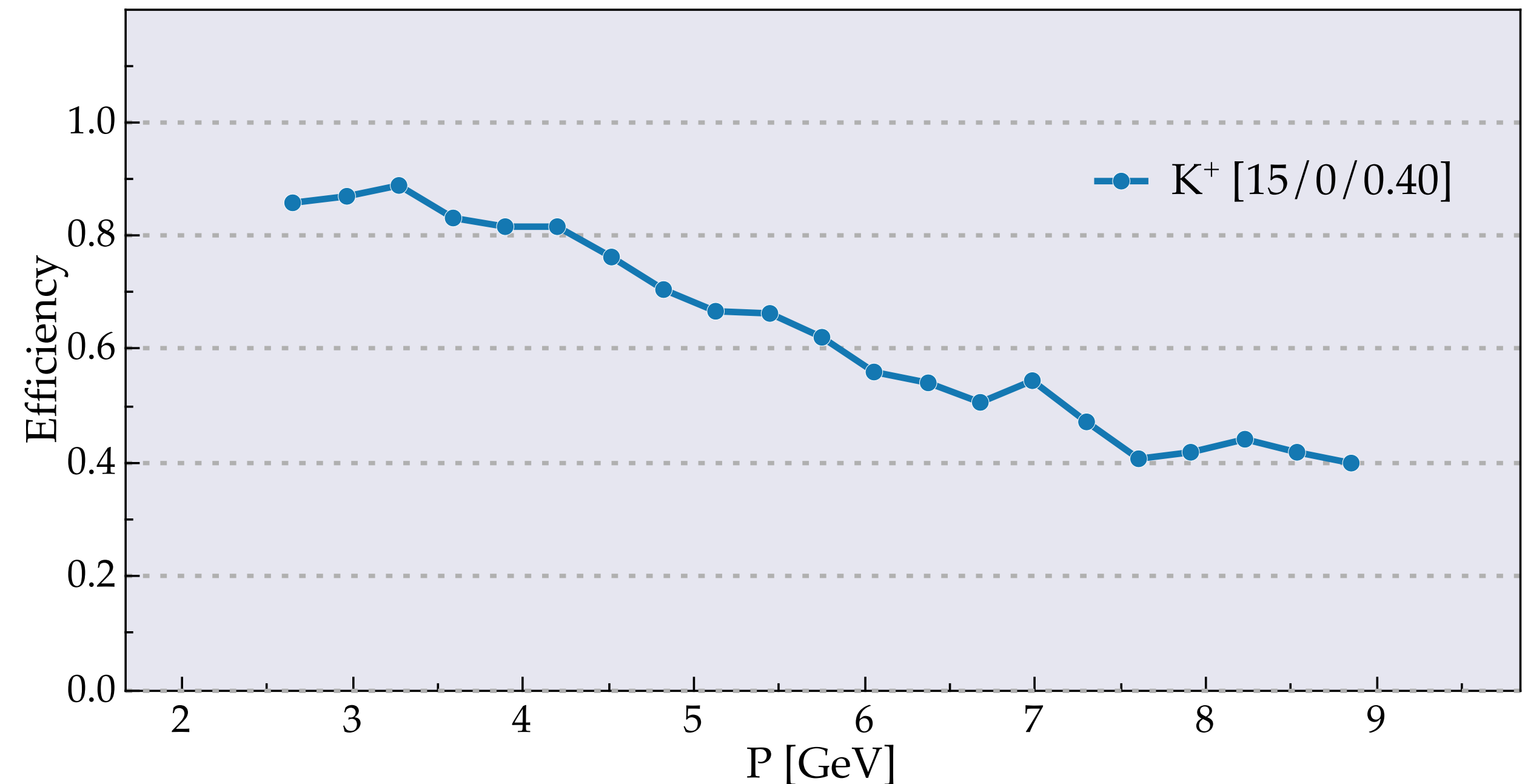
- ▶ **Rings:** Image produced by particle hitting the box at position (0.90,0.25)
- ▶ **Photo-Electrons:** 50 photons are traced on the Cherenkov cone.
- ▶ **Noise:** 10 random noise hits are added to the data.



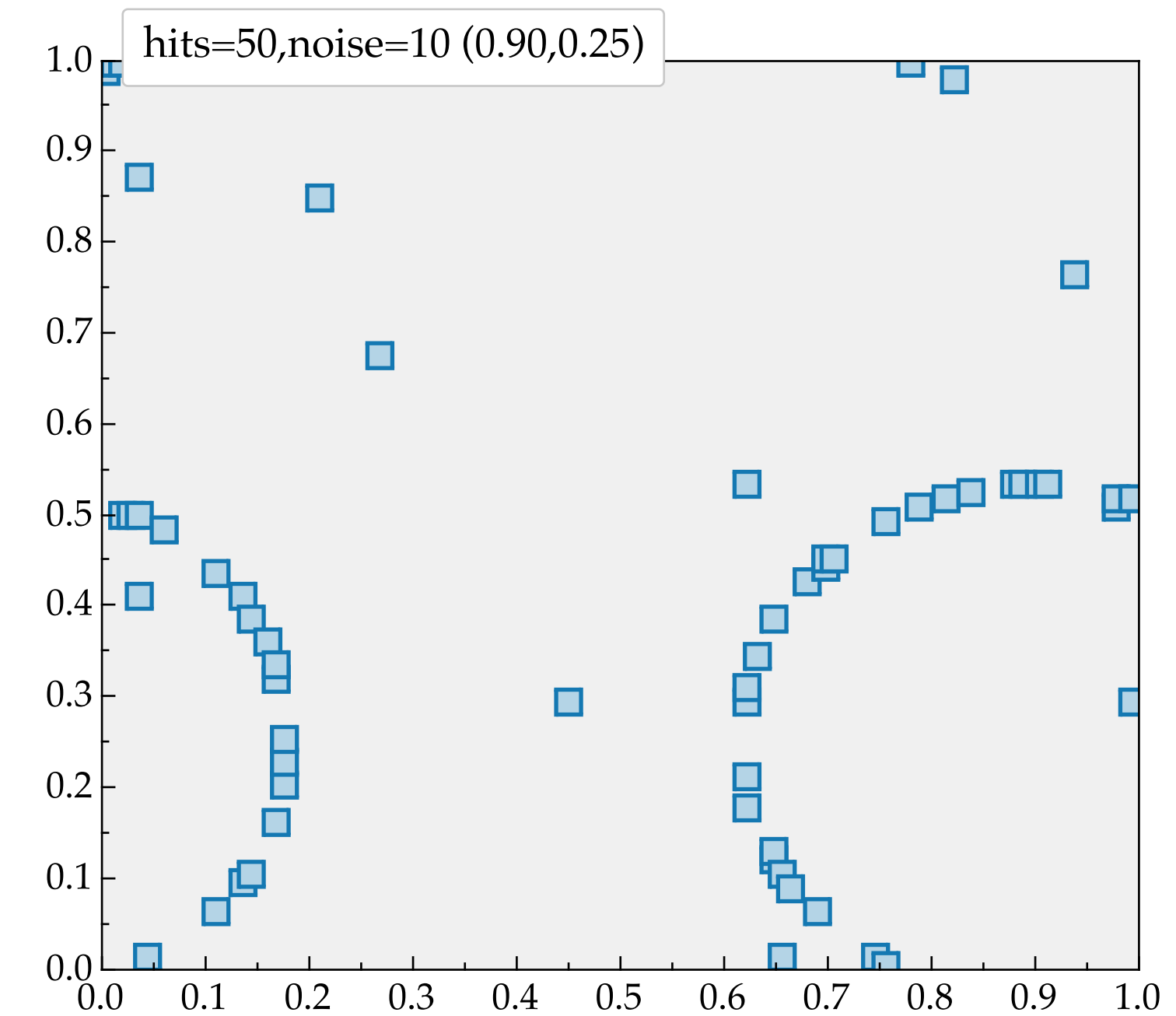
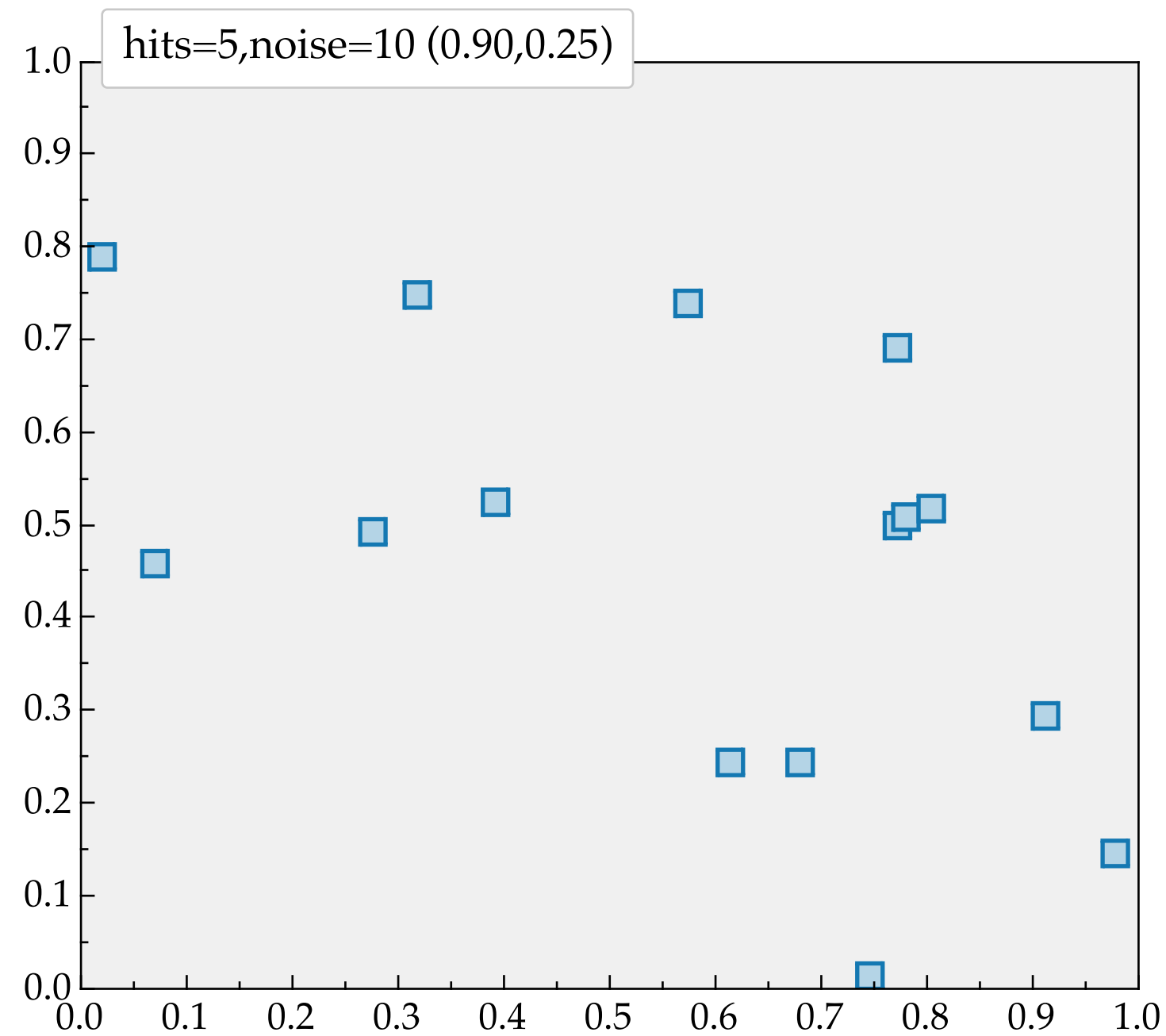
- ▶ **Sample:** Generated random incident position of the incoming particle on the Aerogel, (0.0-0.4) shifted center
- ▶ **Training Network:** Computational Graph Networks with Convolutional Network and Multi-Layer perceptron
- ▶ **Evaluation:** Kaon sample is evaluated by the network provides kaon probability.

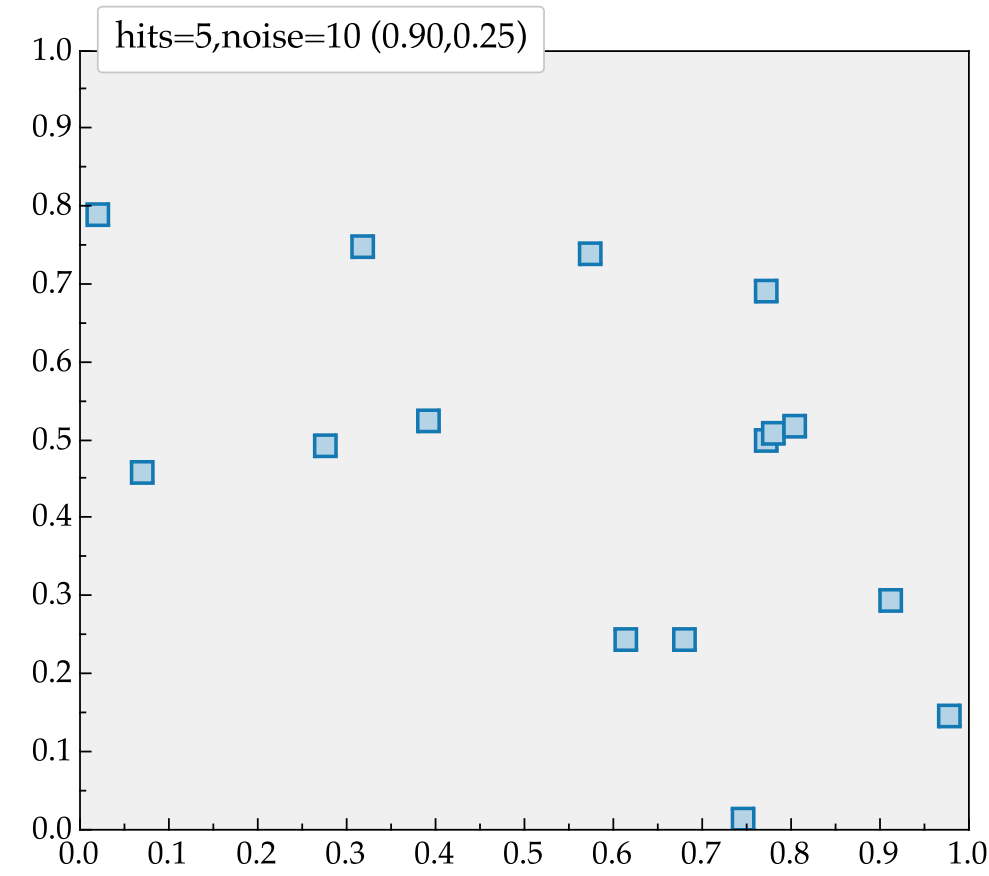


- ▶ **Sample:** Generated random incident position of the incoming particle on the Aerogel, (0.0-0.4) shifted center
- ▶ **Training Network:** Computational Graph Networks with Convolutional Network and Multi-Layer perceptron
- ▶ **Evaluation:** Kaon sample is evaluated by the network provides kaon probability.
- ▶ **Problems:** For more sparse hit patterns (less photo-electrons) the efficiency is worse.
- ▶ **Noise:** Noise contributes to more reduction in Kaon identification reduction.
- ▶ **Solution:** Try to enhance the signal by removing noise and possibly generating pseudo-hits.

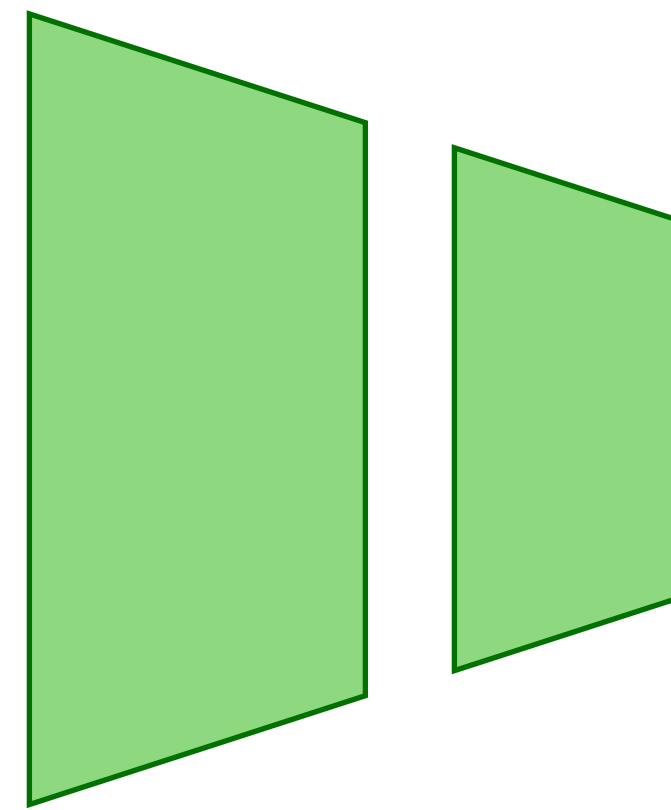


- ▶ **Procedure:** the sparse hit pattern has to be transferred to more populated image.
- ▶ **Particles:** For each particle, hypothesis have to be made by creating a new image based on the hit pattern and the input from particle interaction point.
- ▶ **Network:** A convolutional auto encoder computational graph will be appropriate, or a Generative Adversarial Network (GAN)

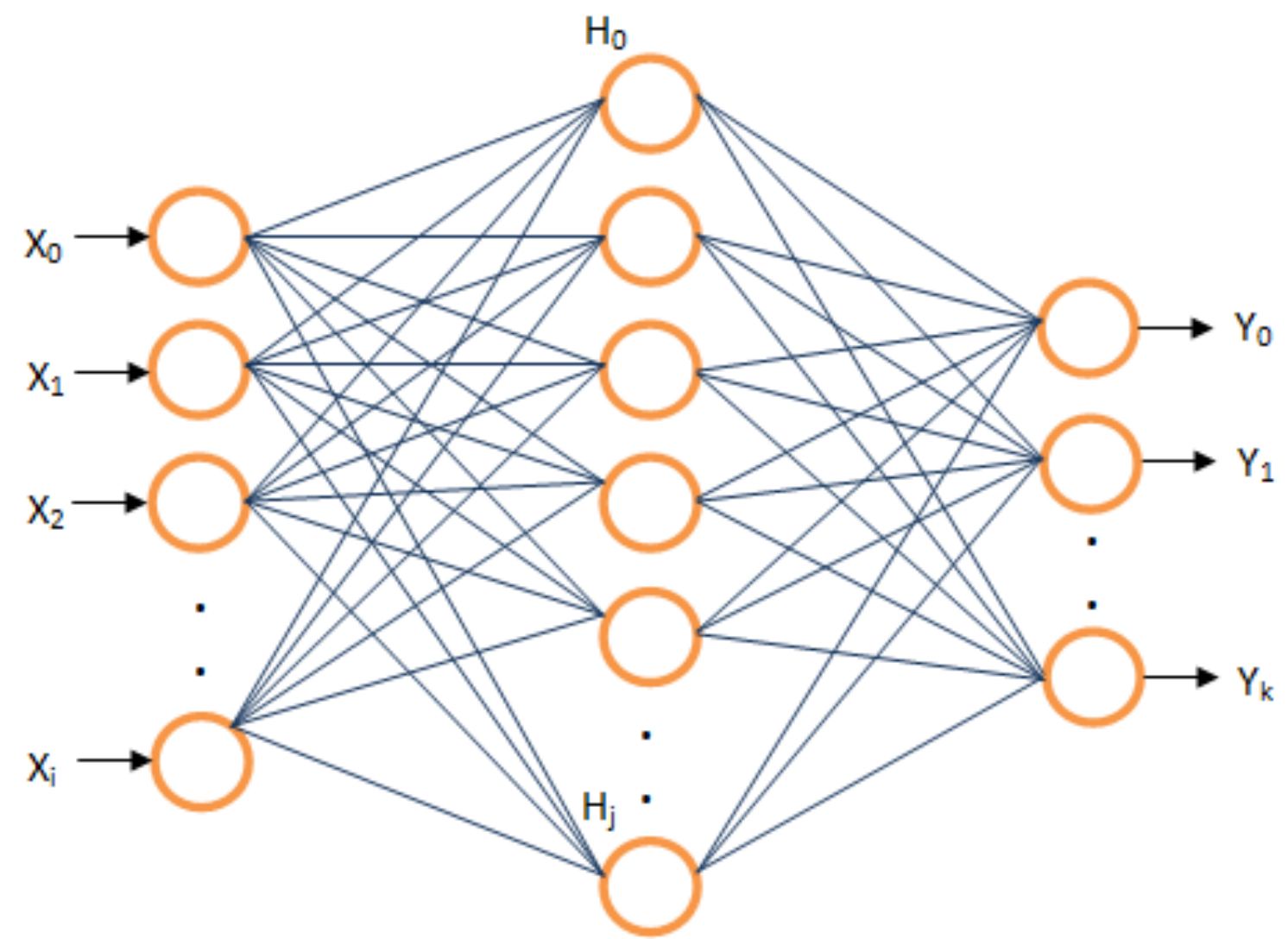
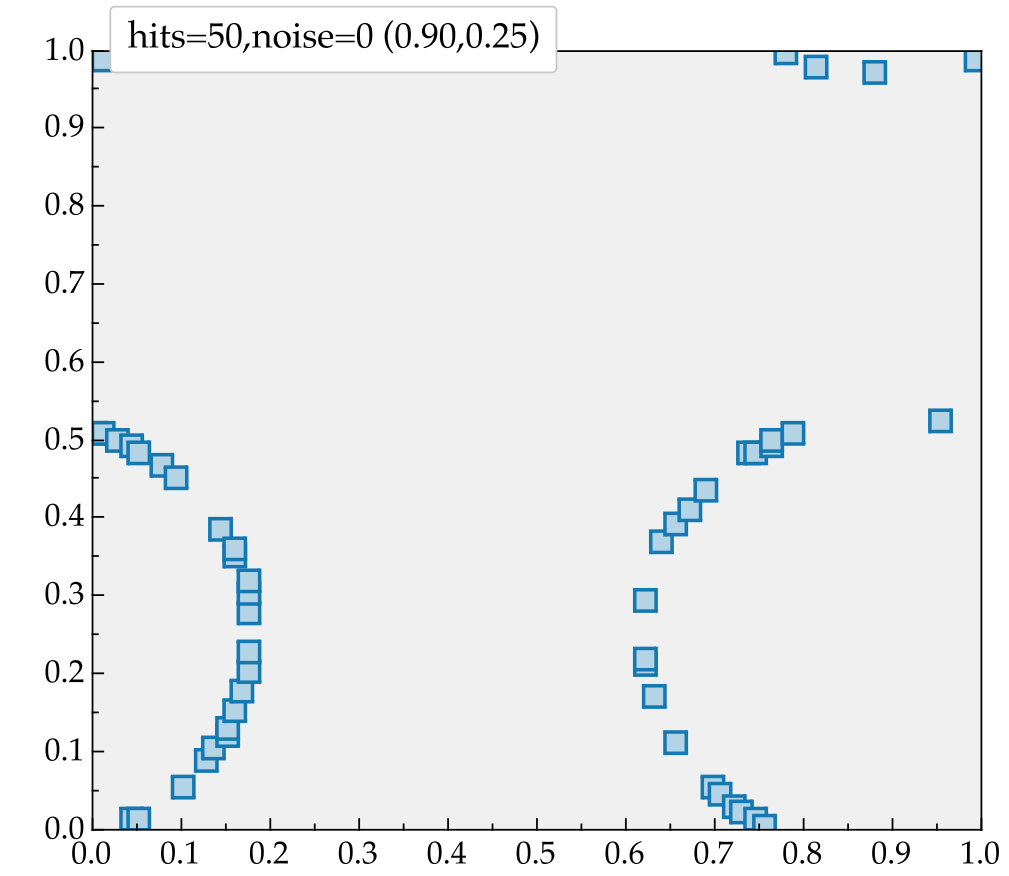
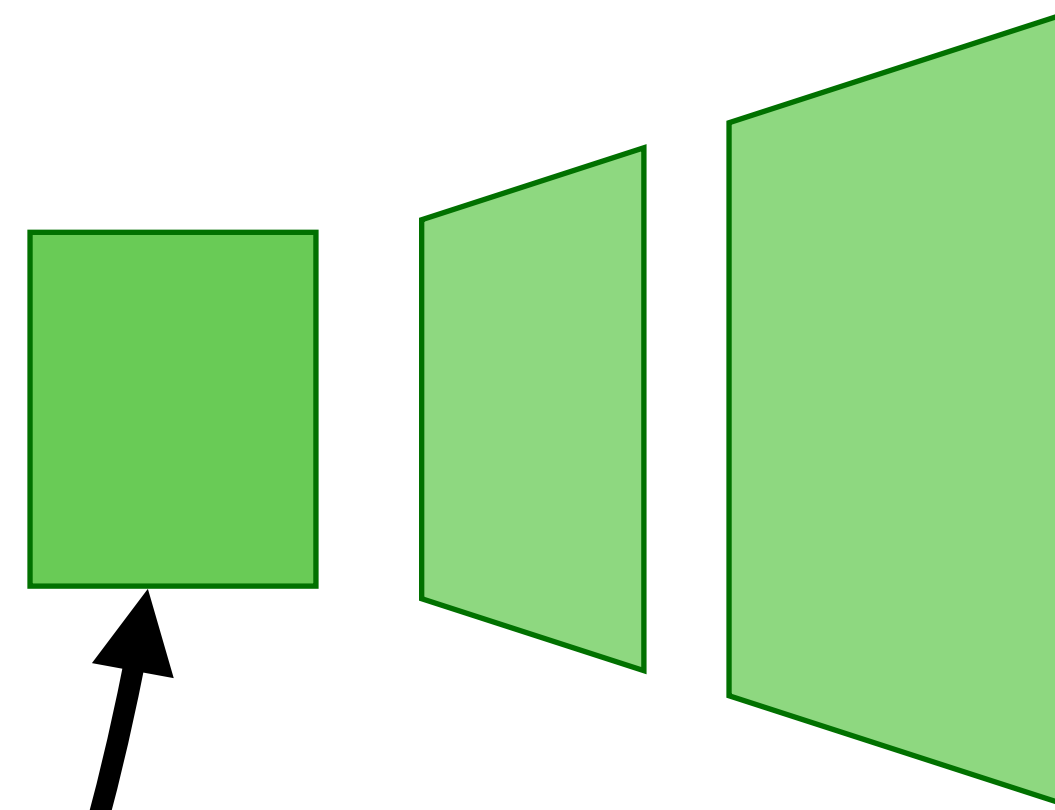




Encoder



Decoder



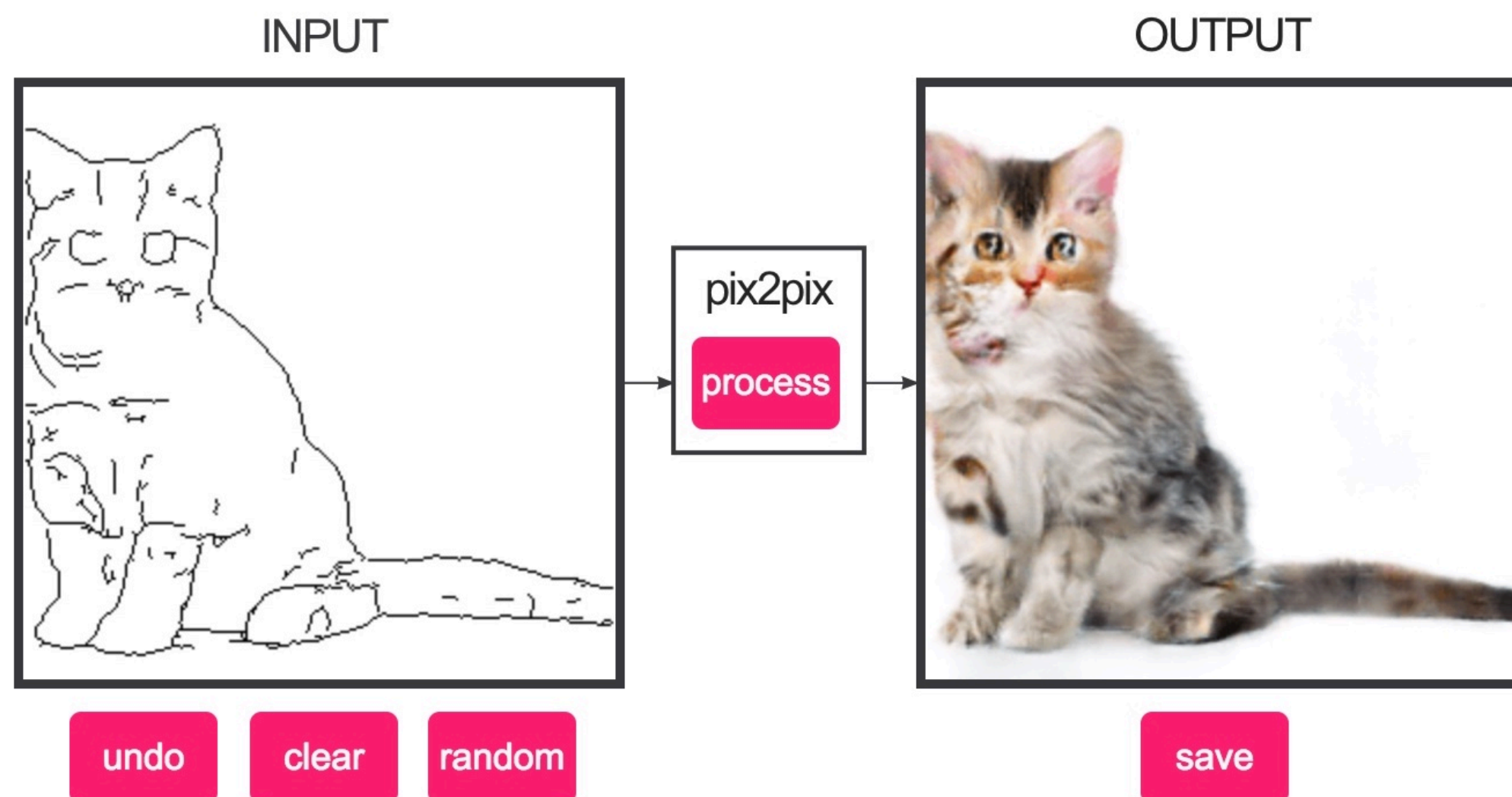
► **Network:** Use computational Graph with MLP and Convolutional Autoencoder.

► **Input to CNN:** The image of hits in RICH detector

► **Input to MLP:** Particle detector intersection parameters and particle momentum and direction.

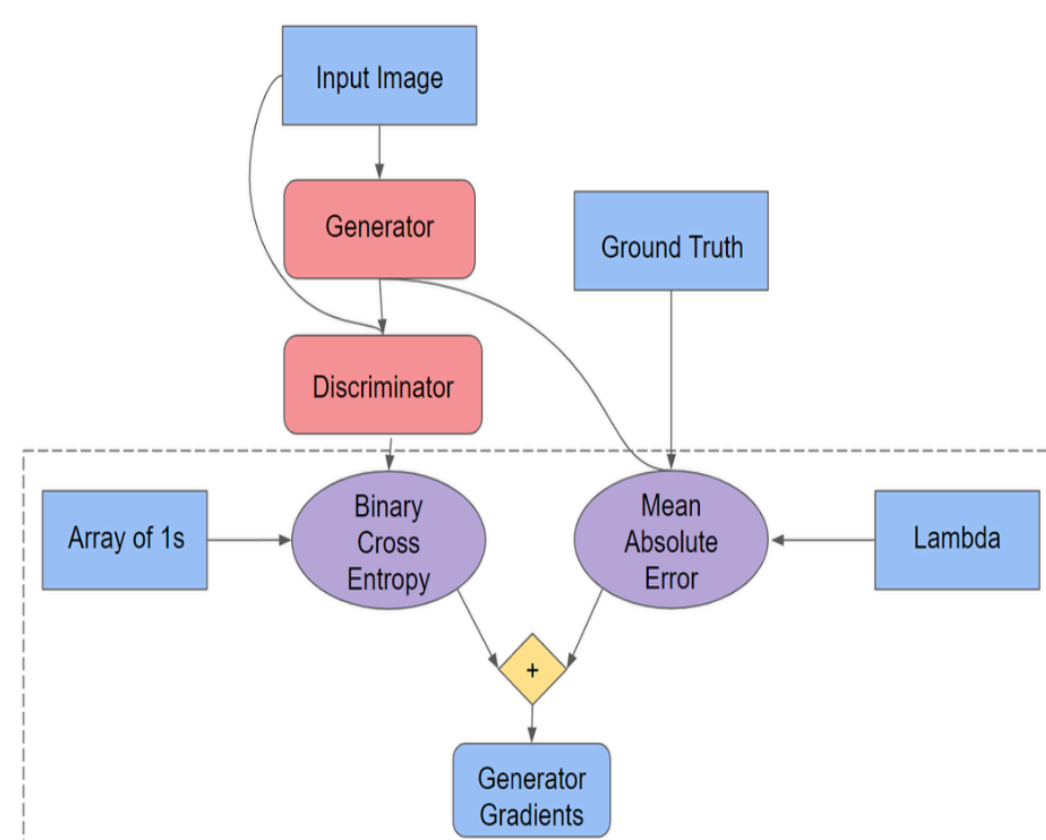
- ▶ **Network:** Use computational Graph with MLP and Convolutional Autoencoder.
- ▶ **Input to CNN:** The image of hits in RICH detector
- ▶ **Input to MLP:** Particle detector intersection parameters and particle momentum and direction.
- ▶ **Output of CNN:** Reconstructed image in RICH of certain particle type
- ▶ **Combined Computational Graph:** Determine the particle type from

Pix2Pix

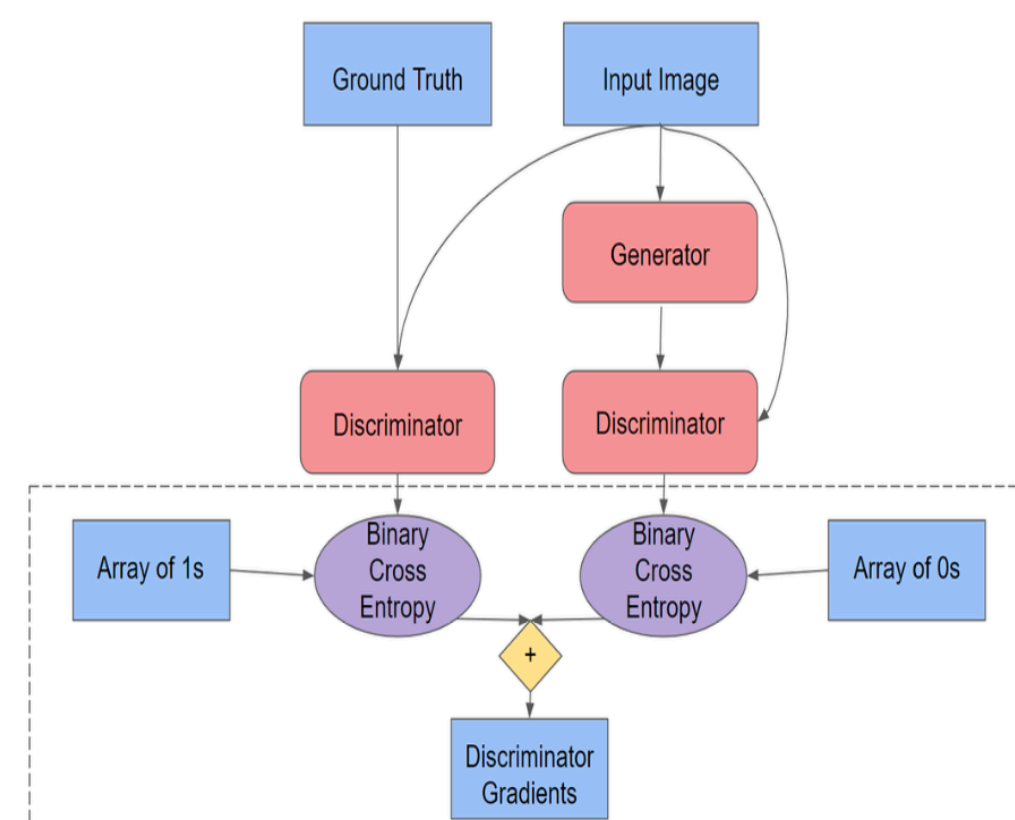


A generative adversarial network (**GAN**) is a class of machine learning frameworks

Two neural networks contest with each other in the form of a **zero-sum game**, where one agent's gain is another agent's loss.



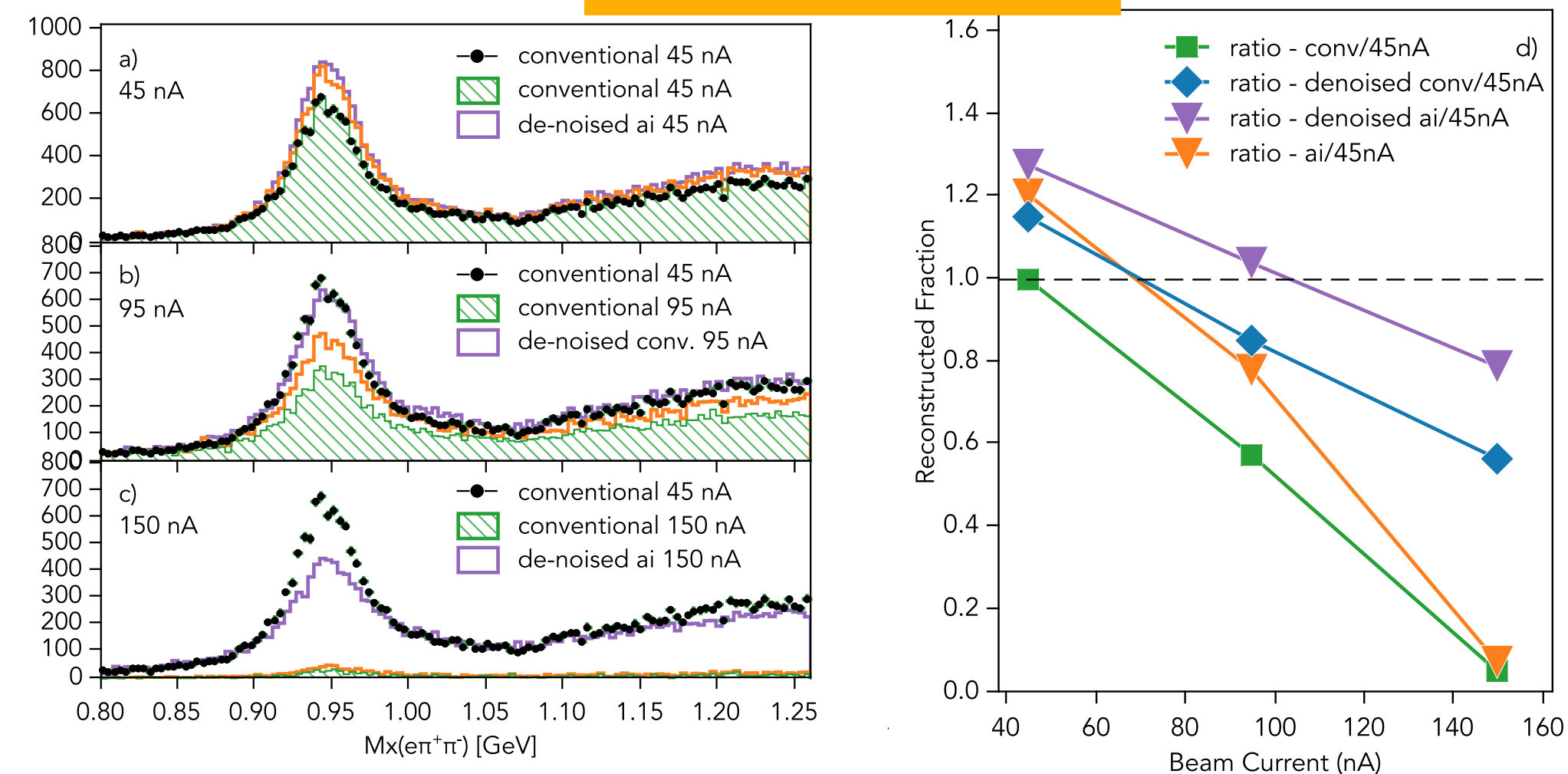
(a) Generator Loop



(b) Discriminator Loop

► **Usage:** Generate hits belonging to a track in CLAS12 drift Chambers given all the hits. (Removes noisy hits)

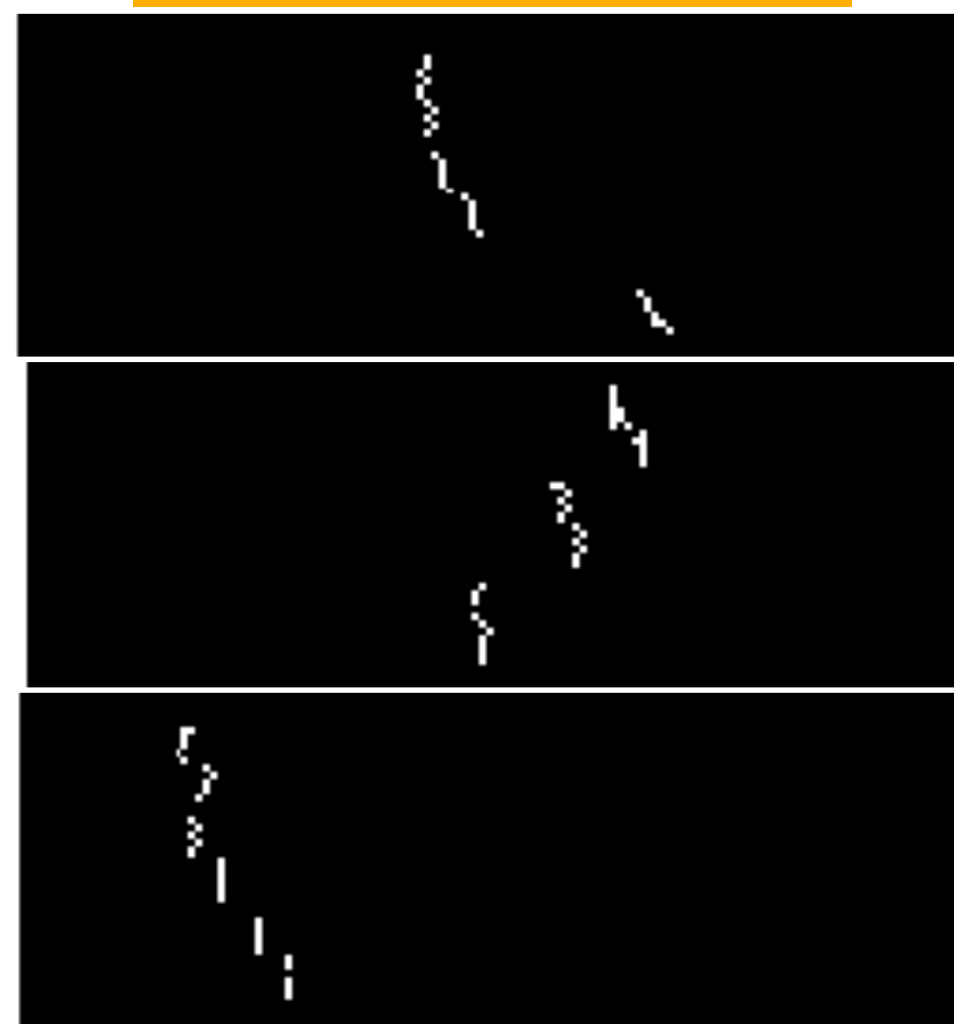
Simulation



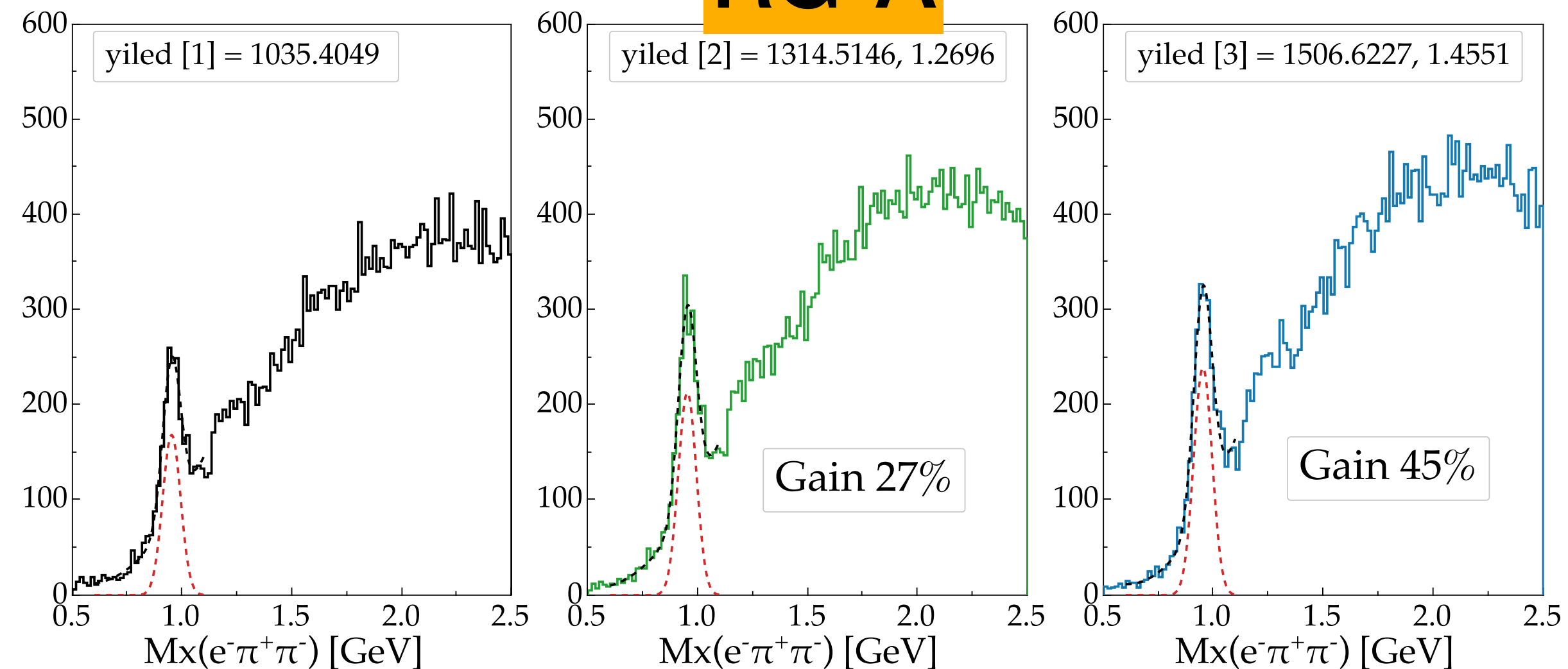
RAW



Pix2Pix



RG-A



▶ **AI approach:**

- ▶ The AI approach is preferred due to simpler implementation and less code base.
 - ▶ Need good simulation to produce training sample
- ▶ When trained on experimental data AI may reduce the need for alignment.
- ▶ Neural Networks trained with Python (Keras/TensorFlow) can be included in the workflow using C++/Java interfaces.

Backup