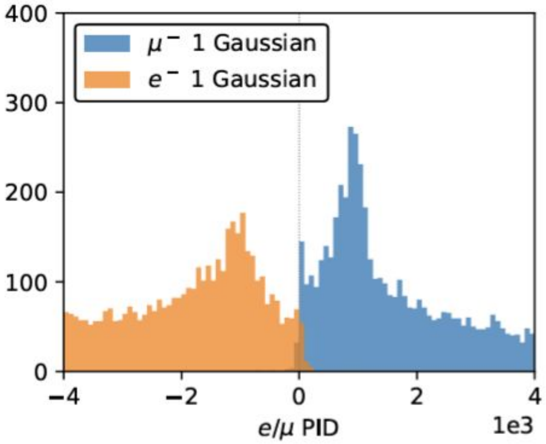
Towards the next benchmark

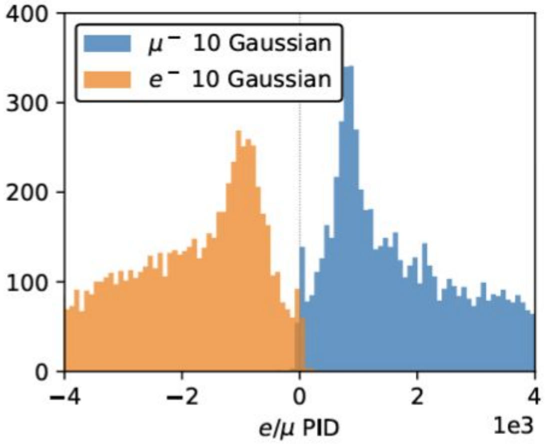
Junjie Xia, Jan 26 2024
CRinGe biweekly meeting

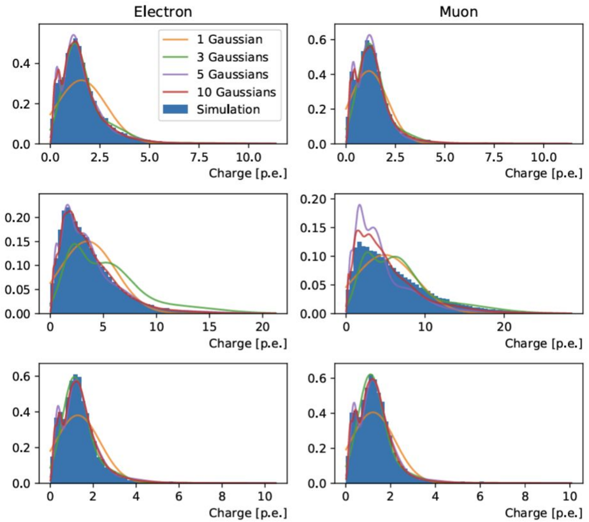
Summary of the work so far

In this paper, we managed to:

- Apply multivariate gaussian model for the PMT response function
- Implement the fiTQun-like likelihood as the loss function
- Train on WCSim single ring e/mu samples (no 2nd particles, no noise)
- Achieve reasonable results for PID and Erec.







To move forward

For the next milestone, we propose to:

- Expand the network to more particles, e.g. gamma, pions, etc.
- Enable dark noise and 2nd particles
- Move away from the analytical likelihood (e.g. multivariate gaussian), and achieve a generative model
- Enable single-vertex multi-ring, e.g. pi0->2gamma, and multi-vertex events, e.g. hadronic interactions.

Brainstorming in December

Training: given the physics and detector responses, learn the forward and backward loop between the real image and noise via a diffusion framework.

Diffusion model

Physics and detector responses

Pure noise

Application: given the trained forward and backward paths, predict the detector responses from pure noses assuming the physics.

Physics **and detector responses**

Pure noise

Initial thoughts

1. To work on the multi-ring events, we need to look at the individual PE hits (i.e. analog hits instead of digitized hits over the trigger window)
2. Once we have the analog hits, the challenge would be to cluster those associated to a ring/particle.
3. Given the above 2 points, I (Junjie) think Transformer models can do a great job. Others might think of GraphNN, but I don’t think it will work as well as Transformer because we have a not-so-easy topology (2D rings on a curved/folded sheet (PMTs) encapsulating a 3D volume) compared to the other hep detectors that has tracks in a continuous 3D volume. People might argue that we can add another dimension of timing, **but we don’t have a good way, that is independent of the 2D rings and curved sheet**, to verify the assumptions of photon propagation in water. We only have the observable of a single slice in the time series of an event. So it is effectively fixing one dimension before fitting the other 2 free parameters – it seems like we have 3D but it is in fact 2D.
4. We can probably combine Transformer with a diffusion framework, can probably work in the vector (latent) space of embeddings. The “long-range” memory of Transformer models is what I think will do a better job than the GraphNN, which focuses more on the local.