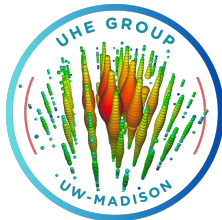


Generative AI for an Enhanced Galactic Center Event Selection in IceCube

Matthias Thiesmeyer, Albrecht Karle, Anirudh Sundara Rajan, Lu Lu,
Maxwell Nakos, Qiannan Wang, Tianlu Yuan, Yong Jae Lee



Muon Background Limits Neutrino Detection

IceCube detects:

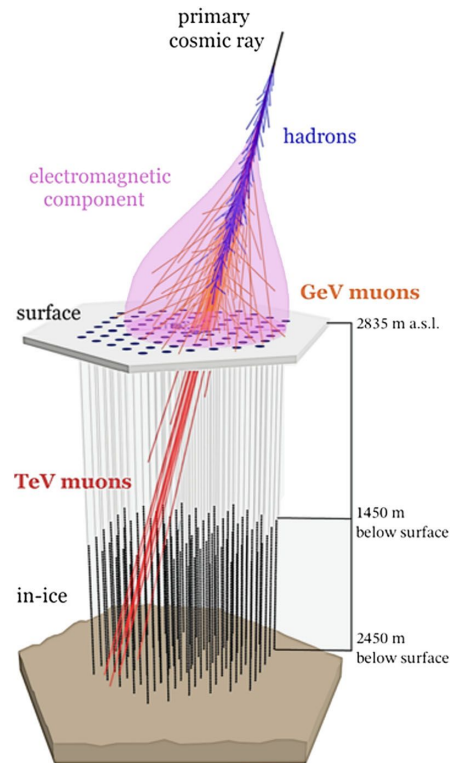
$\sim 10^{11}$ muons per year,

$\sim 10^5$ of which are neutrinos,

$\sim 10^3$ of which are of astrophysical origin

Neutrino astronomy is a needle in the haystack problem where background rejection is key

Modeling the Muon Background is crucial

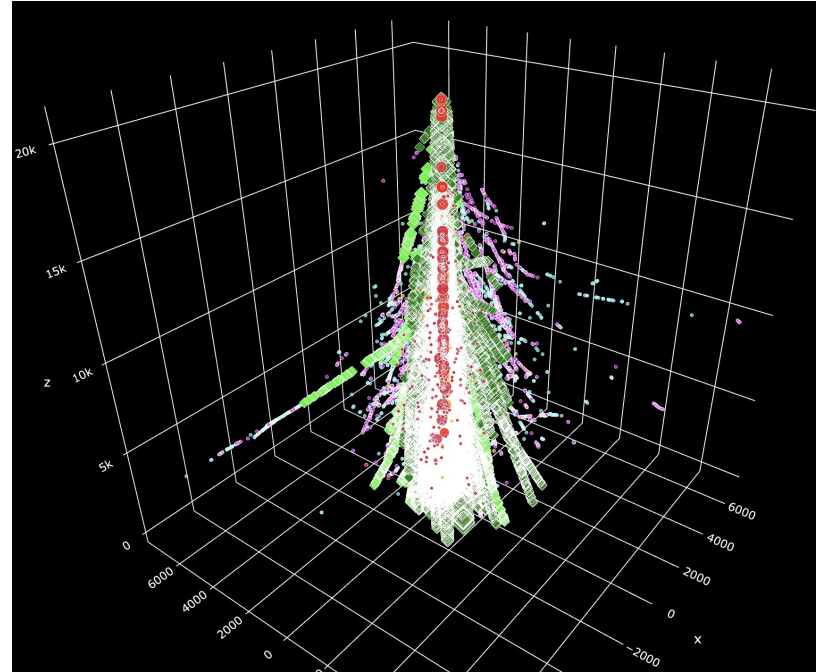


Muon Background Limits Neutrino Detection

CORSIKA

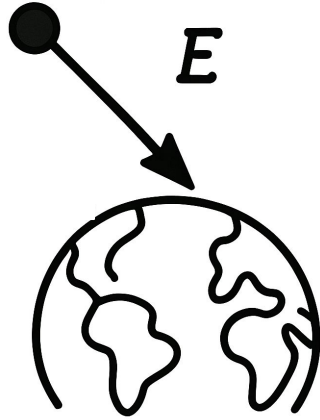
- **High-fidelity** (particle-level simulation)
- **Simulation is slow and background expectation is high** (especially at low energies)

Parameterized models optimize efficiency and performance.

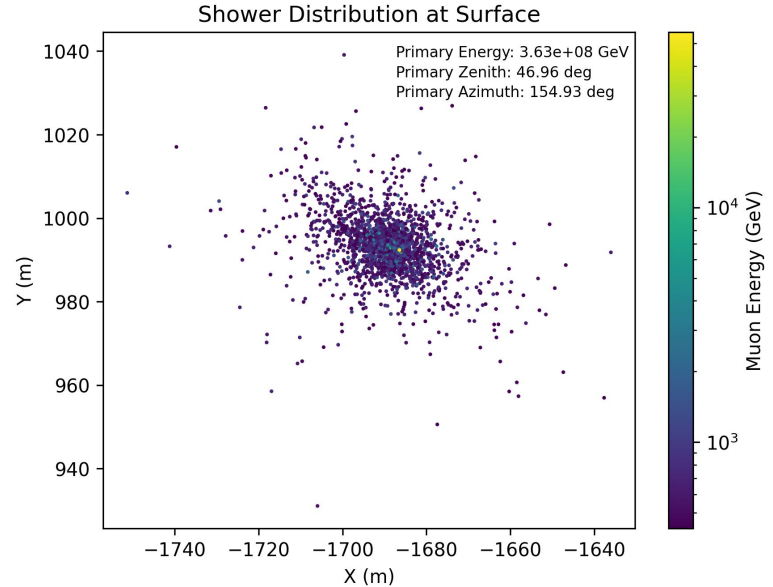
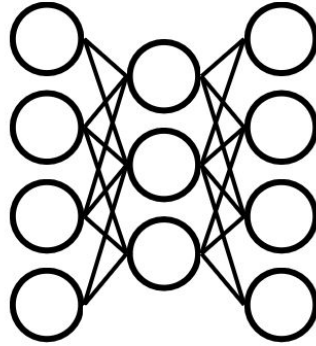


Proton shower produced via corsika8

Muon Map Generation through Deep Neural Networks



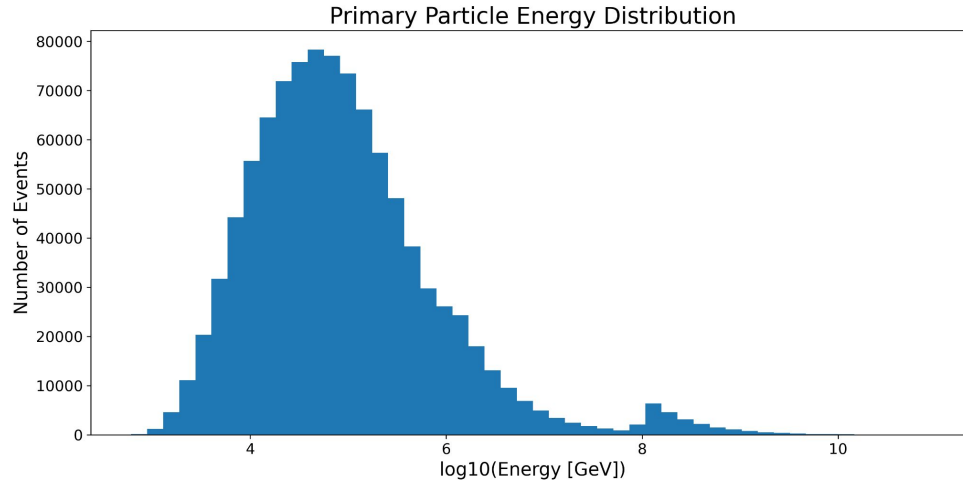
Primary Particle Details



Muon Background

Even for identical primary particles, the stochastic nature of particle processes and atmospheric factors produces a wide range of possible muon showers.

Training dataset



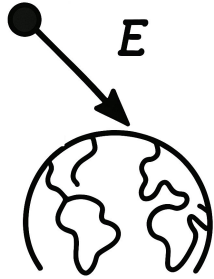
Input Variables (Primary Particle),

- Position (x,y,z)
- Angle (Zenith, Azimuth)
- Energy
- Particle Type

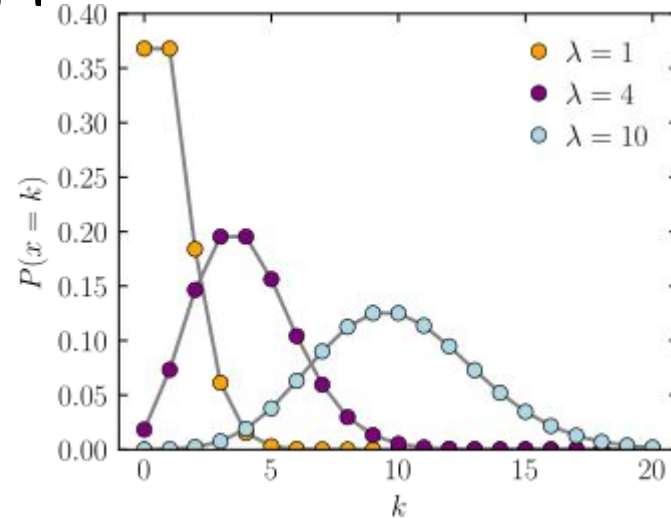
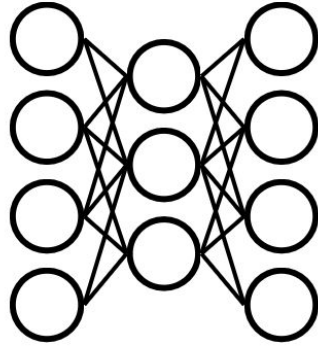
5-Component Corsika Simulation:
Proton, Helium, Nitrogen, Aluminum, Iron

A Wide Range of Multiplicities from 1 to 1e4+

Step-1: Predict the number of particles



Primary Particle Details

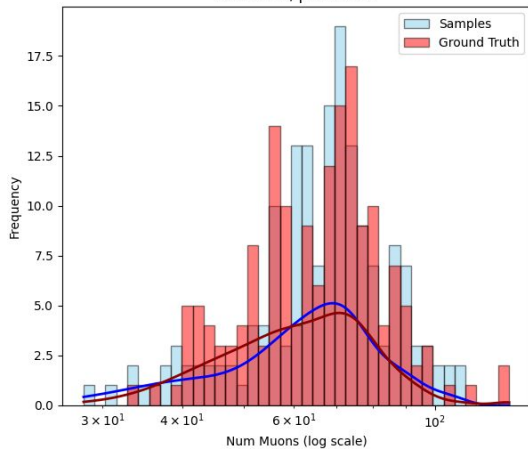


Assume a simple Poisson Distribution

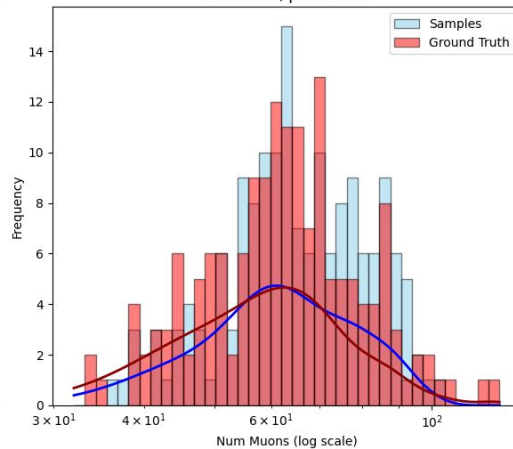
Neural Network predicts the parameter (λ) governing the Poisson Distribution

Objective: Observed data should be highly likely under our model

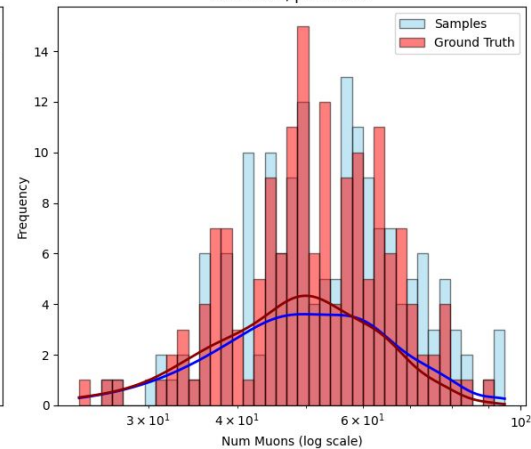
Cluster 1 | Events: 169
Energy: $1.59\text{e}+06$ - $1.68\text{e}+06$ eV
KS=0.112, p=2.4e-01



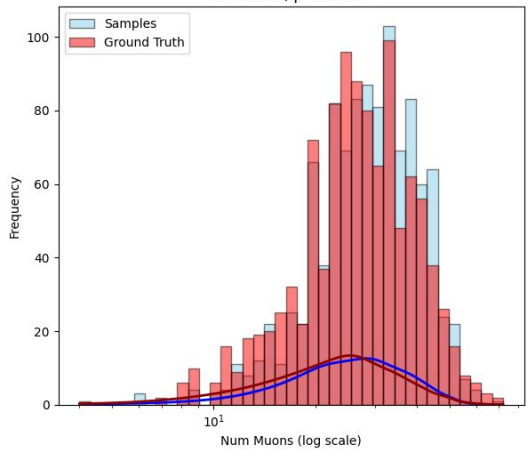
Cluster 2 | Events: 164
Energy: $1.50\text{e}+06$ - $1.59\text{e}+06$ eV
KS=0.110, p=2.8e-01



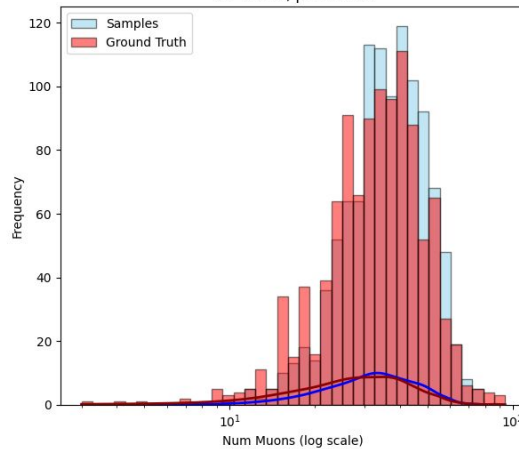
Cluster 3 | Events: 163
Energy: $1.18\text{e}+06$ - $1.23\text{e}+06$ eV
KS=0.104, p=3.4e-01



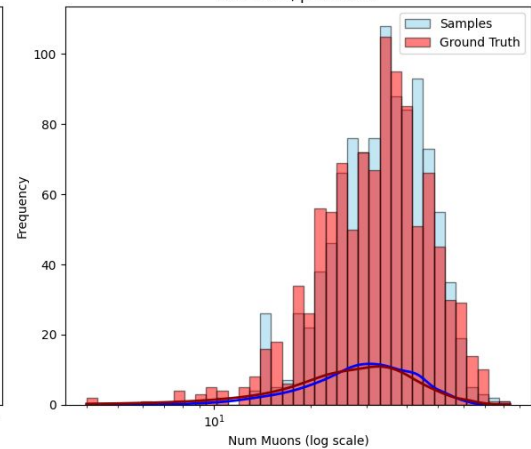
Cluster 1 | Events: 1070
Energy: $1.28\text{e}+06$ - $1.34\text{e}+06$ eV
KS=0.101, p=3.6e-05



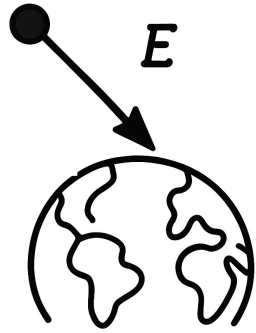
Cluster 2 | Events: 1067
Energy: $1.67\text{e}+06$ - $1.78\text{e}+06$ eV
KS=0.114, p=1.7e-06



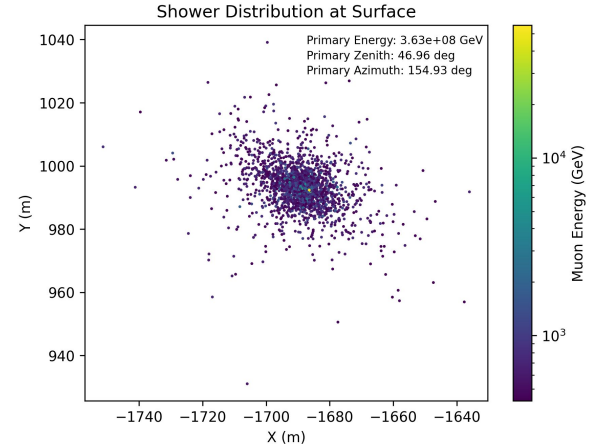
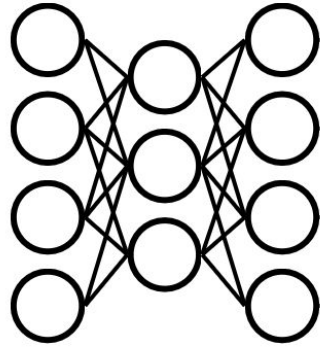
Cluster 3 | Events: 1034
Energy: $1.58\text{e}+06$ - $1.67\text{e}+06$ eV
KS=0.066, p=2.3e-02



Step-2: Predicting the Distribution of Muons



Primary Particle
Details + Multiplicity



Final Muon Map is conditioned on the predicted multiplicity

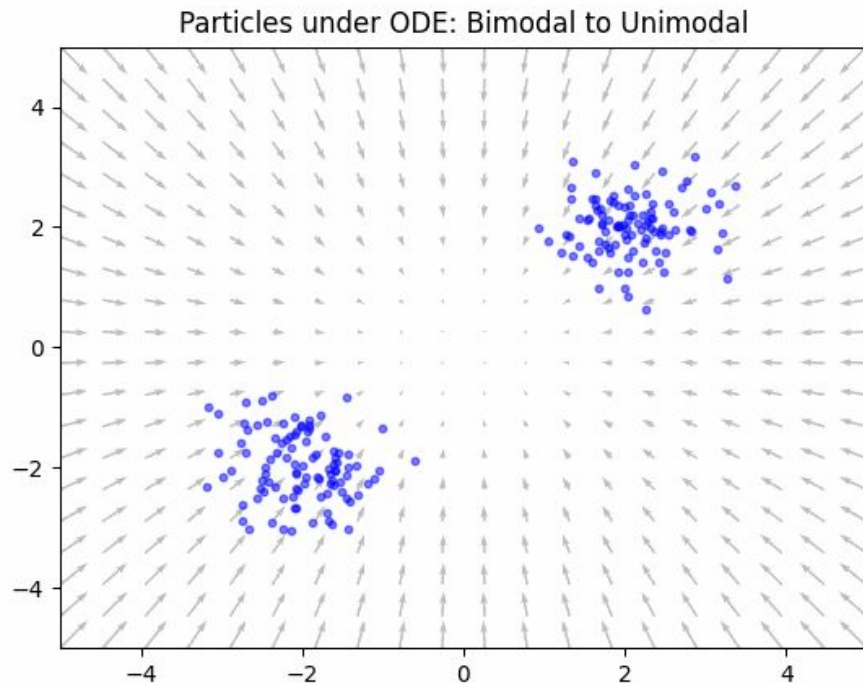
Predicted Muon Properties

1. **Muon Impact Map:** 2D contact position of each muon on the surface.
2. **Muon Arrival Direction:** Incoming direction (zenith, azimuth).
3. **Muon Energy Spectrum:** Energy carried by each detected muon

We use **Flow Matching** to generate the Muon Map

Flow Matching has shown success in image/audio/molecule generation etc.

A Simplified Picture of Flow Matching Inference



Initialize: Start with randomly sampled **Muon** configurations ($t=0$).

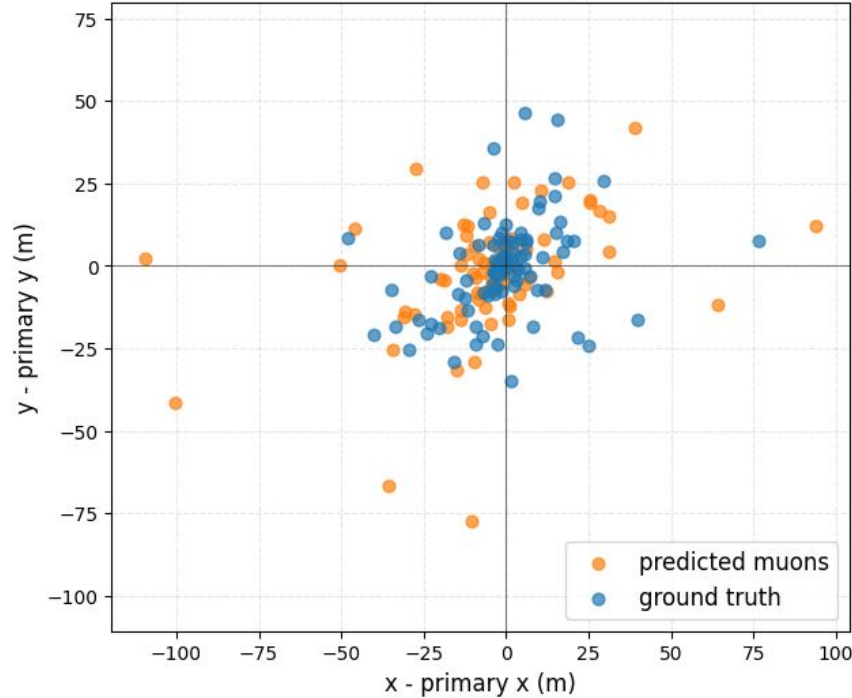
Vector Field: Train a network to map the **velocity** toward the target.

Inference: Follow the learned flow to recover the **configuration**.

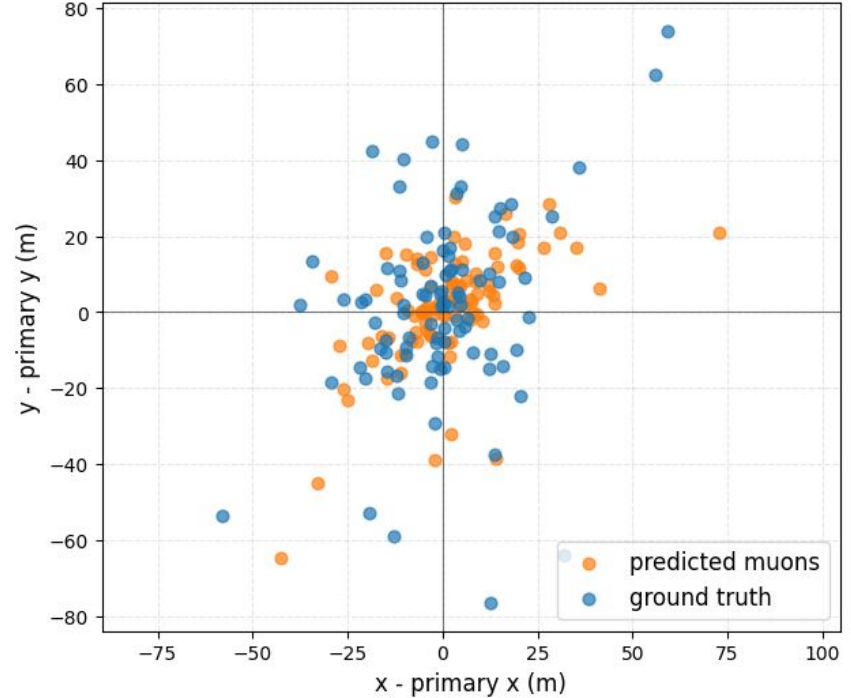
In practice the vector field varies in both space as well as time.

High Multiplicity Events

Predicted Muon Positions — Primary Energy: 5.59 PeV

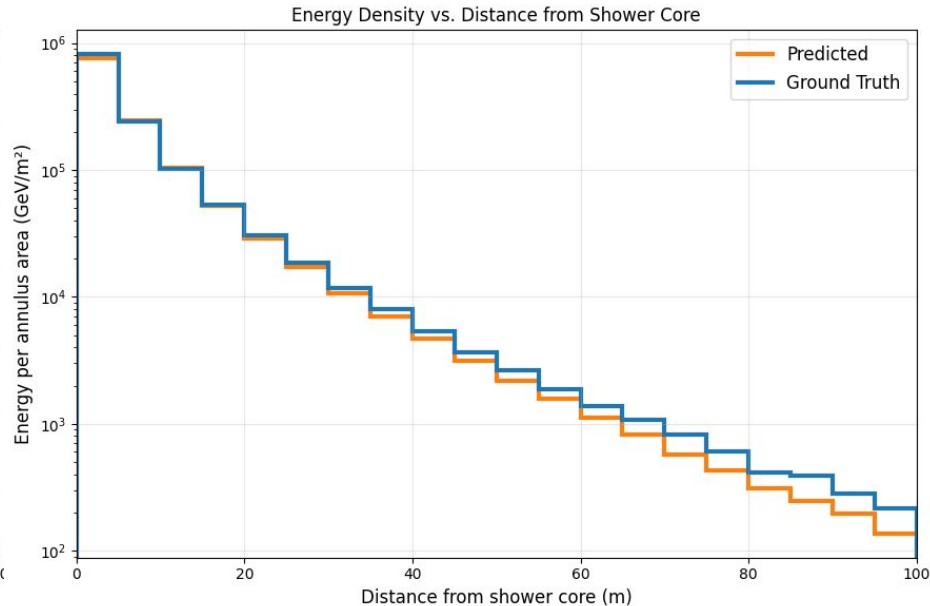
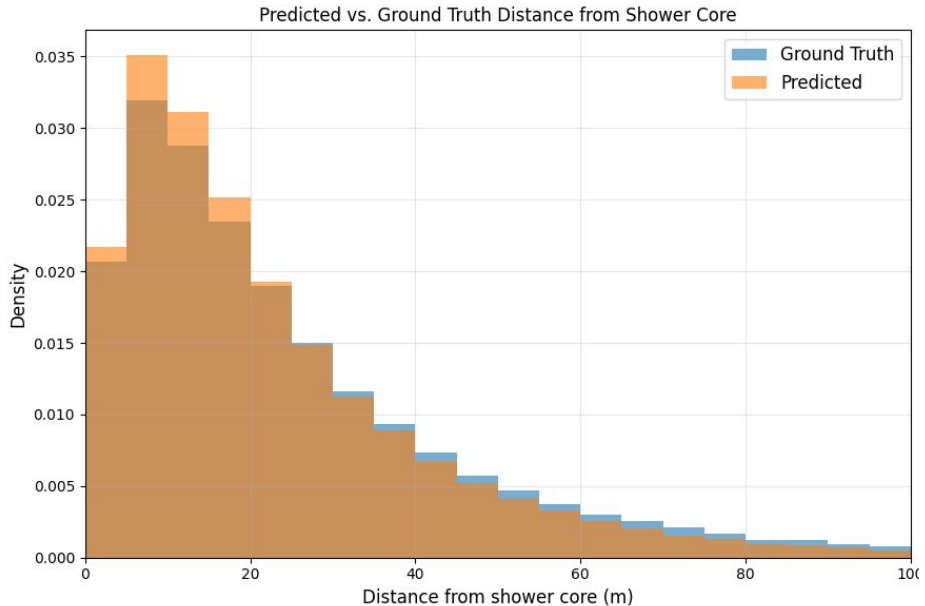


Predicted Muon Positions — Primary Energy: 9.21 PeV



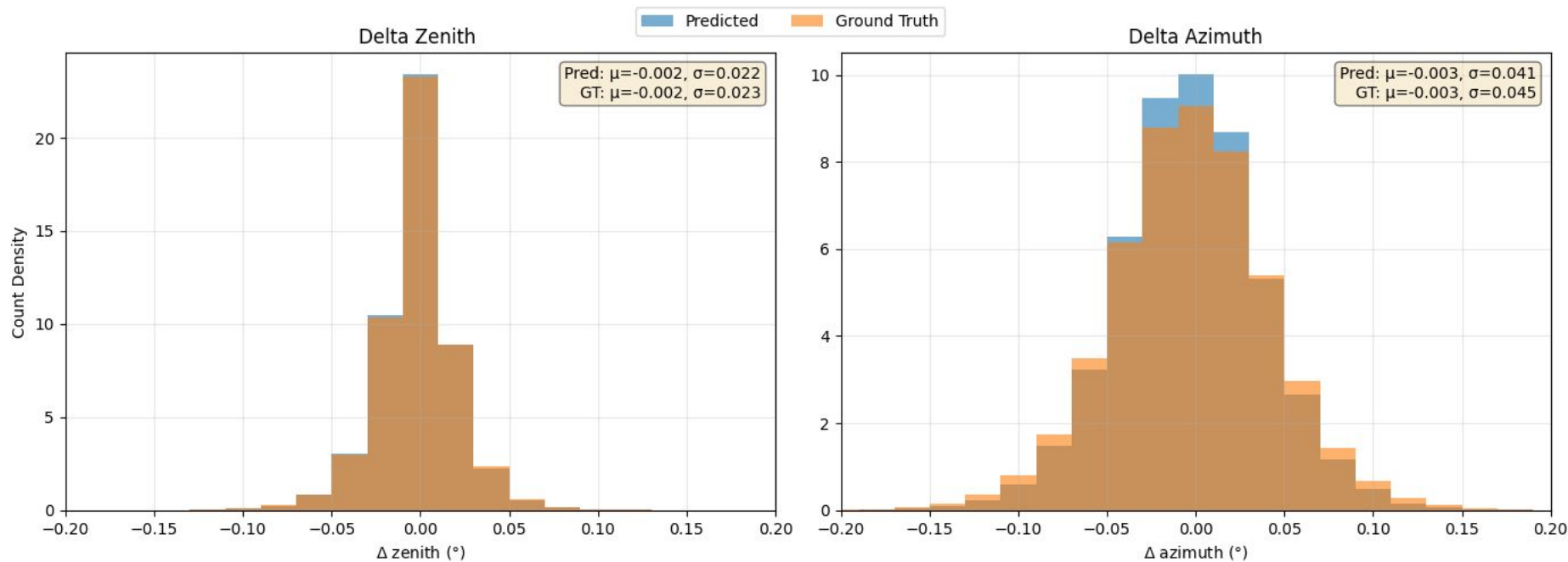
Shower Core: Intersection point of the primary particle with the surface, based on incoming angle and position.

Distribution of energy



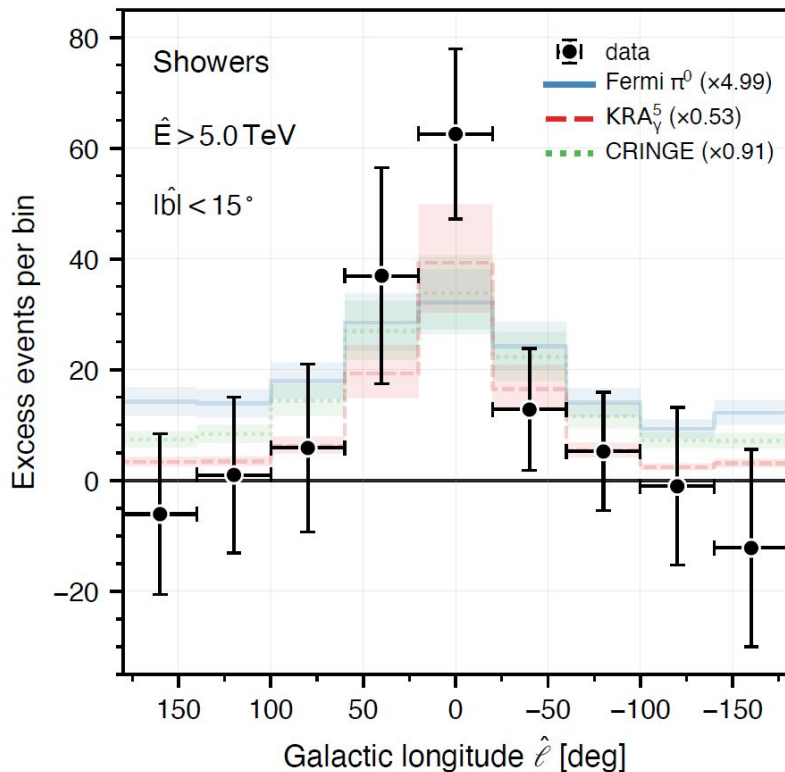
Reproduces the Lateral Energy Distribution: Generated muons follow the expected radial decay of energy density from the shower core.

Distribution of angles



Angle between primary and predicted muons shows good agreement

Future Application: Neutrinos from the Galactic Center

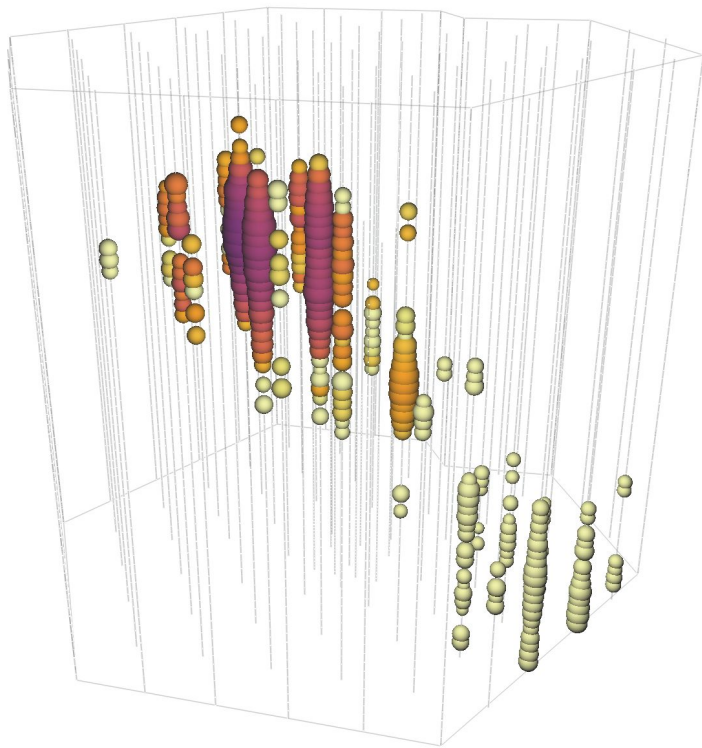


Physics Goal: Maximize sensitivity to a potential galactic center source

Challenge: Resolving a point source at the Galactic Center needs a better angular resolution than what is possible with cascades

Solution: An optimized starting track selection for the galactic center

Future Application: Improving Start Track Selections



Starting Tracks allow effective rejection of atmospheric muons while maintaining the angular resolution of tracks

Selections typically feature two networks, to first reject the **easy to reject background** and then the **difficult background** afterwards

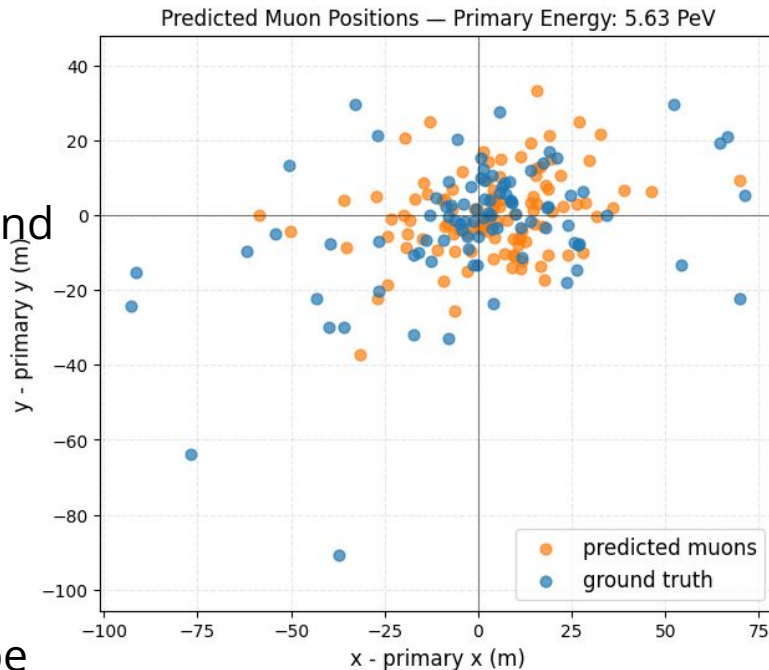
Due to **efficient background rejection** of the first network the second network has **little background to be trained on**

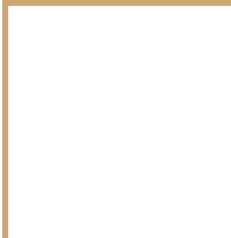
Fast background simulation can effectively increase background for the training

Conclusion and outlook

- Generative AI could provide an efficient alternative to classical CORSIKA simulation
- Pretty Good at modeling Spatial Location and Energy
- Predicted number of muons needs to improve

Once implementation is finalized, it will be used to improve event selections in IceCube

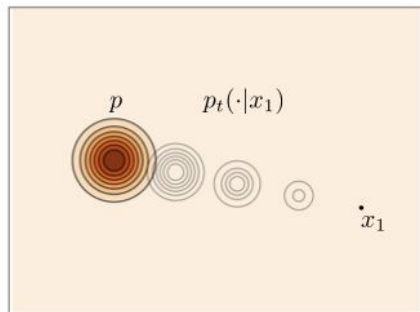




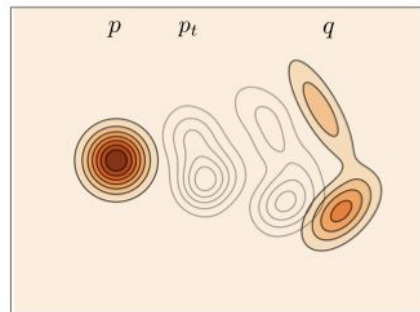
Backup



Training Overview



(a) Conditional probability path $p_t(x|x_1)$.

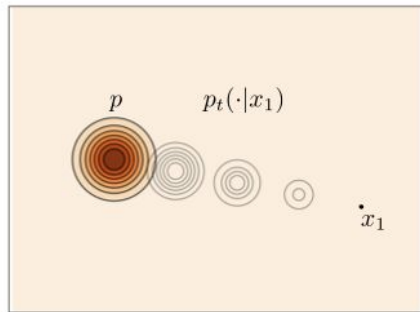


(b) (Marginal) Probability path $p_t(x)$.

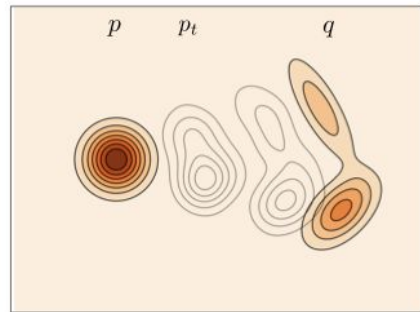
Start at distribution p , finish at distribution q (training data)

Goal: Aggregate conditional paths over the dataset to learn the marginal path

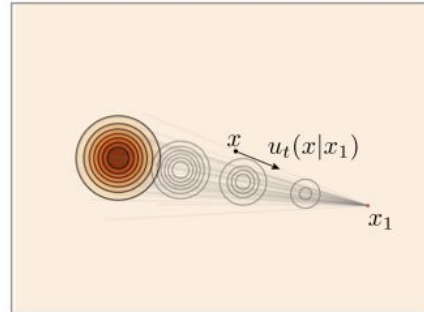
Training Overview



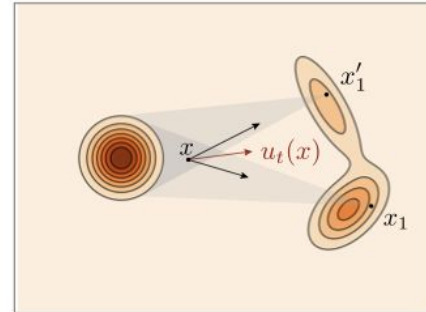
(a) Conditional probability path $p_t(x|x_1)$.



(b) (Marginal) Probability path $p_t(x)$.



(c) Conditional velocity field $u_t(x|x_1)$.



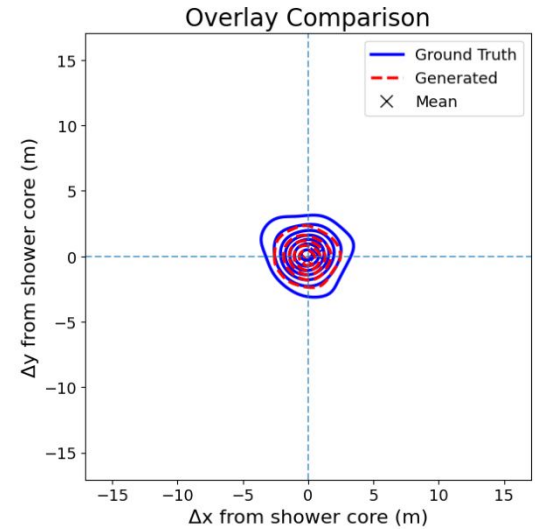
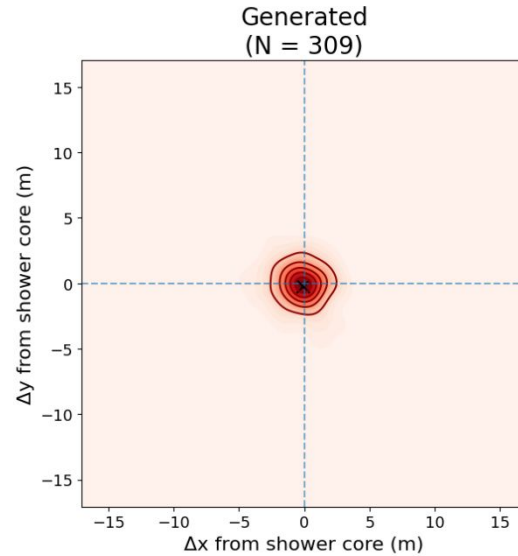
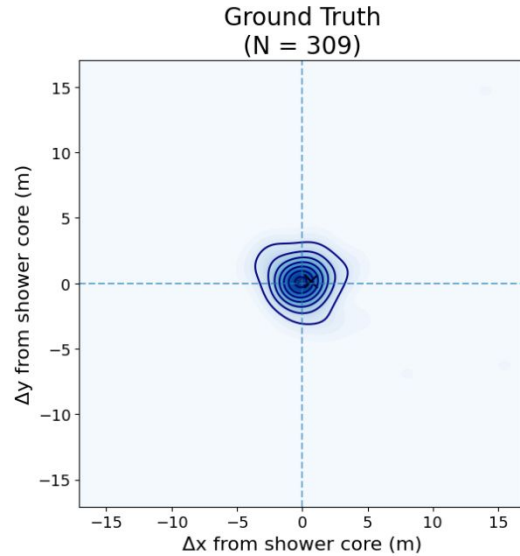
(d) (Marginal) Velocity field $u_t(x)$.

Goal: Aggregate conditional paths over the dataset to learn the marginal path

Implementation: Learn conditional vector field, aggregate over dataset to obtain a marginal vector field.

Centre of Energies

Energy-weighted Centroid Distribution
Deviation from Shower Core (Δx , Δy)



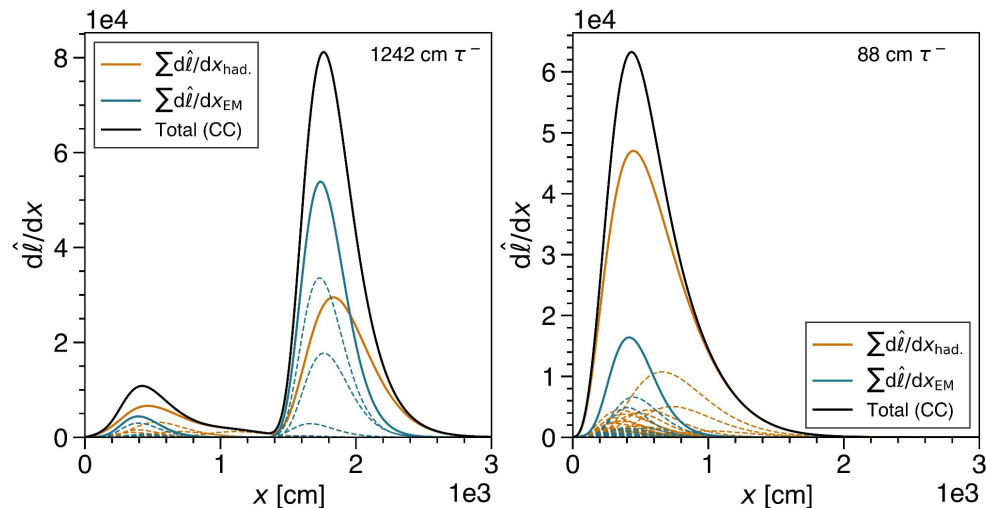
Example parametrizations for in-ice particle showers

Replace averaged profiles with
parameter distributions

Capture event-by-event fluctuations
through sampling

Limited to 1D, along shower axis

Motivates a new approach for 3D
Muon Background Generation



Cut out 1 MuonGun slide (if time crunch), dont mention unless necessary

Talk more about tech details both multiplicity and flow matching

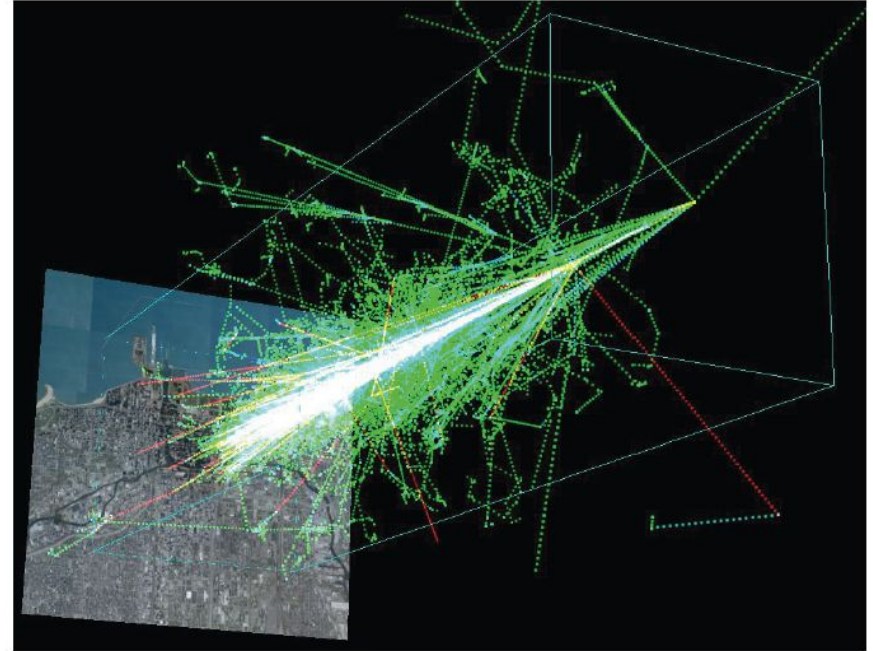
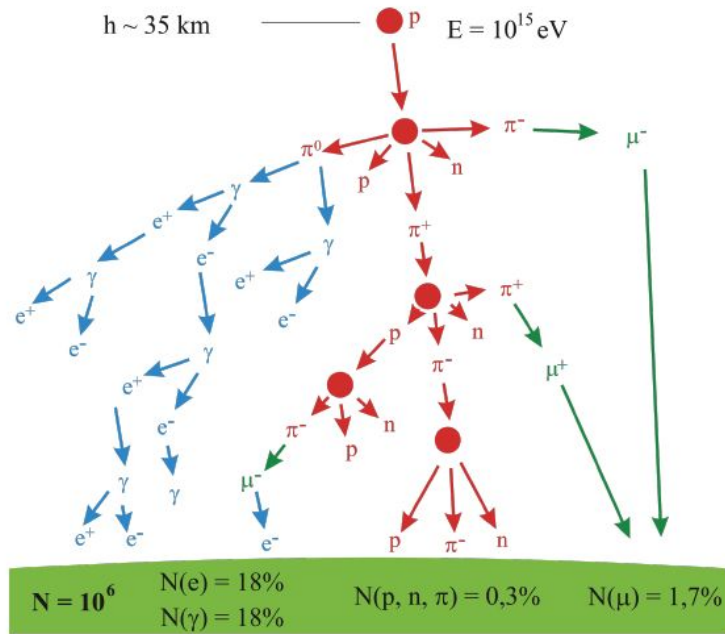
3 + 4 inbtpo 1 slide

Tracking individual particles is hard, parameterized dist, works for 1d, now to make it 3d we need stronger approaches using dnn

Use tianlus slide as a reference on parametrized modeling of events early on (pre corsica)

Consider skipping introducing the approach multiple times (no need global + local)

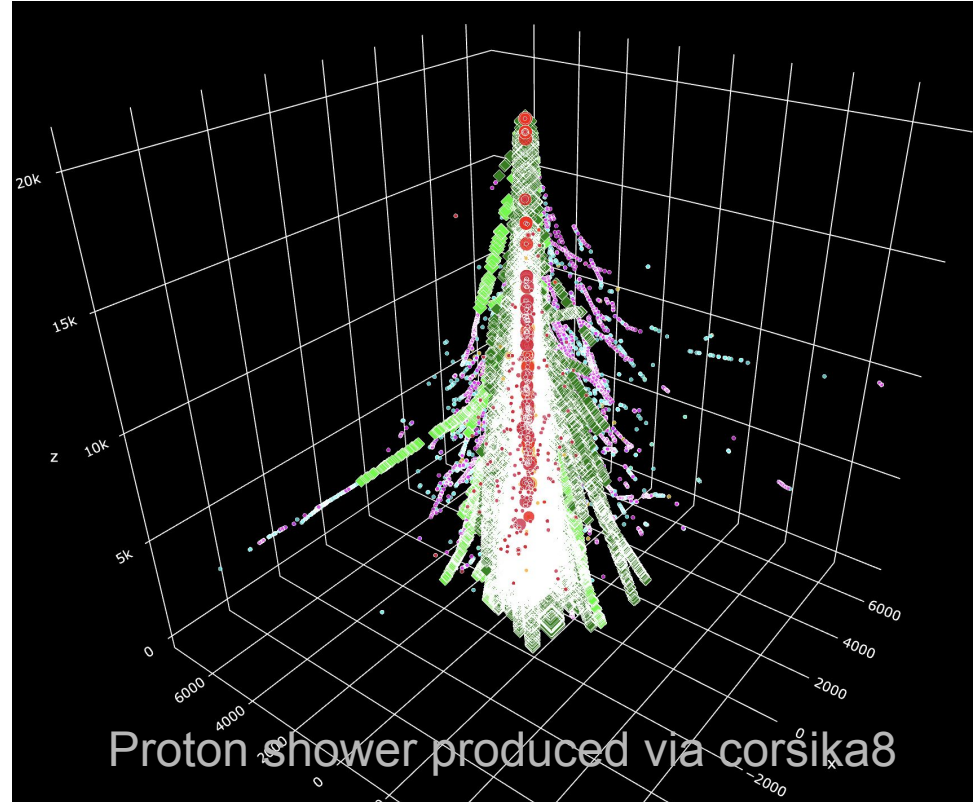
Particle shower universality (atmosphere, ice, water, ...)



Incoming **primary particle** is broken down into secondary particles
Write stuff about for neutrino detectors muon background modeling is needed
Muons key background from the Atmosphere. How do we model muons?

Muon flux predictions

- Brutal force: full air-shower simulation via CORSIKA
- Shortcut: MuonGun (single muon flux workaround)
- Issues:
 - CORSIKA livetime at $< \text{PeV}$ challenging to match data livetime
 - MuonGun only predicts single muon shower while ignoring bundles



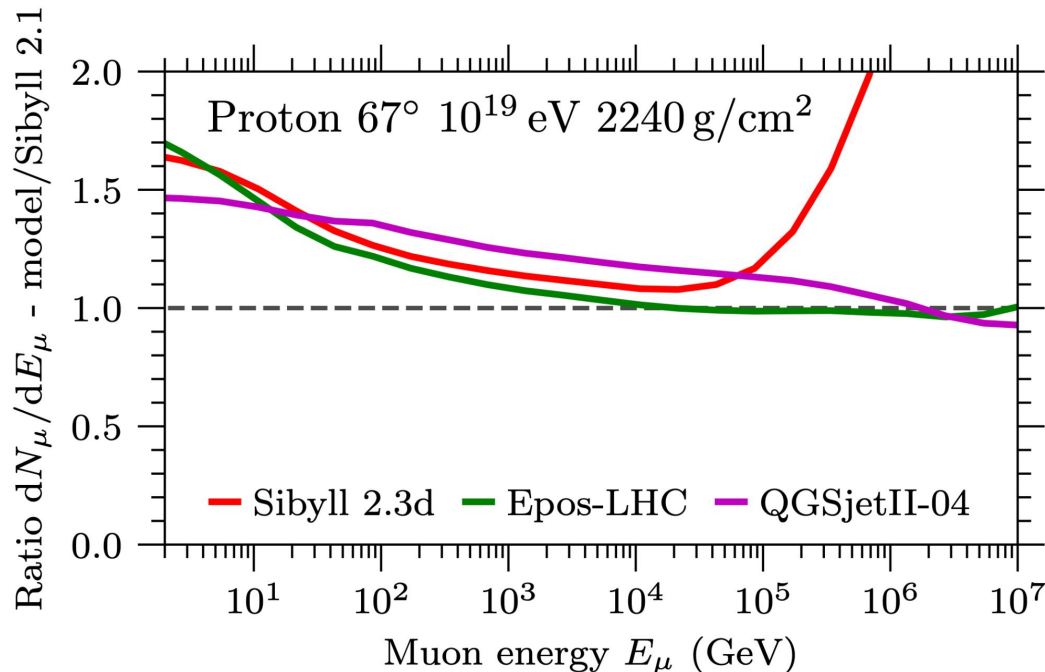
MuonGun in IceCube

Muon flux is determined by

- Primary cosmic-ray mass composition
- Hadronic interaction models
- Slant depth
- Atmospheric properties (temperature, pressure)

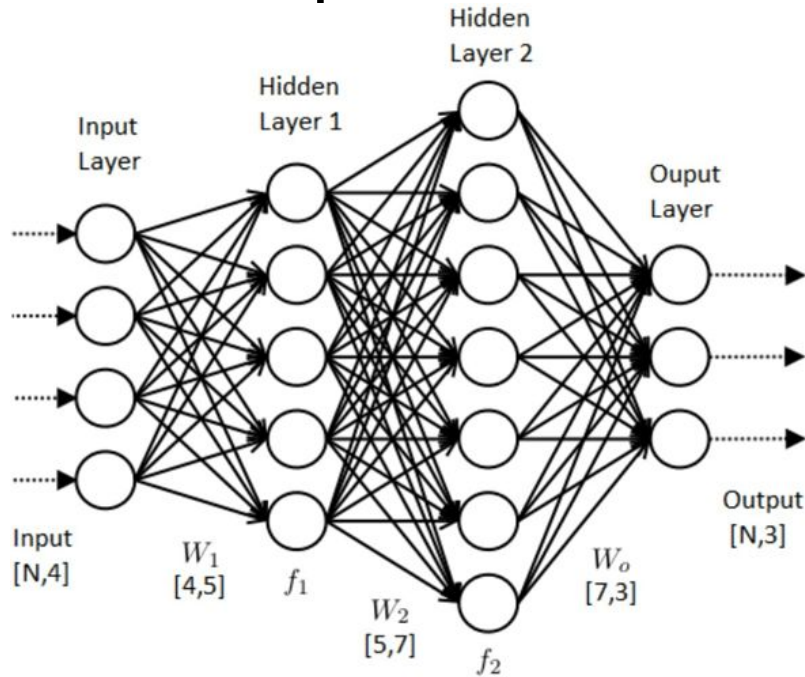
Current MuonGun version:

- Sibyll2.1 (pre-LHC)
- No prompt muons
- Single muon not applicable for all selections



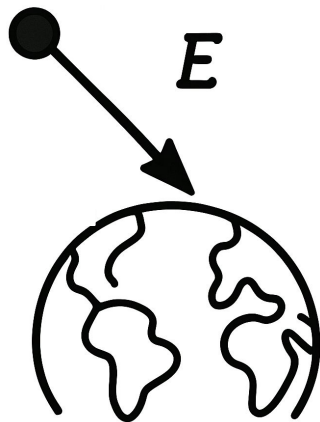
How to improve MuonGun to make muon (bundle) flux generation more efficient and correct?

Use Deep Neural Networks!

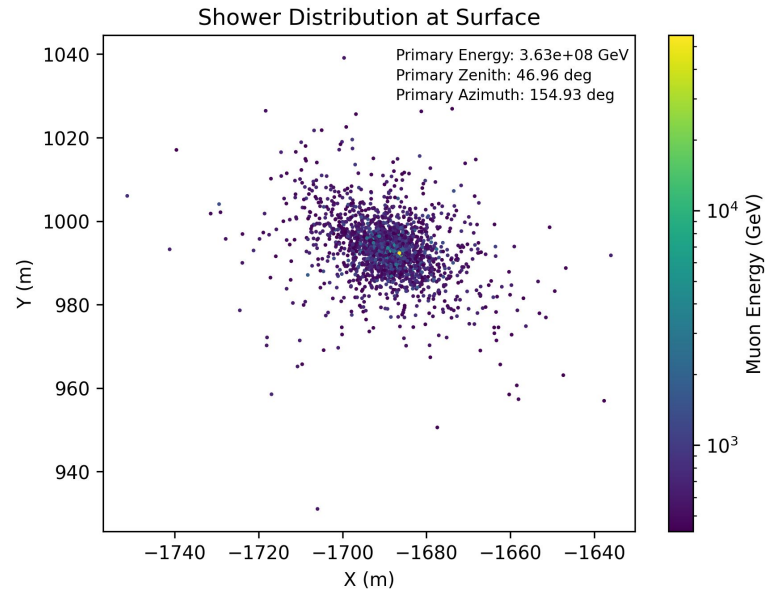
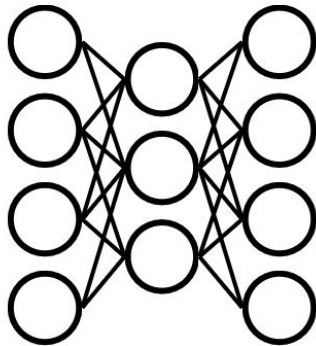


Can potentially latch on to better patterns, **accelerating inference!**

Muon Map Generation through Deep Neural Networks



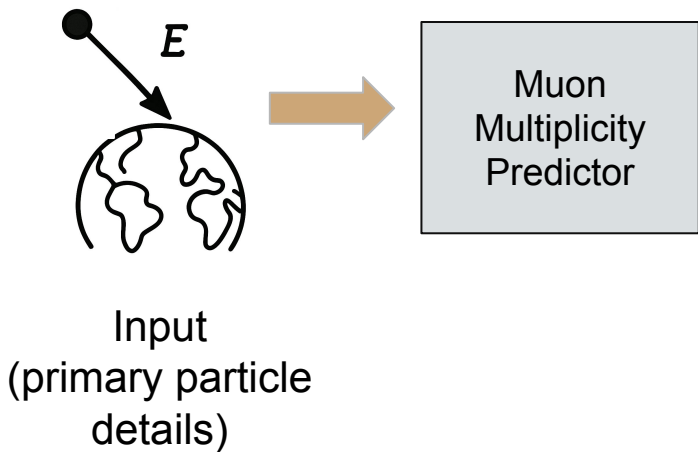
Input
(primary particle details)



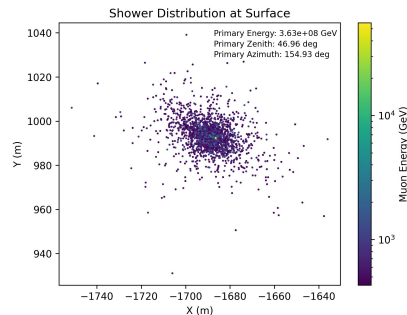
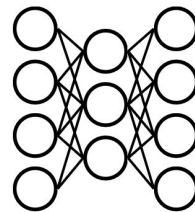
Output
(Distribution of Muons)

Even for identical primary particles, the stochastic nature of particle processes and atmospheric factors produces a wide range of possible muon showers.

Two-Stage Approach

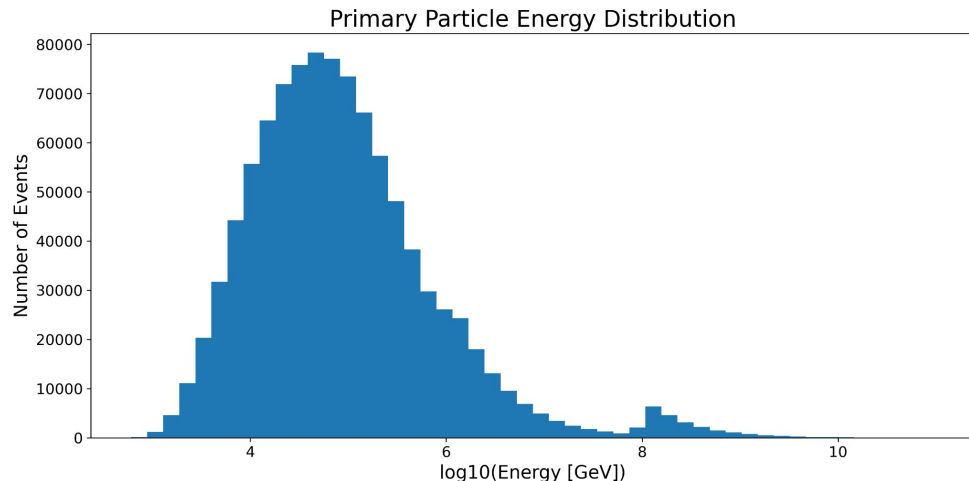


Number of Muons



Output
(Distribution of Muons)

Training dataset



Input Variables (Primary Particle),

- Position (x,y,z)
- Angle (Zenith, Azimuth)
- Energy
- Particle Type

5-Component Corsika Simulation:
Proton, Helium, Nitrogen, Aluminum, Iron

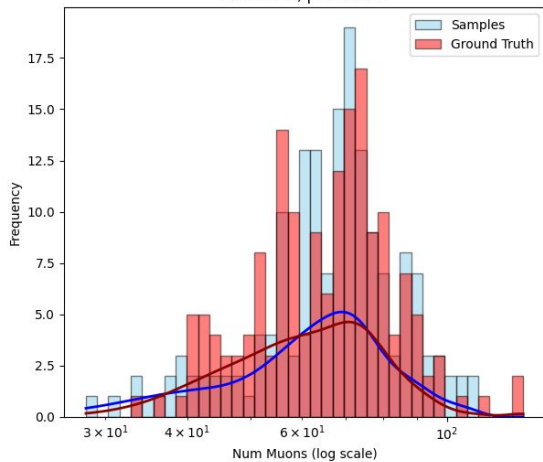
A Wide Range of Multiplicities from 1 to 1e4+

Input Variables

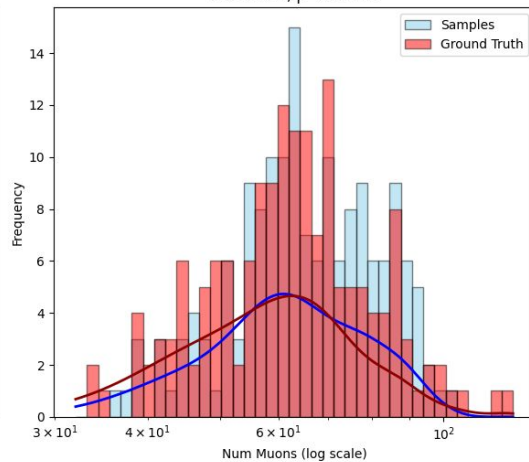
Input Variables (Primary Particle),

- Position (x,y,z)
- Angle (Zenith, Azimuth)
- Energy
- Particle Type

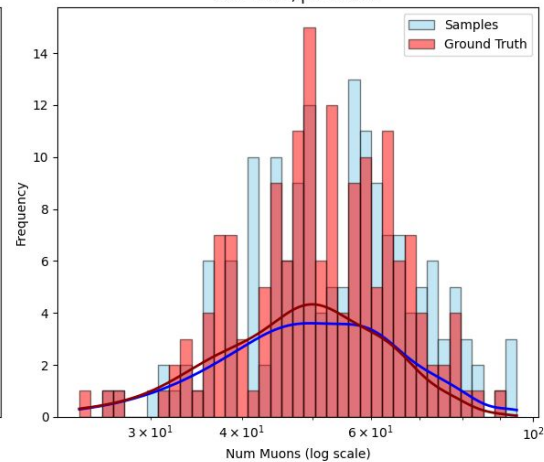
Cluster 1 | Events: 169
Energy: $1.59\text{e}+06$ - $1.68\text{e}+06$ eV
KS=0.112, p=2.4e-01



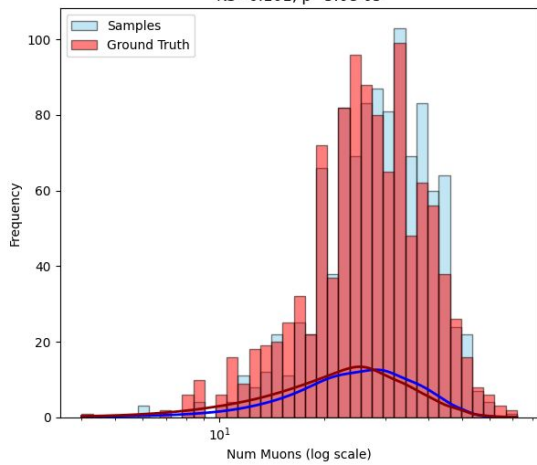
Cluster 2 | Events: 164
Energy: $1.50\text{e}+06$ - $1.59\text{e}+06$ eV
KS=0.110, p=2.8e-01



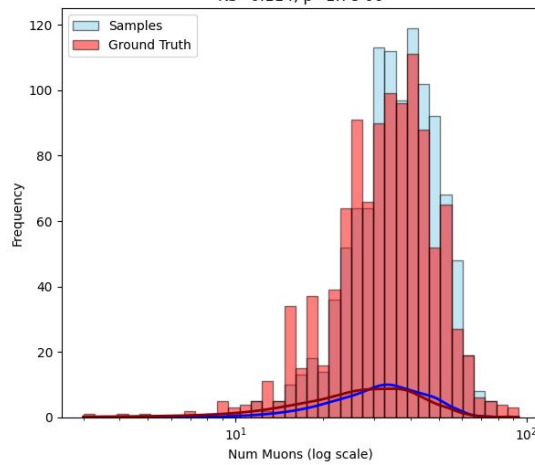
Cluster 3 | Events: 163
Energy: $1.18\text{e}+06$ - $1.23\text{e}+06$ eV
KS=0.104, p=3.4e-01



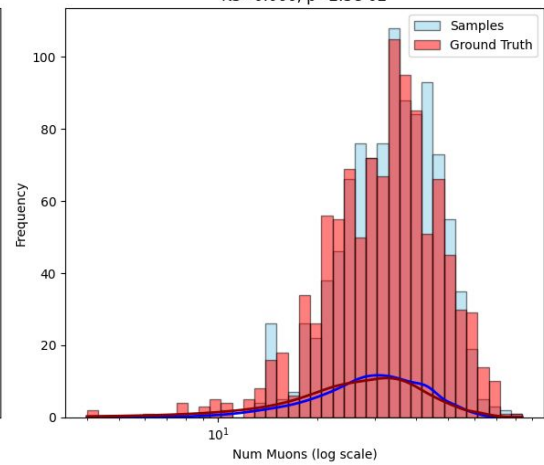
Cluster 1 | Events: 1070
Energy: $1.28\text{e}+06$ - $1.34\text{e}+06$ eV
KS=0.101, p=3.6e-05



Cluster 2 | Events: 1067
Energy: $1.67\text{e}+06$ - $1.78\text{e}+06$ eV
KS=0.114, p=1.7e-06

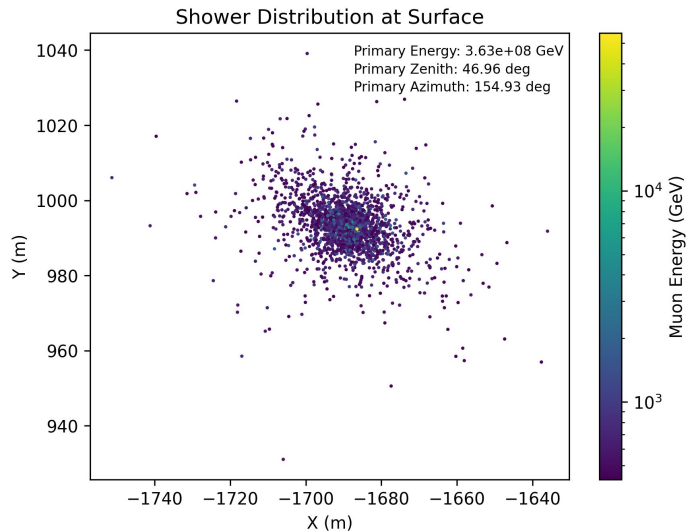
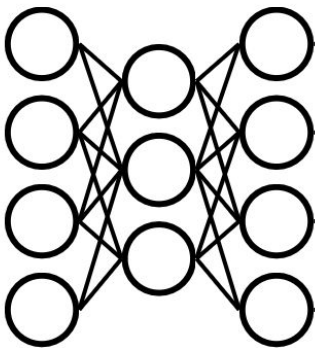


Cluster 3 | Events: 1034
Energy: $1.58\text{e}+06$ - $1.67\text{e}+06$ eV
KS=0.066, p=2.3e-02



Stage-2: Predicting the Distribution of Muons

Primary particle
details + Num Muons

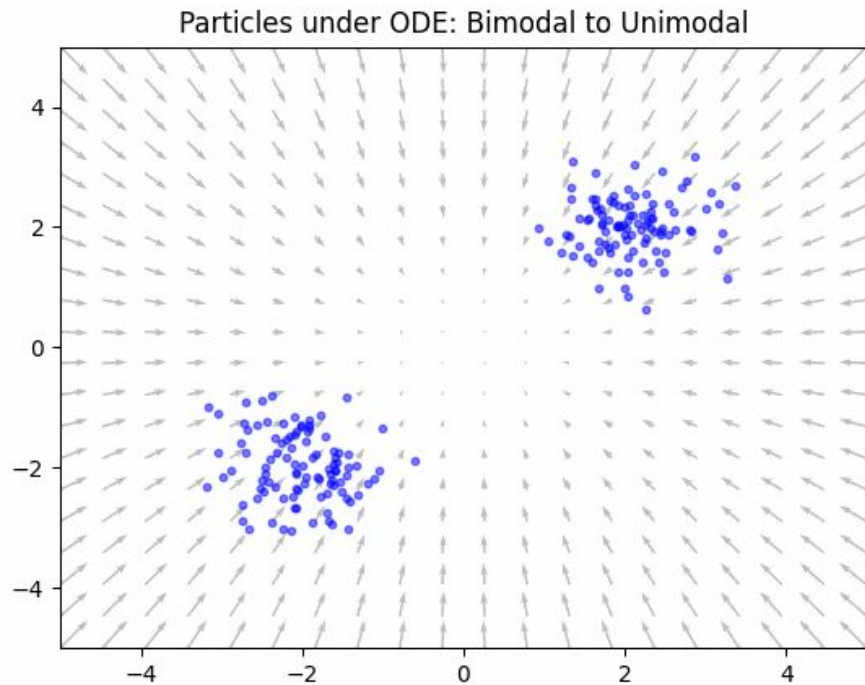


We plan to use Flow Matching/Diffusion to predict the distribution of Muons

Predicted Muon Properties

1. **Muon Impact Map:** 2D contact position of each muon on the ground surface
2. **Muon Arrival Direction:** Incoming trajectory defined by zenith and azimuth angles
3. **Muon Energy Spectrum:** Energy carried by each detected muon

Algorithm: Flow Matching

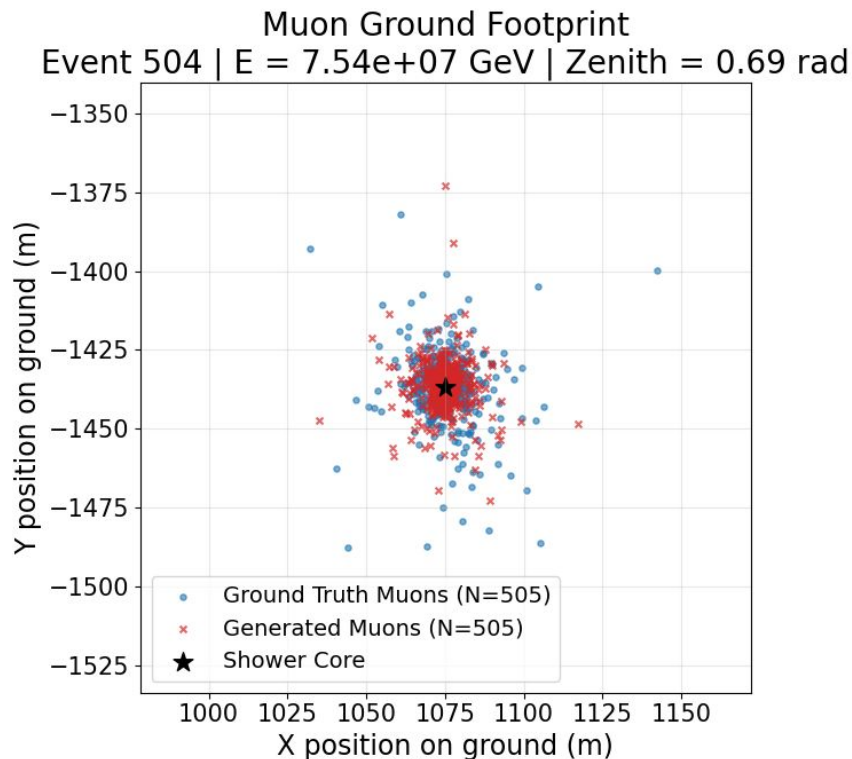
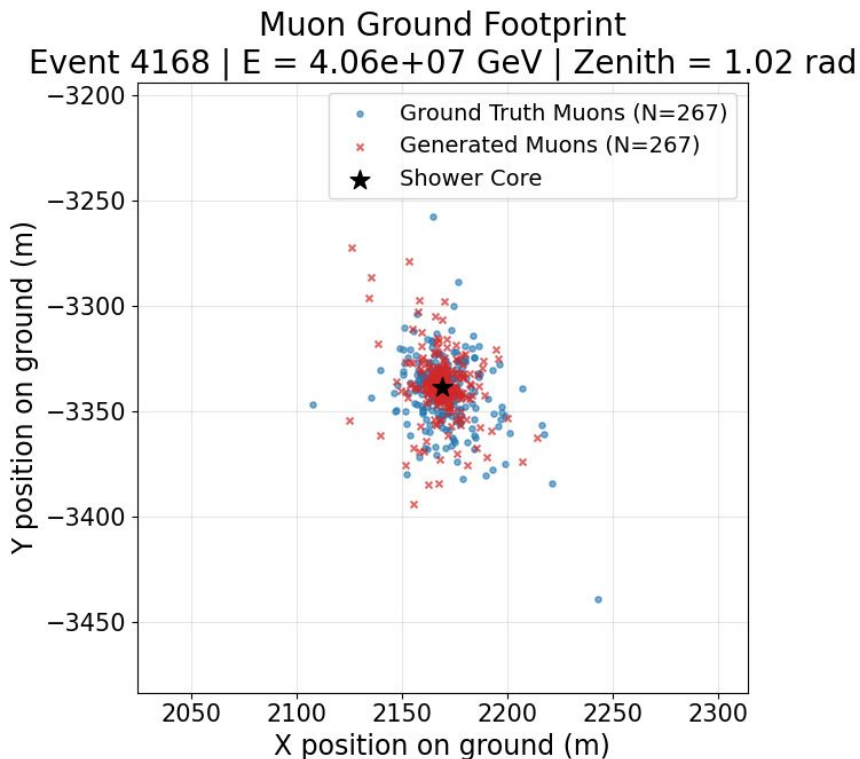


Initialize: Start with randomly sampled **Muon** configurations ($t=0$).

Vector Field: Train a network to map the **velocity** toward the target.

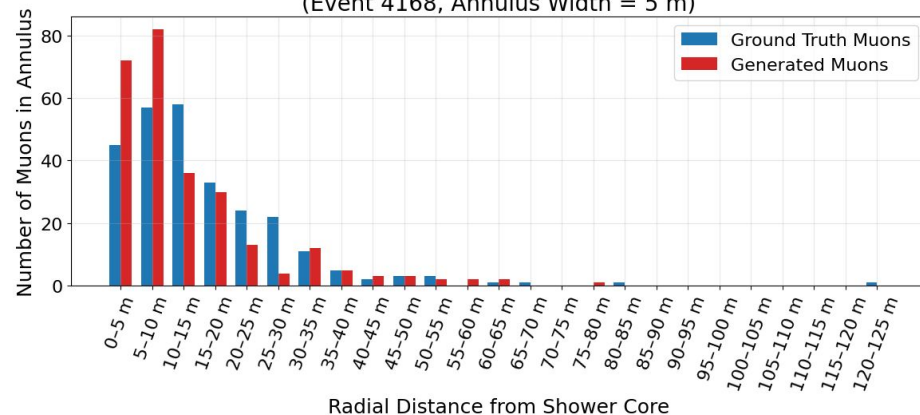
Inference: Follow the learned flow to recover the **configuration**.

High Multiplicity Events

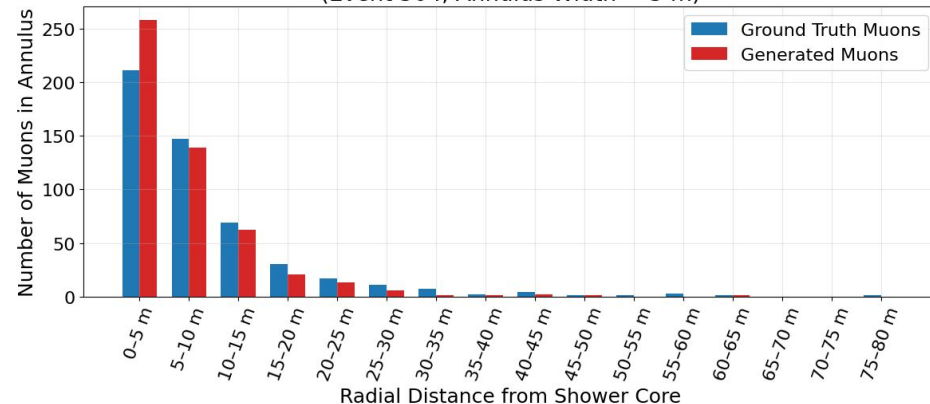


Shower Core: Intersection point of the primary particle with the surface, based on incoming angle and position.

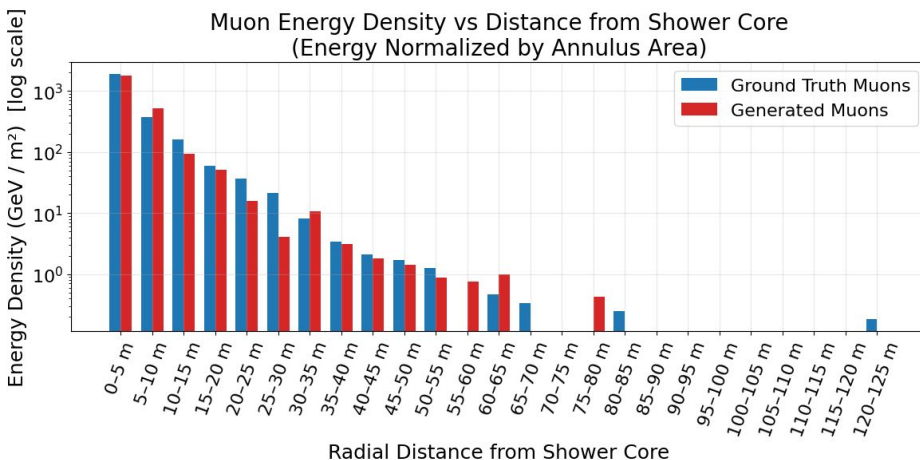
Muon Count vs Distance from Shower Core
(Event 4168, Annulus Width = 5 m)



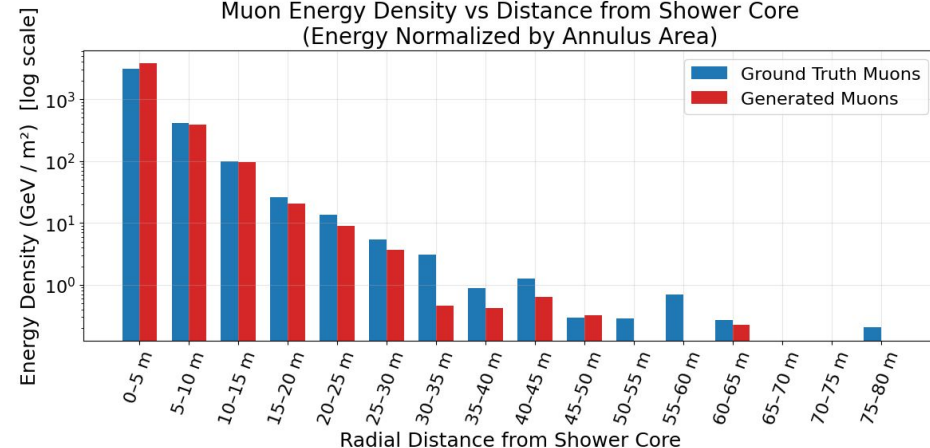
Muon Count vs Distance from Shower Core
(Event 504, Annulus Width = 5 m)



Muon Energy Density vs Distance from Shower Core
(Energy Normalized by Annulus Area)

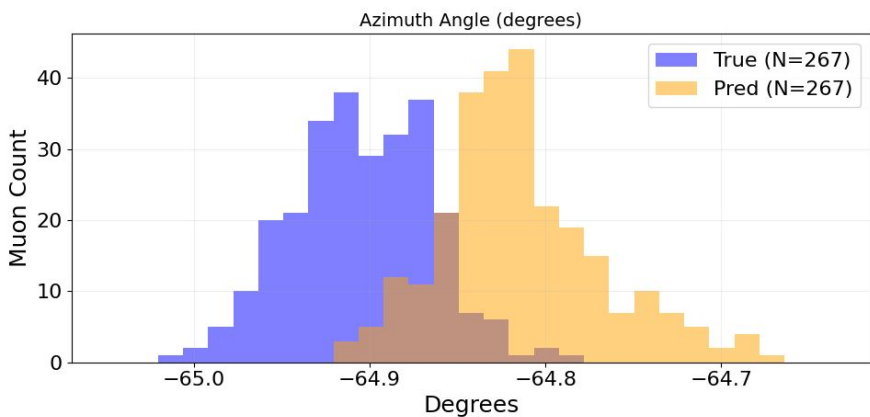
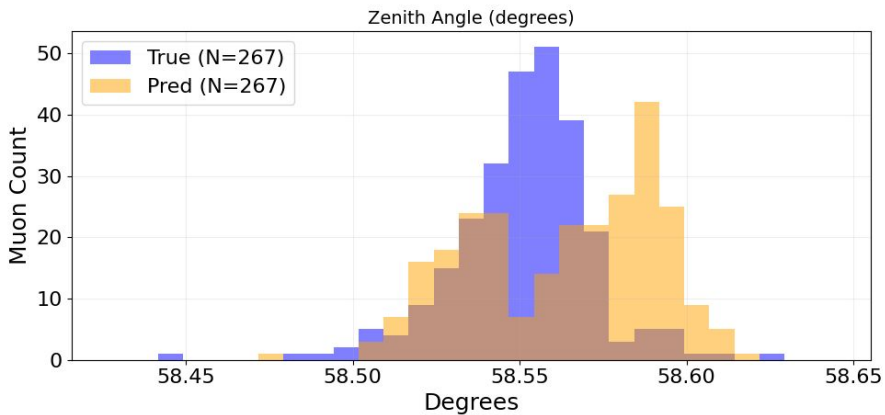


Muon Energy Density vs Distance from Shower Core
(Energy Normalized by Annulus Area)

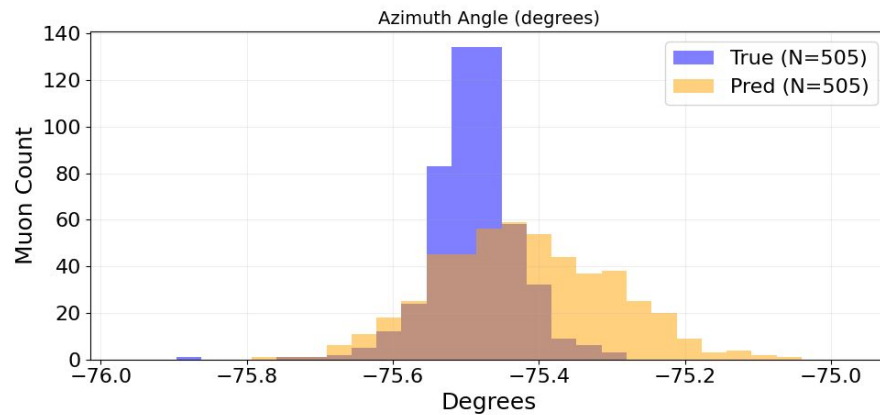
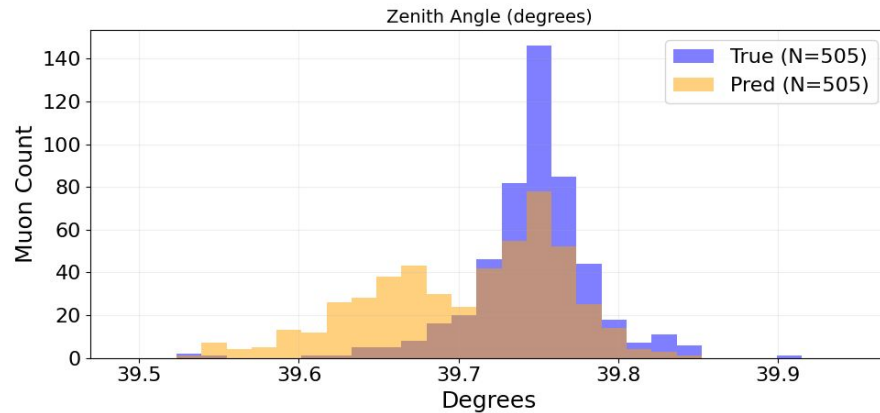


Reproduces the Lateral Energy Distribution: Generated muons follow the expected radial decay of energy density from the shower core.

Event 4168 — Angular Distributions

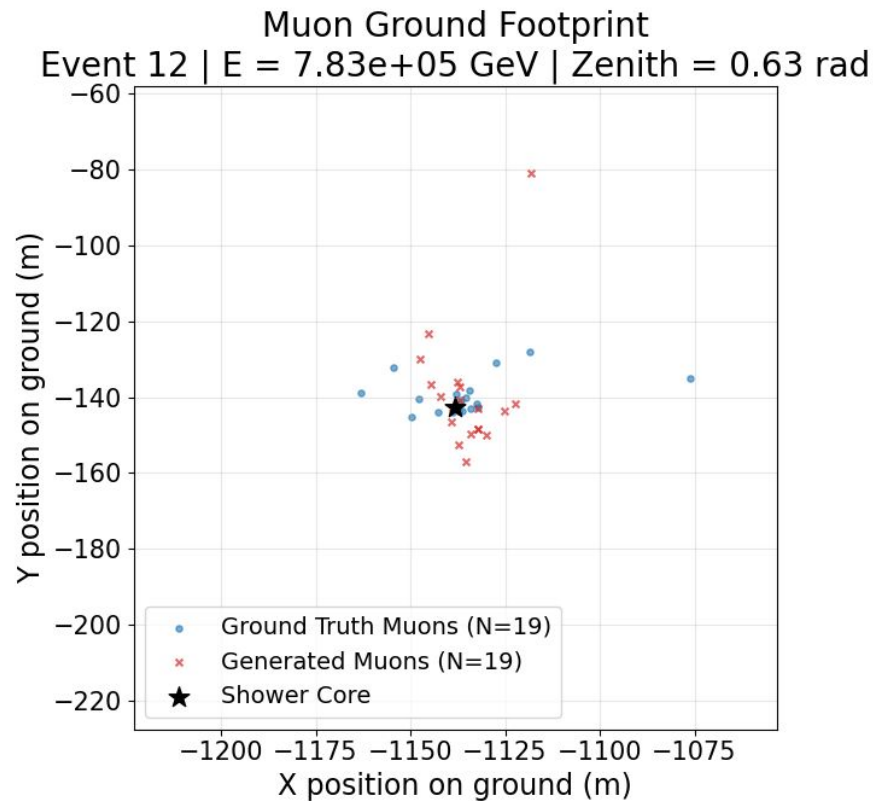
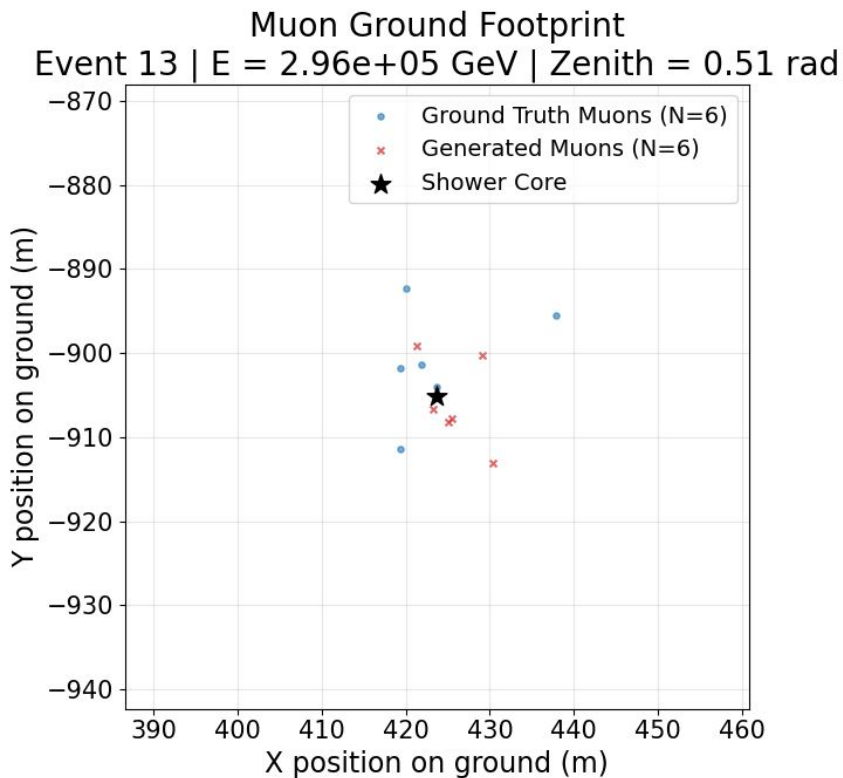


Event 504 — Angular Distributions



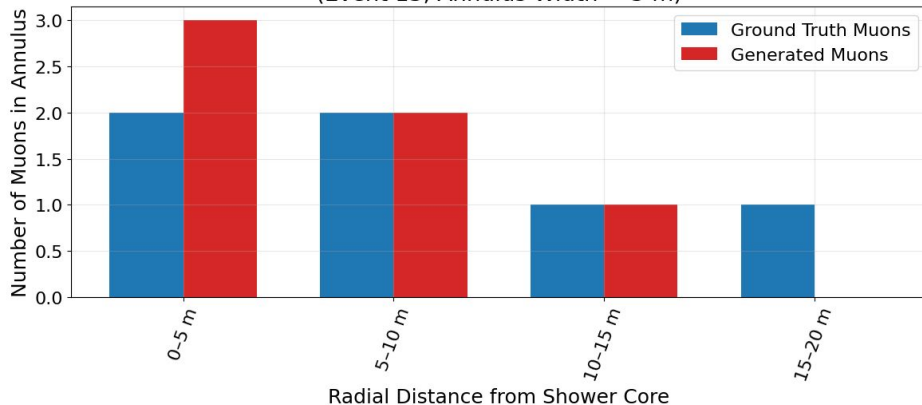
Angular Prediction could be closer

Low Multiplicity Events

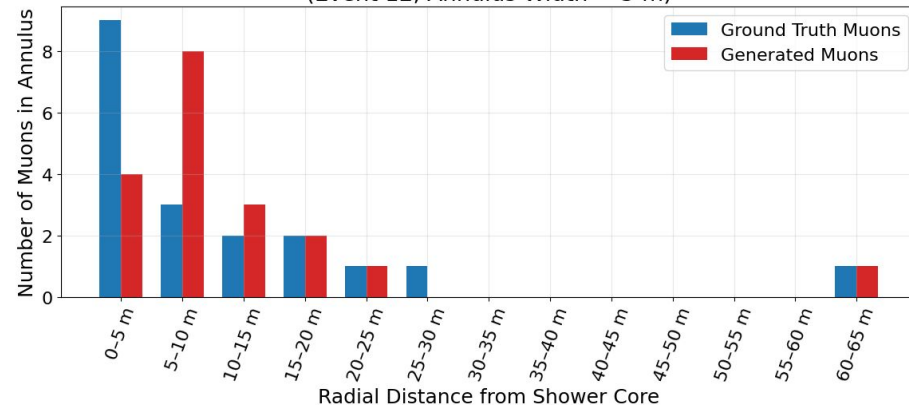


Shower Core: Intersection point of the primary particle with the surface, based on incoming angle and position.

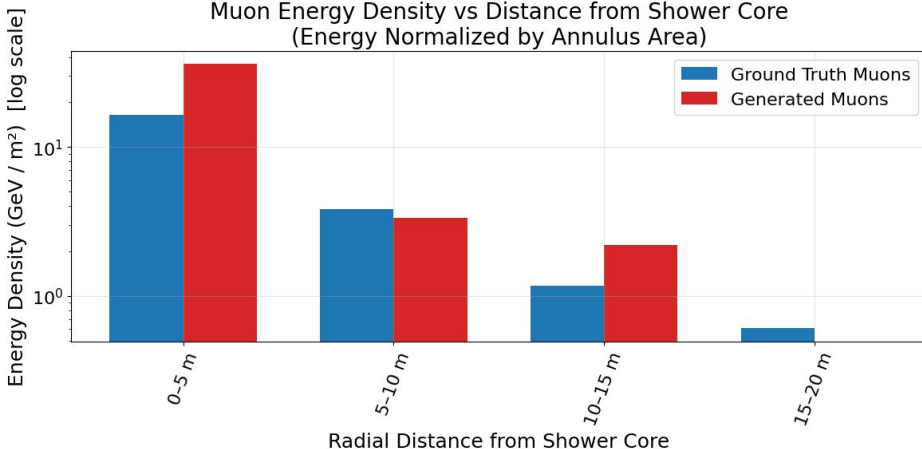
Muon Count vs Distance from Shower Core
(Event 13, Annulus Width = 5 m)



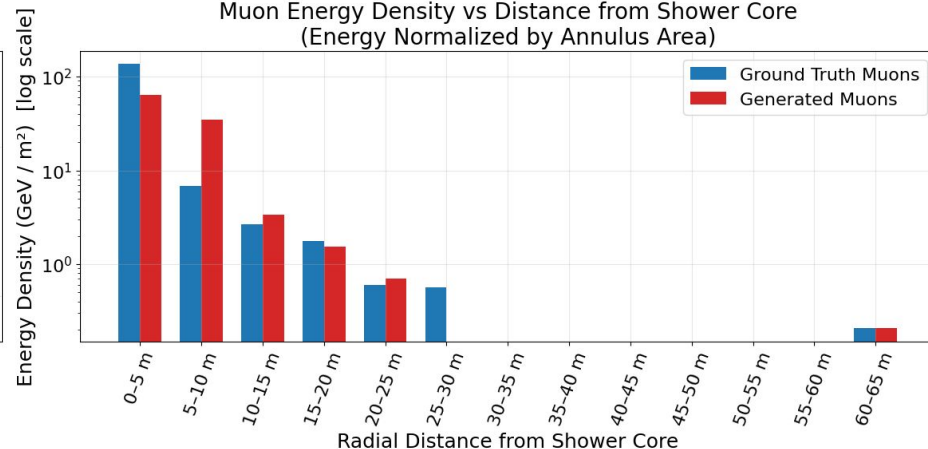
Muon Count vs Distance from Shower Core
(Event 12, Annulus Width = 5 m)



Muon Energy Density vs Distance from Shower Core
(Energy Normalized by Annulus Area)

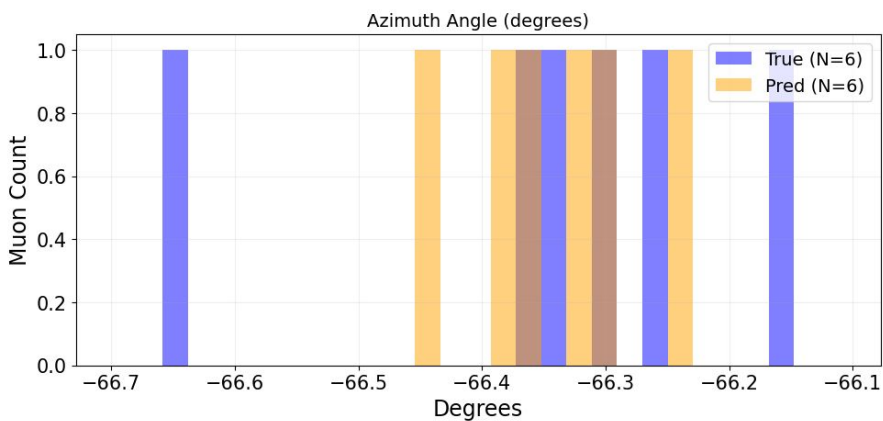
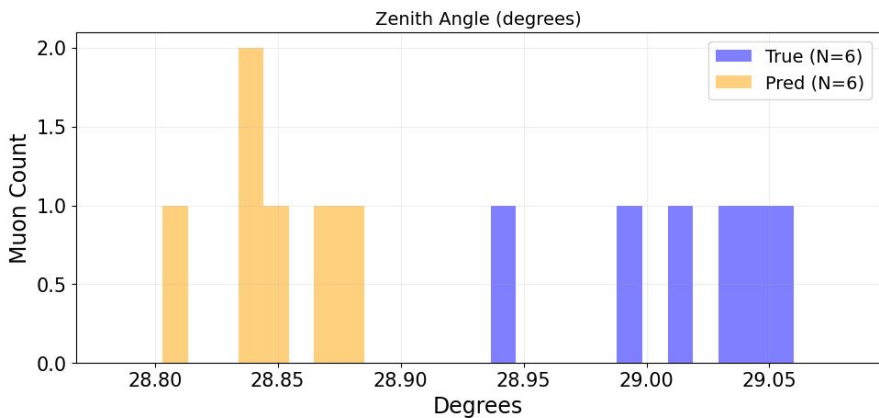


Muon Energy Density vs Distance from Shower Core
(Energy Normalized by Annulus Area)

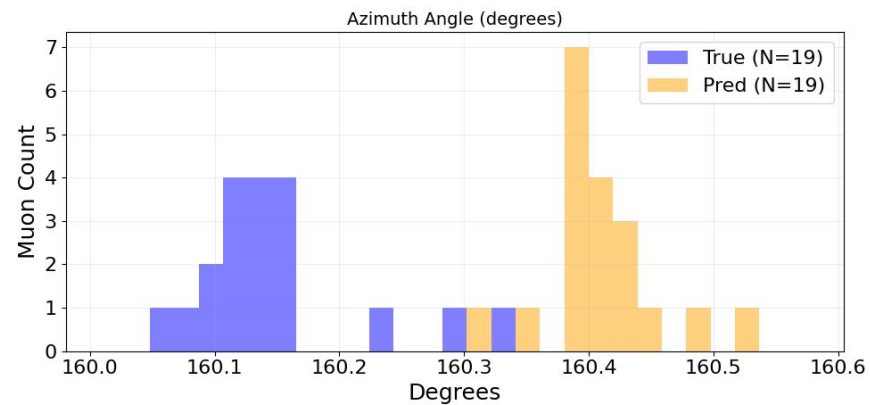
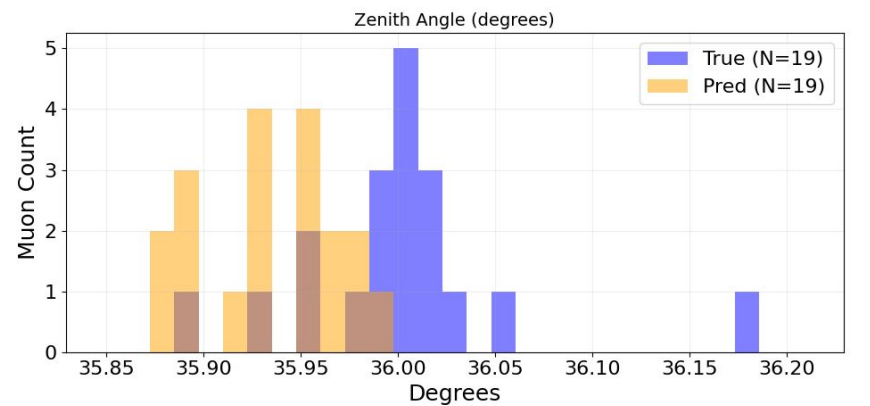


Reproduces the Lateral Energy Distribution: Generated muons follow the expected radial decay of energy density from the shower core.

Event 13 — Angular Distributions



Event 12 — Angular Distributions



Summary

1. Flow Matching for Muon Map Generation
2. Pretty Good at modeling Spatial Location and Energy
3. Angular Resolution needs to improve