DIFFUSION AND FLOW MATCHING MODEL FOR ICECUBE NEUTRINO EVENT SIMULATION AND RECONSTRUCTION

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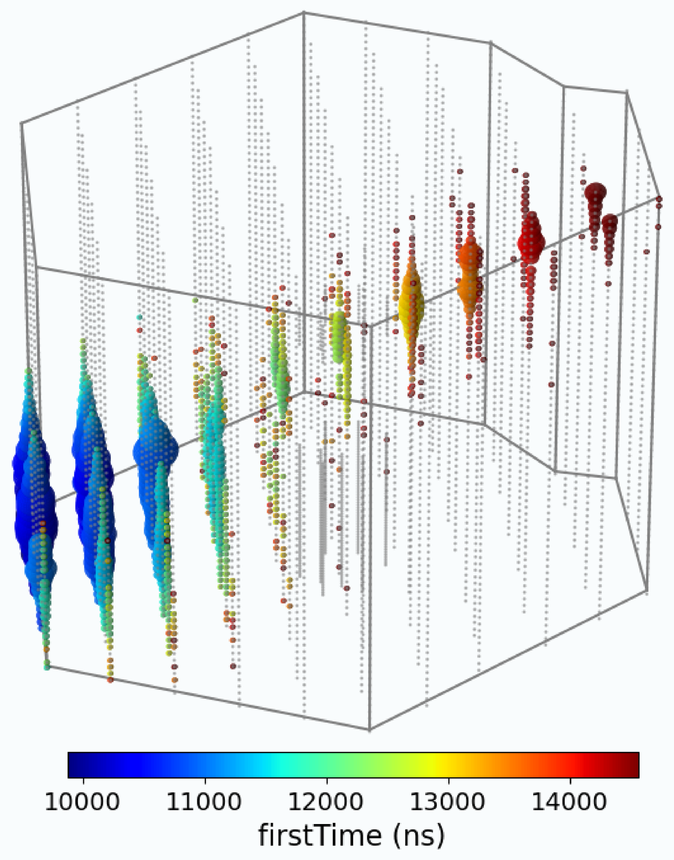
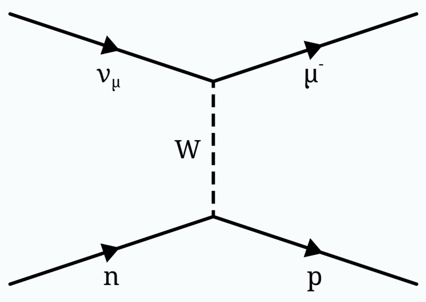
Introduction

The IceCube Neutrino Observatory is a cubic-kilometer-scale detector located beneath the Antarctic ice, designed to capture Cherenkov light emitted by secondary particles produced in neutrino interactions. Reconstructing the physical parameters of such eventssuch as energy, direction, and interaction vertexfrom sparse and noisy photon signals is a key task for physics analyses in IceCube.In recent machine learning research, score-based diffusion models and flow matching techniques have gained attention as powerful generative approaches. These models are capable of capturing complex data distributions and enabling stable conditional generation or inference, making them promising tools for a variety of scientific applications.In this work, we explore the application of these generative frameworks to IceCube. Specifically, we are developing conditional score-based diffusion models and flow matching models trained on simulated IceCube data. These models are designed to operate in both directions: generating detector responses from particle-level parameters, and reconstructing physical properties from observed detector signals. Our approach aims to provide a new, flexible framework for both event simulation and reconstruction in IceCube.

Muon Neutrino Event in IceCube



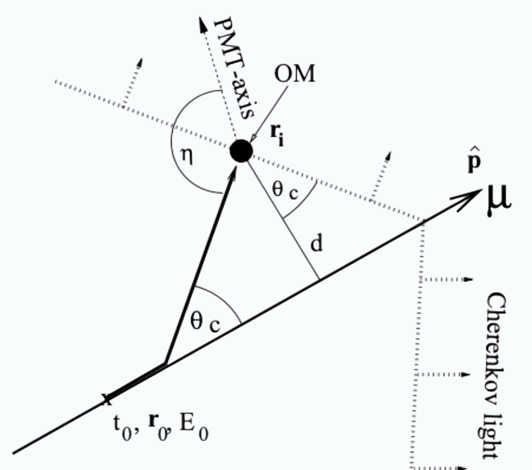
A **muon neutrino** (ν_μ) undergoing a charged-current interaction near or within the detector medium produces a relativistic muon that emits Cherenkov photons.



Due to its long lifetime, a muon can travel through the detector and leave a track-like pattern. This feature results in relatively accurate angular resolution.

Muon-Track Reconstruction

- For a given track $\vec{\theta}$, the geometric arrival time t_{res} of a Cherenkov photon is as follows:



$$t_{\mathrm{geo}} = t_0 + \frac{\hat{\mathbf{p}}\cdot(\mathbf{r_i}-\mathbf{r_0}) + d\tan\theta_c}{c_{\mathrm{vac}}}$$

- Due to the optical properties of the detector medium, the arrival time of a Cherenkov photon is stochastically delayed. The delay, t_{res}, is modeled by the **Pandel function**.

$$p(t_{\mathrm{res}}, \mid d, \vec{\theta}) = \frac{\beta^\alpha}{\Gamma(\alpha)} t_{\mathrm{res}}^{\alpha-1}\exp(-\beta\, t_{\mathrm{tes}})$$

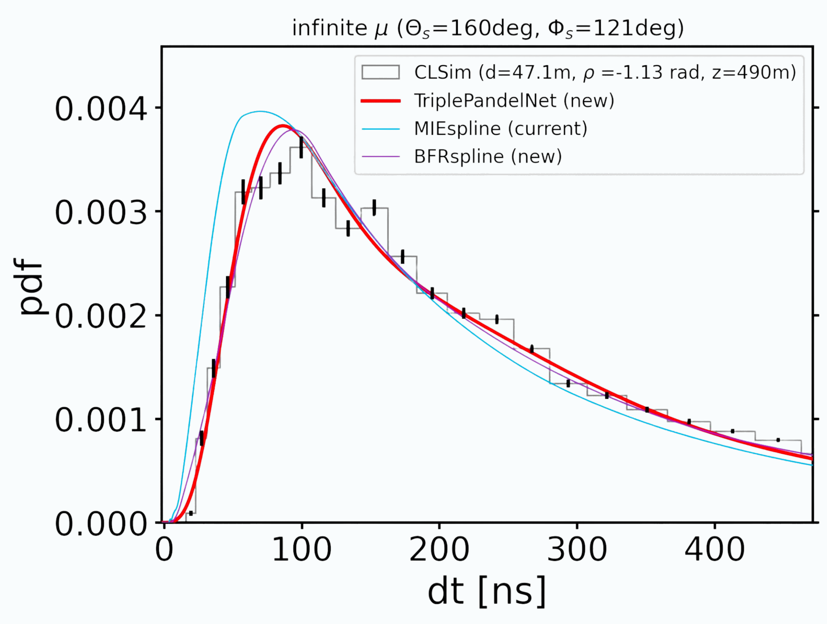
- The track is obtained by maximizing the following - form known as the MPE likelihood

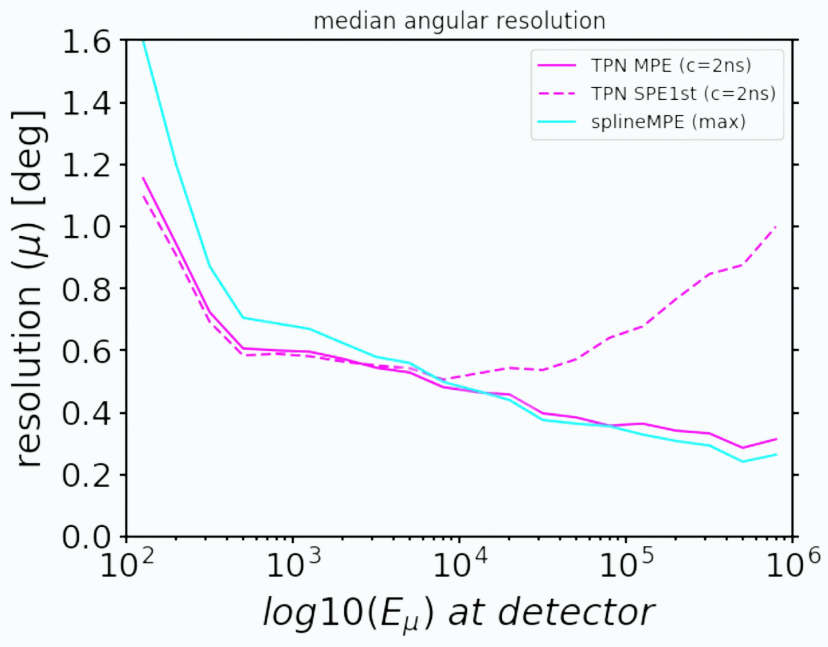
$$\mathscr{L}_{\mathrm{MPE}}(\vec{\theta}) = \prod_i^{\text{1st hits}} n_i \cdot p(t_{\mathrm{res},i} \mid d, \vec{\theta}) \cdot \left(\int_{t_{\mathrm{res},i}}^{\infty} p(t \mid d, \vec{\theta})dt\right)^{n_i-1}$$

Triple Pandel Network and Reconstruction

- Due to the non-homogeneous and anisotropic optical properties of the South Pole ice, accurately determining the probability density function $p(t_{\mathrm{res}} \mid d, \vec{\theta})$ is challenging.
- To address this, we designed a deep learning model, the **Triple Pandel Network**, that maps track and DOM geometry, $d, \vec{\theta}$, to photon arrival distribution $p(t_{res}|d, \vec{\theta})$.

$$p(t_{\mathrm{res}}|d, \vec{\theta}) = \sum_{i=0}^{3} w_i \times \left[\frac{\beta_i^{\alpha_i}}{\Gamma(\alpha_i)} t^{\alpha_i-1}\exp(-\beta_i t)\right]$$

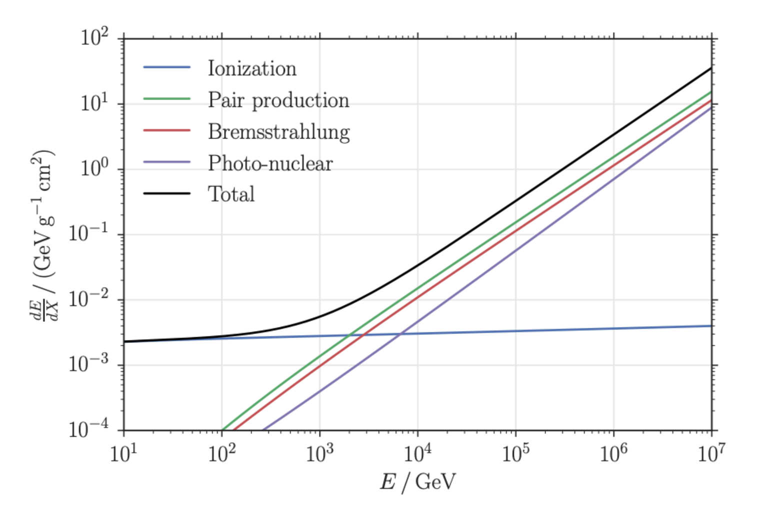




Motivation to New Approach

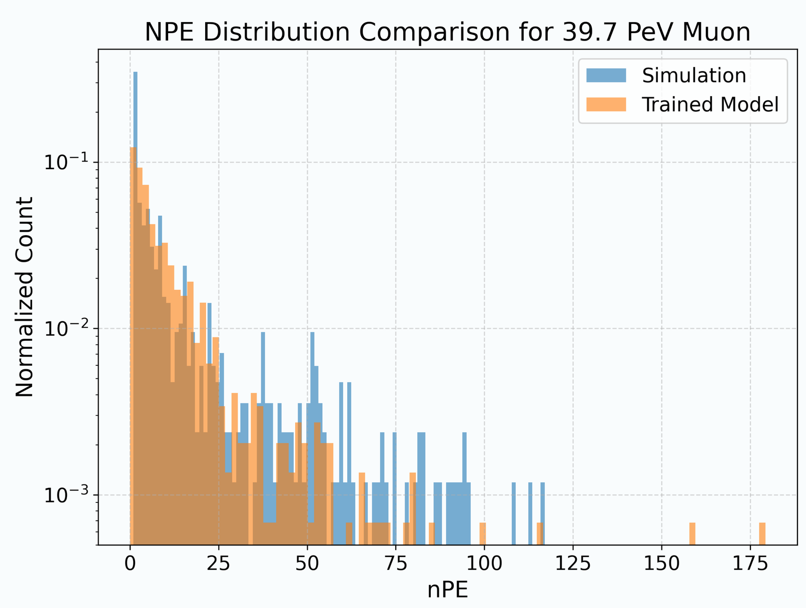
- Above approximately 1 TeV, muons lose energy stochastically via bremsstrahlung, pair production, and nuclear interactions. These processes produce additional signals in the detector that are distinct from the Cherenkov radiation emitted by the muon itself.

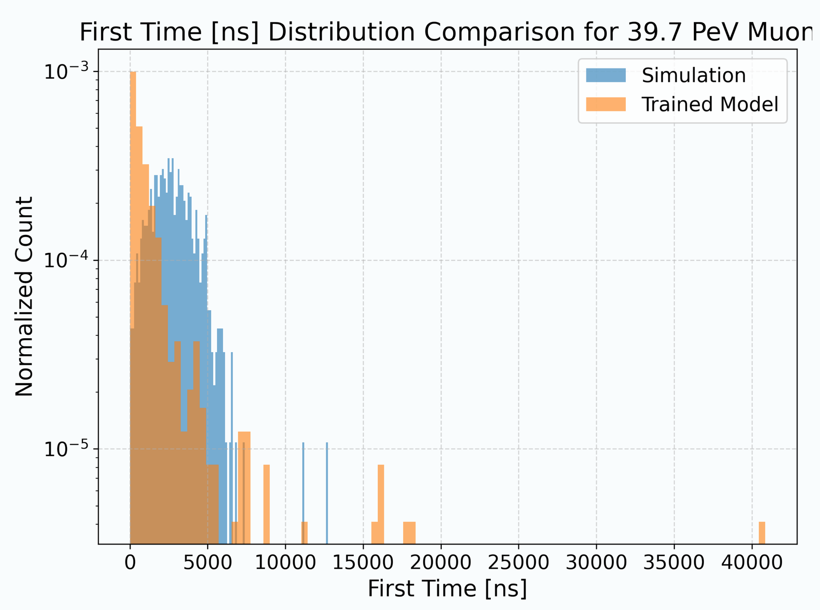
Because it is infeasible to simulate every possible stochastic energy loss scenario, **some variations in photon arrival times cannot be accurately modeled**. Consequently, both the current reconstruction methods and the TPN approach share this fundamental limitation.



Diffusion & Flow Models for Muon Reconstruction

- **Manifold Theorem**:
  The manifold hypothesis states that high-dimensional data, such as IceCube detector signals (e.g., 5160 × 2), lie near a much lower-dimensional manifold. Even stochastic energy losses from muons are likely constrained to this structure.
- **Why Generative A.I**:
  Diffusion and flow-matching models learn the underlying manifolds of the data. By capturing the manifold, they can represent complex variations more robustly than traditional methods. As a result, simulation of every possible scenario is unnecessary, since the learned manifold allows generating or evaluating unseen cases.
- **Then How We Use Generative Models for Muon Reconstruction**:
  We first train a model that can produce realistic muon simulation events. Such models are capable of learning the manifold of the data distribution. So once trained, the model allows us to compute the likelihood of observed data, which can then can be used for reconstruction.





Conclusion

- We have developed the **Triple Pandel Network**, which accurately models $p(t_{\mathrm{res}} \mid d, \vec{\theta})$ across the entire detector volume.
- We have adopted a **Generative A.I.** approach to address the stochastic energy loss phenomena of muons.
- We are developing **Diffusion and Flow-Matching** models for muon simulation.
- The model will be further developed and applied to reconstruction tasks.

References

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Acknowledgements

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