A Convolutional Neural Network Approach for Cherenkov Event Reconstruction (arXiv: 2202.01276v1)

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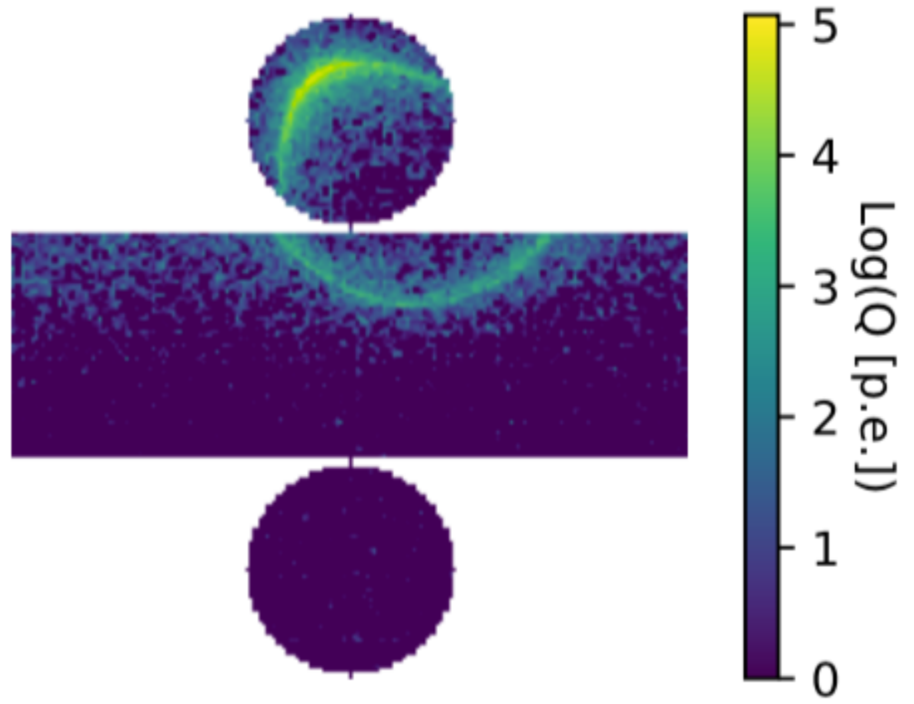


Introduction

The current reconstruction approach (hereafter fiTQun) to events in water Cherenkov detectors, for example SK, relies on maximum-likelihood estimation. The core of this process is to find among many competing hypotheses $\mathbf{x}$ the one that maximizes the likelihood of the detected event, which is evaluated over every PMT by the following equation:

$$L(x) = \prod_{j}^{unhit} P_j(unhit\,|\,x) \prod_{i}^{hit} \{1 - P_i(unhit\,|\,x)\} f_q(q_i\,|\,x) f_t(t_i\,|\,x)$$

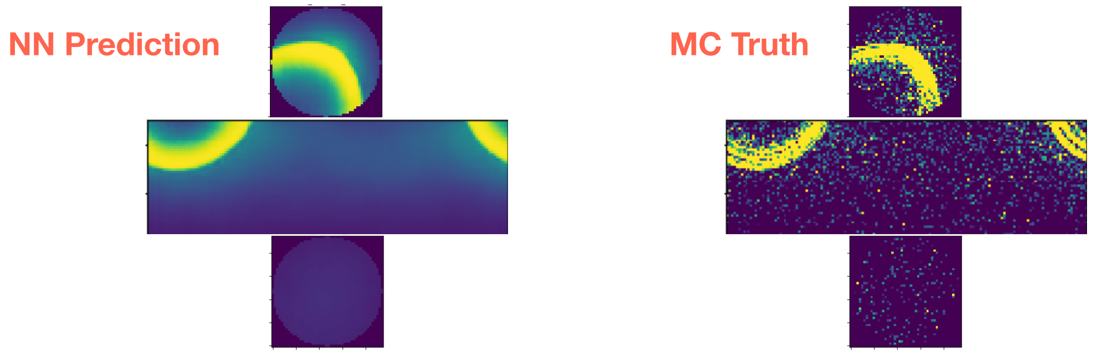
Several simplification/shortcoming exist in fiTQun:

1. The full likelihood function is factorized into a few low-dimension terms;
2. Limited details of PMT responses;
3. Demanding a large amount of "specially" simulated data to tune the algorithm.

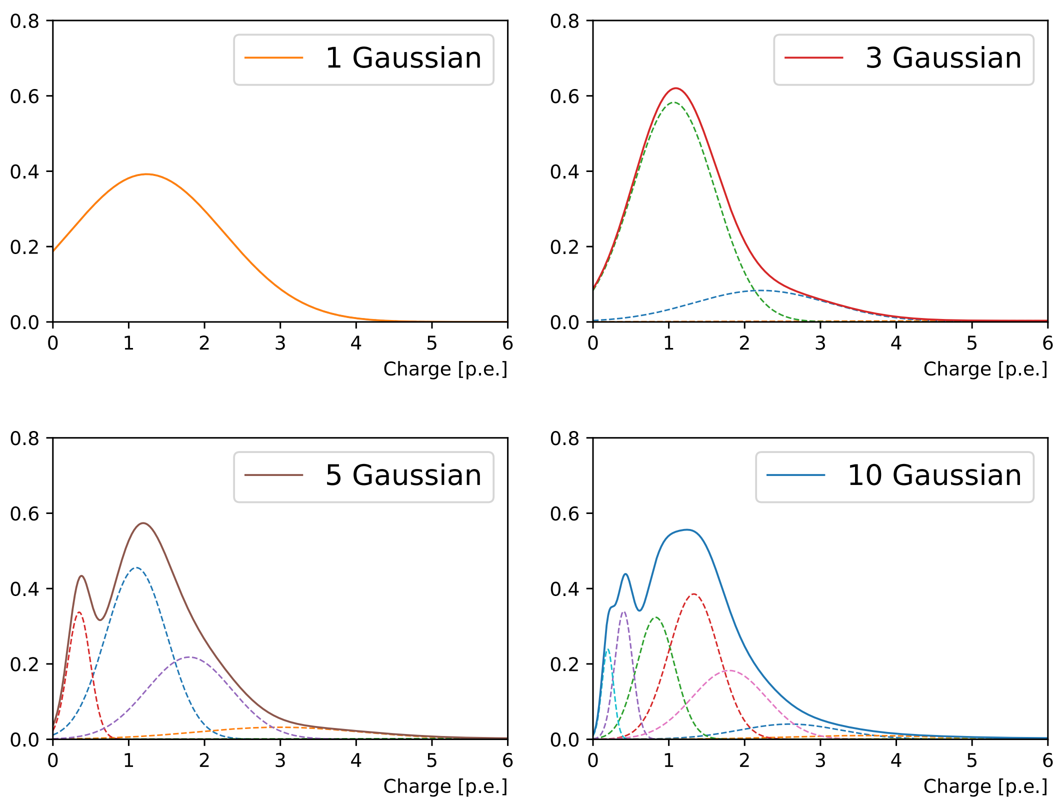
These assumptions cause biases in the prediction of indirect hit in PMTs and the reconstruction of heavier particles like protons.

Generative Neural Network

This neural network takes the Cherenkov event's **PID, position, direction, and energy** as input, and output probability distribution functions (PDF) for **each PMT's charge and time** responses. It is trained with a regular SK Inner Detector (ID) Monte Carlo (MC) consisting of single-ring events, and with a loss function similar to fiTQun's likelihood function.



The hit probability of each PMT is implemented via binary cross entropy, and the PMT PDFs are provided more degrees of freedom by accumulating multiple Gaussian subcomponents. This improves the discrimination of direct and indirect hit PMTs.

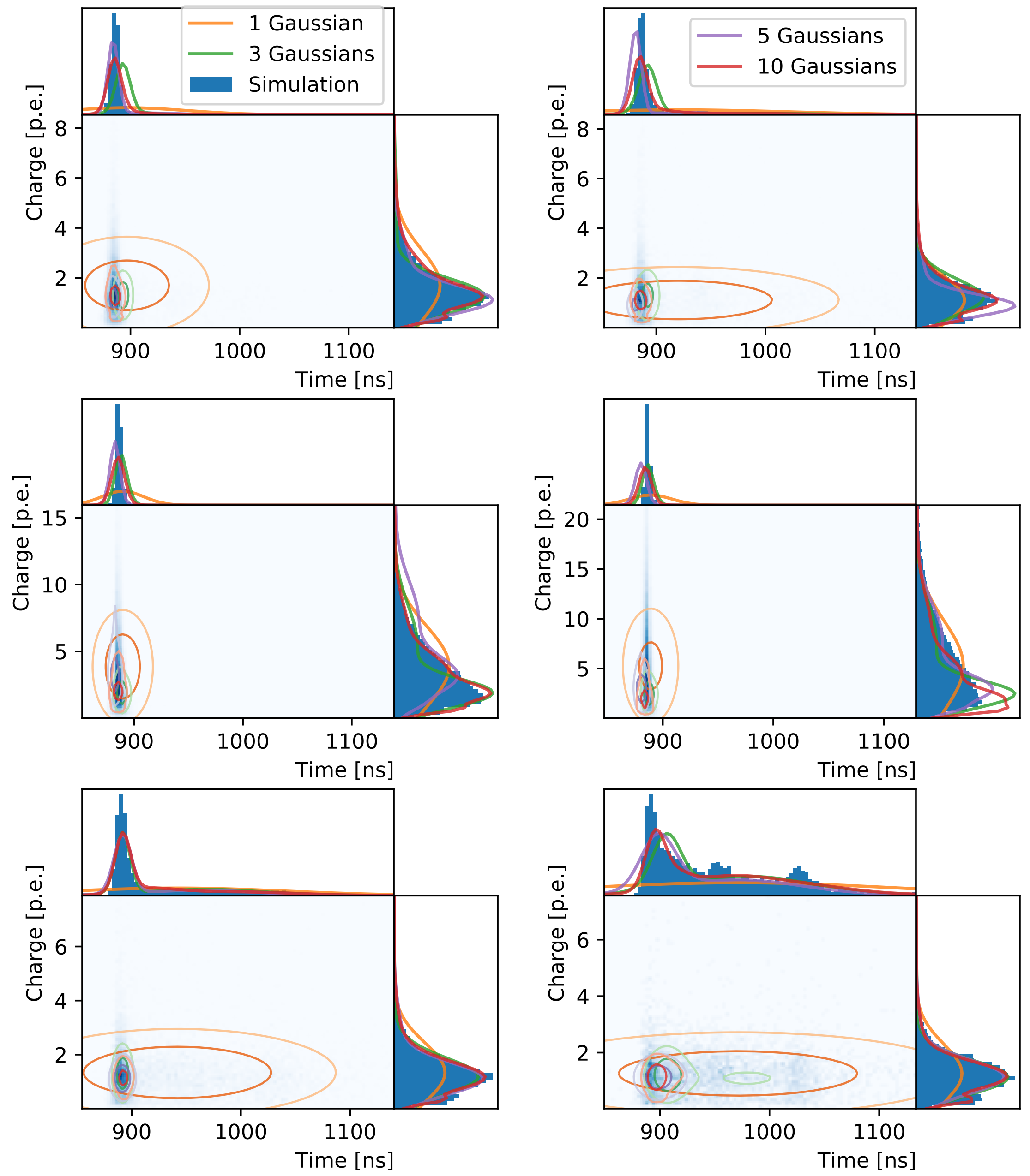


No factorization is included in this network, and the correlation between a PMT's time and charge responses is also included.

Verification by Fixed Particle MC

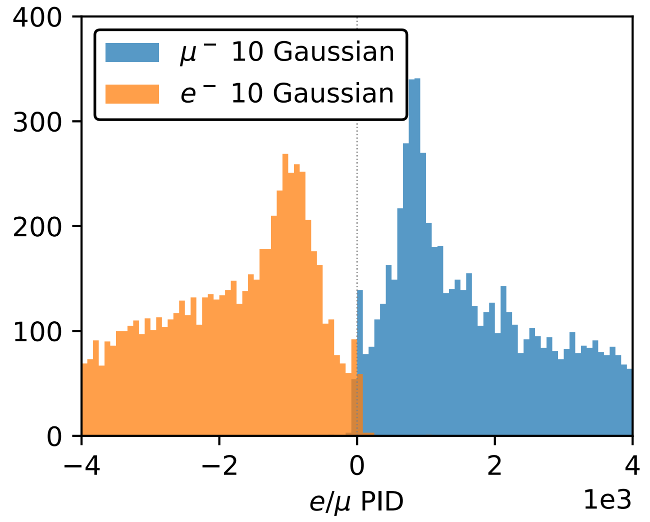
To evaluate the accuracy of the network at predicting PMT responses, the network's prediction is compared to the true PMT responses averaged over a large number of the same MC event. From this comparison it is confirmed that the network is capable of generating the difference between an electron and muon ring — fuzzy vs. sharp rings.

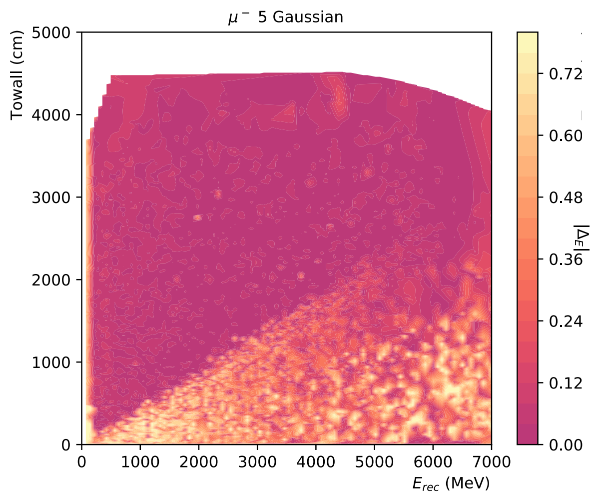
Meanwhile, by adding more Gaussian subcomponents in the PMT PDFs and including the correlation between charge and time responses, we observe a better approximation of the true PMT PDFs predicted by the neural network.



Likelihood Scan over Energy

The reconstruction performance of the neural network is validated by a likelihood scan over particle energy and the corresponding reconstruction result is checked against the truth. A decent energy resolution and PID correctness are achieved, especially for those events being fully contained inside the detector. Due to the lack of constraint for "escaping" particles, in the current study the near-wall events have more room for improvement.





Conclusion

A convolutional neural network is constructed to reconstruct Cherenkov events based on maximum-likelihood method. The first iteration has already shown very promising reconstruction performance. This work was submitted to *Frontiers in Big Data, section Big Data and AI in High Energy Physics*.

In the near future, this network will be expanded to a more sophisticated architecture to include the detector noises and multi-ring events. For longer term, we look forward to implementing this neural network approach in the event reconstruction algorithm of various water Cherenkov experiments.