## Combining Maximum-Likelihood with Deep Learning for Event Reconstruction in IceCube

# 37<sup>th</sup> Internationa **Cosmic Ray Conference** 12-23 July 2021







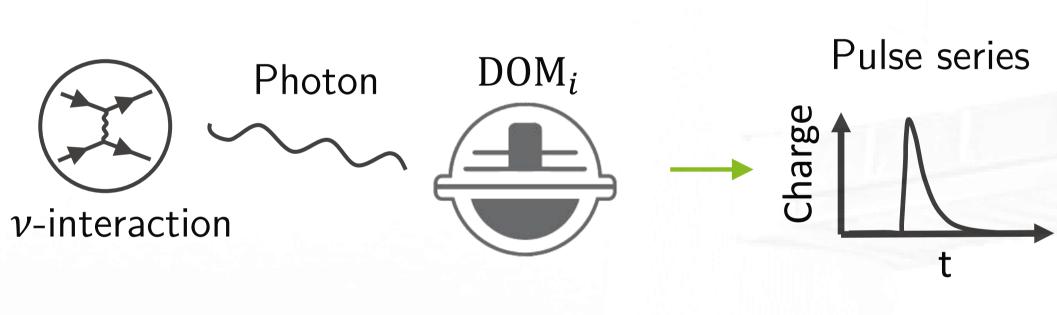
#### Importance of Domain Knowledge

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- Utilization of domain knowledge is crucial to advancing reconstruction performance
- Common deep learning architectures such as CNNs can surpass standard methods[1], but do not fully utilize available information
- In contrast, maximum-likelihood methods can utilize all available information, but are limited due to computational constraints
- Develop method that combines strengths

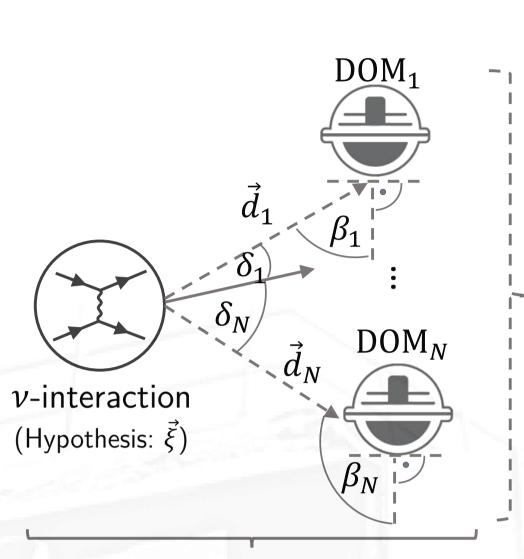
### Domain Knowledge in IceCube



- Processes from neutrino interaction to measured pulse series at each digital optical module (DOM) are simulated and known to great detail [2]
- These processes utilize information such as:
  - Detector geometry
  - > Detector properties such as DOM efficiency
  - > Optical properties of detector medium including dust layers in glacial ice
  - > Translational and rotational invariance of the underlying physics
  - > Time invariance
  - > Linear relationship of measured charge and deposited energy of neutrino interaction
- → Reconstruction methods may benefit from utilizing this information

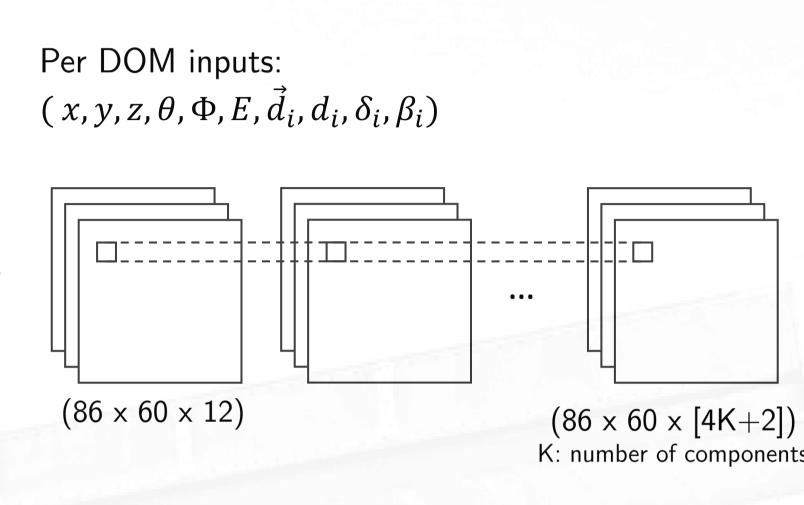
## Combining Maximum-Likelihood with Deep Learning

- Standard maximum-likelihood reconstructions in IceCube[3] can utilize available information, but are forced to simplifications due to computational complexity
- Neural Networks (NN) are universal approximators that excel at interpolating high-dimensional data
- Common deep learning (DL) architectures fail at utilizing all available information
- → Combine strengths of maximum-likelihood and DL:
  - > Utilize generative model to approximate pulse arrival time PDF and expected charge at each DOM
  - > Parameterize time PDF via mixture model of asymmetric Gaussians[4]
  - > Directly include available domain knowledge in network architecture, analogously to simulation



Compute relative displacement vectors  $\vec{d}_i$  and angles  $\delta_i$ ,  $\beta_i$ 

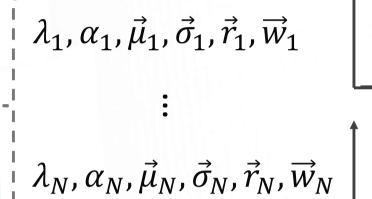
Translational/rotational invariance, detector geometry

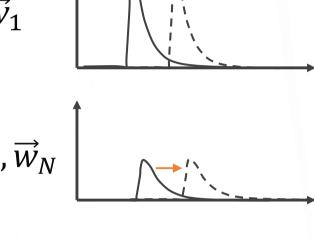


Locally connected layer without weight sharing

Symmetry breaking ice properties

Mixture model components, charge and over-dispersion per DOM





 $\lambda_i \rightarrow \lambda_i'$ Apply shift to

expected charge

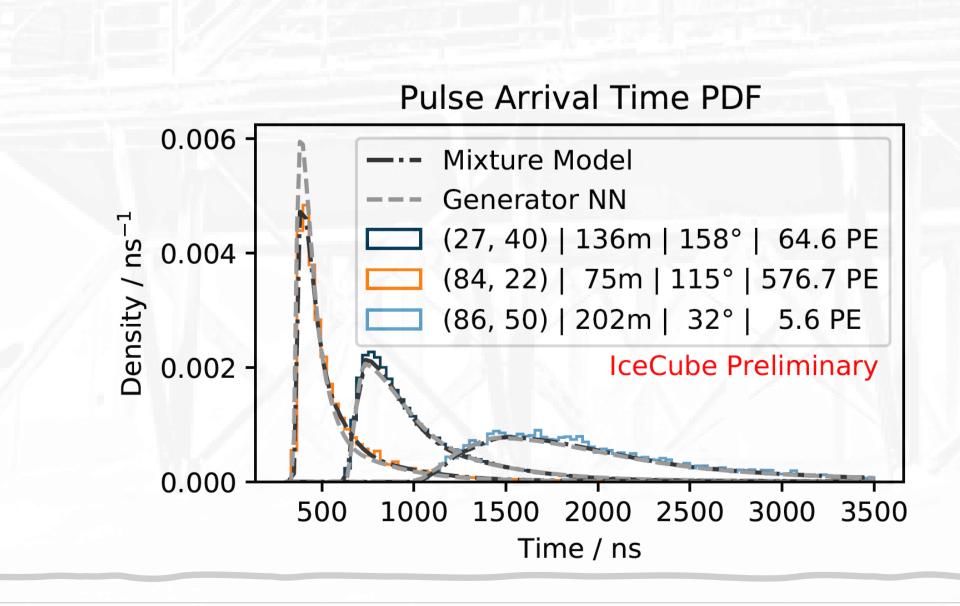
Shift PDF relative to interaction time

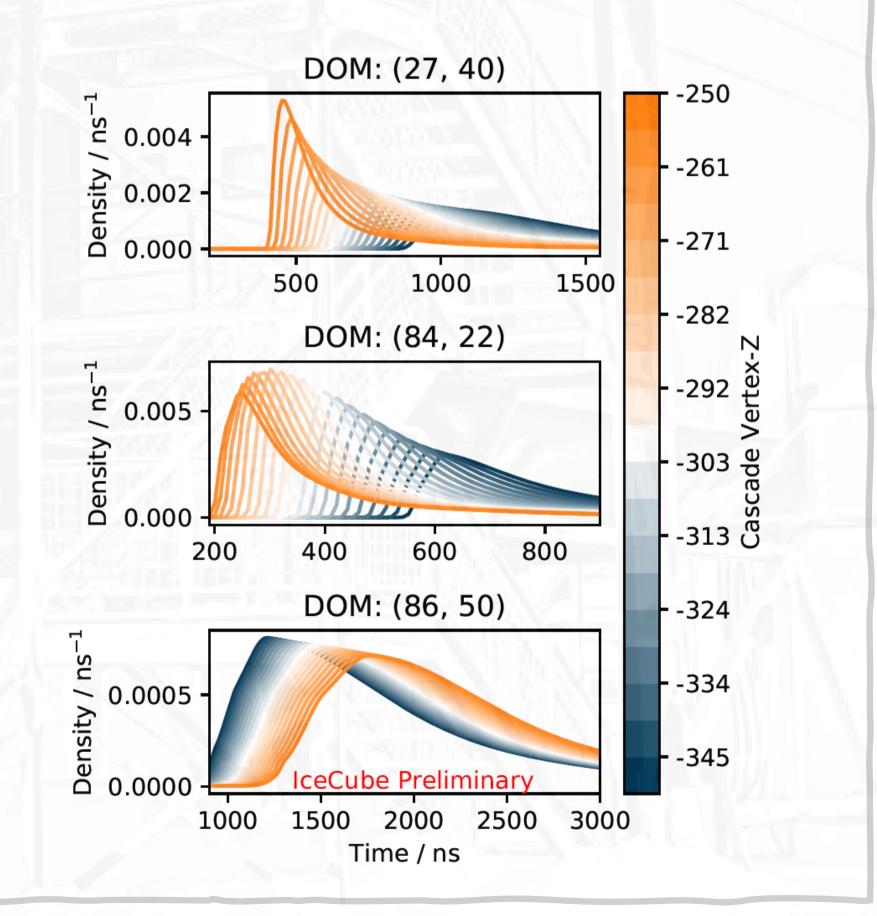
Linear scaling, DOM efficiency

Time invariance

#### Model Performance

- Generative NN is able to model PDF (bottom)
- NN is more interpretable: individual components (such as z-dependence on the right) can be visualized and cross-checked





#### Conclusions

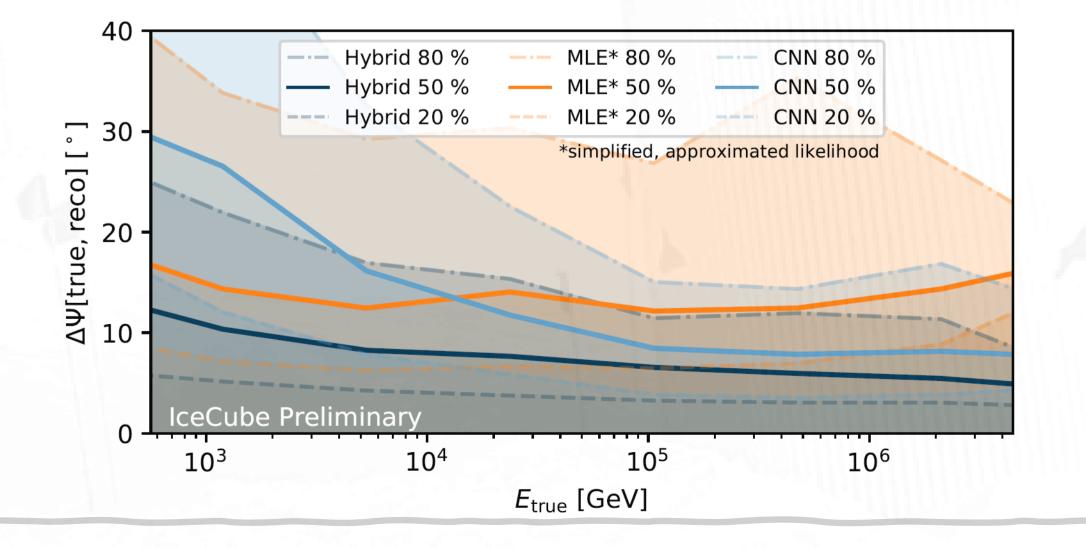
Convolutional layers

with weight sharing

Shared DOM

Properties

- Generative model to approximate high-dimensional PDF
- Generator NN able to utilize available information
- Improved reconstruction resolution of developed hybrid method due to exploitation of symmetries and available domain knowledge, without need for simplifications













[3] IceCube Collaboration, M. Aartsen et al. JINST 9 (2014) P03009. [1] IceCube Collaboration, R. Abbasi et al. arXiv:2101.11589 [hep-ex]. [2] IceCube Collaboration, M. Aartsen et al. JCAP 10 (2019) 048.

[4] T. Kato, S. Omachi, and H. Aso <u>Lecture Notes in Computer Science</u> (2002) 405-413.

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