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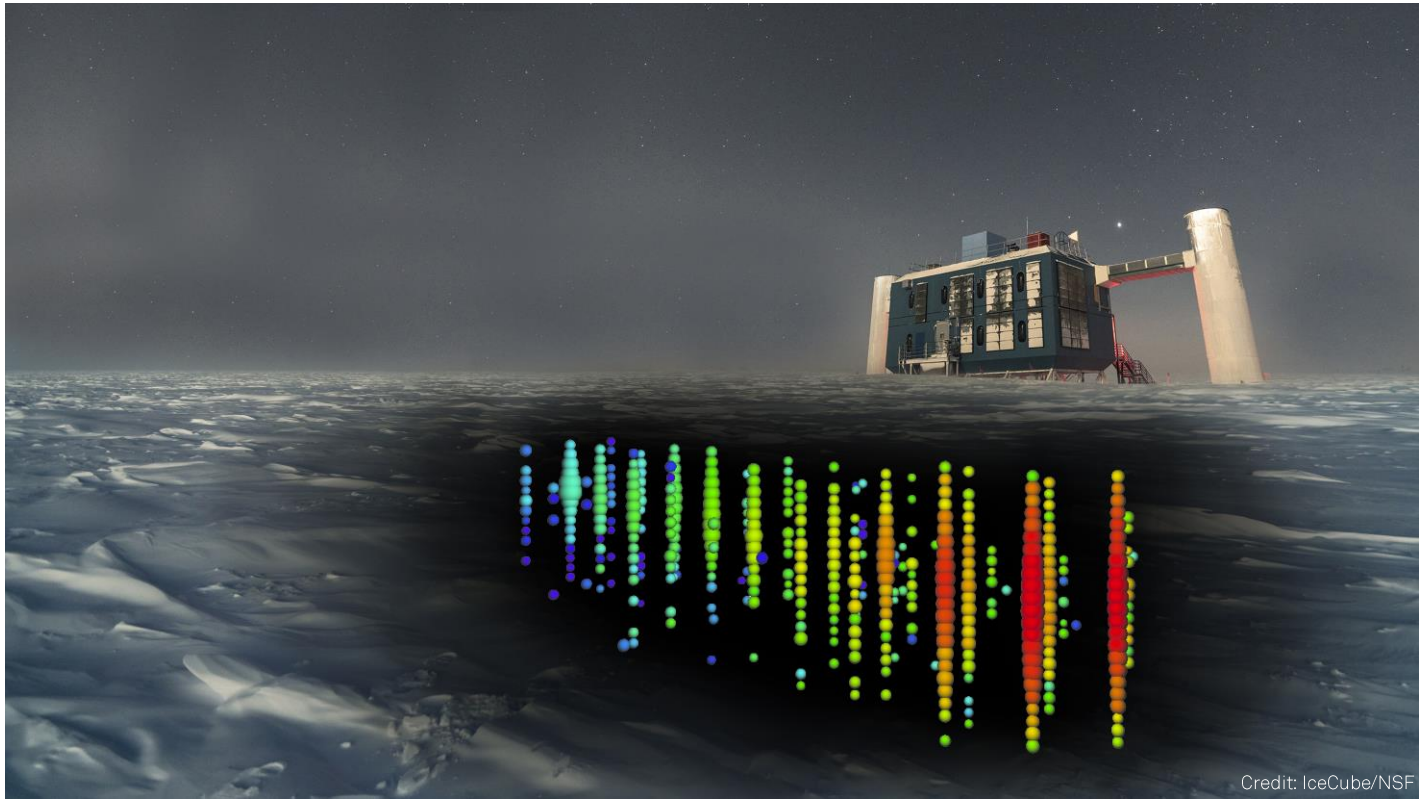
ICECUBE SOUTH POLE NEUTRINO OBSERVATORY

SFB 876 Providing Information by Resource-Constrained Data Analysis

lehrstuhl physik e5



Reconstruction Techniques in IceCube using Convolutional and Generative Neural Networks

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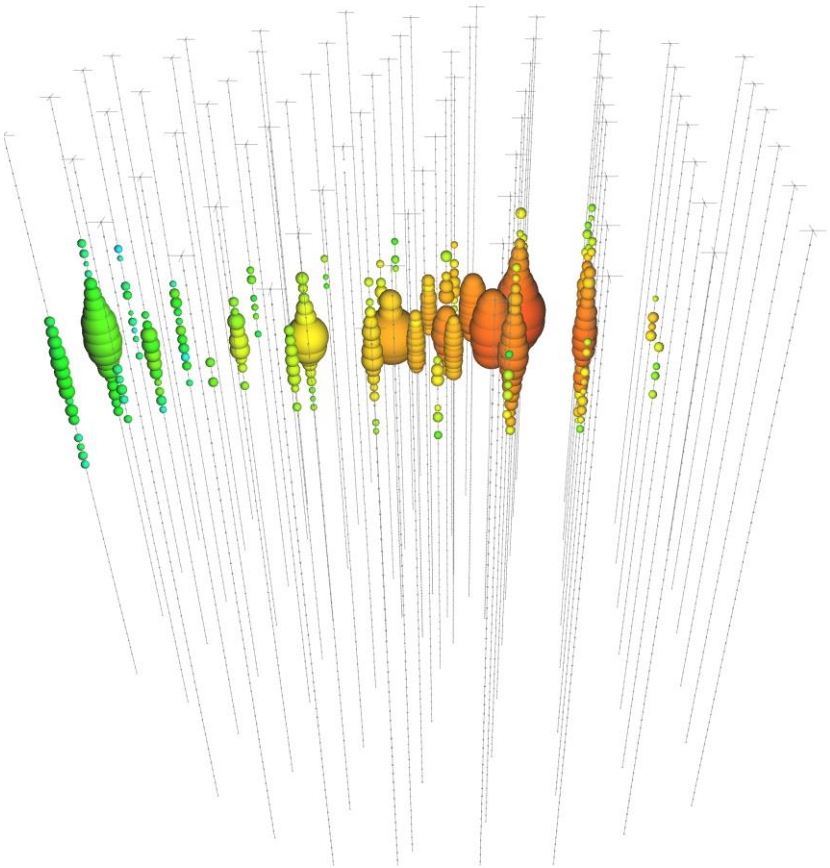
VLVnT 2018

Dubna – October 4th, 2018

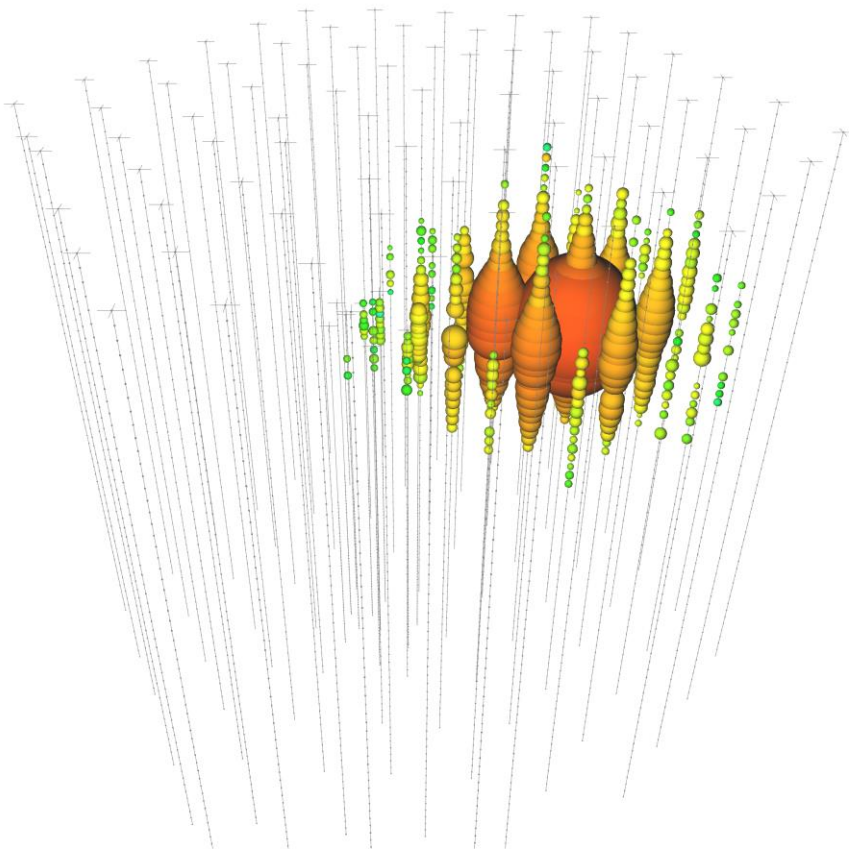
*http://icecube.wisc.edu

IceCube Data – Starting Point of Event Reconstruction

Tracks



Cascades



Can we further improve our event reconstruction?

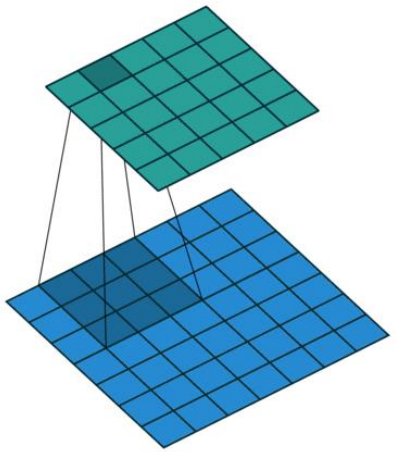
Why Deep Learning?

- Powerful and fast reconstruction methods desired for real-time analyses and follow-up programs
  - Limited resources
  - High data rate
  - Low level data
- Maximum-Likelihood methods have their limitations:
  - Often simplifications and approximations necessary
  - Can be extremely expensive to compute

Deep learning is an excellent candidate for these requirements!

Outline

- Brief introduction to neural networks
- Current Status:
  - Convolutional Neural Network (CNN)
  - Comparison to standard reconstruction methods
- Limitations of CNNs:
  - Need for better suited architectures
  - Exploitation of a priori knowledge
- Next Generation:
  - Generative Neural Network
  - First results



Deep Learning – Deep Neural Networks

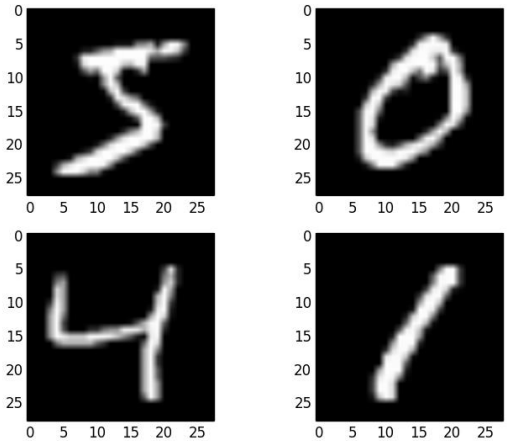
- Neural network defines a function:

$$f_\theta : I \rightarrow O$$

θ: Free parameters defined by model architecture

I: Input data
Greyscale values of pixels (image recognition)
Pulse information of DOMs (IceCube)

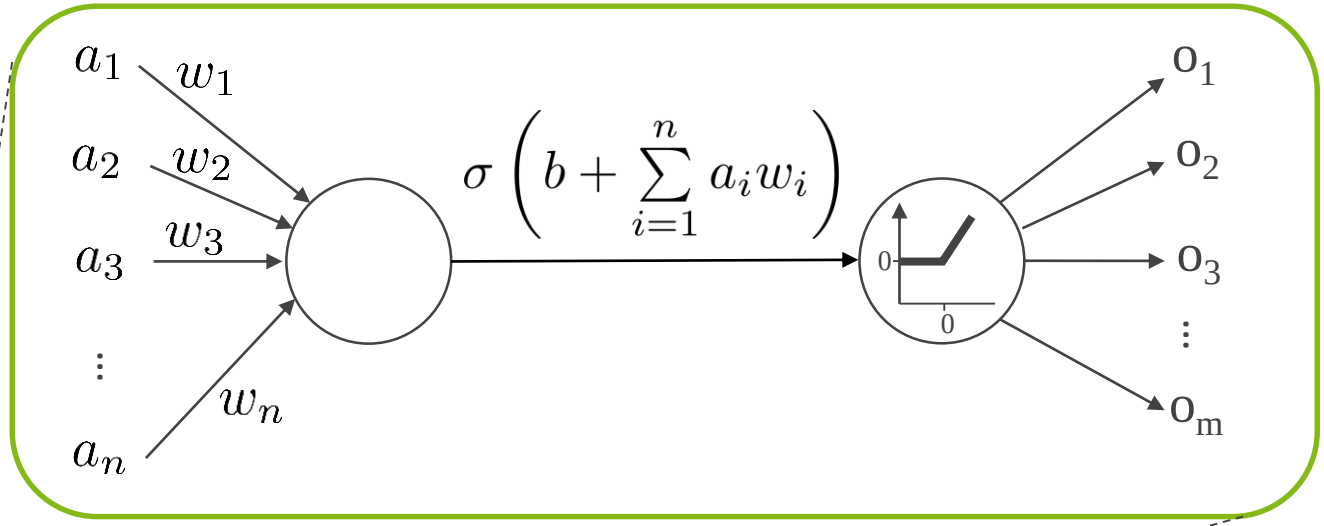
O: Output
Digit (image recognition)
Energy/direction of particle (IceCube)

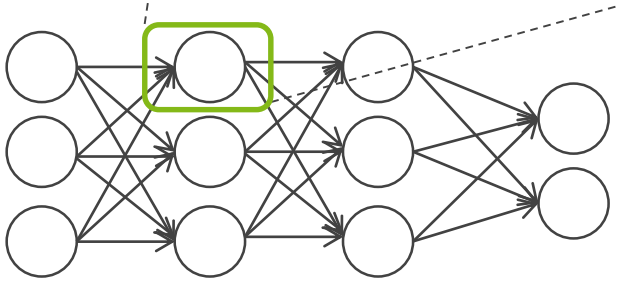


MNIST Dataset

Deep Learning – Deep Neural Networks

Artificial Neuron and fully connected layer





Weights and bias

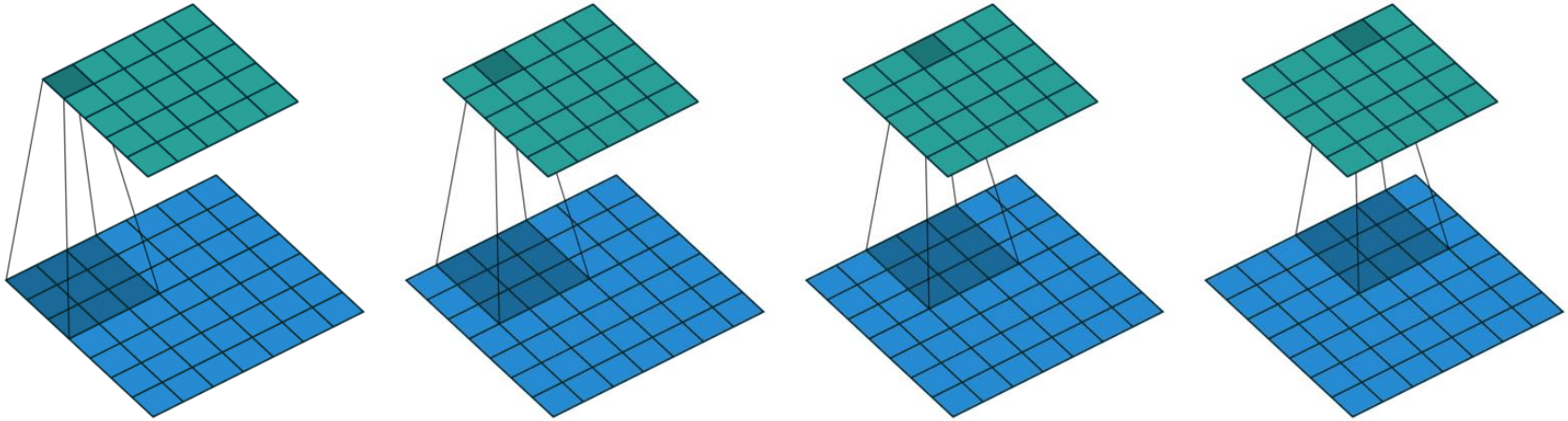
$n + 1$ free parameters per neuron

Nonlinear activation function e.g. ReLU

0 up to a fixed threshold

Deep Learning – Convolutional Neural Nets

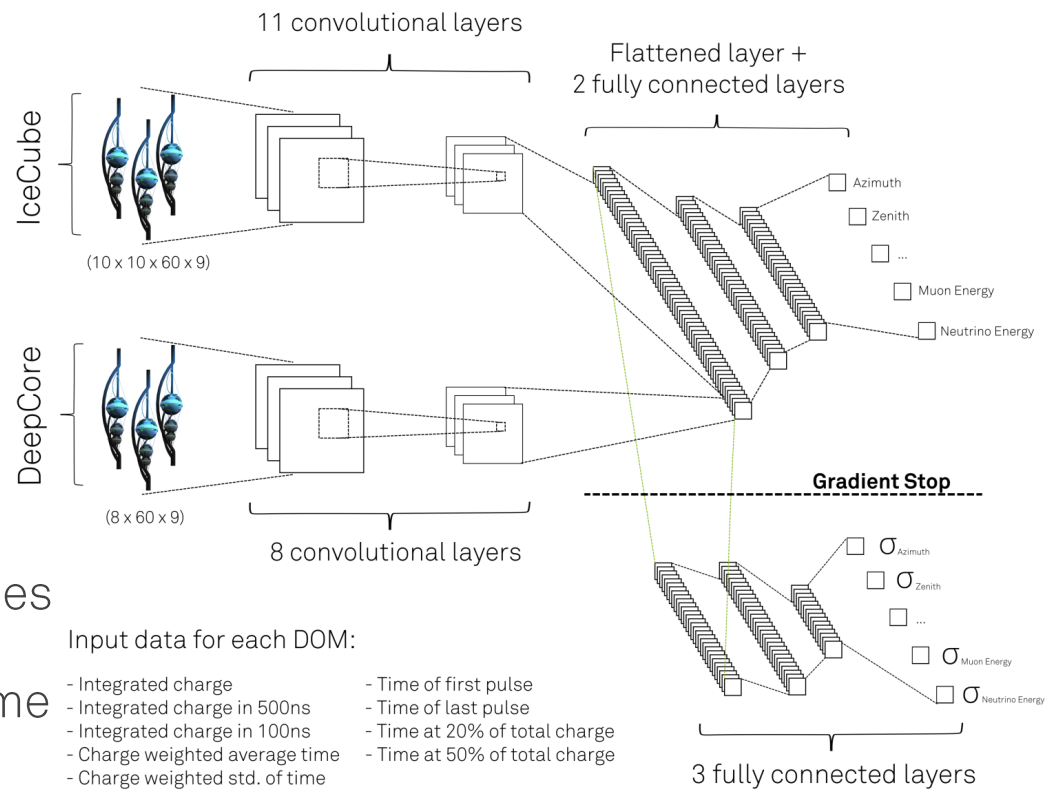
Convolutional Layer



- Only neighboring neurons are connected
- Kernel weights are shared
- Greatly reduces number of free parameters

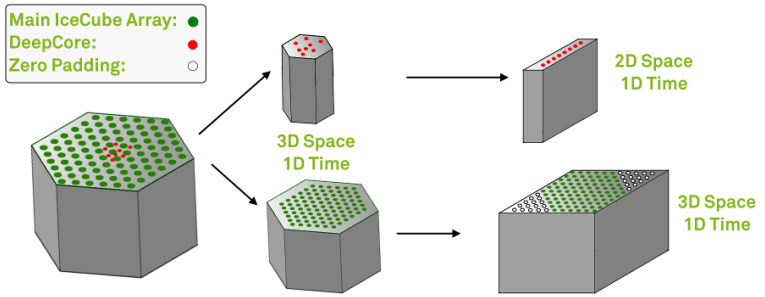
Current Status – CNNs

- Deep convolutional neural network (CNN)
- Energy and directional reconstruction for any event topology
- Easily extendable to other desired reconstruction quantities
- Fast and nearly constant runtime (data preprocessing adds energy dependence)
- Per event uncertainty estimate on each reconstruction quantity



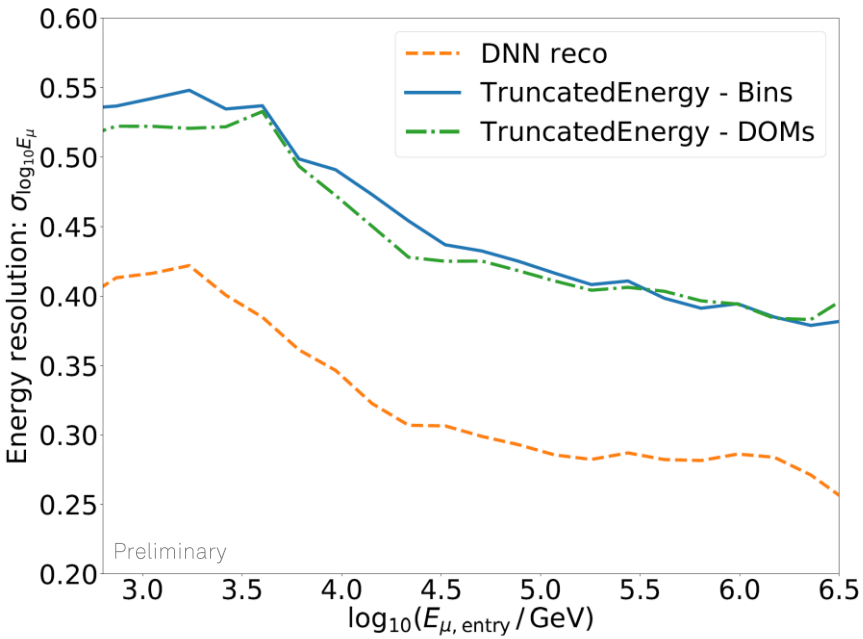
Input data for each DOM:

- Integrated charge
- Integrated charge in 500ns
- Integrated charge in 100ns
- Charge weighted average time
- Charge weighted std. of time
- Time of first pulse
- Time of last pulse
- Time at 20% of total charge
- Time at 50% of total charge

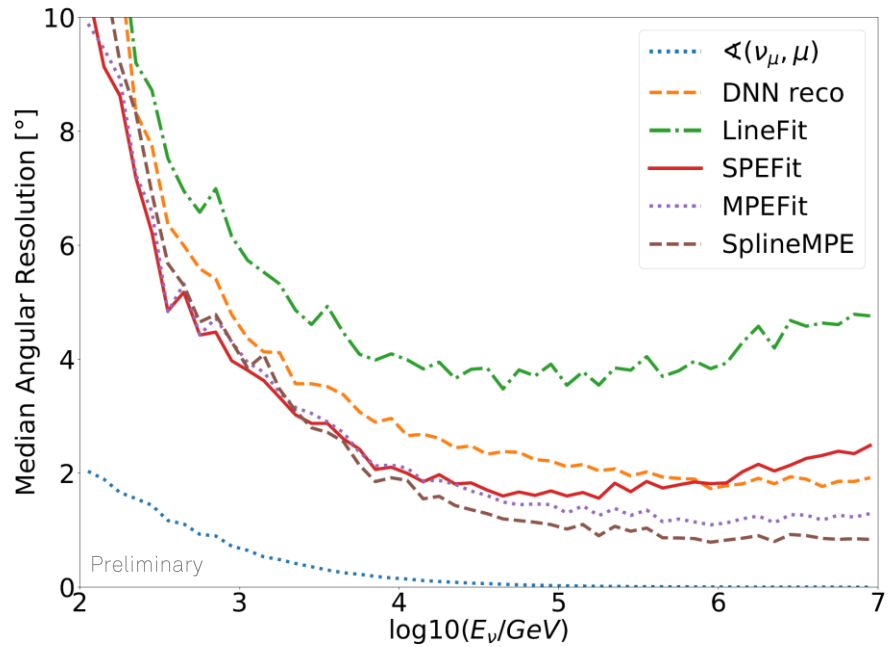


Current Status – Track Performance

Muon Energy at Detector Entry



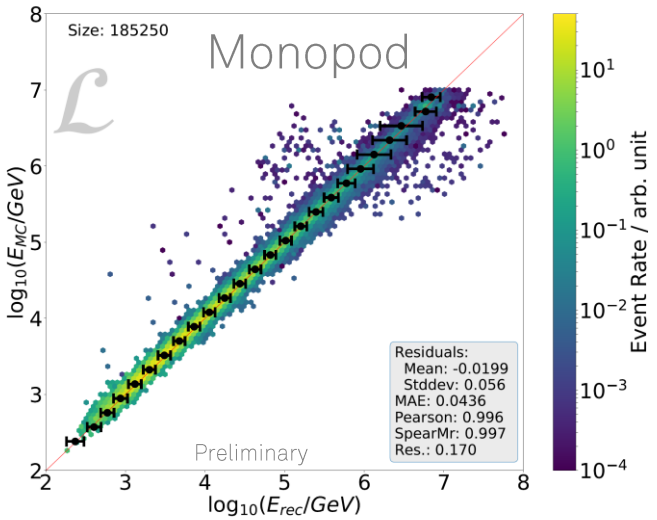
Median Angular Resolution

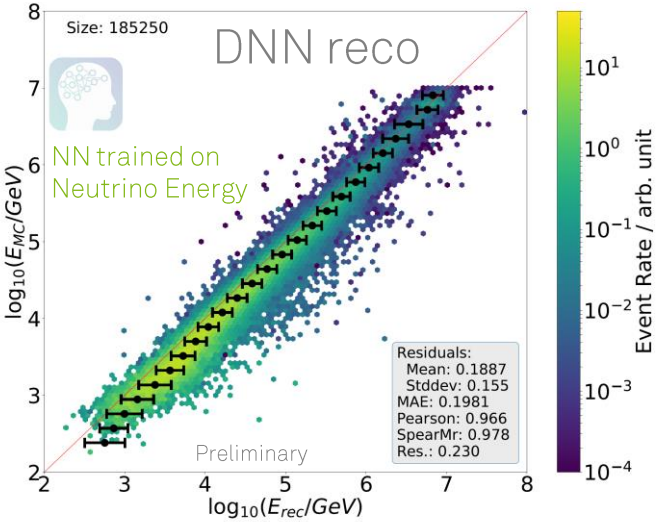


- Level 2 data: Final samples apply additional quality cuts
- Systematic uncertainties not included

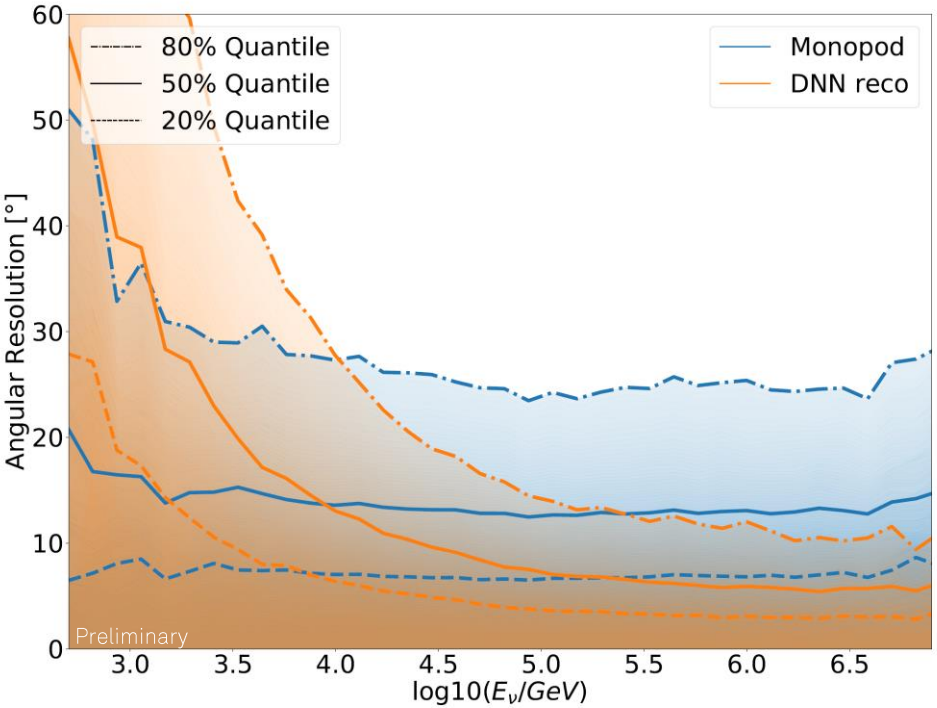
Current Status – Cascade Performance

Deposited Energy





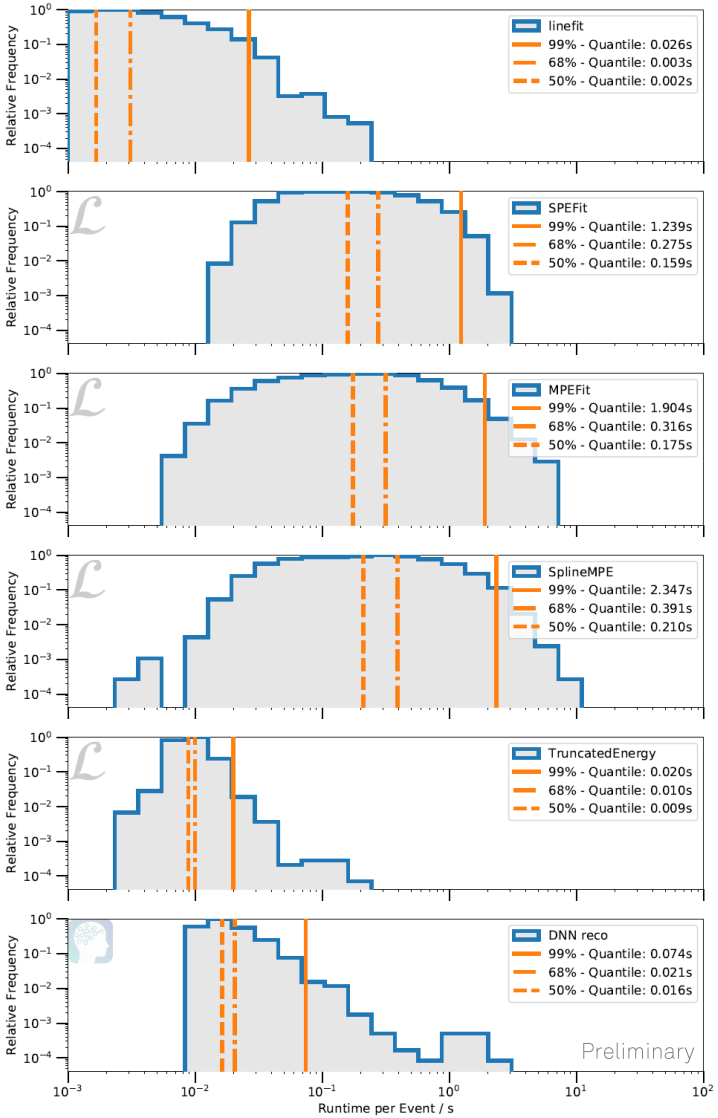
Cascade Angular Resolution



- Systematic uncertainties not included
- Final samples may apply additional quality cuts

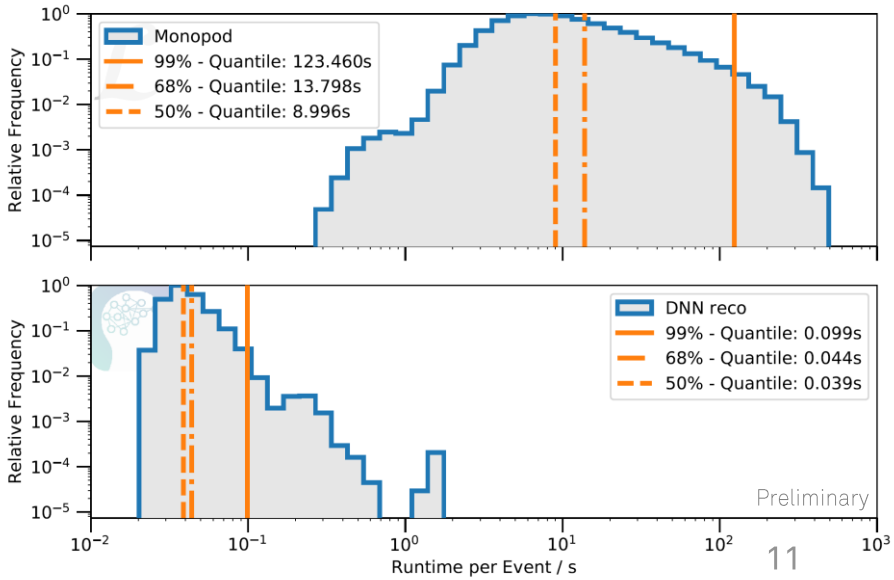
Current Status – Runtime

Track Reconstructions



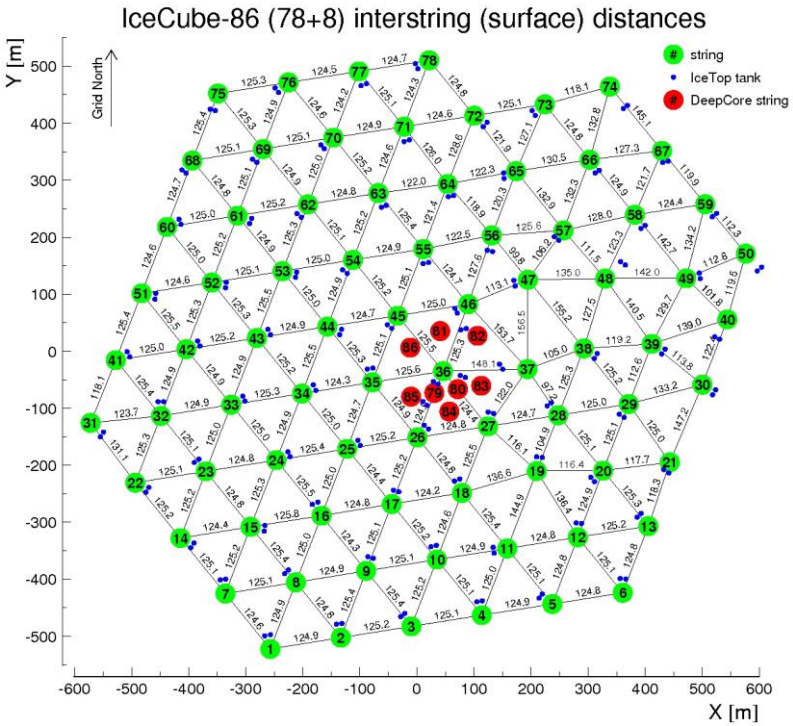
- Per event runtime for reconstruction
- More sophisticated reconstructions excluded in plots
- Smaller neural network architecture used for track reconstruction

Cascade Reconstructions



Limitations of Convolutional Neural Networks (CNNs)

- Only translational invariance and locality is used – More information and symmetries available
- Assumptions imposed by CNNs are only approximately met in IceCube
  - Irregularities in detector grid
  - No real translational invariance in observable space
- CNNs "wash out" data:
  - Great for robustness
  - Bad if exact information is needed

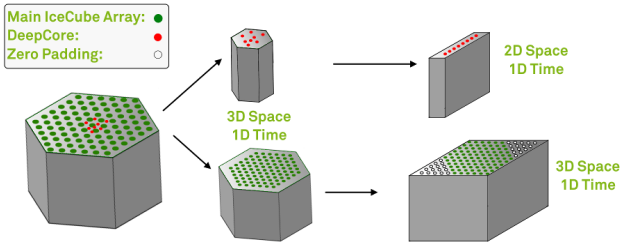


How can we improve?

Requirements for Next Generation

- Need for better suited network architectures:
  - Graph Neural Networks (GNNs) can help with irregularities in detector grid and uniformly handle IceCube + DeepCore
  - Combination of CNNs and recurrent neural networks can better handle time information
- Need to exploit more a priori knowledge:
  - Data generation process is known very well, but not exploited
  - Likelihood methods use this information

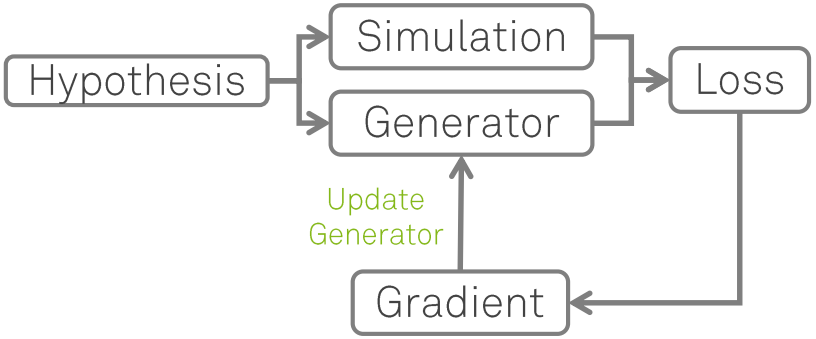
Can these approaches be combined?



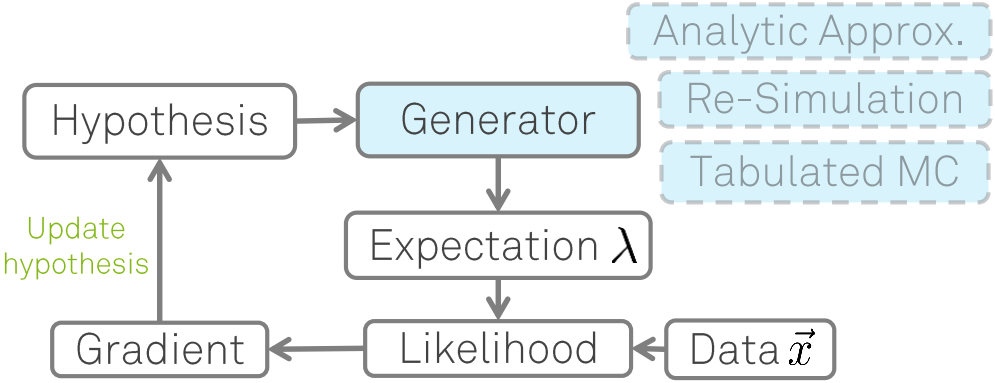
Cascade Generator – General Idea

- Combine strengths of neural networks and maximum-likelihood methods
- Generative network to obtain fast approximation of simulation
- Possible in between of spline-based reconstruction and direct re-simulation
- Once generator is trained, it can be used in reverse mode for reconstruction

Train Generator

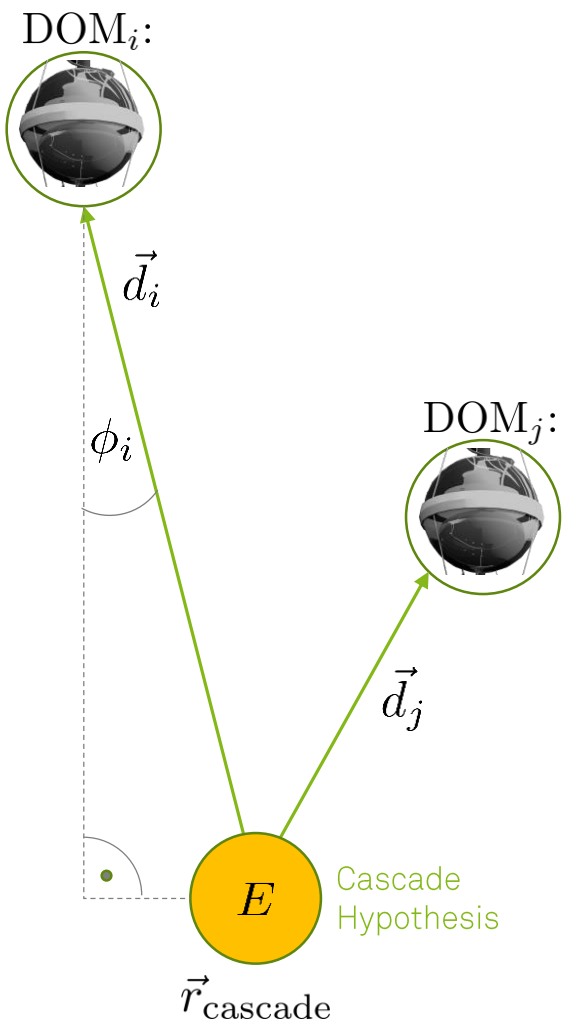


Reconstruct Events



Cascade Generator – Network Architecture

- No adversarial or randomness needed as usually required for Generative Adversarial Networks
- Knowledge of exact detector geometry is included
- Translational invariance in latent variable space is exploited as opposed to observable space
- Currently only trained to generate charge information



Input per DOM:

$\vec{d}, \phi, \ldots$ } Include geometry

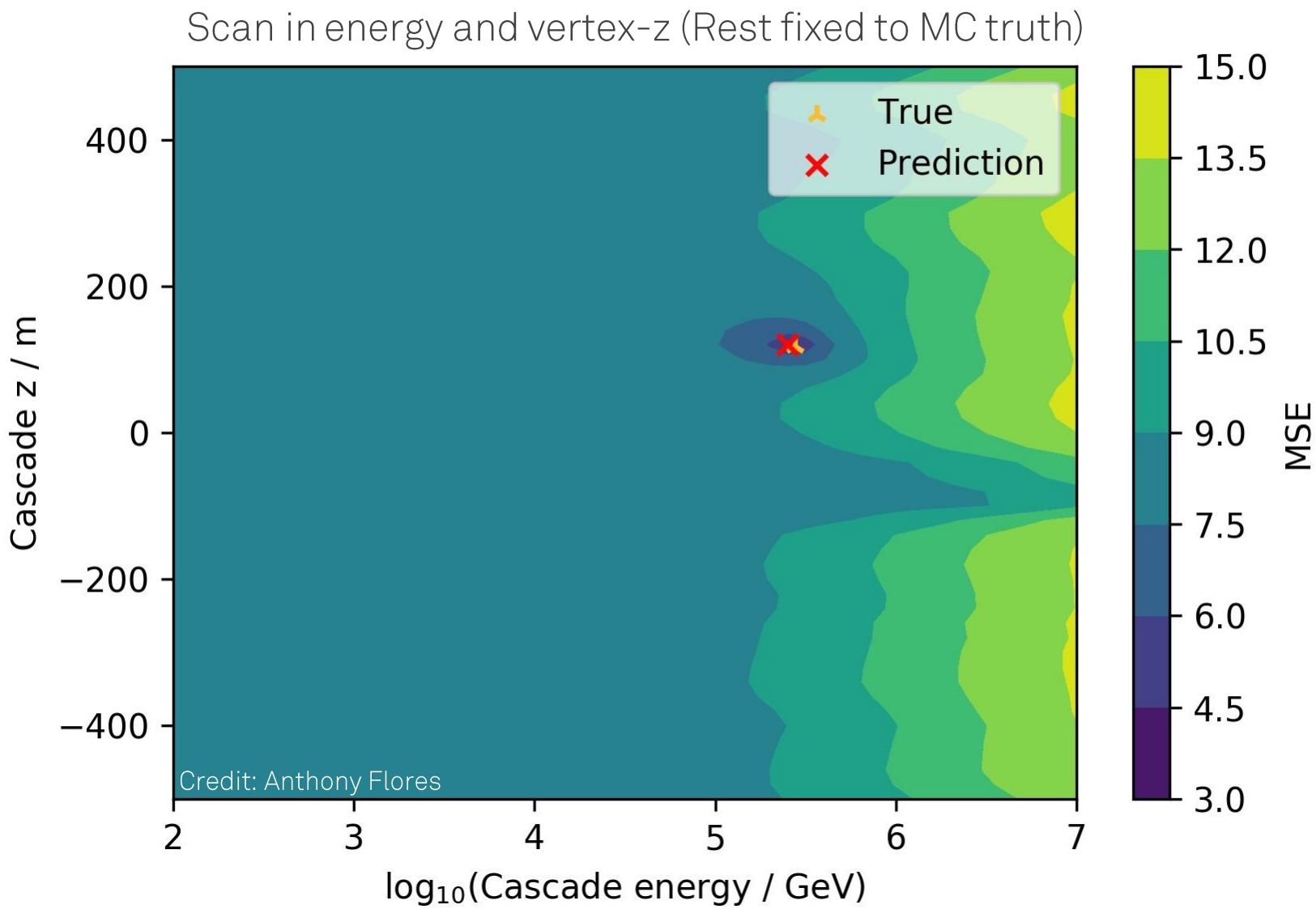
$\varphi_{\mathrm{cascade}}$
$\theta_{\mathrm{cascade}}$
$\vec{r}_{\mathrm{cascade}}$

Weight sharing over DOMs:
Exploit invariances in latent variable space

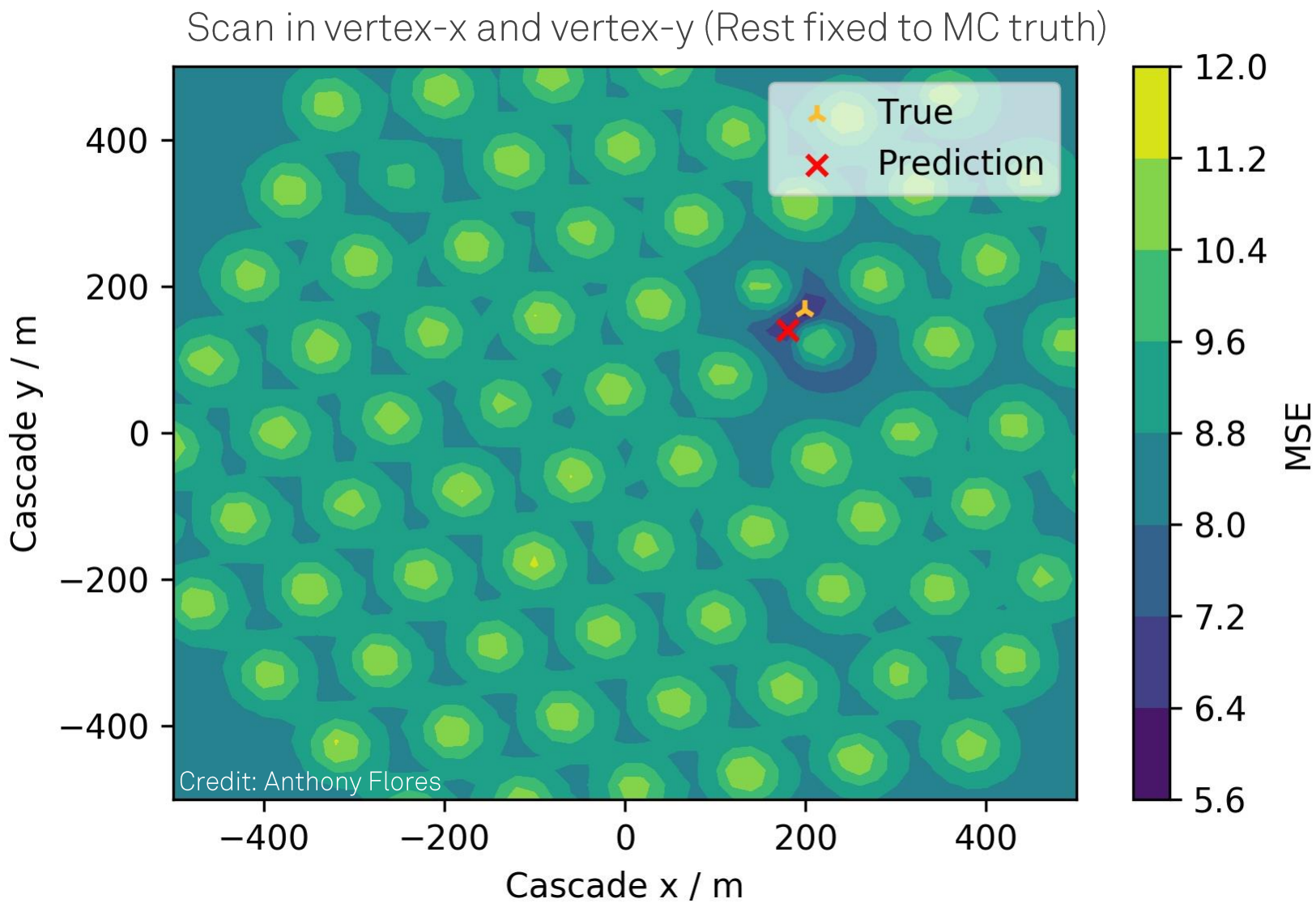
$E, \ldots$

Additional independent weights per DOM:
Account for asymmetries and inhomogeneities

Cascade Generator – Scans



Cascade Generator – Scans



Summary & Outlook

- Conventional neural network architectures provide good results and are well suited for online applications, but have limitations
- Need to adjust methods to fit to our data, not the other way around
- First Cascade Generator results look promising
- Next: create dedicated MC for training, include time information

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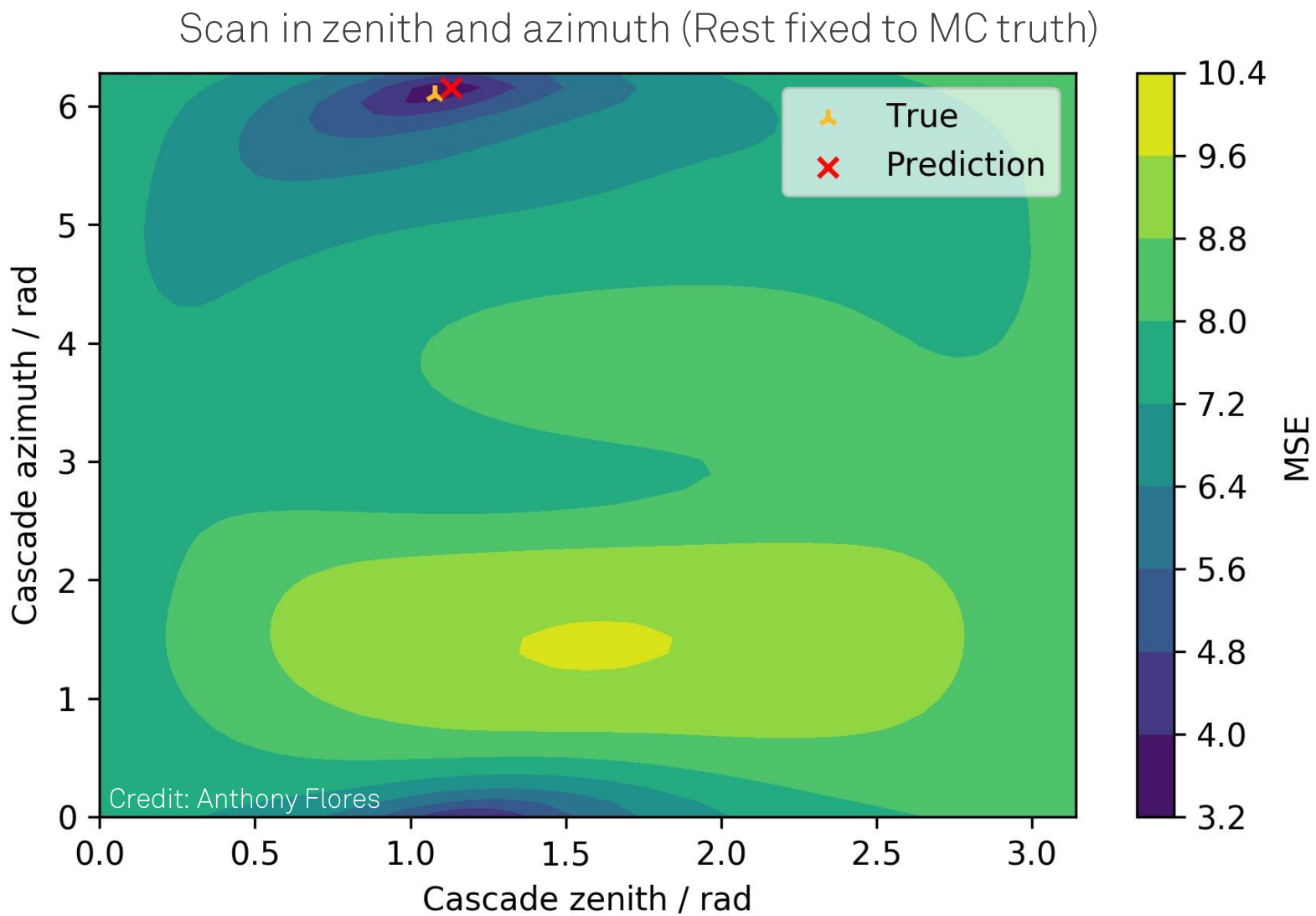
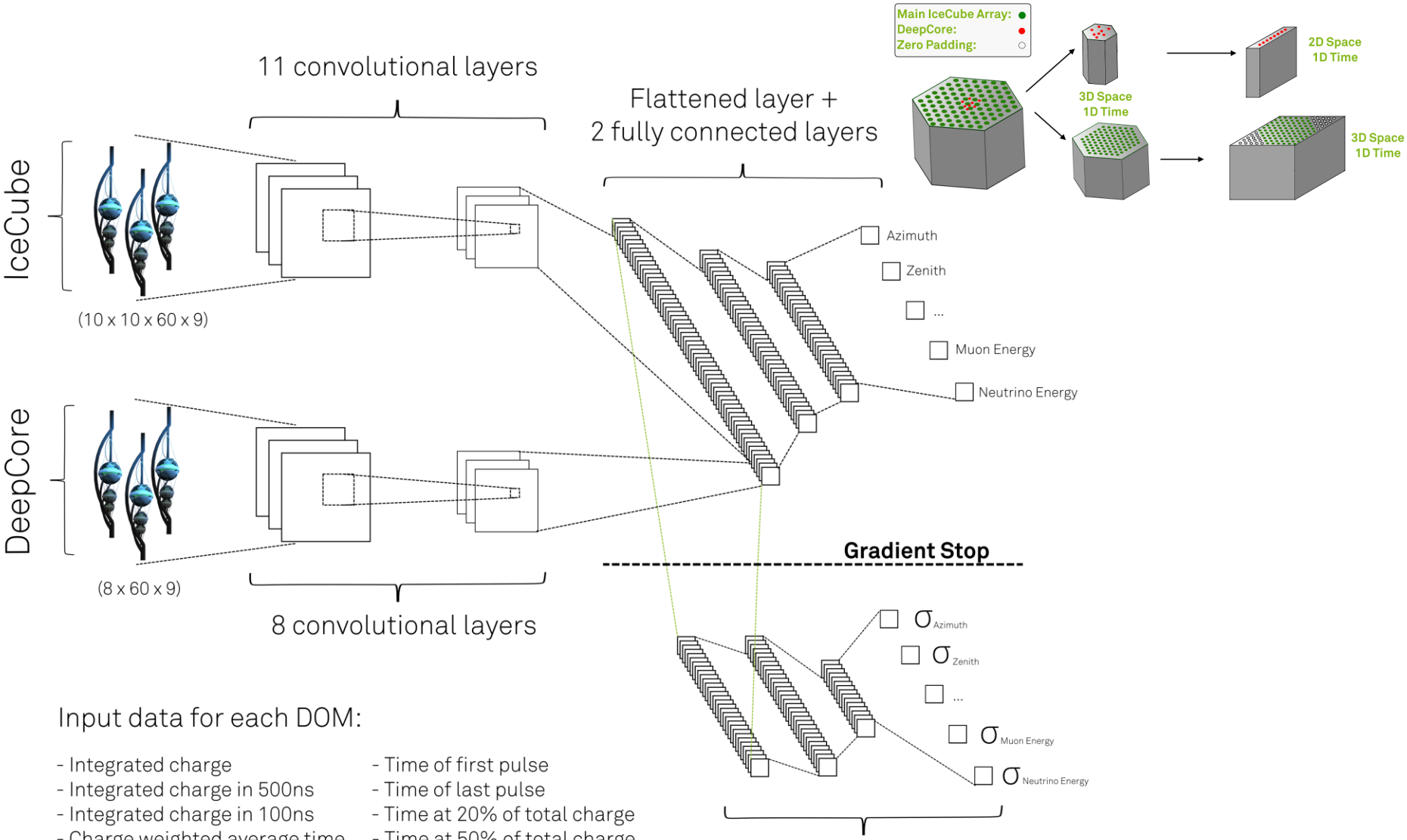
Backup

Cascade Generator – Scans



Network Architecture



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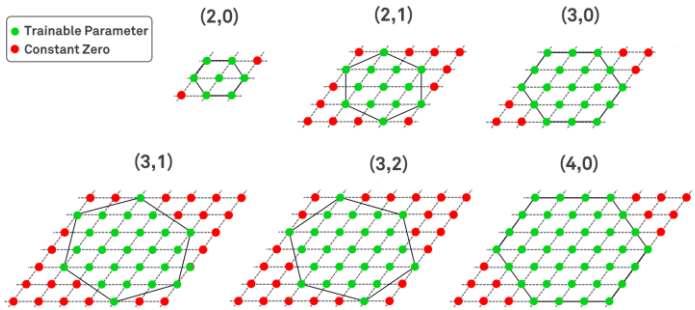
Network Architecture

- Residual additions: $$\text{output} = \text{input} + \underbrace{f(\text{input})}_{\text{residual}}$$

  DOI: 10.1109/CVPR.2016.90

- Hexagonally shaped convolution kernels

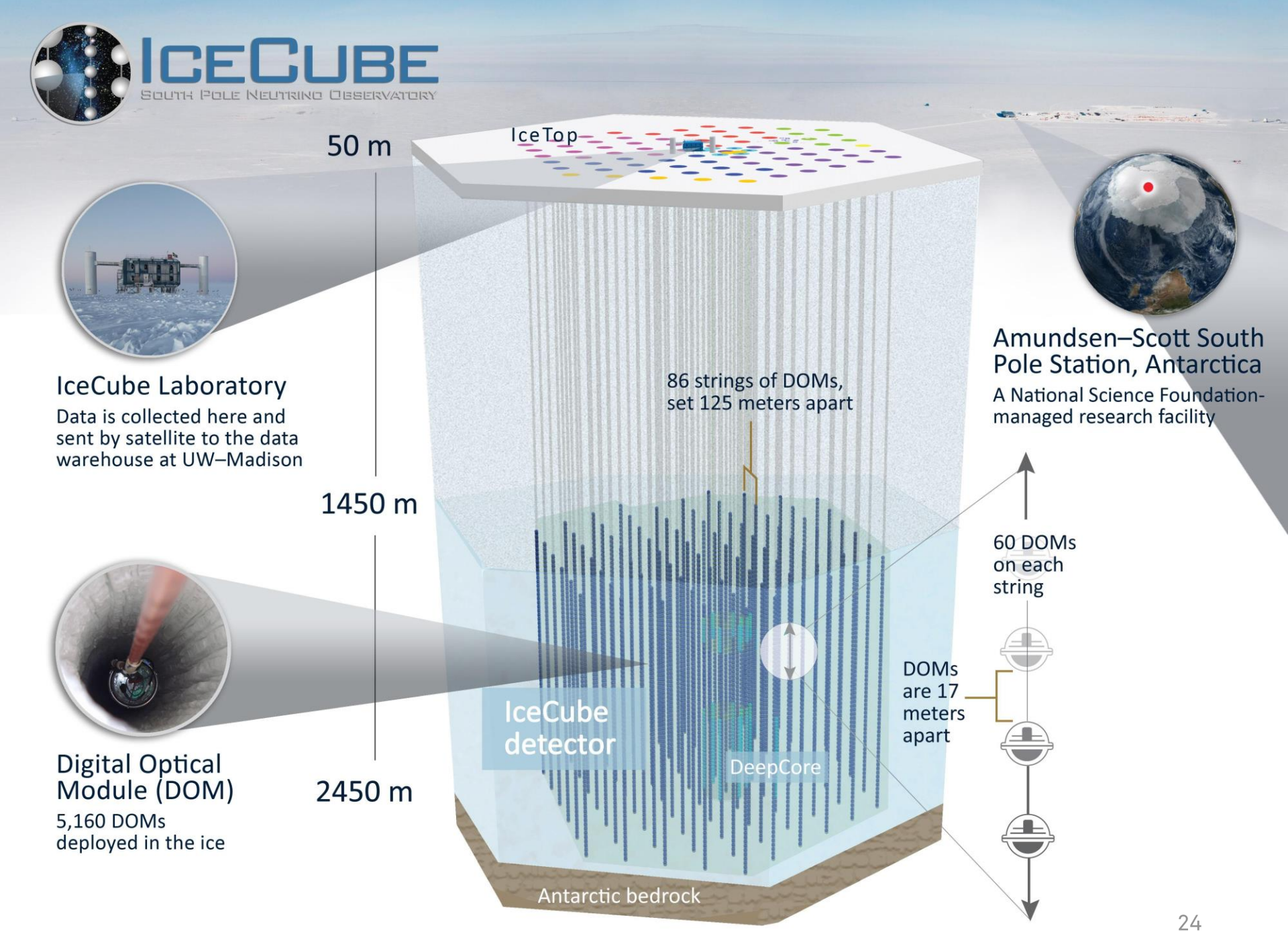


- Normalization of input and labels to mean 0 and variance 1

- Variance control in layers
  - Assuming input into a layer is normalized:

    Ensure that output is normalized as well
  - At initialization: random output is as good as predicting based on the label distribution

- Multilabel loss function
  - Adaptive factors for each label according to predefined importance
  - Ensures that labels are learnt at same speed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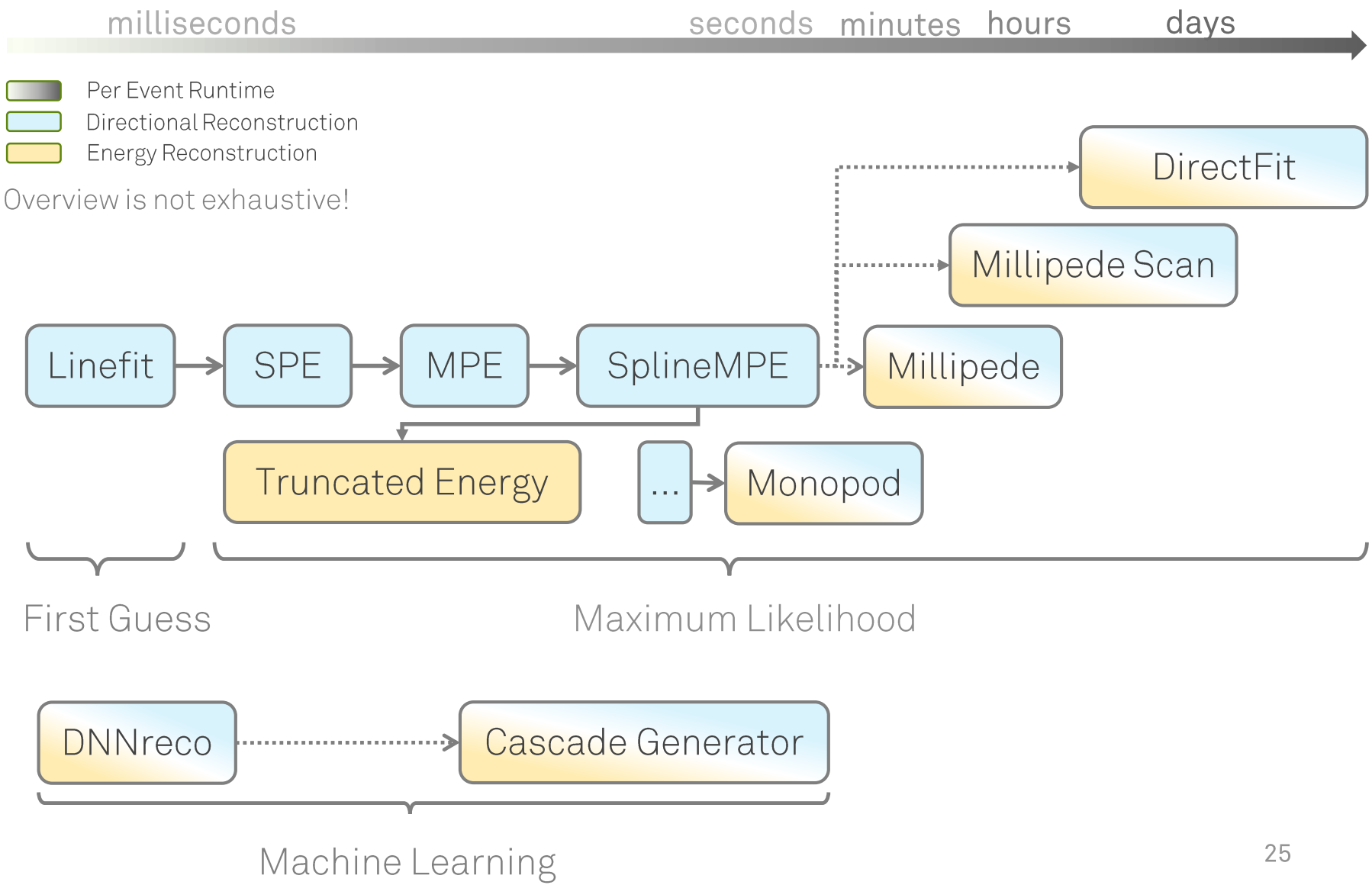
SOUTH POLE NEUTRINO OBSERVATORY
50 m
IceTop
IceCube Laboratory
Data is collected here and sent by satellite to the data warehouse at UW–Madison
Amundsen–Scott South Pole Station, Antarctica
A National Science Foundation-managed research facility
86 strings of DOMs, set 125 meters apart
1450 m
60 DOMs on each string
DOMs are 17 meters apart
IceCube detector
DeepCore
Digital Optical Module (DOM)
5,160 DOMs deployed in the ice
2450 m
Antarctic bedrock

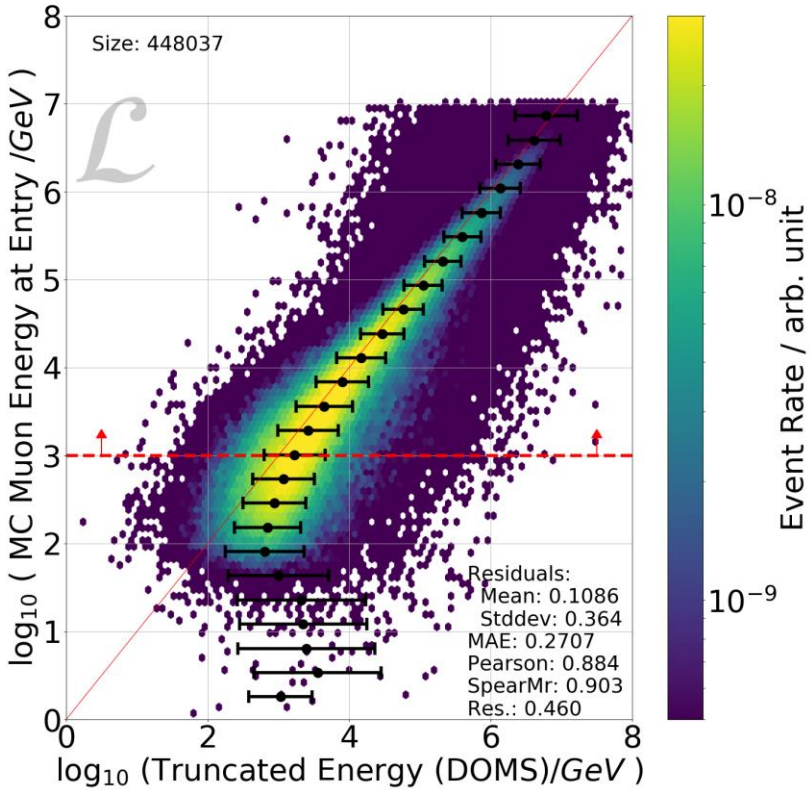
Overview of Reconstruction Methods



Energy Reconstruction – Muon Energy at Entry

OnlineL2 Muon Filter – CC events

Truncated Energy (DOMS)



Deep Learning