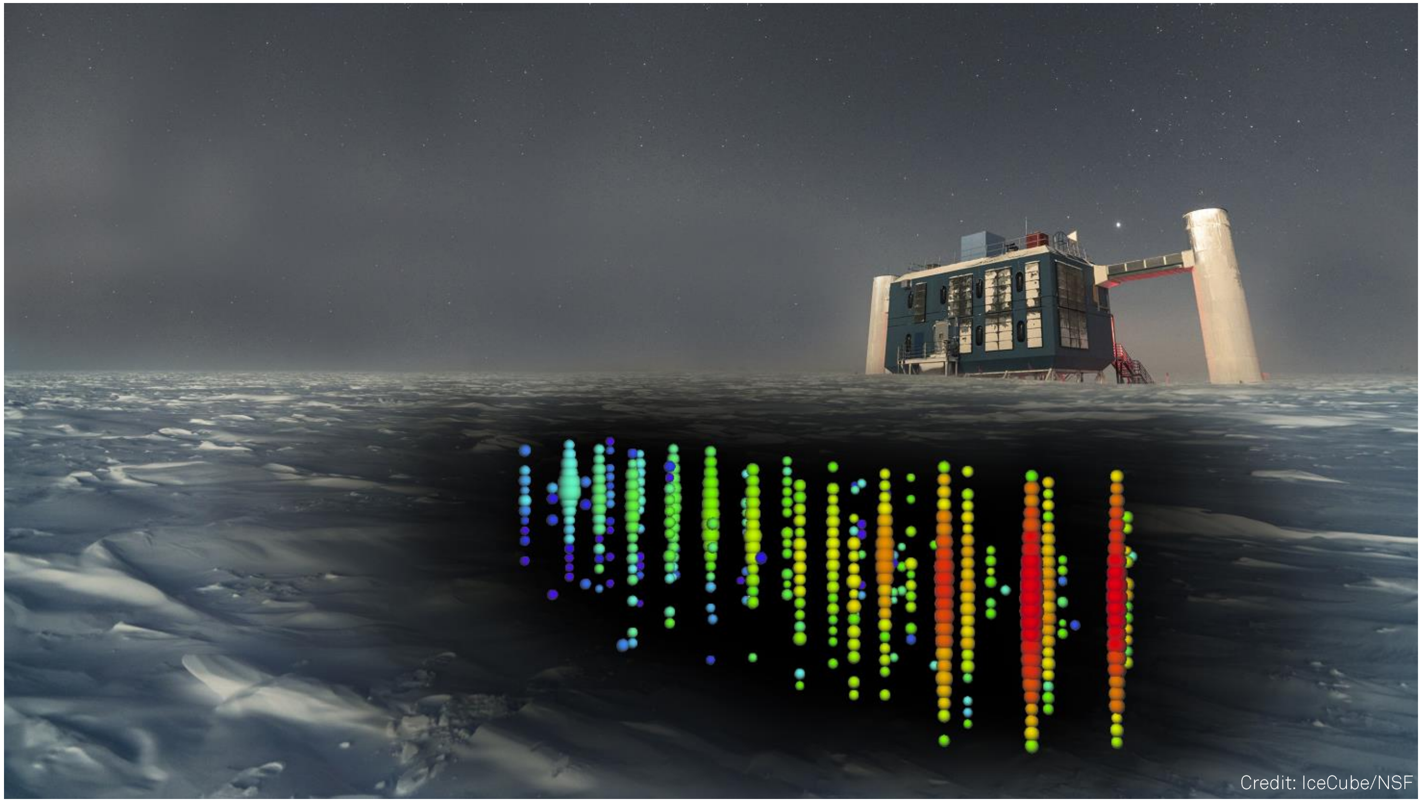
technische universität dortmund

ICECUBE SOUTH POLE NEUTRINO OBSERVATORY

SFB 876 Providing Information by Resource-Constrained Data Analysis

lehrstuhl physik e5



Event Reconstruction Methods in IceCube

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TMEX 2018

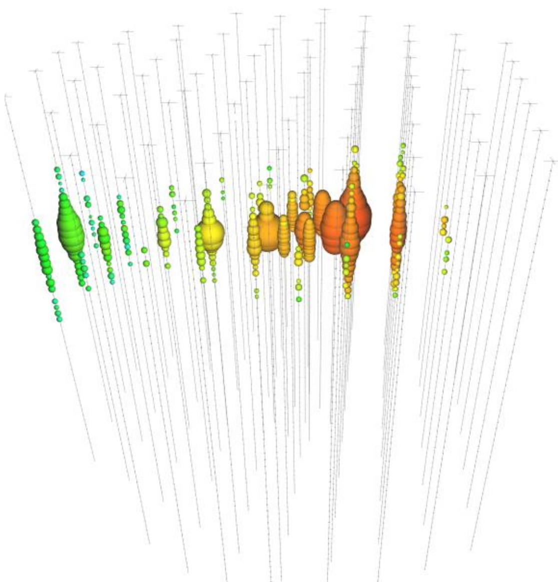
Warsaw – September 19th, 2018

*http://icecube.wisc.edu

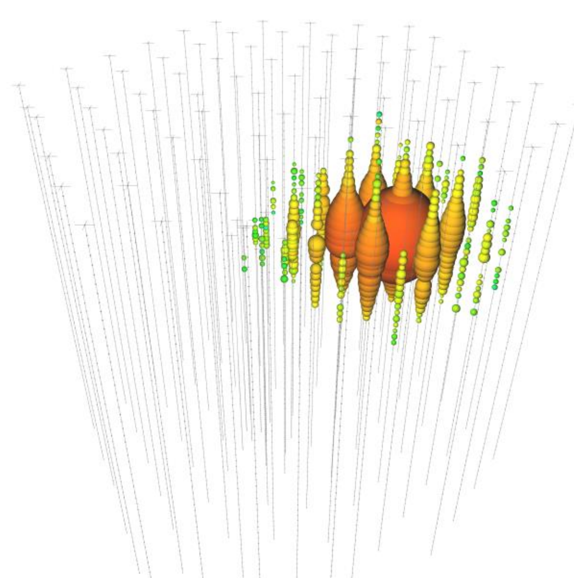
IceCube Data

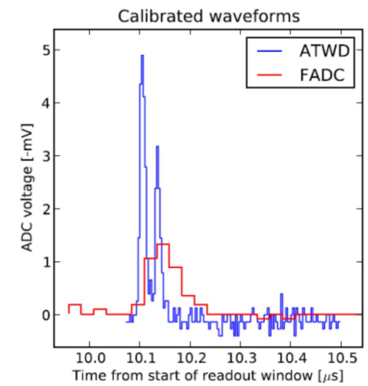
- Indirect detection of neutrinos via Cherenkov light induced by charged secondary particles
- Digital Optical Modules (DOMs) measure waveforms from which pulses are extracted [1]
- Two major event topologies:

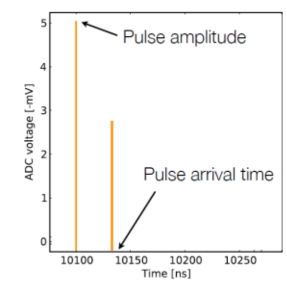
Tracks

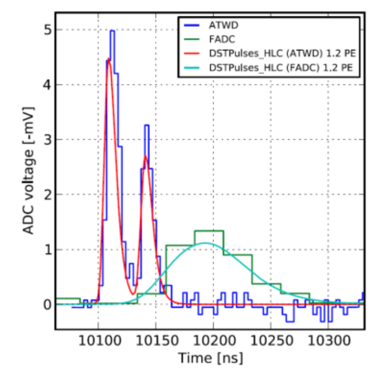


Cascades

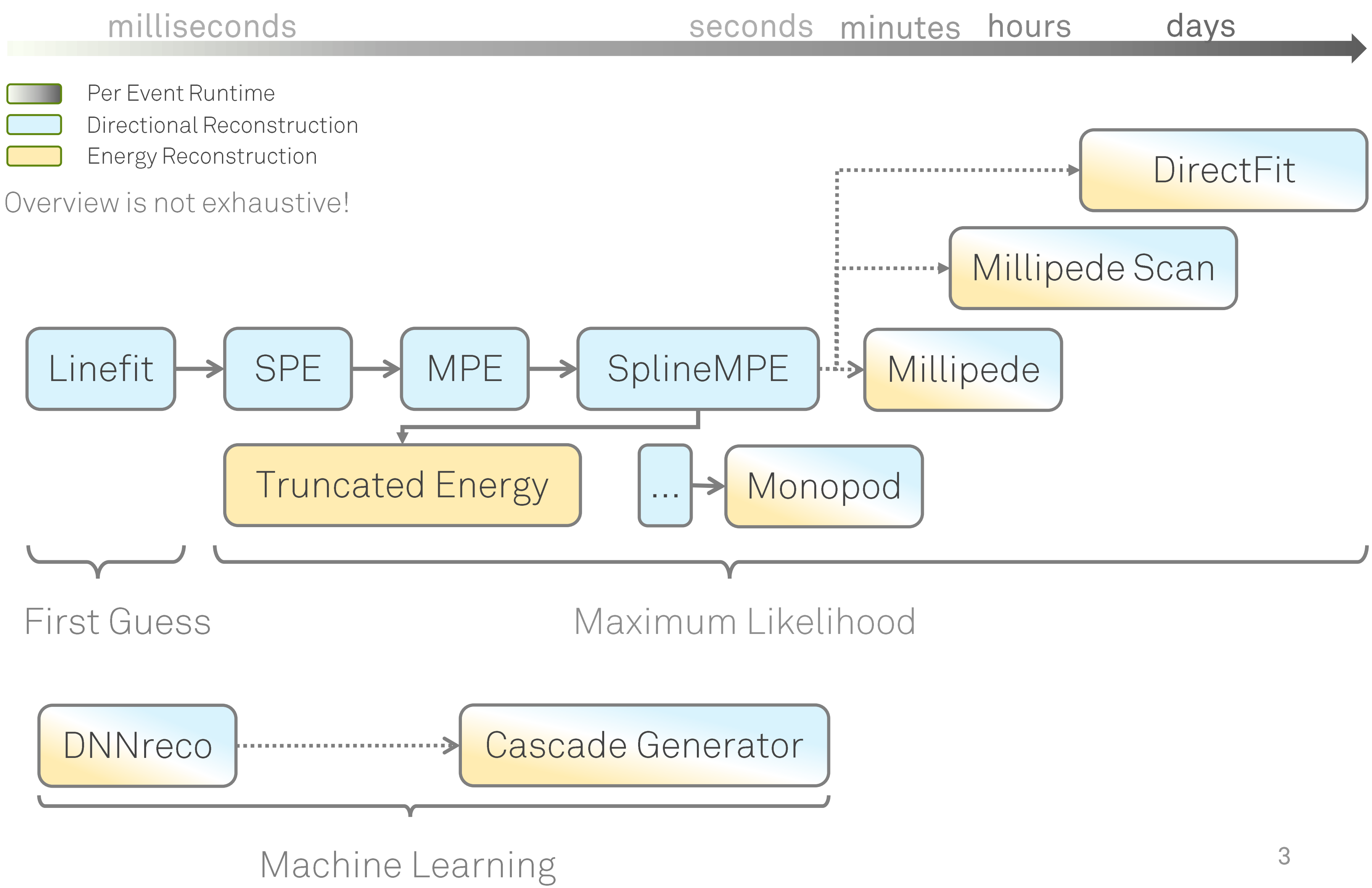








Overview of Reconstruction Methods



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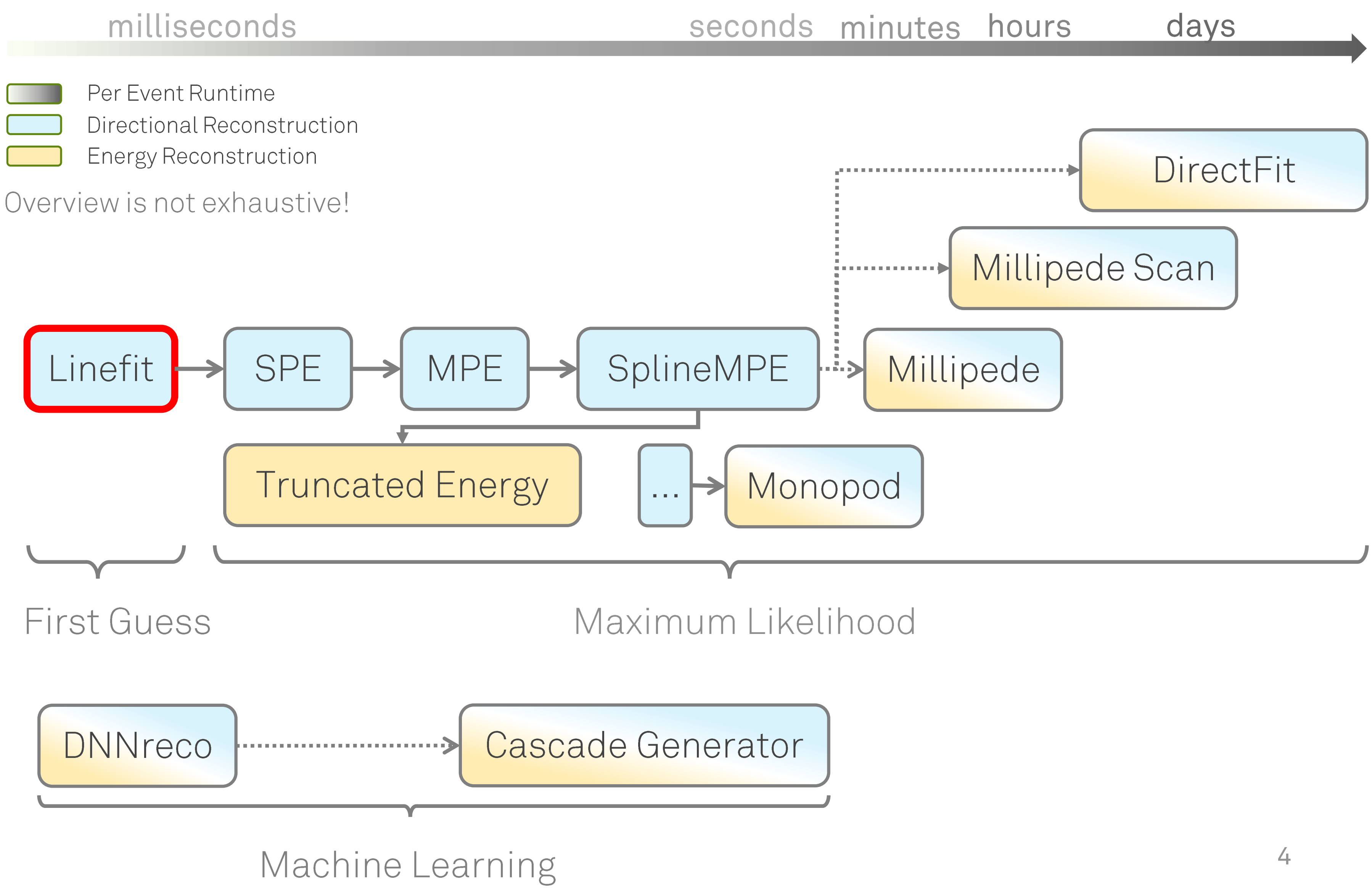


Track Reconstruction – Linefit

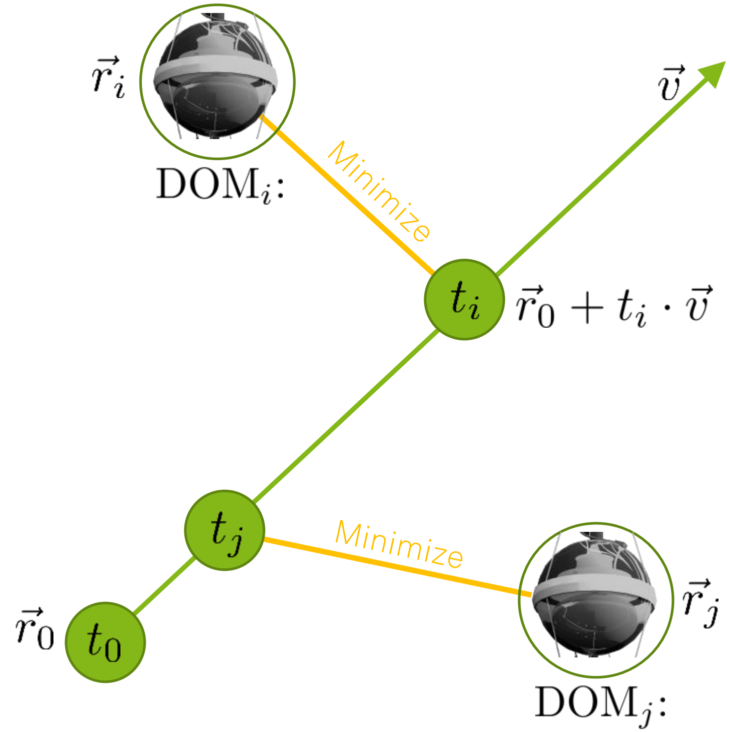
- First guess algorithm
- Fits plane wave of light moving at velocity $\vec{v}$
- Effect of outliers is reducd through hit cleaning and robust loss measure (Huber)
- Fast seed for maximum likelihood methods

$$\chi^2 = \sum_{i=1}^{N_{\mathrm{DOMs}}} (\vec{r}_0 + \vec{v}t_i - \vec{r}_i)^2$$

- Minimizing with respect to $\vec{v}$ and $\vec{r}_0$ yields:

$$\vec{r}_0 = \langle \vec{r}_i \rangle - \vec{v}\langle t_i \rangle$$

$$\vec{v} = \frac{\langle \vec{r}_i t_i - \langle \vec{r}_i \rangle \langle t_i \rangle \rangle}{\langle t_i^2 \rangle - \langle t_i \rangle^2}$$



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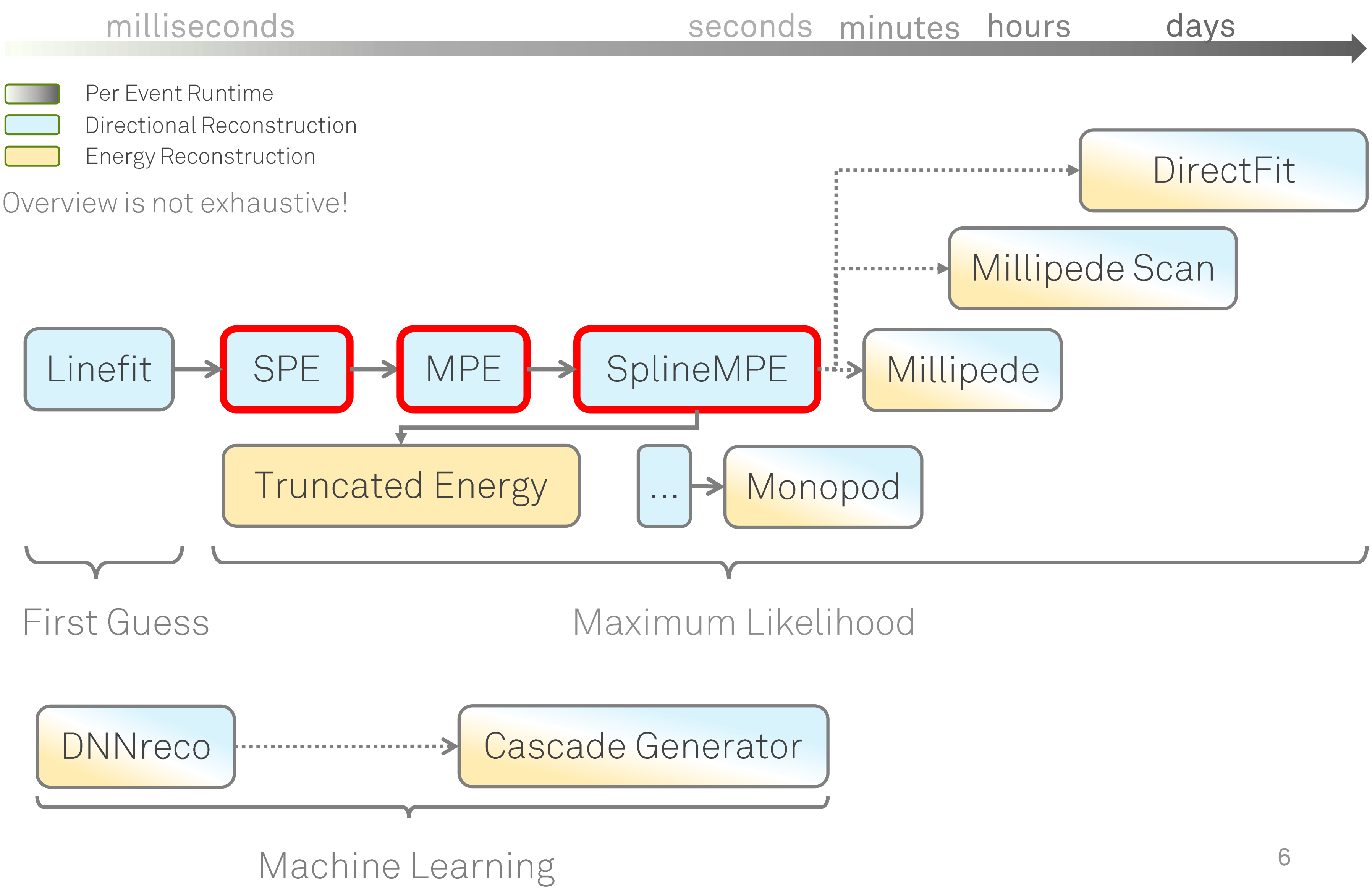


Track Reconstruction – SPE and MPE Likelihood

- Likelihood of measured hits for a given track hypothesis:

$$\mathcal{L}(\vec{x}|\vec{\theta}) = \prod_i p(x_i|\vec{\theta})$$

$$\begin{aligned} p(x_i|\vec{\theta}) &: \ \text{PDF} \\ \vec{\theta} &: \ \text{Track Hypothesis} \\ \vec{x} &: \ \text{Measured Hits} \end{aligned}$$

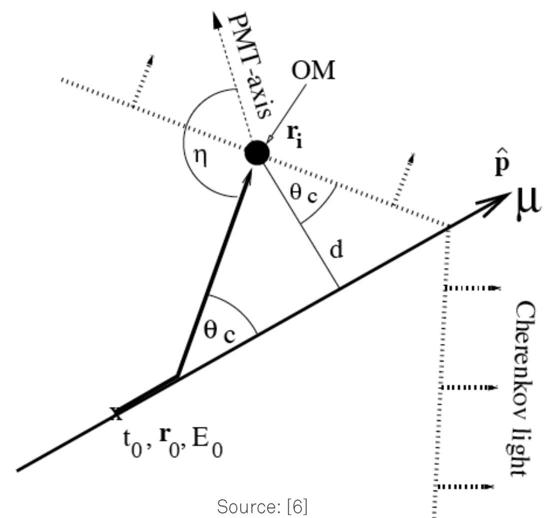
- Convenient to base PDF on time delay caused by scattering :

$$p(t_{\text{res},i}|\vec{\theta})$$

$$t_{\text{res}} = t_{\text{hit}} - t_{\text{geo}}$$

$$\begin{aligned} t_{\text{geo}} &: \ \text{Time of unscattered light} \\ t_{\text{hit}} &: \ \text{Time of measured hit} \end{aligned}$$

$$t_{\text{geo}} = t_0 + \frac{|\vec{p} \cdot (\vec{r}_i - \vec{r}_0)| + d \cdot \tan \Theta_C}{c_{\text{vac}}}$$

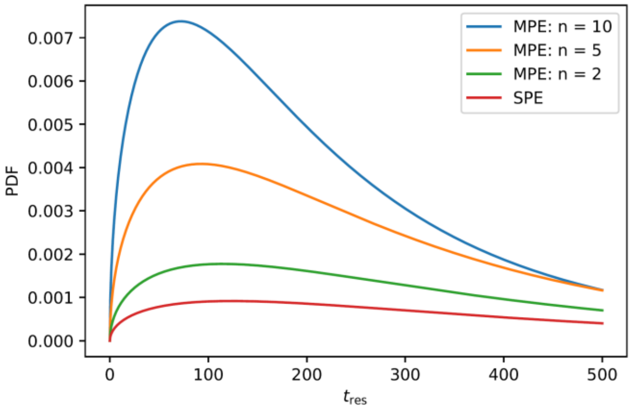


Source: [6]

Track Reconstruction – SPE and MPE Likelihood

- Single-Photo-Electron (SPE) Likelihood:

$$\mathcal{L}_{\mathrm{SPE}}\left(\vec{x}|\vec{\theta}\right) = \prod_{i}^{\text{1st hits}} p\left(t_{\mathrm{res},i}|\vec{\theta}\right)$$



- Multi-Photo-Electron (MPE) Likelihood:

$$\mathcal{L}_{\mathrm{MPE}}\left(\vec{x}|\vec{\theta}\right) = \prod_{i}^{\text{1st hits}} n_i \cdot p\left(t_{\mathrm{res},i}|\vec{\theta}\right) \cdot \left(1 - P\left(t_{\mathrm{res},i}|\vec{\theta}\right)\right)^{n_i - 1}$$

$$P(t_{\mathrm{res},i}|\vec{\theta}) = \int_{-\infty}^{t_{\mathrm{res}}} p(t|\vec{\theta})\mathrm{d}t$$

- Multiple ways to obtain PDF $p(t_{\mathrm{res}}|\vec{\theta})$:
  - Analytic approximation (Pandel Function)
  - Splines fitted to tabulated MC simulation
  - Direct re-simulation (DirectFit)

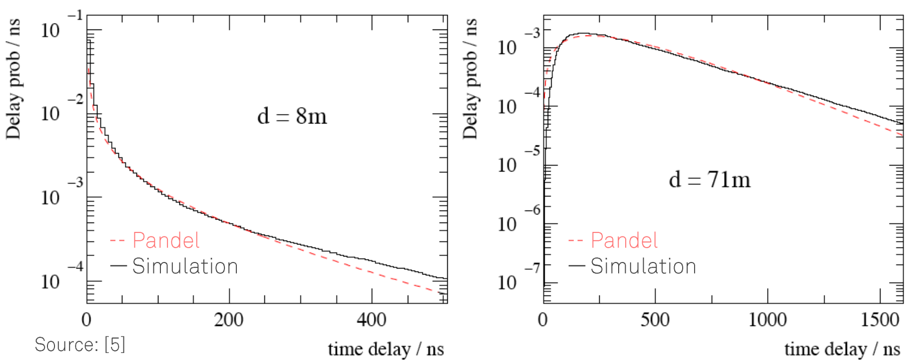
SPE and MPE Likelihood – Pandel Function

- PDF for photon arrival times approximated through Pandel function given by: [3]

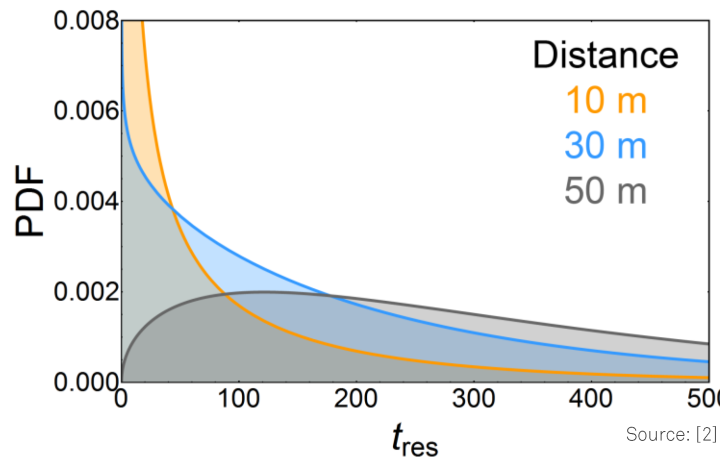
$$p(t_{\mathrm{res}}|\vec{\theta}) = \frac{1}{N(d)} \frac{\tau^{-(d/\lambda)} \cdot t_{\mathrm{res}}^{(d/\lambda-1)}}{\Gamma(d/\lambda)} \cdot \exp\left(-t_{\mathrm{res}} \cdot \left(\frac{1}{\tau} + \frac{c_{\mathrm{medium}}}{\lambda_a}\right) - \frac{d}{\lambda_a}\right)$$

$$N(d) = e^{-d/\lambda_a} \cdot \left(1 + \frac{\tau \cdot c_{\mathrm{medium}}}{\lambda_a}\right)^{-d/\lambda}$$

$$\lambda = 33.3\,\mathrm{m}$$
$$\lambda_a = 98\,\mathrm{m}$$
$$\tau = 557\,\mathrm{ns}$$



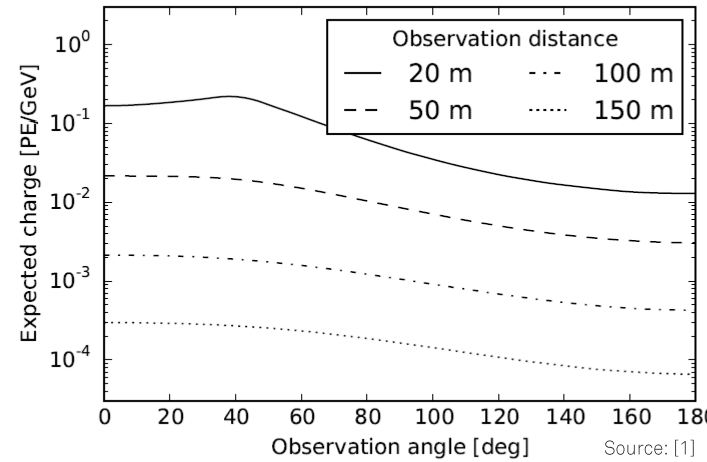
Source: [5]

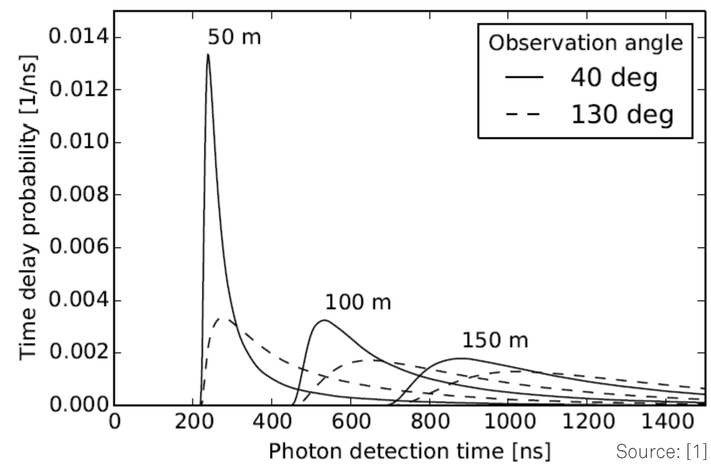


Source: [2]

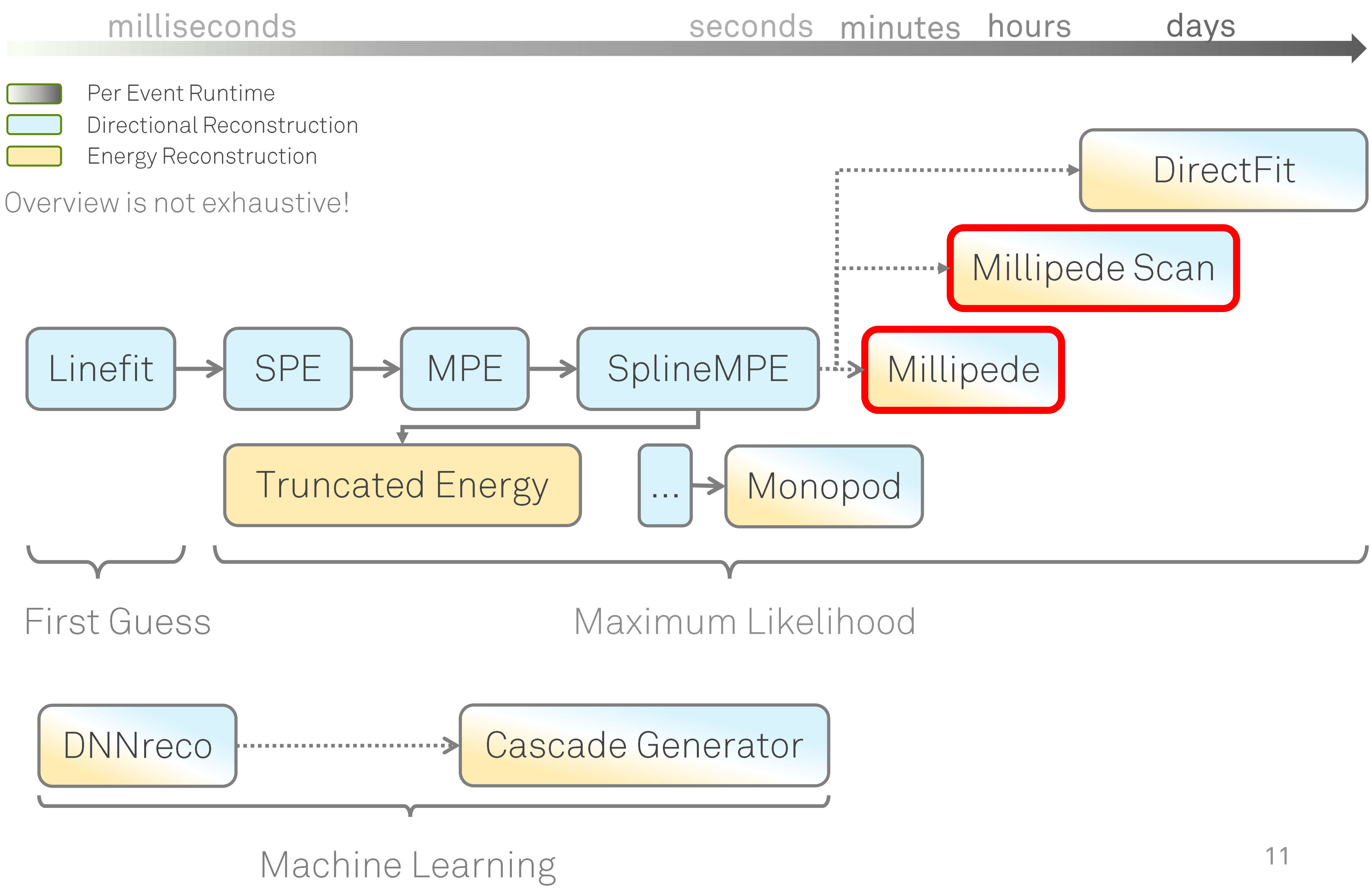
SPE and MPE Likelihood – Splines

- Multi-dimensional spline surface [4] fit to Monte Carlo simulations
- Parameters:
  - Depth and zenith angle of source
  - Displacement vector from source to receiver
  - Difference between the time of light detection and production
- Tables approximately 1GB in size
- Evaluation time for source-receiver configuration: ~1 μs





Overview of Reconstruction Methods



Track Reconstruction – Millipede

- Segmented track hypothesis
- Poisson likelihood:

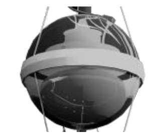
$$\mathcal{L} = \prod_{j}^{\text{DOMs}} \frac{\lambda_j^{k_j}}{k_j!} \cdot e^{-\lambda_j}$$

- First order solution:

$$\vec{k} - \vec{v} = \mathbf{\Lambda} \cdot \vec{E}$$

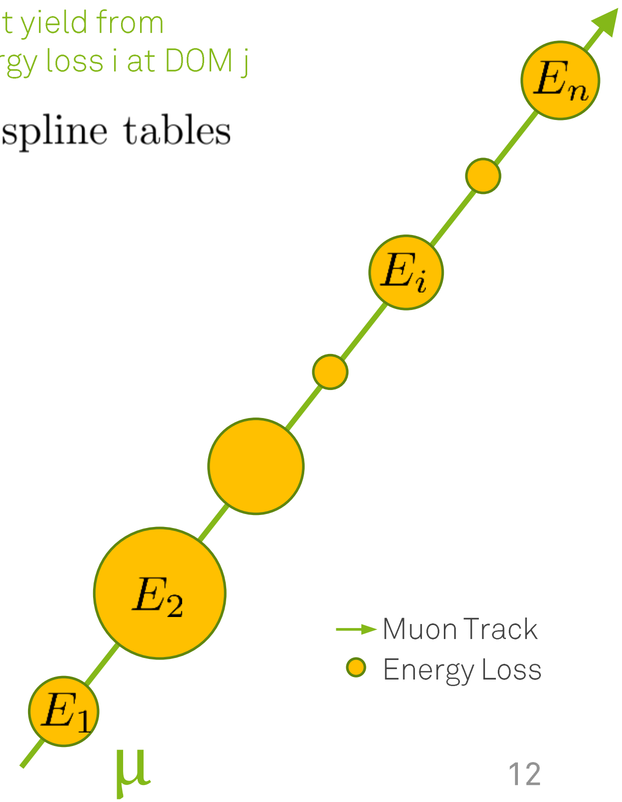
- Non-negative least squares algorithm
- Regularisation terms:
    - Favor small energy losses
    - Penalize variability
- Timing can be included

Expectation at DOM$_j$:



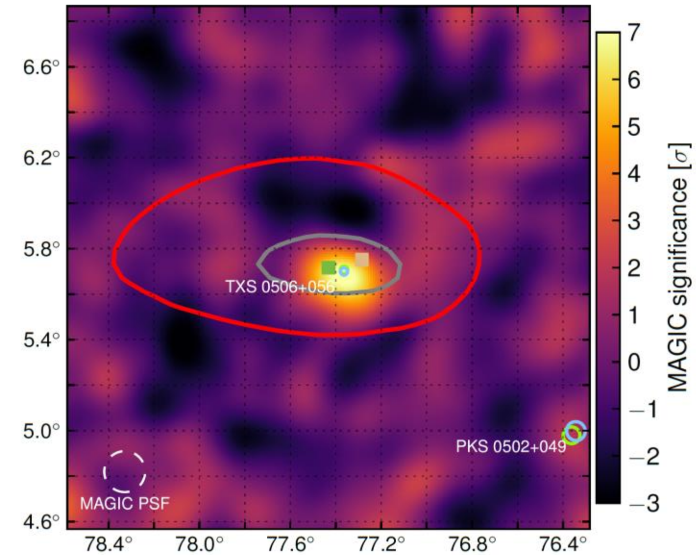
$$\lambda_j = \sum_{i=1}^{n} \underbrace{(E_i \cdot \Lambda_{i,j})}_{\text{Light yield from energy loss i at DOM j}} + \overbrace{v}^{\text{Noise}} = \vec{E} \cdot \vec{\Lambda}_j + v$$

$\Lambda_{i,j}$ from spline tables

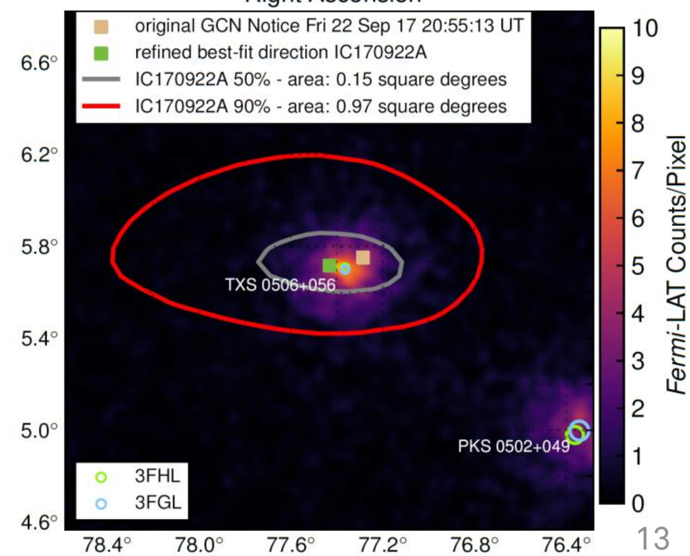


Track Reconstruction – Millipede Scans

- Online reconstruction: up to SplineMPE
- Alert is sent out if event passes online EHE/HESE event selection
- Millipede scans performed offline once event is sent over via satellite
- Runtime: several hours
- Scan in azimuth and zenith angle:
  - First coarse, then finer bins
  - Fit vertex, time, and energy depositions at each grid point



Source: [9]



Source: [9]

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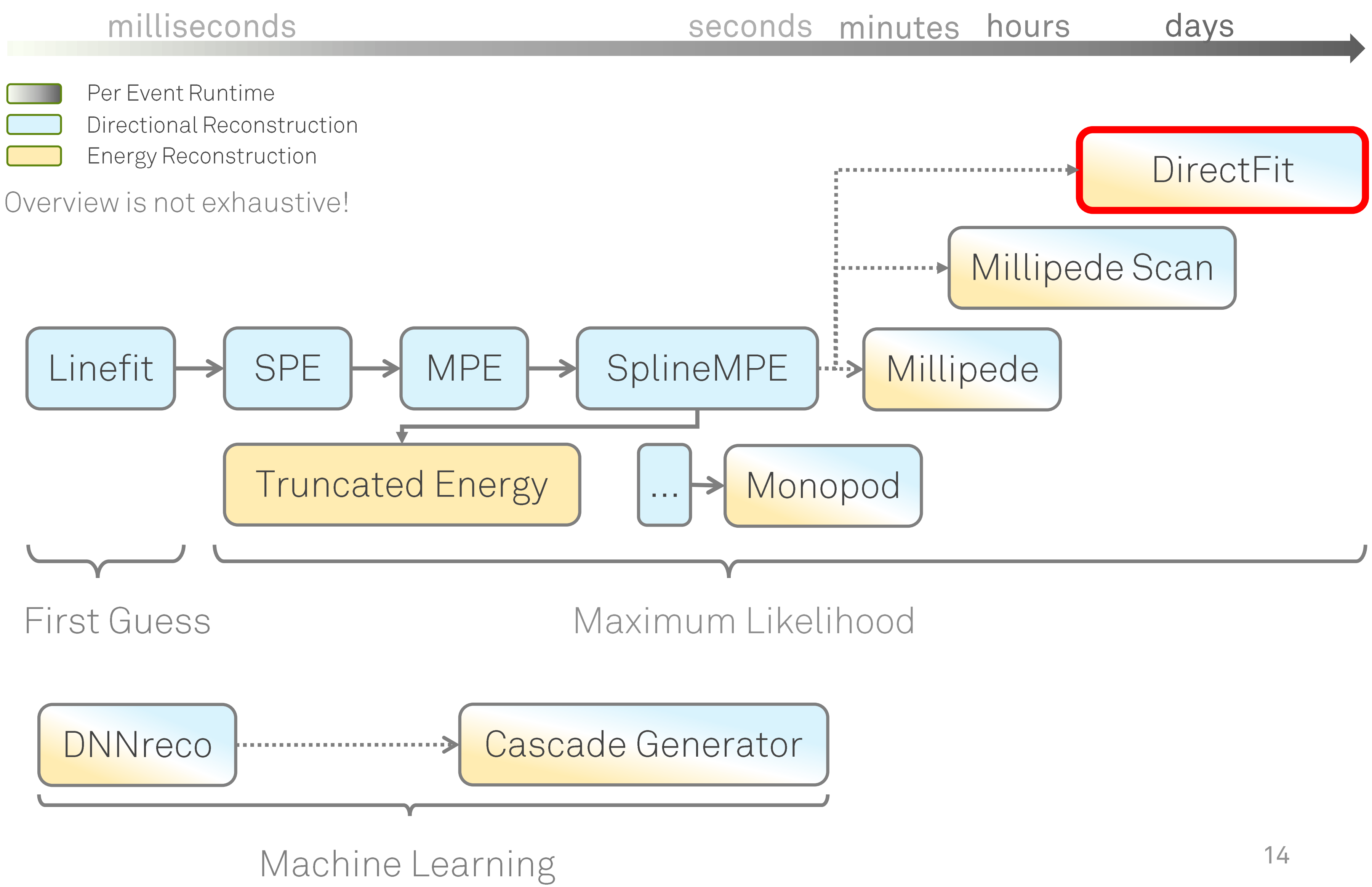
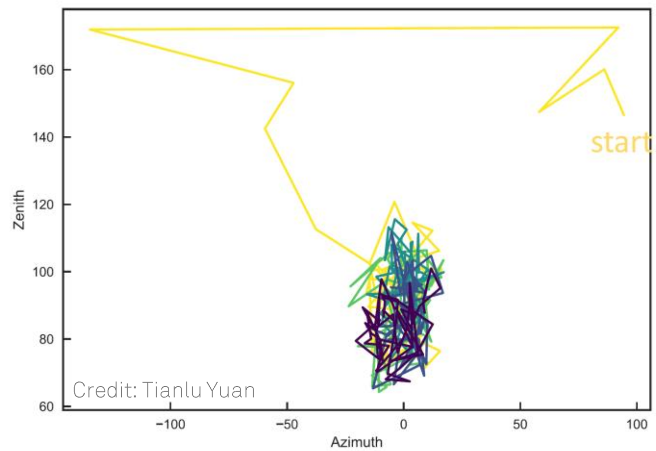
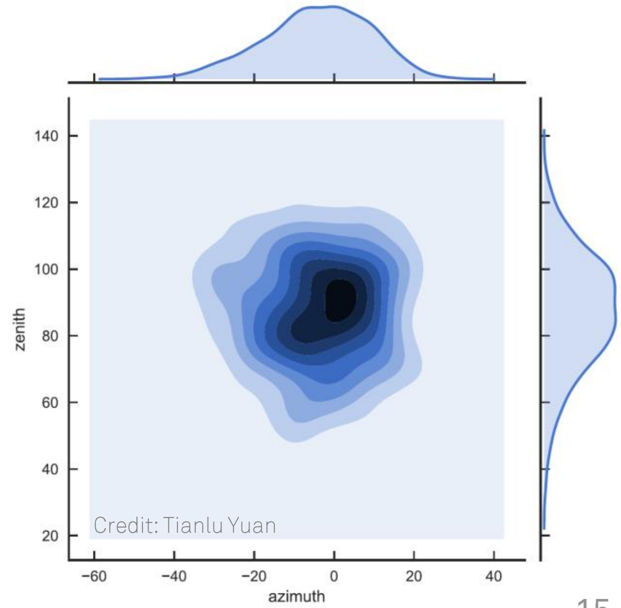


DirectFit

- Direct re-simulation of event hypothesis to obtain PDF $p(t_{\mathrm{res}}|\vec{\theta})$ rather than using Pandel function or spline tables
- Any event hypothesis possible
- Modified poisson likelihood: accounts for limited statistics and model error [7]
- No gradient available: use localized random search to find best fit
- Runtime: hours to days per event
- More information in DirectFit paper [8]: arXiv: 1309.7010





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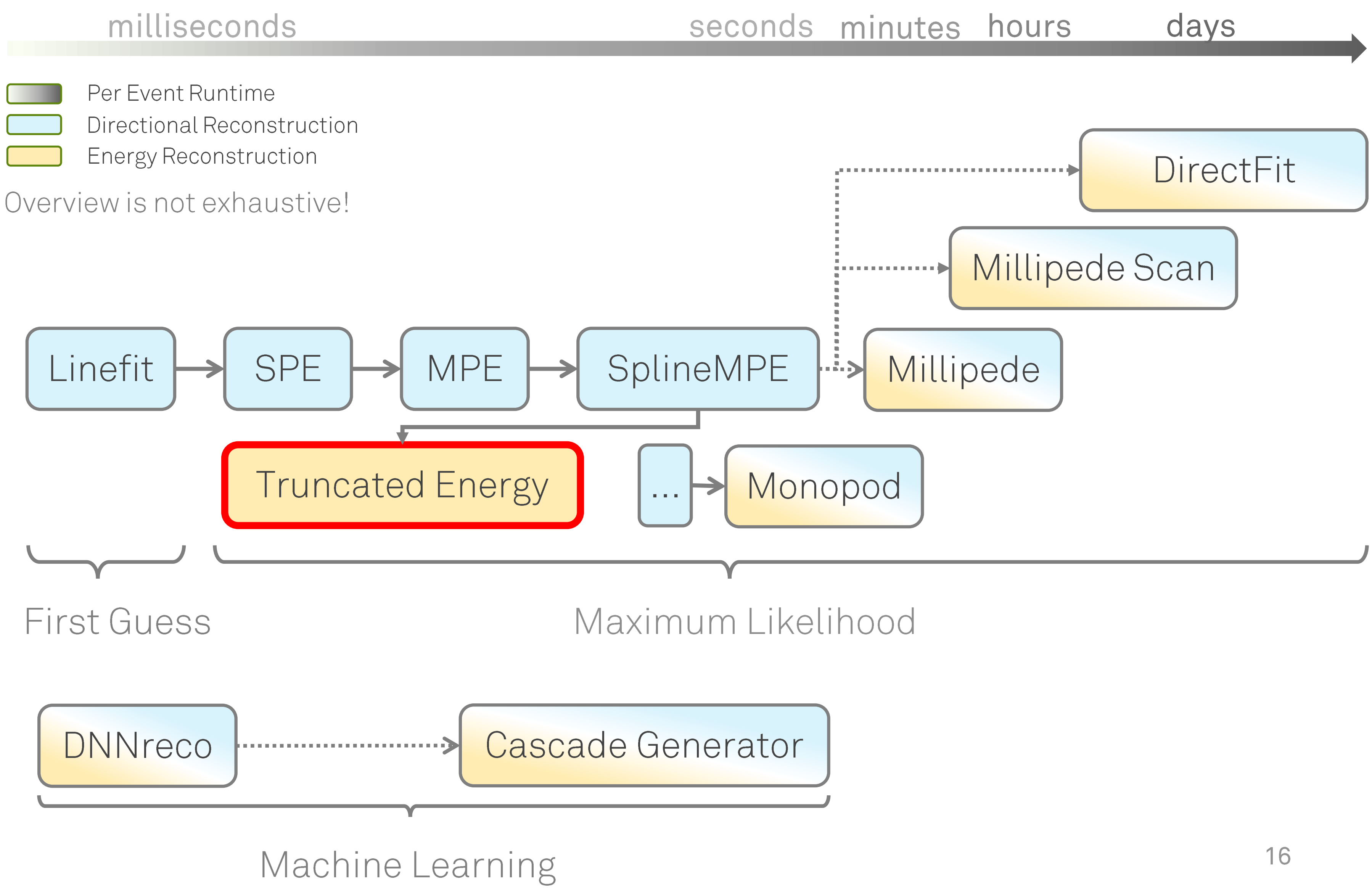
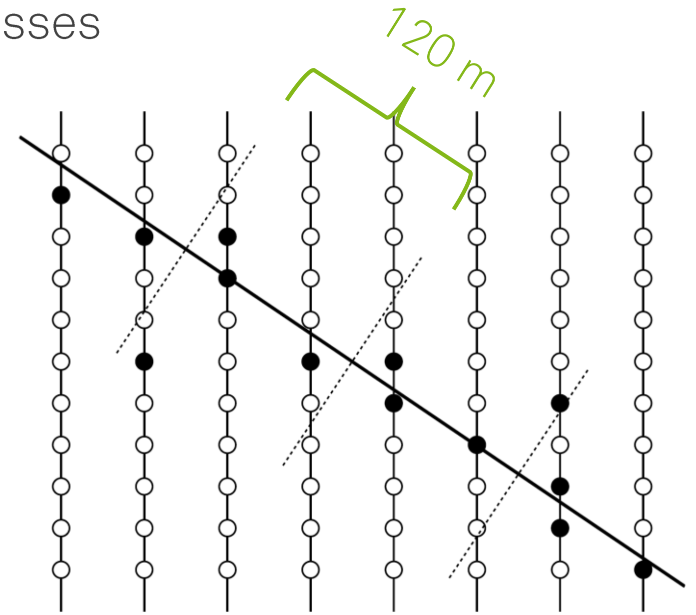


Muon Energy Reconstruction

- Fitting averaged muon template causes bias and poor resolution due to high stochasticity of energy losses
- Segmented reconstruction needed
- Above ~1TeV in ice: $\langle \frac{\mathrm{d}E_\mu}{\mathrm{d}x} \rangle \propto E_\mu$
- Truncated Energy [10]:
  - Divide track into bins (binning method) or use each DOM as a bin (DOM method)
  - Calculate average energy loss for each bin:

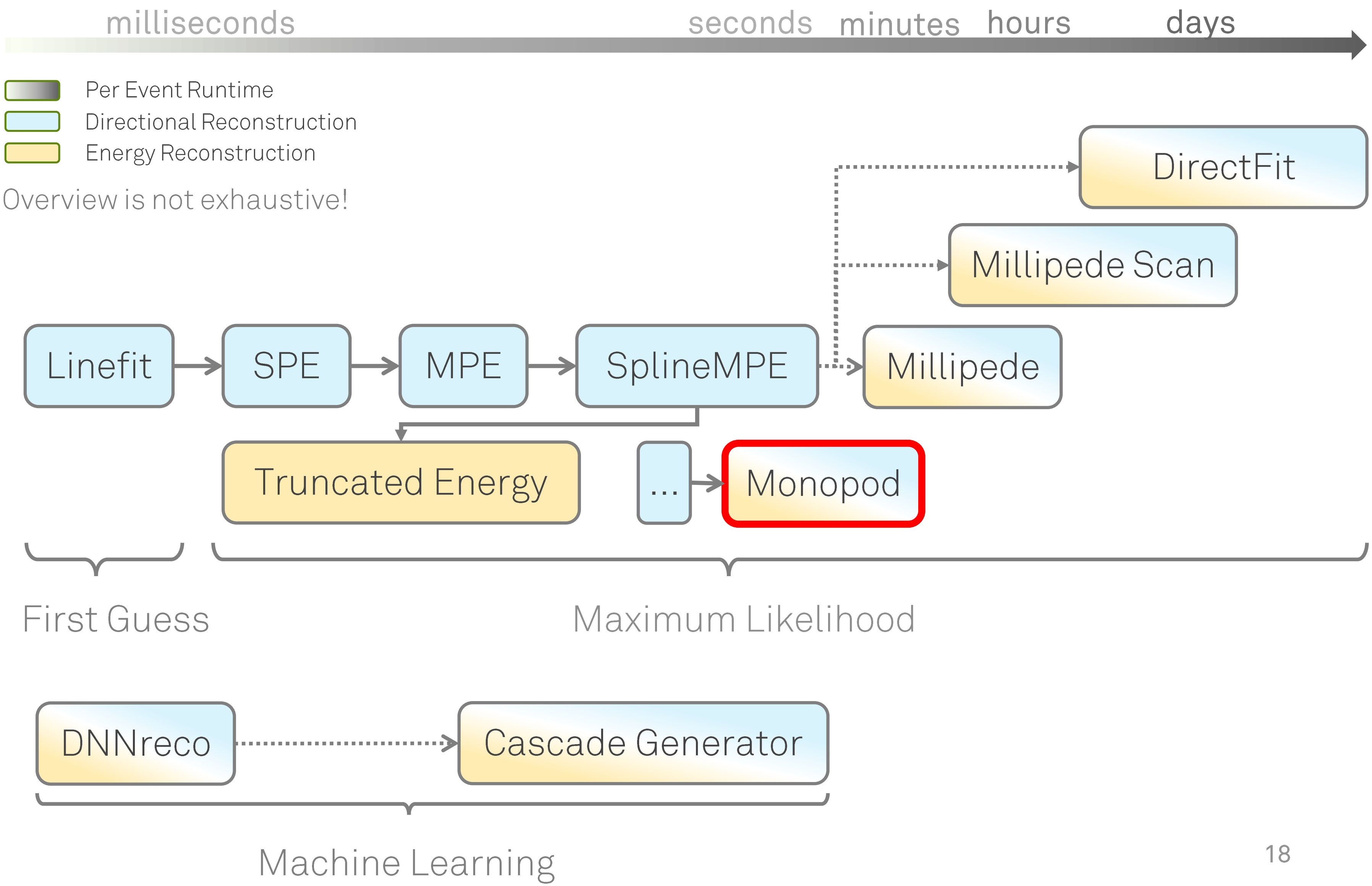
    $\langle \frac{\mathrm{d}E_\mu}{\mathrm{d}x} \rangle = \frac{\lambda_{\mathrm{measured}}}{\lambda_{\mathrm{expected}}(1\,\mathrm{GeV/m})} \cdot \frac{1\,\mathrm{GeV}}{\mathrm{m}}$
  - Calculate truncated mean discarding highest ratios (bin method: 40%, DOM method: 50%)



Source: [1]

Binning Method

Overview of Reconstruction Methods



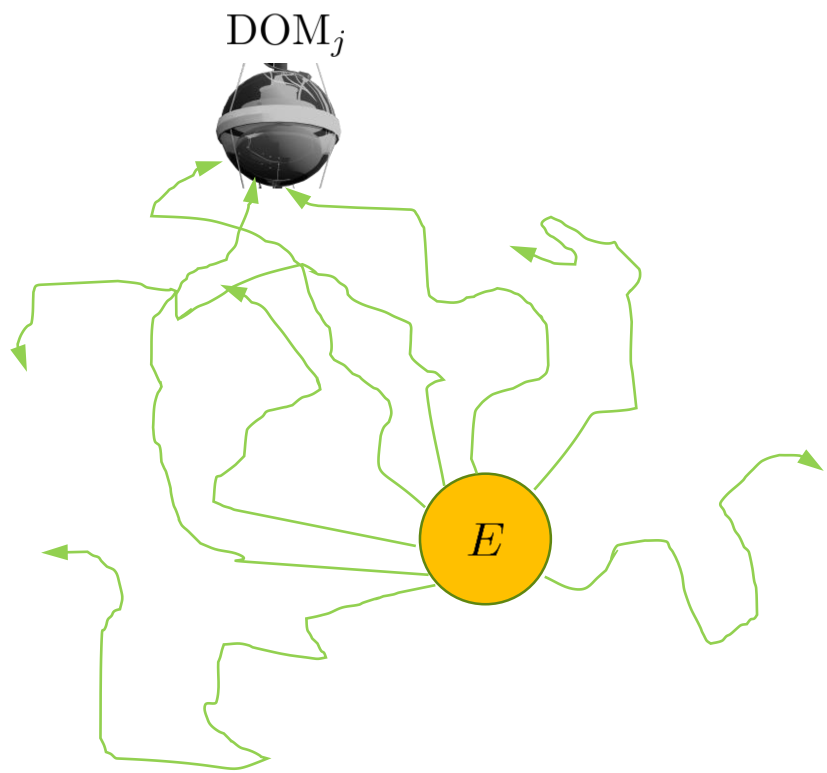
Cascade Reconstruction – Monopod

- Same framework as Millipede
- Single cascade hypothesis
- Likelihood simplifies to:

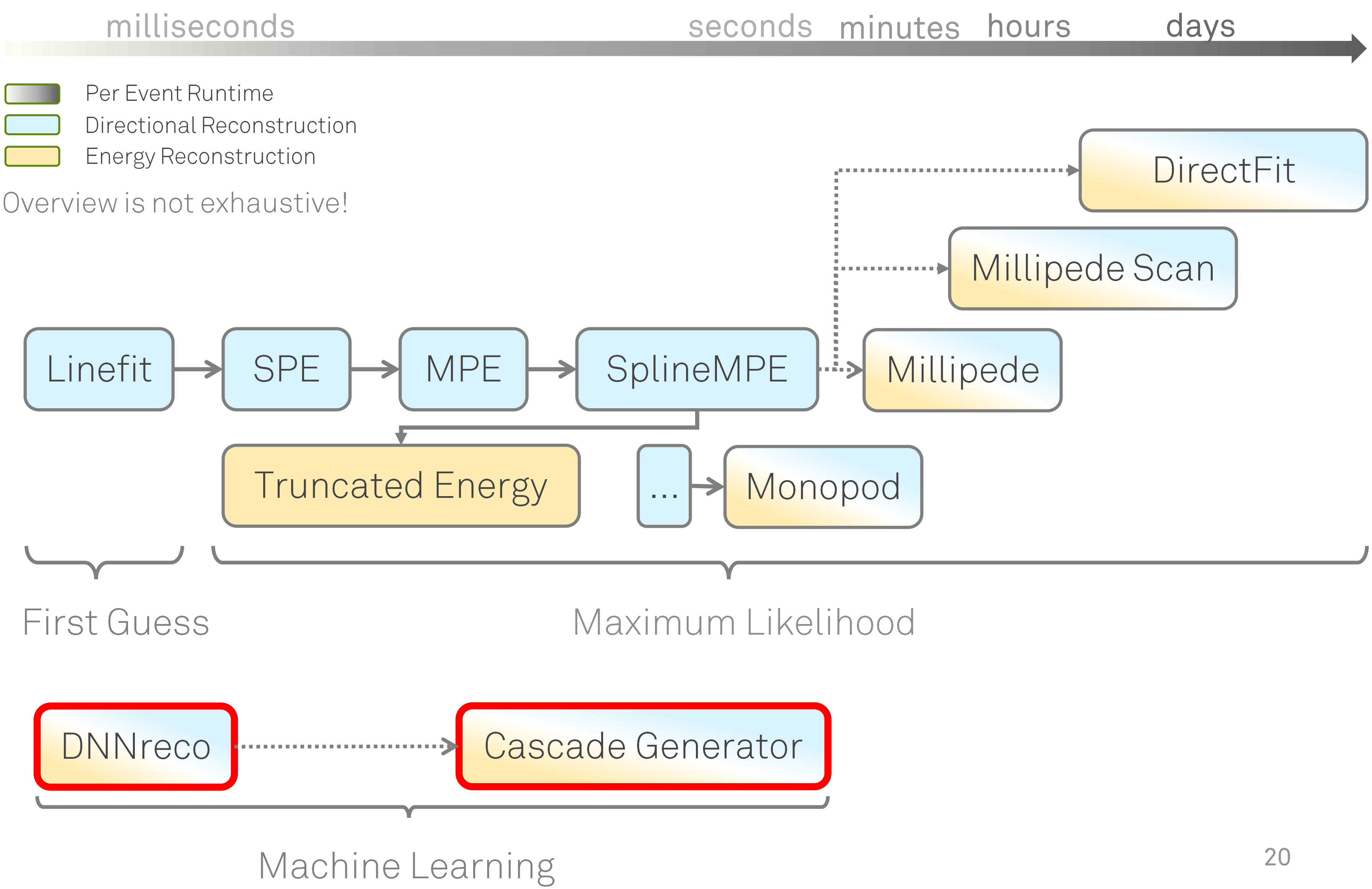
$$\mathcal{L} = \prod_{j}^{\text{DOMs}} \frac{\lambda_j^{k_j}}{k_j!} \cdot e^{-\lambda_j}$$

$$\lambda_j = E \cdot \Lambda_j + v$$

Λ_j from spline tables

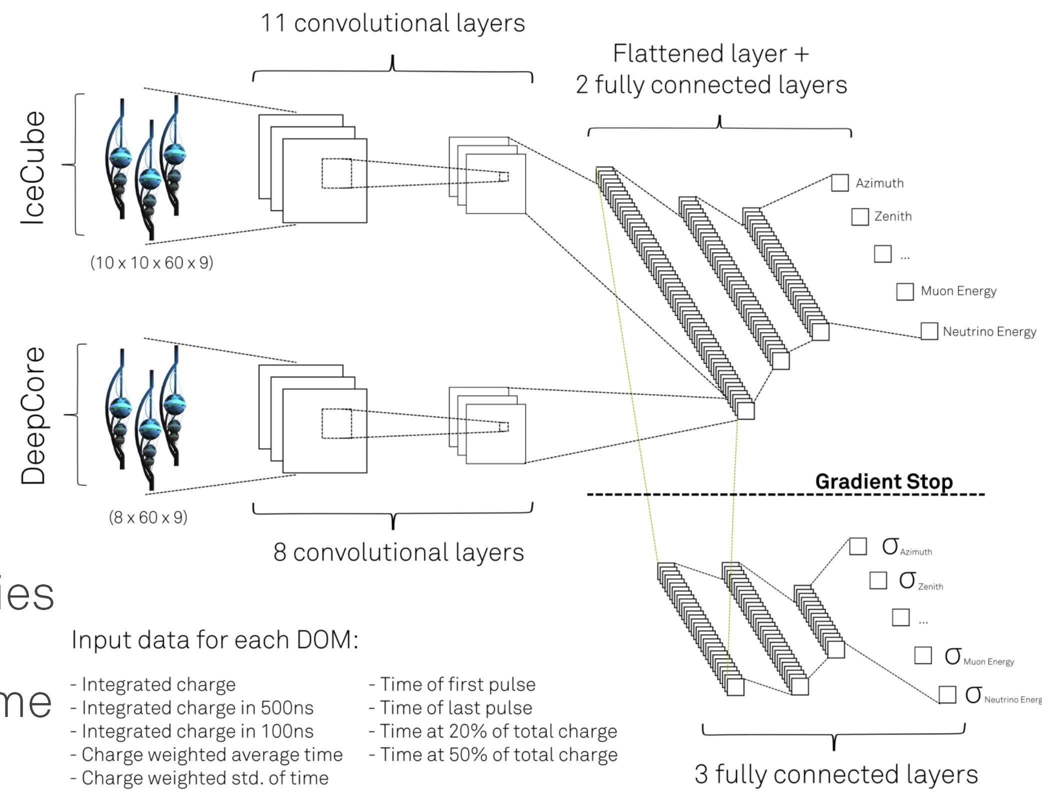


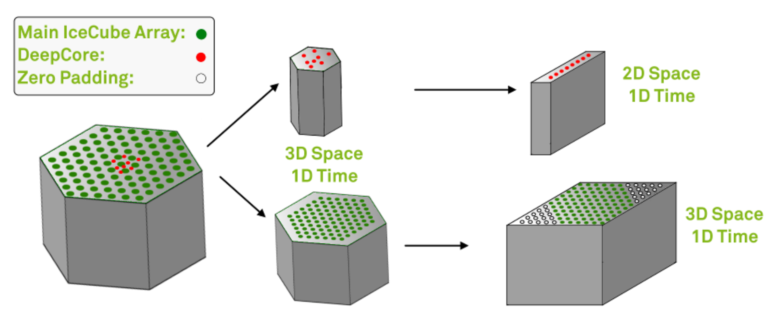
Overview of Reconstruction Methods



Machine Learning – DNN reco

- 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)
- No prior seeds or hit cleaning necessary

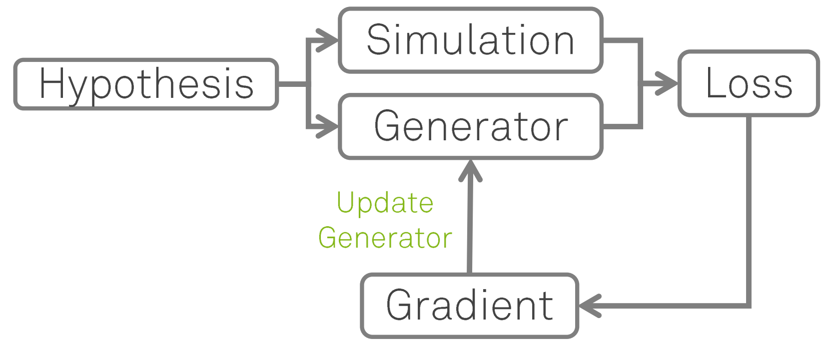




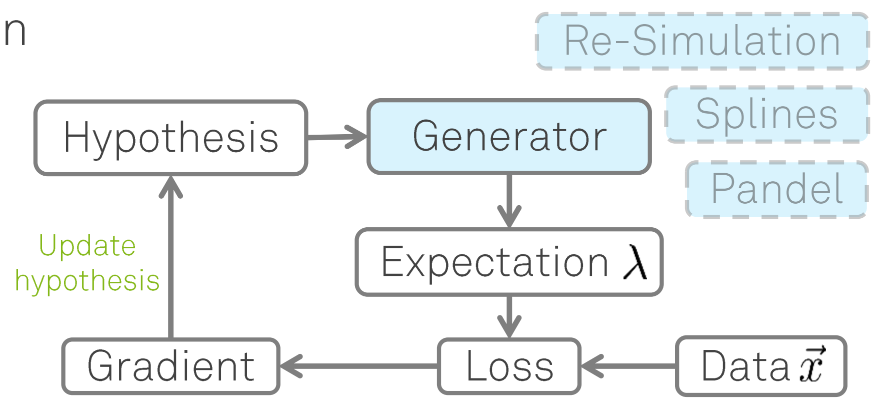
Machine Learning – Cascade Generator

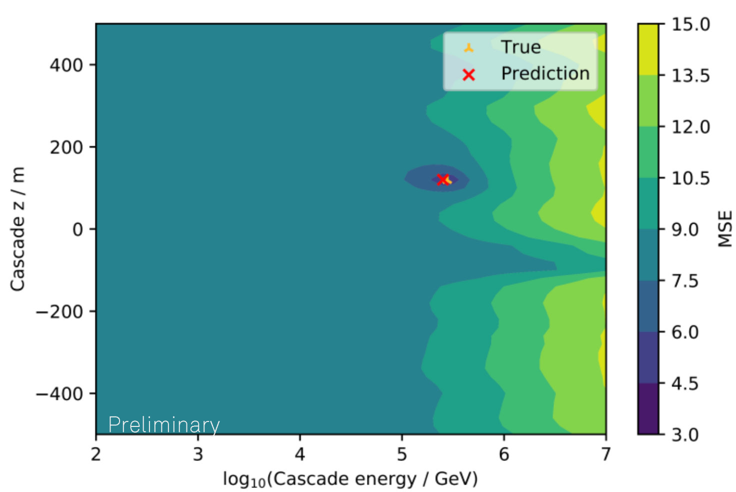
- Possible in between of spline-based reconstruction and direct re-simulation
- Generative network to obtain fast approximation of simulation and PDF: $p(x|\vec{\theta})$
- Once generator is trained, it can be used in reverse mode for reconstruction

Train Generator



Reconstruct Events





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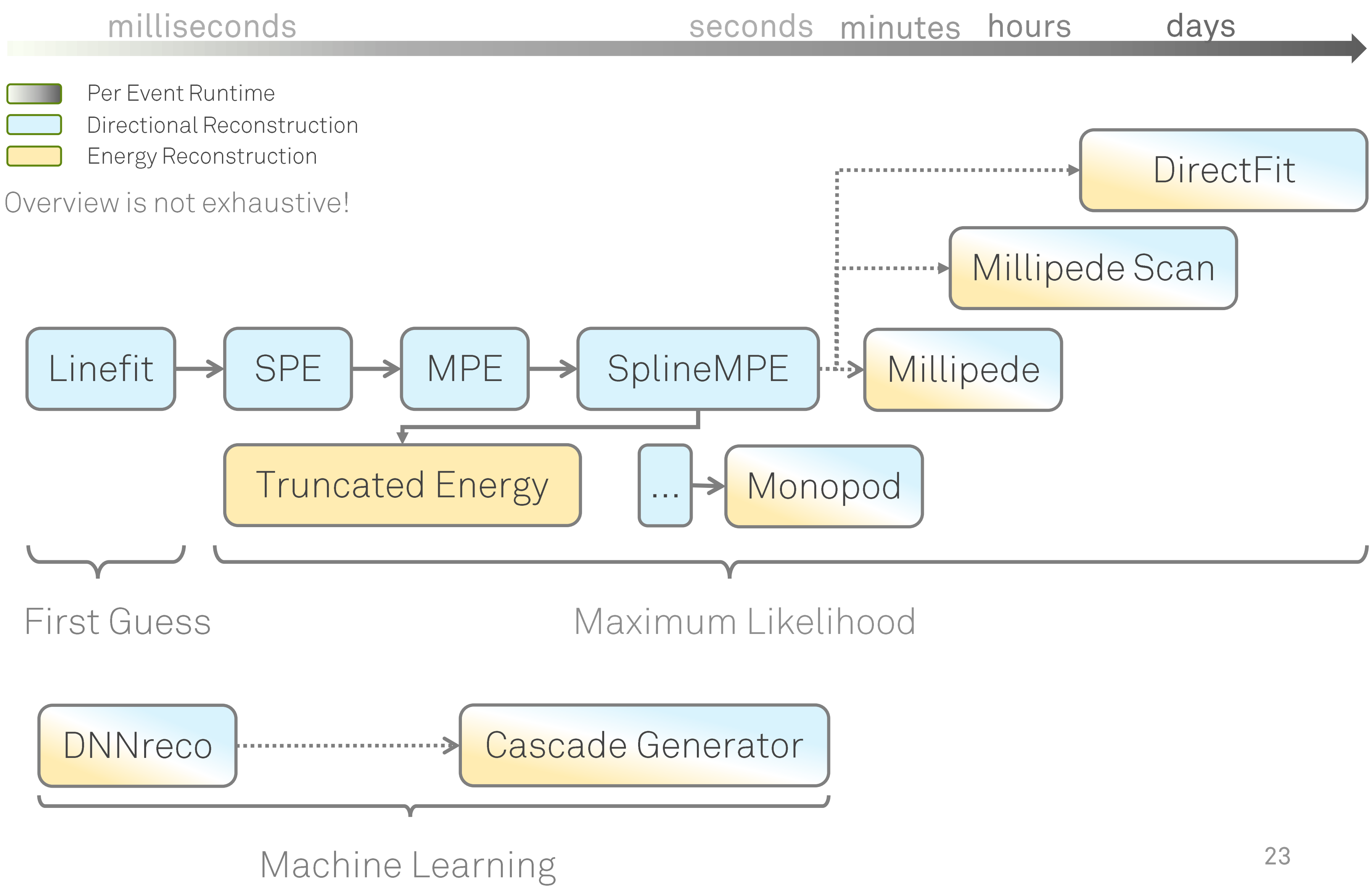
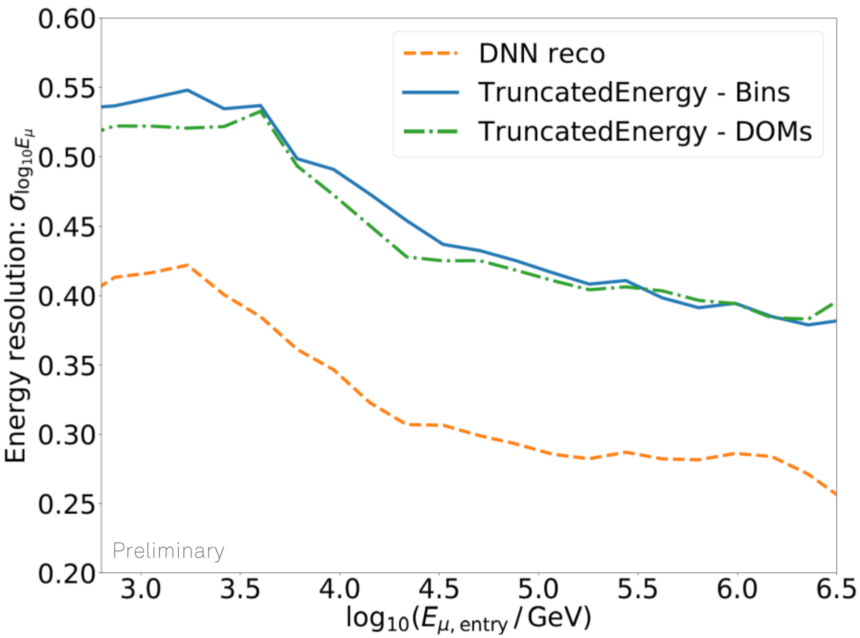
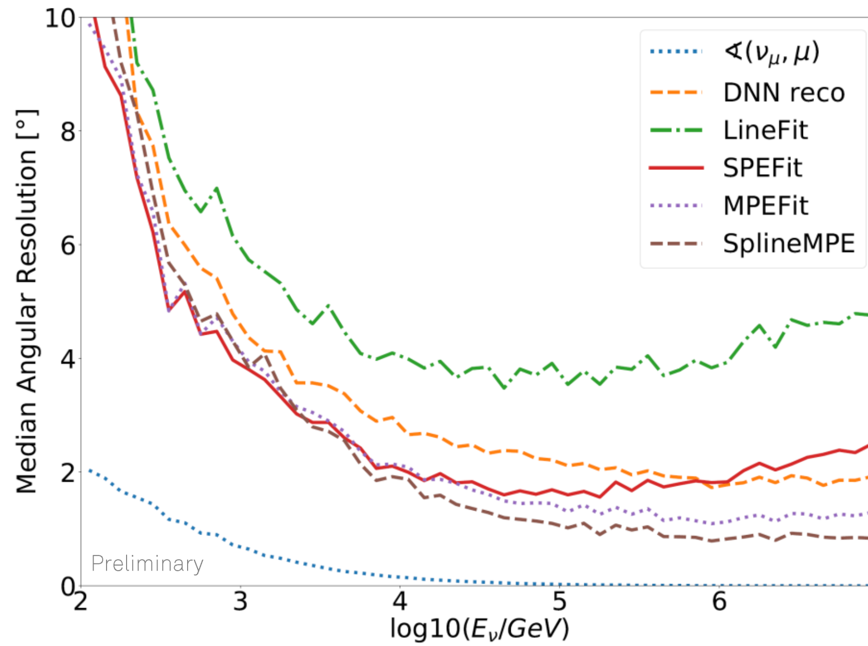


Comparison – Tracks

Muon Energy at Detector Entry



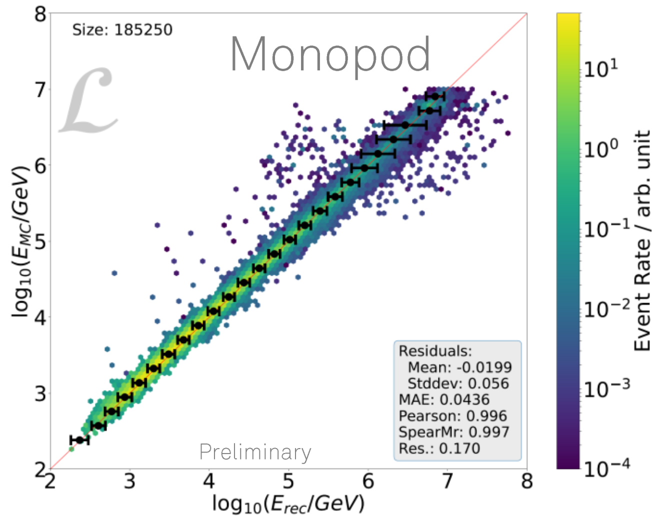
Median Angular Resolution

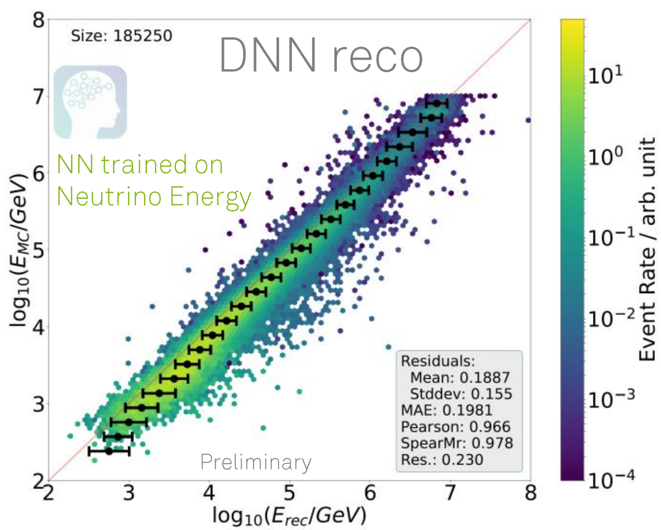


- Level 2 data: Final samples apply additional quality cuts
- Systematic uncertainties not included

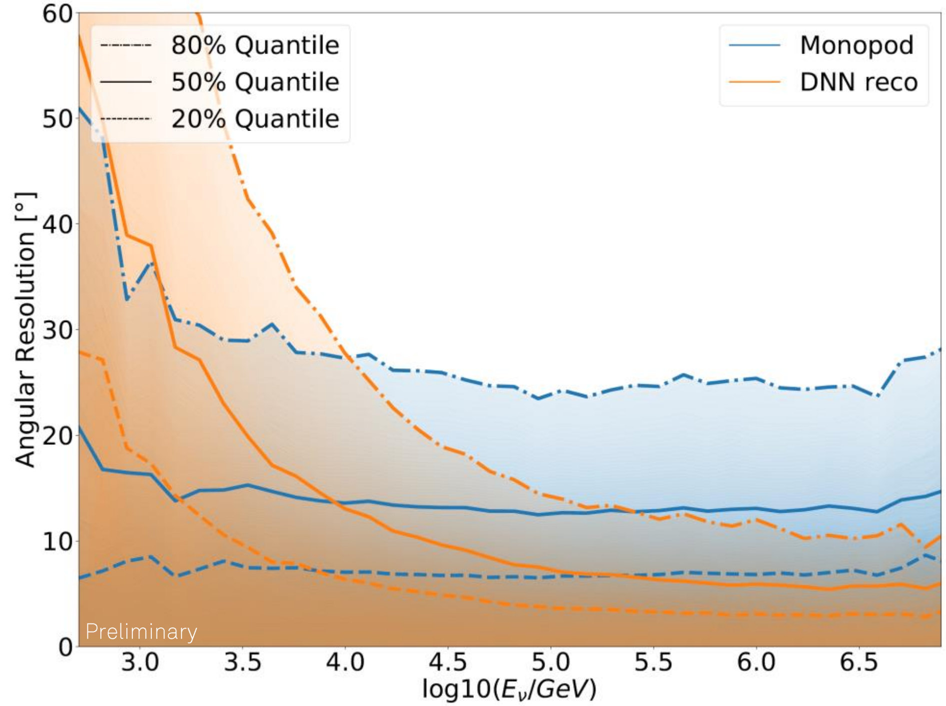
Comparison – Cascades

Deposited Energy





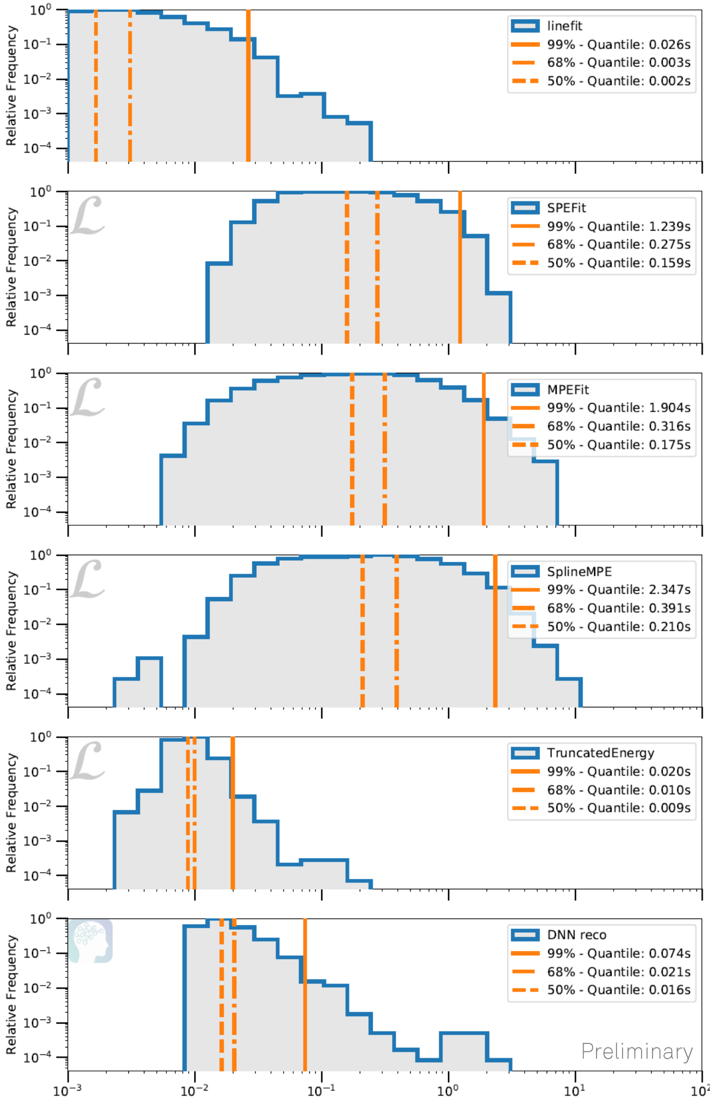
Cascade Angular Resolution



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

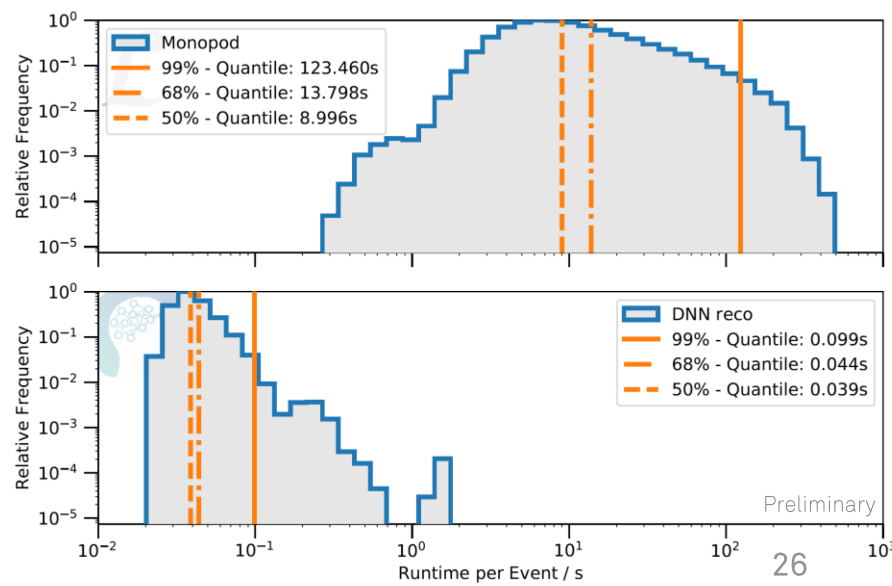
Comparison – Runtime

Track Reconstructions



- Per event runtime
- Millipede, DirectFit, Cascade Generator excluded
- Smaller neural network architecture used for track reconstruction

Cascade Reconstructions



Summary

- Two major event topologies in IceCube: Tracks and Cascades
- Main classes of reconstruction methods:
  - First guess algorithms
  - Likelihood methods
  - Machine learning methods
- Presented methods here are just a subset of existing methods (Focus on high-energy track reconstruction)
- Often trade-off between reconstruction accuracy and computational complexity: machine learning-based methods might help
- Ongoing effort to improve reconstructions

THE ICECUBE COLLABORATION

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Yale University

FUNDING AGENCIES

Fonds de la Recherche Scientifique (FRS-FNRS)
Fonds Wetenschappelijk Onderzoek-Vlaanderen (FWO-Vlaanderen)
Federal Ministry of Education and Research (BMBF)
German Research Foundation (DFG)
Deutsches Elektronen-Synchrotron (DESY)
Japan Society for the Promotion of Science (JSPS)
Knut and Alice Wallenberg Foundation
Swedish Polar Research Secretariat
The Swedish Research Council (VR)
University of Wisconsin Alumni Research Foundation (WARF)
US National Science Foundation (NSF)

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icecube.wisc.edu

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Deep Learning – Deep Neural Networks

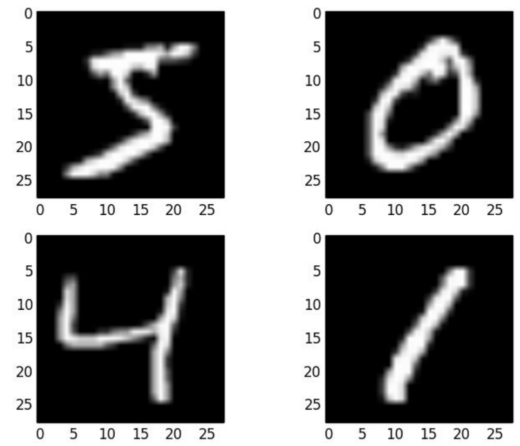
- Neural network defines a function:

$$f_\theta : I \to O$$

θ: Free parameters defined by model architecture

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

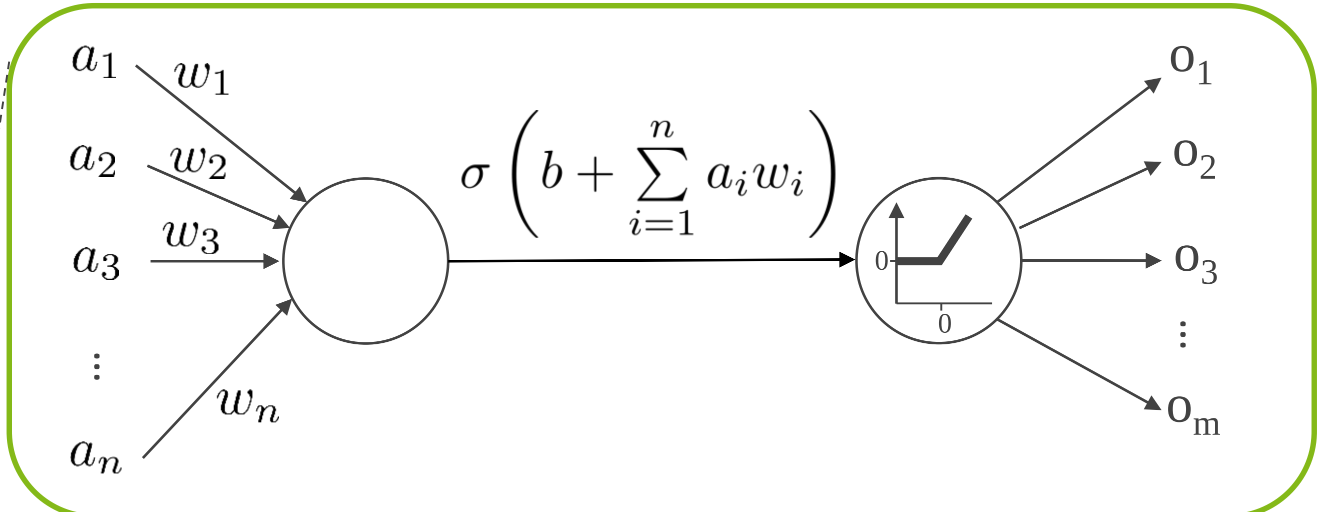
O: Output
Digit (image recognition)
Energy/direction of particle (IceCube)

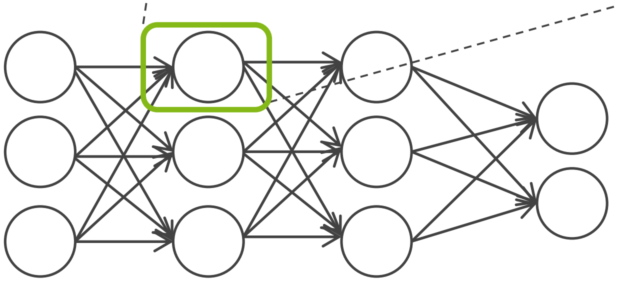


MNIST Dataset

Deep Learning – Deep Neural Networks

Artificial Neuron and fully connected layer





Weights and bias

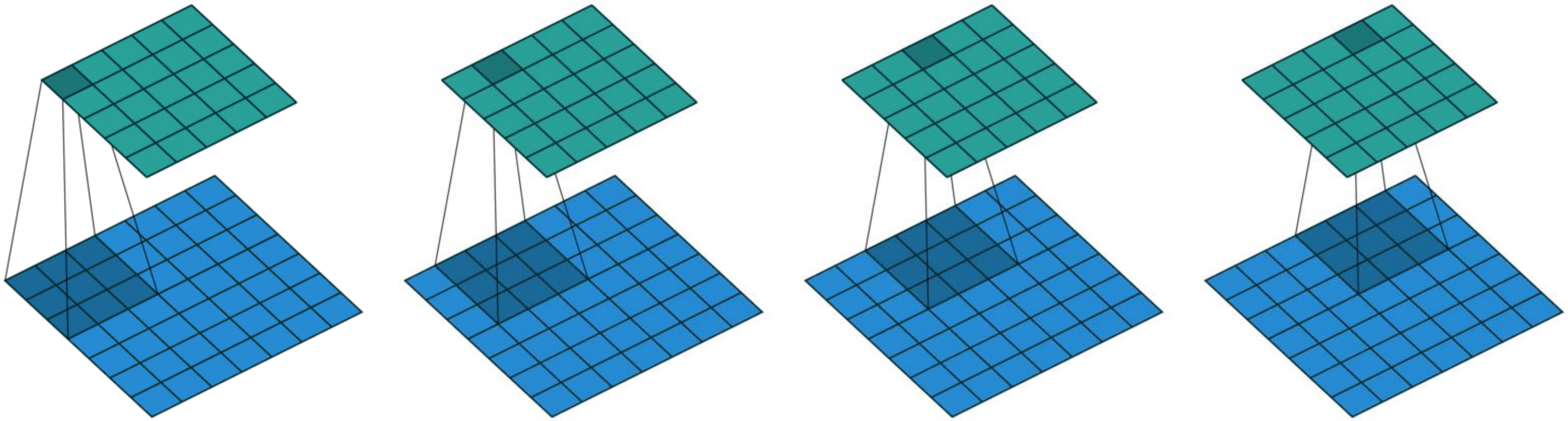
$n + 1$ free parameters per neuron

Nonlinear activation function e.g. ReLU

0 up to a fixed threshold

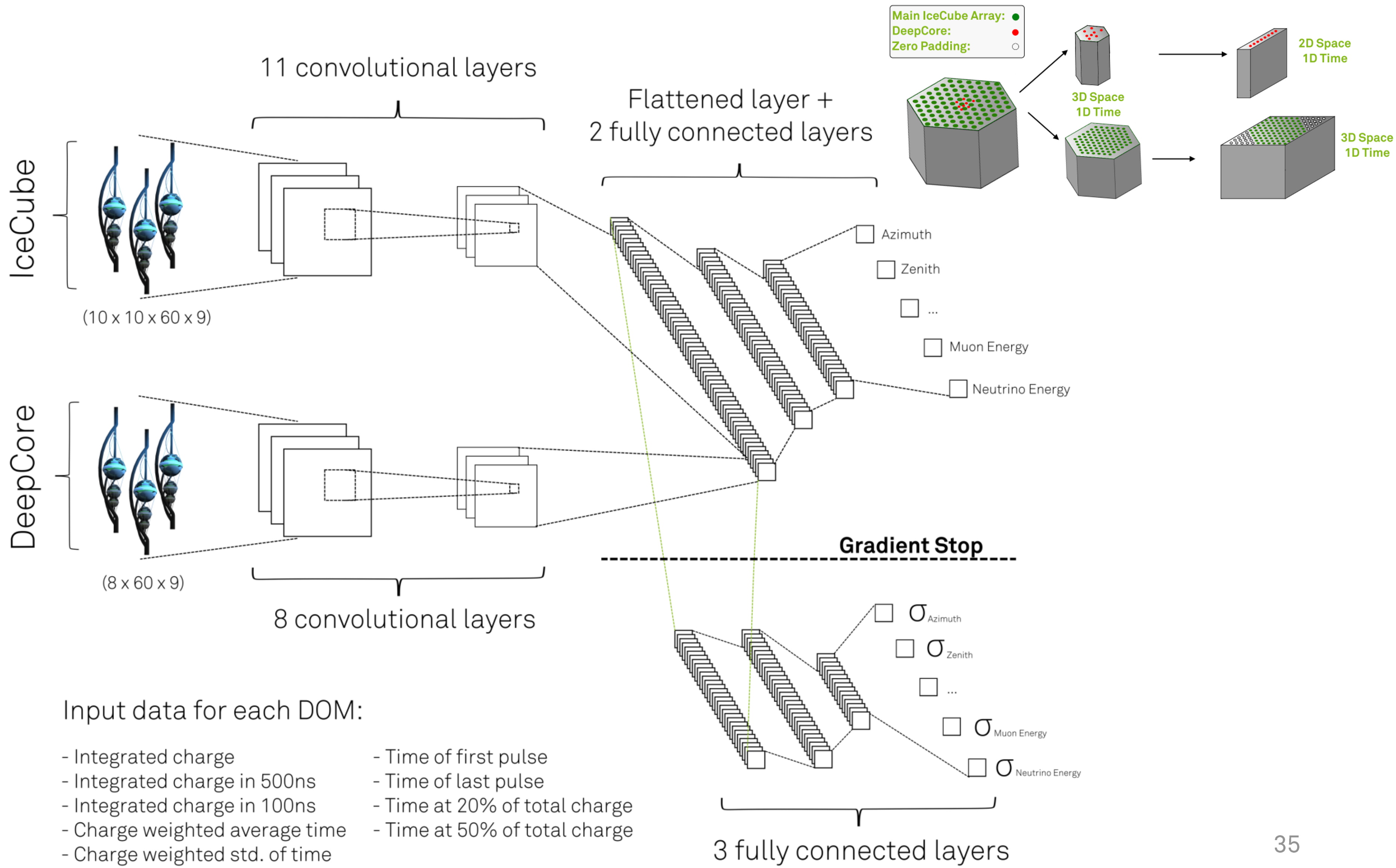
Deep Learning – Convolutional Neural Nets

Convolutional Layer



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

Network Architecture



Input data for each DOM:

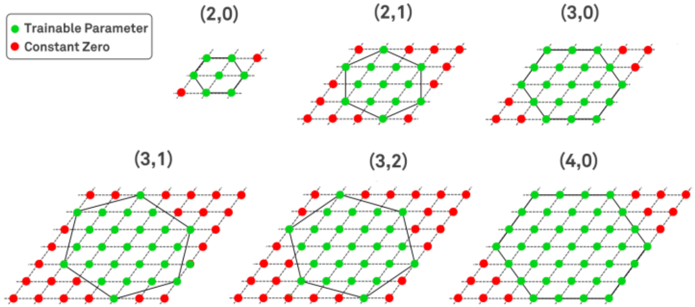
- Integrated charge
- Integrated charge in 500ns
- Integrated charge in 100ns
- Charge weighted average time
- Charge weighted std. of time
- Time of first pulse
- Time of last pulse
- Time at 20% of total charge
- Time at 50% of total charge

Network Architecture

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

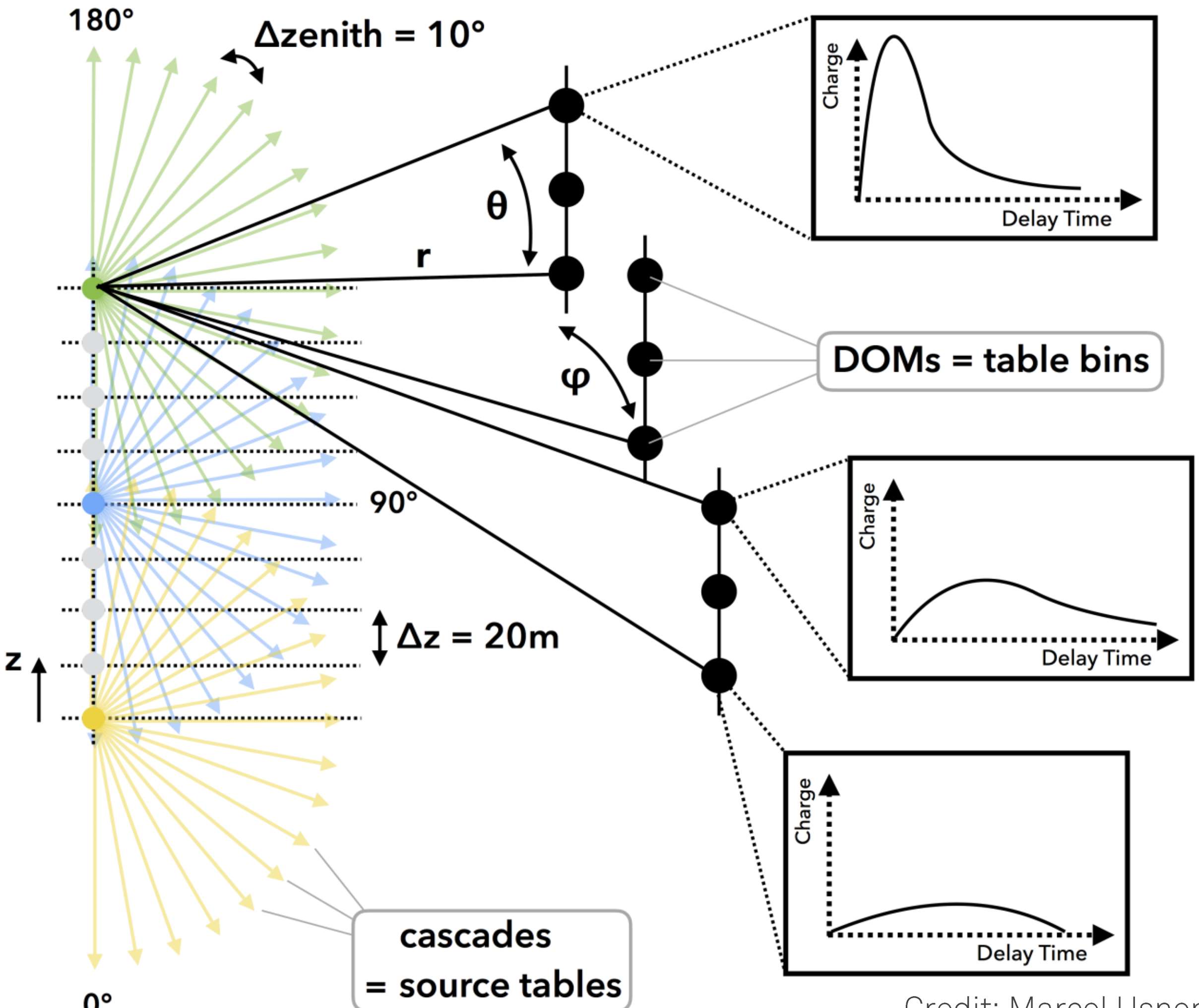
DOI: 10.1109/CVPR.2016.90

- 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

SPE and MPE Likelihood – Splines



Credit: Marcel Usner

SPE and MPE Likelihood – Splines

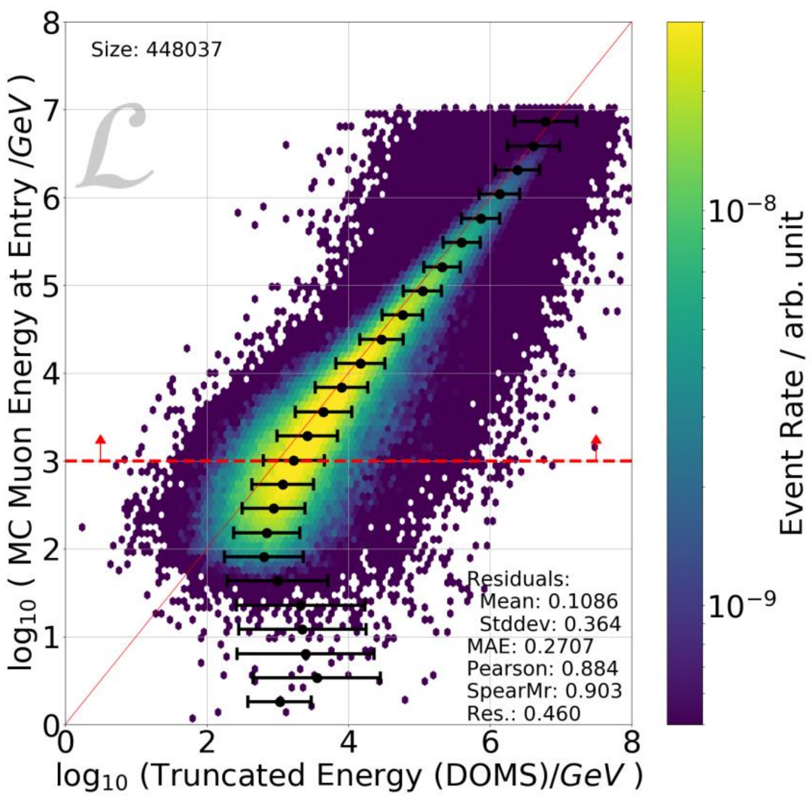
Dimension	# bins per dimension old Photonics	# bins per dimension this work	Minimum	Maximum
Zenith angle Θ_S	18	18	$0°$	$180°$
Depth Z_S	75	75	$-850\,\mathrm{m}$	$650\,\mathrm{m}$
Azimuthal ϕ	9	36	$0°$	$180°$
Distance ρ	30	200	$0\,\mathrm{m}$	$580\,\mathrm{m}$
Time residual t_{res}	50	210	$0\,\mathrm{ns}$	$7000\,\mathrm{ns}$

Photon table binning taken from [2].

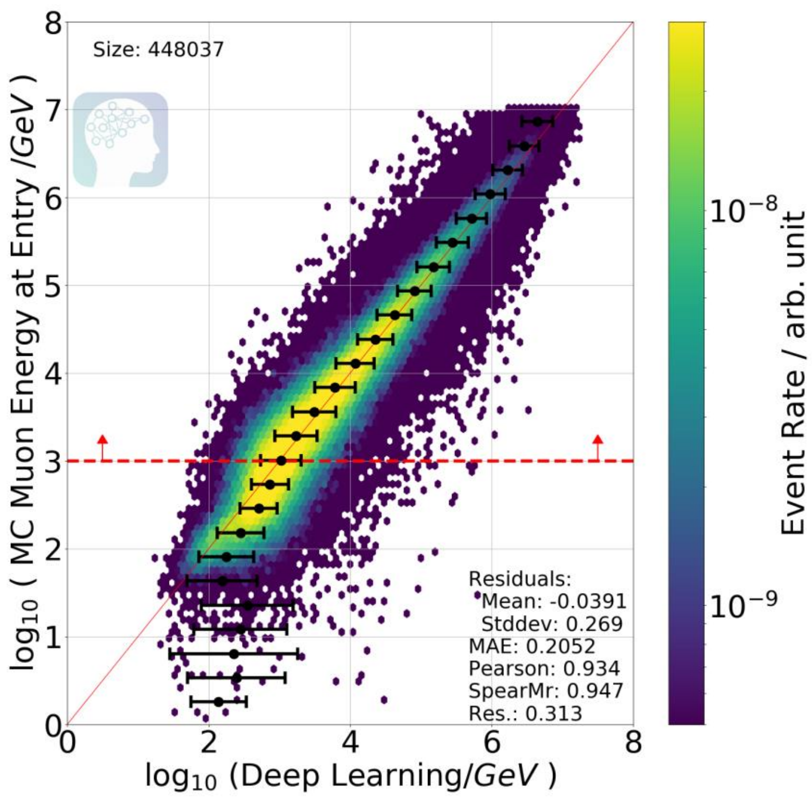
Energy Reconstruction – Muon Energy at Entry

OnlineL2 Muon Filter – CC events

Truncated Energy (DOMS)



Deep Learning



Muon Energy Losses