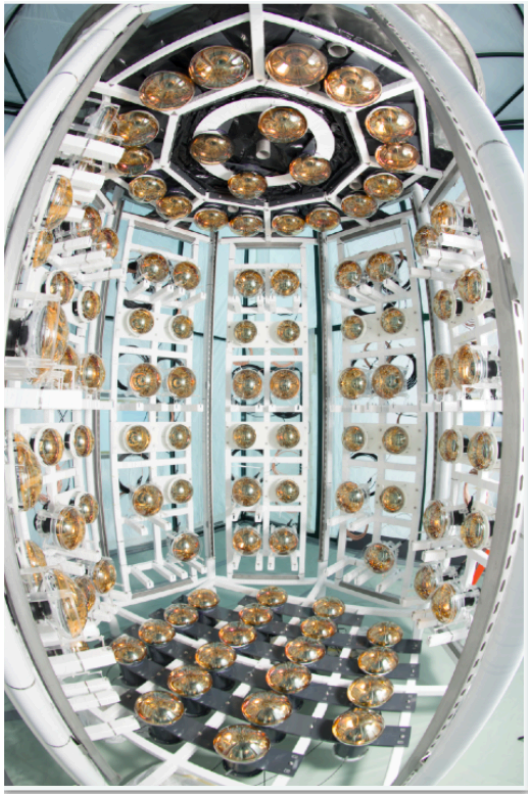
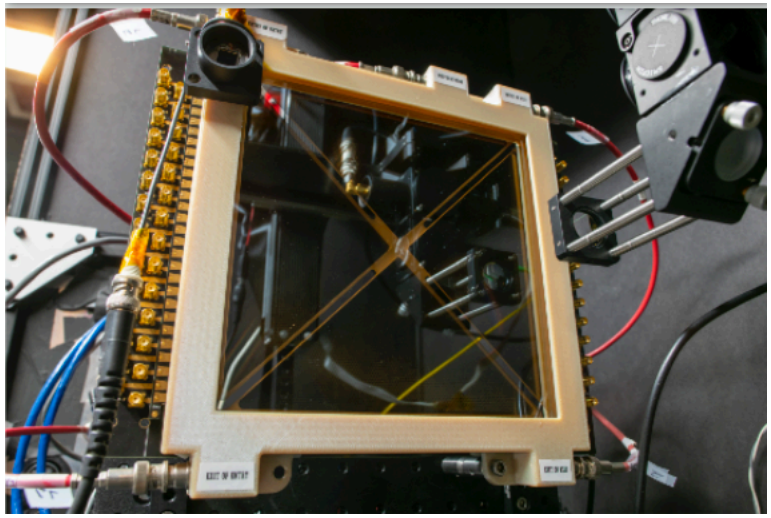
Machine Learning Techniques in ANNIE





Evangelia Drakopoulou for the ANNIE Collaboration

NPML 2020 – 22 July, Chicago

Outline

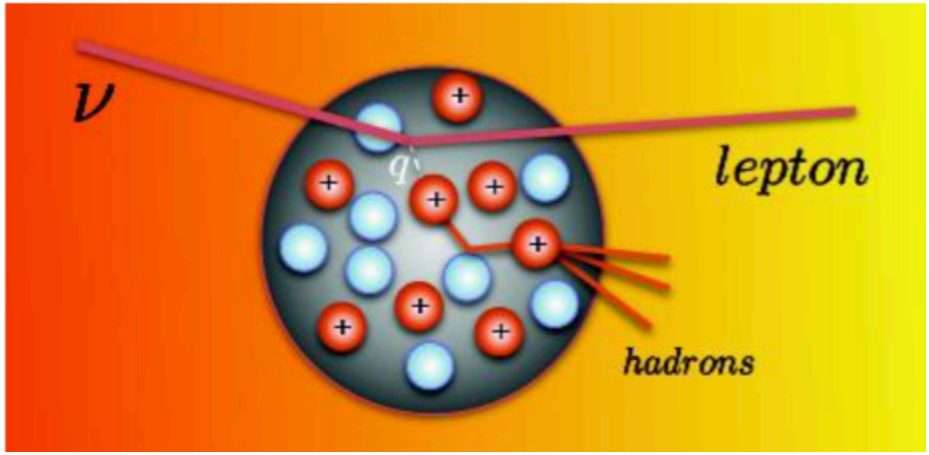
- Physics and Technological Goals
- The ANNIE Experiment
- ANNIE Phase II
- High Energy Reconstruction
- Particle Identification & Ring Counting

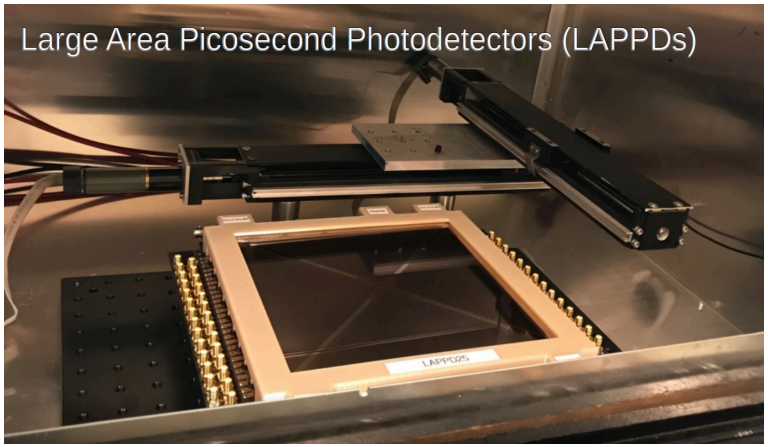
Physics and Technological Goals

Physics & Technological Goals

Two main goals:

- Measure the final state **neutron multiplicity** from Charged Current neutrino-nucleus interactions in water
  - → Reduce systematic uncertainties on neutrino energy reconstruction in oscillation searches
  - → Constrain backgrounds in proton decay searches
- Demonstrate the use of fast-timing Large Area Picosecond PhotoDetectors (**LAPPDs**) for event reconstruction



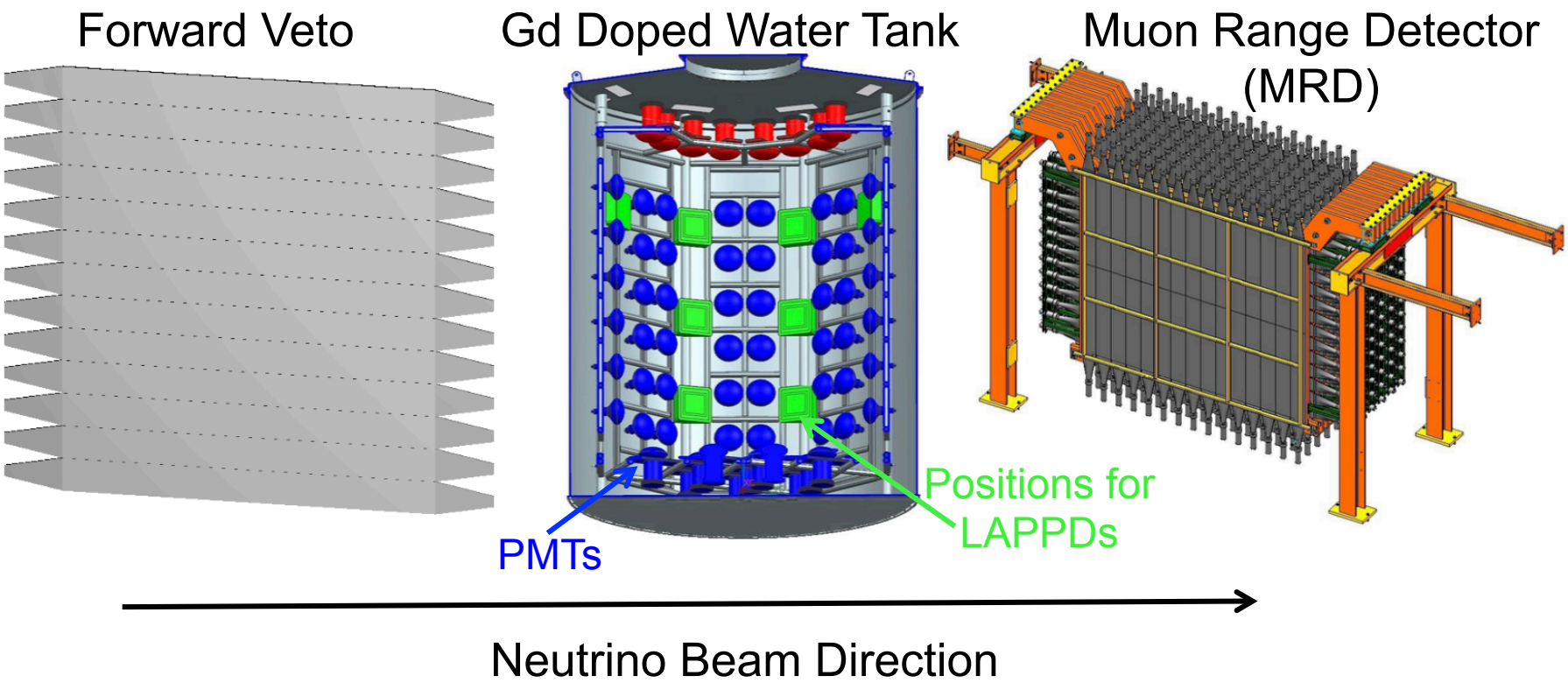


[arXiv:1603.01843 [physics.ins-det]]

The ANNIE Experiment

The ANNIE Detector

- **A**ccelerator **N**eutrino **N**eutron **I**nteraction **E**xperiment (**ANNIE**): a 26-ton Gd-doped water Cherenkov detector installed in the Booster Neutrino Beam at Fermilab (flux peaks at 600 MeV).



Status of the Experiment

2016

2018

2020

ANNIE – Phase I

Completed

- Neutron background measurements in the detector site in Fermilab.
- Successful operation phase of the detector.

ANNIE – Phase II

- Measure the neutron yield from CCQE events in water
- First deployment and use of LAPPDs

ANNIE Phase II

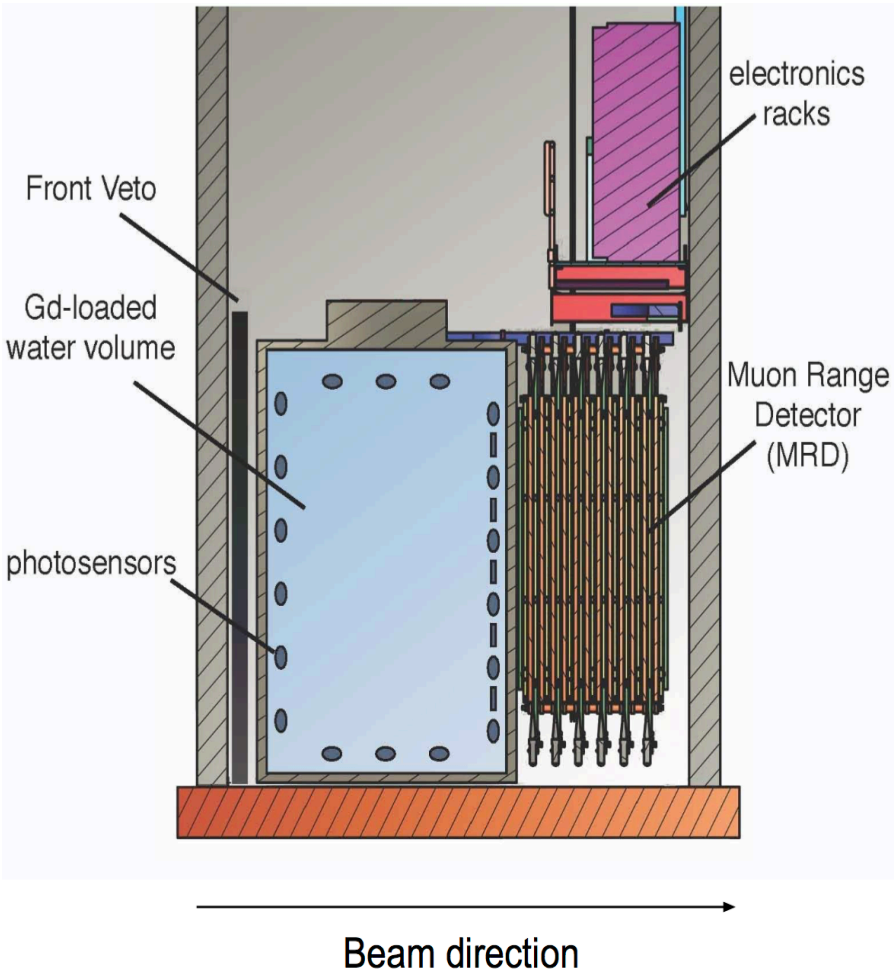
ANNIE Phase II

- 3 m x 4 m tank filled with Gd (0.2%) loaded water

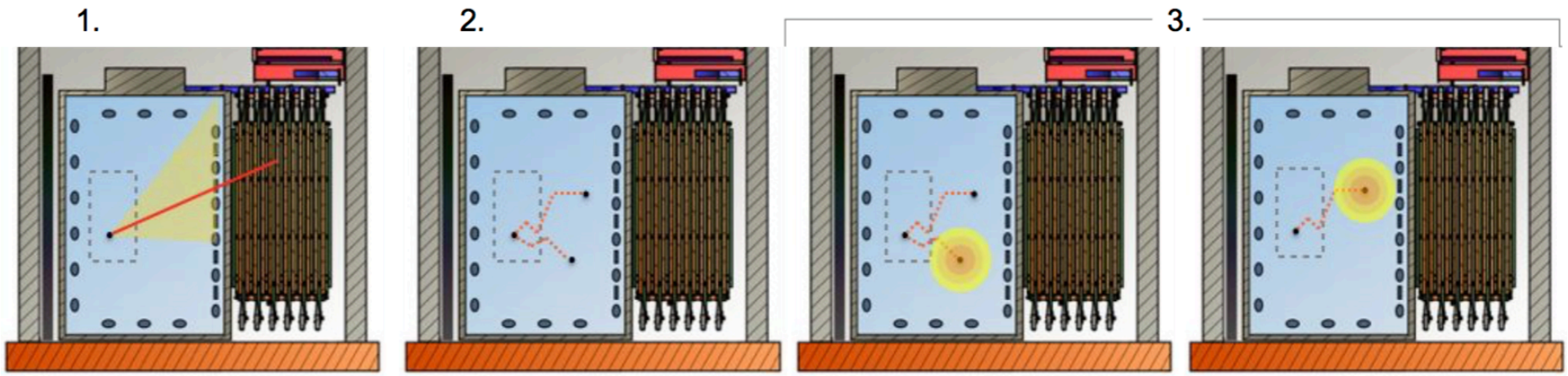
- ~132 PMTs + 5 LAPPDs:
→ LAPPDs will be placed downstream
→ Flexibility to add additional LAPPDs

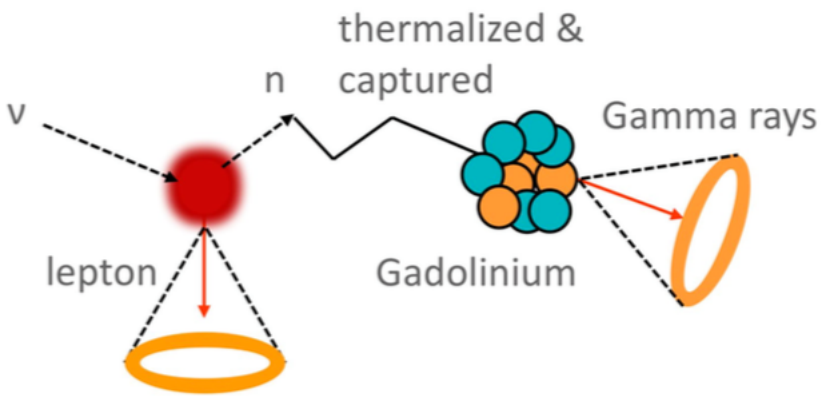
- Fully instrumented MRD
→ 11 layers and 310 channels

- Upgraded electronics and readout



Event Signatures in ANNIE





1. Charged Current neutrino interactions in fiducial volume

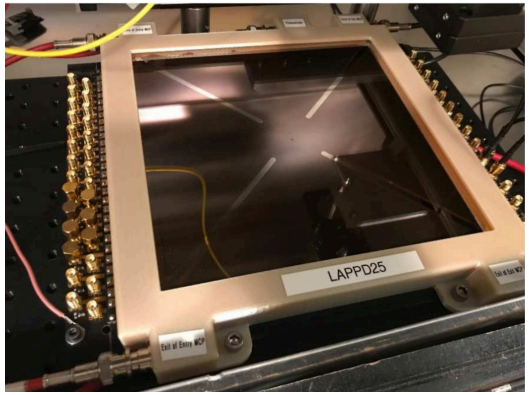
→ Cherenkov cone incident on PMTs and LAPPDs

→ Scintillation light from stopping muons in MRD

2. Final state neutrons thermalised and captured in Gd

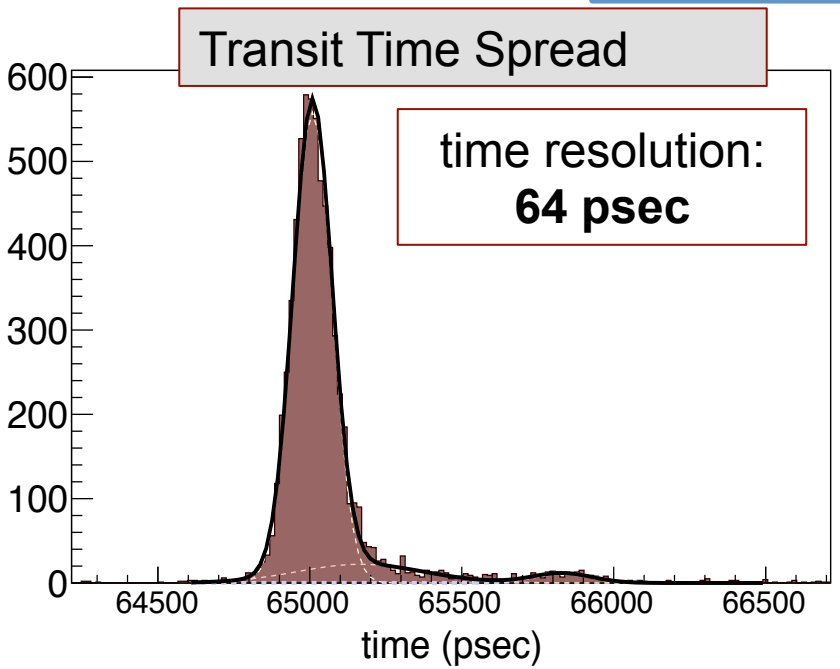
3. Cascade of 8 MeV detected by PMTs

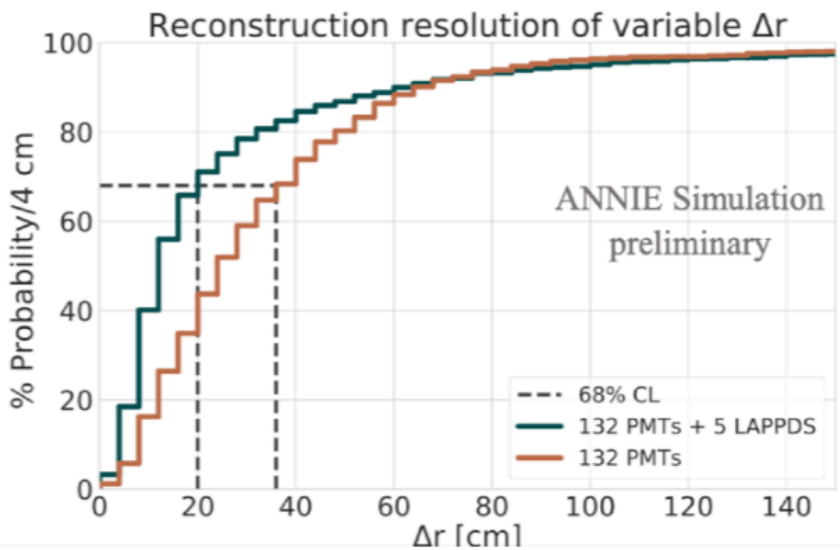
LAPPDs – A new technology tested in ANNIE



Micro-channel plate, fast-timing photodetectors

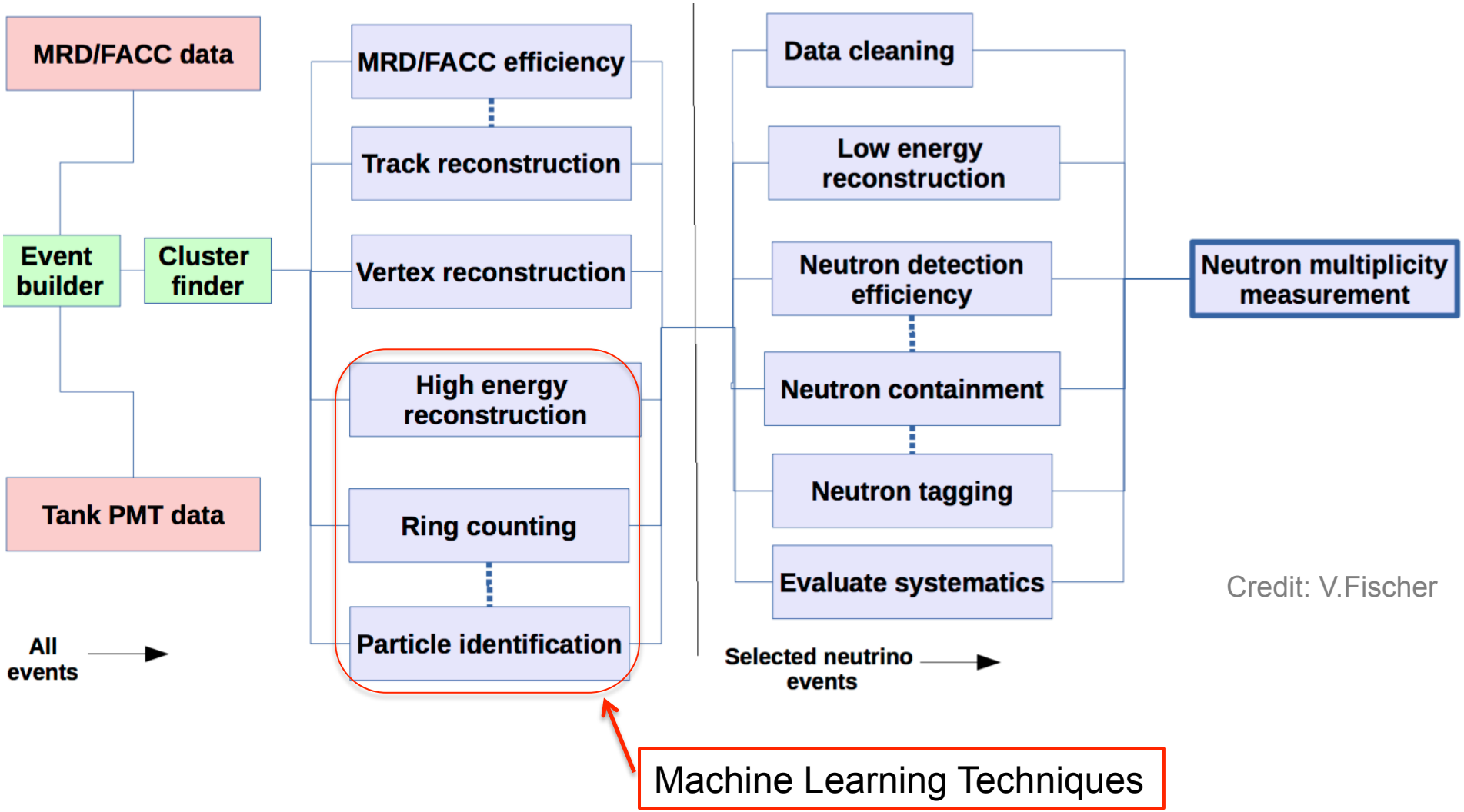
- Large-area: 20 × 20 cm
- Fast timing: <100 ps for a single photoelectron
- High quantum efficiency (QE): >20 %
- Position resolution: sub-mm
- Operable in a magnetic field





For more details see: *Nucl. Instr. and Meth. in Phys. Res. A 822 (2016) 25–33*

ANNIE Analysis flowchart



Credit: V.Fischer

High Energy Reconstruction

Energy Reconstruction Flowchart

Events with reconstructed vertex & direction

↓

DNN to reconstruct the track length in the water tank

↓

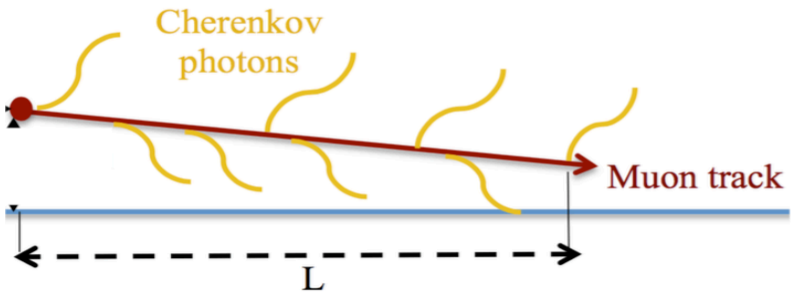
BDTG to reconstruct the muon energy

Track Length Reconstruction

- The track was initially reconstructed as the distance between the first and last Cherenkov photon emission point along the track (L).

- In order to improve the reconstructed track length in the water tank a **Deep Learning Neural Network (DNN)** (in Keras) was used.

- The parameters were optimised using GridSearchCV.

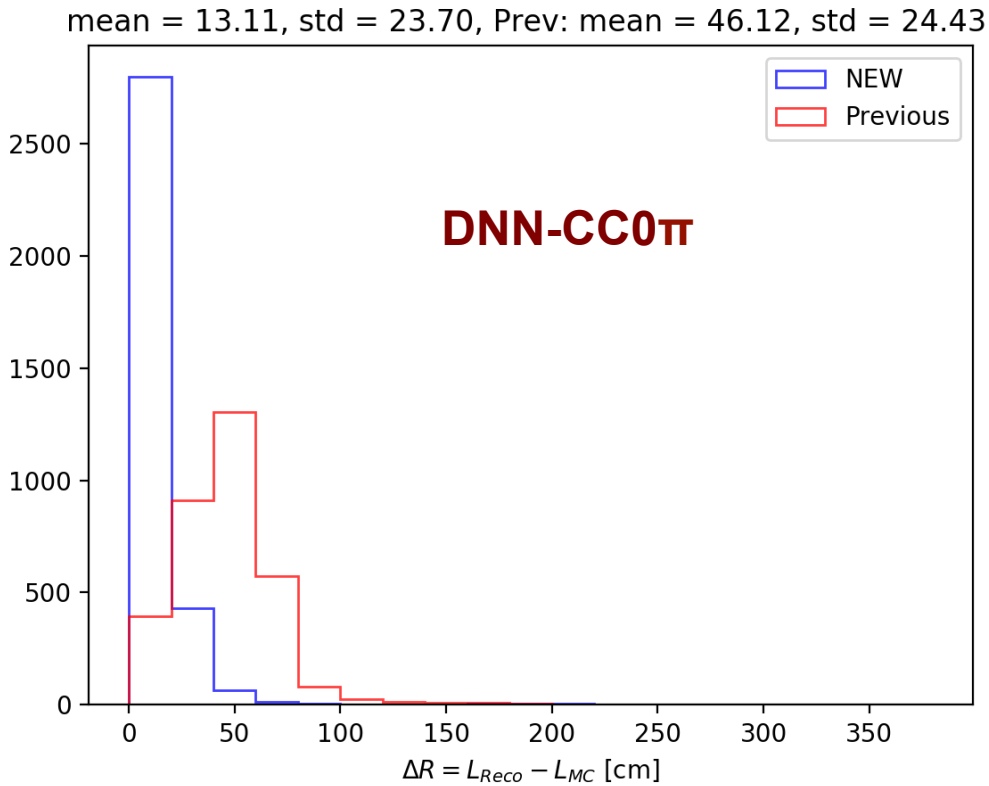


Input variables for DNN:
- All Cherenkov photons emission points
- Hit times
- The previously estimated track length, L
- The total number of hits in PMTs and LAPPDs for each event.

For more details on the reconstruction see: arXiv:1710.05668v3

Track Length Reconstruction

$\Delta R = L_{reco} - L_{MC}$



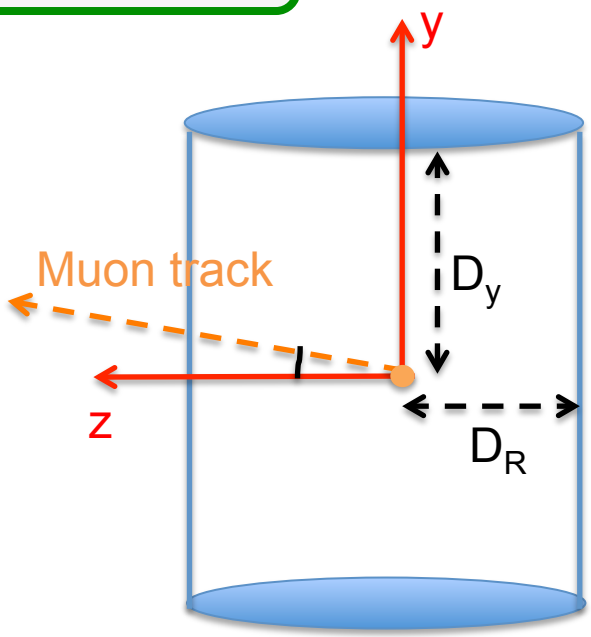
~ 1000 events used for the track length prediction and 1000 for the DNN training

Muon Energy Reconstruction

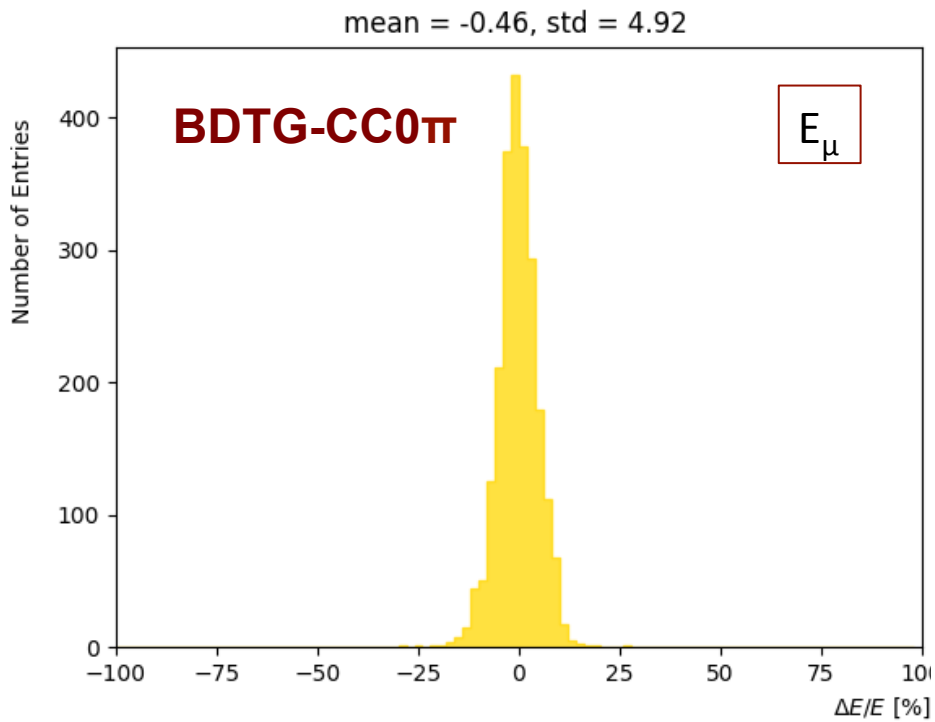
- The track length in water and the track length in the MRD are used among other variables as inputs to a Boosted Decision Tree (BDTG) to reconstruct the muon energy.
- The parameters were optimised using GridSearchCV.
- Results for: Reconstructed CCQE events with E_ν<2GeV passing through the MRD.
- Figure of merit: $\Delta E/E = 100 * (E^{MC} - E^{reco}) / E^{MC}$

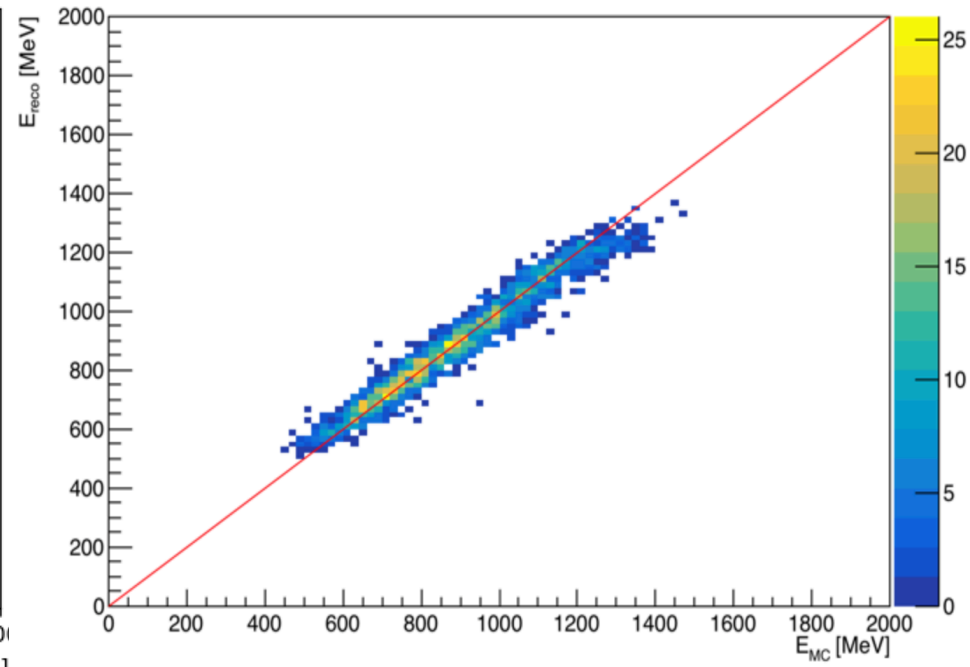
Input Variables for BDTG:

- Track length in water
- Reconstructed track length in the MRD
- Angle difference between the reconstructed z direction and the beam direction at (0,0,1)
- The total number of hits in PMTs and LAPPDs for each event
- The reconstructed vertex coordinates
- The distances of the reconstructed vertex from the detector walls (D_R, D_y)



Muon Energy Reconstruction





95.4% of events in ΔE/E<10%
4.3% of events in10%<=ΔE/E<20%
0.3% of events in ΔE/E>=20%

For more details on the reconstruction see: arXiv:1710.05668v3

Particle Identification & Ring Counting

Multi-Layer Perceptron NN by Michael Nieslony

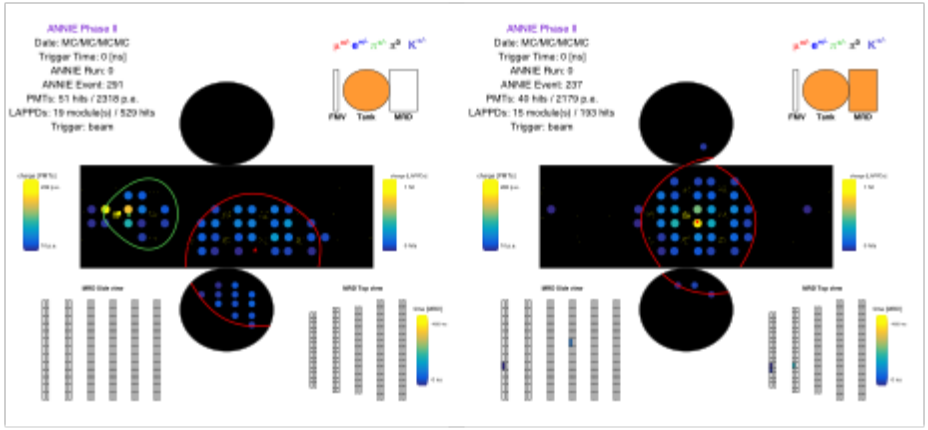
Classification Tasks in ANNIE

CC-0π selection

Ring Counting

- Classification: single- vs multi-rings
- Problems in a small (ANNIE-like) Water-Cherenkov detector: Cherenkov rings not well separable if direction similar
- Event sample: BNB simulation sample (GENIE+WCSim)
- Methods: Multi-Layer Perceptron, Convolutional Neural Network

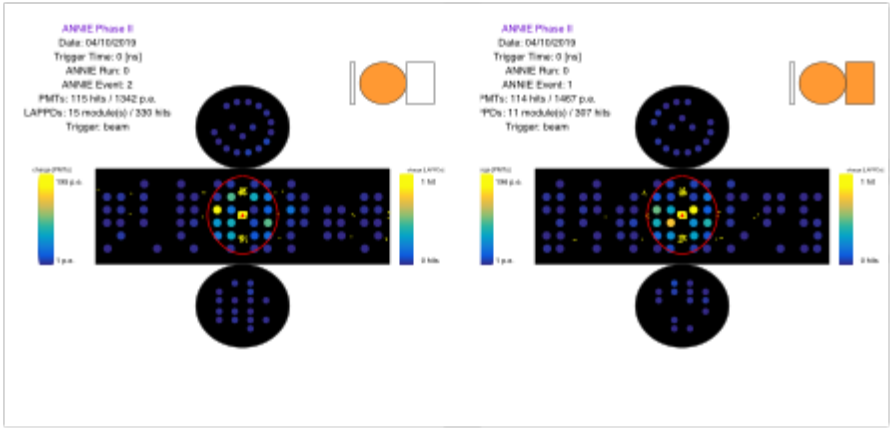
Multi-ring event *Single-ring event*



Particle ID

- Classification: electrons vs. muons
- Problems in a small (ANNIE-like) Water-Cherenkov detector: Observe Cherenkov disks instead of rings → very similar
- Event sample: Electron + muon simulation sample (WCSim)
- Methods: Multi-Layer-Perceptron, Convolutional Neural Network

500 MeV electron *500 MeV muon*

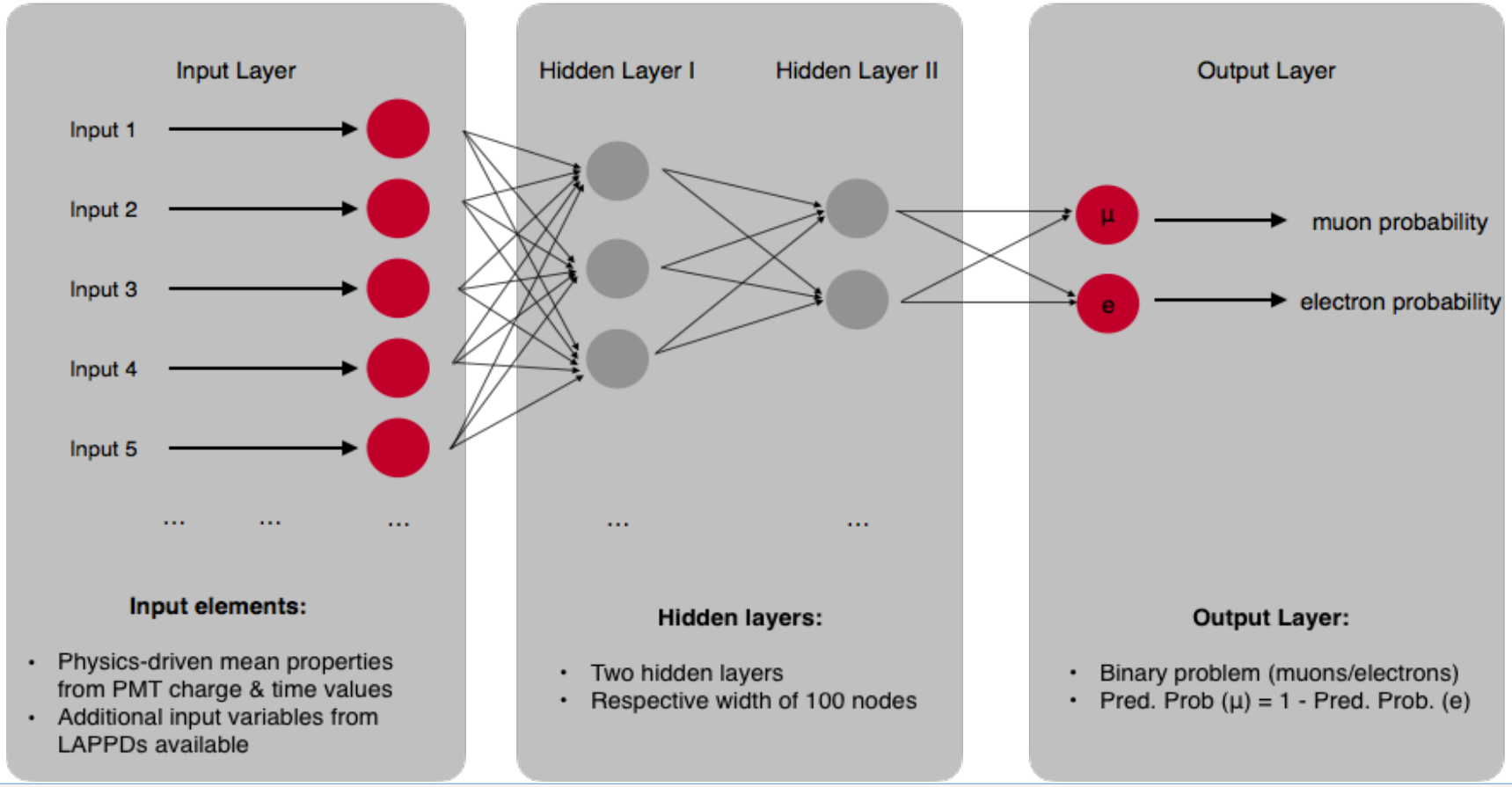


Multi-Layer Perceptron Structure

by Michael Nieslony

Software package:

- MLPClassifier from *sklearn.neural_network* package
- Activation Layer: RELU
- Training set / test set split: 60%/40%



Particle ID - Multi-Layer Perceptron

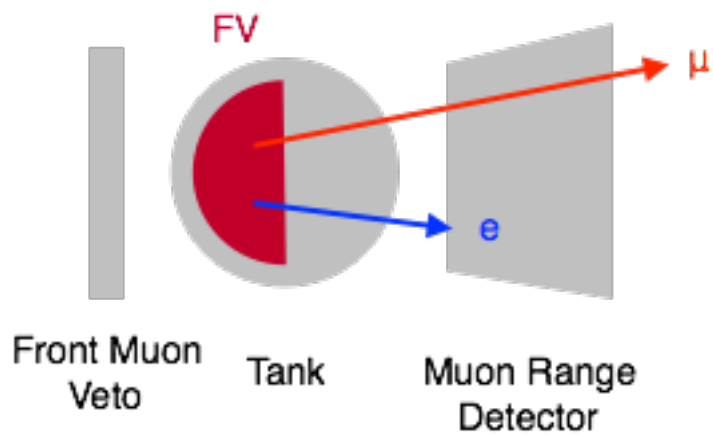
by Michael Nieslony

Input variables - Particle ID:

Total recorded charge
Fraction of downstream charge
Fraction of highest charge PMT
Number of hit PMTs
Variance of time profile
Fraction of PMT hits at large angles
Variance of angular profiles
Number of LAPPD hits
Total recorded LAPPD charge
Number of MRD clusters
Number of paddles/layers in MRD clusters
+ a couple more similar variables

Dataset information:

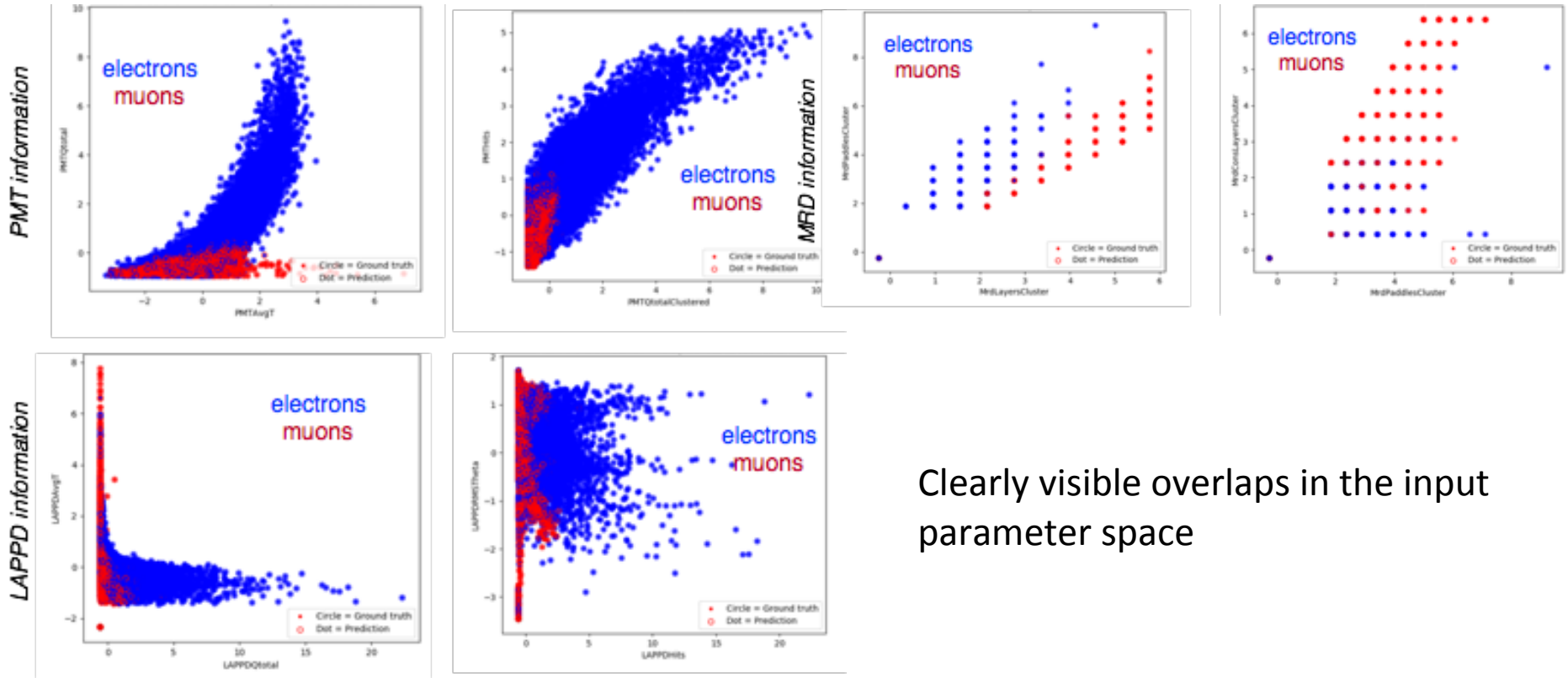
~60,000 muons & ~60,000 electrons simulated with beam-like properties
Require event vertex in Fiducial Volume
Minimum charge for PMT: 10 p.e.



Particle ID - Multi-Layer Perceptron

by Michael Nieslony

A few correlations between input variables:



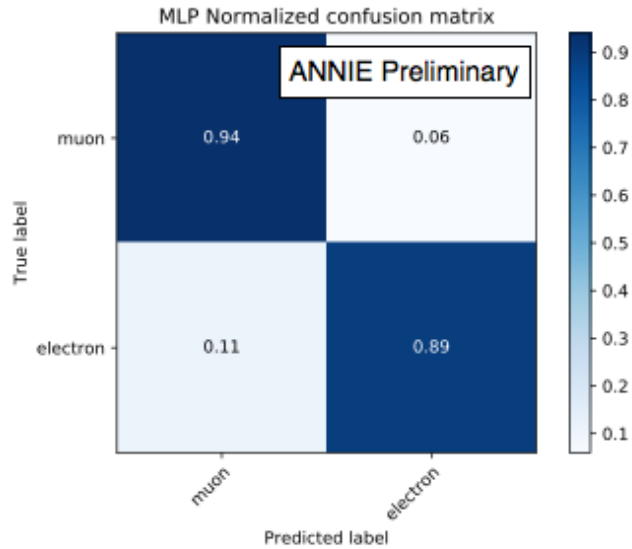
Clearly visible overlaps in the input parameter space

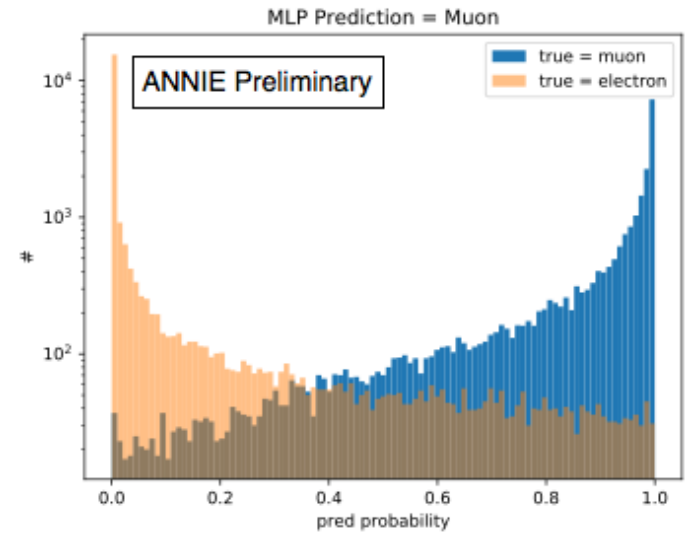
Particle ID - Multi-Layer Perceptron

by Michael Nieslony

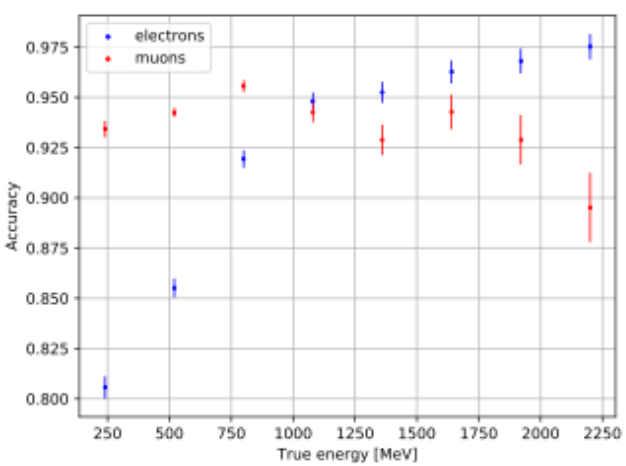
Performance:

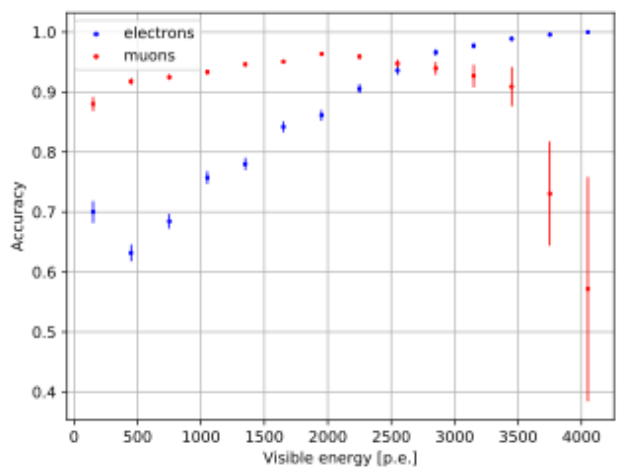
Recall (muons): 94%
Recall (electrons): 89%
Overall accuracy: 91%

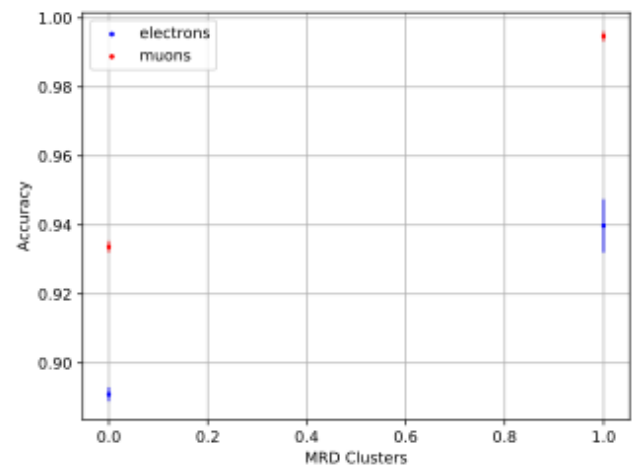




Energy dependence:







Ring Counting - Multi-Layer Perceptron

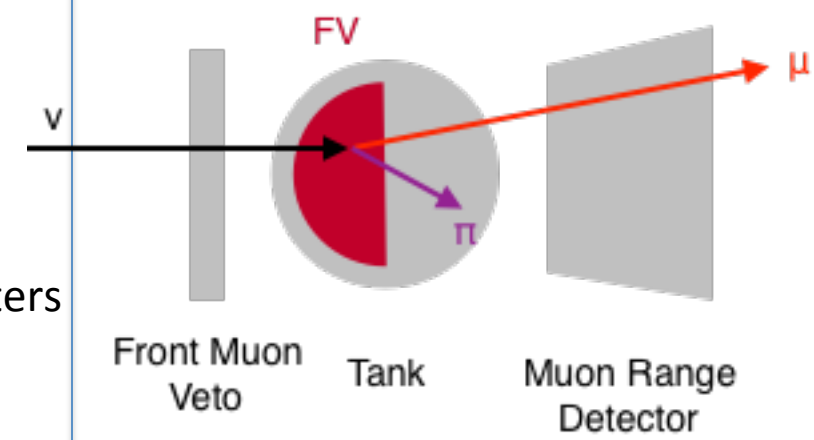
by Michael Nieslony

Input variables – Ring Counting:

Total recorded charge
Fraction of downstream charge
Fraction of highest charge PMT
Number of hit PMTs
Variance of time profile
Fraction of PMT hits at large angles
Variance of angular profiles
Number of LAPPD hits
Total recorded LAPPD charge
Number of MRD clusters
Number of paddles/layers in MRD clusters
+ a couple more similar variables

Dataset information:

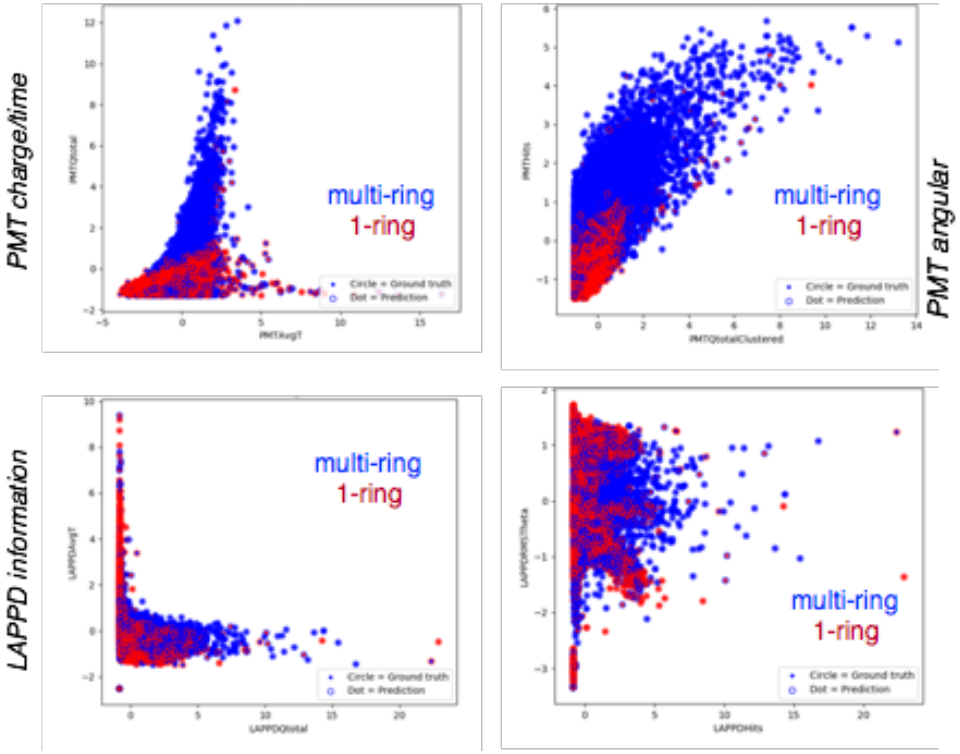
- Complete simulation of BNB neutrino interactions in ANNIE → ~67,000 single-rings + ~39,000 multi-rings
- Require event vertex in Fiducial Volume
- Minimum charge for PMT: 10 p.e.

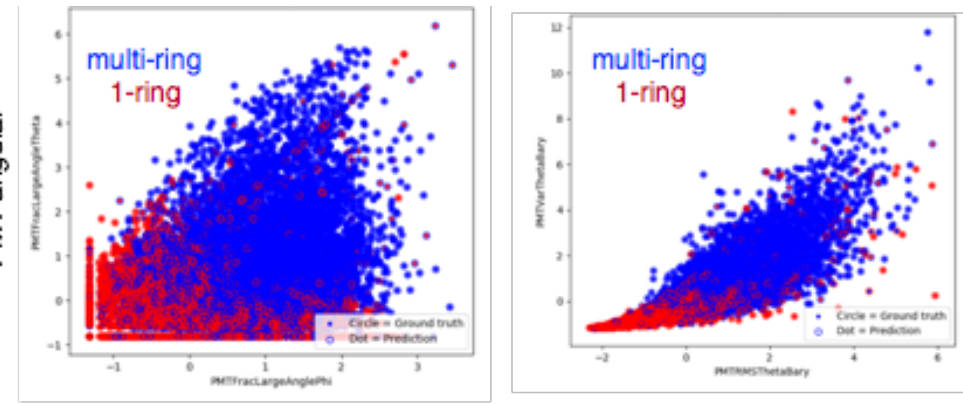


Ring Counting - Multi-Layer Perceptron

by Michael Nieslony

A few correlations between input variables:





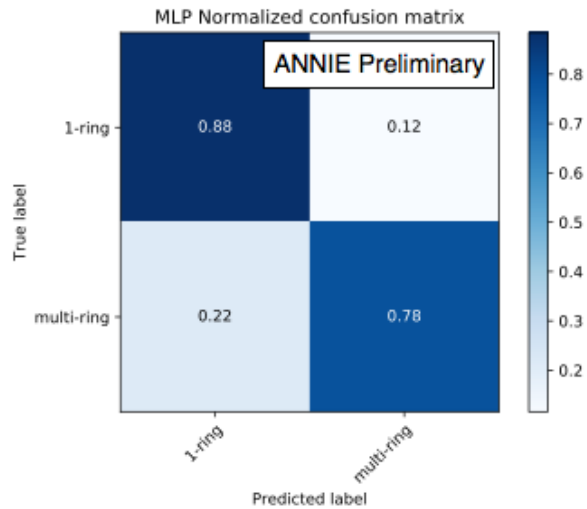
Even stronger overlaps in the input parameter space

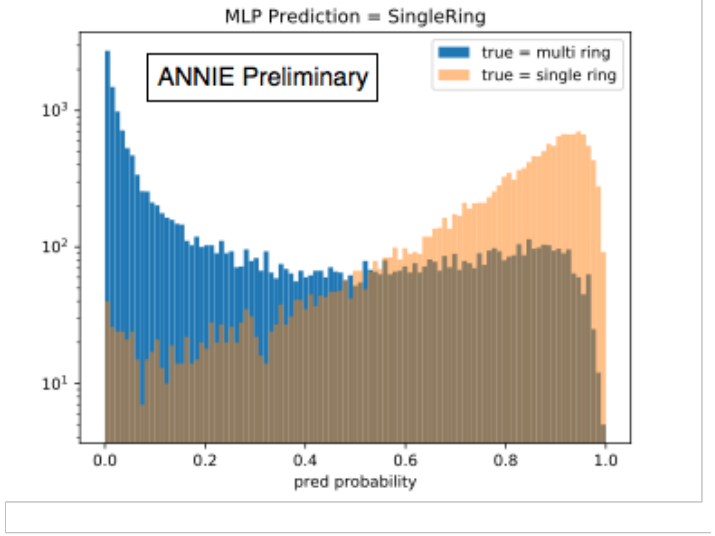
Ring Counting - Multi-Layer Perceptron

by Michael Nieslony

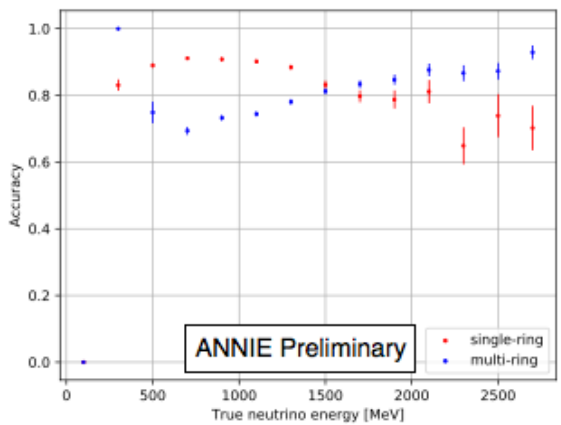
Performance:

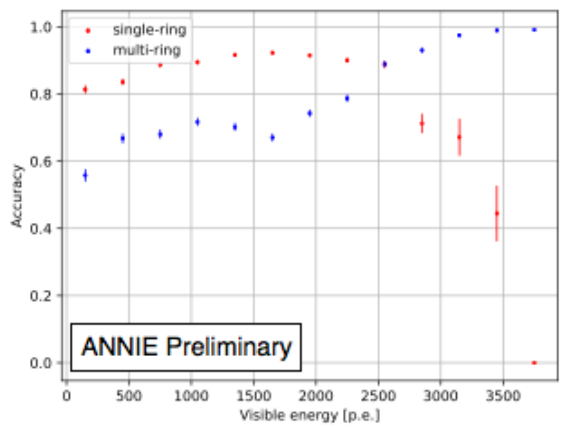
Recall (1-ring): 88%
Recall (multi-ring): 78%
Overall accuracy: 83%

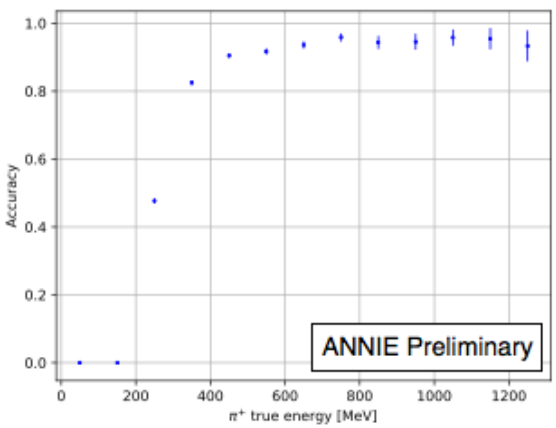




Energy dependence:







Single-rings better classified at lower energies
Multi-rings better classified at higher energies

Multi-ring events favored for high-charge events

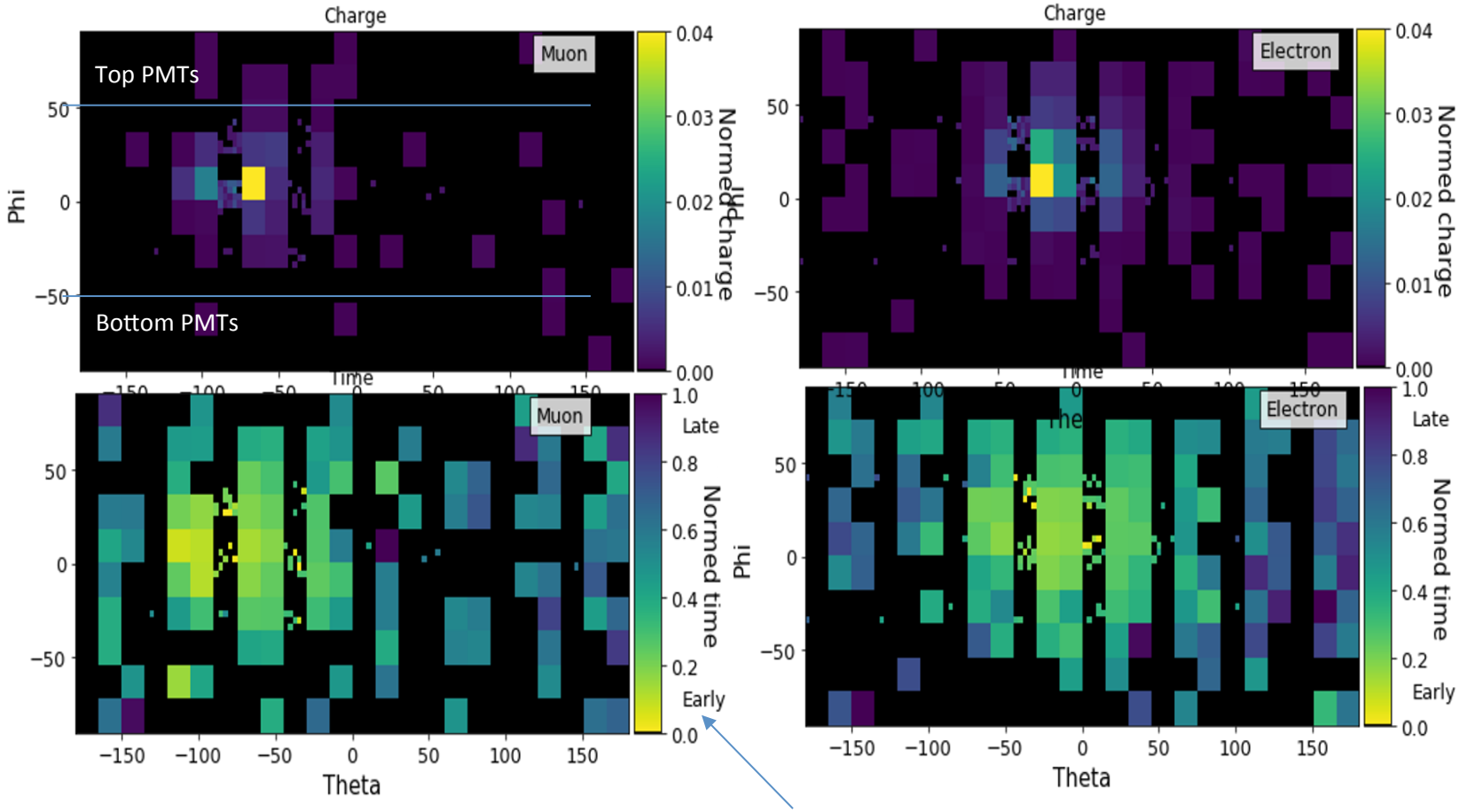
Ring Classification performance highly correlated to pion energy

Particle Identification & Ring Counting

CNN by David Maksimovic

Particle ID - CNN

by David Maksimovic



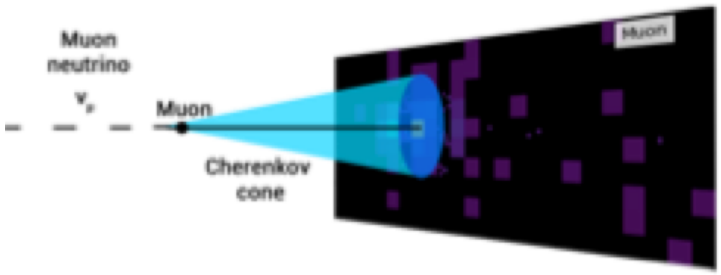
Time values
are flipped for the network
(high values mean earlier arrival time)

Particle ID - CNN

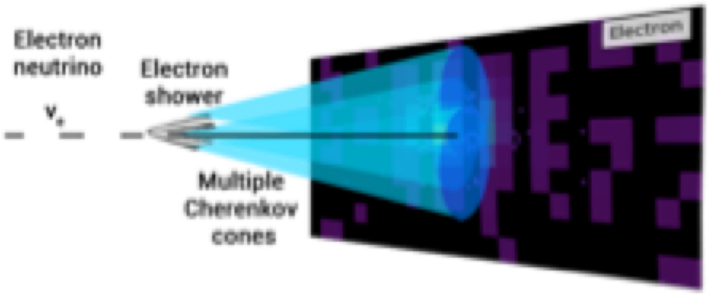
by David Maksimovic

Distinguishing Features:

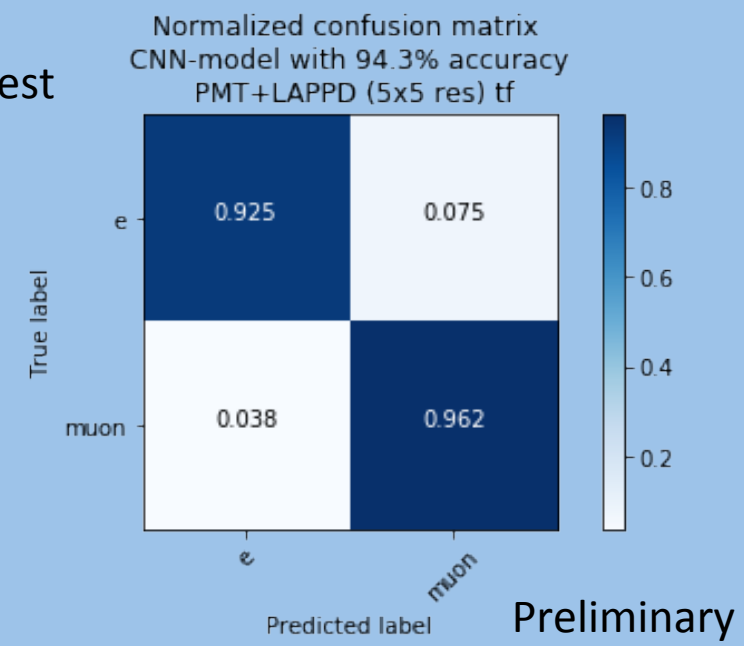
- The muon creates a well-defined Cherenkov cone



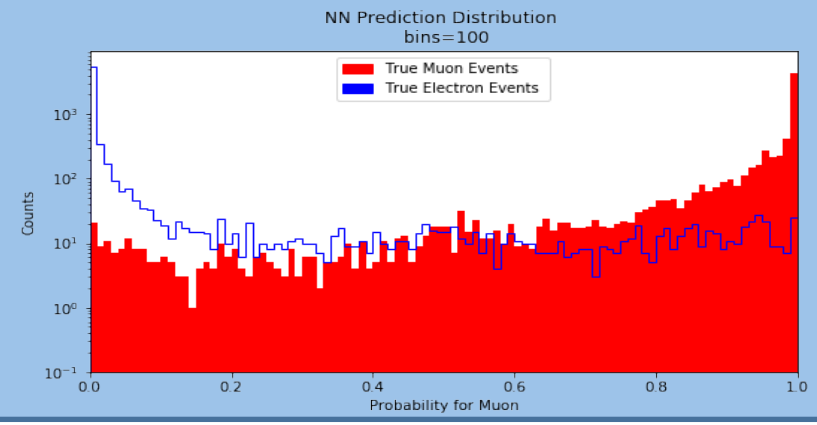
- The multiple electrons from the electron shower give rise to multiple overlapping Cherenkov cones leading to a diffuse disk



20k Test Set



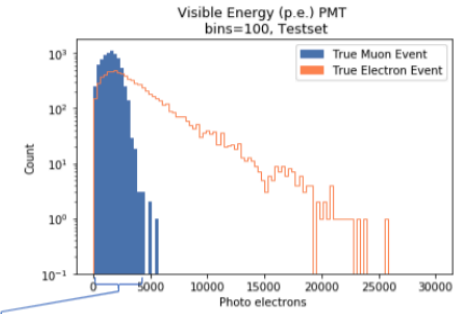
Preliminary

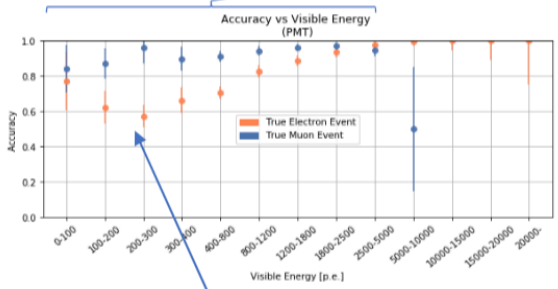


Particle ID - CNN

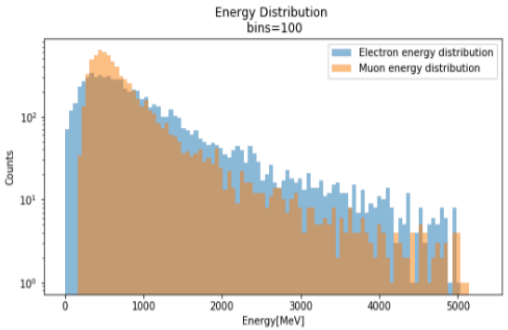
by David Maksimovic

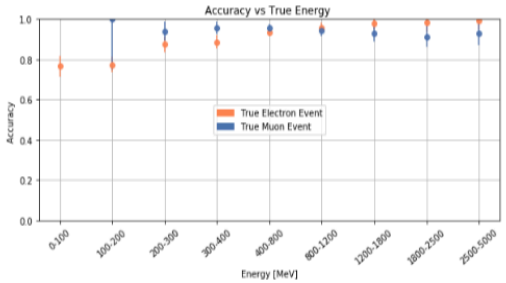
Visible Energy



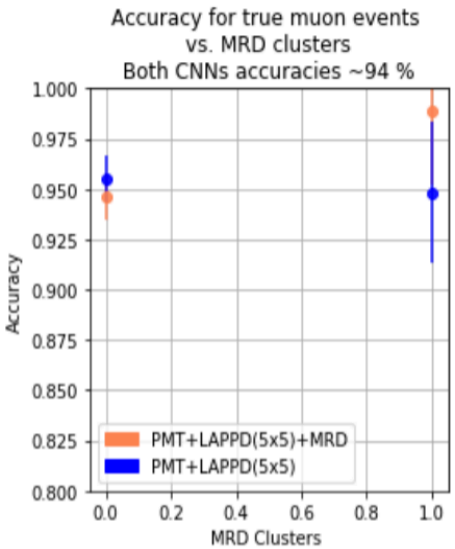


PMT:
We see that the Network has classification problems for low light electron events





Muons are better classified in the relevant energy range from 0 to 1500 MeV

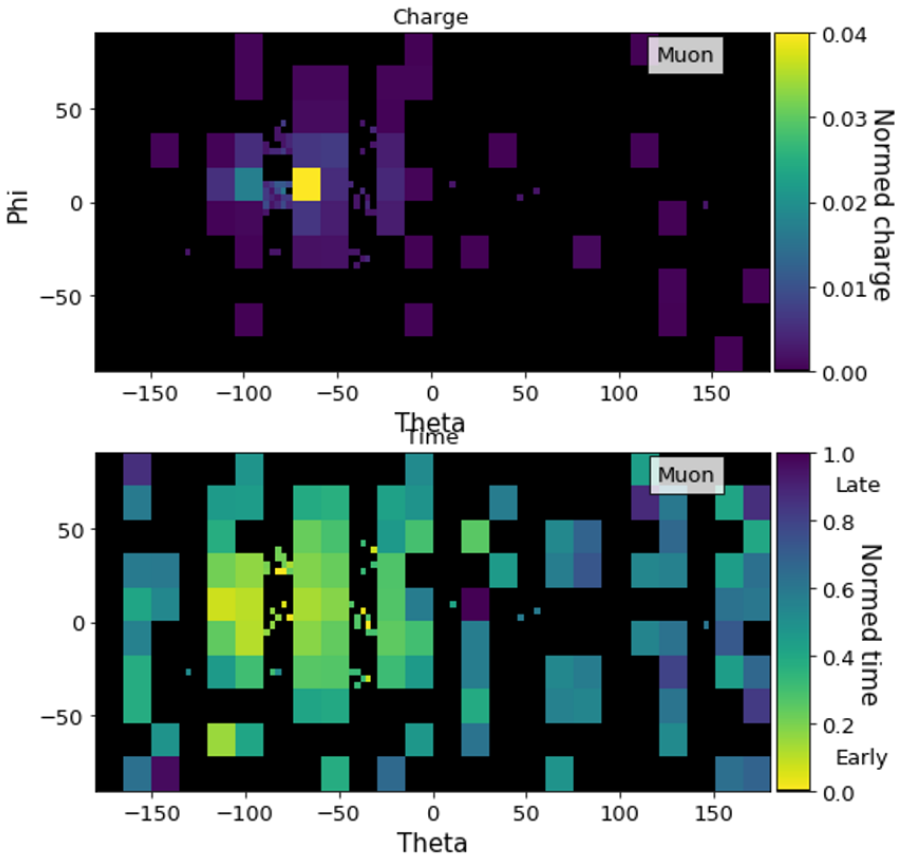


If a selection for at least one MRD clusters is chosen, the accuracy of the CNN increases to 99%

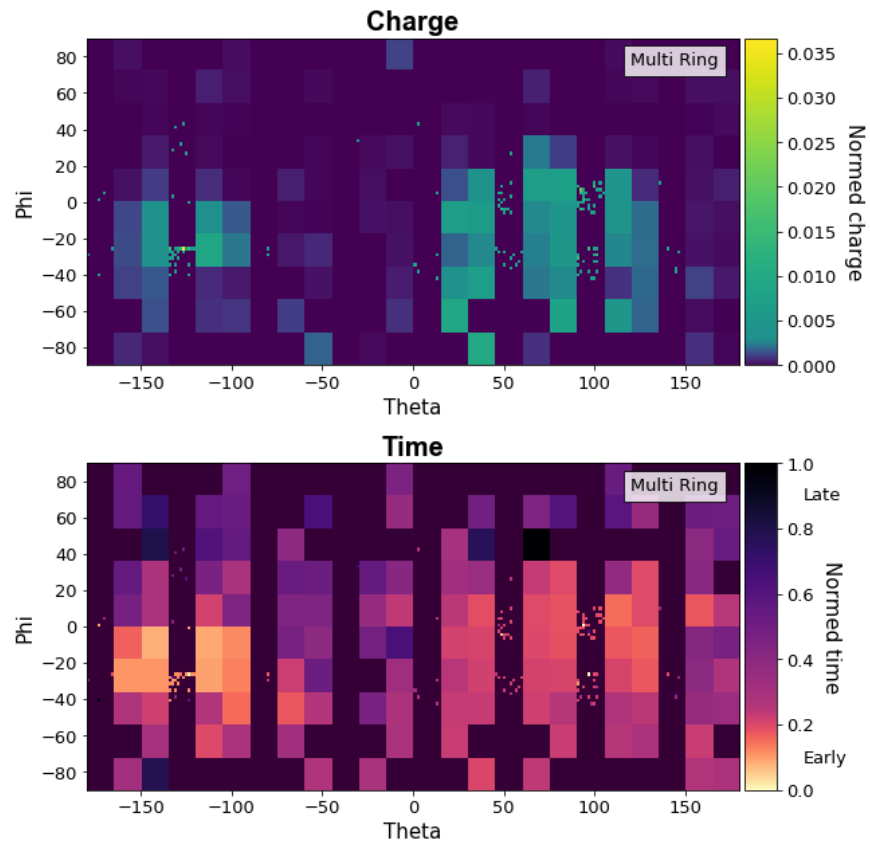
Ring Counting - CNN

by David Maksimovic

Single Rings

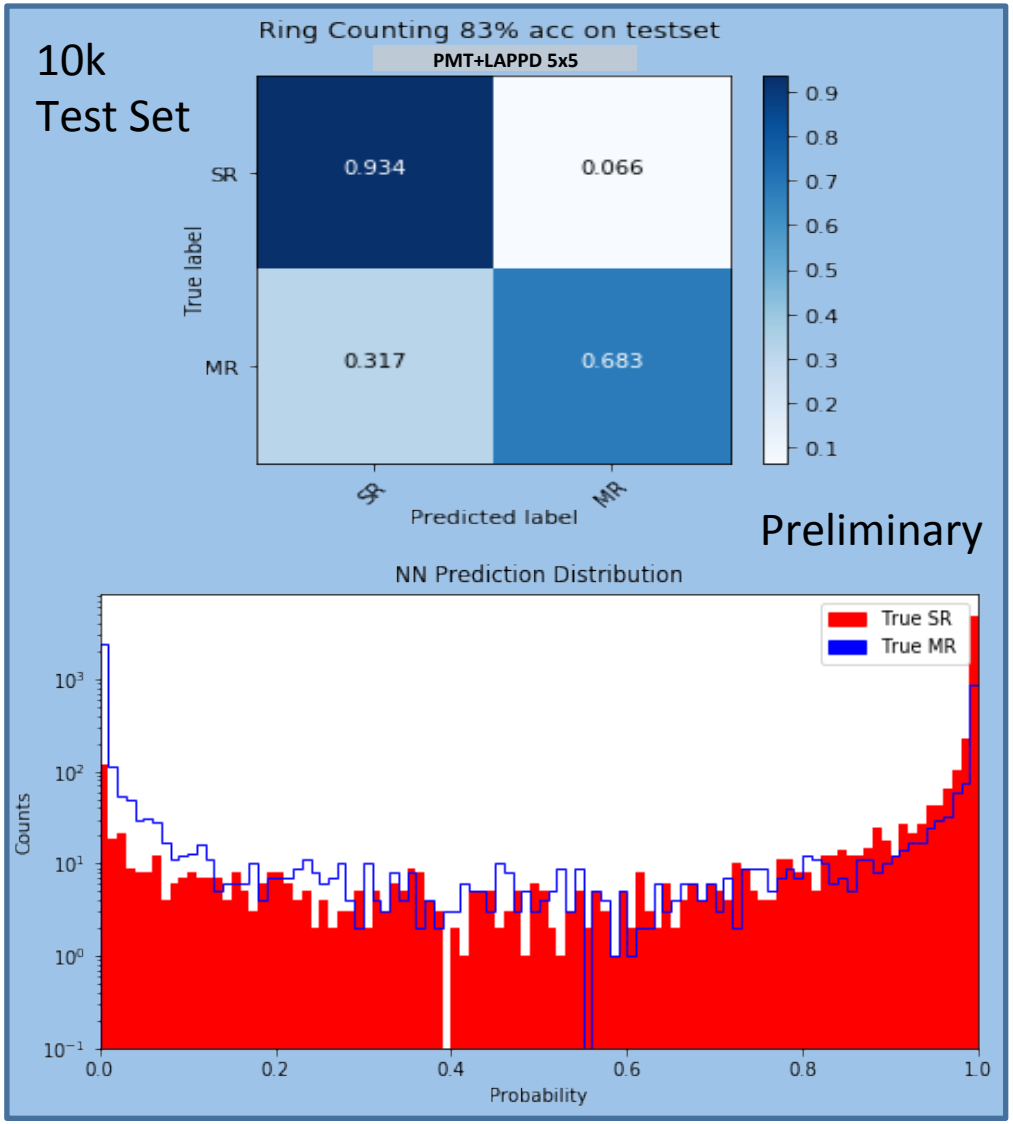


Multi Rings



Ring Counting - CNN

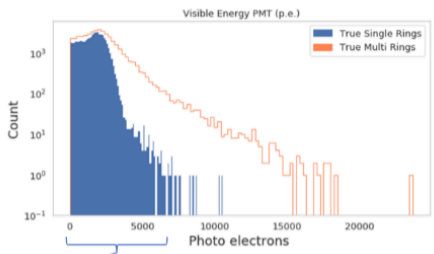
by David Maksimovic

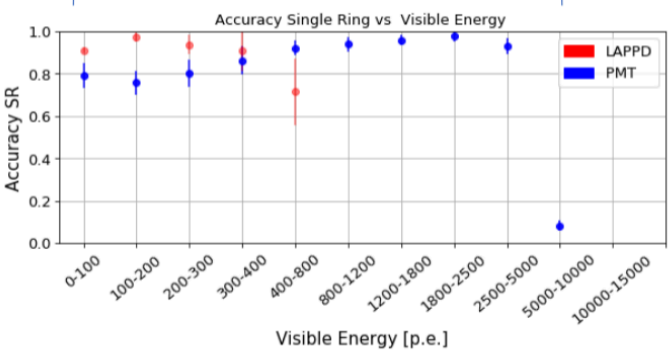


Ring Counting - CNN

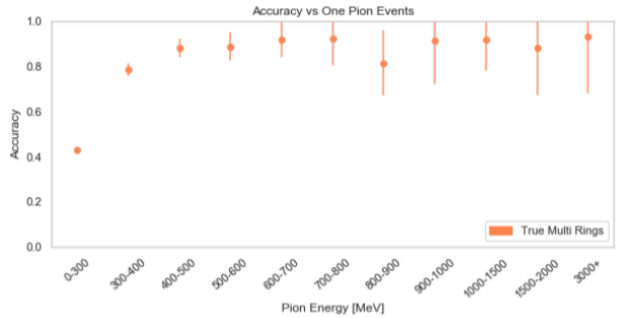
by David Maksimovic

Visible Energy



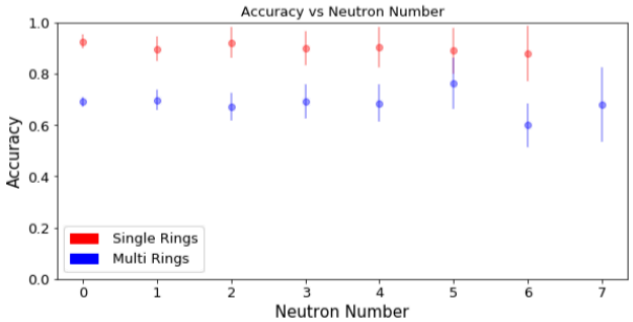


We see that the Network has only classification problems for high energetic single ring events



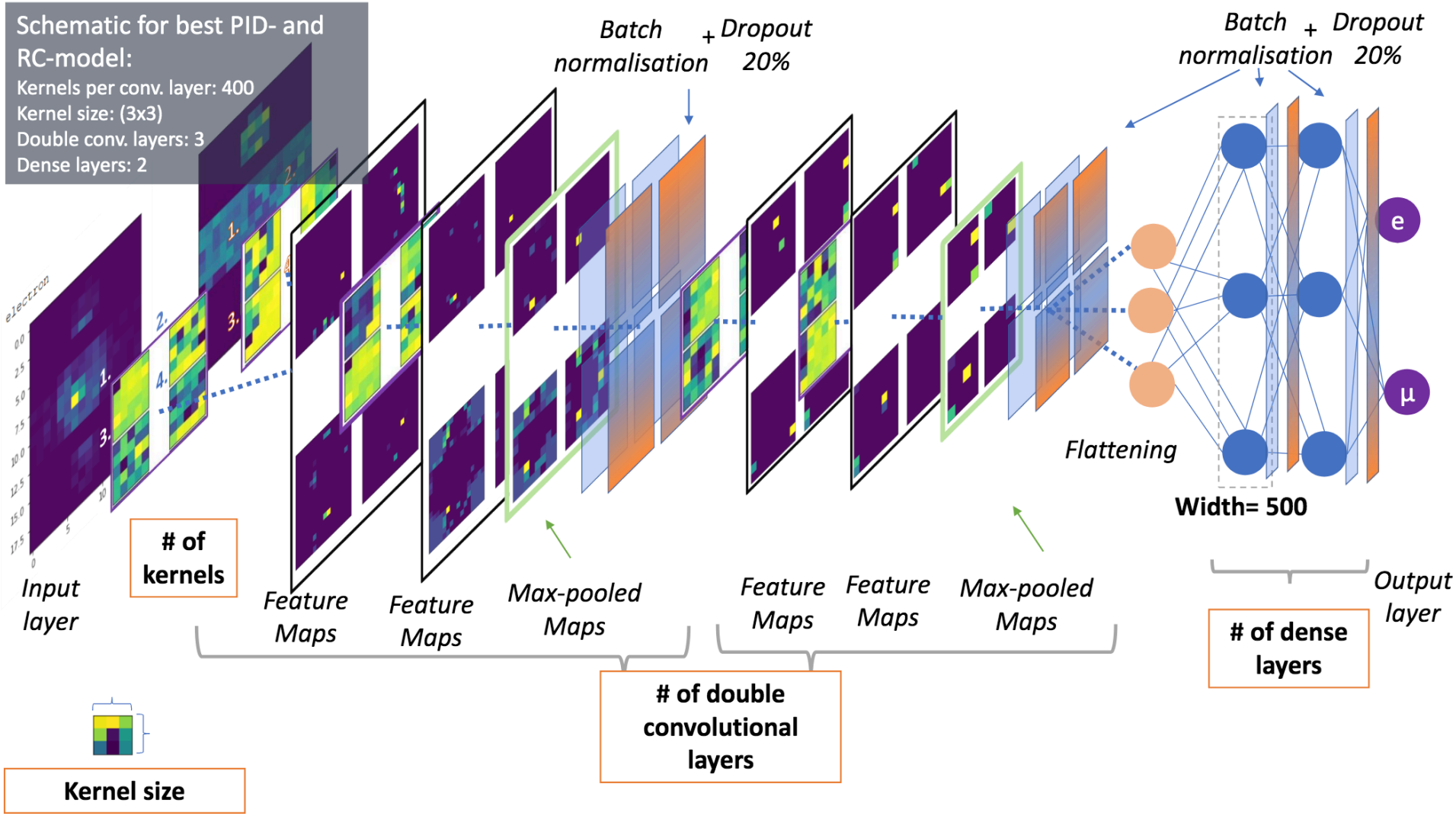
For the CNN, low energy pions look like background within a single ring event rather then multi ring components

Neutron produces within the interactions do not influence the CNN



Ring Counting - CNN

by David Maksimovic



Conclusions

- ANNIE will measure the neutron yield as a function of the momentum transfer from neutrino-nucleus interactions in water.
- To fulfill its scientific goals ANNIE will use LAPPDs and Gd-doped water.
- Machine learning techniques are widely used in ANNIE improving the event reconstruction.
- DNNs and BDTGs are used for the energy reconstruction and MLP and CNN are used for the particle identification and the ring counting.

Thank you !

Backup

Physics Goals (2)

- **Neutrino/Antineutrino separation:**

As neutrino-antineutrino event-rate comparisons are important for δ_{CP} measurements, the relative neutron composition of final hadronic states is significant.

NuSTEC white paper

- **Signal/Background separation:**

Multiplicity and absence of neutrons is also a strong handle for signal-background separation in a number of physics analyses!

ANNIE Letter of Intent
arXiv:1707.08222 [physics.ins-det]

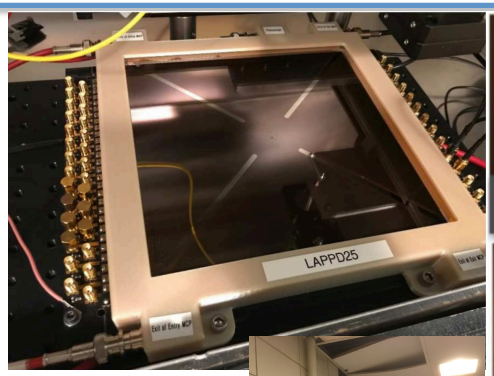
Atmospheric neutrino interactions in water may produce final state neutrons!

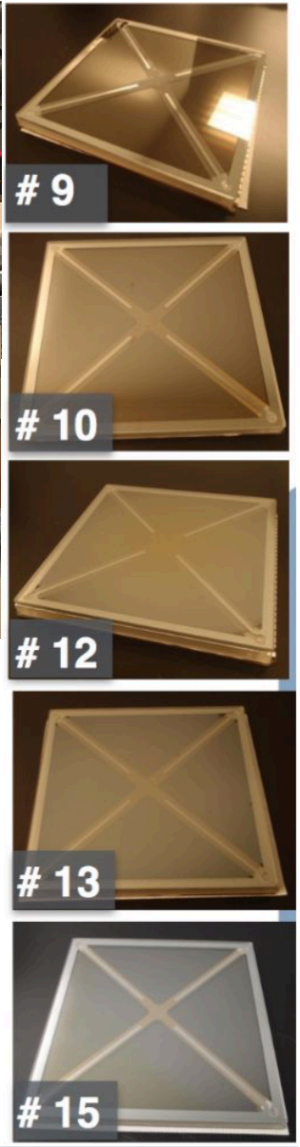
The knowledge of neutron yield will reduce background for:
Proton Decay searches, Diffuse Supernova Background (DSNB)

LAPPDs – A new technology tested in ANNIE

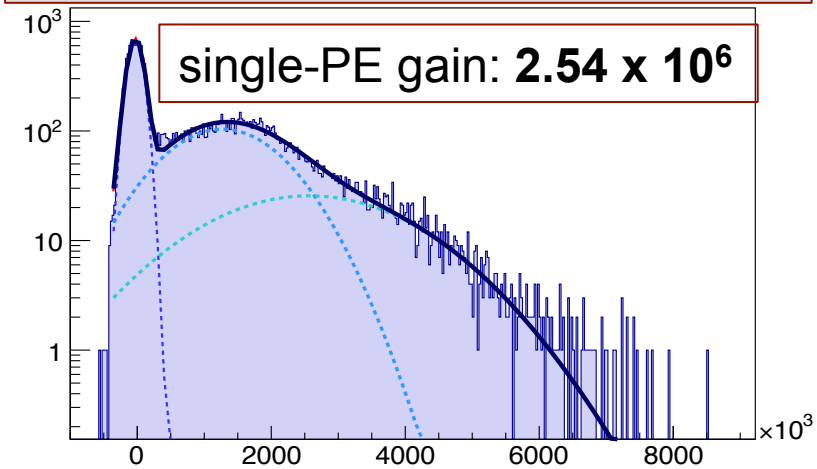
Incom Inc has now produced multiple LAPPD devices http://www.incomusa.com

- A number of tiles have been produced and tested → gain, timing and QE
- Purchased tile #25 from INCOM
  - → Thorough testing ongoing at ISU
  - → Expected to be deployed in ANNIE Phase II

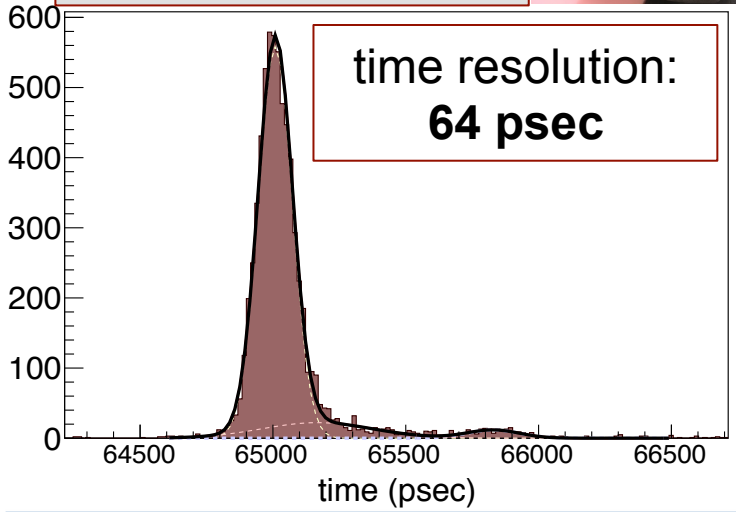




Gain - in units of elementary charge



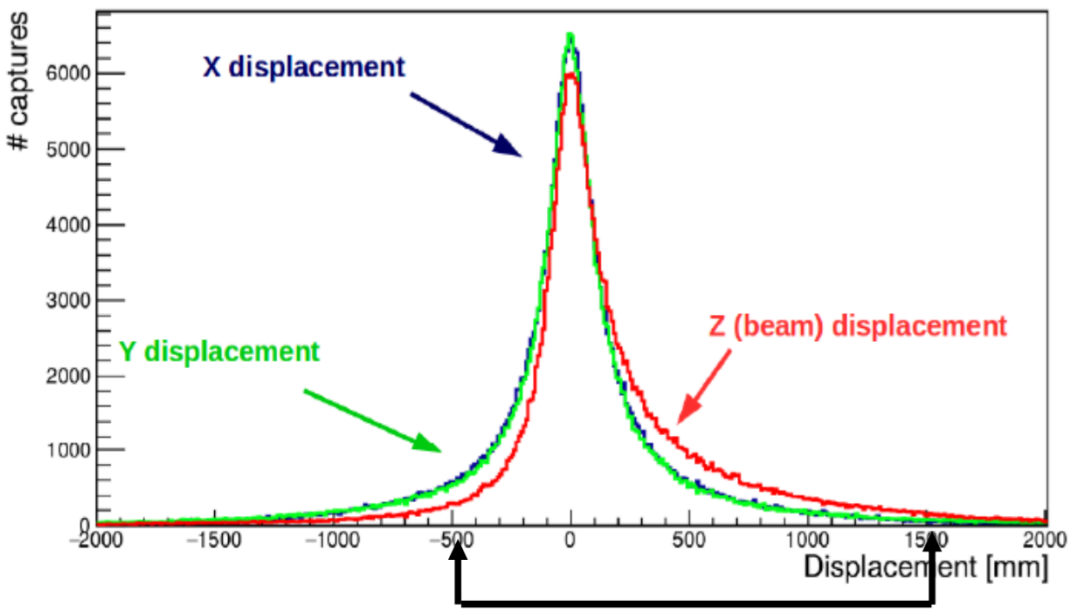
Transit Time Spread



Why LAPPDs in ANNIE?

LAPPDs enable the ANNIE physics:

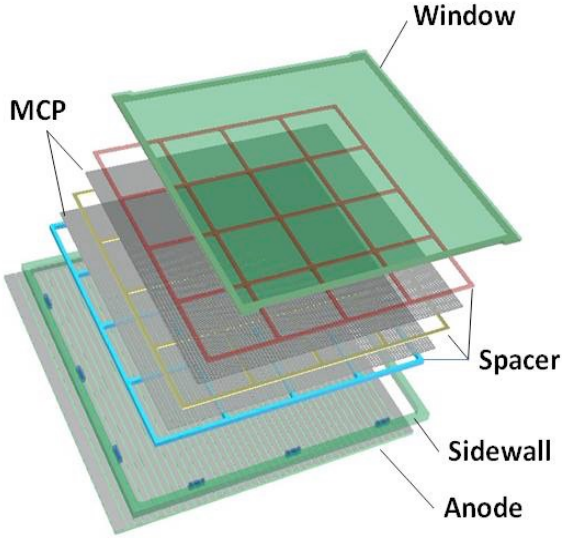
- Neutrons created in ANNIE can drift up to 2 m:
  → drift is symmetric in the direction transverse to beam
  → drift is mostly forward in the beam direction
- Given ANNIE's small size it is crucial to maximize the fiducial volume
- A vertex resolution of ~ 10 cm is needed to properly identify events in the fiducial volume.



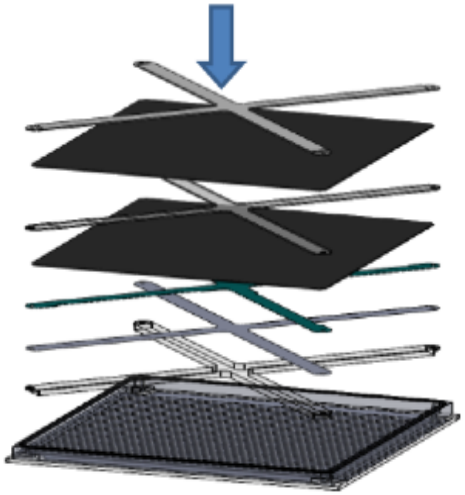
- Such resolution is beyond the capability of traditional PMTs!
- Precise timing-based reconstruction enabled by LAPPDs is essential.

LAPPDs – A new technology tested in ANNIE

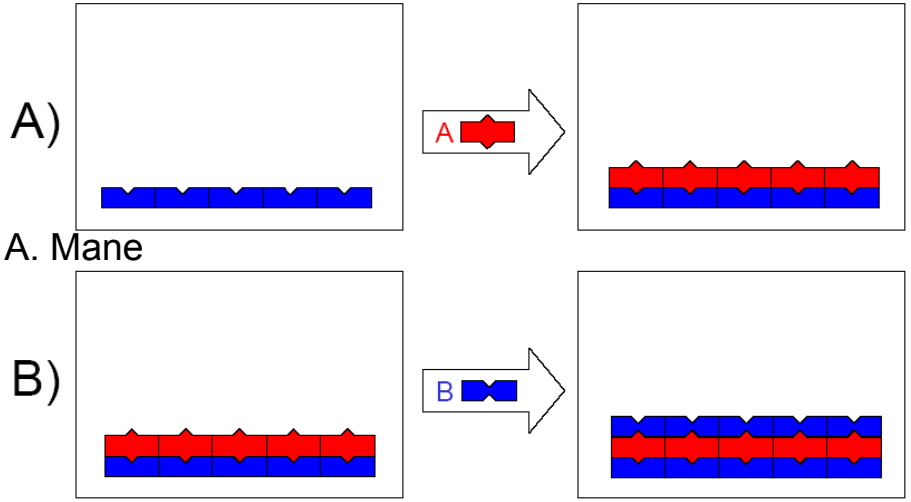
- Glass body, minimal feedthroughs
- MCPs made using atomic layer deposition
- Transmission line anode
- Fast and economical front-end electronics
- Large area, flat panel photocathodes



Design Drawing - September 2010

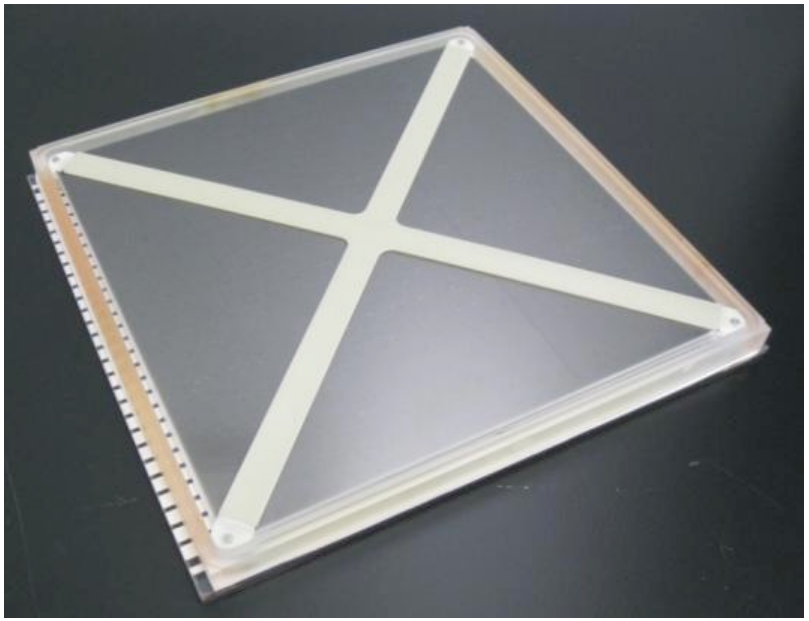


Atomic Layer Deposition



J. Elam, A. Mane

The LAPPD Concept



LAPPD detectors:

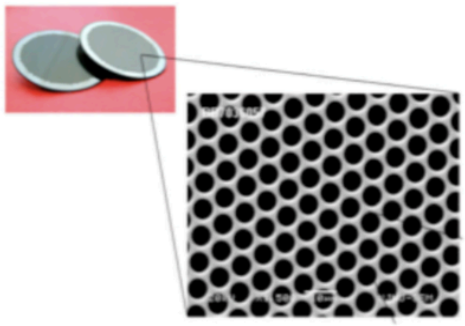
- Thin-films on borosilicate glass
- Glass vacuum assembly
- Simple, pure materials
- Scalable electronics
- Designed to cover large areas

Conventional MCPs:

- Conditioning of leaded glass (MCPs)
- Ceramic body
- Not designed for large area applications

The LAPPD Concept

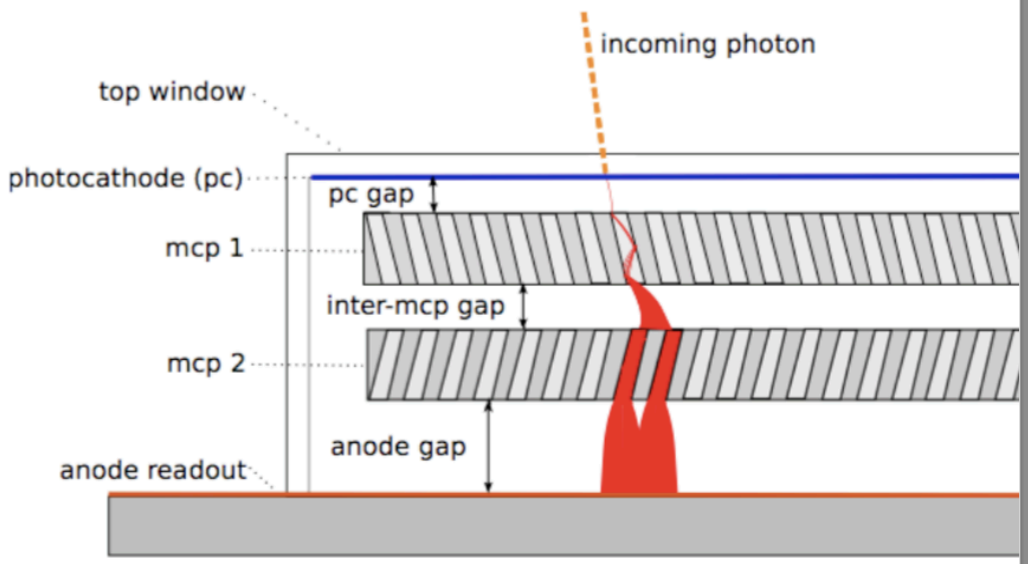
What is an MCP-PMT?



Microchannel Plate (MCP):

- a thin plate with microscopic (typically <50 μm) pores
- pores are optimized for secondary electron emission (SEE).
- Accelerating electrons accelerating across an electric potential strike the pore walls, initiating an avalanche of secondary electrons.

- An MCP-PMT is, sealed vacuum tube photodetector.
- Incoming light, incident on a photocathode can produce electrons by the photoelectric effect.
- Microchannel plates provide a gain stage, amplifying the electrical signal by a factor typically above 10^6.
- Signal is collected on the anode

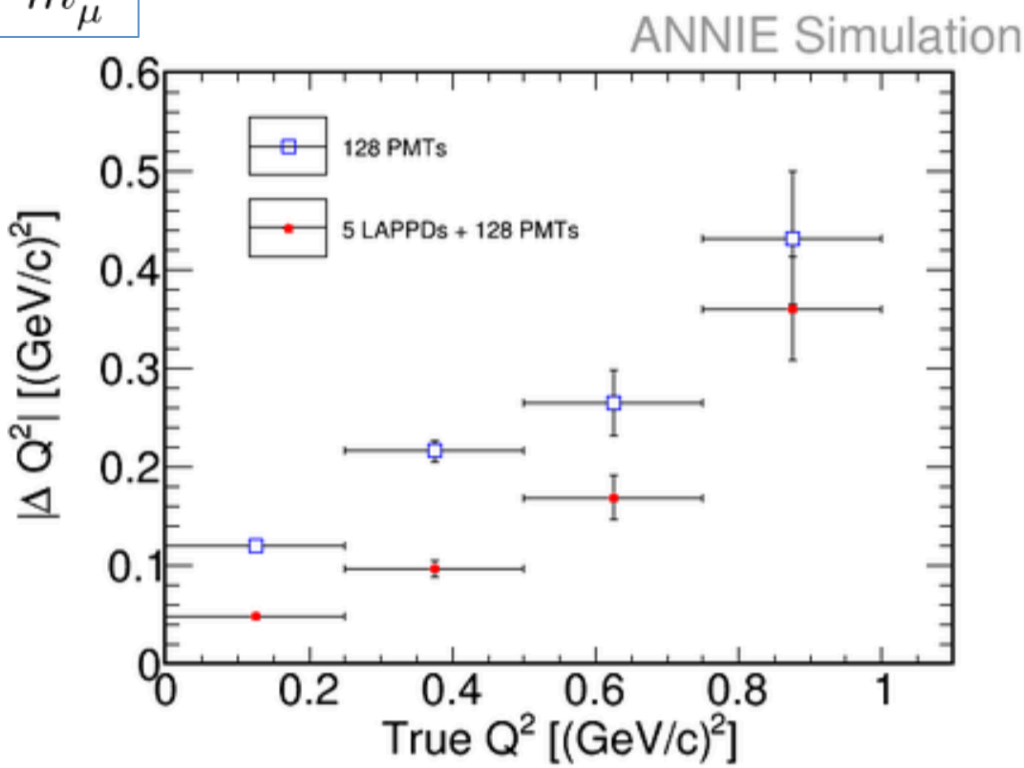


Momentum Transfer: Q^2

- Momentum transfer for CCQE events: the primary interaction channel in ANNIE
- CCQE events are completely described by the energy of the incoming neutrino and the energy and momentum of the outgoing muon.

$$Q^2_{QE} = 2E_\nu^{QE}(E_\mu - p_\mu \cos\theta_\mu) - m_\mu^2$$

- 1-σ Q^2 resolution for four bins in true Q^2
- The addition of LAPPDs considerably improves the Q^2 resolution.



Vertex and Track Reconstruction

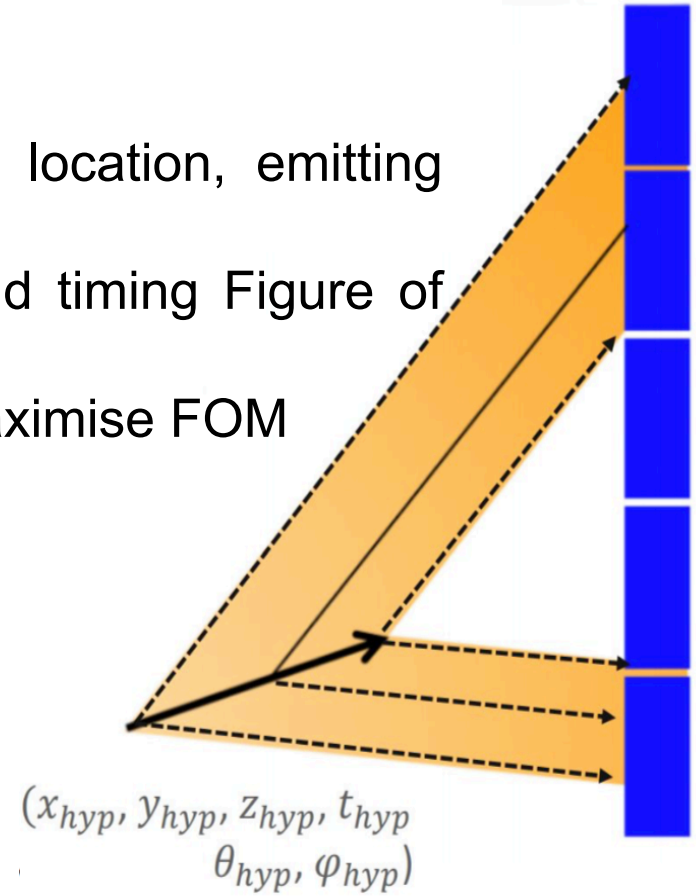
Steps:

1. "Simple vertex" fit → (x, y, z, t)

- Consider a point source at a hypothesised location, emitting Cherenkov light
- For each hit calculate the timing residual and timing Figure of Merit (FOM)
- Adjust the four hypothesised parameters to maximise FOM

2. Extended vertex fit → (x, y, z, t, θ, φ)

- Start with position from simple vertex fit and add hypothesised track direction
- For each hit calculate extended time residual including muon travel time
- Calculate cone FOM by comparing predicted to measured Cherenkov cone
- Adjust all six parameters to maximise total FOM (time FOM + cone FOM)



Credit: Jingbo Wang