Graph Neural Networks Reconstruction for the Hyper Kamiokande Detector

21st Rencontres du Vietnam, Quy Nhon, July 2025

Erwan Le Blévec

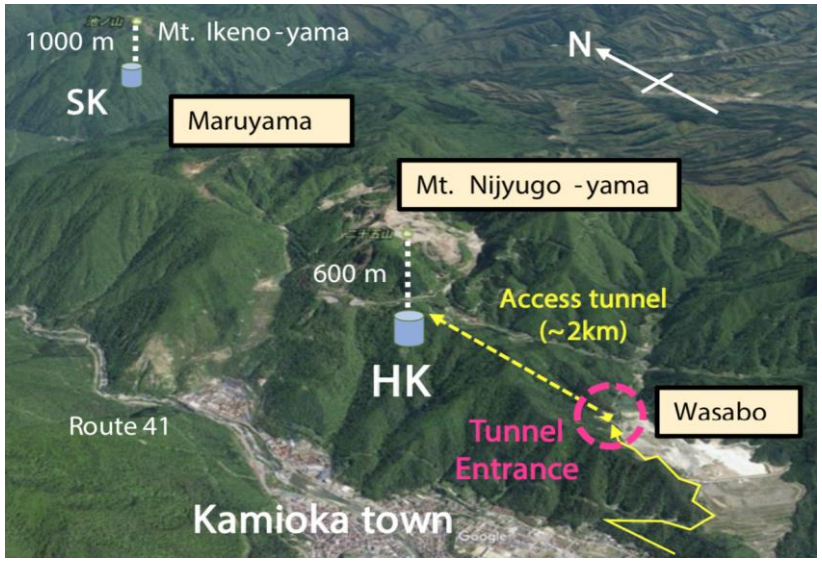
On behalf of the Hyper K collaboration

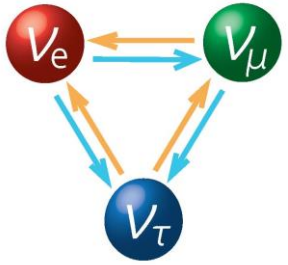
Laboratoire Leprince-Ringuet

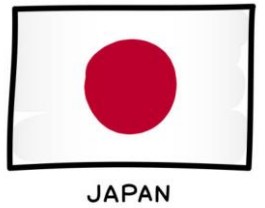
東京大学 THE UNIVERSITY OF TOKYO

ILANCE

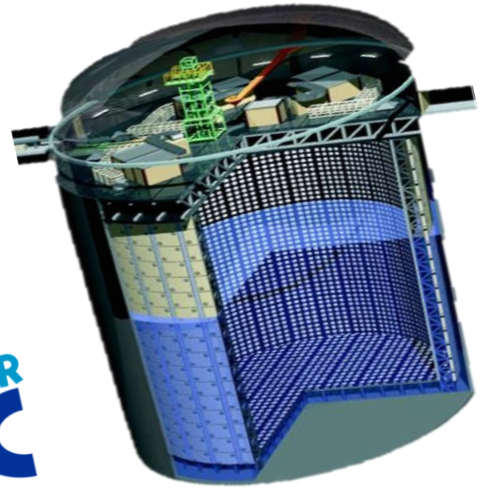
cnrs

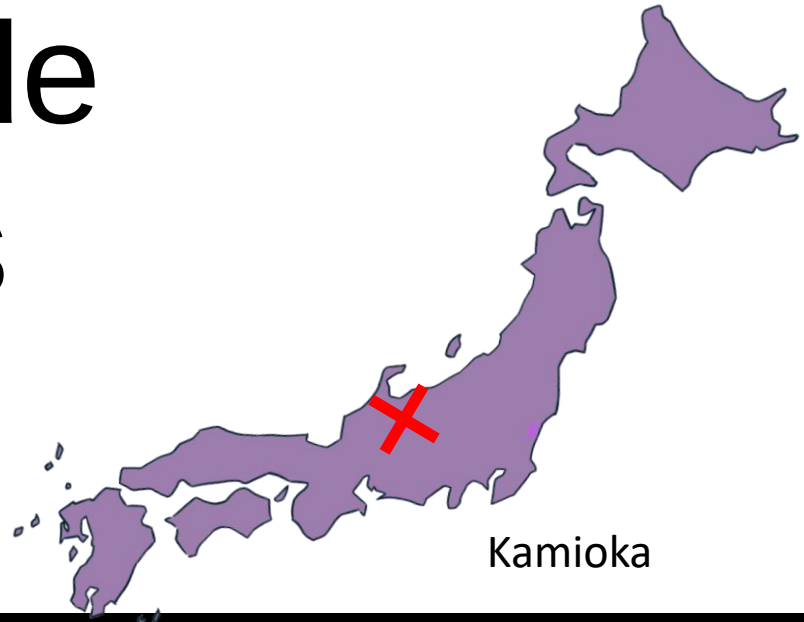






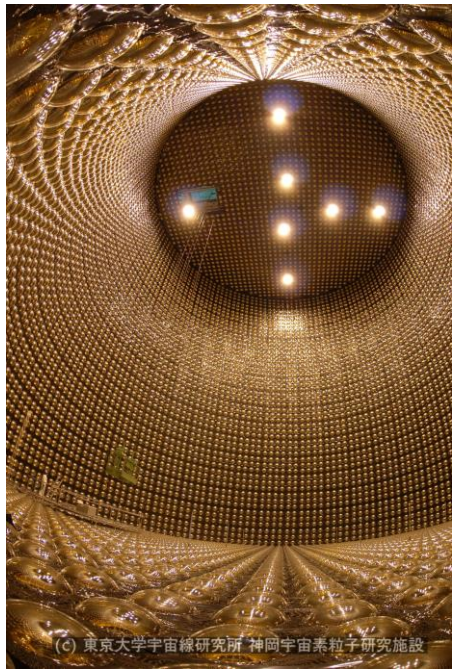
Kamiokande Detectors





From Big to Huge

Super Kamiokande

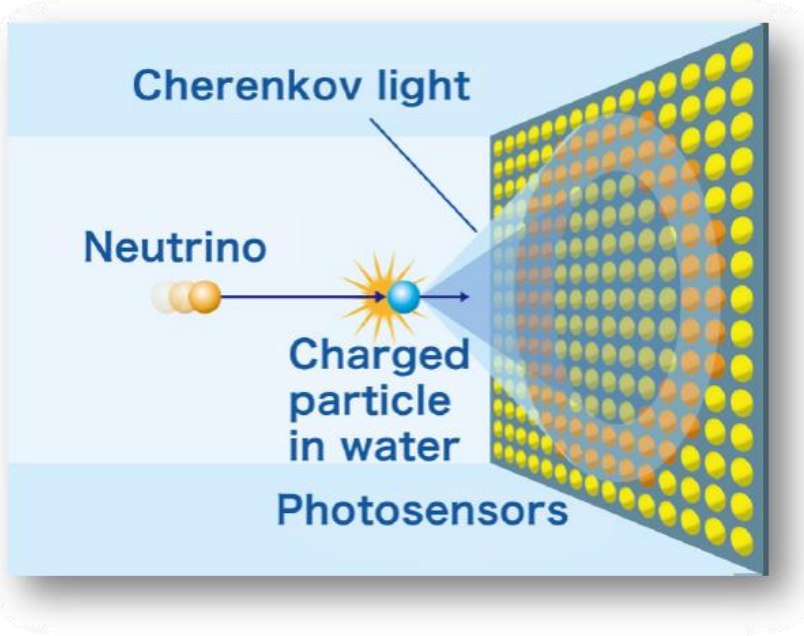


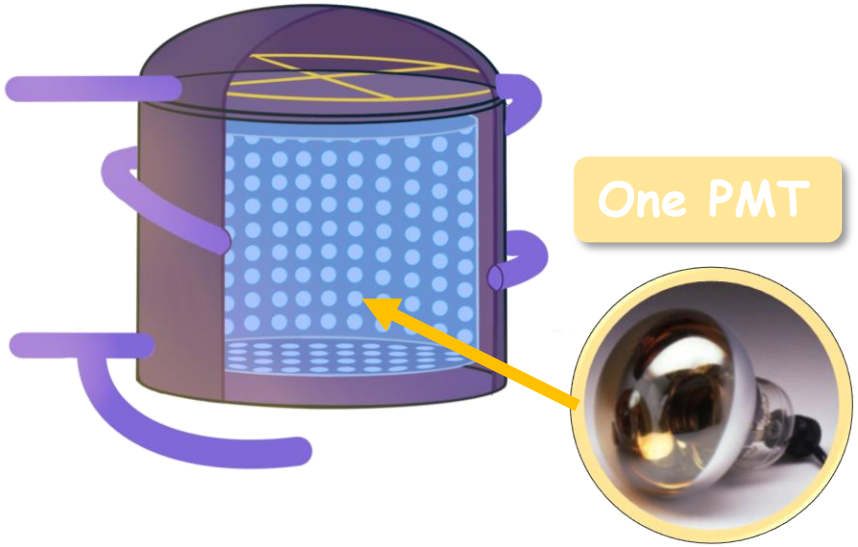
8 x

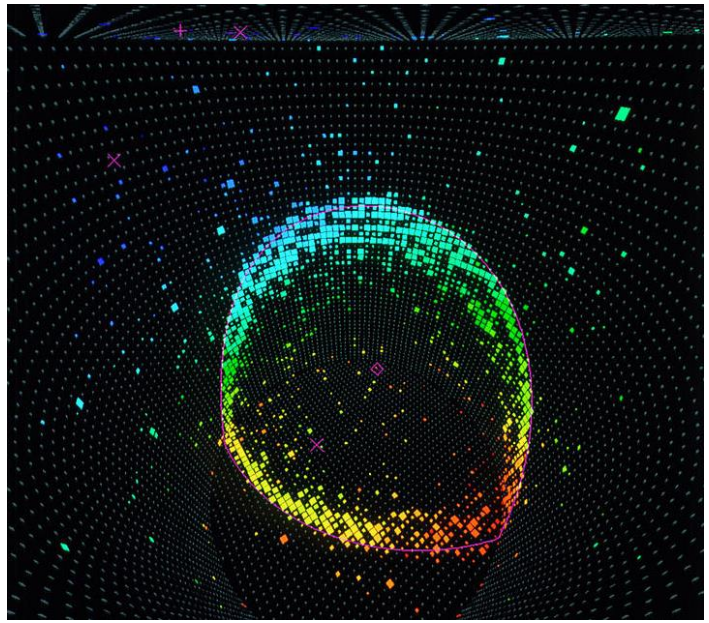
Hyper Kamiokande

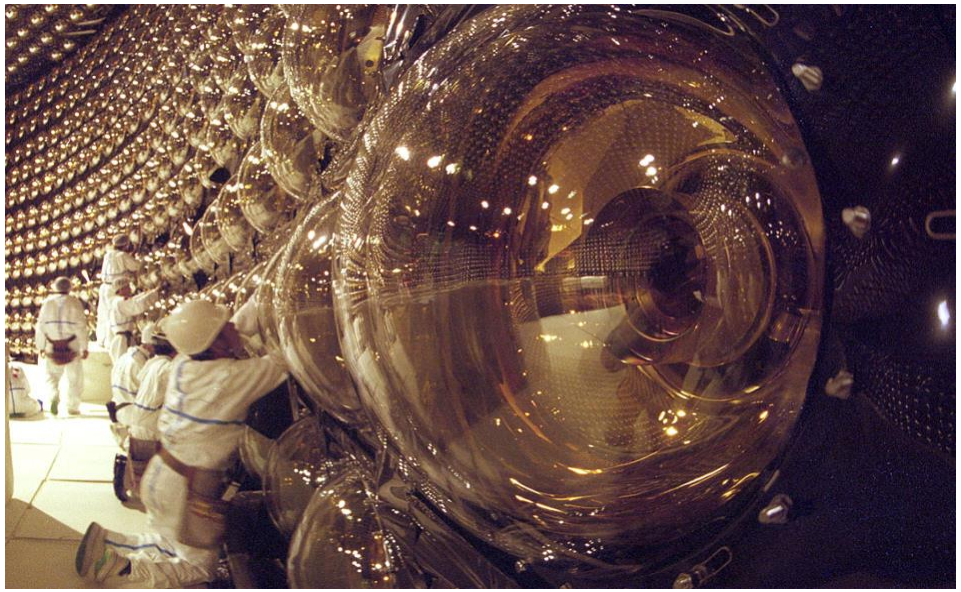
	1996 - today (and beyond)	2028 - (and beyond)
ID PMTs	~11k	20k
Photo Coverage	40%	20% (x2 efficiency)
Mass / Fiducial Mass	50 kton / 22.5 kton	260 kton / 188 kton

Detection Principle





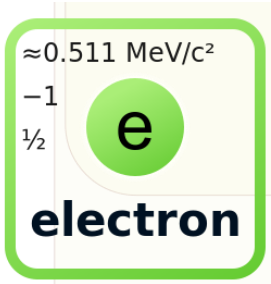


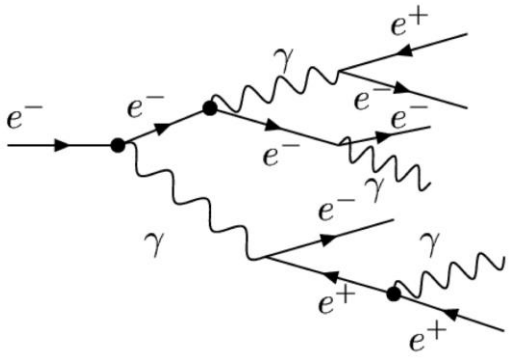


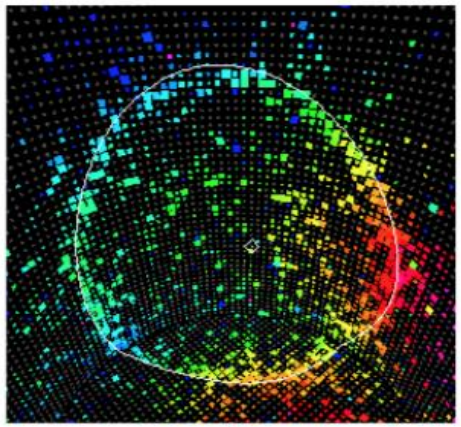
Ultra-sensitive **P**hoto**M**ultiplier **T**ubes (PMTs) to detect Cherenkov light from energetic charged particles.

Reconstruction in Hyper K

Tracing back from light to Particle



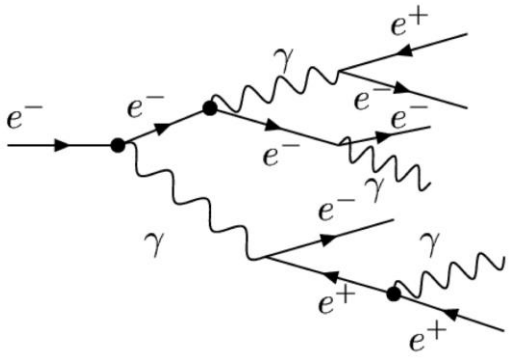


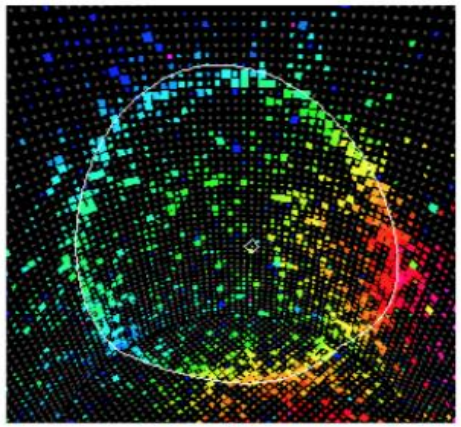


ν_e-like

Tracing back from light to Particle

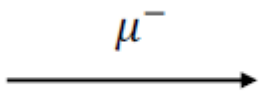
≈0.511 MeV/c²
−1
½
e
electron

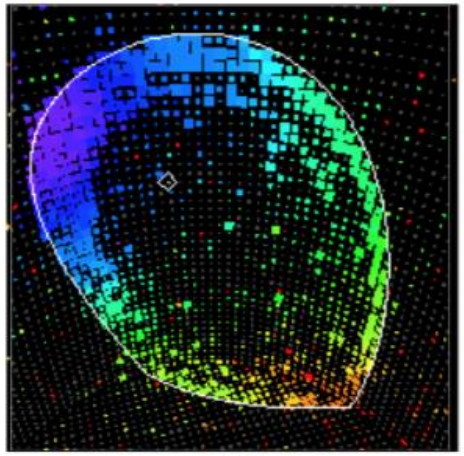




ν_e-like

≈105.66 MeV/c²
−1
½
μ
muon

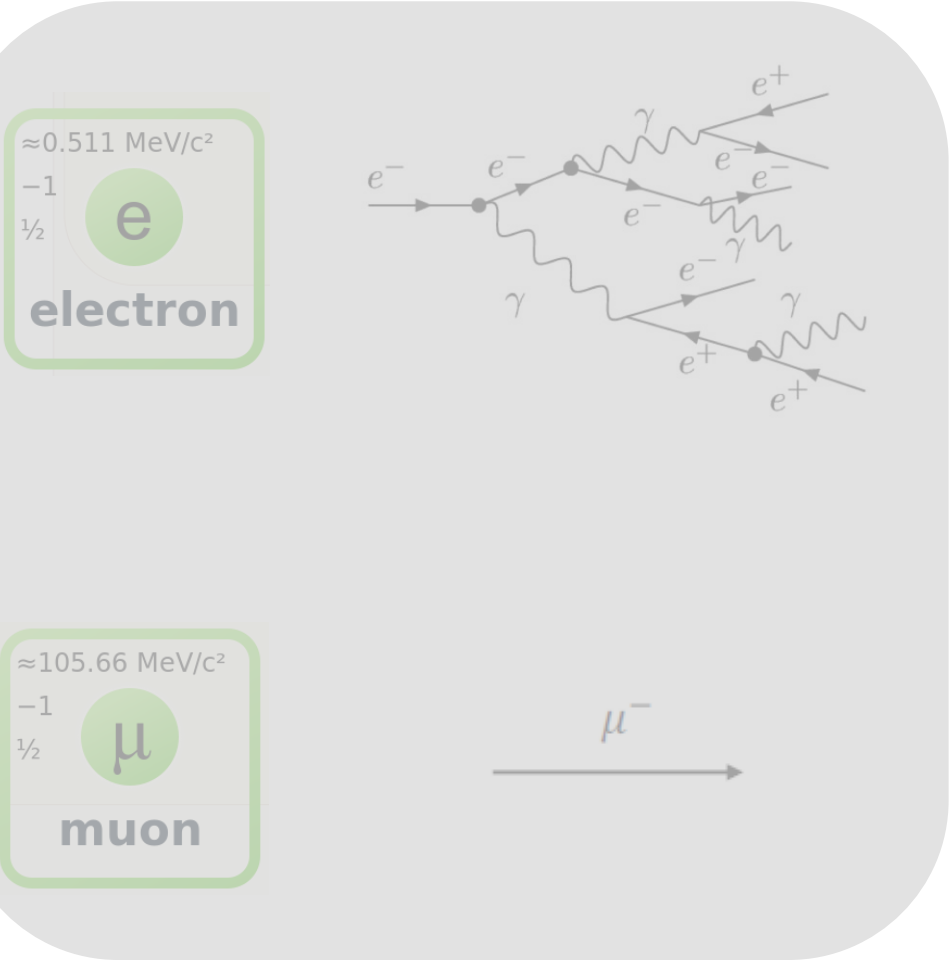


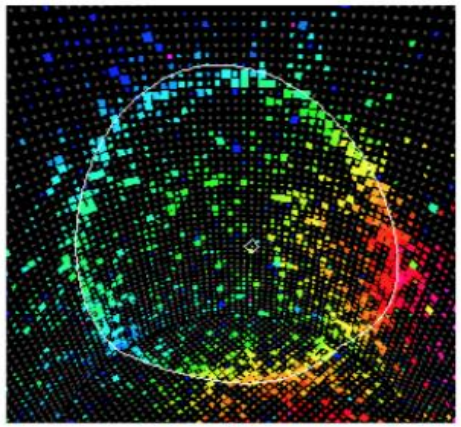


ν_μ-like

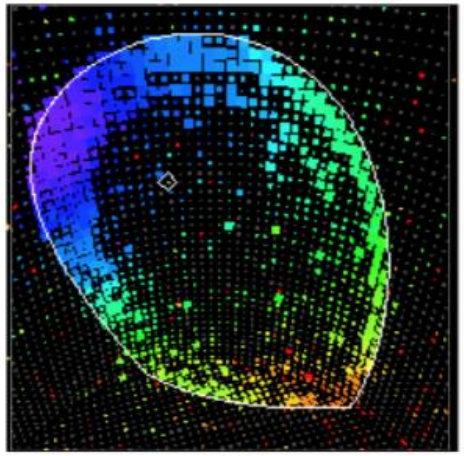
Different behaviors → Different ring patterns

Tracing back from light to Particle





ν_e-like



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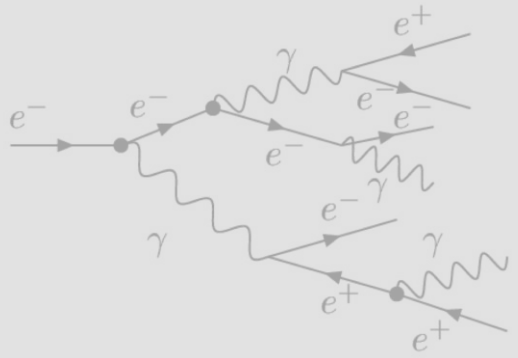

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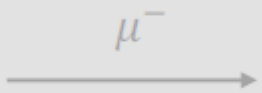

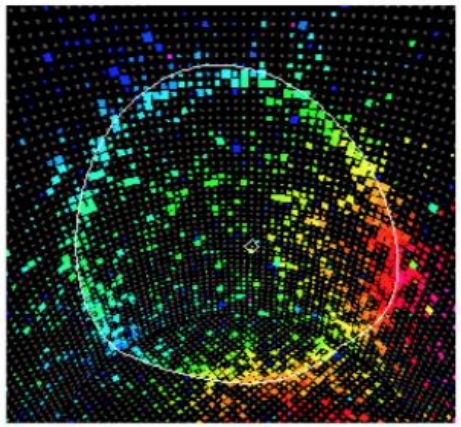

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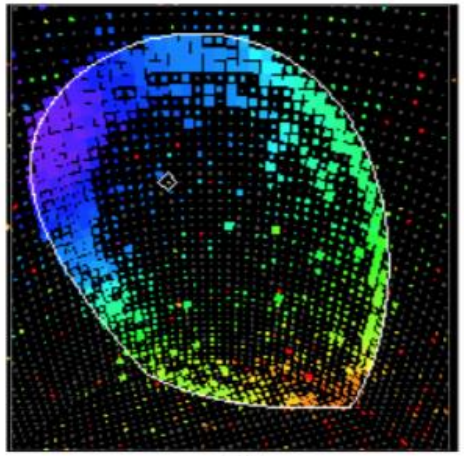

ν_μ-like

Different behaviors → Different ring patterns

Reconstruction Algorithm

≈0.511 MeV/c²
−1
½
e
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+

- Direction
- Energy
- Vertex

Tracing back from light to Particle

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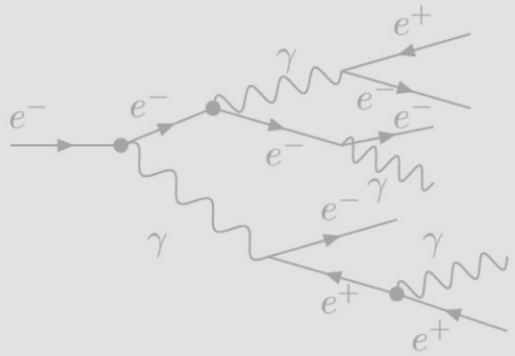

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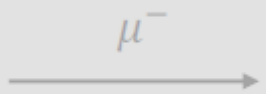

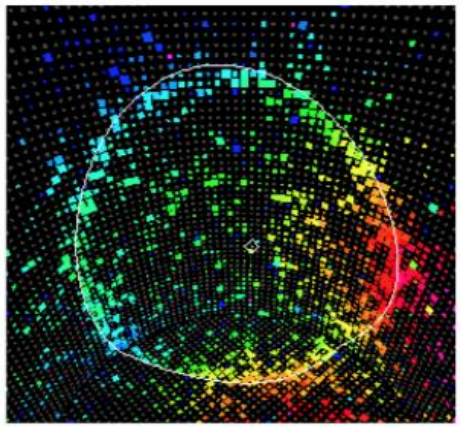

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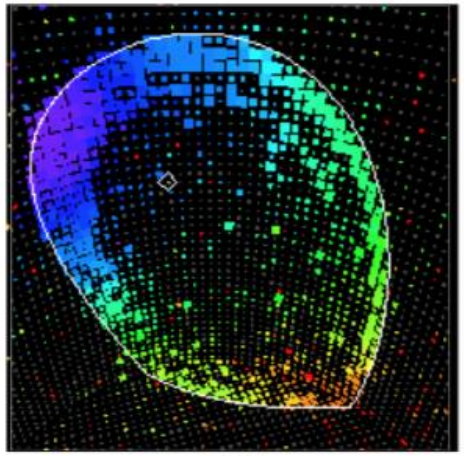

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Reconstruction algorithms & Their Evolutions

Kamiokande

(Low trigger rate / day)

Fiducial V.

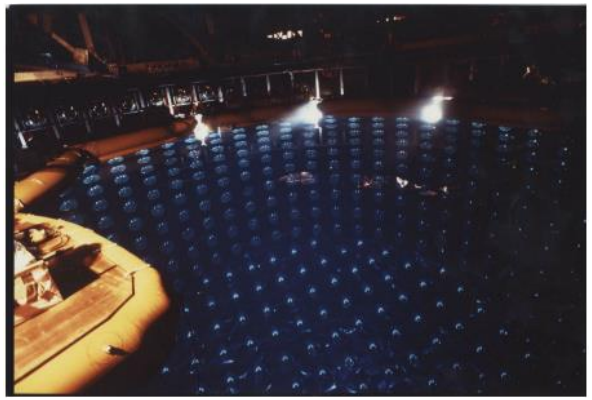
30 x

Super Kamiokande

8 x

Hyper Kamiokande

« Hand » Fit

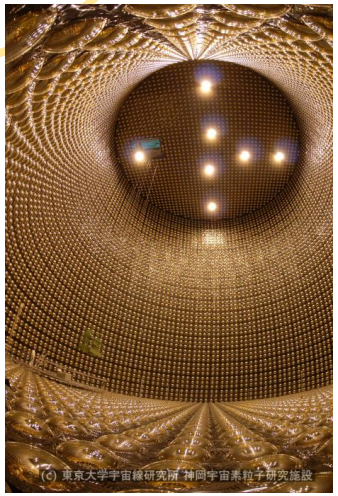


Maximum Likelihood - based Fit

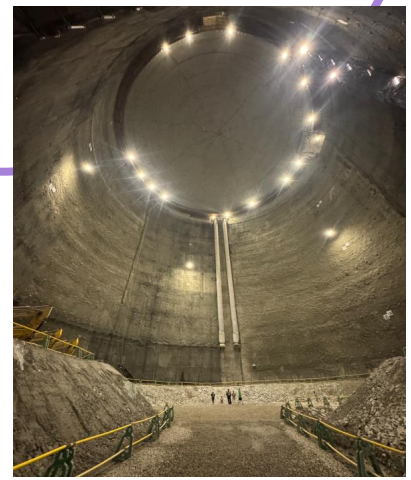
One fit per « candidate » ring

APFit *: 1997 ~ now*

fiTQun *: 2012 ~ now*



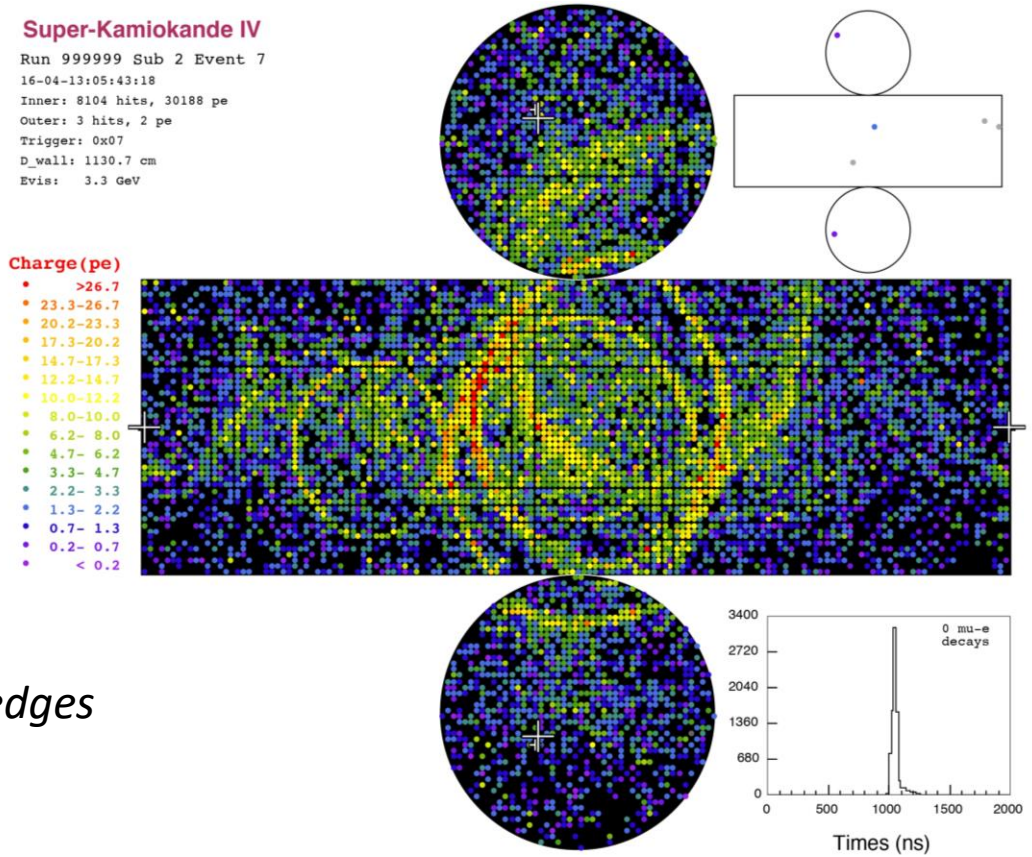
Maximum L. ?
Deep Neural Networks ?
Other .. ?

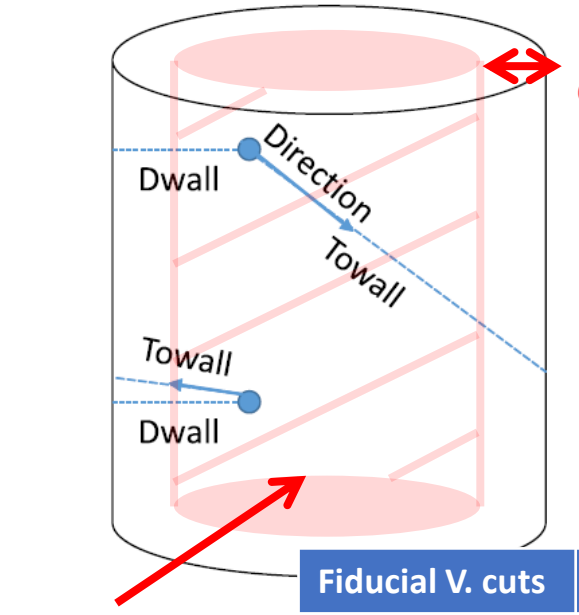


Main limitations of current algorithms

- **Multi rings** events

  (mainly from very energetic neutrinos)





- **Fiducial Volume**

Limited performances close to the edges
=> Limited statistics

Fiducial V. cuts	Super K (cm)	T2K (cm)
Dwall	> 50	> 80
Towall	X	> 170

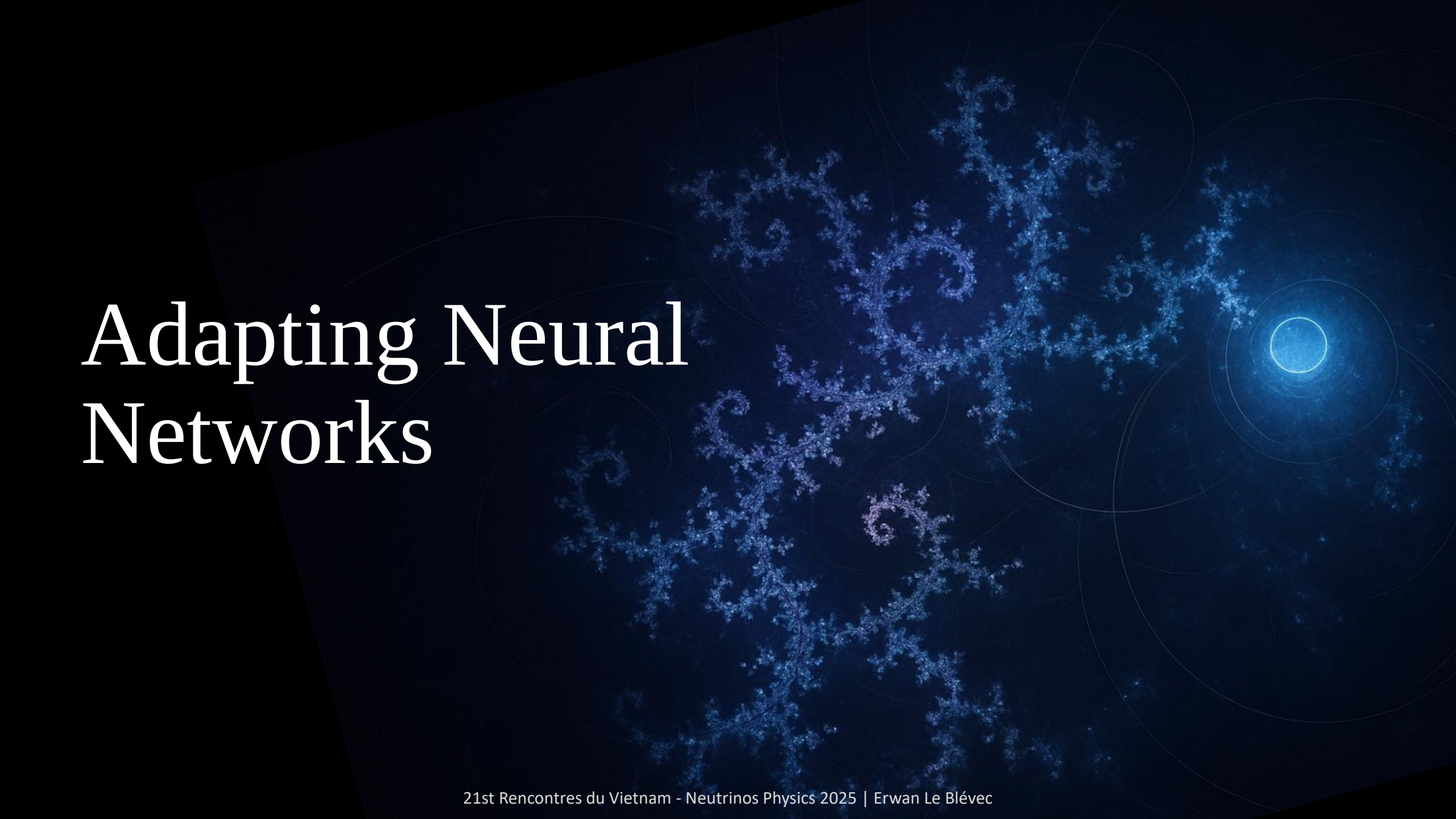
M. Jiang D. Thesis, Atmospheric ν, 2019

T2K, TN465 v1.1, 2024 (for e-)

- **Computational Time**

~30 seconds / event in **Super K**
~1:30 minute / event in **Hyper K**

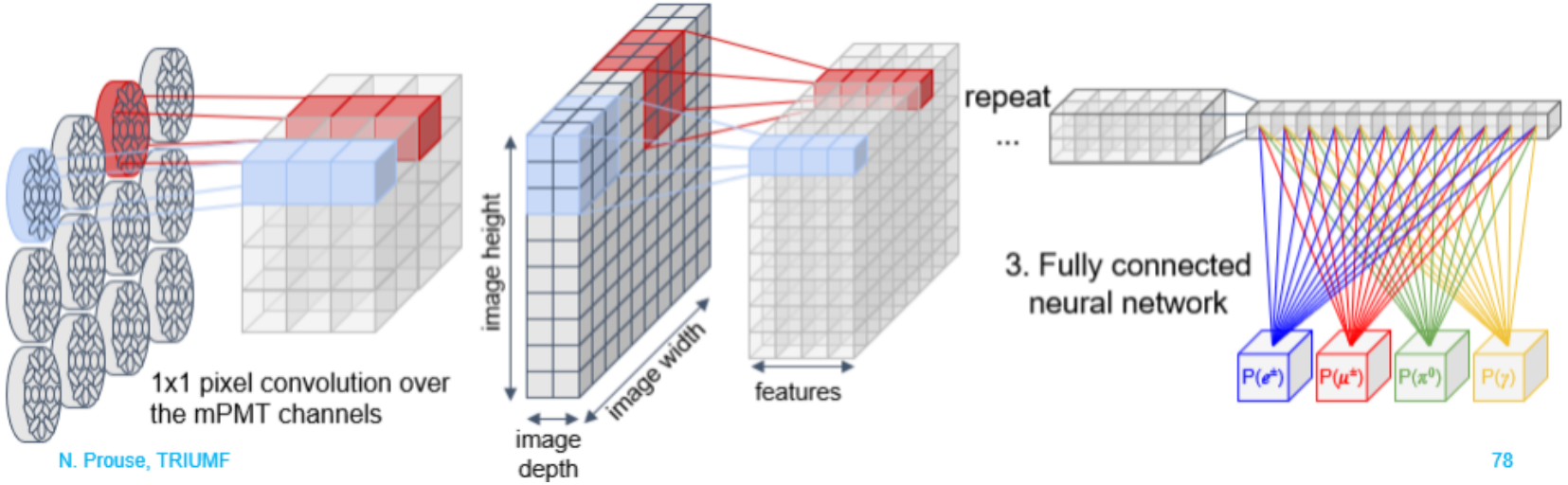
Adapting Neural Networks



Deep Neural Networks : Main architectures

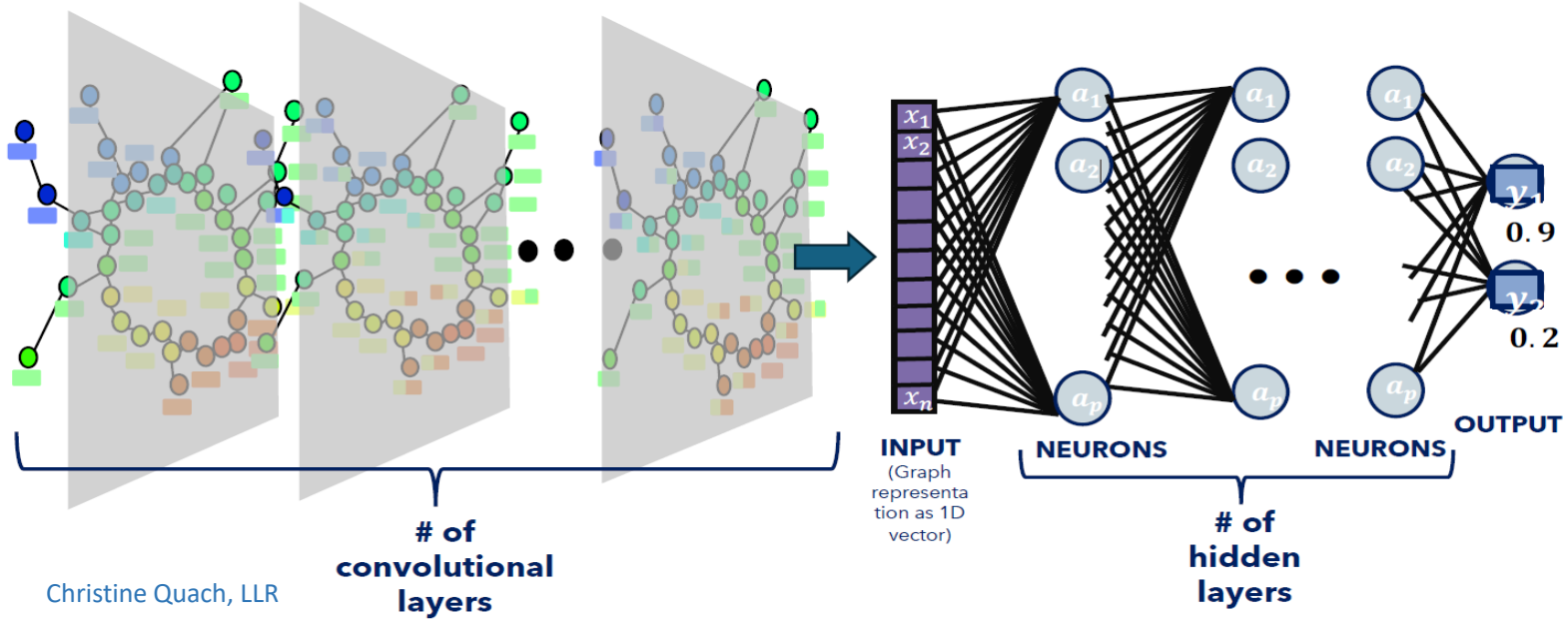
Convolutionnal Neural Networks (CNN)

« Adaptation » of the convolution product to deep neural networks



Graph Neural Networks (GNN)

« Generalization of the convolution product to non-euclidian data »



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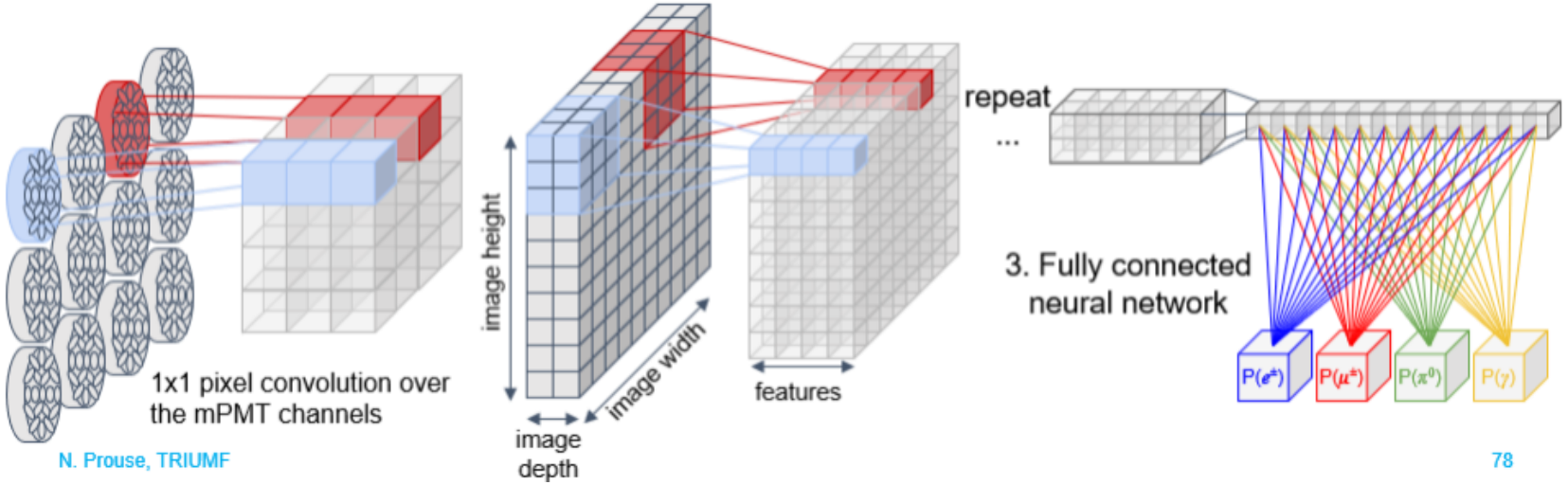
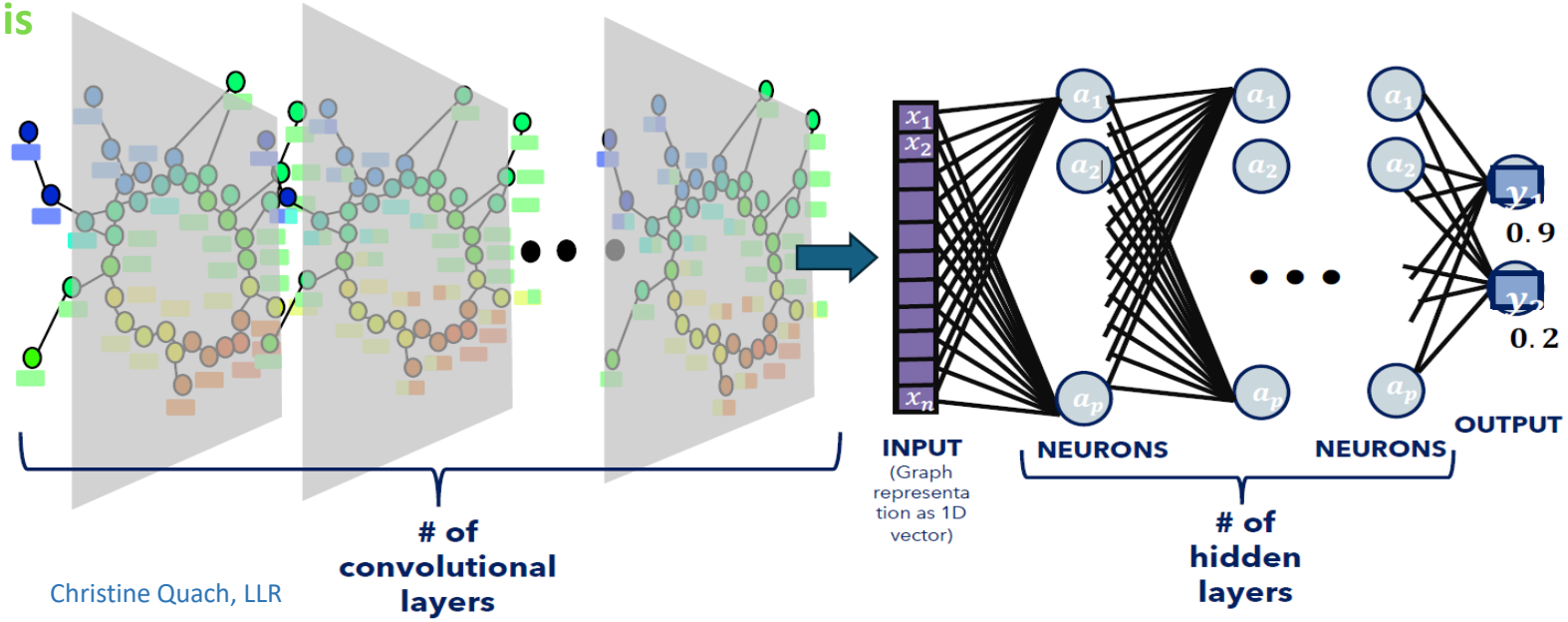


Focus on this

Graph Neural Networks (GNN)

« Generalization of the convolution product to non-euclidian data »



Making a graph

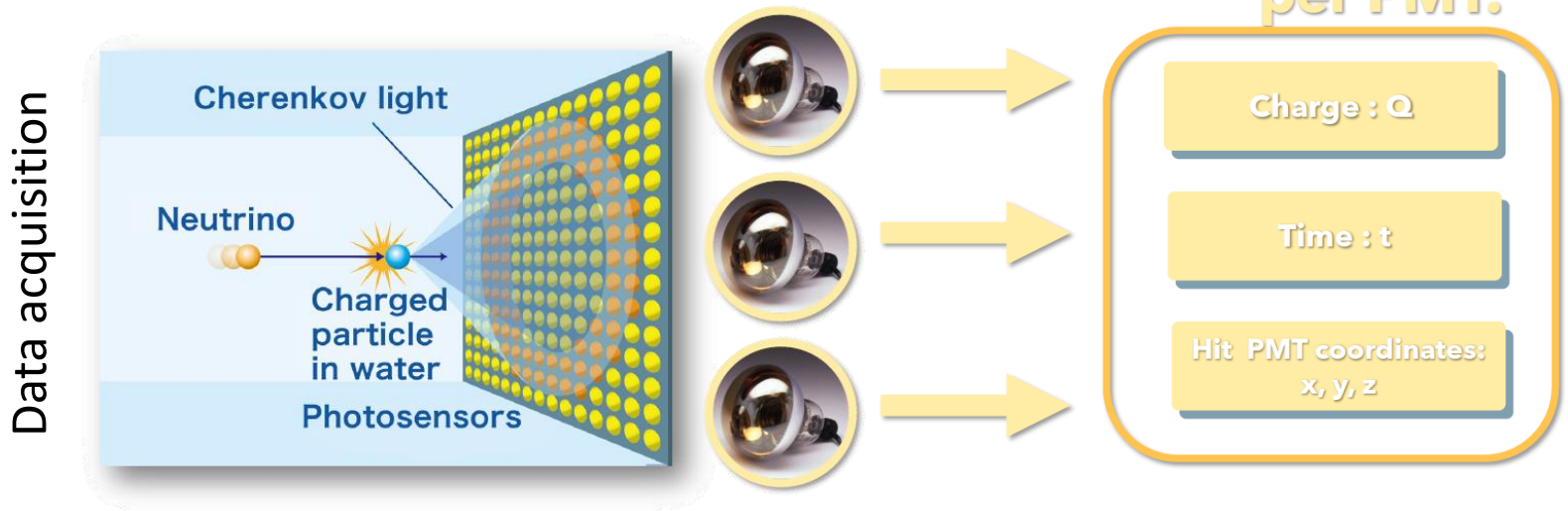
1st step : Get a Point Cloud

2nd step : Build edges to link the points **= define locality**

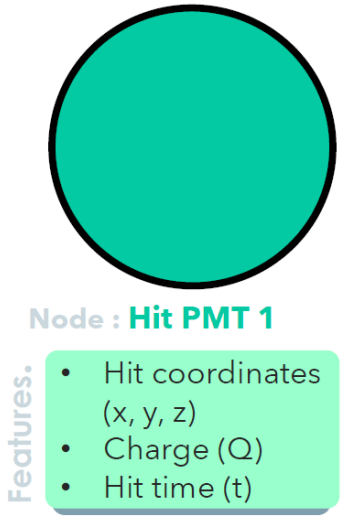
Making a graph

Point Cloud for free !

1st step : Get a Point Cloud



One Hit PMT = One Node



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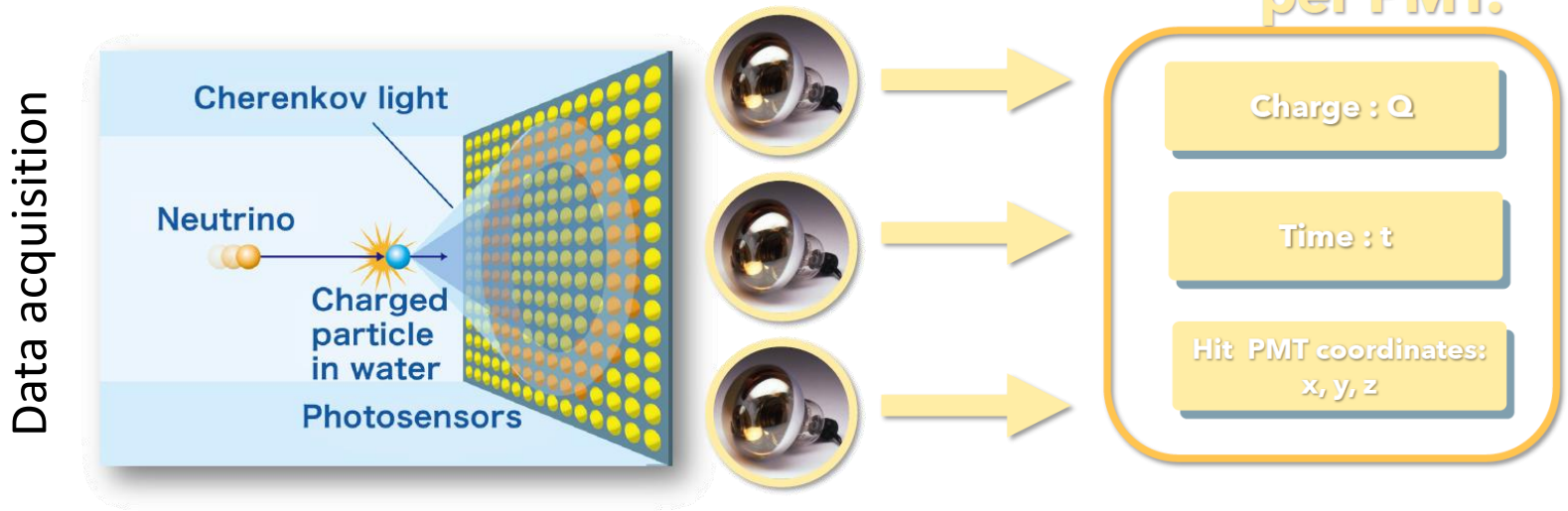

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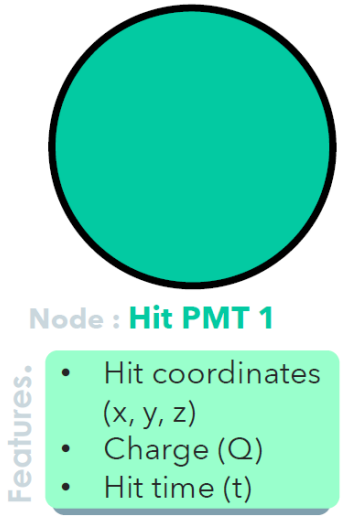
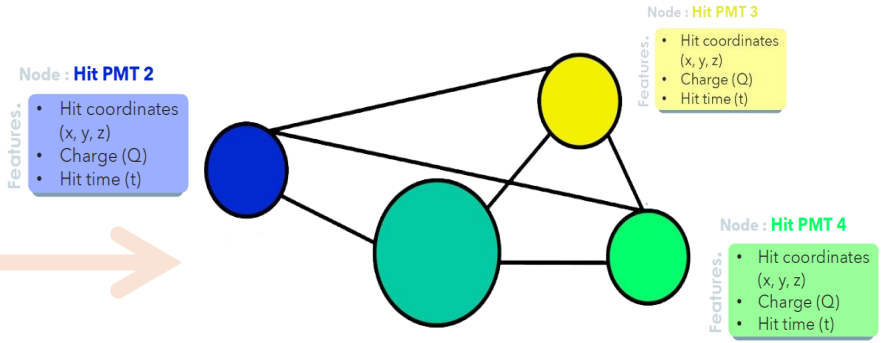


2nd step : Build edges to link the points **= define locality**

Edges Criteria freedom:
- Physical proximity ?
- Time ?
- Charge ?

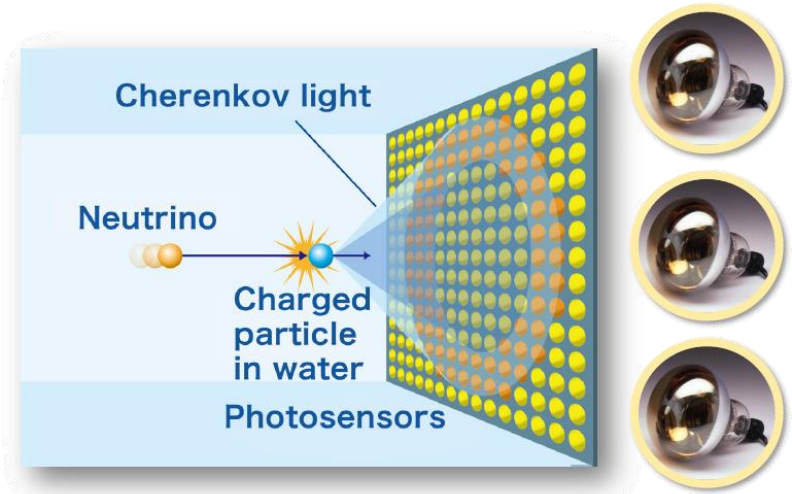


Making a graph

1st step : Get a Point Cloud

Point Cloud for free !

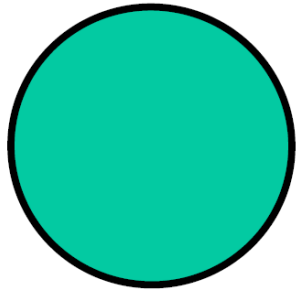
Data acquisition



Output per PMT.

- Charge : Q
- Time : t
- Hit PMT coordinates: x, y, z

One Hit PMT = One Node



Node : **Hit PMT 1**

Features.
- Hit coordinates (x, y, z)
- Charge (Q)
- Hit time (t)

2nd step : Build edges to link the points = **define locality**

Edges Criteria freedom:
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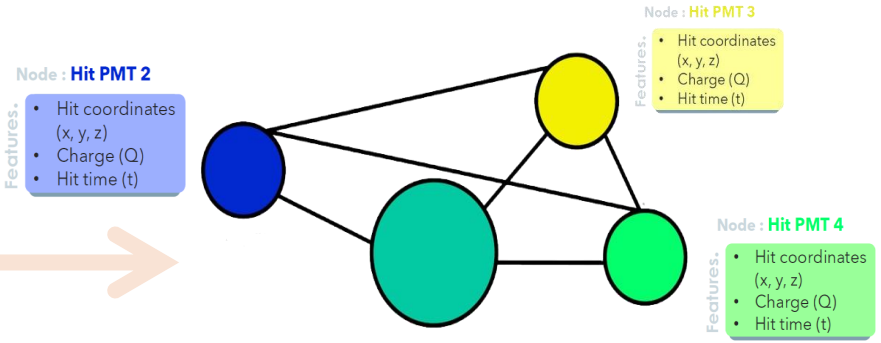
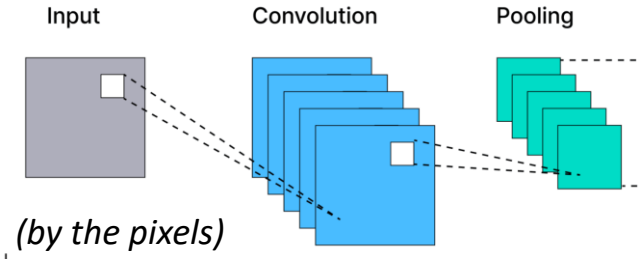
- Charge ?



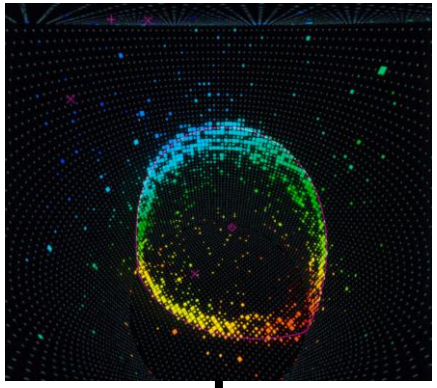
≠

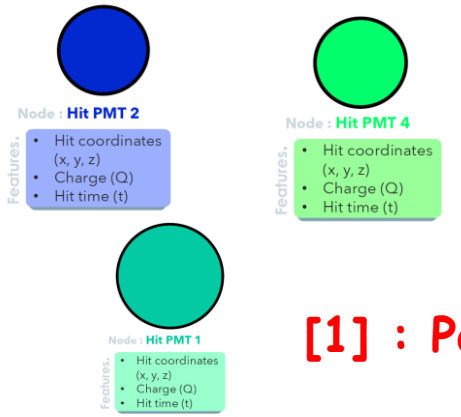
Images where **locality** is **imposed**



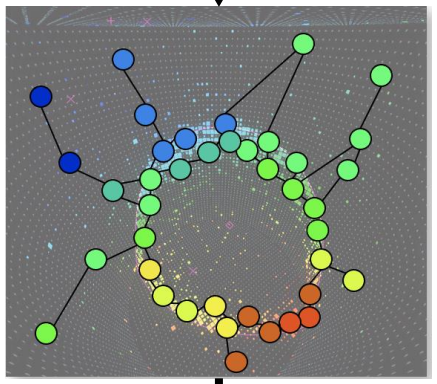
(by the pixels)

Pipeline for GNNs : Summary

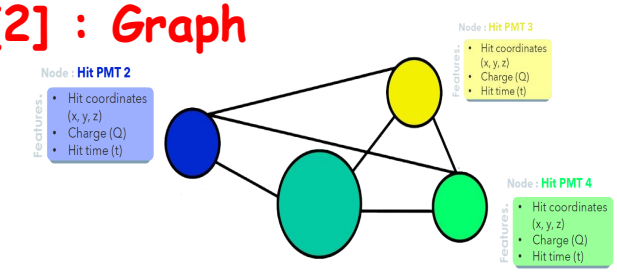




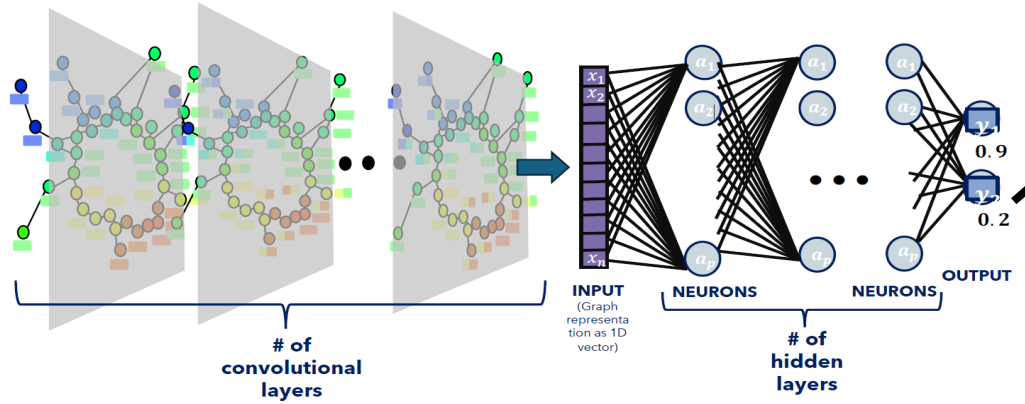
[1] : Point Cloud

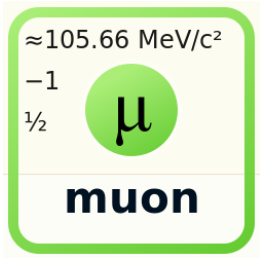


[2] : Graph



[3] : GNN

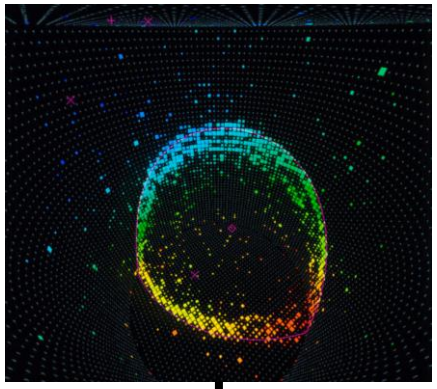


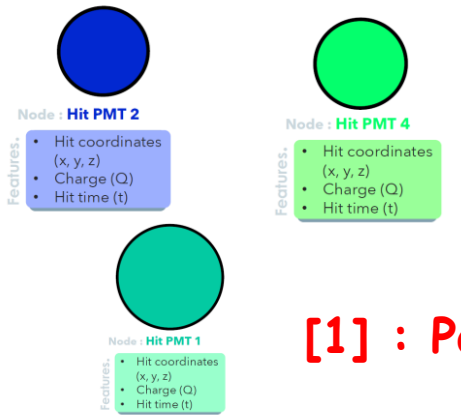


- Direction
- Energy
- Vertex

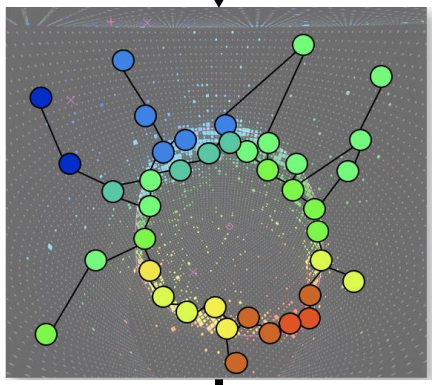
[4] : Reconstructed data

Pipeline for GNNs : Summary

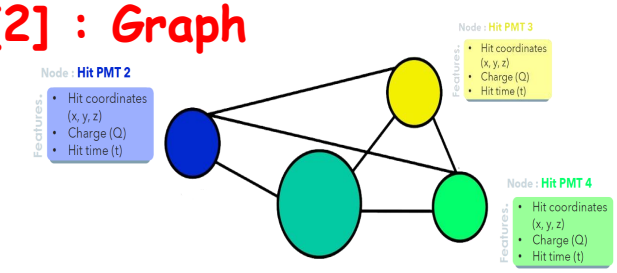


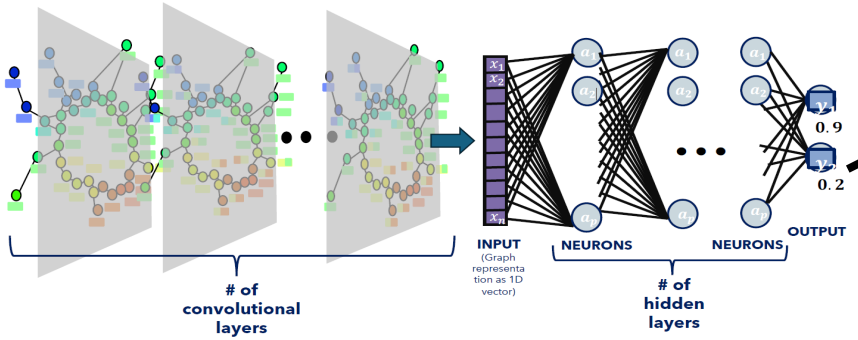


[1] : Point Cloud

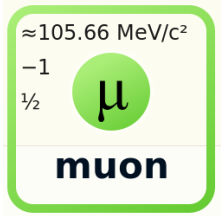


[2] : Graph



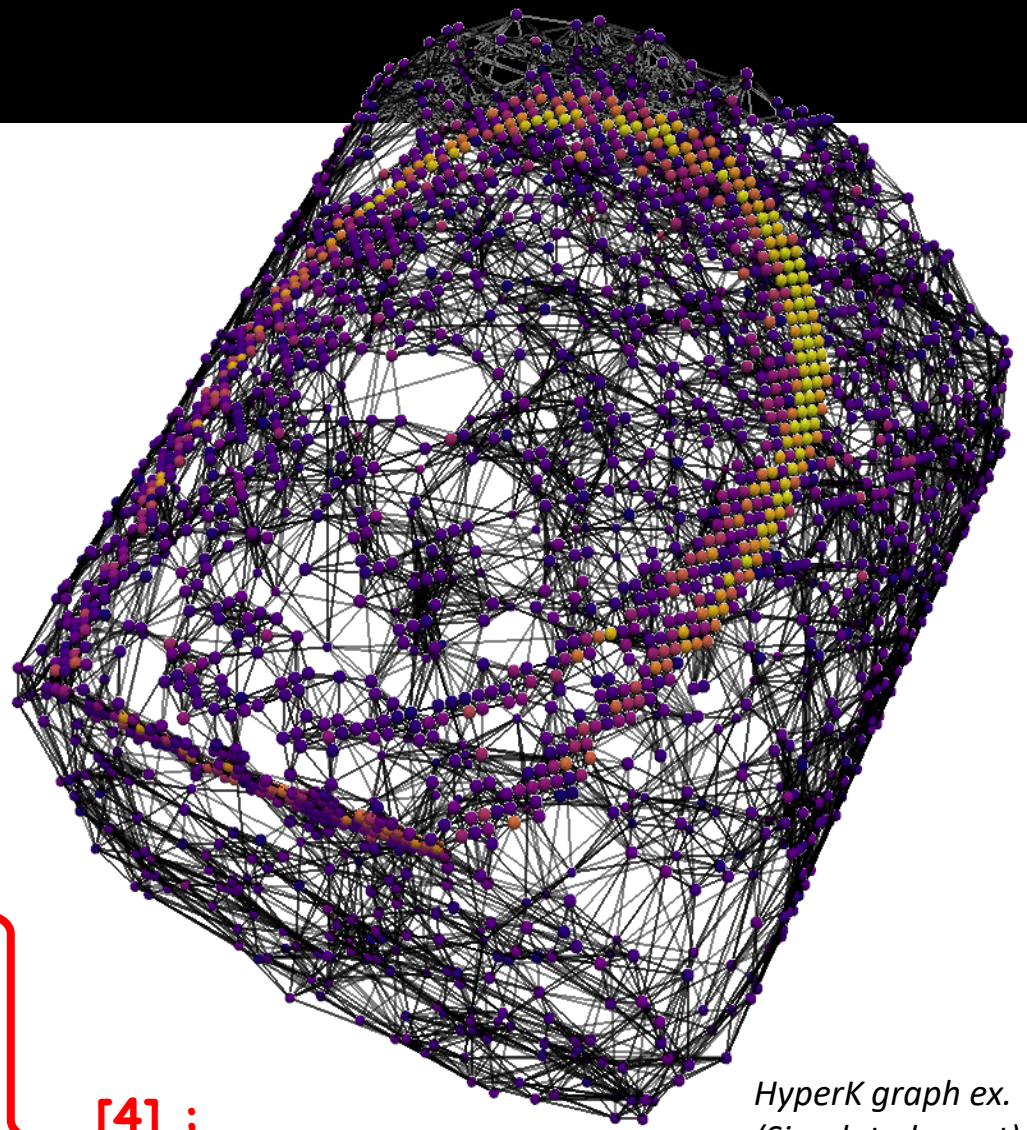


[3] : GNN



- Direction
- Energy
- Vertex

[4] : Reconstructed data



HyperK graph ex. (Simulated event)

Reconstruction status

fiTQun & GNNs

Comparison

Performance Comparison | PID - ROC Curves

Particle Identification | **1. Roc Curves** | 2. Dwall | 3. Towall

Efficiency : Rec. Positive **And** True Positive / Total true **positive** ⟶ *(capacity to find the true class)*

Acceptance : Rec. Positive **But** True Negative / Total true **negative**

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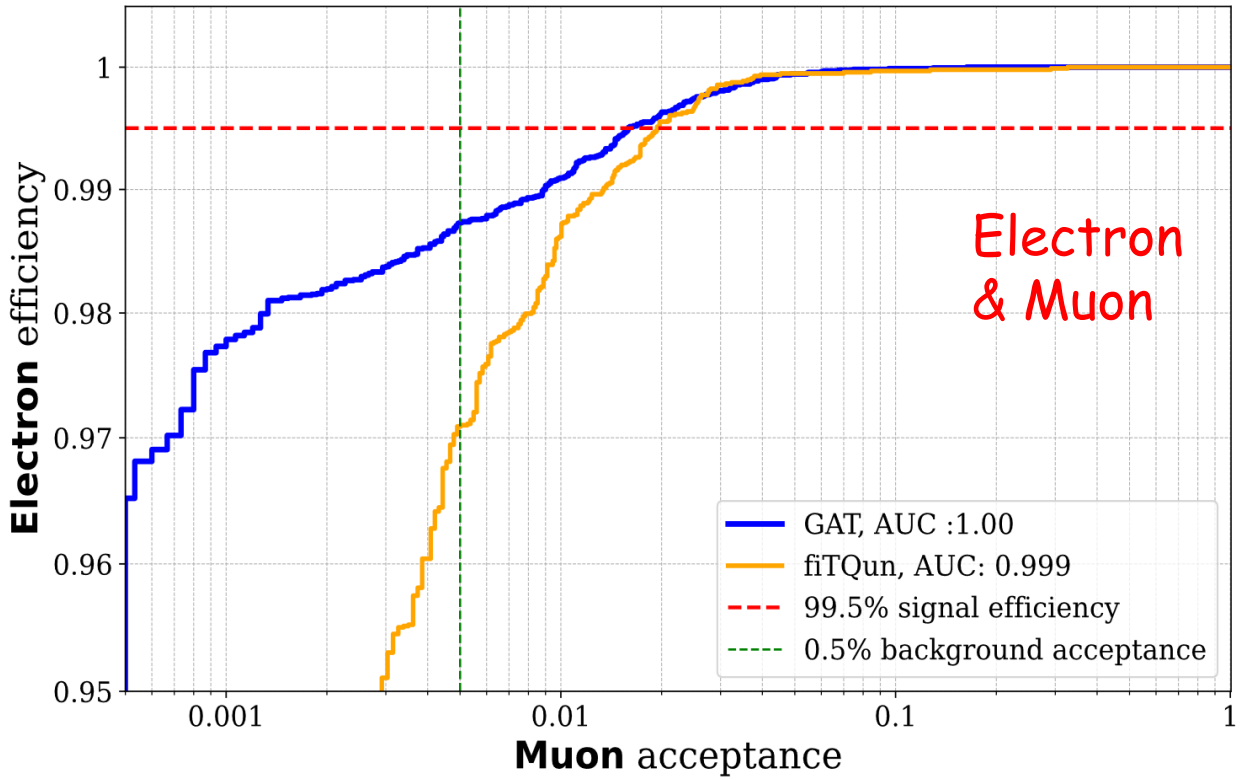

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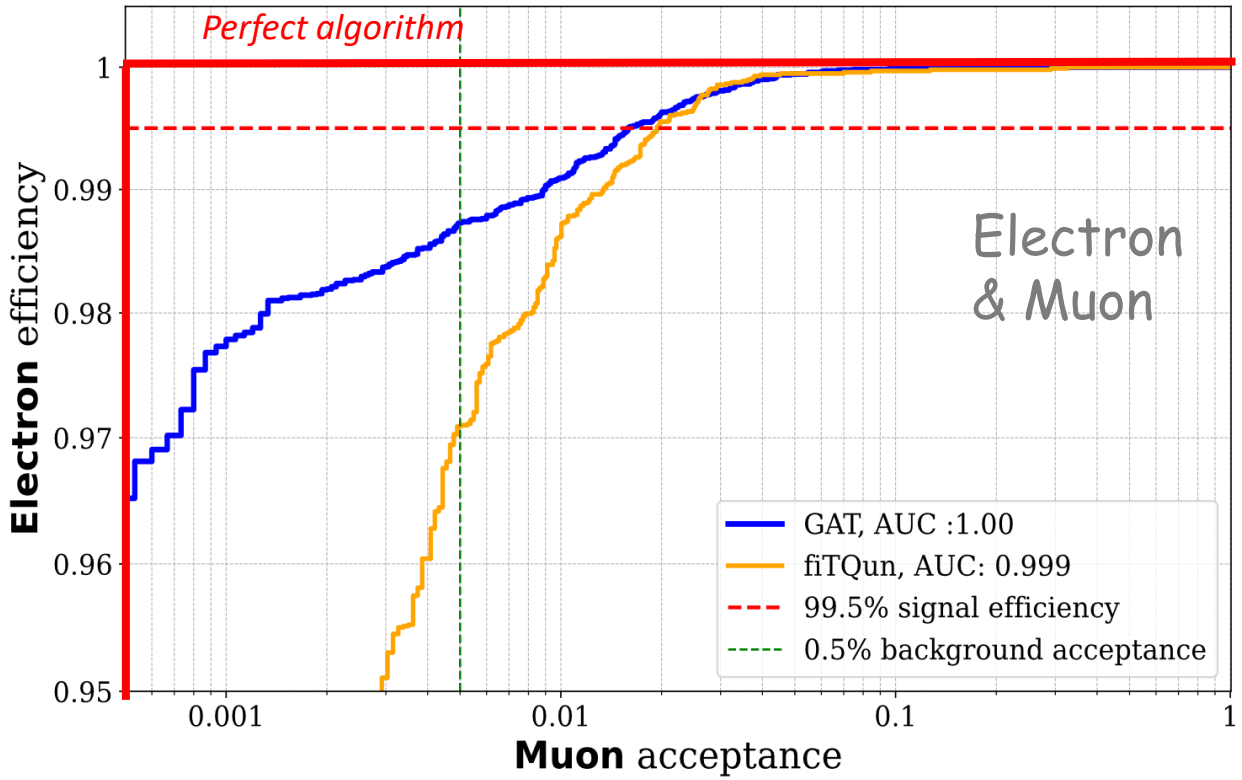

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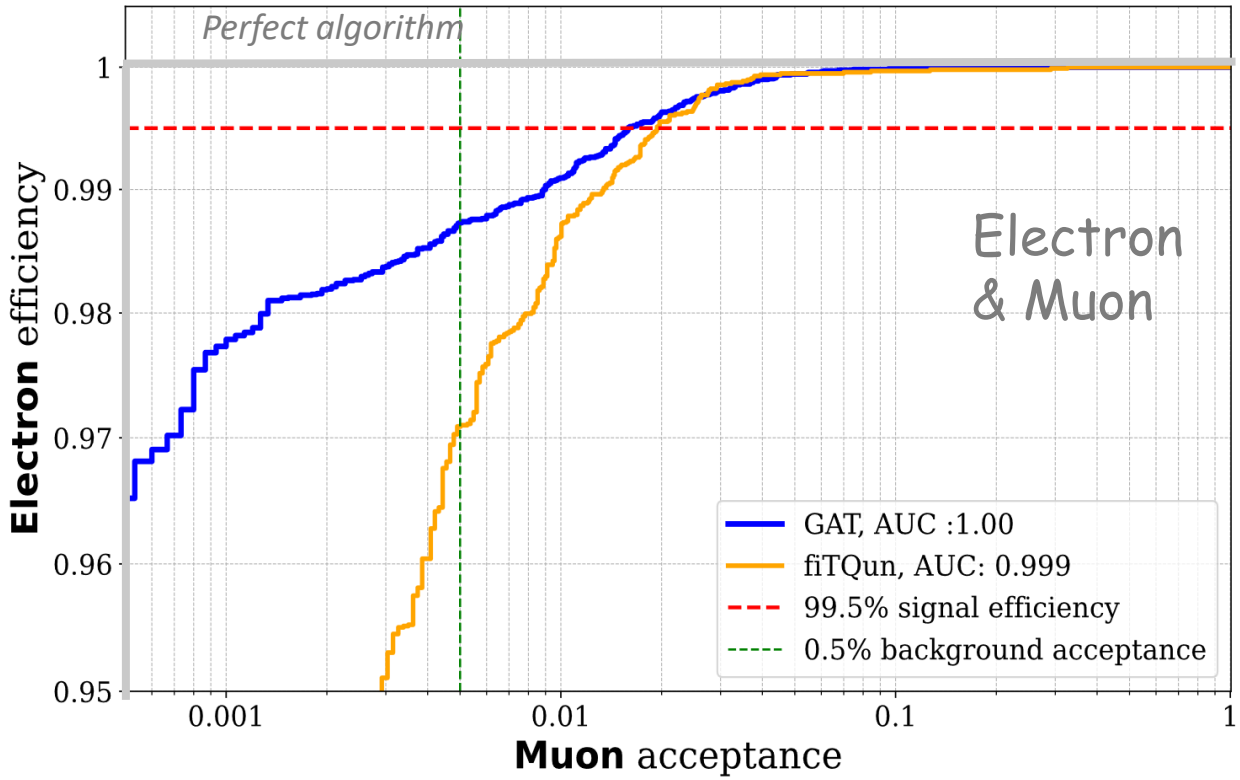

Electron & π^0

Performance Comparison | PID - ROC Curves

Particle Identification | **1. Roc Curves** | 2. Dwall | 3. Towall

Efficiency : Rec. Positive **And** True Positive / Total true **positive** ⟶ *(capacity to find the true class)*

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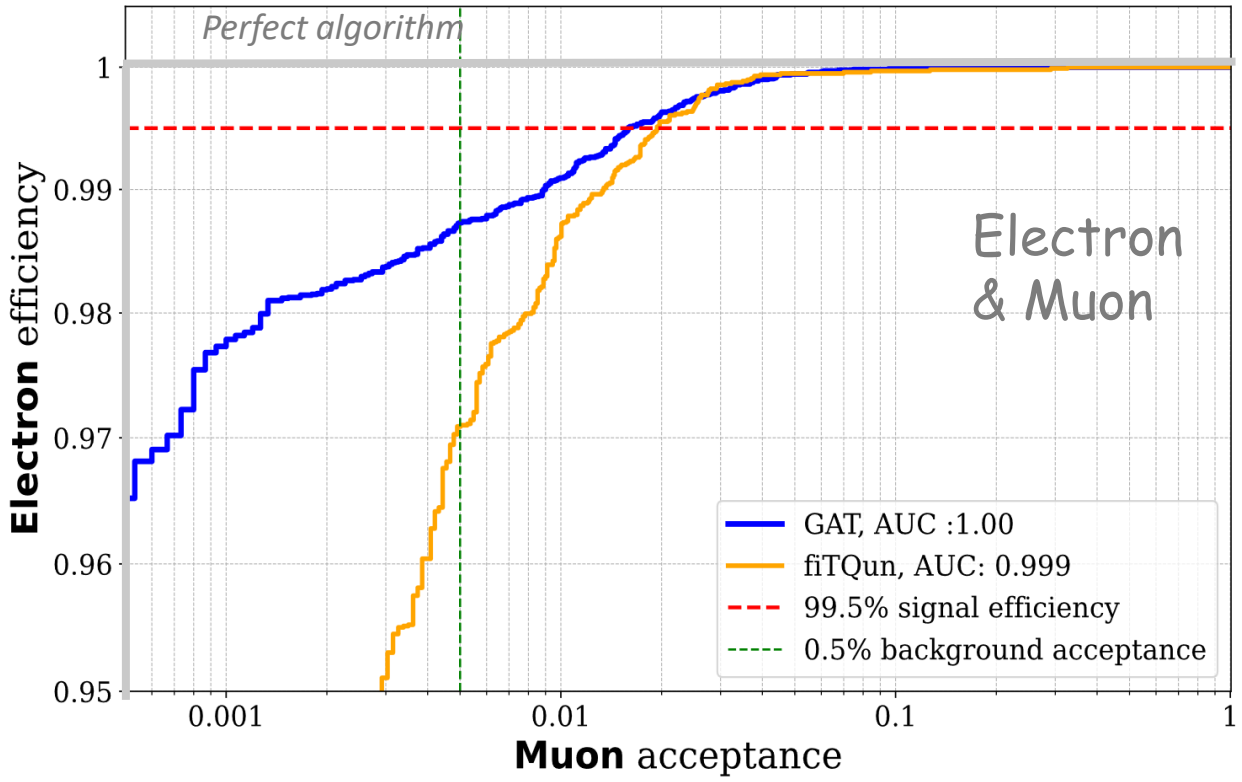
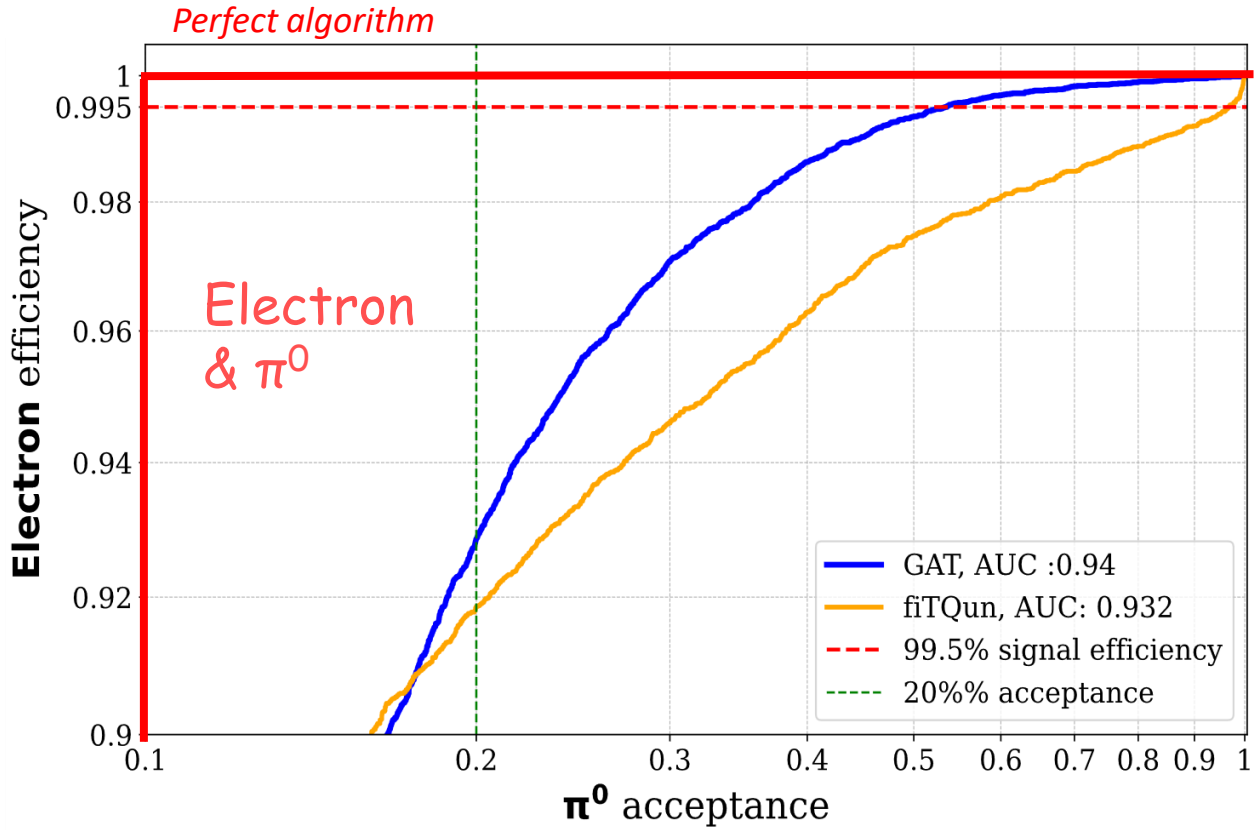


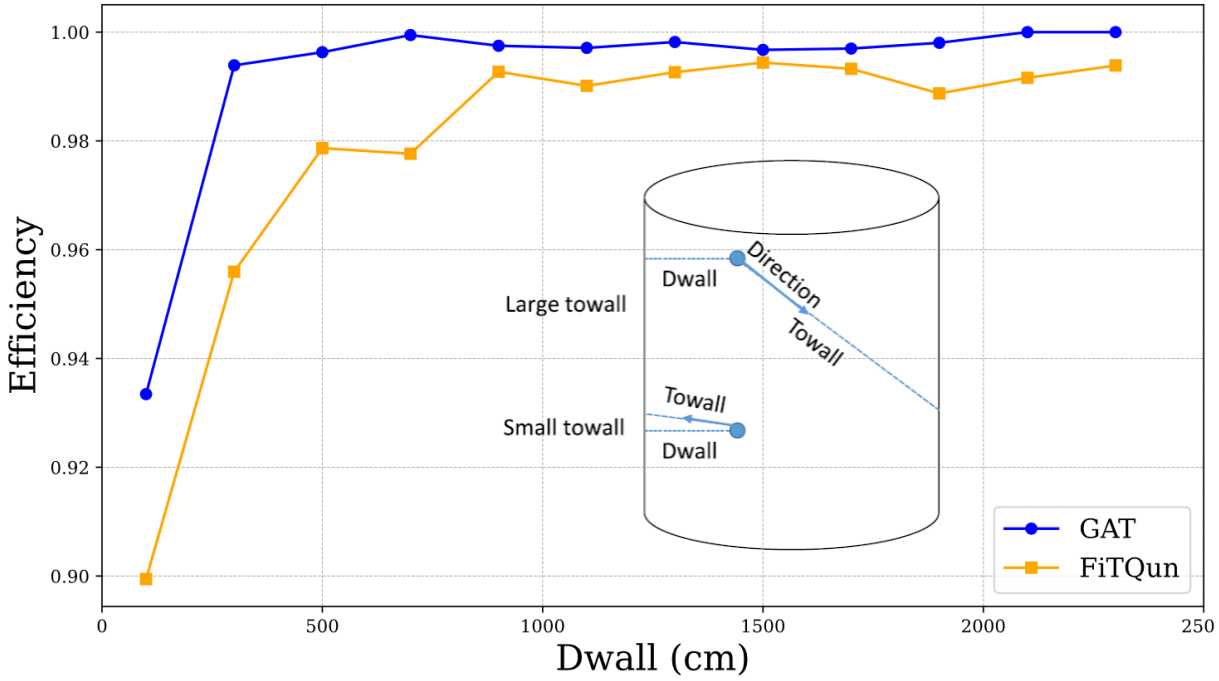


Performance Comparison | PID - Dwall

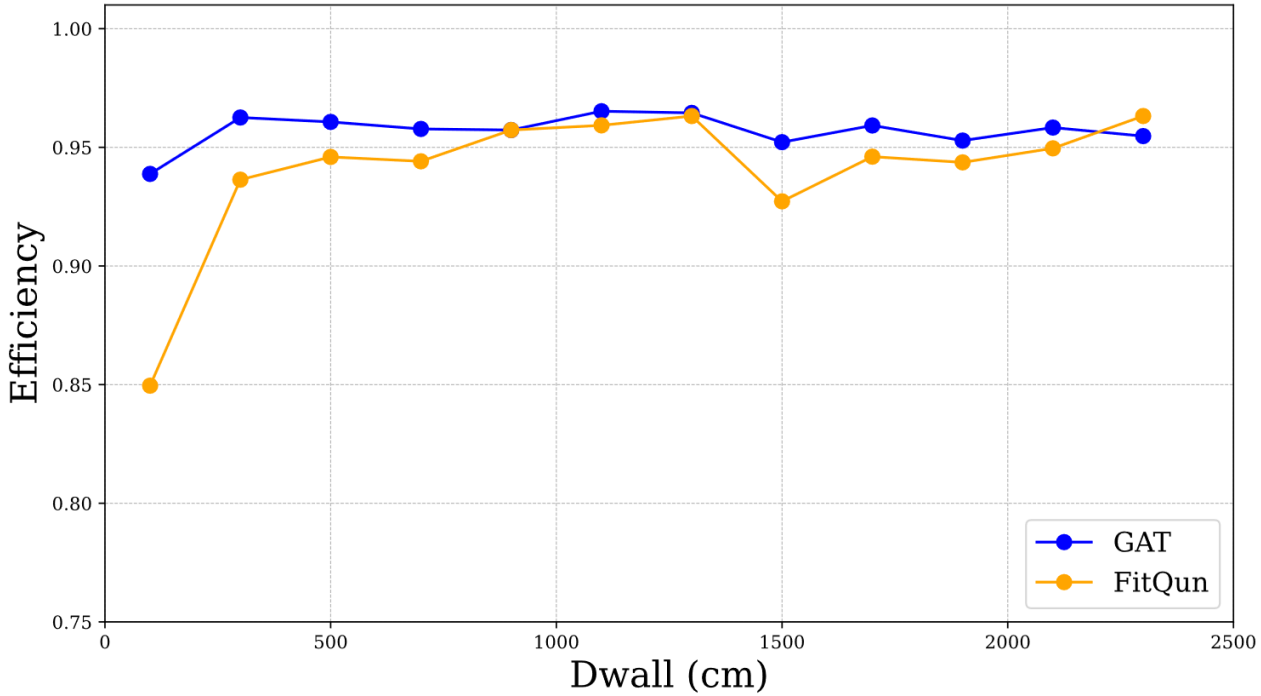
Particle Identification | 1. Roc Curves | **2. Dwall** | 3. Towall

Monitor Fiducial Volume cut impact

Electron & Muon



Electron & π^0

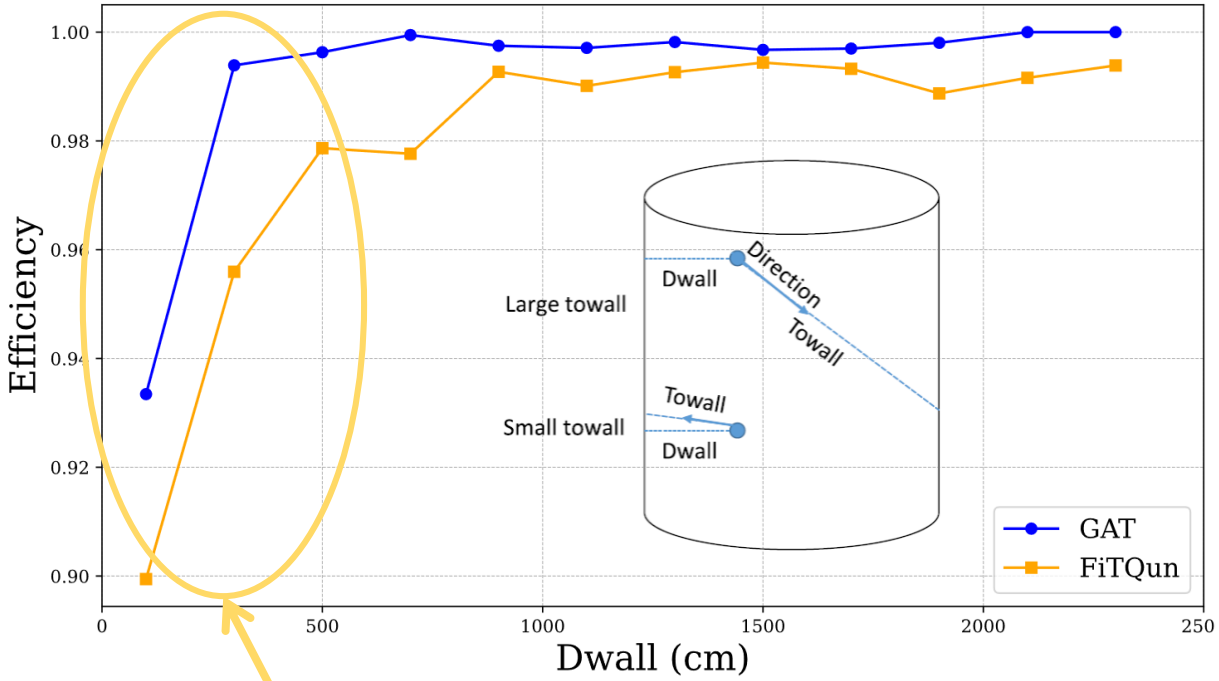


Performance Comparison | PID - Dwall

Particle Identification | 1. Roc Curves | **2. Dwall** | 3. Towall

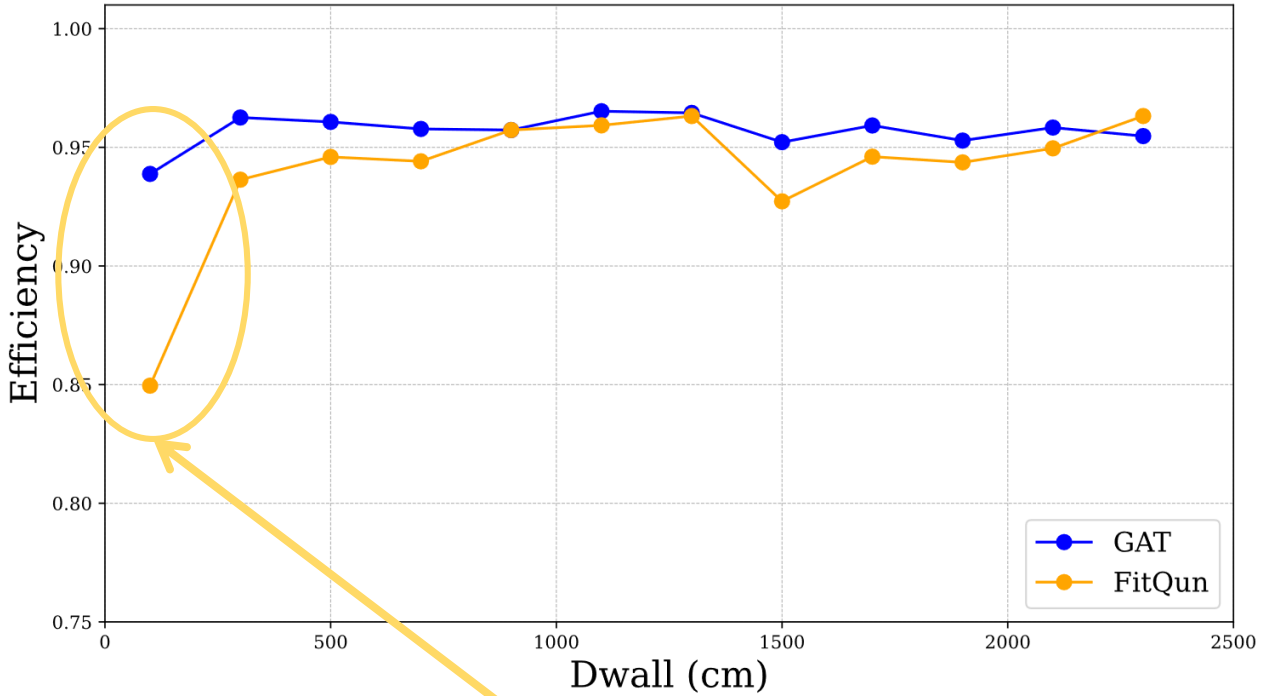
Monitor Fiducial Volume cut impact

Electron & Muon



Efficiency improvement

Electron & π^0



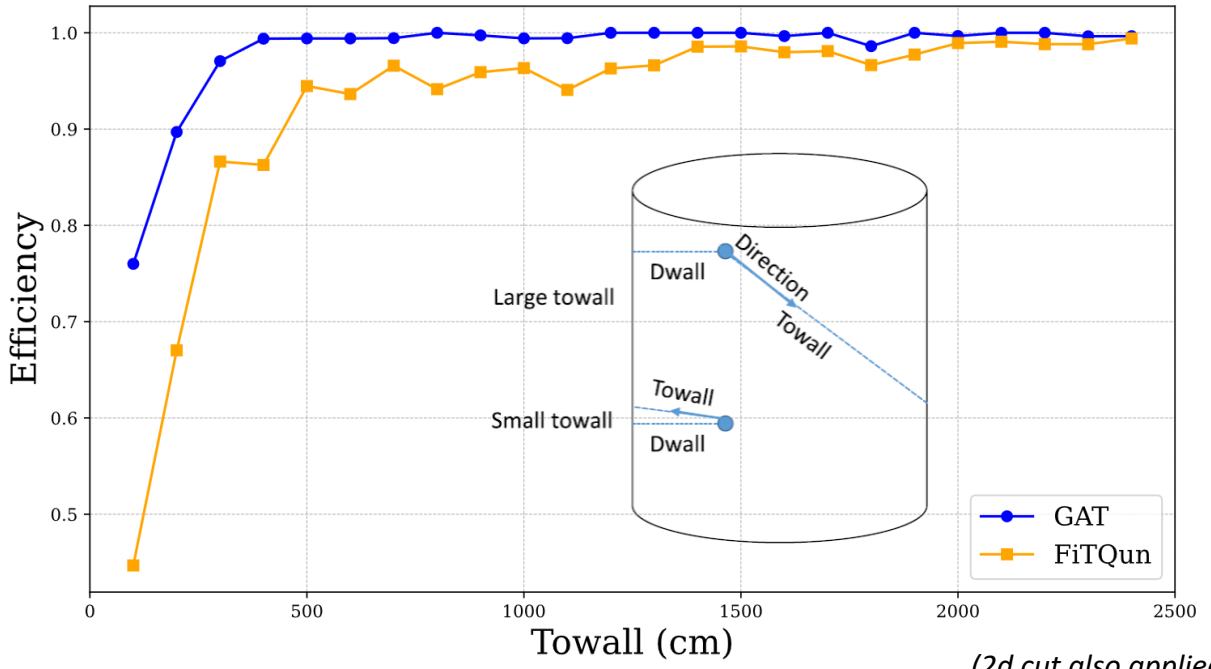
Efficiency improvement

Performance Comparison | PID - Towall

Particle Identification | 1. Roc Curves | 2. Dwall | **3. Towall**

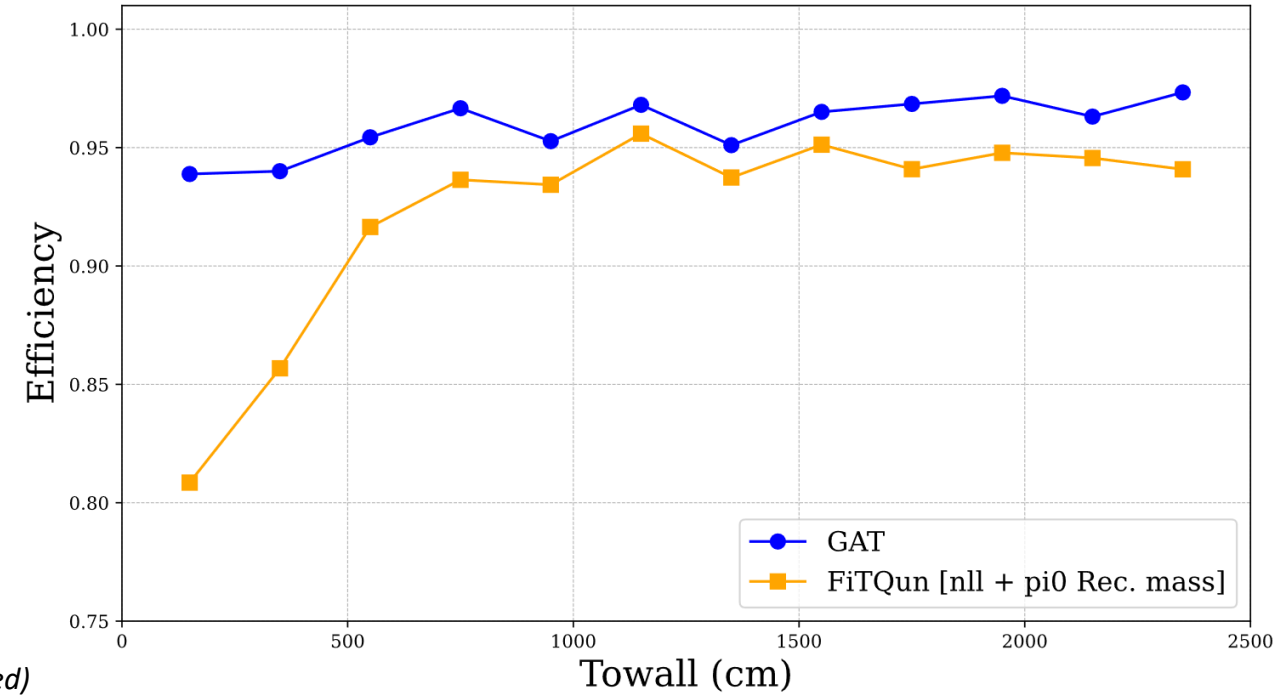
*Resilience to **low number** of **hit PMTs***

Electron & Muon



(2d cut also applied)

Electron & π^0

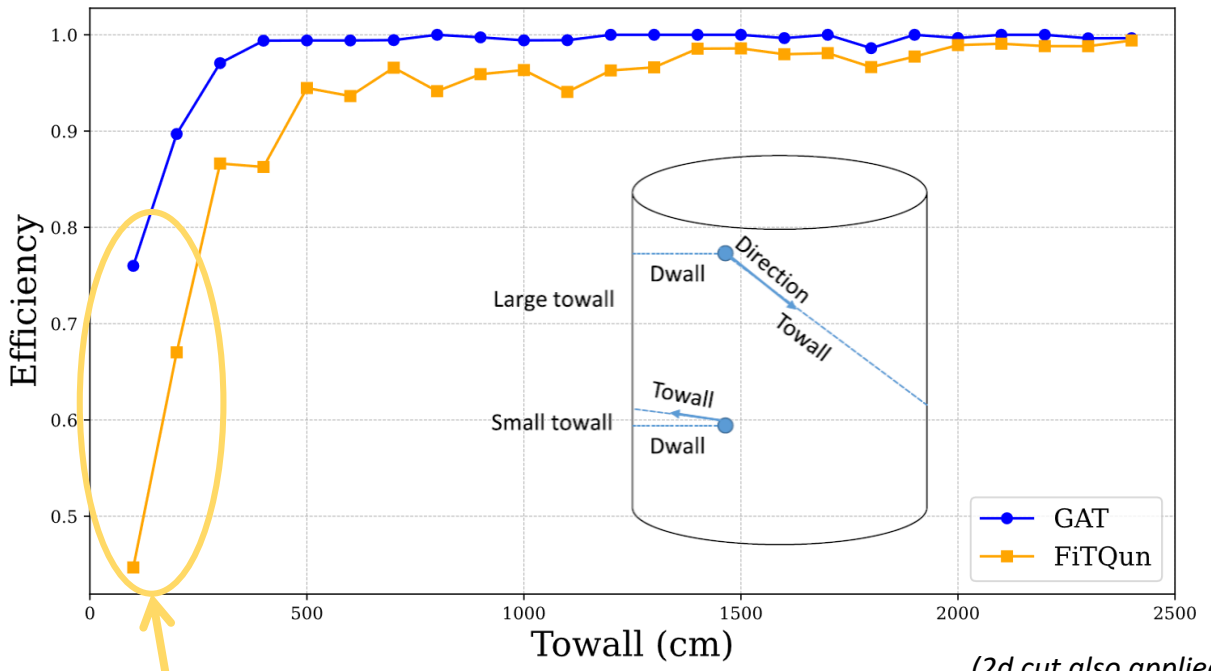


Performance Comparison | PID - Towall

Particle Identification | 1. Roc Curves | 2. Dwall | **3. Towall**

*Resilience to **low number** of **hit PMTs***

Electron & Muon

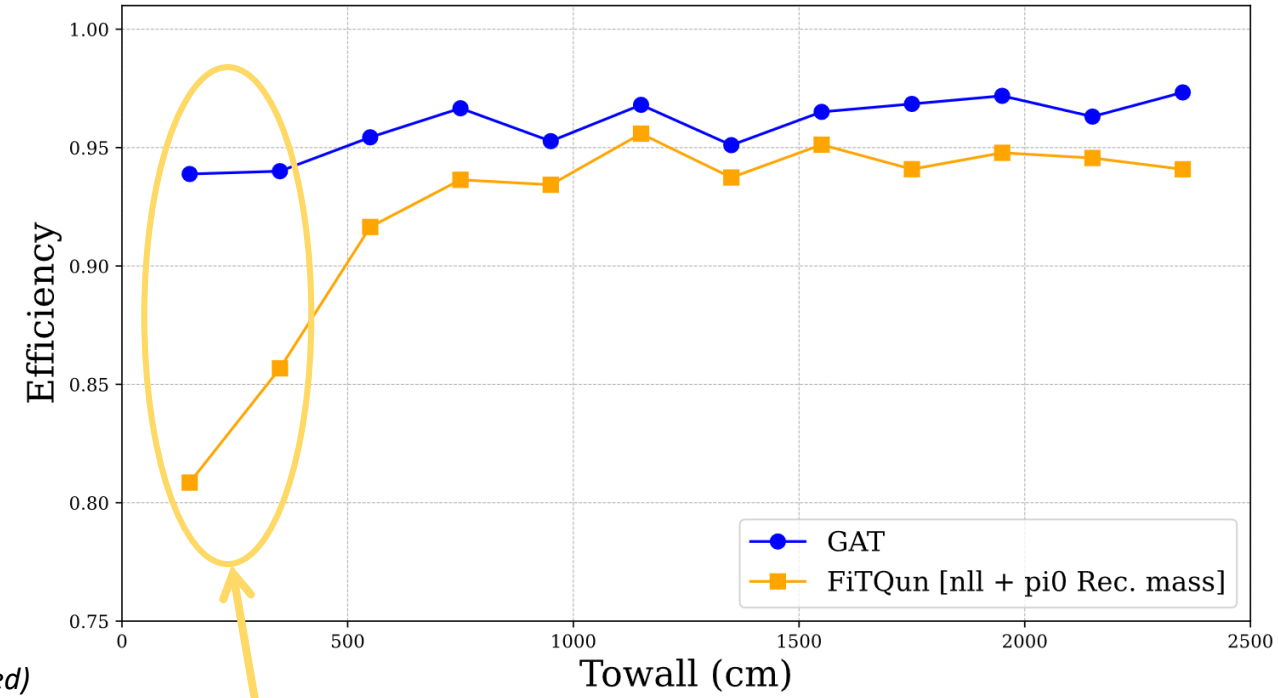


(2d cut also applied)

Efficiency

More than 20% improvement under 2m !

Electron & π^0



Efficiency

Final states & Prospects

- **Graph Neural Networks**
  - Multi rings fitting *To be started soon*
    - Single Ring | Direction & Vertex : Ongoing
  - Computation Time
    - Excellent improvements

	fiTQun	GAT
e- / μ- (0.5%)	97.1 % eff	**98.7 %** eff
e- / π^0 (25 %)	93.3% eff	**95.6 %** eff
Energy (e-, 500MeV)	6 % res **0.1 %** bias	**5.5 %** res 0.3 % bias

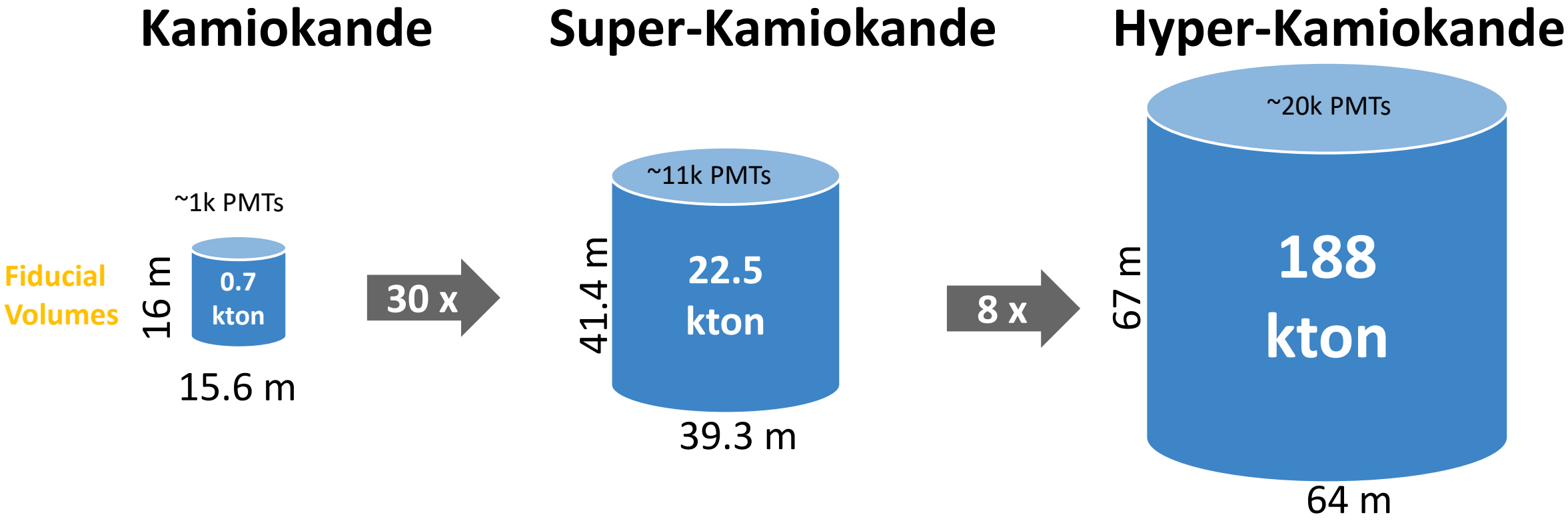
CPU time / event	1 ring e/μ PID	1 ring e/π^0 PID	Energy & vertex reco.	Total
fiTQun	30s	50s	Simulatenous to PID	80s
CAVERNS	0.09s	0.07s	0.05s	0.11s

- **fiTQun**
  - Multi-threads & GPU porting : Ongoing

~ Order 2 gain

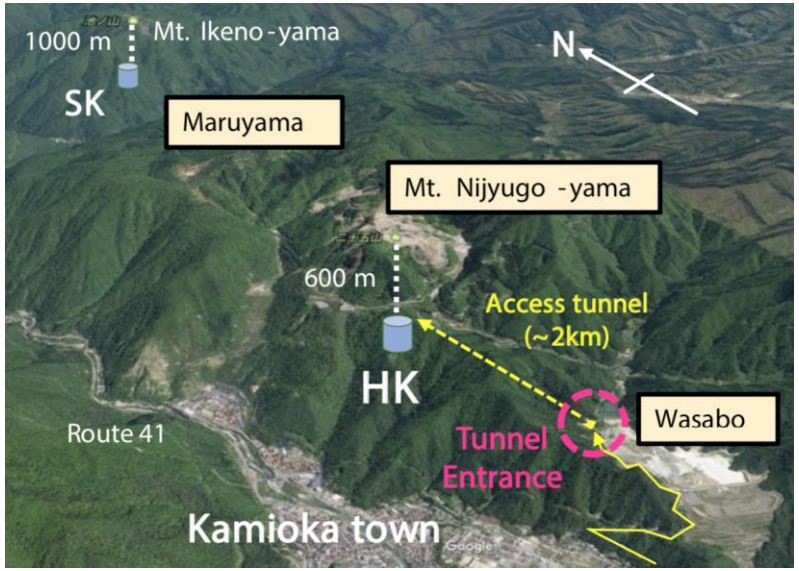

Thank you !

The Three Generations

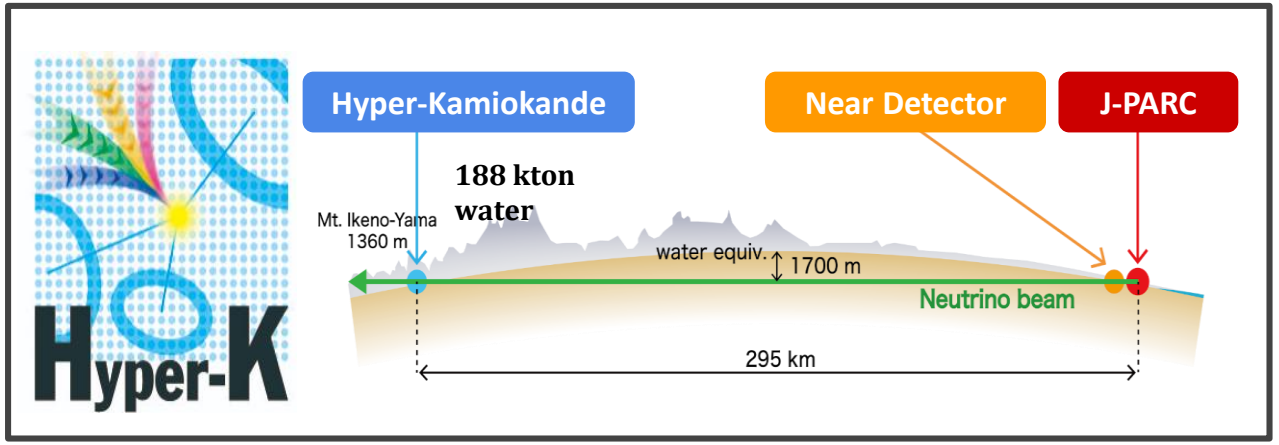


1983 - 1996	1996 - today (and beyond)	2028 - (and beyond)
Supernova 1987A	Atmospheric, Solar, and accelerator (T2K) ν Oscillation	δ_{cp}, proton decay, indirect DM search, more SNs, ...

Hyper K


1000 m
Mt. Ikeno-yama
SK
N
Maruyama
Mt. Nijyugo -yama
600 m
Access tunnel
(~2km)
HK
Route 41
Tunnel
Entrance
Wasabo
Kamioka town

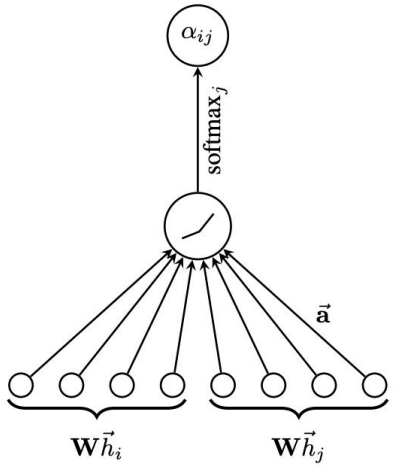

Mozumi

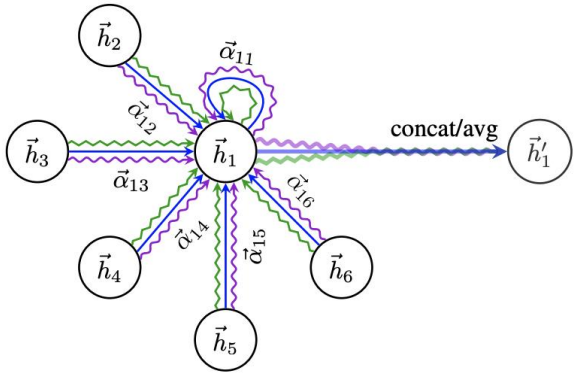

Hyper-K
Hyper-Kamiokande
Near Detector
J-PARC
188 kton
water
Mt. Ikeno-Yama
1360 m
water equiv.
1700 m
Neutrino beam
295 km

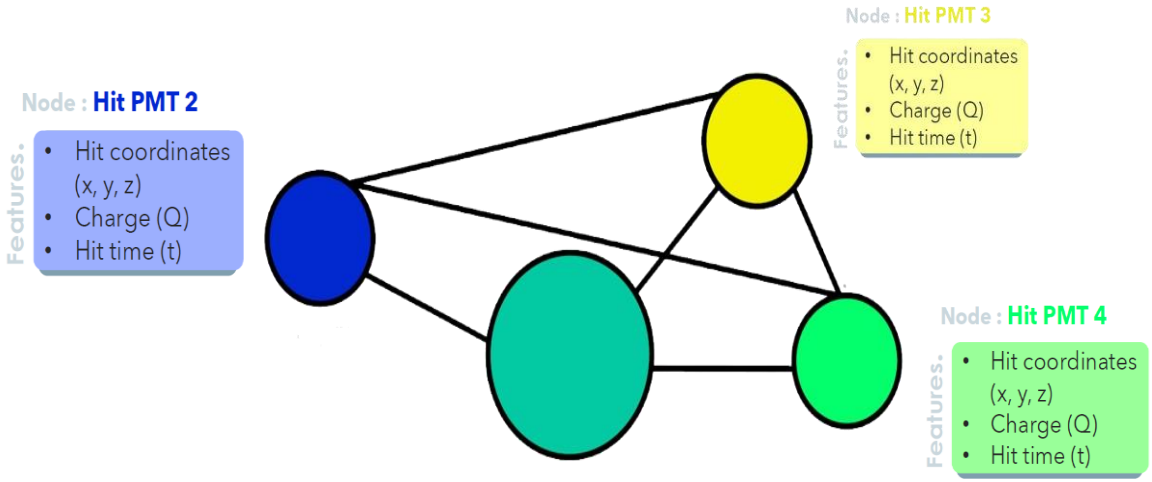

Kamioka

- Attention Mechanism applied to graph : GAT

(Graph Attention neTwork)

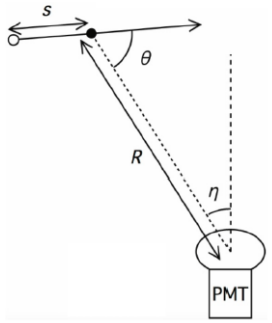






Slides sur le fonctionnement de FQ

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



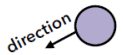
μ_j : Poisson mean of predicted charge

$\mathbf{x}$: predicted time

[PID, direction, energy, vertex],

Hypothesis

(H1) $L(\mathbf{x}) = \prod_{j}^{\text{unhit}} P_j(\text{unhit}|\mu_j) \prod_{i}^{\text{hit}} \{1 - P_i(\text{unhit}|\mu_j)\} f_q(q_i|\mu_j) f_t(t_i|\mathbf{x}).$

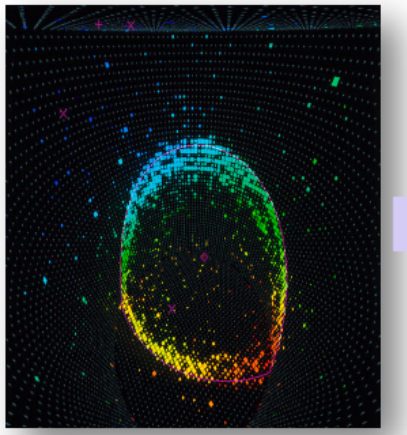


(H2) $L(\mathbf{x}) = \prod_{j}^{\text{unhit}} P_j(\text{unhit}|\mu_j) \prod_{i}^{\text{hit}} \{1 - P_i(\text{unhit}|\mu_j)\} f_q(q_i|\mu_j) f_t(t_i|\mathbf{x}).$

•••

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

FQ Under the hood



Input parameters.

- **Unhit PMT position**
- **Hit PMT position**
- **Charge (measured)**
- **Time (measured)**

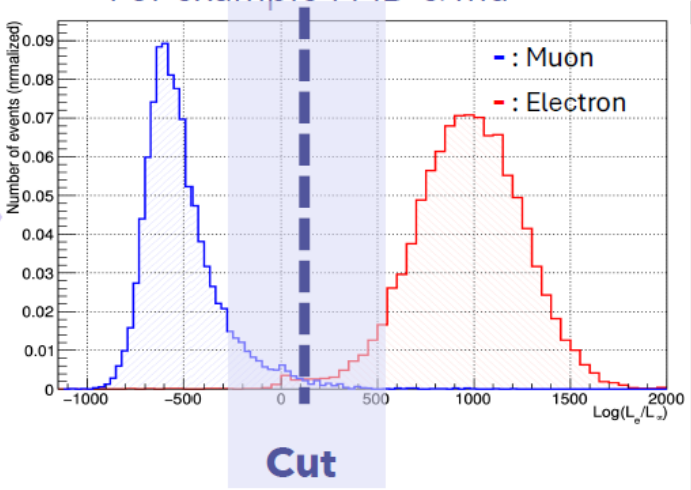
Under **hypothesis**

- **PID**
- **Direction**
- **Energy**
- **Vertex**

Compute and **maximize the likelihood**

$$L(\mathbf{x})$$

For example : PID e/mu



PID

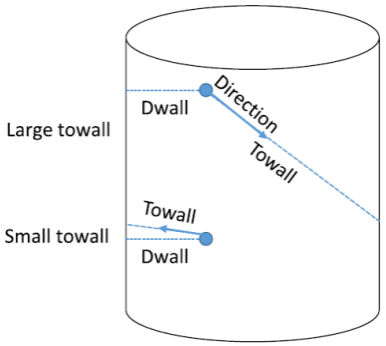
Performance Comparison

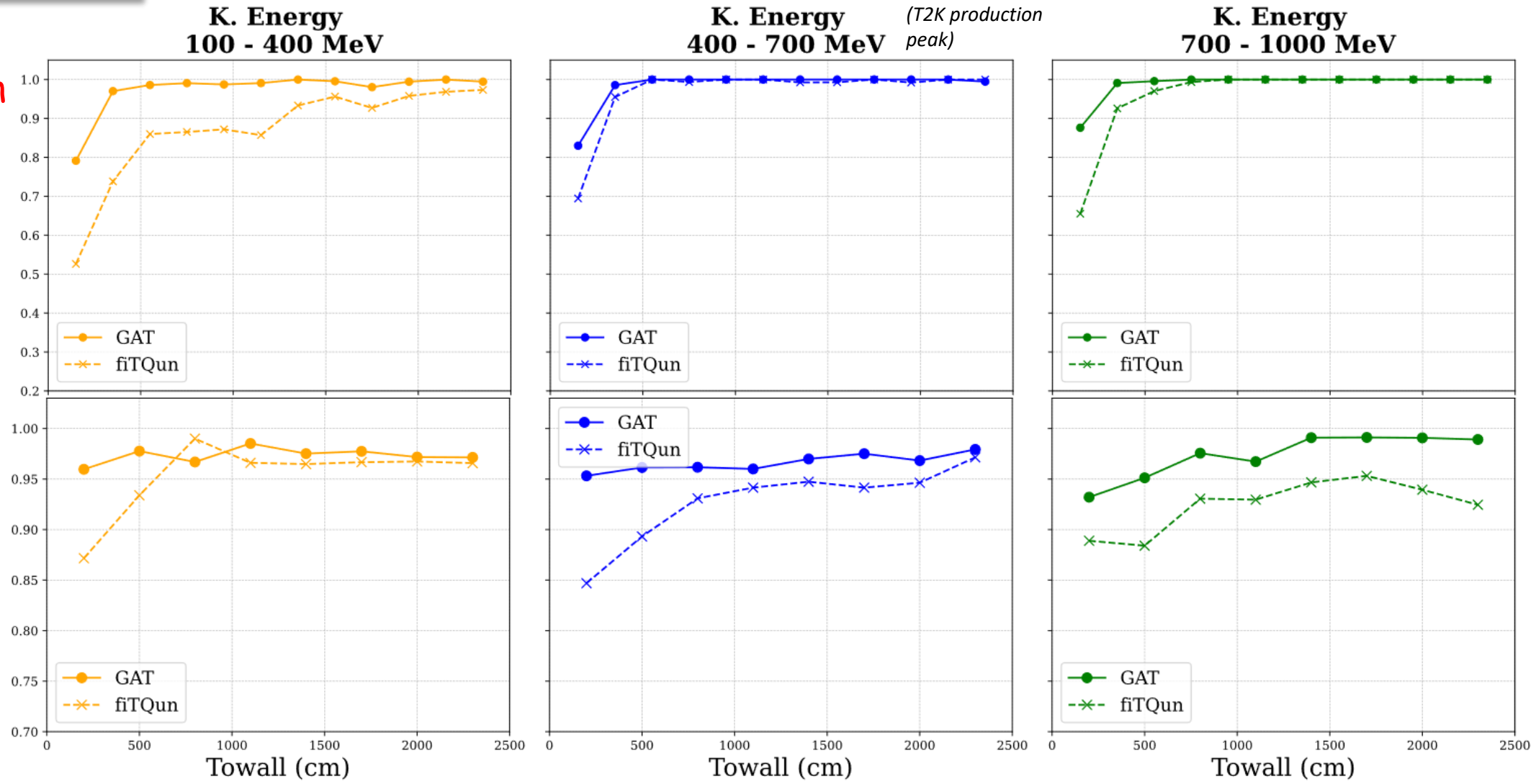
Particle Identification

1. Roc Curves
2. Dwall
3. Towall
4. Towall & Energy

Electron & Muon

Electron & π^0





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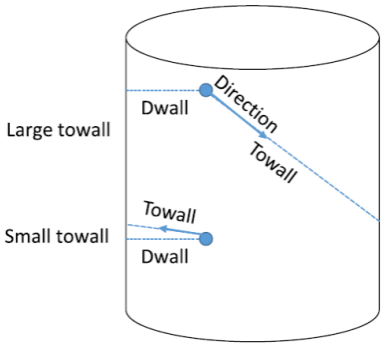
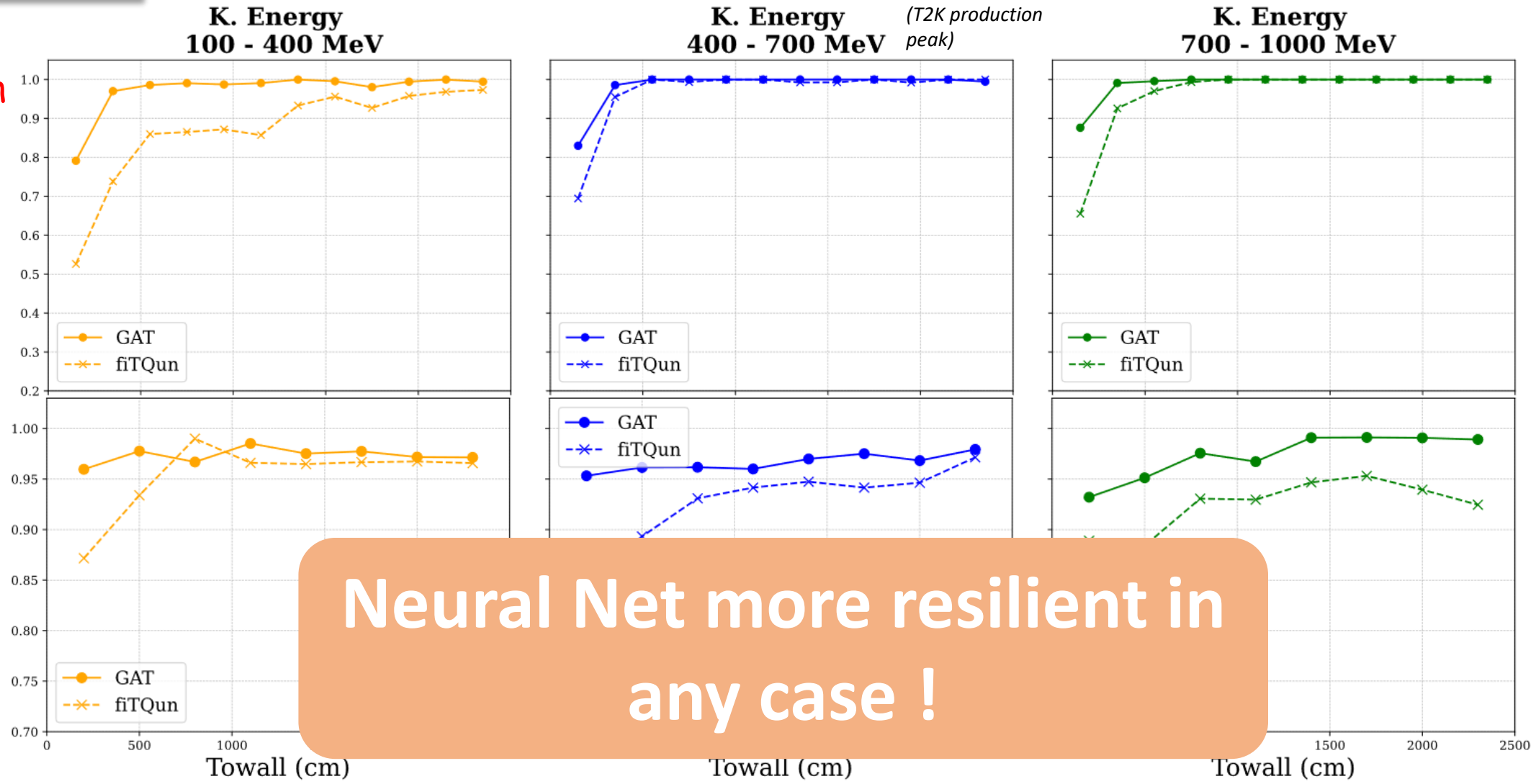
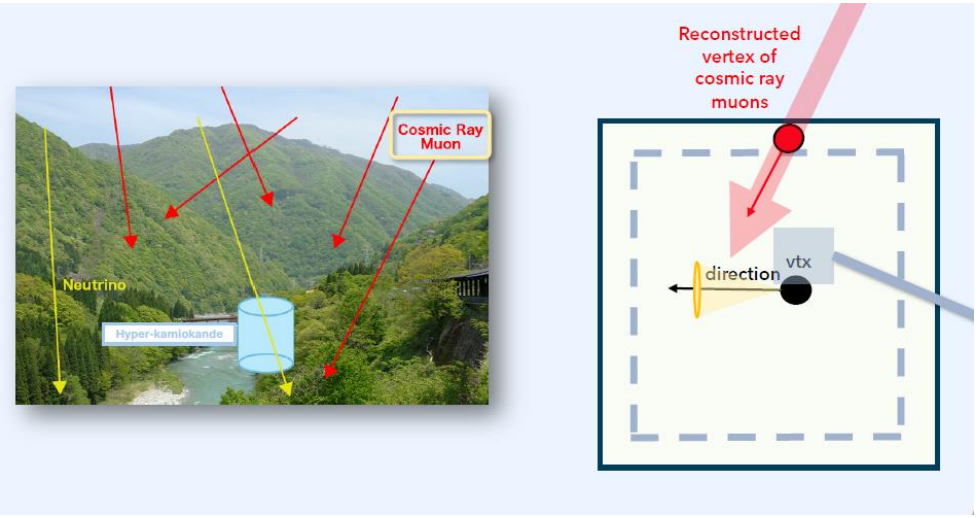




Neural Net more resilient in any case !

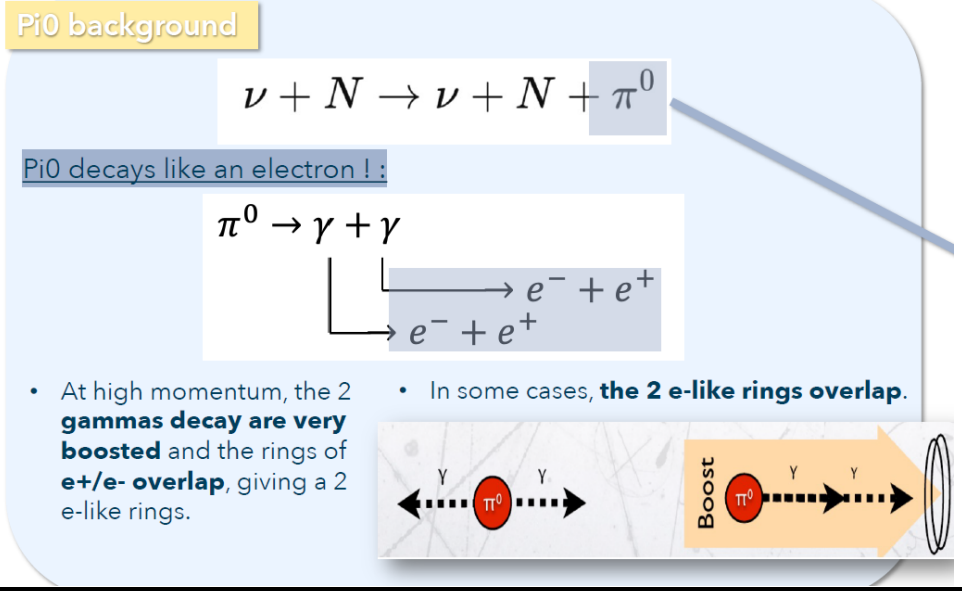
Background : cosmic muon & pi0



Importance of the resolution of

- **Direction**
- **vertex**

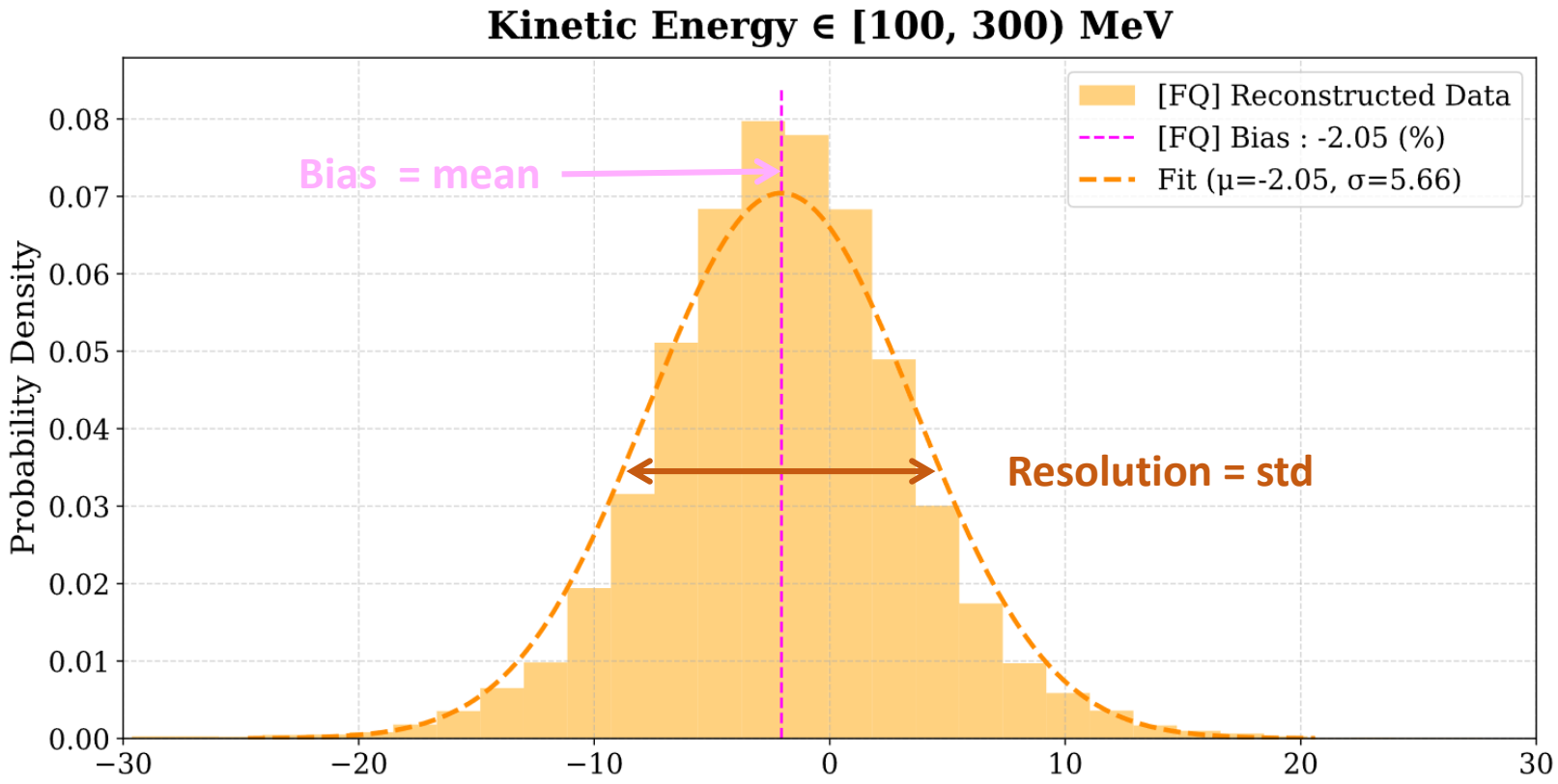
To be able to remove this background



Importance of reconstructing the
- Particle type
(e vs pi0) here

Energy reco

Performance Comparison



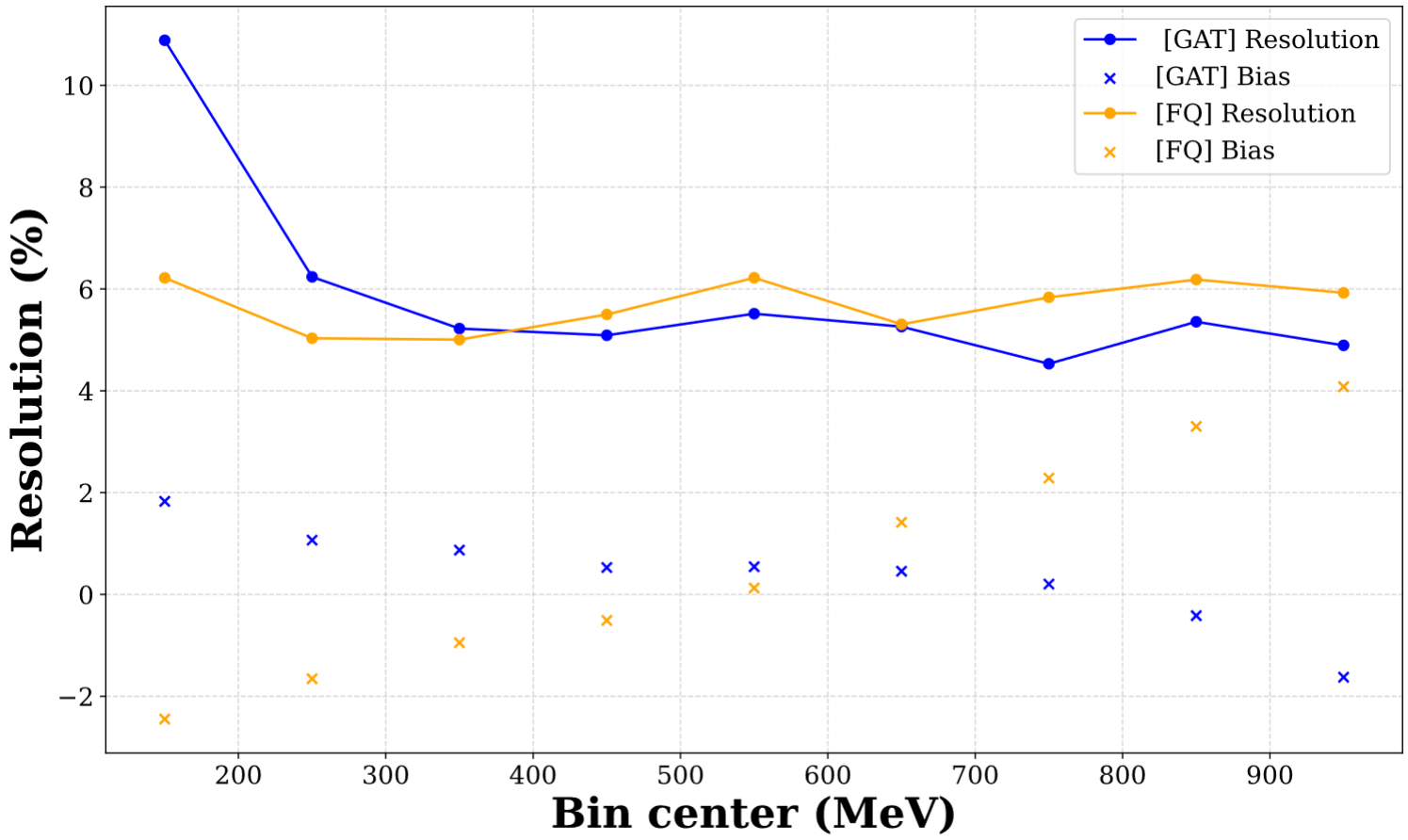
$$\forall i \in \{1..\ N\}\ x_i = \frac{rec - true}{true},$$

$$Resolution = \hat{\sigma}(x_{1..n})$$
$$Bias = \hat{\mu}(x_{1..n})$$

Performance Comparison

Electron Energy

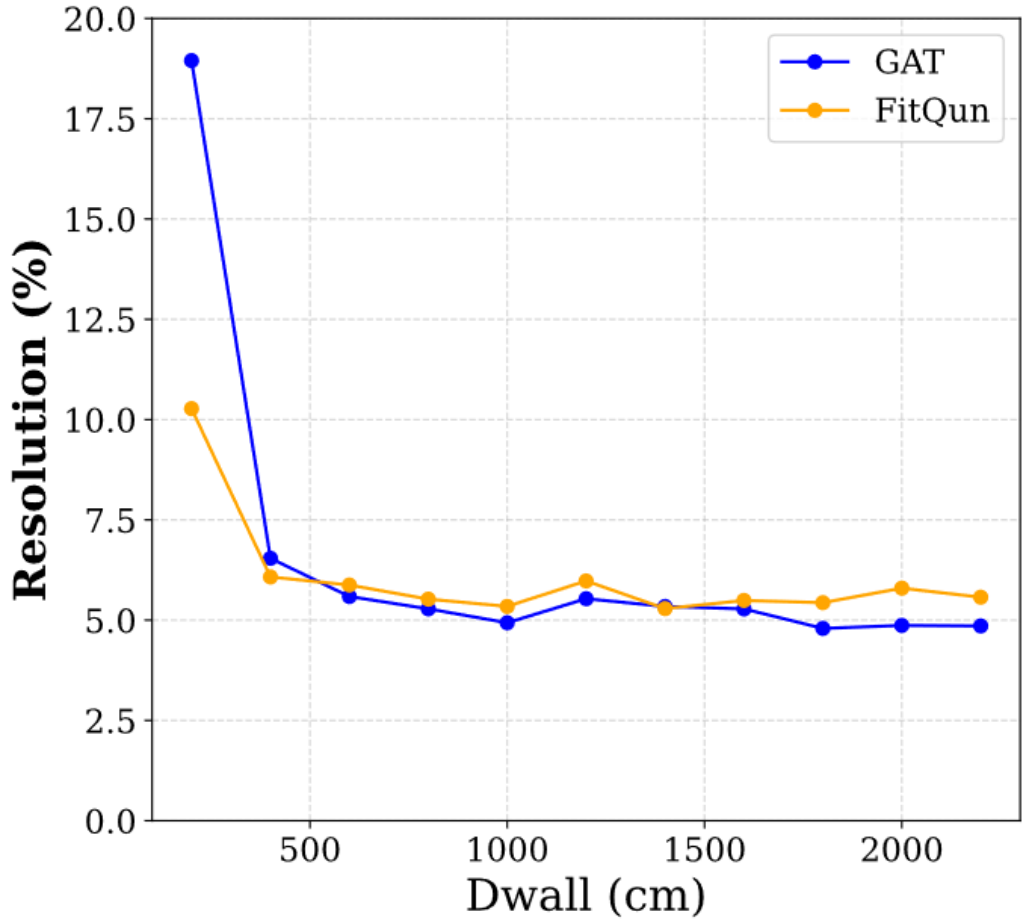
1. Energy | 2. Dwall | 3. Towall & Energy

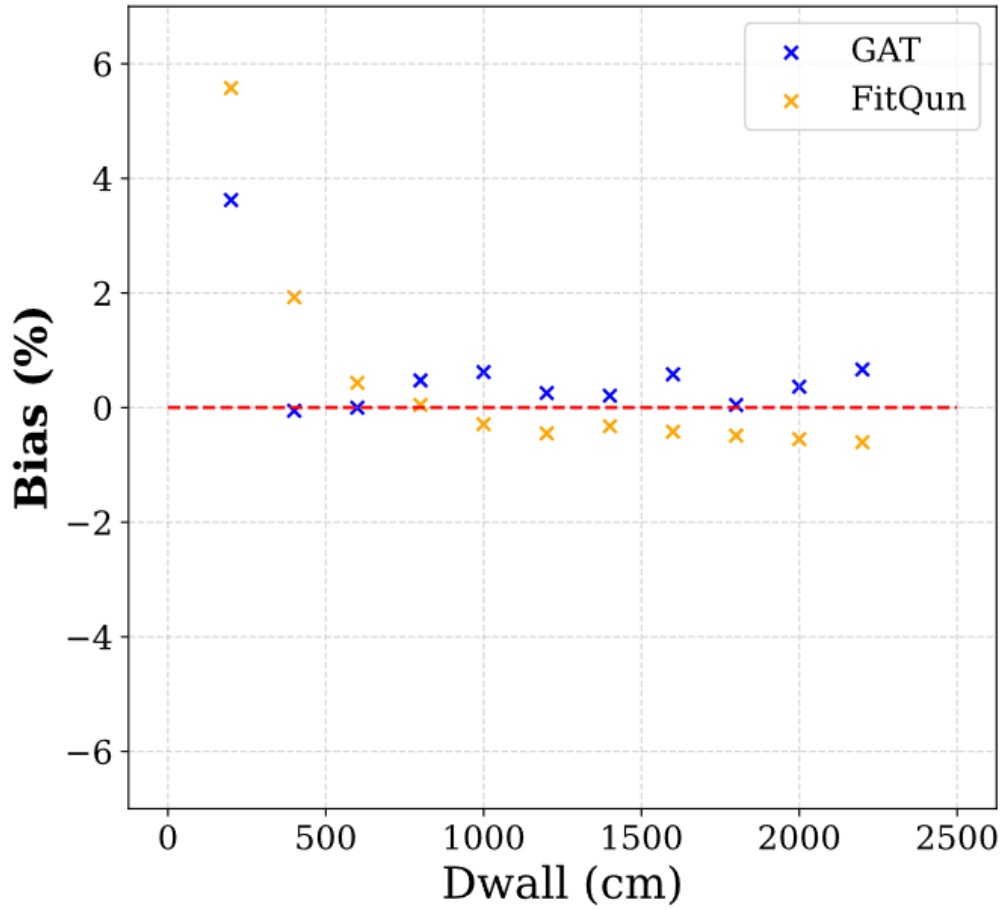


Performance Comparison

Electron Energy

1. Energy | 2. Dwall | 3. Towall & Energy

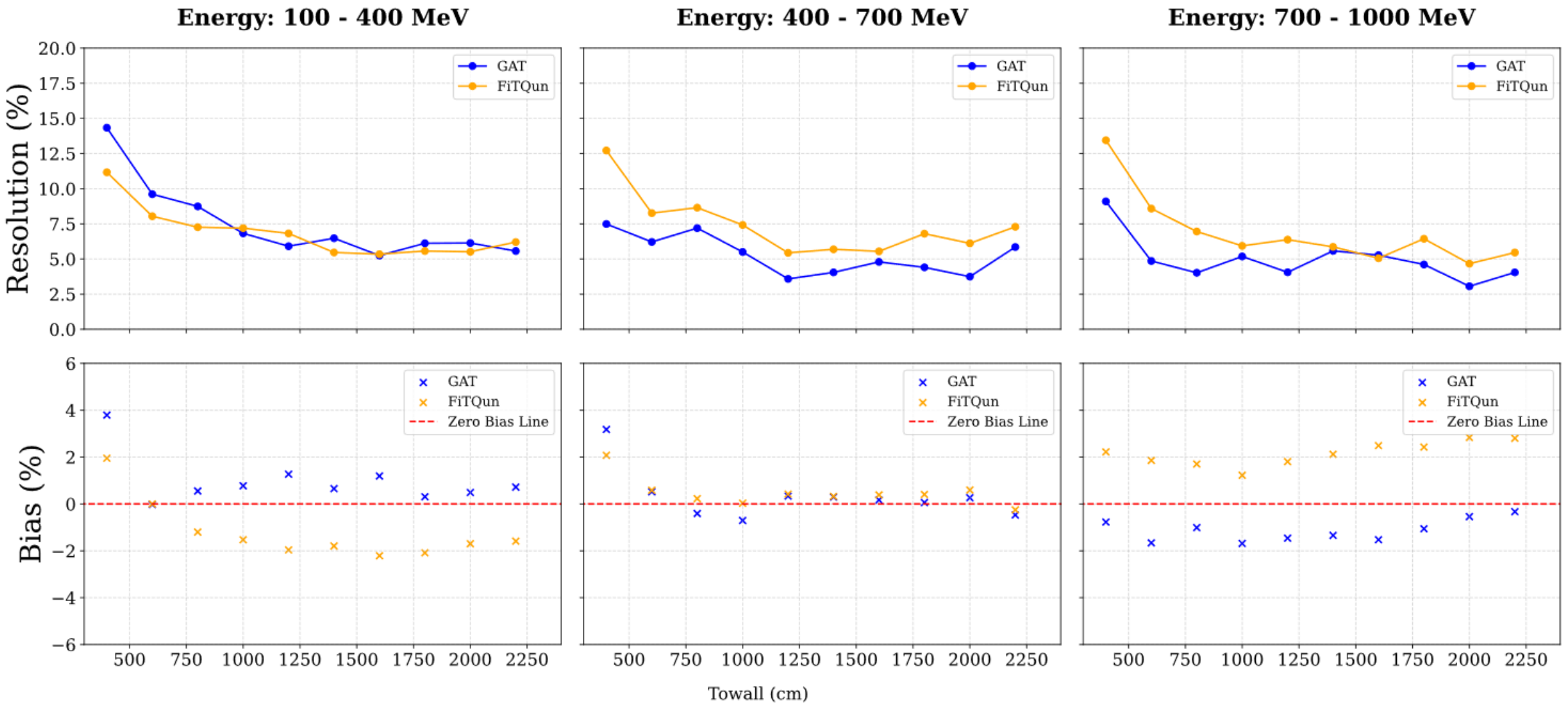




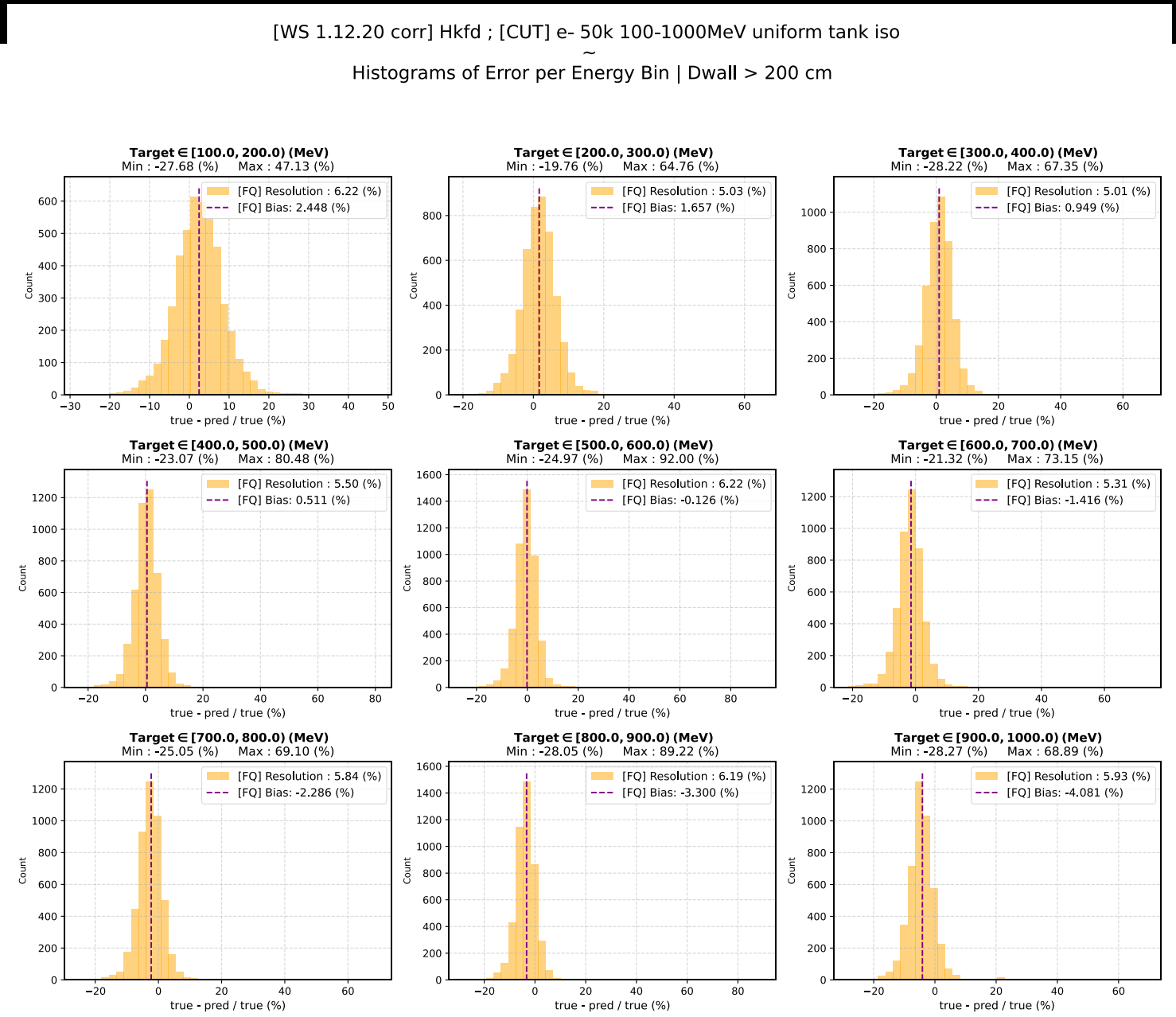
Performance Comparison

Electron Energy

1. Energy | 2. Dwall | 3. Towall & Energy



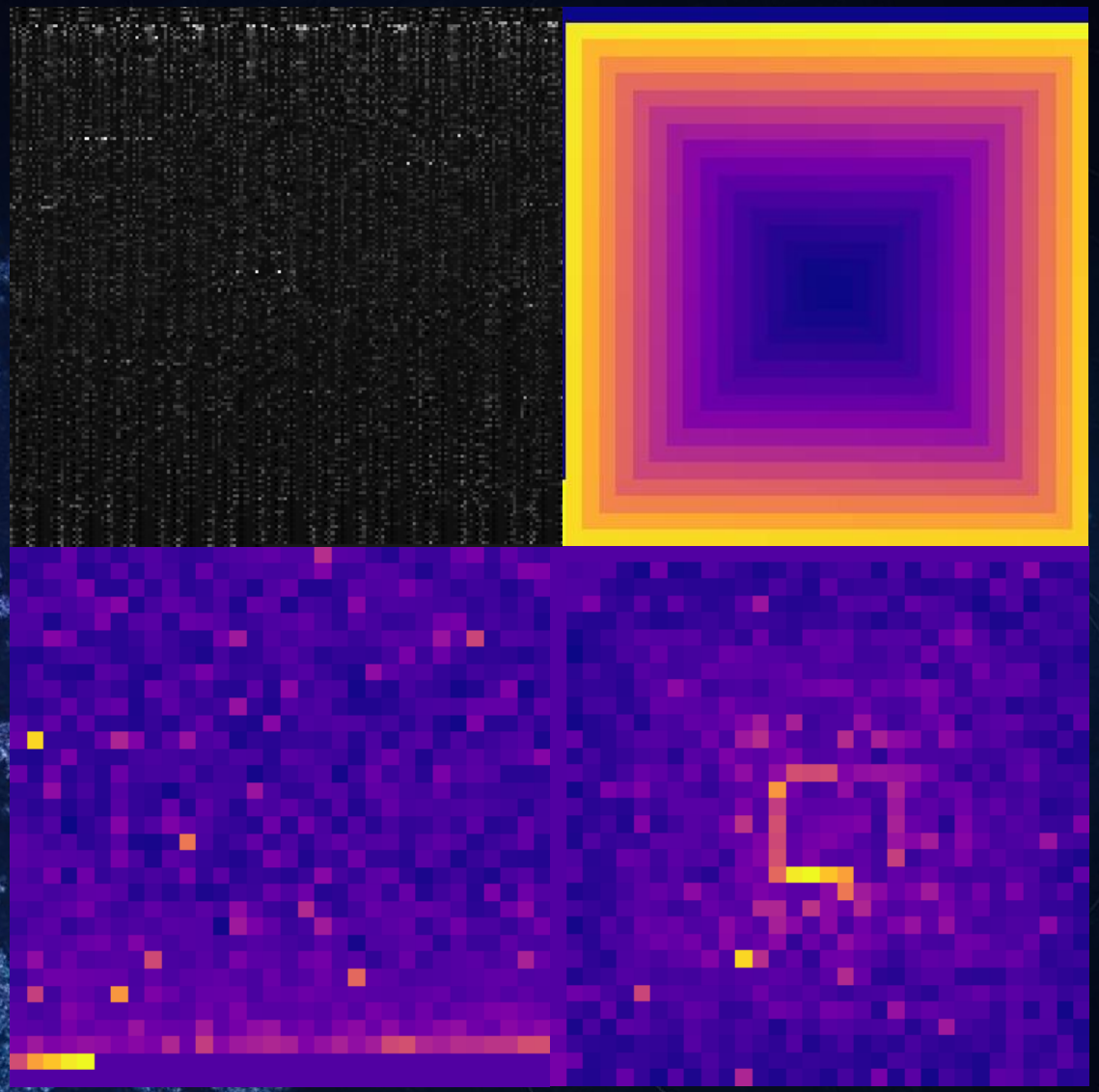
Gaussia hypothesis for e- reconstruction



Data flow in GNNs

Investigating the forward process

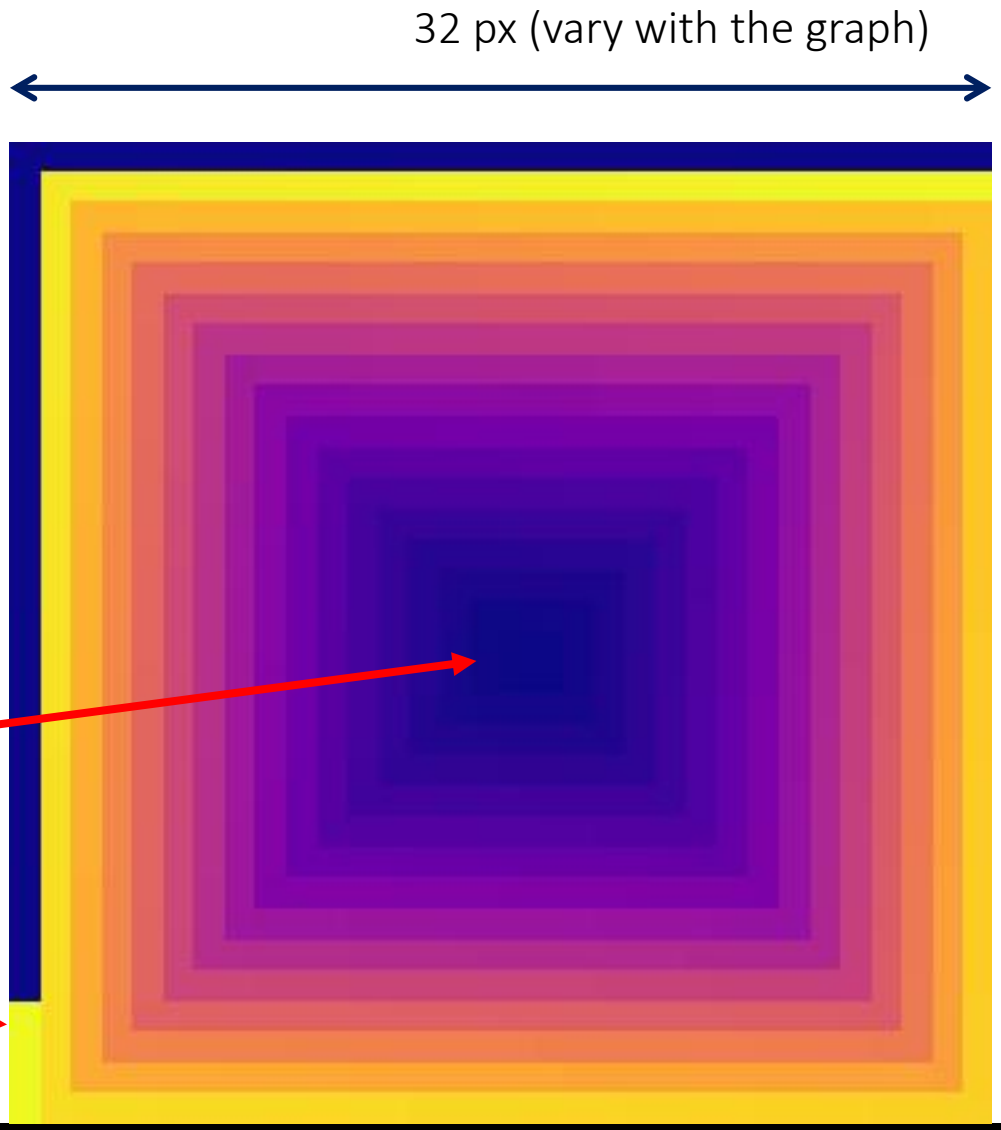
Work started by N. Moreau



Display settings

Making a spiral, sorted by the pmt hit time.

One pixel = one node (PMT)



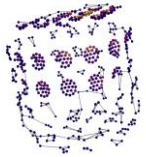
Center = low pmt hit time

Border = high pmt hit time

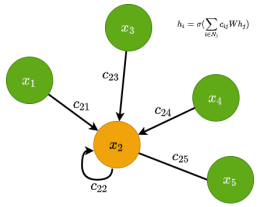
First results

E- 100 -1000MeV
After training for e- / mu- classification

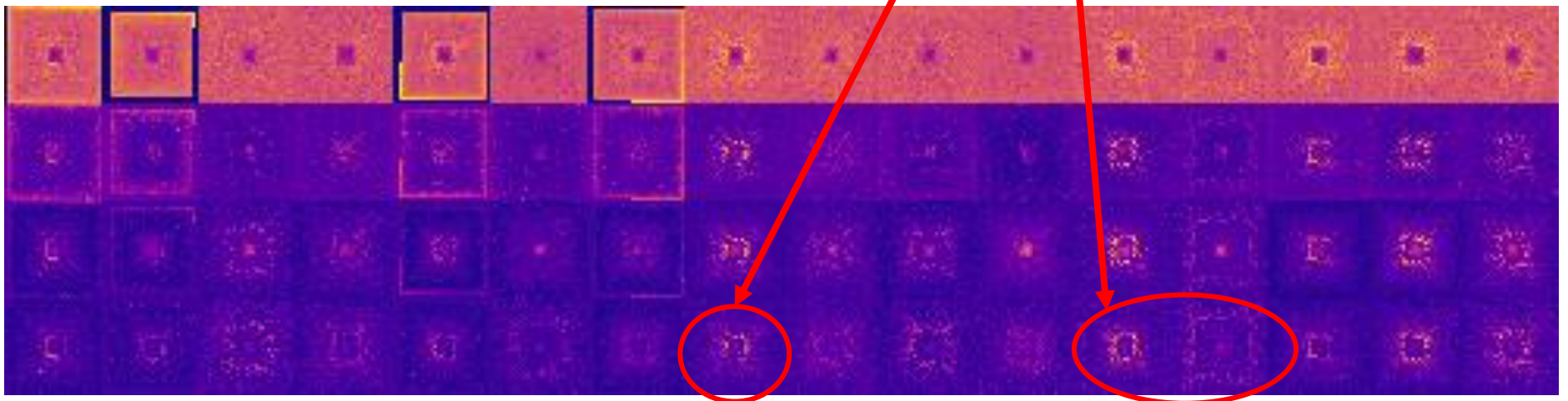
Path to see what is the model « looking » at !



One graph



One convolution step



Purple = low importance
Yellow = high

Encoded graph representation fed to MLP