# High Energy Particle **IDentification (PID)** - An update on what I've been working on so far ———



Quach Christine

# 1. Setting the Context: SK/HK experiments and Existing PID Algorithms 2. My Work: Adapting Algorithms for High Energy Neutrinos

3. What's next?

# Outline.





A. Super-Kamiokande: Operational Principles and Observed Neutrinos

B. Current State of PID Algorithms

#### A. Super-Kamiokande:

Setting the Context

### Super-Kamiokande

- 41.4 m in height and 39.3 m in diameter, which holds approximately 50 ktons of ultrapure water.
- 11,146 PMTs



#### B. Current State of PID Algorithms

#### **Experiments**



### Hyper-Kamiokande

- An order of magnitude bigger than SK,
- 71 m in height and a diameter of 68 m
- 20 000 ultra-high sensitivity PMTs



#### A. Super-Kamiokande:

Setting the Context

#### **Observed neutrinos**

### **Relic Supernova neutrinos**

- Neutrinos were produced in a supernova that occurred in the distant past and is still traveling through the universe today.
- # of events in SK: 10/year.
- Energy: 2 MeV (LOW)
- Provide a unique opportunity to study the properties of supernovae and the physics of the early universe

- Earth
- Most of solar neutrinos have energy below 10 MeV
  - Representation of the flux as a function of the energy of solar neutrinos according to the Standard Model of the Sun

#### B. Current State of PID Algorithms

#### **Solar neutrinos**

Neutrinos produced in the Sun by nuclear fusion reactions. Vast majority of neutrinos passing through the

### **Transient Supernova** neutrinos

- Neutrinos coming from a supernova explosion
- Energy ranging from 10 to 30 MeV. (HIGH)
- Interesting particles to observe to understand the physics behind the explosion as neutrinos hold 99 % of the information about the explosion.





Context

A. Super-Kamiokande:

#### **Neutrino detection method**

**Cherenkov light** Neutrino Charged particle in water Photosensors

#### B. Current State of PID Algorithms

### **Cherenkov light**

- The neutrino that interacts with electrons or nuclei in water produces a charged particle moving faster than the speed of light in water, which is slower than the speed of light in a vacuum.
- A cone of light is formed as a result, which is known as Cherenkov radiation.
- The equivalent in the optical field is the sonic boom. PMTs record the Cherenkov light projected as a ring on the wall of the detector.







Context

#### A. Super-Kamiokande:

#### Neutrino detection method

#### Muon (Sharp)

#### B. Current State of PID Algorithms



#### Electron (Blurry)

#### A. Super-Kamiokande:

Setting the

Context

Merci Anto Architecture

#### Low energy

### Why a <u>Graph Neural Network (GNN)?</u>

- - Use of Deep Learning
- Why not a <u>Convolutional Neural Network</u> (used for image analysis)?
  - -(instead of one small graph for a GNN)
  - -

 $\Rightarrow$  Smaller dataset and faster processes

graphs)  $\Rightarrow$  More flexible inputs

#### B. Current State of PID Algorithms

5

A Boosted Decision Tree (BDT) has been developed. Can we do better?

One would need to stack images to have the time information of an event

Small number of hits for the neutron capture on H (a GNN will not be

confused with useless information and therefore processed faster)

No direct relation between hits (one can add more complex information on

#### A. Super-Kamiokande:

Setting the

Context

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#### Architecture example

- 2 layers of DynamicEdgeConv [1801.07829, Wang et al., 2019]:
- Connects closest (euclidian distance) nodes in feature space by edges
- **Edge features:** Information about  $x_i$  (node feature i) and  $x_i x_i$  (relative difference to nearest neighbours)



#### B. Current State of PID Algorithms

6

#### Low energy



#### B. Current State of PID Algorithms



# 2) My work

A. Key Challenges in PID

- Neutrinos
- Neutrinos

B. Adapting BDT Algorithm for High Energy

# C. Adapting GNN Algorithm for High Energy



### Identification of particles in levels of difficulties

- e/mu particle identification
- e/gamma particle identification
- e/pi0 particle identification
- mu/pi+ particle identification
- Multiple ring fit

#### B. Adapting BDT

#### C. Adapting GNN



#### Muon (Sharp)

#### Electron (Blurry)



#### **Distribution of Discriminating Variables**

### I. DISTRIBUTION OF DISCRIMINANT VARIABLES

TO SEE IF THERE ARE ANY RELEVANT THID VARIABLES





# Distribution of Discriminating Variables Charge Profile



#### B. Adapting BDT

#### C. Adapting GNN

6



# **Distribution of Discriminating Variables** Charge Profile

#### Explication pour le mu :

- Broadening within the ring (see diagram) Hence, the peak shift is not exactly at 42°
- And thus, as the standard deviation is lower (compared to electron and gamma which are also broadened externally), the maximum value is higher.
- Charge per unit angle is higher for muons, dominating over the total charge since they are less scattered.





### B. Adapting BDT



## **Distribution of Discriminating Variables**



### B. Adapting BDT

#### C. Adapting GNN

### **Charge Profile**





# **Distribution of Discriminating Variables**



### B. Adapting BDT

#### C. Adapting GNN

### **Charge Profile**



# **Distribution of Discriminating Variables Explanations t-TOF**





### B. Adapting BDT

#### C. Adapting GNN

Calculation of t-tof as a function of particle progress x:





# **Distribution of Discriminating Variables Explanations t-TOF**



#### B. Adapting BDT



# **Distribution of Discriminating Variables Explications t-TOF**



#### B. Adapting BDT



# **Distribution of Discriminating Variables**



#### B. Adapting BDT

#### C. Adapting GNN



# **Distribution of Discriminating Variables**

#### Explication pour le mu : Shifted peak:

 Muon is about 2 times more energetic than each particle of the positron-electron pair, it will pass through the Cherenkov threshold later, so statistically, there is a higher chance that theta will be small, hence  $x = x_{tof}$ , resulting in negative t-tof. This shifts the peak.

#### **Decreasing part:**

- This corresponds to Cherenkov photons produced by the parent particle moving in its direction, after creation at the vertex.
- We see that Q decreases more quickly than for electrons. This is because muon passes through the Cherenkov threshold more rapidly than electrons.

#### Increasing part:

 Very steep, so few Cherenkov photons coming from charged particles whose trajectory is positively deviated.





### B. Adapting BDT

#### C. Adapting GNN



# **Distribution of Discriminating Variables**

#### Explication pour l'électron : Shifted peak:

Same as for muon.

#### Decreasing part:

- This corresponds to Cherenkov photons produced by the parent particle moving in its direction, after creation at the vertex.
- We see that Q decreases more quickly than for electron. This is due to the fact that muon passes through the Cherenkov threshold more rapidly than electron.

#### Increasing and decreasing parts:

 Increasing part slightly less steep than for muon. Electromagnetic cascade populates both sides of the peak, so the decreasing part is also less steep.





#### B. Adapting BDT

#### C. Adapting GNN



# **Distribution of Discriminating Variables**

Explication pour gamma :

- · Overall: distribution is much broader than for e-.
- Maximum charge per PMT: For the e+/e- pair, 2 times smaller than for e- and mu-. The maximum is found at t=tof. This seems consistent with the fact that when e+ and e- are very close to the vertex, the two generated photons are more likely to hit the same PMT. (The maximum charge per PMT does not allow for differentiation between e- and mubecause at the vertex there is no electromagnetic cascade effect, whereas, for the pair production, there is already a deviation in trajectory.)
- · In the increasing part, the same as for the electron.
- Wider distribution: for t-tof on either side of the peak, less steep rise and fall due to electromagnetic shower effect AND ADDITIONALLY angle between e+/e- direction.
- Conclusion: the difference between e- and e+/e- appears more pronounced concerning the charge profile because t-TOF is a variable equivalent to a length, unlike theta, thus we can better see the energy difference of the pair production.

### B. Adapting BDT

#### C. Adapting GNN





### **Distribution of Discriminating Variables**

### **Reconstruction – Charge Profile**



### B. Adapting BDT

#### C. Adapting GNN

#### Without randomization:

- Mu is less scattered, so lower average std.
- Event by event: the std of gamma is larger than that of e because event by event gamma is more random due to pair production.
- The std of mu is generally larger because it fits Gaussian, and mu is skewed.

#### With random:

 Difficult to distinguish particles from each other... maybe try another fit?

	Gamma	Erreur
0 1 <b>054817</b>	Mean = 7.61257e+00 Sigma = 4.50241e-01 Sig/mean =0.05914441509 Ecart : 0.06415294802 %	Mean : 4.54 e-03, 5.23 e-03, 4.61 e-03 Sigma : 3.84 e-03, 3.55 e-03,
0 1 93847 28%	Mean = 7.84185e+00 Sigma = 5.47913e-01 Sig/mean =0.06987037497 Ecart : 2.29995561617%	Mean : 5.61 e-03, 8.67 e-03, 5.64 e-03 Sigma : 4.61 e-03, 5.82 e-03, 4.85 e-03

2

My work

#### **Distribution of Discriminating Variables**

ndusion

• For mu/e-: +: The difference in charge profile and the total charge is clearly visible. -: The difference is not very noticeable on the tof graphs.

• For e-/gamma: +: A clear difference is seen when studying the tof according to the charge per PMT. -: The difference is not very noticeable on the charge profile; it would be necessary to investigate the angle of the pair production (i.e., perform

exact calculations, but this is in progress...).

### B. Adapting BDT



#### **Distribution of Discriminating Variables**

# 2 My work

### II. STUDY OF THE CORRELATION BETWEEN DISCRIMINANT VARIABLES

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### **Distribution of Discriminating Variables**

# 2 My work

#### B. Adapting BDT

#### C. Adapting GNN

## between variables





#### • Mu

More concentrated near 42°, few events at small tshower, resulting in a very clear break.

Charge peak at t-tof<0, but near 40°.

#### Electron

The charge is more scattered at a given t-tof, due to electromagnetic cascade. The peak at t-tof<0, near 42°. Distributed more or less uniformly around 42°, with a preferential direction.

#### B. Adapting BDT

#### C. Adapting GNN

#### **Distribution of Discriminating Variables**

#### Q(Theta, t-tof)

More concentrated near 42°, few events at small t-tof after 42°. No scattering effect or electromagnetic



# **Distribution of Discriminating Variables** Q(Theta, t-tof)





Gamma

Significantly weaker charge. At t-tof=0, highly scattered, and has no real preferential direction.

#### Electron

The charge is more scattered at a given t-tof, due to electromagnetic cascade. The peak at t-tof<0, near 42°. Distributed more or less uniformly around 42°, with a preferential direction.

#### B. Adapting BDT



# **Distribution of Discriminating Variables** Ratio Q(Theta, t-tof)





#### B. Adapting BDT



# **Distribution of Discriminating Variables** Ratio Q(Theta, t-tof)





#### B. Adapting BDT





# **Distribution of Discriminating Variables** Ratio Q(Theta, t-tof)

Gamma



#### B. Adapting BDT

#### C. Adapting GNN

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#### **Distribution of Discriminating Variables**



## III. STUDY OF THE IMPACT OF DETECTOR EFFECTS

RECONSTRUCTION EFFECT, WATER ABSORPTION EFFECT, AND RAYLEIGH SCATTERING EFFECT







#### B. Adapting BDT

#### C. Adapting GNN

#### **Distribution of Discriminating Variables**



#### **Distribution of Discriminating Variables**

### Q(theta) – Reconstruction Error

We study the **influence of the reconstruction error** on the charge profile with an error of:

- 20 cm on the reconstruction of the vertex position
- 2.5 degrees in the direction

#### Expected effect

We would expect the overall amplitude to be attenuated because changing the initial vertex position results in a more scattered distribution, thus decreased amplitude, increased standard deviation, and unchanged integral.

#### Observation

The charge profile, which takes this error into account, has a lower amplitude, but the mean is preserved: we can still distinguish between a mu and an e. The distinction between e and gamma is more difficult to make after randomization.



#### B. Adapting BDT



### **Distribution of Discriminating Variables**

### Q(TOF) – Reconstruction Error



#### B. Adapting BDT





#### B. Adapting BDT

#### C. Adapting GNN

#### **Distribution of Discriminating Variables**

# rption effects



### **Distribution of Discriminating Variables**

#### Q(theta) – Water absorption



The characteristic length of 1.3 minus 1 sigma = 0.07.

#### The effect of water absorption

We would expect a major influence/ decrease on long-time photons populating the outer ring because those that pass through more material have a higher absorption probability. And less impact on gamma, more on mu and e.

#### Observations

No major changes, a small shift for the muon, because less in the outer ring.



#### B. Adapting BDT



# **Distribution of Discriminating Variables** Q(TOF) – Water absorption

#### Study of the influence of water absorption:

The characteristic length of 1.3 minus 1 sigma = 0.07.

#### The effect of water absorption

We expect less population in the long-time, i.e., outer ring for mu and e (a little for gamma), and internal/ external for e and gamma due to the shower.

#### Observations

Weaker overall impact. Still, presence of a shift for mu and e and a slight shift to the left of gamma, so the distinction is possible between e and gamma.



#### B. Adapting BDT

### **Distribution of Discriminating Variables**

# 2 My work



#### B. Adapting BDT

#### C. Adapting GNN



42



# Distribution of Discriminating Variables Q(theta) – Rayleigh scattering



#### B. Adapting BDT



# **Distribution of Discriminating Variables** Q(TOF) – Rayleigh scattering



#### B. Adapting BDT

### **Distribution of Discriminating Variables**





#### B. Adapting BDT

#### C. Adapting GNN

# distributions from



# **Distribution of Discriminating Variables** Cut for Charge Profile



#### B. Adapting BDT



### **Distribution of Discriminating Variables**

### **Cut for t-TOF Profile**



### B. Adapting BDT



#### Hyper Parameters optimization

Parameter importance with respect to	accuracy ~	
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Config parameter	Importance 🛈 🗸	Correlation
batch_size		
learning_rate		
k		
nb_conv_layers		

Parameter importance with respect to	~	
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Config parameter	Importance 🥡 🗸	Correlation
batch_size		
k		
nb_conv_layers		
learning_rate	48	

#### B. Adapting BDT





#### Hyper Parameters optimization



#### B. Adapting BDT





#### Hyper Parameters optimization



#### B. Adapting BDT





#### Hyper Parameters optimization



#### B. Adapting BDT

#### C. Adapting GNN

51





#### Hyper Parameters optimization



B. Adapting BDT





A. GNN : ideas for improvement B. BDT : ideas for improvement



What's next?

#### GNN

- Finding better cuts and study the correlation • Finishing the Optimization the hyperparameters between built distributions of the GNN
- Quantify the efficiency and precision of the GNN classification mu/e then identify the physical parameters of the GNN by comparing the distributions
- Do the same for e/gamma separation
- Optimize the parameters of the GNN at variable energy.
- Parallelization of the GNN training

#### B. BDT future improvements

#### BDT

• Take GNN's output parameters as inputs for the BDT



