New ML methods for ν_e interaction identification @T2K near detector

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Réunion du vendredi - LPNHE
11/04/2025

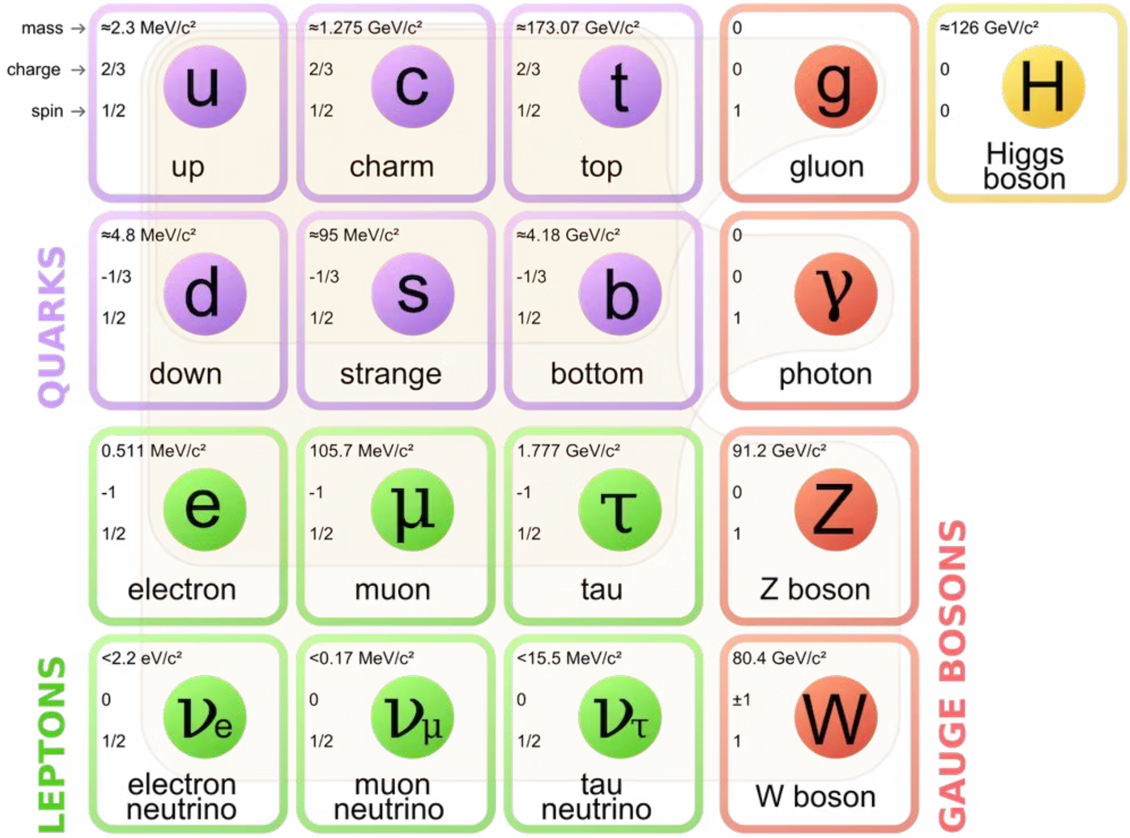
Overview

- Why neutrinos are interesting
- T2K and ν_e (electronic neutrinos)
- Why we need to improve the ν_e selection
- 2 new PID* methods with ML: Transformer & Variational Auto-Encoder
- The Transformer PID method
    - What is a Transformer
    - How we can apply it for the ν_e selection
    - Vision Transformer
    - First performances
- A glanced at the Variational Auto-Encoder method

*PID = Particle IDentification

Why neutrinos are interesting

Standard model of particles



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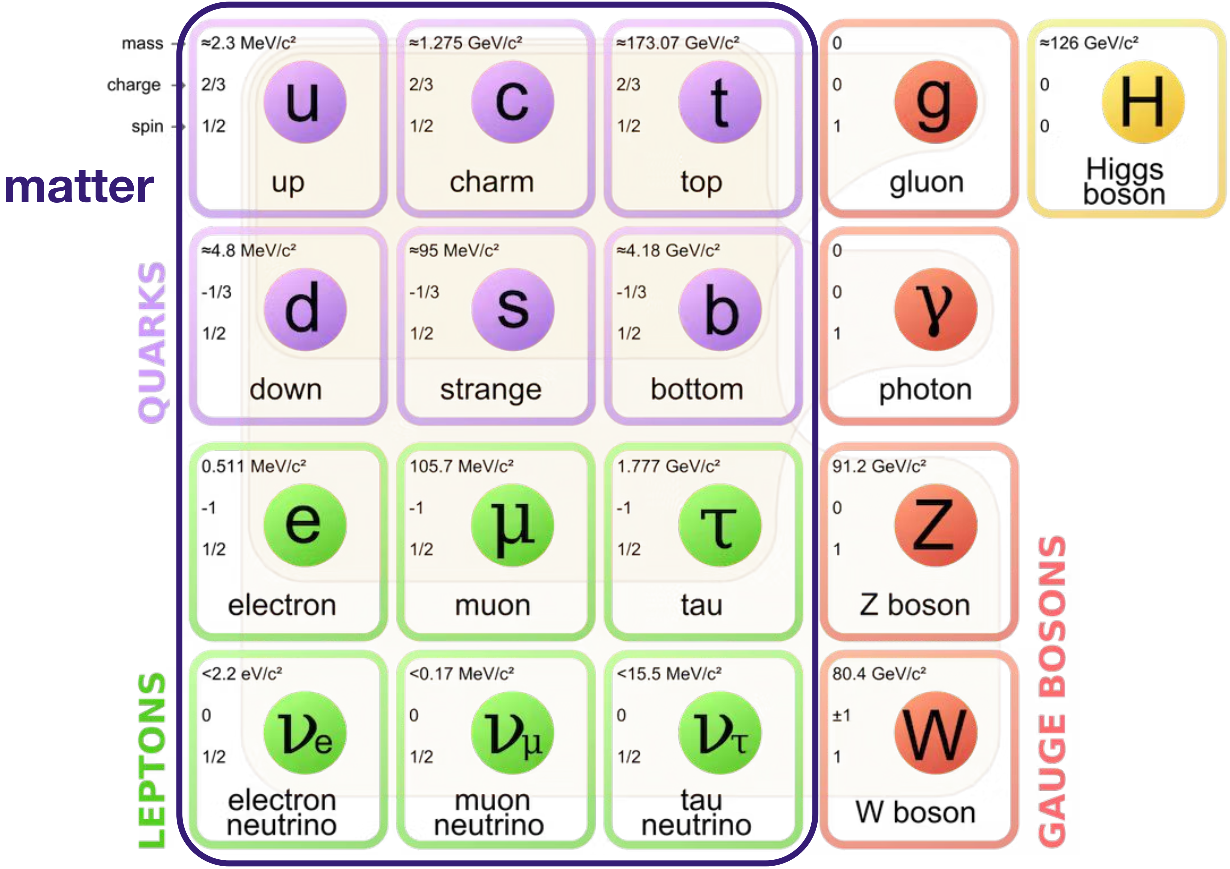

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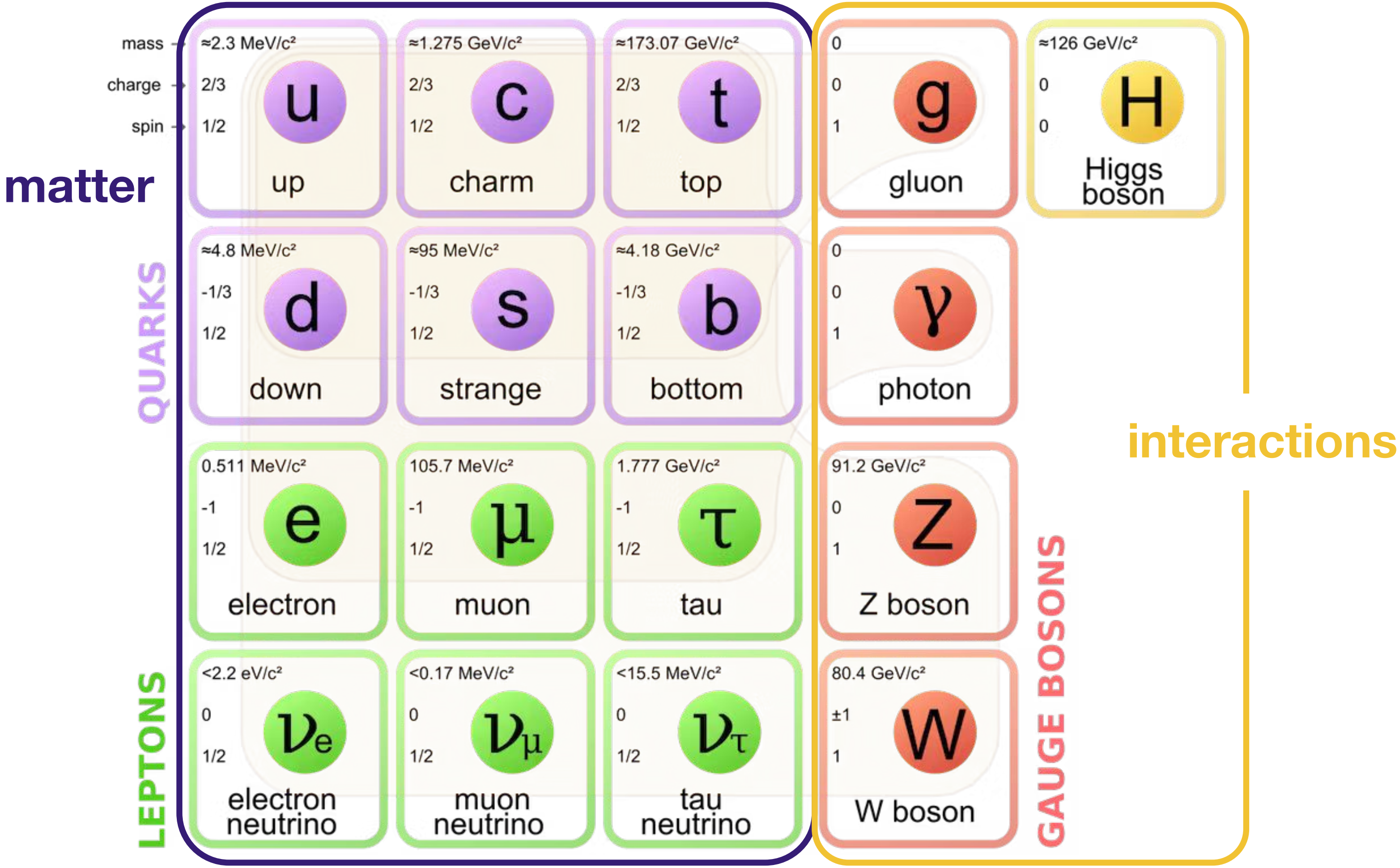

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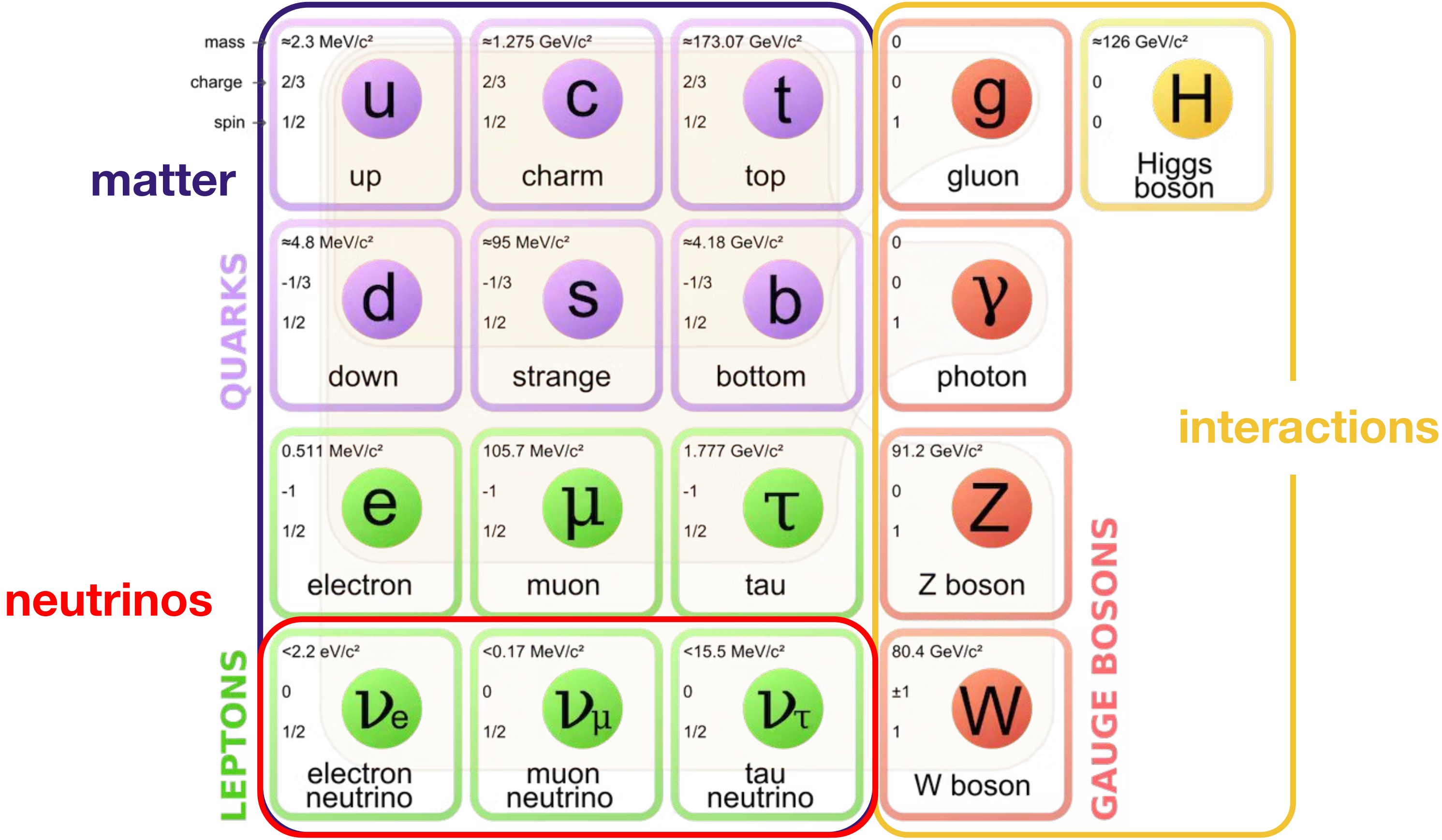
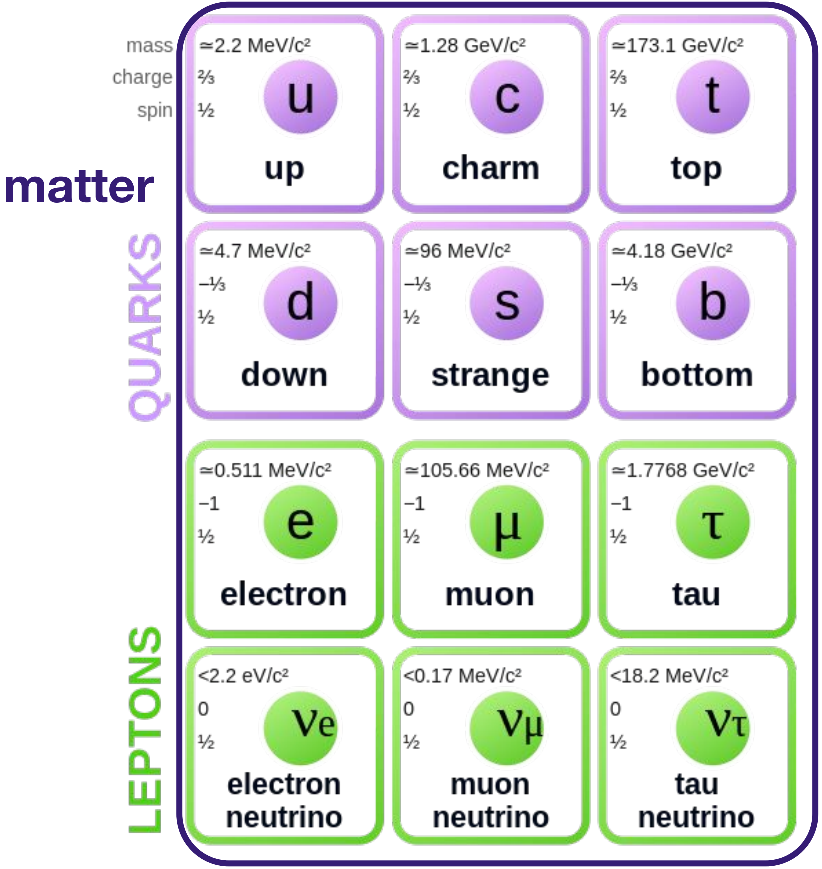


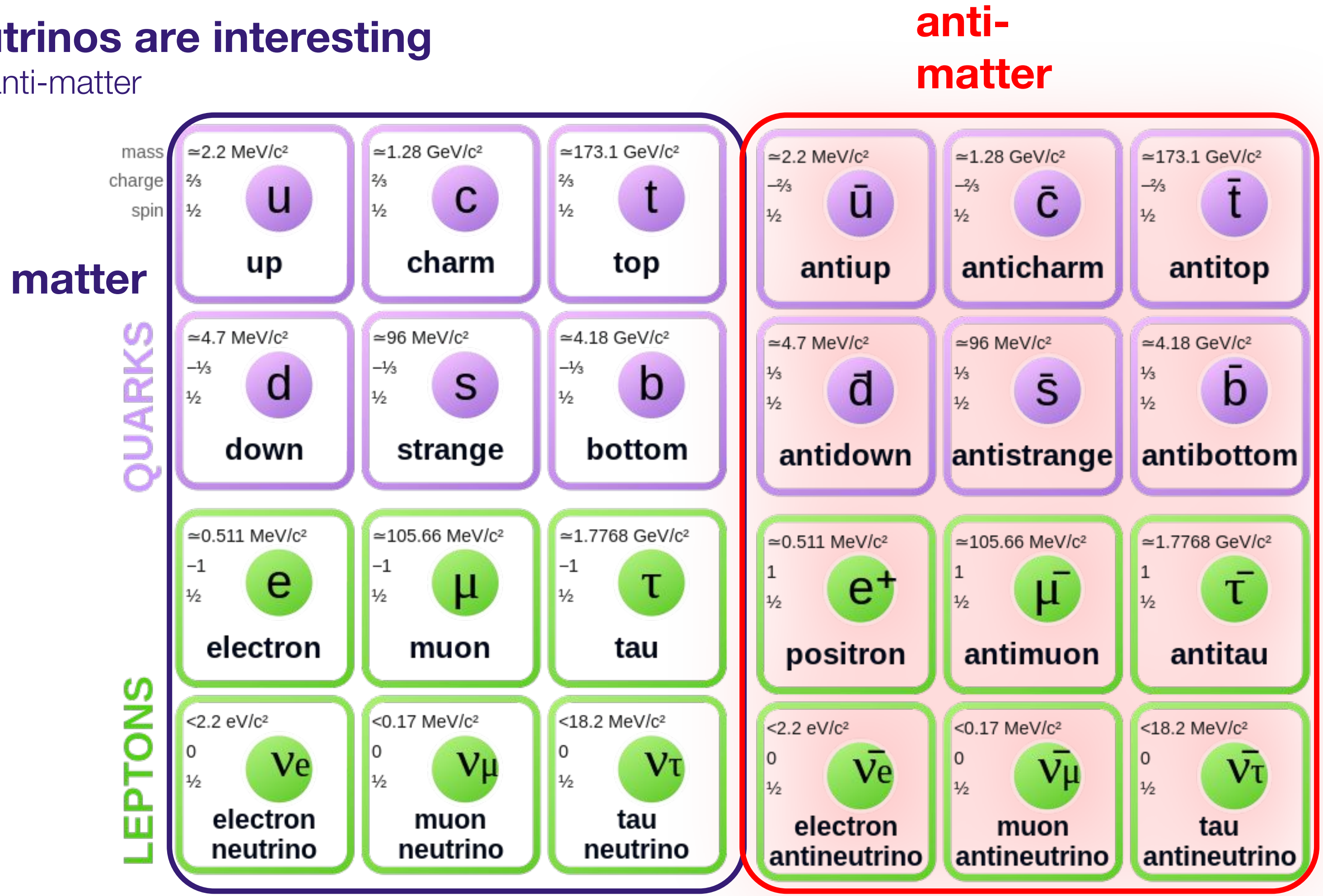
Why neutrinos are interesting

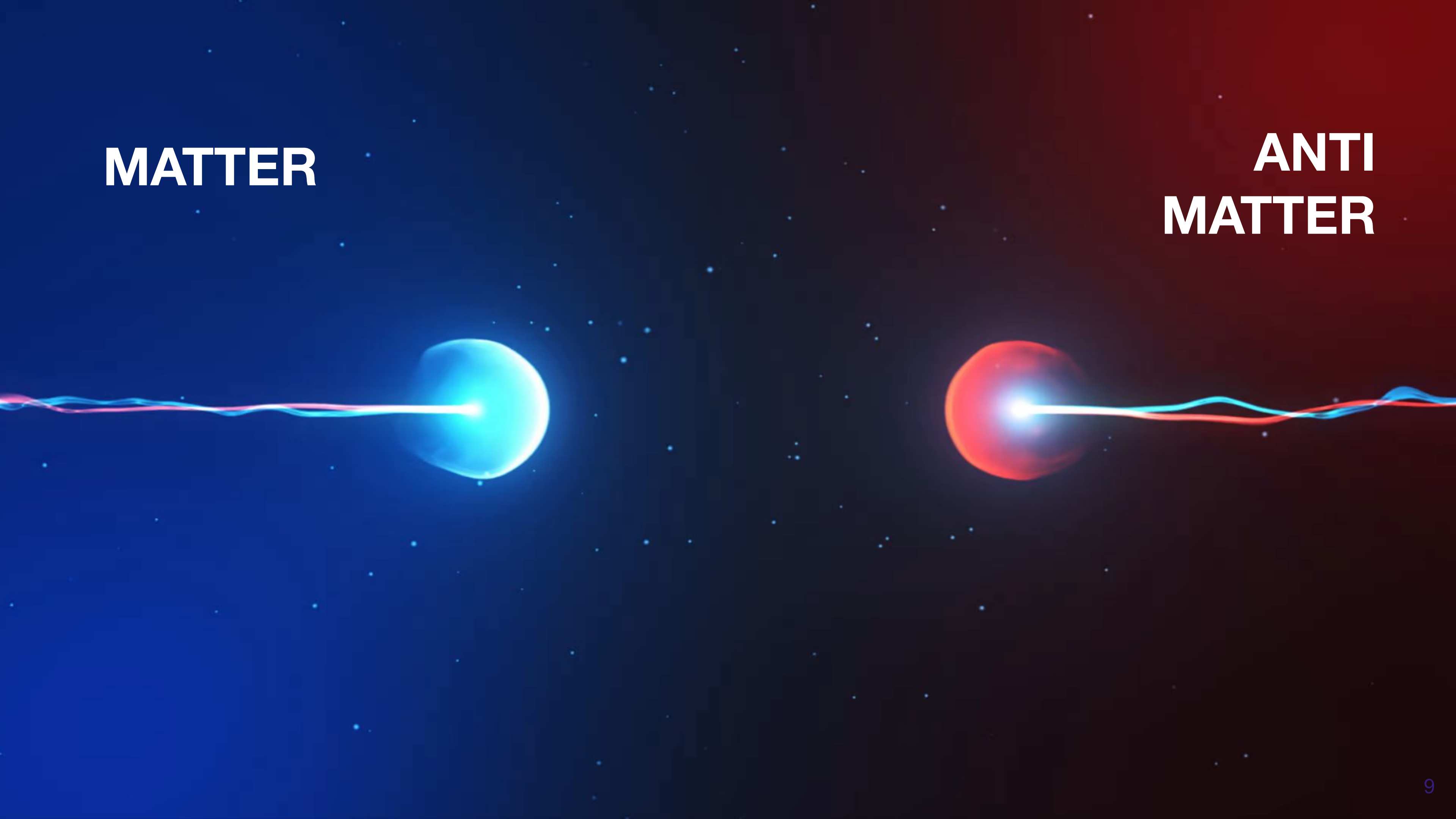
Matter



Why neutrinos are interesting

Matter vs anti-matter




MATTER
ANTI
MATTER

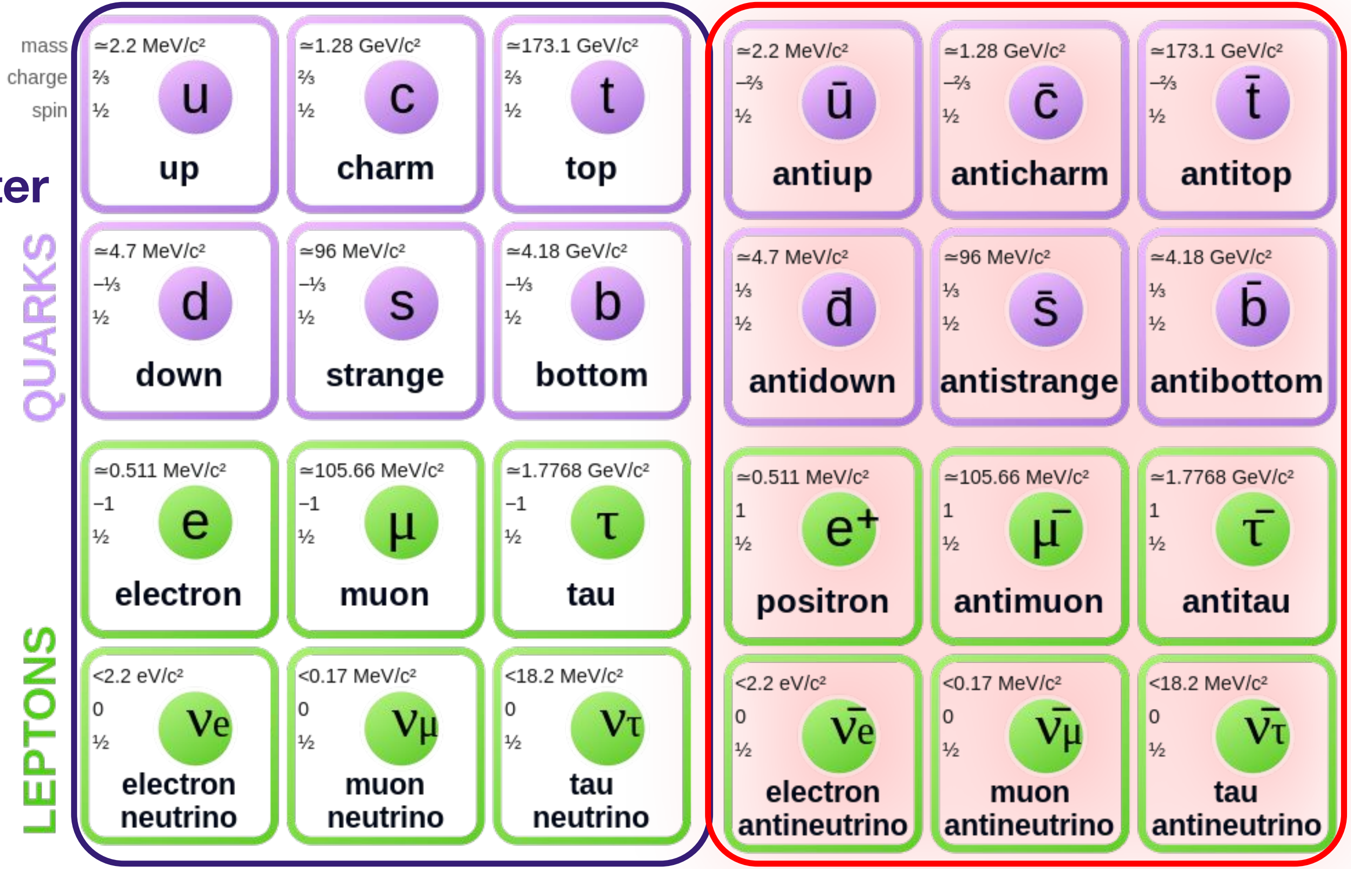
LIGHT

Why neutrinos are interesting

Matter vs anti-matter

anti-matter

matter



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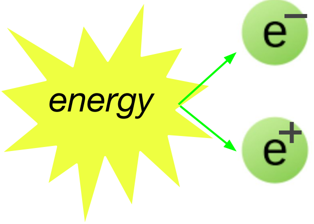
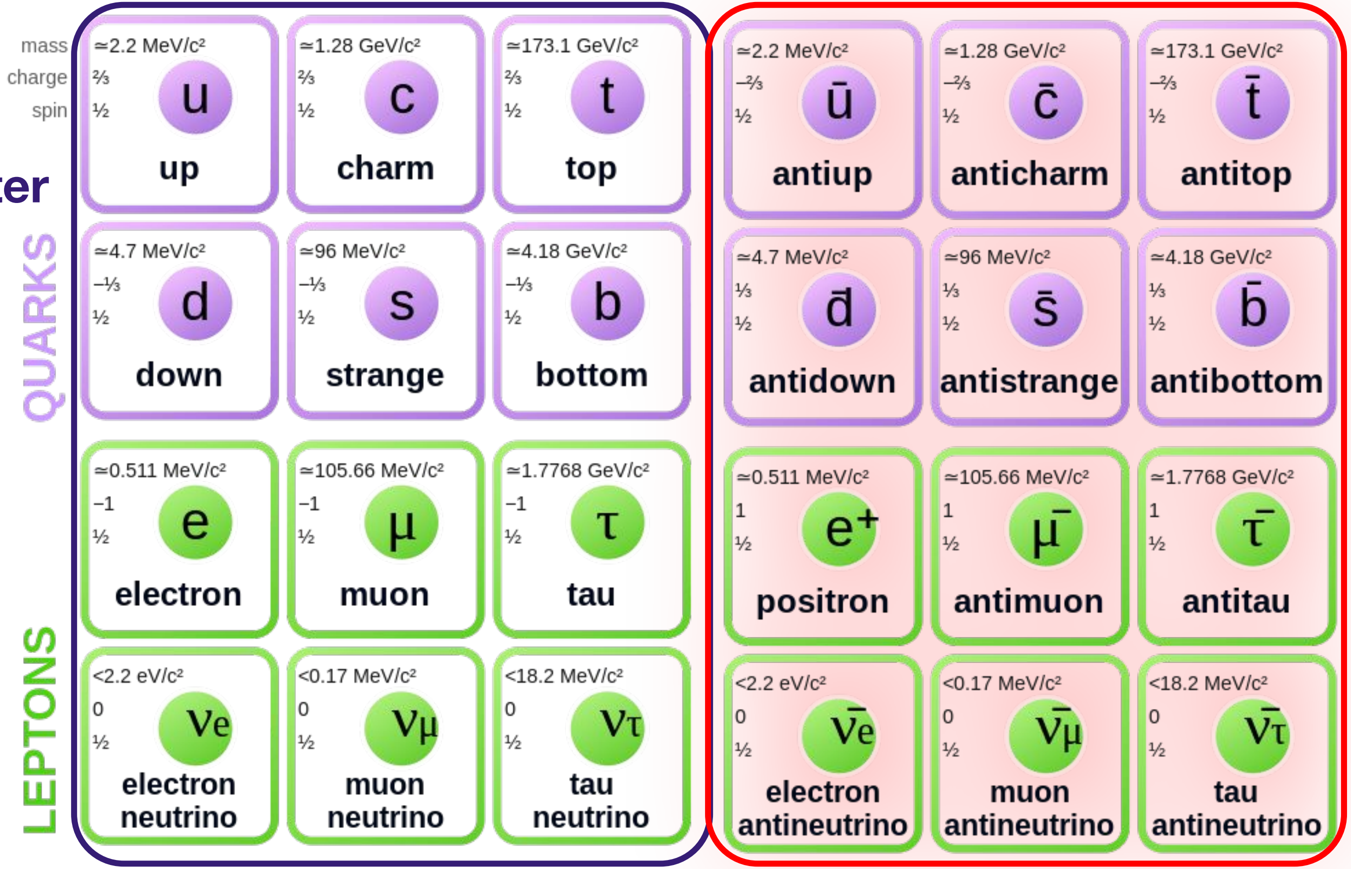


energy ↔ mass

$E = mc^2$

matter

anti-matter



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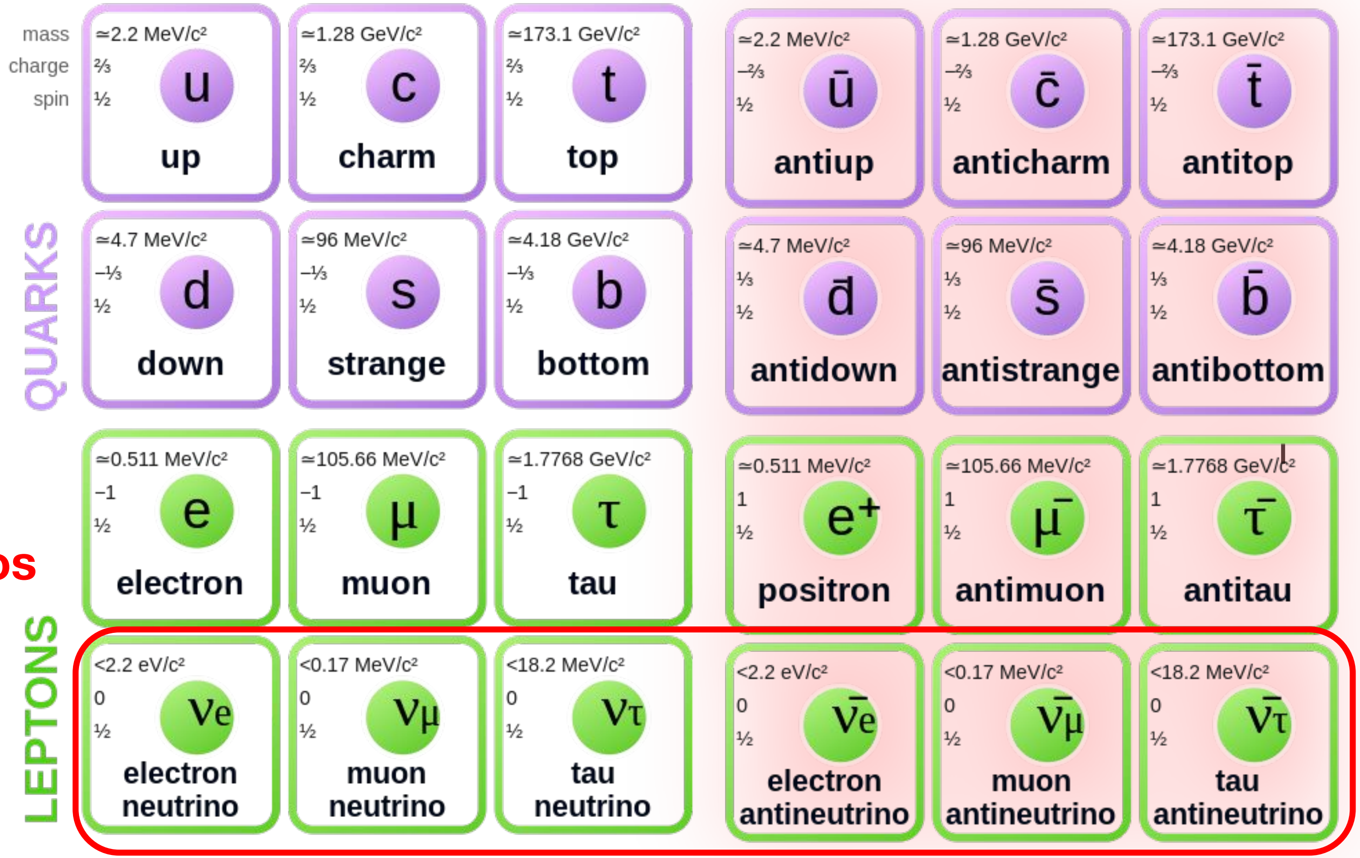
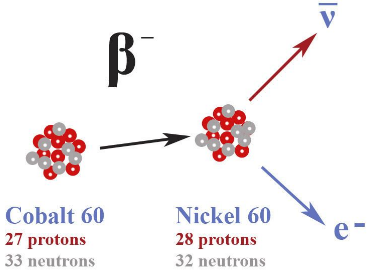


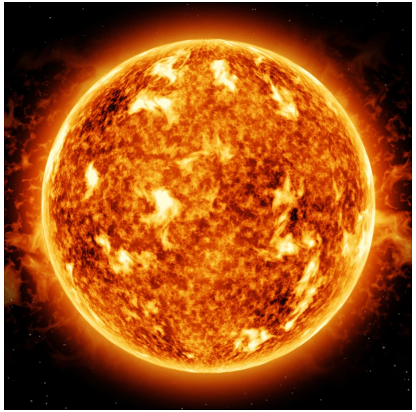
Why neutrinos are interesting

Where are they?

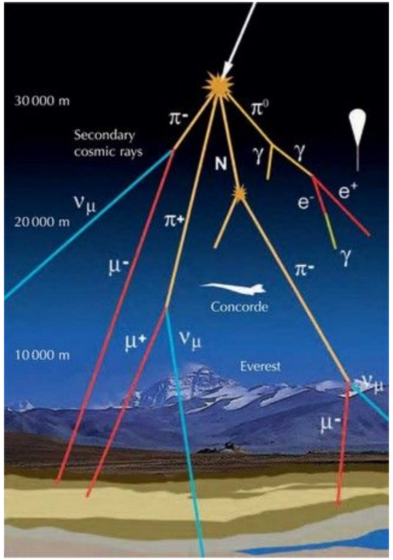


radioactivity

nuclear reactions in nuclear power plants



nuclear reaction in stars

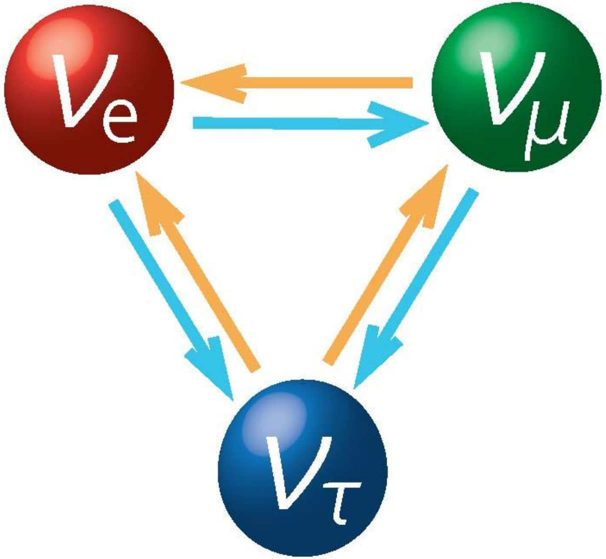


cosmic rays collision with the atmosphere

T2K (and similar experiments) create specifically a beam of neutrinos

Why neutrinos are interesting

They oscillate!



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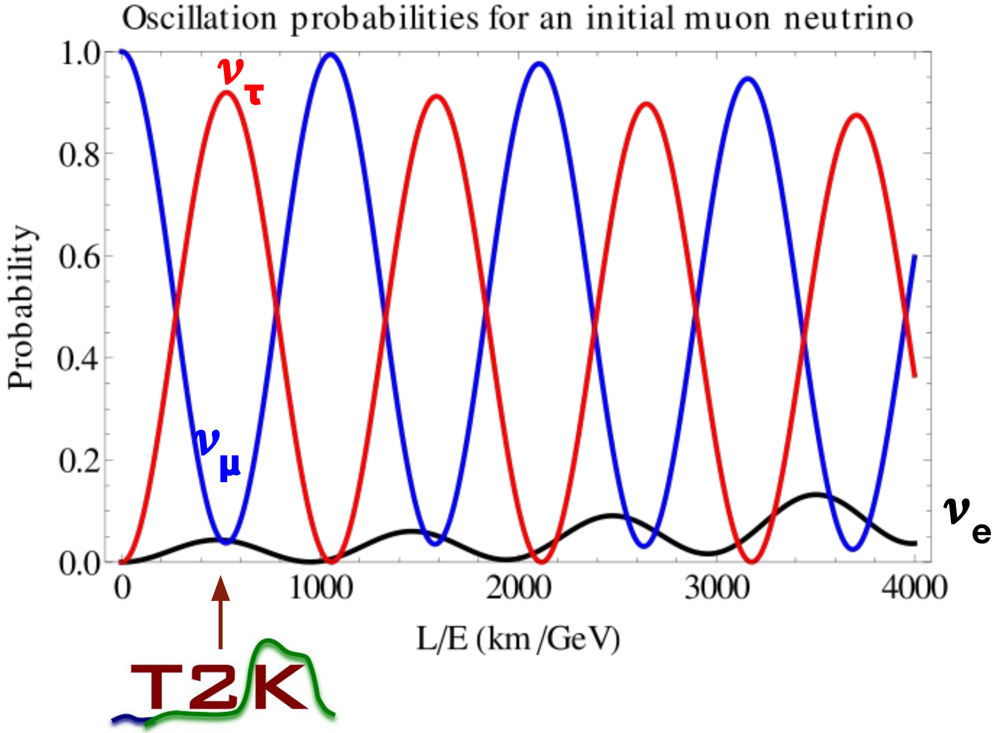
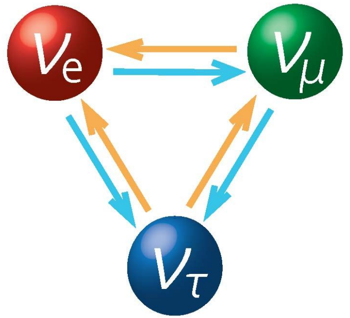


L/E ≃ 492 km/GeV



$$P(\nu_\mu \to \nu_e) = f(\theta, \delta)$$

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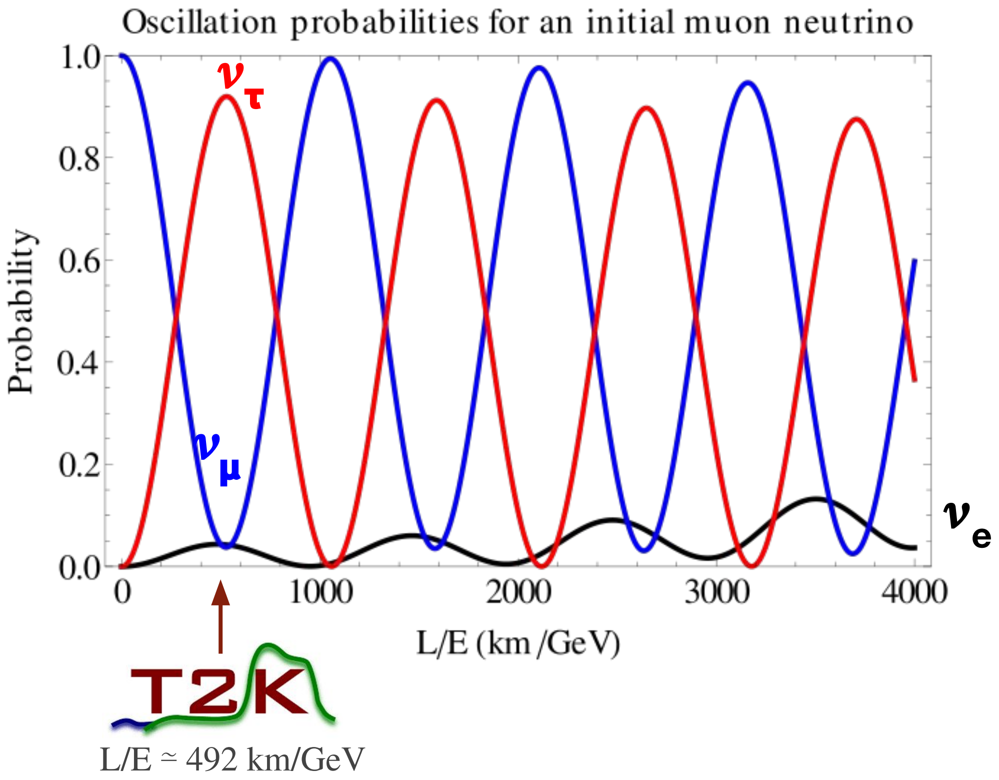

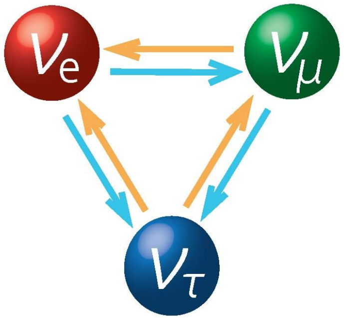

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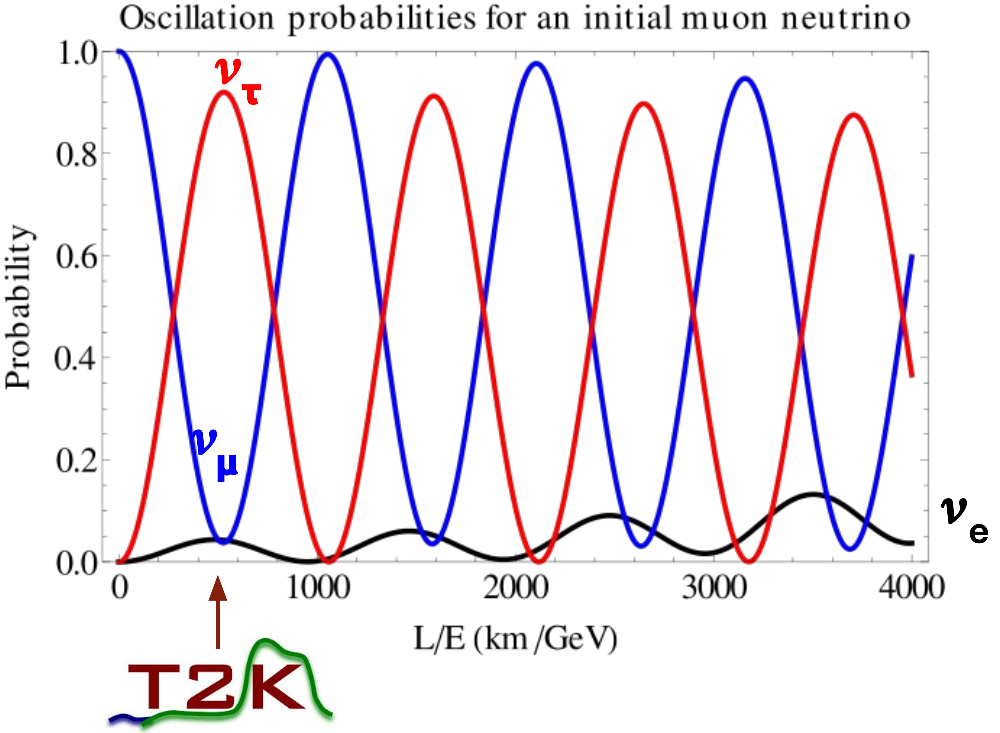

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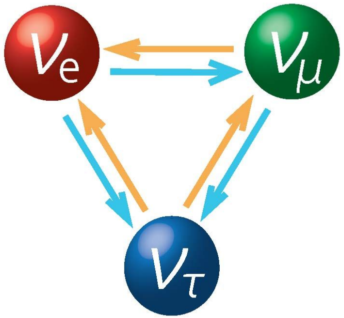

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neutrinos & anti-neutrinos

don't oscillate the same way

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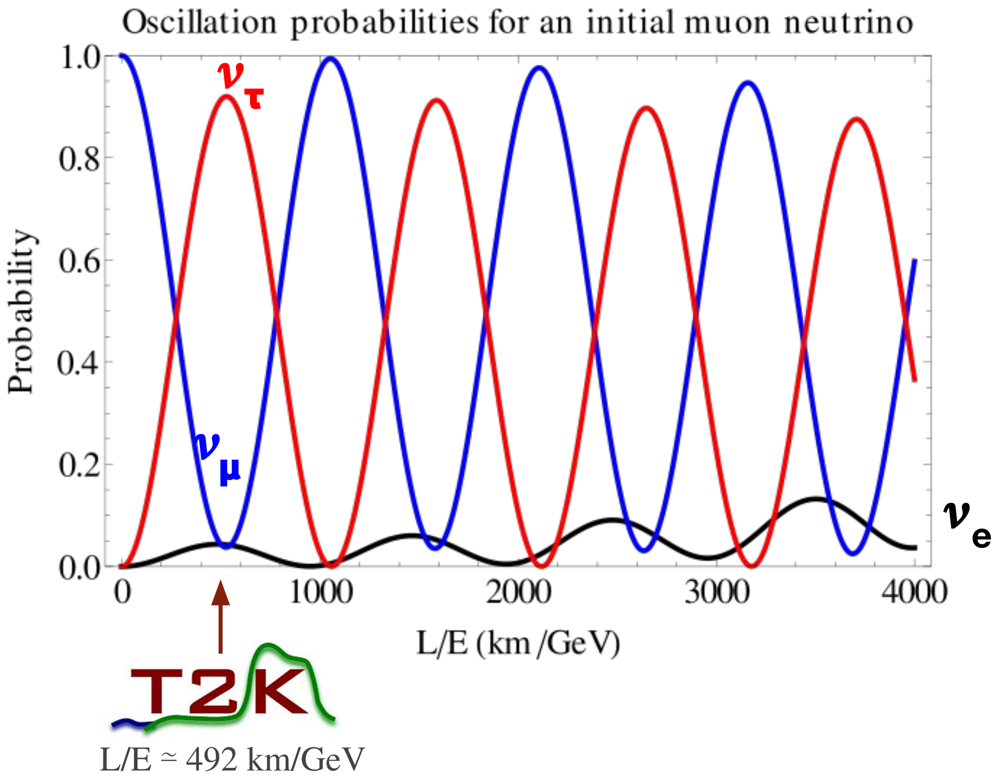

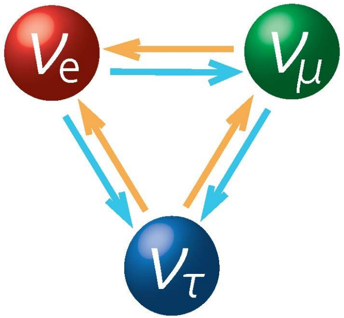

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neutrinos & anti-neutrinos **don't oscillate the same way**

could explain why there was more matter than anti-matter after the big-bang i.e. **why we exists**

T2K and ν_e (electronic neutrinos)

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particle accelerator to create neutrino beam

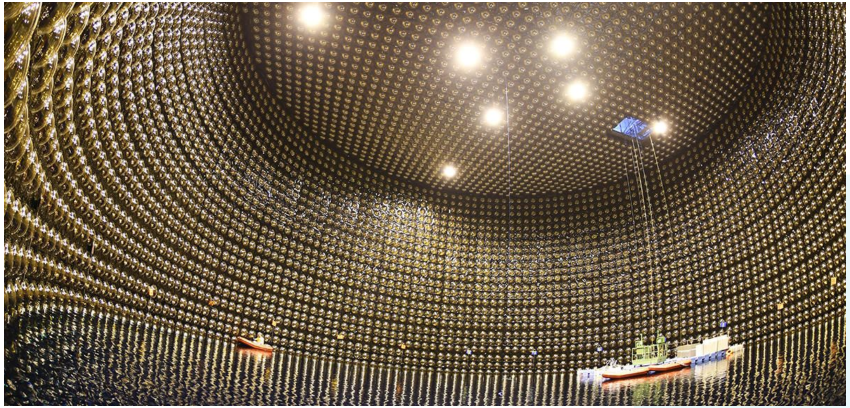
T2K and ν_e (electronic neutrinos)

near detector: ND280

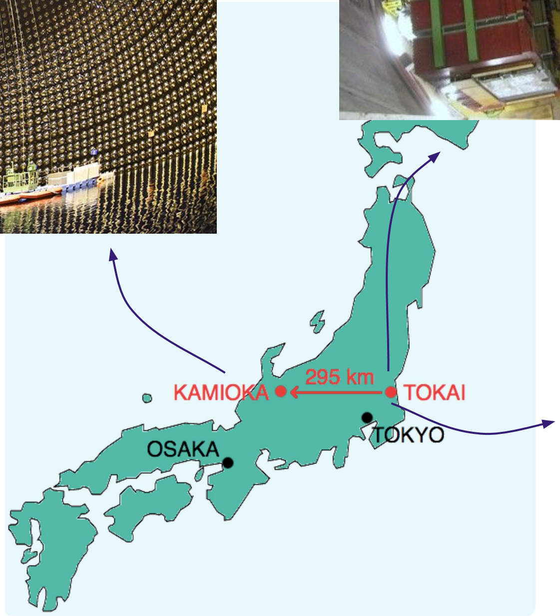
particle accelerator to create neutrino beam

T2K and ν_e (electronic neutrinos)

near detector: ND280

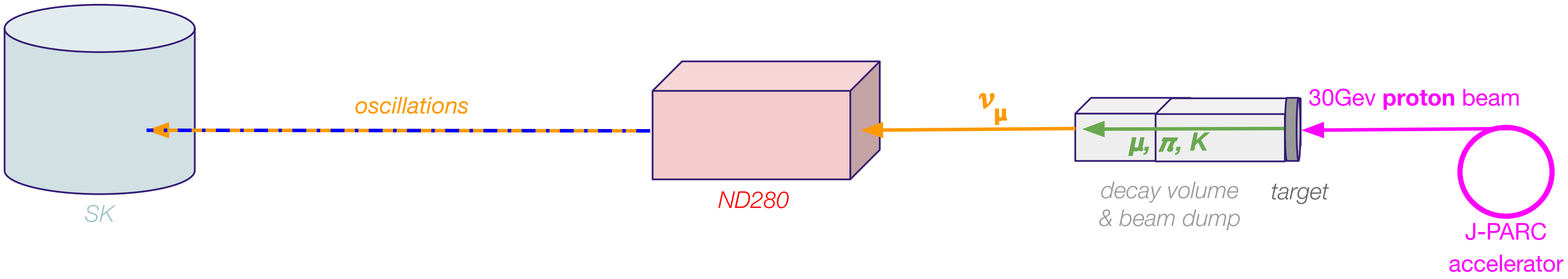


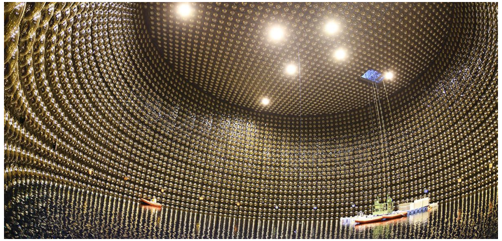
far detector: Super-Kamiokande



particle accelerator to create neutrino beam

T2K and ν_e (electronic neutrinos)





Super-Kamiokande

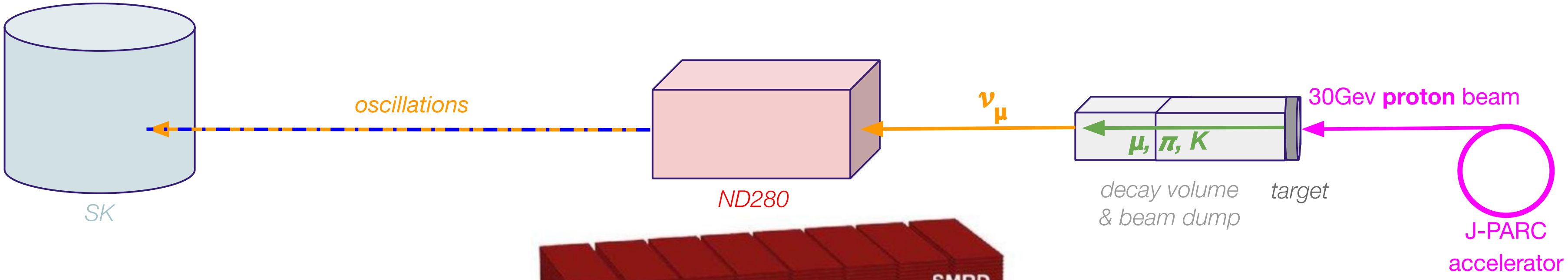
295km

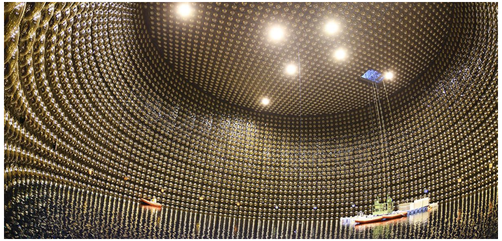
ND280

280m

neutrino beam

T2K and ν_e (electronic neutrinos)





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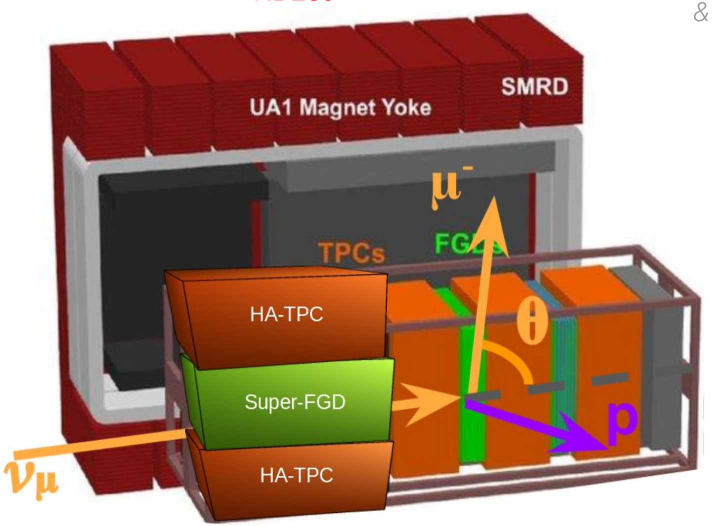

neutrino beam

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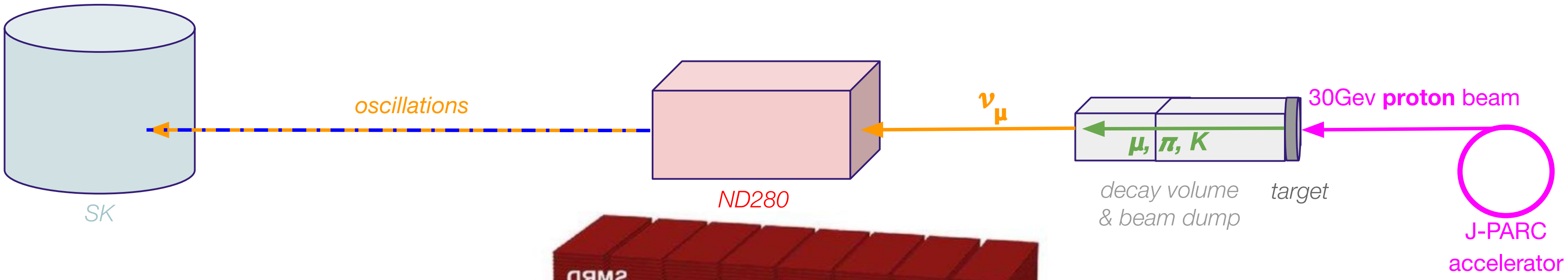

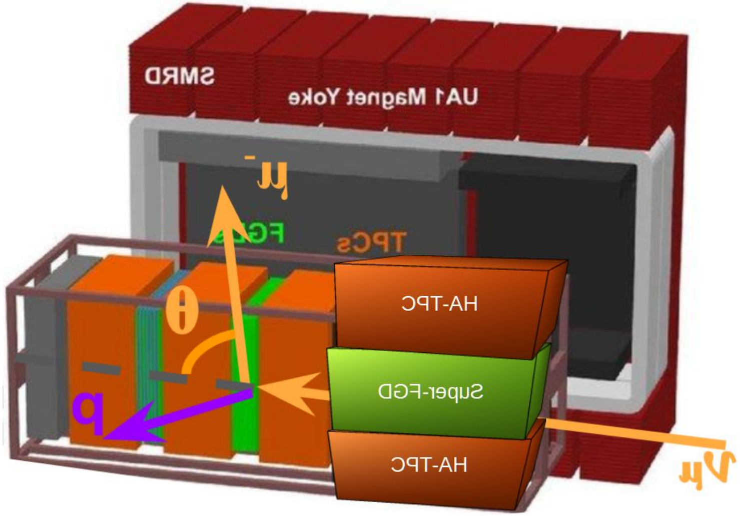

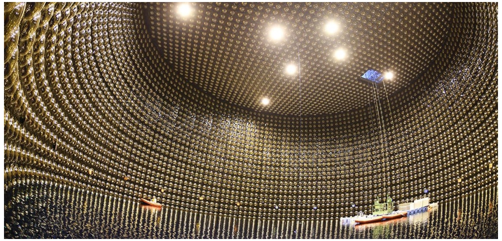
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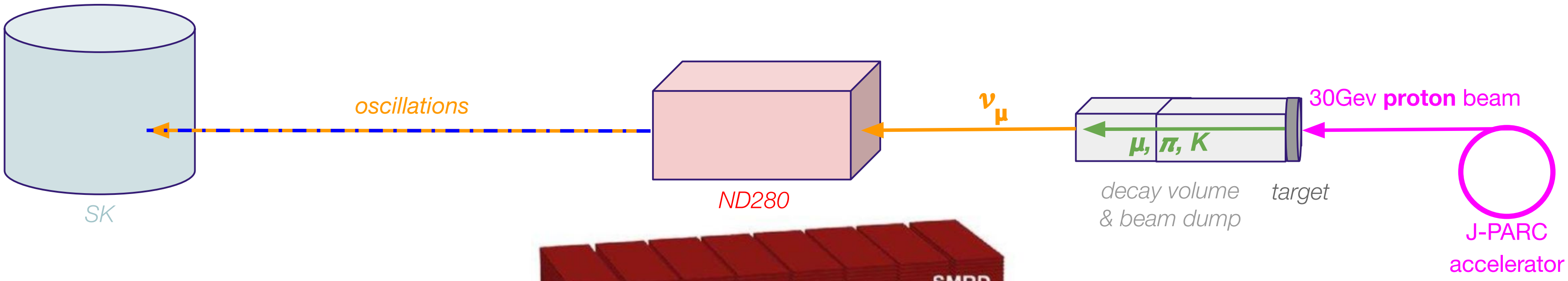

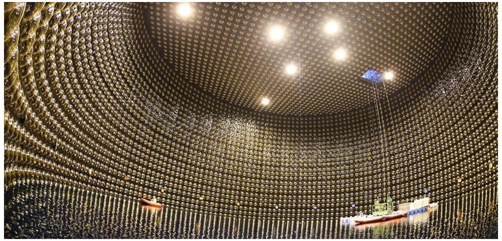

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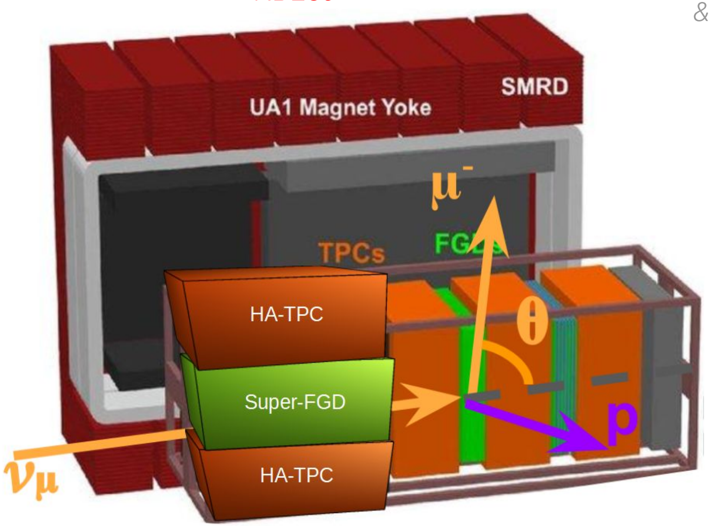

neutrino beam

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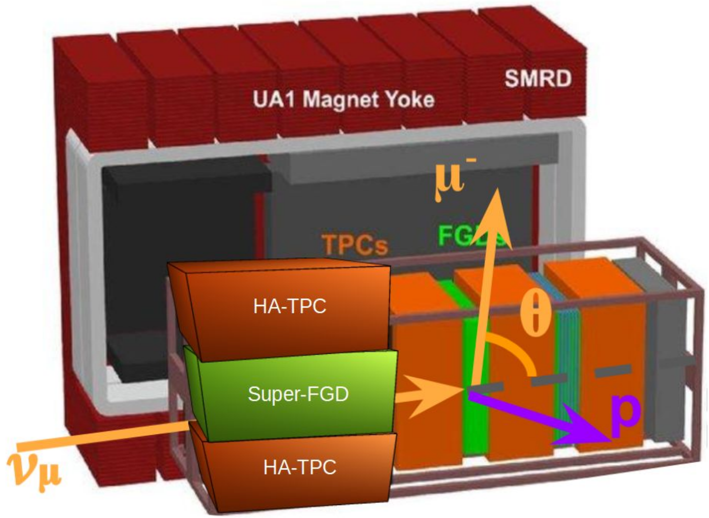

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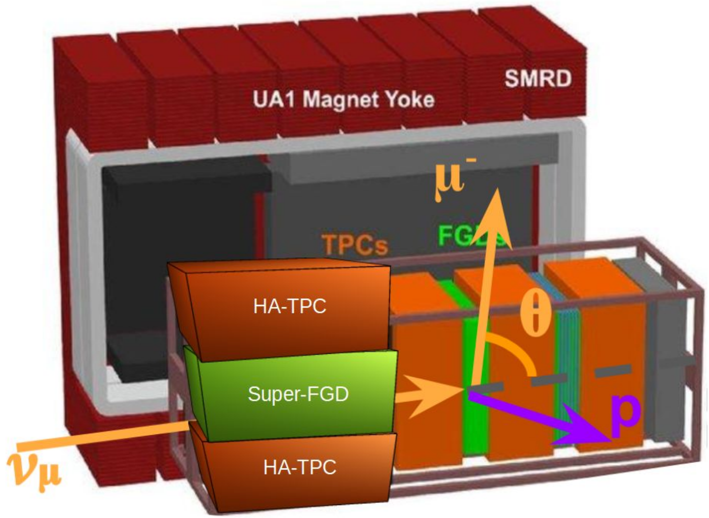

ND280 Upgrade installed last year!

& data taking since end of 2024

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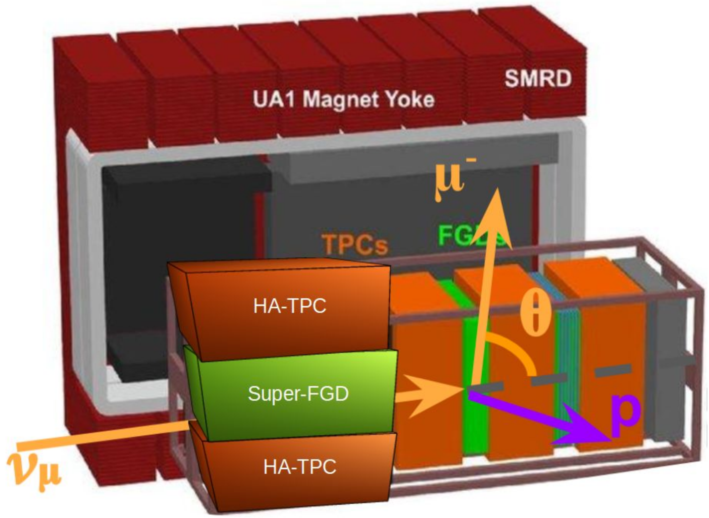

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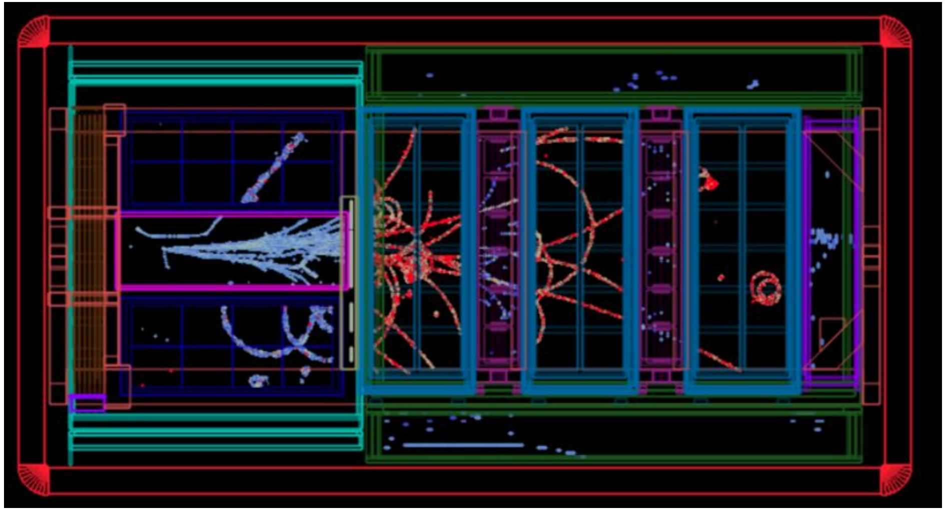

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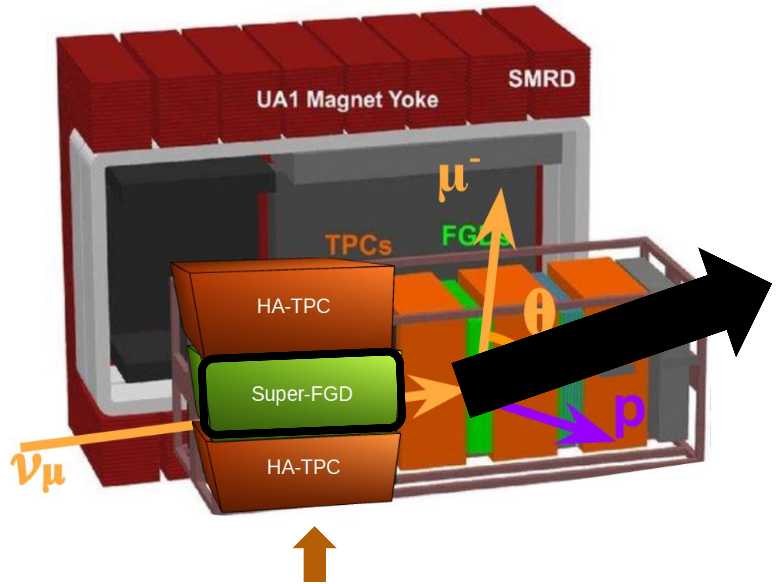

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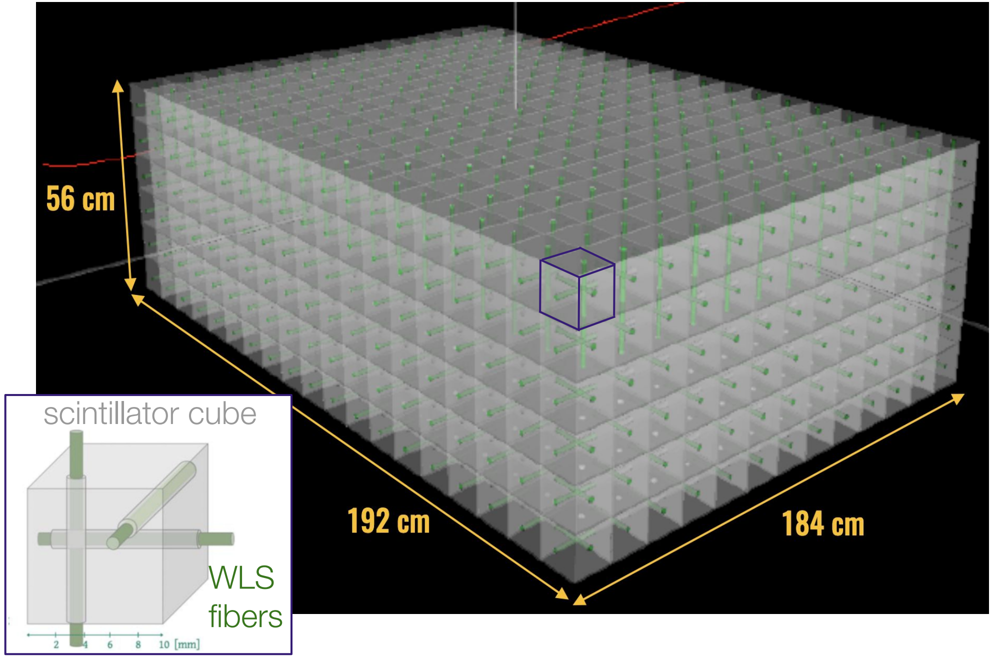
The Super-FGD



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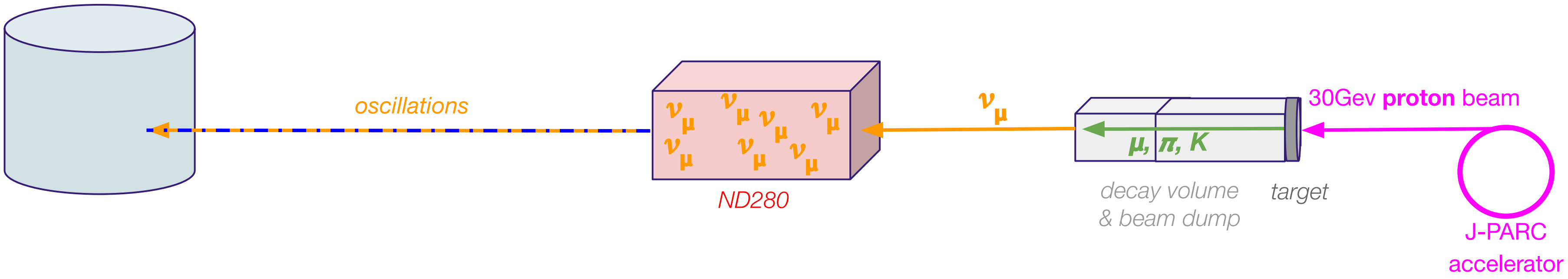

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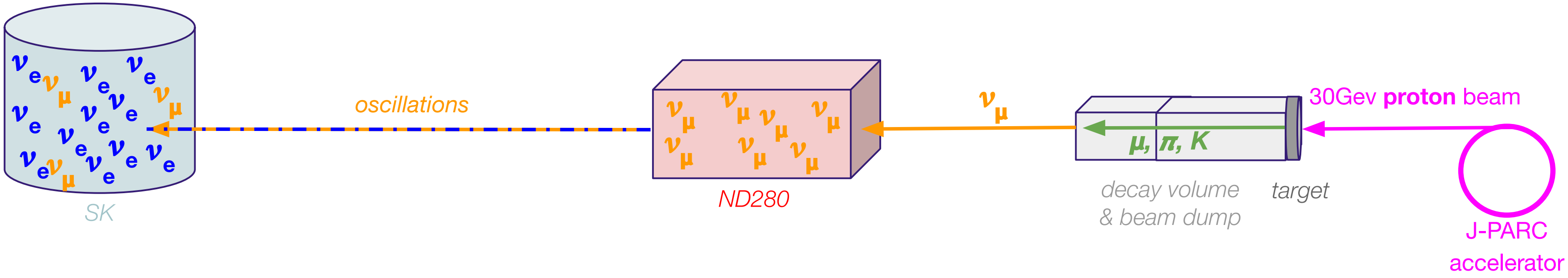

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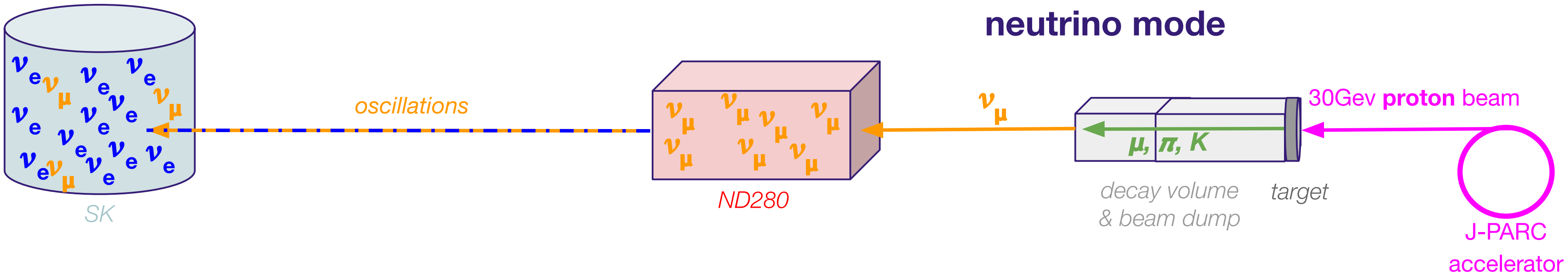

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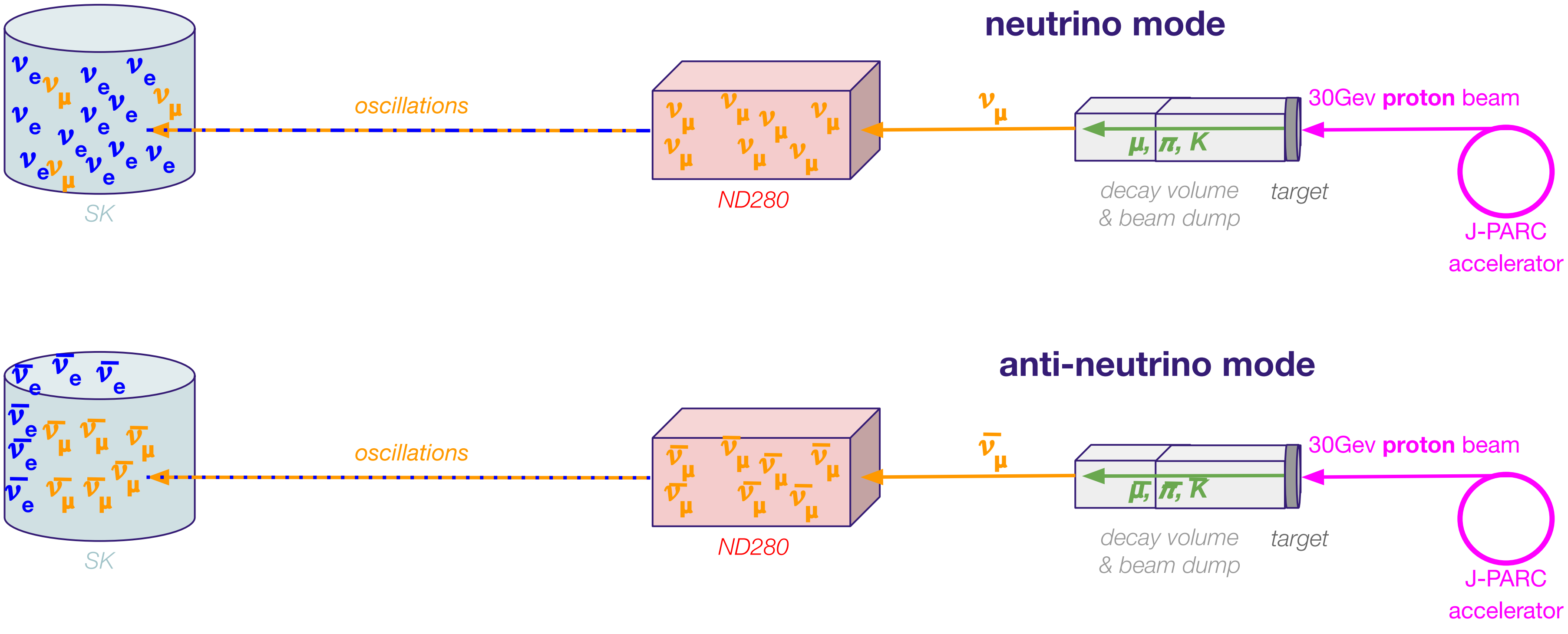

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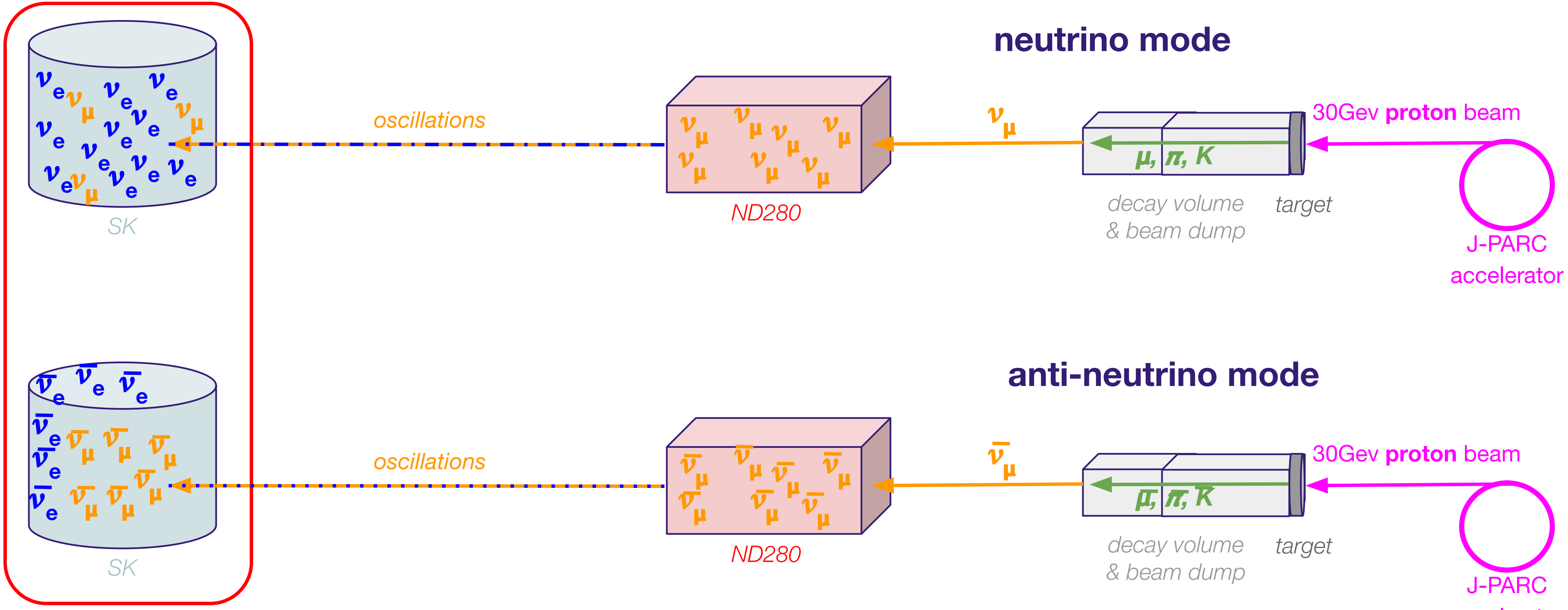
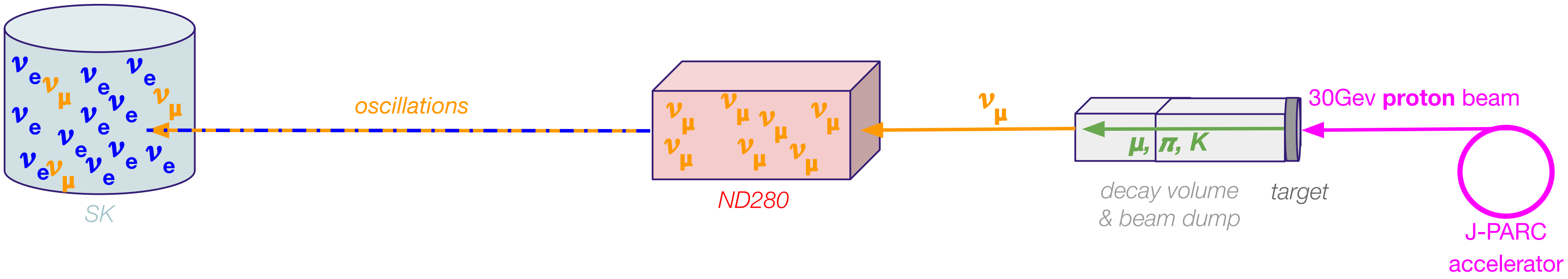


T2K goal: measure this difference!

T2K and ν_e (electronic neutrinos)



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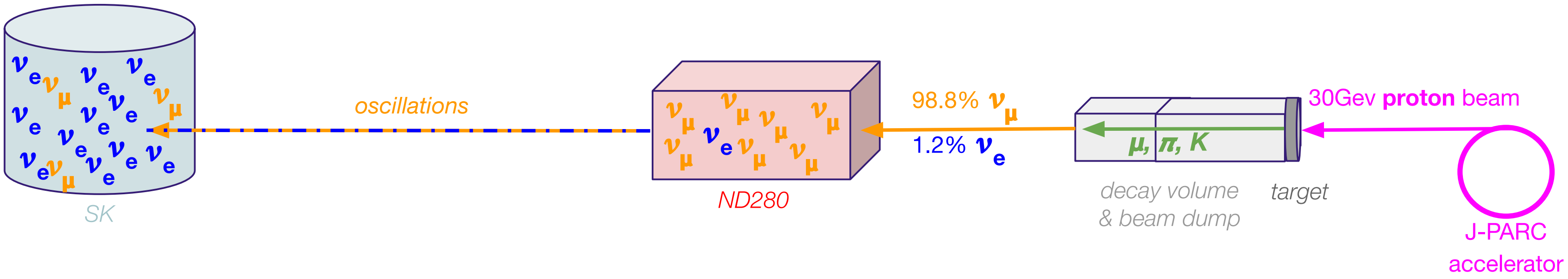

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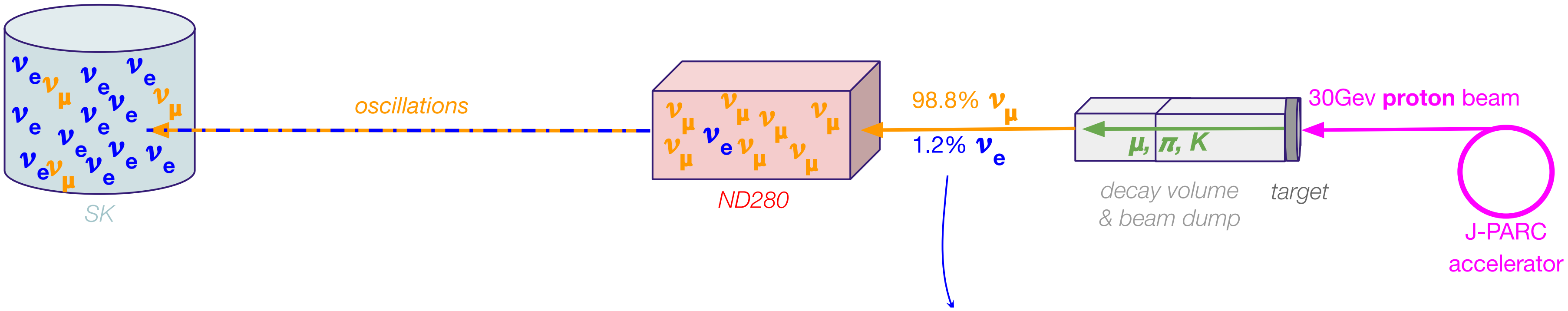

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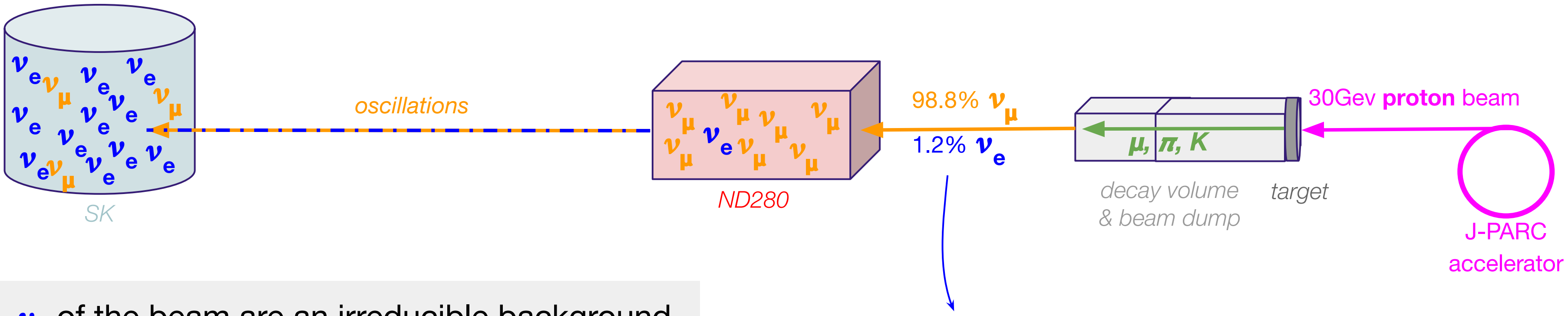

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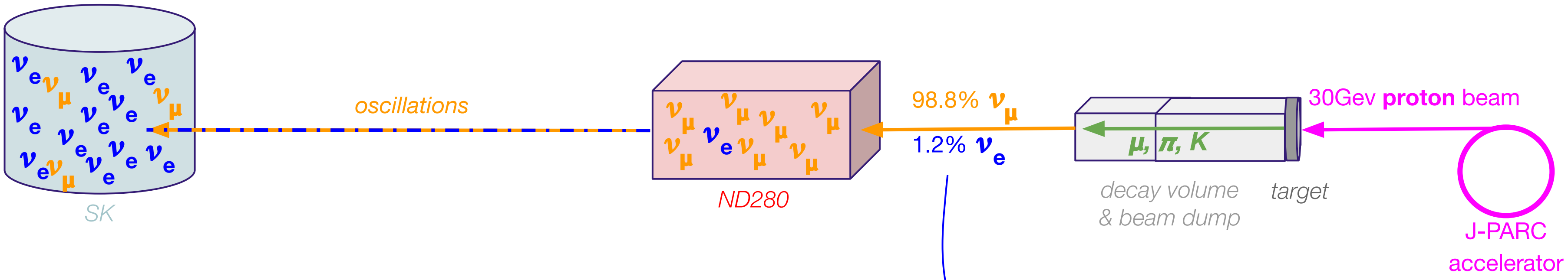

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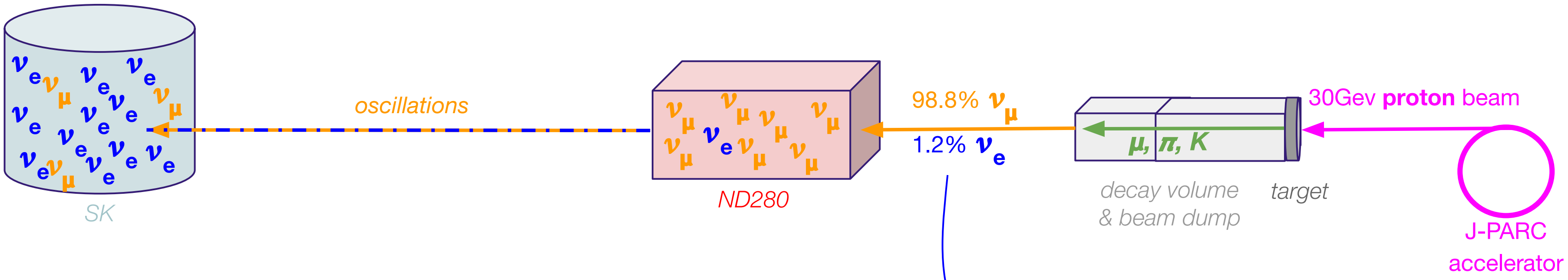

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⇒ very important to characterize the ν_e component at ND280

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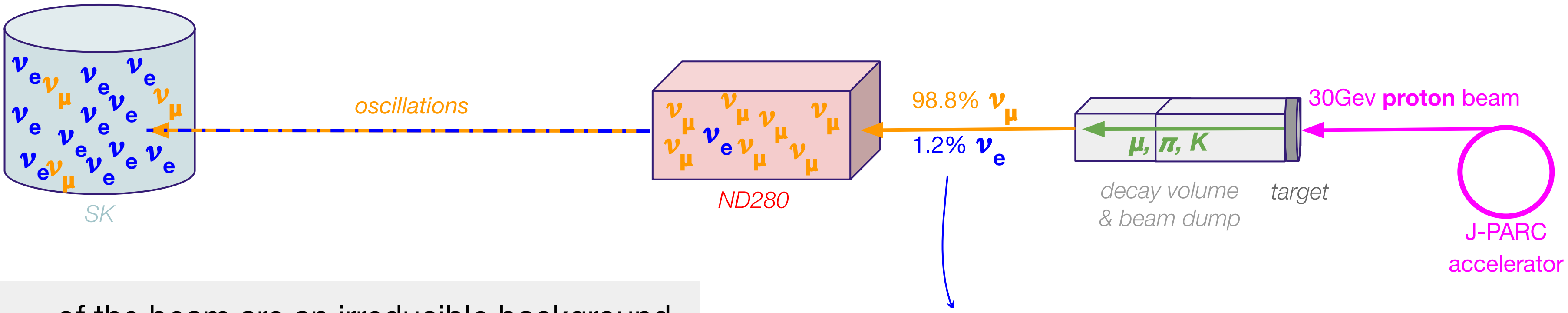

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⇒ need Particle Identification for ν_e selection

⇔ identifying ***e*** vs ***μ***, ***γ***, ***π***, ***p***

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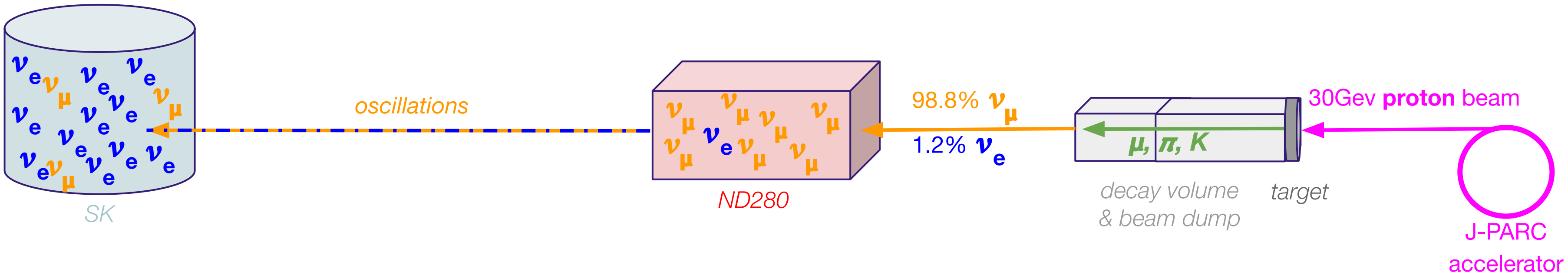

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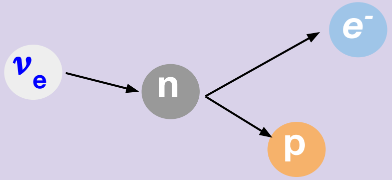
⇔ identifying ***e*** vs $\boldsymbol{\mu, \gamma, \pi, p}$

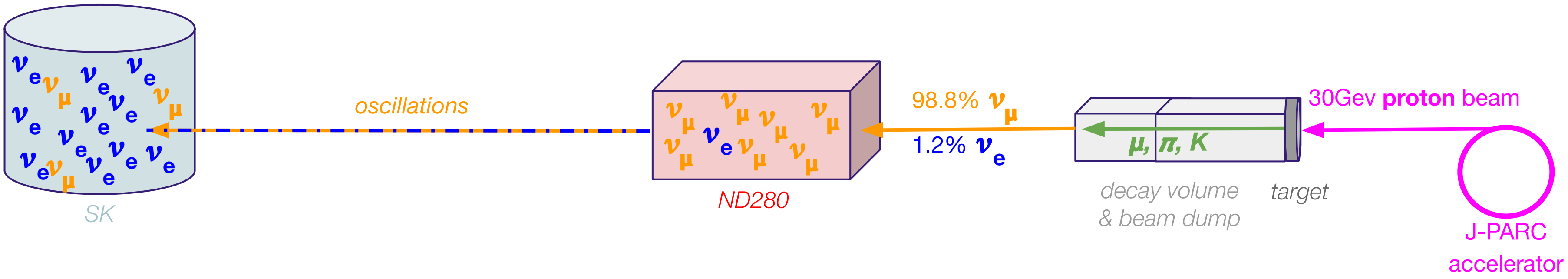
how to detect uncharged particles (like ν) in a detector that can only detect charged ones?

→ by detecting the charged particle from ν interaction* in the detector:



*called Charged Current (CC) interaction

T2K and ν_e (electronic neutrinos)



- ν_e of the beam are an irreducible background
- ν_e are the signal at SK

⇒ very important to characterize the ν_e component at ND280

⇒ need Particle Identification for ν_e selection

⇔ identifying ***e*** vs μ, γ, π, p

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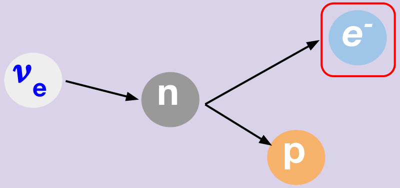

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Why we need to improve the ν_e selection

Selection of a particle =

Particle **ID**entification

1) Define a **PID** method to identify your particle (***e***)

Using simulations of particle:

2) count how many true ***e*** are selected by the method
3) count how many *other particles* are selected by the method

This allows to define:

- **efficiency** = how much true ***e*** we selected
- **purity** = how much background is kept in the selected particles

Important! goes into the T2K uncertainties
→ need method which gives best eff & pur

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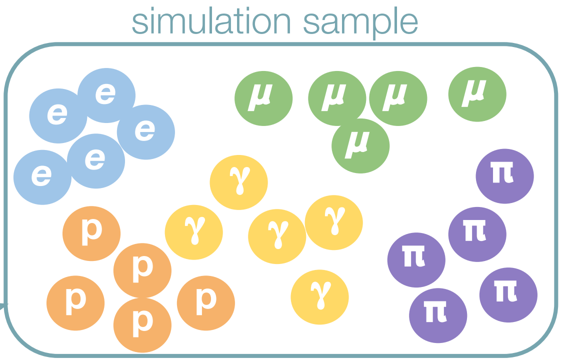

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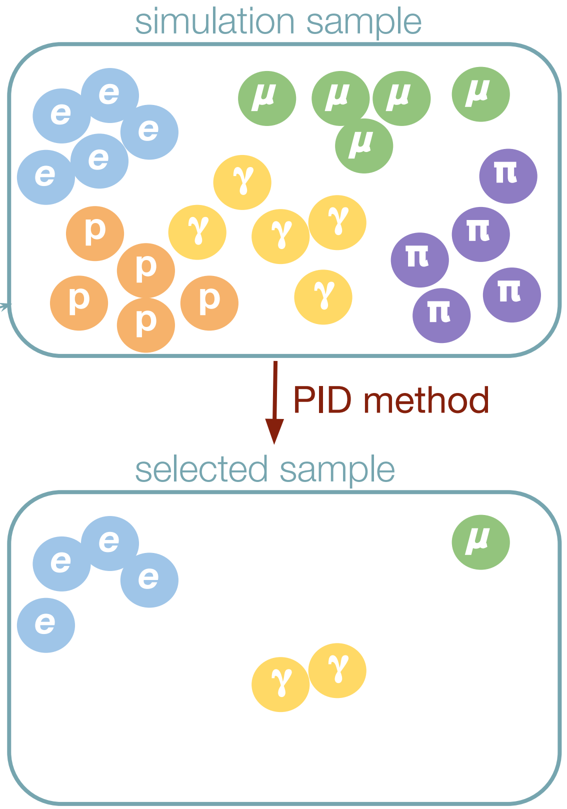

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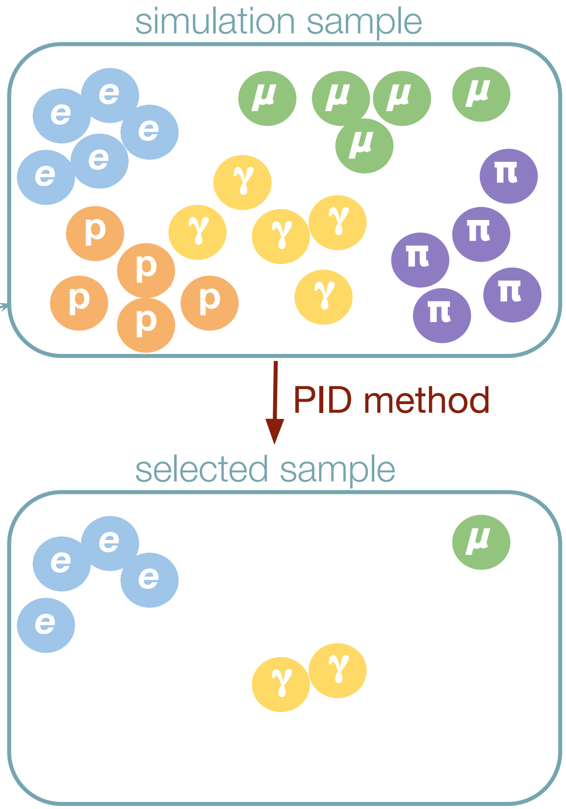

$$\text{efficiency} = \frac{4 \text{ selected } e^-}{5 \text{ simulated } e^-} = 80\%$$

$$\text{purity} = \frac{4 \text{ selected } e^-}{7 \text{ selected in tot}} = 57\%$$

Why we need to improve the ν_e selection

Selection of a particle =

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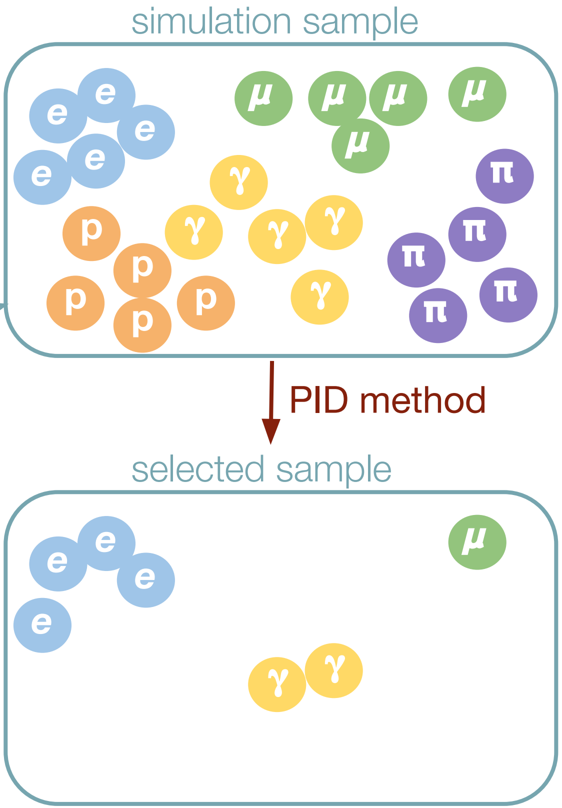

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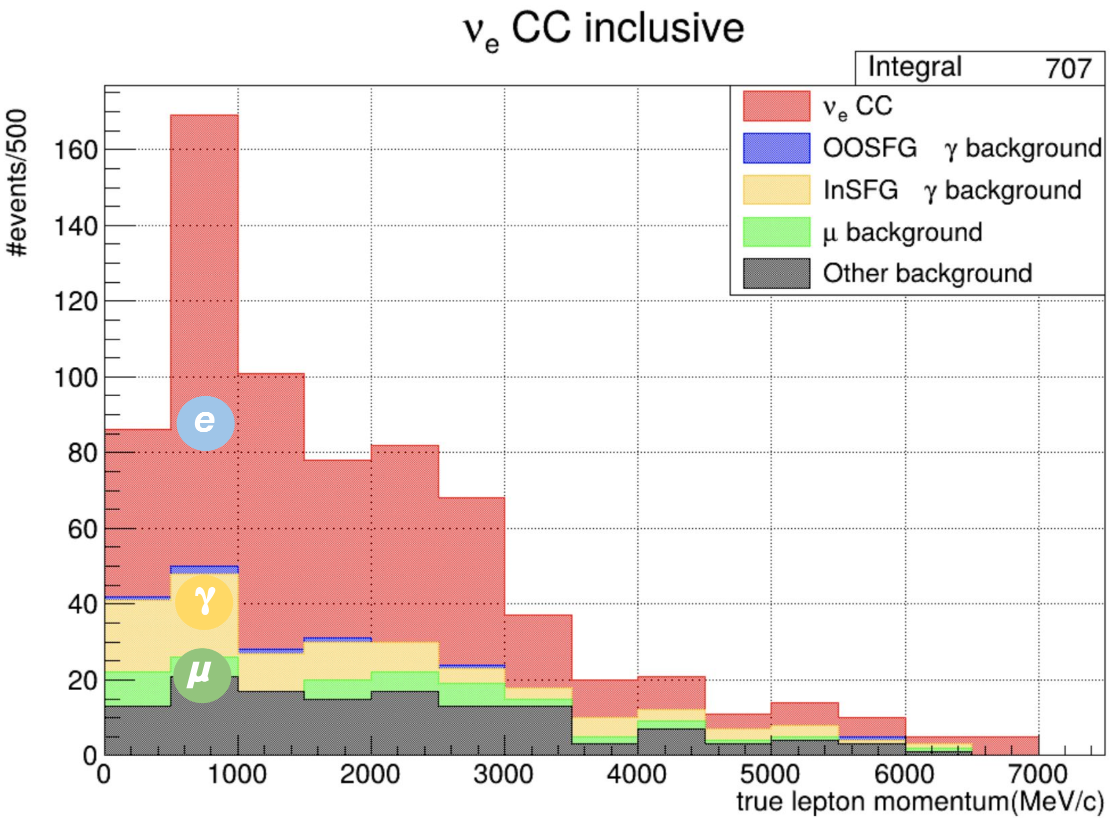
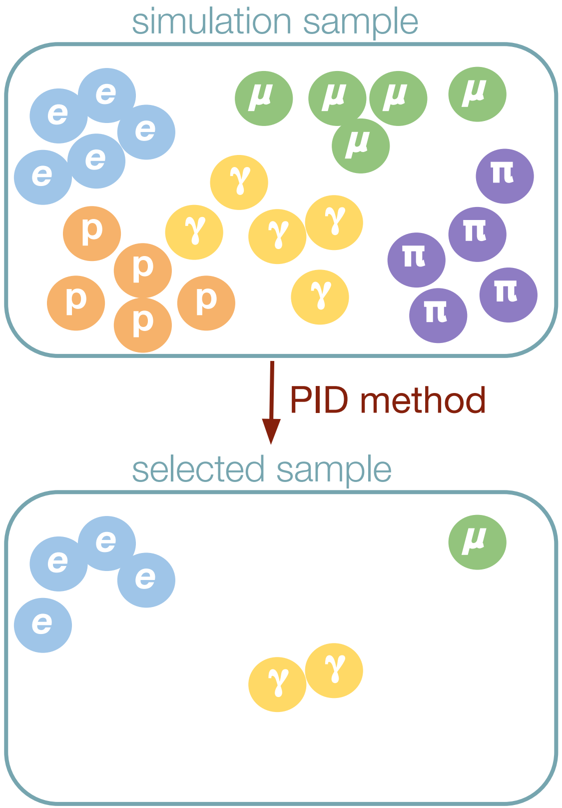
with current method:

efficiency = 18.6%

purity = 68%

Why we need to improve the ν_e selection





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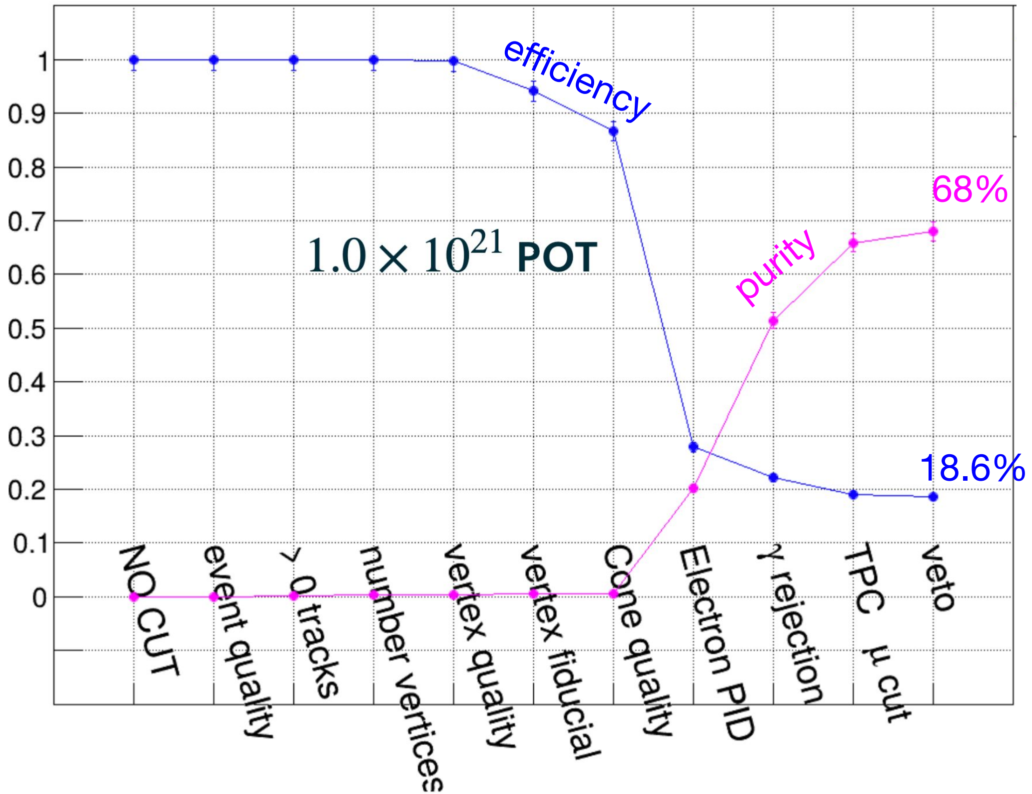

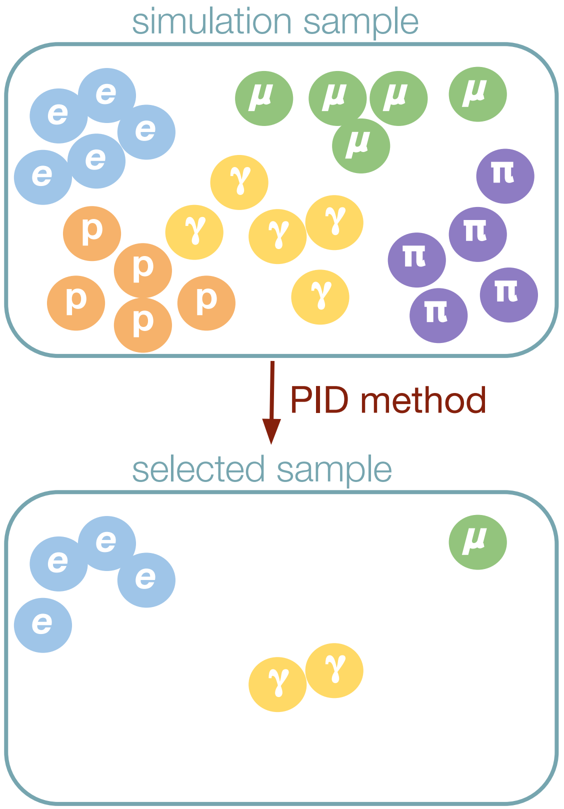

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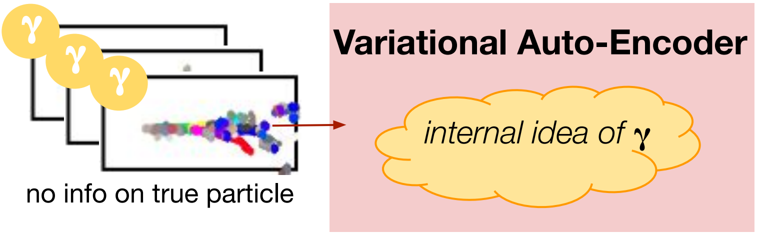
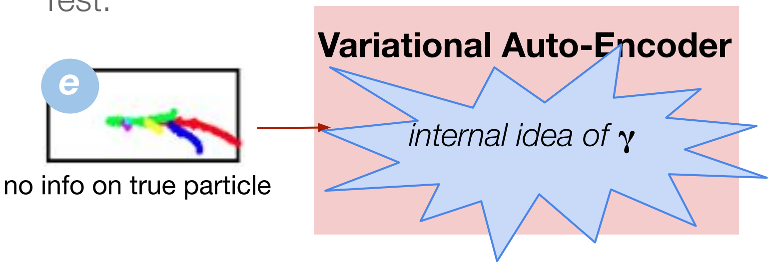
2 new PID methods with ML: Transformer & Variational Auto-Encoder

VAE: un-supervised ML

Training:



Test:



performs worse in controlled, labeled settings but should be better to deals with real data variability

2 new PID methods with ML: Transformer & Variational Auto-Encoder

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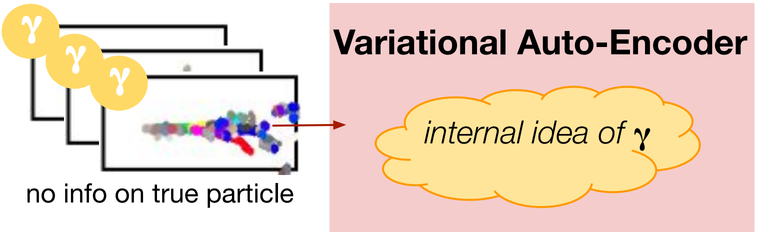

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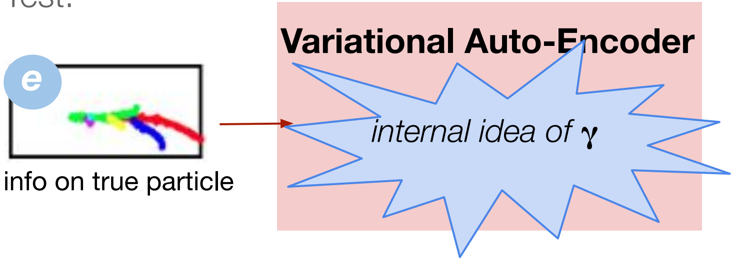
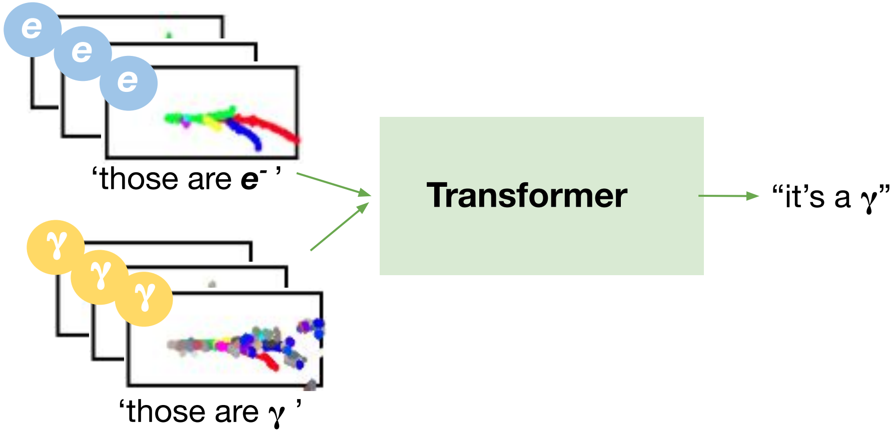


performs worse in controlled, labeled settings but should be better to deals with real data variability

Transformer: supervised ML

Training & test:



performs well in controlled, labeled settings but will probably struggle more with real data variability

The Transformer PID method

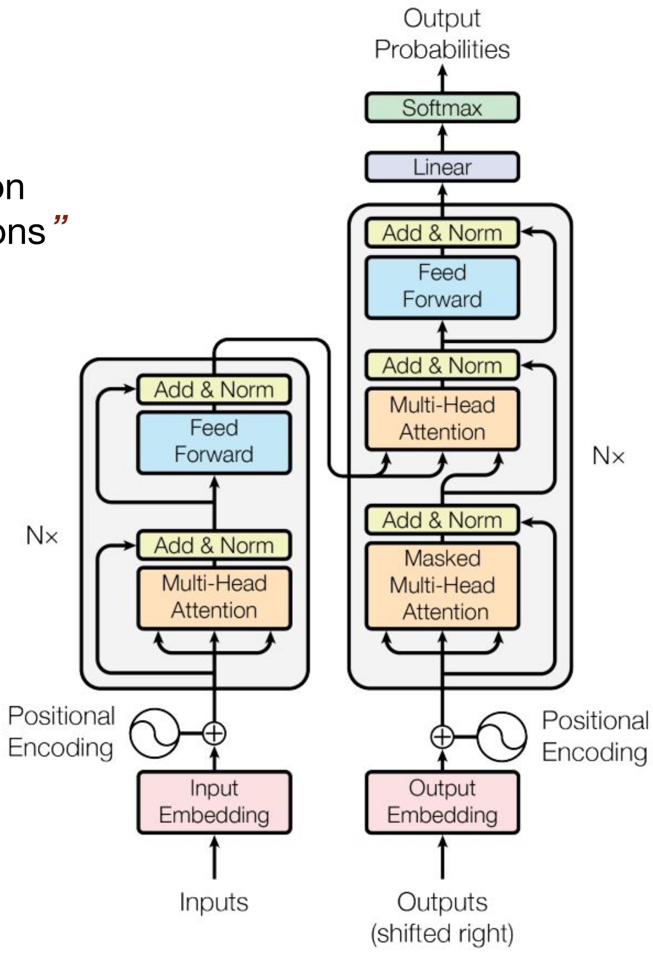
What is a Transformer

"**Transformer** = a new simple network architecture, based solely on attention mechanisms, dispensing with recurrence and convolutions"

[*Attention Is All You Need*]

Key ideas:

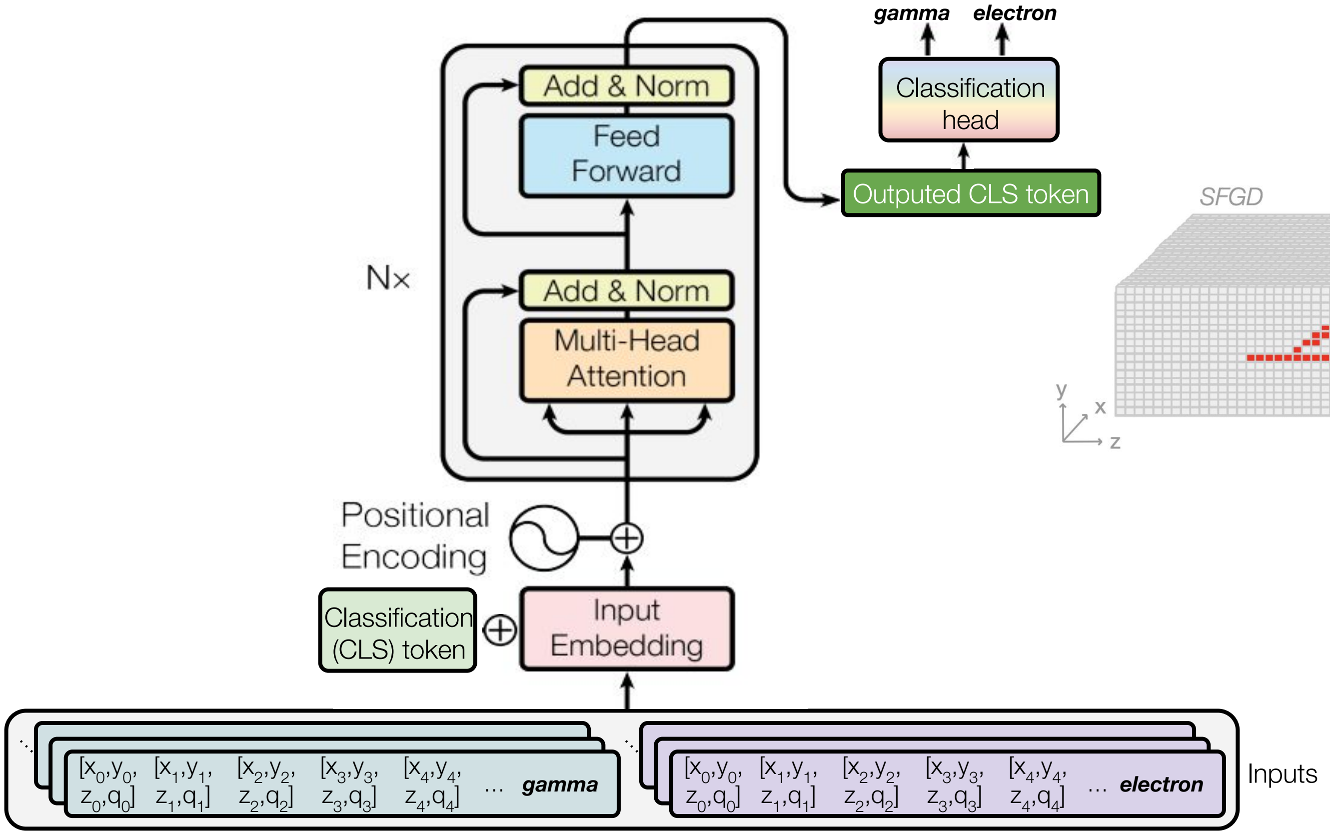
- **takes sequences as inputs**
- **attention mechanisms**: allows the model to focus on the most relevant parts of the input sequence when producing an output
- **multi-head attention:** attending to different parts of the input in parallel allows for the model to capture multiple types of relationship
- **parallelizable architecture**

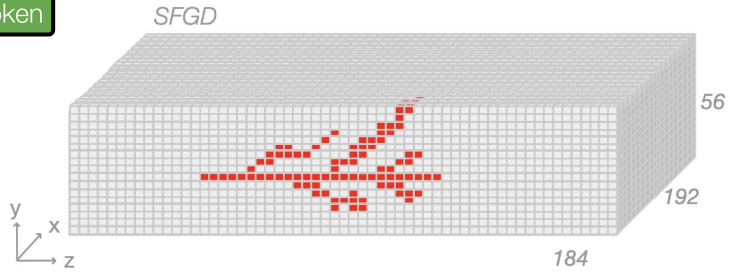


standard BERT architecture

The Transformer PID method

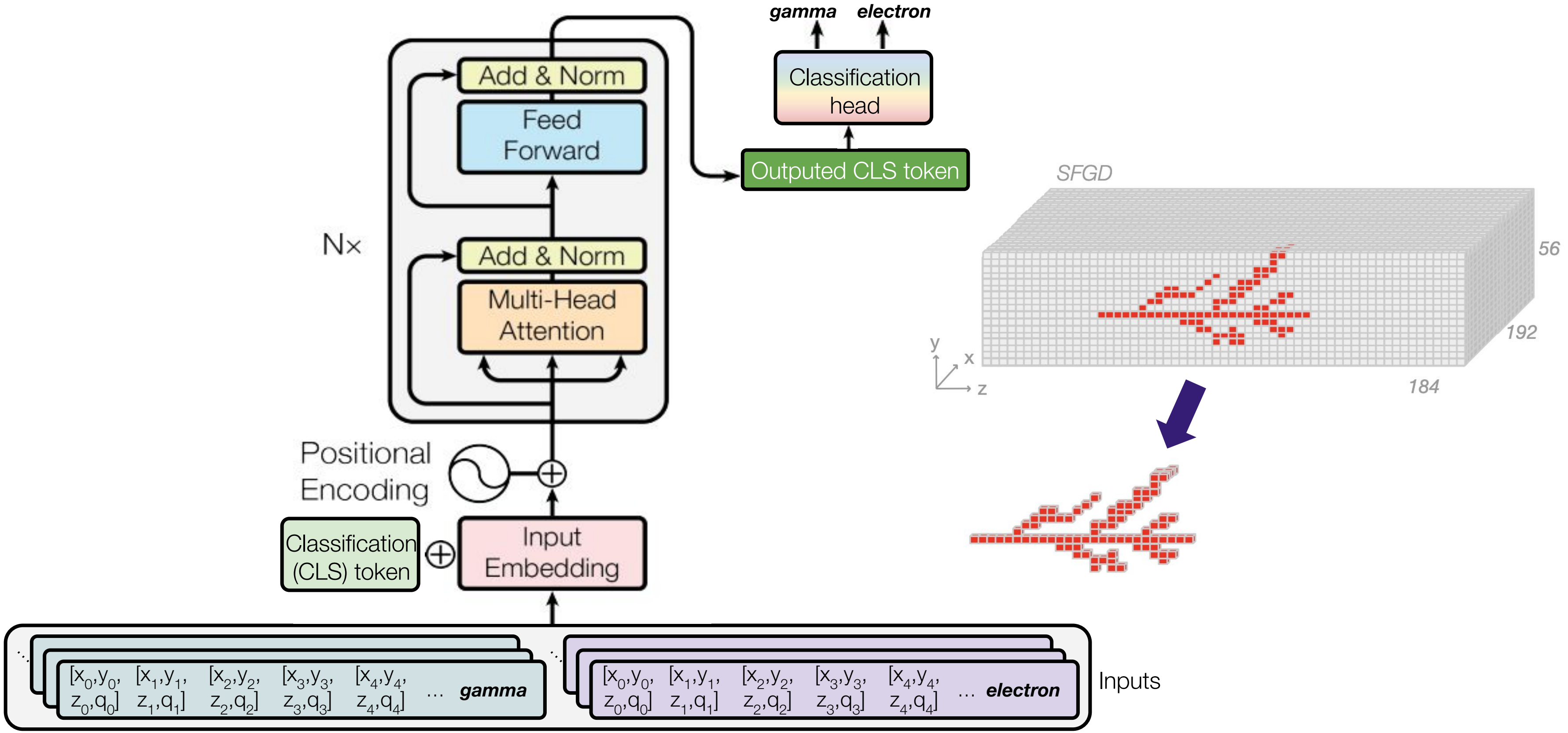
How we can apply it for the ν_e selection





The Transformer PID method

How we can apply it for the ν_e selection



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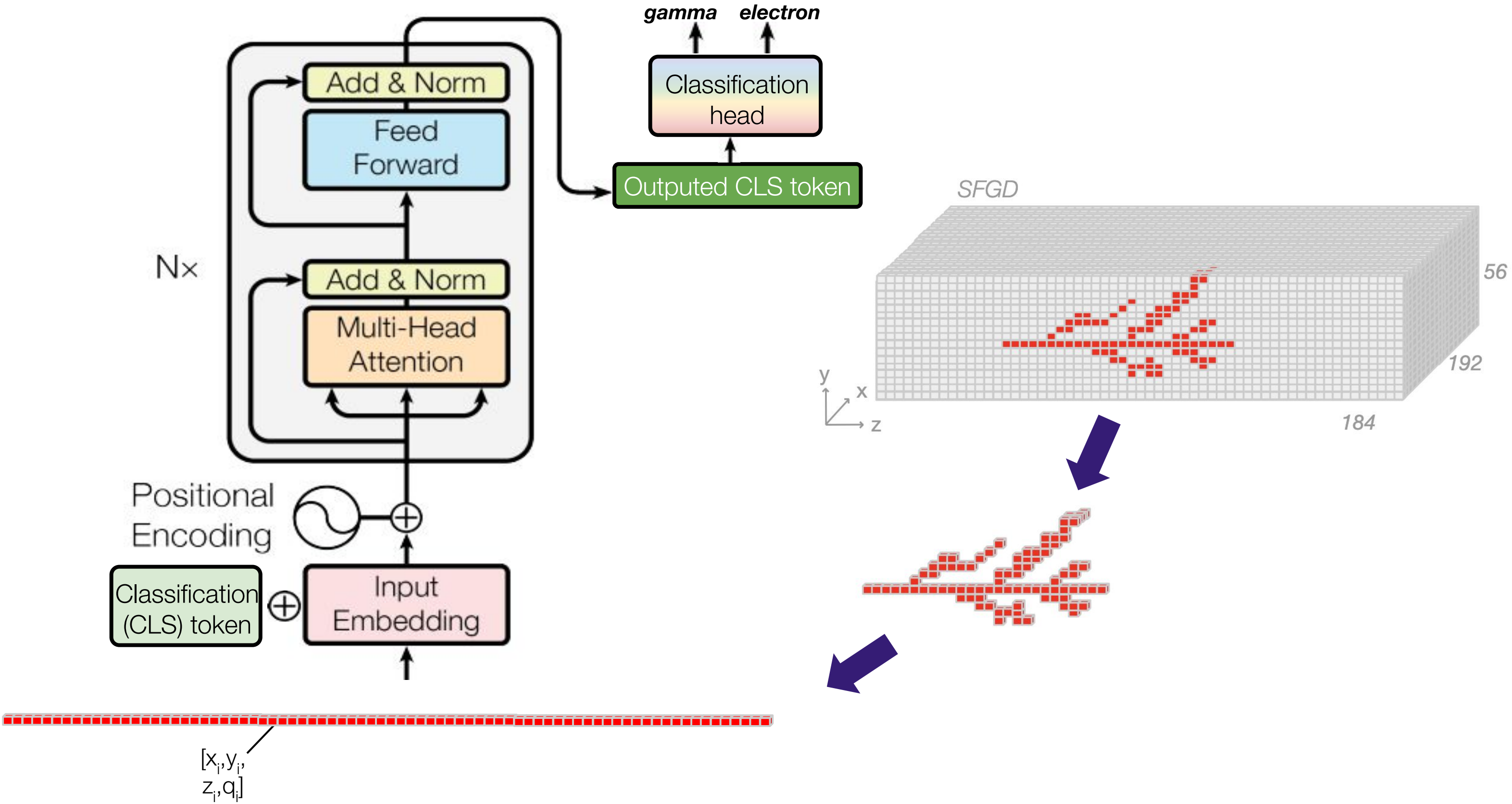

The Transformer PID method
Vision Transformer

- Problem: some sequences of hits are **too long**:

⇒ not computationally efficient as complexity of transformer ~ $O(\text{sequence length}^2)$

⇒ training would take too long

- Solution: use the principle behind **vision transformers**

The Transformer PID method

Vision Transformer

- Problem: some sequences of hits are **too long**:
⇒ not computationally efficient as complexity of transformer ~ O(sequence length^2)

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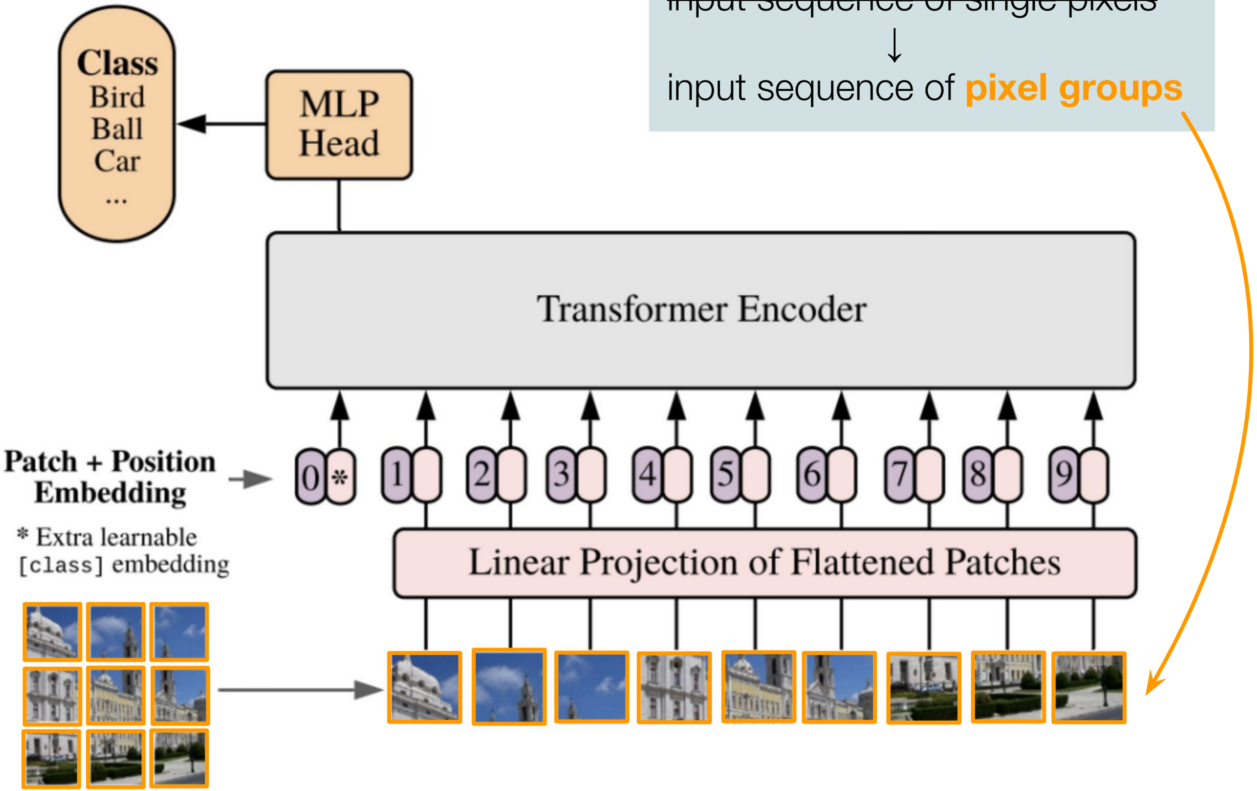
- Solution: use the principle behind **vision transformers**

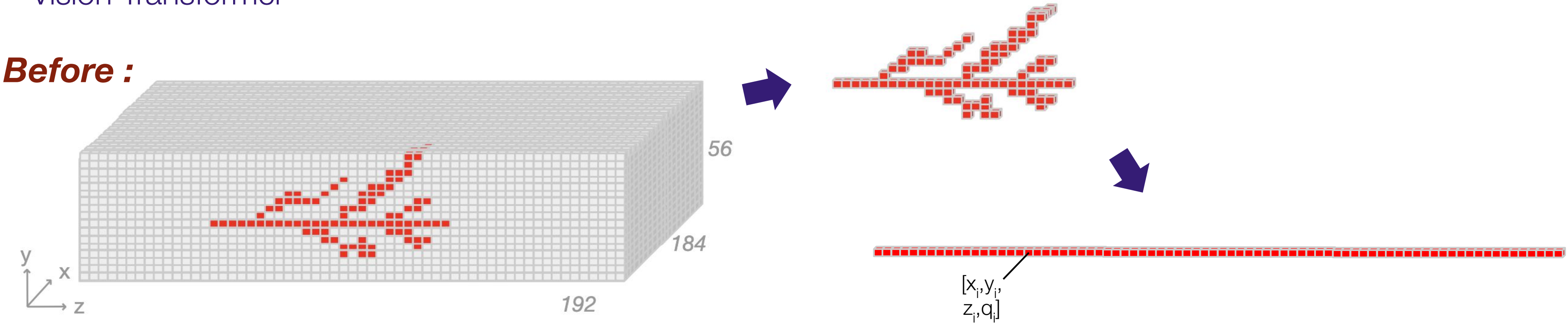
~~input sequence of single pixels~~
↓
input sequence of **pixel groups**



The Transformer PID method

Vision Transformer

Before :



The Transformer PID method

Vision Transformer

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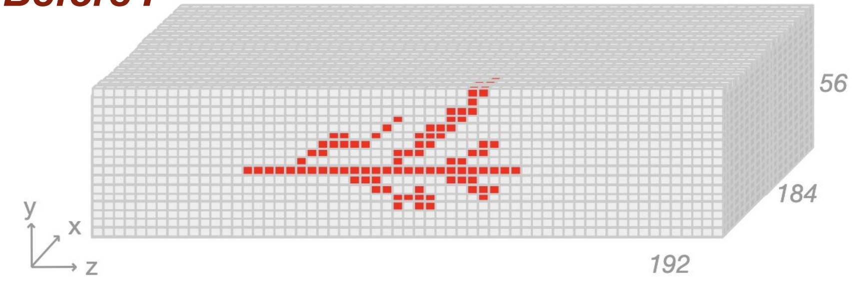
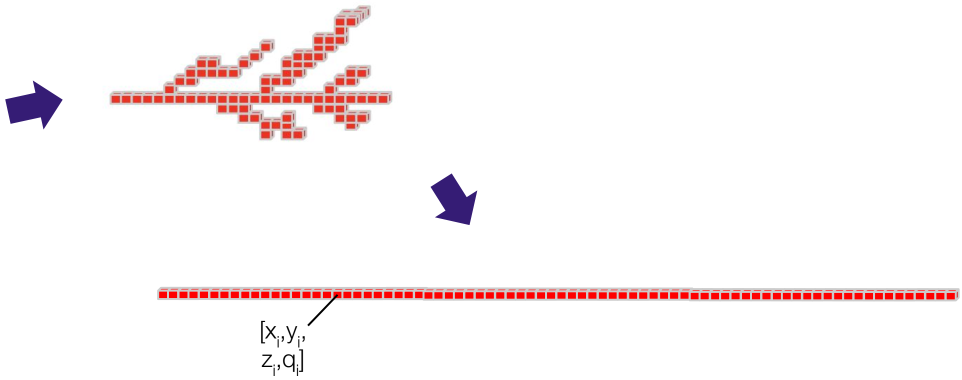
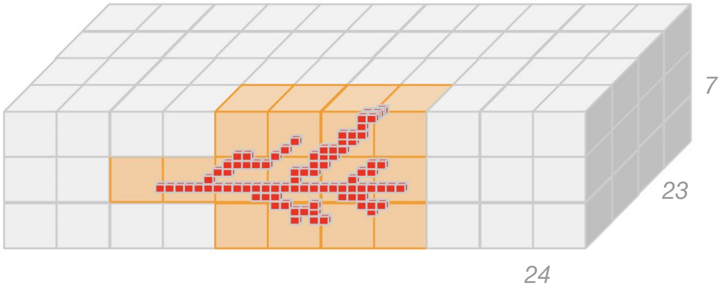
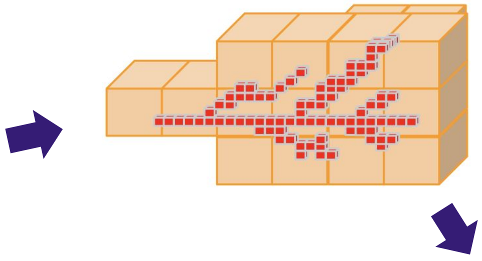




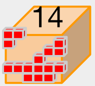
Now (ViT) :

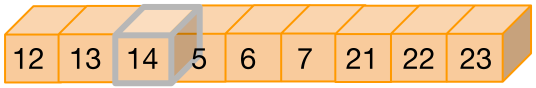
e.g: create parent cubes of size 8x8x8





each parent cube holds the information of its child voxels: relative positions & charge



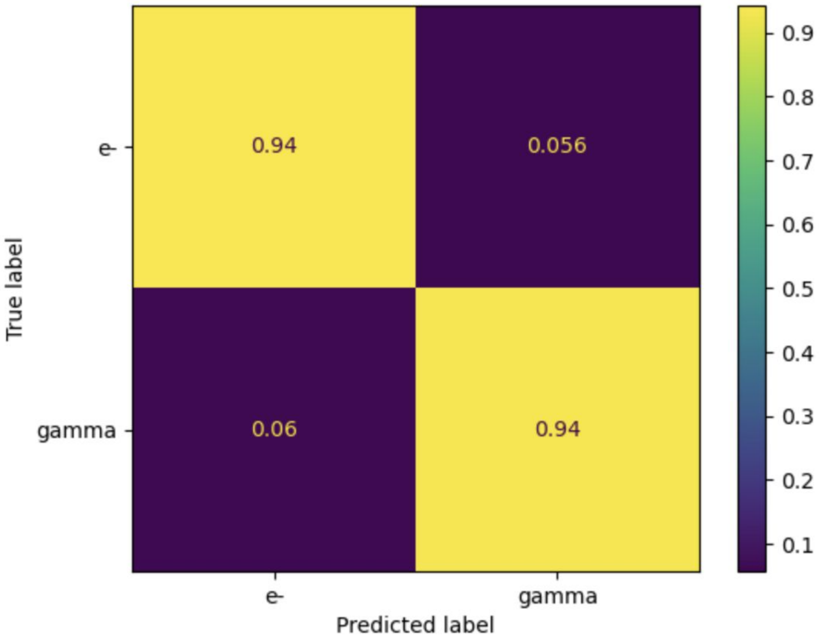


positional encoding of the parent cubes in the parent grid

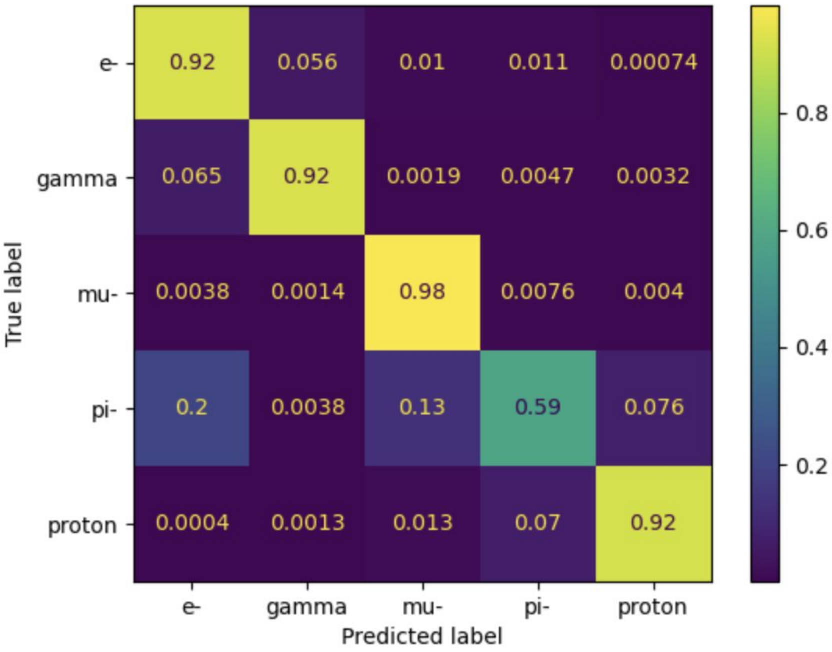
The Transformer PID method

First performances

*model trained for **e**/γ separation*



*model trained for **e**/γ/μ/π/**p** separation*



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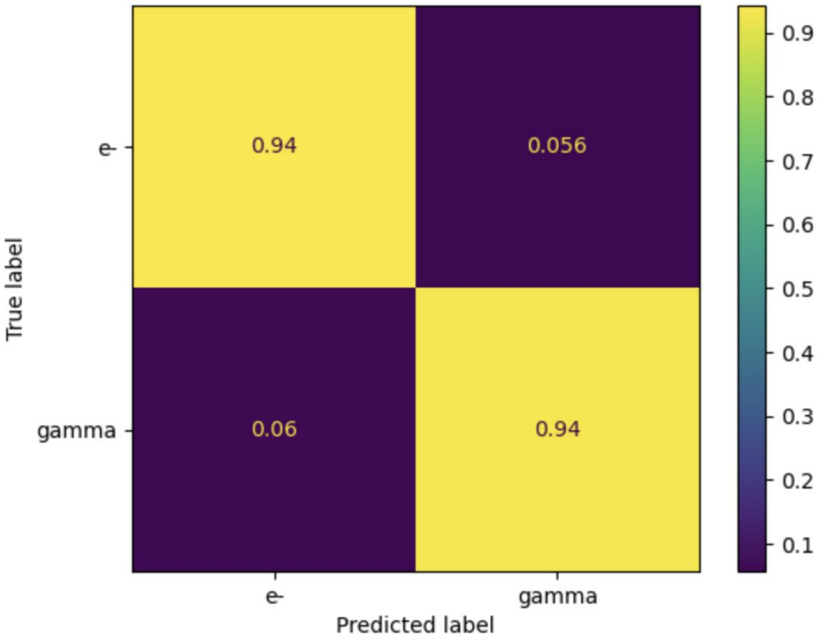

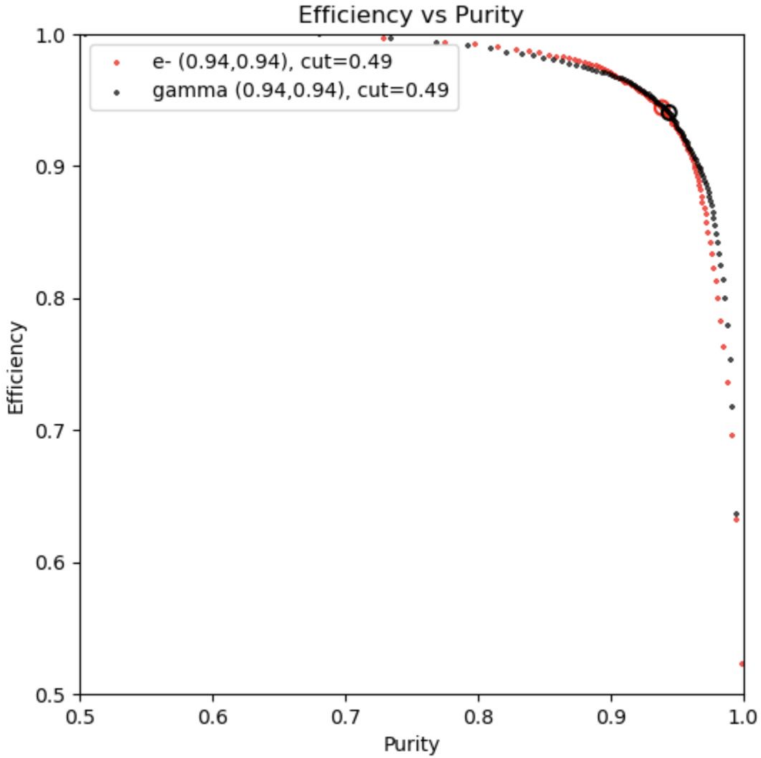

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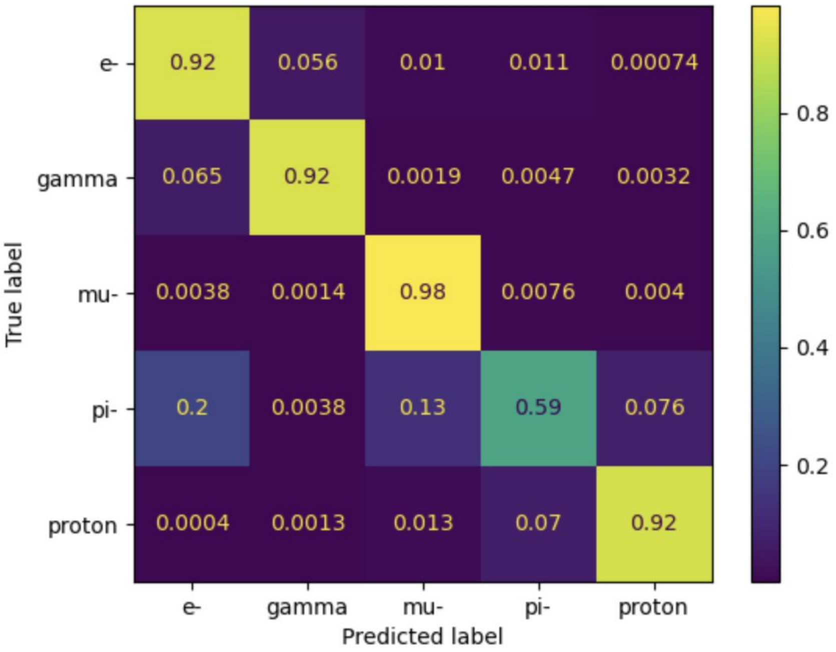
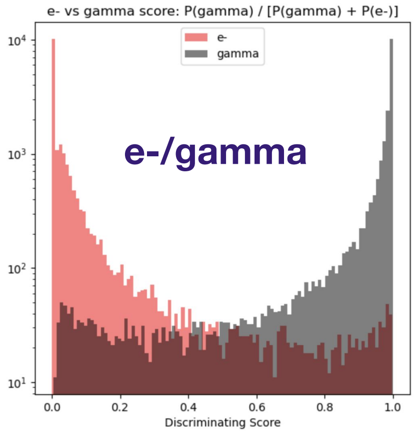
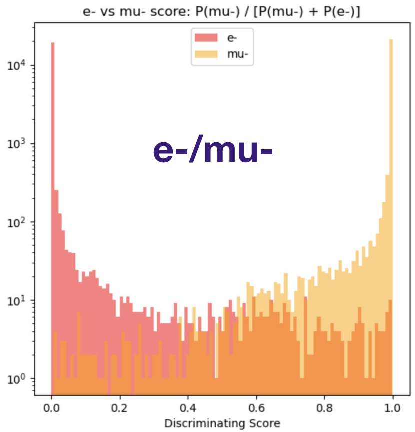
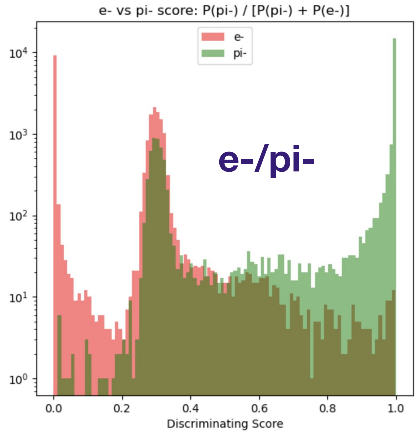
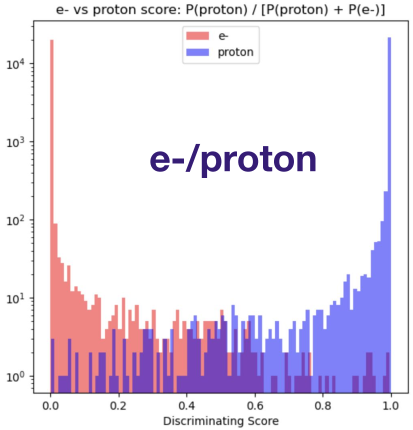






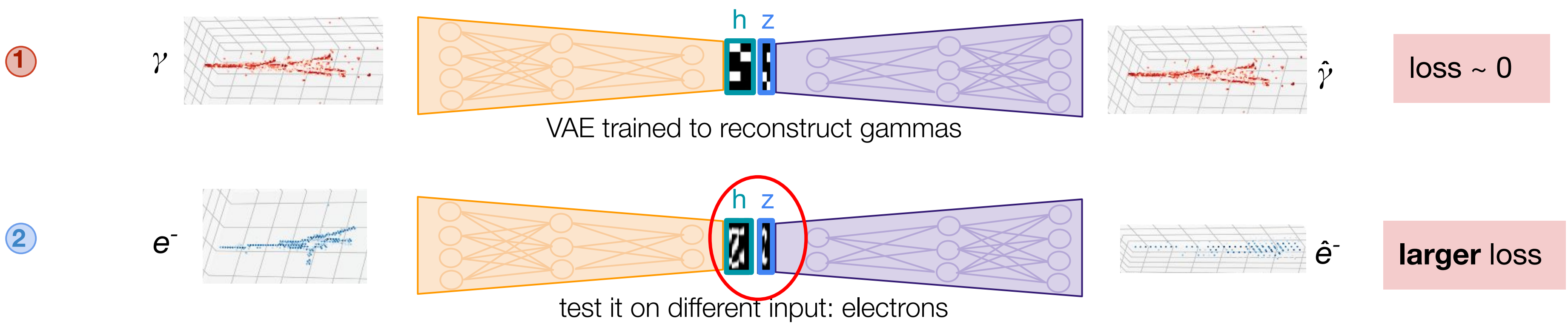




A glanced at the Variational Auto-Encoder method

Key idea: anomaly detection to distinguish *e-* (anomalies) out of γ (trained on)

1. Train the VAE with many gamma conversion in the SFGD: it will learn to reconstruct the gamma events
2. Test it on e- events: the reconstruction should not be as good → anomaly in the loss function



A glanced at the Variational Auto-Encoder method

2 distinction metrics to analyse

latent space

regression loss

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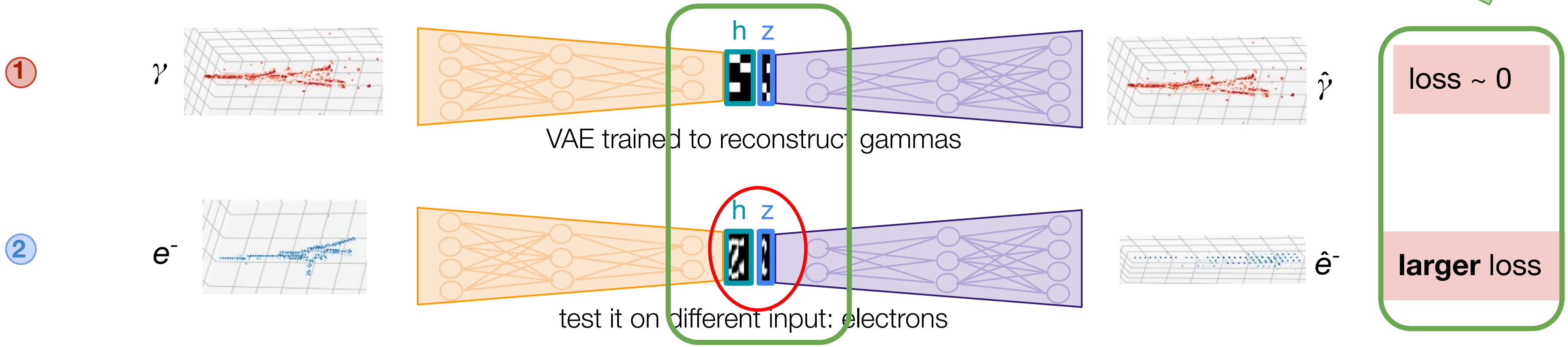
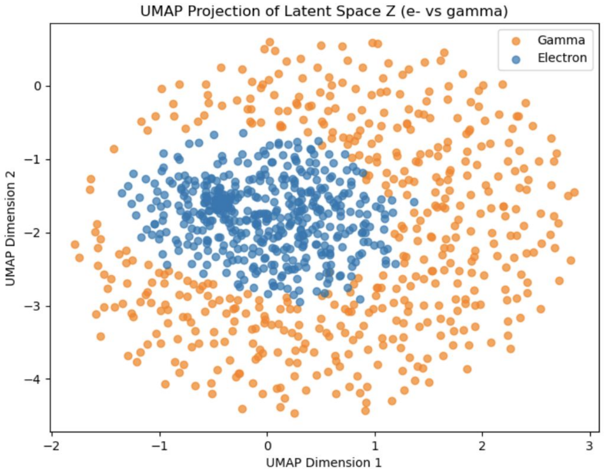


A glanced at the Variational Auto-Encoder method

Separation of e and γ

latent space: dimensionality reduction with UMAP



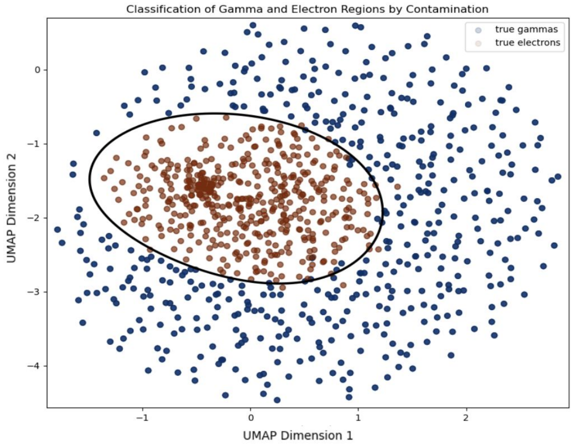
z-distrib for one event: vector of size (1,1024)

→ reduce it to (1,2) using UMAP (dimensionality reduction algo)

→ plot all tested event on this 2D map

Separation of e and γ

separation in the 2D latent space for electron selection



1) compute the **contamination** of each point
2) low-contamination points are fed into a **SVC with an RBF** kernel
3) the SVC creates a **delimitation in this 2D space**
4) **efficiencies** and **purities** using the electron/gamma regions can be computed:

e- efficiency: 98.73%
e- purity: 97.91%
γ efficiency: 97.89%
γ purity: 98.72%

BUT: this 2D umap was *transformed* on the same sample used for *fitting* the 2D umap: those eff,pur are only **upper limits**

Summary

- It's necessary to c**haractize precisely the ν_e background** at the near detector
- New **methods are being developed** for this matter: a **Transformer** and a **VAE**
- The developpement of the **Transformer in the T2K analysis software** is done!
  (first complex ML algo to be implemented there)
- The **Transformer** training shows **promising PID results**: other improvements are needed
- Some **VAE upgrades are on-going**, then new analyses are too come

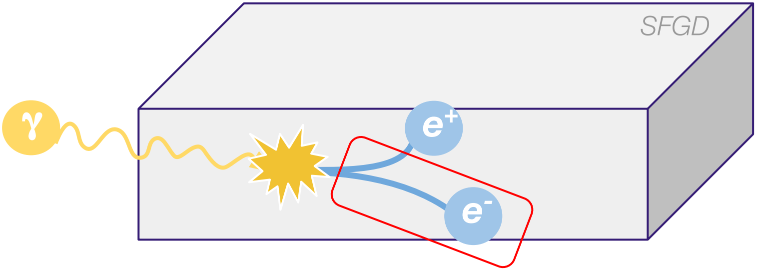
Next steps:

- compare those 2 methods with the old ones on the same samples
- control sample

Back-ups

The gamma background

gamma event



CC electronic neutrino event