Development of reconstruction algorithms for the new TPCs of the upgraded T2K near detector with machine learning techniques

Pre-thesis internship – Oral defense

June 28th, 2023

Anaëlle Chalumeau

Overview

1. Introduction

2. T2K, its near detector and the new TPCs

3. Machine learning: neural network for track reconstruction
    - ▻ How it works
    - ▻ Results
    - ▻ Current challenges and investigations

  - ▻ Internship conclusion

4. Prospects for the PhD

1. Introduction

Neutrinos oscillate:

$$\begin{pmatrix} \nu_e \\ \nu_\mu \\ \nu_\tau \end{pmatrix} = \begin{pmatrix} \text{PNMS} \\ \text{matrix} \end{pmatrix} \begin{pmatrix} \nu_1 \\ \nu_2 \\ \nu_3 \end{pmatrix}$$

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$$\begin{pmatrix}\nu_e\\ \nu_\mu\\ \nu_\tau\end{pmatrix}=\begin{pmatrix}1 & 0 & 0\\ 0 & \cos\theta_{23} & \sin\theta_{23}\\ 0 & -\sin\theta_{23} & \cos\theta_{23}\end{pmatrix}\begin{pmatrix}\cos\theta_{13} & 0 & \sin\theta_{13}e^{-i\delta_{CP}}\\ 0 & 1 & 0\\ -\sin\theta_{13}e^{i\delta_{CP}} & 0 & \cos\theta_{13}\end{pmatrix}\begin{pmatrix}\cos\theta_{12} & \sin\theta_{12} & 0\\ -\sin\theta_{12} & \cos\theta_{12} & 0\\ 0 & 0 & 1\end{pmatrix}D\begin{pmatrix}\nu_1\\ \nu_2\\ \nu_3\end{pmatrix}$$

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Appearance probability

$$P(\nu_\mu \to \nu_e) = |\langle\nu_e|\nu_\mu(t)\rangle|^2 = P(\theta_{12},\, \theta_{23},\, \theta_{13}\,,\, \delta_{CP}\,,\, \Delta m^2_{21} \text{ and } \Delta m^2_{32})$$

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oscillation parameters!

want to know them **precisely**

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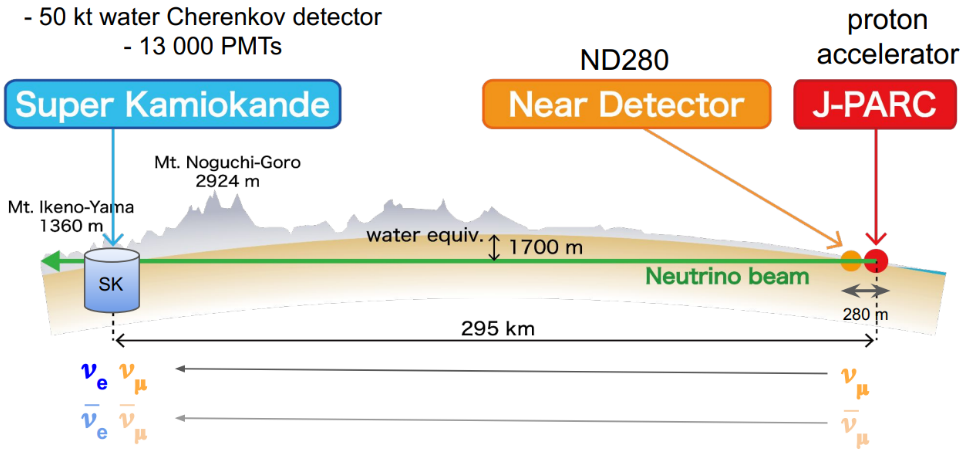

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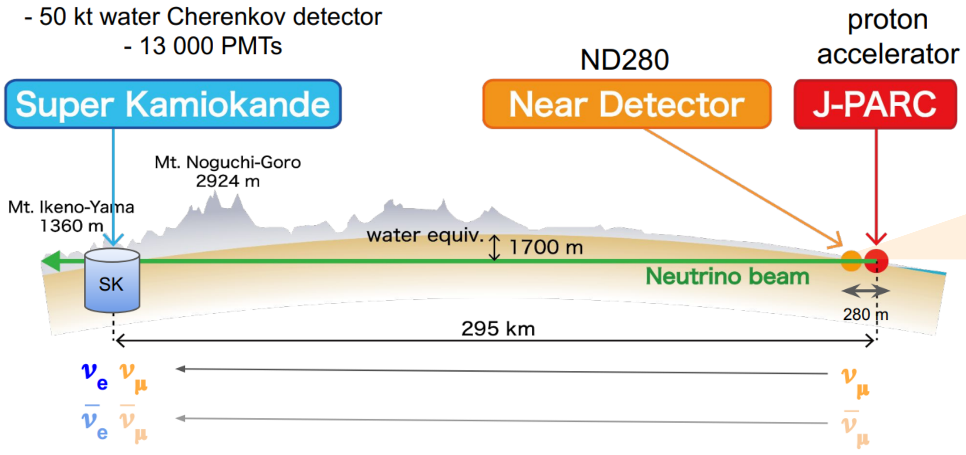

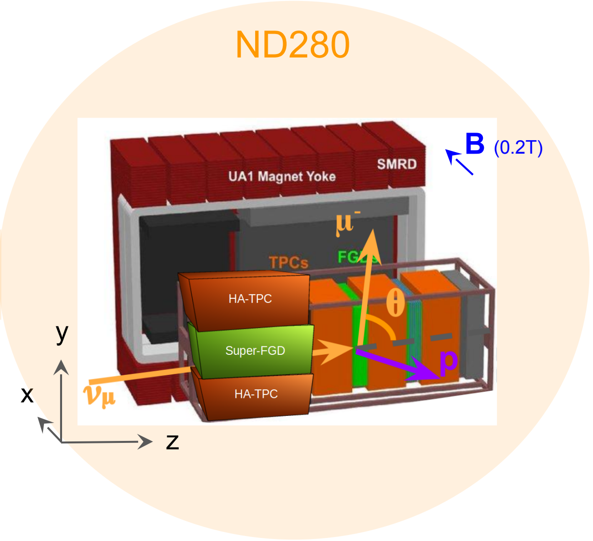

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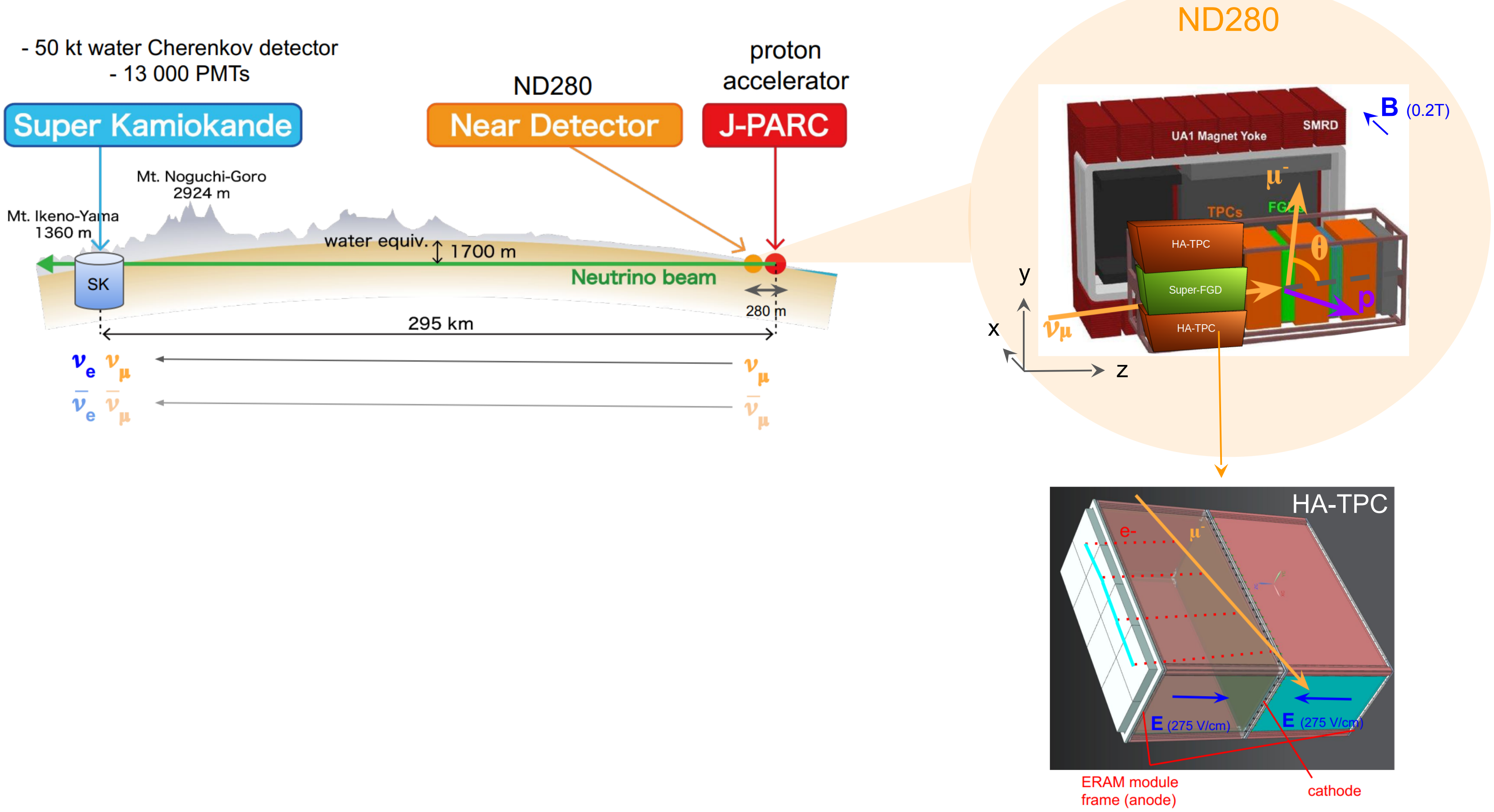

- 50 kt water Cherenkov detector
- 13 000 PMTs

Super Kamiokande

ND280

Near Detector

proton accelerator

J-PARC

ERAM module frame (anode)

cathode

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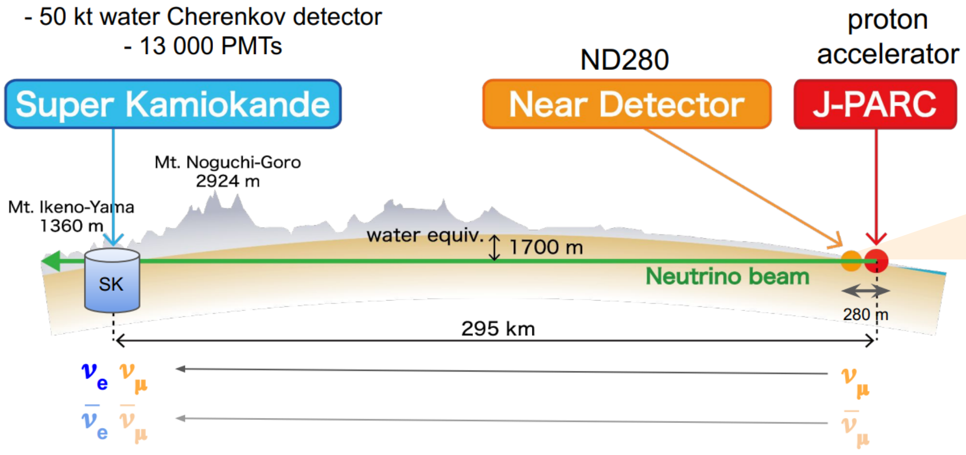
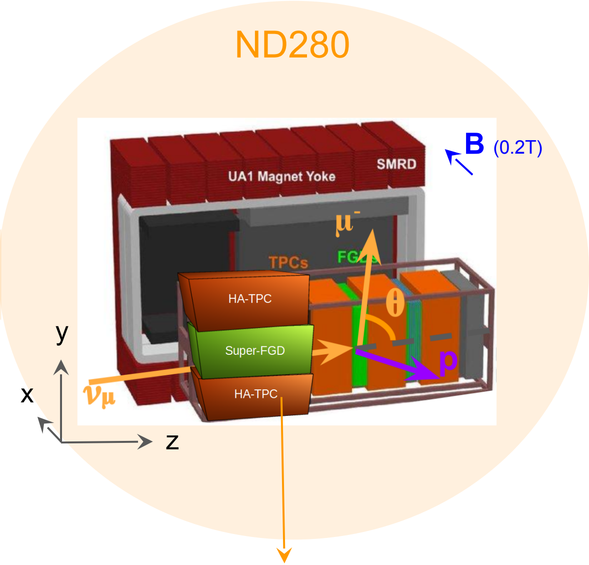
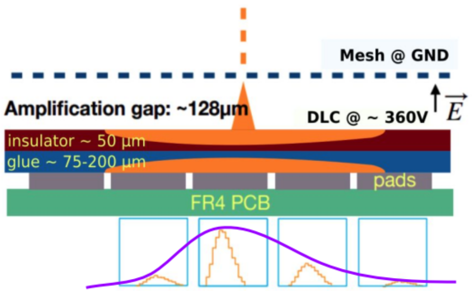
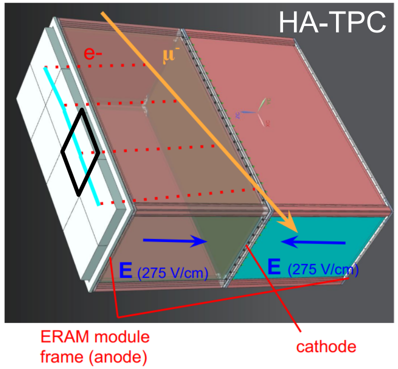




Encapsulated Resistive Anode MicroMegas (ERAM)





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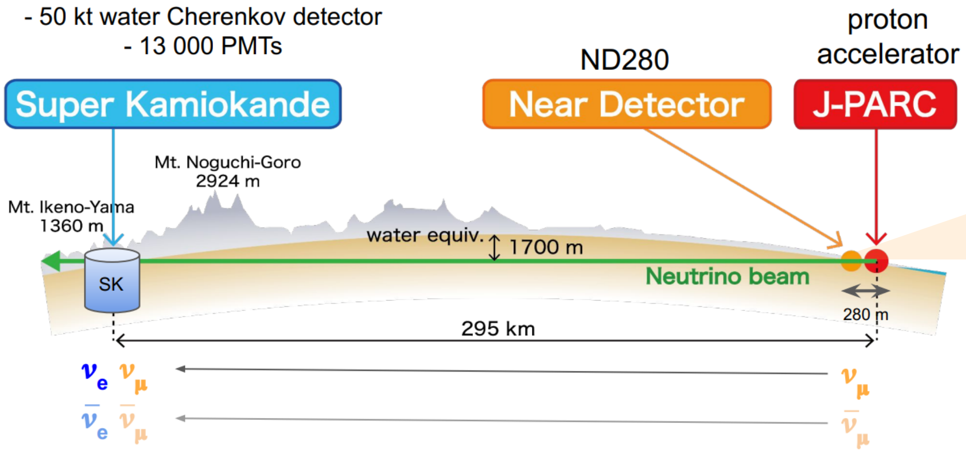

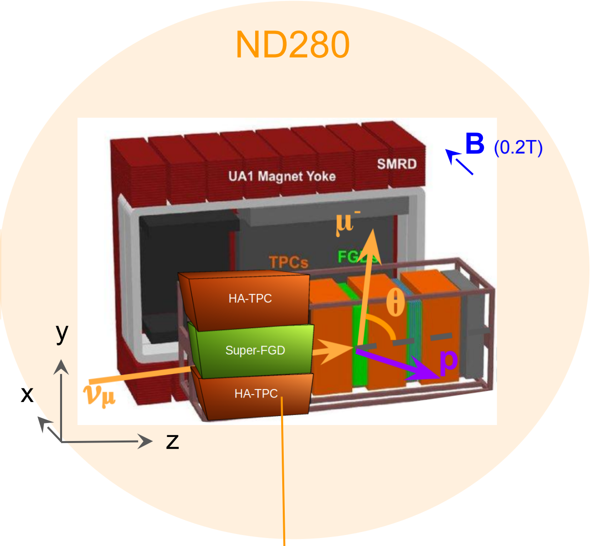

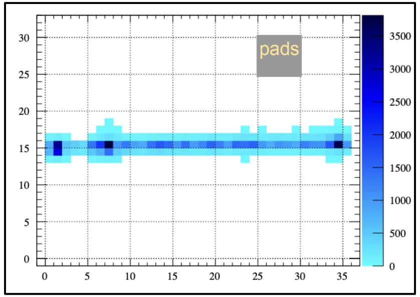

e.g of an event display from a test beam at DESY

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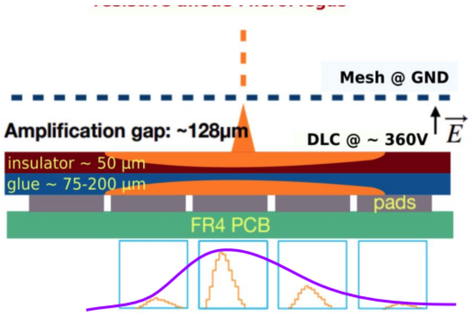

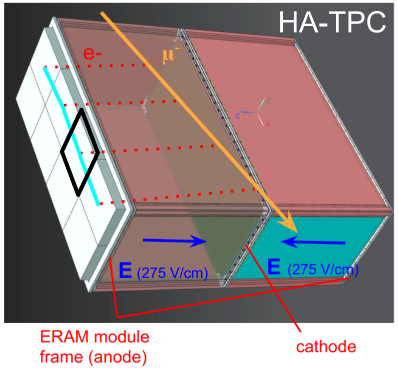

2. T2K, its near detector and the new TPCs

Classical reconstruction in the TPCs

the Pad Response Function method:

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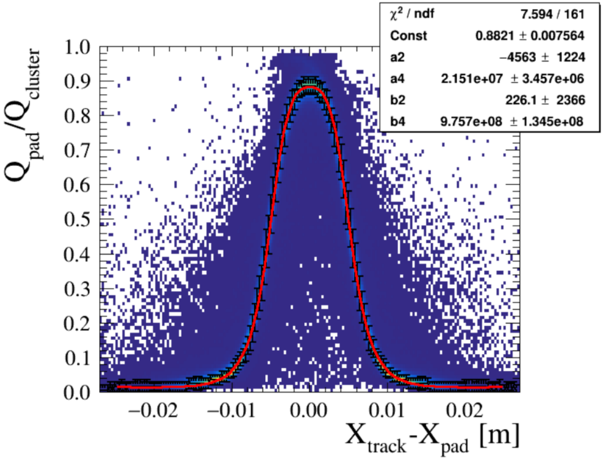

$$PRF(x_{track} - x_{pad}) = \underbrace{Q_{pad}}/Q_{cluster}$$

max of the charge in the pad (later called Qmax)

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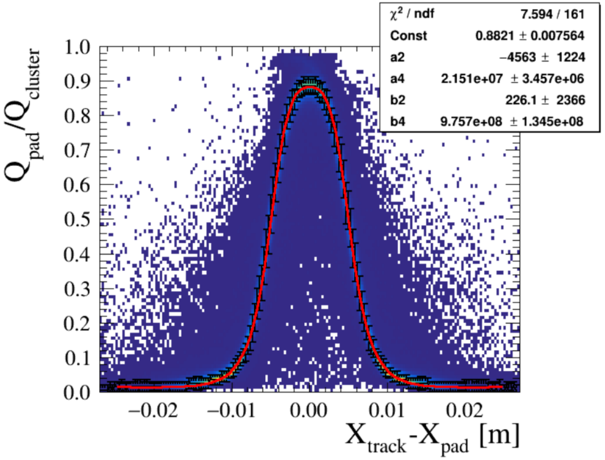

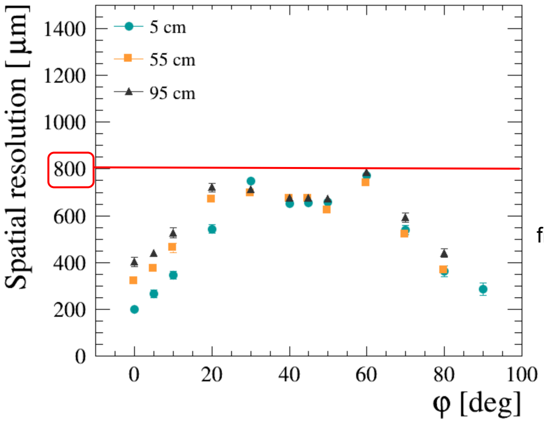

from DESY test beam data with a HA-TPC prototype (2022)

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↳ gives spatial resolution <0.8mm

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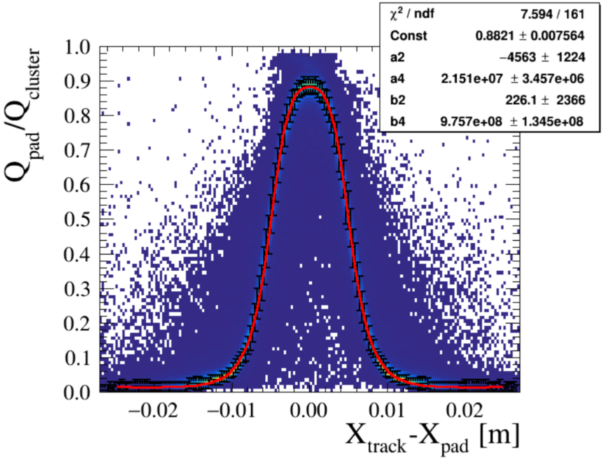

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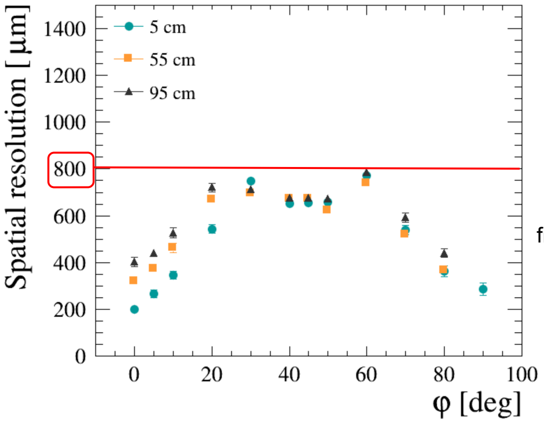
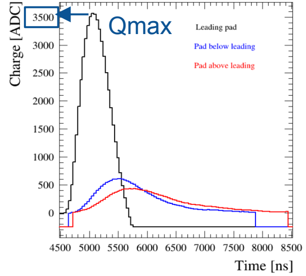


from DESY test beam data with a HA-TPC prototype (2022)

Waveforms
(charge deposited vs time)



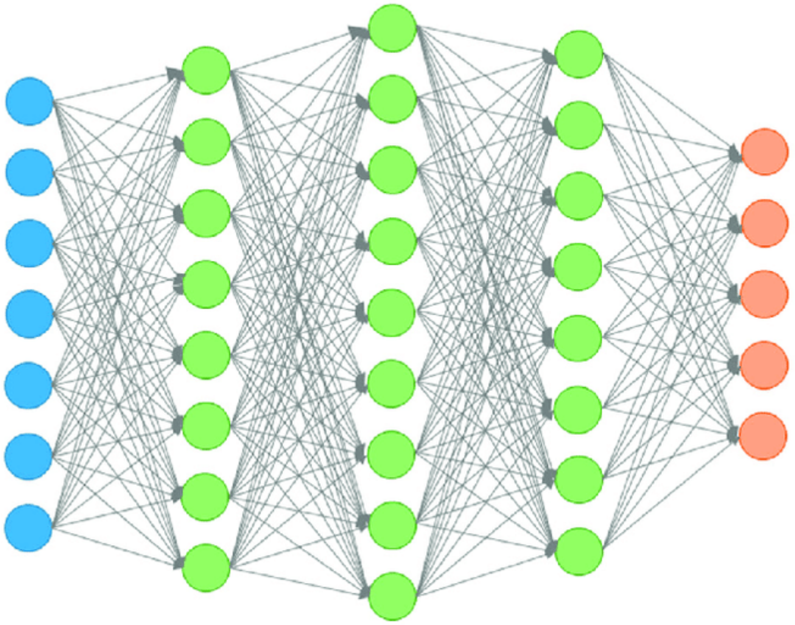
↳ gives spatial resolution <0.8mm

↳ but uses only Qmax of the waveform: limited info!

↳ **could expect better resolutions by using more info from the waveforms**

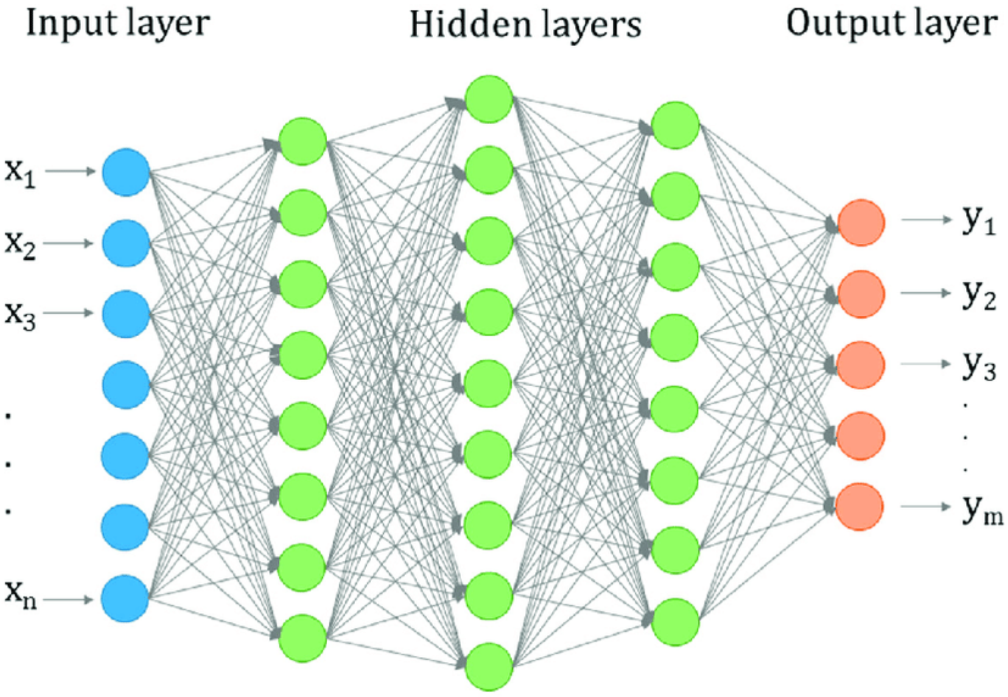
3. Machine learning and deep learning

- ☑ Efficient for large & complexe datasets
- ☑ Power to model non-trivial relationships between inputs/outputs
- ☑ Easily adaptable to various experimental conditions
- ☑ Promising results these past years in particle & neutrino physics
- ☑ Neural networks: very good for image processing



3. Machine learning: neural network for track reconstruction

▻ How it works



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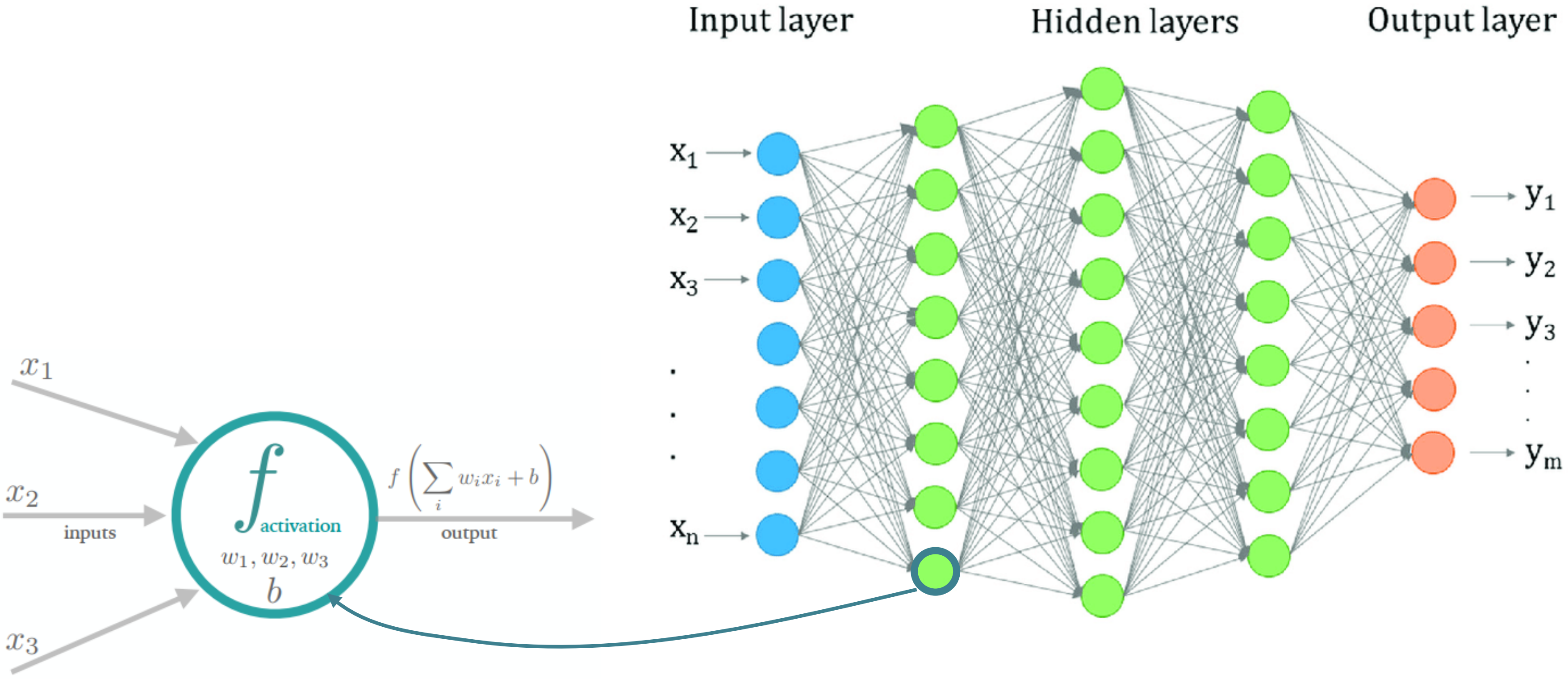

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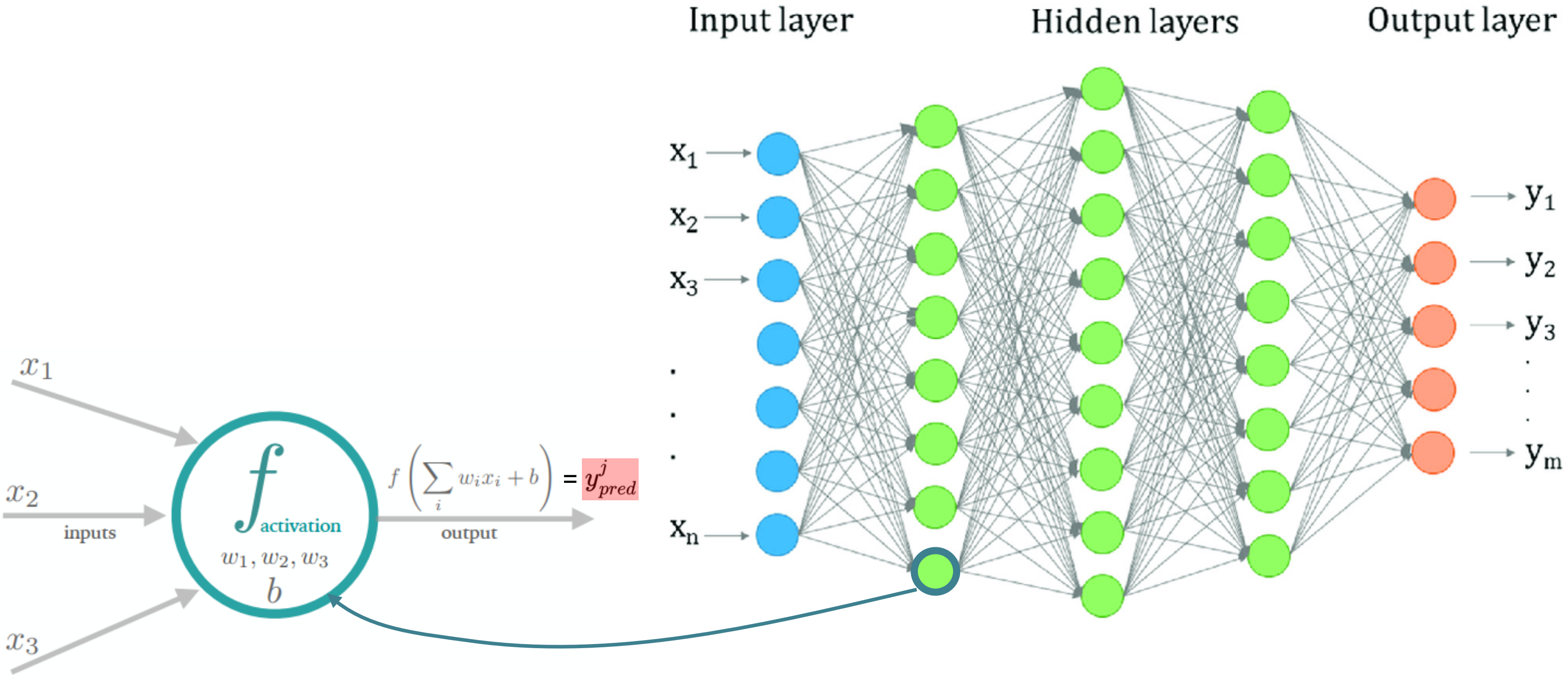

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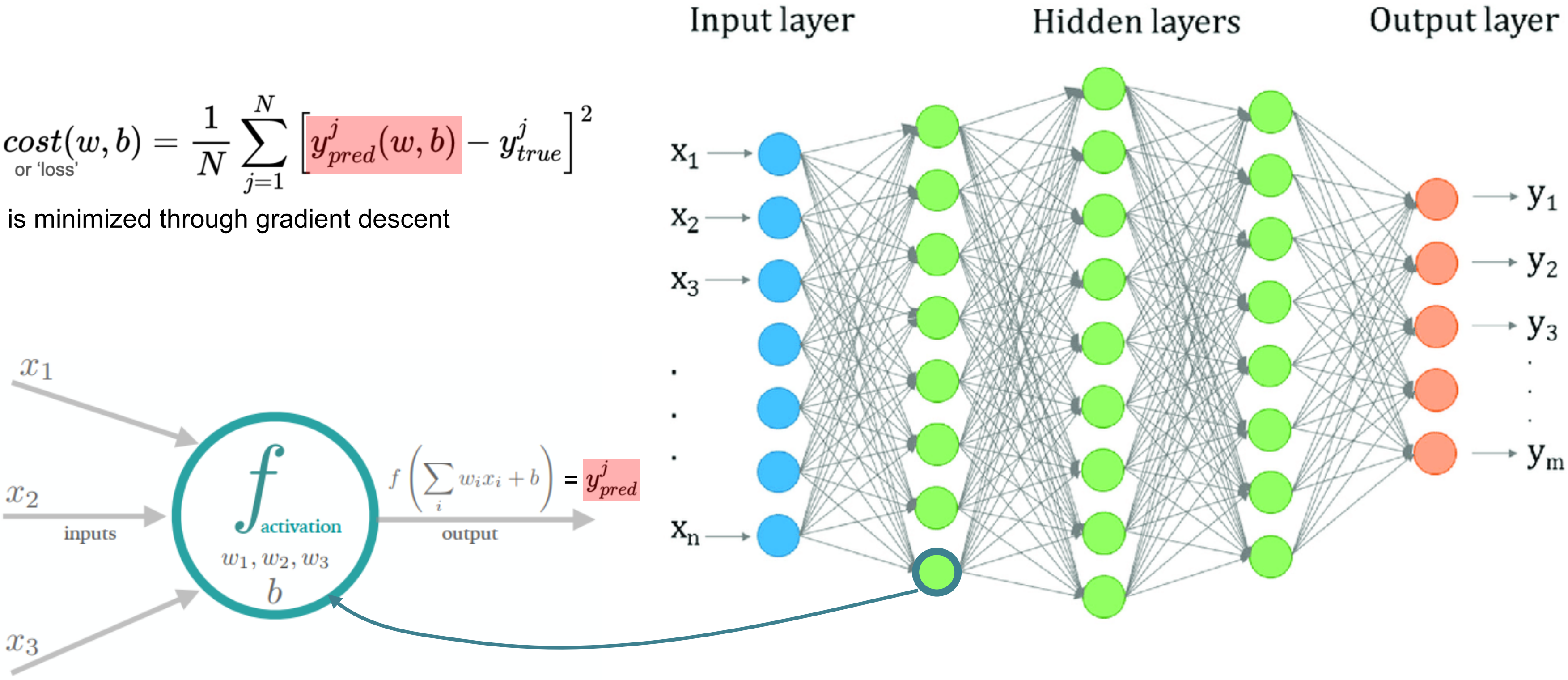
▻ How it works

$$cost(w,b) = \frac{1}{N}\sum_{j=1}^{N}\left[y^{j}_{pred}(w,b) - y^{j}_{true}\right]^2$$

or 'loss'

is minimized through gradient descent



$$f\left(\sum_i w_i x_i + b\right) = y^{j}_{pred}$$

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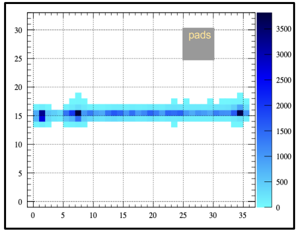
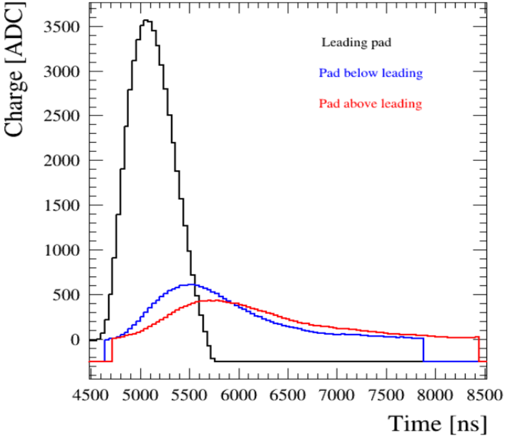
Input data

Real data





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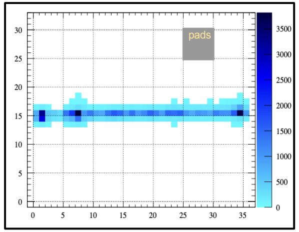

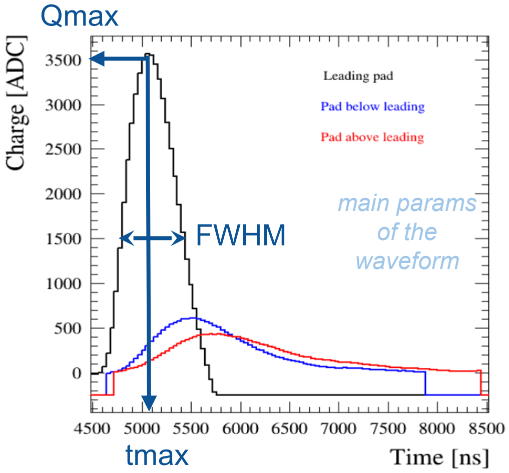

main params of the waveform

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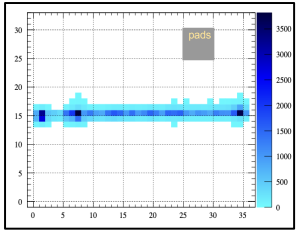
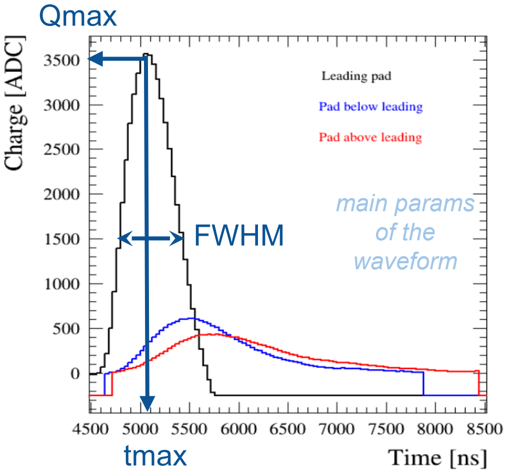




main params of the waveform

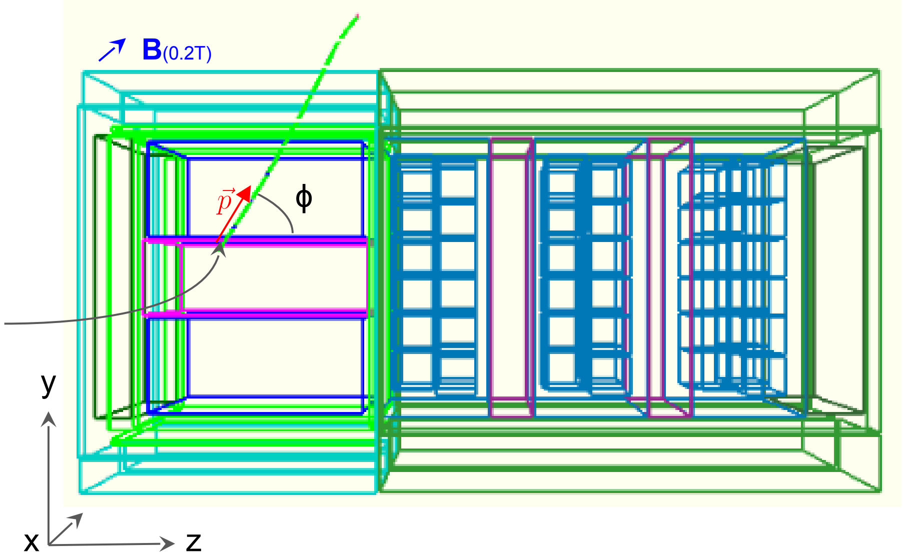
Simulation data ('particle gun')

Simulated data with:

- $p_x = 0$
- $x = 0$

↳ track in (y,z) plane

z_{ini} = track entrance in the top HA-TPC



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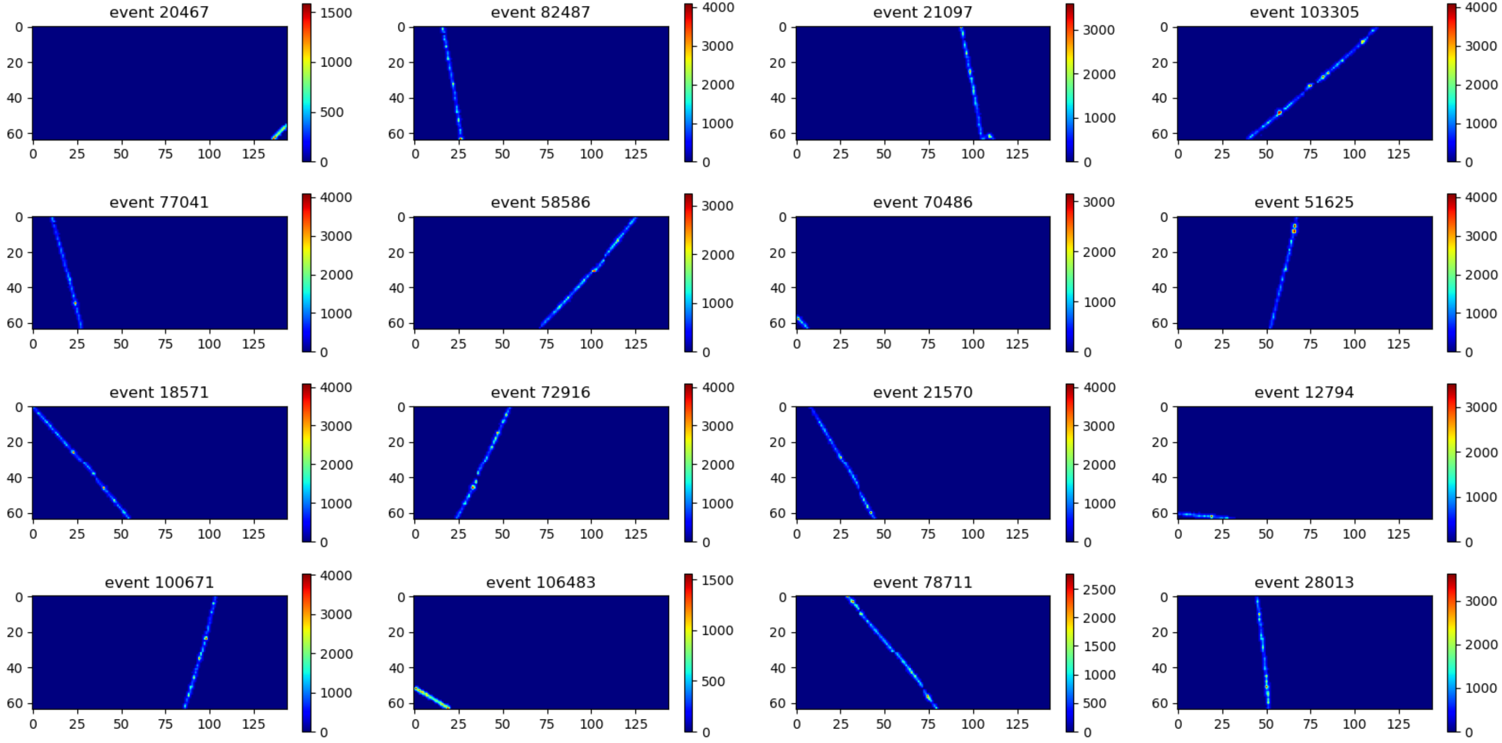

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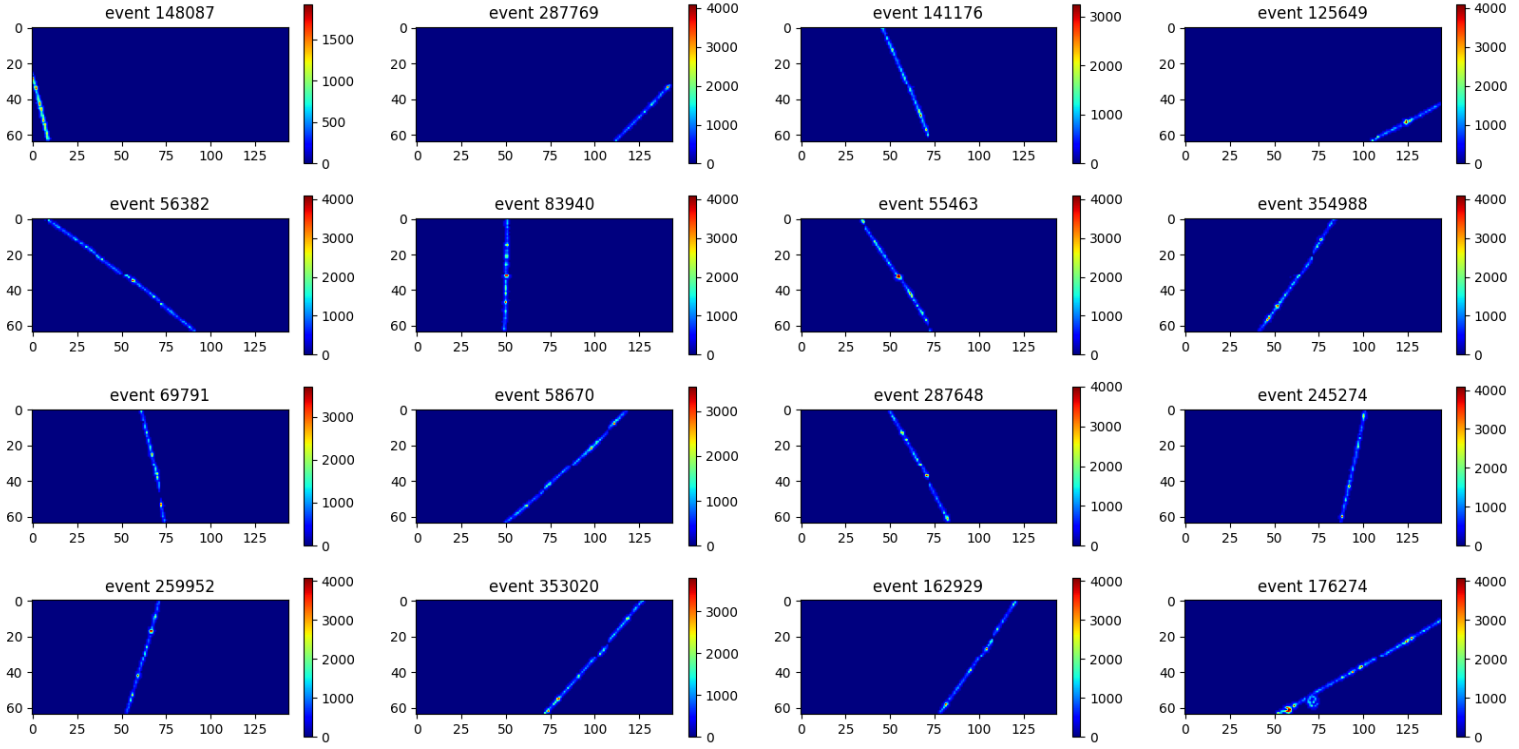

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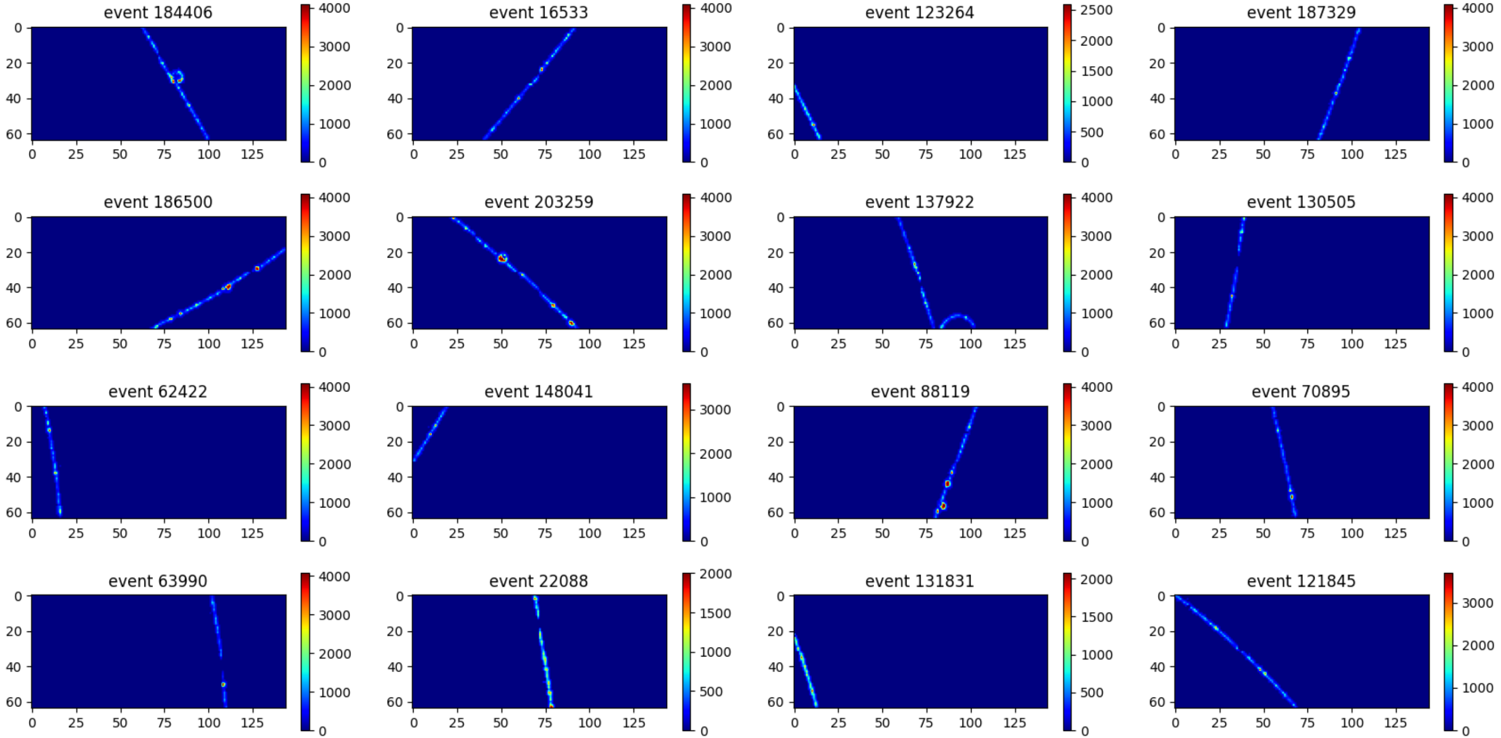

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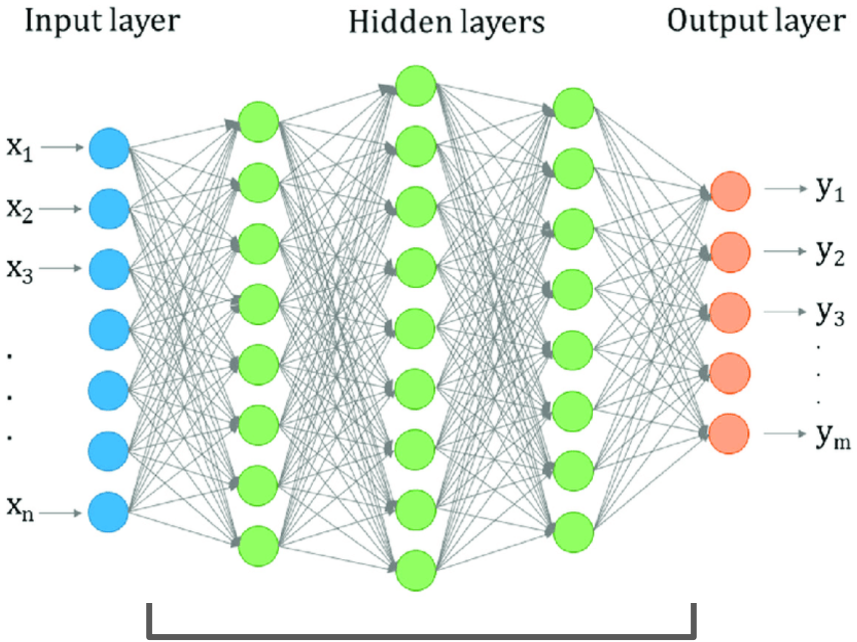

ResNet50 architecture
a convolutional NN

3. Machine learning: neural network for track reconstruction

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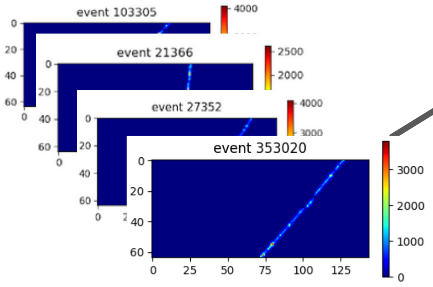
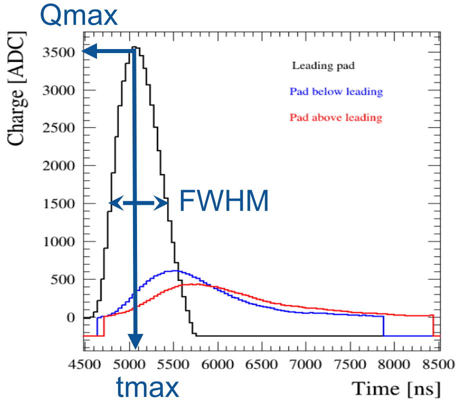
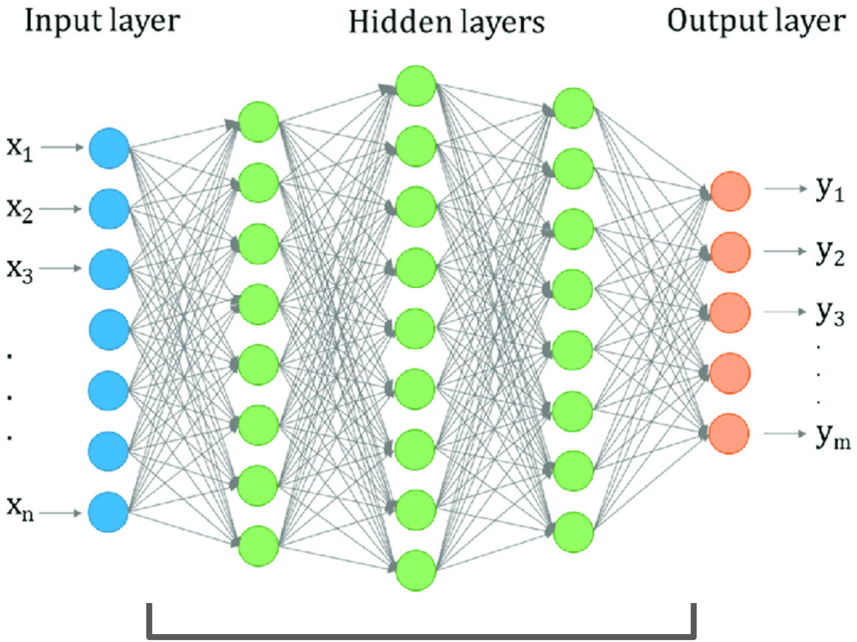


only Qmax values at first





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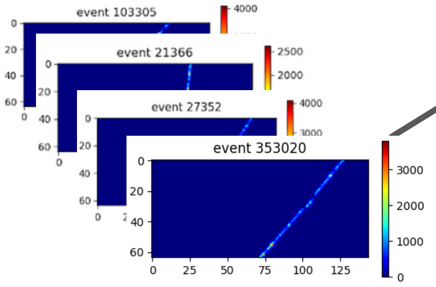

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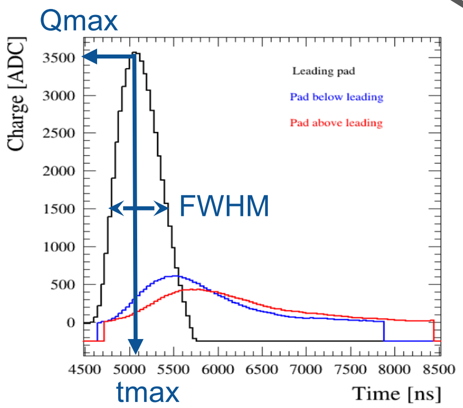
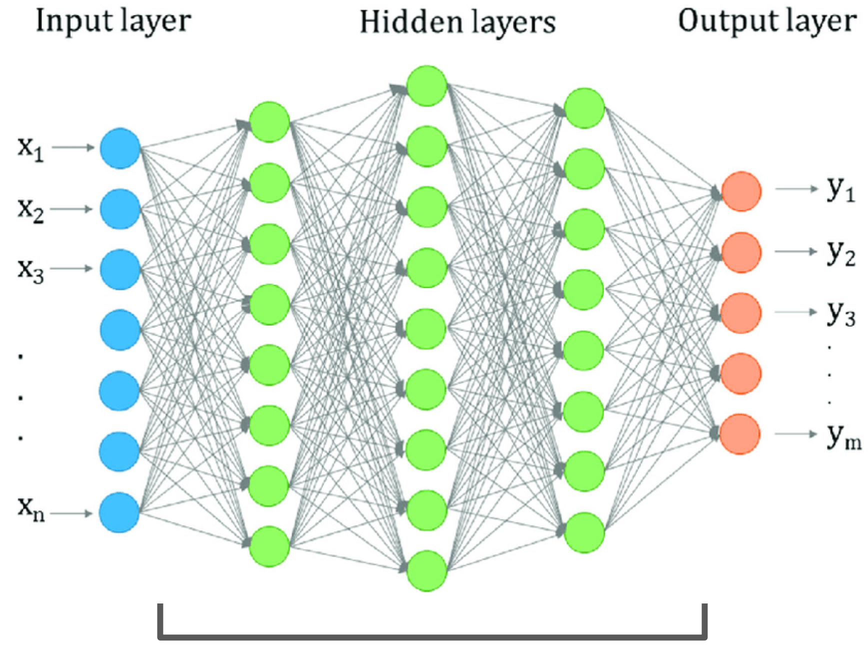




[initial positions z_{ini}]

[momenta p_z, p_y, $||\vec{p}||$]

[track angles ϕ]

.
.
.
etc

ResNet50 architecture

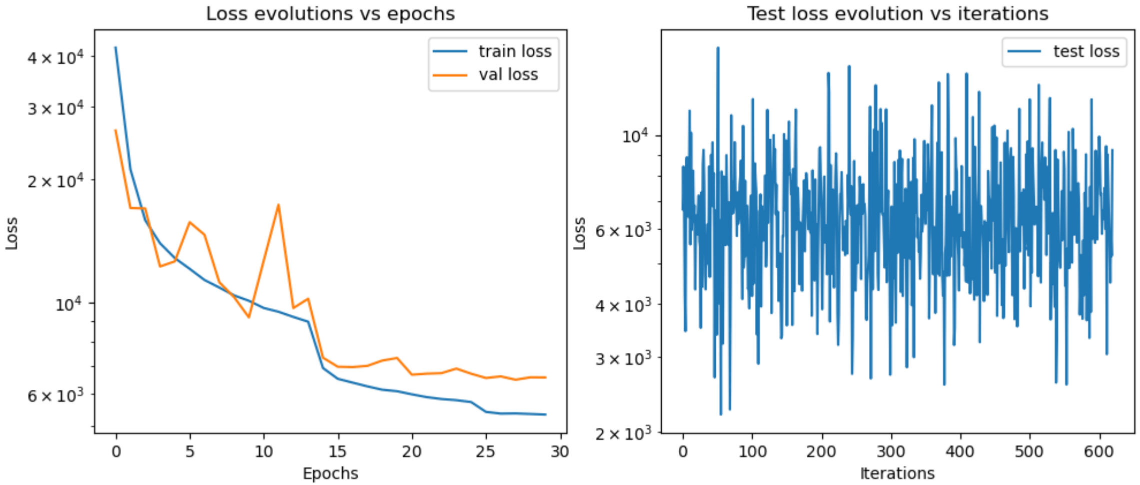
a convolutional NN

3. Machine learning: neural network for track reconstruction

▻ Results

3 predictions: p_y, p_z, p_t
~280 000 events

- Data divided into training/validation/test set (70/15/15%)



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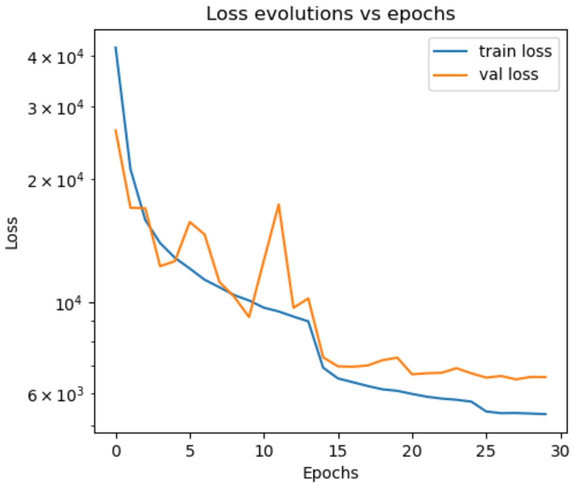

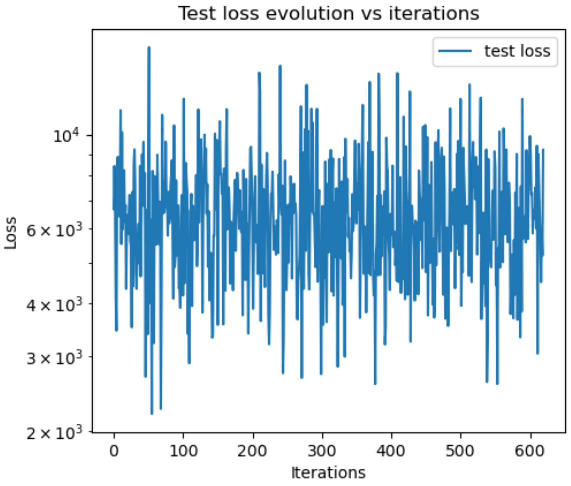

- **Training** set to perform gradient descent and find best parameters (weights & biases)

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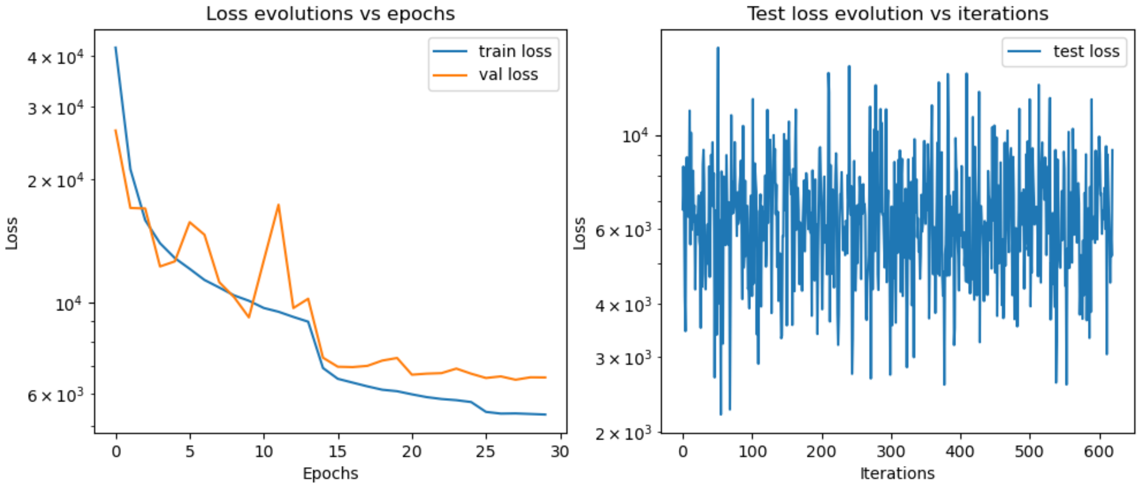

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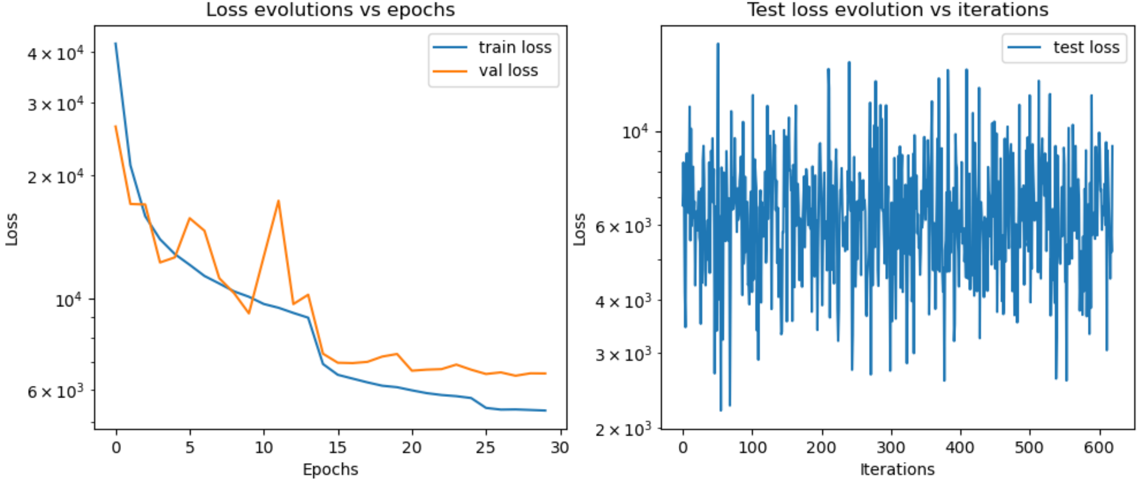

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- **Validation** set to test during training & used to select best parameters
- **Test** set used at the end, after training/validation, to attest the final performance of the model on new/unseen data

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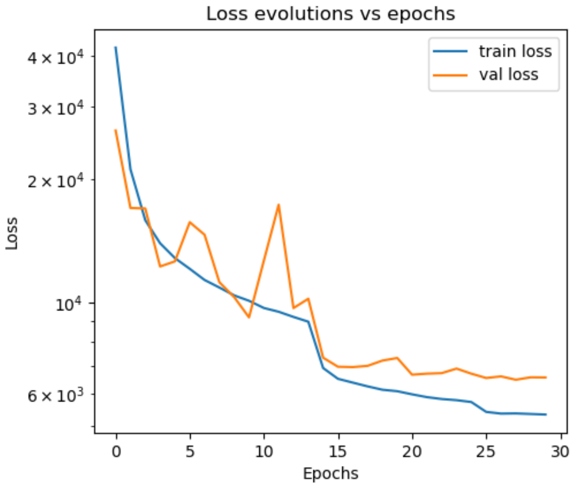
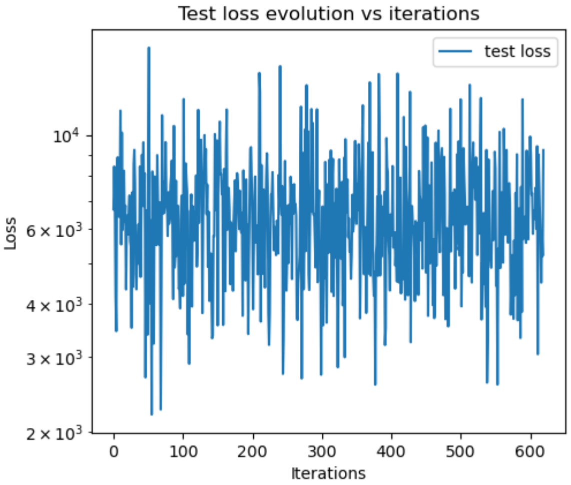
☑ decreases
☑ train/val loss stay close





- ▫ **Training** set to perform gradient descent and find best parameters (weights & biases)
- ▫ **Validation** set to test during training & used to select best parameters
- ▫ **Test** set used at the end, after training/validation, to attest the final performance of the model on new/unseen data

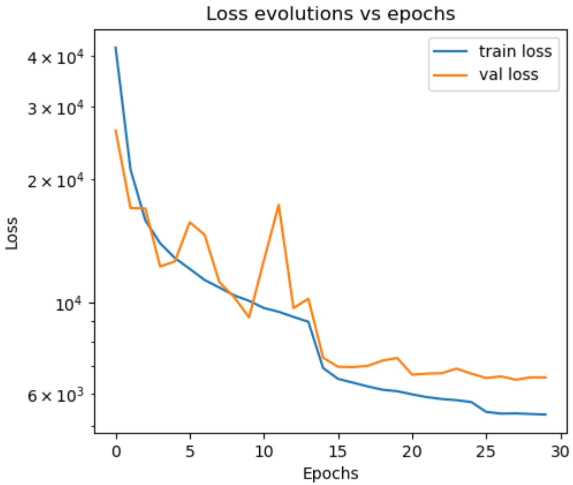
3. Machine learning: neural network for track reconstruction

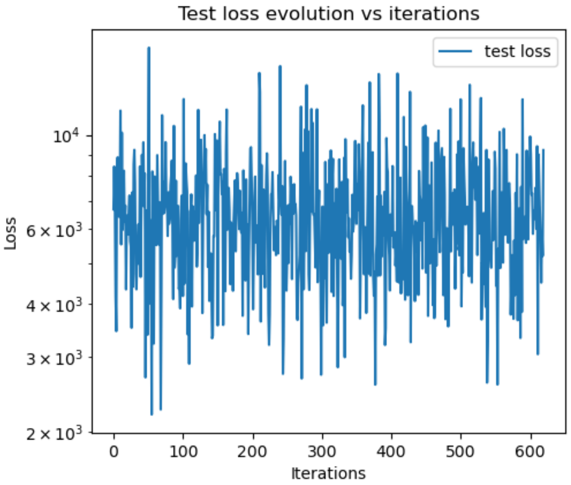
▻ Results

3 predictions: p_y, p_z, p_t
~280 000 events

▫ Data divided into training/validation/test set (70/15/15%)

☑ decreases
☑ train/val loss stay close





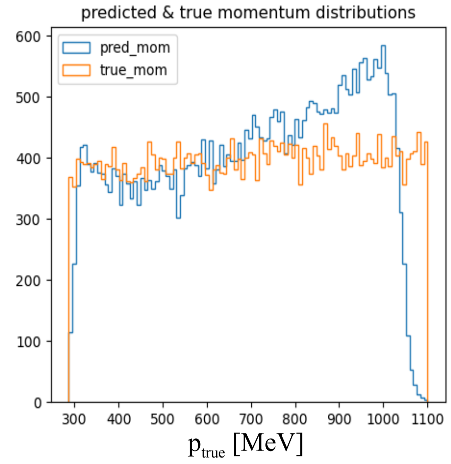
☑ always ~ same OM as final train/val loss

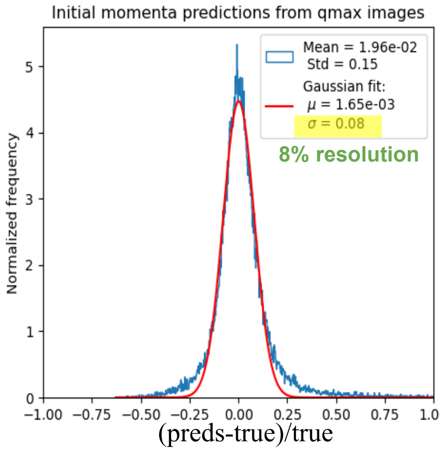
▫ **Training** set to perform gradient descent and find best parameters (weights & biases)
▫ **Validation** set to test during training & used to select best parameters
▫ **Test** set used at the end, after training/validation, to attest the final performance of the model on new/unseen data

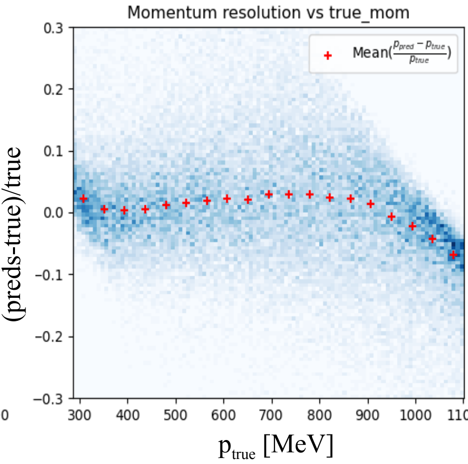
3. Machine learning: neural network for track reconstruction

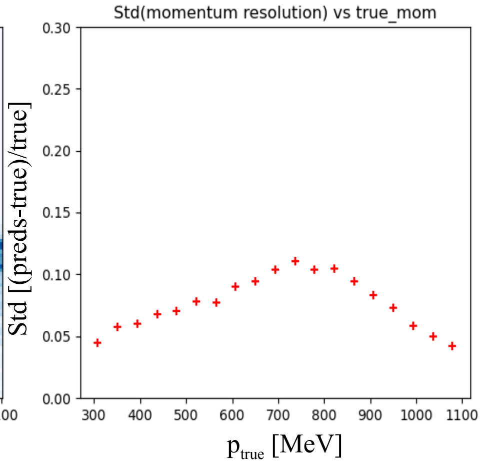
▻ Results

1 prediction: $p_t = \sqrt{p_y^2 + p_z^2}$
~280 000 events


predicted & true momentum distributions


Initial momenta predictions from qmax images


Momentum resolution vs true_mom


Std(momentum resolution) vs true_mom

3. Machine learning: neural network for track reconstruction

▻ Results

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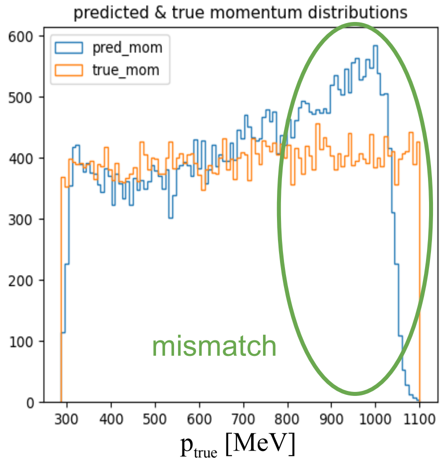
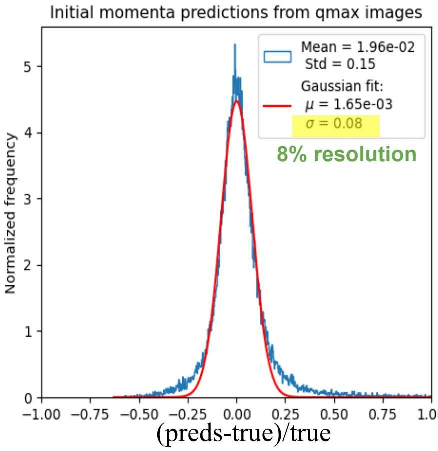
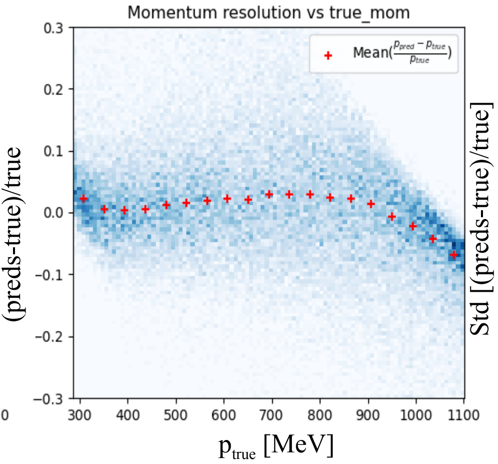
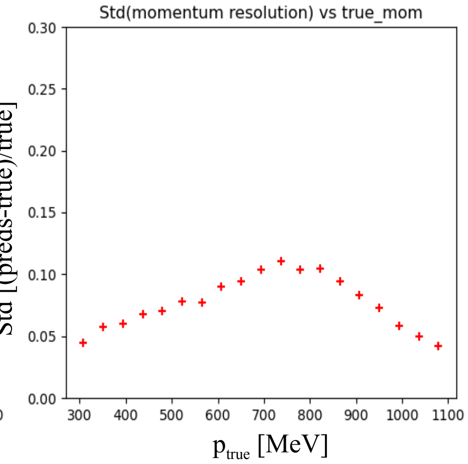


mismatch



8% resolution





3. Machine learning: neural network for track reconstruction

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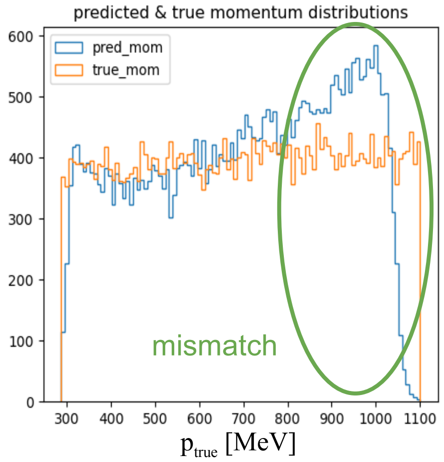
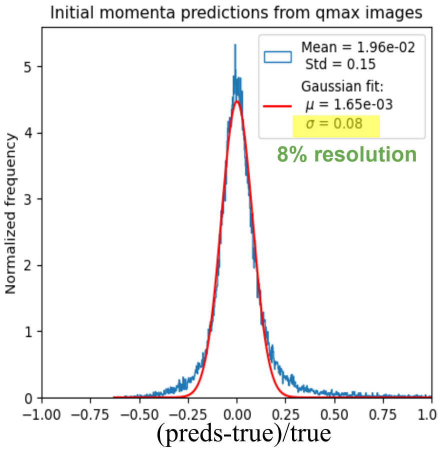
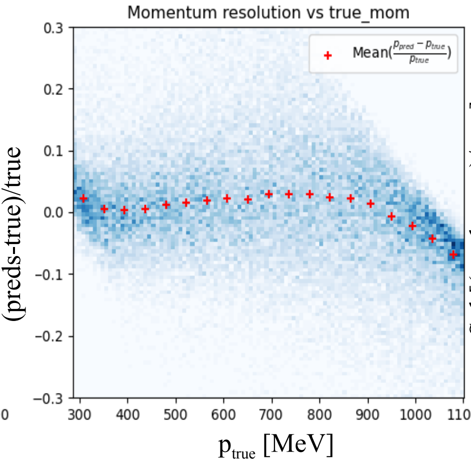
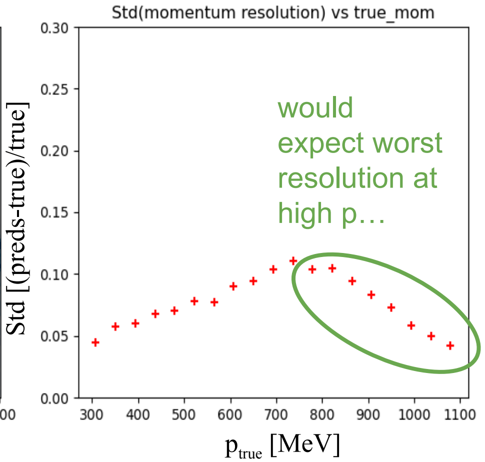


mismatch



8% resolution





would expect worst resolution at high p…

3. Machine learning: neural network for track reconstruction

▻ Results

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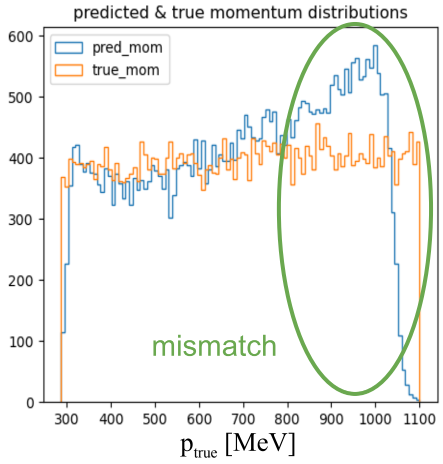
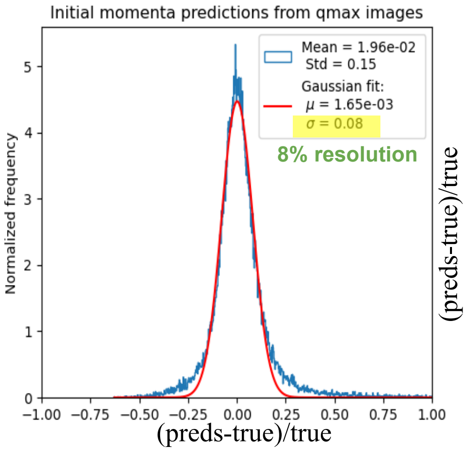
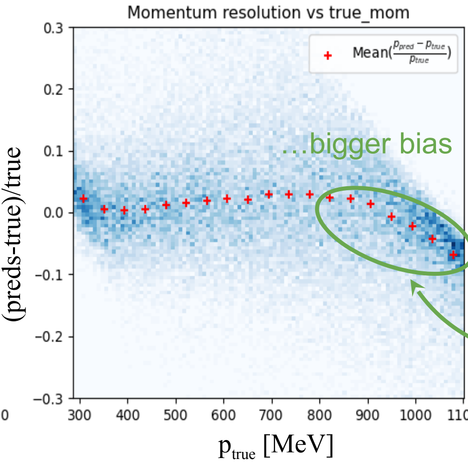
~280 000 events



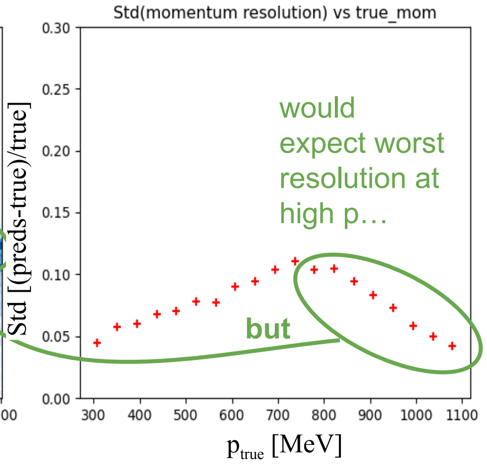
mismatch



8% resolution



…bigger bias



would expect worst resolution at high p…

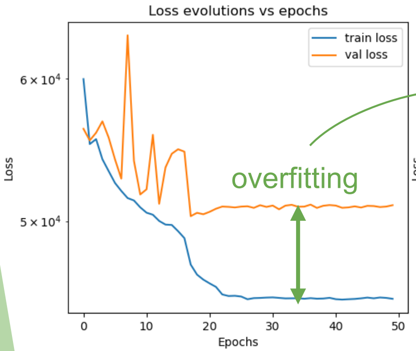
but

3. Machine learning: neural network for track reconstruction

▻ Results

1 prediction: $p_t = \sqrt{p_y^2 + p_z^2}$

~75 000 events



usually because:

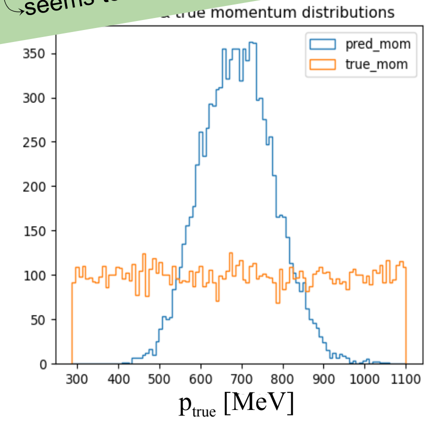
→ not enough data

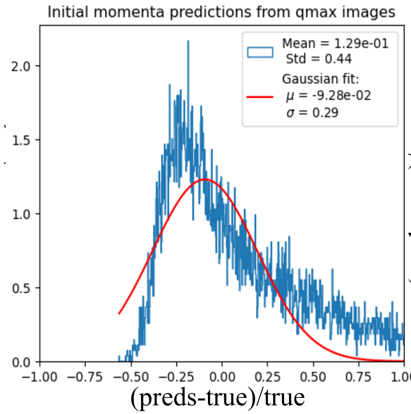
→ complexity of data

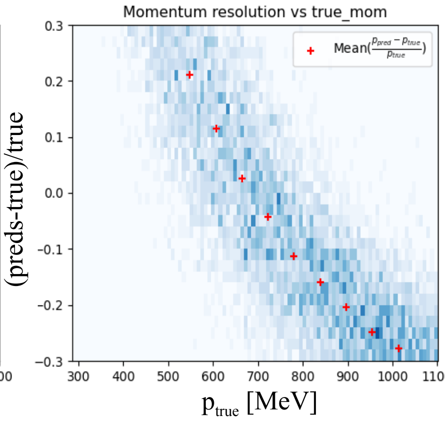
(generalisation is hard)

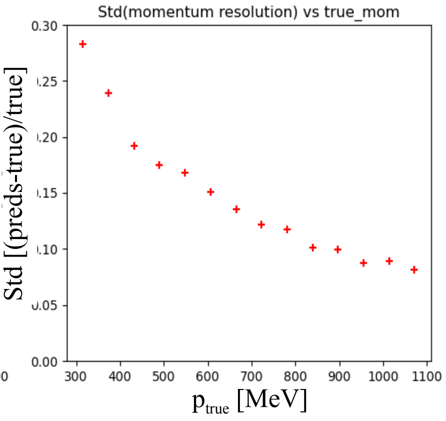
weird behaviour with **3x less events**…

↳seems to **disappear with more data**





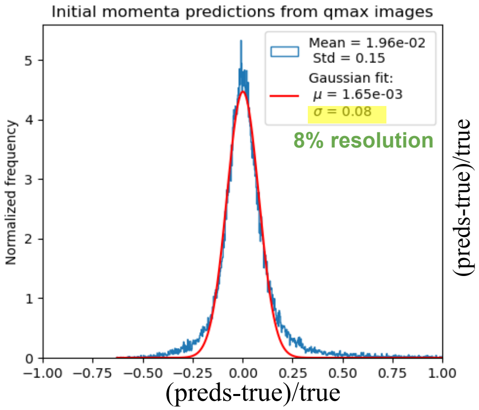




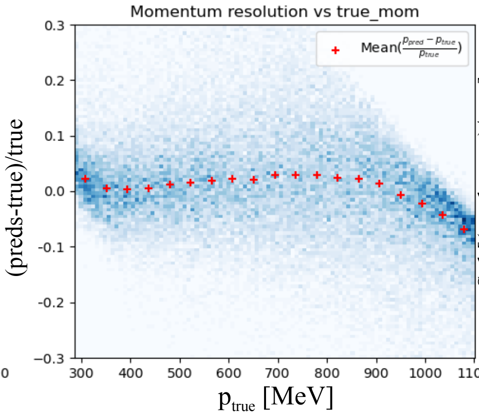
3. Machine learning: neural network for track reconstruction

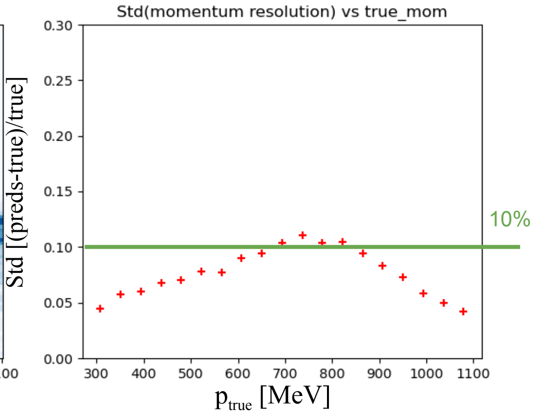
▻ Results

p_t



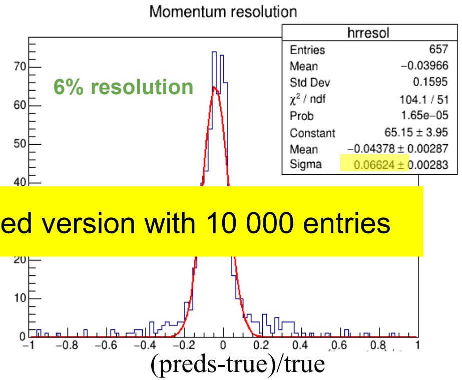
8% resolution





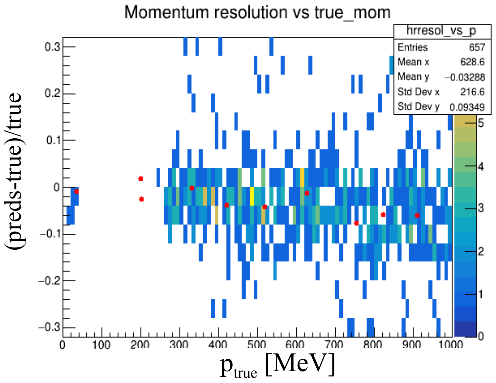
10%

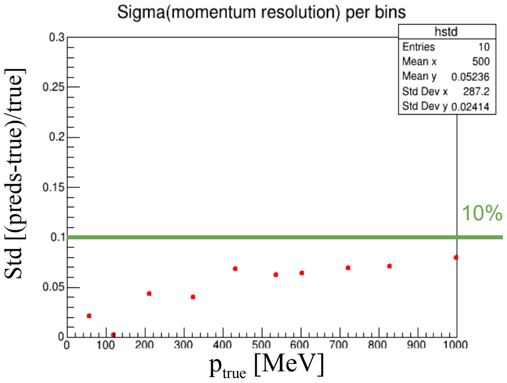
CNN
machine
learning



6% resolution

put updated version with 10 000 entries





10%

‘hatRecon’
classical
reconstruction

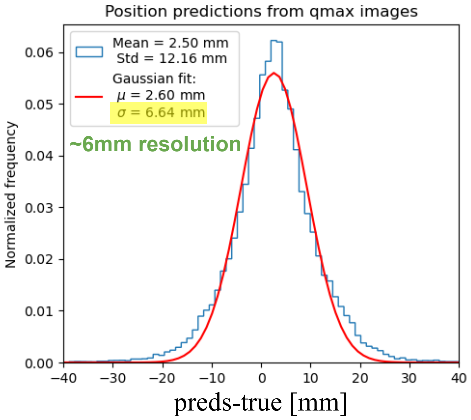
3. Machine learning: neural network for track reconstruction

▻ Results

5 predictions: z_{ini}, p_y, p_z, p_t, ϕ

~280 000 events

z_{ini}



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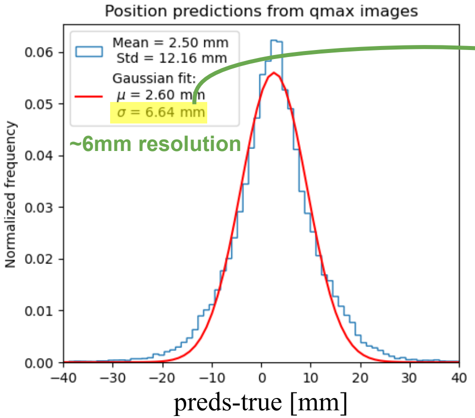

not precise!
1 pad is 10x11mm

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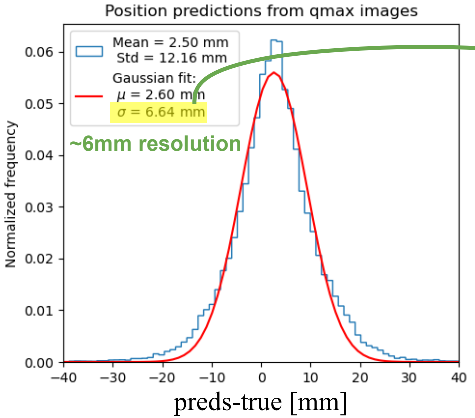

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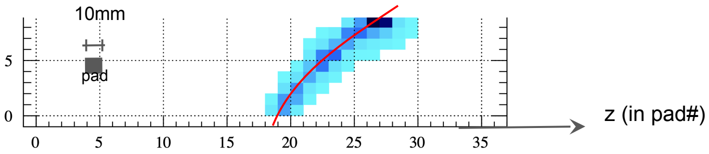

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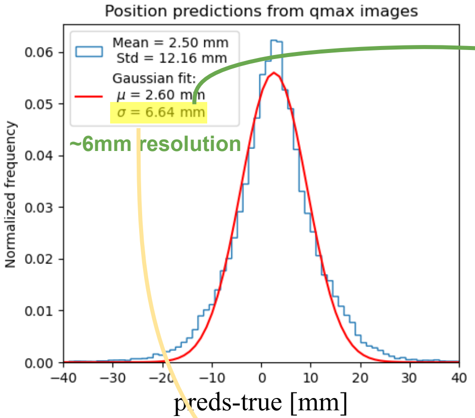

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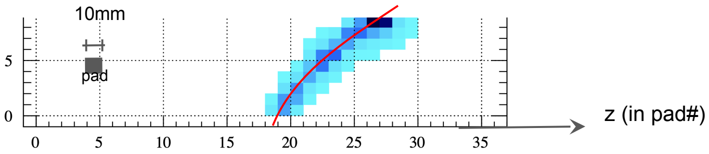
vs classical reconstruction: <0.8mm



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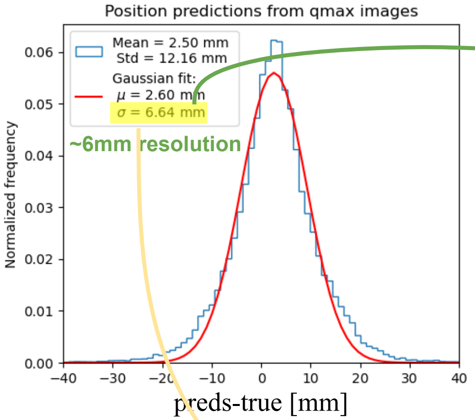

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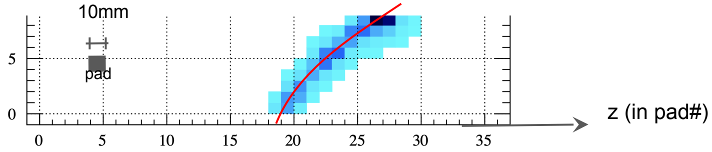

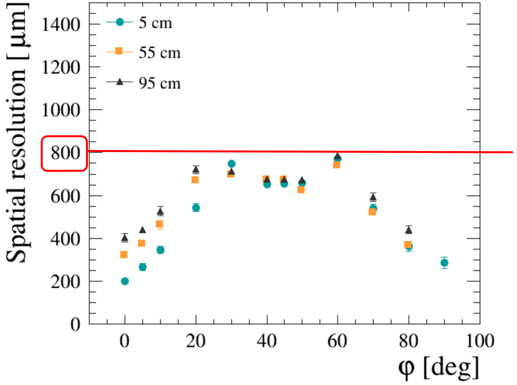

from DESY test beam data with a HA-TPC prototype (2022)

3. Machine learning: neural network for track reconstruction

▻ Current challenges and investigations

❏ Want better spatial resolution

3. Machine learning: neural network for track reconstruction

▻ Current challenges and investigations

❑ Want better spatial resolution:

⤷ understand why it is limited to the resolution of a pad (~10mm)

3. Machine learning: neural network for track reconstruction

▻ Current challenges and investigations

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☑ try predicting projection of z_{ini} on TPC entrance instead of z_{ini}

☑ generate new simulation data with only vertical tracks at different Δz, drift distance

□ try predicting relative z position wrt pad center instead of absolute position (z_{ini})

3. Machine learning: neural network for track reconstruction

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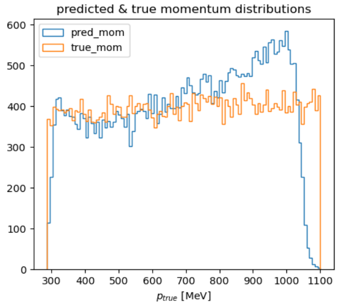

3. Machine learning: neural network for track reconstruction

▻ Current challenges and investigations

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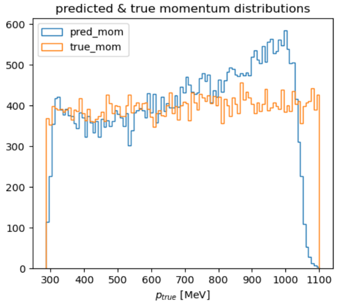
❏ Want better match between distributions of predicted vs true momentum:

☑ standardization of the data: $x_i^{NEW} = \dfrac{x_i - \mu_x}{\sigma_x}$

☑ use more events (75 000 → 280 000)

(☑) border problem? decrease momentum range during test phase (but need more events)

□ generate even more events → ~500 000

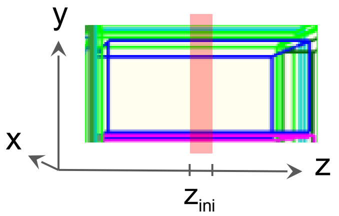


3. Machine learning: neural network for track reconstruction

▻ Current challenges and investigations

Understanding the limitation on z_{ini} resolution

New simu:
vertical tracks
Δz = 1cm (around 1 pad)



3. Machine learning: neural network for track reconstruction

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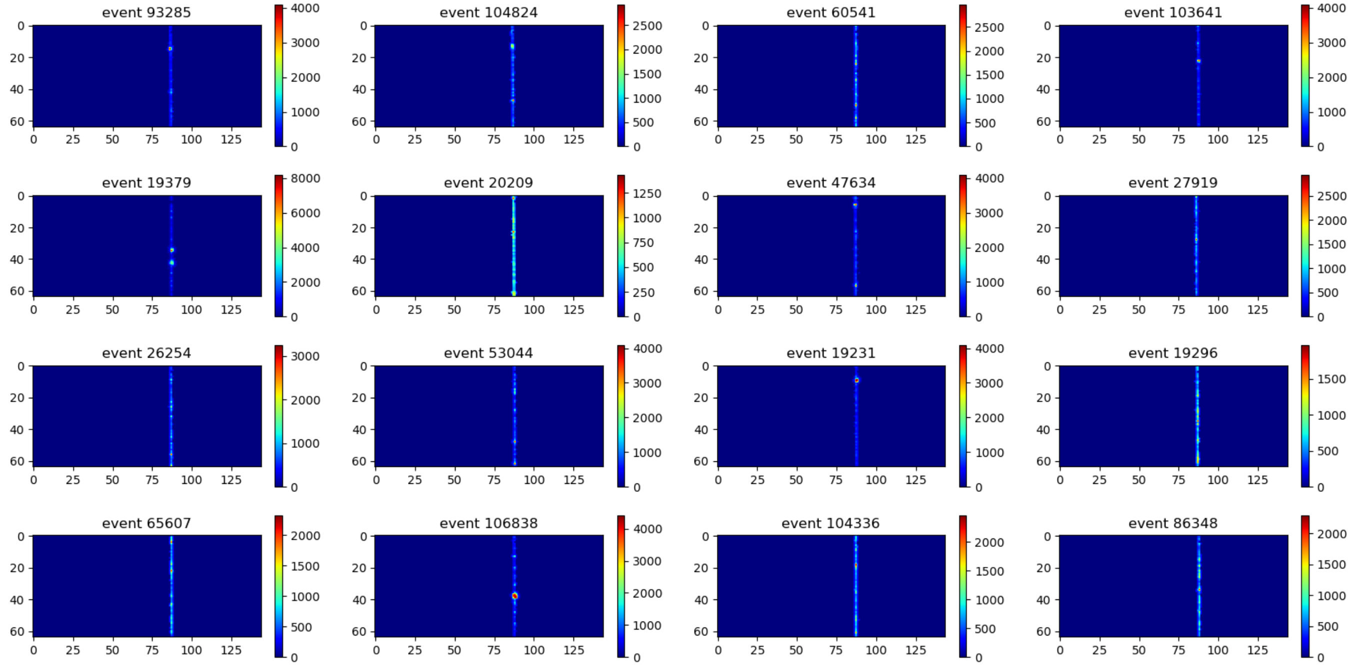

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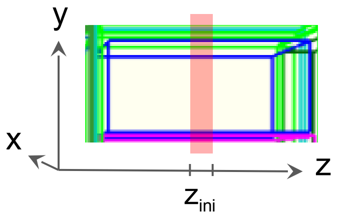
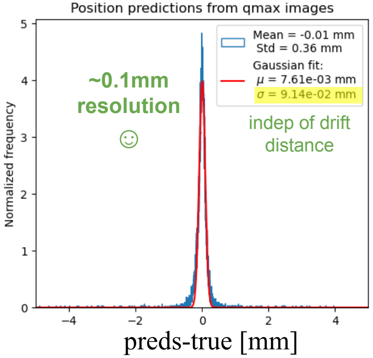


3. Machine learning: neural network for track reconstruction

▻ Current challenges and investigations

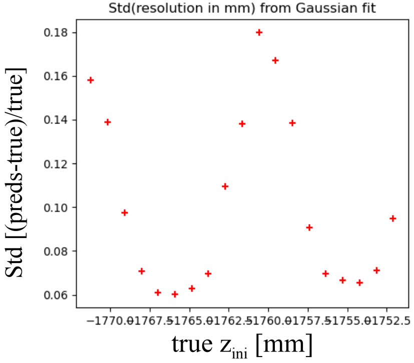
Understanding the limitation on z_{ini} resolution

1 prediction: z_{ini}
~100 000 events



~0.1mm resolution ☺

indep of drift distance



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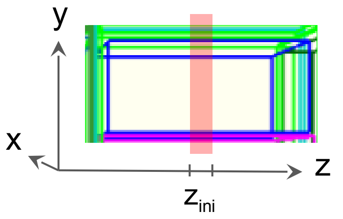

3. Machine learning: neural network for track reconstruction

▻ Current challenges and investigations

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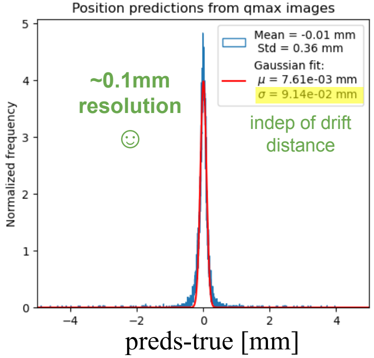

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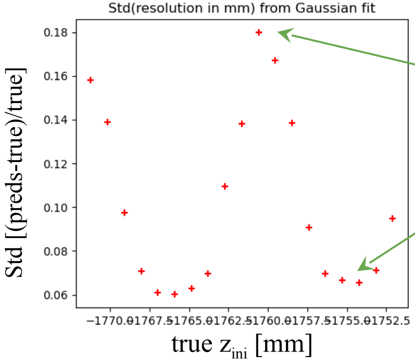
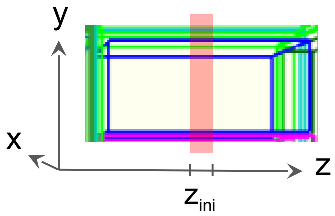


worst at pad center

better when between 2 pads

New simu:
vertical tracks
Δz = 1cm (around 1 pad)



3. Machine learning: neural network for track reconstruction

▻ Current challenges and investigations

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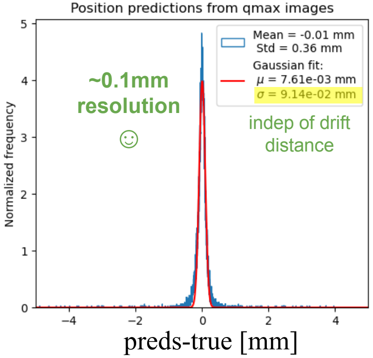
~100 000 events

Understanding the limitation on z_{ini} resolution



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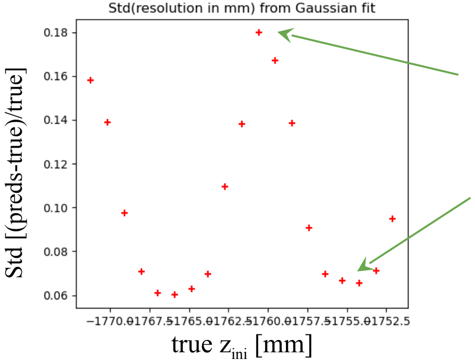

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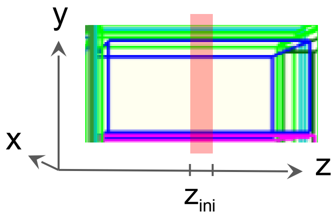
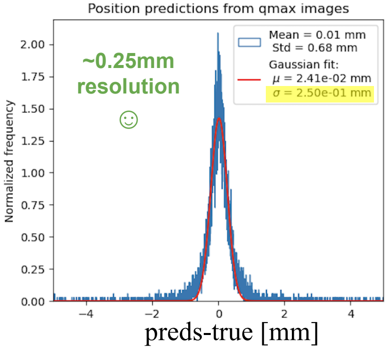
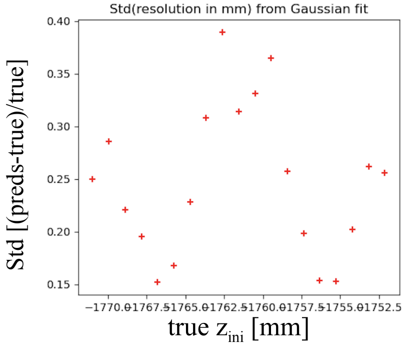




~0.25mm resolution ☺



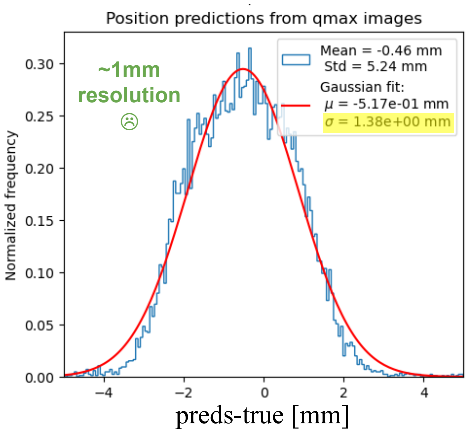
using only the 1rst row of the image, as during test beam

3. Machine learning: neural network for track reconstruction

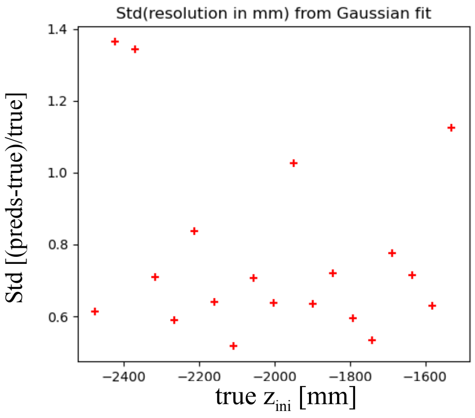
▻ Current challenges and investigations

Understanding the limitation on z_{ini} resolution

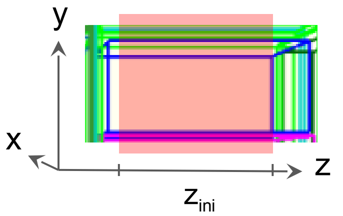
1 prediction: z_{ini}
~100 000 events



~1mm resolution ☹



New simu:
vertical tracks
Δz = 1m (all TPC)



⤷ now try predicting **relative** position
⤷ can also try a simu with intermediate Δz

▻ Internship conclusion

- ★ Development from scratch of a new reconstruction technique with ML
- ★ There remains a lot to understand; biases, resolution vs momentum, initial position resolution
- ★ But gives comparable results to the classical/’official’ reconstruction method

⇢ **Promising! Still work to do & ideas to try!**

4. Prospects for the PhD

Continue the work on this neural network:

Main goal: decrease systematic uncertainties for precise CPV measurements
i.e. need precise track parameters since used in event selection, flux characterizations, cross sections

- aim for same/better resolution on all track parameters (z_{ini}, p_t, ϕ) than with classical reconstruction
- add the FWHM an tmax information to the input images and see how it goes
- try the CNN on test beam data (and later T2K-II data once ND280 upgrade is installed)

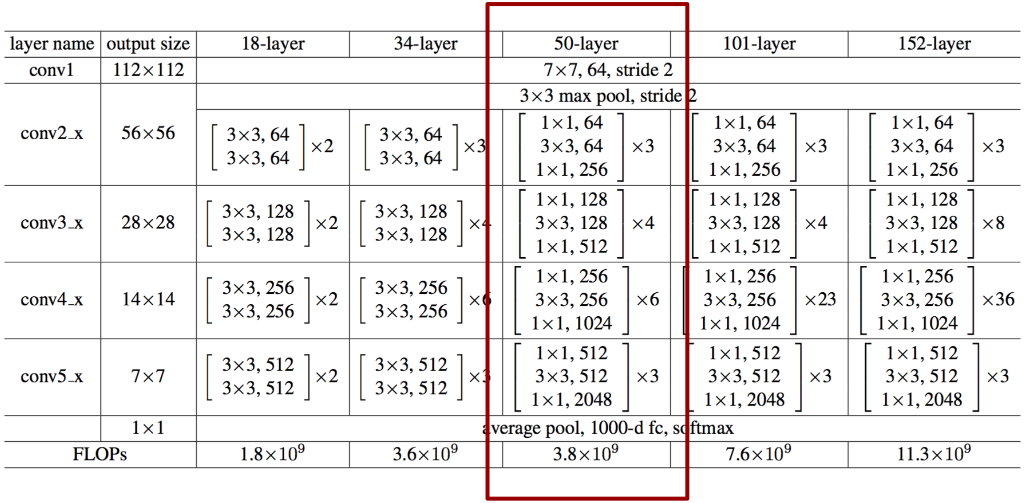
New horizons:

- collaborate more with a T2K ML group (SuperFGD)?
- experiment with another neural network architecture?
- oscillation analysis from ND280 upgrade data: study of ν_e and anti- ν_e interactions

Back-up slides

ML with PyTorch

- ➢ **ResNet50** ⟶



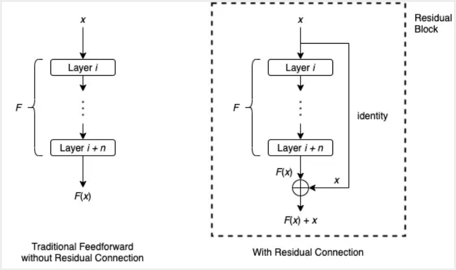
layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times23$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

- ➢ **Loss**: $\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$

- ➢ **Optimizer** (how to update weights): extension of stochastic gradient descent

- ➢ **Hyperparameters:**
  - ▫ training/validation/test set splitting (now: 70/15/15)
  - ▫ **batch size**: commonly used: 64, also tried 1, 16, 32, 128
  - ▫ **learning rate**: initially at 0.01 + scheduler to decrease it dynamically
  - ▫ **patience:** how many epochs before decreasing LR
  - ▫ **epoch size** (1, 10, 30, 50, 100) -> implement dynamical epoch size
  - ▫ ‘model choice’: ResNet50, 101, 152 for now but mostly ResNet50

Residual NN

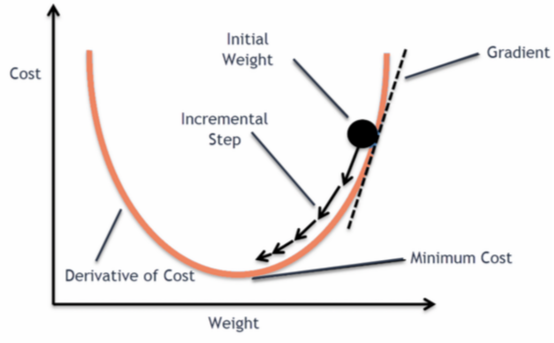


Traditional Feedforward without Residual Connection

With Residual Connection

ML with PyTorch

NNlearning process:



1/ Measures how wrong the NN predictions are:

$$\underset{\text{or 'loss'}}{cost}(w, b) = \frac{1}{N} \sum_{j=1}^{N} \left[y^{j}_{pred}(w, b) - y^{j}_{true} \right]^{2}$$

2/ Performs a **gradient descent** algo to find the weight/bias values which best minimize the cost

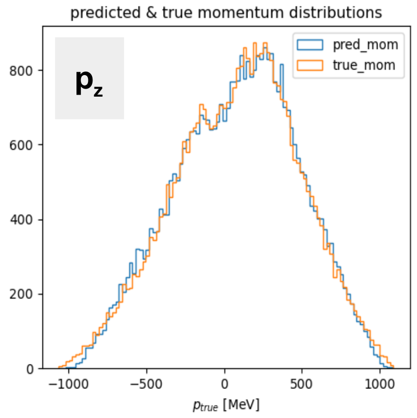
This is done by looping several times over the all dataset (1 loop = 1 'epoch')

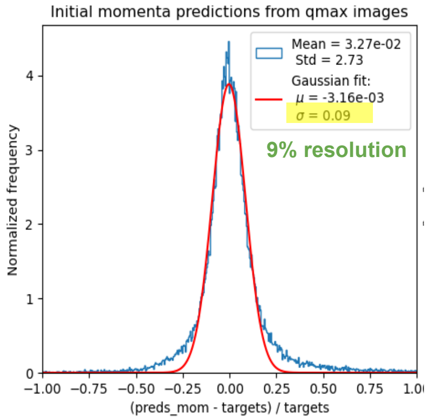
$$\theta_j = \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

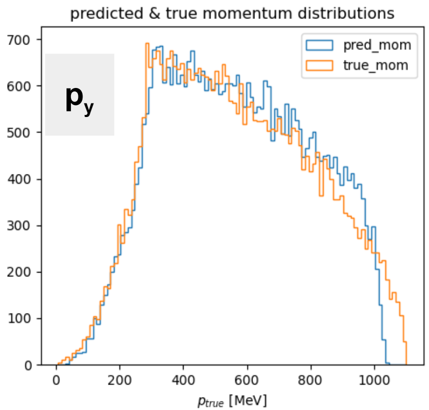
params (w,b) learning rate cost function

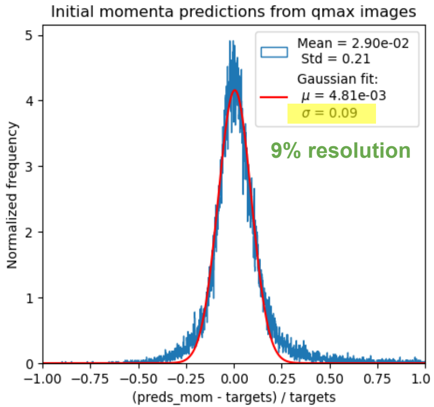
Other results

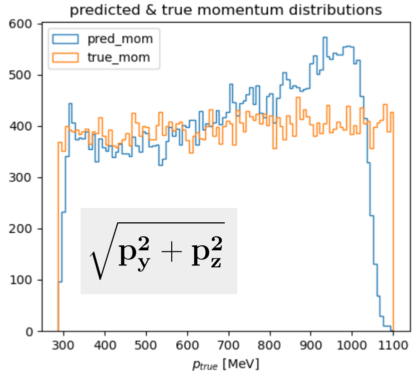
3 predictions: p_y, p_z, p_t
~280 000 events

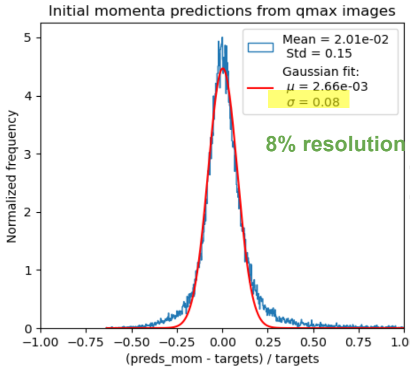


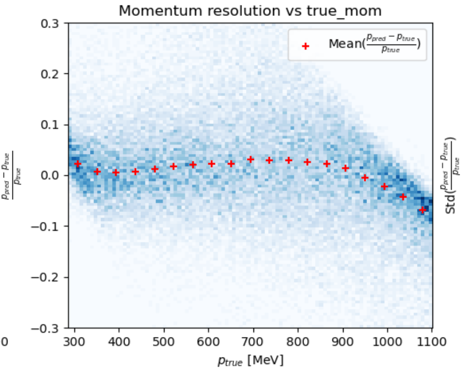


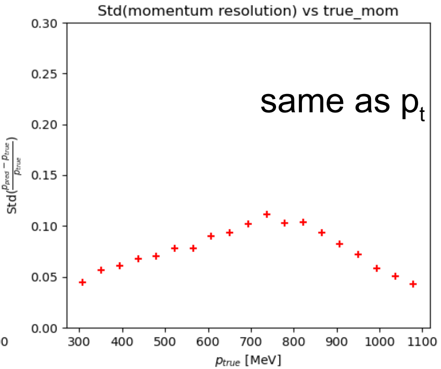




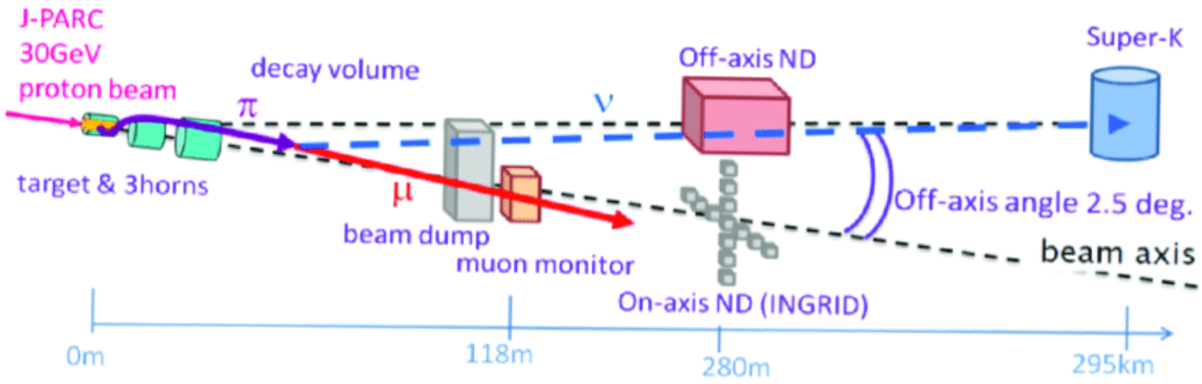






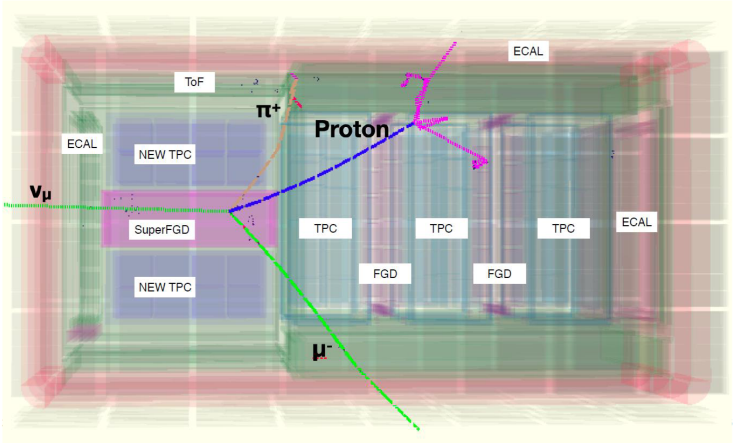


T2K beam production

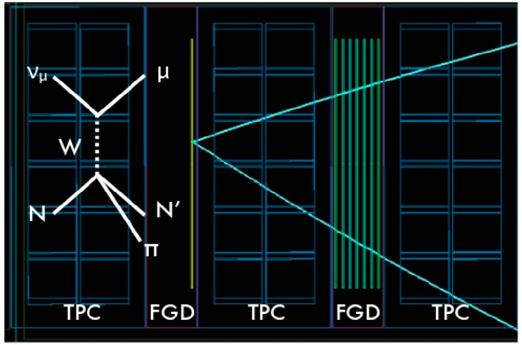


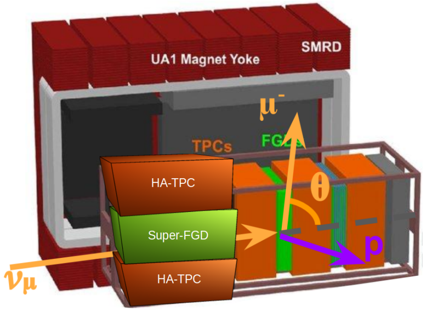
Event displays before/after ND280 upgrade

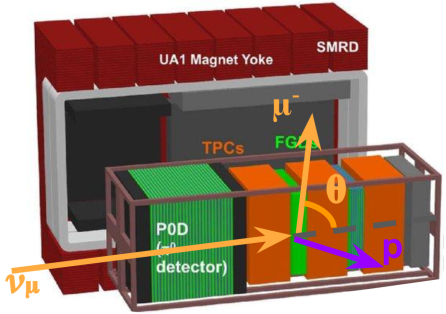
event simulated with ND280 upgrade configuration



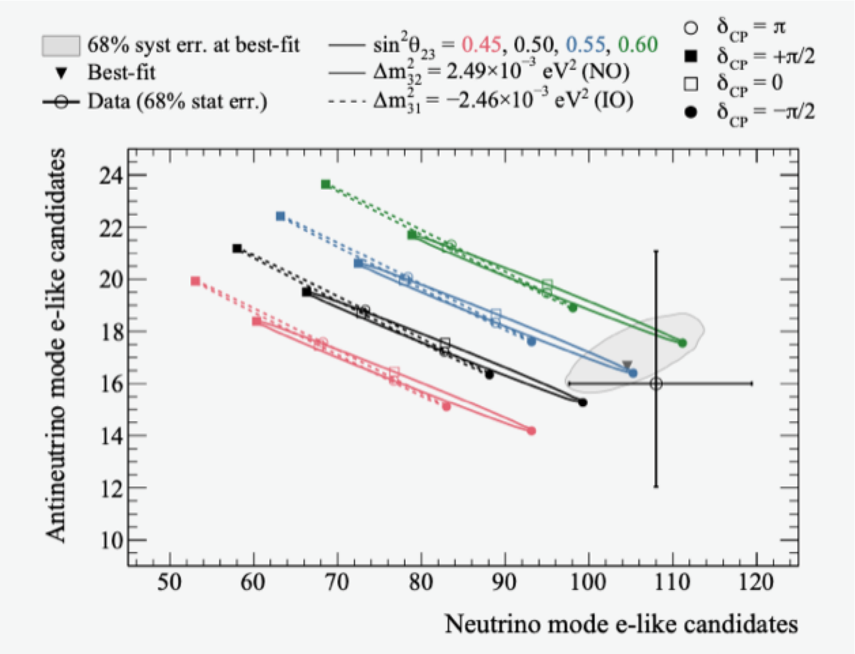
event display in old configuration







δ_{CP} measurements with T2K



Apparition number of anti-ν_e vs apparition number of ν_e at the far detector SK