



# AFB studies at 500 GeV

## LCFI+ Flavour Tag Optimization

*ILD Top/HF group meeting  
3/02/23*

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**AITANA**



- 1 Particle Swarm Optimization: Final results.
  - ROC plots, ROC Integrals and efficiency-purity plots.
- 2 Introducing dEdx to LCFI+.
  - Implementation finished.
    - Need to be reviewed.
- 3 Re-training of flavour tag weights using dEdx.
  - In *preliminary phase*.



# Particle Swarm Optimization

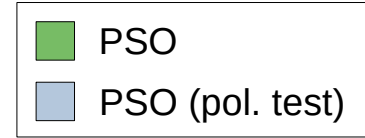


# PSO – Performance plots

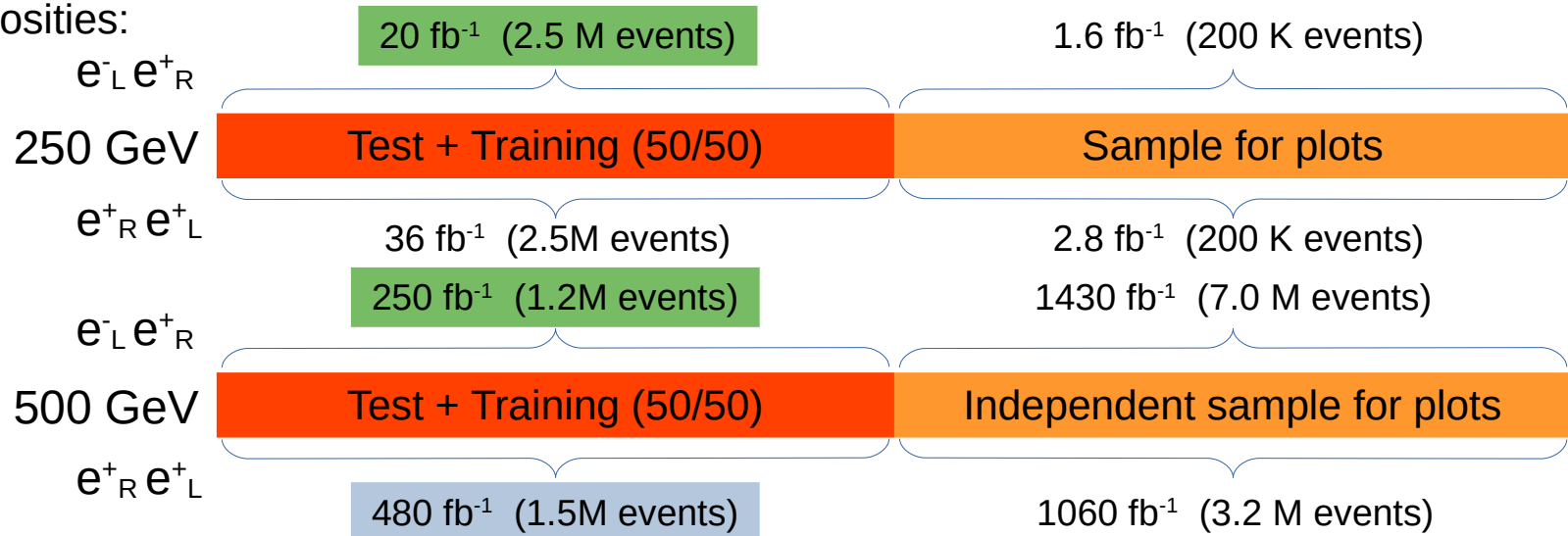
- On the next slides:

- Plots for b-tag and c-tag:

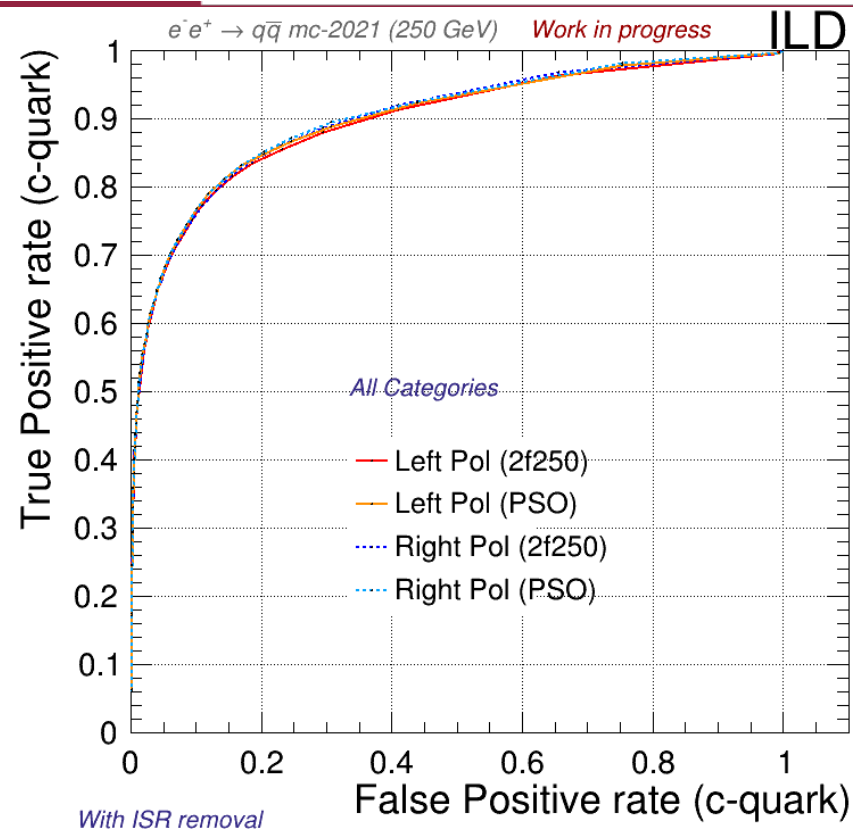
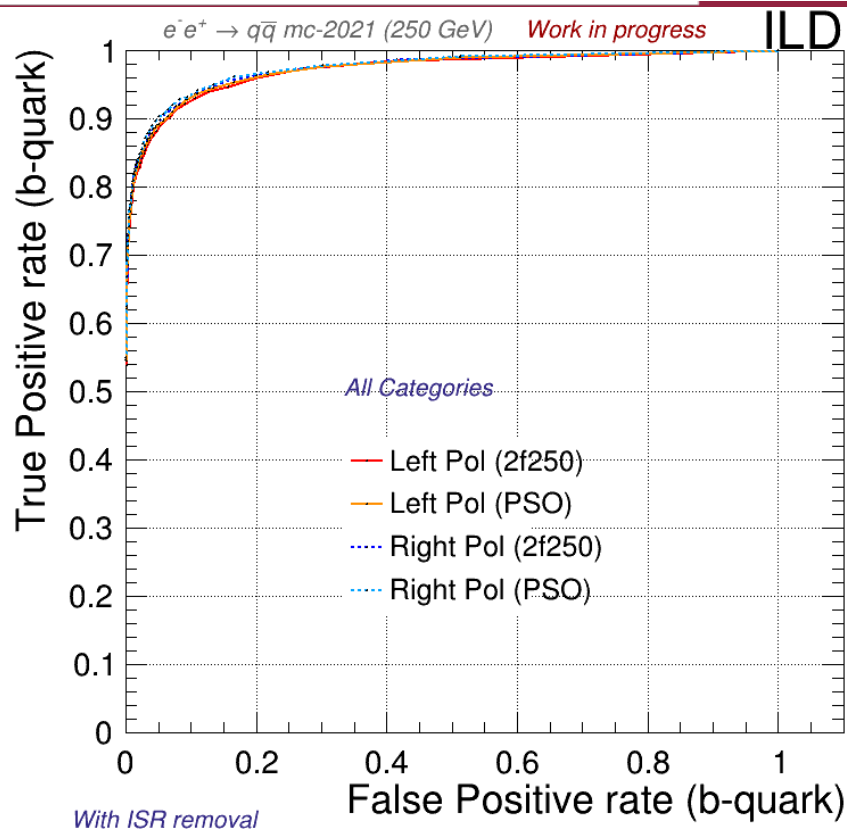
- ▶ ROC, considering the desired flavour as signal and the others as background.
  - Also approximated AUC (ROC Integral) values to compare
- ▶ Purity vs Efficiency.



- Luminosities:



# PSO Performance (250 GeV)

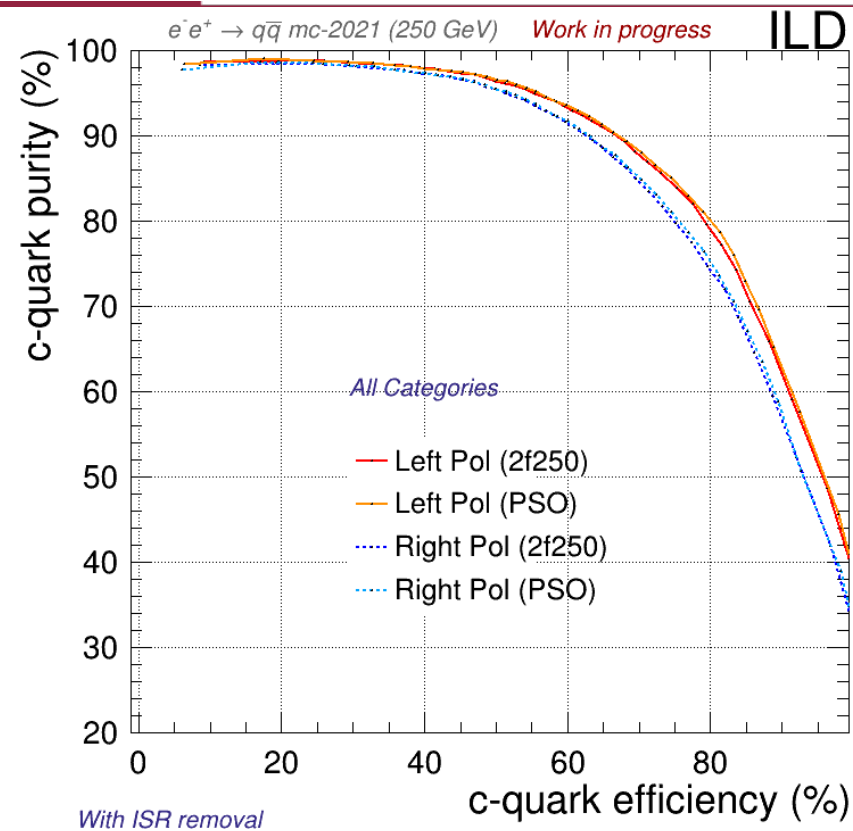
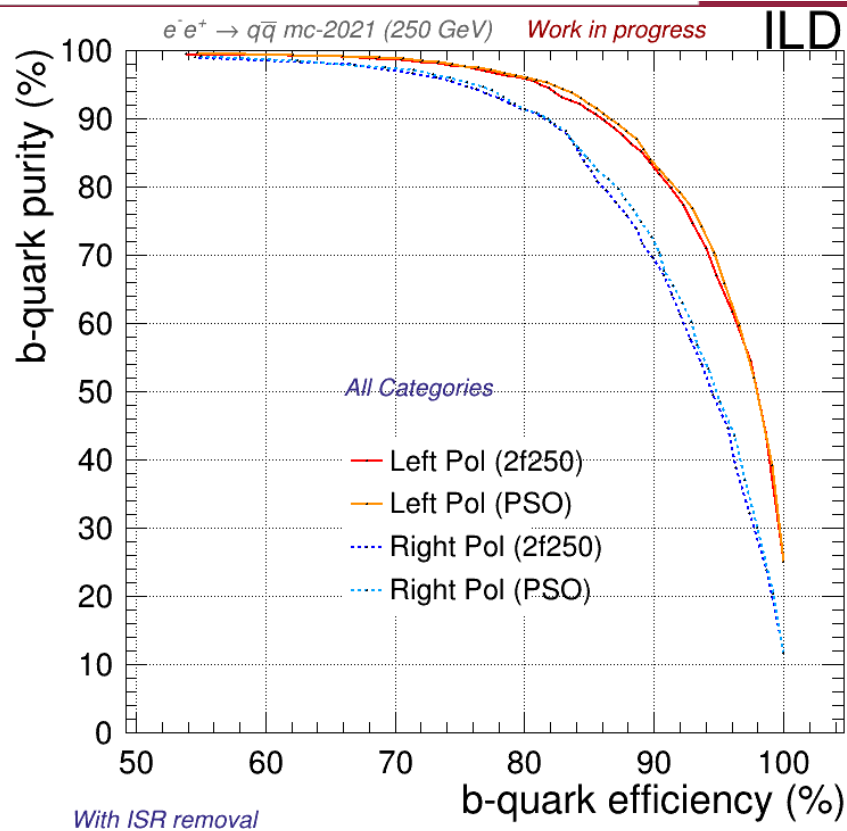


[Integrals 2f250]  $e^-_L$ : 0.971 |  $e^-_R$ : 0.973  
[Integrals PSO]  $e^-_L$ : 0.973 |  $e^-_R$ : 0.976

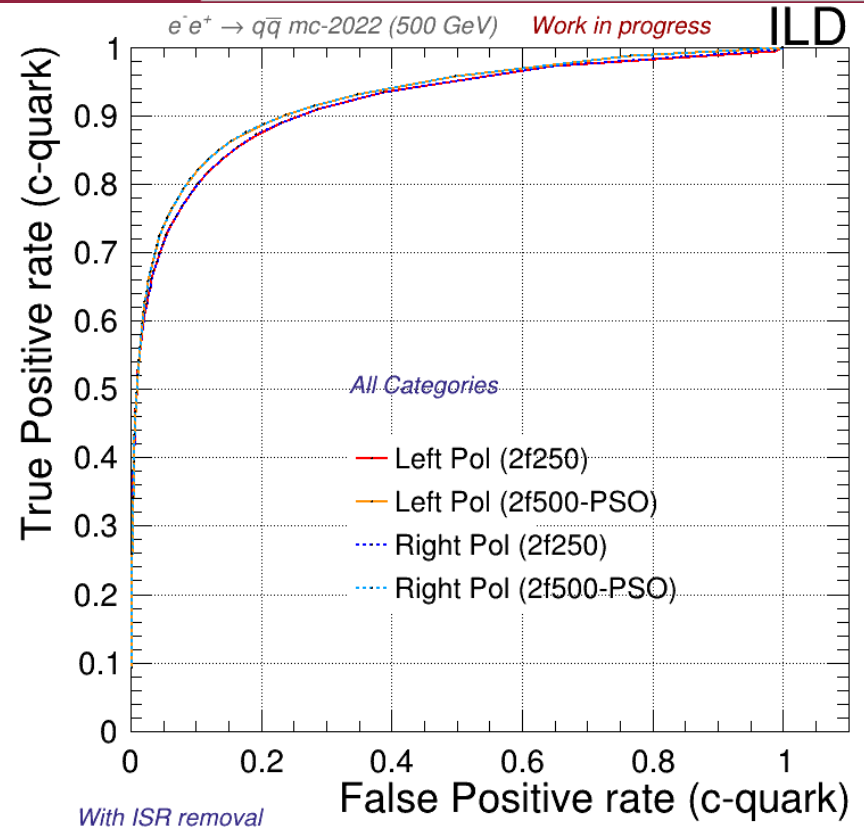
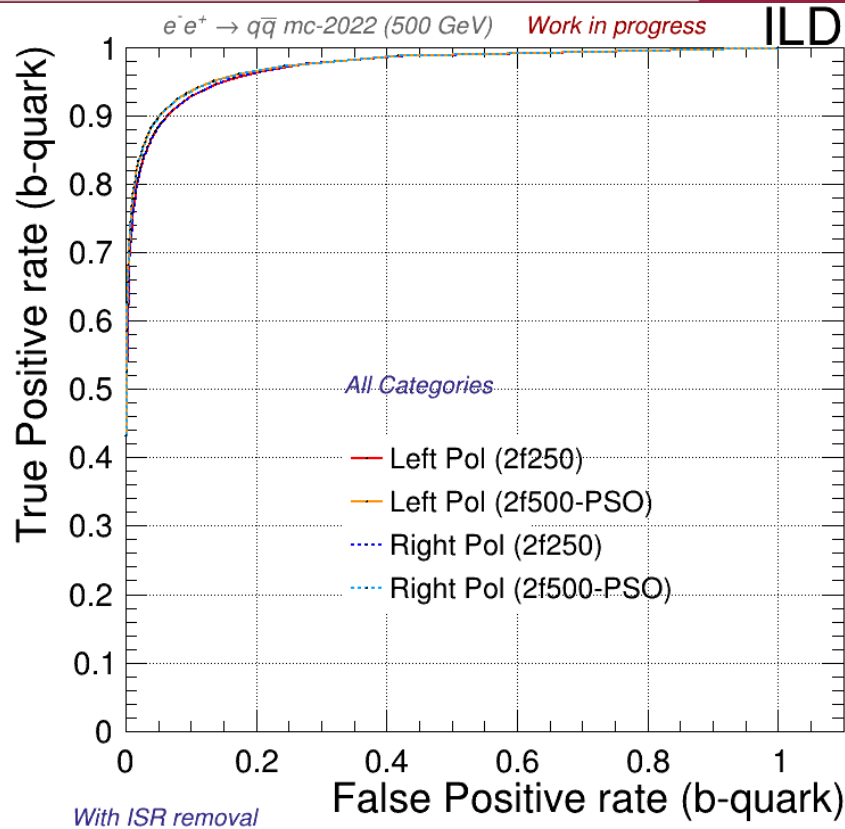
[Integrals 2f250]  $e^-_L$ : 0.898 |  $e^-_R$ : 0.902  
[Integrals PSO]  $e^-_L$ : 0.901 |  $e^-_R$ : 0.904



# PSO Performance (250 GeV)



# PSO Performance (500 GeV)

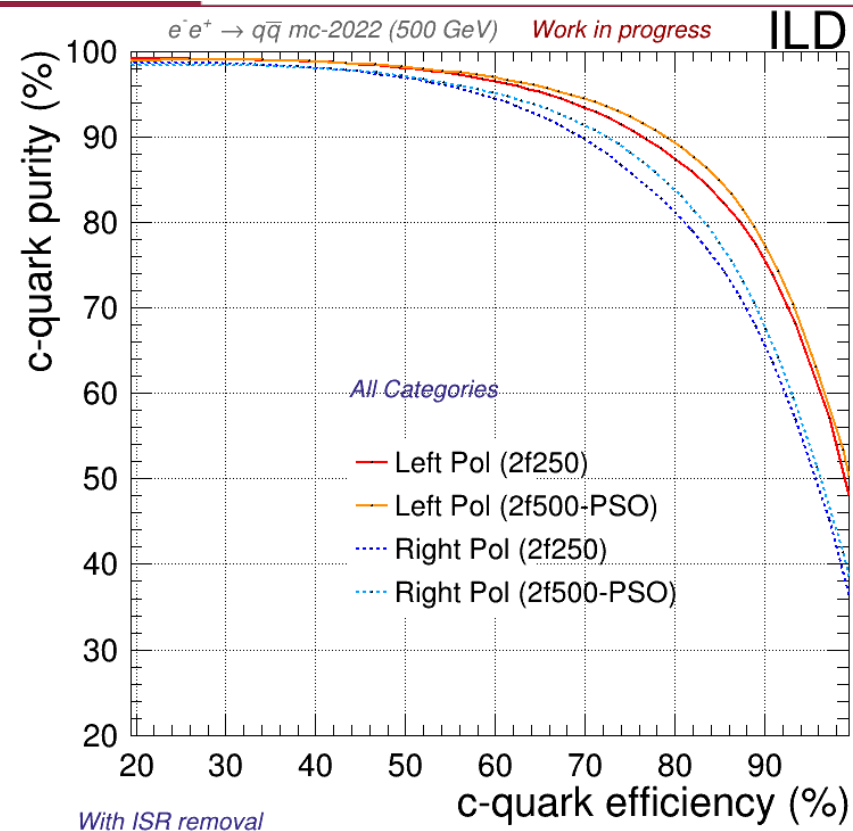
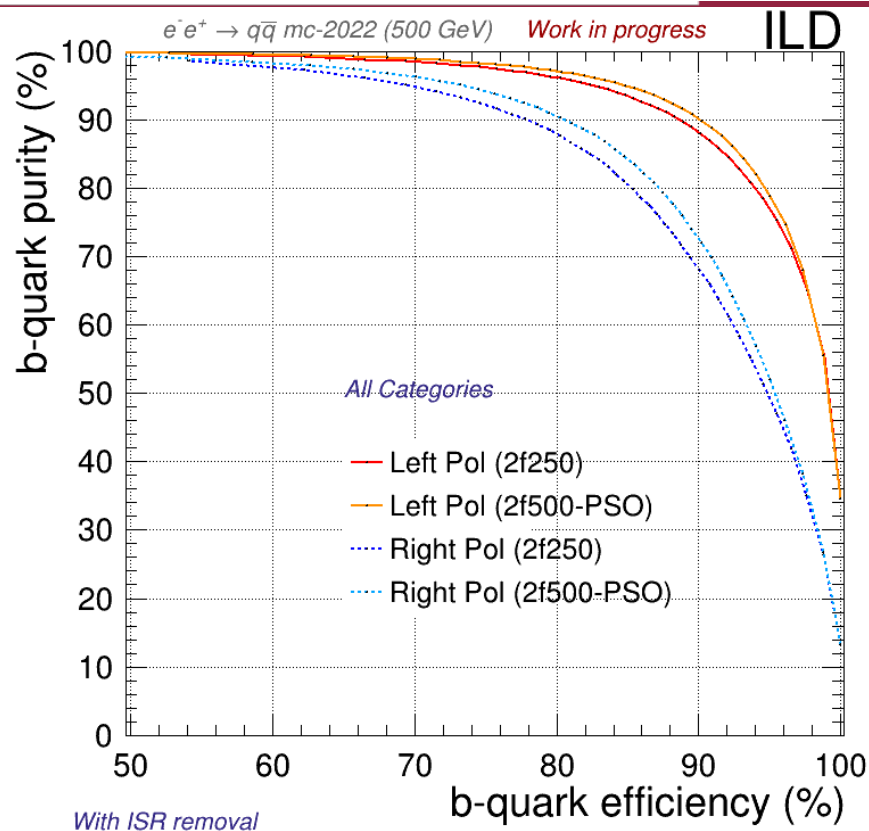


[Integrals 2f250]  $e^-_L$ : 0.972 |  $e^-_R$ : 0.971  
[Integrals PSO]  $e^-_L$ : 0.974 |  $e^-_R$ : 0.974

[Integrals 2f250]  $e^-_L$ : 0.917 |  $e^-_R$ : 0.917  
[Integrals PSO]  $e^-_L$ : 0.925 |  $e^-_R$ : 0.925

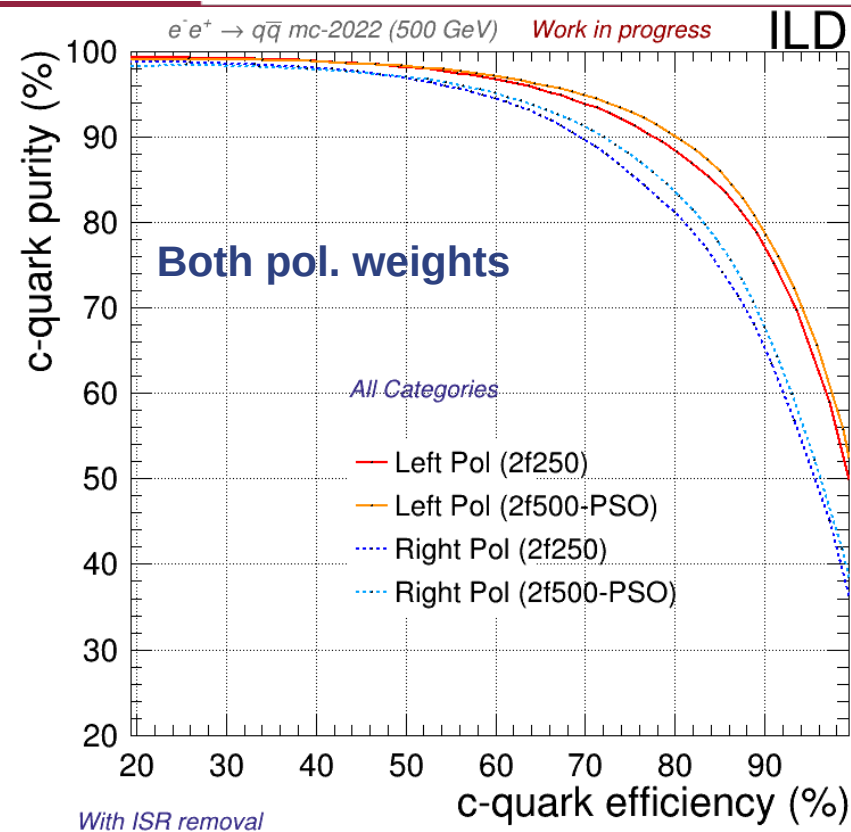
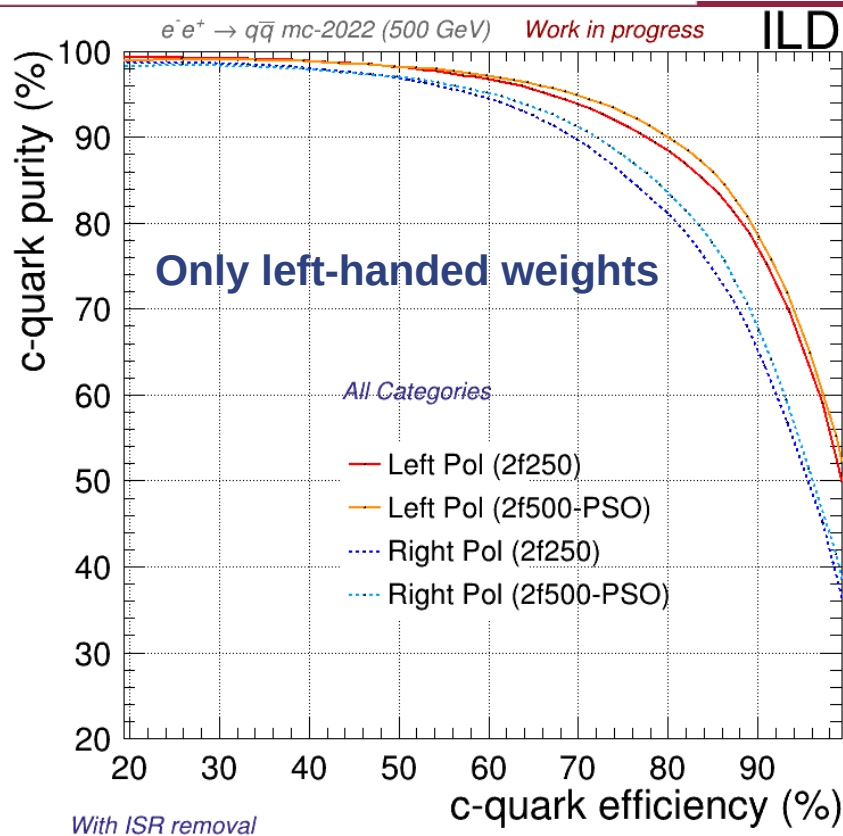


# PSO Performance (500 GeV)





# Polarization dependence (500 GeV)



Minimal impact when training with sets of specific polarization



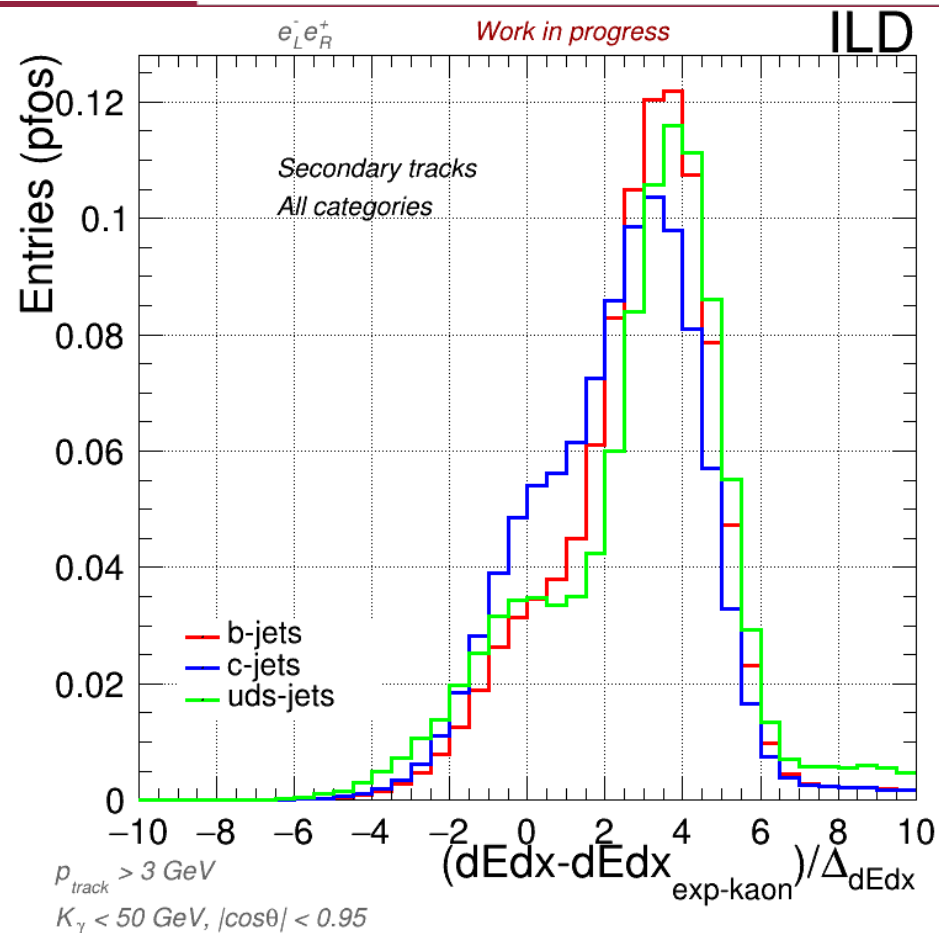
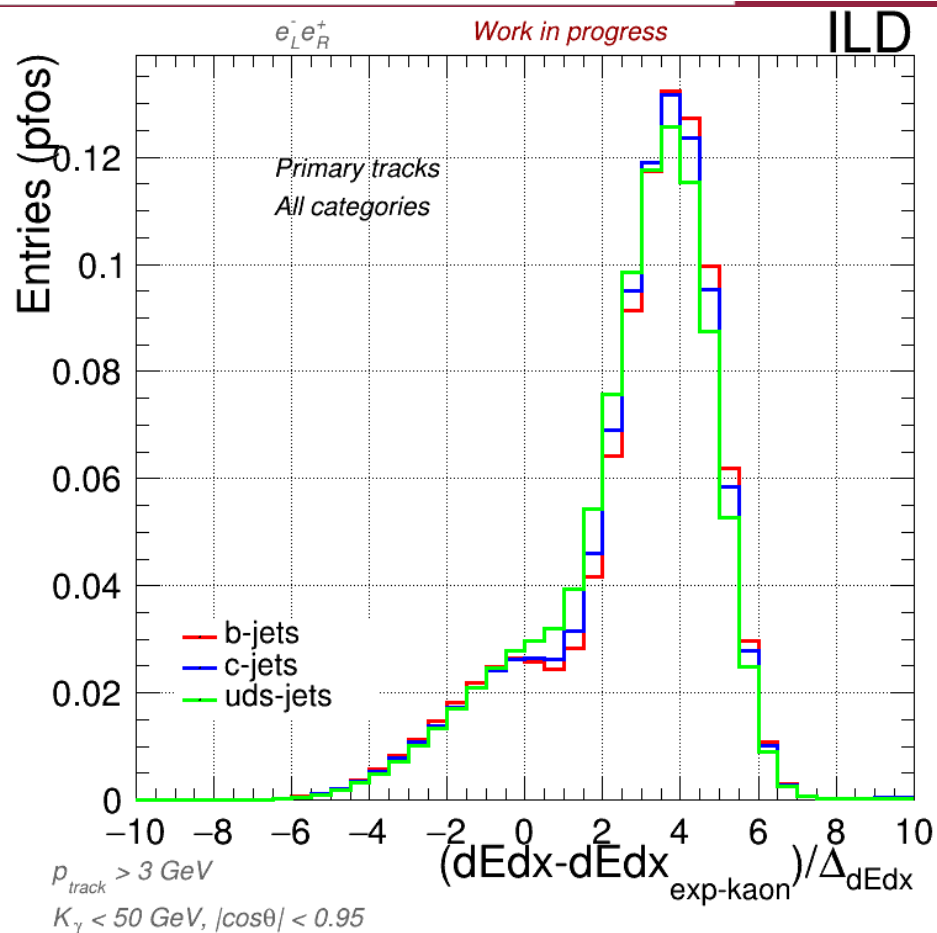
- We can notice:
  - An **improvement** in b-tag and c-tag.
    - At 250 GeV and 500 GeV.
  - The impact in efficiency if we train for different polarizations is **negligible**.
  
- Other observations (*behind the scenes*):
  - The new weights produce more stable results:
    - Performed as good with the data used for training and the new and bigger samples used for the final results.



# Introducing dEdx to LCFI+



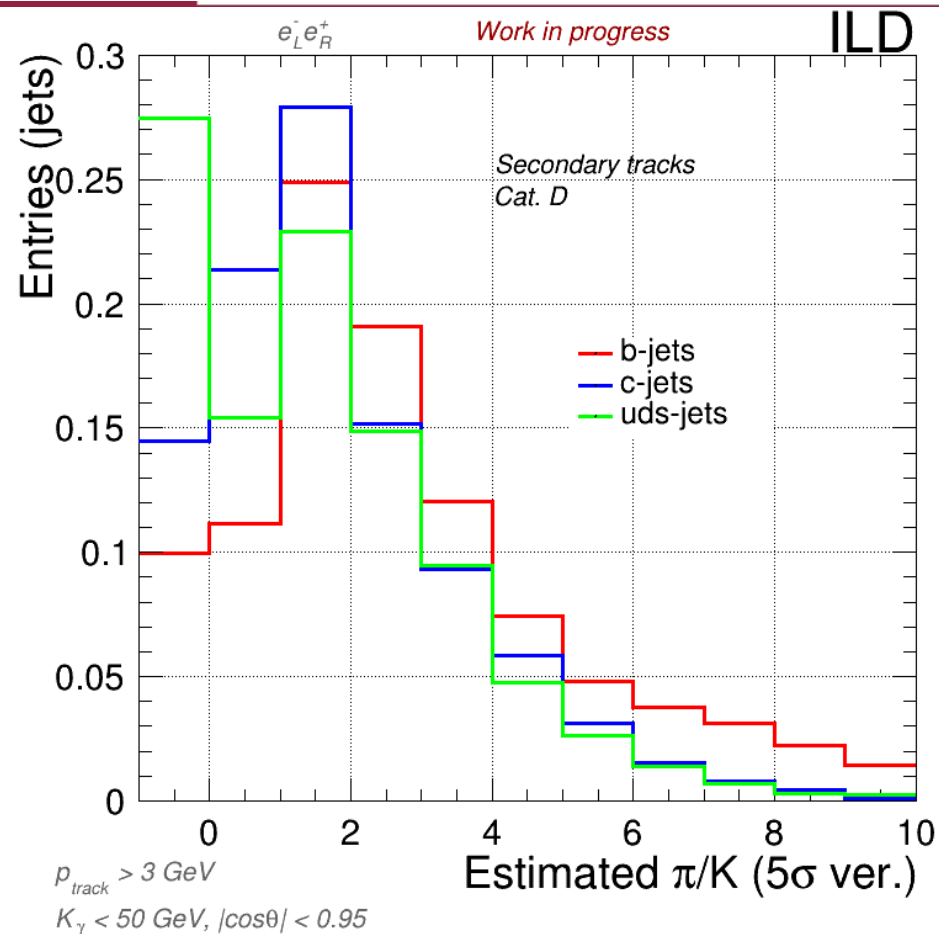
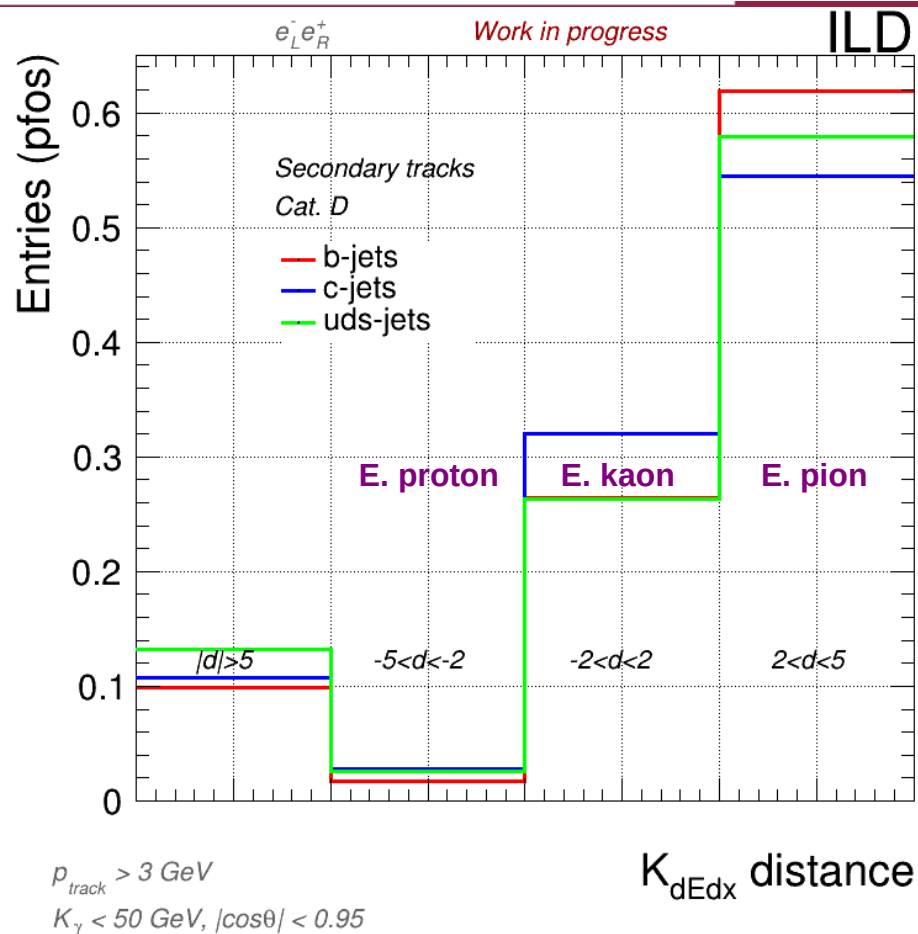
# dEdx – KDS for different quark flavours



We classify the pfos depending on the Kaon Distance Significance (loaded in our .Icio files)



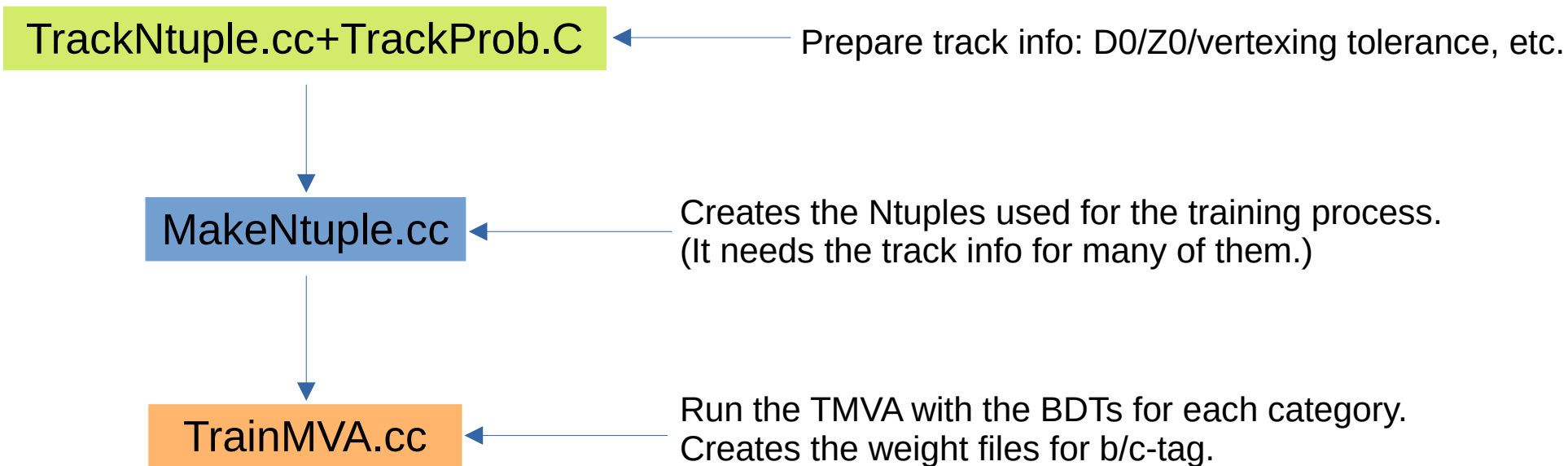
# dEdx - KDS classification comparison



We build estimated  $\pi/K$ ,  $\pi/p$  and  $K/p$ . If the denominator is 0, we set the ratio to -1.



# Re-training flavor tagging (coding)

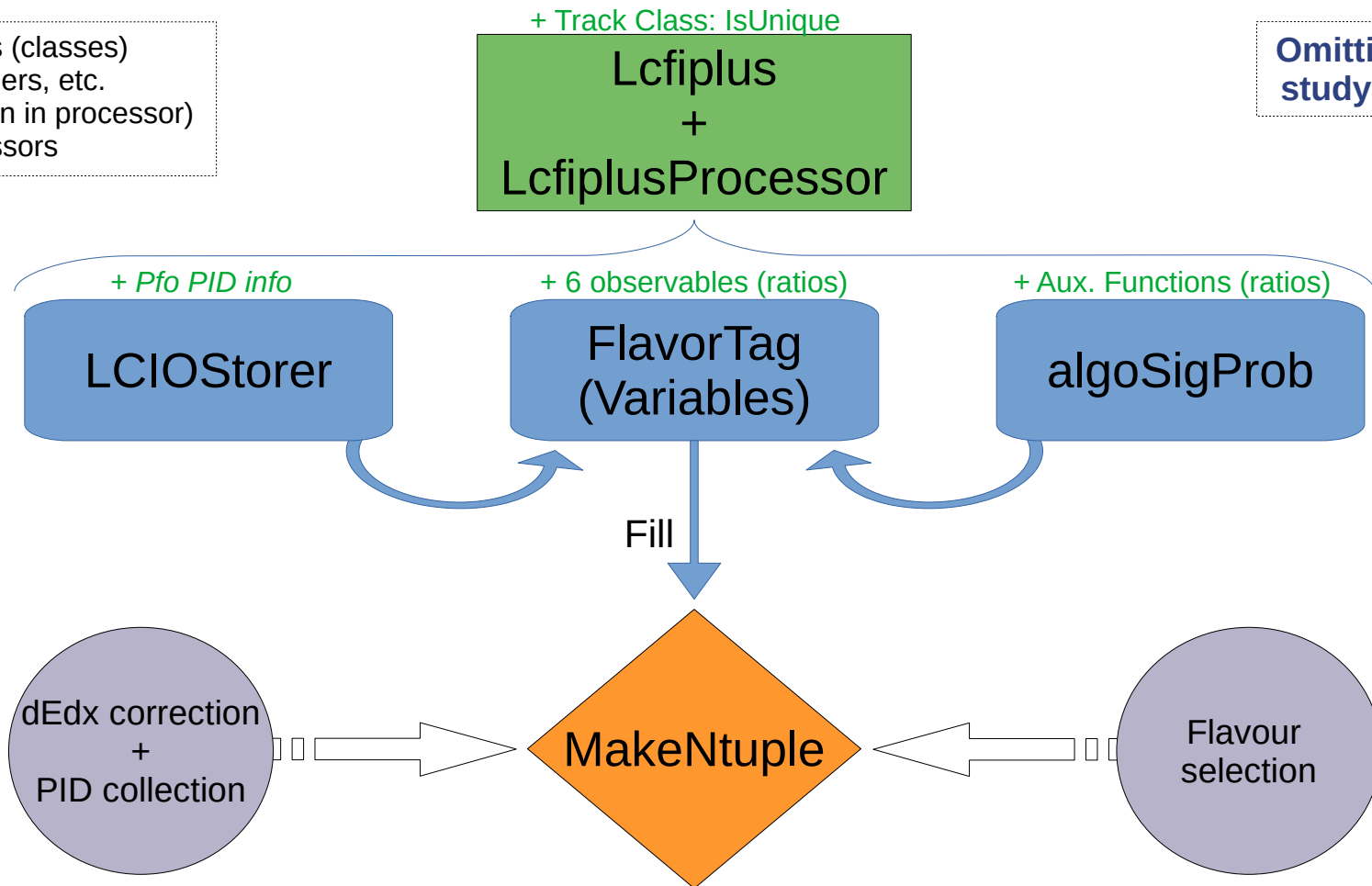


To introduce dEdx in the training process we need to load it into the Ntuples when we run MakeNtuple.cc

# LCFI+ MakeNtuple Workflow (+dEdx)

Omitting parts I didn't study or interact with

- Main definitions (classes)
- Functions, readers, etc.
- Algorithm (to run in processor)
- External processors



# Retraining of flavour tagging using dEdx

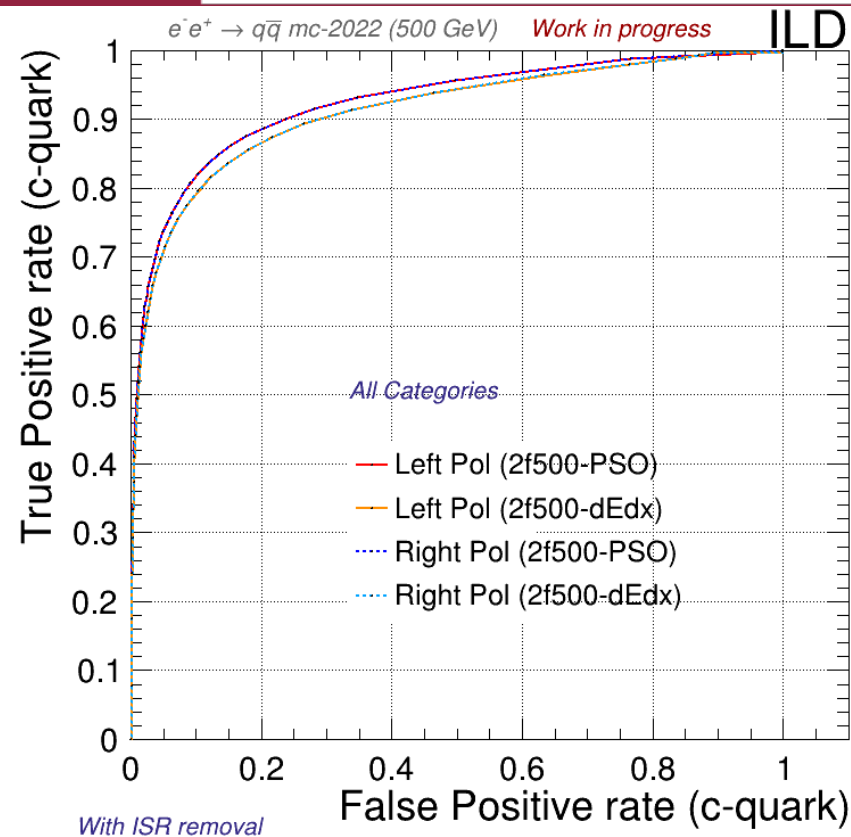
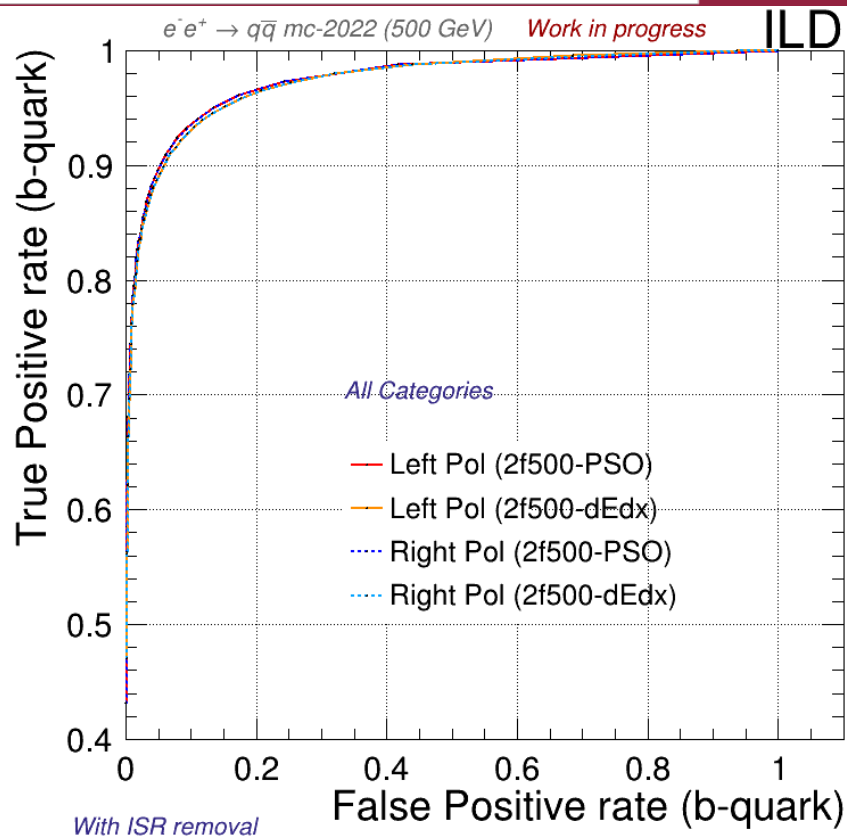




- I ran a first test using the same samples than the 500 GeV PSO studies.
  - Using the same configurations for the BDTs but with the 6 extra variables in the Ntuples.
- On the next slides:
  - ROC plots.
    - ROC Integral values.
  - Efficiency vs purity plots.



# PSO vs dEdx Performance (500 GeV)

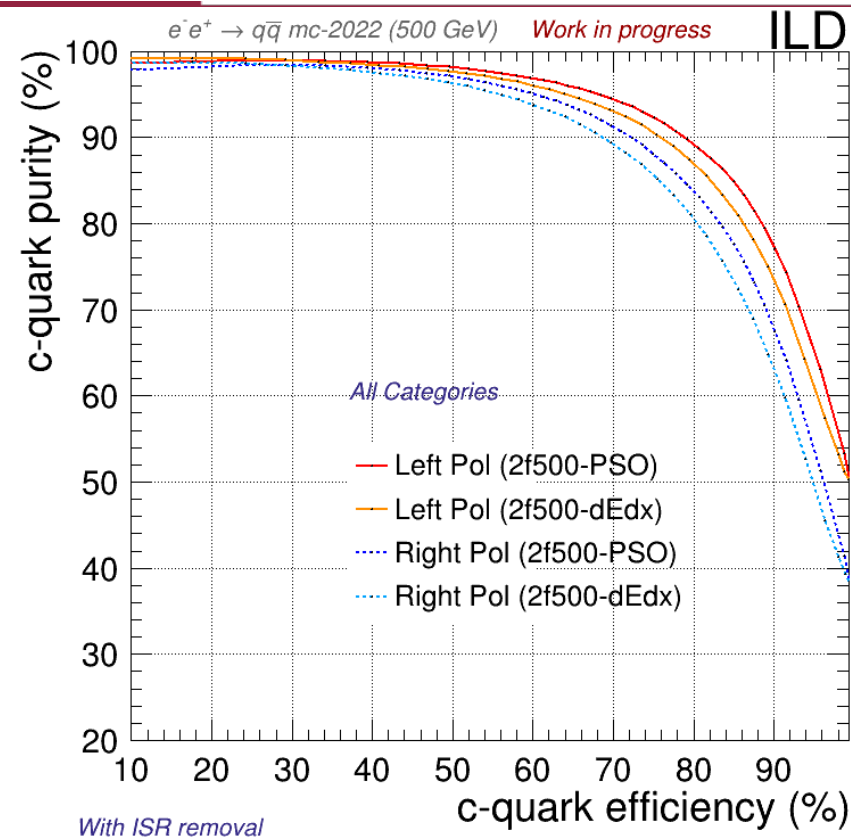
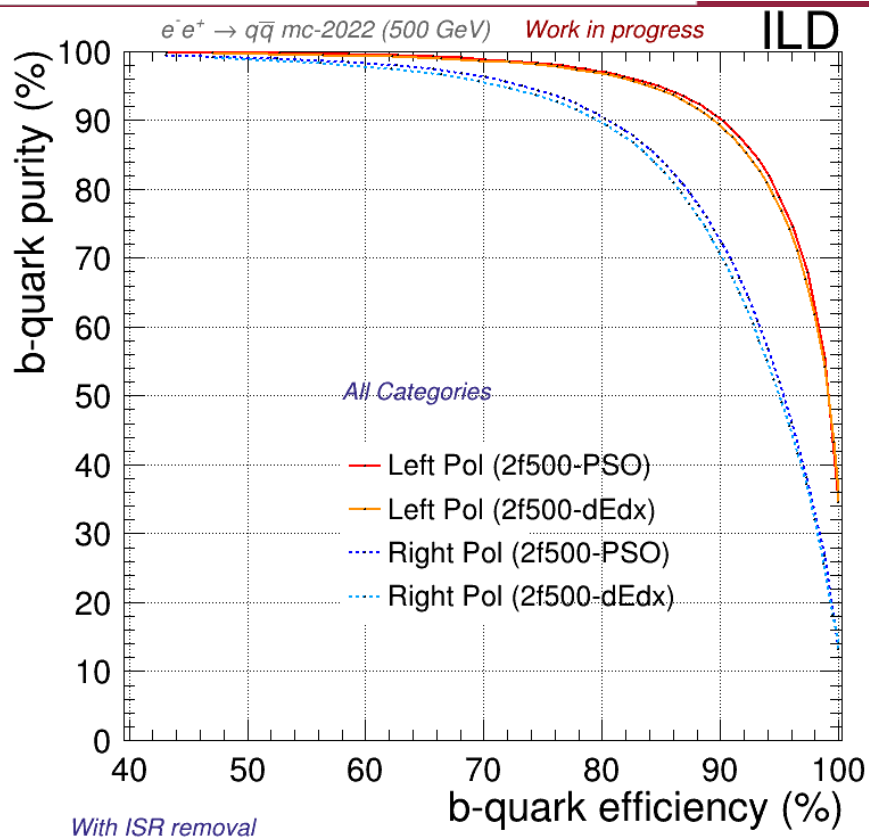


[Integrals PSO]  $e^-_L$ : 0.974 |  $e^-_R$ : 0.974  
[Integrals dEdx]  $e^-_L$ : 0.973 |  $e^-_R$ : 0.973

[Integrals PSO]  $e^-_L$ : 0.925 |  $e^-_R$ : 0.925  
[Integrals dEdx]  $e^-_L$ : 0.912 |  $e^-_R$ : 0.912



# PSO vs dEdx Performance (500 GeV)



Now we have worst performance! :(



- Now, dEdx can be implemented in LCFI+ and used for Flavour Tagging.
  - Needs to be reviewed.
- We have more information available but *worse performance*?!
  - Since we are using BDTs highly optimized (PSO) to a specific set of variables:
    - We were *underfitting* the new set.
- We have to fix the underfitting problem and check the real impact of dEdx.
  - Run the PSO again, using all variables.
    - Run for 250 GeV as well.
- After it, select the final set of weights.
  - Then, move to **physical studies** ( $R_q$  &  $A_{FB}$ )!





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**Thanks for your attention**

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# Back-up

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With ISR removal

Z-Pole (LCFI+ paper<sub>1</sub>)

250 GeV samples

500 GeV samples

Events (%)			
Cat.	b jets	c jets	uds jets
A	22.9	59.5	98.1
B	39.7	39.8	1.80
C	13.5	0.54	0.02
D	23.8	0.19	0.04

Events (%)			
Cat.	b jets	c jets	uds jets
A	13.9	46.2	98.2
B	30.5	51.0	1.59
C	23.9	2.29	0.11
D	31.7	0.55	0.14

Events (%)			
Cat.	b jets	c jets	uds jets
A	11.2	35.8	96.7
B	28.6	58.3	2.64
C	22.9	4.65	0.26
D	37.3	1.27	0.42

1. LCFIPlus: A Framework for Jet Analysis in Linear Collider Studies

Category	A	B	C	D
Number of vertices	0	1	1	2
Number of single-track pseudovertrices	0-2	0	1	0



- We are already working with these Gradient Boosted Decision trees using ROOT's Toolkit for MultiVariate data Analysis (TMVA). We use the following parameters:
  - **BoostType=Grad.**
  - NTrees.
  - Shrinkage.
  - UseBaggedBoost:BaggedSampleFraction.
    - **Bagging:** A new sampling is performed before each step (removes biases).
  - NCuts (binning used when sampling).
  - MaxDepth (N<sup>o</sup> of leaves).

**The Particle Swarm Algorithm optimizes the use of *these parameters***

**We used all but the orange ones, which are method definitions**





- Particle Swarm Optimization is a Gradient-free, bio-inspired, stochastic, population-based algorithm to optimize any kind of process towards a certain goal:
  - No maths involved in the optimization (no gradients or loss functions!).
  - It just keeps trying configurations and saves the best-performing one.
    - It mimics how animals look for resources, by trial and error.
- How it works:
  - We have N “particles” (in our case: configurations of the BDT). Then:
    - 1) The BDT runs with the configuration of the particle.
    - 2) When finished, each particle gets a performance score.
      - We define a Function Of Merit (FOM) for this scoring
    - 3) We track each particle’s best configuration and the best global one.
    - 4) The particles moves to a new configuration (next slide).

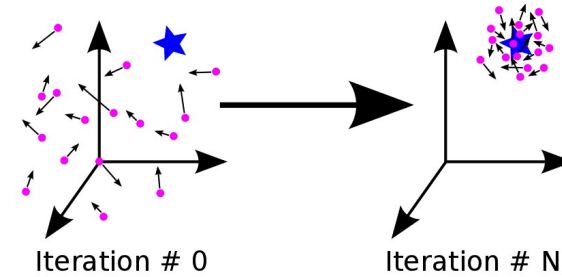


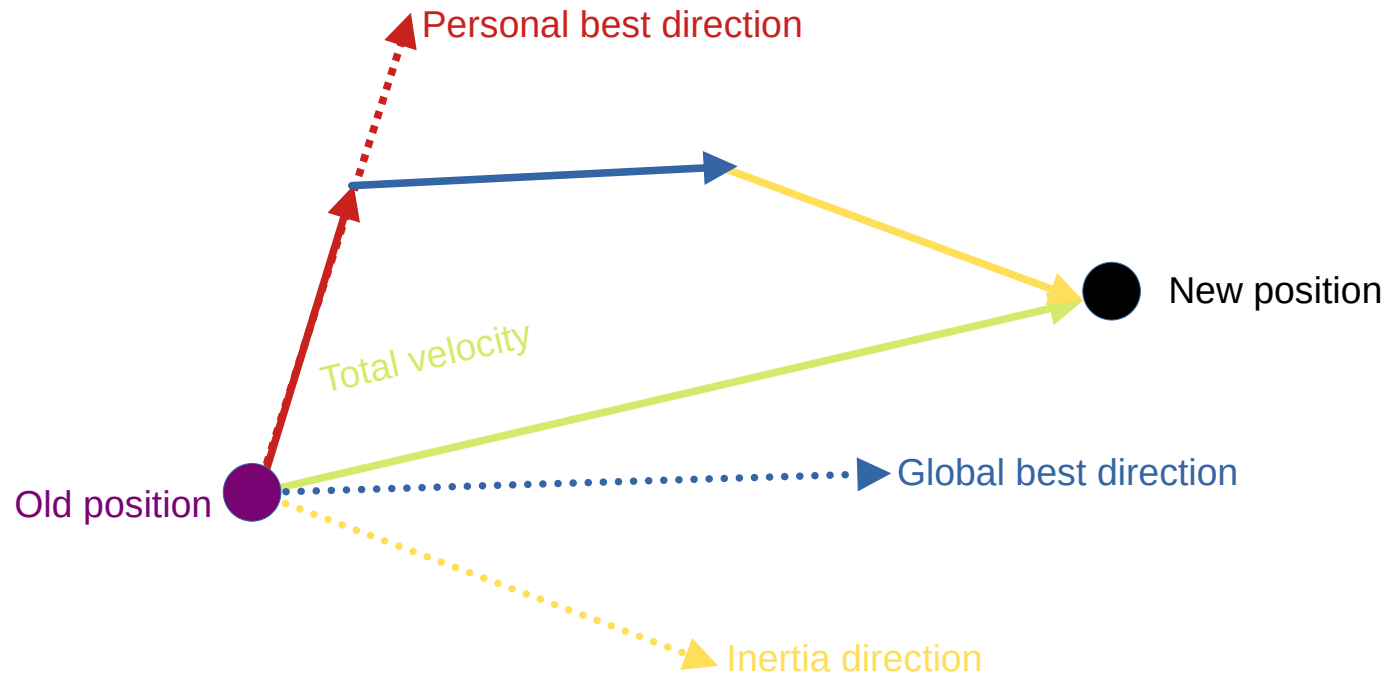
Image taken from a [website](#)

**For each iteration**

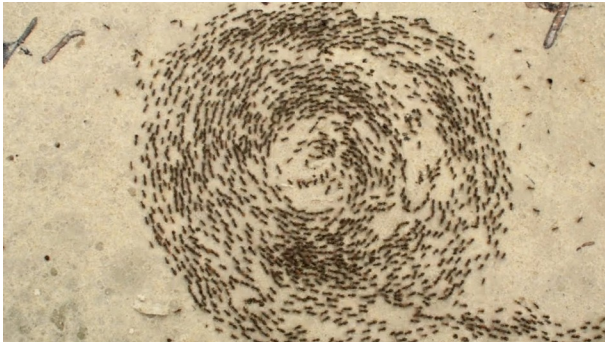


Position:  $\vec{X}_i^{t+1} = \vec{X}_i^t + \vec{V}_i^{t+1}$

Velocity:  $\vec{V}_i^{t+1} = w\vec{V}_i^t + c_1r_1(\vec{P}_i^t - \vec{X}_i^t) + c_2r_2(\vec{G}^t - \vec{X}_i^t)$



- We need:
    - A 3-class classifier (b quarks, c quarks, uds quarks).
    - We also want to avoid overfitting:
      - Kolmogorov-Smirnov test
      - Anderson-Darling test
- Control biased test scores. (more info in back-up)  
Each of them have flaws, so using both is a safer way to go!
- We need a FOM adapted to 3 different classes.
  - A final check is **always needed**:



Trial and error can go wrong sometimes!

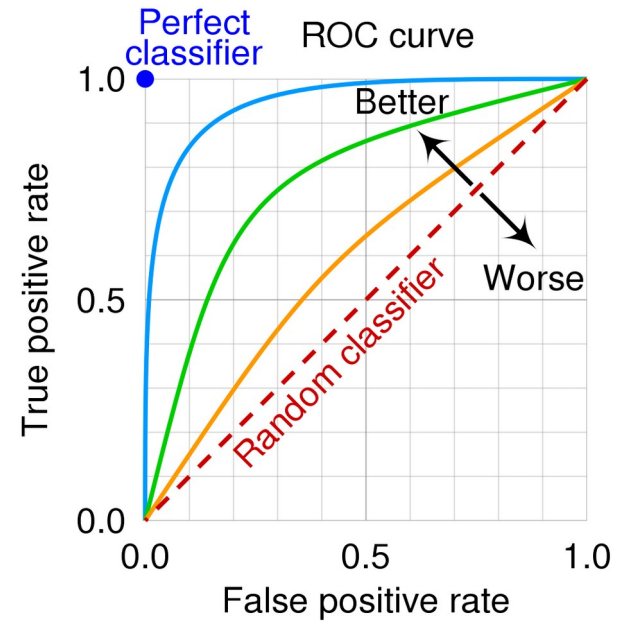


- The FOM being used is the averaged value of the Integral of the Receiver Operating Characteristic curve for each of the 3 data classes.
  - Considering the target class as signal and the others as background.

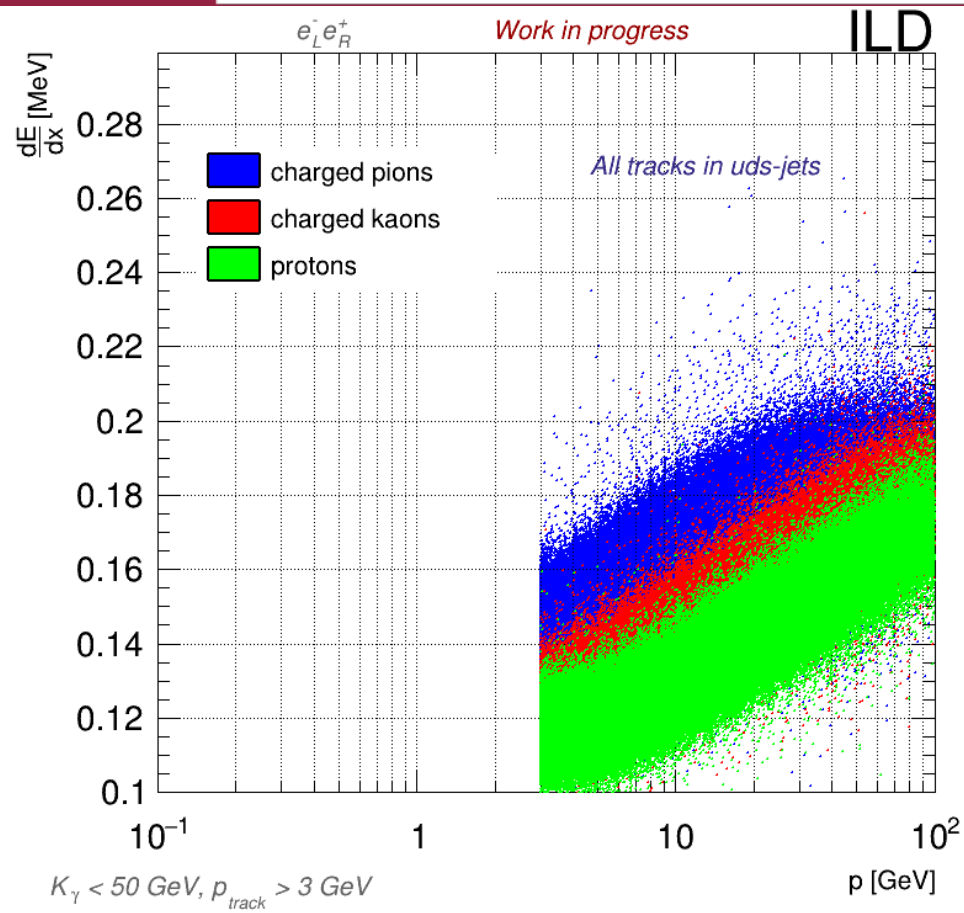
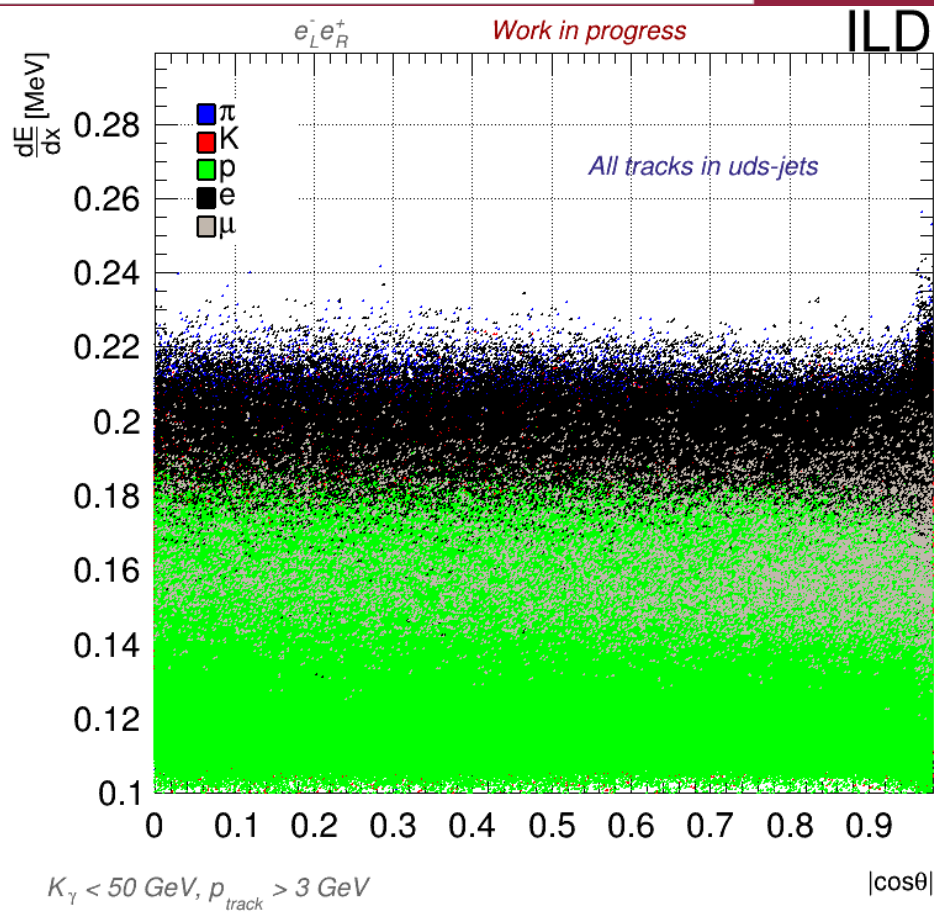
- The FOM is simply:

$$\text{FOM} = ( \text{AUC}[b_{\text{quark}}] + \text{AUC}[c_{\text{quark}}] + \text{AUC}[uds_{\text{quarks}}] ) / 3,$$

where AUC = "Area Under Curve" (ROC Integral).



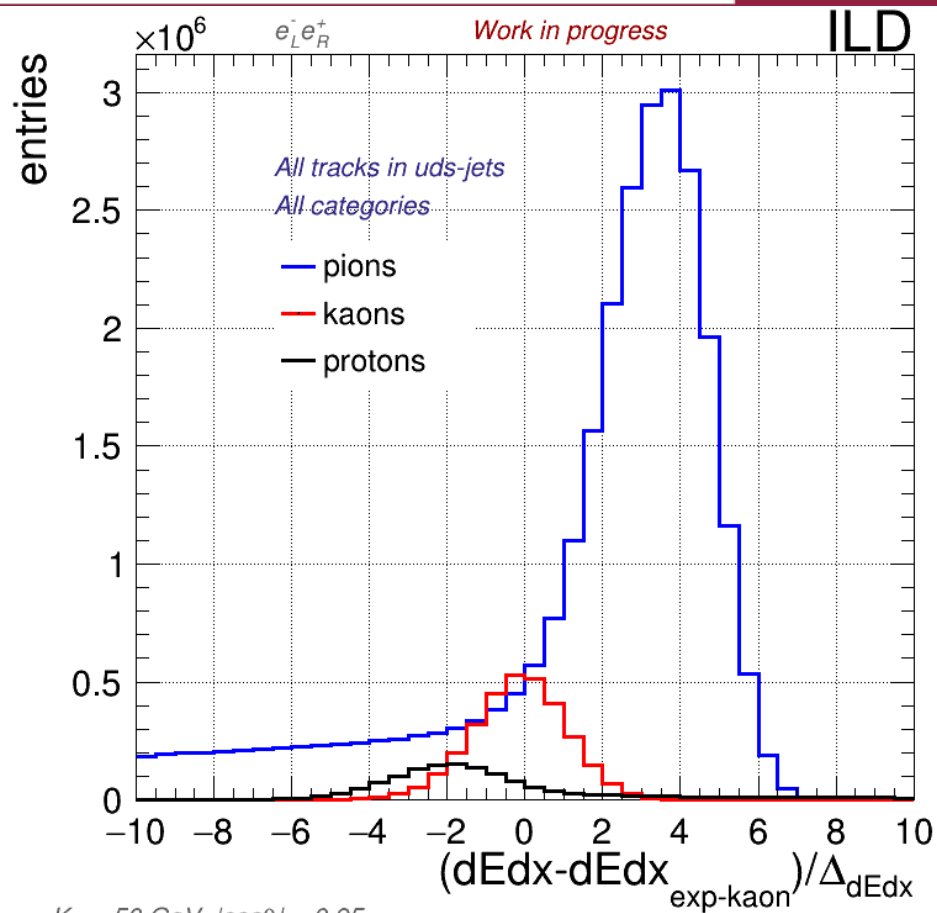
# dEdx – Cut in tracks' momentum



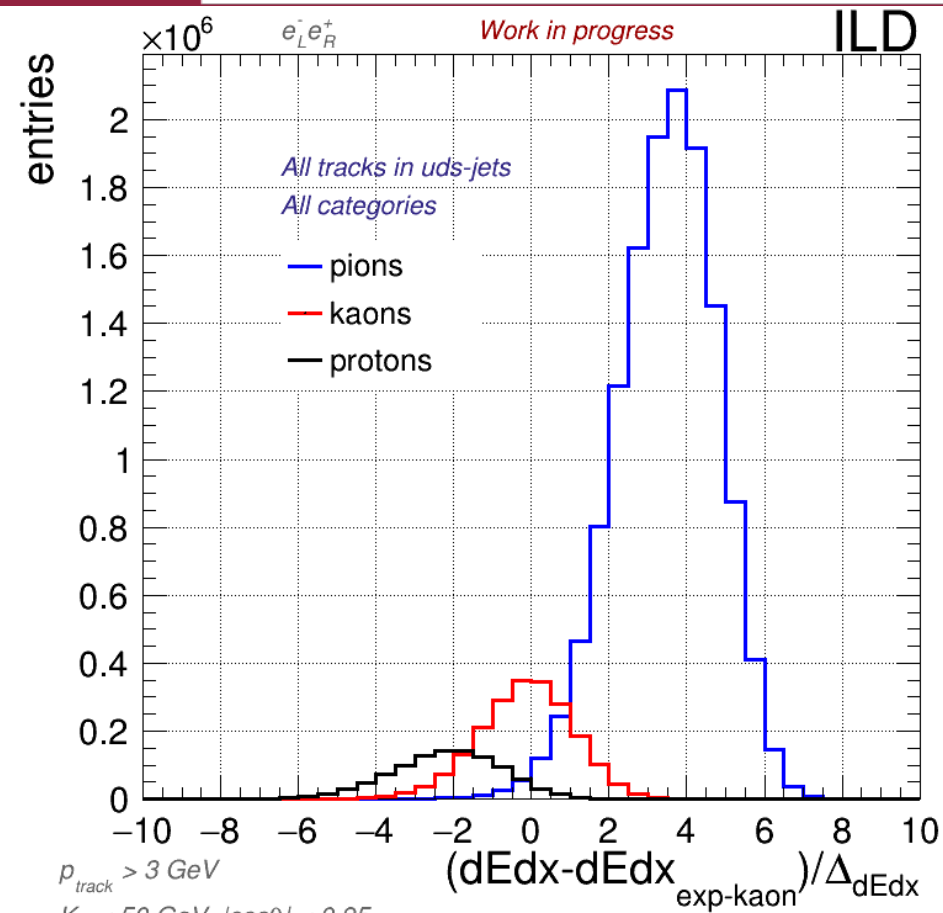
Effects of cutting the signals at 3 GeV. This behavior is similar to b and c jets.



# dEdx – Kaon Distance Significance (KDS)



$K_\gamma < 50 \text{ GeV}, |\cos\theta| < 0.95$



$K_\gamma < 50 \text{ GeV}, |\cos\theta| < 0.95$

Effects of cutting the signals at 3 GeV, removing pfos with  $1_{d_{kaon}} = 0$  &  $|\cos\theta| < 0.95$



# dEdx – KDS for different quark flavours

