DNN-based Particle Flow and jet flavor tagging at Higgs factories

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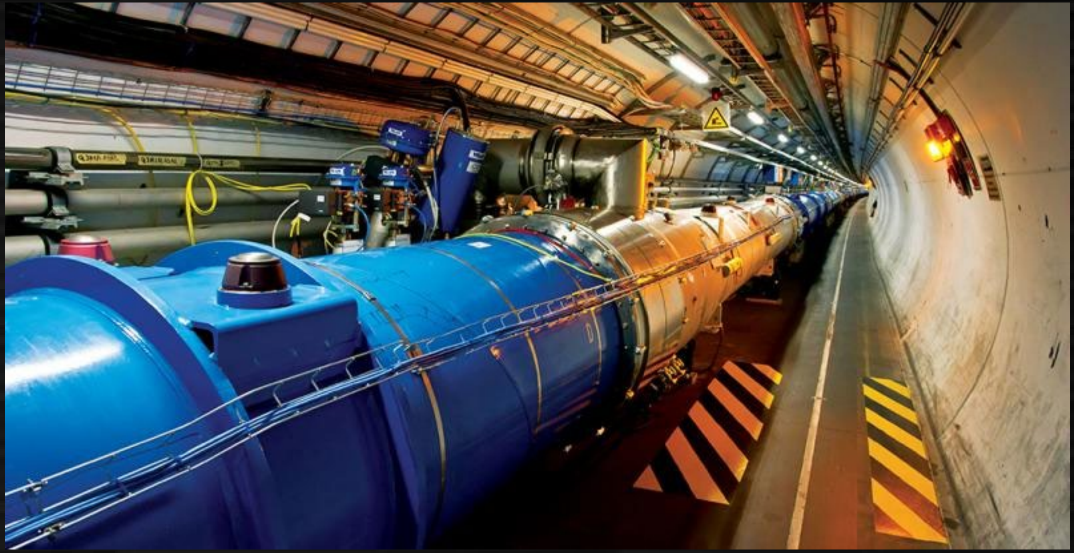
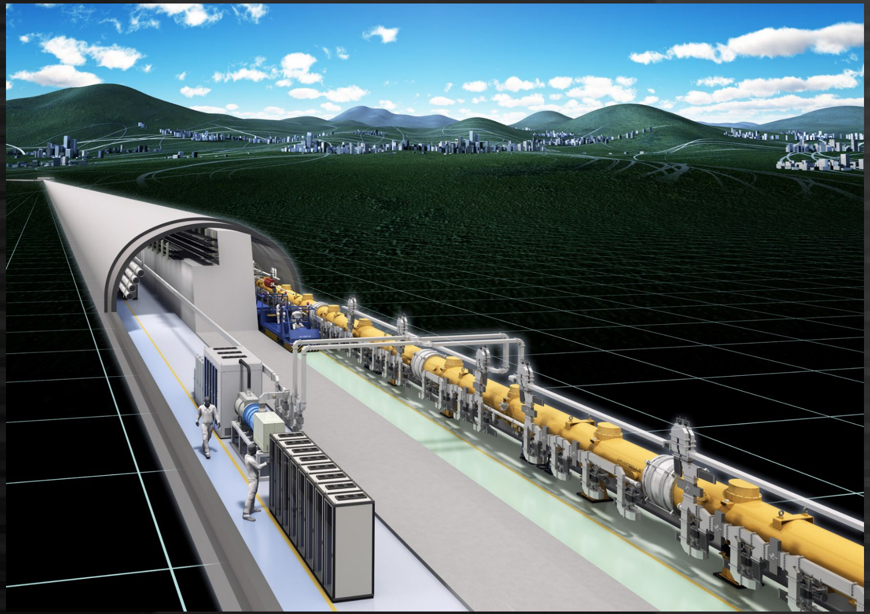
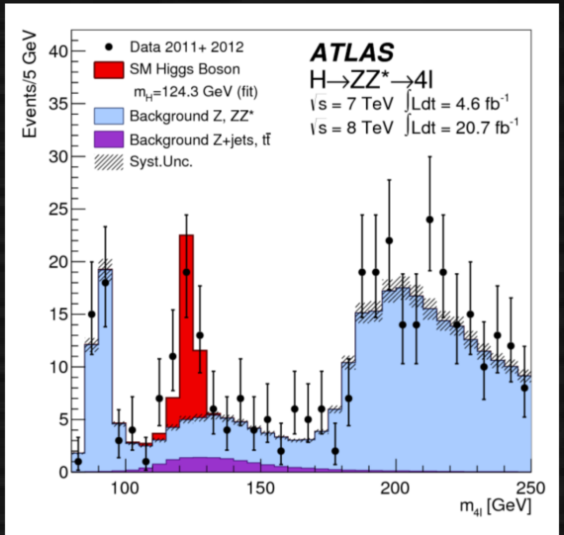
Higgs factory!



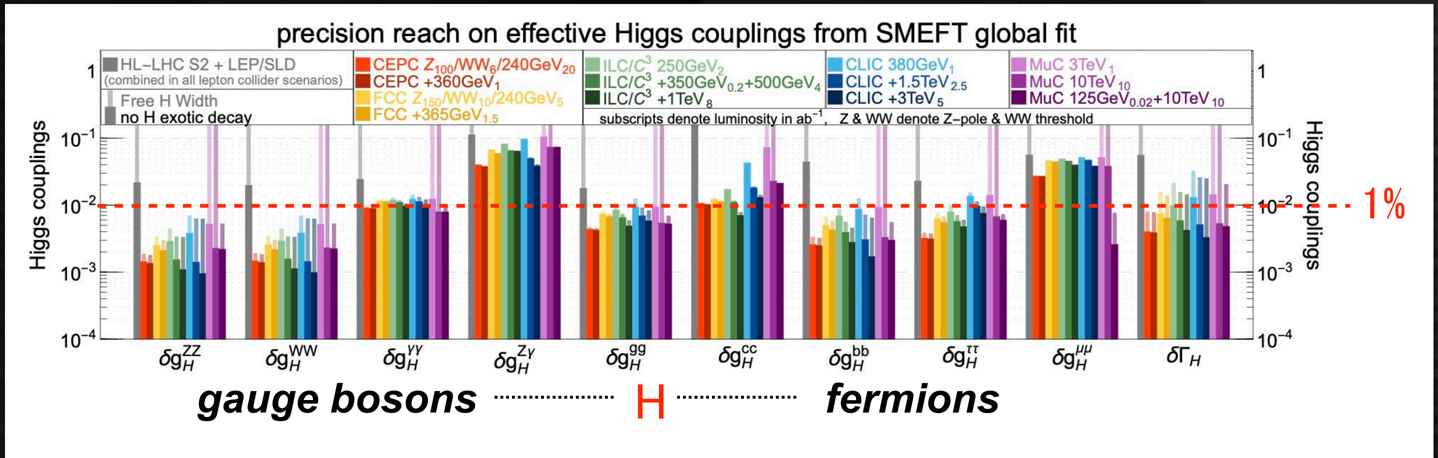
LHC discovered Higgs in 2012



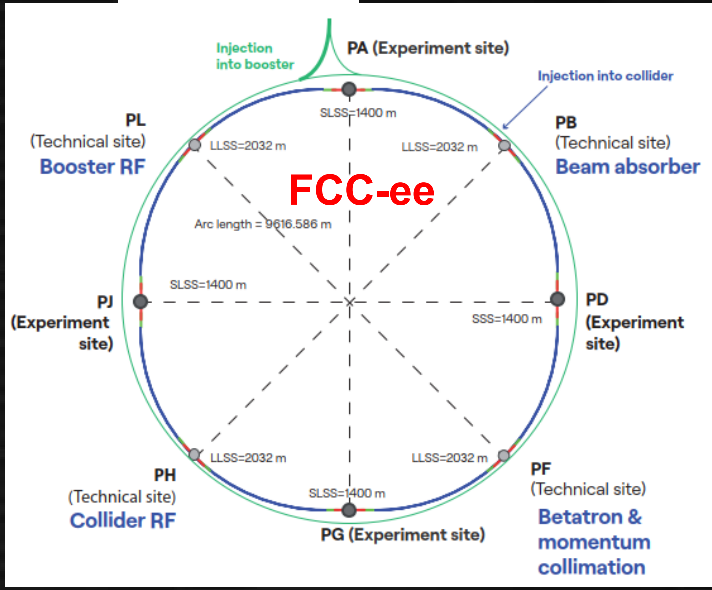
~10 times better Higgs measurements at Higgs factories to observe effect from new physics!



LHC and HL-LHC will pin-down Higgs properties up to ~2041

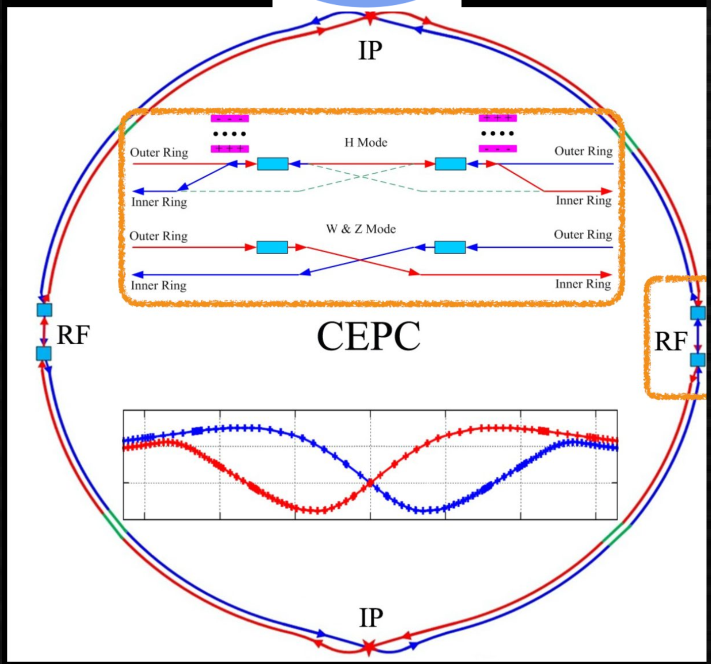


Higgs factory proposals in discussion



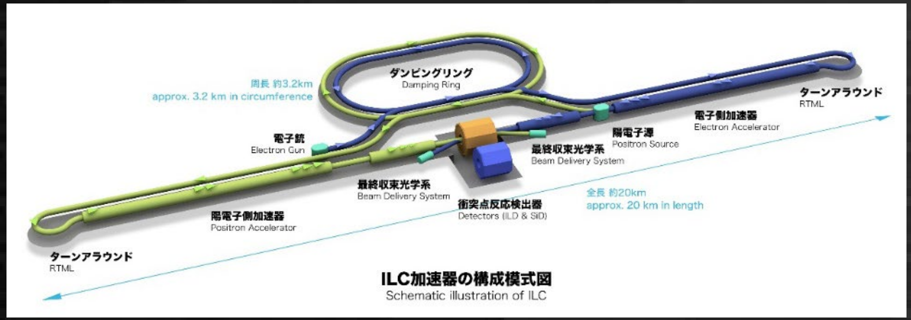
Circular e+e- collider at CERN with 90 km tunnel
91 to 365 GeV CM energy
Operation target: 2045-48

Hope to upgrade to hh collider with 85 TeV (in ~2070?)



Similar design to FCCee with a little conservative parameter

/ LCF



Linear e+e- Higgs factory projects
ILC: 20 km tunnel, 1IP, global project
LCF@CERN: 31 km tunnel, 2IP

Will operate from 250 GeV CME for Higgs factory + upgrade to ~550 GeV for Higgs self coupling (~10%

Path to multi-TeV e+e- collider with various technology (NC, Plasma…)

Target Energies of e+e- colliders

91~250 GeV — Oblique parameters, W/Z mass, b/τ rare decays

250 GeV — Higgs couplings (~1%), Higgs rare decay (light BSM)
(TeV BSM indirect search)

350 GeV — Top mass → vacuum stability

↓Only possible with Linear Colliders

500–550 GeV — Higgs self coupling (~10%), ttH coupling
→ EW baryogenesis

1 TeV — Higgs self coupling (<10%)

250 GeV – a few TeV — TeV BSM direct search

Natural SUSY (250 GeV – 1 TeV) 1 TeV Higgsino 3 TeV Wino

Flavor physics and Higgs factories

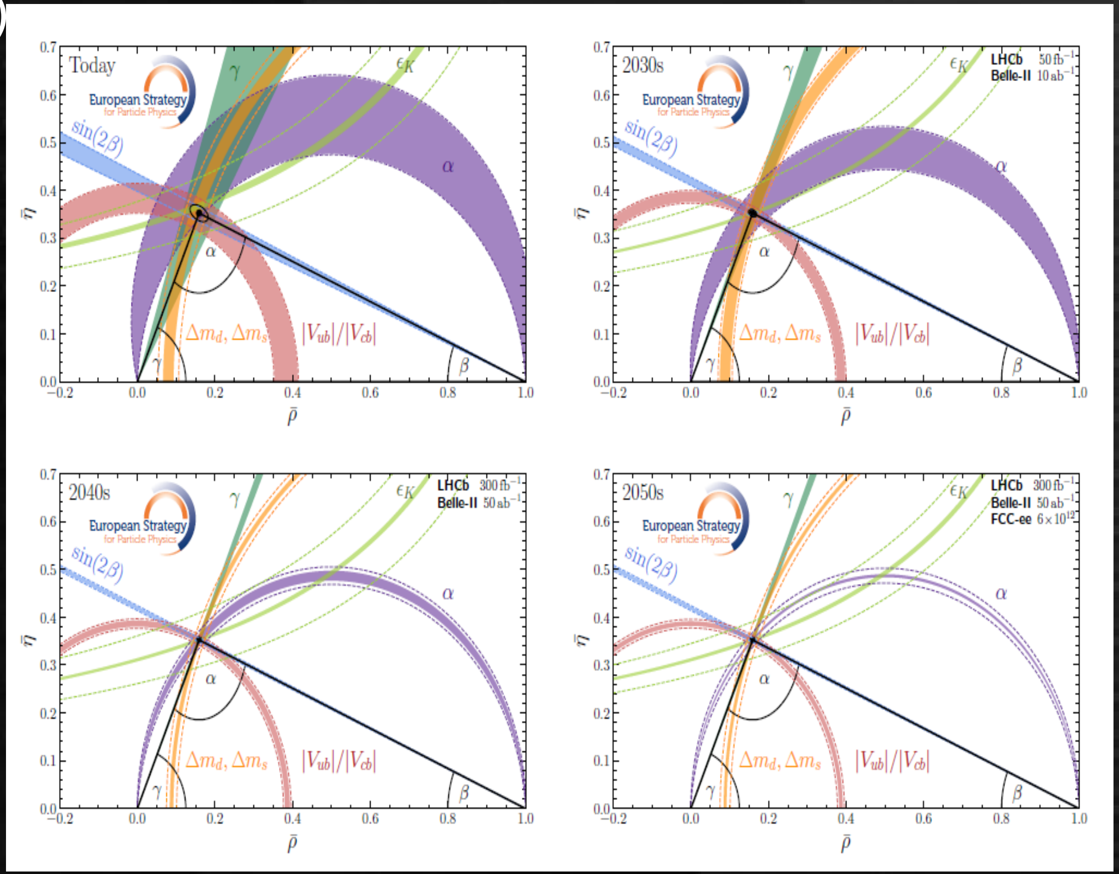
- Flavor physics is one of the targets in circular Higgs factories
  - ~10 times more B-mesons wrt. Belle II (at FCCee)
  - Flavor physics at CEPC: arXiv:2412.19743v1
- Flavor physics at Linear Higgs factories
  - H → bs, τμ (H → bs is especially difficult in LHC)
  - W inclusive hadronic BR → CKM unitarity (LEP ~ b-factory on V_{cs})

$\Gamma(W^+ \to \text{hadrons})/\Gamma_{total}$

OUR FIT value is obtained by a fit to the lepton branching ratio data as

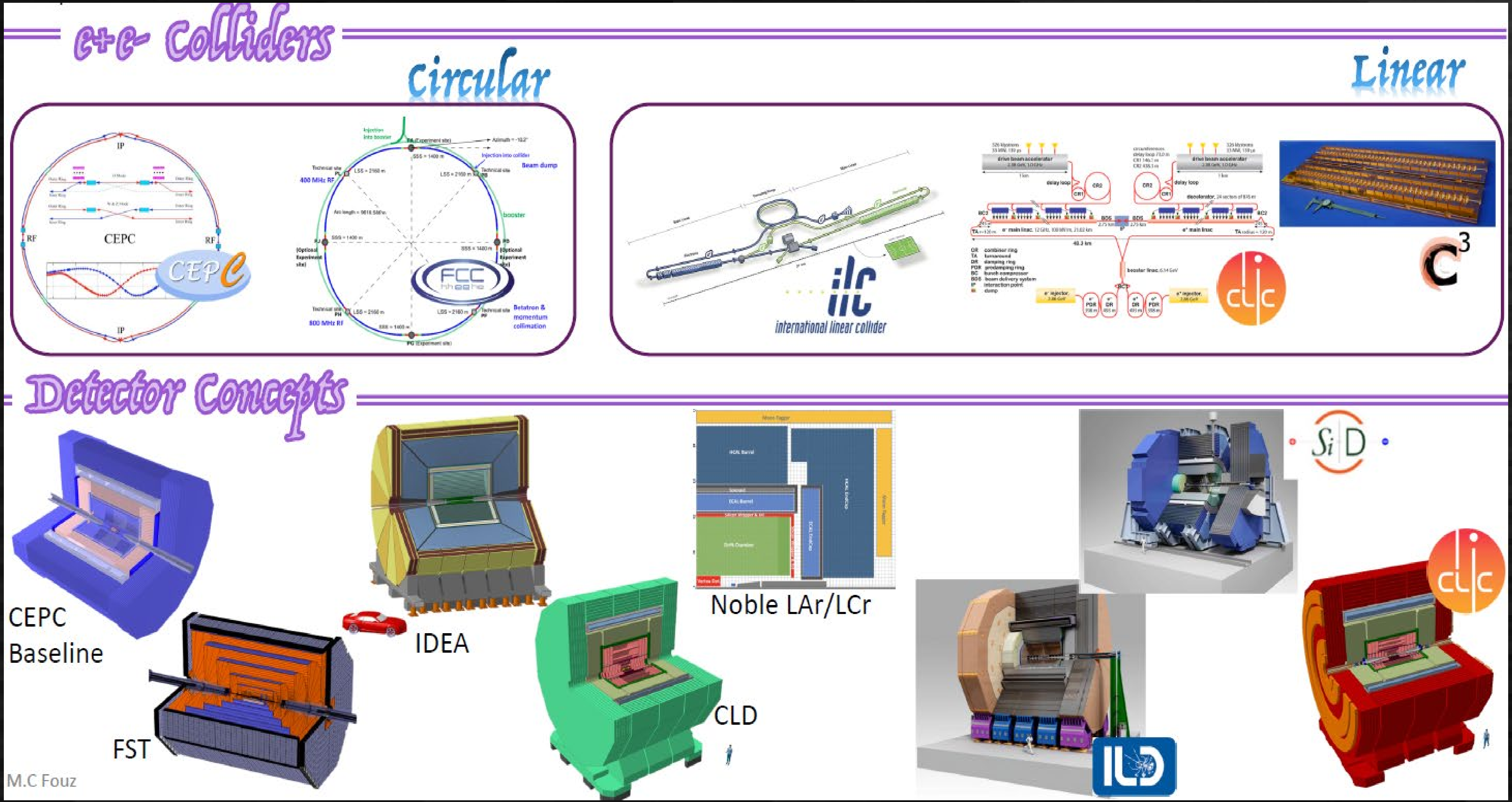
LHC: systematics dominant

VALUE (10^{-2})	*EVTS*	*DOCUMENT ID*		*TECN*
67.41 ± 0.27 OUR FIT				
67.32 ±0.02 ±0.23		TUMASYAN	2022F	CMS
67.41 ±0.37 ±0.23	16438	ABBIENDI	2007A	OPAL
67.45 ±0.41 ±0.24	13600	ABDALLAH	2004G	DLPH
67.50 ±0.42 ±0.30	11246	ACHARD	2004J	L3
67.13 ±0.37 ±0.15	16116	SCHAEL	2004A	ALEP



Accuracy of CKM matrix by future experiments

Detectors for Higgs factories

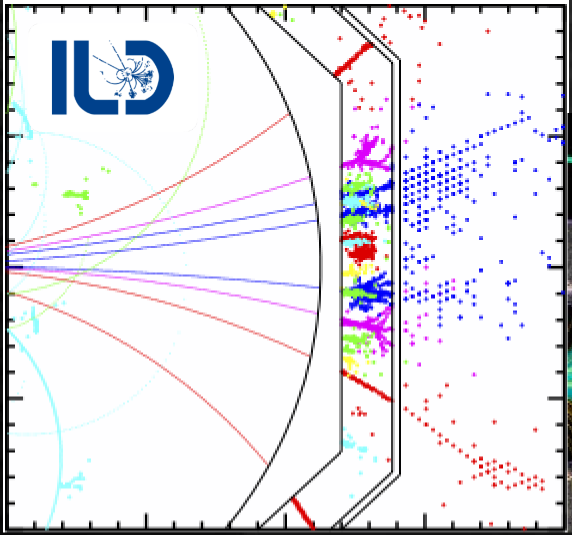


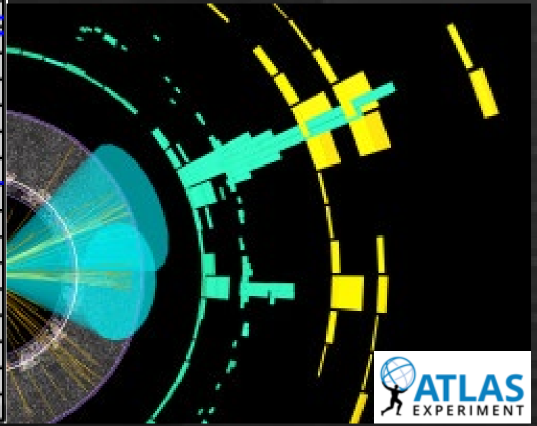
Particle flow concept

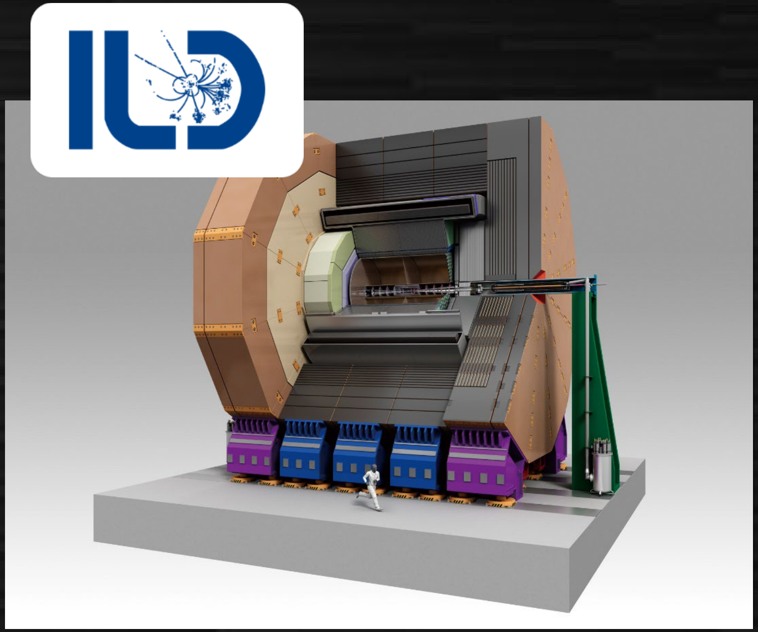
Separating particles inside jets to do track-cluster matching

Requiring
- Highly-granular calorimeters
- Intelligent pattern recognition

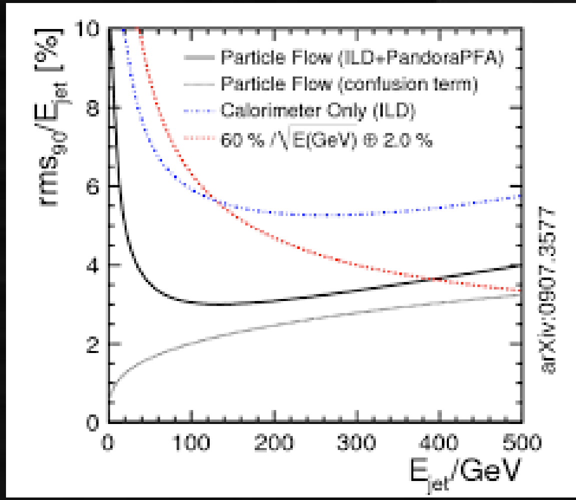
Different granularity on ILD - ATLAS







LC detectors (e.g. ILD) are fully based on Particle-flow design
- 3D pixelated calo (~100M readout ch)
- Low material tracker
- 3.5 Tesla solenoid outside HCAL

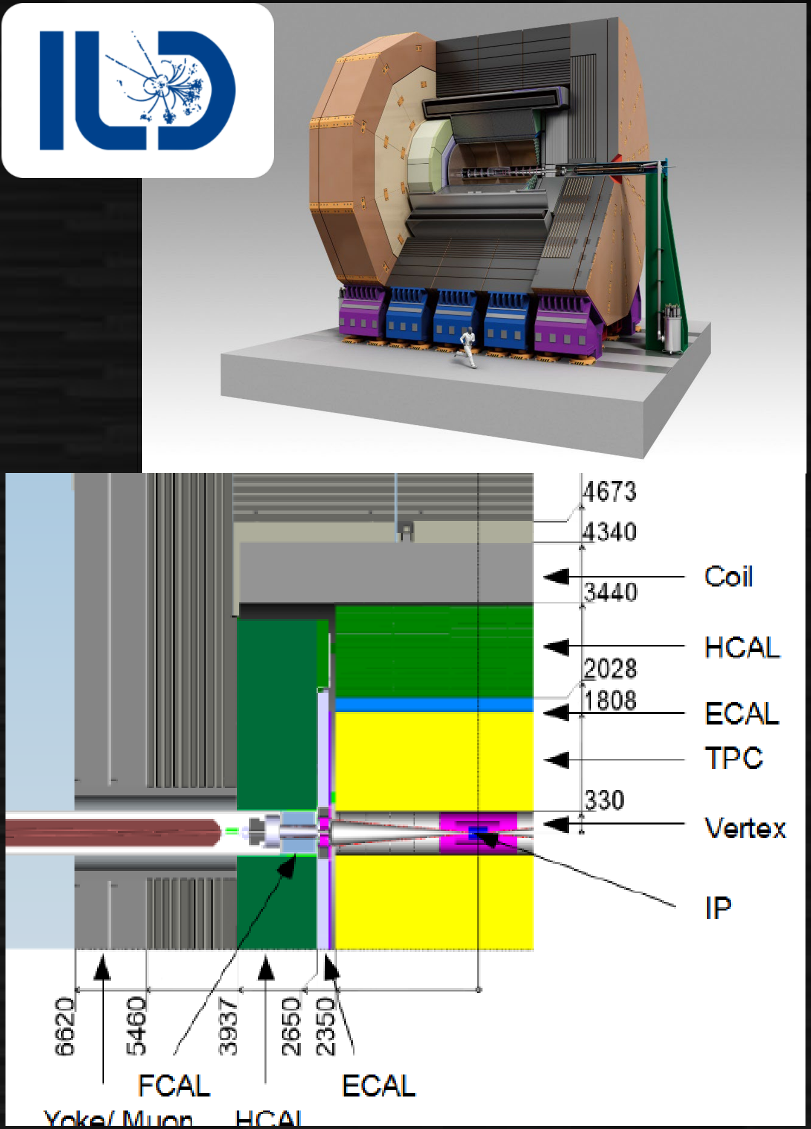


Possible to obtain jet energy resolution of

$$\frac{\delta E_{\mathrm{jet}}}{E_{\mathrm{jet}}} \cong \frac{30\%}{\sqrt{E_{\mathrm{jet}}[\mathrm{GeV}]}}$$

~2 times better than calo-only

ILD: A detector for Higgs factories

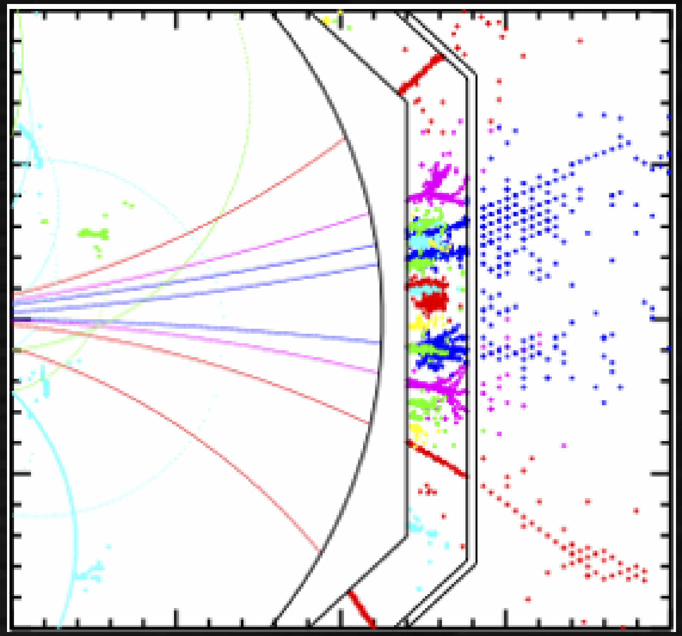


- Fully designed for Particle Flow
  - Highly-granular calorimeters
    - 5 x 5 mm^2 x 30 layer ECAL, 3 x 3 cm^2 x 48 layer HCAL
  - Particle inside jets separated 1-by-1
    - Giving 2x better JER (~30%/sqrt(E [GeV]))
  - Optional ToF at calorimeter (~100 psec/hit)
- Tracker: silicon + TPC combined
  - Vertex: a few μm resolution at r ~ 15 mm
    - Significant impact on c-tagging (wrt. LHC)
  - TPC: good for dE/dx (discussed later)
    - Important for strange tagging
- Magnet (3.5T) outside HCAL
  - Minimal material before calorimeters

Today's topics

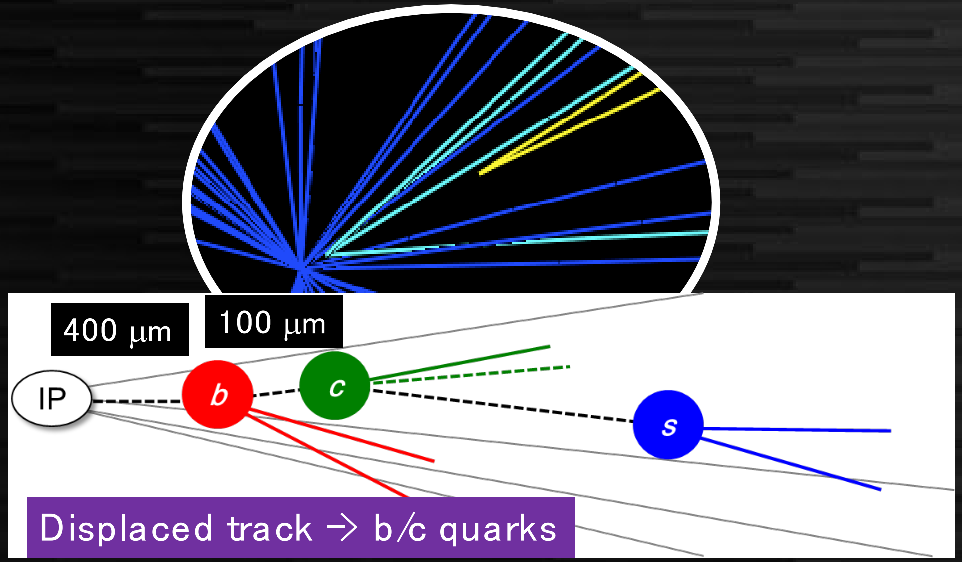
All works done with ILD full simulation (plus FCCee Delphes for comparison)

Particle flow with DNN



Key algorithm for particle flow detectors
Essential for detector optimization

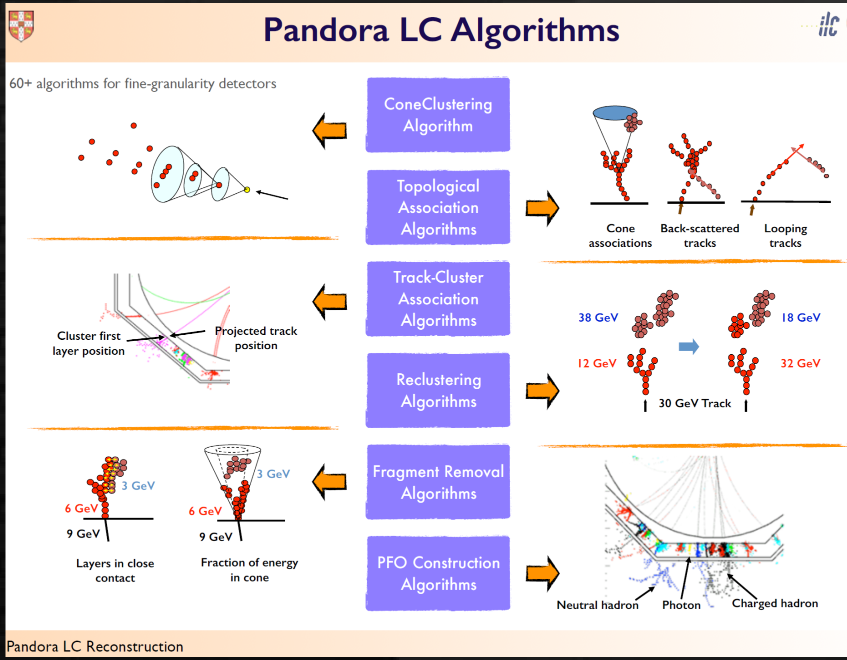
Flavor tagging with Particle Transformer (ParT)



Big impact on Higgs studies including self coupling
Strange tagging is also a scope

Particle flow in Higgs factories

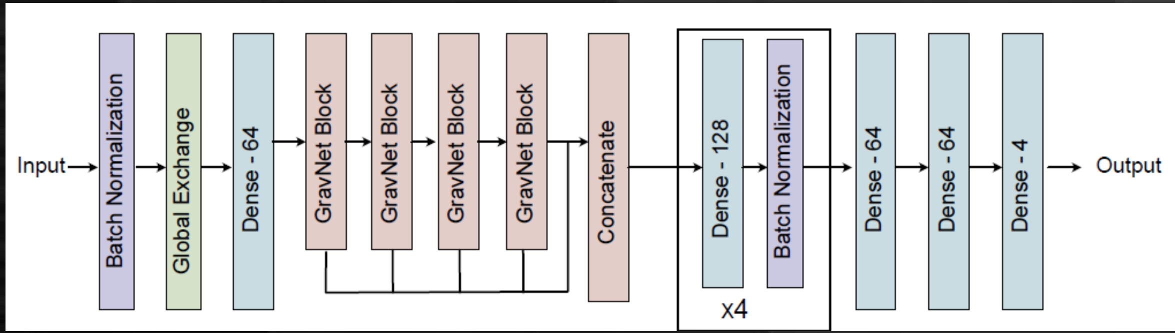
- PandoraPFA is used since 2008 as standard for >15 years
  - Good-old technology but fully tuned only minor modifications since 2008
  - Exceeding PandoraPFA is a long-lasting target for development of PFA
    - Several algorithms gave challenge but no algorithm significantly exceeds the performance and thus not replaced



- Our primary target is to exceed PandoraPFA
  - In addition, DNN-based algorithm has many benefits
    - eg. Easier adaptation to geometries and additional features

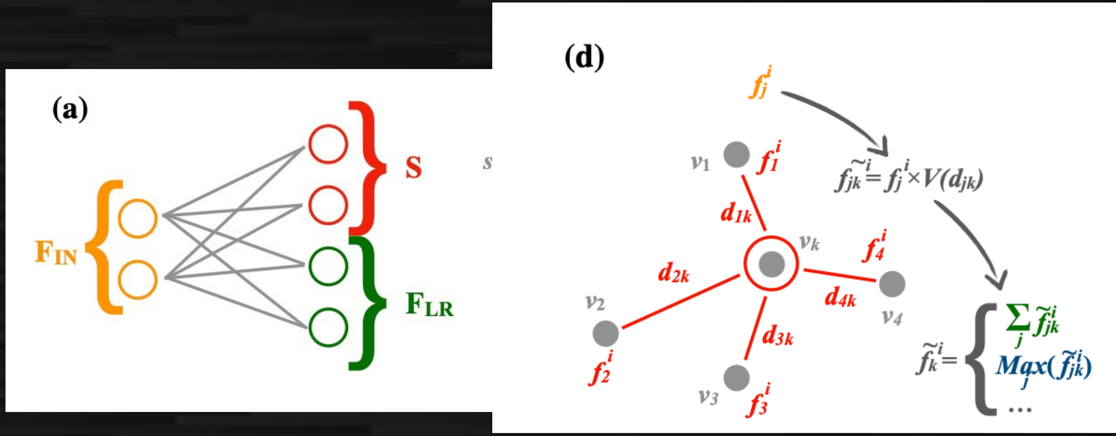
GNN-based PFA

- Originally developed for CMS HGCAL
- Input: position/energy/timing of each hit
- Output: virtual coordinate and β for each hit



GravNet arXiv:1902.07987

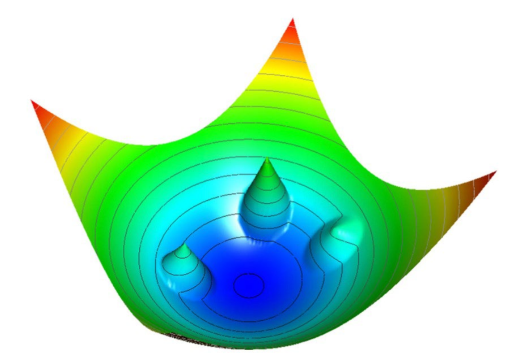
- The virtual coordinate (S) is derived from input variables with simple MLP
- Convolution using "distance" at S (bigger convolution with nearer hits)
- Concatenate the output with MLP



Object Condensation (loss function)

arXiv:2002.03605

$$L = L_p + s_C(L_\beta + L_V)$$



- Condensation point: The hit with largest β at each (MC) cluster
- L_V: Attractive potential to the condensation point of the same cluster and repulsive potential to the condensation point of different clusters
- L_β: Pulling up β of the condensation point
- L_p: Regression to output features

What we implemented: track-cluster matching

- PFA is essentially a problem "to subtract hits from tracks"
- HGCAL algorithm does not utilize track information
  - Only calorimeter clustering exists
- Putting tracks as "virtual hits"
  - Located at entry point of calorimeter
  - Having "track" flag (1=track, 0=hit)
  - Energy deposit = 0
- Modification on object condensation to forcibly treat tracks as condensation points

$$L = L_p + s_C(L_\beta + L_V)$$

L_V: attractive/repulsive potential to condensation points / tracks

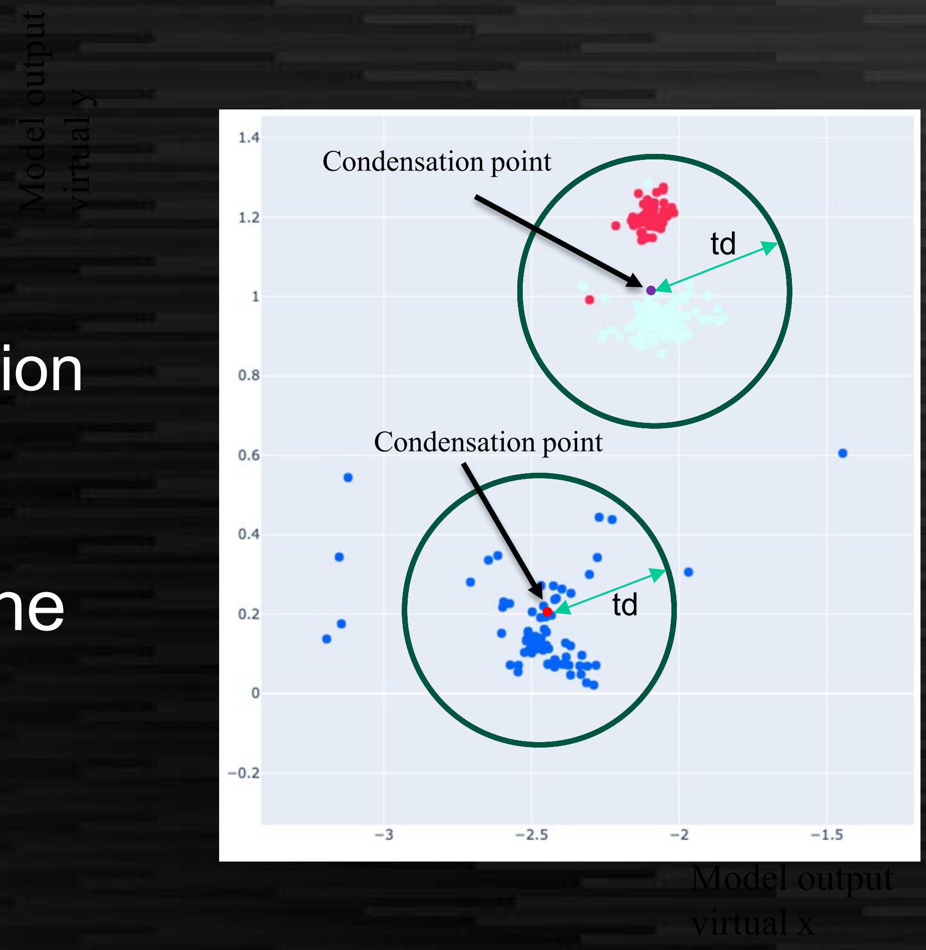
L_β: Pulling up β of the condensation points / tracks

Tracks are prioritized over other condensation points

Current number of parameters: ~420K

Clustering algorithm

- Output of the network is position and β of each hit → need clustering
- List all condensation points with β > tbeta
- Associate hits to condensation points if they are within a distance (td) from the condensation point at the output coordinate
  - If hits can be associated to multiple condensation points, the nearest one is taken
- Take the highest β point from the remaining hits, and cluster neighbor hits as similar to the previous step
- td/tbeta are tunable parameters



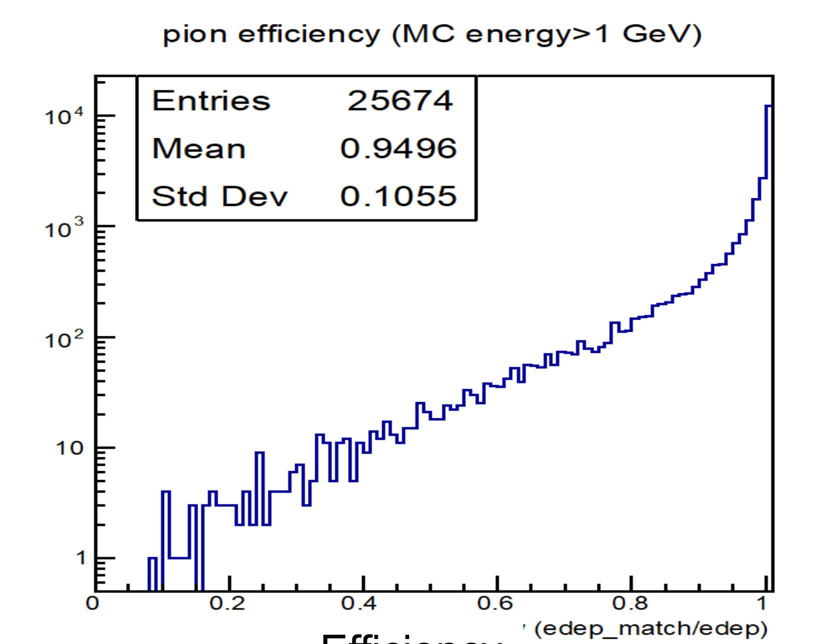
Our samples for performance evaluation

- ILD full simulation with SiW-ECAL and AHCAL
  - ECAL: 5 x 5 mm^2, 30 layers, HCAL: 30 x 30 mm^2, 48 layers
  - Taus overlayed with random direction
    - 100k events, 10 GeV x 10 taus / event → 1 million taus
  - qq (q=u, d, s) sample at 91 GeV
    - ~75k events
    - Official sample for PFA calibration (other energies available)
  - ZH → ννqq (q=u/d) sample at 250 GeV
    - For energy regression

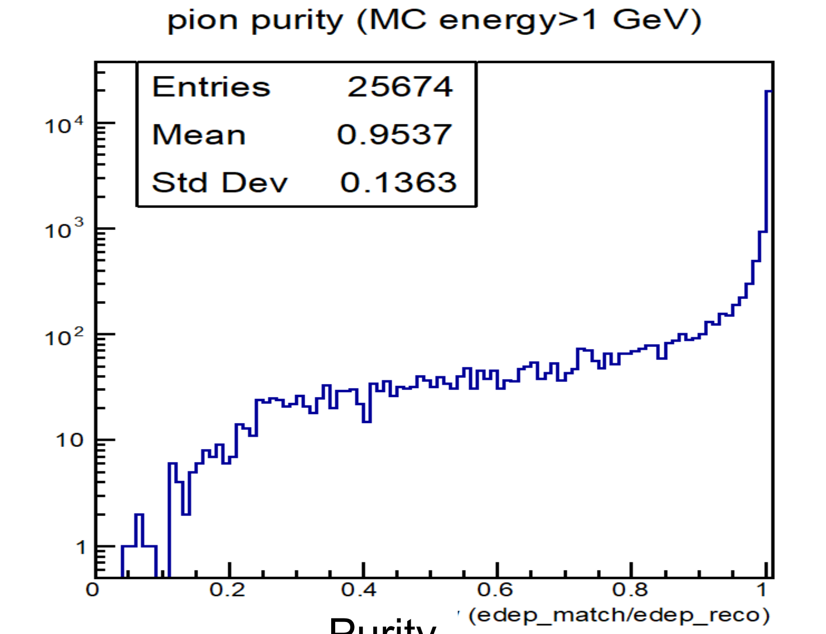
Taus: good mixture of hadrons, leptons and photons with some isolation
Good for training

Quantitative evaluation

- Make 1-by-1 connection of MC and reconstructed cluster
  - Reconstructed cluster with highest fraction of hits from the MC is taken
  - Multiple reconstructed clusters may connect to one MC cluster → encourage splitting too much
- Quantitative comparison with PandoraPFA
  - Compared "efficiency" and "purity" of particle flow
    - Efficiency : (reconstructed cluster energy that matches the MC cluster) / (MC cluster energy)
    - Purity : (reconstructed cluster energy that matches the MC cluster) / (reconstructed cluster energy)

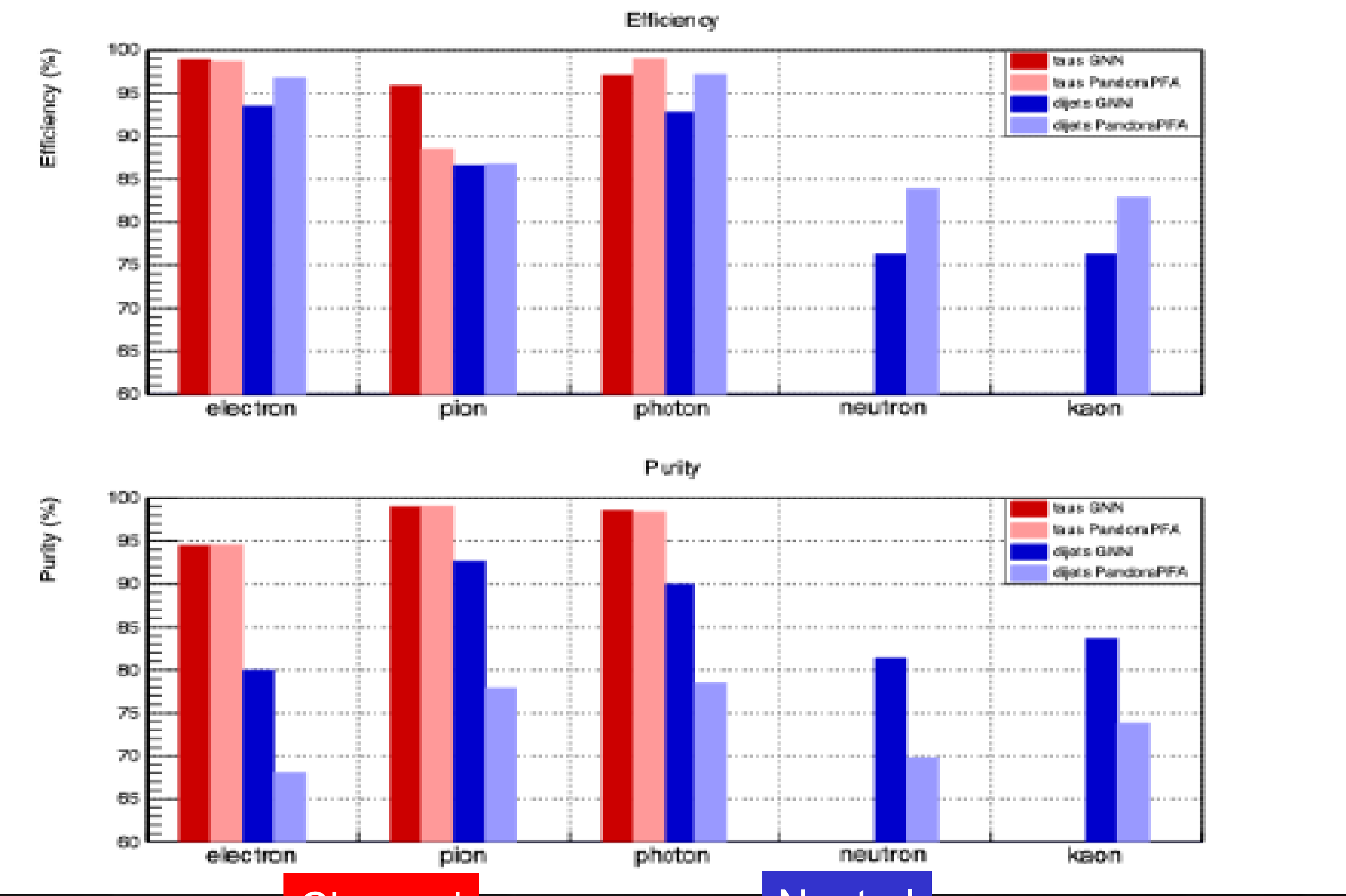


Efficiency



Purity

Efficiency and purity: comparison with Pandora



Charged

Neutral

Red: 10 taus
Blue: di-jets
Thick color: GNN-based PFA
Thin color: PandoraPFA

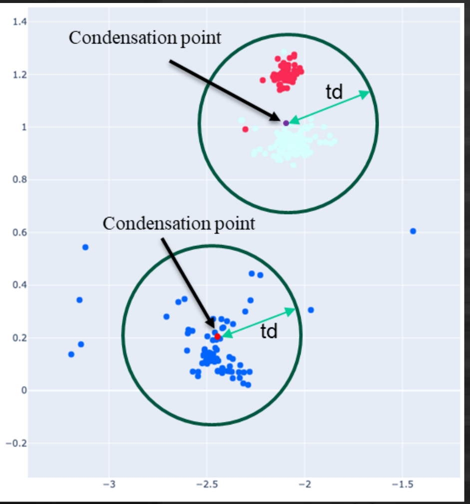
Pion: GNN > Pandora

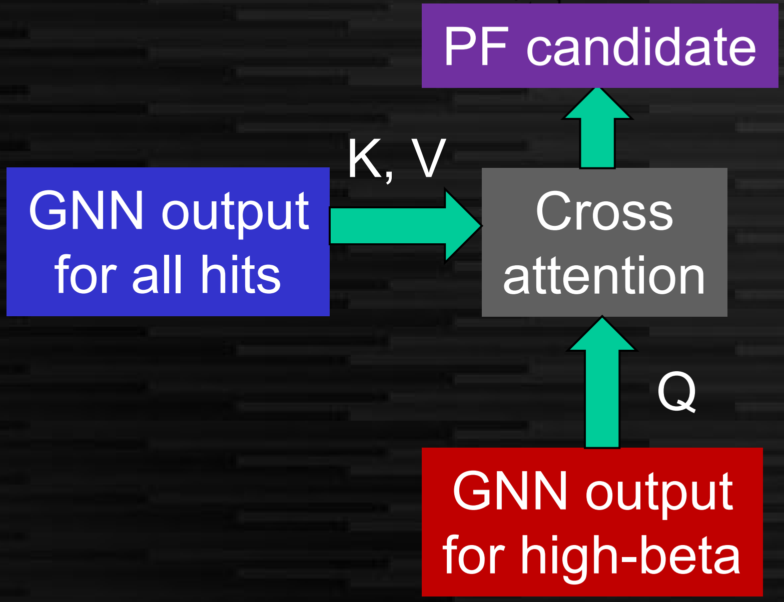
Electron, photon, neutron, kaon:
Efficiency: GNN < Pandora
Purity: GNN > Pandora

Overall:
competitive performance achieved
Pion reconstruction is especially important in jet reconstruction
→ good expectation

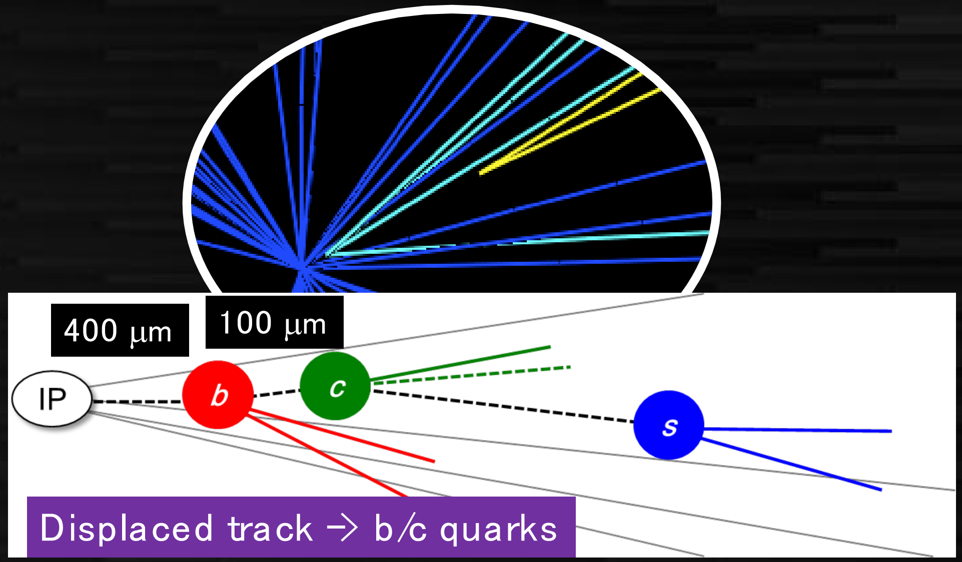
Ongoing work: DNN-based clustering

- Current issue: clustering not intelligent
  - Simply gathering hits around cond-point
  - Not based on ML – issue on energy regression
- Implementing ML-based clustering
  - Use high-beta points as "query" of transformer → particle candidate (pfcand)
  - Cross attention of hits to pfcand
  - Derive particle properties (or tagged as fake)
    - Attention weights used for hit-particle mapping
  - Eventually unified to single network
- Under investigation





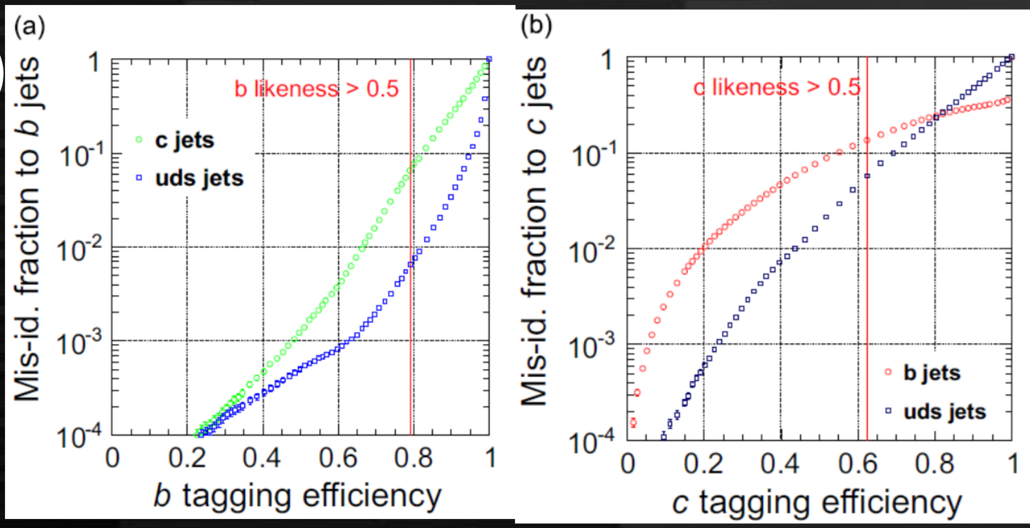
Flavor tagging with Particle Transformer (ParT)

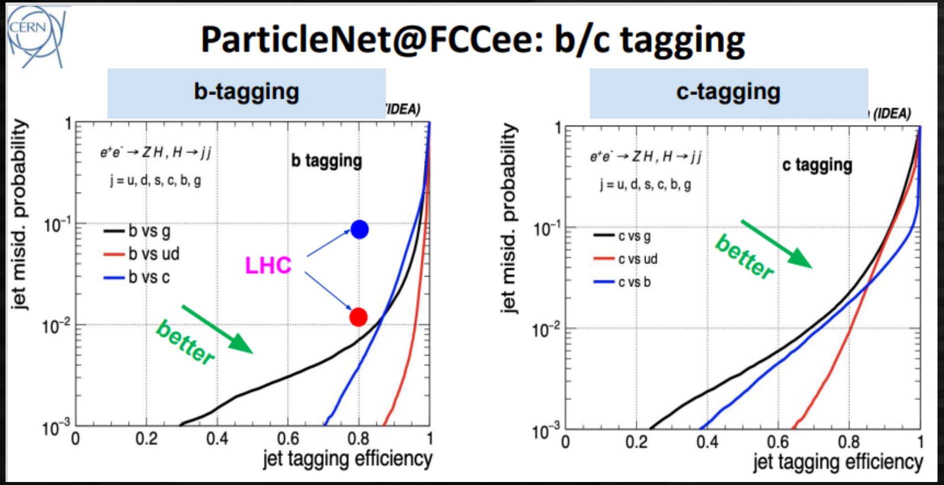


Flavor tagging for Higgs factories

- Jet flavor tagging is essentially important for Higgs studies (including self coupling)
- LCFIPlus (published 2013) was long used for flavor tagging
  - All physics performance in ILD/SiD/CLIC are based on LCFIPlus
- FCCee reported >10x better rejection using ParticleNet (GNN) in 2022
  - Delphes is used for simulation
- We studied DNN-based flavor tag with ILD full simulation to confirm it
  - Using latest algorithm: Particle Transformer (ParT)

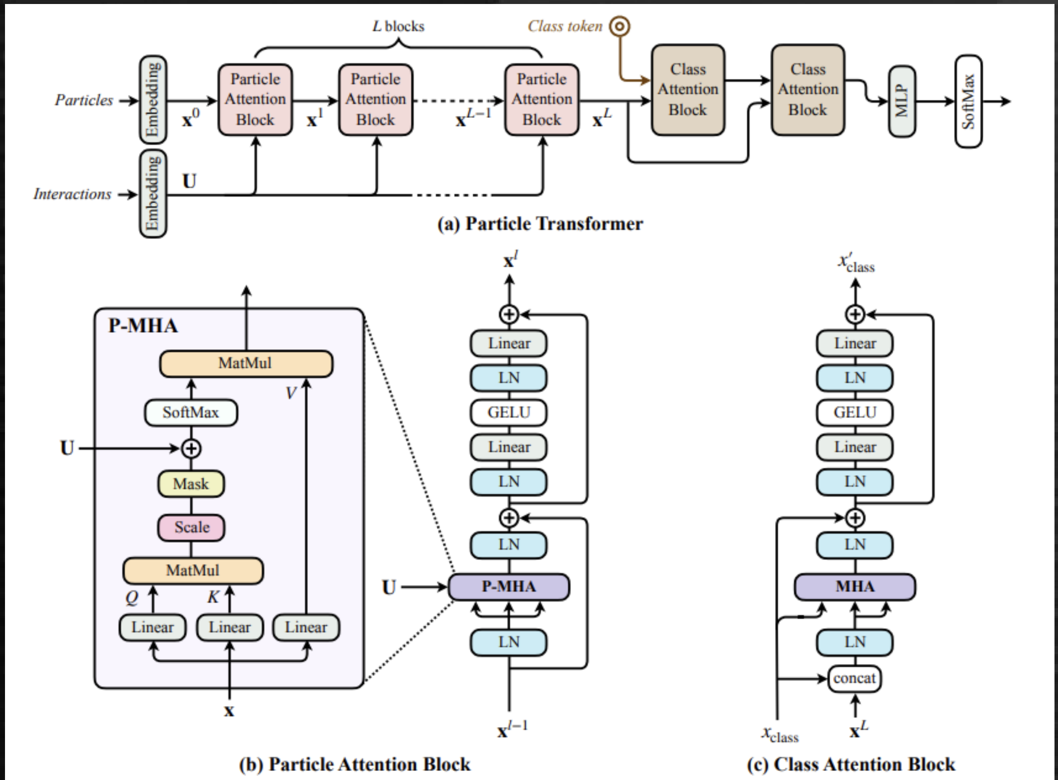
LCFIPlus performance plots





Particle Transformer (ParT)

- Transformer: self-attention-based algorithm intensively used for NLP (e.g. chatGPT)
  - Weak biasing: possible to train big samples efficiently (with more learnable weights) but demanding big training sample for high performance
- ParT is a new Transformer-based architecture for Jet tagging, published in 2022.
  - Pair-wise variable (angle, mass etc.) is added to plain Transformer encoder to boost attention
- Surpasses the performance of ParticleNet
  - ParticleNet only looks “neighbor” particles while Transformer uses attention to learn where to look



	All classes	
	Accuracy	AUC
PFN	0.772	0.9714
P-CNN	0.809	0.9789
ParticleNet	0.844	0.9849
ParT	**0.861**	**0.9877**

Performance with JetClass event classification (100M sample)

Software implementation

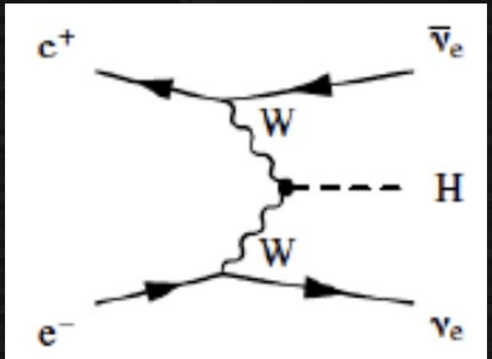
- Training done in python/weaver framework
  - New LCFIPlus algorithm (MLMakeNtuple) to create input ROOT files
  - ROOT files used for training ParT
    - nnqq 250 GeV, ~1M jets / each flavor
    - MC/jet matching inside LCFIPlus (only for q/qbar training)
      - Color-singlet tagging by RecoMCTruthLink, q/g identified based on angle
        - » If multiple jets assigned to the same q/g, jet with highest energy taken
  - Training with GPU (~a half day for 20 epochs with Tesla V100)
- Weights (checkpoint) converted to onnx
  - Using onnx 1.15.0, onnxruntime 1.17.1 (to be compatible with key4hep)
- Inference with CPU in LCFIPlus framework
  - New processor MLInferenceWeaver with onnx files (uploaded in LCFIPlusConfig)
- Currently on private repository (pulling to official repository being processed)
  - LCFIPlus github with ParT, https://github.com/suehara/LCFIPlus/tree/onnx
  - LCFIPlusConfig with weight/steering files, https://github.com/suehara/LCFIPlusConfig

Data Samples and Input Variables

Data samples

q = b,c,uds
j=b,c,u,d,s,g

- ILD full simulation
  - e+ e- → ννH → ννjj (at 250 GeV)
    1M jets for each flavor
- ILD fast simulation (SGV)
  - Real tracking + smearing on calo
  - e+ e- → ννH → ννjj (at 250 GeV)
    20M jets each flavor



80% for training
5% for validation
15% for test

Input variables

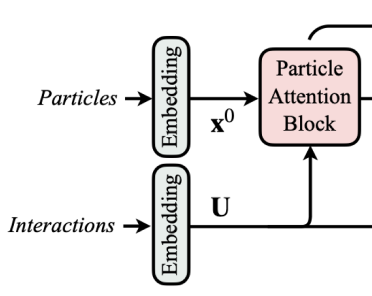
Particles: for every track/neutral

- Impact parameters (6)
  - 2D/3D, from primary vertex
- Jet distance (2)
  - Displacement from jet axis
- Covariant matrix (15)
- Kinematics (4)
  - Energy fraction, angles, charge
- Particle ID (6)
  - Probability (or binary selection) of e, μ, hadron, gamma, neutral hadron

Interactions: for every particle pair

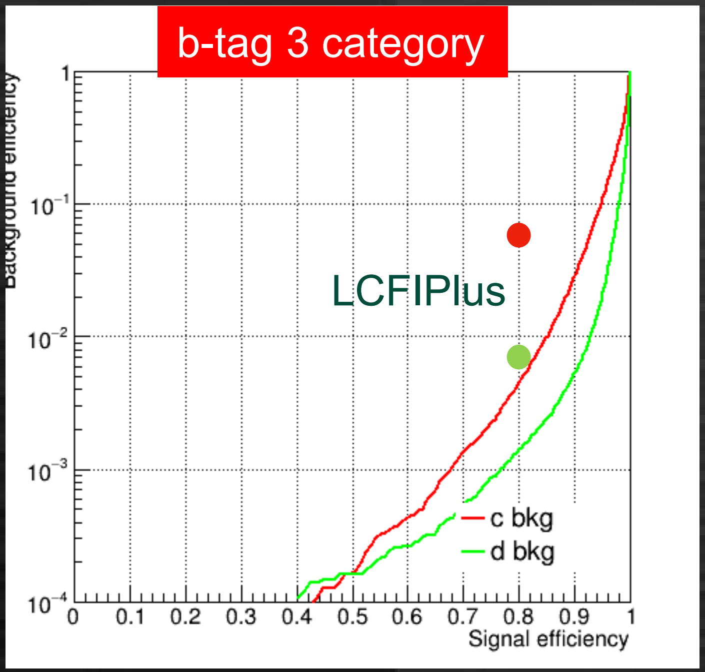
- δR^2, k_t, Z, mass

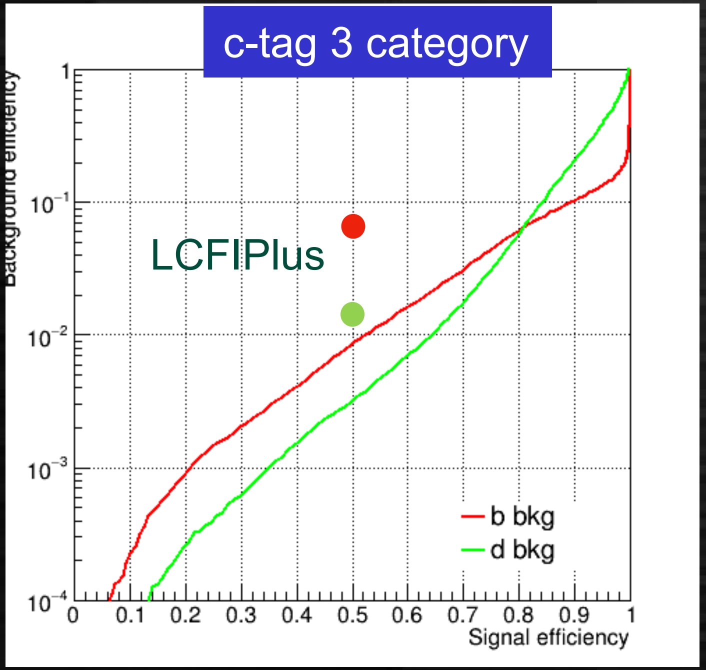
Input of ParT



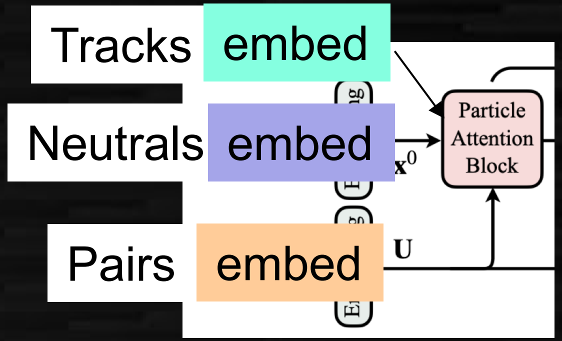
Improvements wrt. LCFIPlus

- Factor (3-9) improvement at ParT from LCFIPlus without any tuning
- Another factor (max 3) improvement by tuning
  - Optimizing input variables
  - Separate embedding for tracks/neutrals





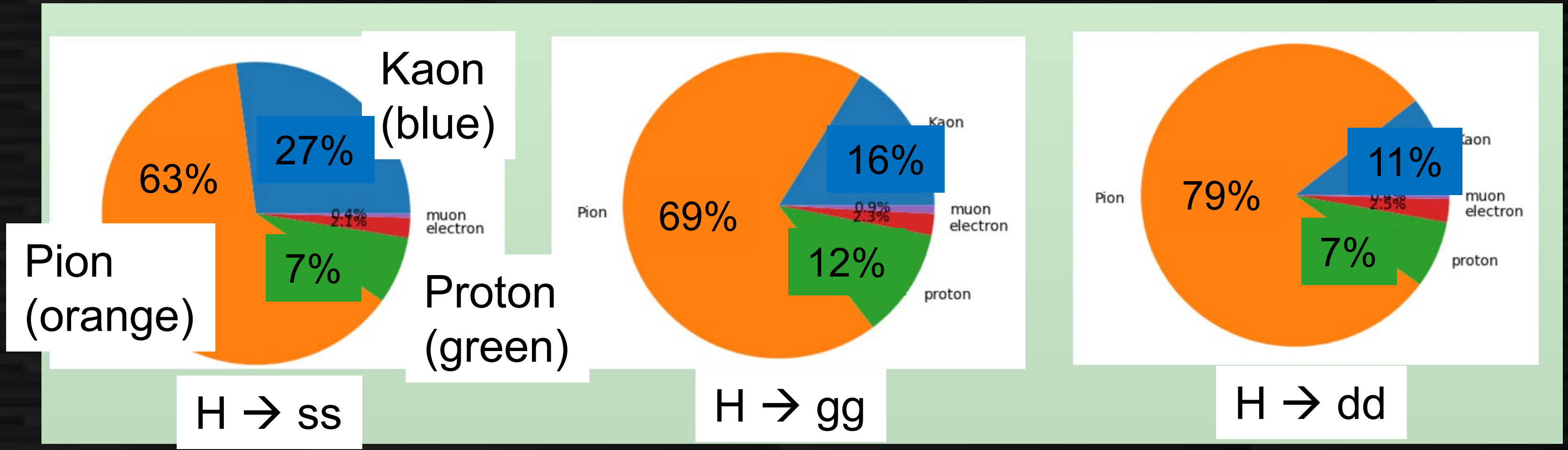
	b-tag 80% eff.		c-tag 50% eff.	
background	c jets	uds jets	b jets	uds jets
+LCFIPlus (BDT)	6.3%	0.79%	7.4%	1.2%
*ParT (initial)	1.3%	0.25%	1.0%	0.43%
**ParT (improved)	0.48%	0.14%	0.86%	0.34%



+LCFIPlus (BDT) 250 GeV nnqq
*ParT (initial) 91 GeV qq, default settings
**ParT (improved) 250 GeV nnqq, b/c/d separation

Strange tagging

- Recently focused as “new probe”
  - AFB studies in $e^+e^- \to qq$ (LEP anomaly)
  - $H \to ss$ (Br: 0.02%): nearly accessible at high-luminosity Higgs factories
- High-momentum kaon in jet is a clue to strange jets
  - Contamination from $g \to ss$ give relatively low momentum
- Strange tagging with hadron ID and ParT has been implemented

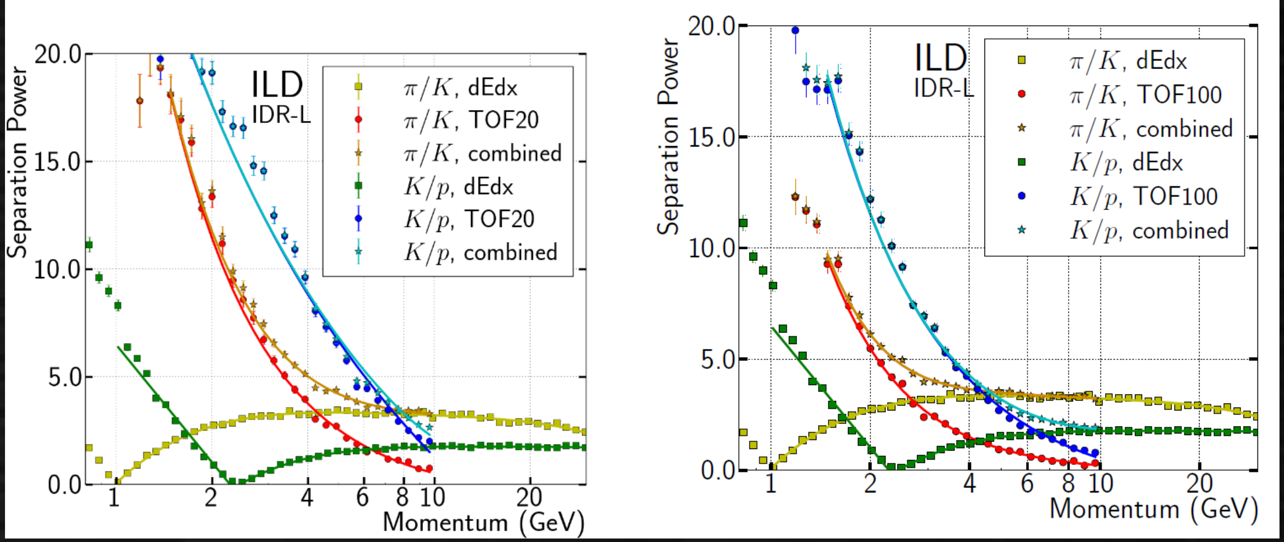


More Kaons in ss
More protons in gg

Fractions of tracks having > 5 GeV

Hadron ID for strange tagging

- Hadron ID at Higgs factories are possible at
  - dE/dx (or dN/dx) at gas tracker (TPC / drift chamber)
    - Not possible in with silicon
    - dN/dx gives better (but high-granular readout necessary)
- Time-of-flight at calorimeter (or outer silicon)
  - Currently 100 psec assumed (average over 10 hits)
  - More optimization necessary
- Comprehensive PID: BDT-based PID algorithm



Fraction of true particles

True particle (columns) / CPID prediction (rows)

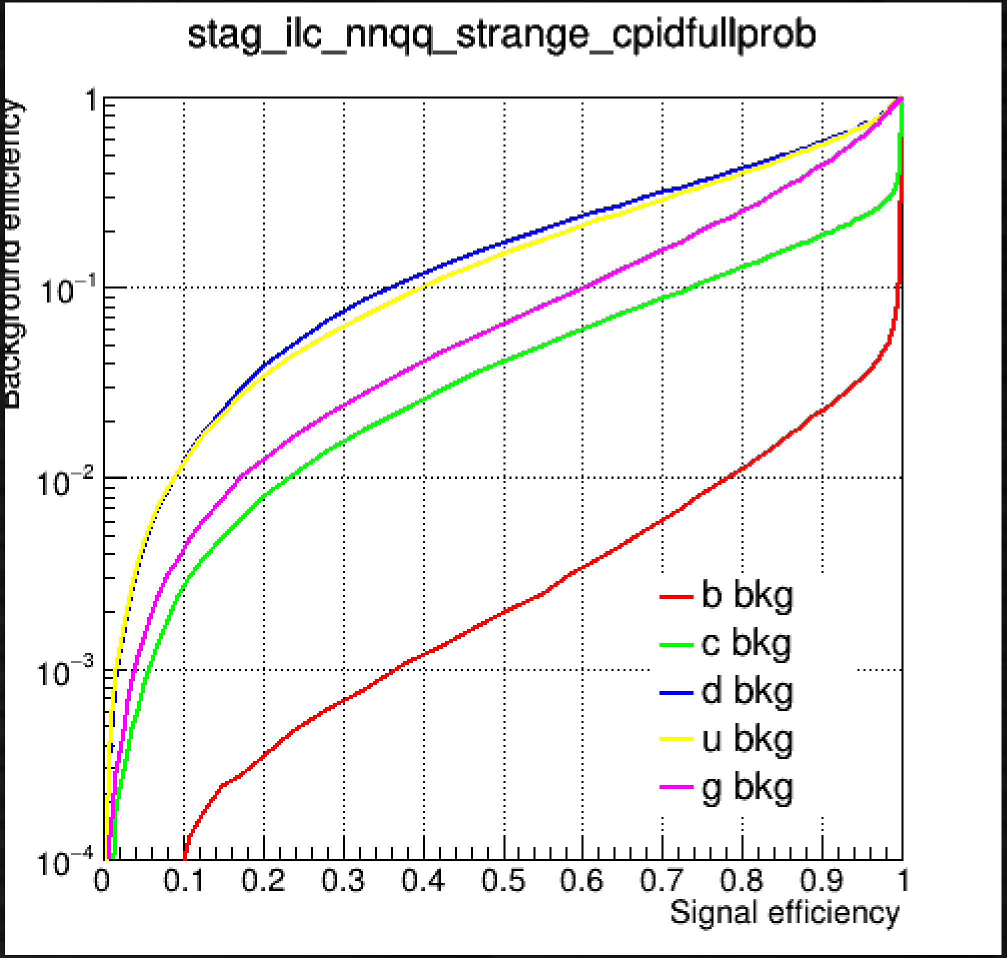
	K	π	p	e	μ
K	0.65	0.04	0.20	0.04	0.10
π	0.08	0.90	0.04	0.32	0.28
p	0.26	0.04	0.76	0.09	0.08
e	0.00	0.00	0.00	0.53	0.01
μ	0.01	0.02	0.00	0.01	0.53

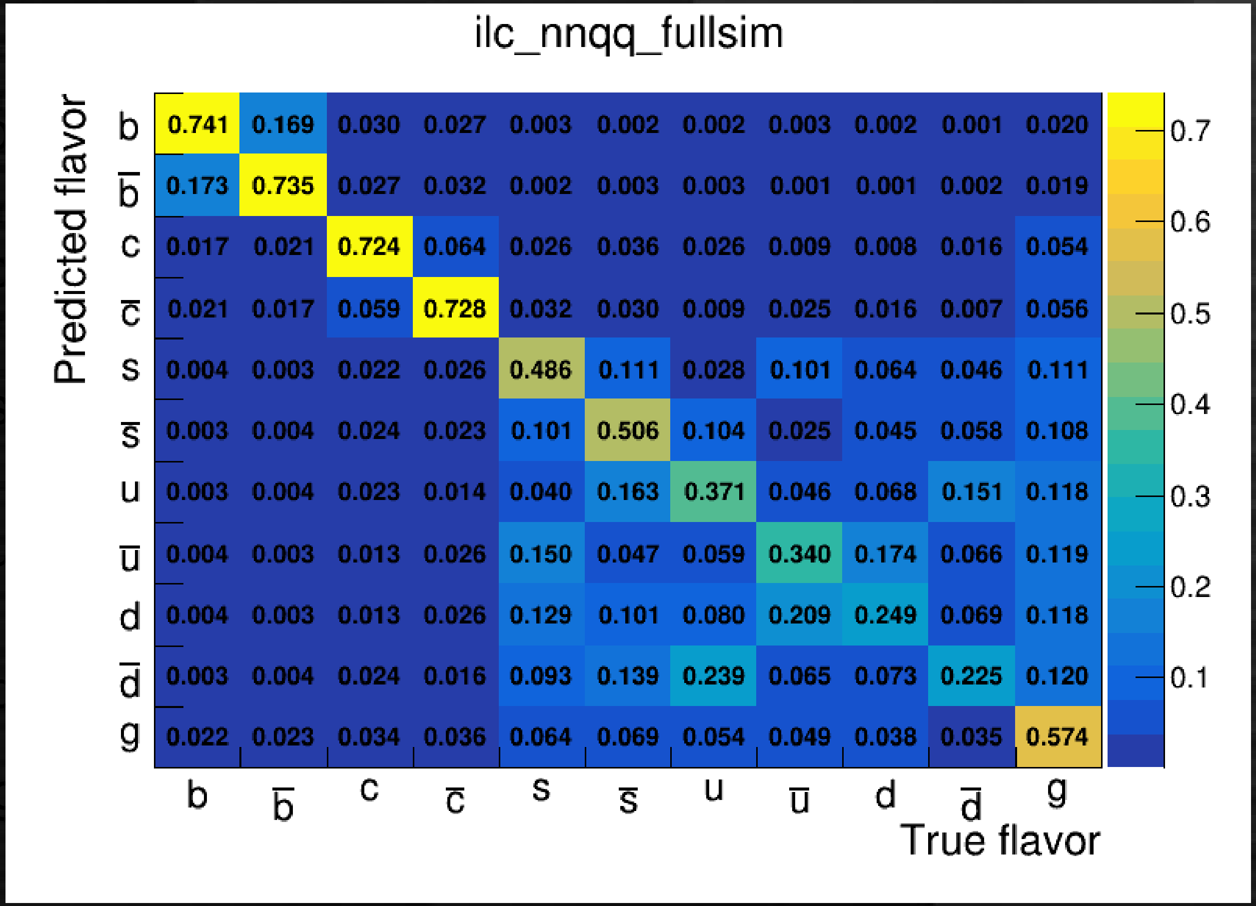
↑ 3 < p < 5 GeV

	K	π	p	e	μ
K	0.74	0.07	0.20	0.13	0.16
π	0.07	0.89	0.03	0.40	0.37
p	0.18	0.03	0.76	0.09	0.06
e	0.00	0.00	0.00	0.38	0.01
μ	0.01	0.01	0.00	0.01	0.40

↑ p > 5 GeV

11-category q/qbar tag (nnqq sample)





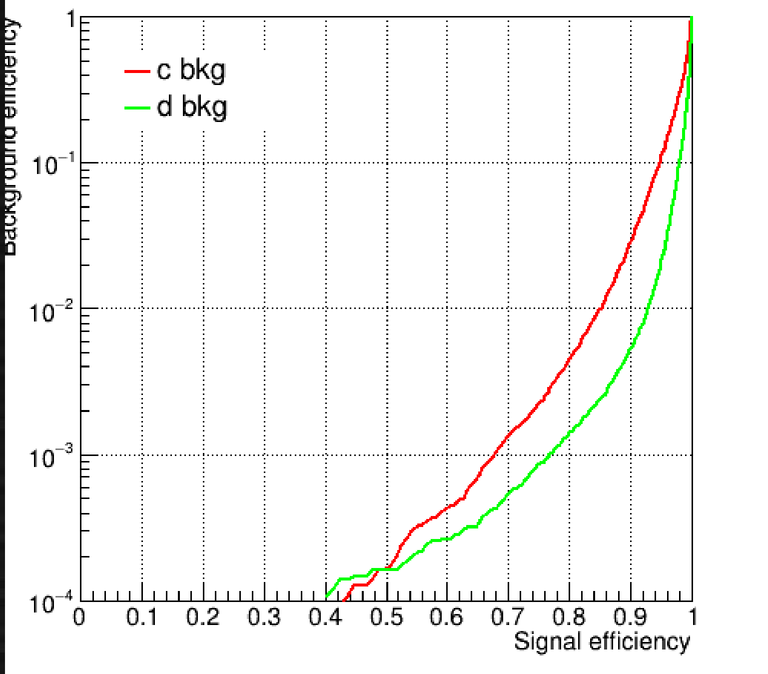
CPID (K/π/p probability)
with 100 ps TOF (x 10 hits) + dE/dx

Vertical: truth jet PDG, horizontal: predicted jet PDG
PDG with highest score taken

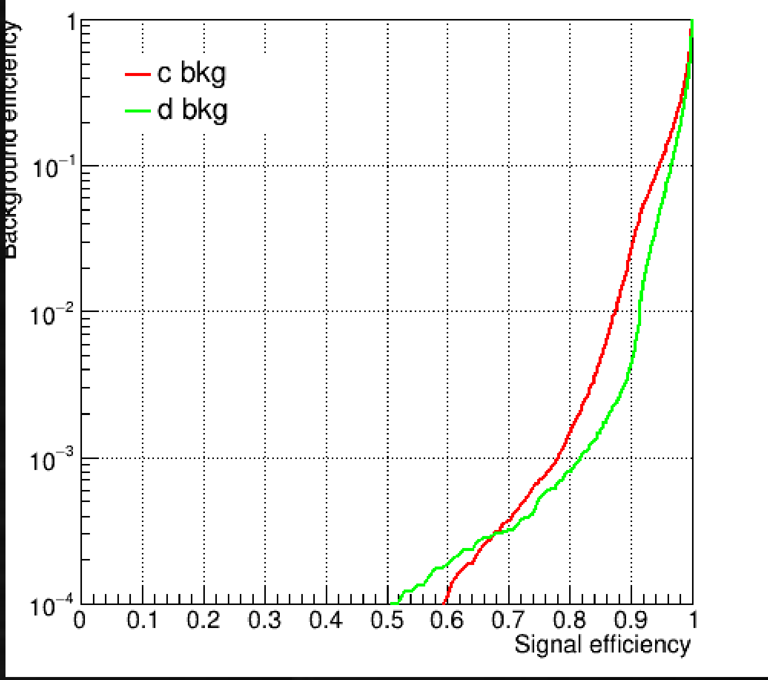
Comparison of fast/full sim and scaling law

B-tag performance, 3-category

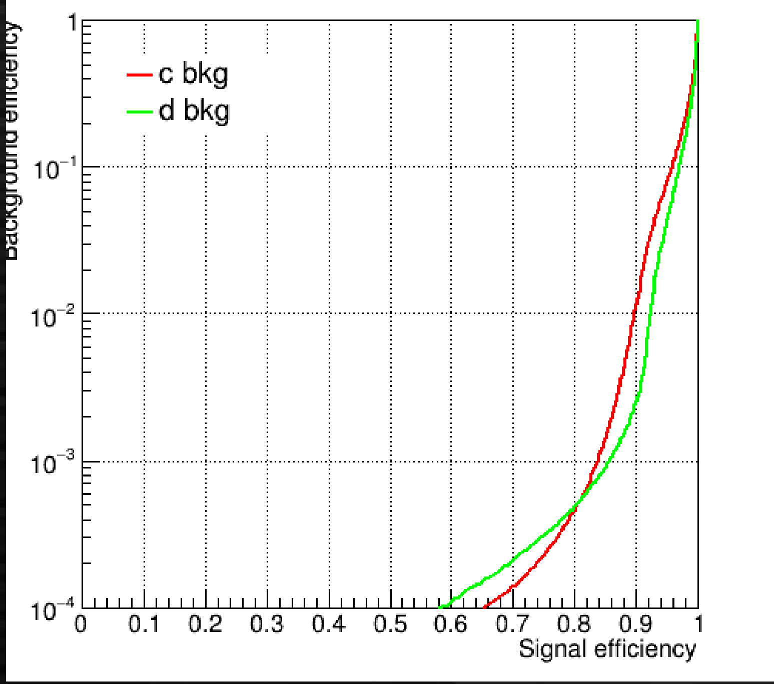
Full sim 1M sample



Fast sim (SGV) 1M sample



SGV 10M sample

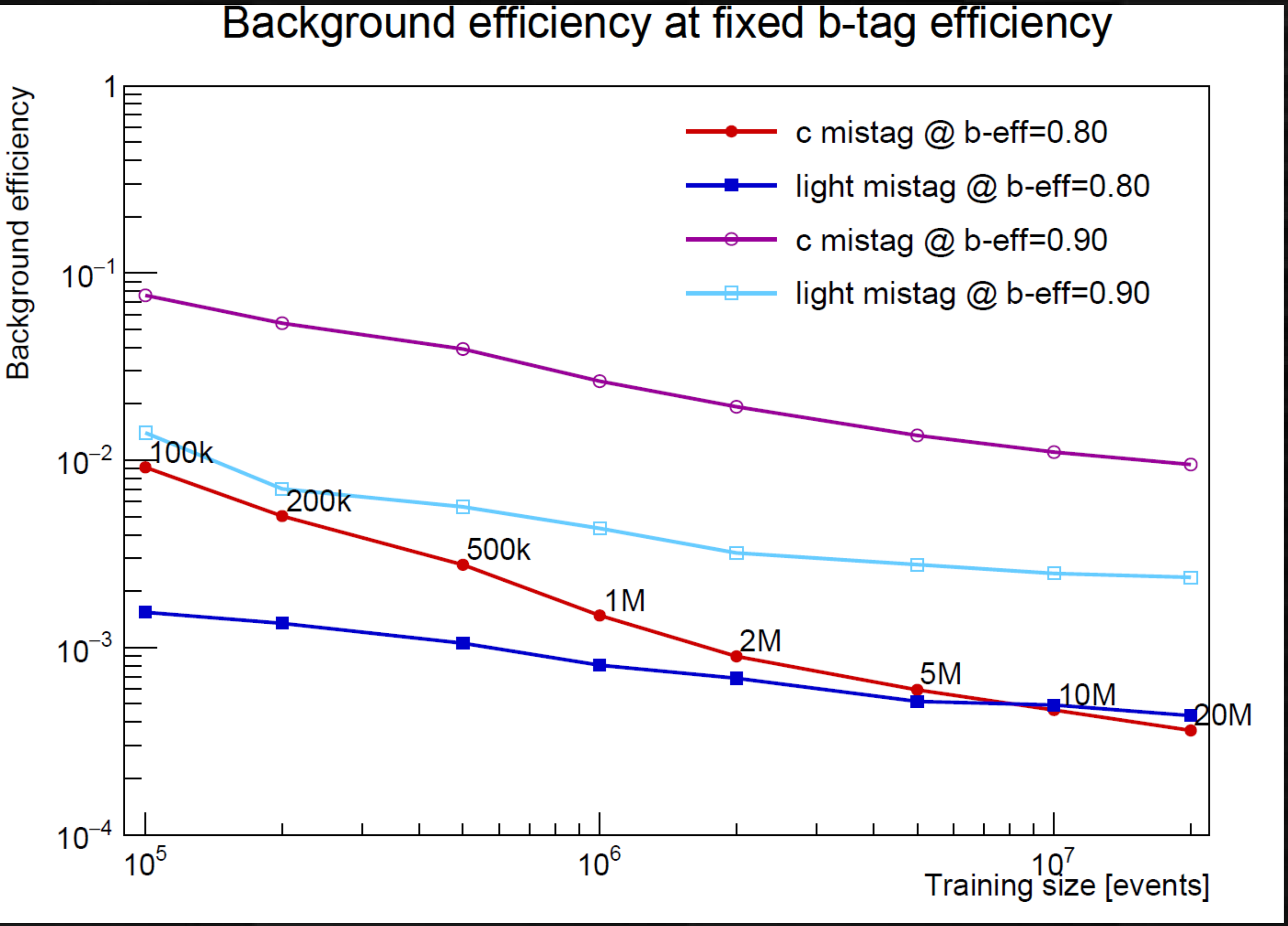


b-tag 90% eff.	c bkg.	d bkg.
Full sim 1M	2.77%	0.521%
Fast sim 1M	2.74%	0.447%
Fast sim 10M	1.16%	0.256%

b-tag 80% eff.	c bkg.	d bkg.
Full sim 1M	0.454%	0.142%
Fast sim 1M	0.142%	0.080%
Fast sim 10M	0.047%	0.050%

- Full ←→ fast: to be corrected
- 1M ←→ 10M: ~2x difference
  Significant for physics analysis
  Fullsim needs to be checked

Testing scaling law with SGV



Same network, same parameter
Do not see clear saturation
until 20M sample

C-mistag rate @ b-eff = 80% shows
clear improvements at sample > 1M
→ To be checked with full simulation

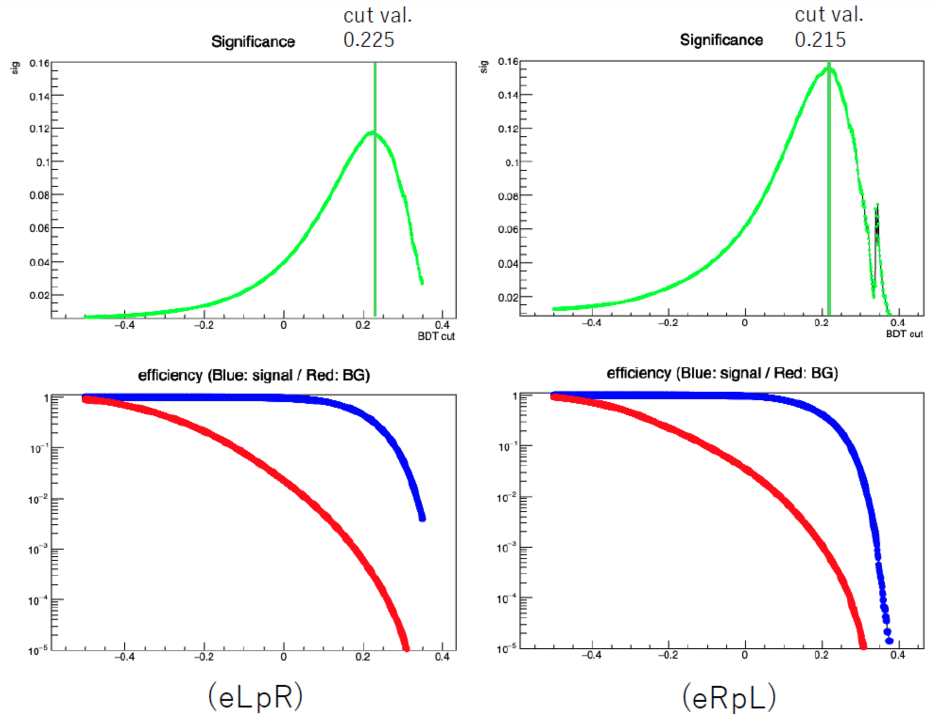
Further investigation on scaling law

- Up to 100M sample
- Hyperparameter tuning

Physics analysis on Higgs to ss (ongoing)

H → ss search is one of the primary target of s-tag
but Br ~ 0.02% → ~10 events / ab^{-1}
Analysis with ParT being done on all Z decay modes

BDT analysis done after preselection (~50 variables)
- 11-category flavor tagging probabilities
- Kinematics of jets (masses etc.) / leptons
- Jet clustering values



BDT selection on Z → νν channel

ILC	$Z \to \nu\nu$ eLpR	$Z \to \nu\nu$ eRpL	$Z \to ee$ eLpR	$Z \to ee$ eRpL	$Z \to \mu\mu$ eLpR	$Z \to \mu\mu$ eRpL	$Z \to qq$ eLpR	$Z \to qq$ eRpL
S	3.86	2.19	0.506	0.406	0.584	0.434	3.29	5.58
B	1074	197	104	59	103	46	7957	13361
sig.	0.1176	0.1552	0.0494	0.0527	0.0573	0.0634	0.0369	0.0483

We can probe μ ~ 5 at ILC
(with FCCee, μ ~ 1 reported)
Background with strange quarks significant → strange tagging is not the only performance driver

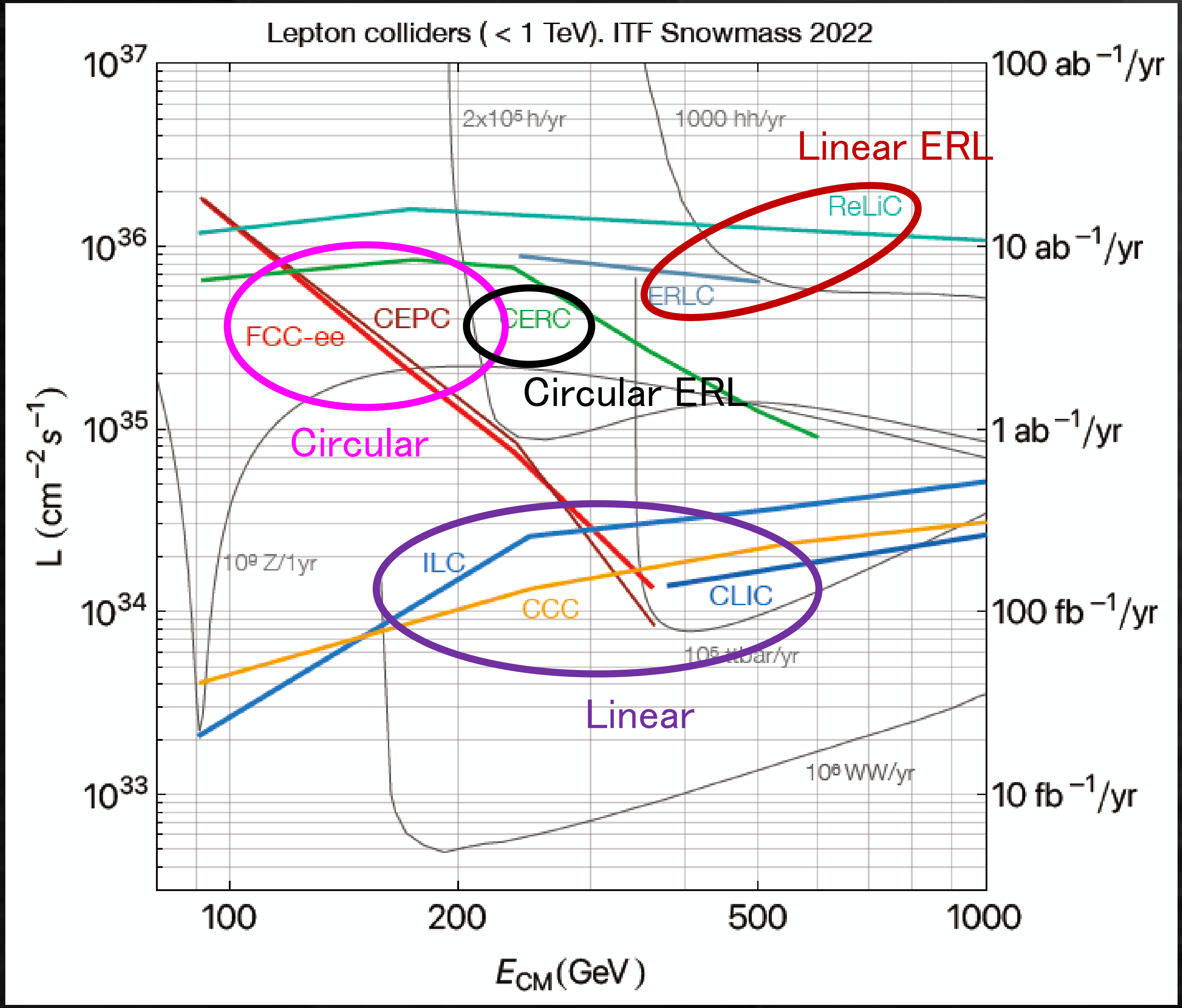
Summary

- AI-based reconstruction became essential for collider analyses
  - Higgs factory studies as well as LHC studies
- Flavor tag: already a game changer
  - ~10x better performance (both in LHC and HF)
  - Want to know "ultimate performance" with sufficient data/parameters
  - Combination with jet clustering / physics analyses to be pursued
- Particle flow: progress towards application
  - Working on energy regression with several ways
  - Important for detector optimization/modelling

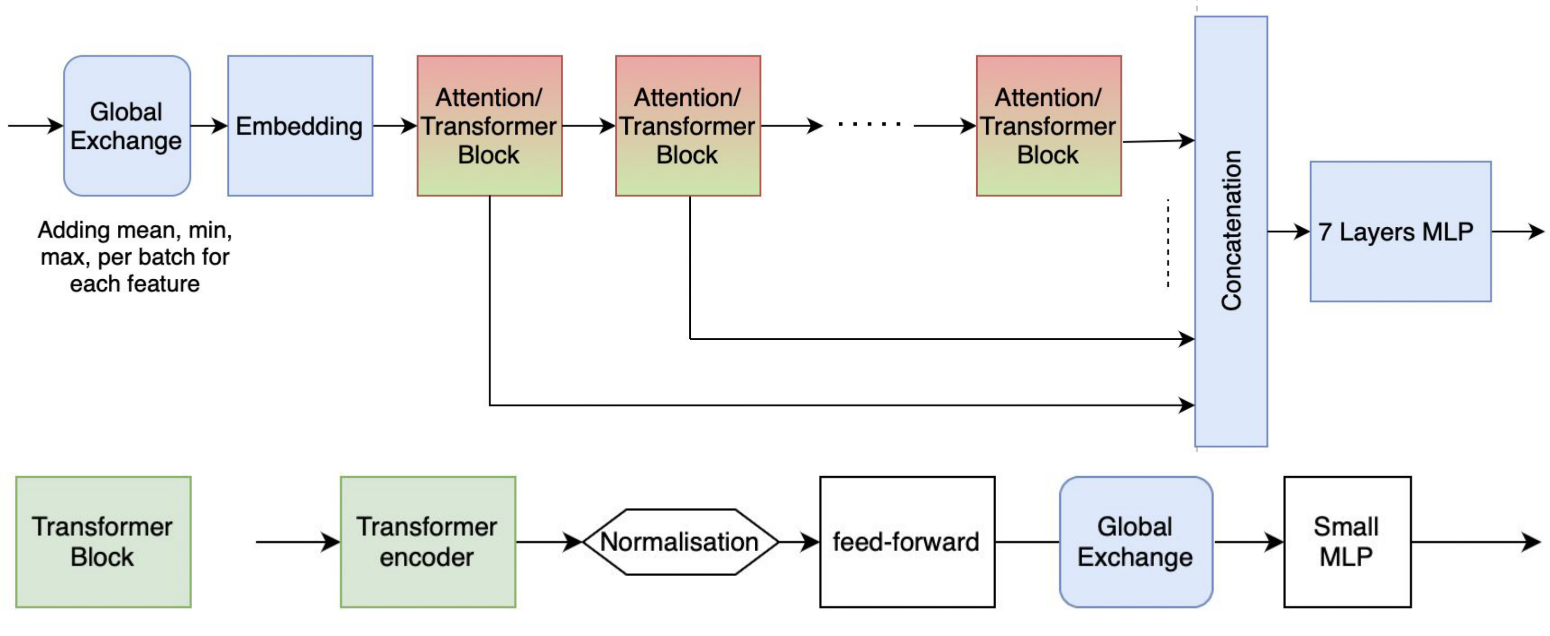
Backup

Circular and Linear collider?

- Luminosity @ 240/250 GeV
  - A few times higher at circular colliders
- Luminosity @ 350 GeV
  - Less efficient with circular
- Polarization
  - Obvious in LC
  - Not excluded but not guaranteed in circular
- Self coupling, ttH
  - Indirect only in circular



Replacing GravNet with Transformer



Work by internship student (S. Barbu)
Summarized in BOOST2025 poster
https://indico.physics.brown.edu/event/18/contributions/396/

Using similar structure to GravNet but replace GravNet block with transformer encoder block

Use the same loss (object condensation)

Metric	Tr-model	GSA-GravNet	GravNet	Improvement (Tr-model-GravNet)
Number of parameters (M)	2	0.9	0.4	
Electron Efficiency/Purity	99.4 / 91.3	98.2 / 91.5	98.9 / 94.5	+0.5 / -3.2
Pion Efficiency/Purity	98.0 / 98.5	95.7 / 98.4	95.9 / 99.0	+2.1 / -0.5
Photon Efficiency/Purity	97.2 / 97.1	93.3 / 97.1	97.1 / 98.6	+0.1 / -1.5

Performance comparison with 10 taus

Some improvement seen in pion efficiency – details to be checked

Yet another prospects: treating real data

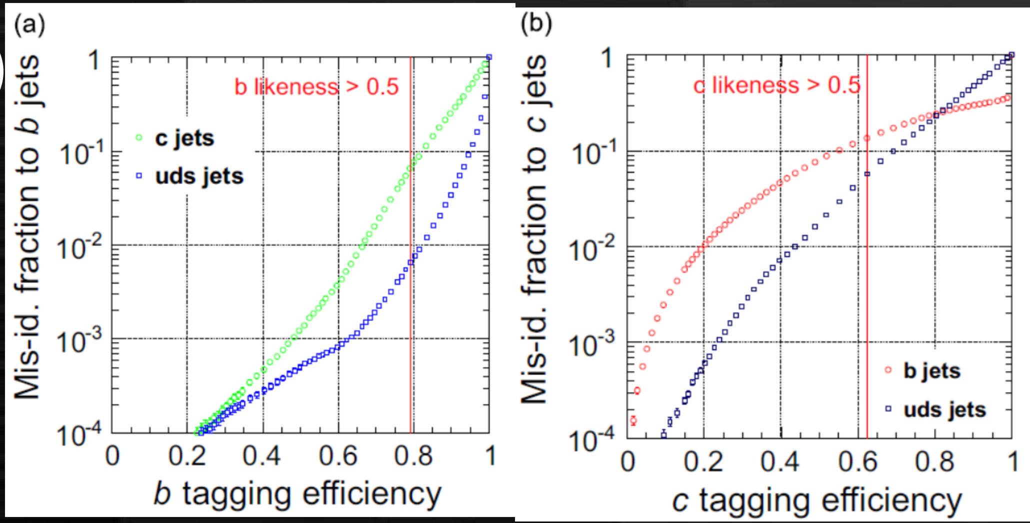
- Real calorimeter suffers from inhomogeneous response
  - Channel-by-channel gain difference (to calibrate/correct)
  - Dead channels, noisy channels
- Can ML be used for correction from MC to data?
  - "FiLM" technique – additional (small) ML to derive linear (ax+b) correction (FiLM calculates a and b to each hit)
  - Train initial network with simulation and train additional FiLM layer later by real data
  - Under investigation (to try calibration of test beam data)

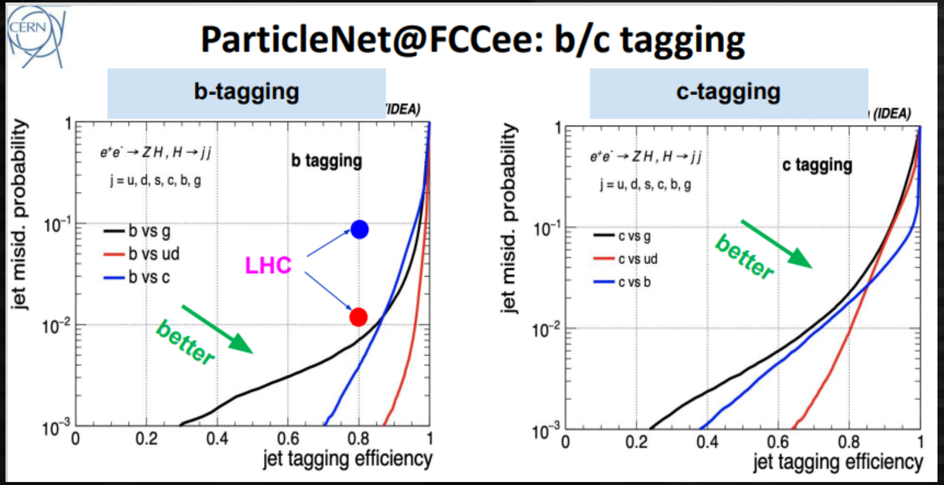
→ Towards "modeling" of imperfect detector response

Flavor tagging for Higgs factories

- Jet flavor tagging is essentially important for Higgs studies (including self coupling)
- LCFIPlus (published 2013) was long used for flavor tagging
  - All physics performance in ILD/SiD/CLIC are based on LCFIPlus
- FCCee reported >10x better rejection using ParticleNet (GNN) in 2022
  - Delphes is used for simulation
- We studied DNN-based flavor tag with ILD full simulation to confirm it
  - Using latest algorithm: Particle Transformer (ParT)

LCFIPlus performance plots





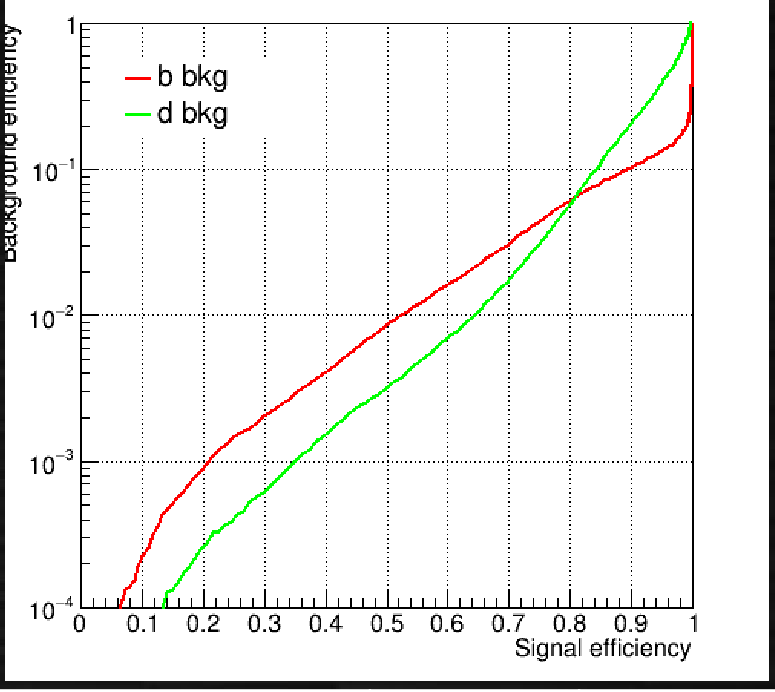
Software implementation

- Training done in python/weaver framework
  - New LCFIPlus algorithm (MLMakeNtuple) to create input ROOT files
  - ROOT files used for training ParT
    - nnqq 250 GeV, ~1M jets / each flavor
    - MC/jet matching inside LCFIPlus (only for q/qbar training)
      - Color-singlet tagging by RecoMCTruthLink, q/g identified based on angle
        - » If multiple jets assigned to the same q/g, jet with highest energy taken
  - Training with GPU (~a half day for 20 epochs with Tesla V100)
- Weights (checkpoint) converted to onnx
  - Using onnx 1.15.0, onnxruntime 1.17.1 (to be compatible with key4hep)
- Inference with CPU in LCFIPlus framework
  - New processor MLInferenceWeaver with onnx files (uploaded in LCFIPlusConfig)
- Currently on private repository (pulling to official repository being processed)
  - LCFIPlus github with ParT, https://github.com/suehara/LCFIPlus/tree/onnx
  - LCFIPlusConfig with weight/steering files, https://github.com/suehara/LCFIPlusConfig

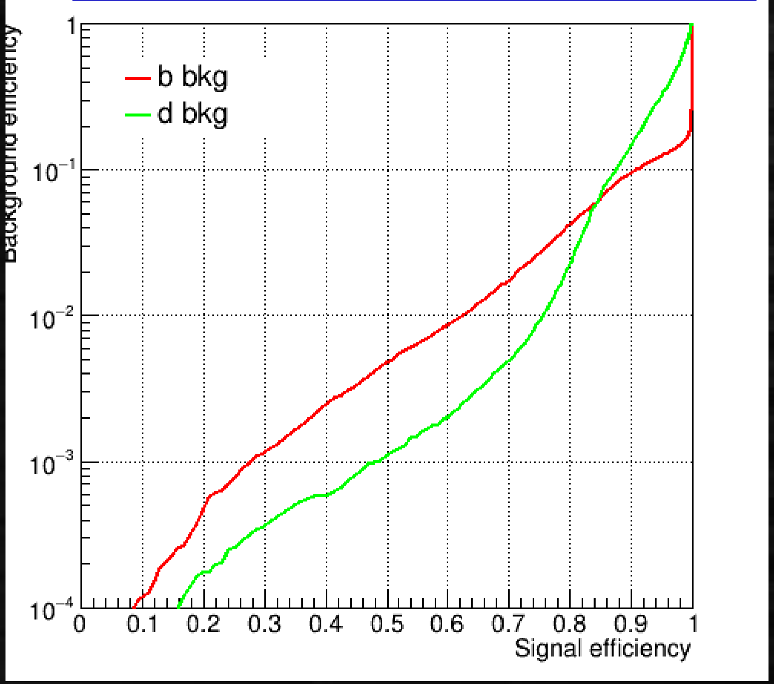
Comparison of fast/full sim and scaling law

C-tag performance, 3-category

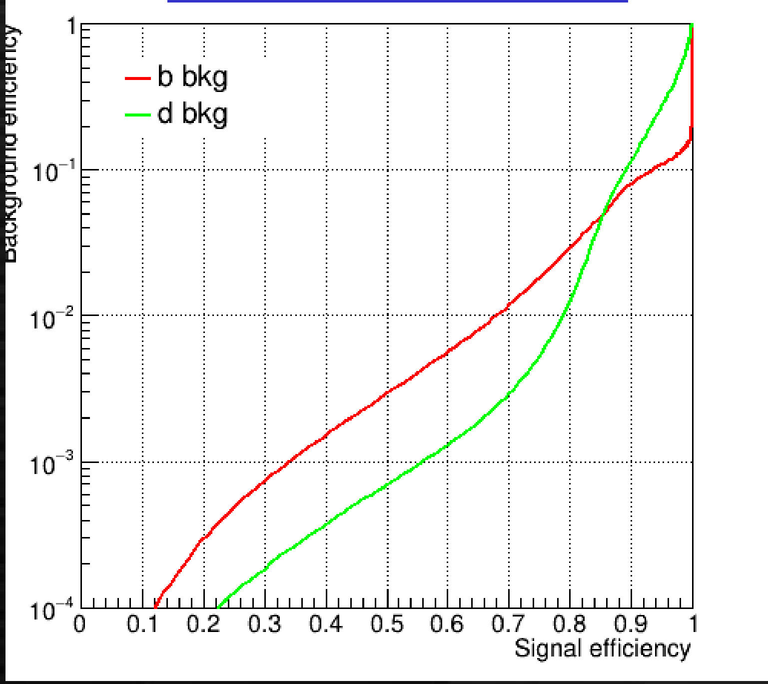
Full sim 1M sample



Fast sim (SGV) 1M sample



SGV 10M sample



c-tag 80% eff.	c bkg.	d bkg.
Full sim 1M	6.19%	5.98%
Fast sim 1M	4.32%	2.38%
Fast sim 10M	2.93%	1.27%

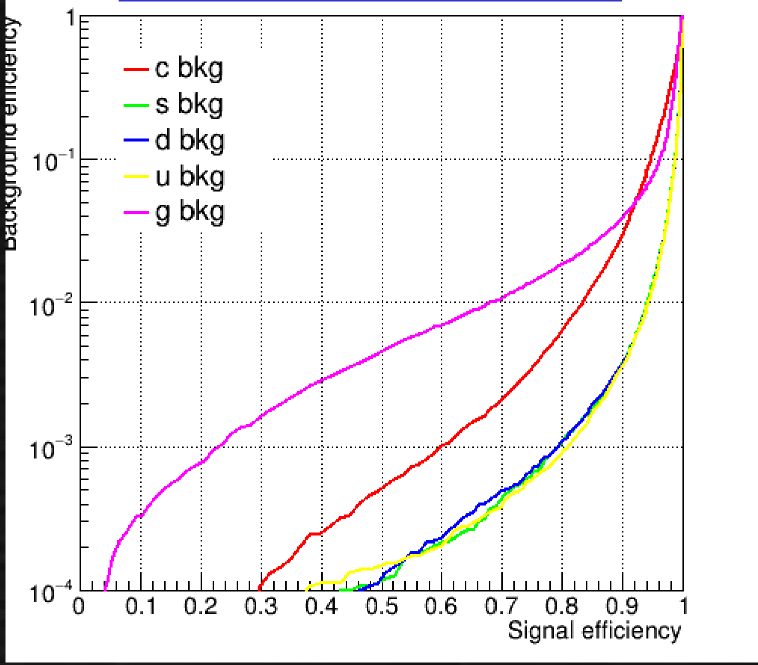
c-tag 50% eff.	c bkg.	d bkg.
Full sim 1M	0.890%	0.337%
Fast sim 1M	0.477%	0.111%
Fast sim 10M	0.288%	0.073%

Full ←→ fast: to be corrected
1M ←→ 10M: ~2x difference
Significant for physics analysis
Fullsim needs to be checked

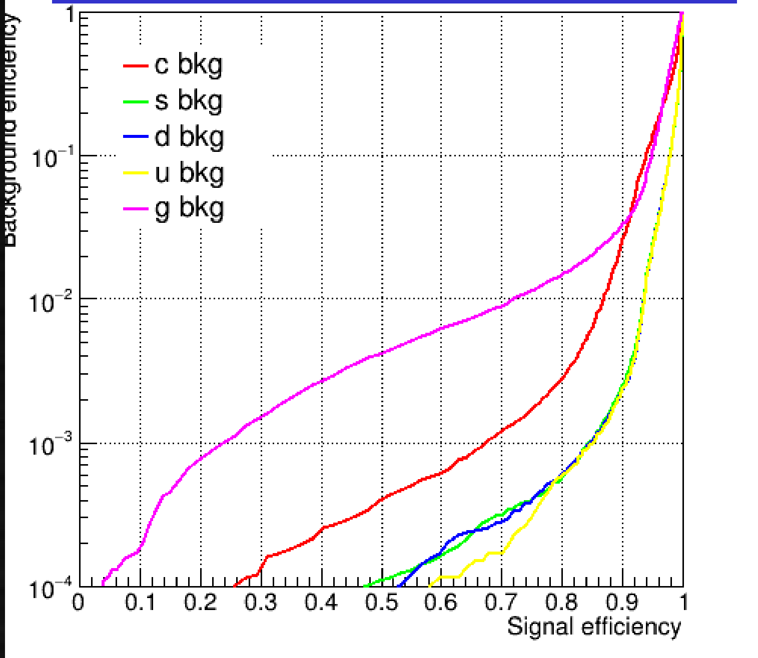
Comparison of fast/full sim and scaling law

B-tag performance, 6-category

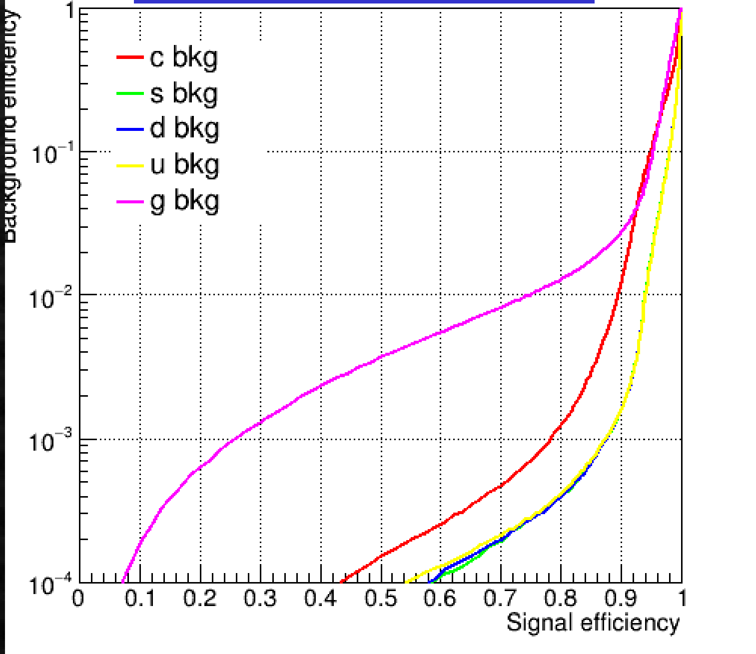
Full sim 1M sample



Fast sim (SGV) 1M sample



SGV 10M sample



b-tag 80% eff.	c bkg.	s bkg.	d bkg.	u bkg.	g bkg.
Full sim 1M	0.627%	0.105%	0.106%	0.088%	1.839%
Fast sim 1M	0.289%	0.059%	0.063%	0.061%	1.511%
Fast sim 10M	0.120%	0.039%	0.039%	0.041%	1.274%

Comparison with FCCee Delphes (2023)

b-tag 90% eff.	c bkg.	d bkg.
ILD Full 1M	2.77%	0.521%
ILD SGV 1M	2.74%	0.447%
FCC delphes 1M	1.66%	0.292%
ILD SGV 10M	1.16%	0.256%
FCC delphes 10M	0.074%	0.0039%

b-tag 80% eff.	c bkg.	d bkg.
ILD Full 1M	0.454%	0.142%
ILD SGV 1M	0.142%	0.080%
FCC delphes 1M	0.267%	0.078%
ILD SGV 10M	0.047%	0.050%
FCC delphes 10M	0.006%	0.005%

c-tag 80% eff.	c bkg.	d bkg.
ILD Full 1M	6.19%	5.98%
ILD SGV 1M	4.32%	2.38%
FCC delphes 1M	3.11%	0.925%
ILD SGV 10M	2.93%	1.27%
FCC delphes 10M	0.743%	0.218%

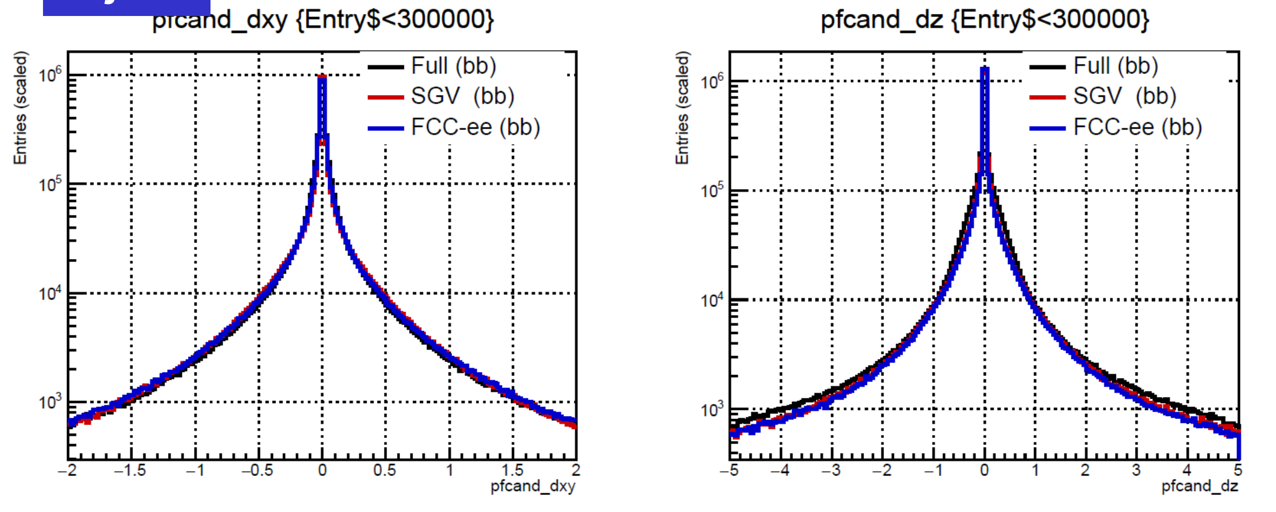
c-tag 50% eff.	c bkg.	d bkg.
ILD Full 1M	0.890%	0.337%
ILD SGV 1M	0.477%	0.111%
FCC delphes 1M	0.401%	0.064%
ILD SGV 10M	0.288%	0.073%
FCC delphes 10M	0.080%	0.017%

Caution: FCC 10M b-tag is too good: reason unknown

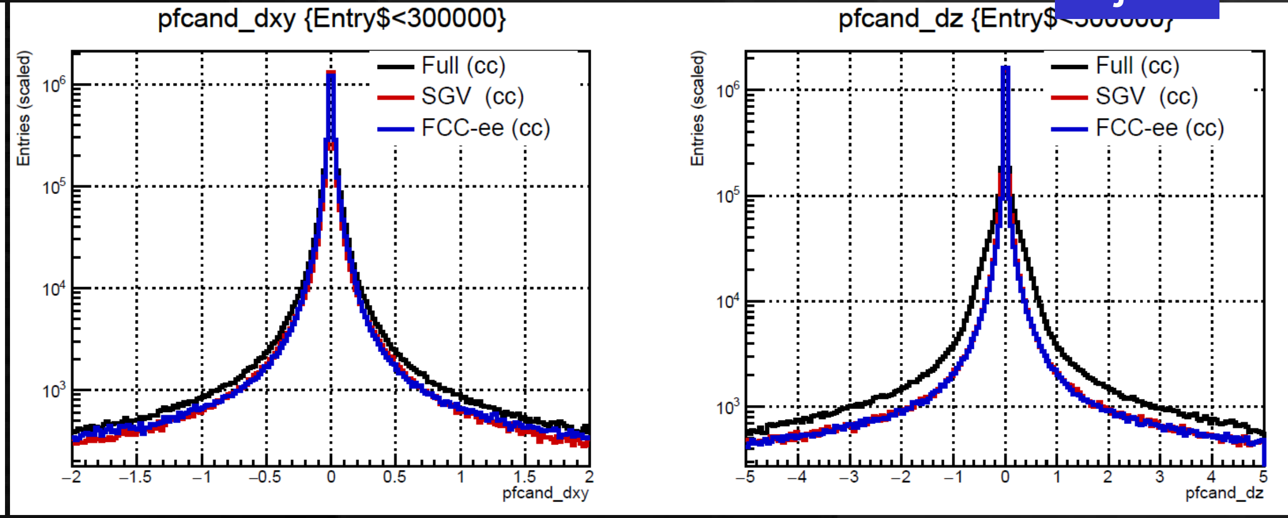
Performance on fast simulation should be not too reliable (esp. for high purity)

Comparison of d0/z0 (wrt primary vertex), fullsim / SGV / FCC Delphes

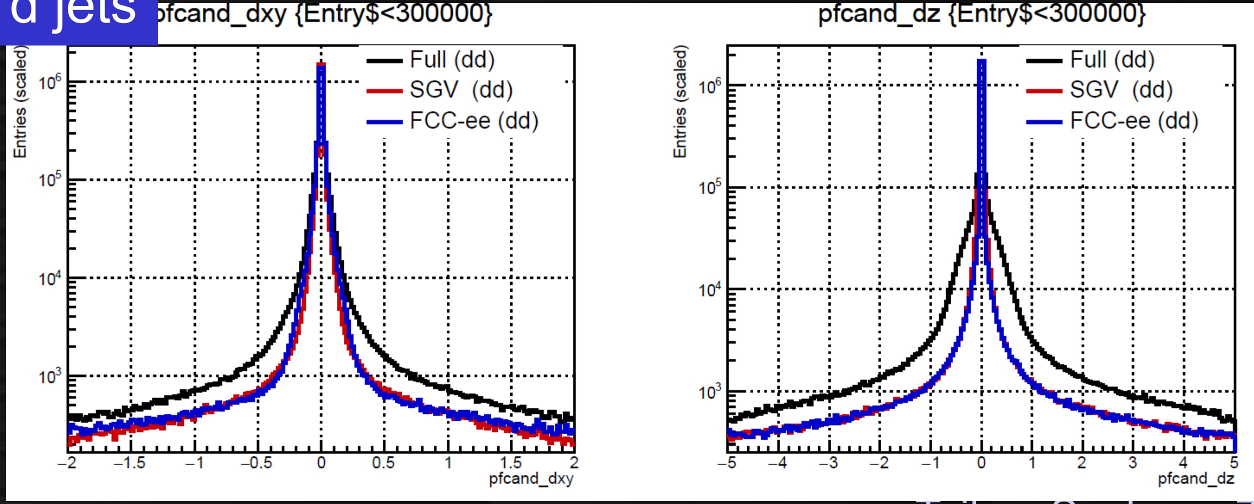
b jets



c jets



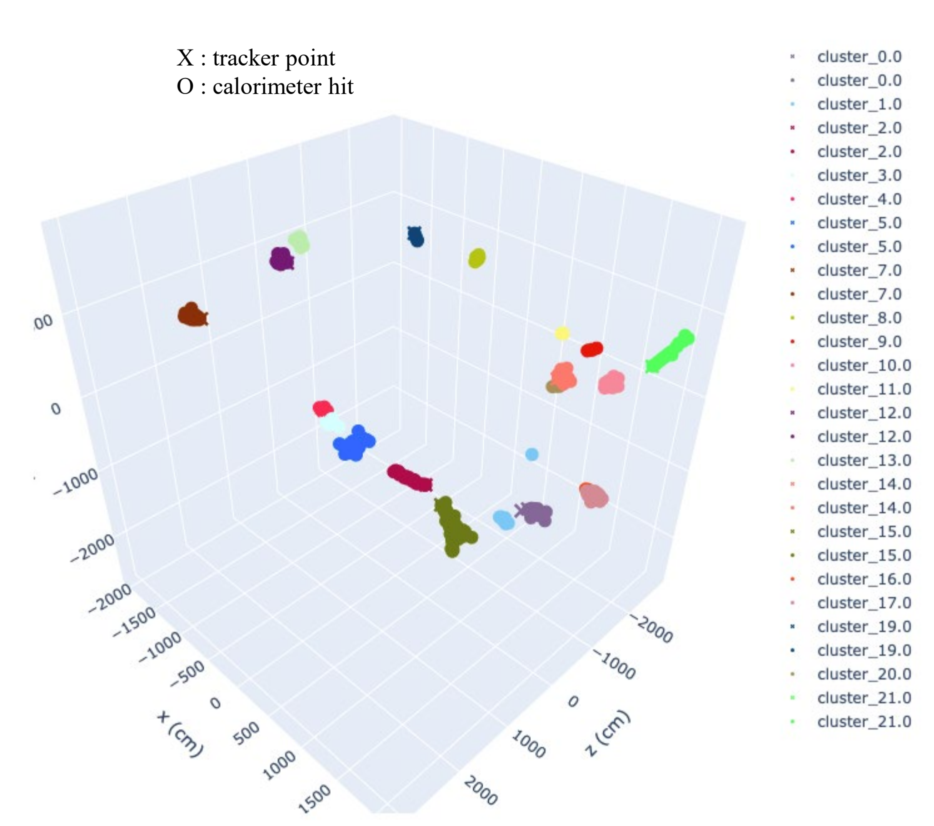
d jets



Significant difference on tail of the distribution (hard scattering?) with light flavor

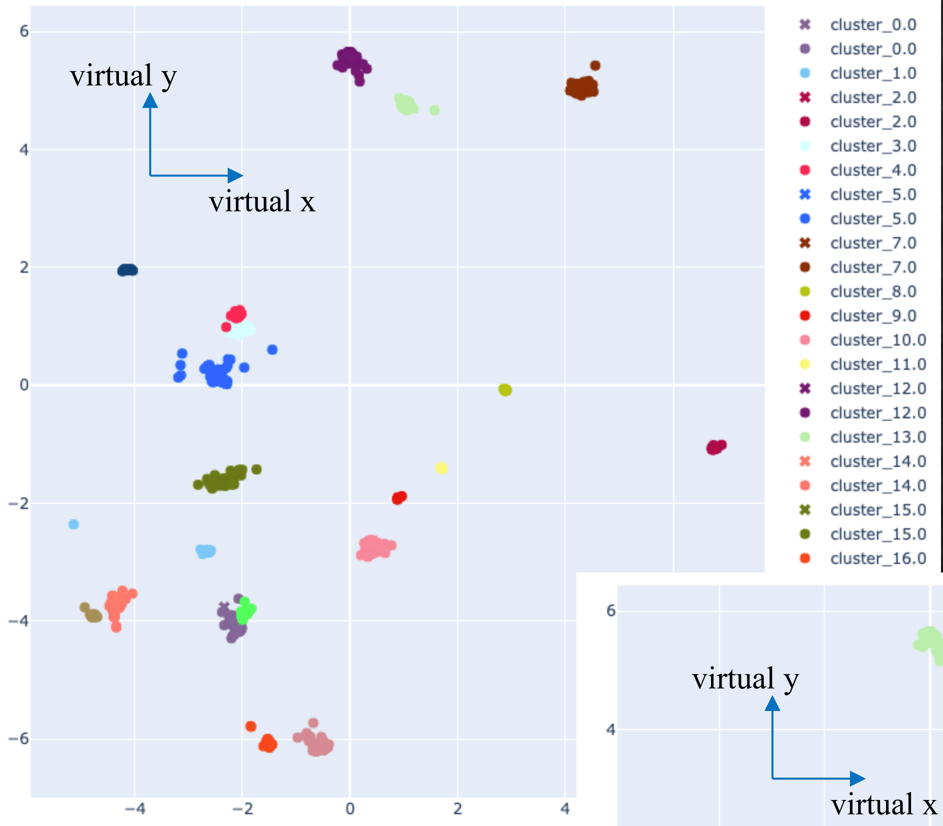
ILD SGV and FCC Delphes nearly consistent

Event display



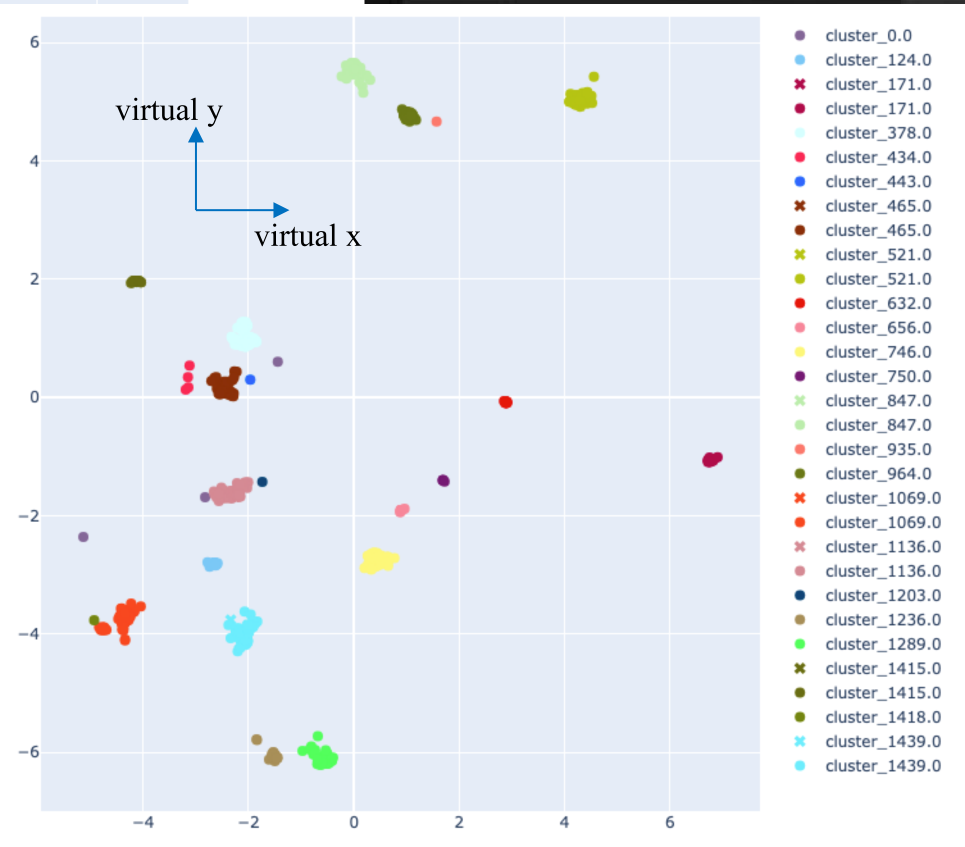
Input features
Real coordinate in detector

Colored by true clusters



Output features
Virtual coordinate

Colored by
true clusters



Colored by
reconstructed clusters

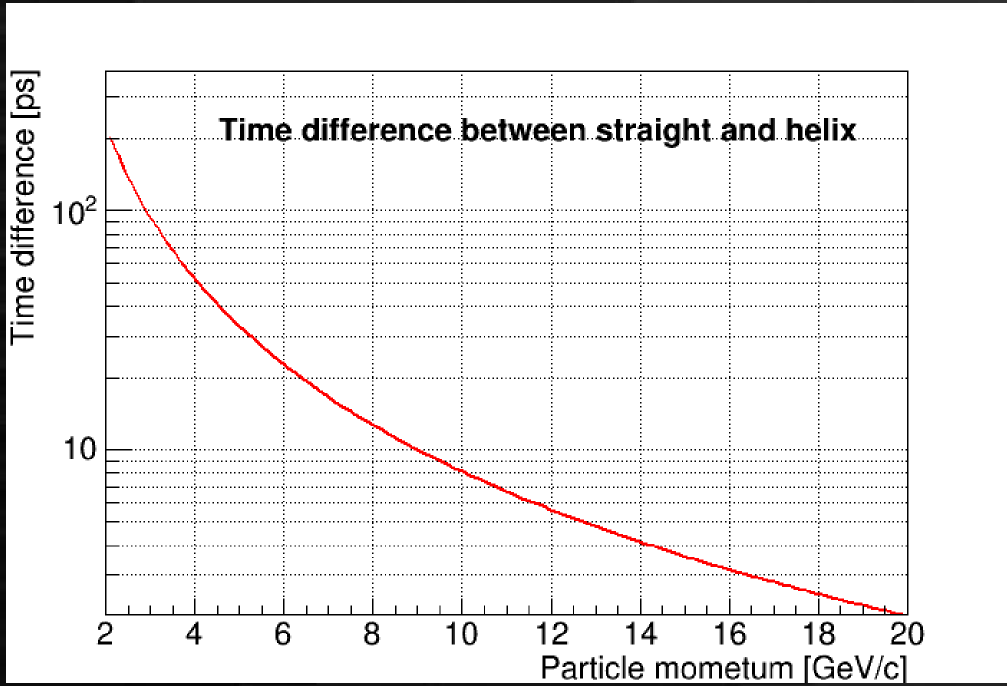
Summary and prospects for PFA

- GNN-based particle flow has possibility to replace PandoraPFA
  - Clustering performance is comparable with current optimization
  - Energy regression is being tried (reasonable performance with truth clustering)
- Possible improvements on algorithm (study ongoing)
  - Clustering algorithm (possibly with additional network)
  - Transformer-based network (in various ways)
- Test bench for detector design/optimization
  - Effects/advantages on new variables/measurements
    - Timing information (how much precision required?)
    - Particle ID (dE/dx, tof, …)
    - Pixel size (silicon pads vs scintillator vs MAPS), detector size, magnetic field etc.
- Application to physics analyses

Example: timing information

Timing information can be utilized in many ways

- Particle ID by ToF (e.g. pi/K/p separation)
  - Essential for strange tag
  - Should be good for PFA as well
- Separation of helix and straight path
  - Charged and neutral particles
- Off-axis photons (but need ~1psec resolution)
  - Should be useful for flavor tagging
    - b/c separation by mass



Performance on e.g. PID/PFA heavily depends on reconstruction software

- For PID: simple introducing timing info and check the performance should be easy
  - With any timing smearing
  - For non-ML, need to implement new algorithms and heavily tune it

Software for Particle Transformer

- Public in github, with instruction provided
  - https://github.com/jet-universe/particle_transformer
- Input: ROOT files for training (80%), validation (5%), test (15%)
  - Input variables can be provided via steering file (XML)
    - Input for each particle (tracks, neutral clusters)
    - Input for “interaction” → currently momentum only
    - Input for “coordinate” → theta/phi plan wrt. jet axis
- Output: ROOT files including evaluation results (likeness) for test events
  - To be analyzed with ROOT or so
- We implemented a processor (inside LCFIPlus) to produce ROOT files for input as much as compatible to FCCee variables
  - Except for PID values, which are not fully implemented
- Easy for testing, but not direct to be used for physics analyses

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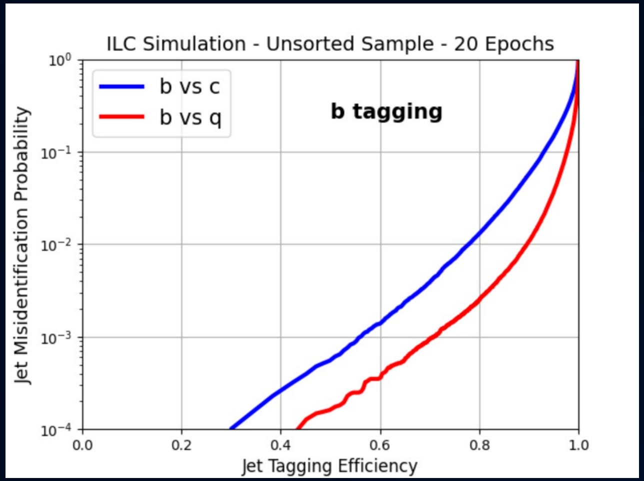
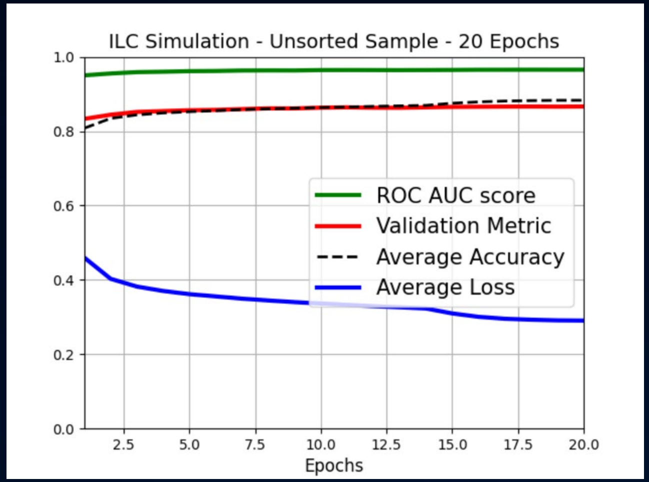
  - Except for PID values, which are not fully implemented
- Easy for testing, but not direct to be used for physics analyses

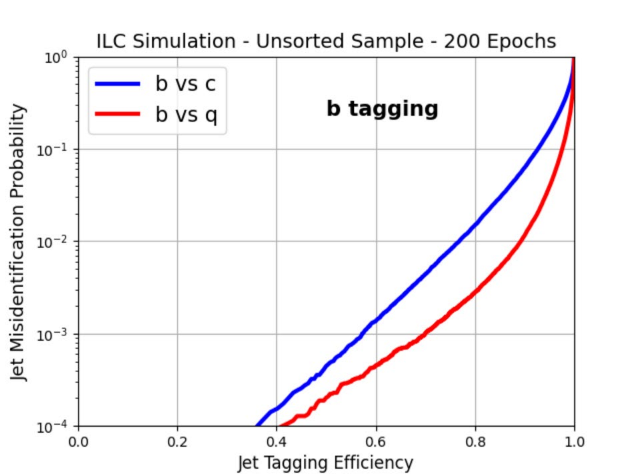
Training parameters - epochs

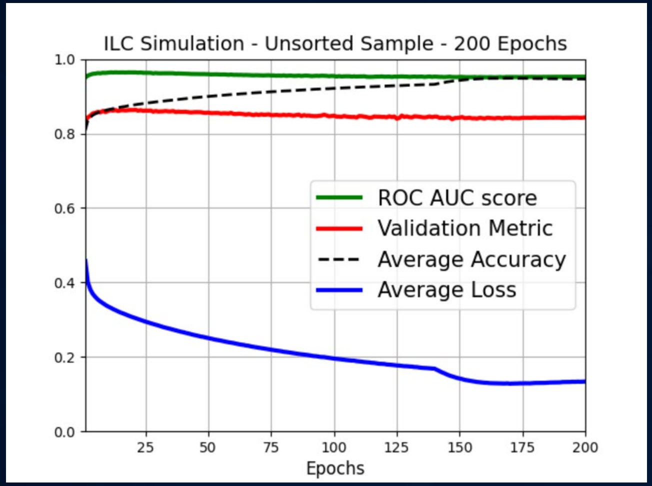
- Run on NVIDIA TITAN RTX (memory: 24 GB)
  - 20 Epochs: 3 hours
  - 200 Epochs: 30 hours
- No significant improvement in tagging efficiency
- Both ROC AUC score and Validation Metric reaches a maximum around 20 epochs.
- Overtraining after 20 epochs.
- Hence 20 epochs of training is selected to avoid overtraining.





20 epochs (ILD qq 91 GeV)





200 epochs (ILD qq 91 GeV)

Input Variables - Features

*Naming follows FCCee scheme – may not express exact meaning

- Impact Parameter (6):
  - pfcand_dxy
  - pfcand_dz
  - pfcand_btagSip2dVal
  - pfcand_btagSip2dSig
  - pfcand_btagSip3dVal
  - pfcand_btagSip3dSig

*d0/z0 and 2D/3D impact parameters, 0 for neutrals

- Jet Distance (2):
  - pfcand_btagJetDistVal
  - pfcand_btagJetDistSig

*Displacement of tracks from line passing IP with direction of jet
0 for neutrals

- Particle ID (6):
  - pfcand_isMu
  - pfcand_isEl
  - pfcand_isChargedHad
  - pfcand_isGamma
  - pfcand_isNeutralHad
  - pfcand_type

* Not including strange-tagging related variables (TOF, dE/dx etc.)
* Simple PID for ILD, not optimal

- Kinematic (4):
  - pfcand_erel_log
  - pfcand_thetarel
  - pfcand_phirel
  - pfcand_charge

*Fraction of the particle energy wrt. jet energy (log is taken)

- Track Errors (15):
  - pfcand_dptdpt
  - pfcand_detadeta
  - pfcand_dphidphi
  - pfcand_dxydxy
  - pfcand_dzdz
  - pfcand_dxydz
  - pfcand_dphidxy
  - pfcand_dlambdadz
  - pfcand_dxyc
  - pfcand_dxyctgtheta
  - pfcand_phic
  - pfcand_phidz
  - pfcand_phictgtheta
  - pfcand_cdz
  - pfcand_cctgtheta

*each element of covariant matrix
0 for neutrals

Input Variables - Interactions

- FCC data uses p (scalar momentum) as interaction:

  - pfcand_p

- ILD data contains p_x, p_y, p_z (vector momentum) as interaction:

  - pfcand_px
  - pfcand_py
  - pfcand_pz

- But it's possible to transfer ILD's interaction to FCC's form for fair comparison:

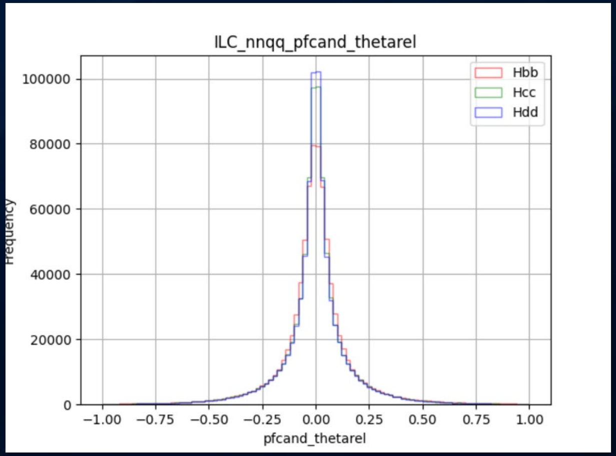
$$p = \sqrt{{p_x}^2 + {p_y}^2 + {p_z}^2}$$

Use px, py, pz instead of p (Interaction)

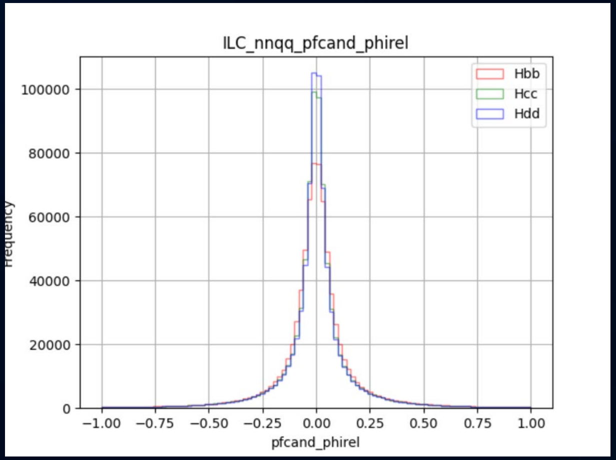
				c-bkg acceptance @ b-tag 80% eff.		b-bkg acceptance @ c-tag 50% eff.	
Particle ID	Impact Parameters	Jet Distance	Track Errors	p	p_x p_y p_z	p	p_x p_y p_z
✗	●	●	●	0.62%	0.49%	1.14%	1.01%
✗	● +log(abs)	● +log(abs)	● +log(abs)	0.54%	0.52%	1.06%	1.00%
✗	● +log(abs)	●	●	0.47%	0.50%	1.03%	0.97%

- ILD (ννqq 250 GeV) data shows that application of px, py, pz has better performance than p.
- However, application of log(abs) of the parameters becomes less significant.
- Can be because that application of px, py, pz changes the way log(abs) interacts with other parameters.
- Other potential treatments can be investigated.

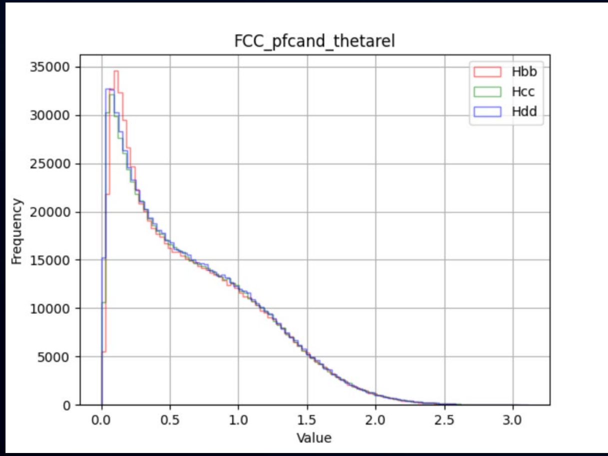
ILD vs. FCC – theta/phi distribution



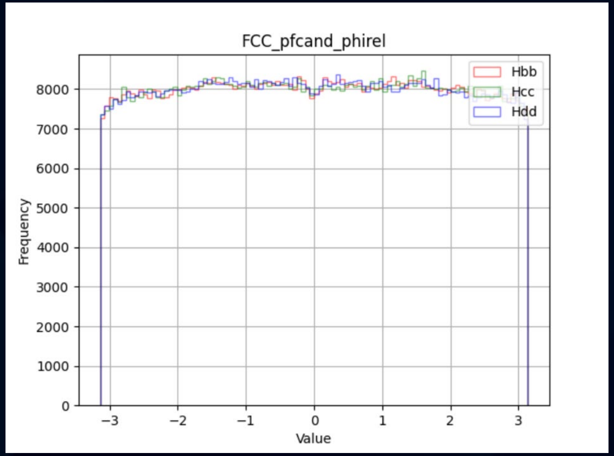
ILD theta



ILD phi



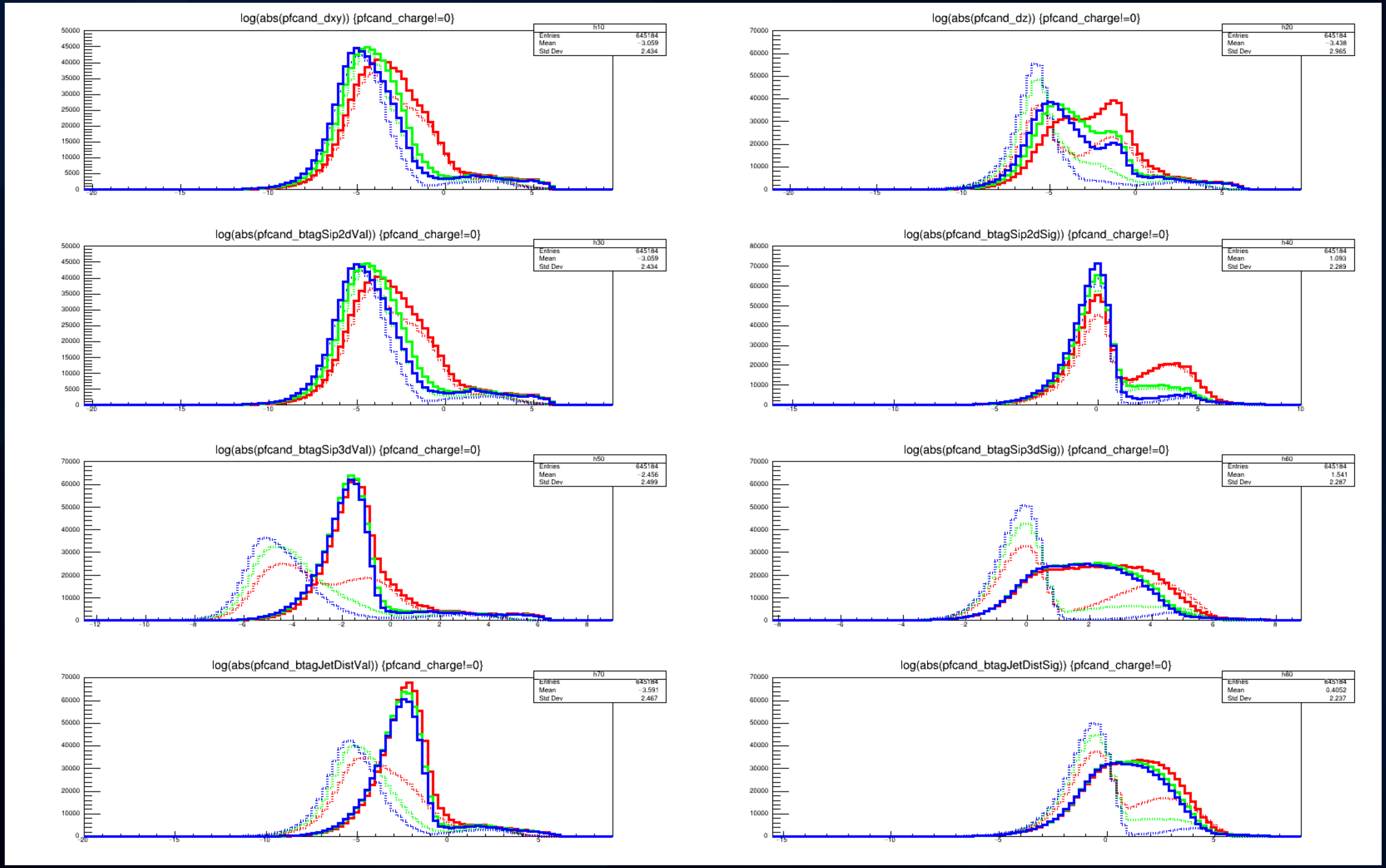
FCC theta



FCC phi

- ILD theta/phi are calculated from the difference between particle and jet theta/phi in the frame of the detector.
- FCC theta/phi are obtained from relative trace of the particle compared to the jet.
- This can cause some differences in the interaction of other parameters in the model.

Difference in impact parameters



Dotted – FCCee
Solid – ILD

Red – nnbb
Green – nncc
Blue – nndd

Significant difference on dz seen
- beam spot smearing?

Fine tuning

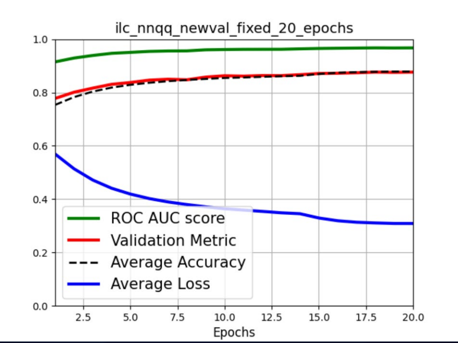
Two objectives
- Pretrained with fast sim and fine-tune with full sim
- Pretrained with large central production and fine-tune with dedicated physics samples in each analysis

							c-bkg acceptance @ b-tag 80% eff.		b-bkg acceptance @ c-tag 50% eff.	
Particle ID	Impact Parameters	Jet Distance	Track Errors	Fine-Tuning Sample	Training Sample	Similar theta/phi ?	No Fine-Tuning	With Fine-Tuning	No Fine-Tuning	With Fine-Tuning
✗	●	●	●	FCC 240 GeV (8M)	ILD 250 GeV (800k)	✗	0.62%	1.37%	1.14%	1.95%
✗	●	●	●	FCC 240 GeV (8M)	ILD 250 GeV (800k)	●	1.77%	1.32%	2.22%	2.01%
●	●	●	●	ILD 250 GeV (800k)	ILD 91 GeV (80k)	●	4.49%	0.97%	3.79%	1.53%

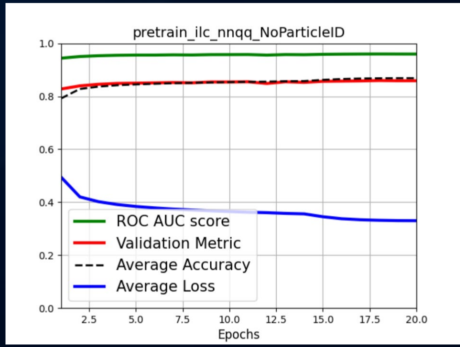
- Use result of 8M FCC data to train ILD 800k data
- Improves performance only when setups are similar
- Training of same setup (pretrain ILD 91 GeV data with ILD 250 GeV data) gives best performance
- Further investigation should be conducted on how to maximise the outcome for fine-tuning between different data sets

Fine tuning – Training curves

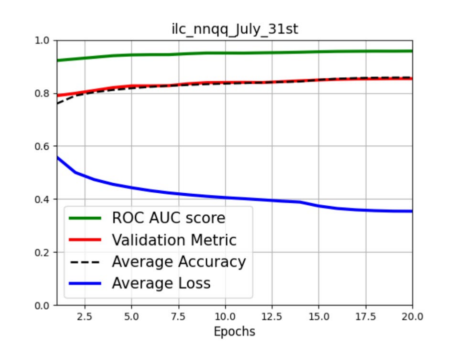
(1)



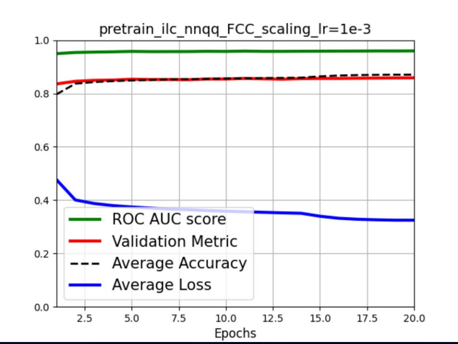
(2)



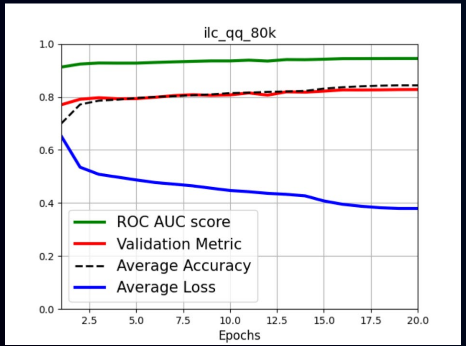
(3)



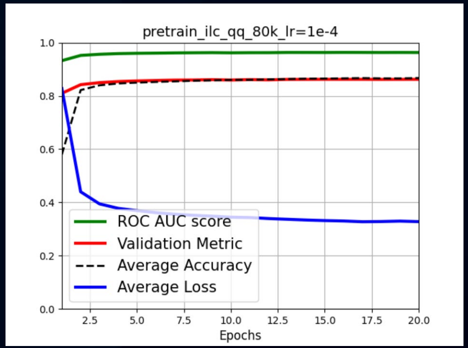
(4)



(5)



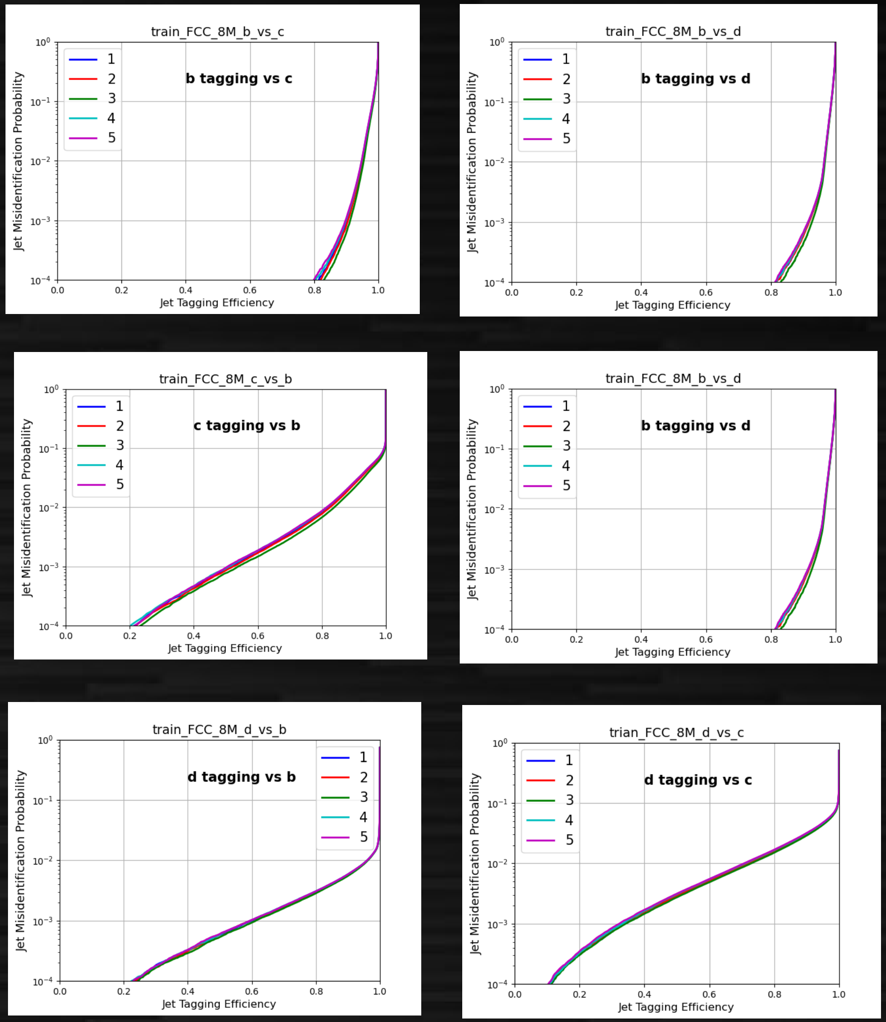
(6)



							Plot Indices	
Particle ID	**Impact Parameters**	**Jet Distance**	**Track Errors**	**Fine-Tuning Sample**	**Training Sample**	**Similar theta/phi?**	**No Fine-Tuning**	**With Fine-Tuning**
✗	●	●	●	FCC 240 GeV (8M)	ILD 250 GeV (800k)	✗	(1)	(2)
✗	●	●	●	FCC 240 GeV (8M)	ILD 250 GeV (800k)	●	(3)	(4)
●	●	●	●	ILD 250 GeV (800k)	ILD 91 GeV (80k)	●	(5)	(6)

- With fine-tuning, the training is obviously accelerated for the initial epochs (even for those with worse eventual performance)
- This is particularly obvious between plots (5) & (6) – similar simulation setup data

Multiple Training Runs

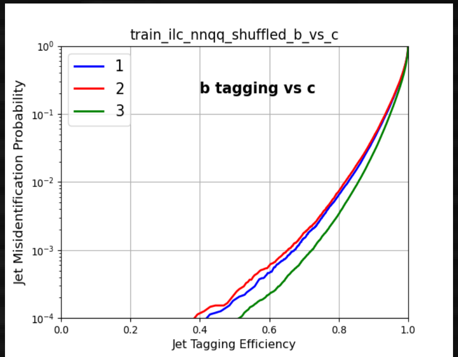


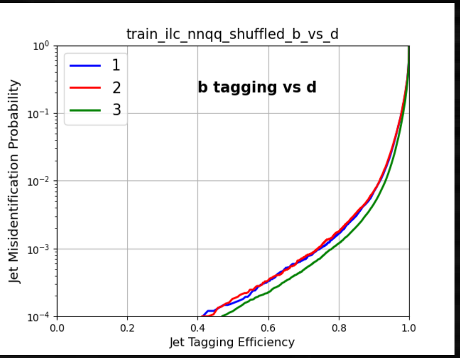
5 times training of FCC_8M data

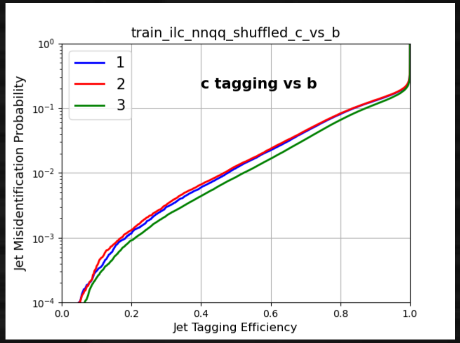
- Multiple training runs don't give significant impacts on results.
- The smaller data size is, the bigger impacts on results multiple runs give.
- The results of no Particle ID trainings varies more than those of with Particle ID.

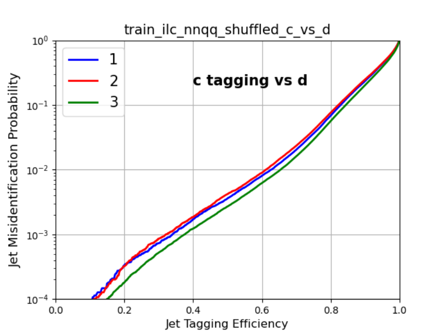
data	Particle ID	b vs c 0.8 Score	variation
FCC 4M	○	4.82e-4	0.43e-4
FCC 8M	○	8.14e-5	1.58e-5
FCC 4M	×	1.69e-3	0.14e-3
FCC 8M	×	7.04e-4	3.49e-4

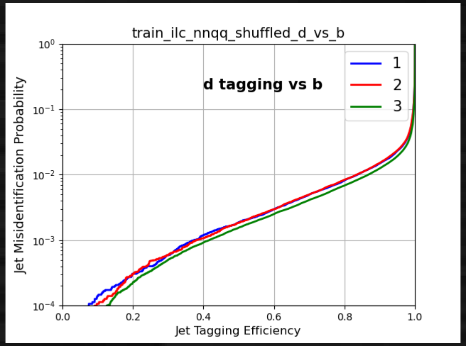
Data Shuffled

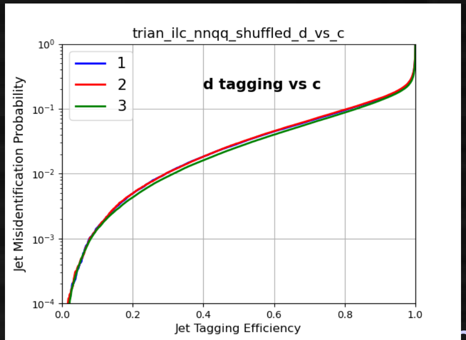












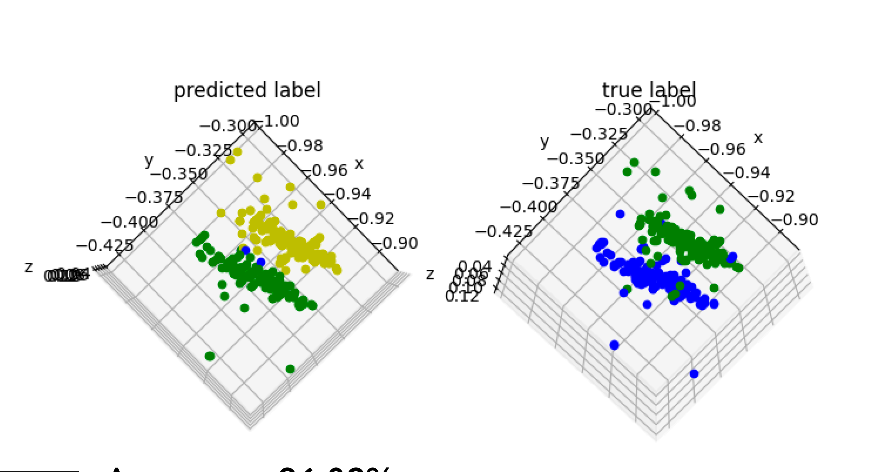
- ILC nnqq dataset
  - 80% training, 5% validation, 15% test
- Shuffled the order of train/test/val making root files
  - Pattern 1: train/val/test
  - Pattern 2: val/train/test
  - Pattern 3: train/test/val

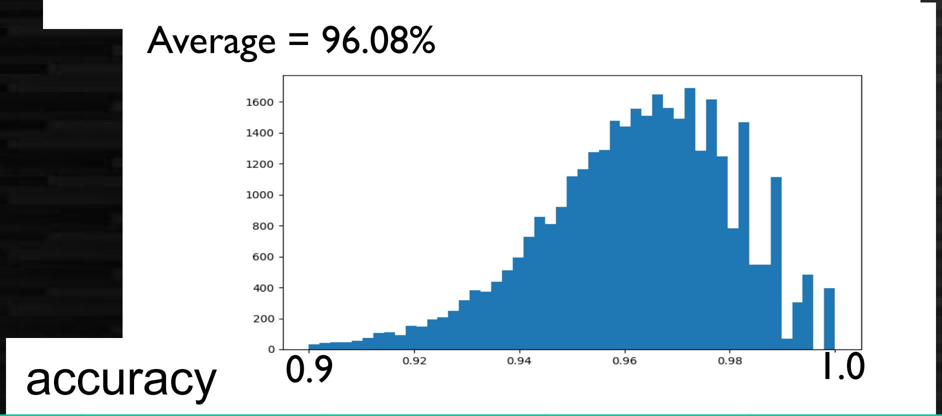
data	b vs c 0.8 score
Shuffle pattern 1	0.00647
Shuffle pattern 2	0.00734
Shuffle pattern 3	0.00338

Importing to ILD full simulation

- Prepare features from ILD full simulation
  - With recent versions (> v02-02)
- Input features: (x, y, z, edep)
- True cluster info
  from MCParticle and LCRelation
- Produced events
  - Two photons
    (5/10 GeV, fixed opening angles)
  - (n x) taus (5/10 GeV)
- Evaluation
  - Fraction of hits associated to the correct cluster (accuracy)

Example of a two-photon event
(5 GeV, 30 mrad)



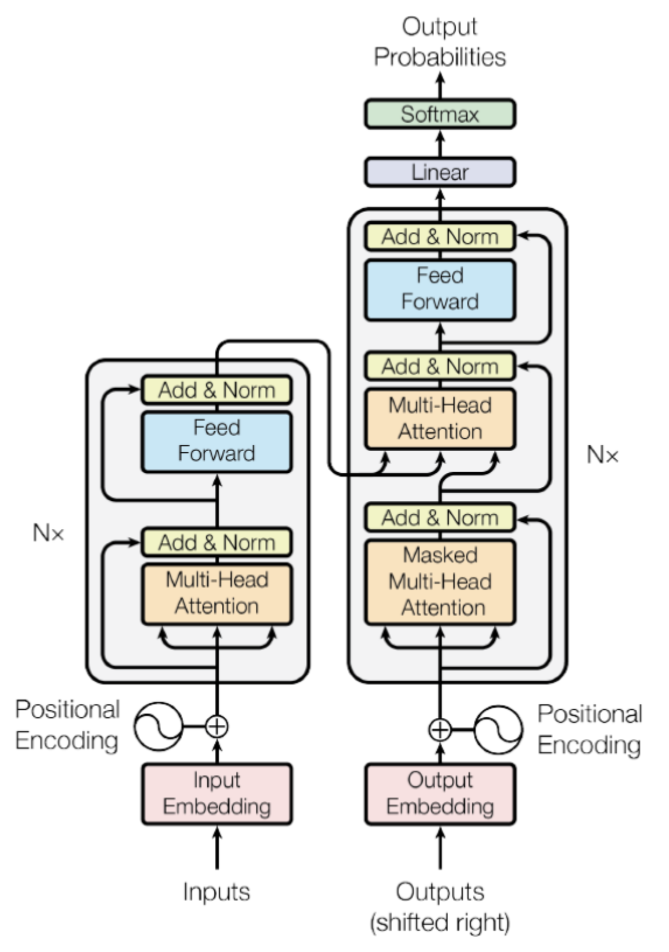


Reasonable
performance seen

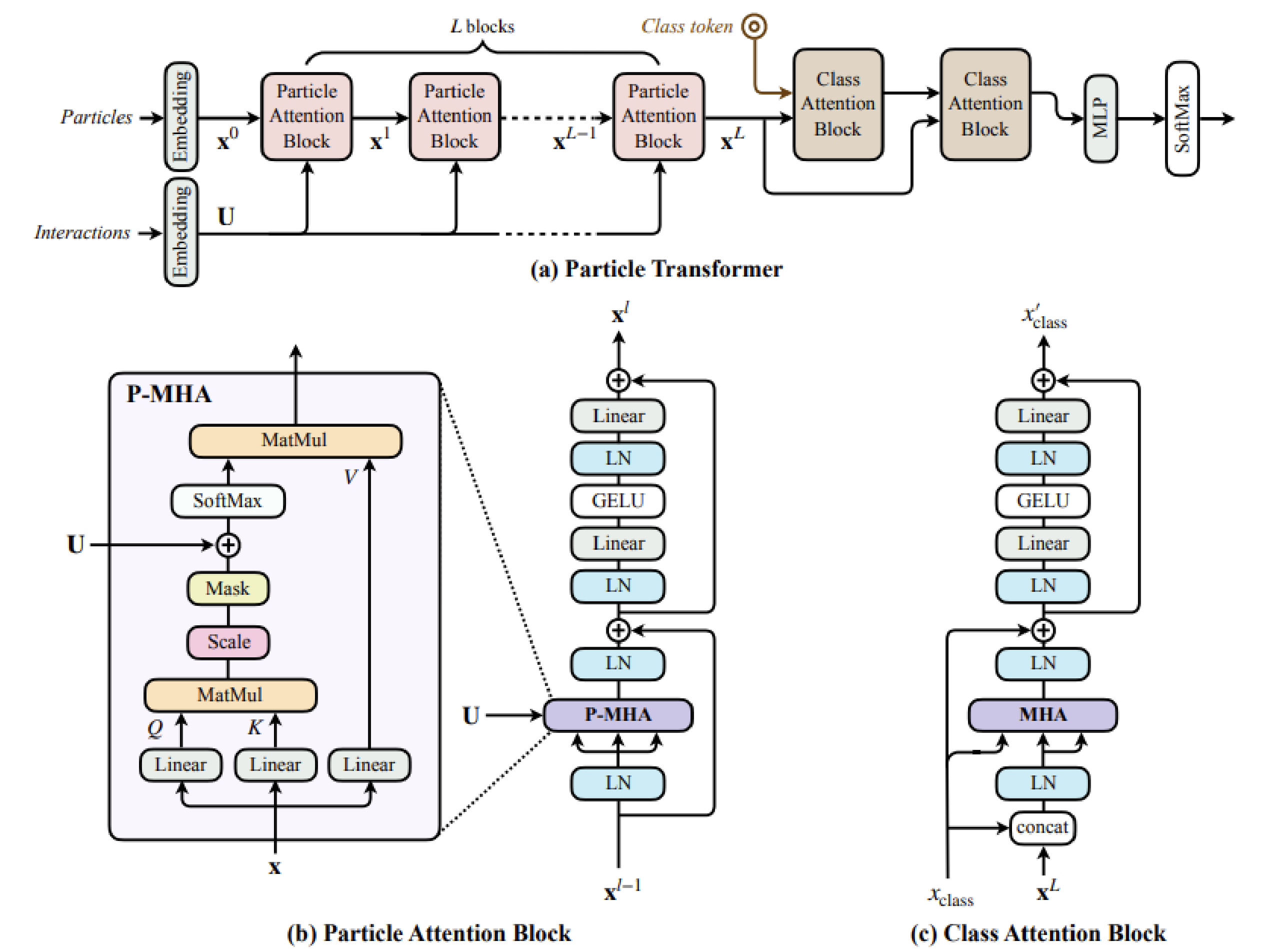
Angle[mrad]	30	60	90	120	150
Accuracy[%]	96.08	98.64	99.30	99.68	99.56

For details, refer eg. https://indico.slac.stanford.edu/event/7467/contributions/5948/attachments/2887/8032/230517-lcws2023-hlreco-suehara.pdf

Comparison between regular Transformer and Particle Transformer



Regular Transformer



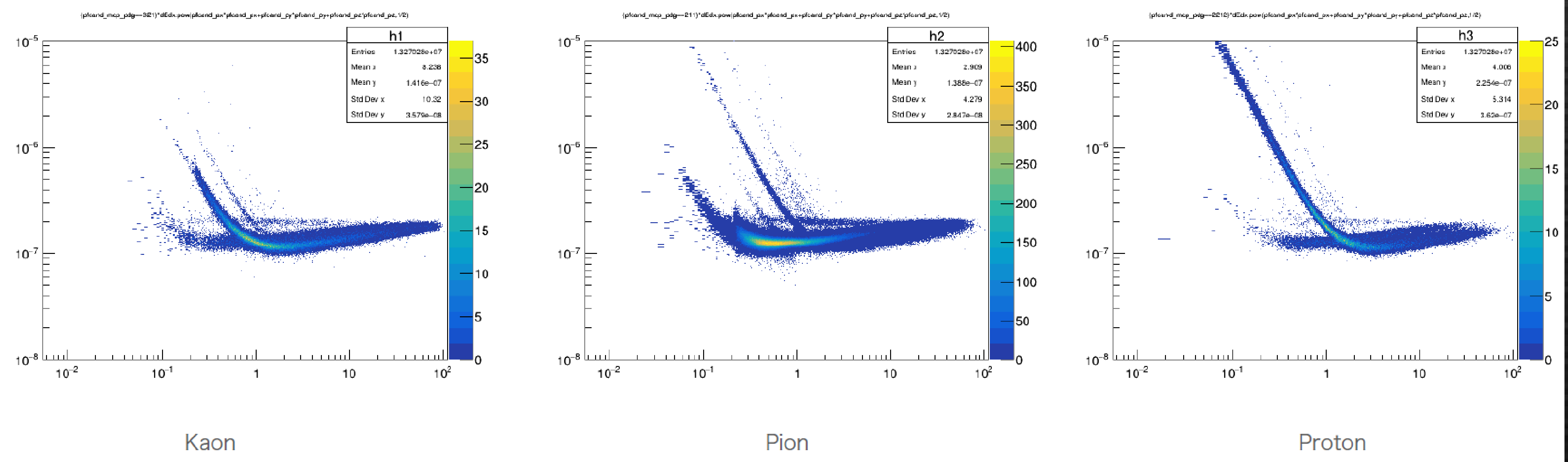
Particle Transformer

Note:
- MHA – MultiHeadAttention
- P-MHA – Augmented version of MHA by Particle Transformer that involves Interactions Embeddings instead of Positional Embeddings

Progress in strange tag

	s vs c	s vs g	s vs u
0.8 efficiency	0.138	0.288	0.466

Current performance with ParT
(under investigation yet)

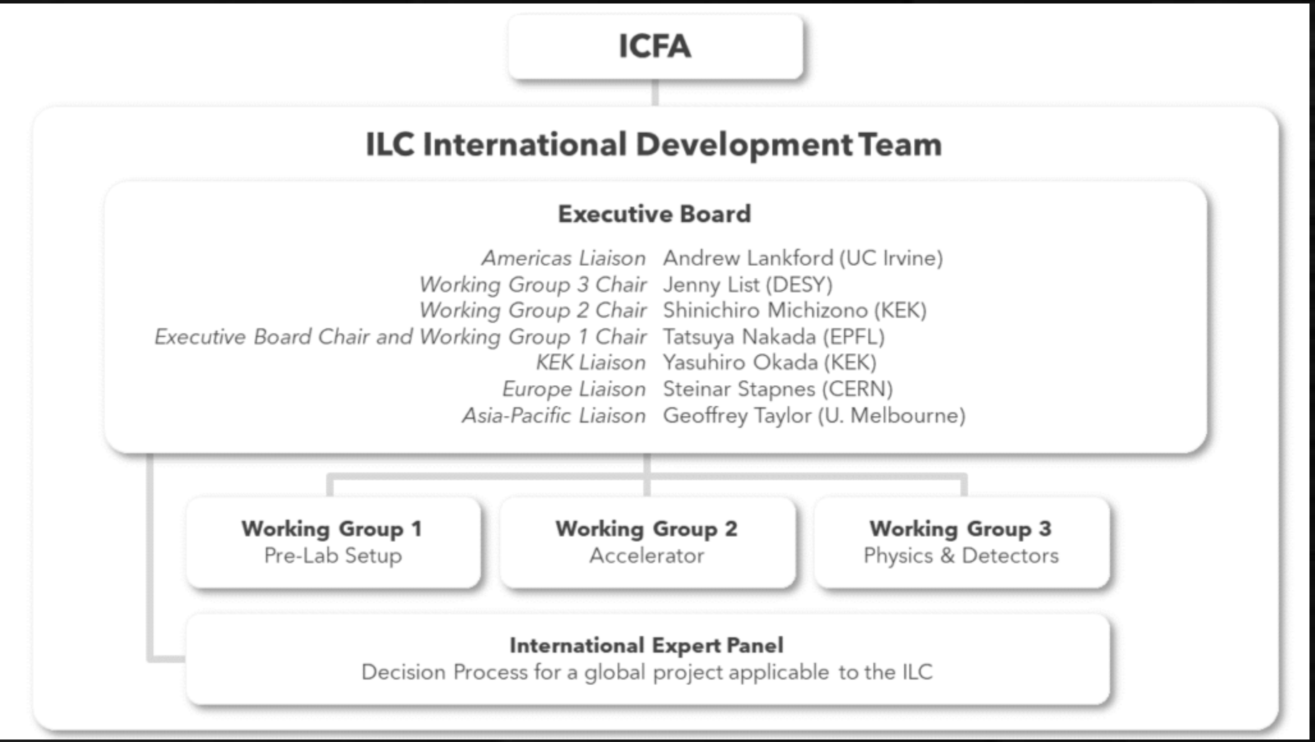


dE/dx inside strange jets (separated by MC PID)

Inference within LCFIPlus

- Training done in python/weaver framework
  - New LCFIPlus algorithm (MLMakeNtuple) to create input ROOT files
  - ROOT files used for training ParT
    - nnqq 250 GeV, ~1M jets / each flavor
    - MC/jet matching inside LCFIPlus (only for q/qbar training)
      - Color-singlet tagging by RecoMCTruthLink, q/g identified based on angle
        - » If multiple jets assigned to the same q/g, jet with highest energy taken
  - Training with GPU (~a half day for 20 epochs with Tesla V100)
- Weights (checkpoint) converted to onnx
  - Using onnx 1.15.0, onnxruntime 1.17.1 (to be compatible with key4hep)
- Inference with CPU in LCFIPlus framework
  - New processor MLInferenceWeaver with onnx files (uploaded in LCFIPlusConfig)
- Currently on private repository (pulling to official repository being processed)
  - LCFIPlus github with ParT, https://github.com/suehara/LCFIPlus/tree/onnx
  - LCFIPlusConfig with weight/steering files, https://github.com/suehara/LCFIPlusConfig

ILC: International Development Team



See LCWS2023: https://indico.slac.stanford.edu/event/7467/

WG3 physics group hosts series of physics meetings
https://agenda.linearcollider.org/category/266/
(Next: July 13th)
Mailing list subscription:
https://agenda.linearcollider.org/event/9154/

Established in 2020: aiming for ILC pre-lab
Pre-lab proposal in 2021
https://arxiv.org/abs/2106.00602
→ MEXT expert panel (2021)

- Not mature enough for proceeding to pre-lab
  - Mainly in international situation
- Accelerator technology should be developed in preparation for next step

→ Two steps towards pre-lab

- International Technology Network (ITN)
  - Collaboration framework with US/Europe
  - Doing time-critical works of pre-lab
  - Japanese part is funded by MEXT
- International Expert Panel
  - Among researchers connected to FA
  - Discussing how to proceed “global” projects