High level reconstruction with deep learning at ILD full simulation

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Today's topics

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

Flavor tagging with Particle Transformer (ParT)

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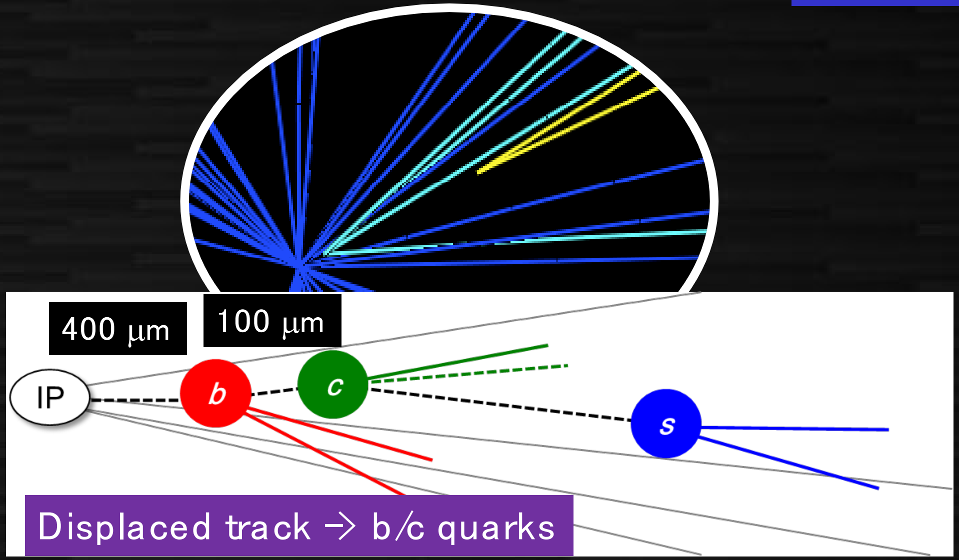

Big impact on Higgs studies including self coupling

Strange tagging is also a scope

Particle flow with DNN

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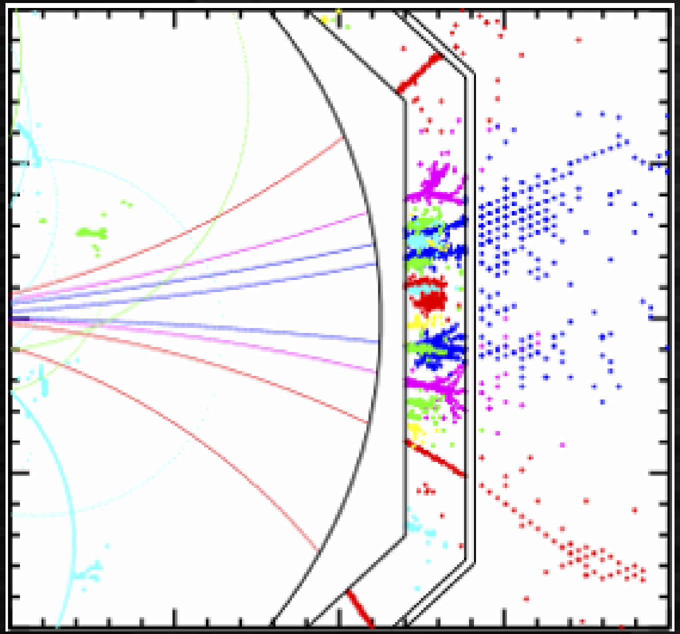


Key algorithm for particle flow detectors

Essential for detector optimization

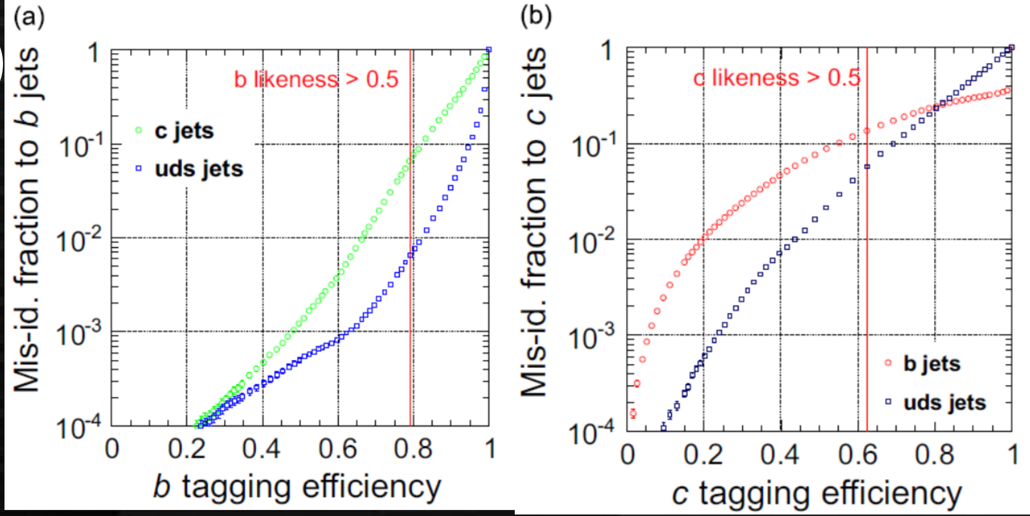
Flavor tagging with Particle Transformer (ParT)

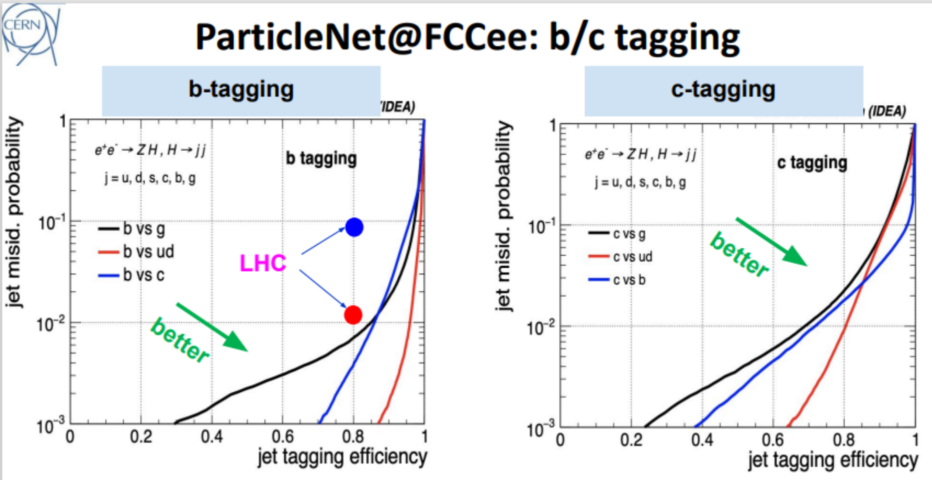
Talks in this FY:
Risako Tagami: JPS 2024au 19aWB208-3
https://kds.kek.jp/event/52312/contributions/275174/attachments/182925/245258/19aWB208-03.pdf
Risako Tagami: LCWS2024 (proceedings in progress)
https://agenda.linearcollider.org/event/10134/contributions/54564/attachments/39666/62637/20240709LCWS.pdf
Taikan Suehara: ICHEP2024 (along with particle flow, proceedings in progress)
https://indico.cern.ch/event/1291157/contributions/5892381/attachments/2900836/5086981/240720-ichep2024-recodnn-suehara.pdf

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

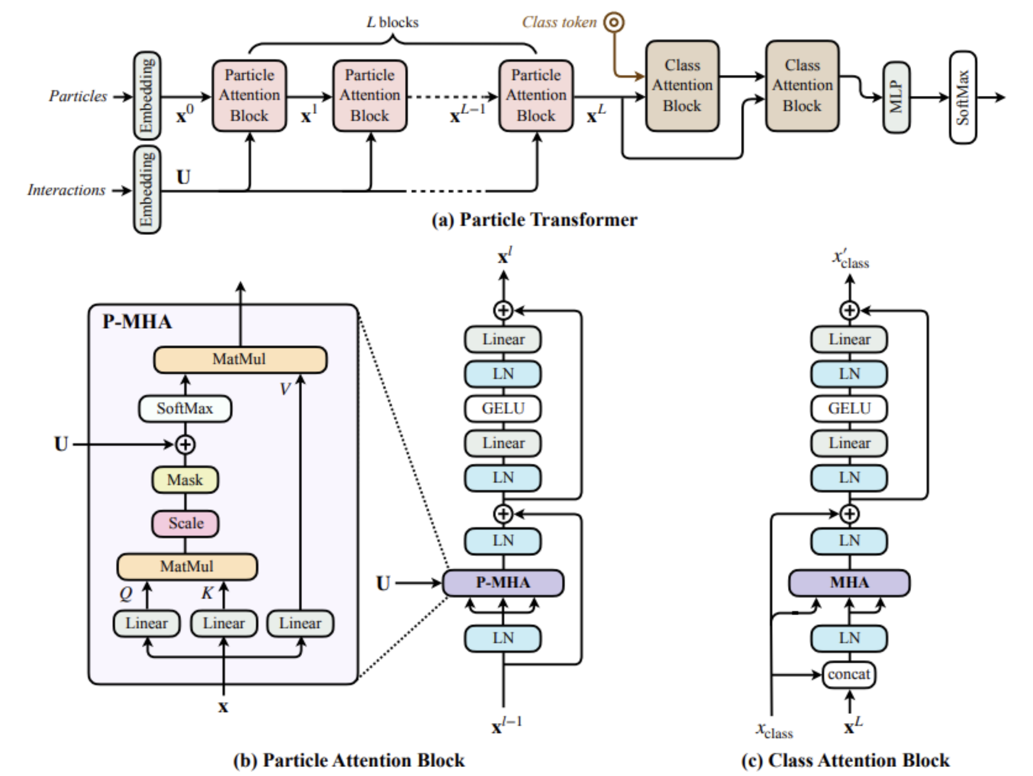




ParticleNet@FCCee: b/c tagging

Particle Transformer (ParT)

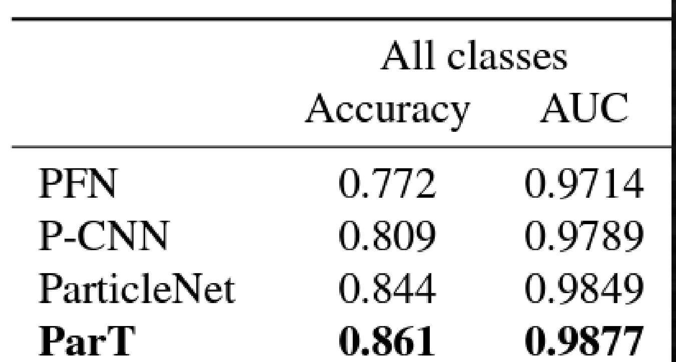
- Transformer: self-attention-based algorithm intensively used for NLP (e.g. chatGPT)
  - Weak biasing: possible to train big samples efficiently (with more learnable weights) but demanding big training sample for high performance
- ParT is a new Transformer-based architecture for Jet tagging, published 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



(a) Particle Transformer

(b) Particle Attention Block

(c) Class Attention Block



	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)

Data Samples and Input Variables

Data samples

- ILD full simulation

  1. e+ e- → qq (at 91 GeV) (used in LCFIPlus study)

  2. e+ e- → ννH → ννjj (at 250 GeV) (2020 production)

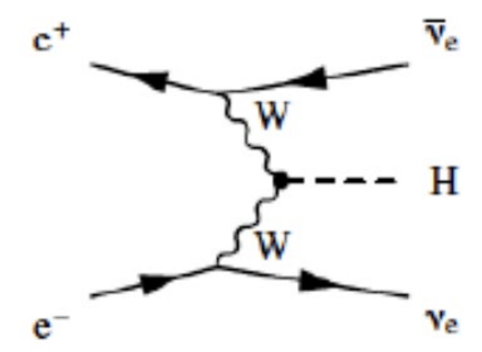
q = b,c,uds
j=b,c,u,d,s,g

1M jets (500k events) for each flavor

- FCCee fast simulation (Delphes with IDEA detector):

  e+ e- → ννH → ννjj (at 240 GeV)

10M jets (5M events) each flavor



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

Input variables

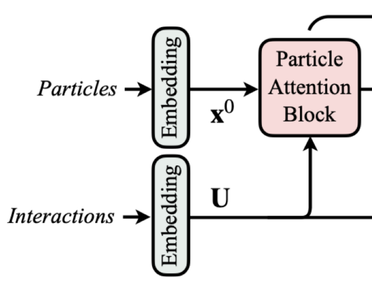
Particles: for every track/neutral

- 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

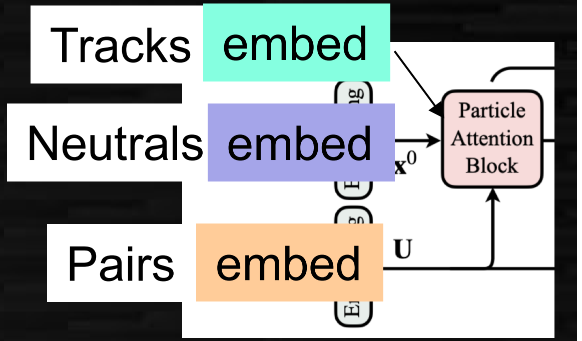
Input of ParT



Improvements wrt. LCFIPlus

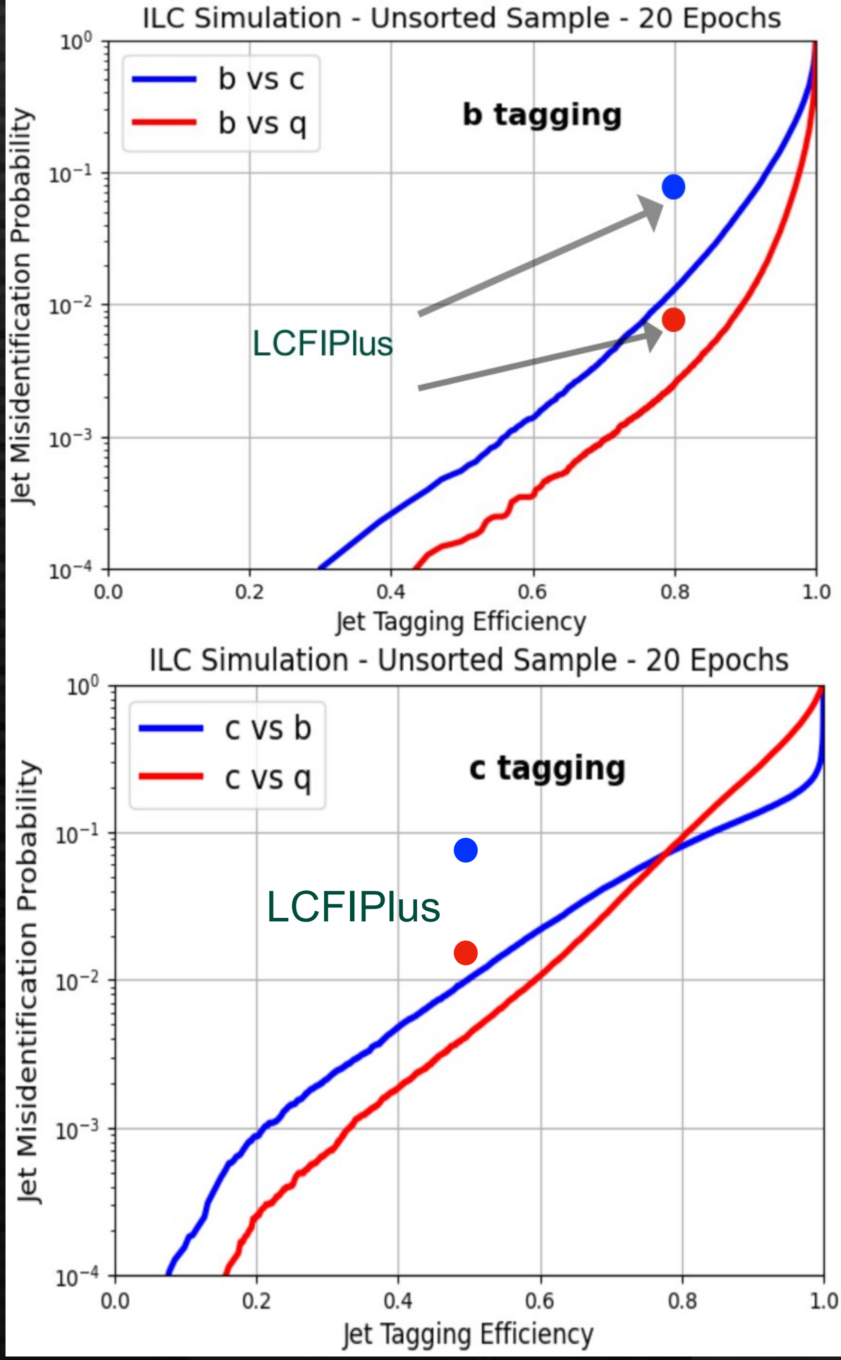
- Factor (3-9) improvement at ParT from LCFIPlus without any tuning
- Another factor (max 3) improvement by tuning
  - Optimizing input variables
  - Separate embedding for tracks/neutrals

	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%


Tracks embed

Neutrals embed

Pairs embed



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

Comparison with FCCee results

Conditions

- FCCee data provided by M. Selvaggi (as ROOT files including input variables)
- Processed with our script (using weaver (by H. Qu) and based on provided configuration)

Results

- FCCee 1M gives ~2x better
  - Comparable with reduced inputs
- FCCee 4/6/8M gives much better
  - Sample size dependence needs to be investigated with ILD (maybe difficult with full simulation)
  - (JetClass has 100M events)

1M: 800k jets for training
4/6/8M: 4/6/8M jets for training

Sample / sample size	b-tag 80% eff.		c-tag 50% eff.	
background	c jets	uds jets	b jets	uds jets
ILD full-sim 1M (optimized)	0.48%	0.14%	0.86%	0.34%
FCCee Delphes 1M (reduced)	0.47%	0.12%	0.64%	0.10%
FCCee Delphes 1M (full)	0.21%	0.054%	0.36%	0.059%
FCCee Delphes 4M	0.045%	0.025%	0.20%	0.033%
FCCee Delphes 6M	0.014%	0.010%	0.13%	0.022%
FCCee Delphes 8M	0.007%	0.006%	0.076%	0.021%

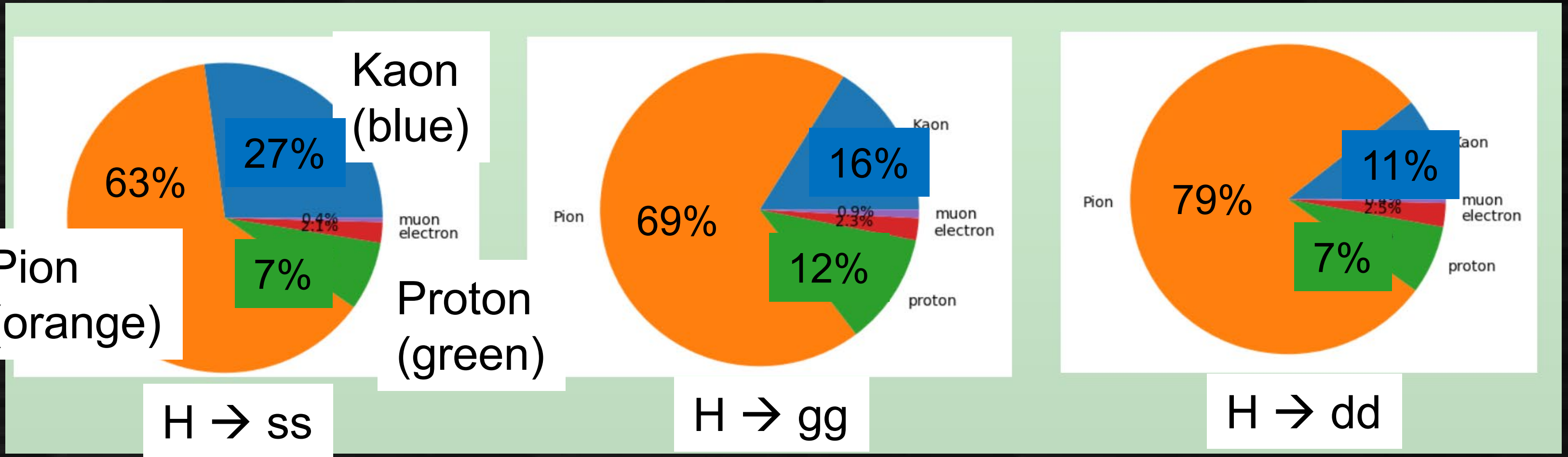
We see mild consistency between ILD and FCC!

FCCee configurations:

- Simulation: Delphes (IDEA geometry)
- Input: Kinematic/Impact parameter/Track error /Particle ID (including TOF and dn/dx) (not with reduced)
- Slight difference with ILD variables (e.g. interaction)

Strange tagging

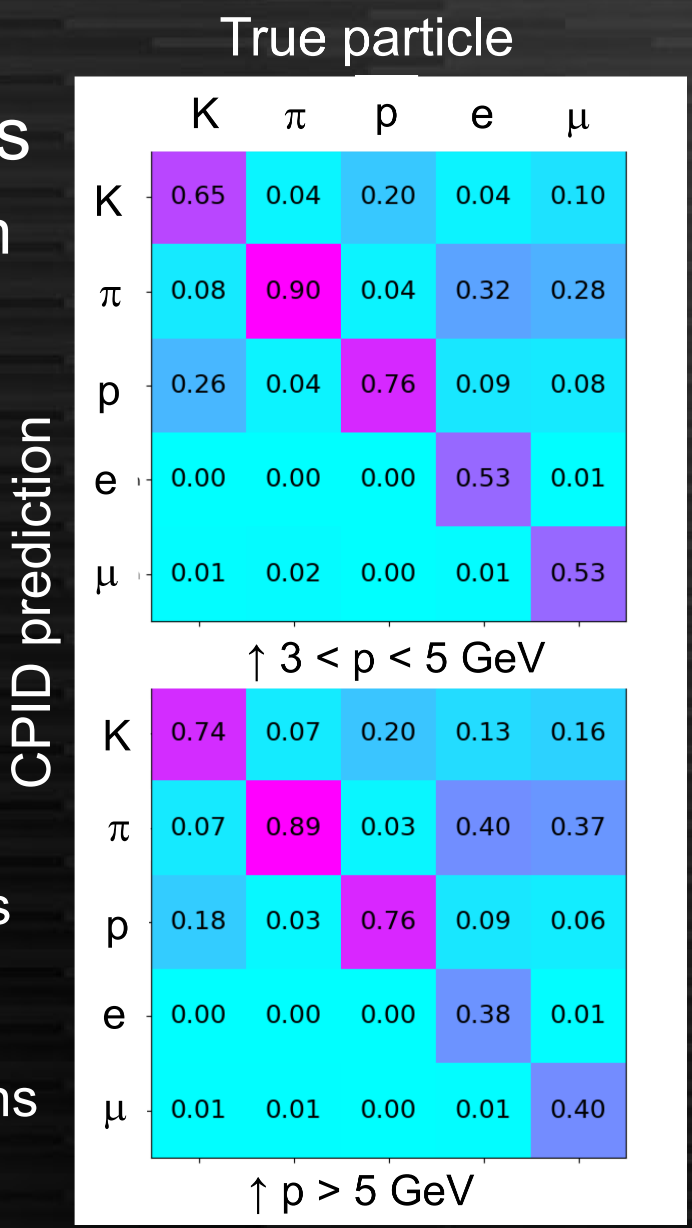
- High-momentum kaon in jet is a clue to strange jets
  - Contamination from g→ss give relatively low momentum
- dE/dx is essential for Particle ID in ILD
  - As well as ToF, but only effective in low energy tracks (which are less important in strange tagging)
- Using newly-developed comprehensive PID
  - Giving much better separation than previous PID



Fractions of tracks having > 5 GeV

More Kaons in ss
More protons in gg

Fraction of true particles



	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

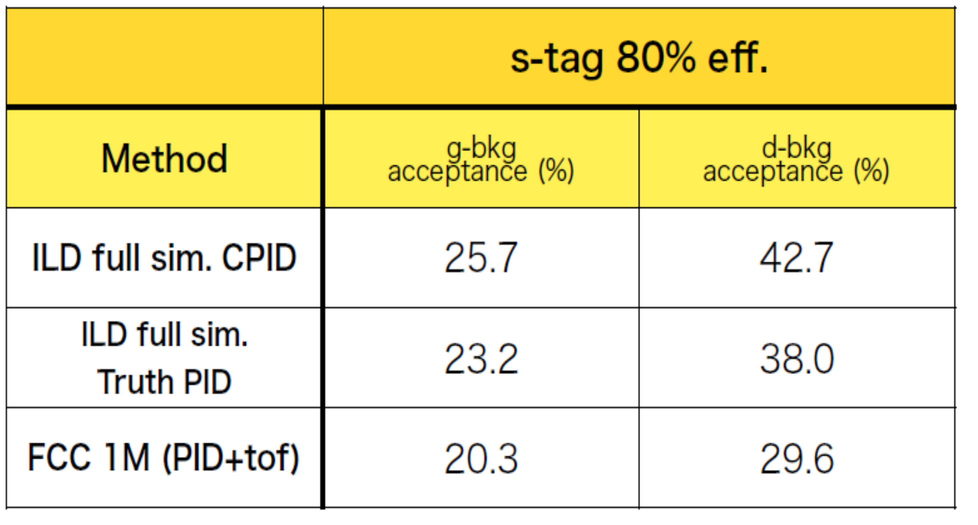
↑ 3 < p < 5 GeV

	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

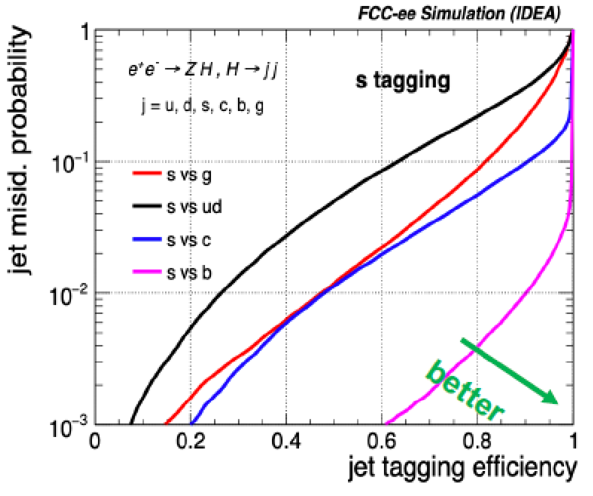
Strange tagging: initial results

- First results obtained with CPID
  - No significant improvements from old PID: investigating
  - Compared with truth PID: some difference
  - FCC (1M) better than ILD Truth PID
    - Reason needs to be investigated (maybe non-perfect assignment of truth PID)
- Still needs study

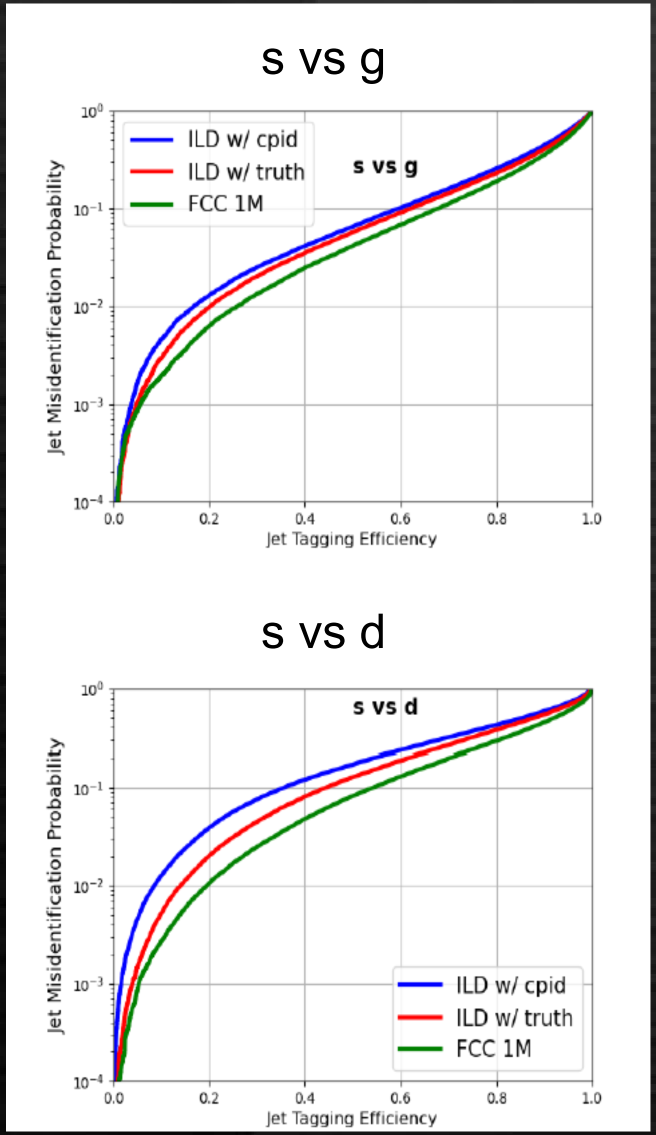


	s-tag 80% eff.	
Method	g-bkg acceptance (%)	d-bkg acceptance (%)
ILD full sim. CPID	25.7	42.7
ILD full sim. Truth PID	23.2	38.0
FCC 1M (PID+tof)	20.3	29.6

Strange tagging performance



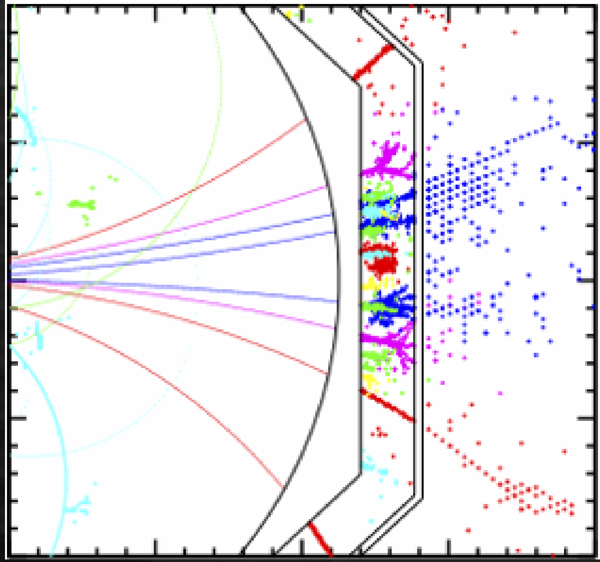
FCCee plot (in their study)



Flavor tagging: summary and plans

- Significantly better performance of flavor tagging with ParT
  - Implementation to the reconstruction framework foreseen to be applied to real physics analysis
    - Fighting with TorchScript now…
  - Further optimization still possible
- Strange tagging under investigation
  - Performance still needs to be understood more
  - To be fixed soon → to be used for physics analysis (e.g. H→ss)
  - Dependence on PID performance to be investigated
    - Coming with various detector configurations

Particle flow with DNN



Talks in this FY:

Tatsuki Murata: JPS 2024au 19aWB208-5
https://kds.kek.jp/event/52312/contributions/275176/attachments/182927/245260/19aWB208-05.pdf

Tatsuki Murata: LCWS2024 (proceedings in progress)
https://agenda.linearcollider.org/event/10134/contributions/54574/attachments/39729/62737/LCWS2024.pdf

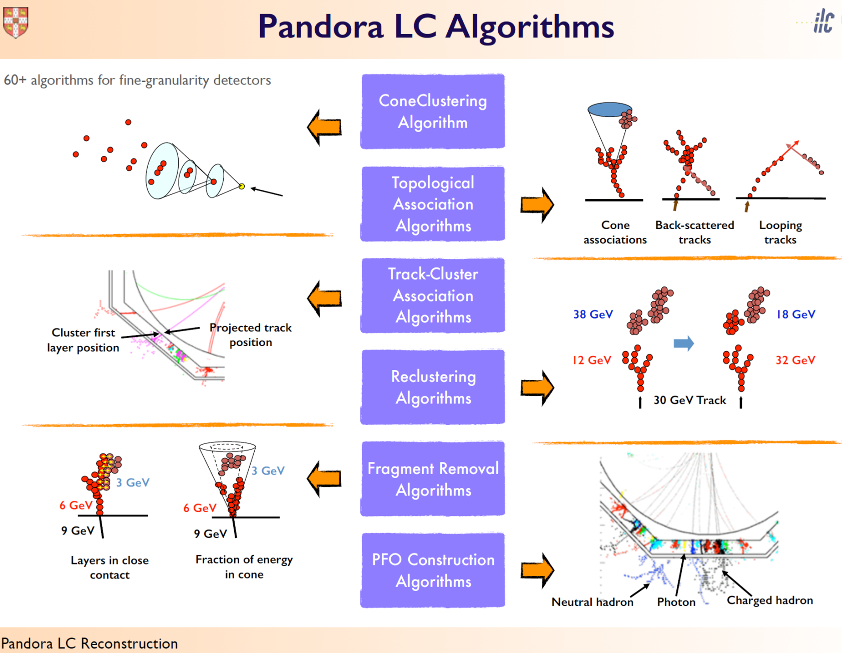
Paul Wahlen: LCWS2024 (poster, proceedings in progress)
https://agenda.linearcollider.org/event/10134/contributions/54561/attachments/39825/62938/WAHLEN_Poster_LCWS3.pdf

Taikan Suehara: ICHEP2024 (the same talk as ParT flavor tagging)
https://indico.cern.ch/event/1291157/contributions/5892381/attachments/2900836/5086981/240720-ichep2024-recodnn-suehara.pdf

Taikan Suehara: CALOR2024
https://indico.cern.ch/event/1339557/contributions/5898545/attachments/2861099/5005705/240522-calor2024-gnnpfa-suehara.pdf

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



Pandora LC Algorithms

60+ algorithms for fine-granularity detectors

ConeClustering Algorithm

Topological Association Algorithms

Track-Cluster Association Algorithms

Reclustering Algorithms

Fragment Removal Algorithms

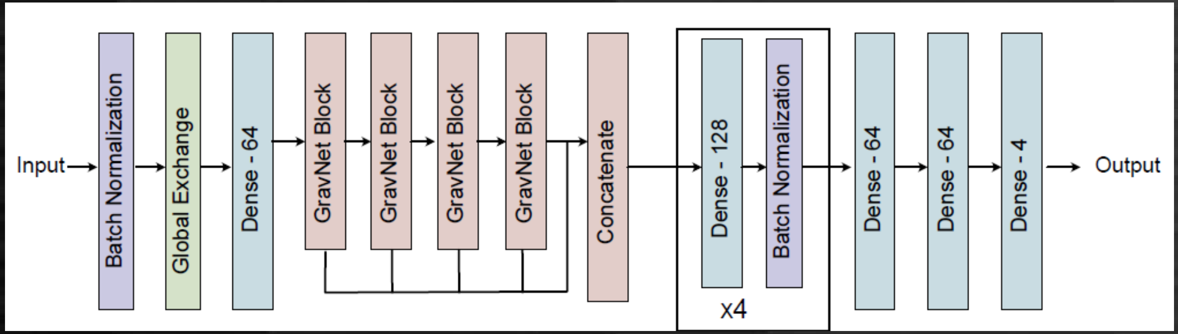
PFO Construction Algorithms

Pandora LC Reconstruction

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

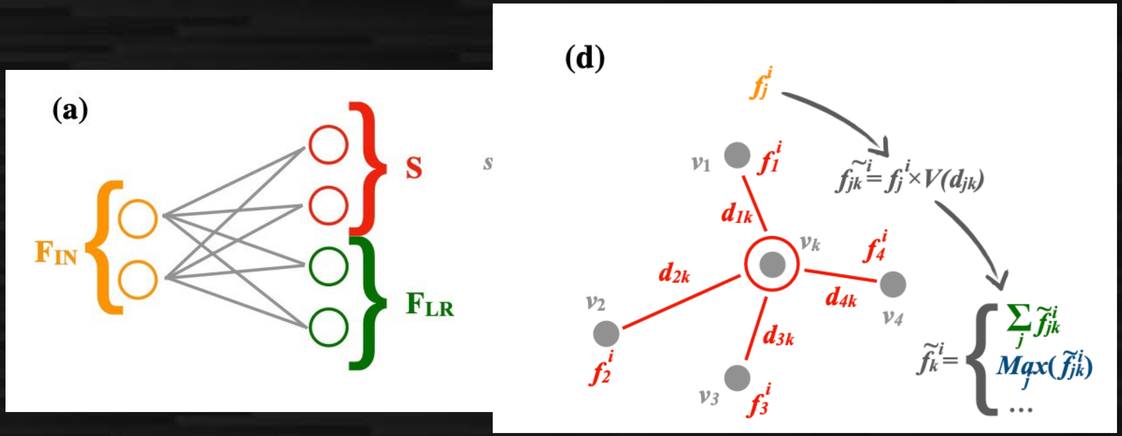
GNN-based PFA

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



GravNet arXiv:1902.07987

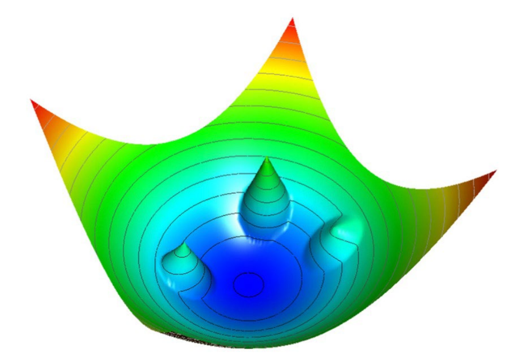
- The virtual coordinate (S) is derived from input variables with simple MLP
- Convolution using "distance" at S (bigger convolution with nearer hits)
- Concatenate the output with MLP



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

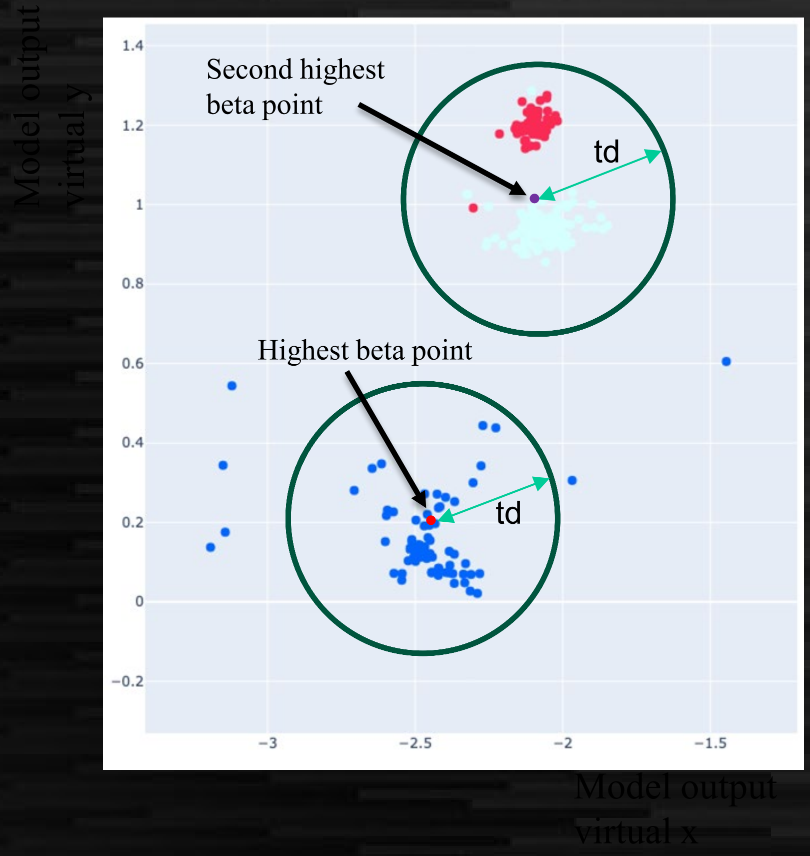
L_β: Pulling up β of the condensation points / tracks

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
- Hits that are within a certain distance (td) from the highest β point assume as a cluster
- Continues clustering until all hits are clustered or β of remaining hits are below threshold (tbeta)
- td/tbeta are tunable parameters

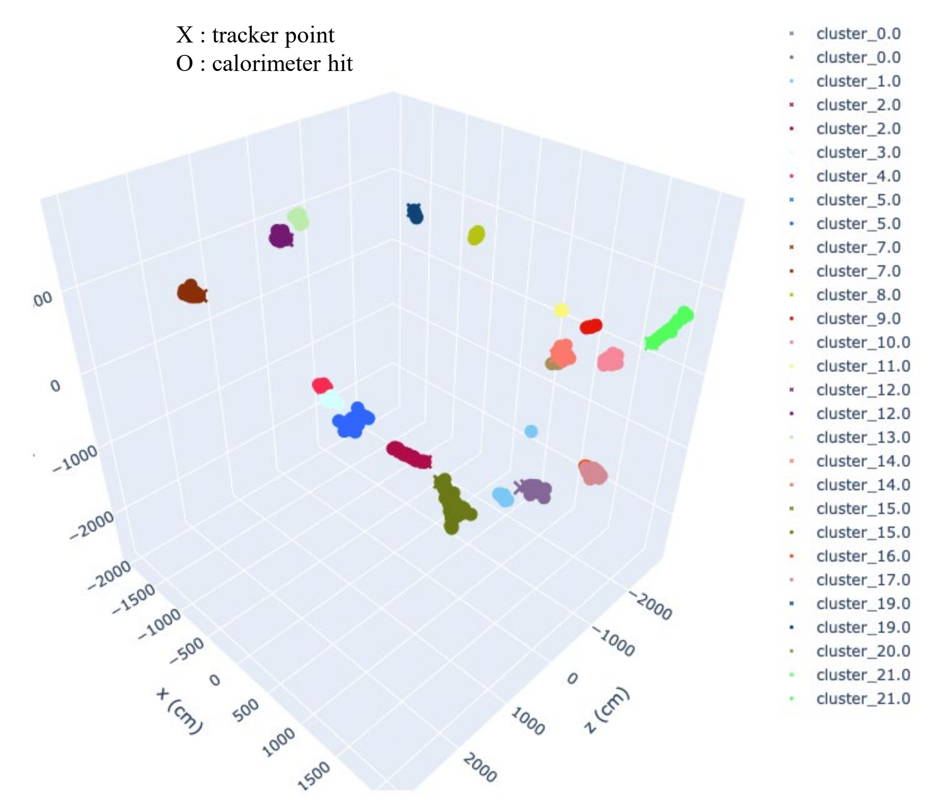


Our samples for performance evaluation

- 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)
  - Converted to awkward array stored in HDF5 format
    - A few 10 GB each

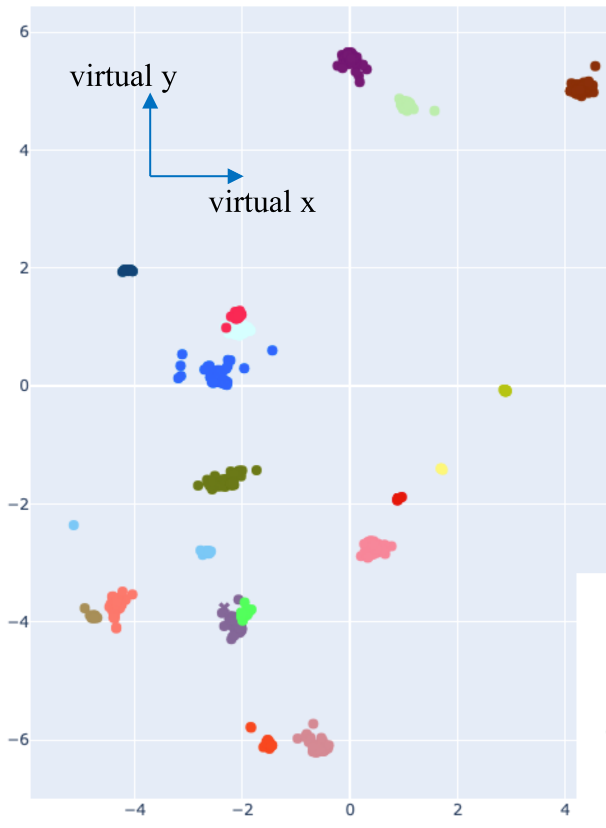
Taus: good mixture of hadrons, leptons and photons
with some isolation
Good for training

Event display



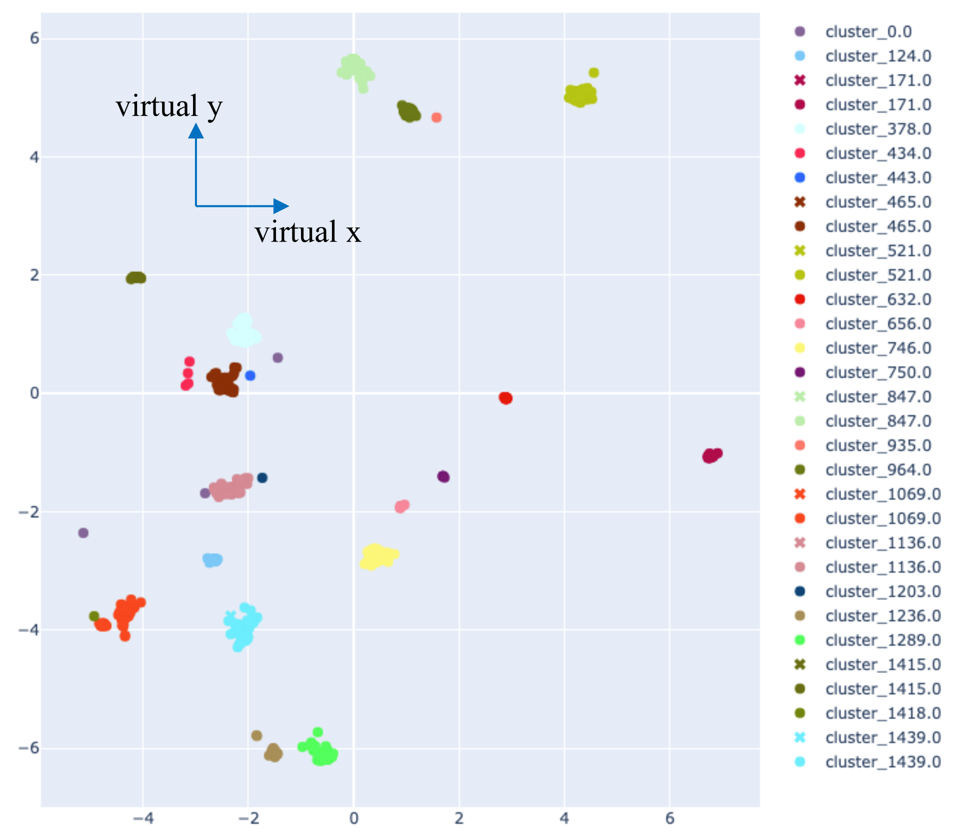
Input features
Real coordinate in detector

Colored by true clusters



Output features
Virtual coordinate

Colored by
true clusters

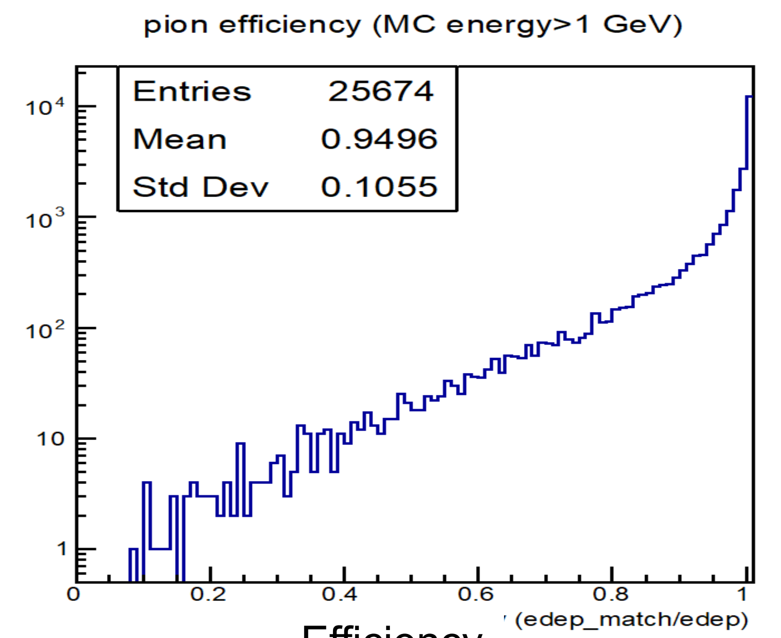


Colored by
reconstructed clusters

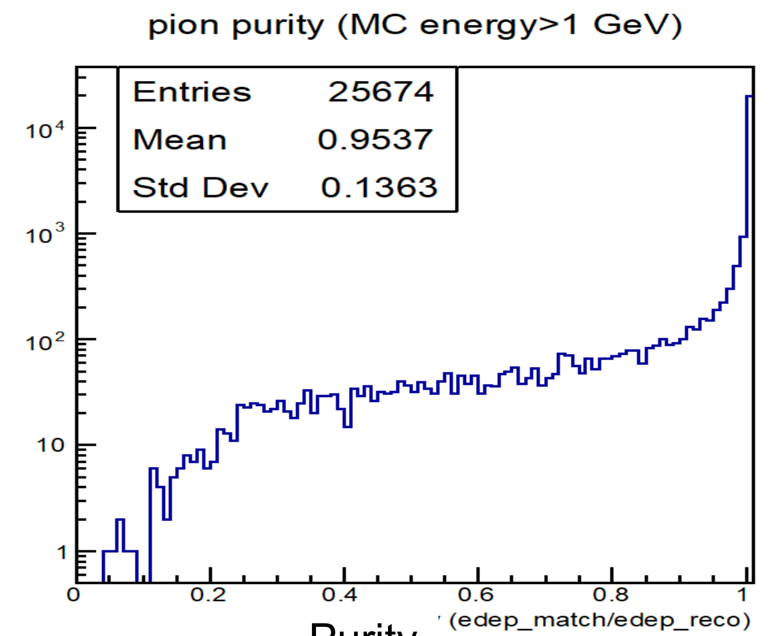
Taikan Suehara et al., ILD Softw

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 cluster may connect to one MC cluster
- 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)

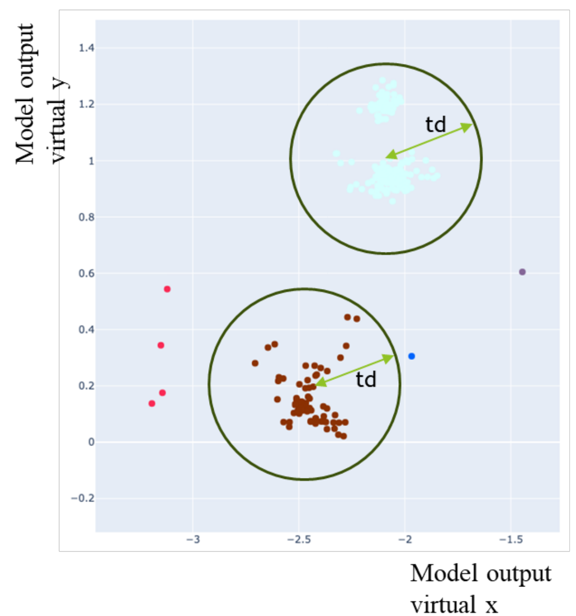


Efficiency



Purity

Optimization of performance

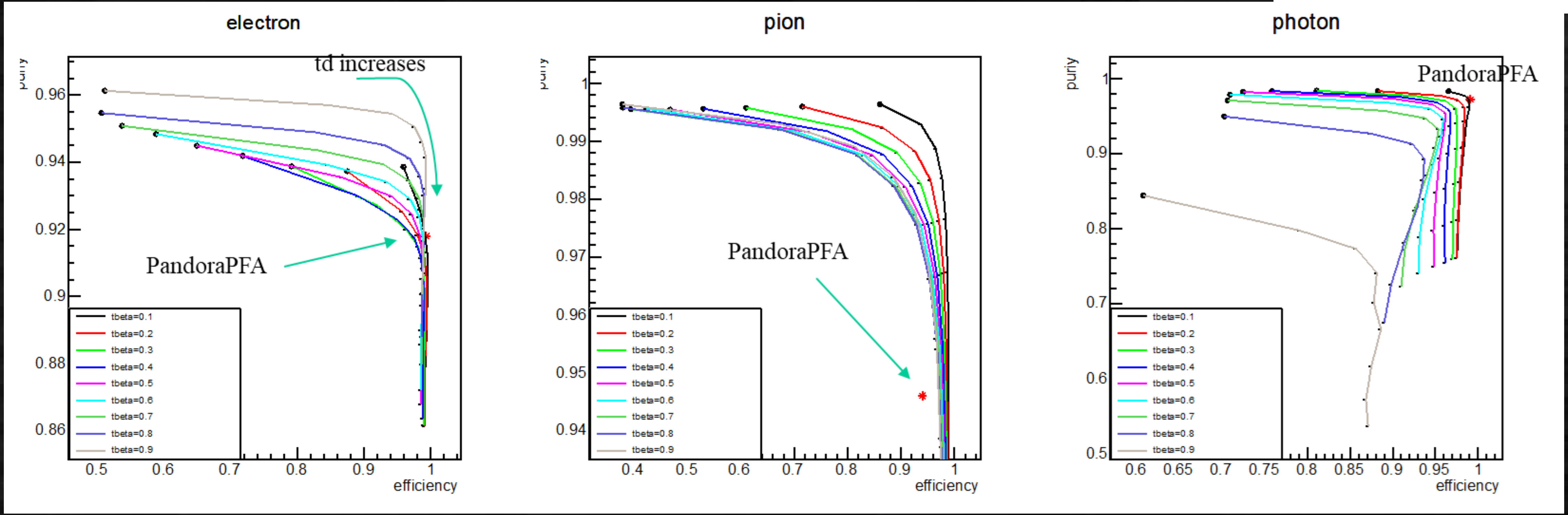


Output dimension of the coordinate

- The initial work done with output coordinate dimension D = 2 (for visibility)
- Tried D=3,4,8,16 → D=4 selected

Clustering parameters (td, tbeta)

- td: radius which hits are treated as coming from the same cluster
- tbeta: threshold of beta to form clusters



Scanning result: tbeta=0.1, td=0.3/0.4 selected

Results on efficiency and purity

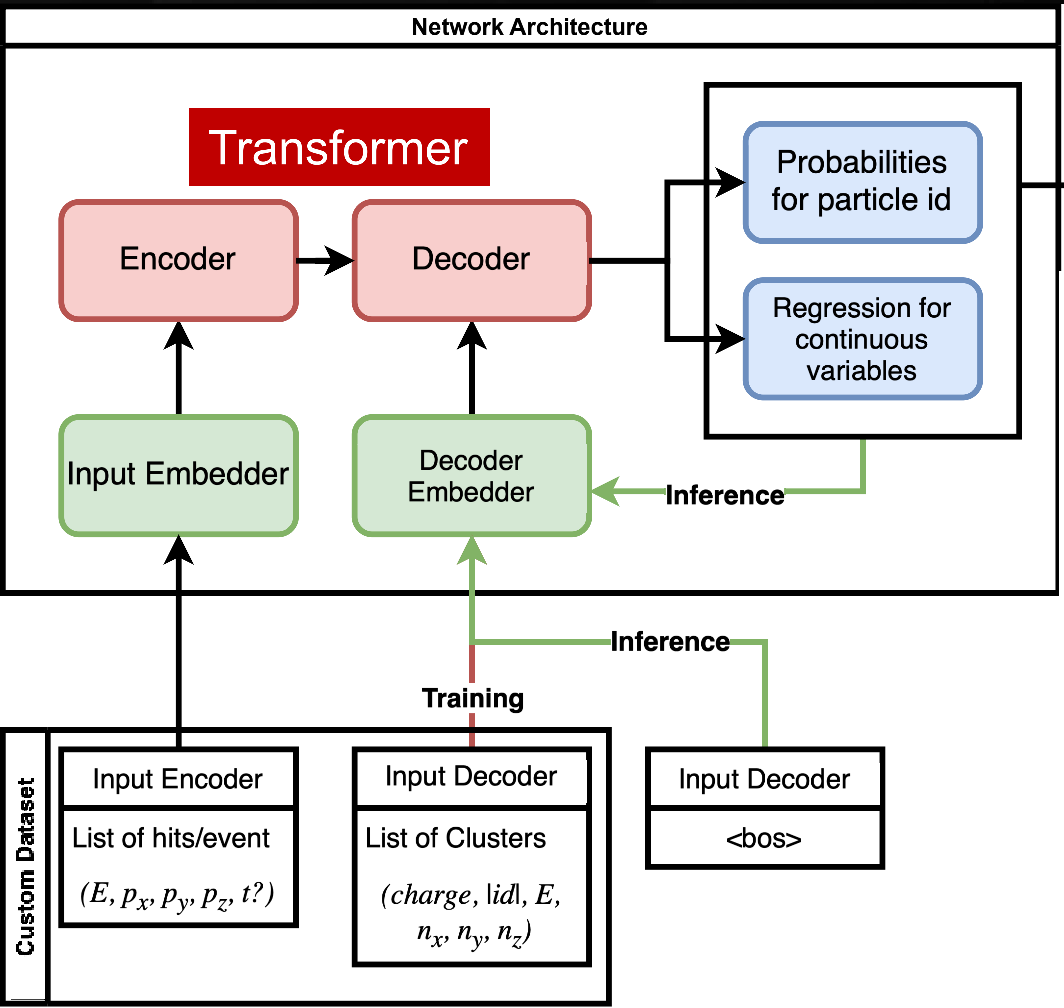
Algorithm train/test	Electron eff.	Pion eff.	Photon eff.	Electron pur.	Pion pur.	Photon pur.
GravNet 10 taus/10 taus	99.1%	96.5%	99.0%	91.8%	98.9%	97.1%
PandoraPFA 10 taus	99.3%	94.0%	99.1%	91.8%	94.6%	97.2%
GravNet jets/jets	94.5%	93.1%	95.2%	94.6%	93.2%	92.4%
PandoraPFA jets	80.2%	90.4%	79.0%	75.0%	90.6%	77.7%
PandoraPFA jets (ILCSoft truth)	96.7%	95.5%	96.4%	97.1%	90.4%	97.7%

At least in our measure, performance of GravNet-based algorithm exceeds PandoraPFA
→ Promising as full PFA (but energy regression to be done)
Definition of MC truth clusters needs to be tuned (see ILCSoft truth)

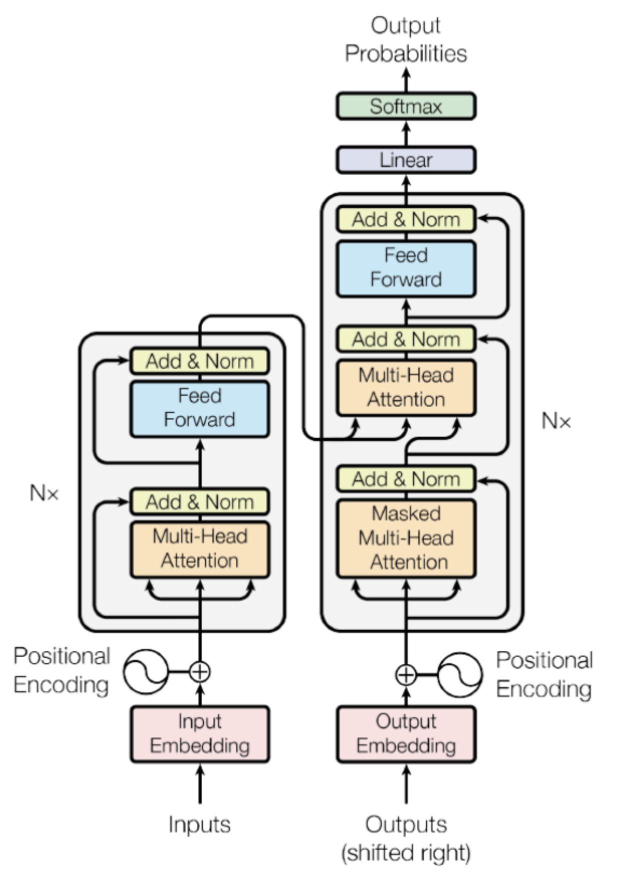
More NLP-like model: transformer

Submitted to E1
in FY2025-26

Transformer: training relation among elements (hits in PFA) with (multi-head) self-attention mechanism
(used in GPT etc.)



Planned structure for PFA

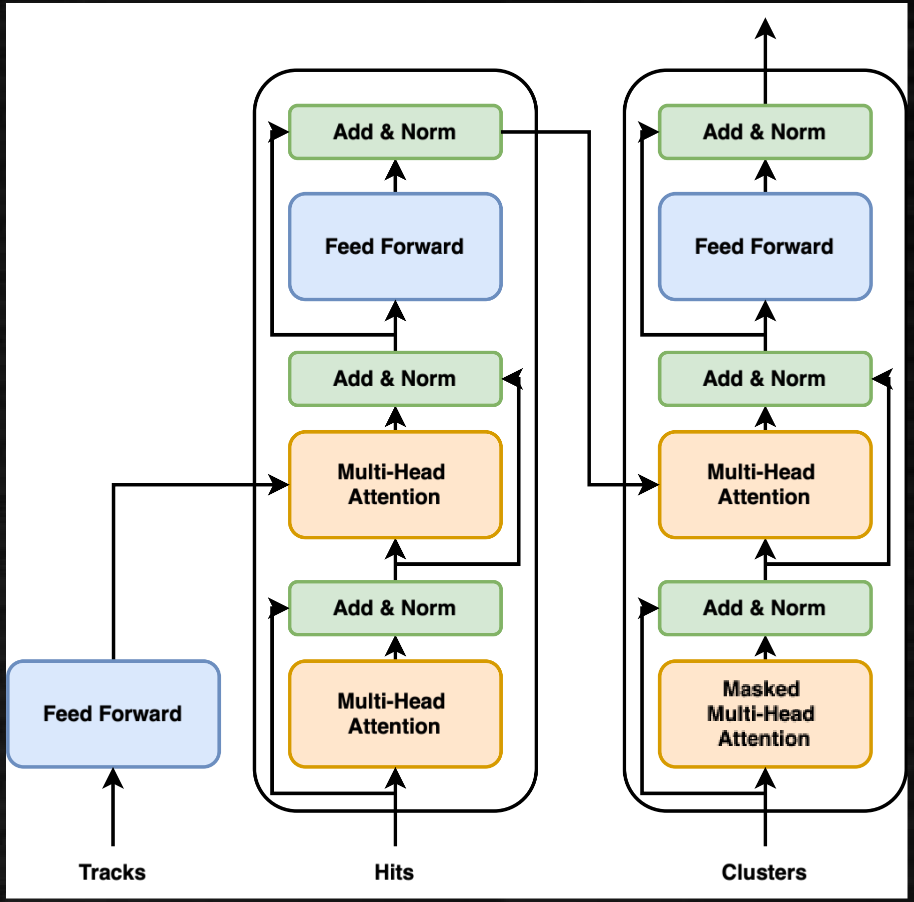


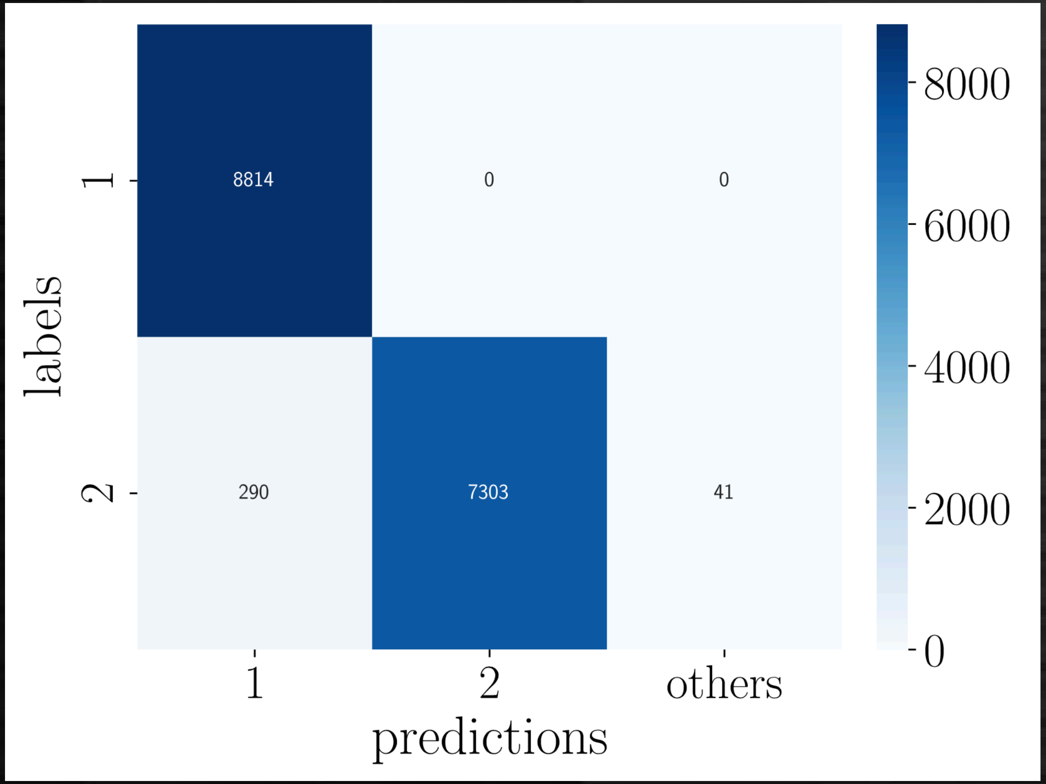
Transformer

Encoder: accumulate info of all hits/tracks by transformer

Decoder:
Input cluster info one by one
Output info of next cluster
(training) MC truth clusters
(inference) just provide <bos> to derive first cluster, using output as next input until <eos> obtained
(Inspired by translation NN)

Transformer-based PFA: some quick view





Separation of single and double photons - random opening angle – not too bad but worse than GNN-based study now

Proposal from collaborator: should investigate independent training of encoder part by e.g. masking some particles in each event (as often done in NLP)

Particle flow: summary and plans

First target achieved!

- GNN-based particle flow has possibility to replace PandoraPFA
  - Performance seems significantly exceeded at least in our measure
  - Difference on MC truth definition to ILCSoft to be investigated
    - (ILCSoft uses MCParticlesSkimmed while our method uses MCParticle collection)
- Regression of cluster energy being investigated
  - Necessary for complete PFA
  - Jet energy resolution would be compared with PandoraPFA
- Possible improvements
  - Momenta of tracks currently not used (improvements of clustering possible)
  - Incorporation of timing information etc.
- Another new idea to “ask network the next cluster” being tried
  - Next proposal for the new 公募研究

Overall summary

- High level reconstruction @ ILD has a lot of room to incorporate with DNN to improve performance
  - Also easier to use for detector optimization
- Flavor tagging with ParT significantly better than LCFIPlus
  - To be applied to physics analysis
  - Strange tagging also under investigation
- Particle flow with GNN gives competitive performance
  - Energy regression to be done
  - Hope to replace PandoraPFA in ~a few years
  - NLP-like method also being investigated

Higgs to ss study: status

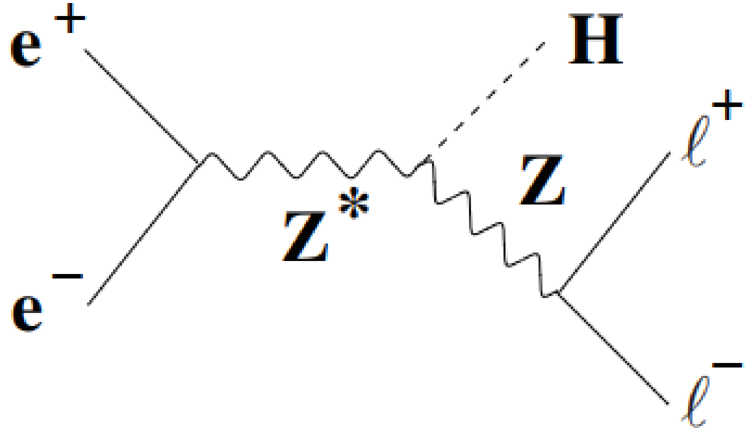
Ryuki Sugawara, Ritsuya Hosokawa, Shinya Narita (Iwate U.)
Taikan Suehara (ICEPP, U. Tokyo)

Objective.

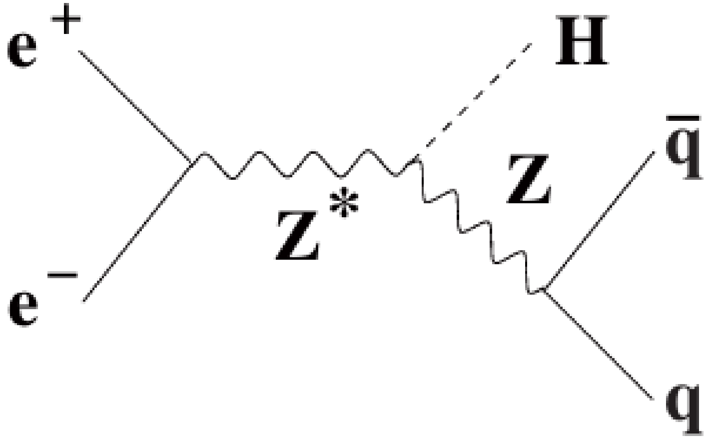
In this study, we estimate the cutting conditions for the Higgs-generated events and background events simulated in the International Linear Collider Experiment.

In addition, the process of background decays to leptons and hadrons is analyzed.

The analysis was performed with reference to H.Ono「Evaluation of measurement accuracies of the Higgs boson branching fractions in the International Linear Collider」



Leptonic Channel signal event



Hadronic Channel signal event

Leptonic channel Analysis Process

After finding the lepton pair, the remaining particles are reconstituted in two jets (2 leptons + 2 jets).

① Find lepton pairs using IsolatedLeptonTagging Processors (signal event)

② Except for the lepton pair I found. Then jetclustering with 2 jets

③ Use MakeClass to apply cuts

④ Perform steps ① ~ ③ again, adding BackGround as well.

Signal Event Result

Results were normalized using cross section and luminosity.

$$Normalized\ Events = Events \times \frac{CrossSection}{Generated} \times Luminosity$$

Change in the number of events when cuts are made to signal events

cut name	reference	my data	normalized
Generated	2917	8219	2717
track ID	2668	7682	2539
Di-lepton mass (GeV)	2287	6538	2161
Z direction	1889	5350	1768
Di-jet mass (GeV)	1445	2401	793
Recoil mass (GeV)	1365	2107	696

cross-section: 10.8691 fb

The signal events did not differ greatly from the reference, but differences were observed in the Di-Jet Mass and Recoil Mass.

- Muon identification by calorimeter information
- Cutting of lepton masses to match Z masses
- Cutting in the Z direction for BGremoval of bosons
- Cutting jets to match Higgs mass
- Cut recoil masses to lepton pairs

These cuts were made for muon events

About the Background

The main background for lepton events is Z boson or W boson-derived events.
The following four events were used in the analysis.

- ZZ_semileptonic
- ZZ_leptonic
- WW_semileptonic
- WW_leptonic

semilptonic : Events contain one lepton pair
leptonic : Events contain two lepton pairs

BackGround Events Result

$$Normalized\ Events = Events \times \frac{CrossSection}{Generated} \times Luminosity$$

This one does not deviate greatly from the reference as well.
However, Di-Jet Mass and Recoil Mass differ slightly from the reference.

Normalized						
cut name	reference	ZZsemi	WWsemi	ZZlepton	WWlepton	total
Generated	45122520	209519	4694775	22239	390855	5317389
track ID	28175	19749	443	1861	4834	26889
Di-lepton mass (GeV)	12901	12277	104	1323	1441	15146
Z direction	8036	7620	78	509	995	9204
Di-jet mass (GeV)	1955	375	0	8	0	383
Recoil mass (GeV)	983	303	0	5	0	308
cross section		838.079	18779.1	88.9574	1563.42	

Hadronic channel Analysis Process

①Use SelectReconstructedParticle(Processor) for signal events to calculate minimum momentum.

②Use ThrustReconstruction(Processor) to calculate thrust.

③Jet clustering with 4 jets.

④Analyze in the same way in the background.

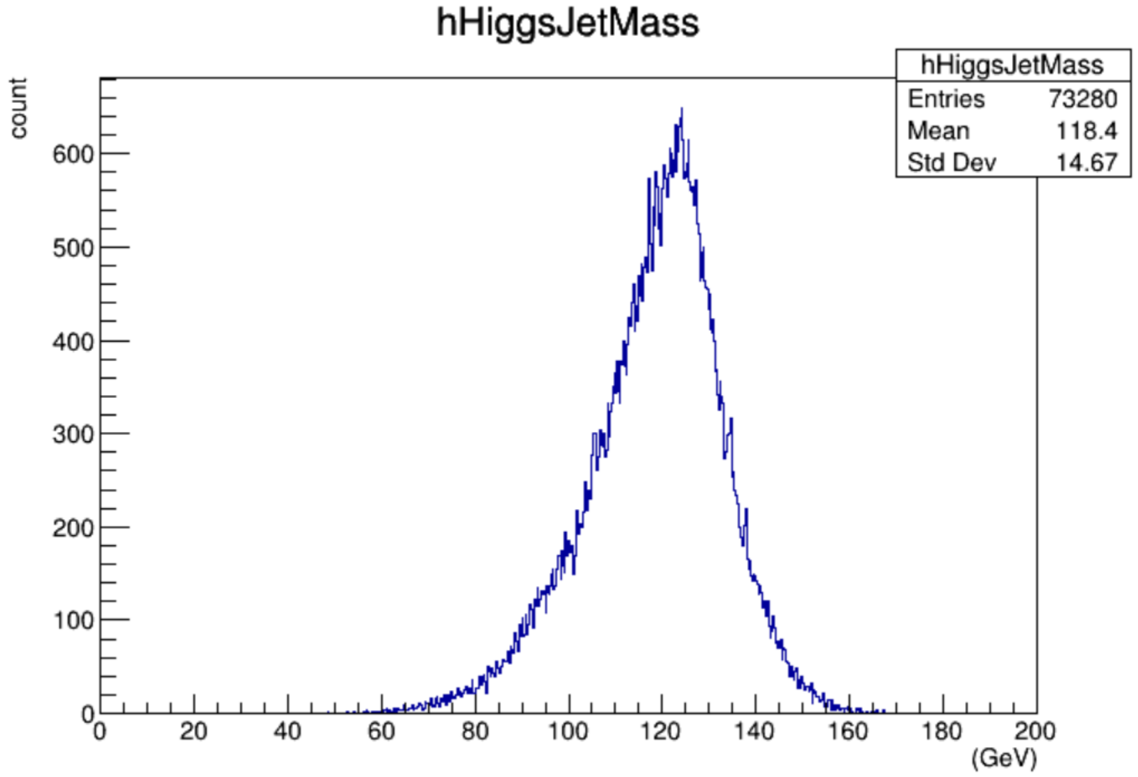
4-jet sorting(signal)

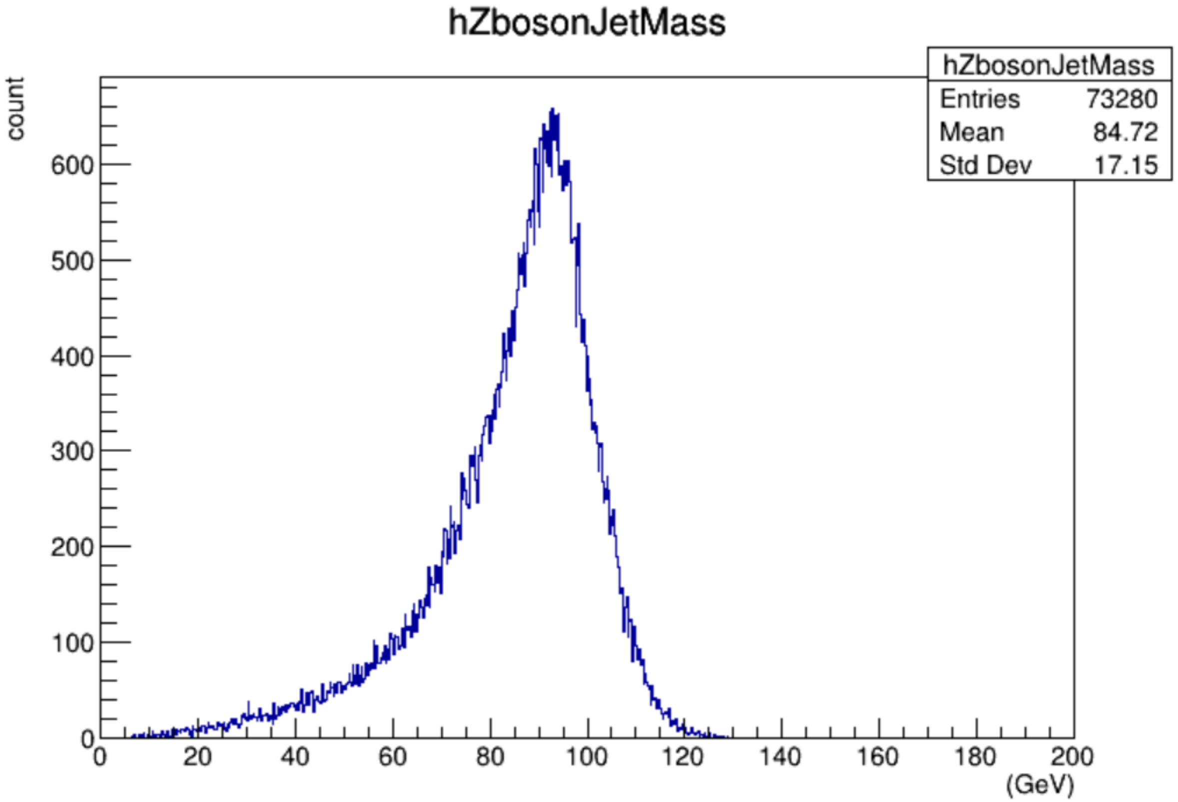
The jets were chosen so that χ^2 in this equation is the smallest.

$$\chi^2 = \left(\frac{M_{j_1 j_2} - M_Z}{\sigma_Z}\right)^2 + \left(\frac{M_{j_3 j_4} - M_H}{\sigma_H}\right)^2 ,$$

※$M_Z = 91.2\ GeV$, $M_H = 125\ GeV$

$\sigma_H = 4.4\ GeV$ $\sigma_Z = 4.7\ GeV$





Signal Event Result

Results were normalized using cross section and luminosity.

$$Normalized\ Events = Events \times \frac{CrossSection}{Generated} \times Luminosity$$

Change in the number of events when cuts are made to signal events

	reference	my data	normalized
generated	52507	75149	85757
$\chi 2$	32447	33806	38578
charge tracks	25281	33806	38578
Y value	25065	33673	38426
thrust	24688	33159	37839
thrust angle	21892	29137	33250
Z di-jet mass	16359	22109	25230
H di-jet mass	16359	17480	19947
		crossSection : 343.03	

More signal events remained in my data than in the reference.

About the Background

The main background of hadronic events are Z boson or W boson-derived events.
The following two events were used in the analysis

○4f_hadronic
- ZZ_hadronic
- WW_hadronic
- ZZWWMix_hadronic

○2f_hadronic

BackGround Events Result

$$Normalized\ Events = Events \times \frac{CrossSection}{Generated} \times Luminosity$$

More background remained than references.In particular, the cutting of charge tracks does not seem to have been done well.

	reference	4f normalized	2f normalized	total
generated	45904900	3716600	31991500	35708100
$\chi 2$	268980	850391	949192	1799583
charge tracks	1120950	850391	949192	1799583
Y value	1002125	844053	589446	1433499
thrust	935950	839494	453161	1292655
thrust angle	696201	627746	323115	950861
Z di-jet mass	411863	475288	229700	704988
H di-jet mass	411863	355931	169555	525486
cross section		14866.4	127966	

Misc & Plans

- Applying ParT to ILCSoft
  - The framework has "onnx" output – we implemented the adapter
    - Still confirming the performance
- Apply ParT to H → ss
  - Complete H → ss analysis with applying ParT flavor tagging
  - The very first result must come by 20th Oct.
    - To be included in the ECFA study
  - Major channels should be covered with reasonable quality in end of this year!
- PFA: if significantly exceed PandoraPFA in JER, start to think of implementation to ILCSoft (not in ECFA timescale)

Backup

Results on efficiency and purity (another view)

Algorithm train/test	**Electron eff.**	**Pion eff.**	**Photon eff.**	**Electron pur.**	**Pion pur.**	**Photon pur.**
GravNet 10 taus/10 taus	98.8%	99.6%	99.1%	92.6%	99.3%	97.7%
PandoraPFA 10 taus	99.3%	94.0%	99.1%	91.8%	94.6%	97.2%
GravNet jets/jets	94.6%	93.1%	95.2%	77.4%	93.1%	92.4%
PandoraPFA jets	80.2%	90.4%	79.0%	75.0%	90.6%	77.7%
PandoraPFA jets (ILCSoft truth)	96.7%	95.5%	96.4%	97.1%	90.4%	97.7%

At least in our measure, performance of GravNet-based algorithm exceeds PandoraPFA

→ Promising as full PFA (but energy regression to be done)

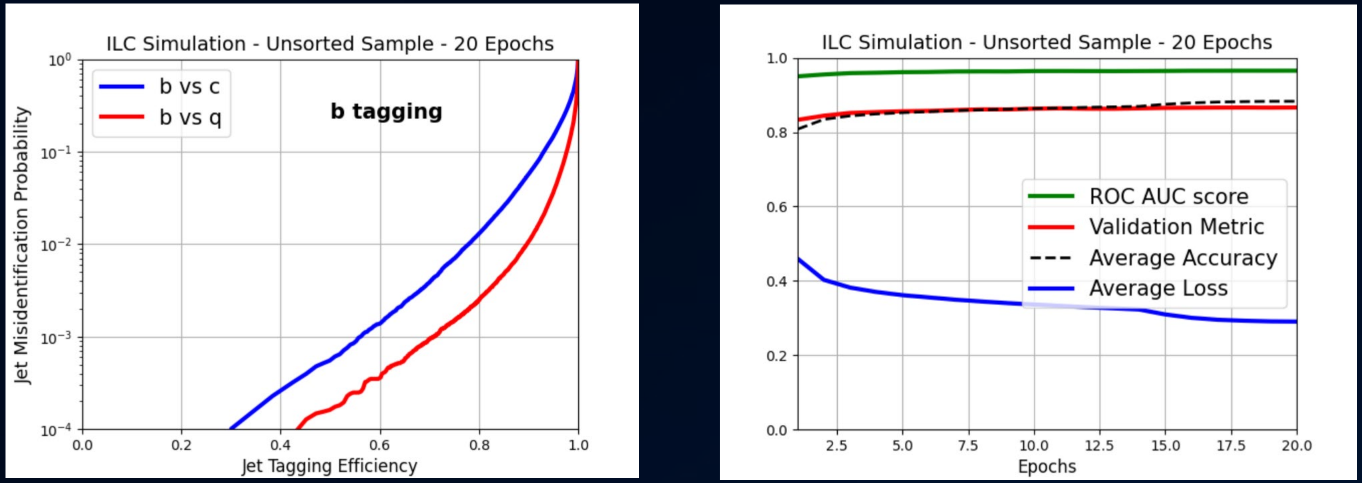
Definition of MC truth clusters needs to be tuned (see ILCSoft truth)

Software for Particle Transformer

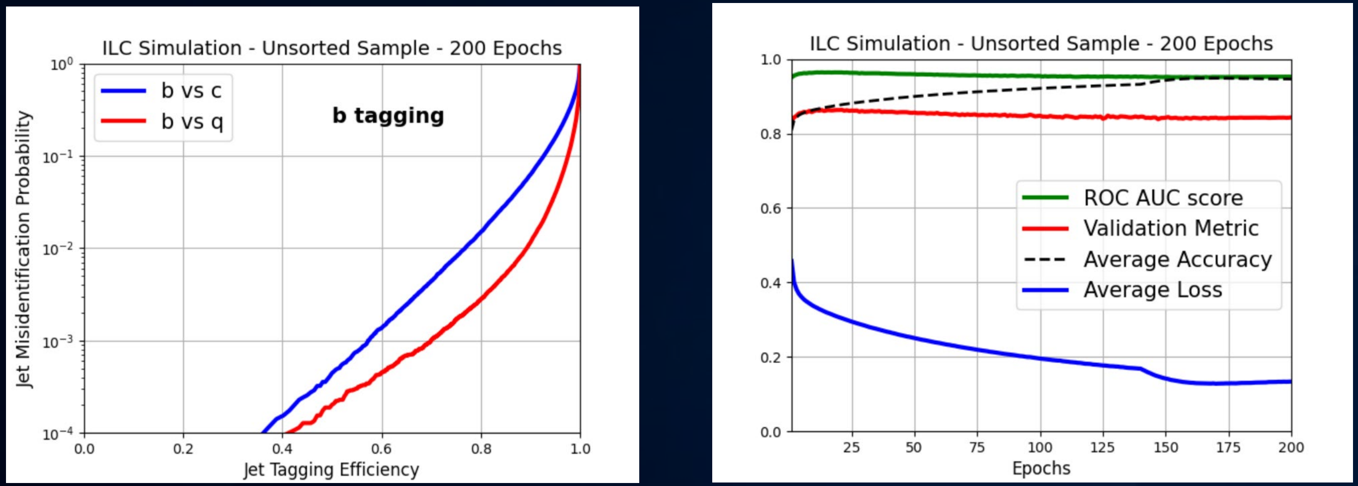
- Public in github, with instruction provided
  - https://github.com/jet-universe/particle_transformer
- Input: ROOT files for training (80%), validation (5%), test (15%)
  - Input variables can be provided via steering file (XML)
    - Input for each particle (tracks, neutral clusters)
    - Input for “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

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:

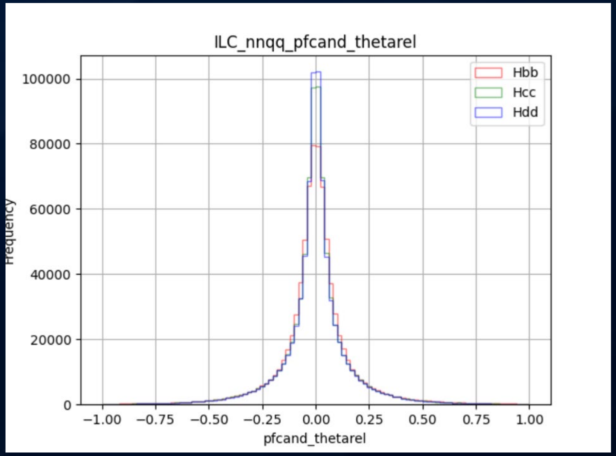
$$p = \sqrt{{p_x}^2 + {p_y}^2 + {p_z}^2}$$

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

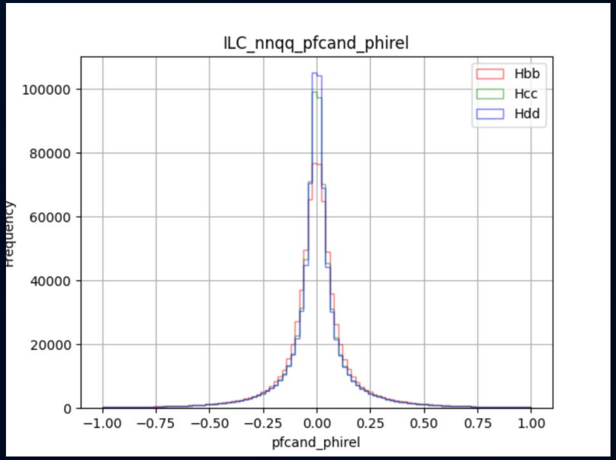
				c-bkg acceptance @ b-tag 80% eff.		**b-bkg acceptance @ c-tag 50% eff.**	
Particle ID	**Impact Parameters**	**Jet Distance**	**Track Errors**	**p**	**p_x p_y p_z**	**p**	**p_x p_y p_z**
✗	●	●	●	**0.62%**	**0.49%**	**1.14%**	**1.01%**
✗	● +log(abs)	● +log(abs)	● +log(abs)	**0.54%**	**0.52%**	**1.06%**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

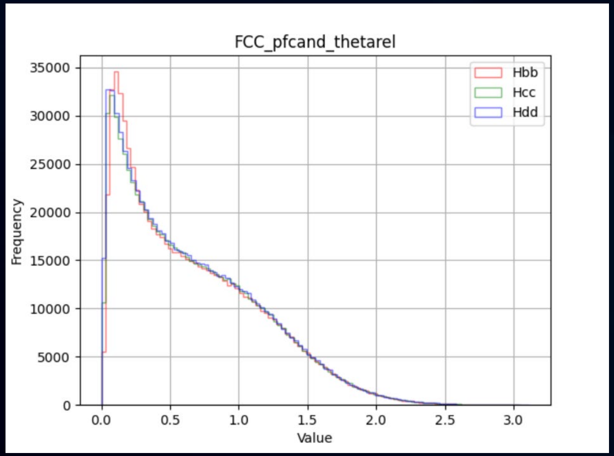
ILD vs. FCC – theta/phi distribution



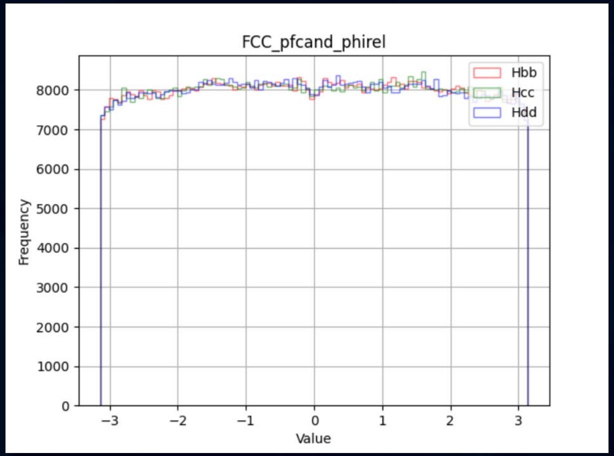
ILD theta



ILD phi



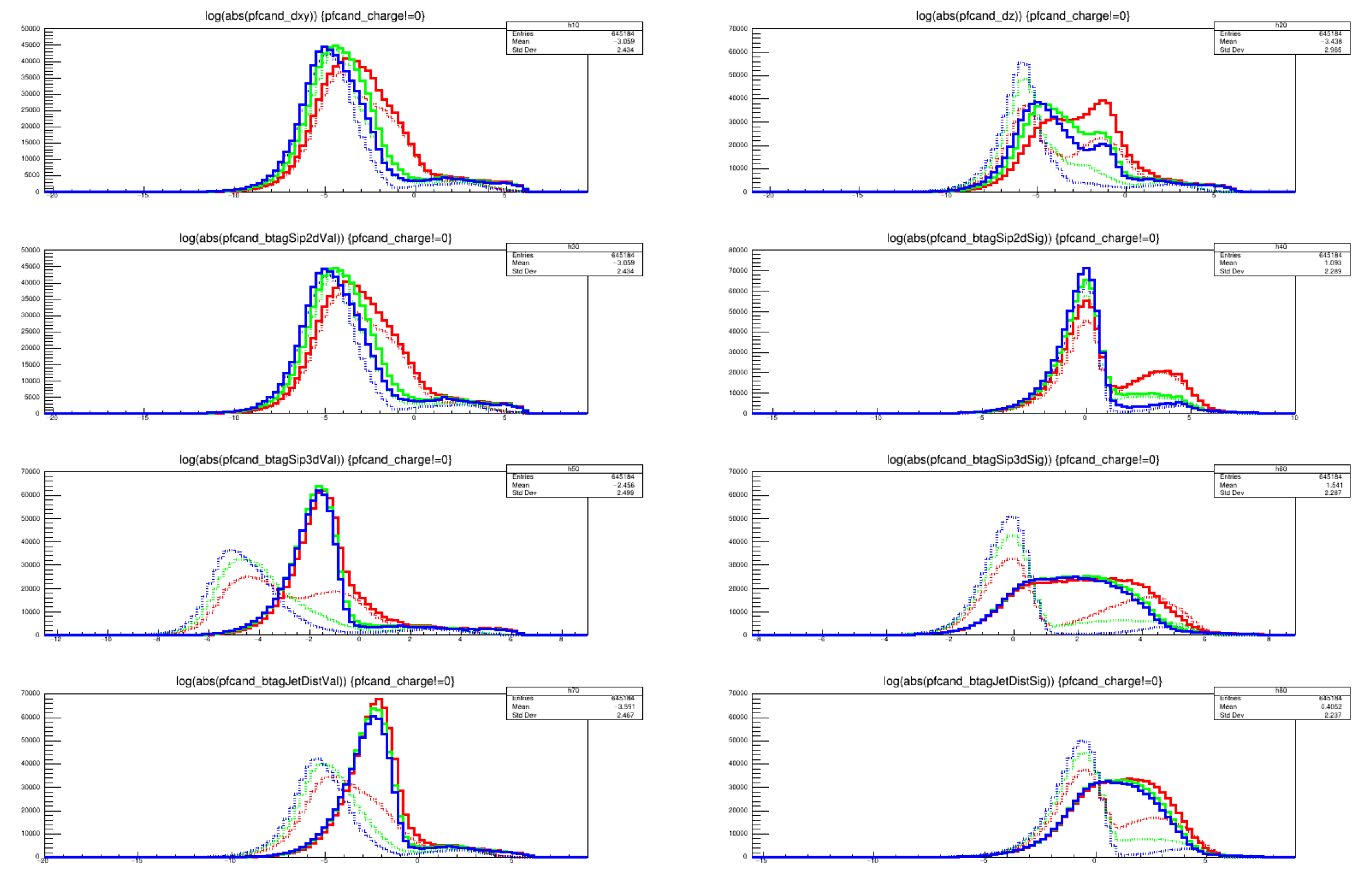
FCC theta



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

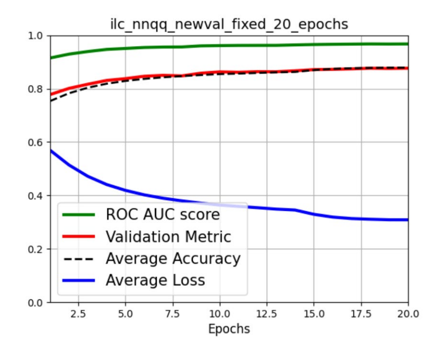
- Pretrained with fast sim and fine-tune with full sim
- Pretrained with large central production and fine-tune with dedicated physics samples in each analysis

							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%

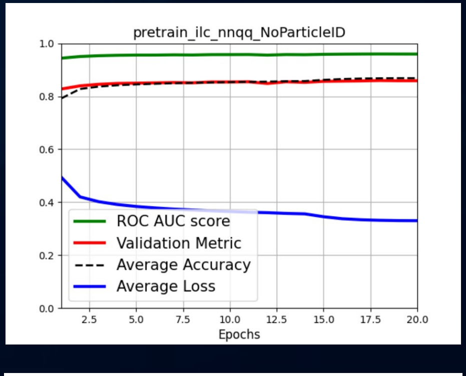
- Use result of 8M FCC data to train ILD 800k data
- Improves performance only when setups are similar
- Training of same setup (pretrain ILD 91 GeV data with ILD 250 GeV data) gives best performance
- Further investigation should be conducted on how to maximise the outcome for fine-tuning between different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

Fine tuning – Training curves

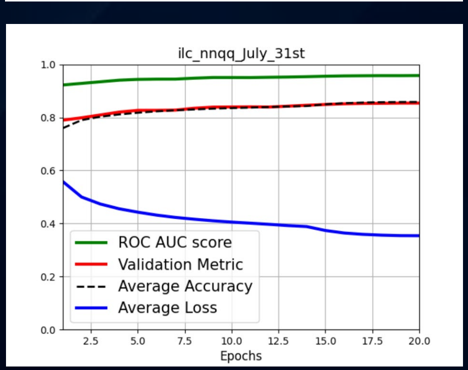
(1)



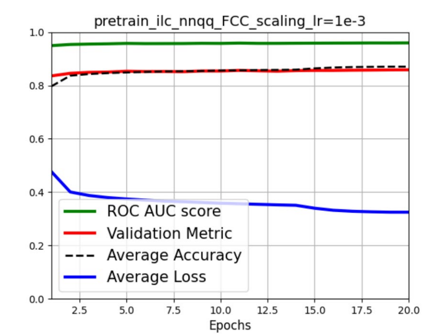
(2)



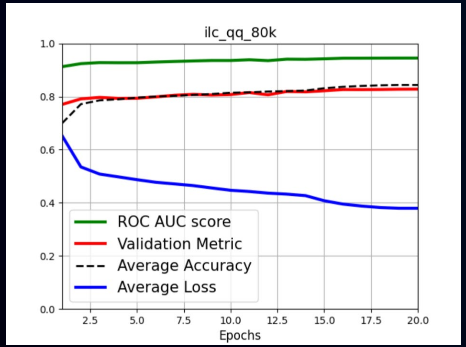
(3)



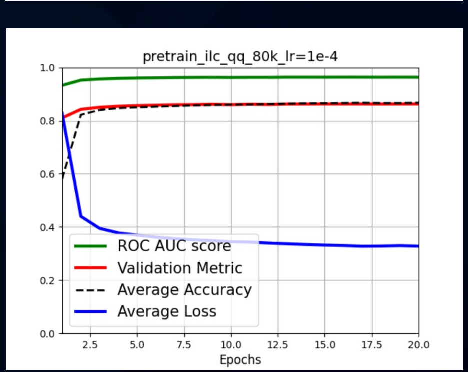
(4)



(5)



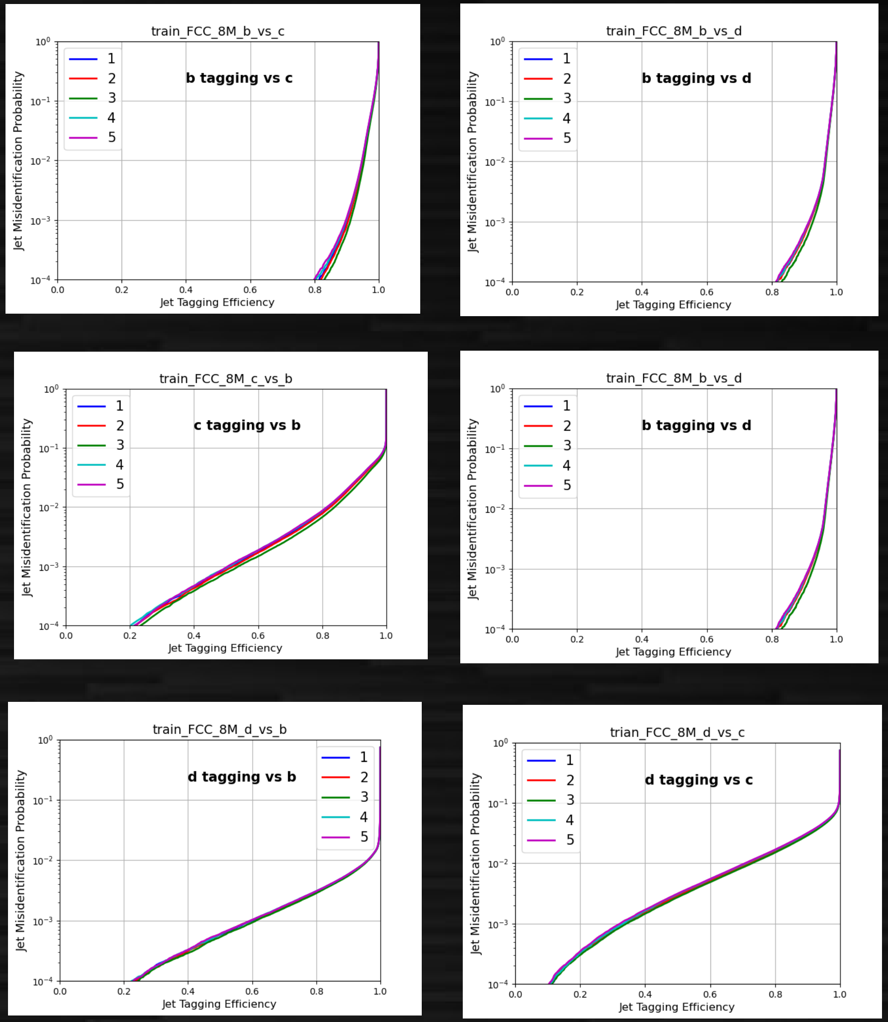
(6)



							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

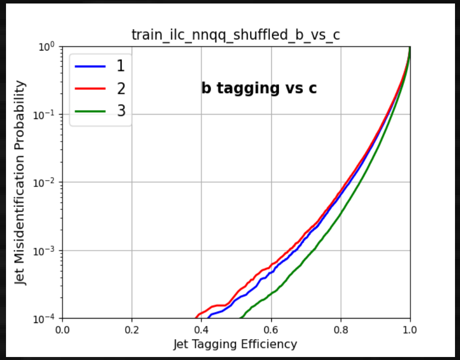


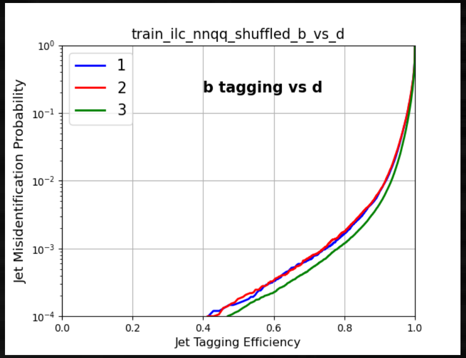
5 times training of FCC_8M data

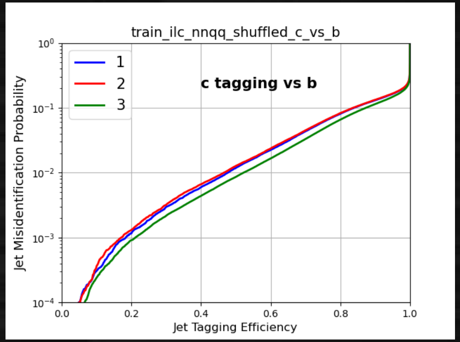
- Multiple training runs don't give significant impacts on results.
- The smaller data size is, the bigger impacts on results multiple runs give.
- The results of no Particle ID trainings varies more than those of with Particle ID.

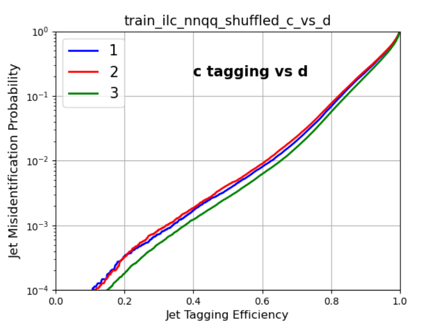
data	Particle ID	b vs c 0.8 Score	variation
FCC 4M	○	4.82e-4	0.43e-4
FCC 8M	○	8.14e-5	1.58e-5
FCC 4M	×	1.69e-3	0.14e-3
FCC 8M	×	7.04e-4	3.49e-4

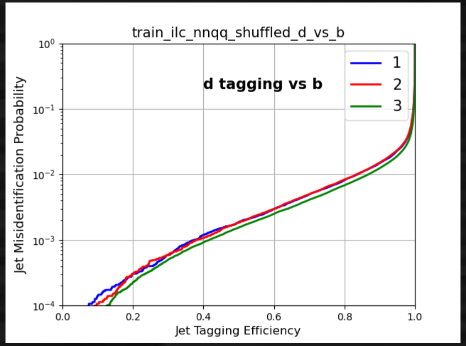
Data Shuffled

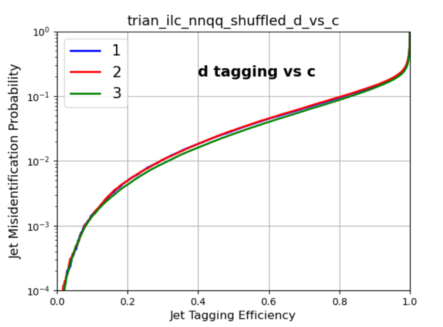












- ILC nnqq dataset
  - 80% training, 5% validation, 15% test
- Shuffled the order of train/test/val making root files
  - Pattern 1: train/val/test
  - Pattern 2: val/train/test
  - Pattern 3: train/test/val

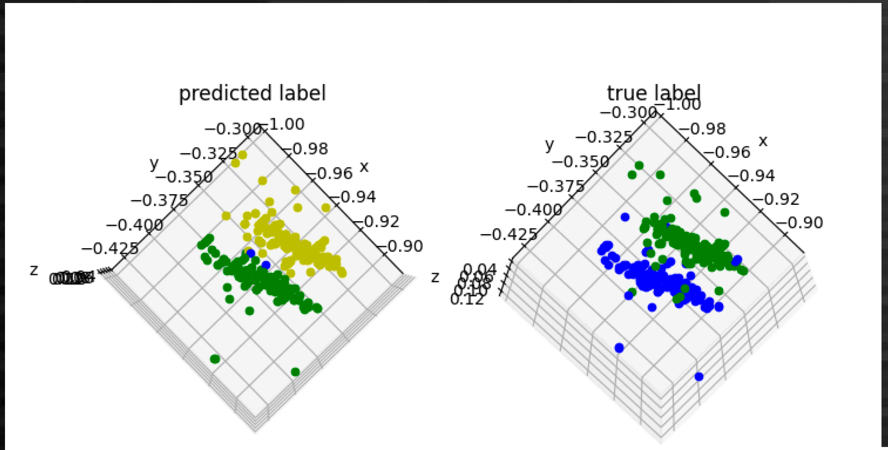
e

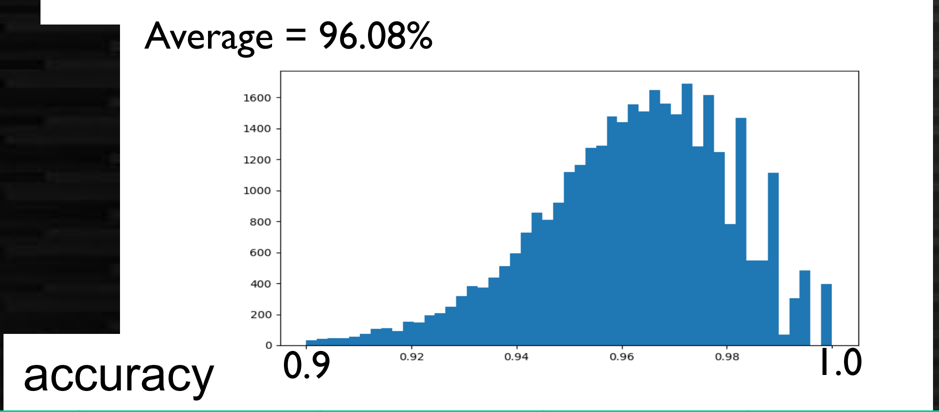
data	b vs c 0.8 score
Shuffle pattern 1	0.00647
Shuffle pattern 2	0.00734
Shuffle pattern 3	0.00338

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)



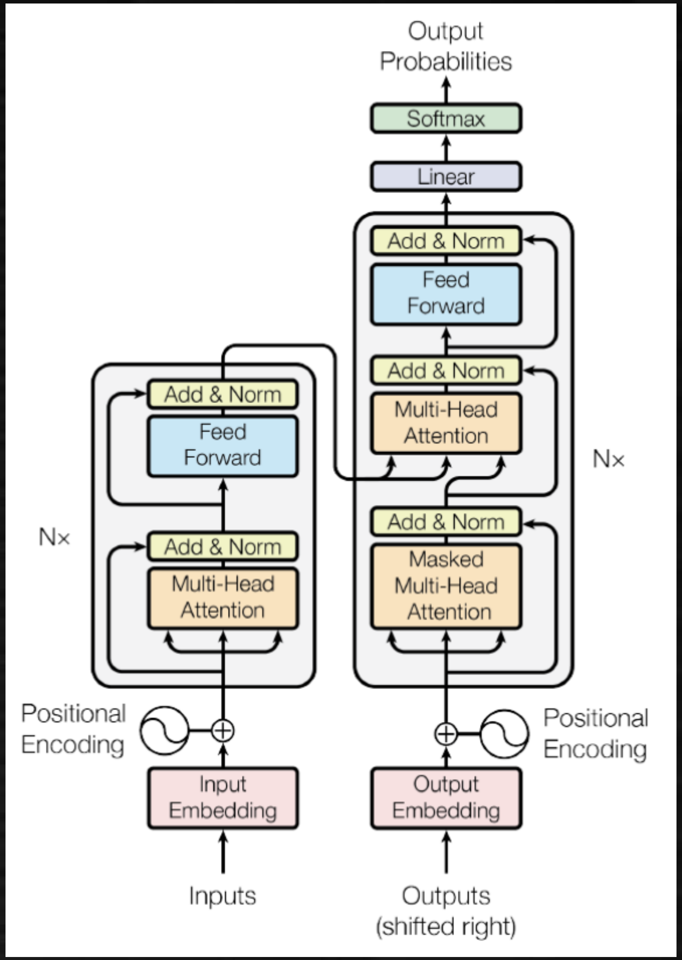


Reasonable
performance seen

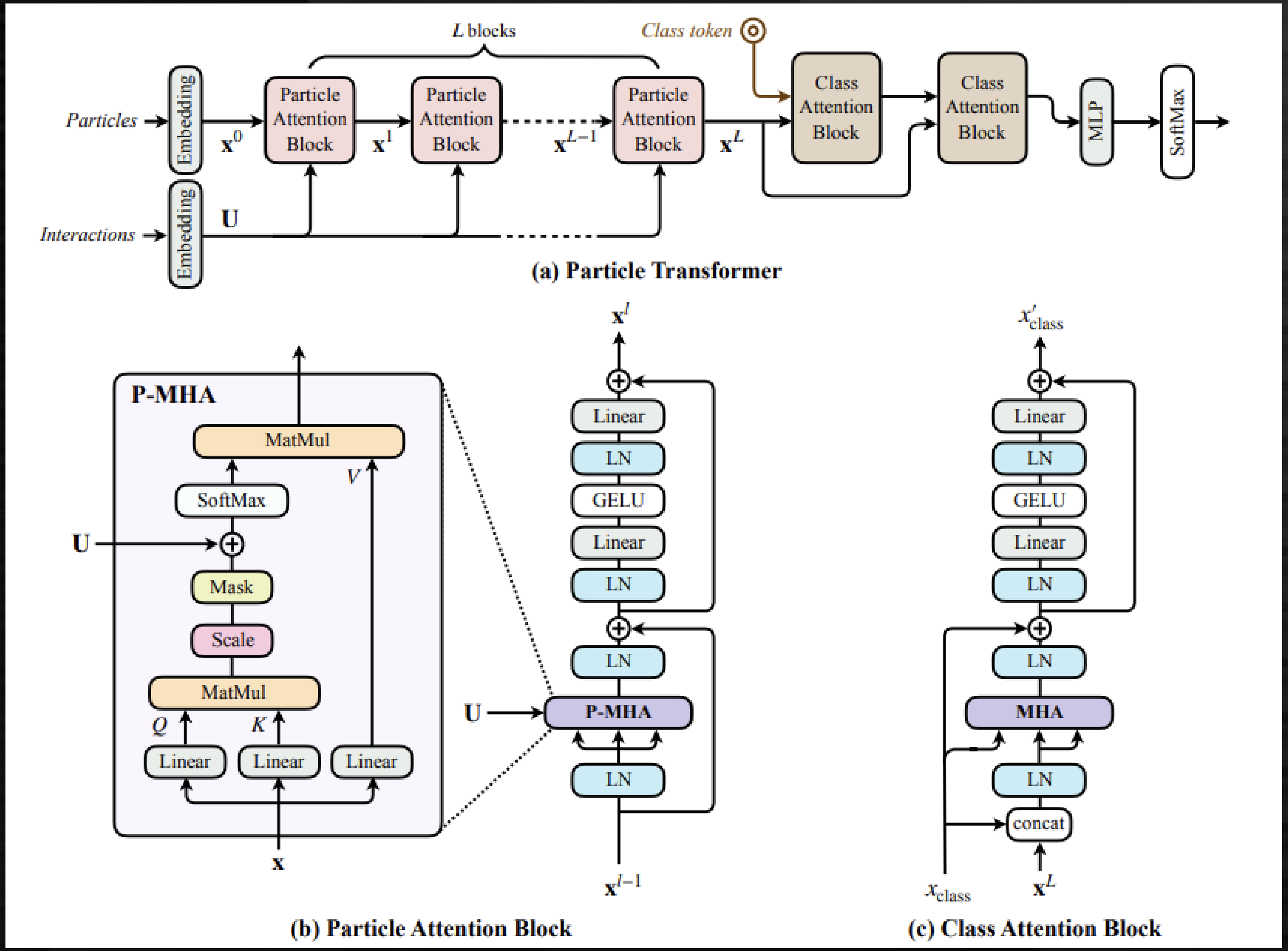
Angle[mrad]	30	60	90	120	150
Accuracy[%]	96.08	98.64	99.30	99.68	99.56

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



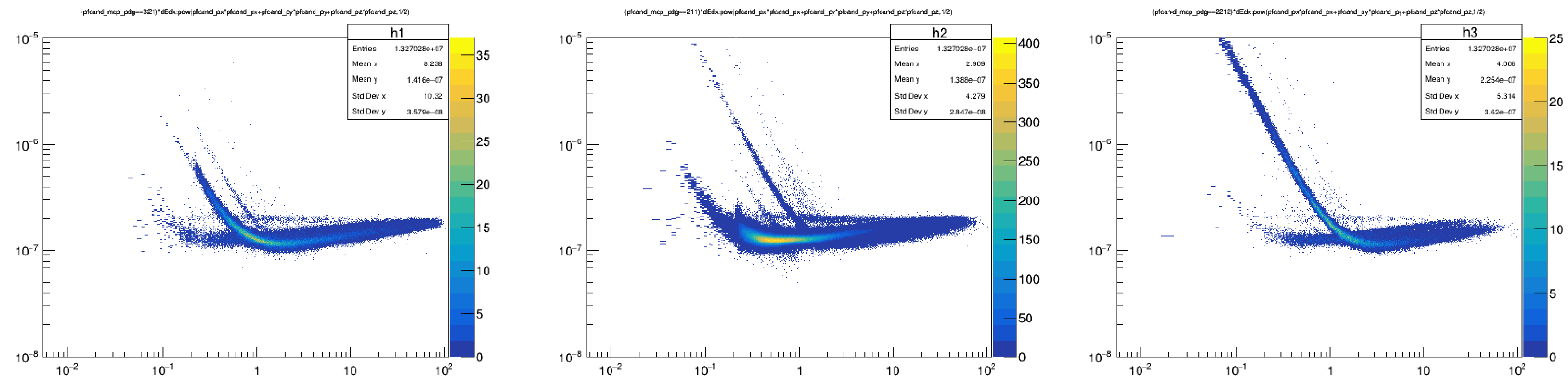
Particle Transformer

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)



Kaon Pion Proton

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