ParticleNet (PN)
&&
its application at CECP Jet Flavor Tagging (JFT)

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CEPC味物理-新物理和相关探测技术研讨会

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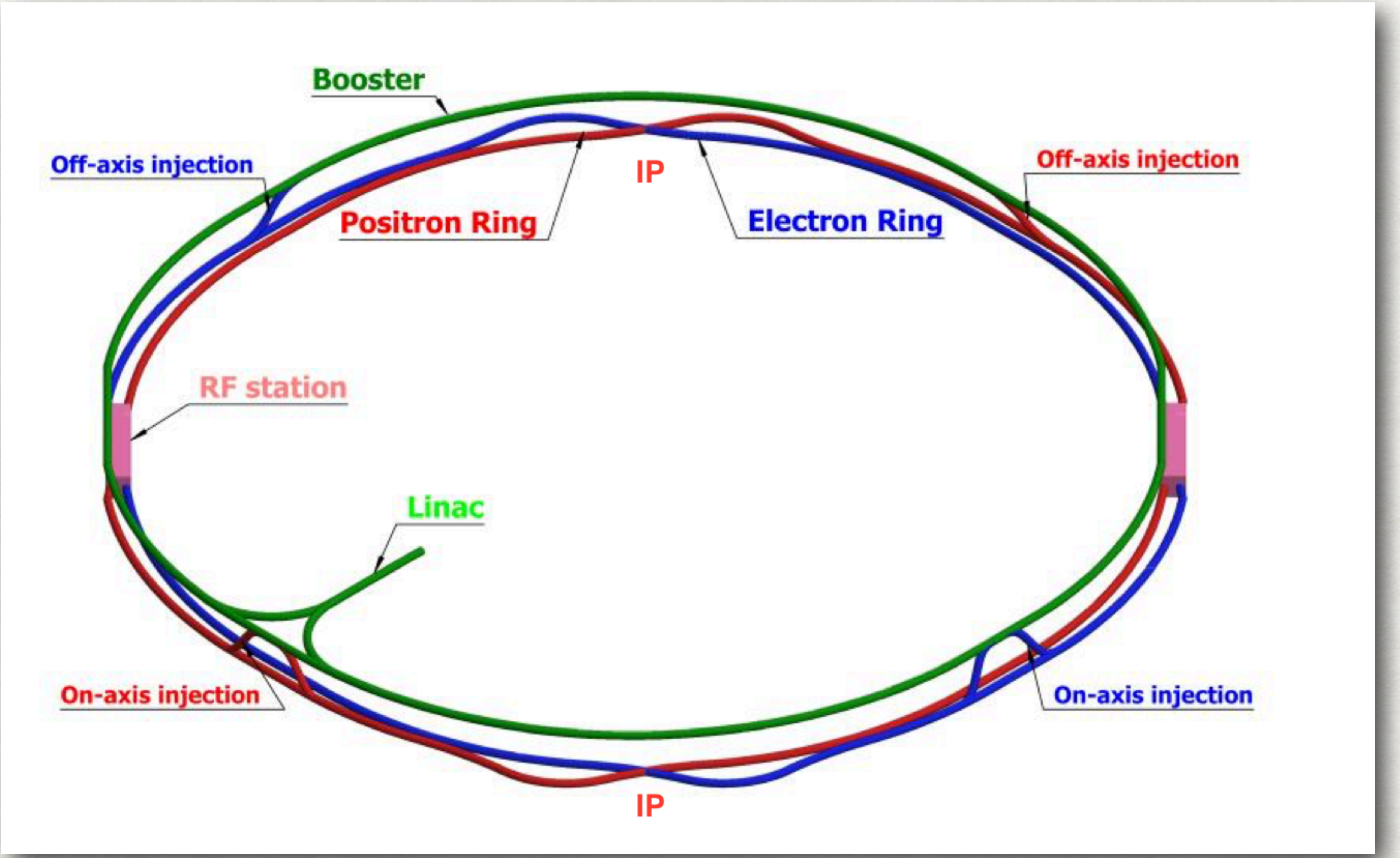
the CEPC project



proposed : 2012
circumference : 100 km
two interaction points
Pre-CDR : 2015
CDR : 2018
Snowmass report : 2022

arXiv:2306.11512

Operation mode	Z factory	W^+W^-	Higgs factory	$t\bar{t}$
$\sqrt{s}$ (GeV)	91.2	160	240	360
Run time (year)	2	1	10	5
Instantaneous luminosity ($10^{34}\,\mathrm{cm}^{-2}\mathrm{s}^{-1}$, per IP)	191.7	26.6	8.3	0.83
Integrated luminosity (ab^{-1}, 2 IPs)	100	6	20	1
Event yields	3×10^{12}	1×10^{8}	4×10^{6}	5×10^{5}

two JFT algorithms

BDT based

LCFIPlus: A framework for jet analysis in linear collider studies

CrossMark

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A B S T R A C T

We report on the progress in flavor identification tools developed for a future e^+e^- linear collider such as the International Linear Collider (ILC) and Compact Linear Collider (CLIC). Building on the work carried out by the LCFIVertex collaboration, we employ new strategies in vertex finding and jet finding, and introduce new discriminating variables for jet flavor identification. We present the performance of the new algorithms in the conditions simulated using a detector concept designed for the ILC. The algorithms have been successfully used in ILC physics simulation studies, such as those presented in the ILC Technical Design Report.

GNN based

Jet Tagging via Particle Clouds

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How to represent a jet is at the core of machine learning on jet physics. Inspired by the notion of point clouds, we propose a new approach that considers a jet as an unordered set of its constituent particles, effectively a "particle cloud". Such a particle cloud representation of jets is efficient in incorporating raw information of jets and also explicitly respects the permutation symmetry. Based on the particle cloud representation, we propose ParticleNet, a customized neural network architecture using Dynamic Graph Convolutional Neural Network for jet tagging problems. The ParticleNet architecture achieves state-of-the-art performance on two representative jet tagging benchmarks and is improved significantly over existing methods.

the ParticleNet architecture

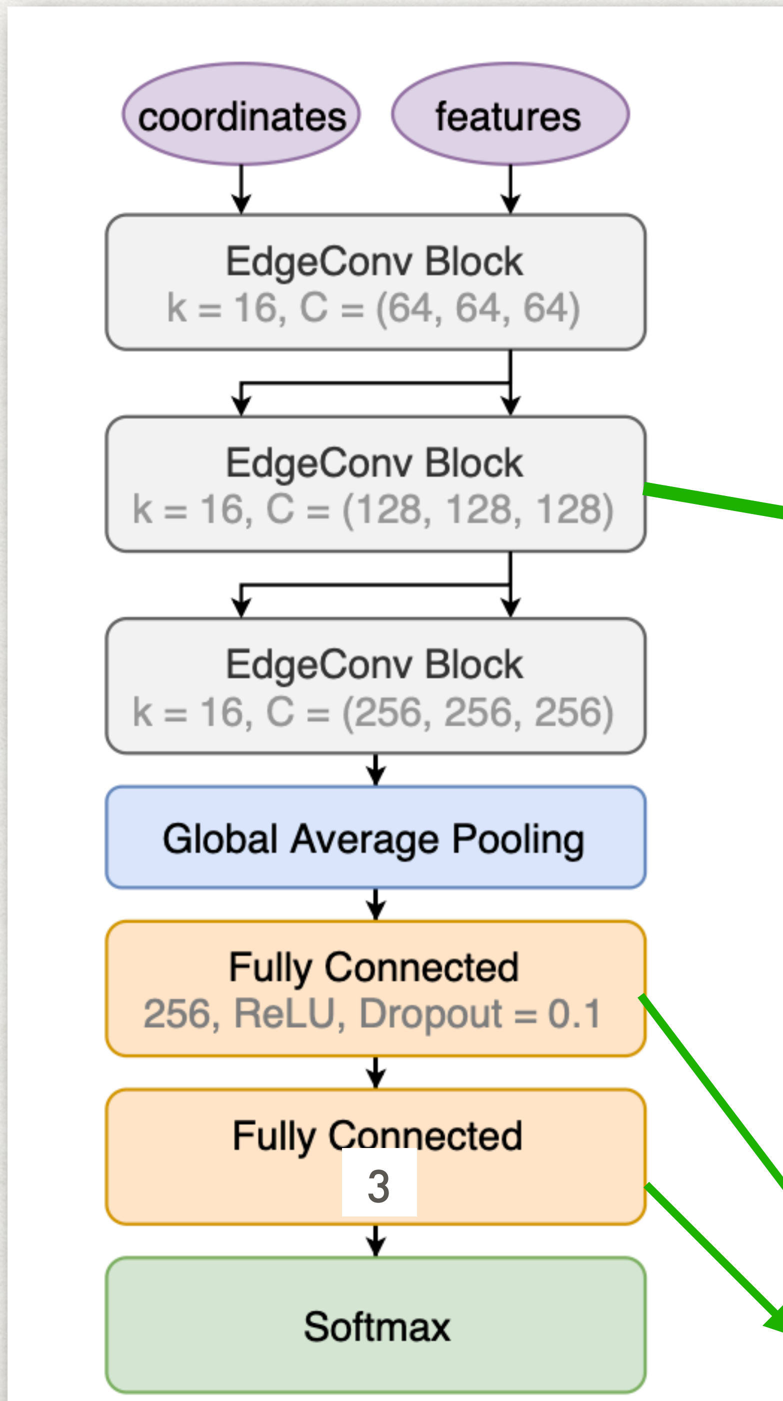
particles ordered independent and permutation symmetry

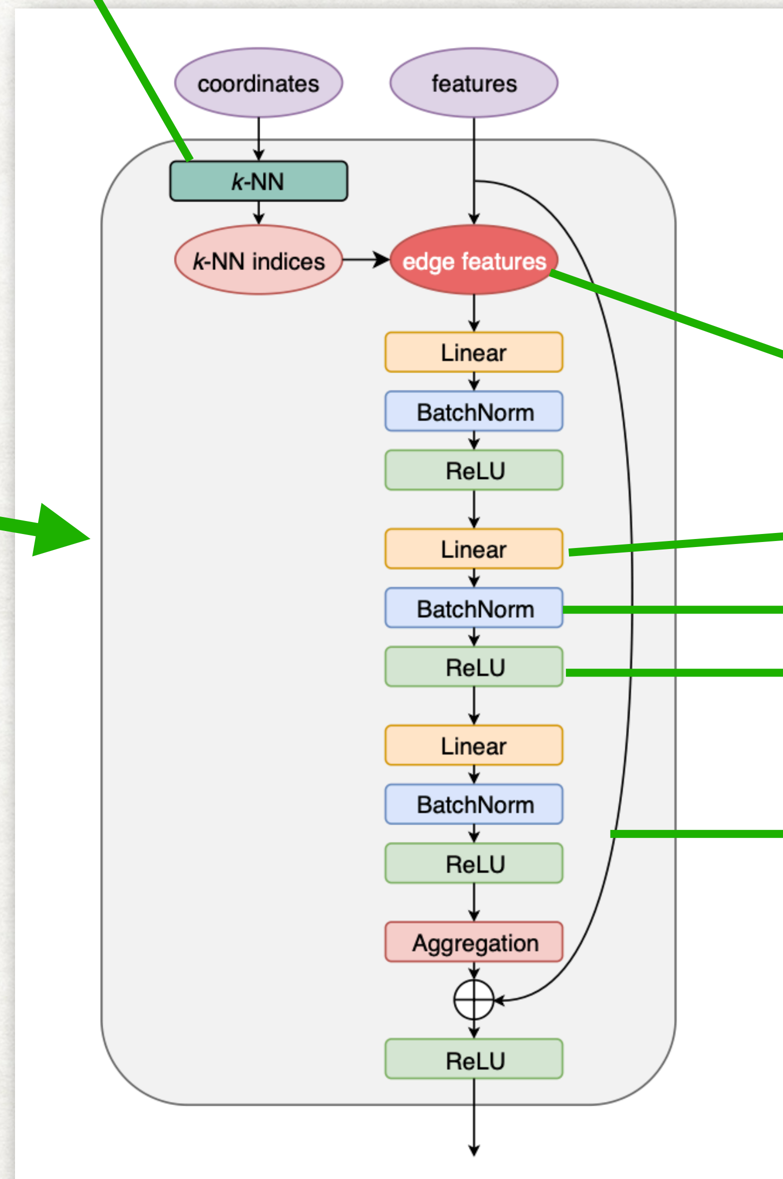
find the nearest k neighbor particles for each particle

input features :

```
- [part_isElectron, null]
- [part_isMuon, null]
- [part_isNeutralHadron, null]
- [part_isPhoton, null]
- [part_d0, null]
- [part_d0err, 0, 1, 0, 1]
- [part_dz, null]
- [part_dzerr, 0, 1, 0, 1]
- [part_deta, null]
- [part_dphi, null]
```

```
- [part_pt_log, -1.5, 1.0]
- [part_e_log, -0.687, 1.0]
- [part_logptrel, -4.7, 1.0]
- [part_logerel, -4.473, 1.0]
- [part_deltaR, 2.1, 2.3]
- [part_charge, null]
- [part_isChargedHadron, null]
```





$$(\boldsymbol{x}_i, \boldsymbol{x}_{i_j} - \boldsymbol{x}_i)$$

nn.Conv2d(128, 128, kernel_size=1, bias=True)

nn.BatchNorm2d(128)

nn.ReLU()

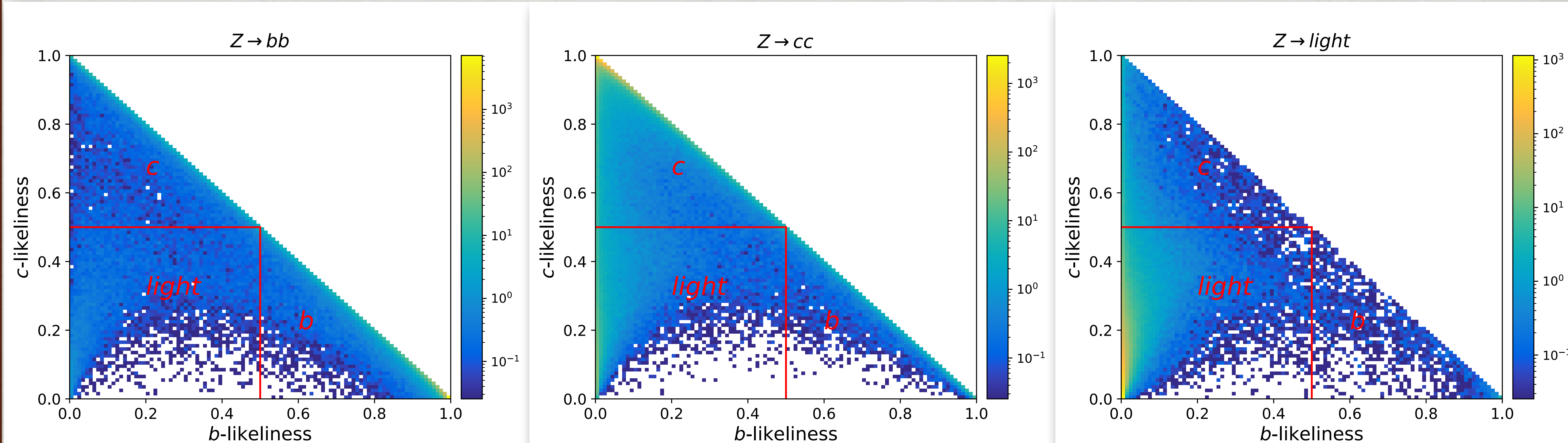
nn.Conv1d(64, 128, kernel_size=1, bias=True)
+
nn.BatchNorm1d(128)

https://doi.org/10.1103/PhysRevD.101.056019

nn.Sequential(nn.Linear(256, 256), nn.ReLU(), nn.Droupout(0.1))

nn.Sequential(nn.Linear(256, num_classes))

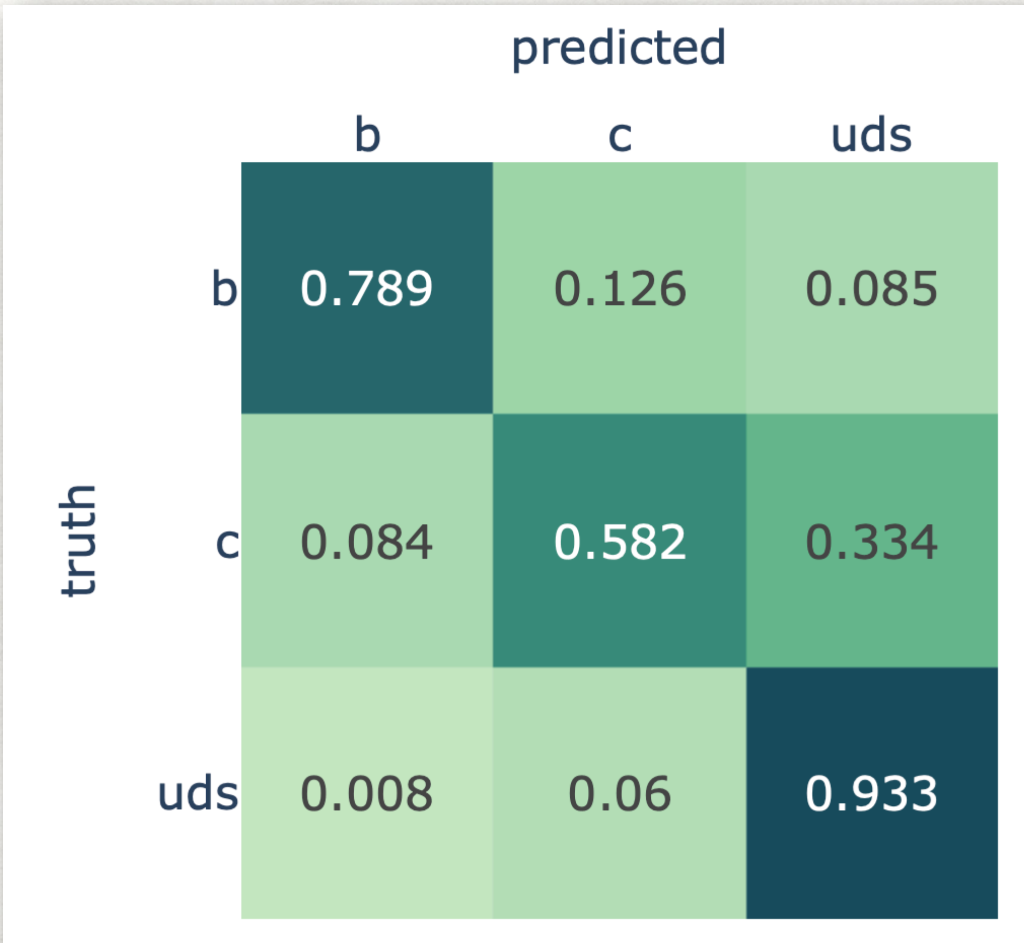
JFT evaluation



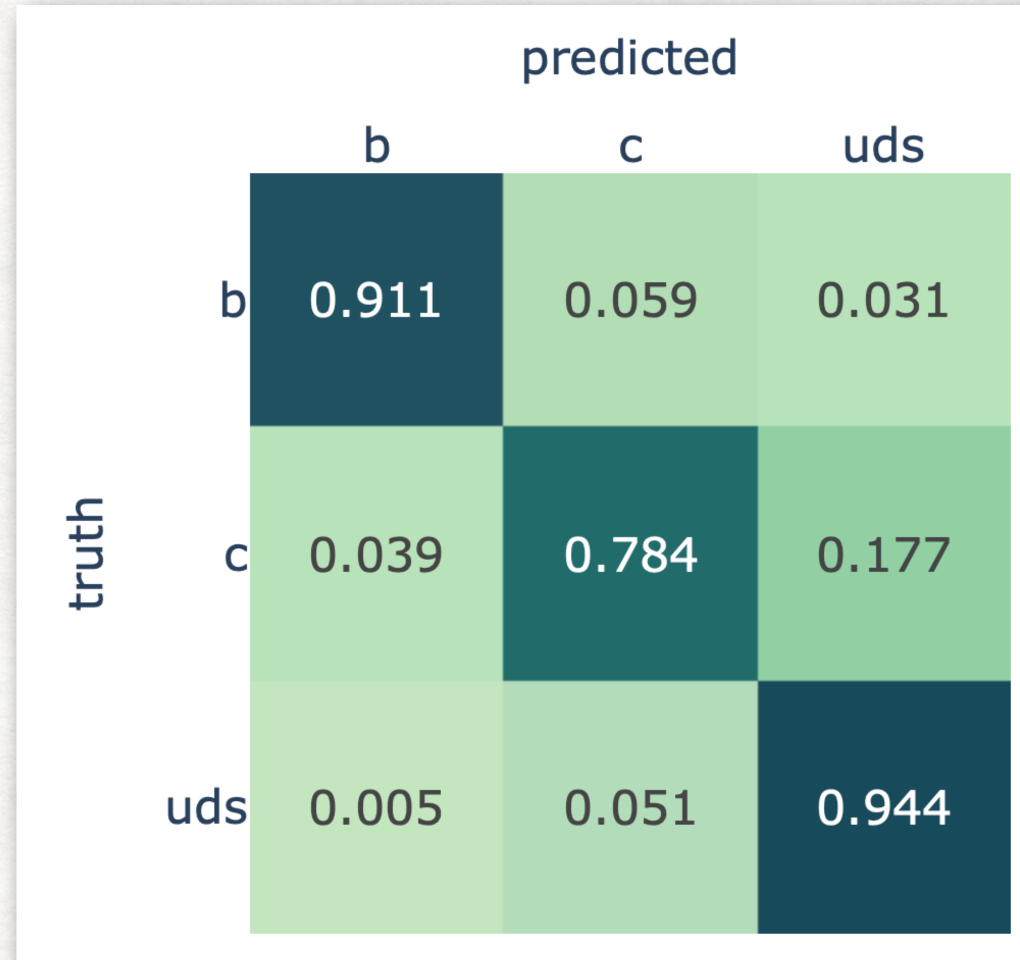
FT matrix, whose trace can be used
to describe the FT performance.
In the following, we use Tr_{mig} to represent
the trace.

truth \ predicted	b	c	uds
b	0.911	0.059	0.031
c	0.039	0.784	0.177
uds	0.005	0.051	0.944

Migration matrix of LCFIPlus v.s. PN



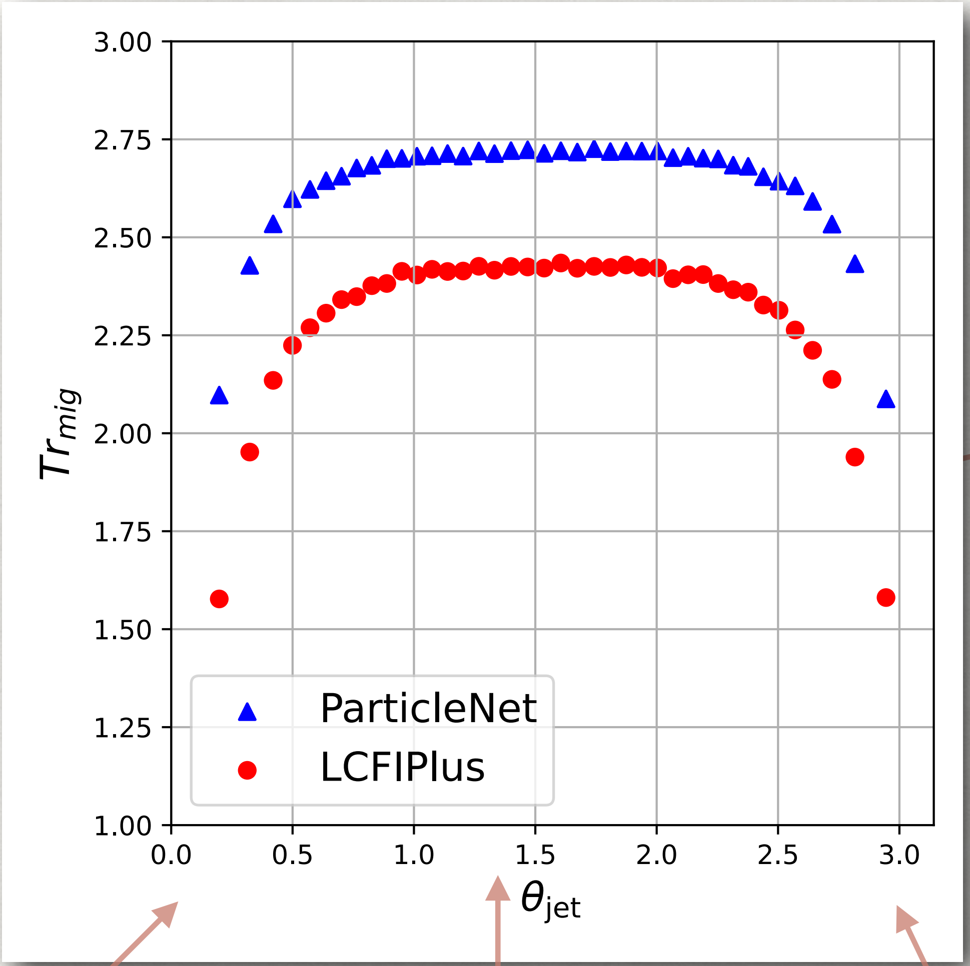
LCFIPlus



PN

- PN could improve the FT performance by 14% in trace compared to the default algorithm at the CEPC.
- b/c tagging efficiency is improved by 15%/34%
- c-tagging is more challenging as its properties lie between those of b and light

FT v.s. jet direction



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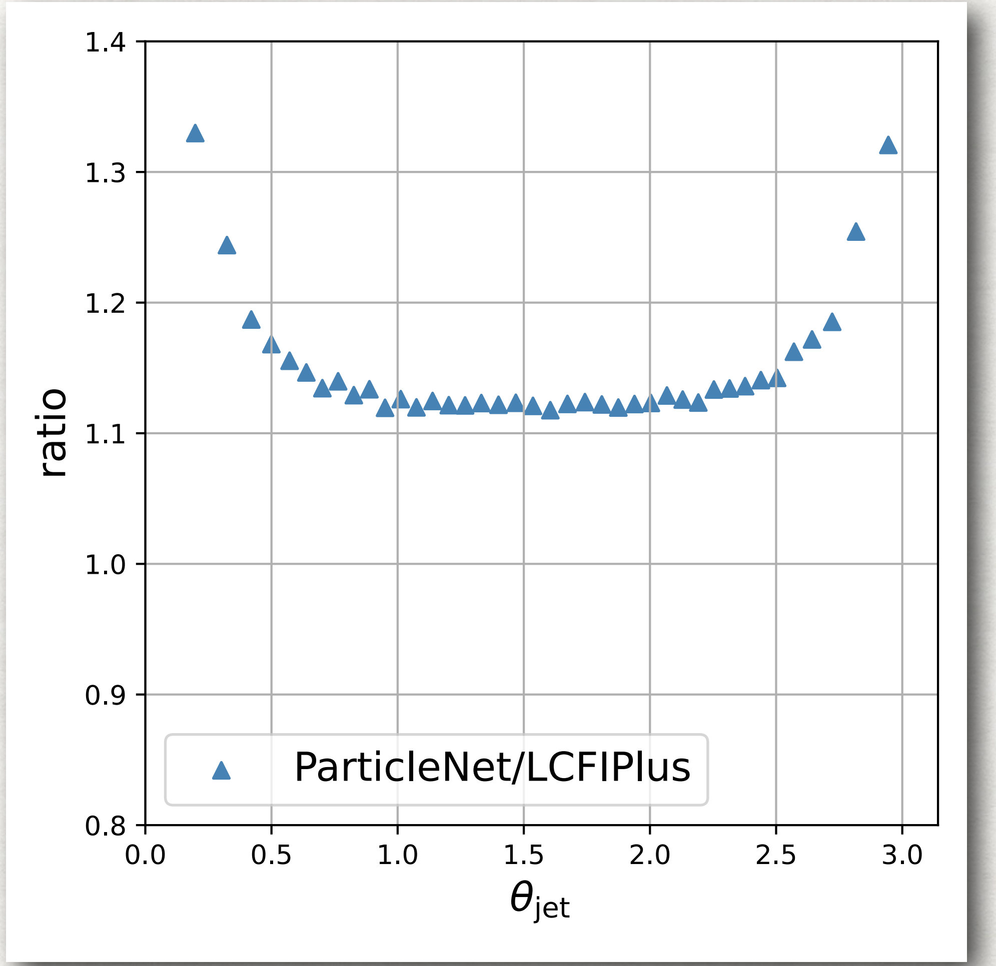
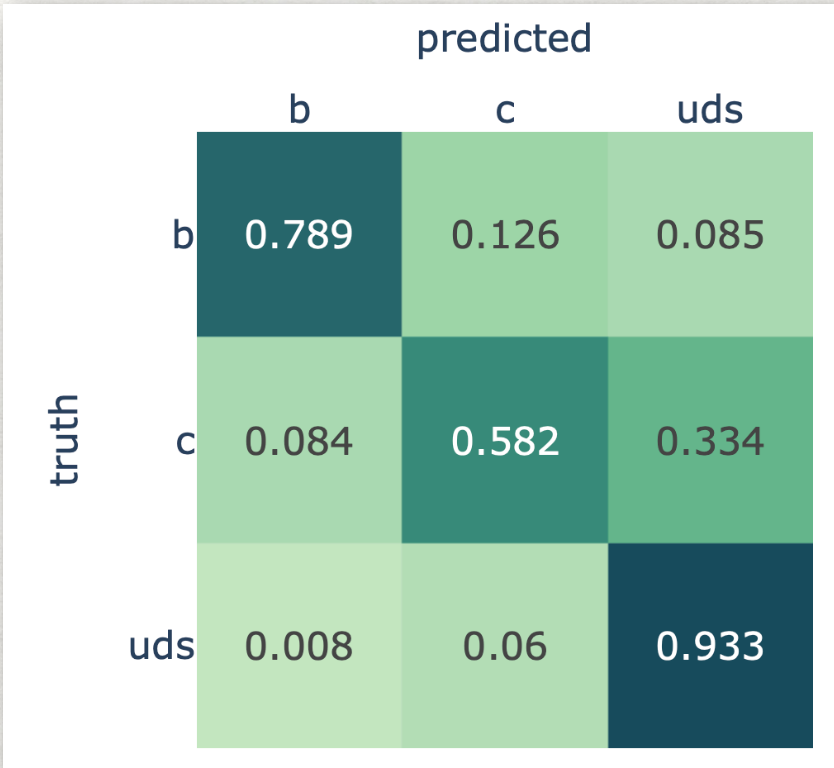


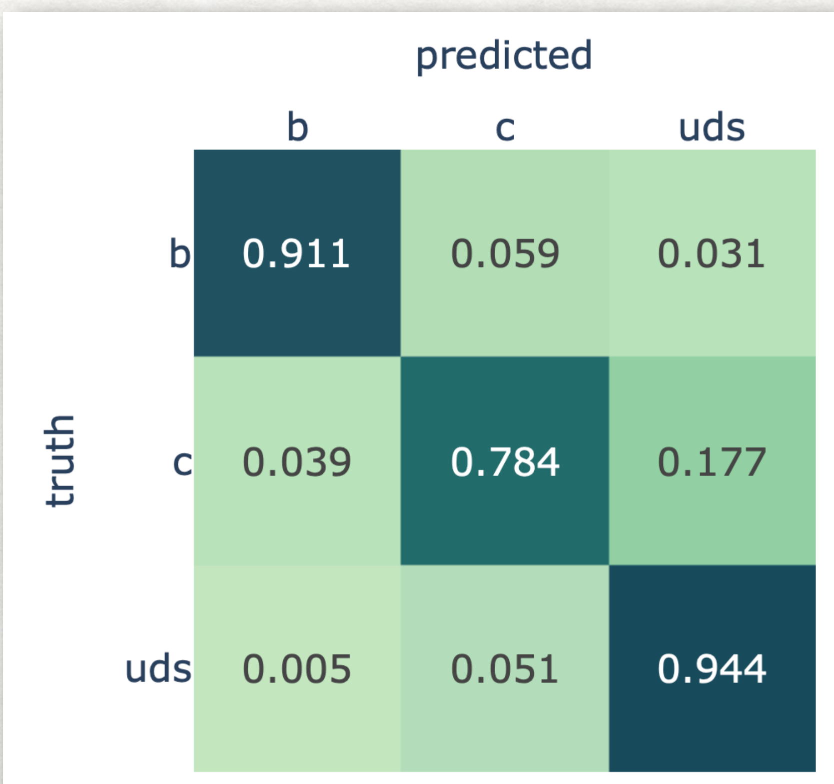
endcap barrel endcap

The FT performance in endcap is not as well as that of barrel. (resolution of Pt and impact parameters)
The FT performance improves much significant in the endcap region.

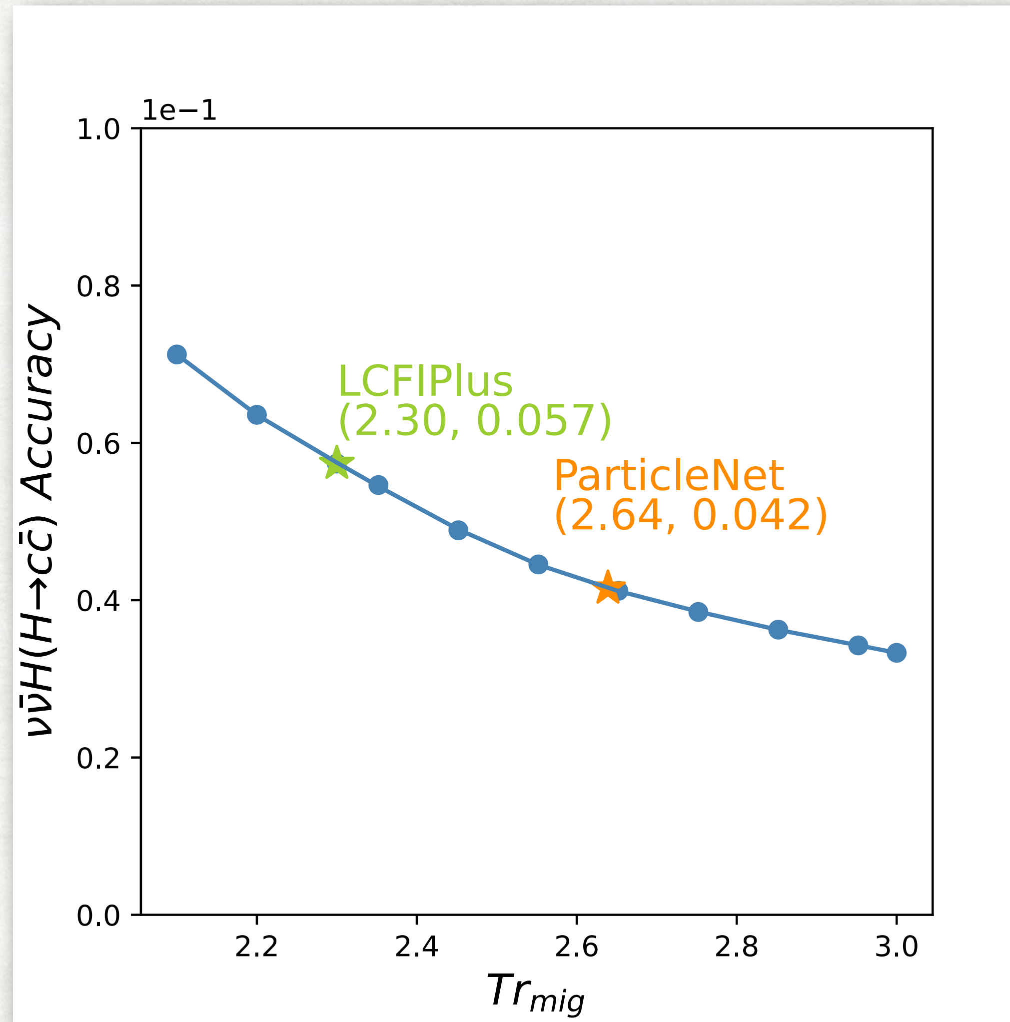
benchmark performance

https://doi.org/10.1007/JHEP11(2022)100



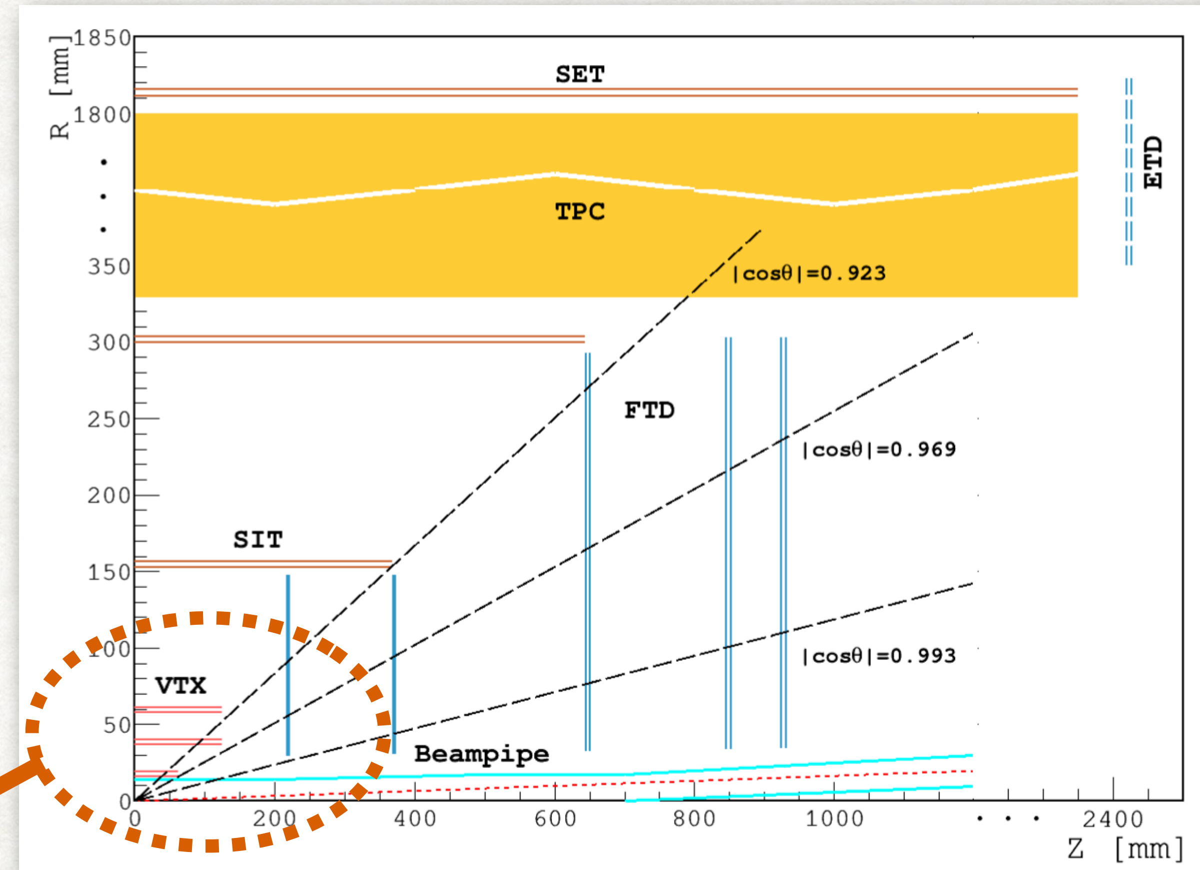


240 GeV $e^+e^- \to Z(\nu\bar{\nu})H(c\bar{c})$



improved more than 35%

the dependence of JFT on vertex detector configuration



the baseline tracking system

the VXD configuration

Table 1. The baseline design parameters of the CEPC vertex system.

	R(mm)	*Z*(mm)	single-point resolution(μm)	material budget
Layer 1	16	62.5	2.8	$0.15\%/X_0$
Layer 2	18	62.5	6	$0.15\%/X_0$
Layer 3	37	125.0	4	$0.15\%/X_0$
Layer 4	39	125.0	4	$0.15\%/X_0$
Layer 5	58	125.0	4	$0.15\%/X_0$
Layer 6	60	125.0	4	$0.15\%/X_0$

the dependence of JFT on vertex detector configuration

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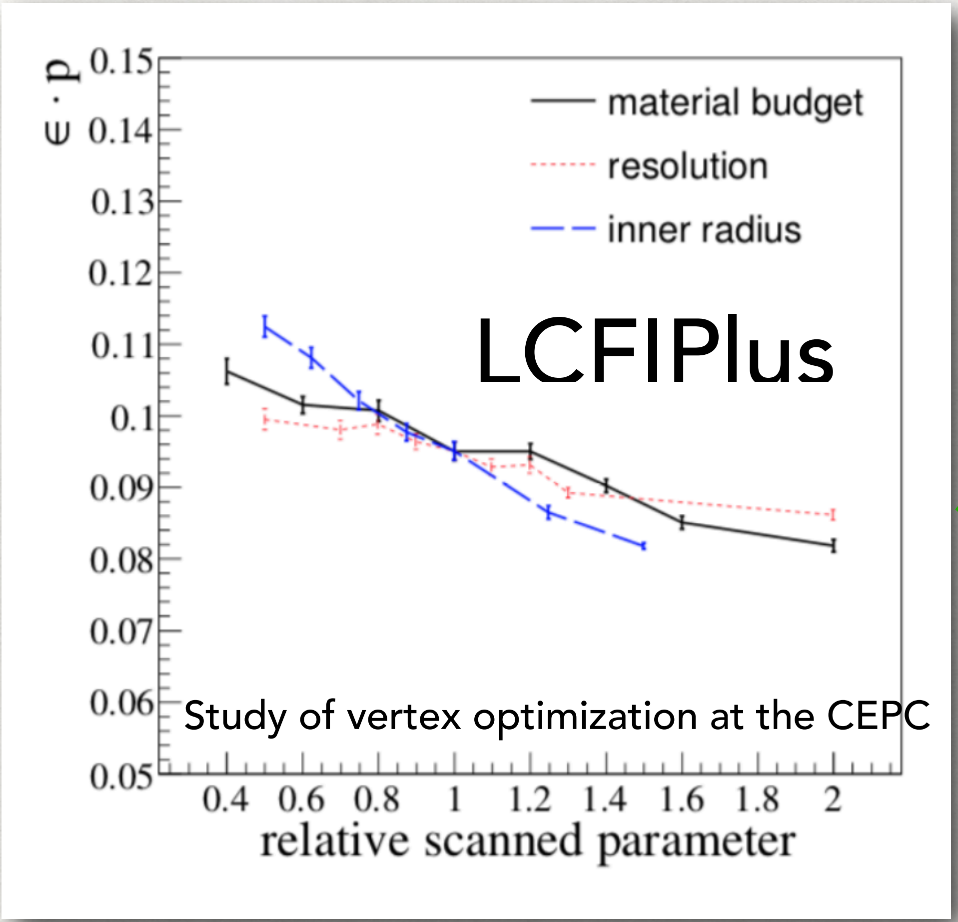

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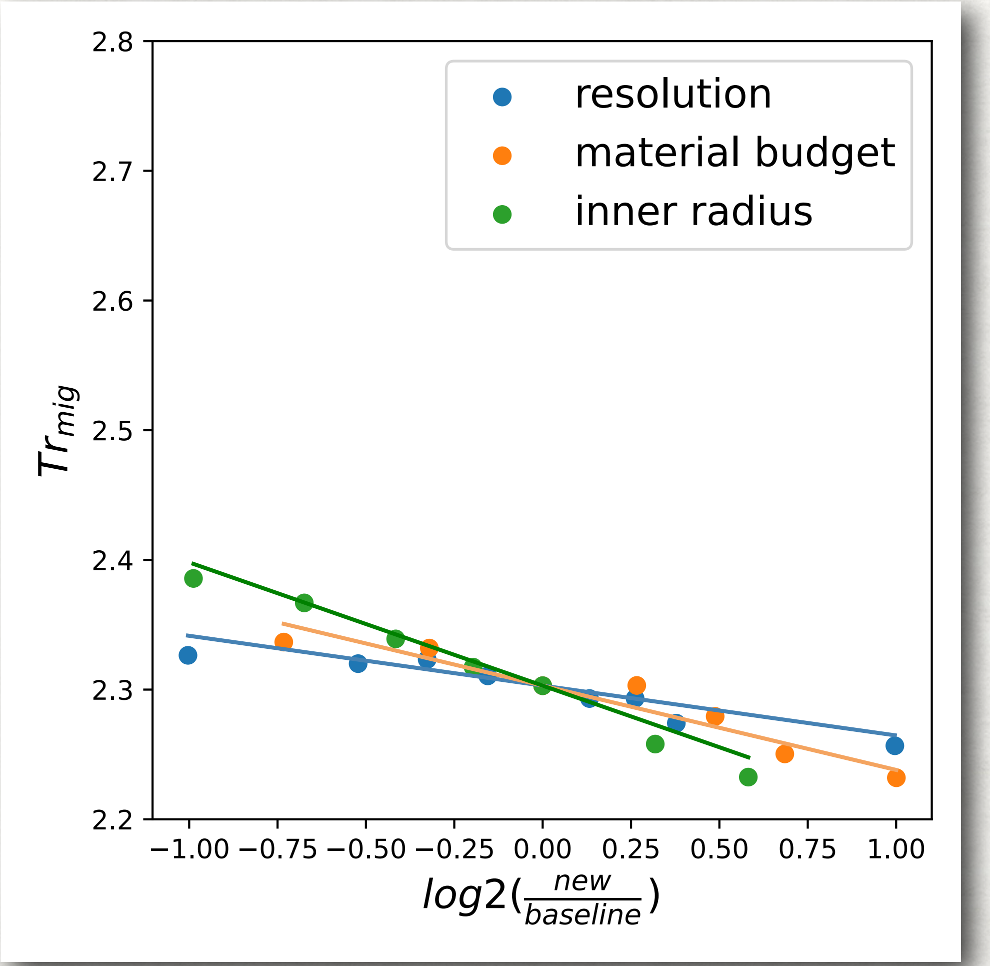
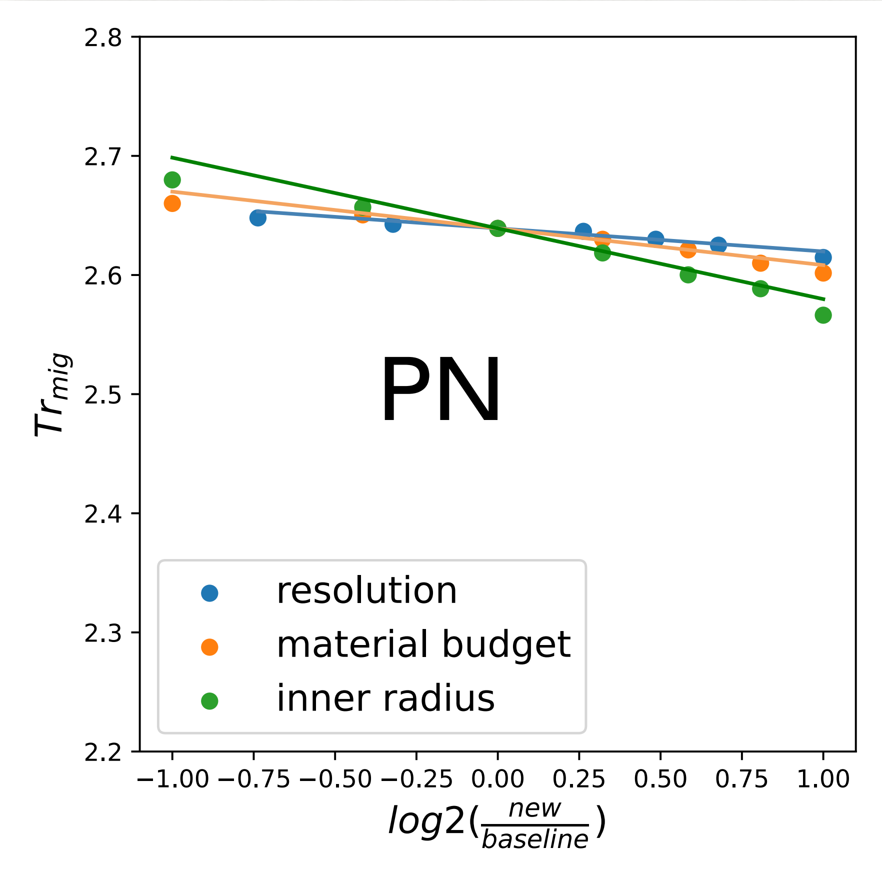


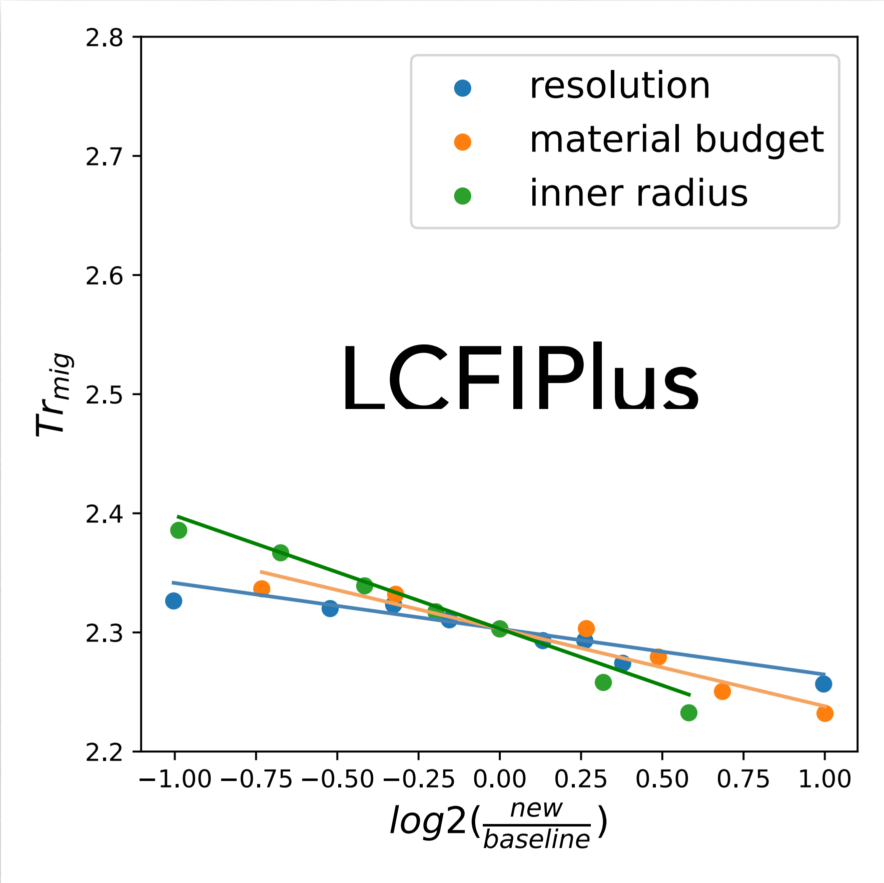
$$Tr_{mig} = 1.12 \cdot log_{10}(\epsilon \cdot p) + 3.28$$

https://doi.org/10.1007/JHEP11(2022)100

$$Tr_{mig} = 2.303 + 0.065 \cdot log_2\frac{R^0_{material}}{R_{material}} + 0.038 \cdot log_2\frac{R^0_{resolution}}{R_{resolution}} + 0.095 \cdot log_2\frac{R^0_{radius}}{R_{radius}}$$

the dependence of JFT on vertex detector configuration





$$\text{PN}: Tr_{mig} = 2.639 + 0.031 \cdot log_2 \frac{R^0_{material}}{R_{material}} + 0.019 \cdot log_2 \frac{R^0_{resolution}}{R_{resolution}} + 0.059 \cdot log_2 \frac{R^0_{radius}}{R_{radius}}$$

$$\text{LCFIPlus}: Tr_{mig} = 2.303 + 0.065 \cdot log_2 \frac{R^0_{material}}{R_{material}} + 0.038 \cdot log_2 \frac{R^0_{resolution}}{R_{resolution}} + 0.095 \cdot log_2 \frac{R^0_{radius}}{R_{radius}}$$

- Overall, the FT performance is closer to ideal condition ($Tr_{mig} = 3$) with PN.
- The FT performance is more sensitive to the vertex radius, then the material budget, and the last single point resolution.
- The dependence of FT performance on VTX configuration with PN is consistent with that of LCFIPlus, which gives a solid evidence for the effectiveness of PN applying to the CEPC.

Summary

- Flavor tagging is crucial in many physics analyses tasks.
- The dependency of FT performance on vertex detector configuration is consistent with previous study, we conclude that the PN is effective at the CEPC.
- The pN can improve the measurement of the relative statistical uncertainty of vvHcc by more than 35% compared to that of the LCFIPlus.

Thank you !

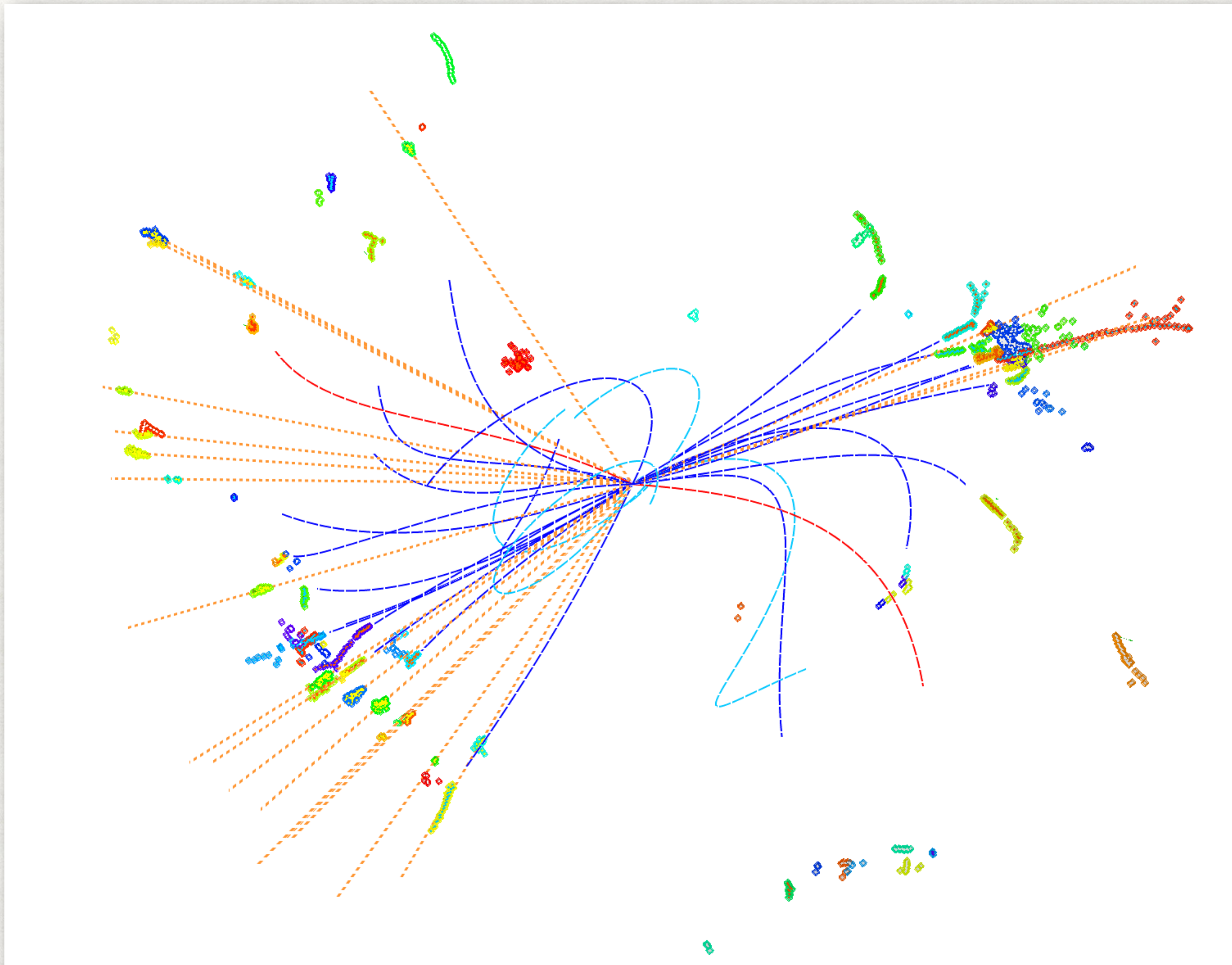
Backup

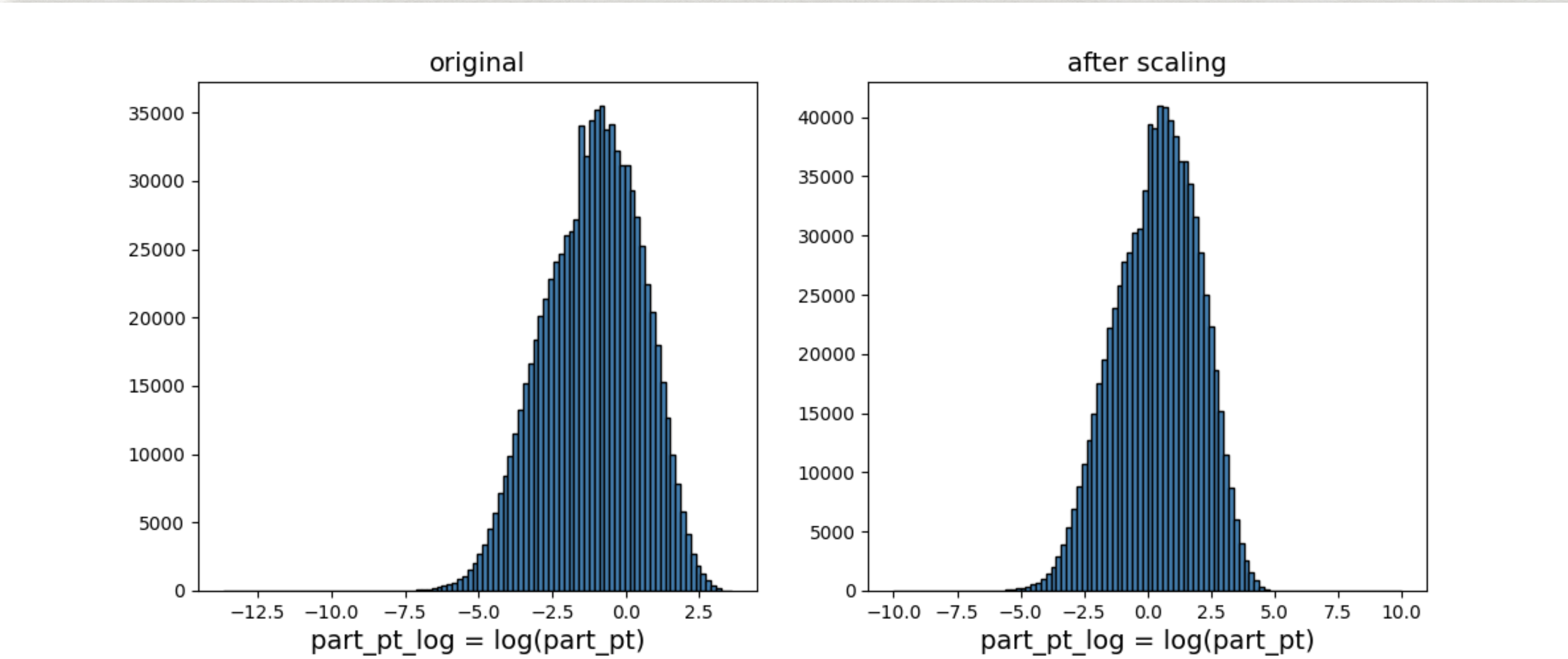
```
part_pt: np.hypot(part_px, part_py)
part_pt_log: np.log(part_pt)
part_e_log: np.log(part_energy)
part_logptrel: np.log(part_pt/jet_pt)
part_logerel: np.log(part_energy/jet_energy)
part_deltaR: np.hypot(part_deta, part_dphi)
part_d0: np.tanh(part_d0val)
part_dz: np.tanh(part_dzval)
```

$$M_{mig} = \frac{Tr_{mig} - Tr_{opt}}{Tr_l - Tr_{opt}} \cdot (M_l - M_{opt}) + M_{opt}$$

$$M_{mig} = \frac{Tr_{mig} - Tr_{opt}}{Tr_{1/3} - Tr_{opt}} \cdot (M_{1/3} - M_{opt}) + M_{opt}$$

Jet





original
35000
30000
25000
20000
15000
10000
5000
0
−12.5
−10.0
−7.5
−5.0
−2.5
0.0
2.5
part_pt_log = log(part_pt)
after scaling
40000
35000
30000
25000
20000
15000
10000
5000
0
−10.0
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0
part_pt_log = log(part_pt)