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Performance of jet flavor tagging and measurement of R_b using ParticleNet at CEPC

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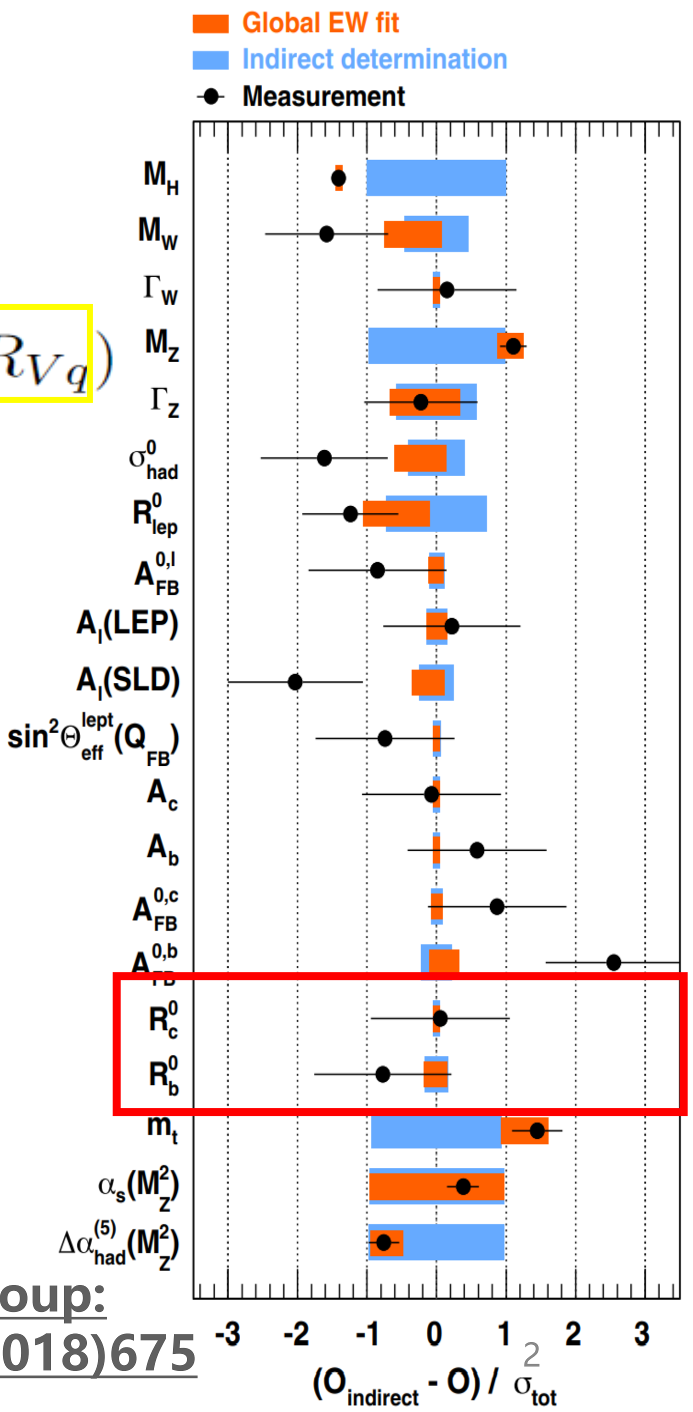
CEPC味物理-新物理和相关探测技术研讨会

Introduction

- Relative decay width： $R_q = \Gamma_q/\Gamma_h$
  - SM testing $\Gamma(Z \to q\bar{q}) = 12\boxed{\Gamma_0}\left(\boxed{g_{Aq}^2}\boxed{R_{Aq}} + \boxed{g_{Vq}^2}\boxed{R_{Vq}}\right)$
  - Searching for new physics
  - Precision electroweak measurement
- Status of R_b and R_c measurements in experiment and theory
  - Theoretical << Experimental

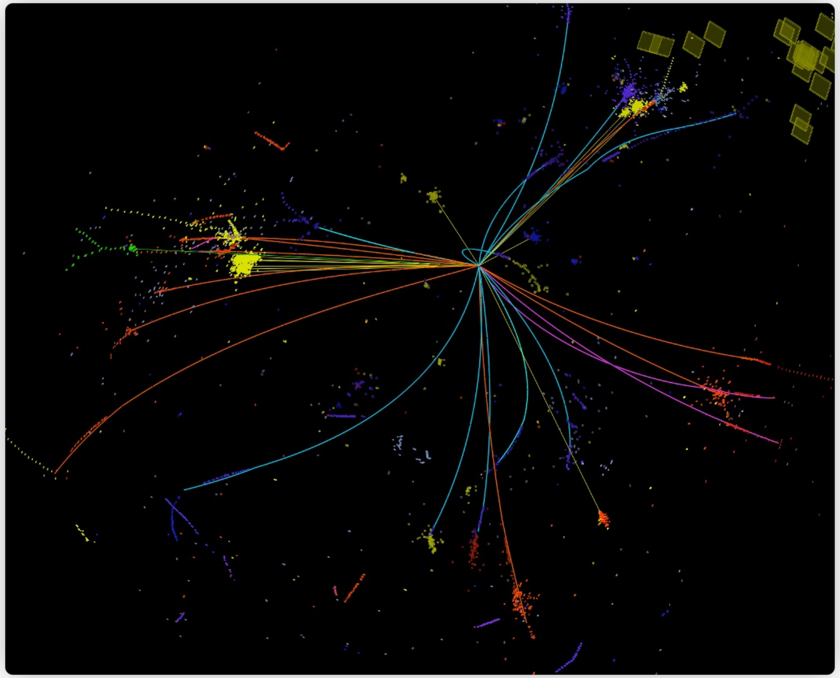
	Experiment	Gfitter results
R_b	0.21629 ± 0.00066	0.21582 ± 0.00011
R_c	0.1721 ± 0.0030	0.17224 ± 0.00008



Gfitter Group: EPJC78 (2018)675

Introduction

- New colliders to perform precision electroweak studies
  - CEPC/FCC-ee/ILC/......
- Jet: Key physics object
  - Vertexing->Clustering->Tagging
- Tagging methods
  - Cut-based->TMVA->Deep Learning

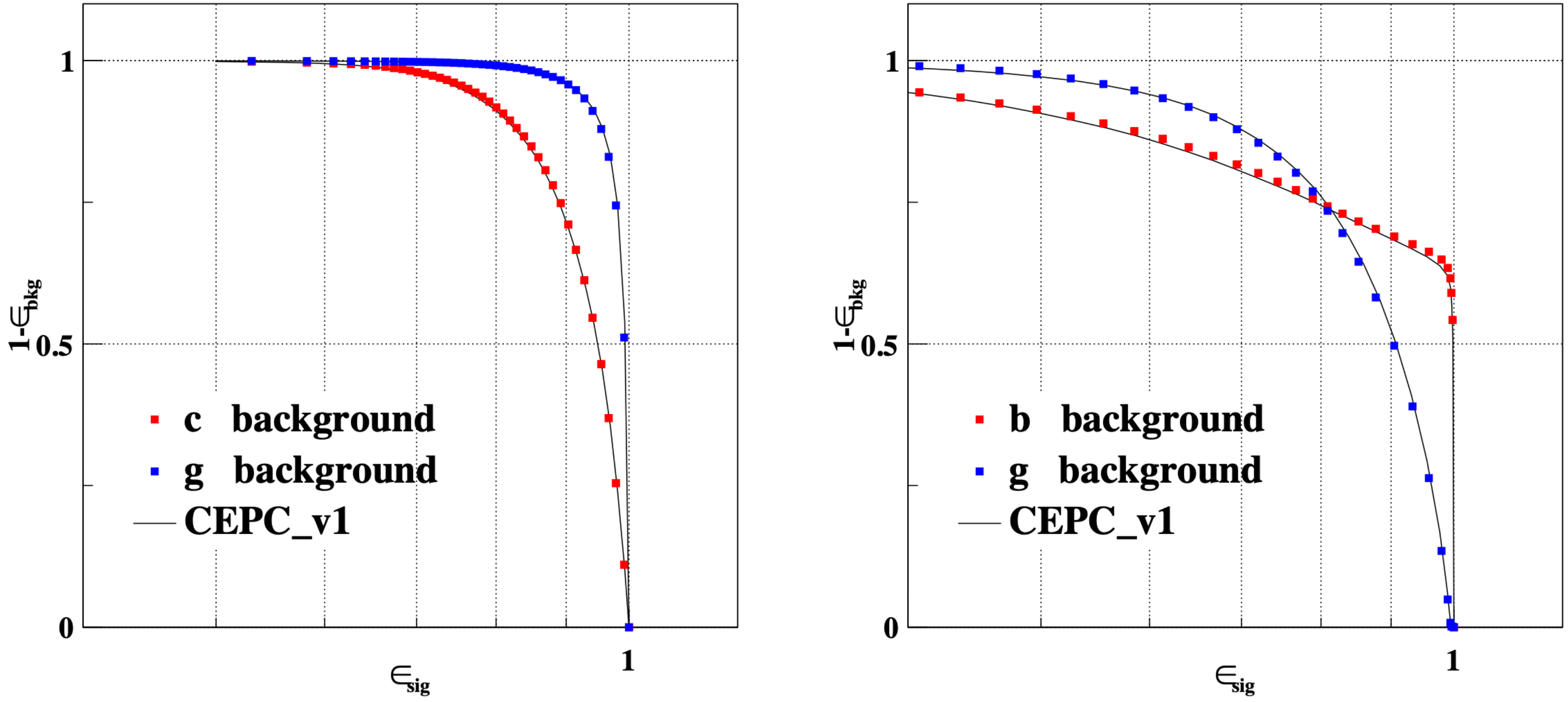


Flavor tagging @ CDR

- CEPC baseline detector (TMVA/BDT)

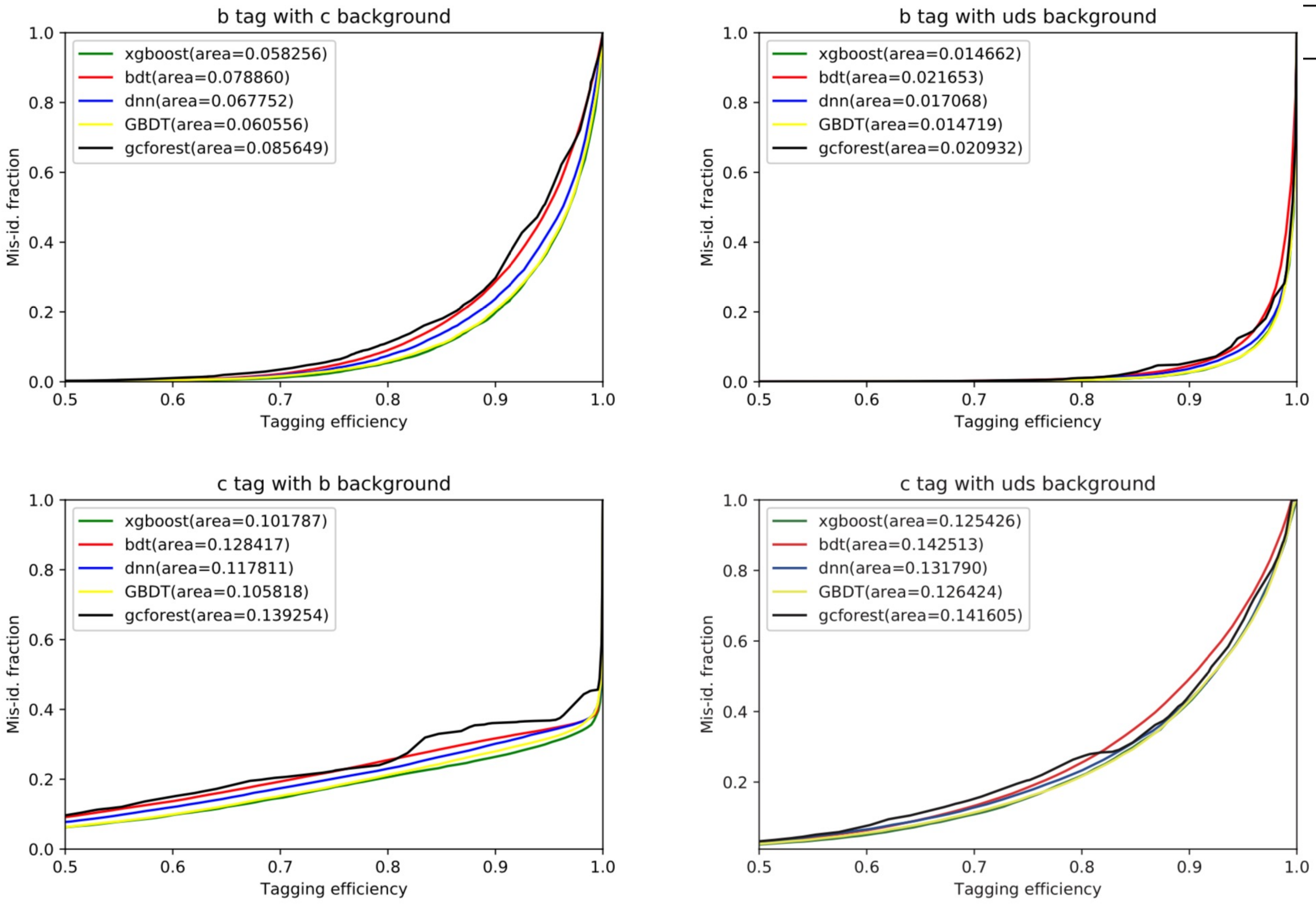
  80% eff. & 90% purity in b-tagging

  60% eff. & 60% purity in c-tagging



Flavor tagging @ CDR

Fan Yang: Flavor Tagging Using Machine Learning Algorithms



Algorithm	DNN	BDT	GBDT	gcforest	xgboost
Accuracy	0.788	0.776	0.794	0.785	0.801

tag-background	efficiency (%)	Mis-id fraction (%)				
		xgboost	DNN	GBDT	BDT	gcforest
b-c	80	5.4	7.5	5.8	9.3	10.8
	90	20.1	23.7	20.6	29.2	26.3
	95	39.0	43.5	39.6	50.2	56.3
b-uds	80	0.5	0.7	0.5	1.0	1.1
	90	2.7	3.7	2.8	4.7	4.9
	95	7.8	9.7	7.8	11.3	13.6
c-b	80	20.8	23.1	21.5	25.6	25.1
	90	26.5	30.2	28.1	32.1	36.1
	95	30.6	33.9	31.8	34.4	36.8
c-uds	80	22.3	23.3	22.3	26.0	27.4
	90	43.4	43.5	43.8	51.9	43.5
	95	63.6	61.7	62.1	68.8	66.1

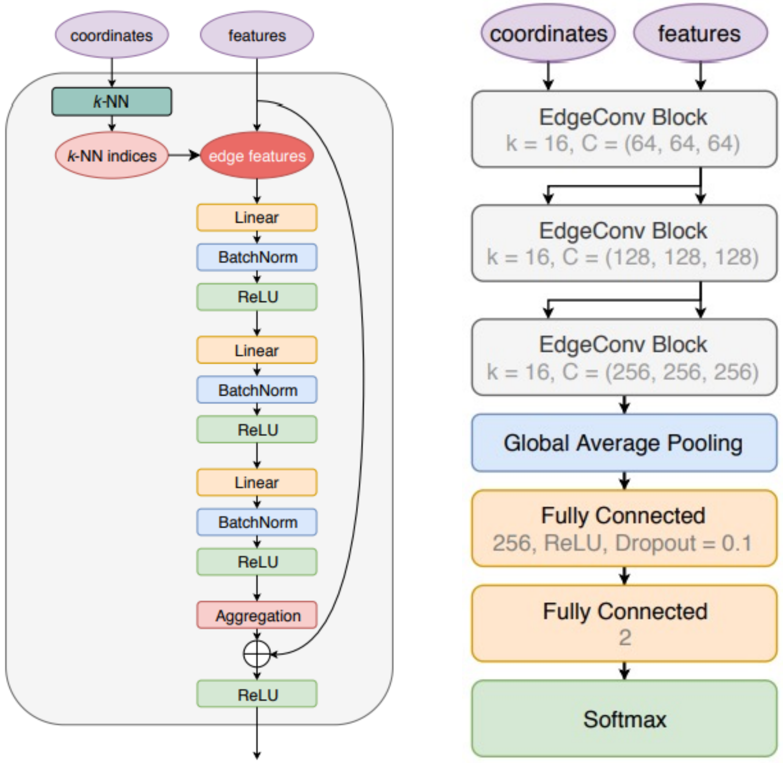
Deep learning architectures

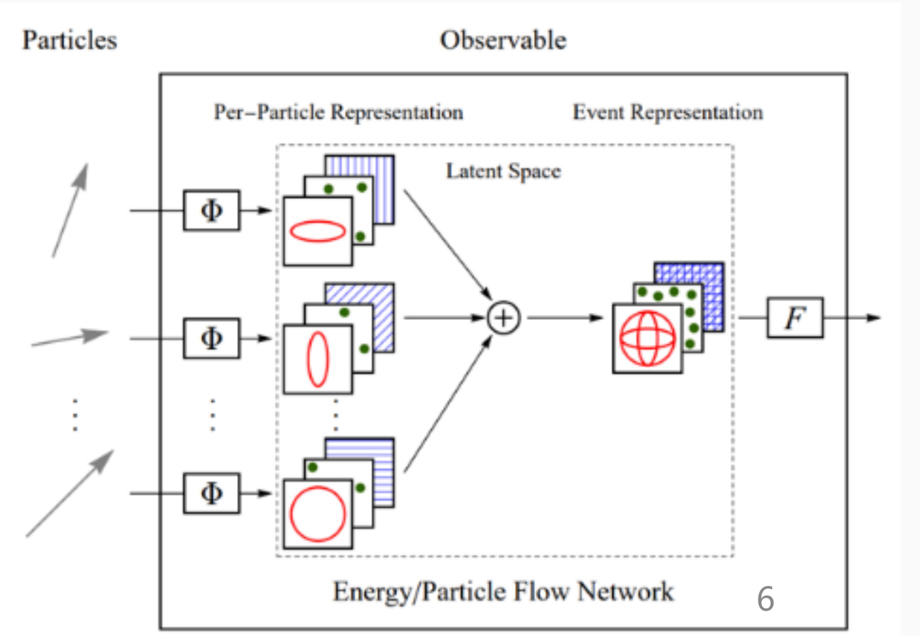
[Jet tagging via particle clouds]

- ParticleNet
  - Treating a jet as an unordered set of particles in space
  - Using permutation-invariant graph neural networks

[Energy flow networks: deep sets for particle jets]

- Particle Flow Network (PFN)
  - Based on "point clouds"
  - As a cross check



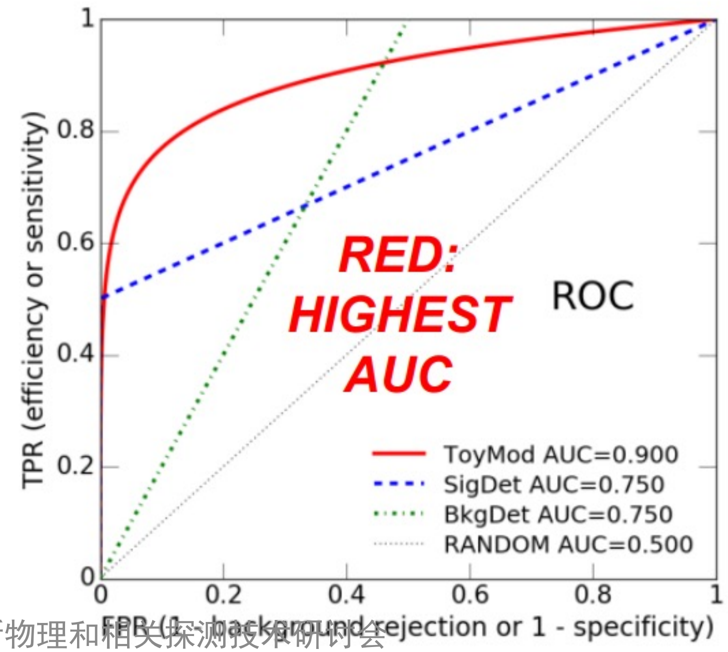


Evaluation metrics

- Efficiency ϵ_s = TP/(TP+FN)
- Purity ρ_s = TP/(TP+FP)
- Accuracy = (TP+TN)/ALL
- ROC/AUC
- $\epsilon_s \times \rho_s$: between 0 and 1
  - The higher, the better
  - Proportional to 1/error2

$$(\Delta R_i)^2 \propto \frac{1}{\epsilon_i \rho_i}$$

TP ($S_{\rm sel}$), FP ($B_{\rm sel}$), FN ($S_{\rm rej}$), TN ($B_{\rm rej}$)	TP ($S_{\rm sel}$), FP ($B_{\rm sel}$), FN ($S_{\rm rej}$), TN ($B_{\rm rej}$)	TP ($S_{\rm sel}$), FP ($B_{\rm sel}$), FN ($S_{\rm rej}$), TN ($B_{\rm rej}$)
$\mathbf{TPR} = \frac{\mathbf{TP}}{\mathbf{TP}+\mathbf{FN}}$	$\mathbf{PPV} = \frac{\mathbf{TP}}{\mathbf{TP}+\mathbf{FP}}$	$\mathbf{TNR} = \frac{\mathbf{TN}}{\mathbf{TN}+\mathbf{FP}} = \mathbf{1}-\mathbf{FPR}$
HEP: "efficiency" $\epsilon_s = \frac{S_{\rm sel}}{S_{\rm tot}}$	HEP: "purity" $\rho = \frac{S_{\rm sel}}{S_{\rm sel}+B_{\rm sel}}$	HEP: "background rejection" $1-\epsilon_b = 1-\frac{B_{\rm sel}}{B_{\rm tot}}$



Andrea Valassi : ROC's, AUC's and alternatives in HEP and other domains

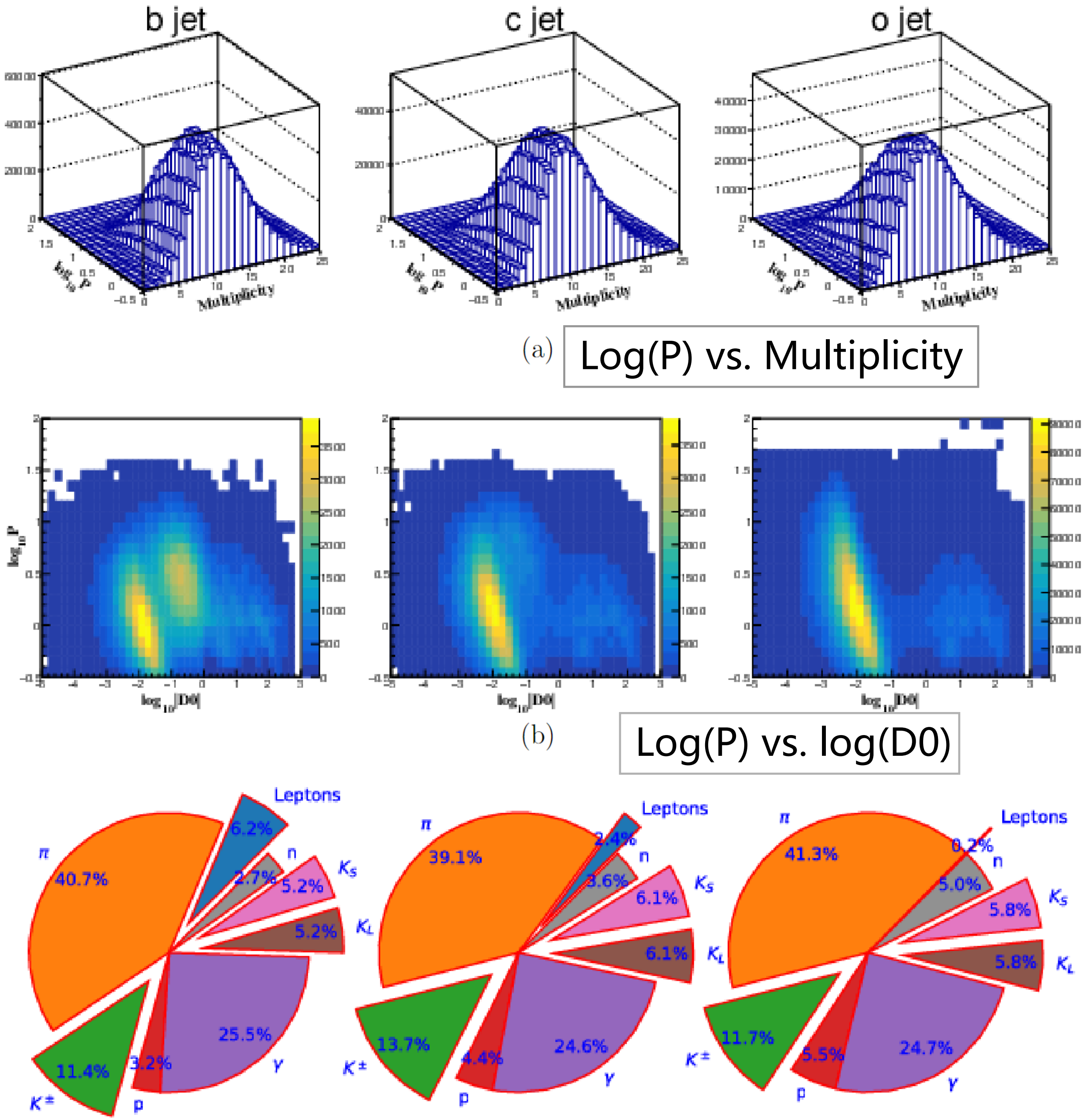
Datasets

- Full simulation with CEPC baseline detector at Z-pole
- PID used as a feature by matching reconstruction and MC truth
- 900k jets for each flavor($b, c, o = uds$)
- Clustered by $ee - kt$ into 2 jets

Variable	Definition
$\cos\theta$	cosine of polar angle of particle
$\phi\sin\theta$	azimuth angle times sine of polar theta of particle
ΔR	$\sqrt{\delta\theta^2 + \delta\phi^2}$, angular separation between the particle and the jet axis
PID	particle ID
E	energy of a particle
Q	electric charge of a particle
$\log E$	logarithm of the particle's energy
$\log P$	logarithm of the particle's momentum
D_0	impact parameter of a track in the r-ϕ plane
Z_0	impact parameter of a track along the z axis
D_0/σ_{D_0}	significance of the impact parameter in the r-ϕ plane
Z_0/σ_{Z_0}	significance of the impact parameter along the z axis
prob	the probability for a certain Chi-squared and number of degrees of freedom

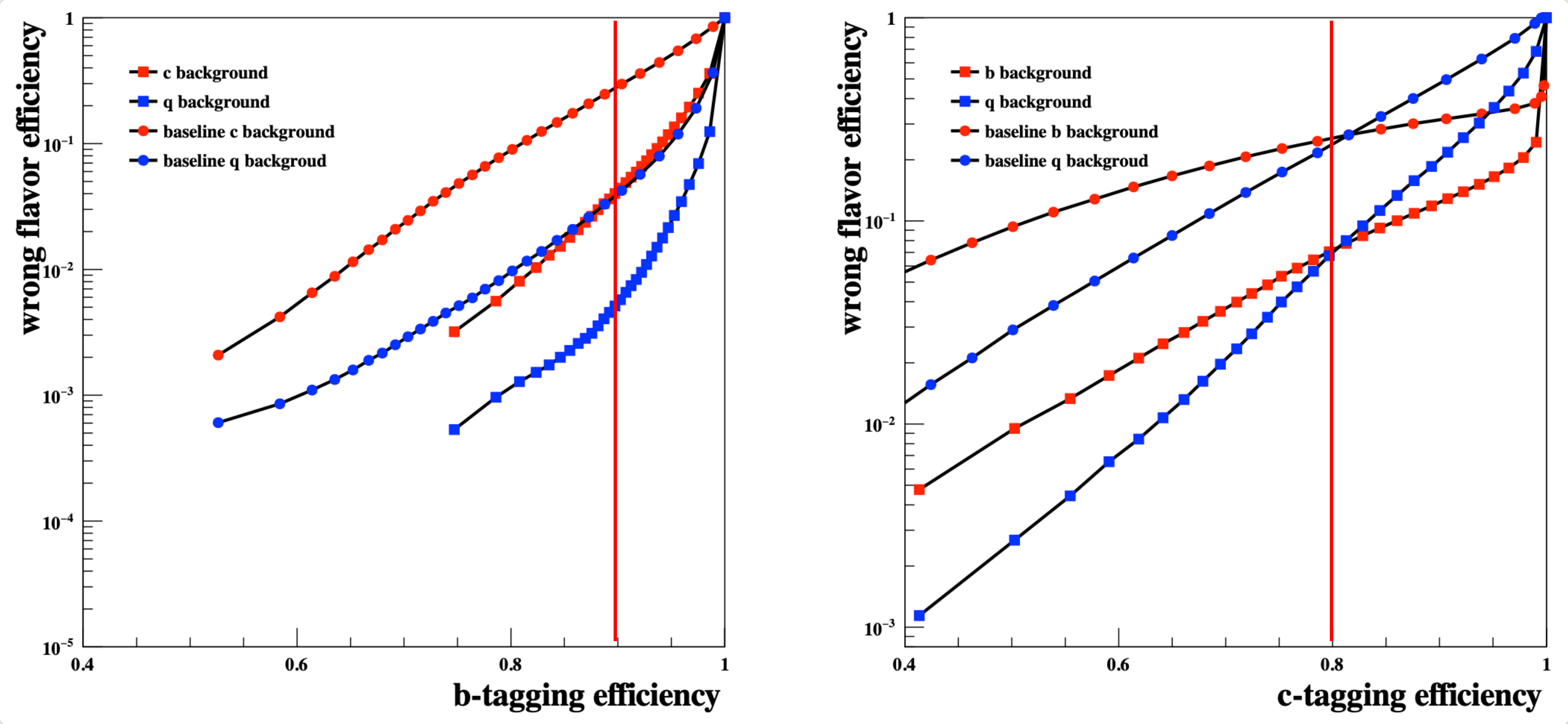
Jet features

- (a) Multiplicity
  - $b > c > o$
- (b) Impact parameters
  - Larger impact parameters, more energetic tracks in b
- (c) The weighted fractions of particles
  - Far more energetic leptons in b
  - Slightly more energetic K in c



Jet tagging

tagging efficiencies vs. the corresponding wrong flavour efficiencies

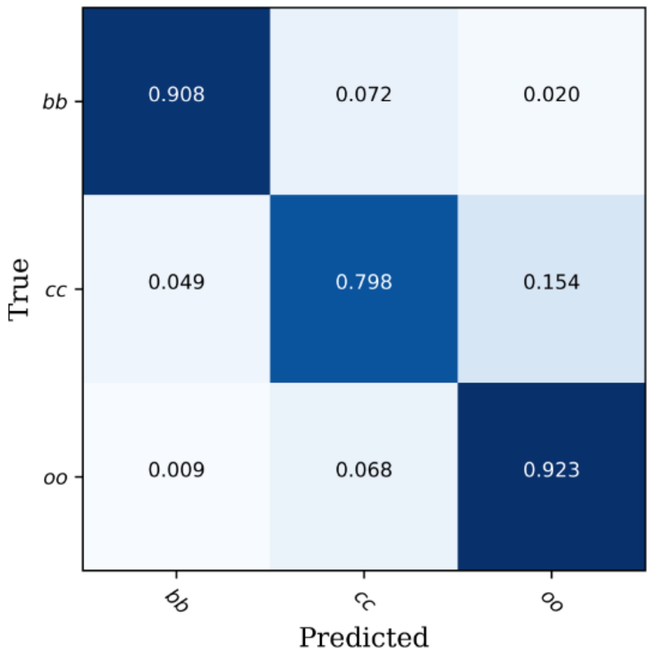


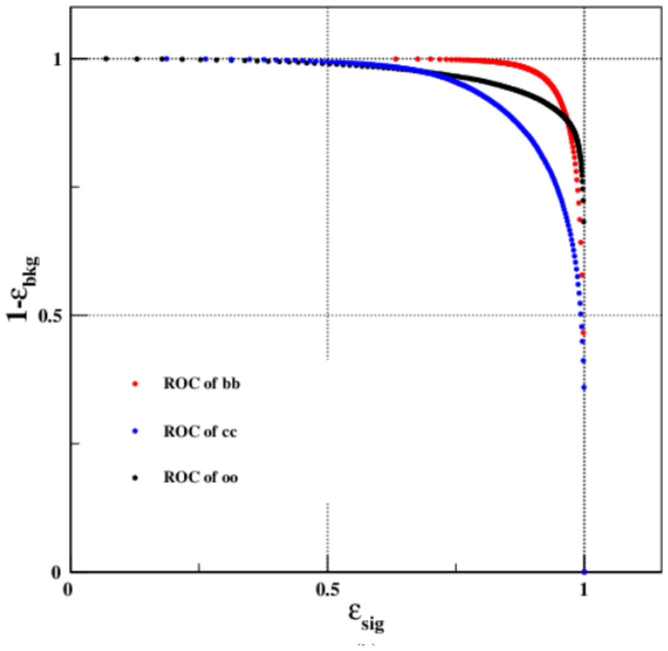
Jet tagging

Fan Yang: Flavor Tagging Using Machine Learning

Algorithm	ParticleNet	PFN	DNN	BDT	GBDT	gcforest	XGBoost
Accuracy	0.876	0.850	0.788	0.776	0.794	0.785	0.801

- At least 9% improvement in ParticleNet at global accuracy
  - Richer information
  - Strong inductive bias
- The performance of b-tagging and o-tagging are much better than c-tagging
- ParticleNet is better than the PFN
  - Consistent with the study [Jet tagging via particle clouds]





tag	ParticleNet		PFN	
	Efficiency	AUC	Efficiency	AUC
b	0.908	0.986	0.870	0.979
c	0.798	0.951	0.765	0.930
o	0.923	0.974	0.911	0.966

Physics impacts of jet tagging

- Take LCFIPlus & XGBoost(CDR baseline) as reference
  - ParticleNet & PFN are better than the baseline, especially in c-tagging
- Statistical uncertainty can be improved
  - roughly 30%(sqrt(0.597/0.345)) in counting c jets

tag	$\epsilon_S(\%)$	$\epsilon \times \rho$			
		LCFIPlus	XGBoost	ParticleNet	PFN
b	80	-	0.747	0.786	0.763
	90	0.72	0.713	0.821	0.752
c	60	0.36	-	0.554	0.485
	70	-	-	0.605	0.497
	80	-	0.345	0.597	0.467
	90	-	0.292	0.532	0.402

Applied in R_q measurement

R_b & R_c measurement

$$N_s^{i,\text{obs}} = 2N^{h,\text{pro}} \cdot (R_b \varepsilon_{ib} + R_c \varepsilon_{ic} + R_o \varepsilon_{io}) \,,$$

$$N_d^{i,\text{obs}} = N^{h,\text{pro}} \cdot [R_b \varepsilon_{ib}^2 (1 + C_{ib}) + R_c \varepsilon_{ic}^2 (1 + C_{ic}) + R_o \varepsilon_{io}^2 (1 + C_{io})] \,,$$

- Double tagging:
  - Neglect the correlation of jets
  - Choose the working point
  - Solved 6 equations by the least square method
- References
  - LEP+SLC: Limited by statistics & flavor tagging
  - Template fit: Much larger statistics & better flavor tagging in CEPC baseline
- Our work:
  - Statistic of 10^{11} Z bosons, same as template fit
  - Comparable with template fit in R_b
  - Improved more than 60% in R_c measurement

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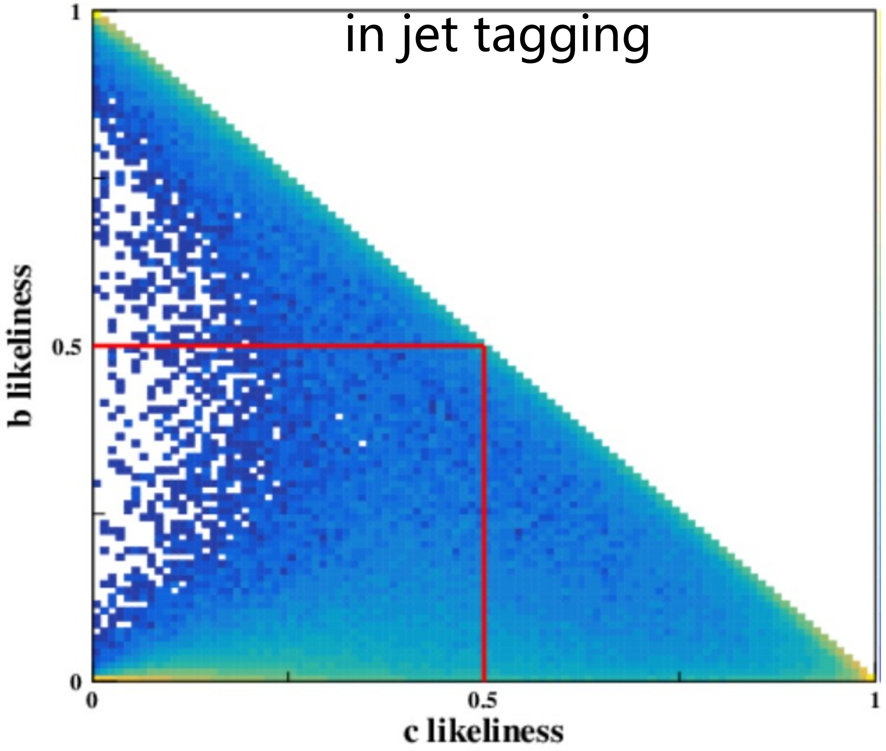
b likelihood vs. c likelihood in jet tagging



	σ_{R_b}	σ_{R_c}	σ_{R_q}
LEP+SLC	659	3015	-
Template fit	1.2	2.3	2.1
Double tag	1.3	1.4	-

All results in 10^-6

Conclusion

- Two novel deep learning methods are used to enhance the performance of jet flavor tagging
  - Significant improvement in jet tagging, especially for c tagging
  - Maximize the usage of information in a jet
  - Strong inductive bias
- R_q measurement is taken to demonstrate the physics impacts
  - Statistical uncertainty improved 60+% in R_c measurement
  - Systematic uncertainties pose a significant challenge and require careful investigation

Thank you!

Comparison of the performance of ParticleNet with three alternative models

TABLE II: Performance comparison on the top tagging benchmark dataset. The ParticleNet, ParticleNet-Lite, P-CNN and ResNeXt-50 models are trained on the top tagging dataset starting from randomly initialized weights. For each model, the training is repeated for 9 times using different randomly initialized weights. The table shows the result from the median-accuracy training, and the standard deviation of the 9 trainings is quoted as the uncertainty to assess the stability to random weight initialization. Uncertainty on the accuracy and AUC are negligible and therefore omitted. The performance of PFN on this dataset is reported in Ref. [52], and the uncertainty corresponds to the spread in 10 trainings.

	Accuracy	AUC	$1/\varepsilon_b$ at $\varepsilon_s = 50\%$	$1/\varepsilon_b$ at $\varepsilon_s = 30\%$
ResNeXt-50	0.936	0.9837	302 ± 5	1147 ± 58
P-CNN	0.930	0.9803	201 ± 4	759 ± 24
PFN	-	0.9819	247 ± 3	888 ± 17
ParticleNet-Lite	0.937	0.9844	325 ± 5	1262 ± 49
ParticleNet	**0.940**	**0.9858**	$\mathbf{397 \pm 7}$	$\mathbf{1615 \pm 93}$