Jet Tagging in the Era of Deep Learning

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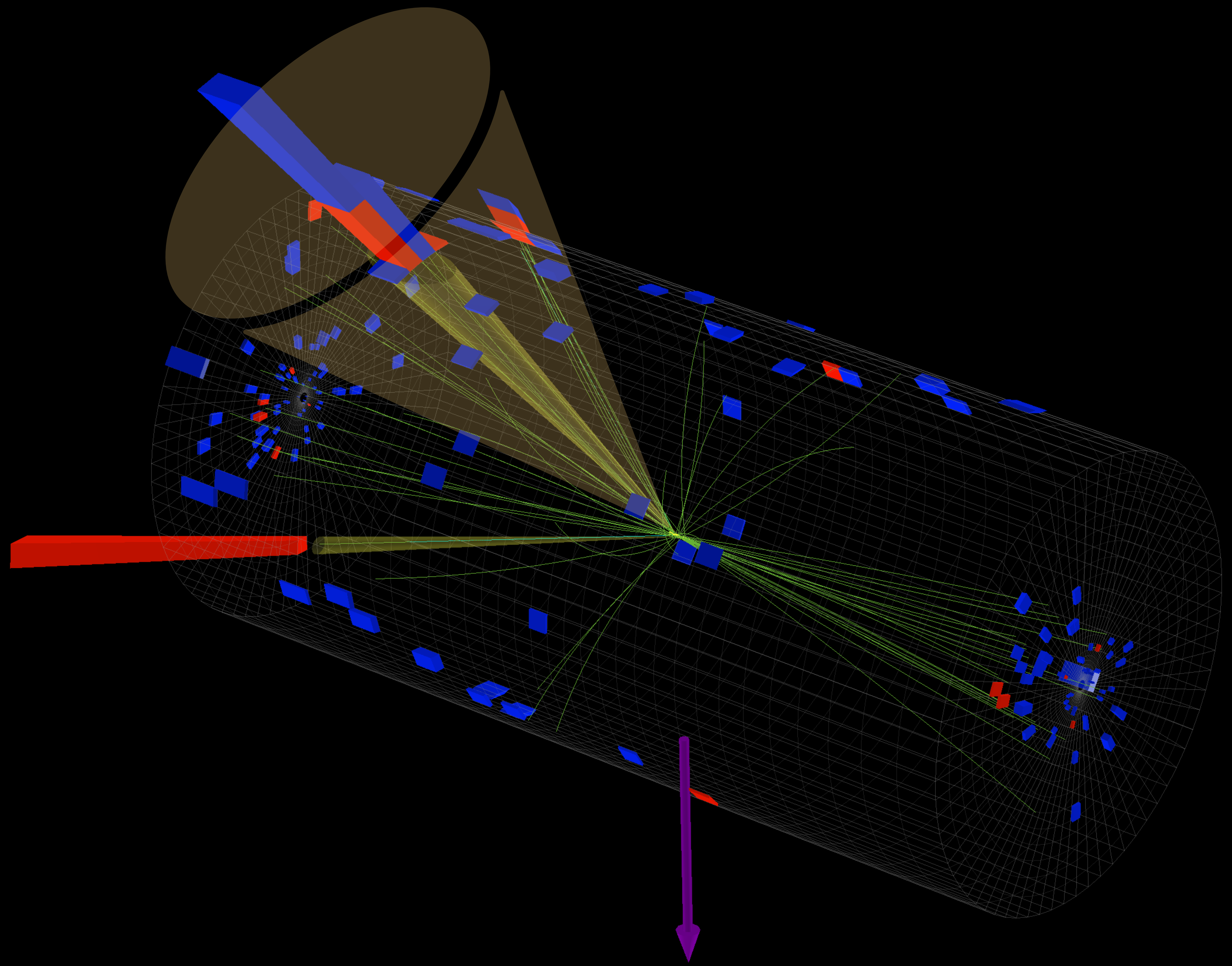
LPHE Seminar

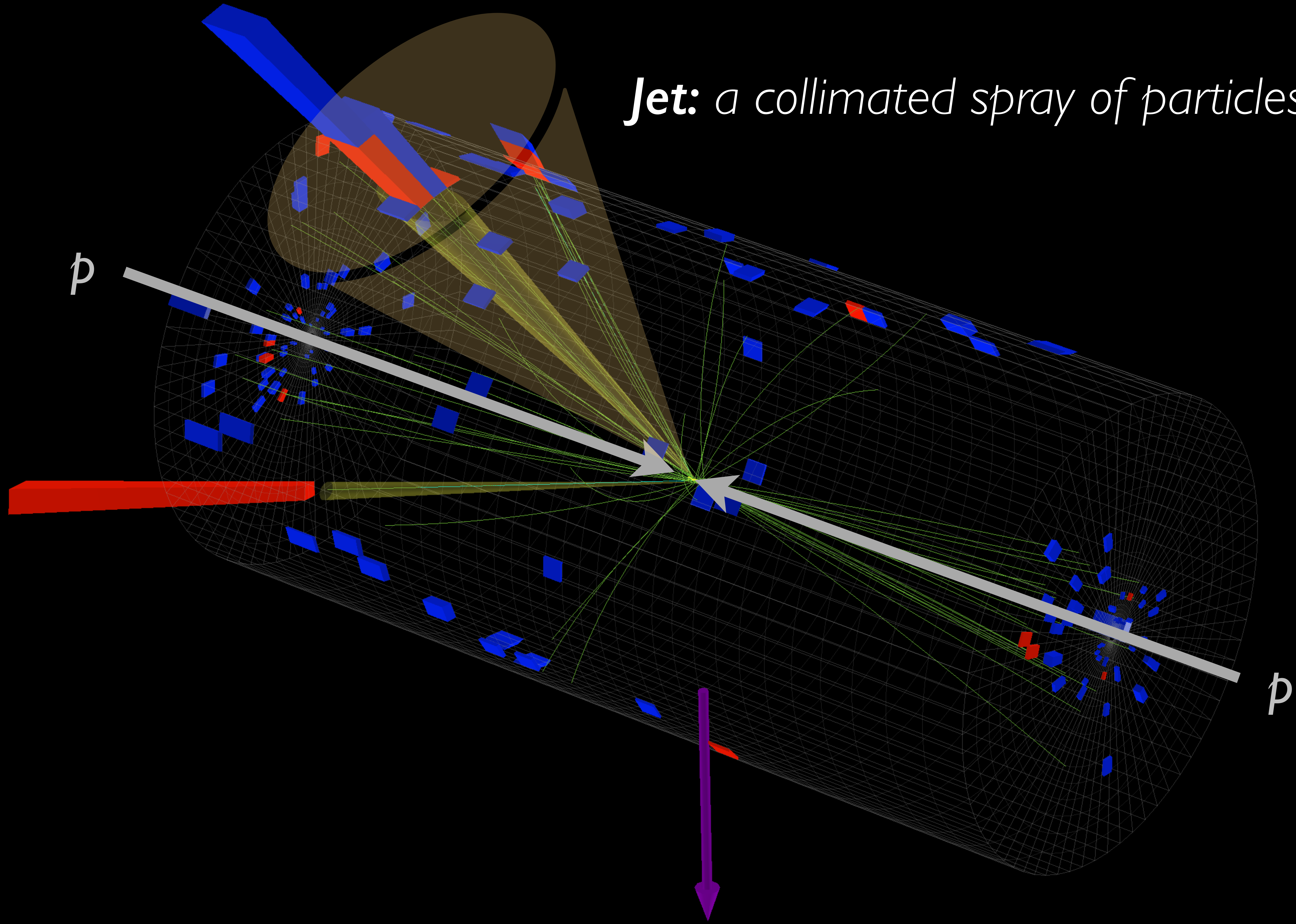
September 25, 2023



CMS Experiment at LHC, CERN
Data recorded: Sat Aug 5 15:32:22 2017 CEST
Run/Event: 300515 / 205888132

What is a Jet?

Jet: *a collimated spray of particles*

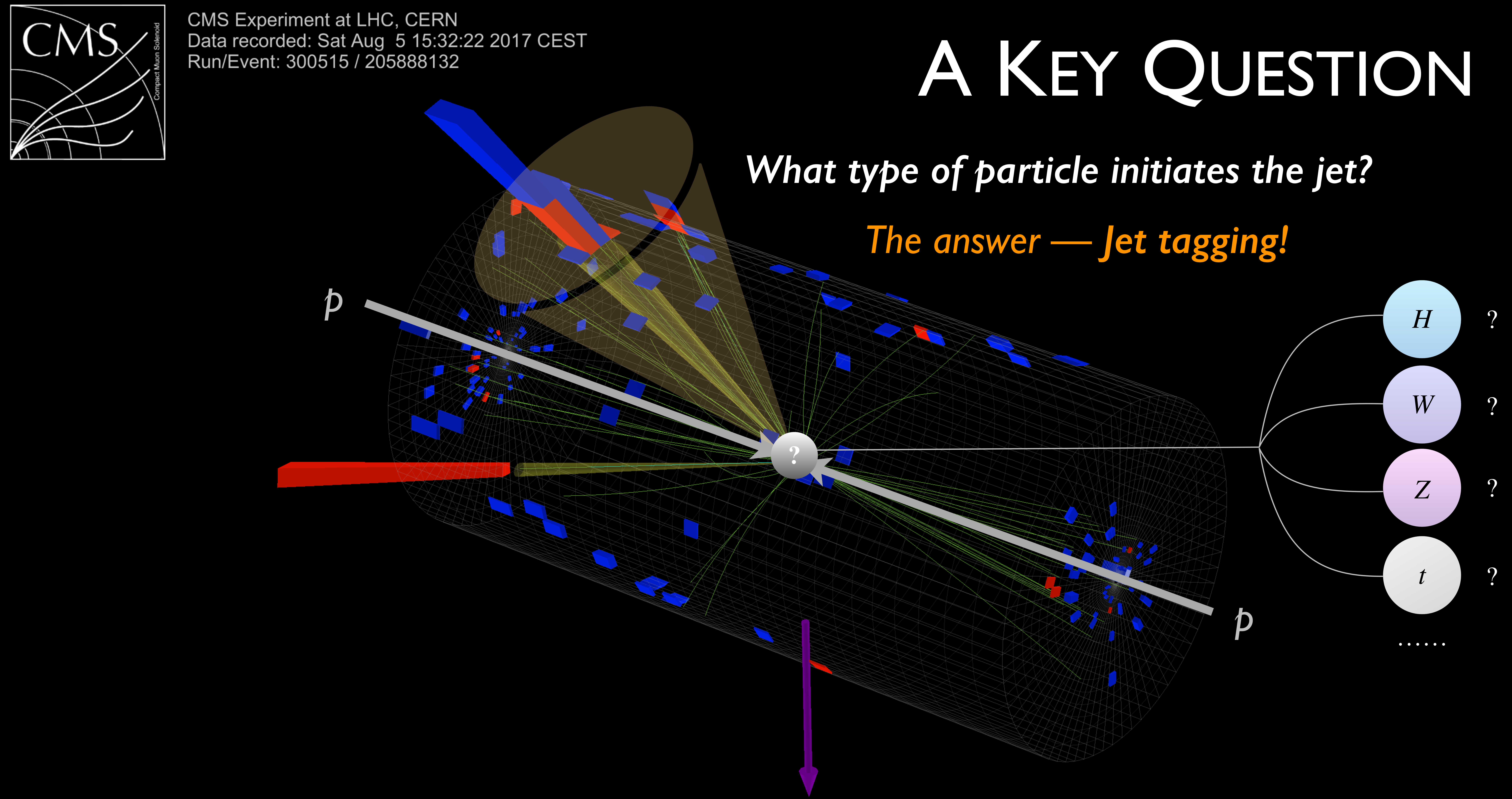


Why Jets?

Jet: a collimated spray of particles

Powerful handle to search for new phenomena

A KEY QUESTION



What type of particle initiates the jet?

The answer — Jet tagging!

Jet Tagging

- Jet tagging: identifying the origin of a jet, i.e., what kind of particle initiates the jet
  - essentially a classification task from the machine learning perspective

Jet flavor tagging

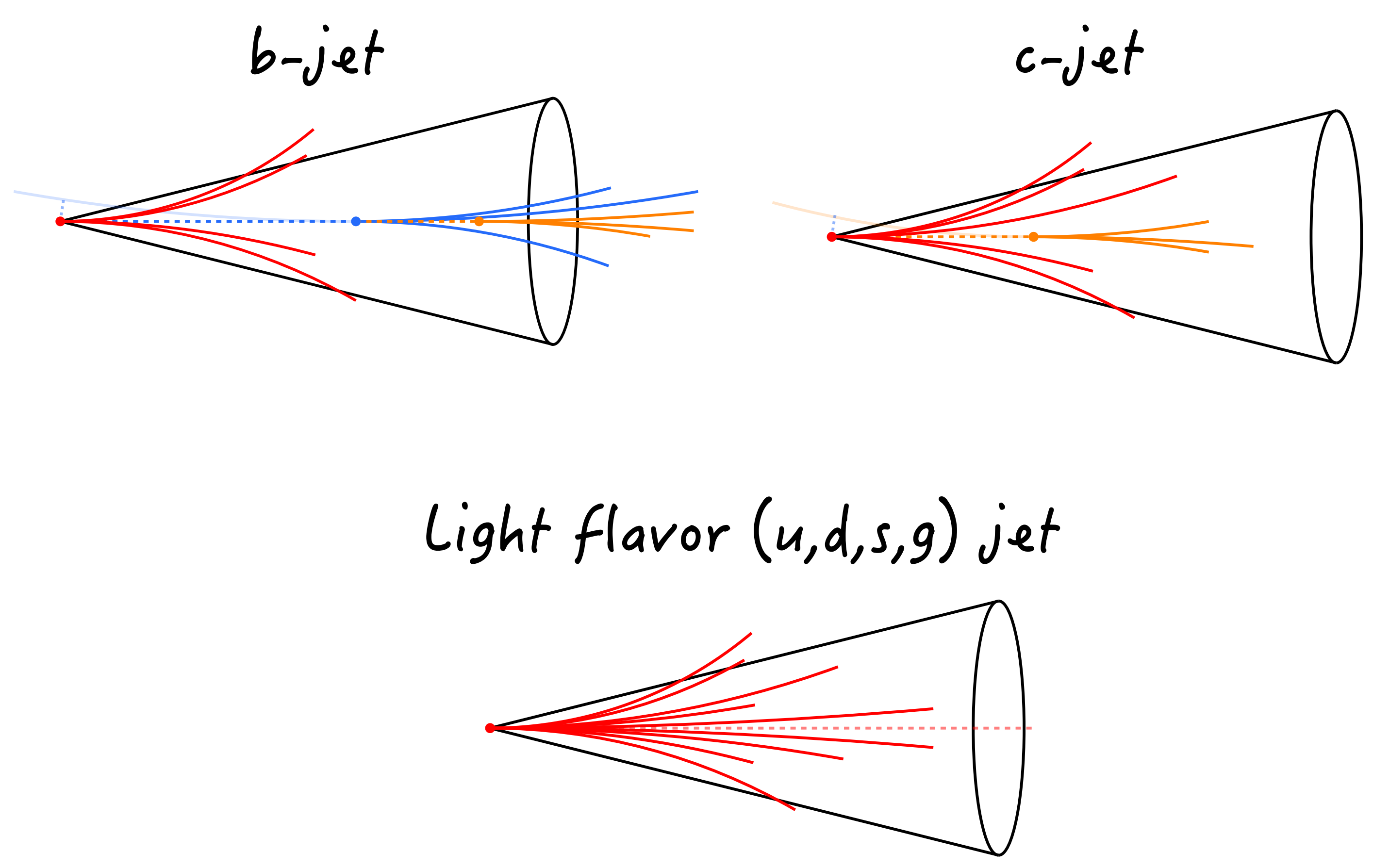


Image credit

Focus of today

Boosted jet tagging

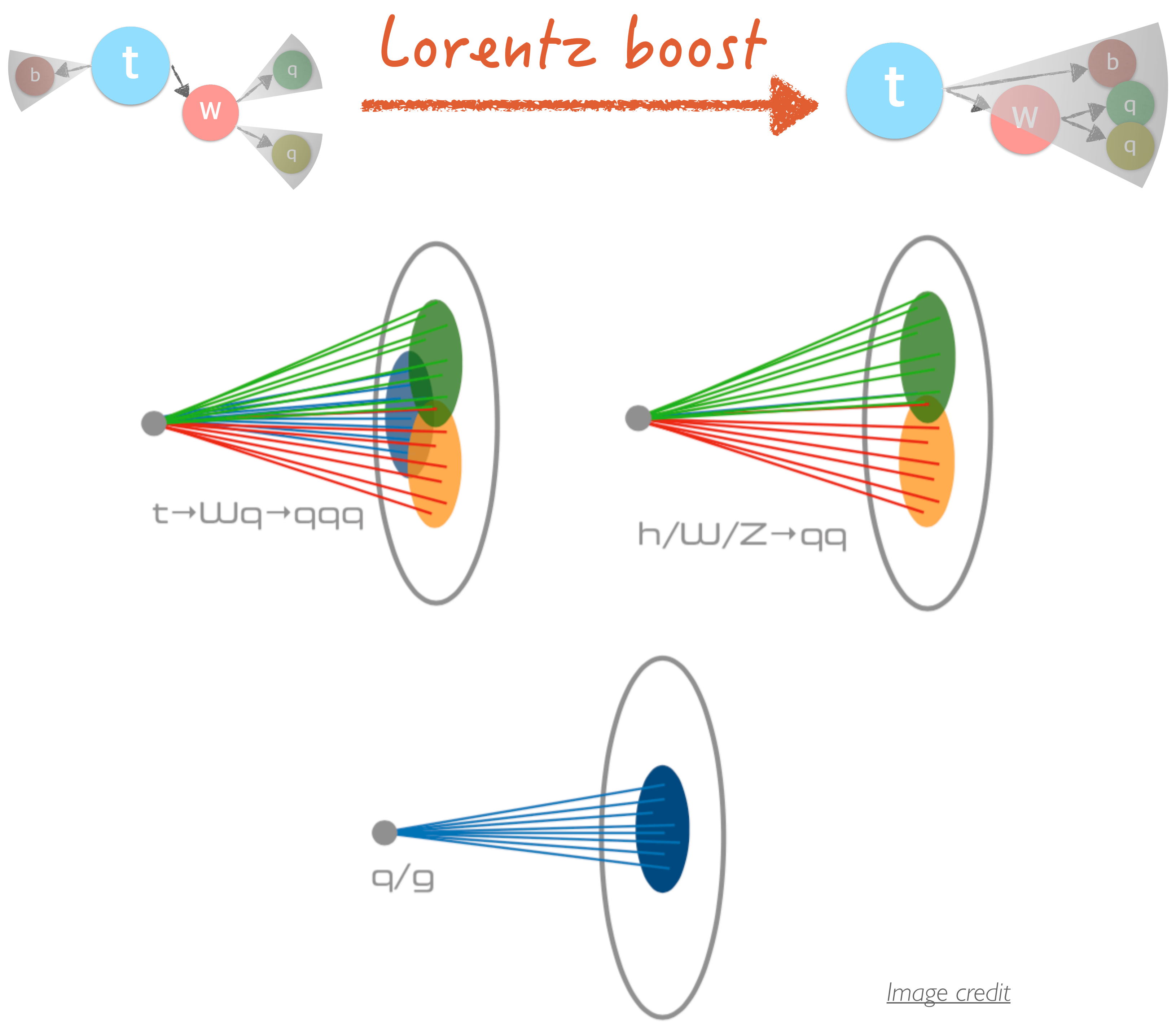


Image credit

Hadronic τ tagging

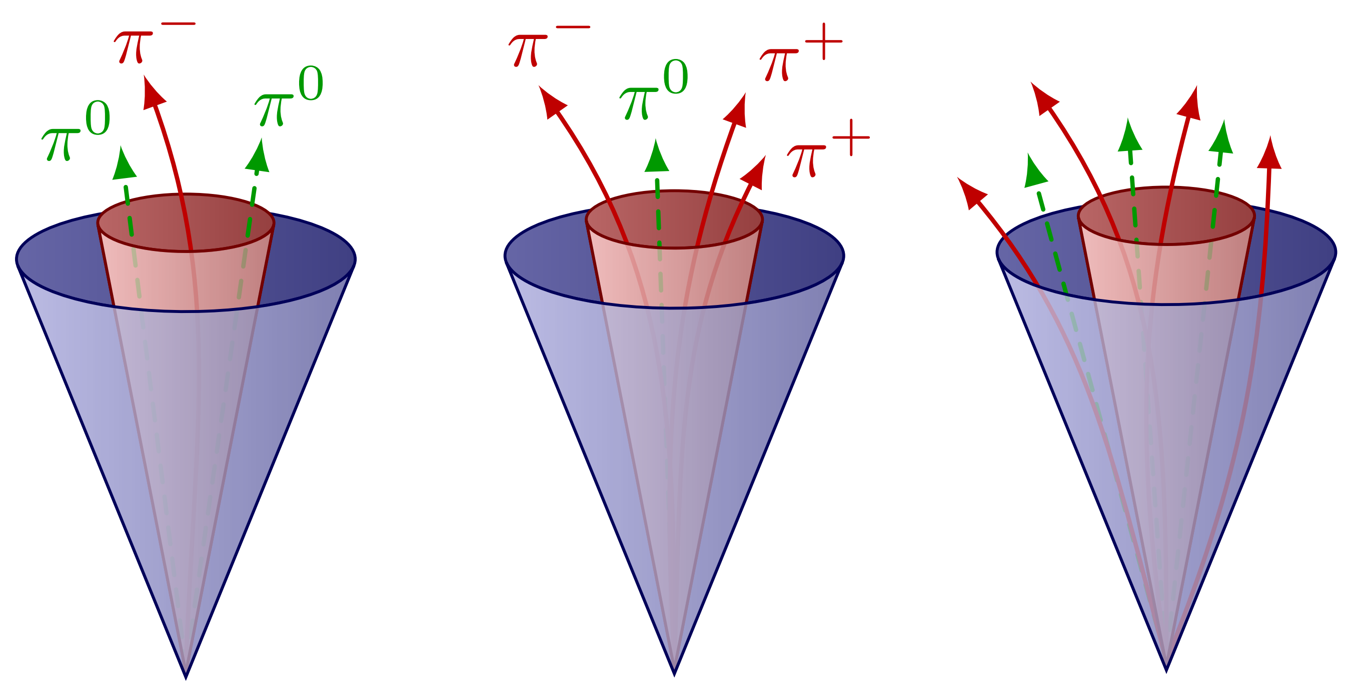
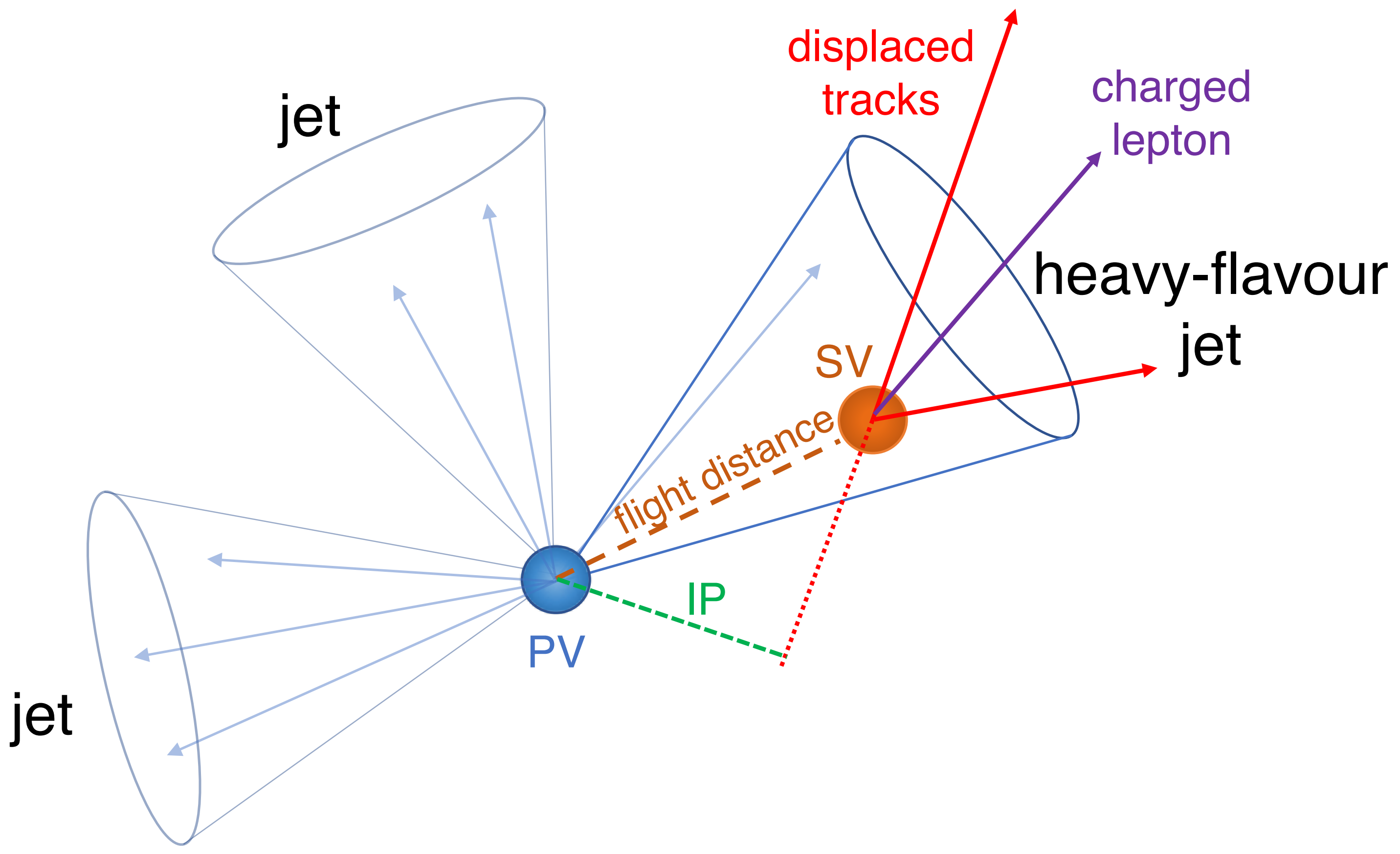


Image credit

Boosted Jet Tagging

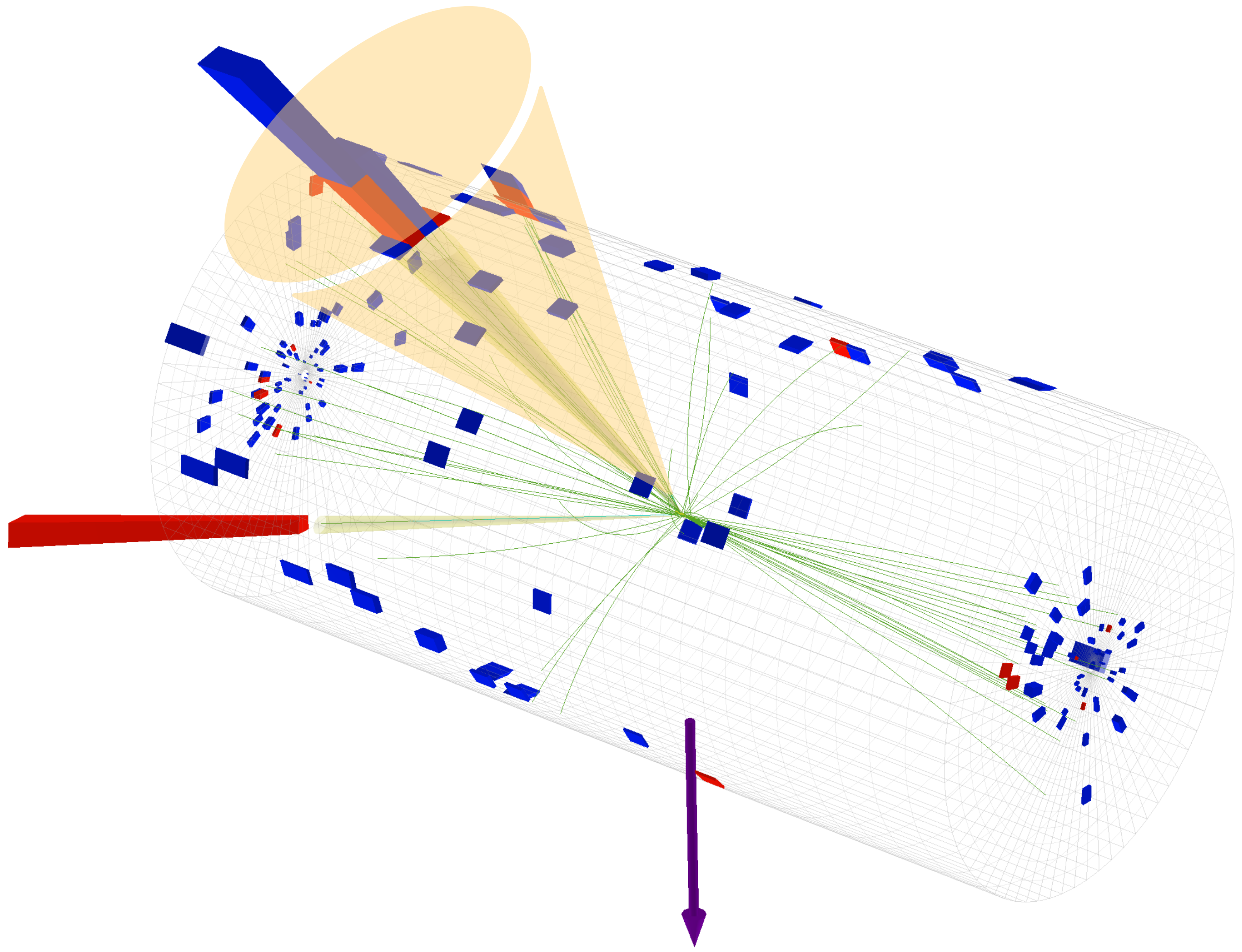
- Hadronic decays of highly Lorentz-boosted heavy particles (Higgs/W/Z/top) lead to large-radius jets with distinctive characteristics:
  - different radiation patterns ("**substructure**")
    - 3-prong (top), 2-prong (W/Z/H) vs 1-prong (gluon/light quark jet)
  - different **flavor** content: existence of one or more b-/c-quarks
- Boosted jet tagging:
  - simultaneously exploiting both **substructure** and **flavor** to maximize the performance
  - significant performance leap thanks to deep learning techniques



Jet Representation for Deep Learning

Jet Representation

Jet



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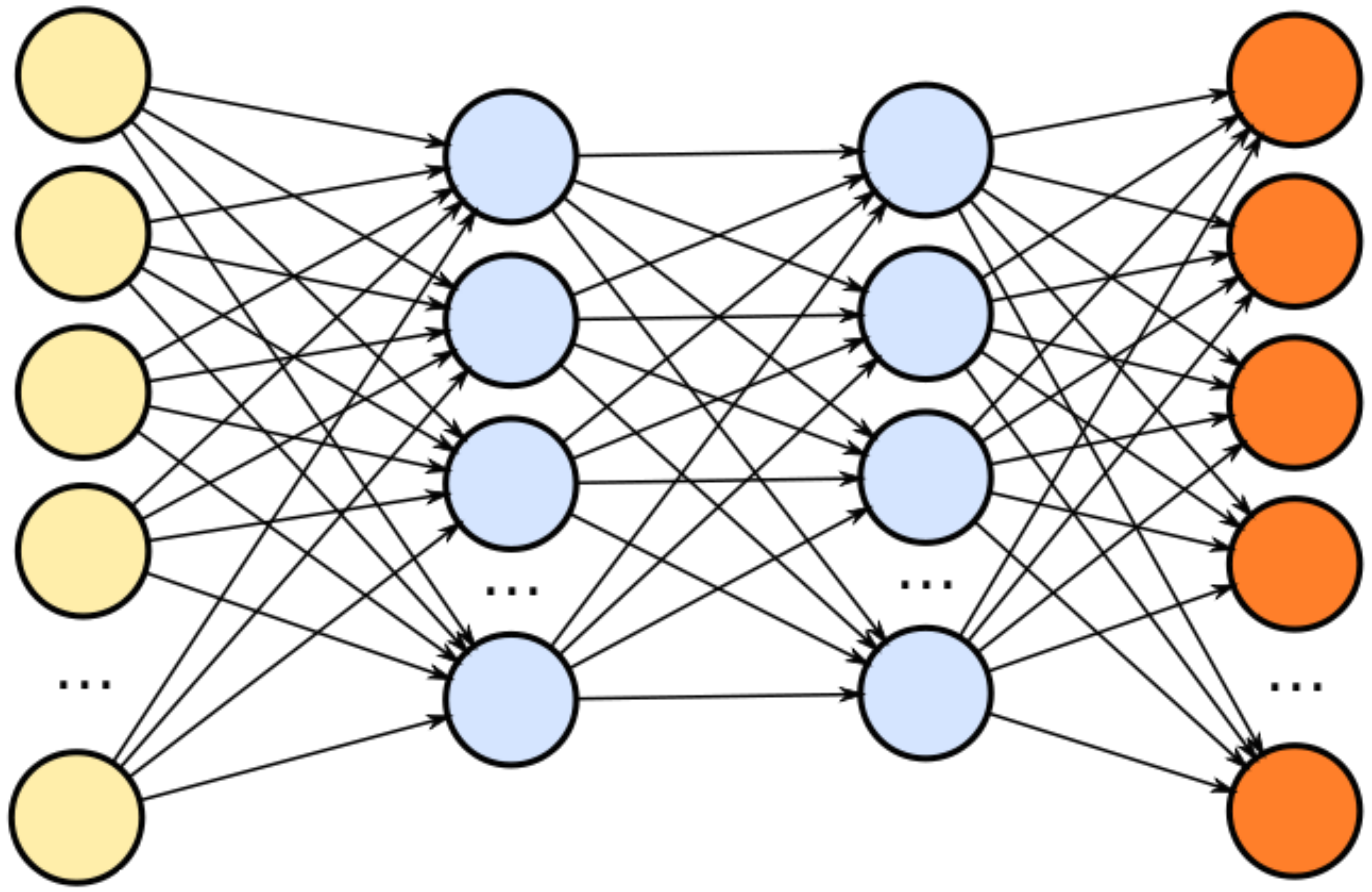
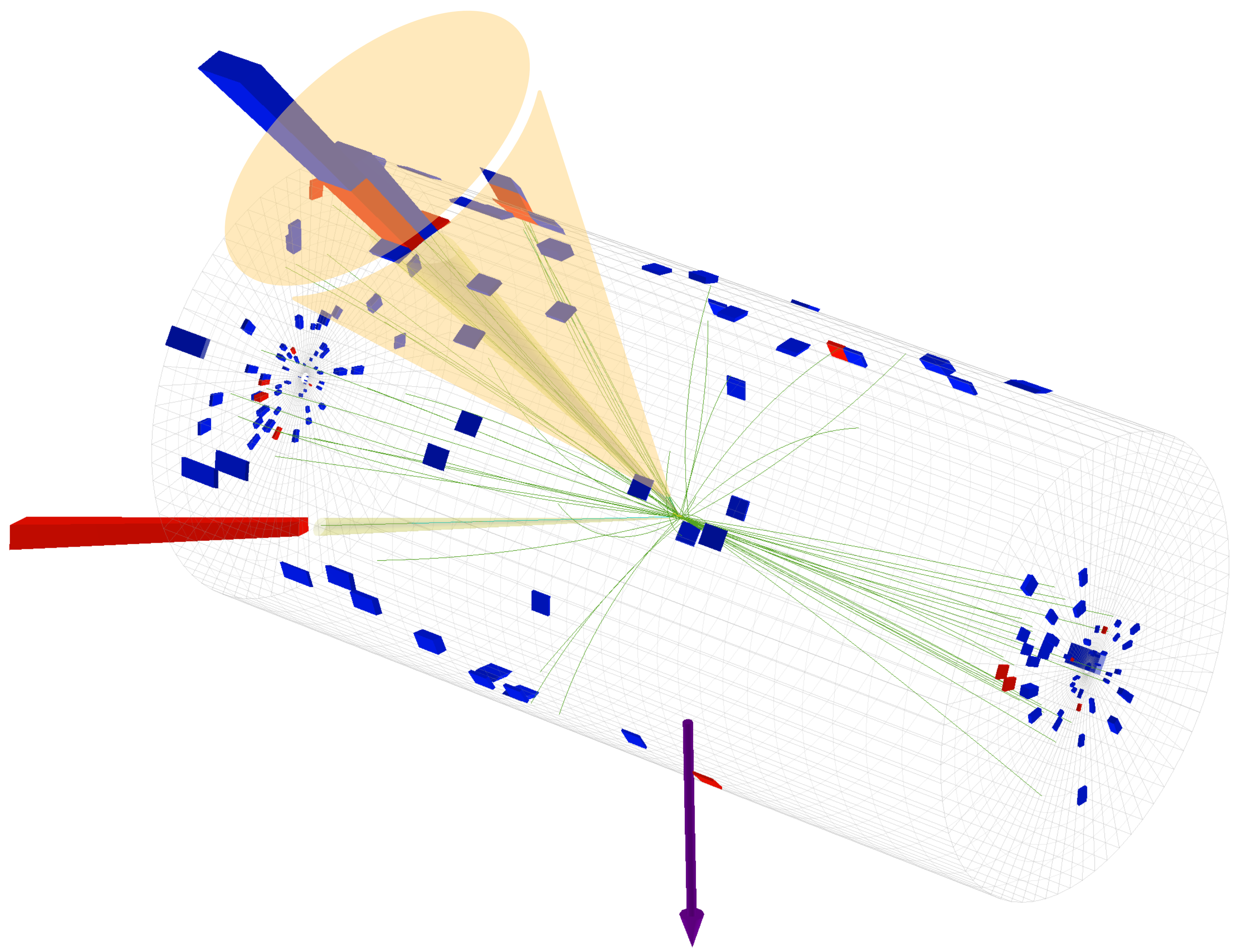


First and foremost:

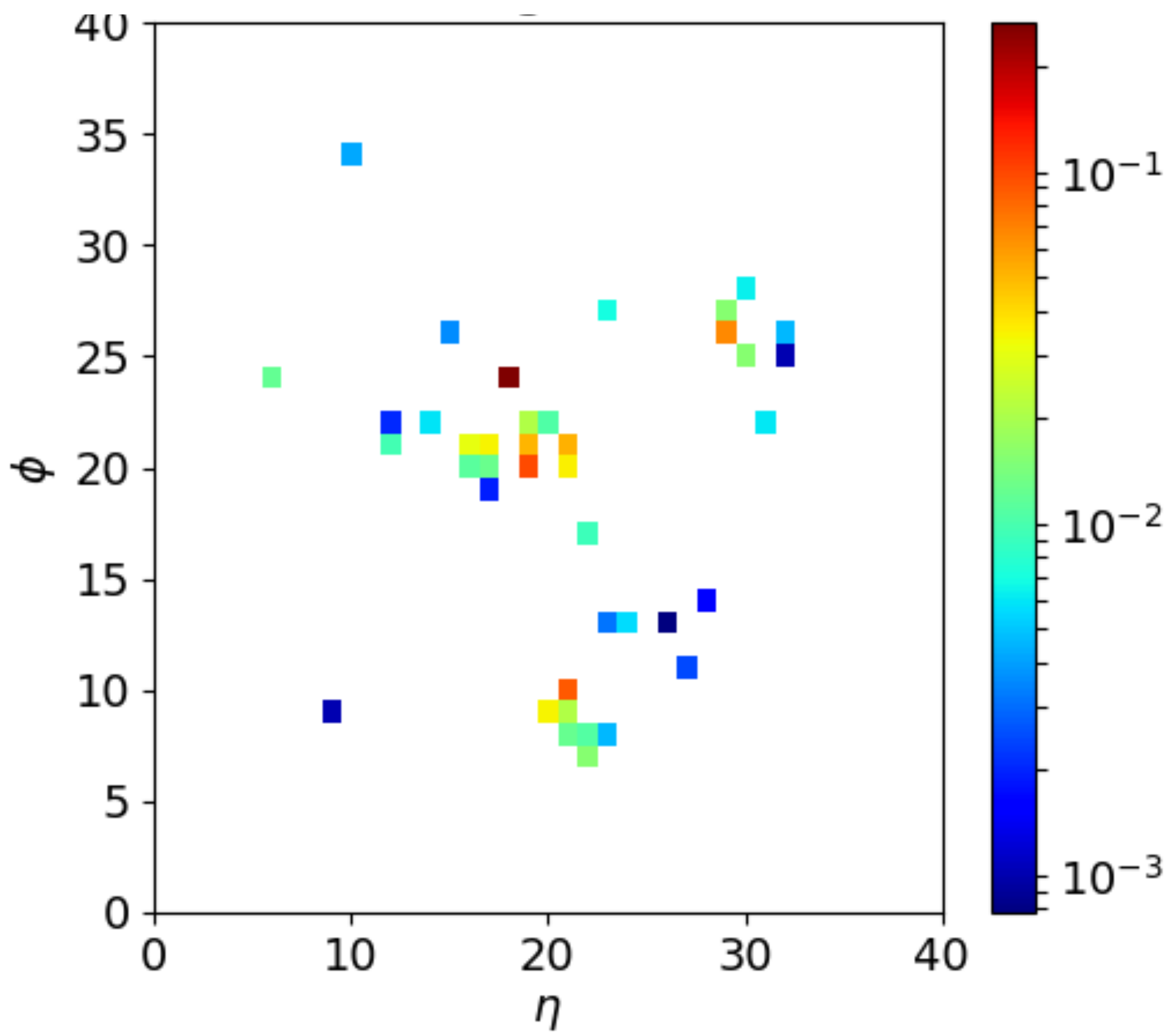
How to represent the data?

Jet Representation: Image

Jet



Image

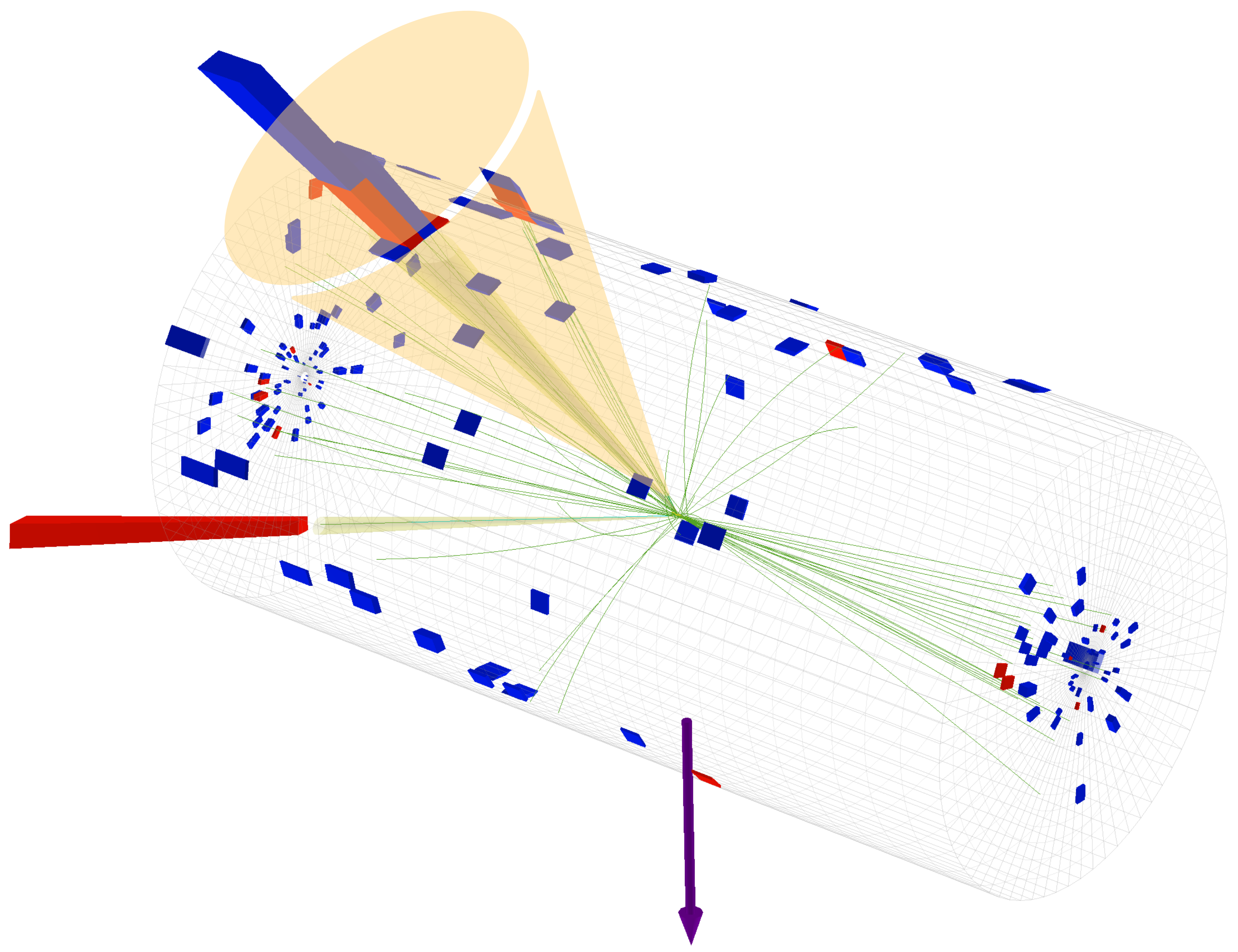


e.g., review in Kagan, arXiv:2012.09719

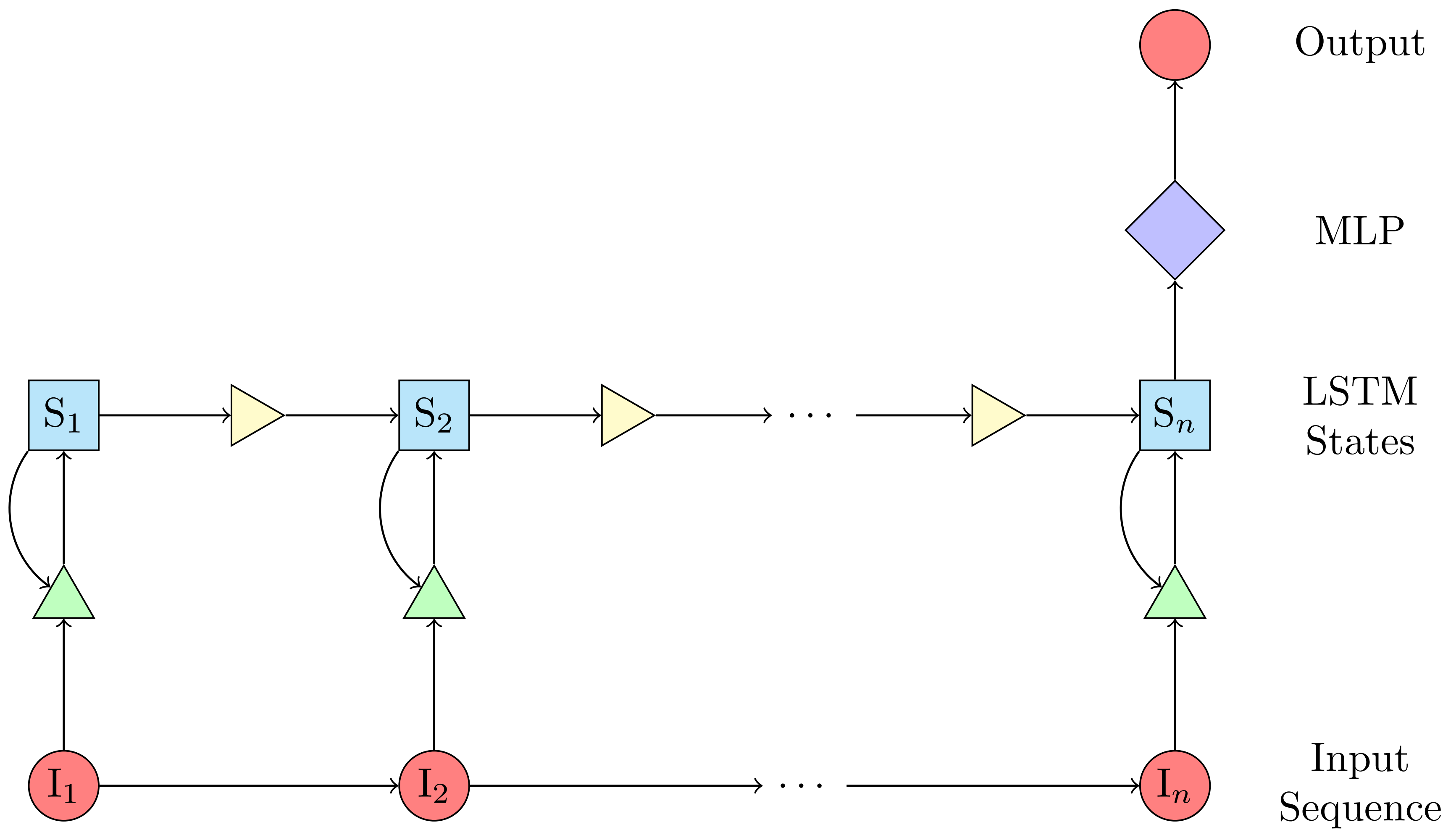
- Convert to 2D/3D image => **Computer vision**
  - then use convolutional neural networks (CNNs)
  - but:
    - inhomogeneous geometry, high sparsity, …

Jet Representation: Sequence

Jet



Sequence



e.g., Guest, Collado, Baldi, Hsu, Urban, Whiteson
arXiv: 1607.08633

- Convert to a sequence => **Natural language processing (NLP)**
  - recurrent neural network (RNN), e.g., GRU/LSTM; 1D CNNs; etc.

DeepAK8

- Advanced deep learning-based algorithm for boosted jet tagging, using AK8 (anti-k_T R=0.8) jets
  - **multi-class classifier** for top quark and W, Z, Higgs boson tagging
  - **directly uses jet constituents** (particle-flow candidates / secondary vertices)
  - **1D convolutional neural network (CNN)**, based on the ResNet [arXiv: 1512.03385] architecture

Inputs

Substructure — Particles

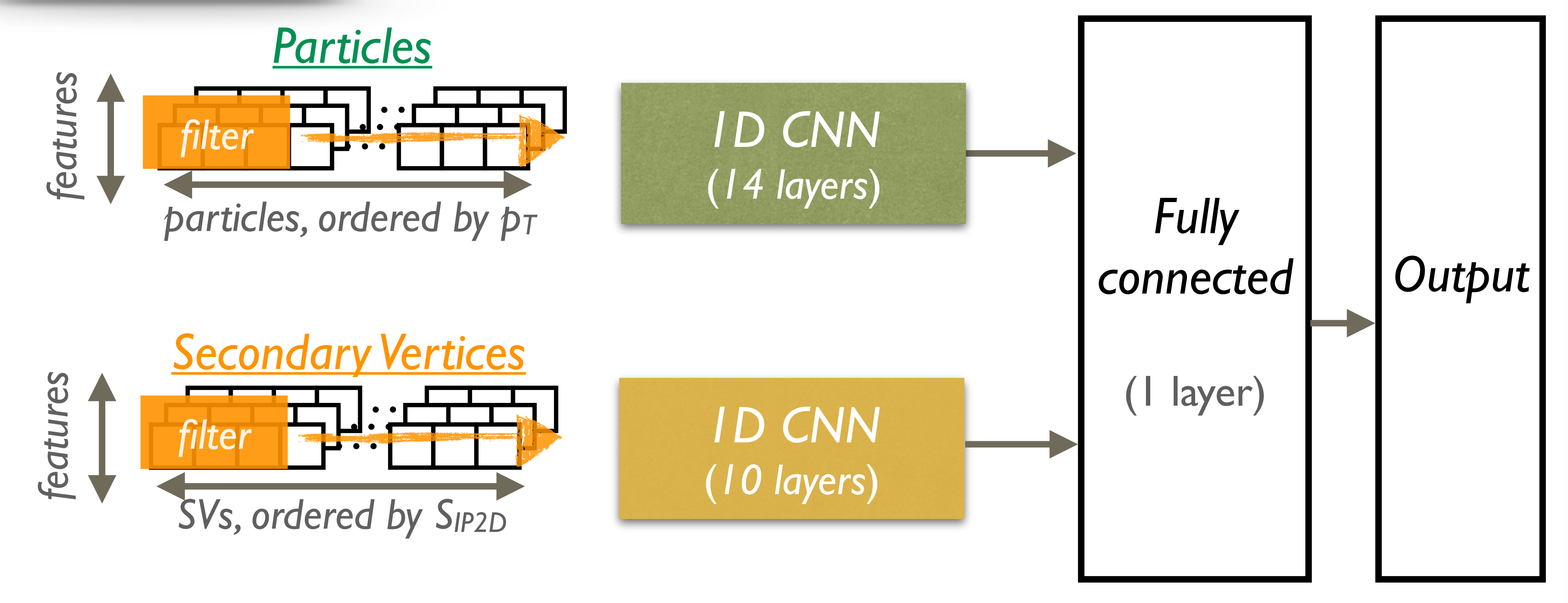
- Up to 100 PF candidates(*)
- Sorted in descending p_T order
- Uses basic kinematic variables, Puppi weights, and track properties (quality, covariance, displacement, etc.)

Flavour — Secondary vertices

- Up to 7 SVs(*) (inside jet cone)
- Sorted in descending S_{IP2D} order
- Uses SV kinematics and properties (quality, displacement, etc.)

(*) Number chosen to include all candidates for ≥ 90% of the events

Architecture



Output

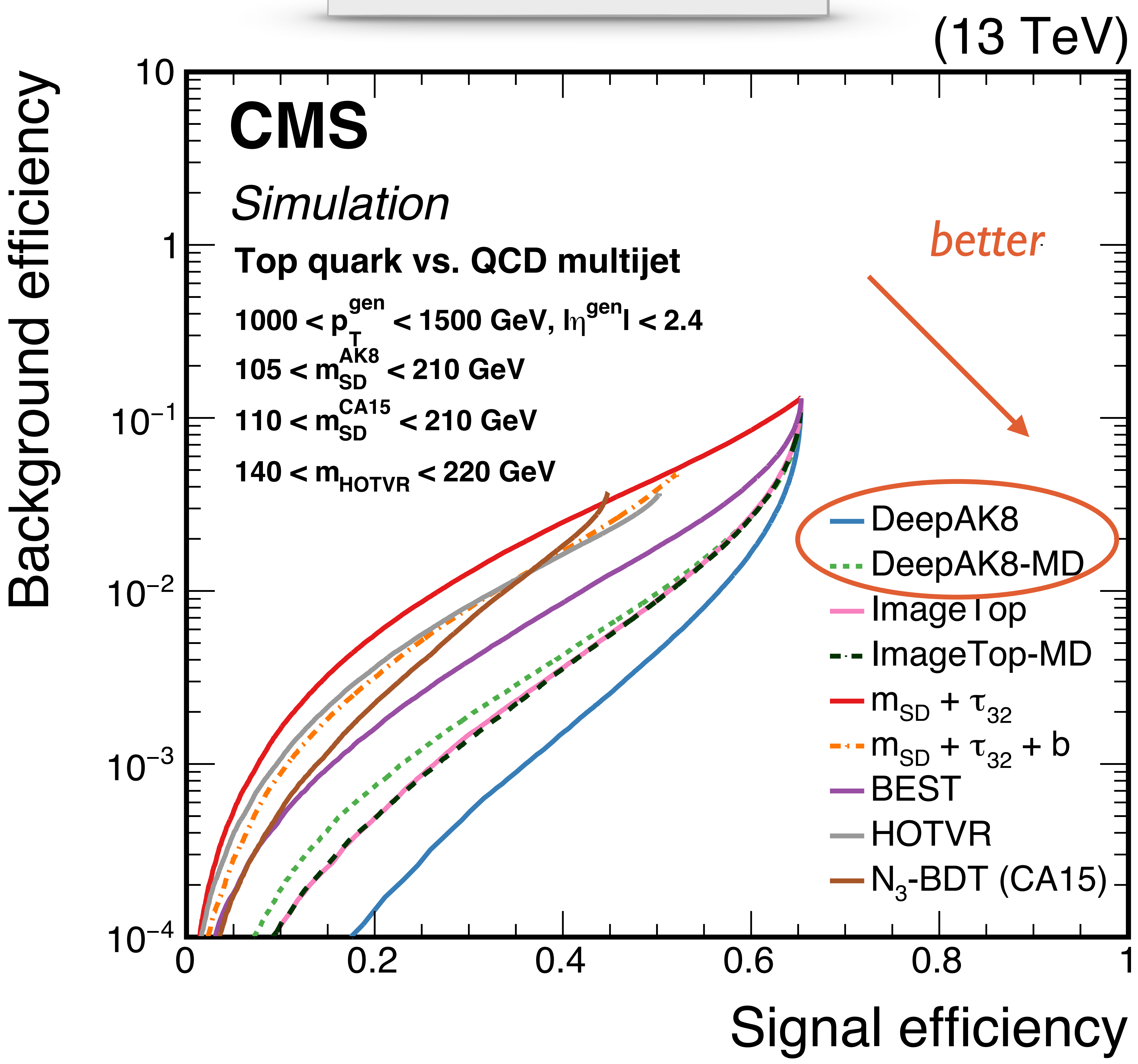
Category	Label
Higgs	H (bb)
	H (cc)
	H (VV*→qqqq)
Top	top (bcq)
	top (bqq)
	top (bc)
	top (bq)
W	W (cq)
	W (qq)
Z	Z (bb)
	Z (cc)
	Z (qq)
QCD	QCD (bb)
	QCD (cc)
	QCD (b)
	QCD (c)
	QCD (others)

DeepAK8 Performance

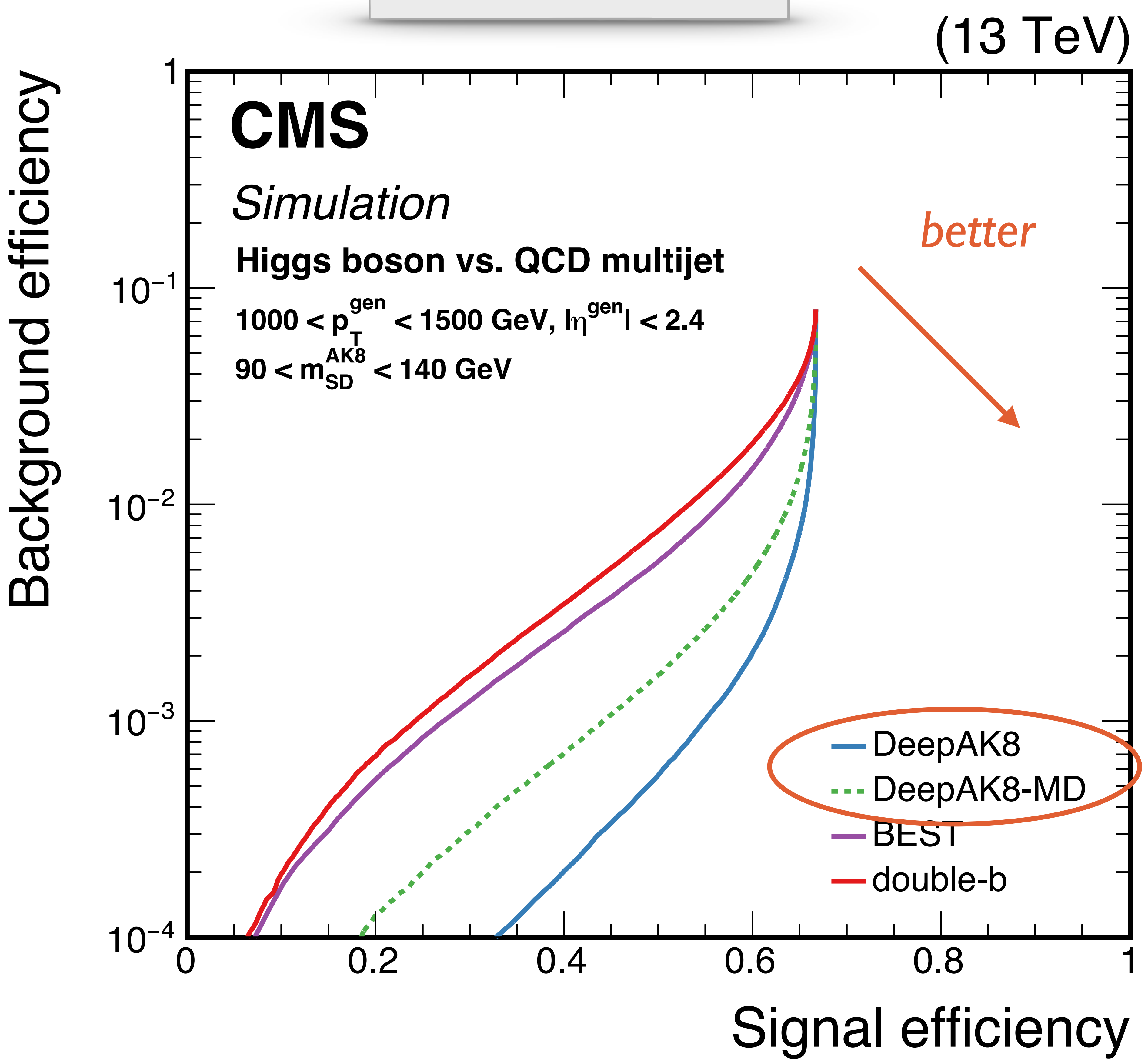
CMS, JINST 15 (2020) P06005

- Significant performance improvement compared to traditional approaches

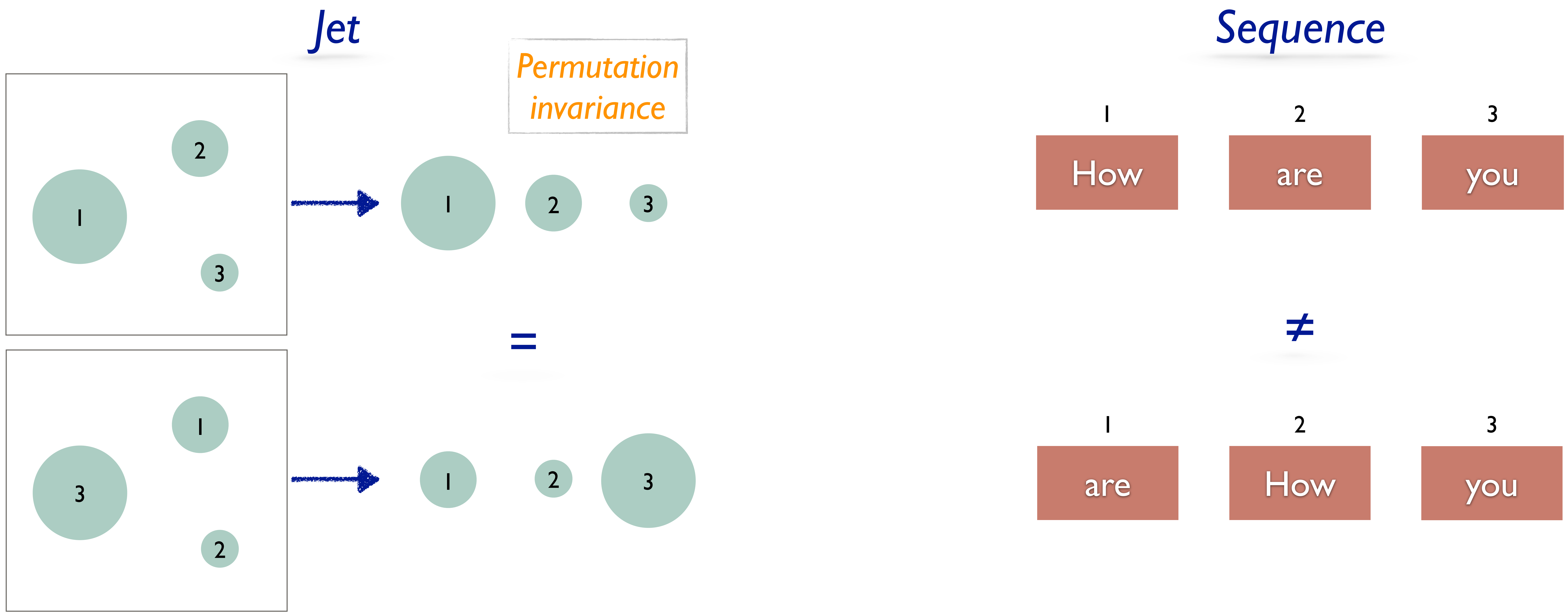
Top quark tagging



H→bb tagging

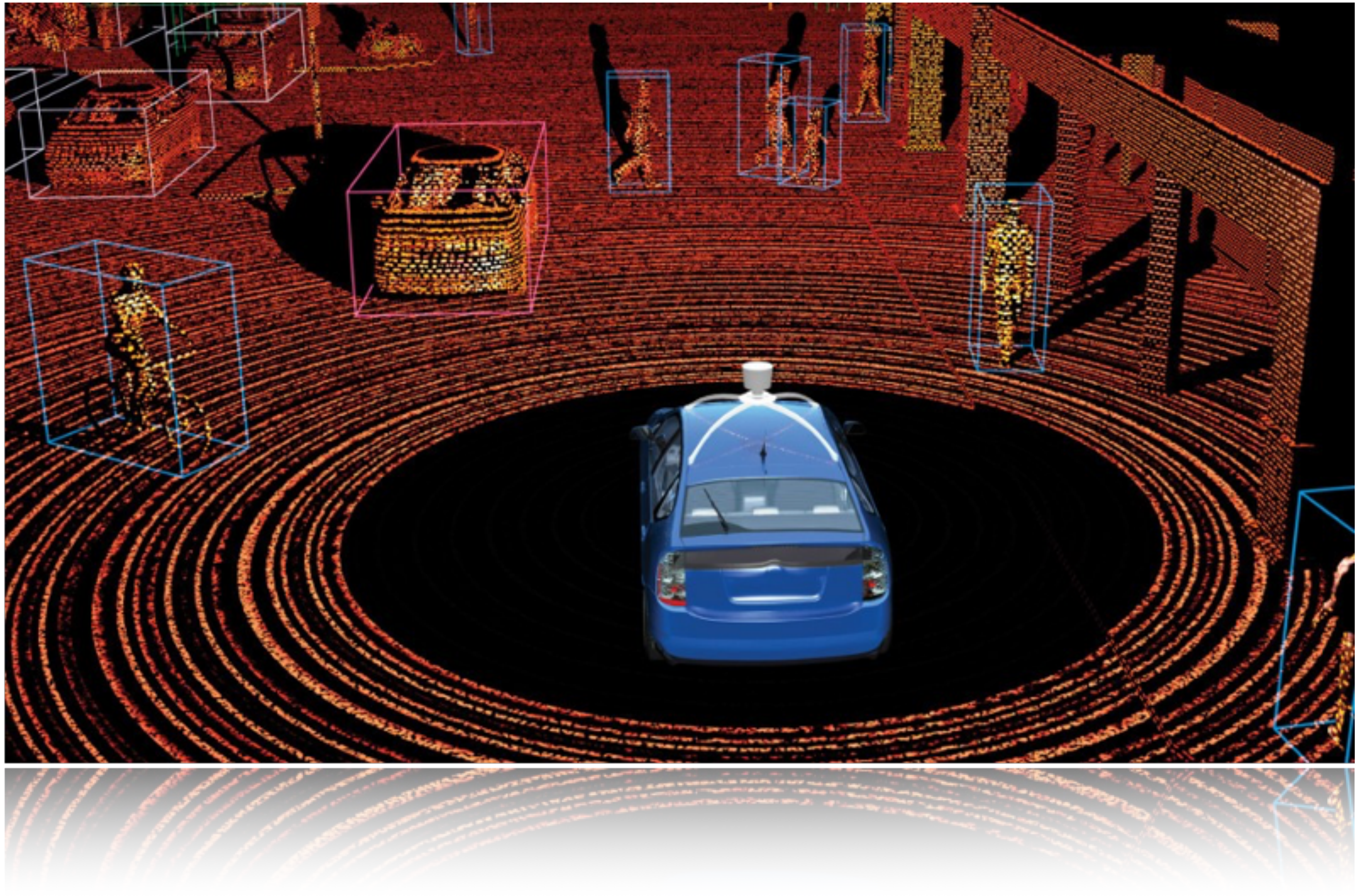


Jet Representation: Sequence



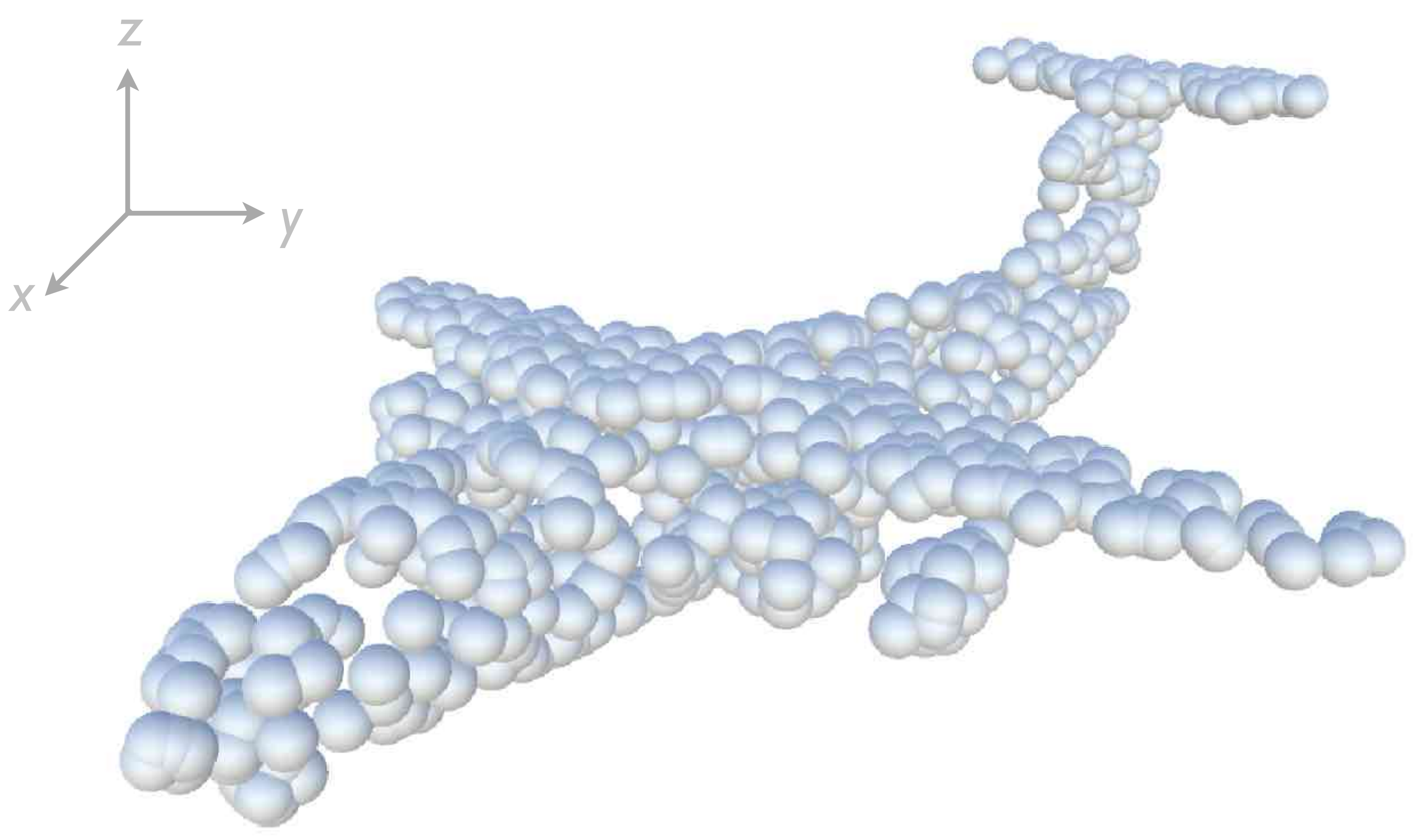
- Limitations
  - while words are naturally ordered in natural languages, particles are intrinsically **unordered** in a collision event
    - an ordering has to be ***imposed*** (p_T, distance, …), which can limit the learning performance

Point Cloud

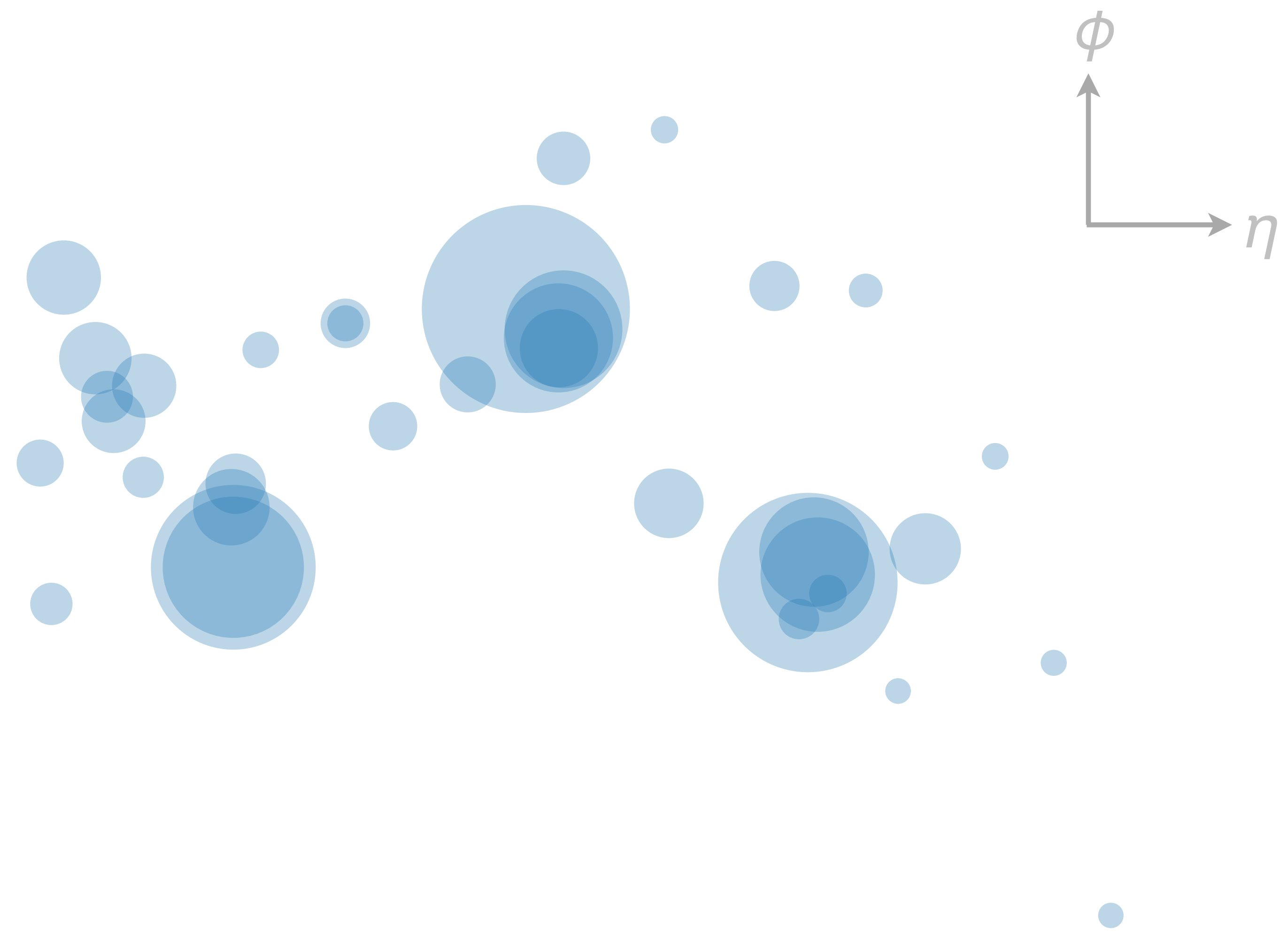


- Point cloud
  - an **unordered** set of points in space
    - typically produced by a LiDAR / 3D scanner
  - spatial distribution of points
    - geometric structure of the objects

JET REPRESENTATION: PARTICLE CLOUD



Permutation invariance



Point cloud

From Wikipedia, the free encyclopedia

A **point cloud** is a set of data points in space. Point clouds are generally produced by 3D scanners, which measure a large number of points on the external surfaces of objects around them.

Jet (Particle cloud)

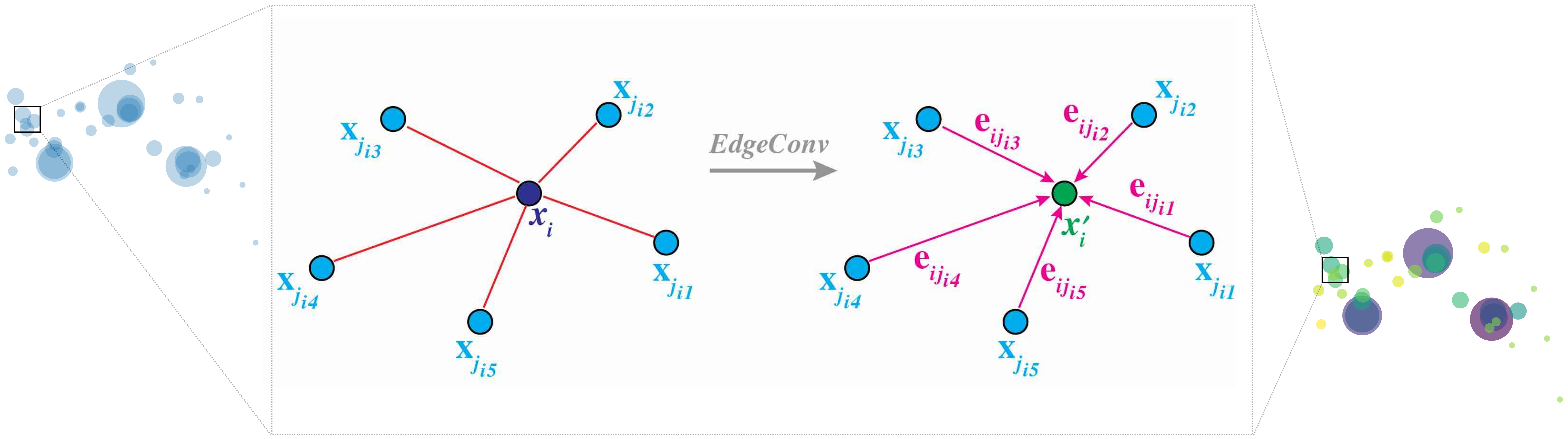
From Wikipedia, the free encyclopedia

A **jet (particle cloud)** is a set of particles in space. Particle clouds are generally created by clustering a large number of particles measured by particle detectors, e.g., ATLAS EXPERIMENT and CMS.

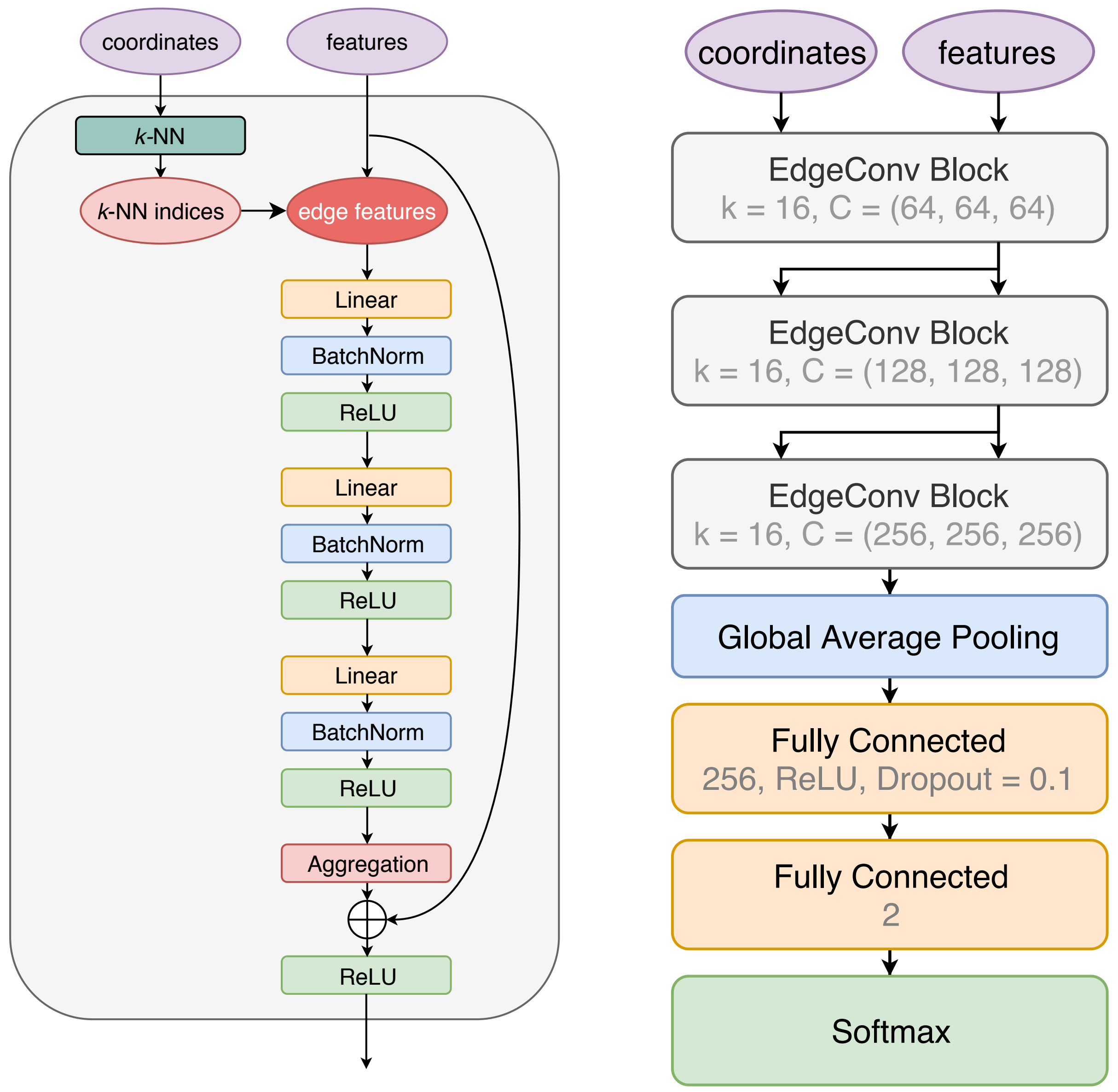
ParticleNet

H. Qu and L. Gouskos
Phys.Rev.D 101 (2020) 5, 056019

- ParticleNet: jet tagging via particle clouds
  - treating a jet as an **unordered set of particles**, distributed in the $\eta - \phi$ space
  - **graph neural network architecture**, adapted from Dynamic Graph CNN [arXiv:1801.07829]
    - treating a point cloud as a graph: each point is a vertex
      - for each point, a local patch is defined by finding its k-nearest neighbors
    - designing a permutation-invariant "convolution" function
      - define "edge feature" for each center-neighbor pair: $e_{ij} = h_\Theta(x_i, x_j)$
      - aggregate the edge features in a symmetric way: $x_i' = \mathrm{mean}_j\, e_{ij}$



ParticleNet architecture



cf. P.T. Komiske, E. M. Metodiev and J. Thaler, JHEP 01 (2019) 121;
V. Mikuni and F. Canelli, Eur. Phys. J. Plus 135, 463 (2020); Mach.Learn.Sci.Tech. 2 (2021) 3, 035027.

ParticleNet: Performance

G. Kasieczka et al.
SciPost Phys. 7 (2019) 014

- Top performance among a variety of deep learning taggers on the community-wide top tagging benchmark

	AUC	Acc	$1/\epsilon_B$ ($\epsilon_S = 0.3$) single	mean	median	#Param
CNN [16]	0.981	0.930	914±14	995±15	975±18	610k
ResNeXt [30]	0.984	0.936	1122±47	1270±28	1286±31	1.46M
TopoDNN [18]	0.972	0.916	295±5	382± 5	378 ± 8	59k
Multi-body N-subjettiness 6 [24]	0.979	0.922	792±18	798±12	808±13	57k
Multi-body N-subjettiness 8 [24]	0.981	0.929	867±15	918±20	926±18	58k
TreeNiN [43]	0.982	0.933	1025±11	1202±23	1188±24	34k
P-CNN	0.980	0.930	732±24	845±13	834±14	348k
ParticleNet [47] (Preliminary ver.)	0.985	0.938	1298±46	1412±45	1393±41	498k
LBN [19]	0.981	0.931	836±17	859±67	966±20	705k
LoLa [22]	0.980	0.929	722±17	768±11	765±11	127k
Energy Flow Polynomials [21]	0.980	0.932	384			1k
Energy Flow Network [23]	0.979	0.927	633±31	729±13	726±11	82k
Particle Flow Network [23]	0.982	0.932	891±18	1063±21	1052±29	82k
GoaT	0.985	0.939	1368±140		1549±208	35k
ParticleNet-Lite	0.984	0.937	1262±49			26k
ParticleNet	**0.986**	**0.940**	**1615±93**			366k

Architecture used by DeepAK8

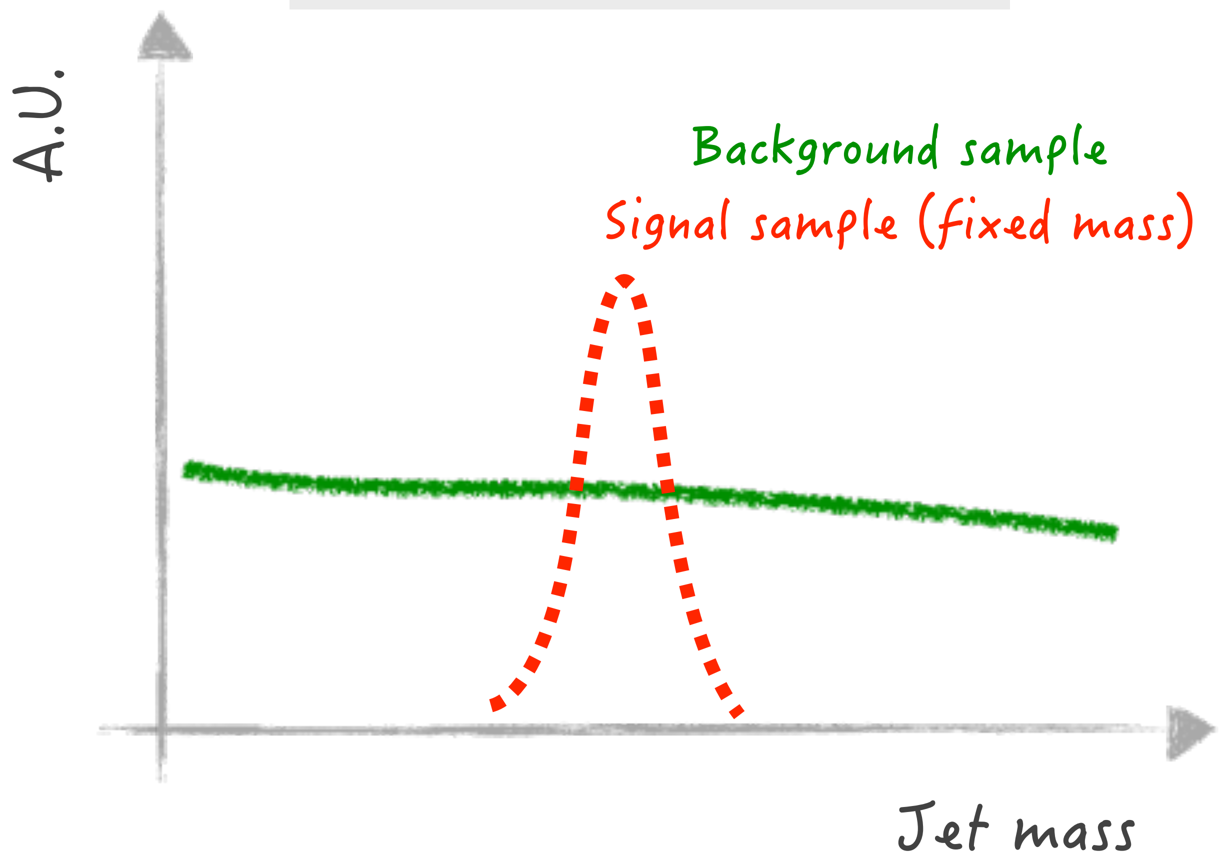
Ensemble of all taggers

Boosted Jet Tagging in Action

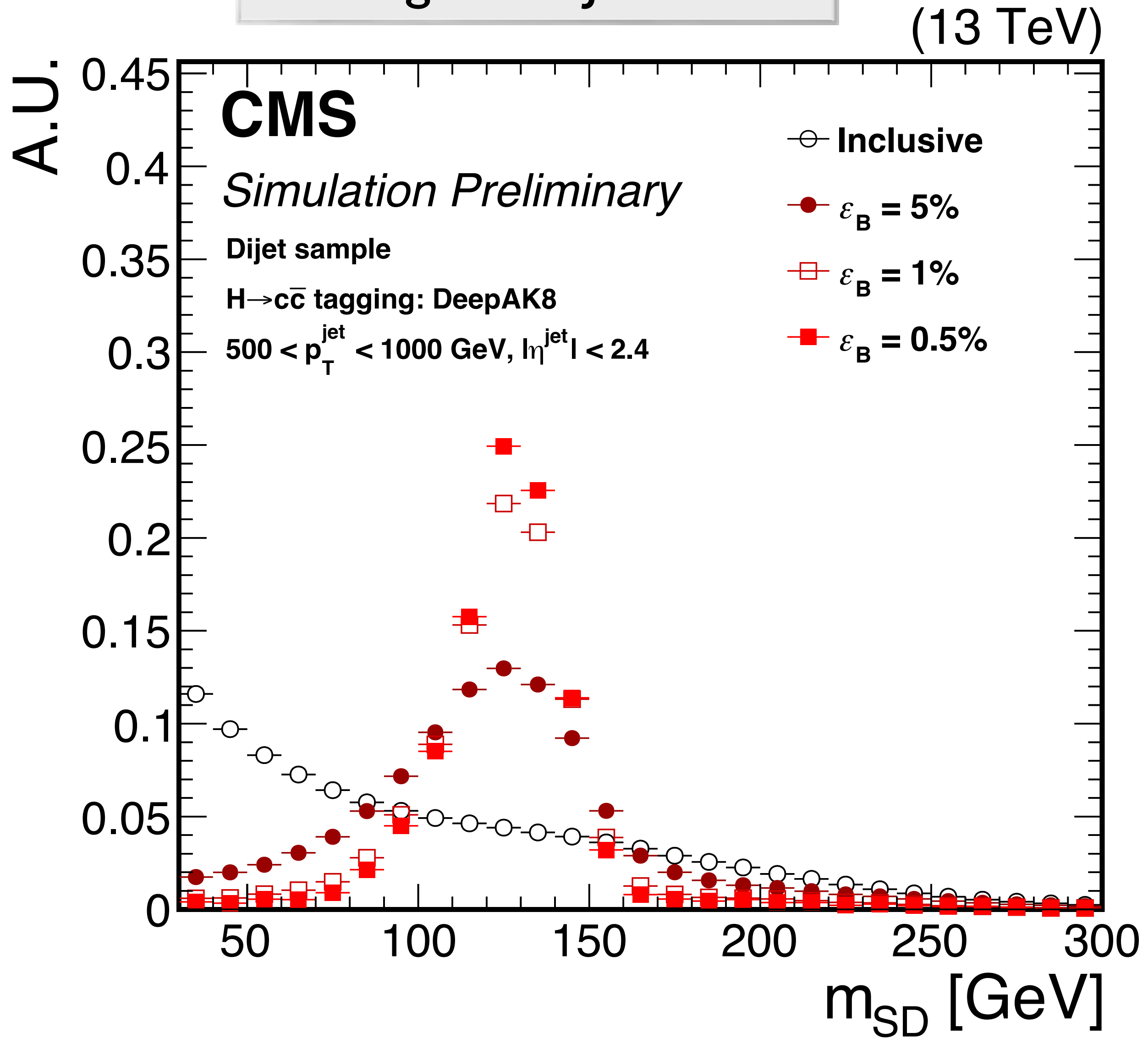
Correlation with the Jet Mass

CMS DP-2020/002

Plain training:
no mass decorrelation



Background jet mass

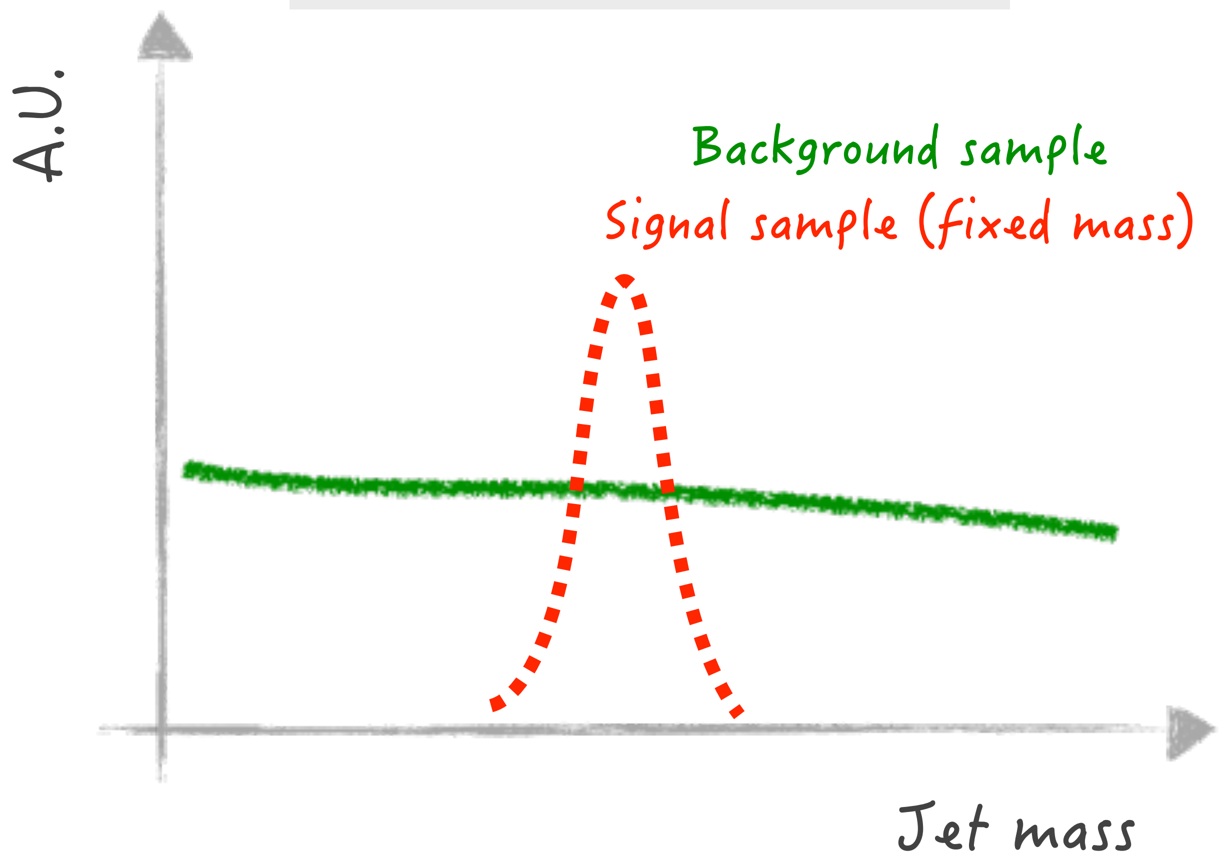


- One feature of these taggers is the correlation with the jet mass
  - jet mass shape of the background becomes similar to that of the signal after selection with the tagger: **"mass sculpting"**
  - not necessarily a problem, but a mass-independent tagger is often more desirable:
    - allows to use the mass variable to further separate signal and background
    - enables tagging signal jets with an unknown mass
    - …

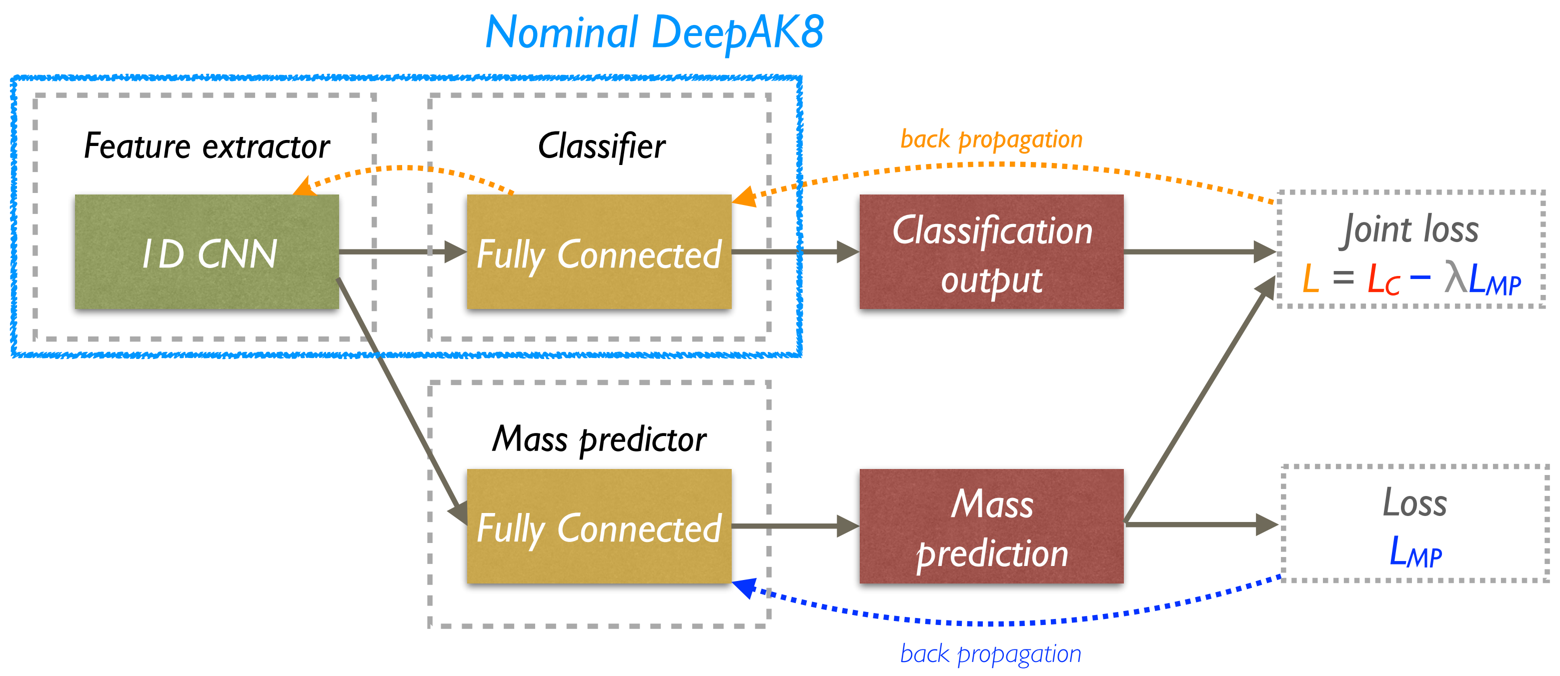
DECORRELATION WITH THE JET MASS

CMS DP-2020/002

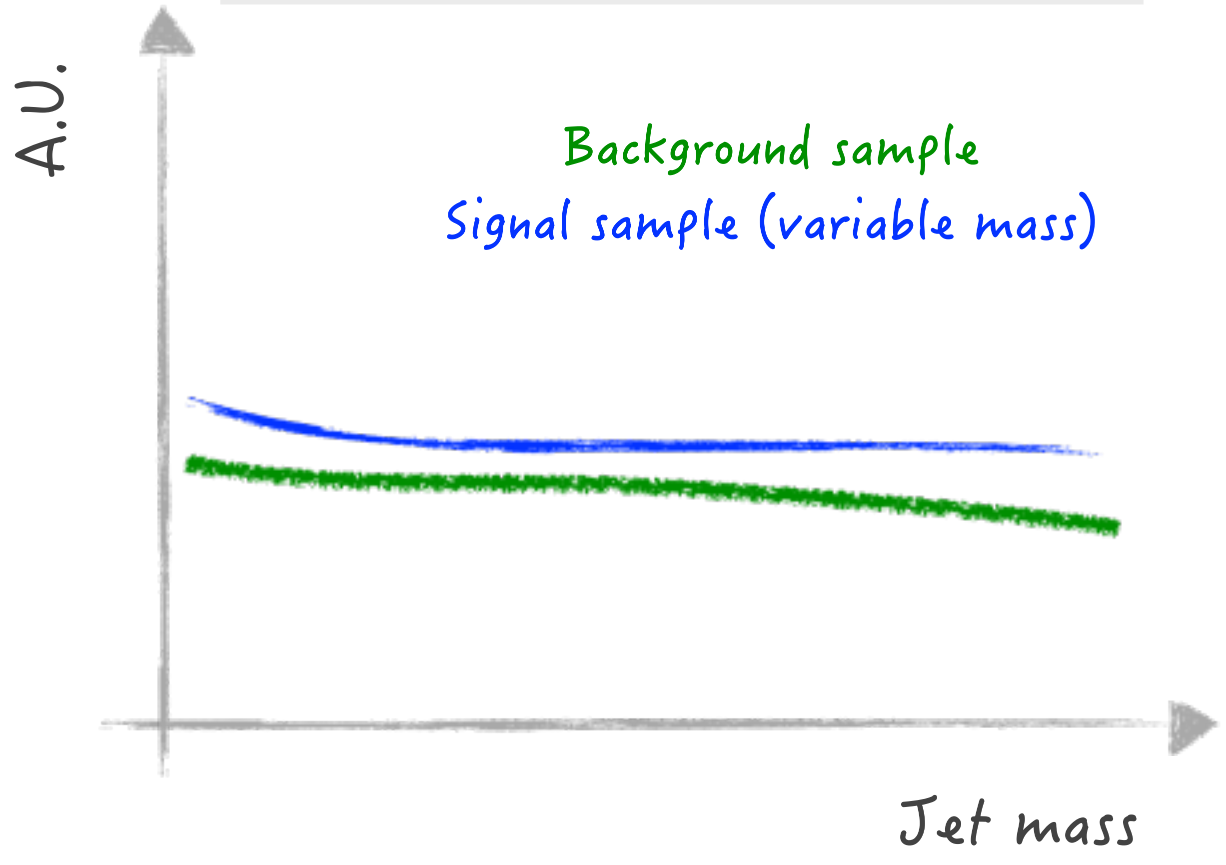
Plain training: no mass decorrelation



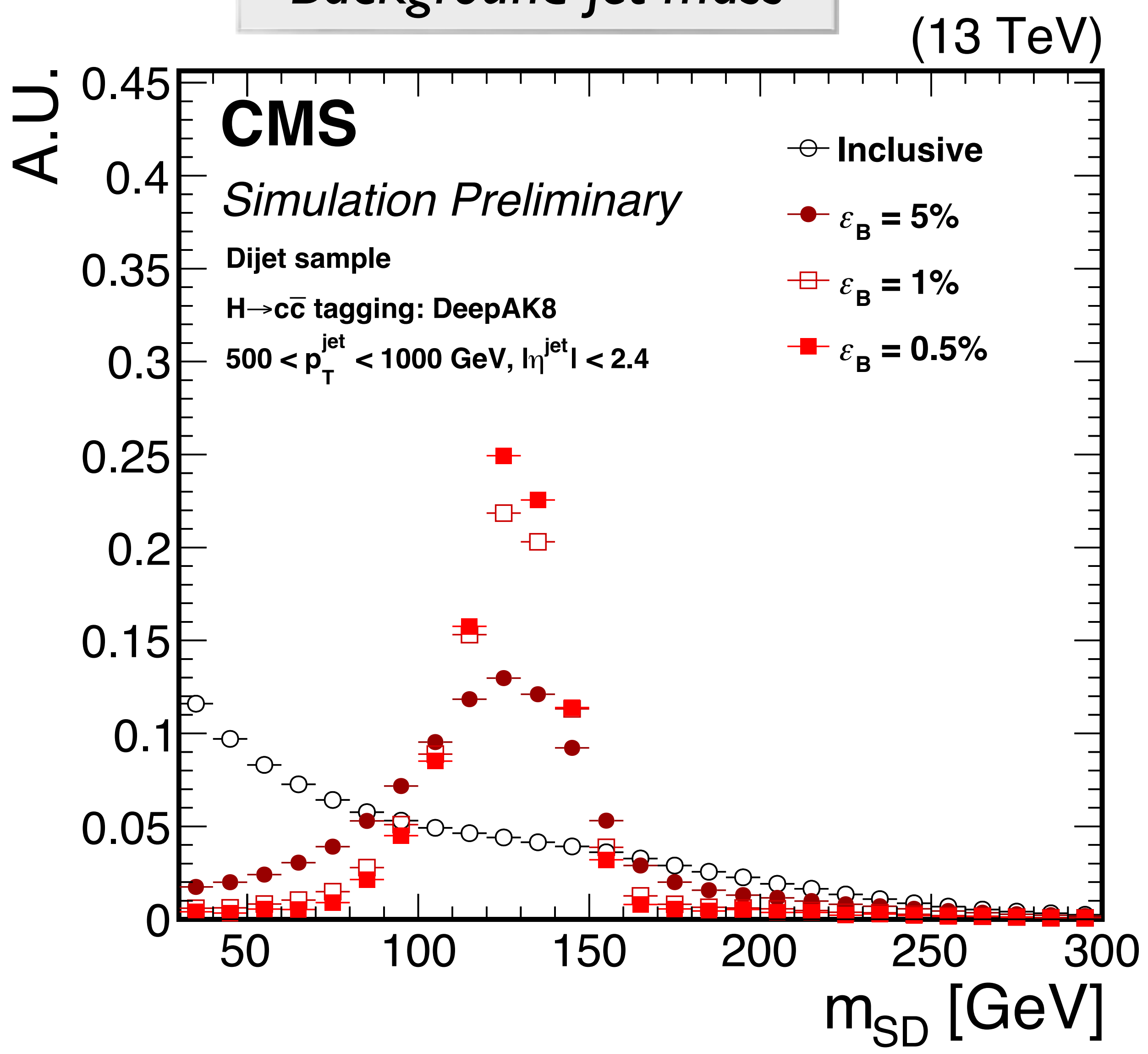
Mass-decorrelated DeepAK8: "adversarial training"



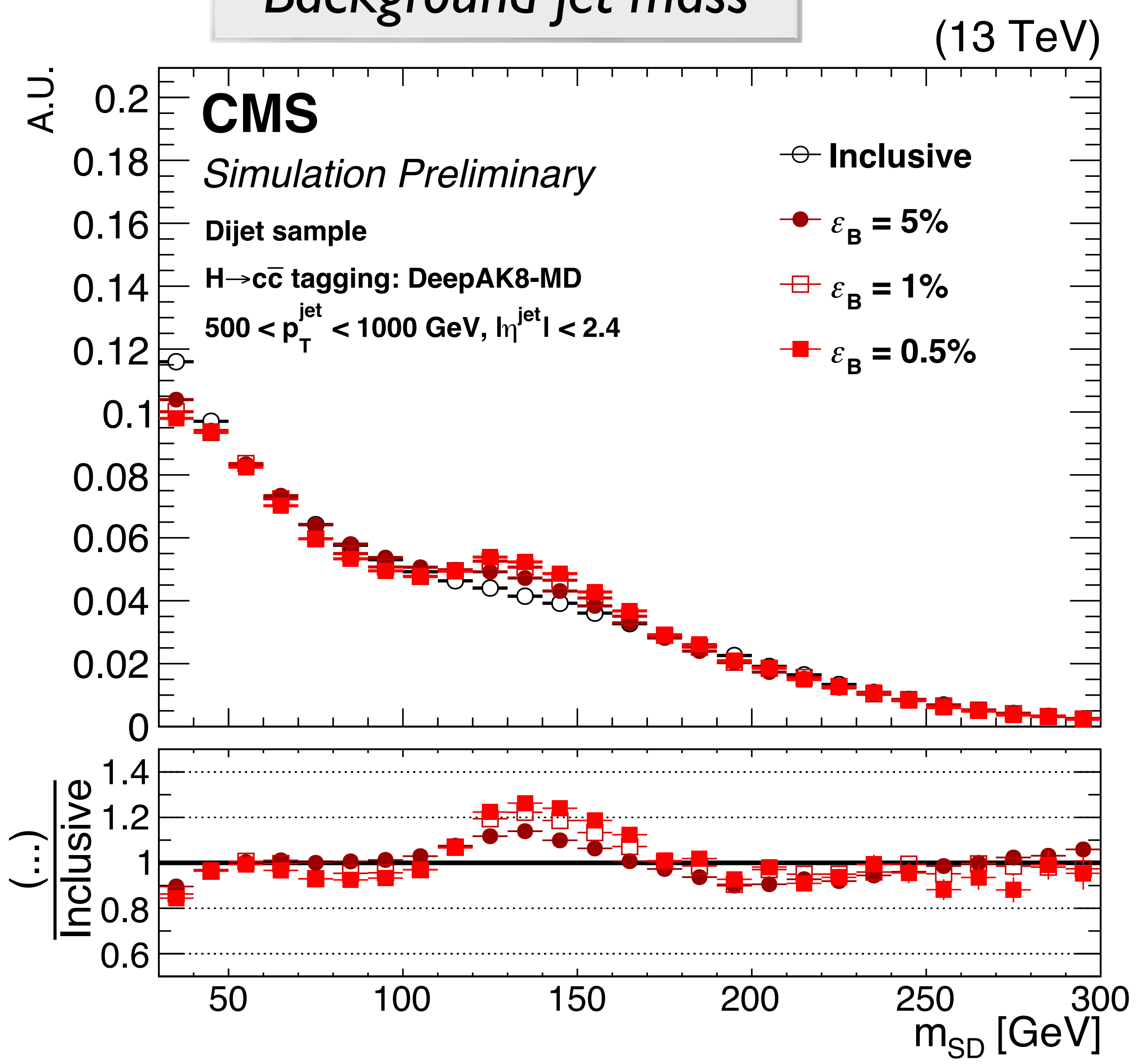
Mass-decorrelated ParticleNet: training with variable-mass signal



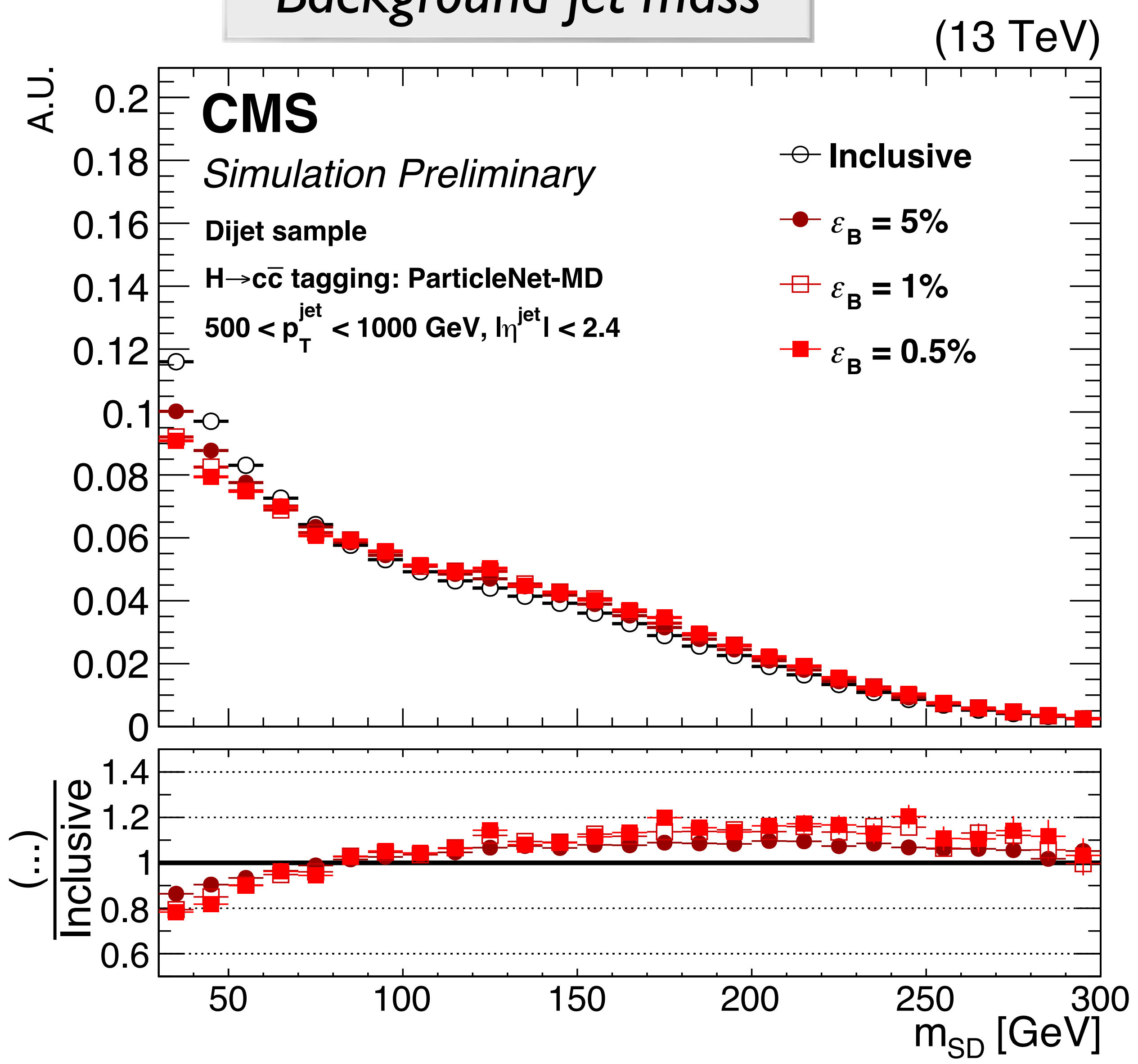
Background jet mass



Background jet mass



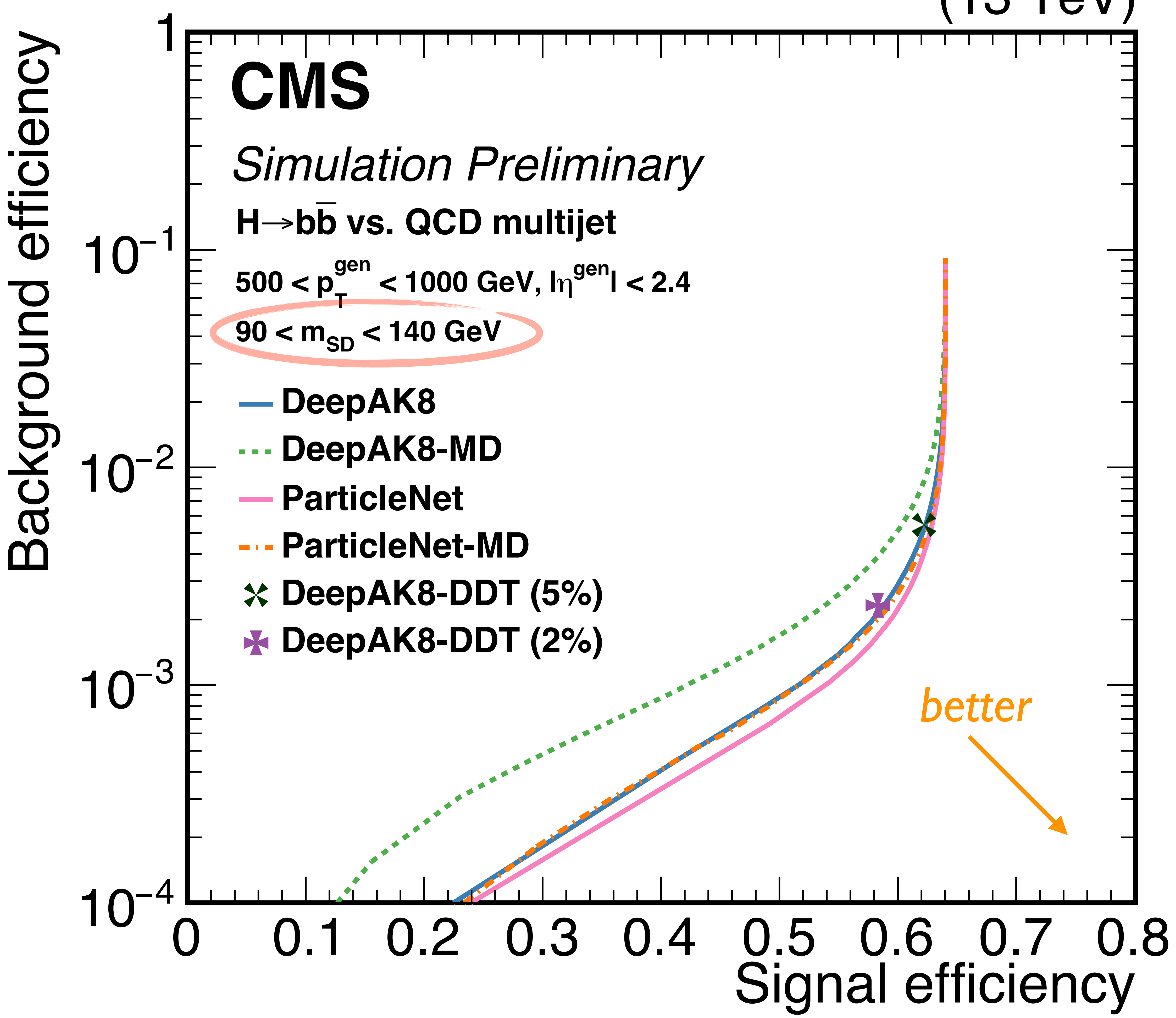
Background jet mass



Performance Comparison

CMS DP-2020/002

H→bb tagging performance



- ParticleNet-MD
  - using a special signal sample for training
    - hadronic decays of a spin-0 particle X
      - X → bb, X → cc, X → qq
    - not a fixed mass, but a flat mass spectrum
      - m(X) ∈ [15, 250] GeV
    - allows to easily reweight both signal and background to a ~flat 2D distribution in (p_T, mass) for the training
- ParticleNet-MD shows the best performance
  - ~3-4x better background rejection compared to DeepAK8-MD (based on "adversarial training")
  - only slight performance loss compared to the nominal version w/o mass decorrelation

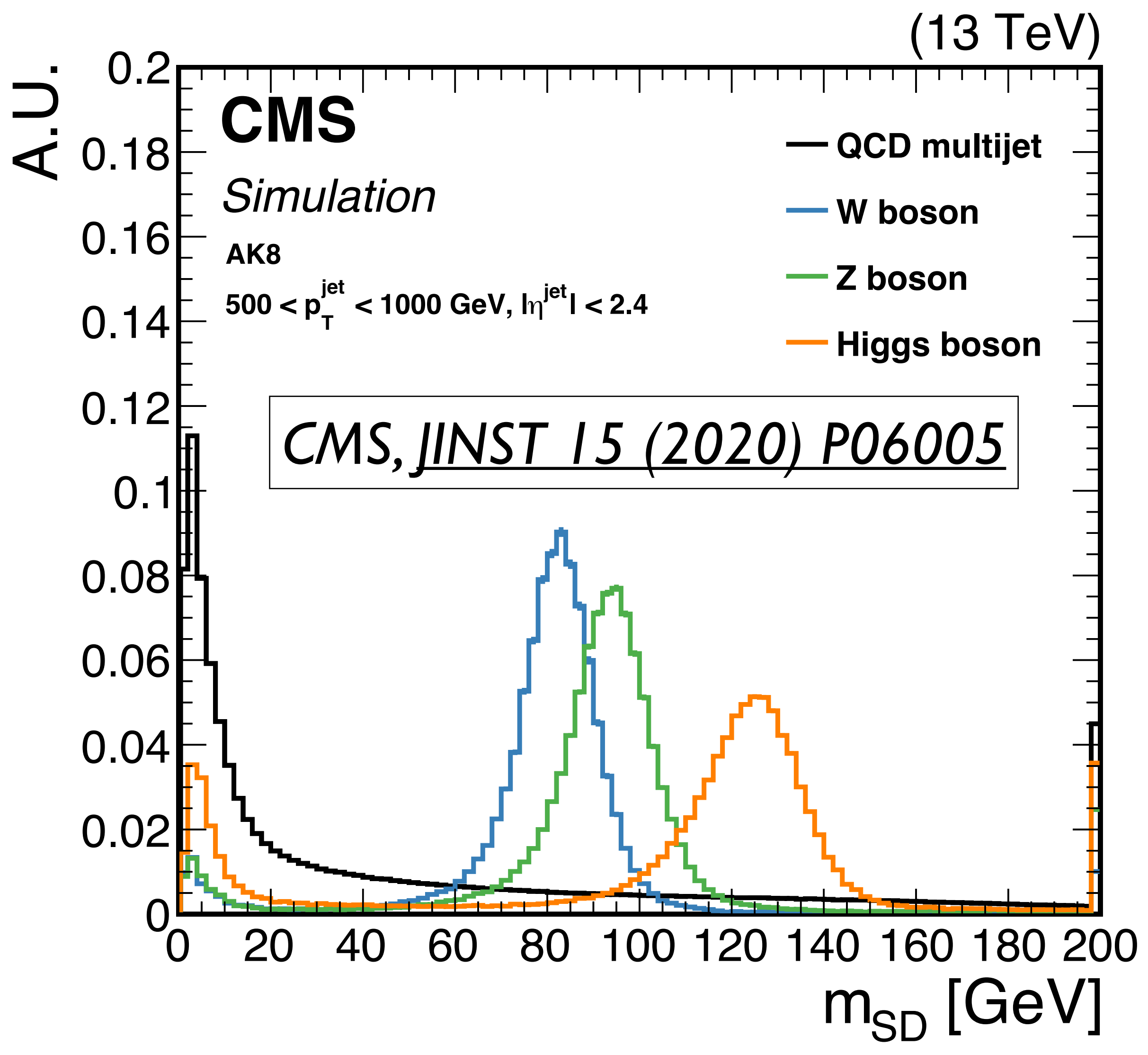
Mass Regression

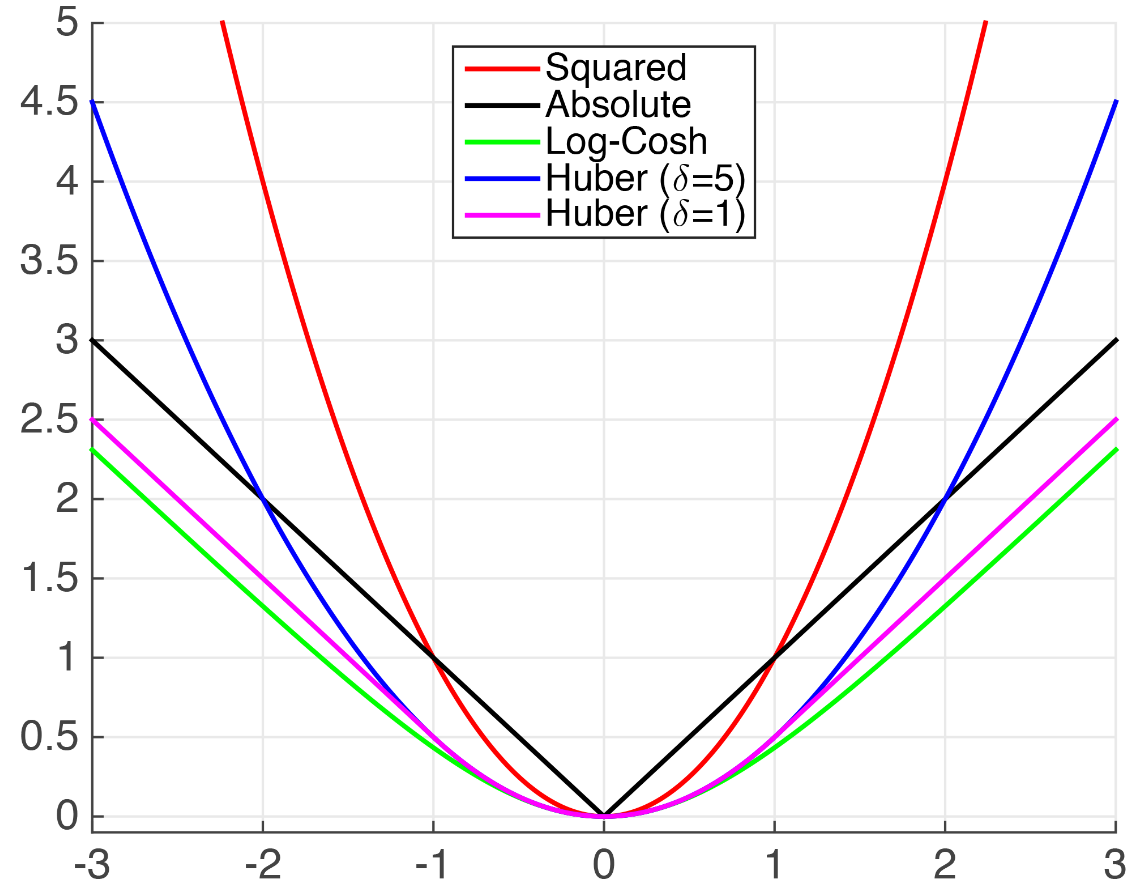
- Jet mass: one of the most powerful observables for boosted jet tagging
  - characteristic mass peak for top/W/Z/H jets v.s. continuum for QCD jets

- Mass regression:
  - exploit deep learning to reconstruct jet mass with the highest possible resolution
  - training setup similar to the ParticleNet tagger
    - but: predict the jet mass directly from the jet consitituents

- Regression target:
  - signal (X → bb/cc/qq): generated particle mass of X [flat spectrum in 15 – 250 GeV]
  - background (QCD) jets: soft drop mass of the generated particle-level jet

- Loss function
  - LogCosh: $L(y, y^p) = \sum_{i=1}^{n} \log(\cosh(y_i^p - y_i))$

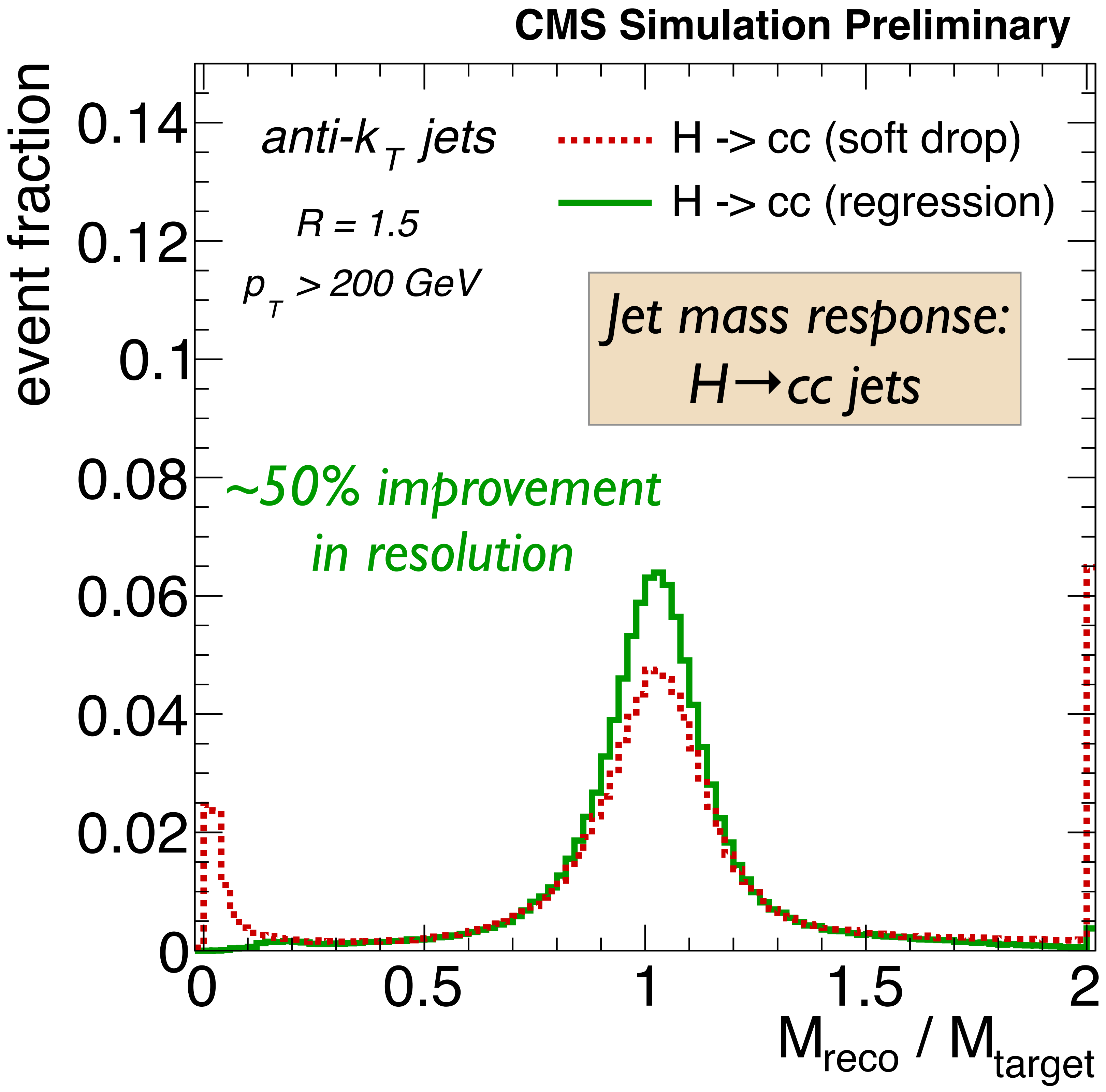


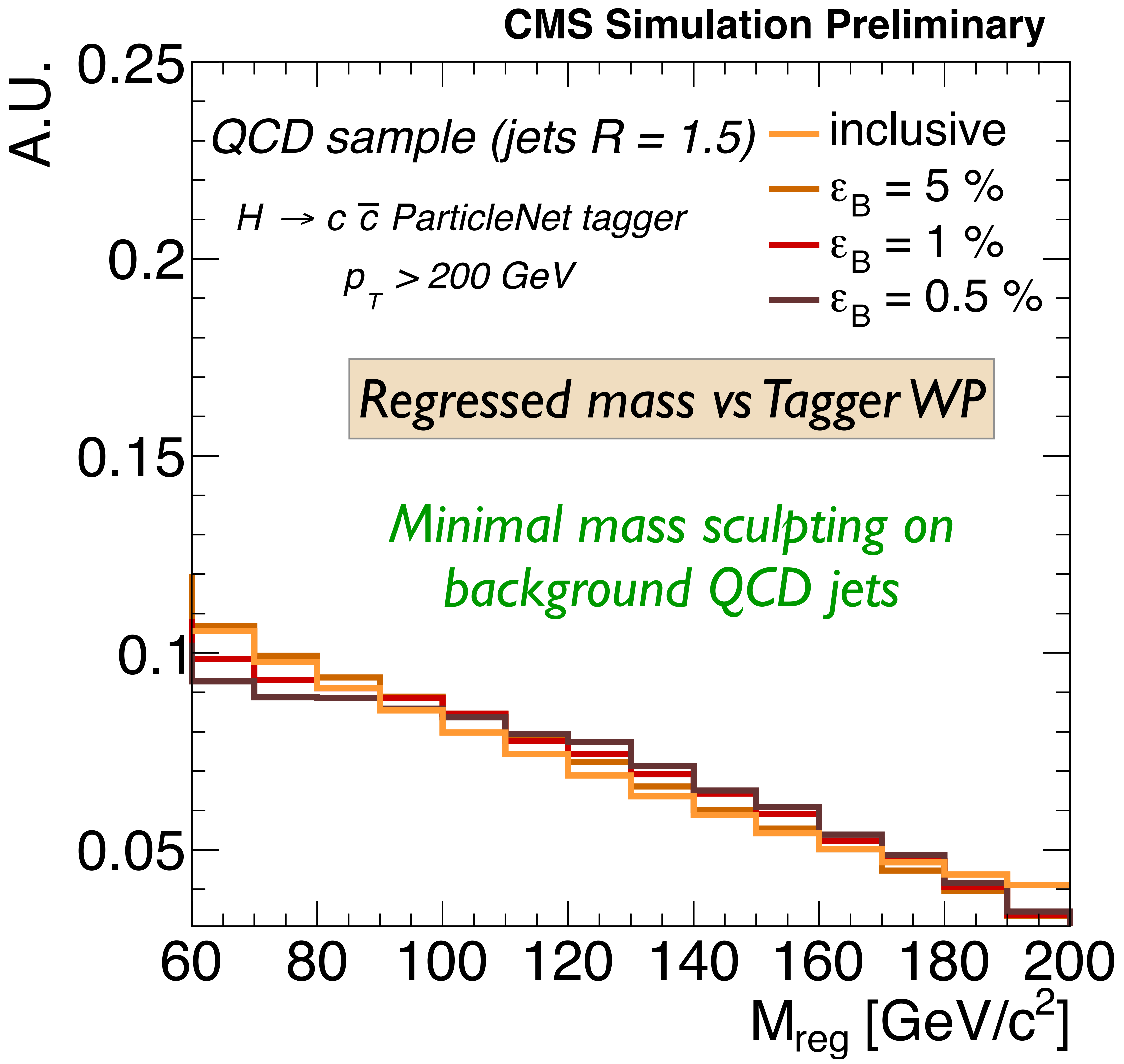


https://www.cs.cornell.edu/courses/cs4780/2015fa/web/lecturenotes/lecturenote10.html

MASS REGRESSION: PERFORMANCE

CMS DP-2021/017

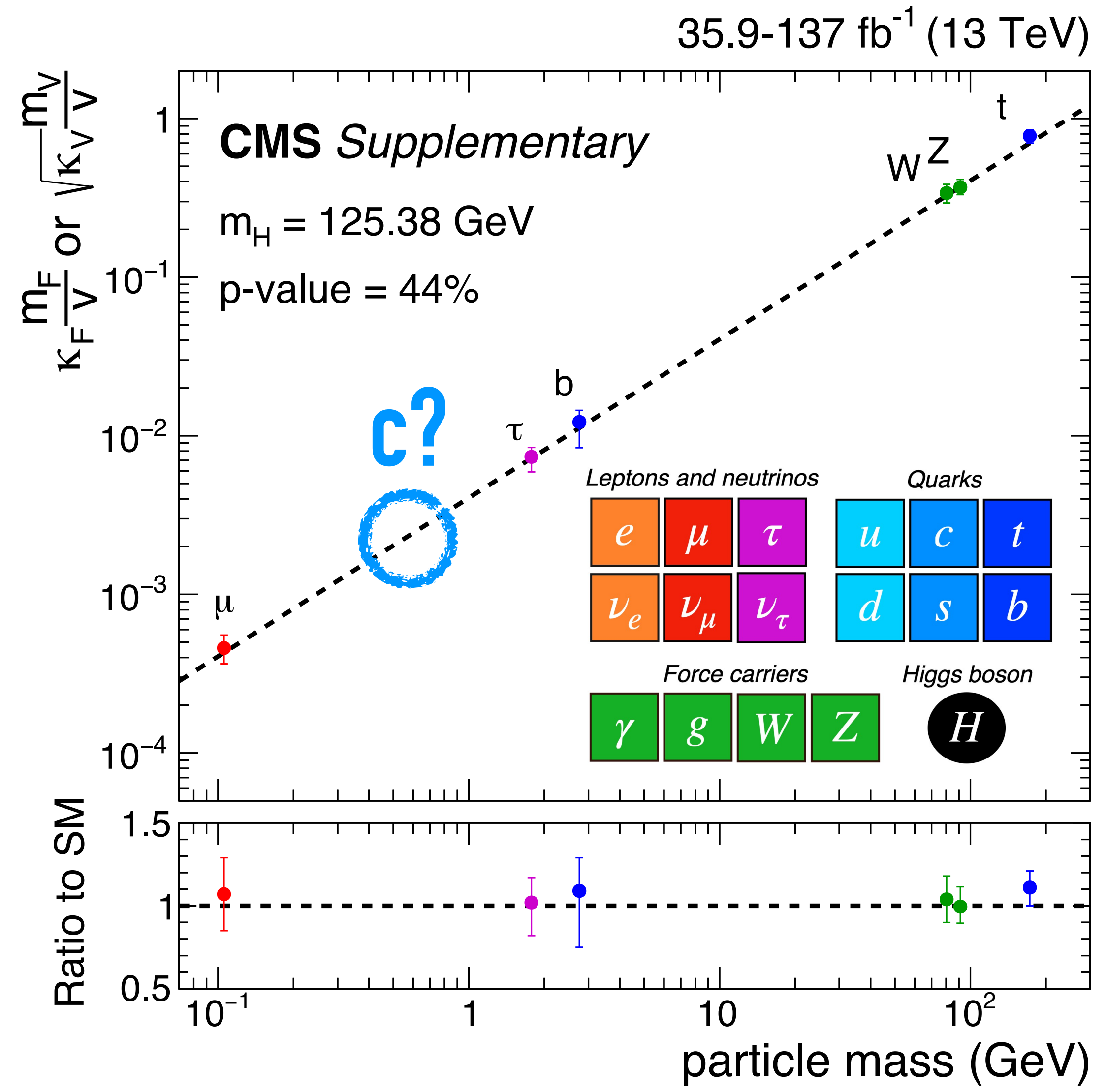


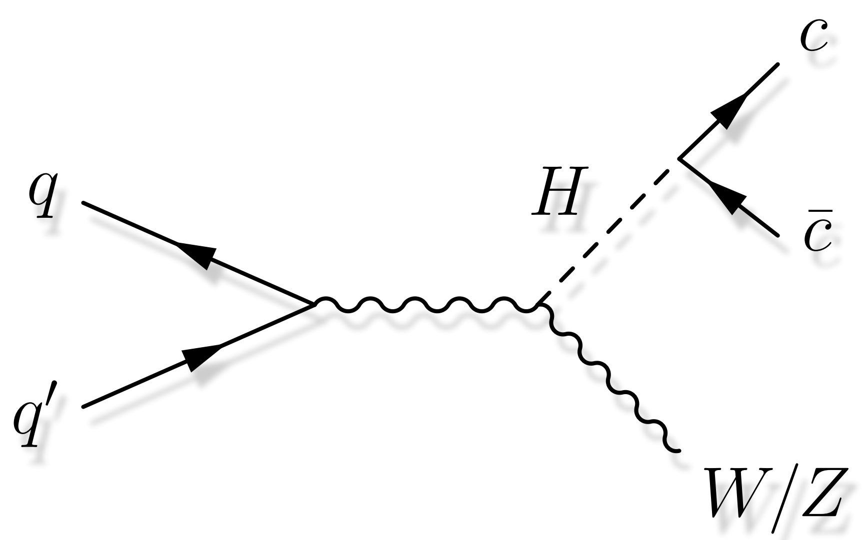


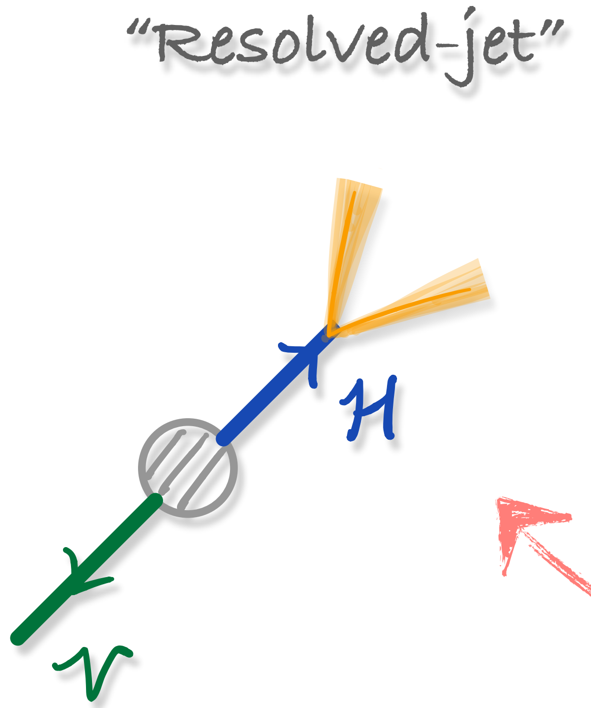
~20-25% improvement in the final sensitivity for H→bb / H→cc analyses

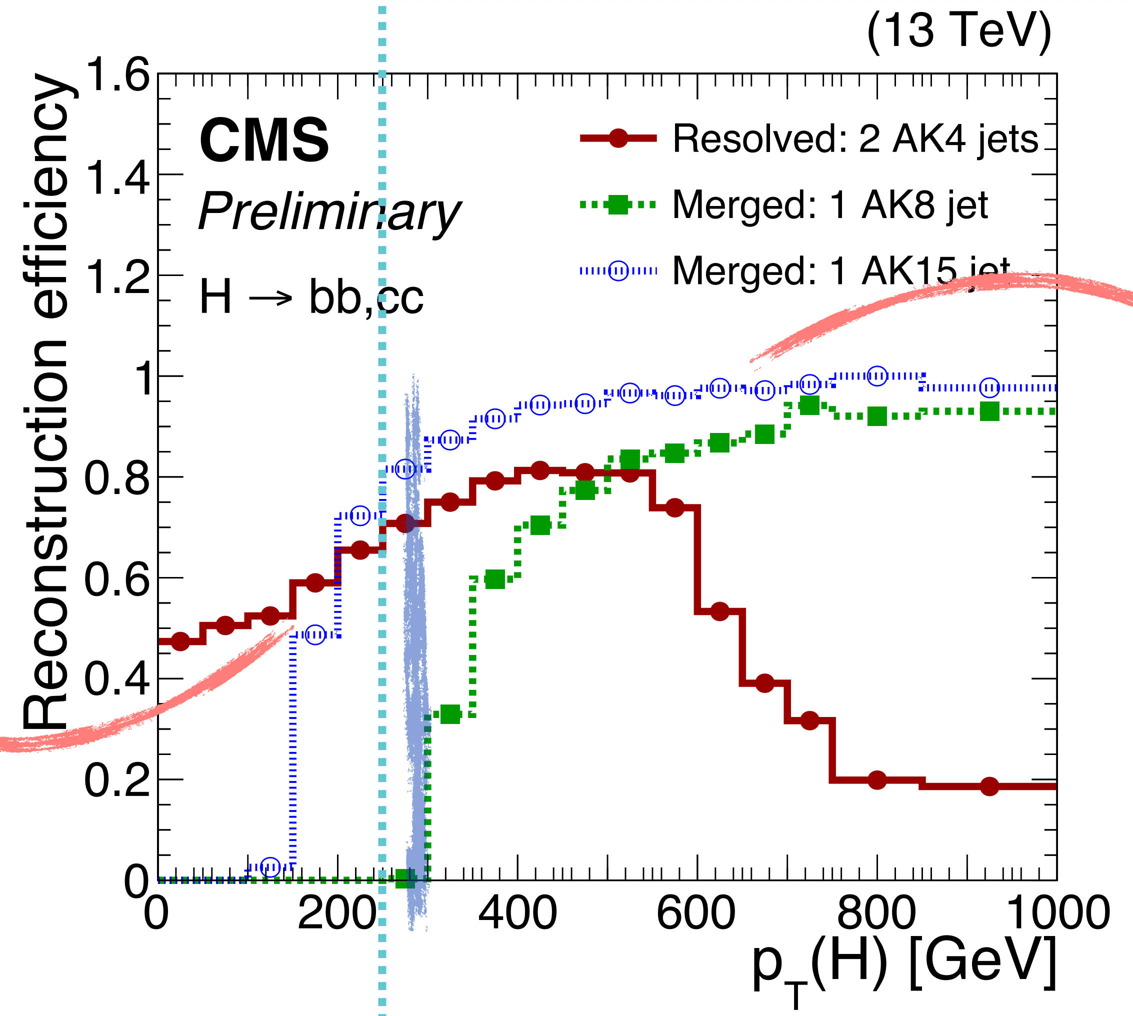
Search for H→cc

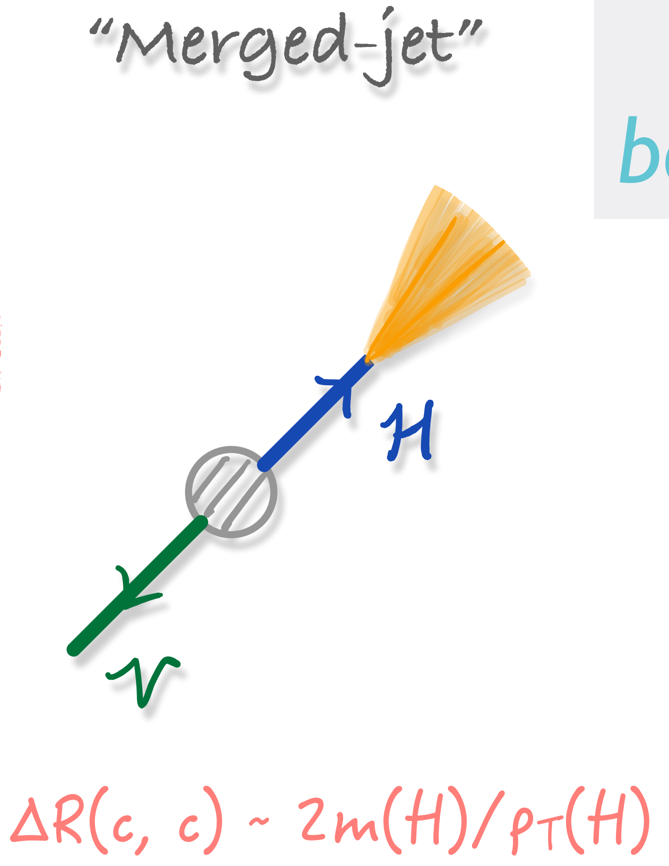
- Search for the Higgs boson decay to a pair of charm quarks (H→cc)
  - next milestone in Higgs physics — couplings to second generation quarks
  - extremely challenging at the LHC:
    - small branching fraction (~3%) vs enormous backgrounds; difficulty in charm tagging
- H→cc search at CMS
  - targets WH/ZH production, with 3 channels: Z→νν (0L), W→ℓν (1L), Z→ℓℓ (2L) (ℓ = e, μ)
  - two complementary approaches to fully explore the H→cc decay topologies











Powered by boosted jet tagging

Resolved-jet topology

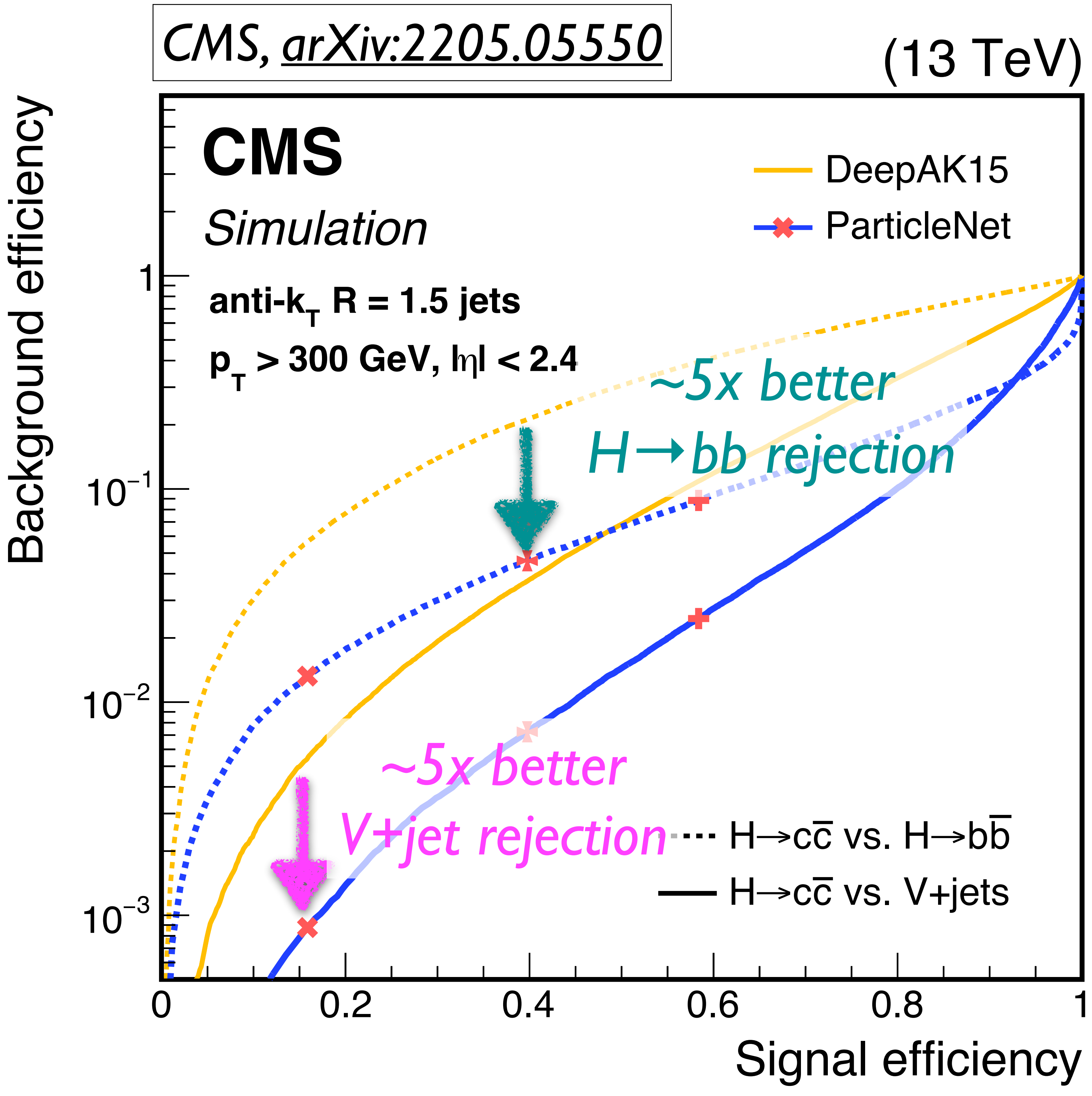
- reconstructs H→cc decay with two resolved jets (R=0.4)
- probes the bulk of the phase space

Merged-jet topology

- reconstructs H→cc decay with one large-R jets (R=1.5)
- higher purity, but lower acceptance

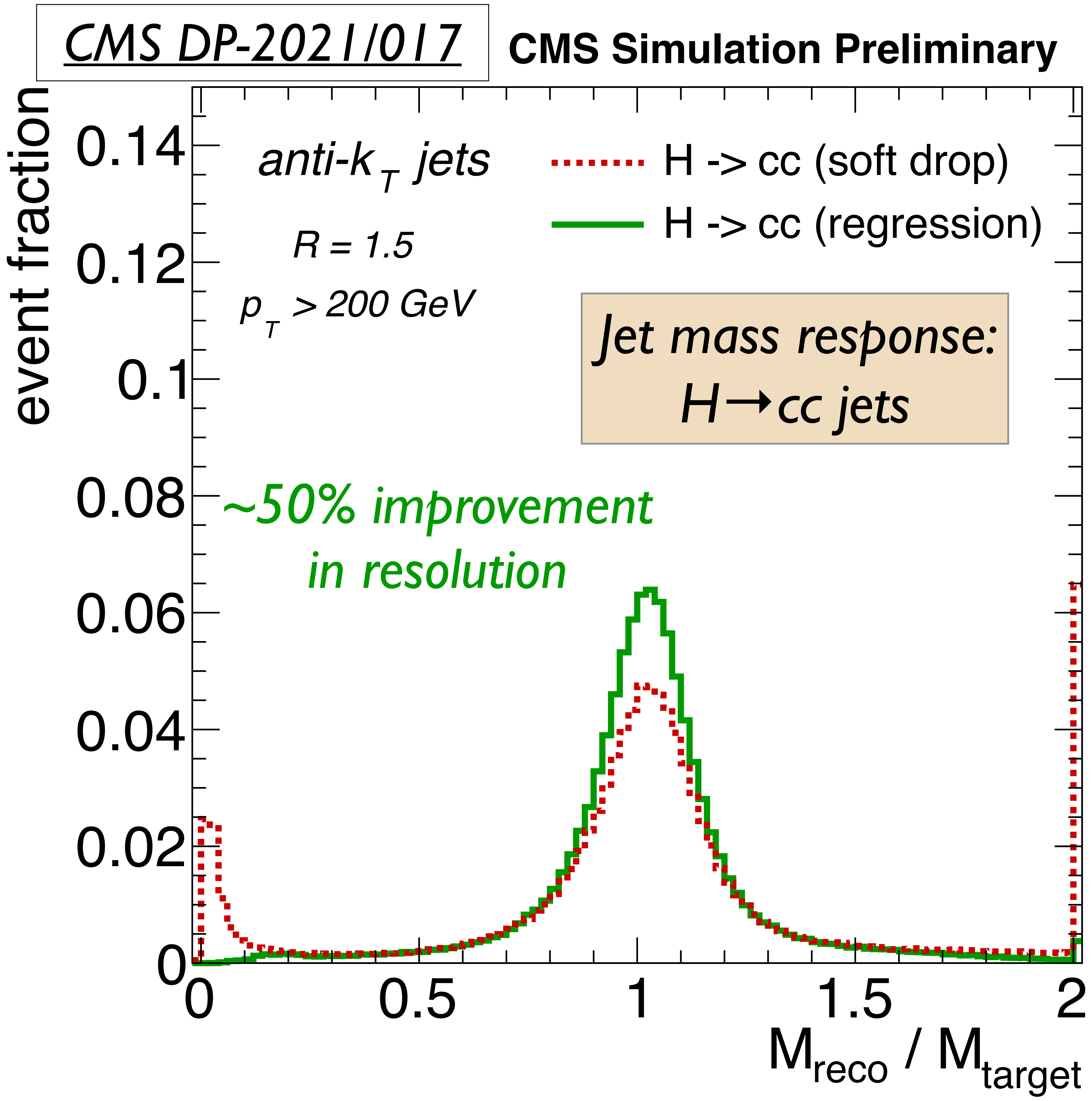
Improvements in H→cc Reconstruction

- The ParticleNet H→cc tagger and mass regression bring substantial improvements to the analysis



ParticleNet tagger for H→cc tagging

>2x improvement in final sensitivity



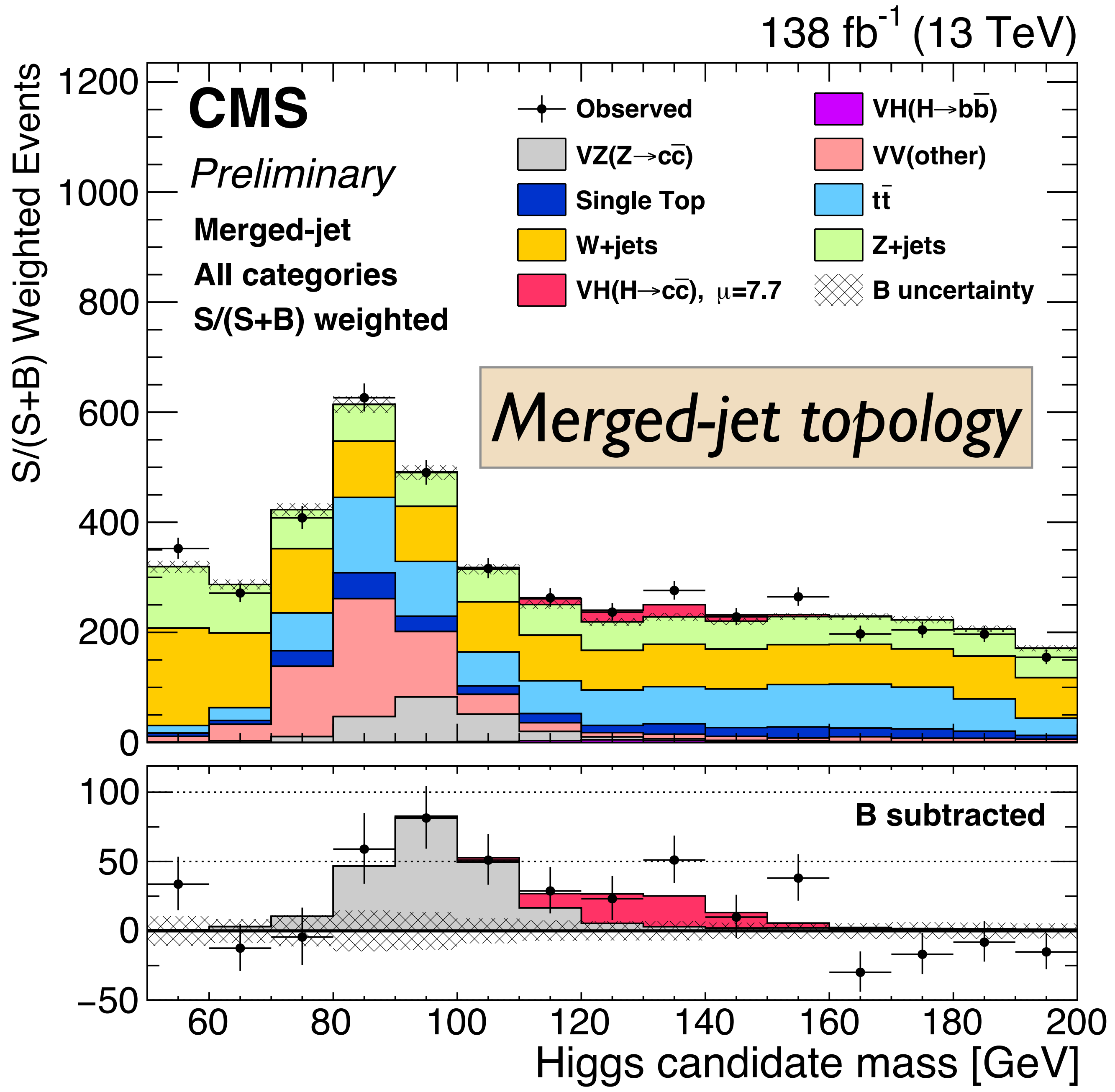
ParticleNet-based jet mass regression

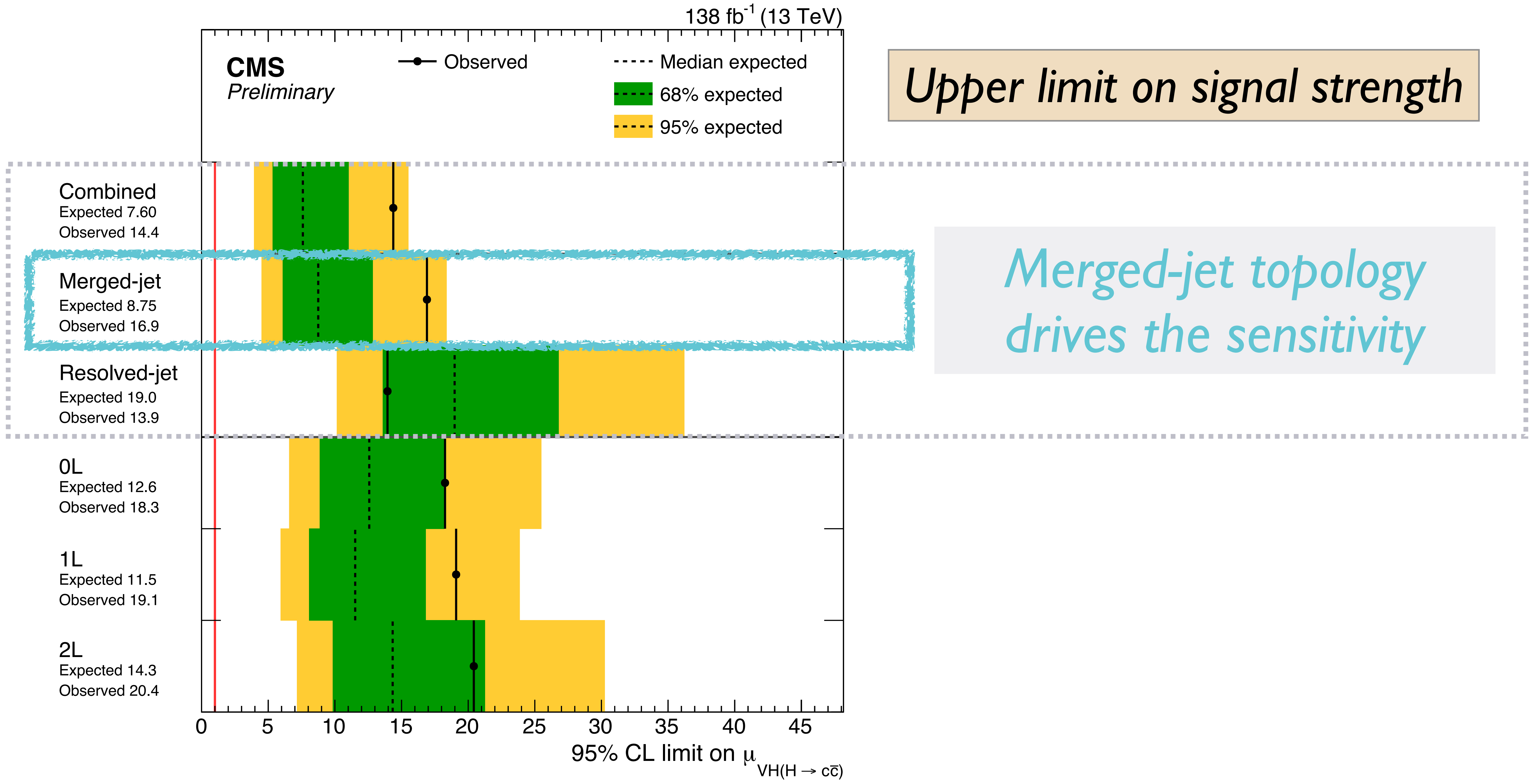
~20-25% improvement in final sensitivity

H→cc Results

CMS, arXiv:2205.05550

- VH(H→cc) results with the full Run-2 data set (138 fb-1)
  - $\mu_{VH(H\rightarrow c\bar{c})} < 14\ (7.6)$ observed (expected)
  - substantially stronger than the ATLAS full Run-2 result: $\mu_{VH(H\rightarrow c\bar{c})} < 26\ (31)$ obs. (exp.) [arXiv:2201.11428]
  - expected sensitivity already comparable to the previous projection for HL-LHC w/ 3000 fb-1: μ < 6.4 [ATL-PHYS-PUB-2021-039]
- Analysis validated by measuring VZ(Z→cc): $\mu_{VZ(Z\rightarrow c\bar{c})} = 1.01^{+0.23}_{-0.21}$
  - **First observation of Z→cc at a hadron collider,** with a significance of 5.7σ



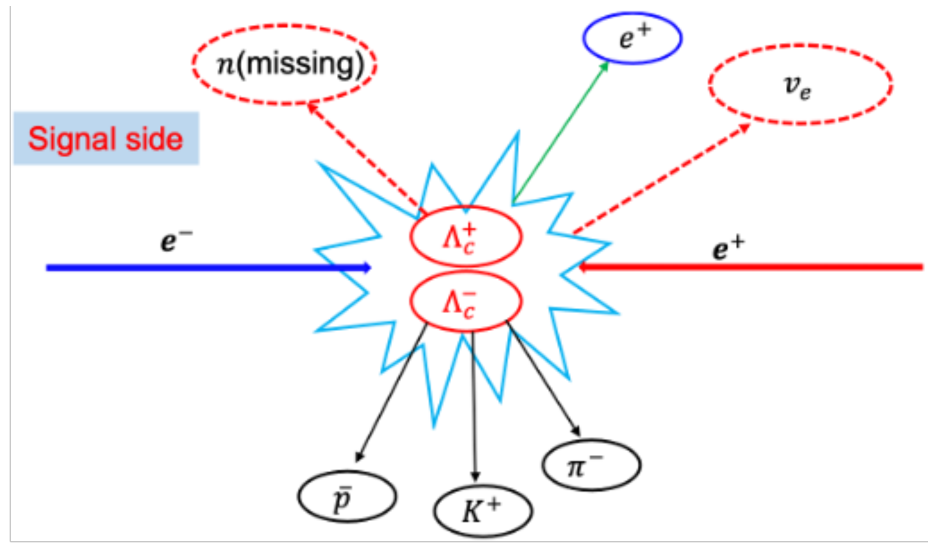


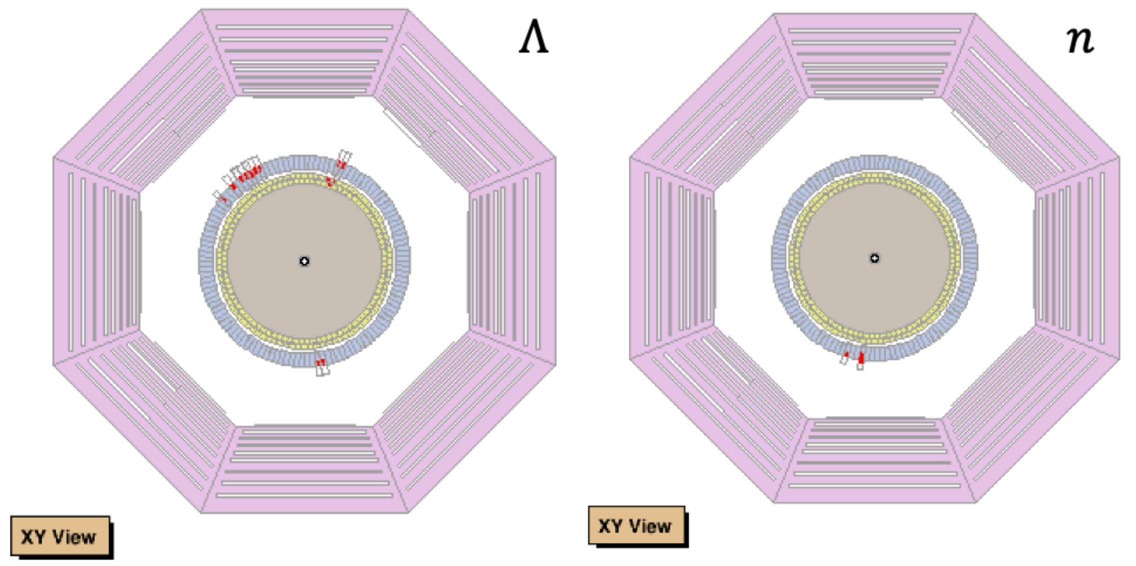
ParticleNet: Beyond Jet Tagging

- The notion of point/particle clouds and GNNs inspired by ParticleNet have found wider applications in HEP

$\Lambda_c^+ \to n e^+ \nu$ search

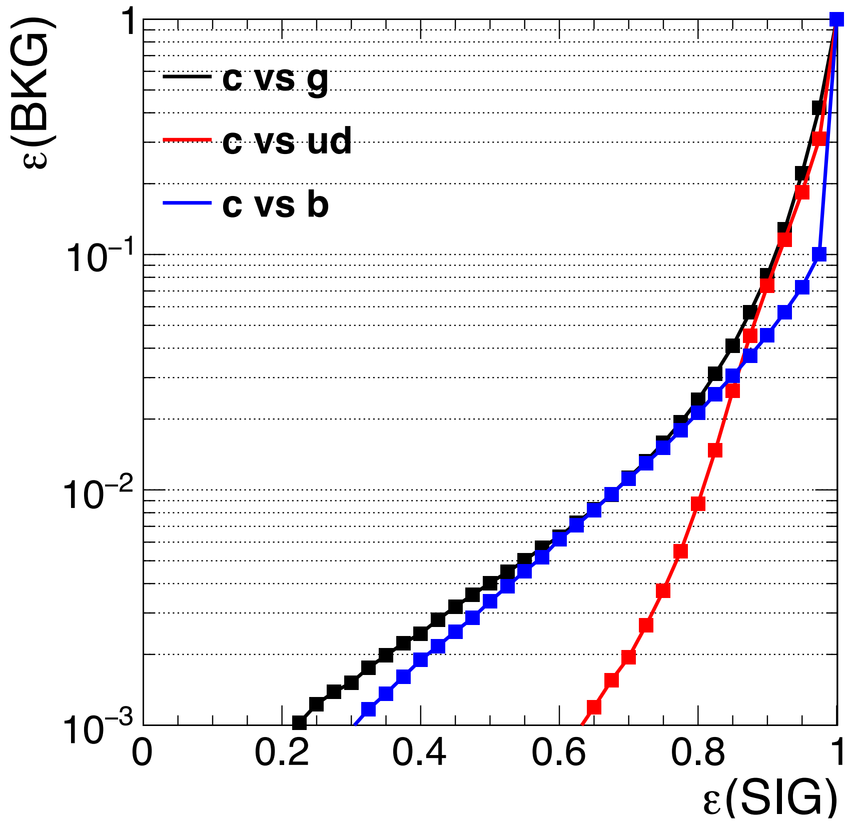
Yunxuan Song, Yangu Li et al.

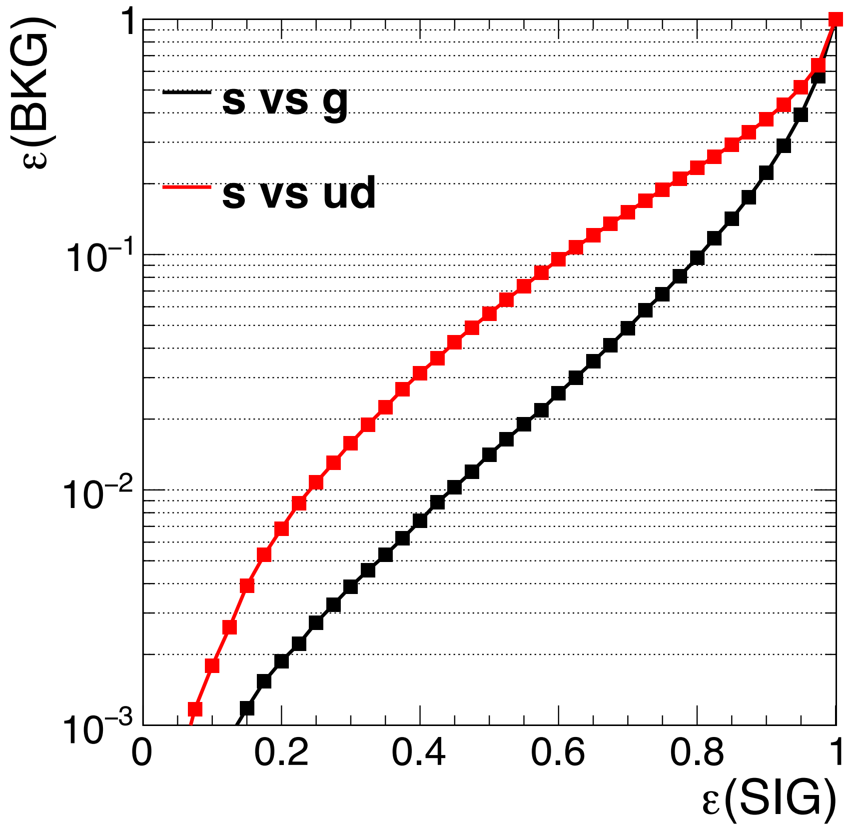




Particle identification

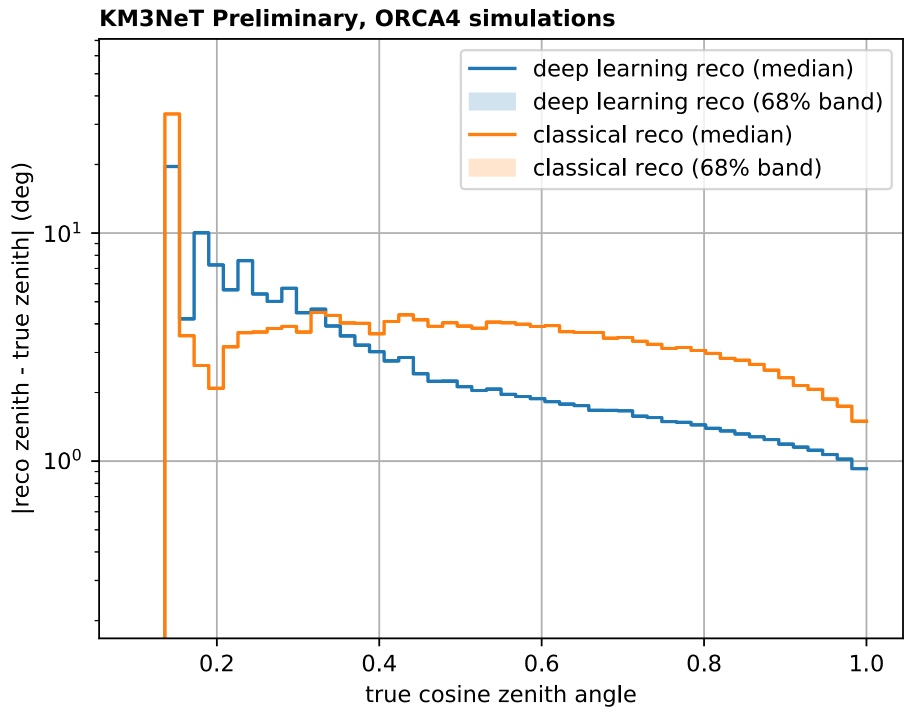
Eur.Phys.J.Plus 137 (2022) 1, 39
Eur.Phys.J.C 82 (2022) 7, 646



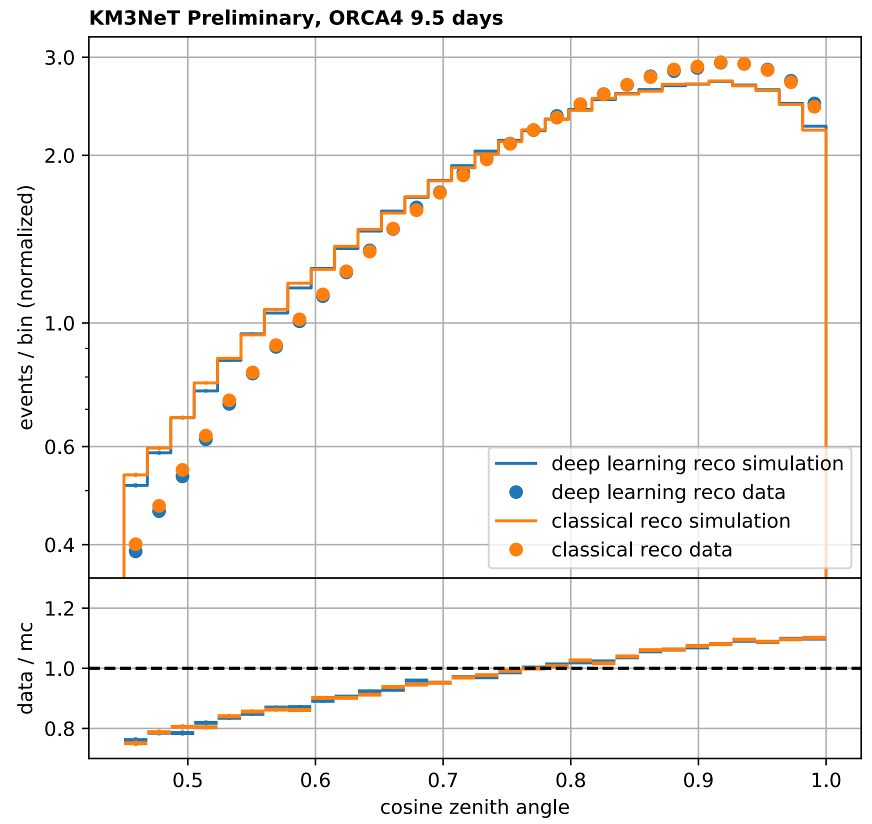


Muon bundle reconstruction

JINST 16 (2021) 10, C10011,
PoS ICRC2021 (2021) 1048

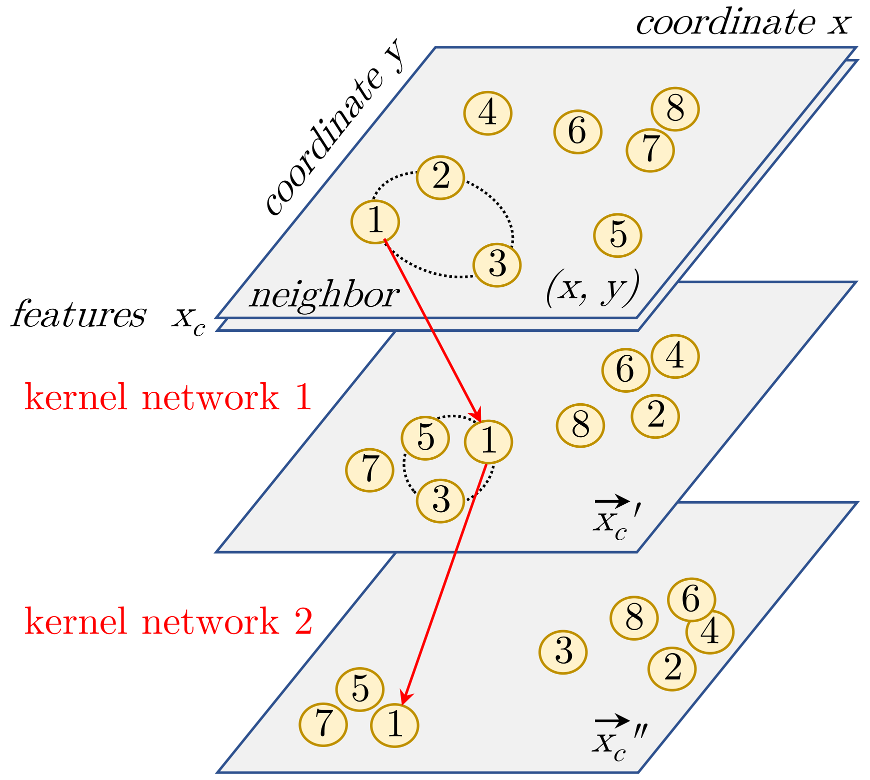


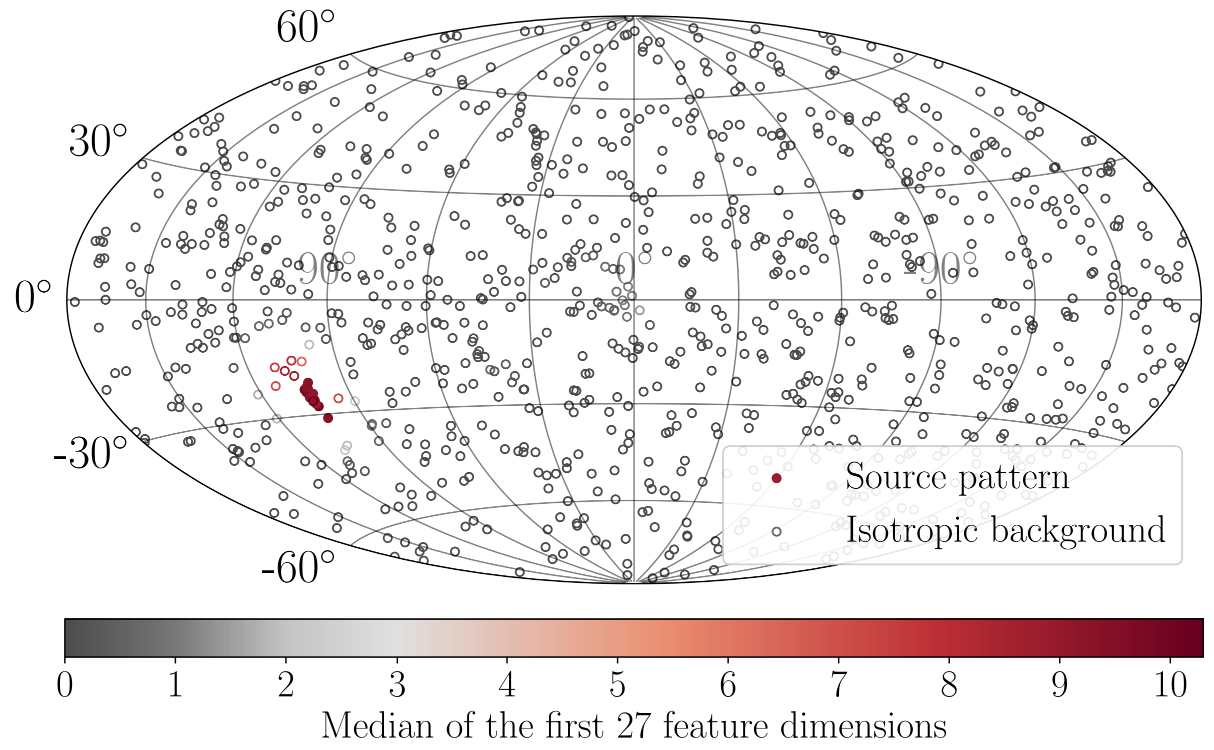
(b) events with two or more muons



Cosmic ray pattern identification

Astropart.Phys. 126 (2021) 102527





Going Beyond

LorentzNet

LORENTZNET

- Incorporating Lorentz symmetry into graph neural network architecture

S. Gong, Q. Meng, J. Zhang, HQ, C. Li, S. Qian, W. Du, Z. M. Ma and T.Y. Liu,
JHEP 07 (2022) 030

Coordinate input: x^0

Feature input: h_i^0

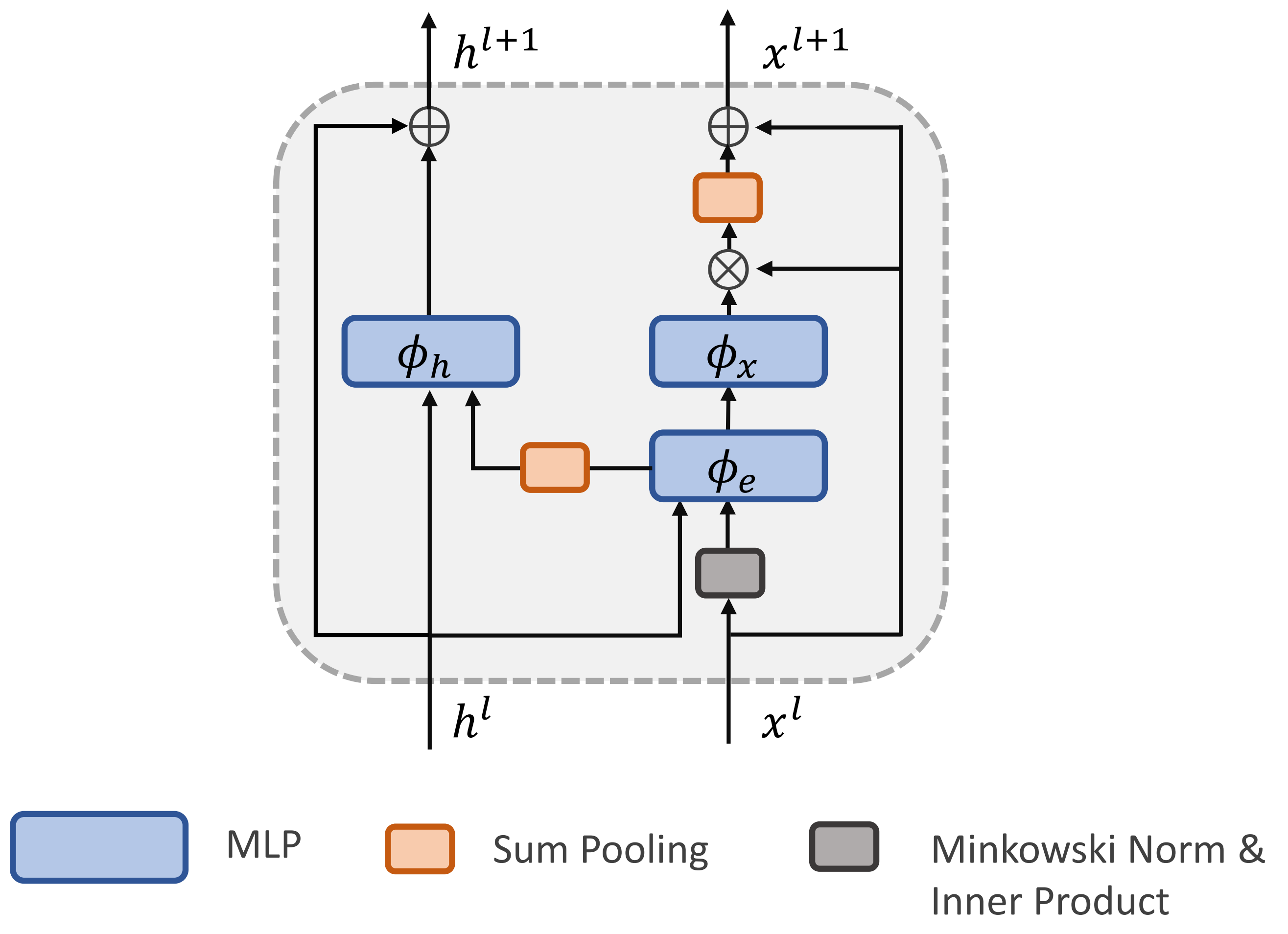
Lorentz 4-vector
Lorentz scalar

Message: $m_{ij}^l = \phi_e\left(h_i^l, h_j^l, \psi(\|x_i^l - x_j^l\|^2), \psi(\langle x_i^l, x_j^l\rangle)\right)$

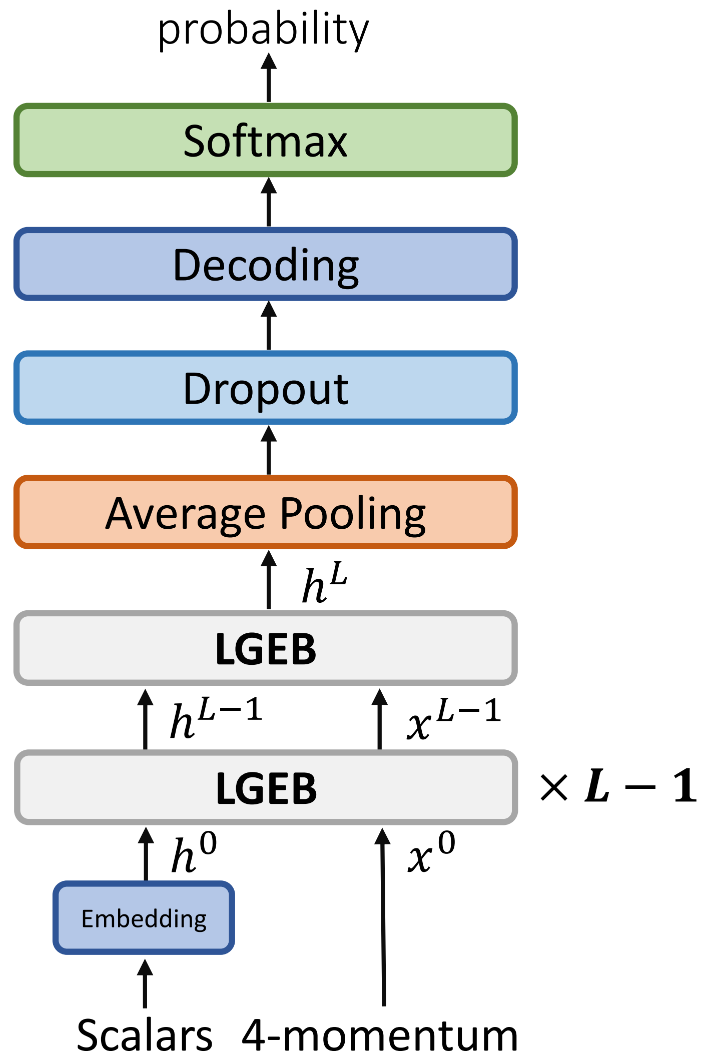
Scalars — Pairwise Lorentz invariants

Coordinate update: $x_i^{l+1} = x_i^l + c \sum_{j\in[N]} \phi_x(m_{ij}^l)\cdot x_j^l$

Feature update: $h_i^{l+1} = h_i^l + \phi_h(h_i^l, \sum_{j\in[N]} w_{ij} m_{ij}^l)$



Lorentz Group Equivariant Block (LGEB)



LorentzNet

cf. A. Bogatskiy, B. Anderson, J. Offermann, M. Roussi, D. Miller and R. Kondor, arXiv: 2006.04780

LorentzNet: Performance

- Significant performance improvement, with fewer trainable parameters

S. Gong, Q. Meng, J. Zhang, HQ, C. Li, S. Qian, W. Du, Z. M. Ma and T.Y. Liu,
JHEP 07 (2022) 030

Performance on top-tagging benchmark [SciPost Phys. 7 (2019) 014]

Model	Accuracy	AUC	$1/\varepsilon_B$ ($\varepsilon_S = 0.5$)	$1/\varepsilon_B$ ($\varepsilon_S = 0.3$)
ResNeXt	0.936	0.9837	302 ± 5	1147 ± 58
P-CNN	0.930	0.9803	201 ± 4	759 ± 24
PFN	0.932	0.9819	247 ± 3	888 ± 17
ParticleNet	0.940	0.9858	397 ± 7	1615 ± 93
EGNN	0.922	0.9760	148 ± 8	540 ± 49
LGN	0.929	0.9640	124 ± 20	435 ± 95
LorentzNet	**0.942**	**0.9868**	$\mathbf{498 \pm 18}$	$\mathbf{2195 \pm 173}$

Model complexity

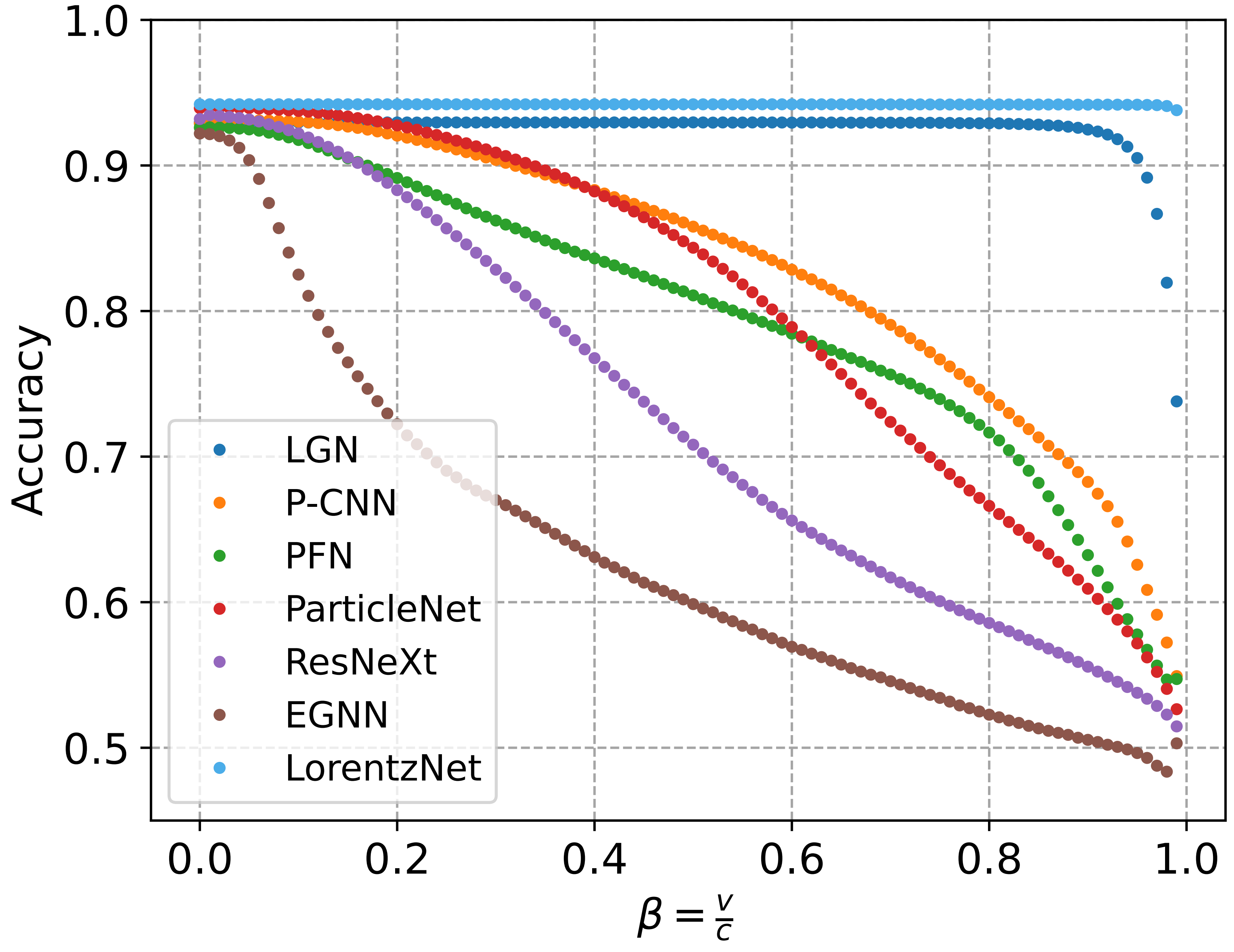
Model	Equivariance	Time on CPU (ms/batch)	Time on GPU (ms/batch)	#Params
ResNeXt	✗	5.5	0.34	1.46M
P-CNN	✗	**0.6**	**0.11**	348k
PFN	✗	**0.6**	0.12	82k
ParticleNet	✗	11.0	0.19	366k
EGNN	E(4)	30.0	0.30	222k
LGN	$SO^+(1,3)$	51.4	1.66	4.5k
LorentzNet	$SO^+(1,3)$	32.9	0.34	224k

LorentzNet: Benefits from Symmetry

S. Gong, Q. Meng, J. Zhang, HQ, C. Li, S. Qian, W. Du, Z. M. Ma and T.Y. Liu, JHEP 07 (2022) 030

- Benefits from the symmetry preservation
  - model response invariant under Lorentz transformation
  - sample efficiency: incorporation of Lorentz symmetry allows to train with very few samples

Model stability under Lorentz boost



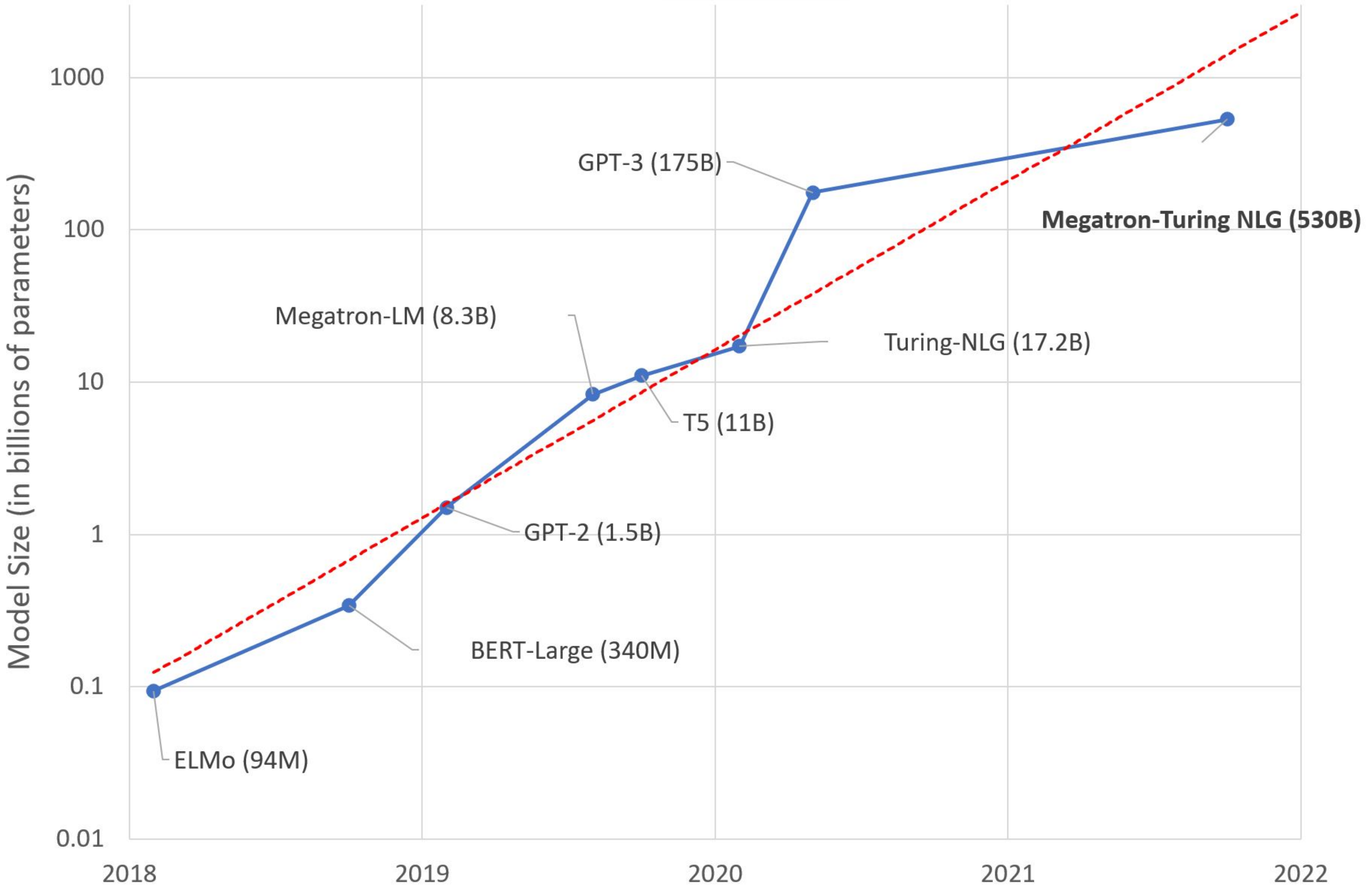
Performance when trained on a fraction of the top-tagging dataset

Training Fraction	Model	Accuracy	AUC	$1/\varepsilon_B$ ($\varepsilon_S = 0.5$)	$1/\varepsilon_B$ ($\varepsilon_S = 0.3$)
0.5% (~6k jets)	ParticleNet	0.913	0.9687	77 ± 4	199 ± 14
	LorentzNet	**0.929**	**0.9793**	$\mathbf{176 \pm 14}$	$\mathbf{562 \pm 72}$
1%	ParticleNet	0.919	0.9734	103 ± 5	287 ± 19
	LorentzNet	**0.932**	**0.9812**	$\mathbf{209 \pm 5}$	$\mathbf{697 \pm 58}$
5%	ParticleNet	0.931	0.9807	195 ± 4	609 ± 35
	LorentzNet	**0.937**	**0.9839**	$\mathbf{293 \pm 12}$	$\mathbf{1108 \pm 84}$

Particle Transformer

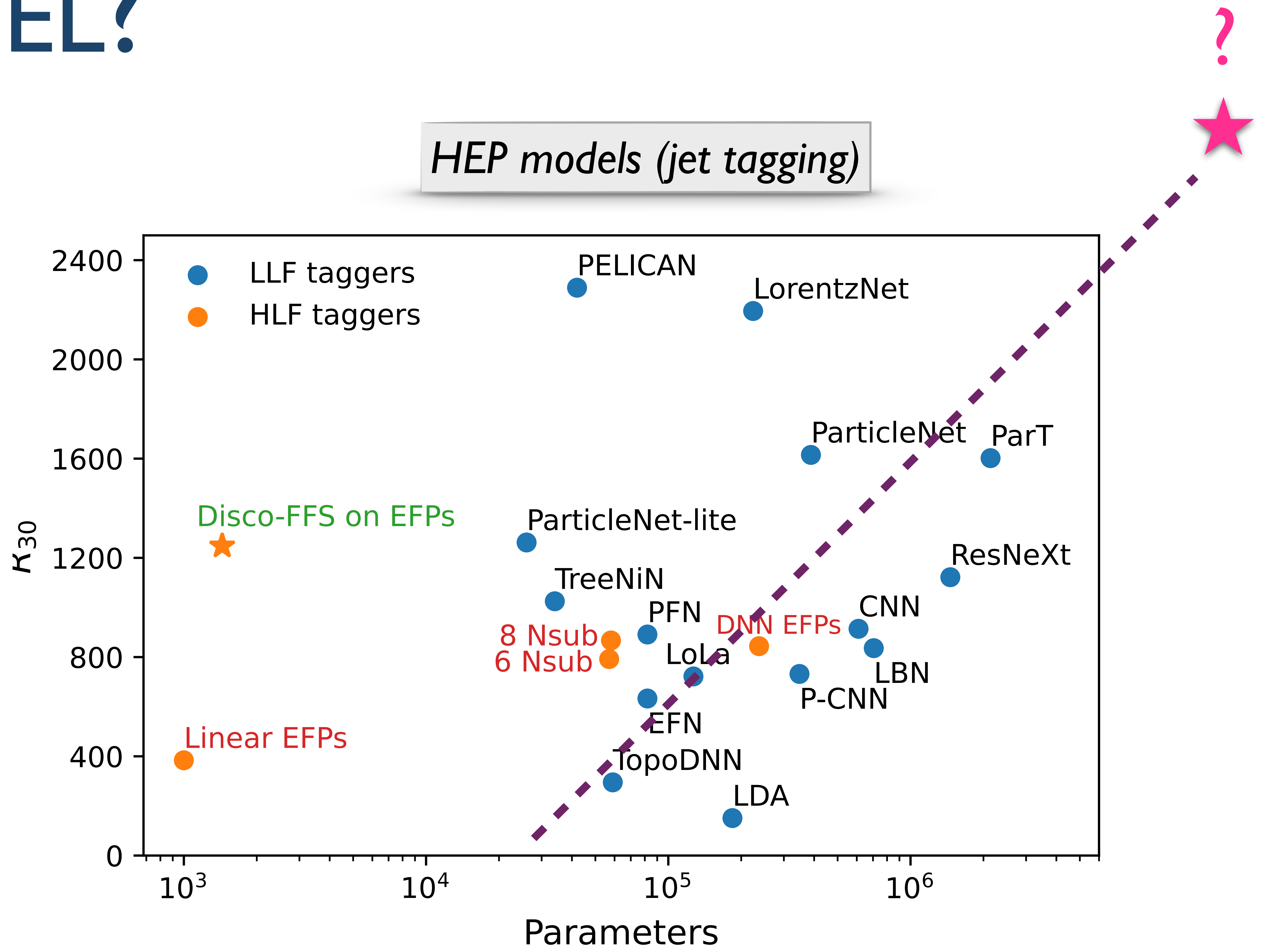
LARGE PHYSICS MODEL?

Natural language models



https://huggingface.co/blog/large-language-models

HEP models (jet tagging)



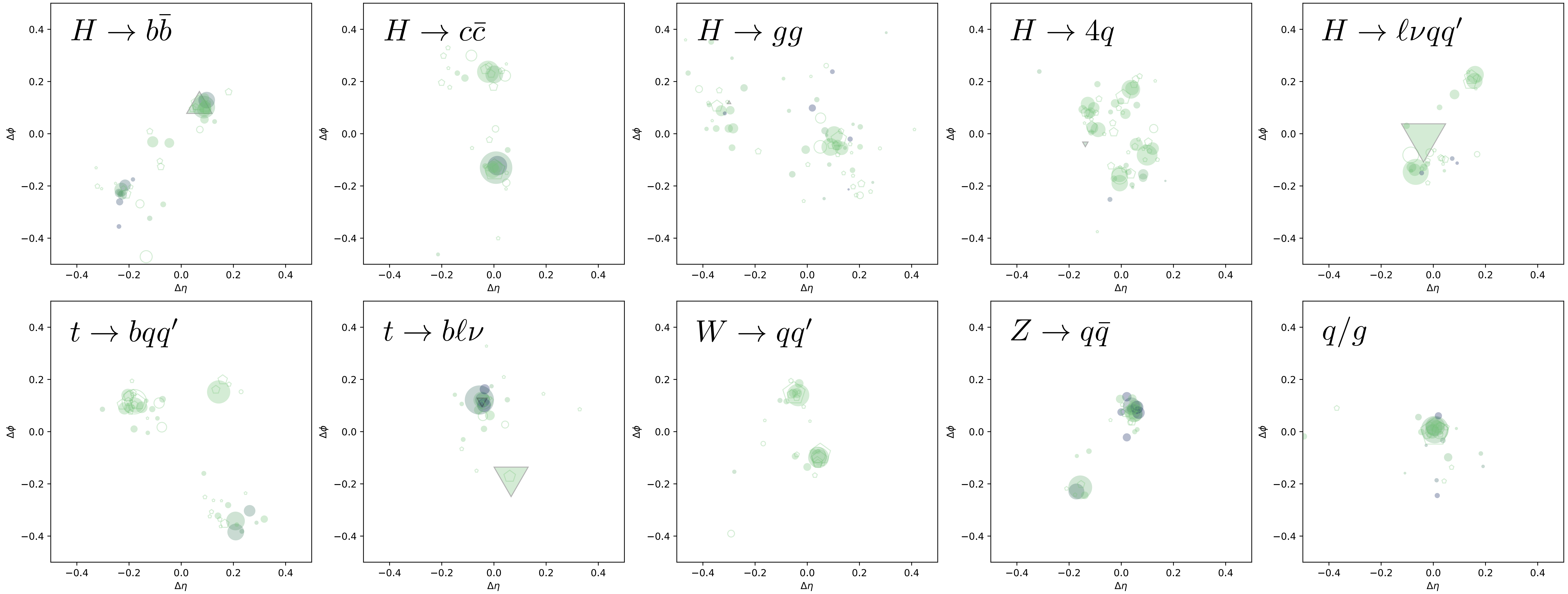
R. Das, G. Kasieczka and D. Shih, arXiv: 2212.00046

Large Language Models (like GPT) has transformed NLP.
What if a Large Physics Model?

A First Step

HQ, C. Li, S. Qian, ICML 2022

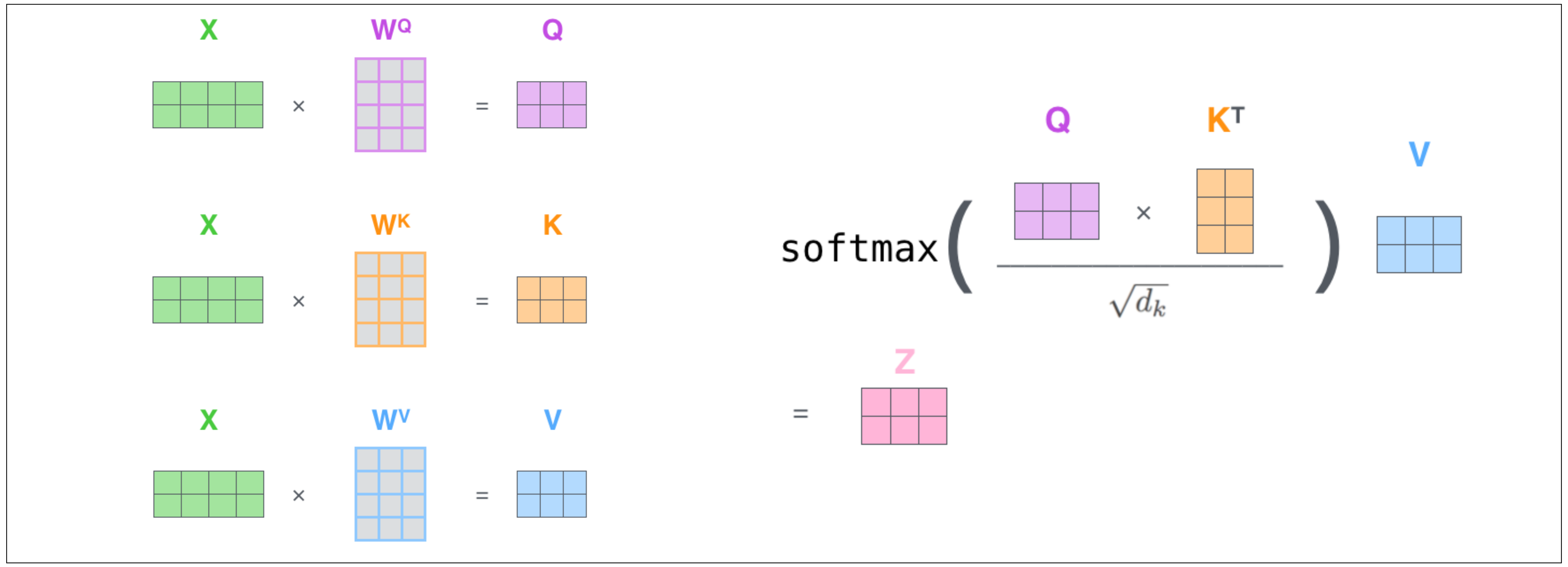
- **JetClass**: a new large and comprehensive jet simulation dataset
  - 100M jets in 10 classes: ~two orders of magnitude larger than existing public datasets

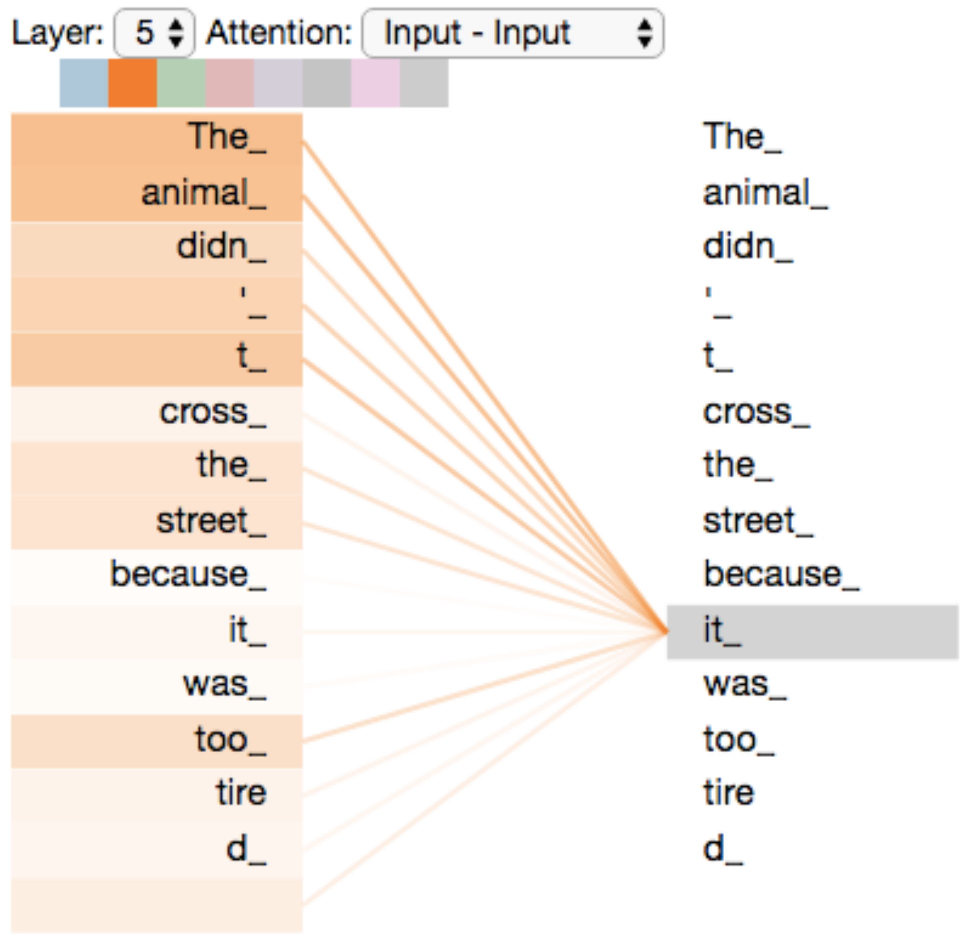


We invite the community to explore and experiment with this dataset and extend the boundary of deep learning and HEP even further.

PARTICLE TRANSFORMER

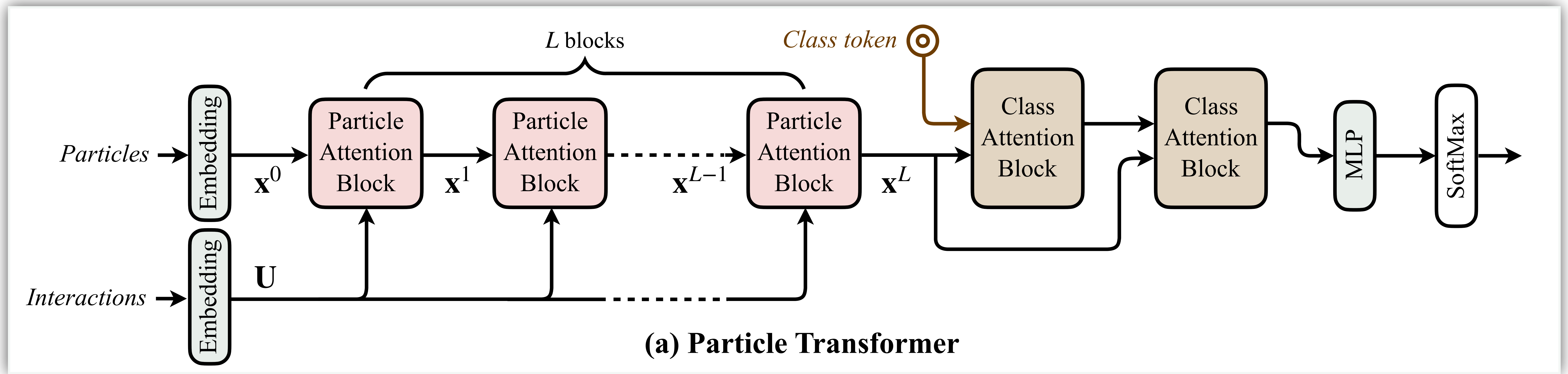
- **Transformers**: the new state-of-the-art architecture in ML – foundation of LLM like BERT/GPT
  - core concept: self-attention mechanism





- **Particle Transformer** (ParT): Transformer model **tailored for particle physics**

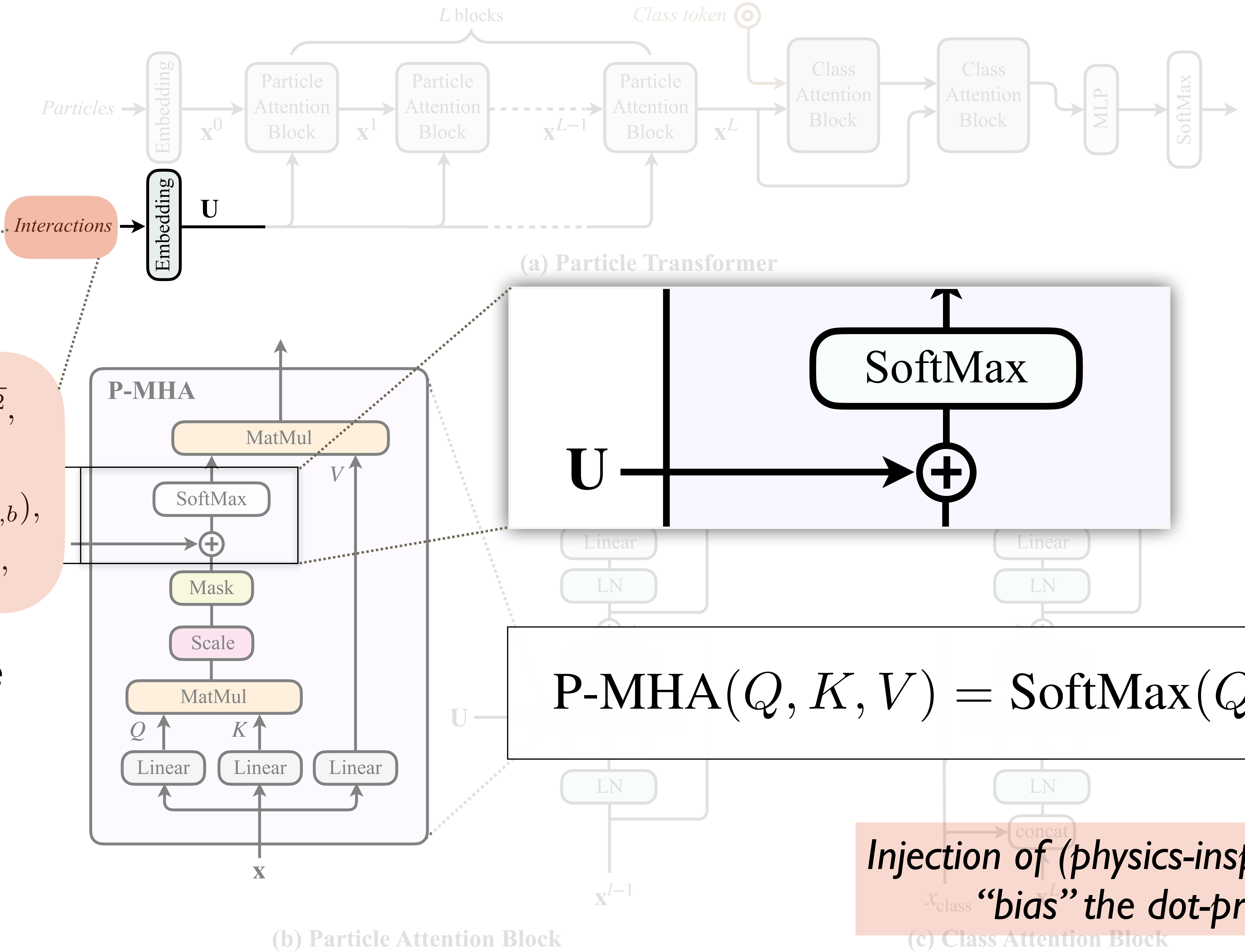
HQ, C. Li, S. Qian, ICML 2022



(a) Particle Transformer

Particle Transformer: Architecture

HQ, C. Li, S. Qian, ICML 2022



$$\Delta = \sqrt{(y_a - y_b)^2 + (\phi_a - \phi_b)^2},$$
$$k_\mathrm{T} = \min(p_{\mathrm{T},a}, p_{\mathrm{T},b})\Delta,$$
$$z = \min(p_{\mathrm{T},a}, p_{\mathrm{T},b})/(p_{\mathrm{T},a} + p_{\mathrm{T},b}),$$
$$m^2 = (E_a + E_b)^2 - \|\mathbf{p}_a + \mathbf{p}_b\|^2,$$

and many other possible pairwise features…

$$\text{P-MHA}(Q, K, V) = \mathrm{SoftMax}(QK^T/\sqrt{d_k} + \mathbf{U})V,$$

Injection of (physics-inspired) pairwise features to "bias" the dot-product self-attention

PARTICLE TRANSFORMER: PERFORMANCE

	All classes		$H \to b\bar{b}$	$H \to c\bar{c}$	$H \to gg$	$H \to 4q$	$H \to \ell\nu qq'$	$t \to bqq'$	$t \to b\ell\nu$	$W \to qq'$	$Z \to q\bar{q}$
	Accuracy	AUC	$\mathrm{Rej}_{50\%}$	$\mathrm{Rej}_{50\%}$	$\mathrm{Rej}_{50\%}$	$\mathrm{Rej}_{50\%}$	$\mathrm{Rej}_{99\%}$	$\mathrm{Rej}_{50\%}$	$\mathrm{Rej}_{99.5\%}$	$\mathrm{Rej}_{50\%}$	$\mathrm{Rej}_{50\%}$
PFN	0.772	0.9714	2924	841	75	198	265	797	721	189	159
P-CNN	0.809	0.9789	4890	1276	88	474	947	2907	2304	241	204
ParticleNet	0.844	0.9849	7634	2475	104	954	3339	10526	11173	347	283
ParT	**0.861**	**0.9877**	**10638**	**4149**	**123**	**1864**	**5479**	**32787**	**15873**	**543**	**402**
ParT (plain)	0.849	0.9859	9569	2911	112	1185	3868	17699	12987	384	311

JETCLASS dataset (100M jets)

- Particle Transformer (ParT): significant performance improvement!
  - compared to the existing state-of-the-art, ParticleNet
    - 1.7% increase in accuracy
    - **up to 3x increase in background rejection** ($\mathrm{Rej}_{X\%}$)

$$\mathrm{Rej}_{X\%} \equiv 1/\mathrm{FPR} \text{ at TPR} = X\%,$$

Particle Transformer: Performance

	All classes Accuracy	AUC	$H \to b\bar{b}$ Rej$_{50\%}$	$H \to c\bar{c}$ Rej$_{50\%}$	$H \to gg$ Rej$_{50\%}$	$H \to 4q$ Rej$_{50\%}$	$H \to \ell\nu qq'$ Rej$_{99\%}$	$t \to bqq'$ Rej$_{50\%}$	$t \to b\ell\nu$ Rej$_{99.5\%}$	$W \to qq'$ Rej$_{50\%}$	$Z \to q\bar{q}$ Rej$_{50\%}$
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JetClass dataset (100M jets)

- Particle Transformer (ParT): significant performance improvement!
  - compared to the existing state-of-the-art, ParticleNet
    - 1.7% increase in accuracy
    - **up to 3x increase in background rejection** (Rej$_{X\%}$)
- ParT (plain): plain Transformer w/o interaction features
  - 1.2% drop in accuracy compared to full ParT
  - **Physics-driven modification of self-attention plays a key role!**

Model complexity

	Accuracy	# params	FLOPs
PFN	0.772	86.1 k	4.62 M
P-CNN	0.809	354 k	15.5 M
ParticleNet	0.844	370 k	540 M
ParT	**0.861**	2.14 M	340 M
ParT (plain)	0.849	2.13 M	260 M

Particle Transformer: Pre-Training + Fine-Tuning

- The large Transformer-based model enables new training paradigm
  - (supervised) pre-training on a large dataset (e.g., JetClass) & fine-tuning to downstream tasks
  - significantly outperforms existing models

Top quark tagging benchmark (~2M jets) [SciPost Phys. 7 (2019) 014]

	Accuracy	AUC	$\mathrm{Rej}_{50\%}$	$\mathrm{Rej}_{30\%}$
P-CNN	0.930	0.9803	201 ± 4	759 ± 24
PFN	—	0.9819	247 ± 3	888 ± 17
ParticleNet	0.940	0.9858	397 ± 7	1615 ± 93
JEDI-net (w/ $\sum O$)	0.930	0.9807	—	774.6
PCT	0.940	0.9855	392 ± 7	1533 ± 101
LGN	0.929	0.964	—	435 ± 95
rPCN	—	0.9845	364 ± 9	1642 ± 93
LorentzNet	0.942	0.9868	498 ± 18	2195 ± 173
ParT	0.940	0.9858	413 ± 16	1602 ± 81
ParticleNet-f.t.	0.942	0.9866	487 ± 9	1771 ± 80
ParT-f.t.	**0.944**	**0.9877**	$\mathbf{691 \pm 15}$	$\mathbf{2766 \pm 130}$

Quark-gluon tagging benchmark (~2M jets) [JHEP 01 (2019) 121]

	Accuracy	AUC	$\mathrm{Rej}_{50\%}$	$\mathrm{Rej}_{30\%}$
$\mathrm{P\text{-}CNN}_{\mathrm{exp}}$	0.827	0.9002	34.7	91.0
$\mathrm{PFN}_{\mathrm{exp}}$	—	0.9005	34.7 ± 0.4	—
$\mathrm{ParticleNet}_{\mathrm{exp}}$	0.840	0.9116	39.8 ± 0.2	98.6 ± 1.3
$\mathrm{rPCN}_{\mathrm{exp}}$	—	0.9081	38.6 ± 0.5	—
$\mathrm{ParT}_{\mathrm{exp}}$	0.840	0.9121	41.3 ± 0.3	101.2 ± 1.1
$\mathrm{ParticleNet\text{-}f.t.}_{\mathrm{exp}}$	0.839	0.9115	40.1 ± 0.2	100.3 ± 1.0
$\mathbf{ParT\text{-}f.t.}_{\mathbf{exp}}$	**0.843**	**0.9151**	$\mathbf{42.4 \pm 0.2}$	$\mathbf{107.9 \pm 0.5}$
$\mathrm{PFN}_{\mathrm{full}}$	—	0.9052	37.4 ± 0.7	—
$\mathrm{ABCNet}_{\mathrm{full}}$	0.840	0.9126	42.6 ± 0.4	118.4 ± 1.5
$\mathrm{PCT}_{\mathrm{full}}$	0.841	0.9140	43.2 ± 0.7	118.0 ± 2.2
$\mathrm{LorentzNet}_{\mathrm{full}}$	0.844	0.9156	42.4 ± 0.4	110.2 ± 1.3
$\mathrm{ParT}_{\mathrm{full}}$	0.849	0.9203	47.9 ± 0.5	129.5 ± 0.9
$\mathbf{ParT\text{-}f.t.}_{\mathbf{full}}$	**0.852**	**0.9230**	$\mathbf{50.6 \pm 0.2}$	$\mathbf{138.7 \pm 1.3}$

Summary & Outlook

SUMMARY & OUTLOOK

- The rise of deep learning has brought lots of progress in jet physics
  - new approaches, particularly graph neural networks, significantly improved the jet tagging performance
  - leads to substantial increase in the physics reach at the LHC
- Towards the future
  - pushing the performance even further
    - new (physics-inspired) architectures: graph networks, Transformers, ...
    - training strategy: end-to-end training => supervised pre-training => un-/semi-/self-supervised training (on real data)?
  - increasing the robustness and controlling the systematics
    - robust architectures and training schemes
    - improvements in the simulation
  - beyond classification:
    - representation learning? anomaly detection? ...
    - JetClass: a large-scale open dataset to explore
- **Your innovation and creativity can make a big difference!**

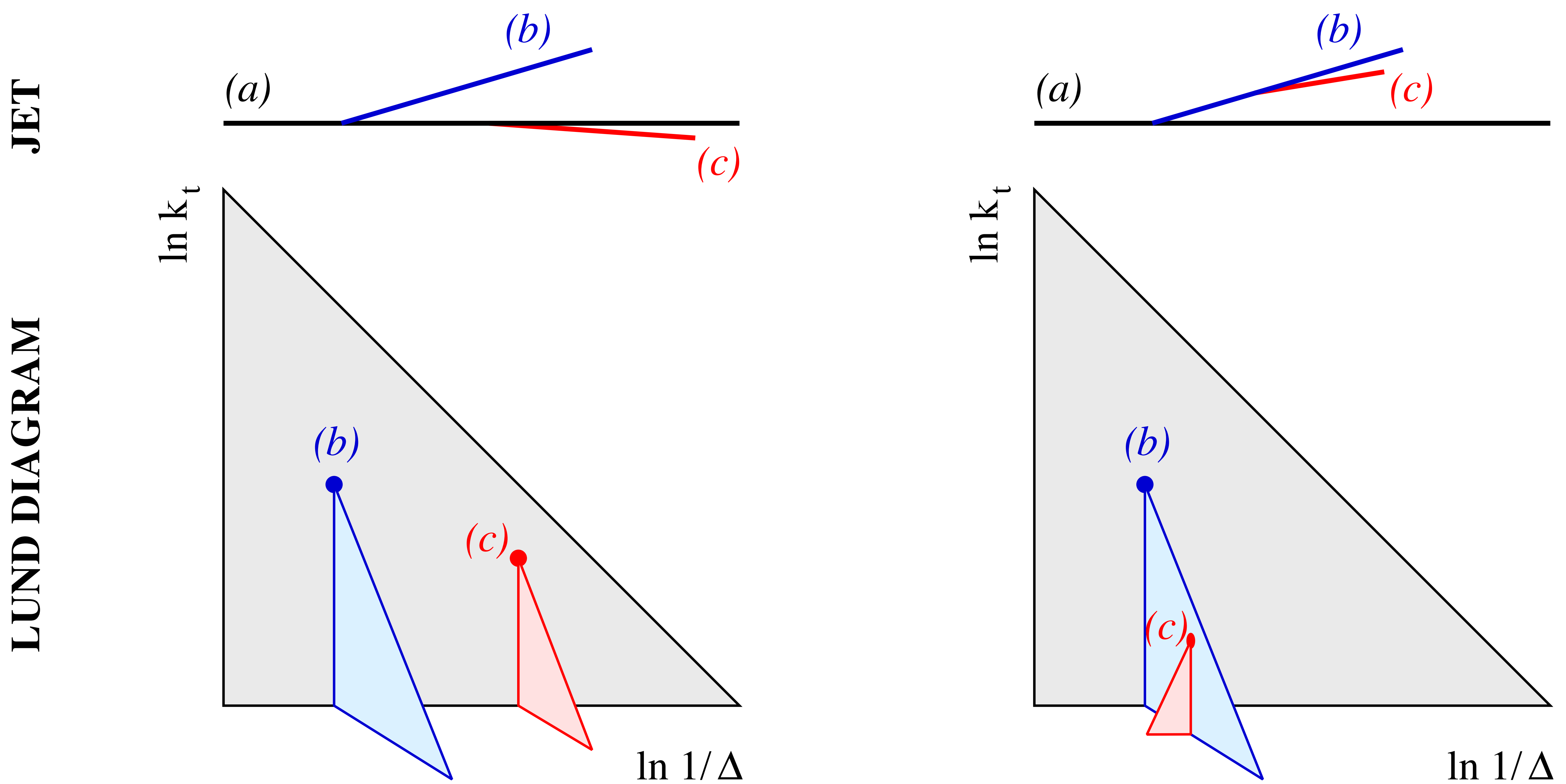
BACKUPS

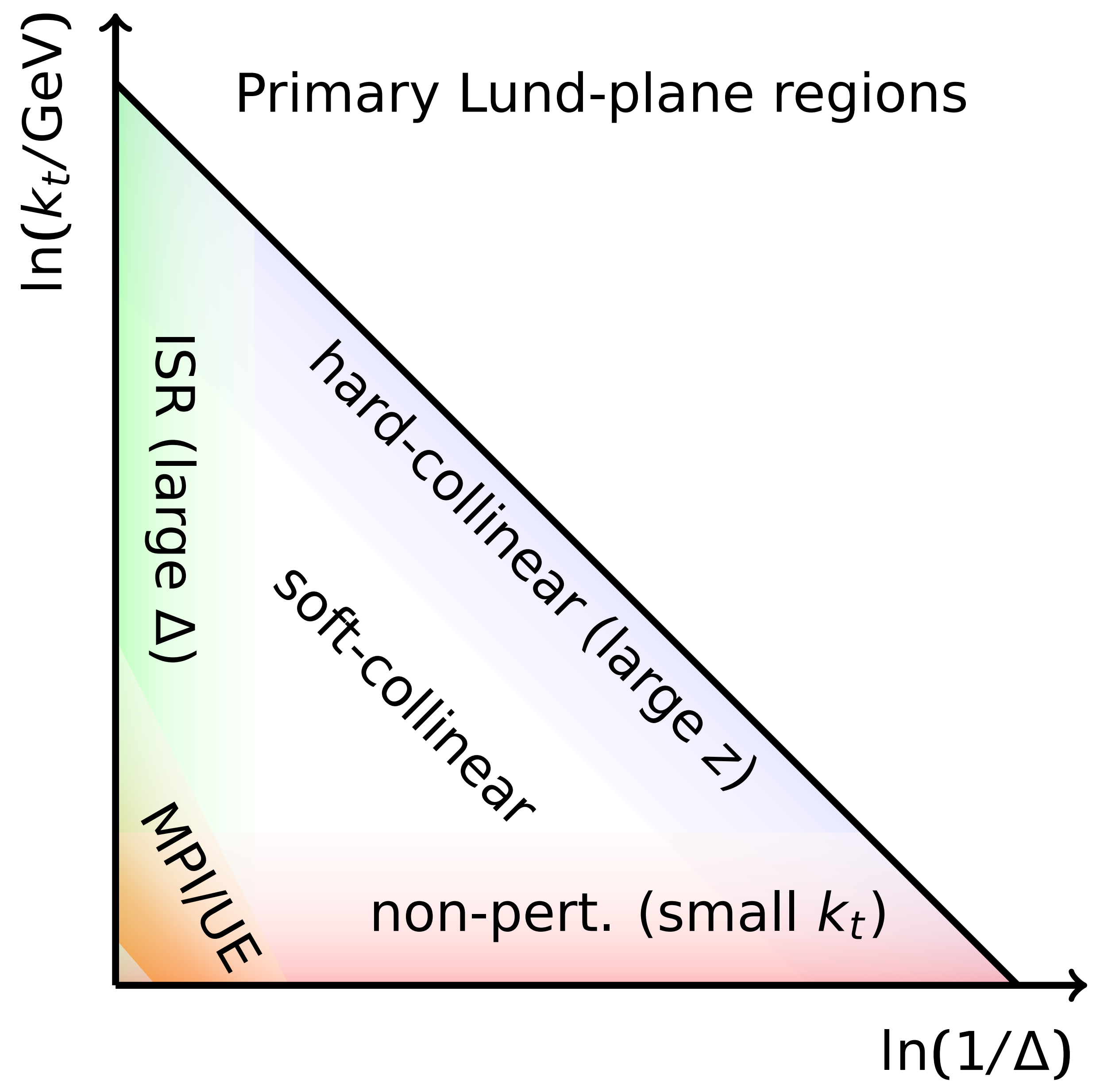
LundNet

JETS IN THE LUND PLANE

F. Dreyer, G. Salam and G. Soyez, JHEP 12 (2018) 064

- The Lund jet plane provides an efficient description of the radiation patterns within a jet



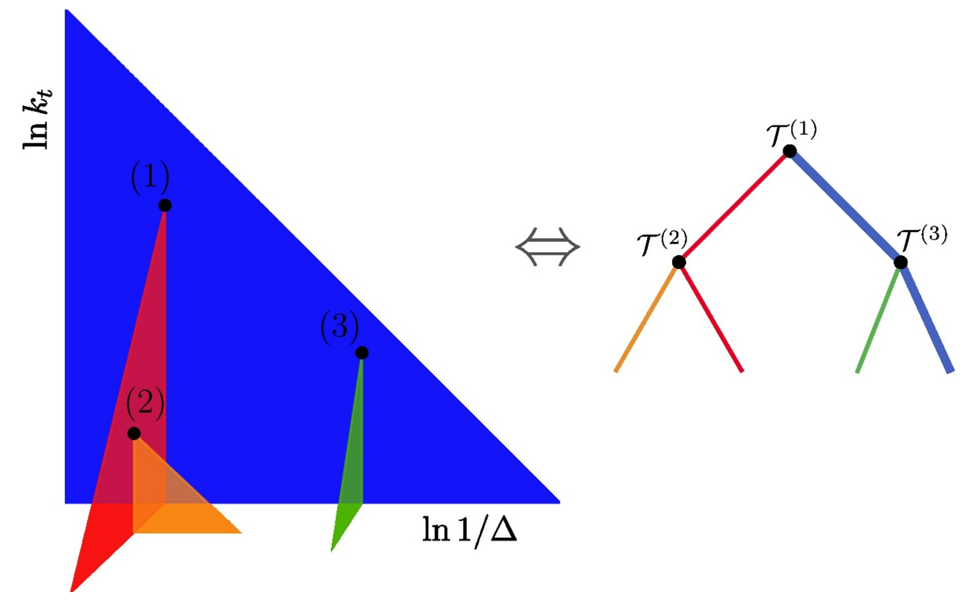


- each emission (splitting) is mapped to a point in the 2D (angle, transverse momentum) plane
  - further emissions (of the secondary particles) are represented in additional leaf planes
- different kinematic regimes are clearly separated in the Lund plane
- a natural input for ML algorithms on jets since it essentially encodes the full radiation patterns of a jet

LundNet

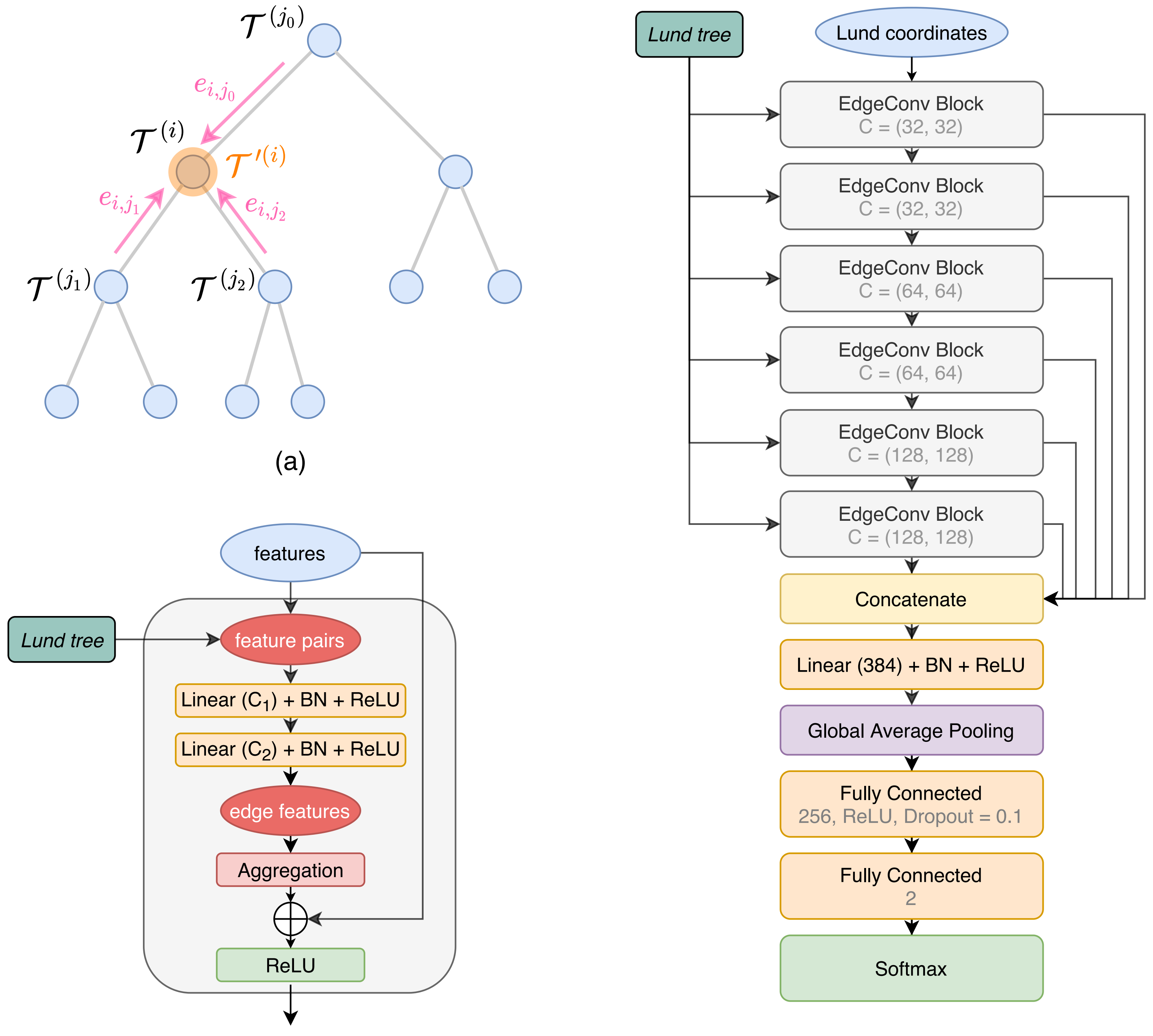
F. Dreyer and H. Qu, JHEP 03 (2021) 052

- LundNet: a graph neural network based on the Lund jet plane
  - technically, the input is a binary tree (from Cambridge/Aachen clustering)
    - equivalent to the **full** Lund plane
  - each node corresponds to an emission
    - a set of variables are be defined for the current splitting



$$\Delta^2 = (y_a - y_b)^2 + (\phi_a - \phi_b)^2, \quad k_t \equiv p_{tb}\Delta_{ab}, \quad m^2 \equiv (p_a + p_b)^2,$$
$$z \equiv \frac{p_{tb}}{p_{ta}+p_{tb}}, \quad \kappa \equiv z\Delta\,, \quad \psi \equiv \tan^{-1}\frac{y_b - y_a}{\phi_b - \phi_a},$$

- Similar network architecture as ParticleNet
  - but the graph structure is fixed by the Lund tree
    - instead of the (dynamic) k-nearest neighbors
- Two variants of LundNet studied
  - LundNet-5: using all five Lund variables, $(\ln k_t, \ln\Delta, \ln z, \ln m, \psi)$
  - LundNet-3: using only three Lund variables, $(\ln k_t, \ln\Delta, \ln z)$

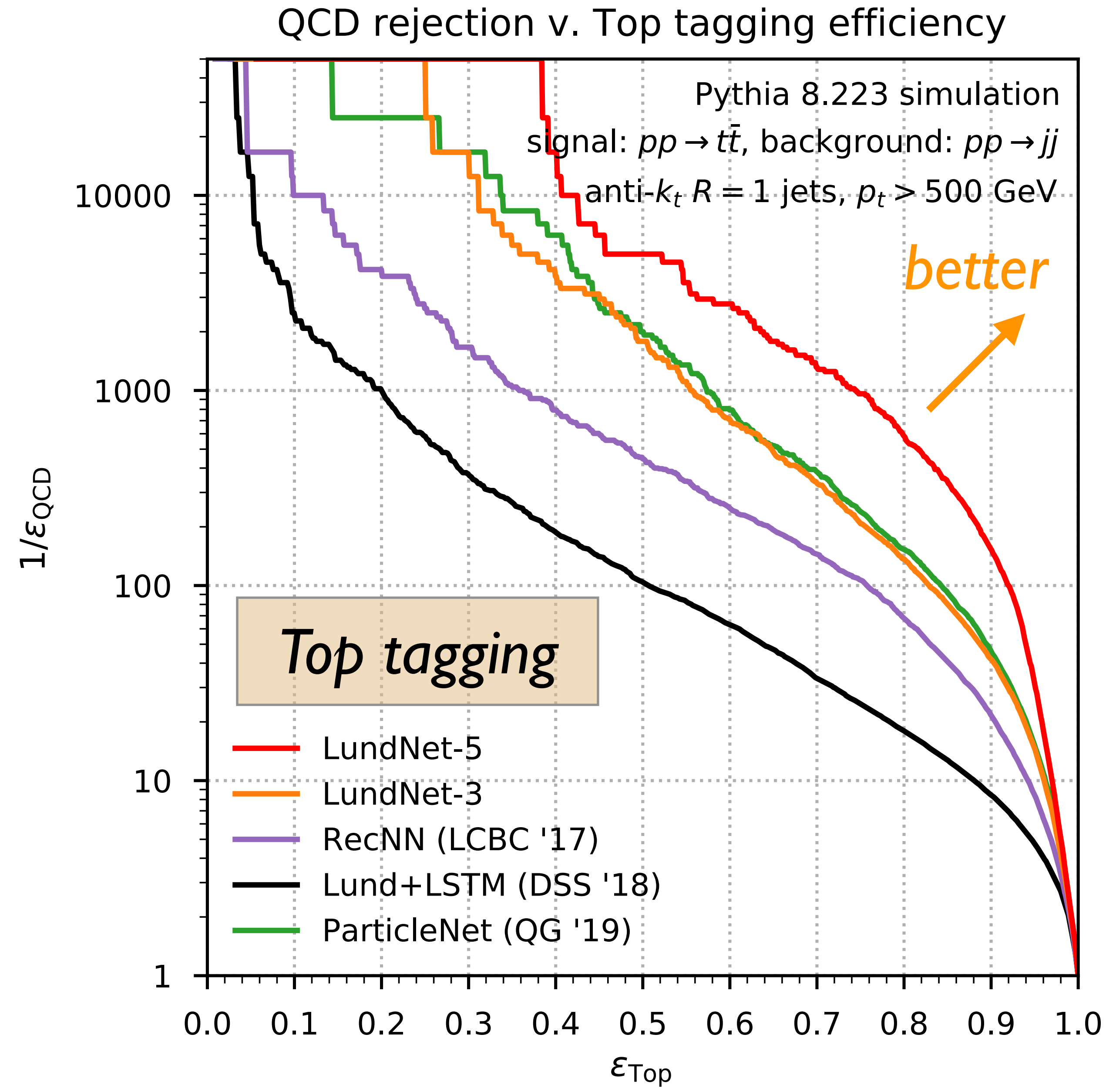


(a) (b) (c)

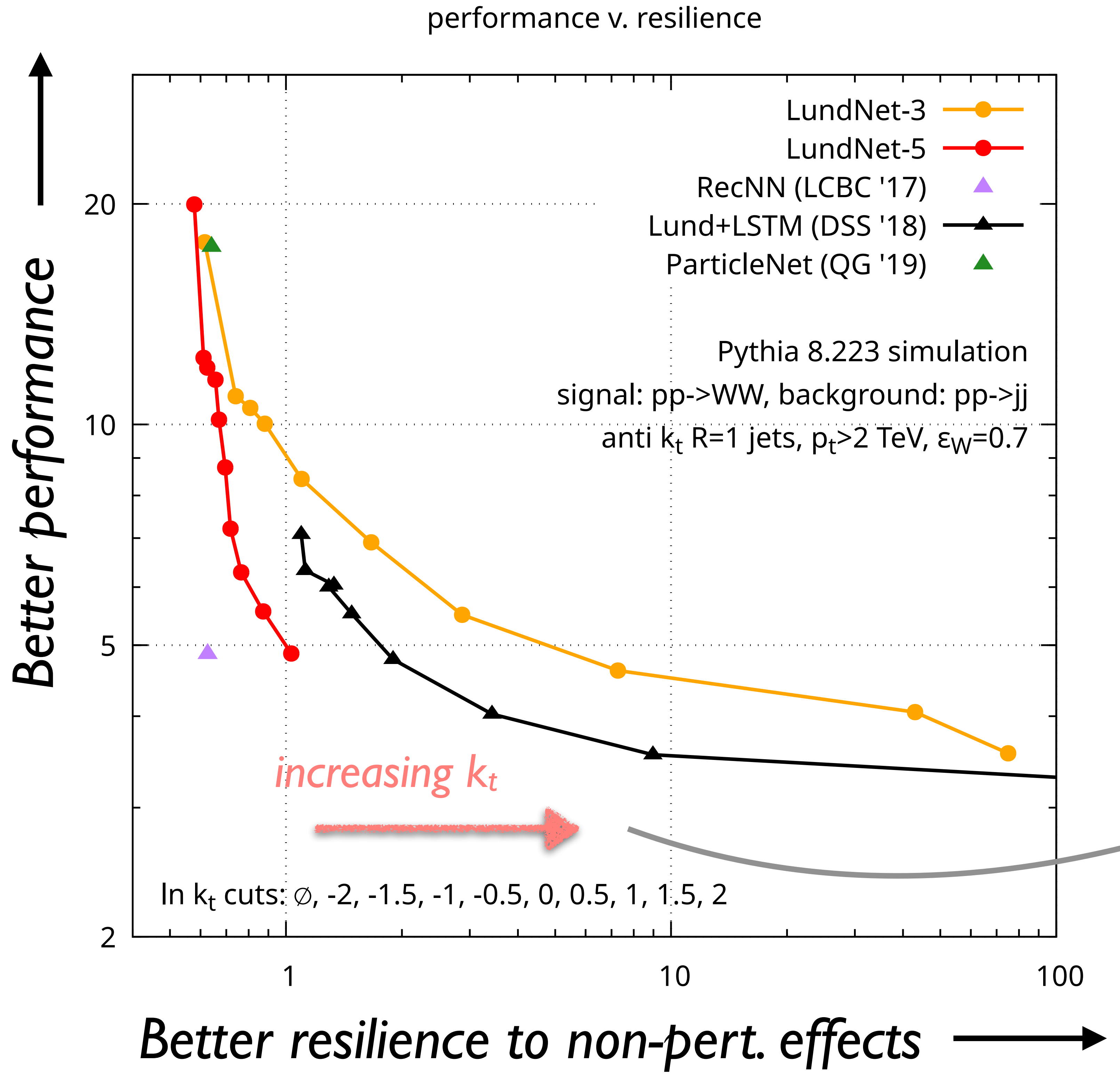
LundNet: Performance

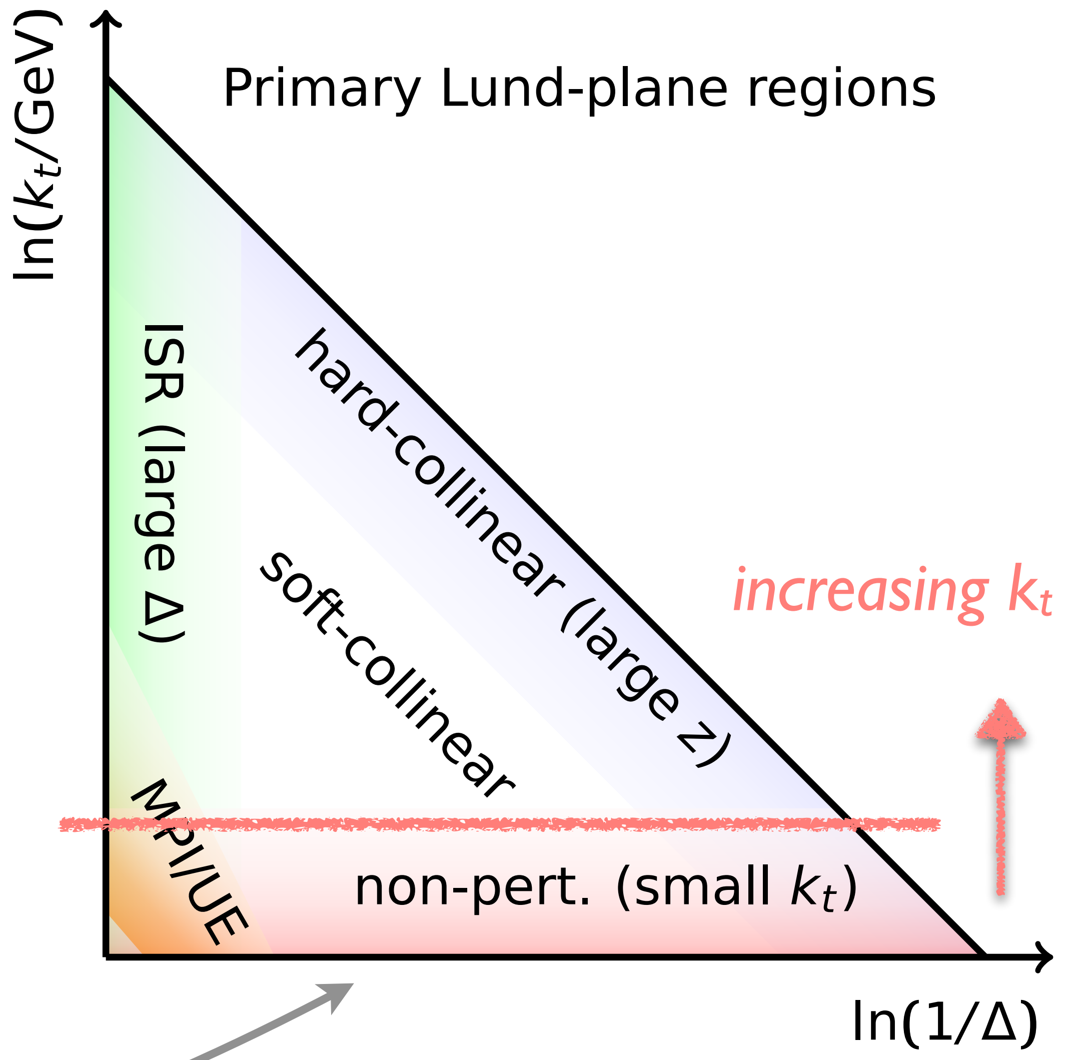
F. Dreyer and H. Qu,
JHEP 03 (2021) 052

- LundNet achieves very high performance at significant lower computational cost than ParticleNet
  - due to fewer number of neighbors in a binary tree & static graph structure
- Moreover, LundNet provides a systematic way to control the robustness of the tagger
  - the non-perturbative region can be effectively rejected by applying a k_t cut on the Lund plane



	Number of parameters	Training time [ms/sample/epoch]	Inference time [ms/sample]
LundNet	395k	0.472	0.117
ParticleNet	369k	3.488	1.036
Lund+LSTM	67k	0.424	0.131



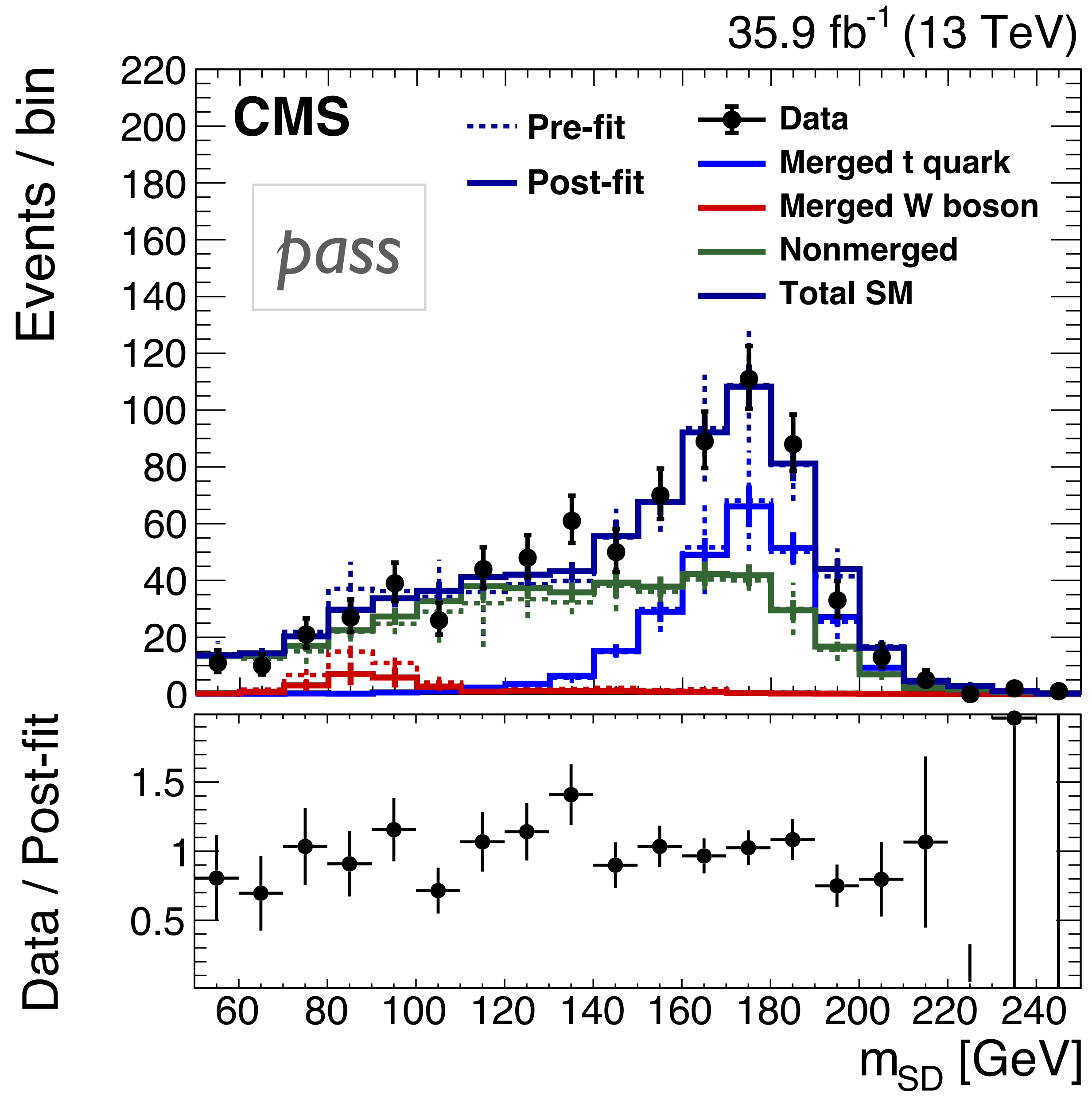


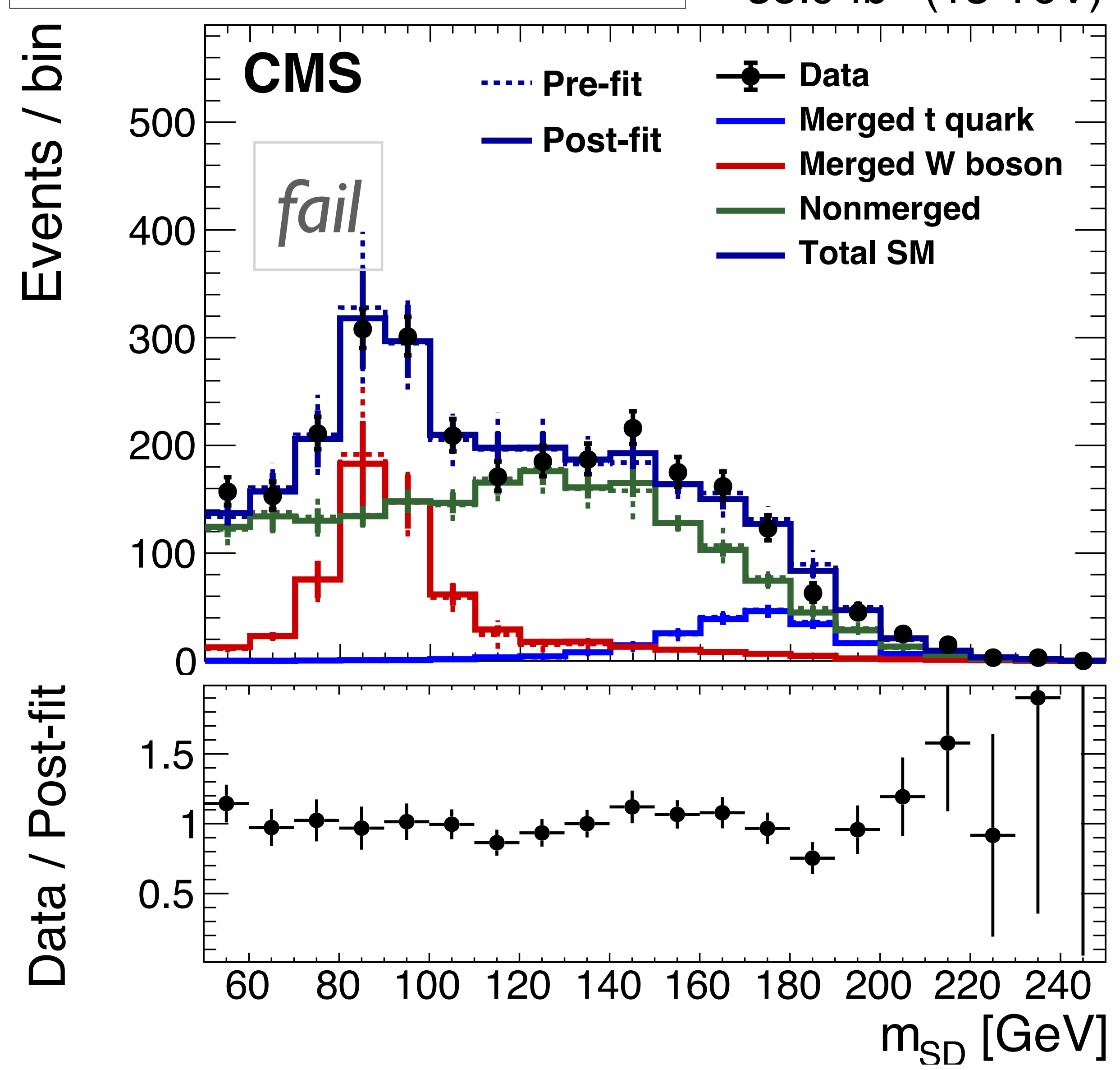
* Resilience assessed by applying the model trained on hadron-level samples to parton-level samples and compare the difference

Tagger Calibration in Data

- Crucial to calibrate these taggers in real data for them to be used in analyses
- Top/W tagging efficiency

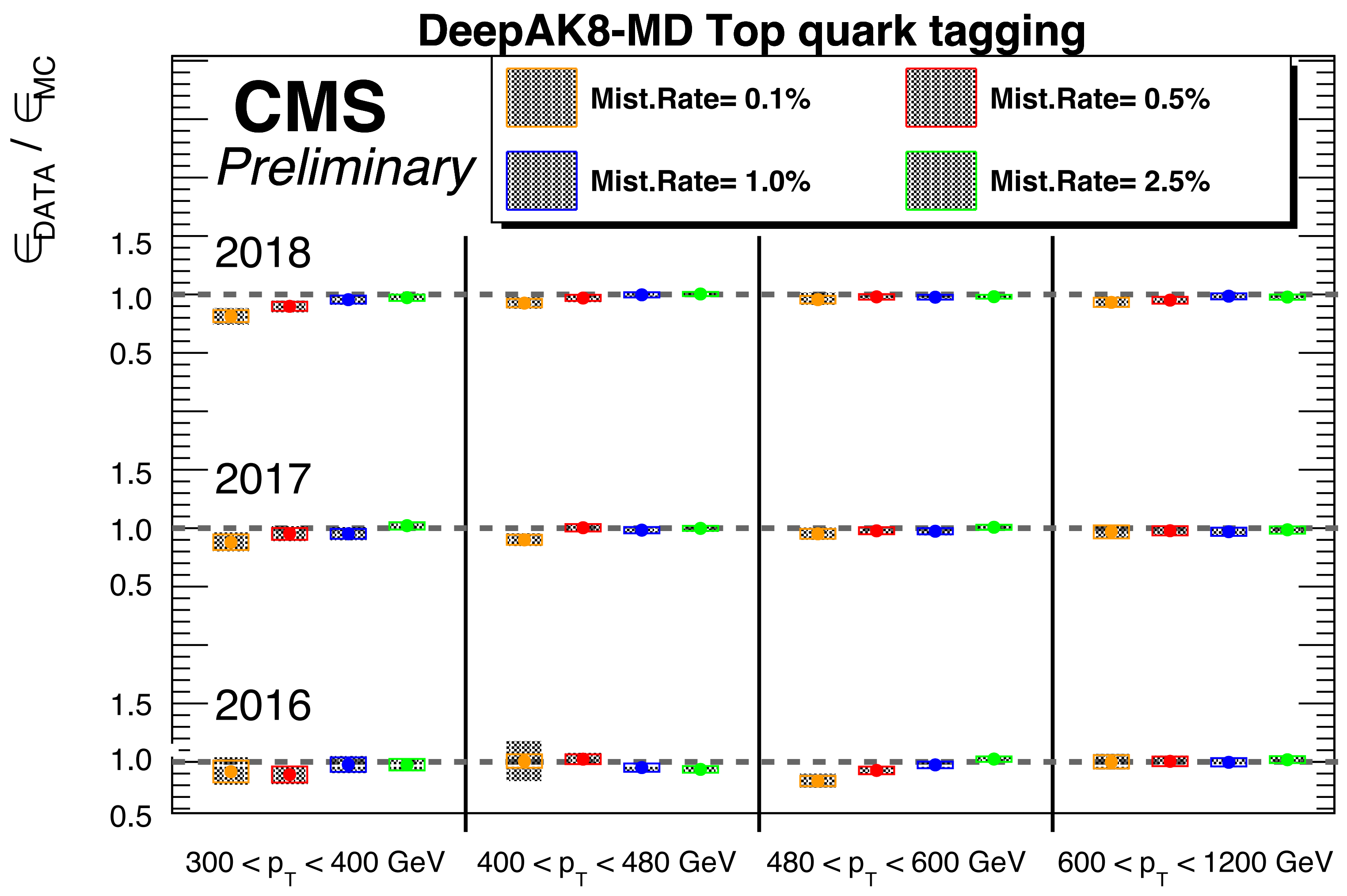
JINST 15 (2020) P06005





Top tagging: DeepAK8-MD

CMS DP-2020/025



  - measured using the single-μ sample enriched in semi-leptonic ttbar events
  - fit jet mass templates in the “pass” and “fail” categories simultaneously to extract efficiency in data
    - simulation-to-data scale factors SF := eff(data) / eff(MC) derived to correct the simulation
  - jet mass scale and resolution scale factors can also be extracted
- Mistag rates of background jet typically derived directly from analysis-specific control regions

Calibration of the cc-tagger

- Need to measure ParticleNet cc-tagging efficiency in data
  - no pure sample of H → cc jets (or even Z → cc) in data
  - using g → cc in QCD multi-jet events as a proxy
- Difficulty: select a phase-space in g → cc that resembles H → cc
  - solution: a **dedicated BDT** developed to distinguish **hard 2-prong splittings** (*i.e., high quark contribution to the jet momentum*) from **soft cc radiations** (*i.e., high gluon contribution to the jet momentum*)
  - also allows to adjust the similarity between proxy and signal jets
    - by varying the sfBDT cut — treated as a systematic uncertainty
- Perform a fit to the secondary vertex mass shapes in the “passing” and “failing” regions simultaneously to extract the scale factors
  - three templates: cc (+ single c), bb (+ single b), light flavor jets
- Derived cc-tagging scale factors typically 0.9—1.3
  - corresponding uncertainties are 20—30%