Graph Neural Network Based Flavor Tagging at LHC

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Advanced jet flavour tagging : ILC

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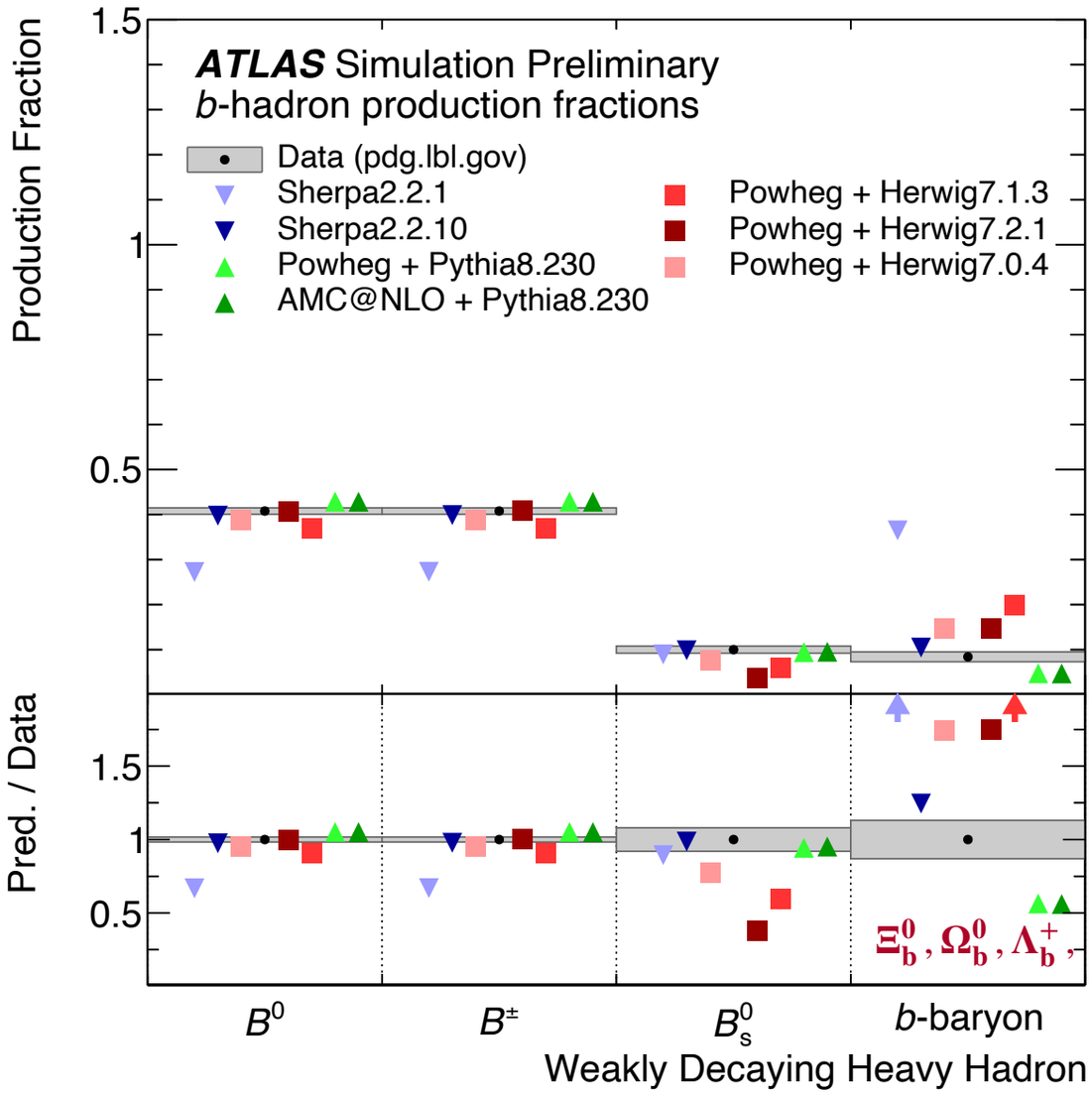
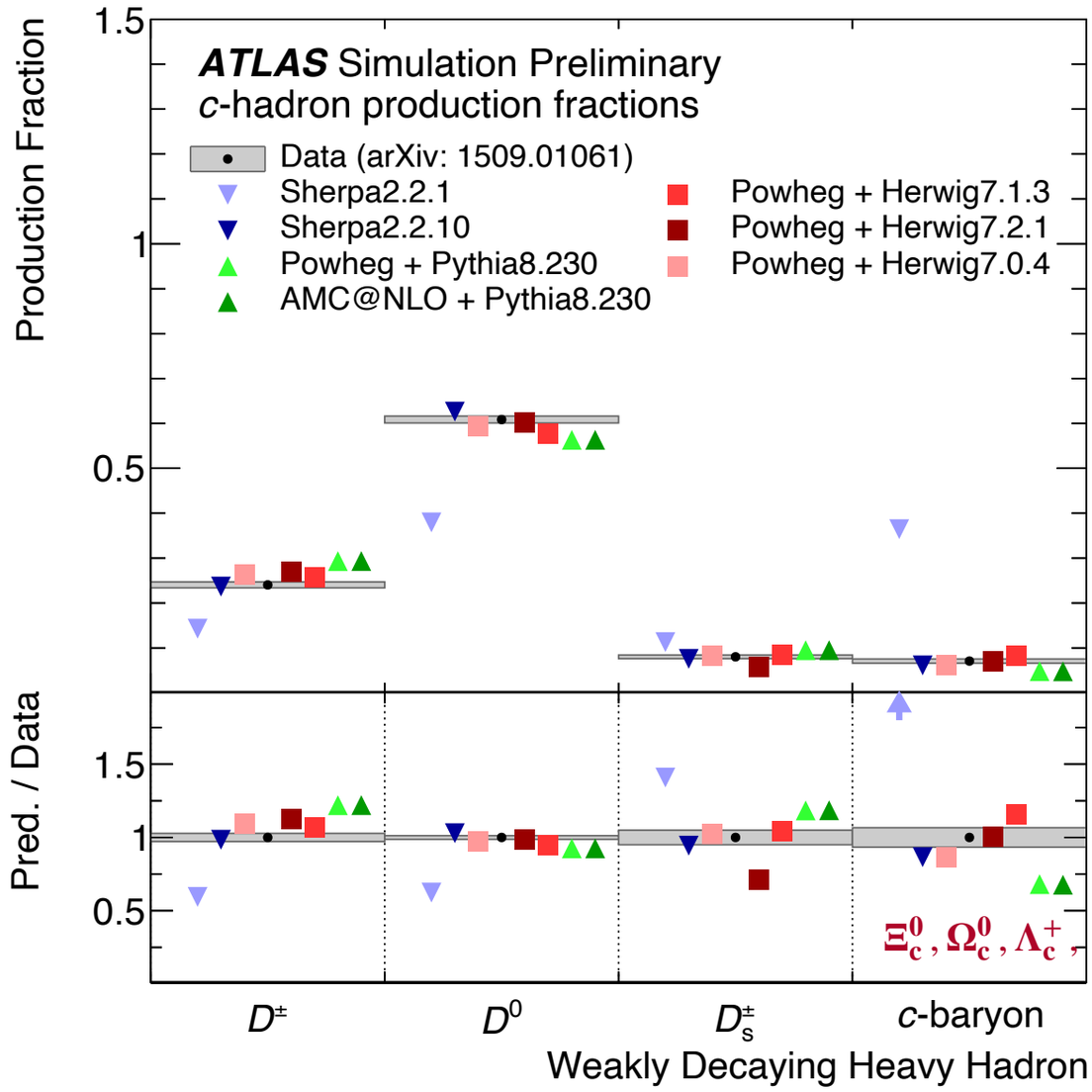
ICEPP The University of Tokyo

Beyond AI

Anatomy of heavy-quark hadronization

How bottom/charm quark decays ?
ATL-PHYS-PUB-2022-035



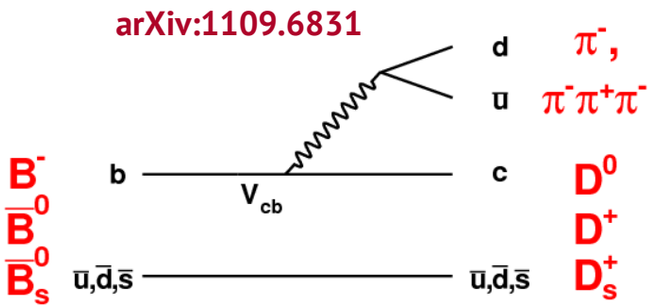


B-hadrons often decays to (D-hadrons + X) via b to c transition.
D-hadrons further decays to bunch of Kaons, Pions, leptons etc.

Anatomy of heavy-quark hadronization

The causal direction

arXiv:1109.6831



$\beta\ \gamma\ \tau_B \sim 1/|V_{bc}|^2$

$\langle \tau_B \rangle \sim$ 1.566 *ps*

K^+

l

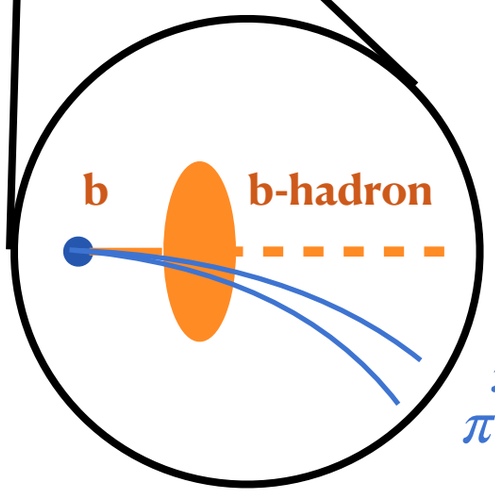
π^-

$\langle \tau_D \rangle \sim$ 0.1 – 1 *ps*

l

K^+

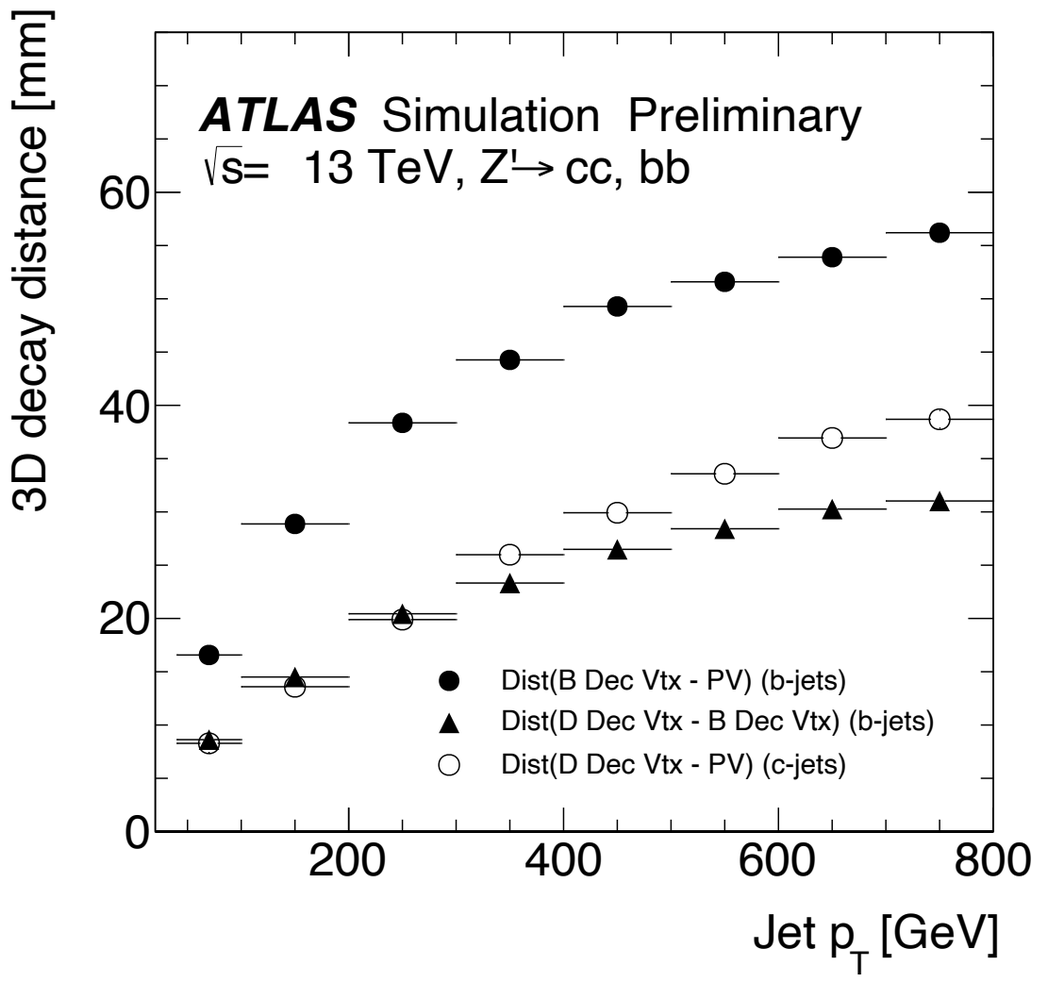
π^-



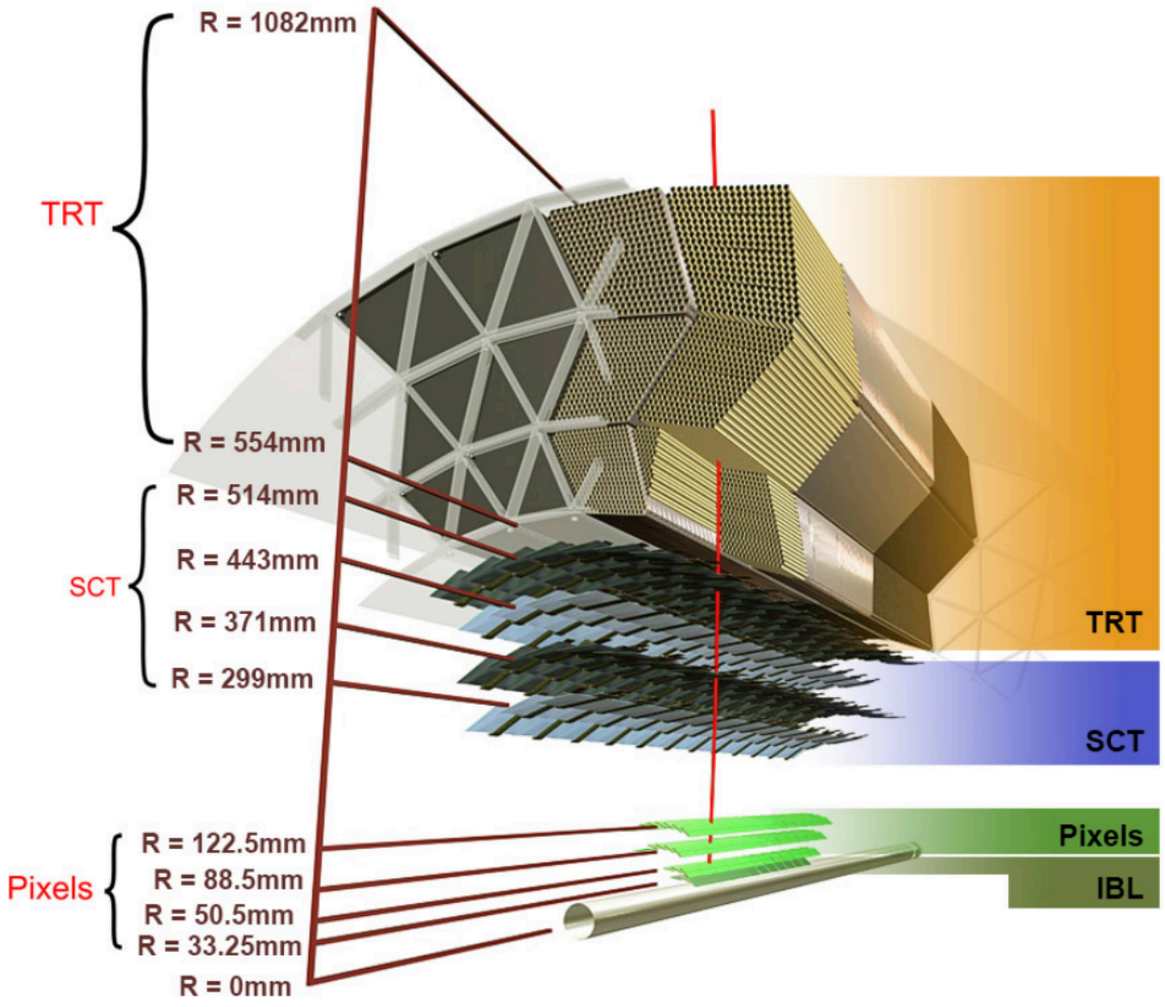
$\tau_{had} \sim \Lambda_{QCD}^{-1} \sim 10^{-24}$ sec

The decay topology in detector

ATL-PHYS-PUB-2018-025



arXiv : 2007.07624

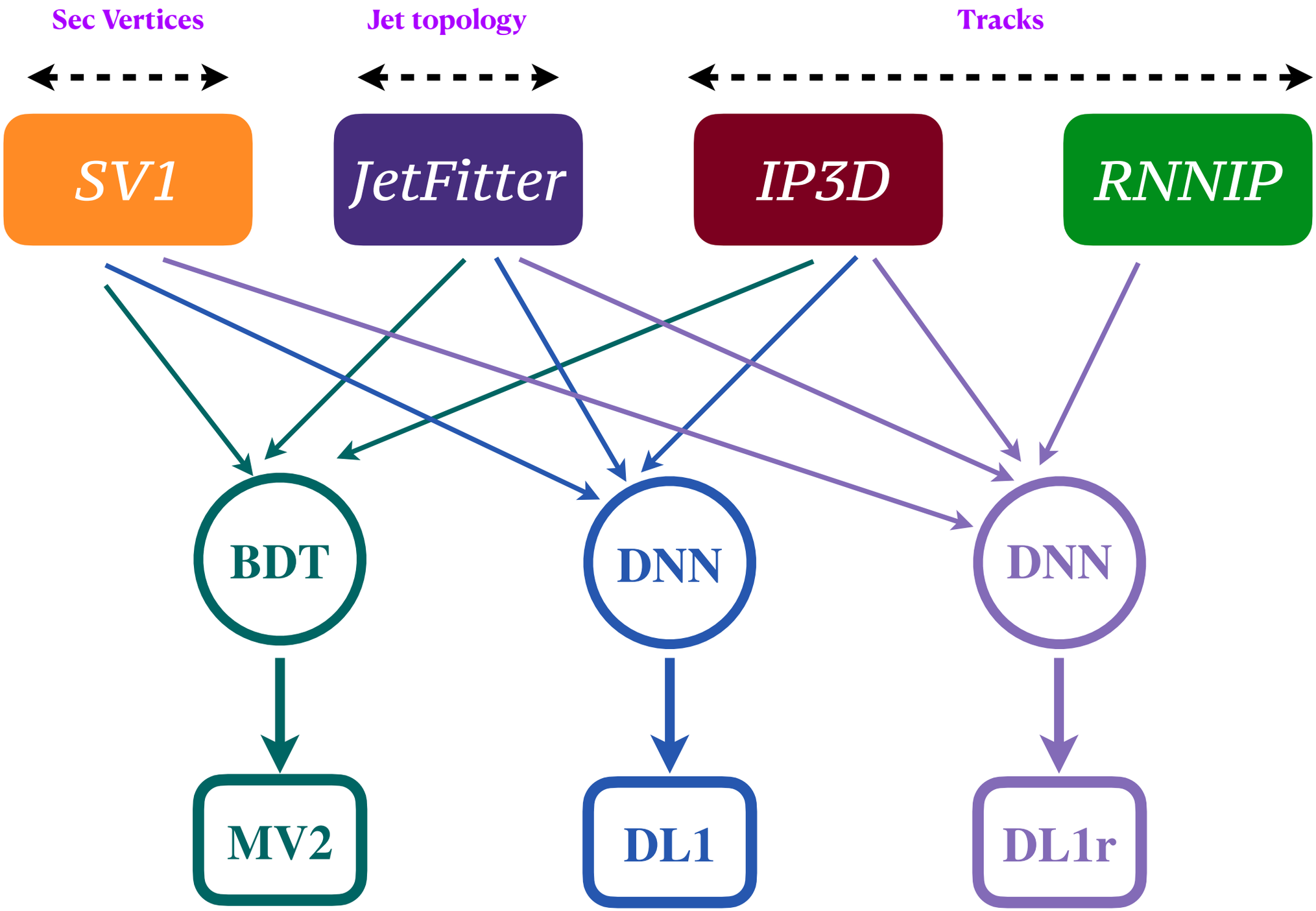


Track : constructed from ID and pT > 500 MeV.

Primary vertex : every event should have one with $\sigma(z) \sim 30\ \mu m$ and $\sigma(r) \sim 10\ \mu m$

Jets : reconstructed with Ak4 algorithm, with $p_T > 20$ GeV and $|\eta| < 4.5$ + a jet-PV association.

High level algorithms

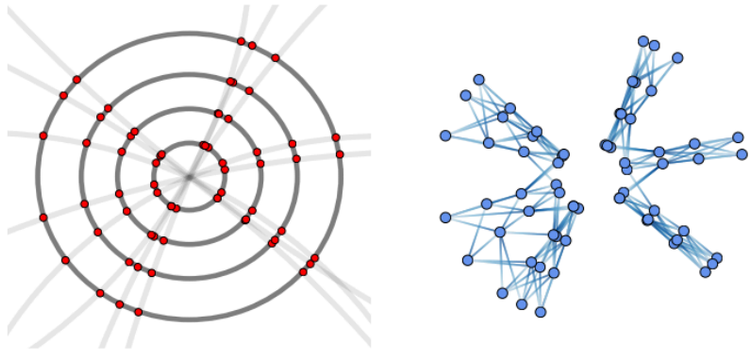


MV2 vs DL1 : same input, different architecture.

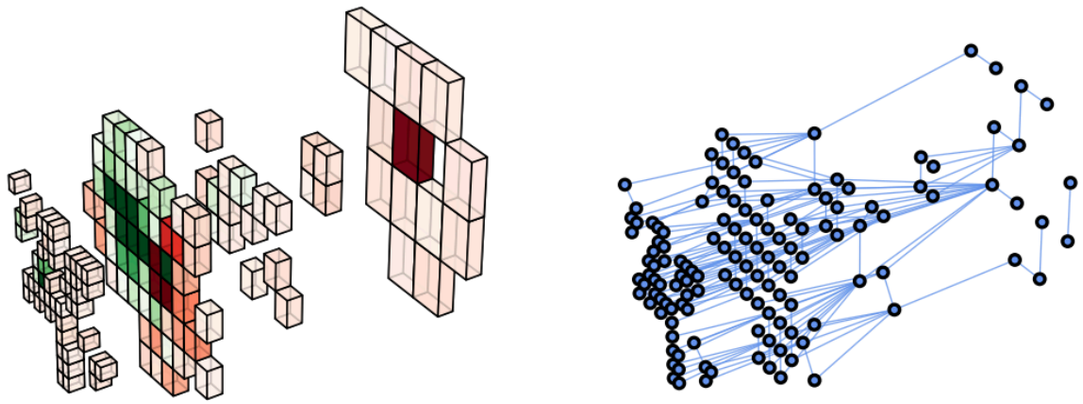
DL1r has extra RNNIP input compared to DL1.

HEP events & objects as graph

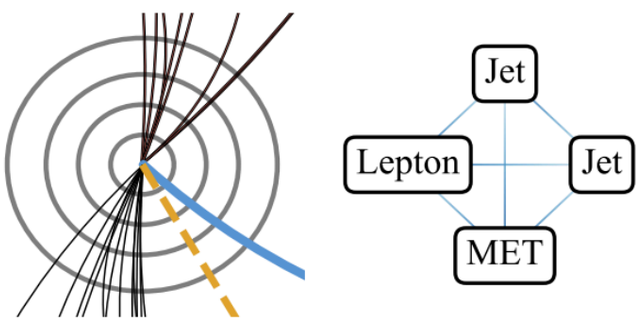
arXiv : 2007.13681



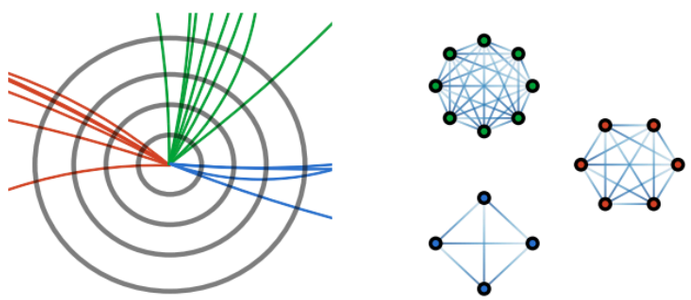
(a)



(b)

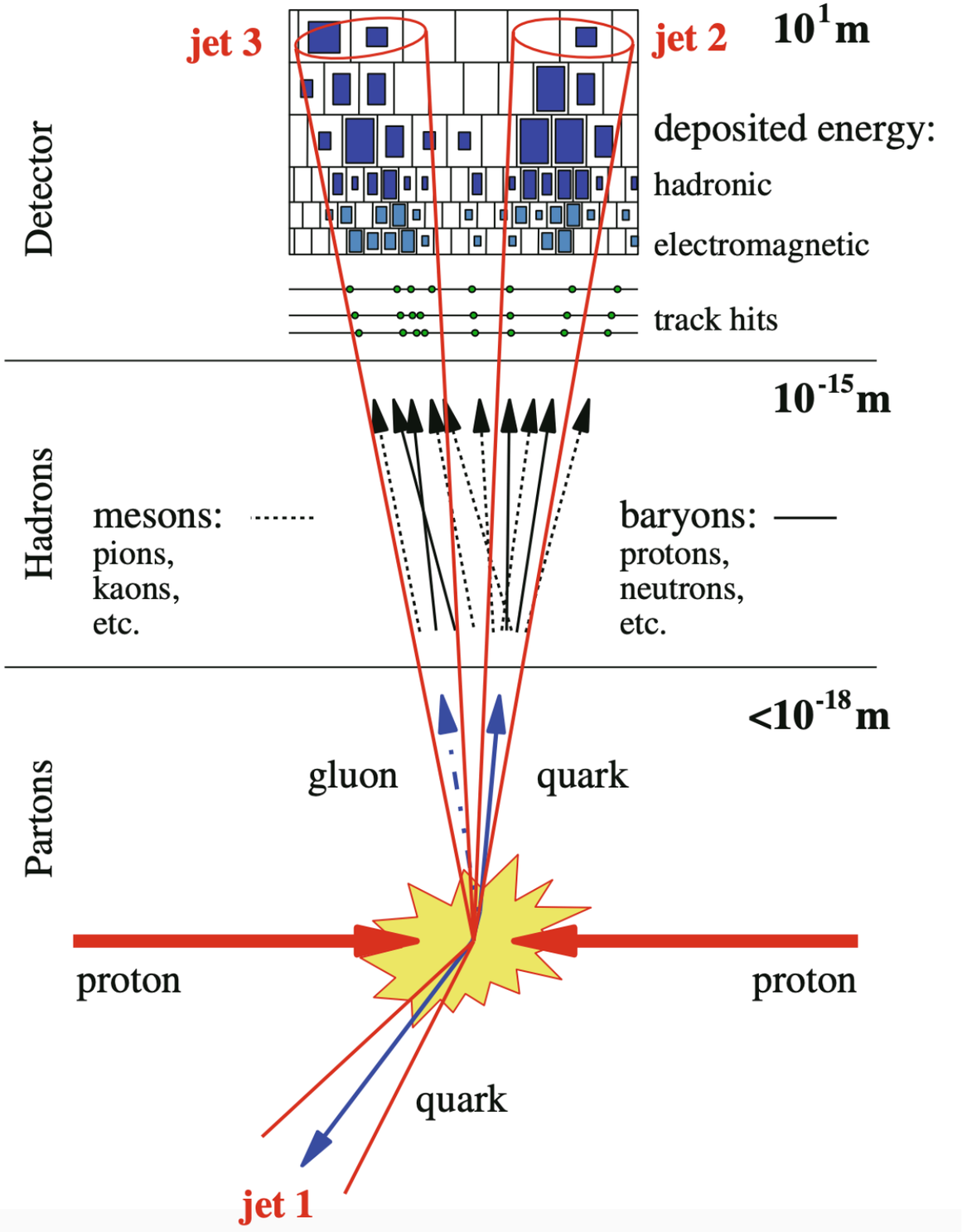


(c)



(d)

Jet tagging ~ Graph classification



The Large Hadron Collider
Editors: Thomas Schörner-Sadenius

$$\{p_1, p_2, \ldots, p_n\}$$

Jet Algorithm (for CA, kT, anti-kT)

$$\{j_1, j_2, \ldots, j_k\}$$

$$\{p_1, p_2, \ldots, p_n\} = F(q)$$

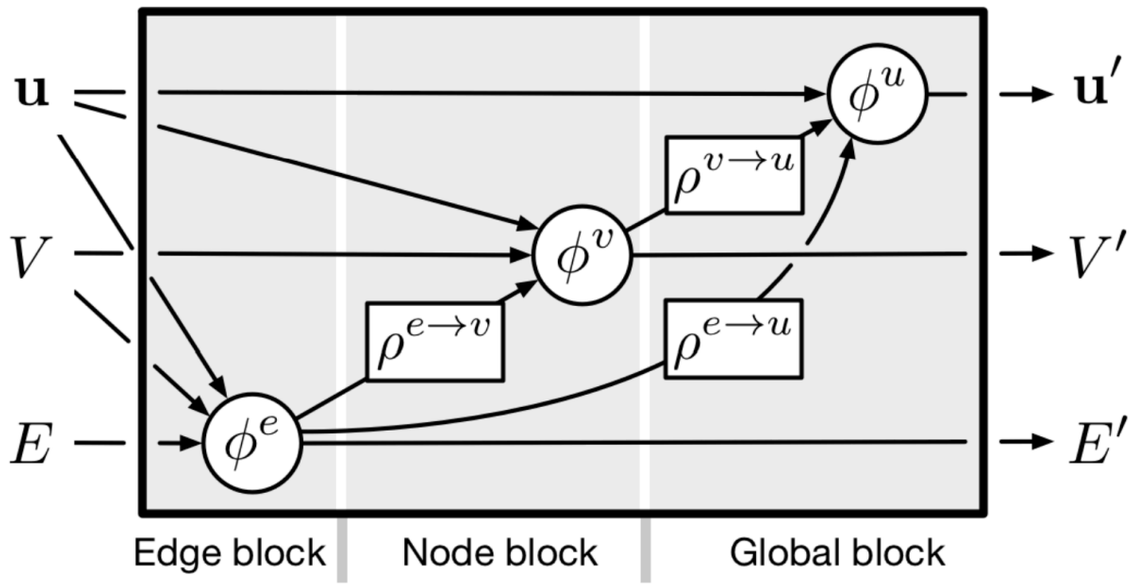
The forward problem is not computable from first principle

The question of jet tagging is how do we define the inverse problem?

$$q = F^{-1}\Big(\{p_1, p_2, \ldots, p_n\}\Big) \; ?$$

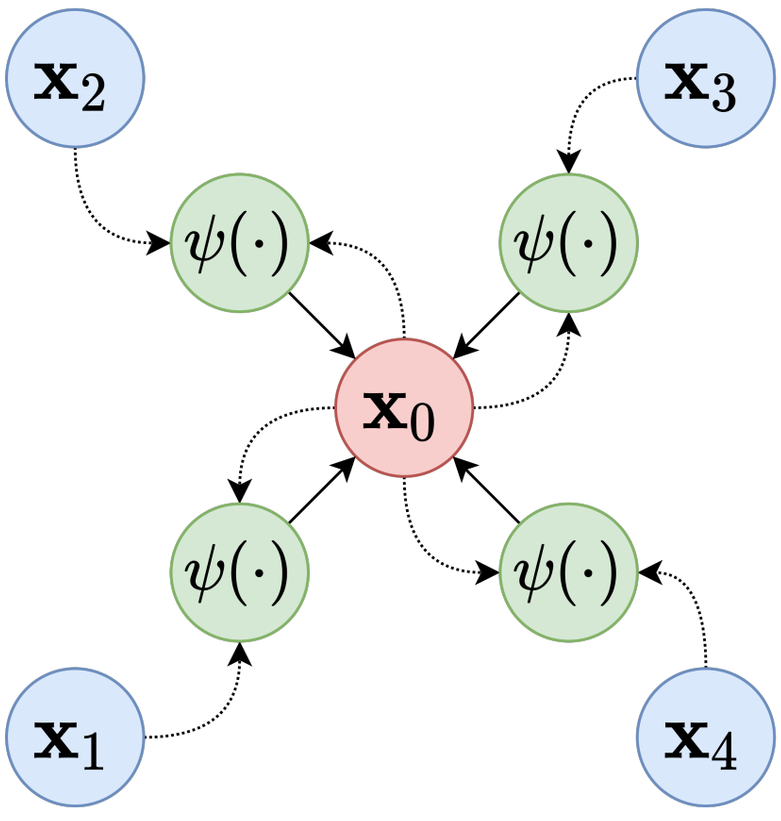
What is GNN?

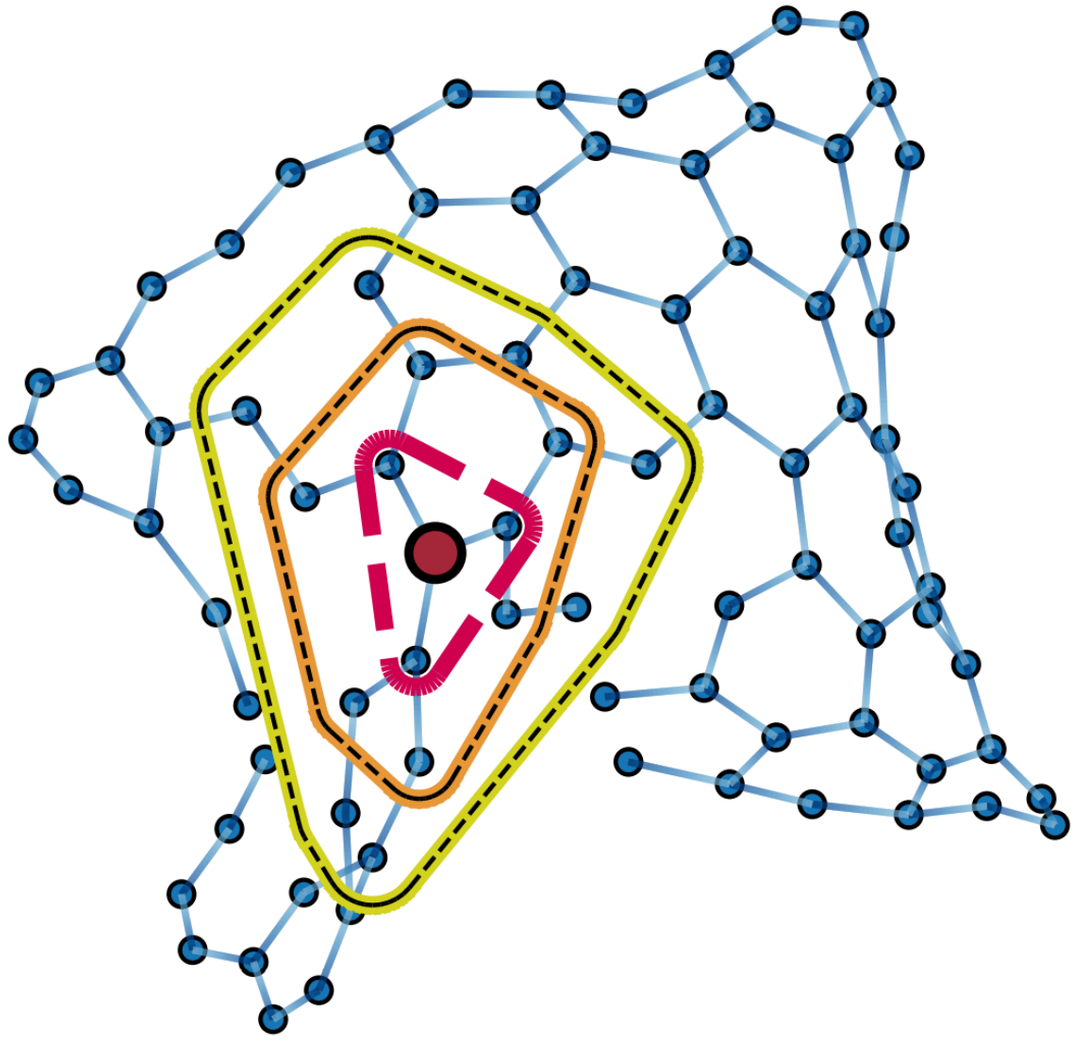
$$G = (u, V, E)$$



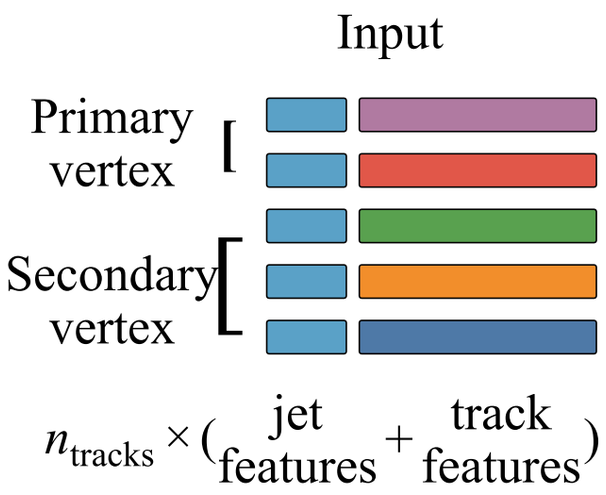
arXiv : 1806.01261

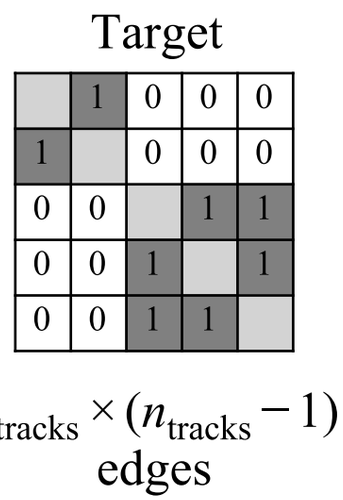
$$x_i' = \phi\left(x_i, \oplus_{i\in\mathcal{N}_i}\psi(x_i, x_j, e_{ij})\right)$$

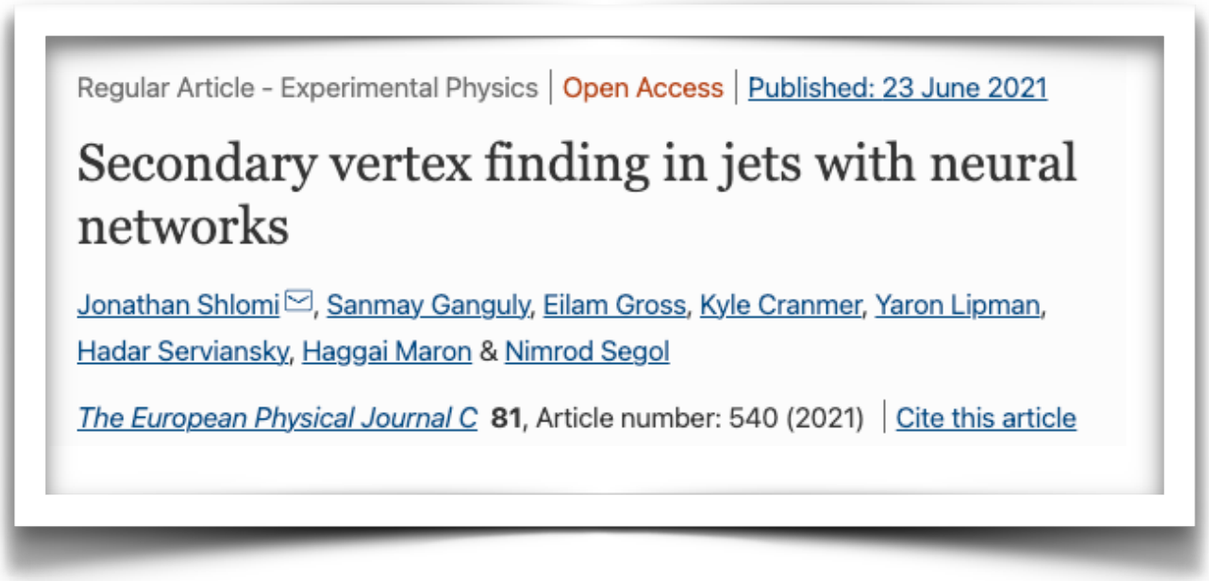


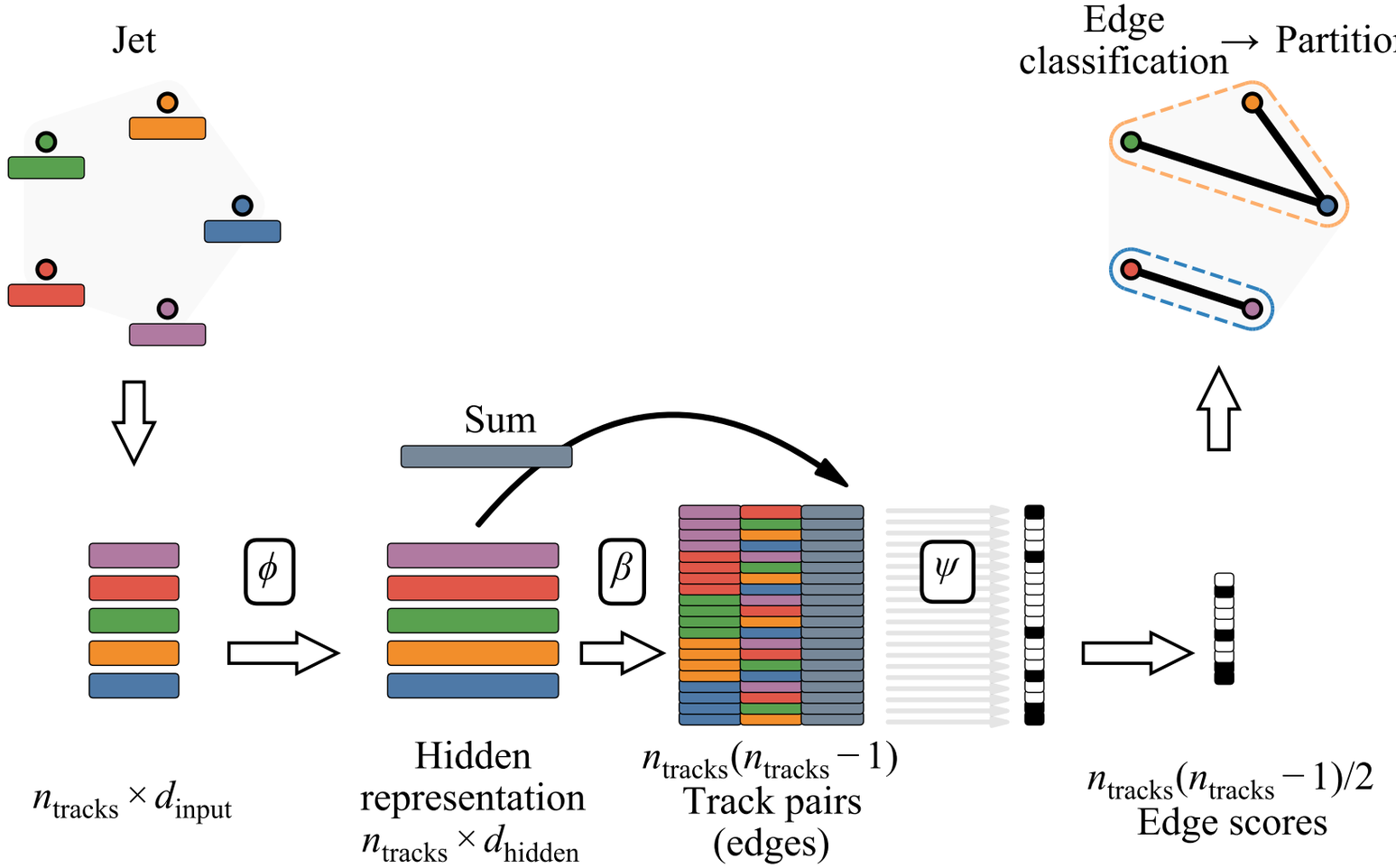


Set2Graph proposal for flavor-tagging

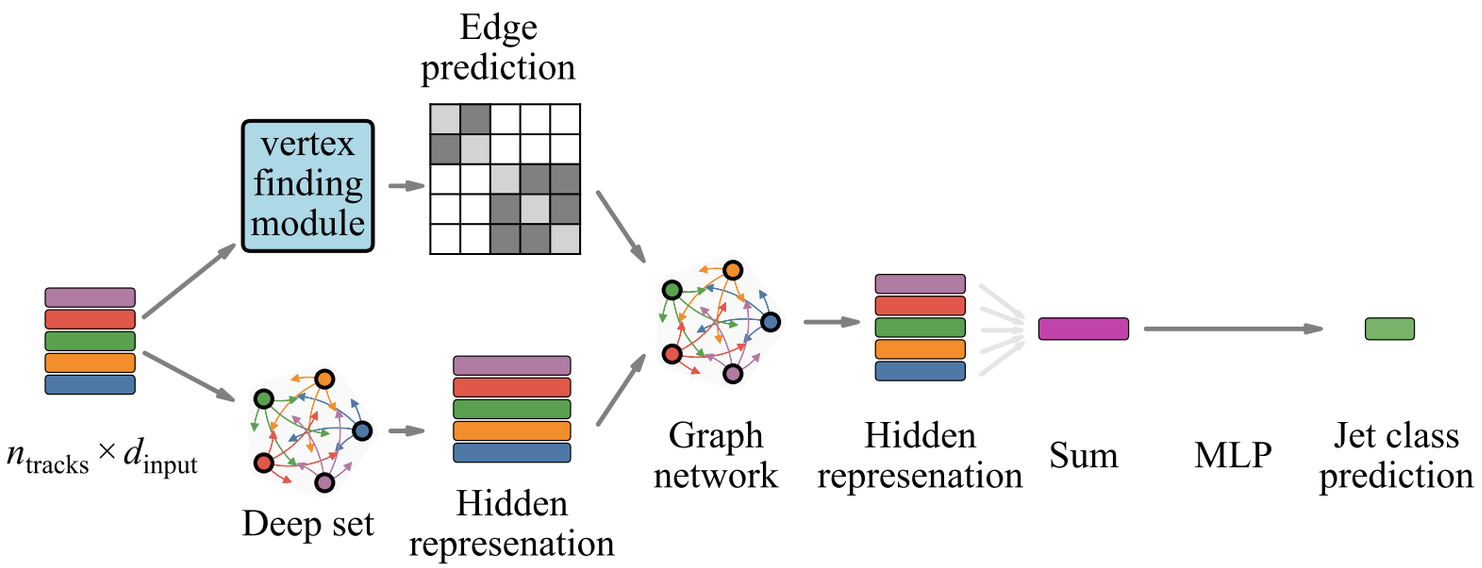


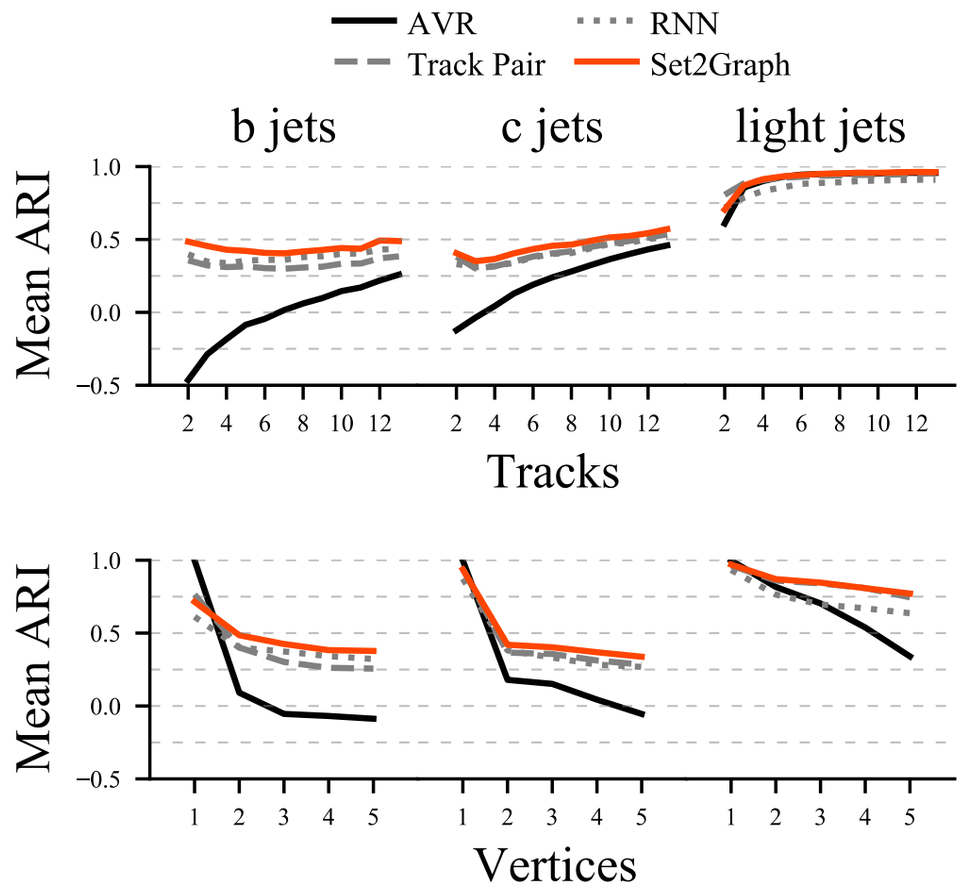






Set2Graph proposal for flavor-tagging





$$\text{RI} = \frac{\text{number of correct edges}}{\text{number of edges in the set}}$$

$$\mathbb{E}[\text{RI}] = \frac{B_{N-1}}{B_N}\frac{\sum_i \binom{g_i}{2}}{\binom{N}{2}} + \left(1 - \frac{B_{N-1}}{B_N}\right)\left(1 - \frac{\sum_i \binom{g_i}{2}}{\binom{N}{2}}\right)$$

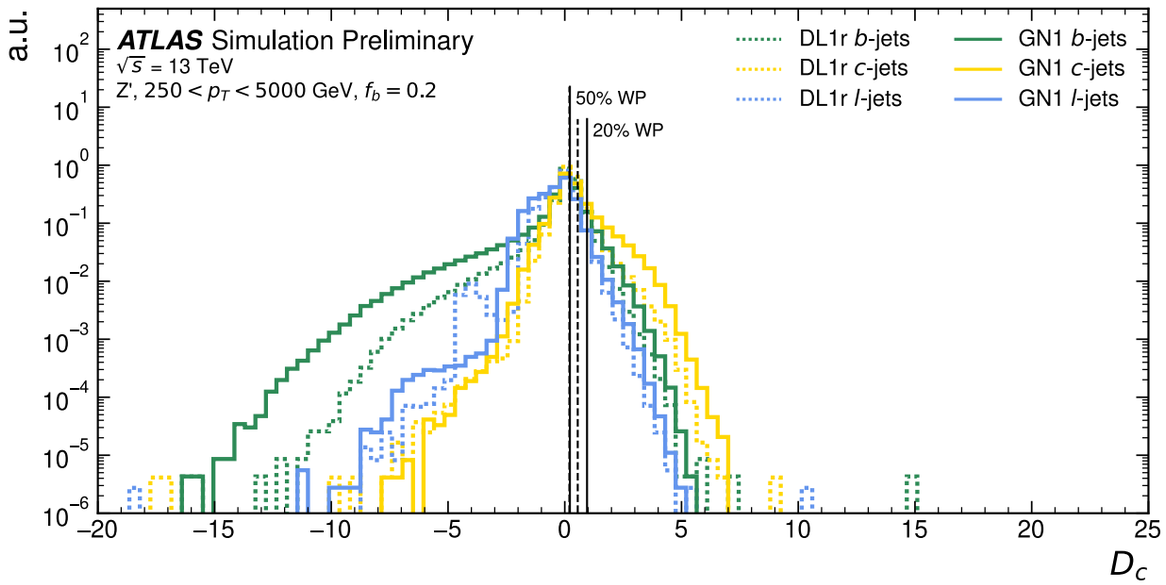
$$\text{ARI} = \frac{\text{RI} - \mathbb{E}[\text{RI}]}{1 - \mathbb{E}[\text{RI}]}$$

	Algorithm	Jet			Vertex			Vertex-Pair				
		F1	RI	ARI	internal	external	combined	internal_1	internal_2	interpair	external	combined
b jets	AVR	0.56	0.61	-0.01	**0.91**	0.51	0.46	**0.59**	**0.90**	0.54	0.58	0.18
	Track Pair	0.62	0.74	0.32	0.86	0.71	0.60	0.55	0.87	0.72	0.74	0.29
	RNN	0.59	0.75	0.37	0.79	**0.77**	0.60	0.48	0.84	**0.78**	**0.80**	0.27
	Set2Graph	**0.66**	**0.78**	**0.43**	0.86	0.76	**0.65**	0.54	0.88	**0.78**	0.79	**0.33**
c jets	AVR	0.70	0.65	0.22	**0.95**	0.41	0.39	**0.49**	**0.91**	0.49	0.66	0.14
	Track Pair	0.74	0.73	0.40	0.92	0.58	0.52	0.47	0.88	0.65	0.76	0.24
	RNN	0.71	0.72	0.40	0.86	**0.60**	0.50	0.39	0.85	0.65	0.77	0.19
	Set2Graph	**0.75**	**0.75**	**0.45**	0.94	**0.60**	**0.56**	0.47	**0.91**	**0.67**	**0.78**	**0.26**
light jets	AVR	**0.97**	**0.96**	0.93	**0.99**	0.89	0.88	**0.33**	**0.98**	0.73	0.89	0.14
	Track Pair	0.96	**0.96**	0.93	0.97	**0.93**	0.90	0.32	0.97	0.87	**0.95**	**0.26**
	RNN	0.93	0.92	0.87	0.93	0.90	0.84	0.25	0.94	0.82	0.93	0.18
	Set2Graph	**0.97**	**0.96**	**0.94**	0.98	**0.93**	**0.91**	0.32	**0.98**	**0.88**	**0.95**	**0.26**

B_N : # of possible partition of a set with N elements

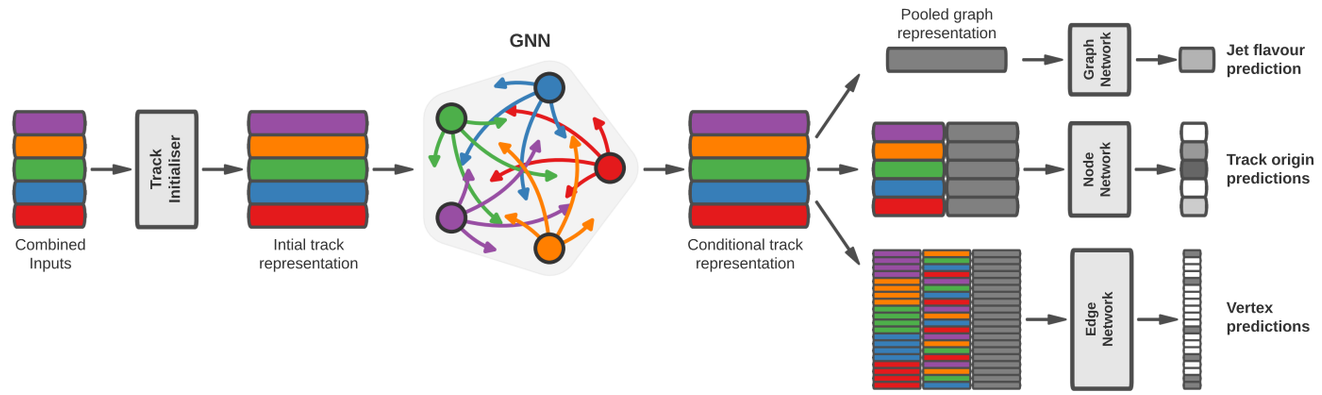
g_i : # of tracks associated with i-th vertex in the jet.

Set2Graph model within ATLAS



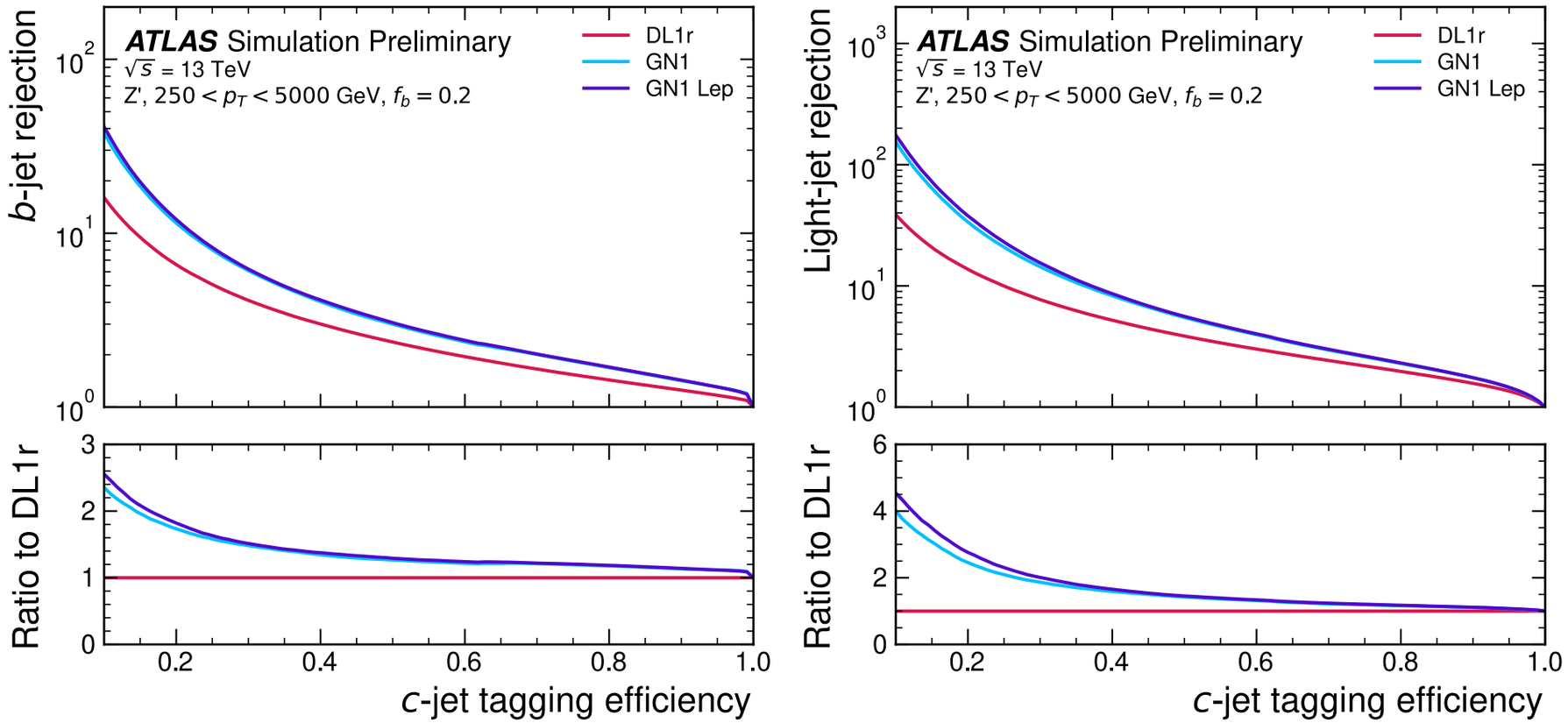
$$D_{DL1}^{b-tag} = ln\left(\frac{p_b}{f_c \cdot p_c + (1-f_c) \cdot p_l}\right)$$

ATL-PHYS-PUB-2022-027



Sizable improvement over the current DL1r algorithm.

For a c-tagging working point ~ 30%, a significant gain in Rejection rate is obtained.



The pointcloud classification

Dynamic Graph CNN for Learning on Point Clouds

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SANJAY E. SARMA, Massachusetts Institute of Technology
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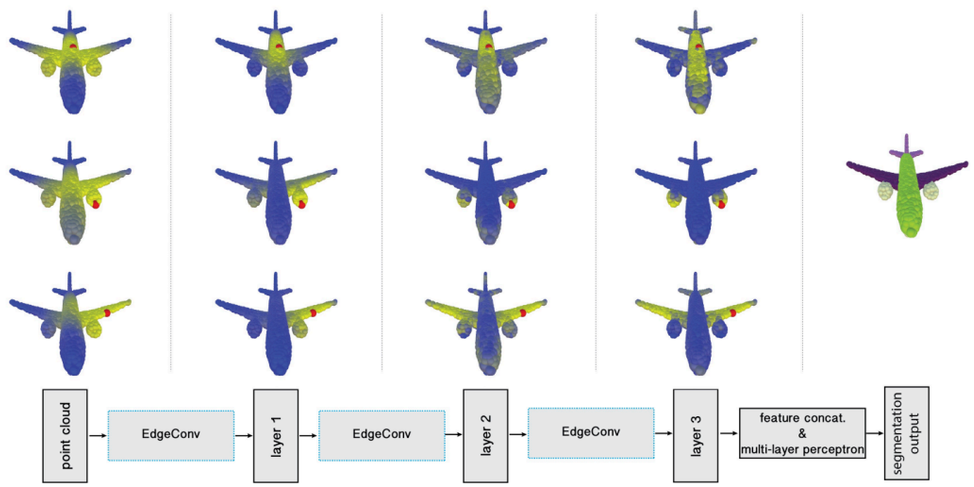
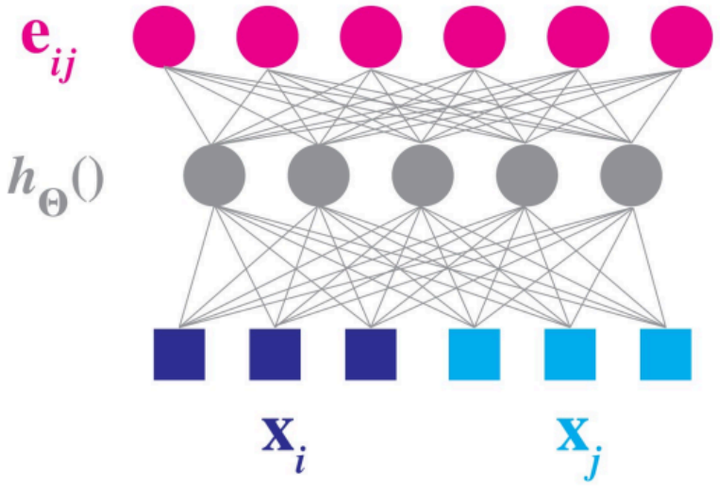
JUSTIN M. SOLOMON, Massachusetts Institute of Technology

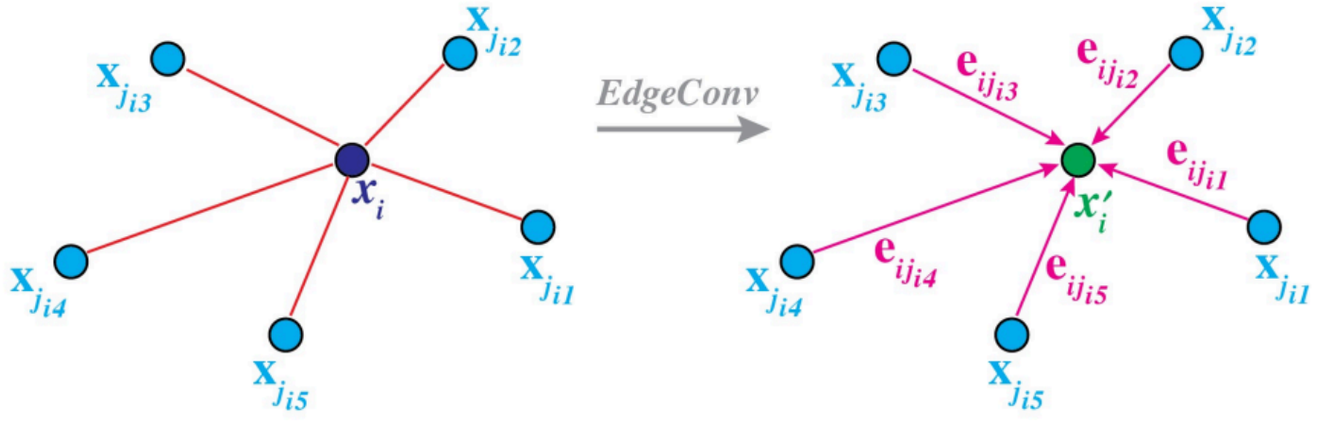
arXiv : 1806.01261



$$\mathbf{x}'_i = \max_{j:(i,j)\in\mathcal{E}} h_{\Theta}(\mathbf{x}_i, \mathbf{x}_j)$$

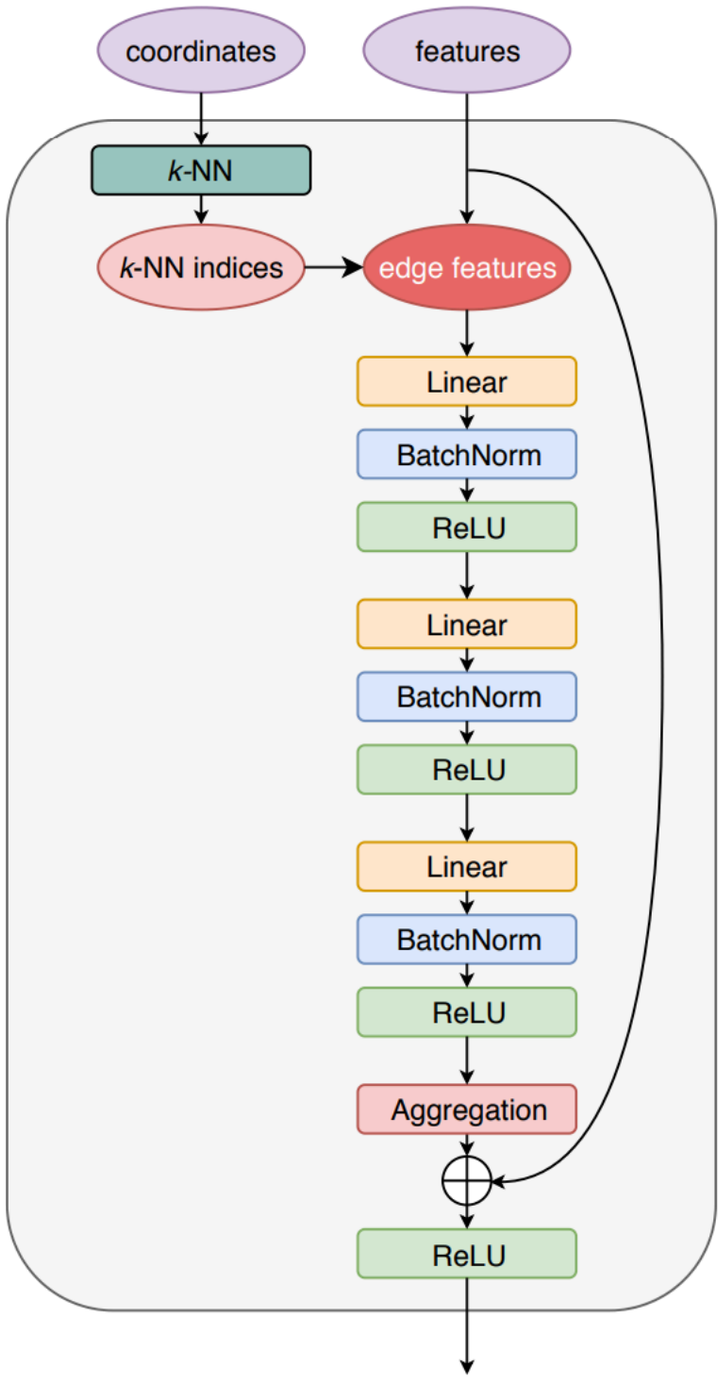
$$e'_{ijm} = \mathrm{ReLU}(\boldsymbol{\theta}_m \cdot (\mathbf{x}_j - \mathbf{x}_i) + \boldsymbol{\phi}_m \cdot \mathbf{x}_i),$$

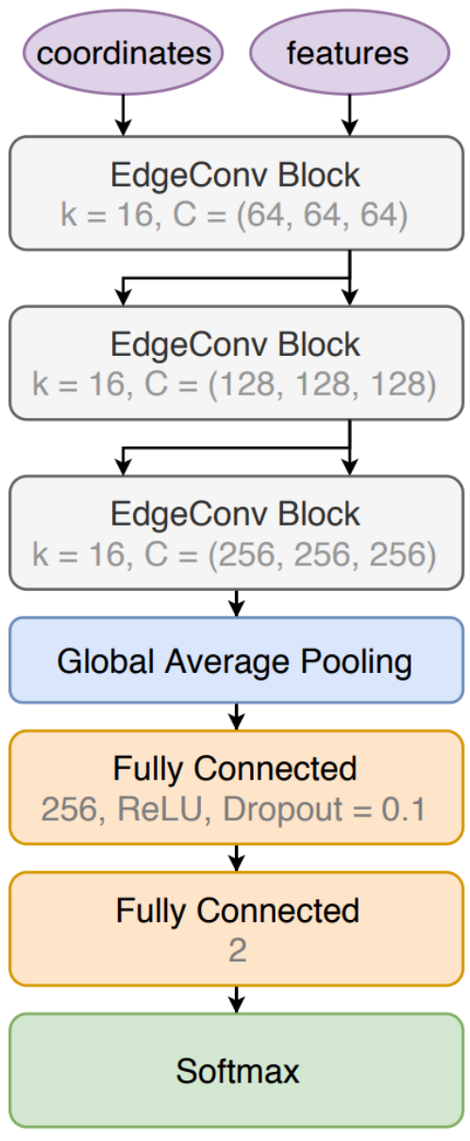




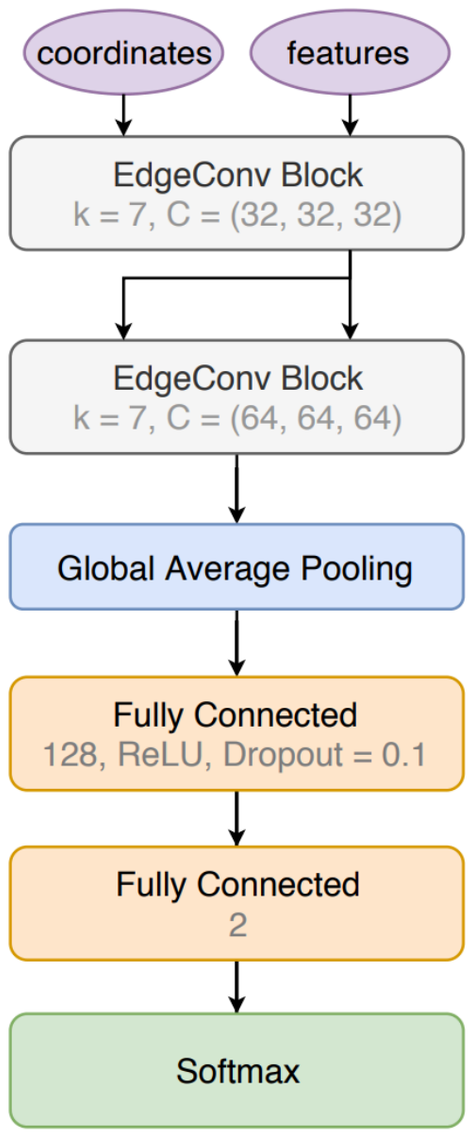
The particlenet network

arXiv : 1902.08570





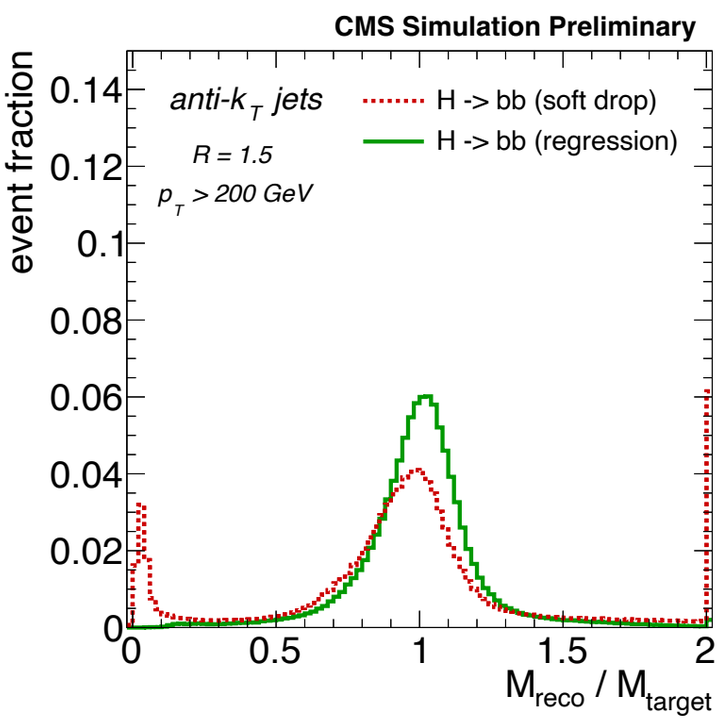
(a) ParticleNet

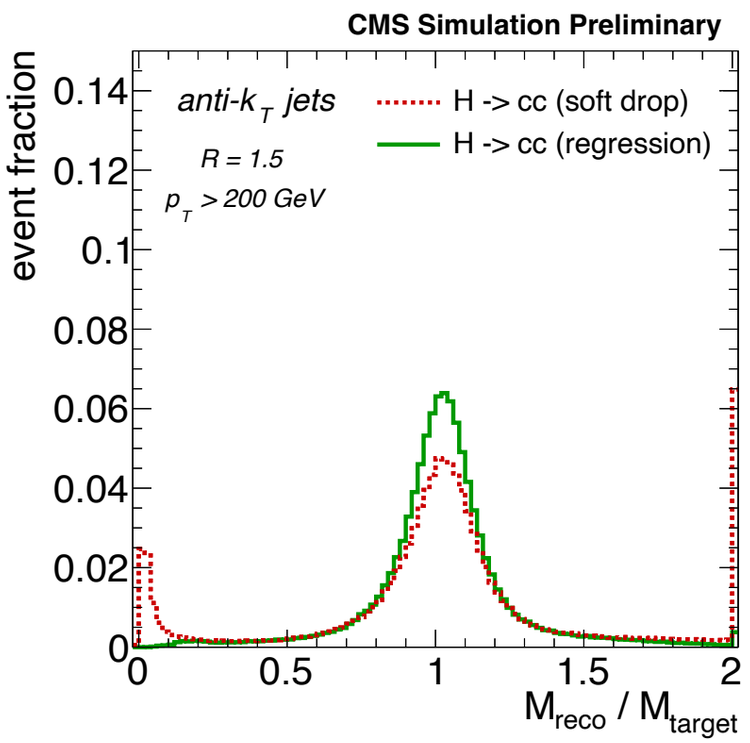


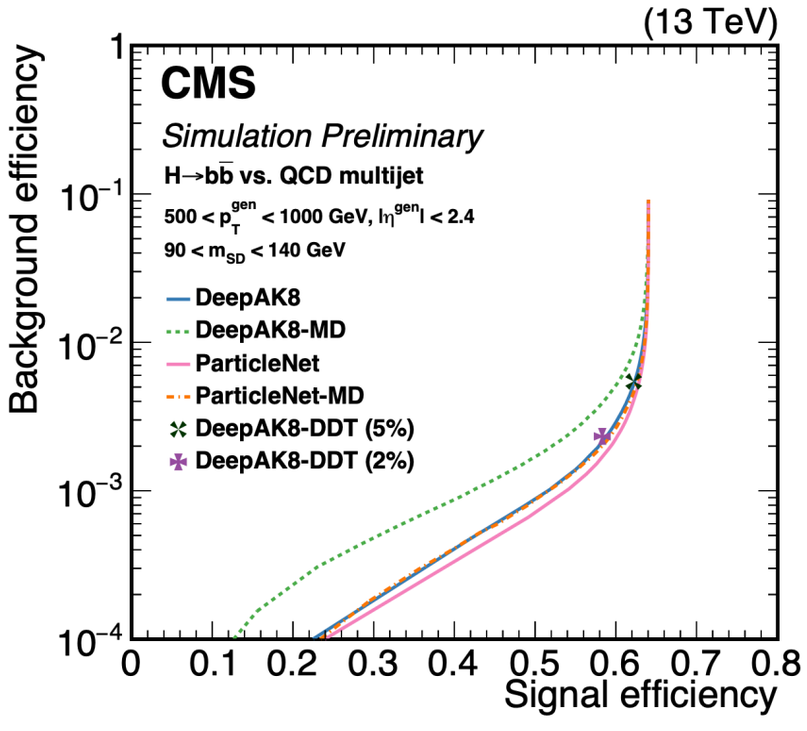
(b) ParticleNet-Lite

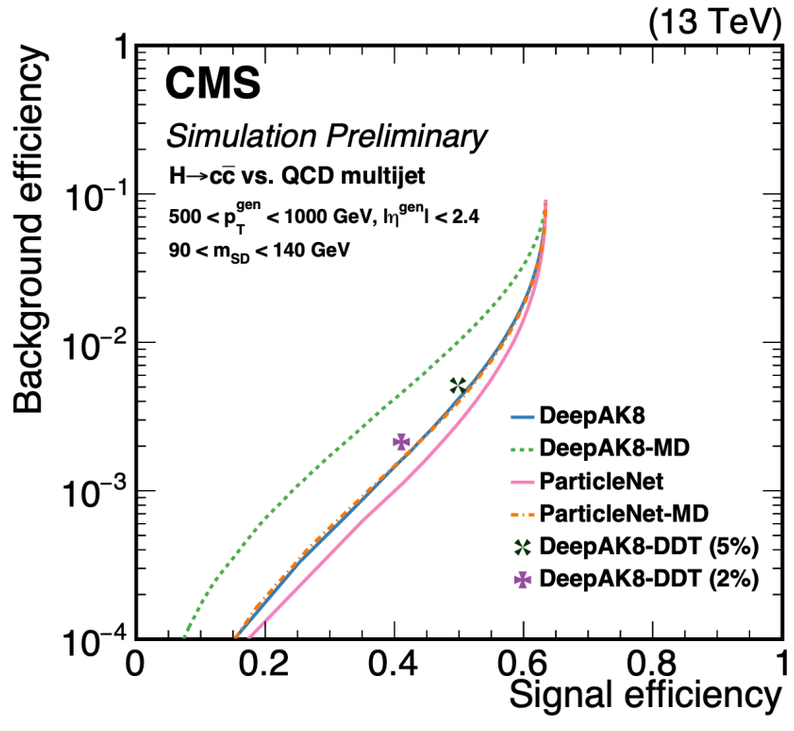
The large-R mass regression

CMS-DP-21017



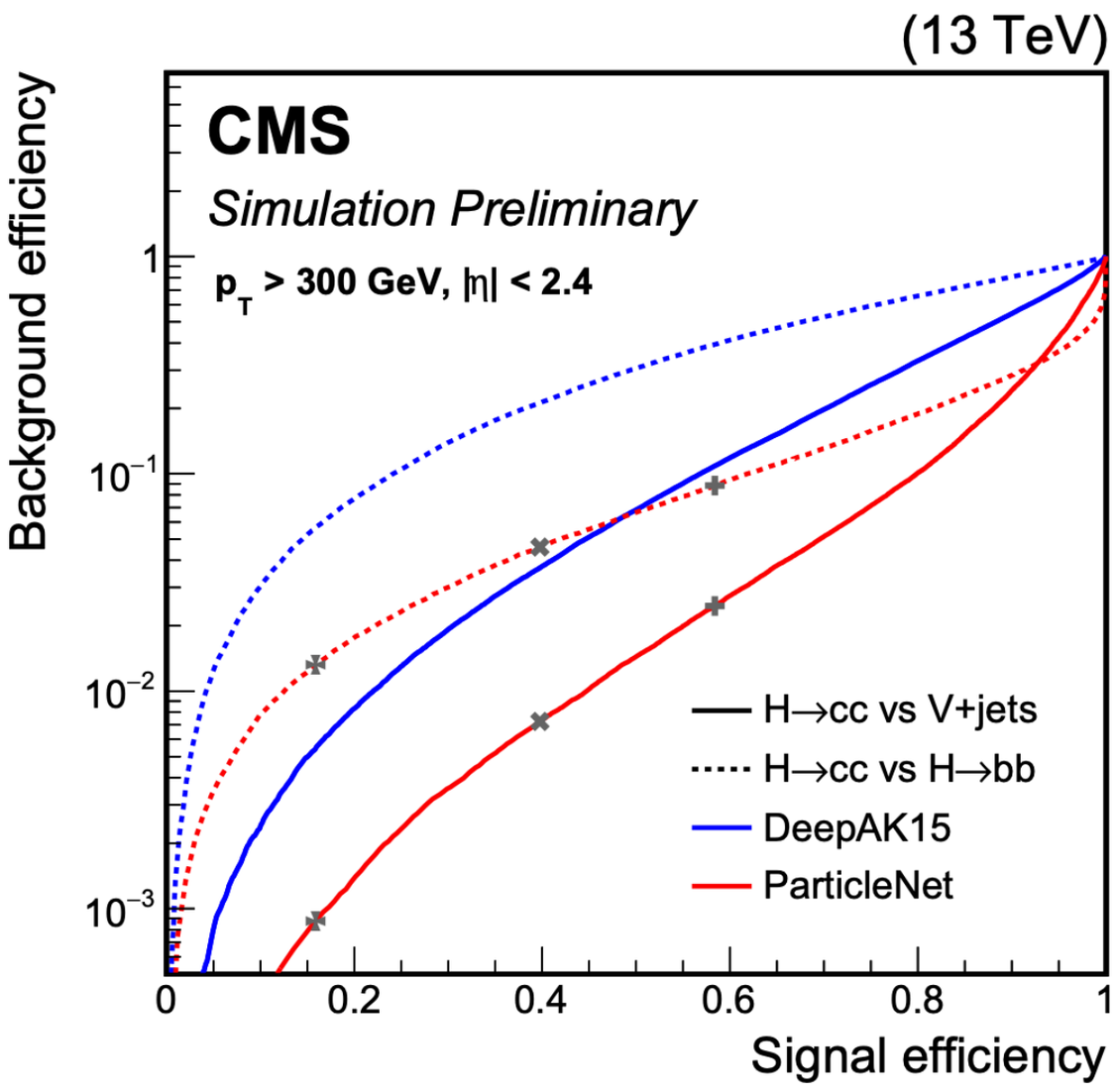


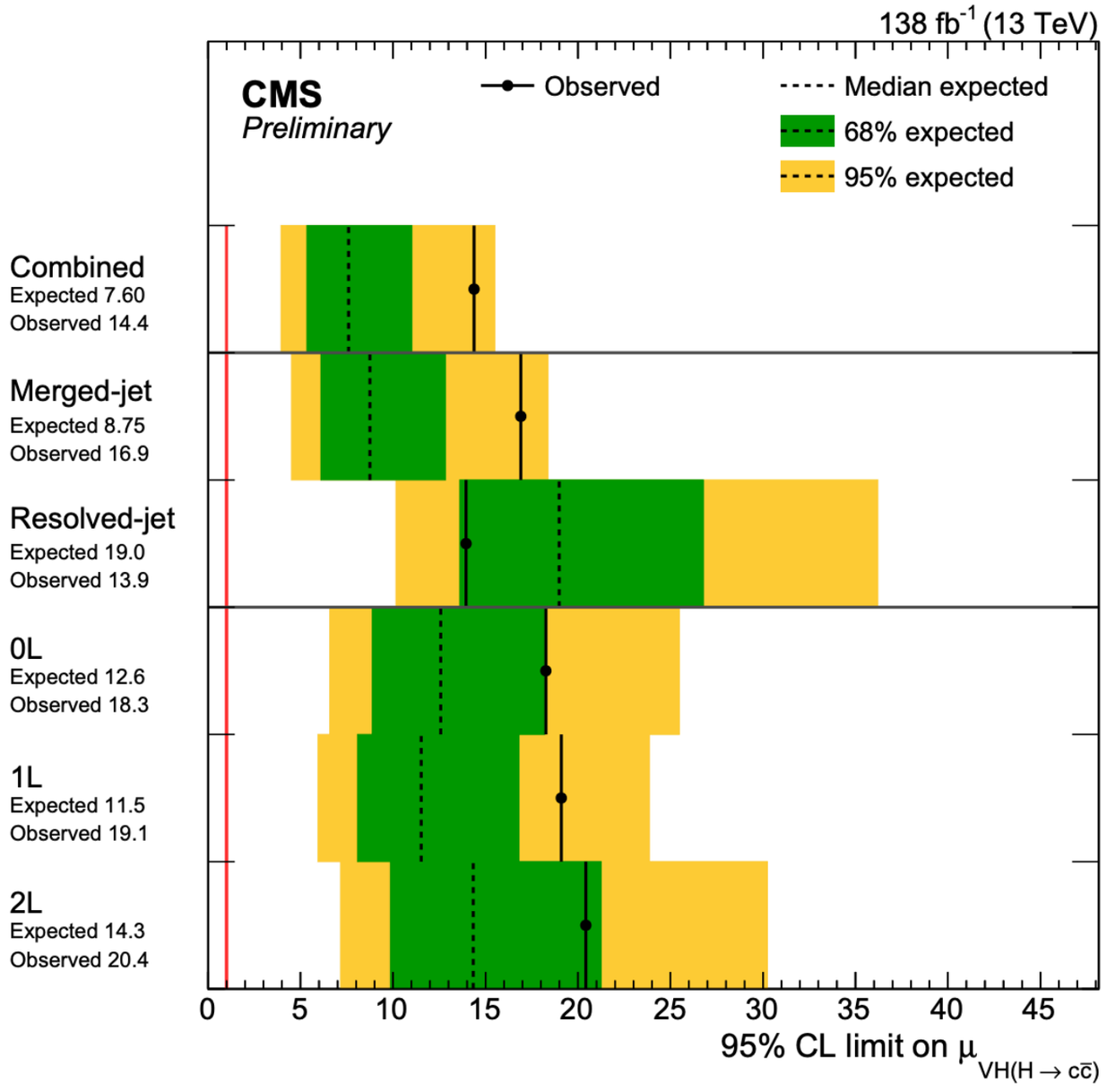




CMS-DP-2020/002

Impact of GNN on physics results





CMS-HIG-21-008

Take away

- ☑ **GNN is turning out to be the state of art ML technique to be used for HEP applications.**
- ☑ **GNN has its own limitation, need to understand how HEP analysis is effected.**
- ☑ **We need to emphasize on explainable AI and correlate to physics interpretation.**
- ☑ **Let's see what it can bring for ILC.**

THANK YOU!!