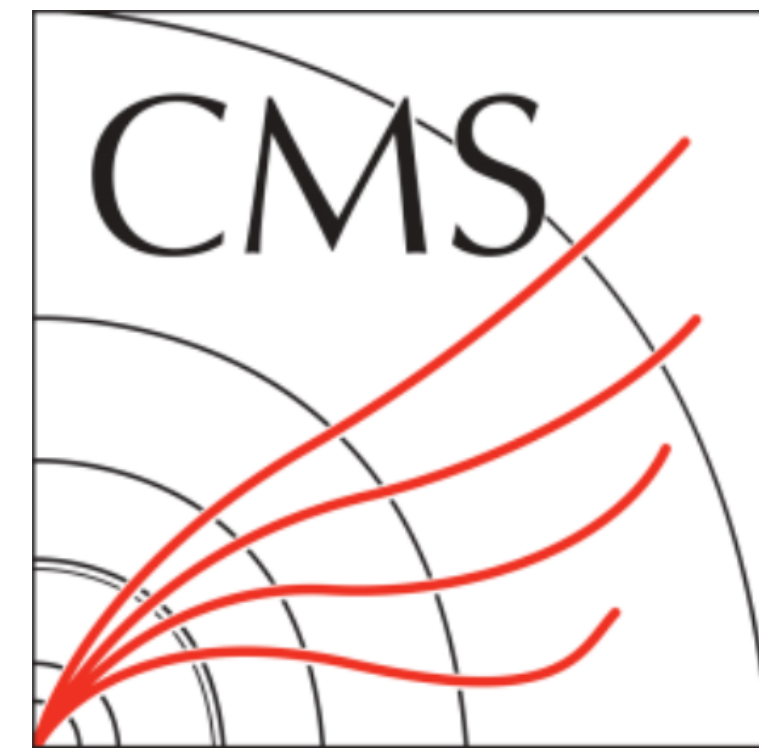


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# CMS jet tagging

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Working group meeting

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# outline

## contents

- Introduction
- AK4 jets tagging
  - DeepCSV model
  - DeepFlavour model
- AK8 jets tagging
  - DeepAK8 model
  - ParticleNet model
  - ParticleTransformer model
- Calibration of the taggers
  - SFsBDT method
  - LundJetPlane method





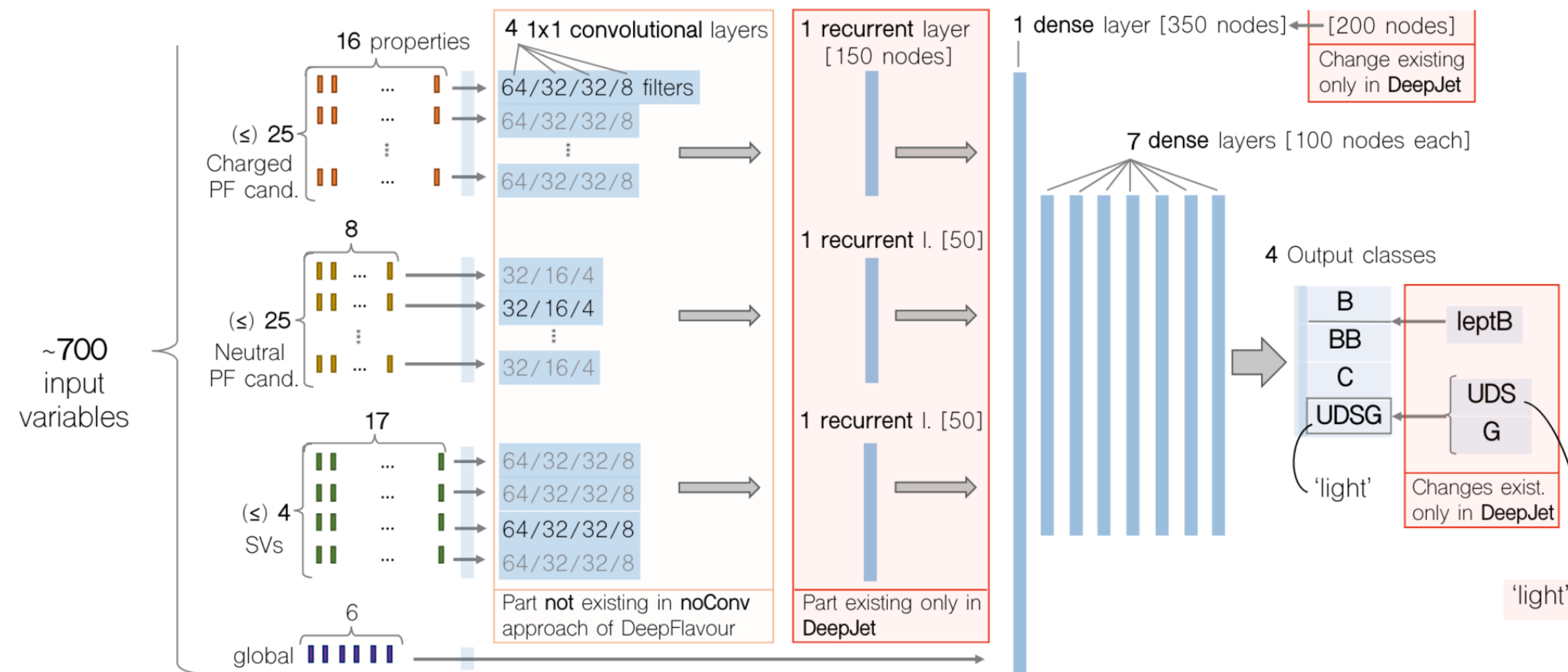
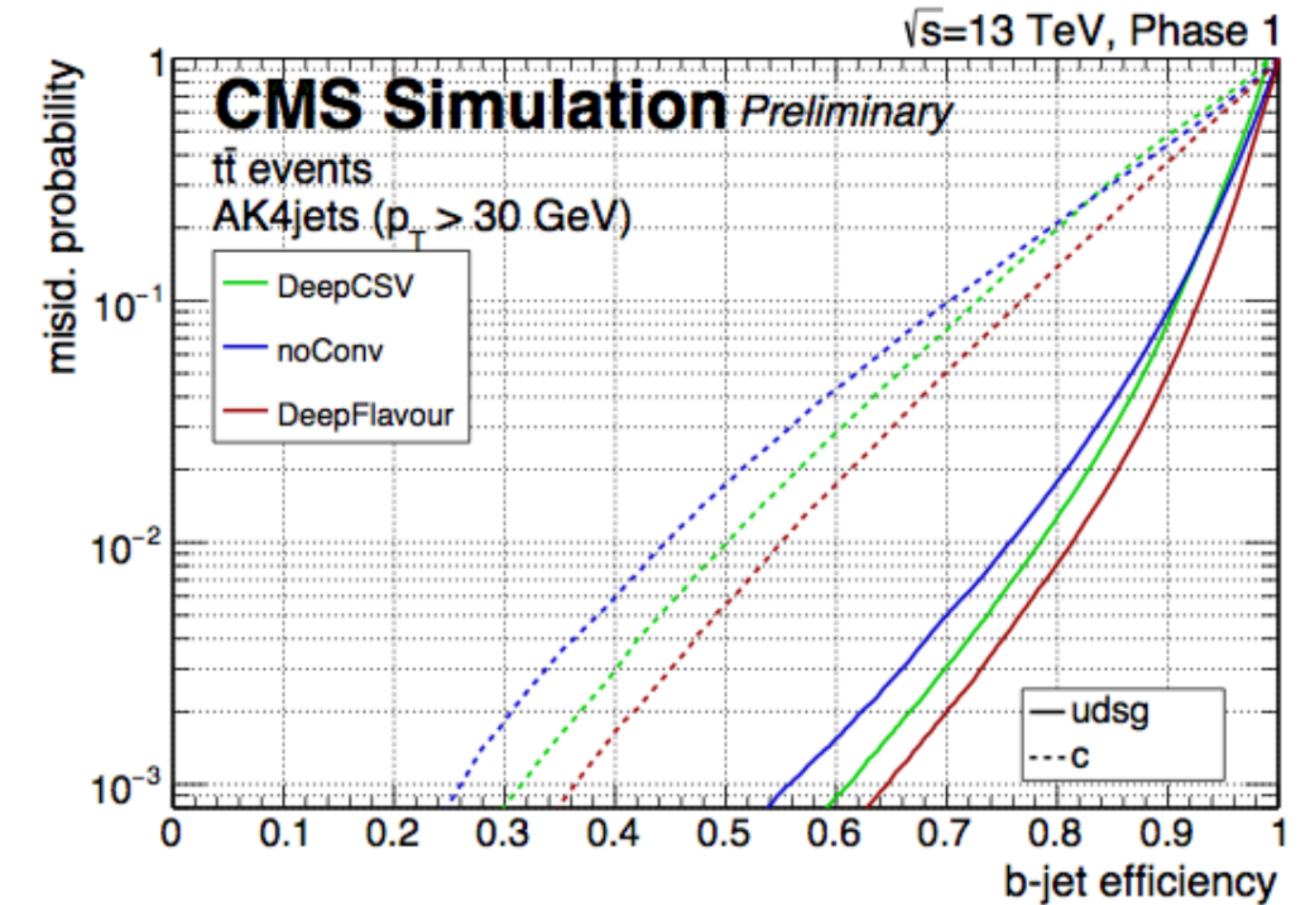
- Jet is one of the most ubiquitous but also fascinating objects at the LHC
- Very common in CMS to use ML method to tag jets:
  - heavy flavour tagging (bottom/charm)
  - heavy resonance tagging (top/W/Z/Higgs)
  - quark/gluon discrimination
  - ...
- One of the most active areas for ML
  - lots of deep approaches have been proposed in the past few years
  - trending: low-level inputs + deep learning



# AK4 jets tagging



- DeepCSV model (CMS DP 2017-005 [cds.cern.ch/record/2255736](https://cds.cern.ch/record/2255736)) :
  - Pure deep NN, multi-classification with combine secondary vertex inputs
- ★ DeepFlavour model (CMS DP 2017-013 [cds.cern.ch/record/2263802](https://cds.cern.ch/record/2263802))
  - Larger inputs, deeper NN + convolutional, recurrent layers
  - Best so far

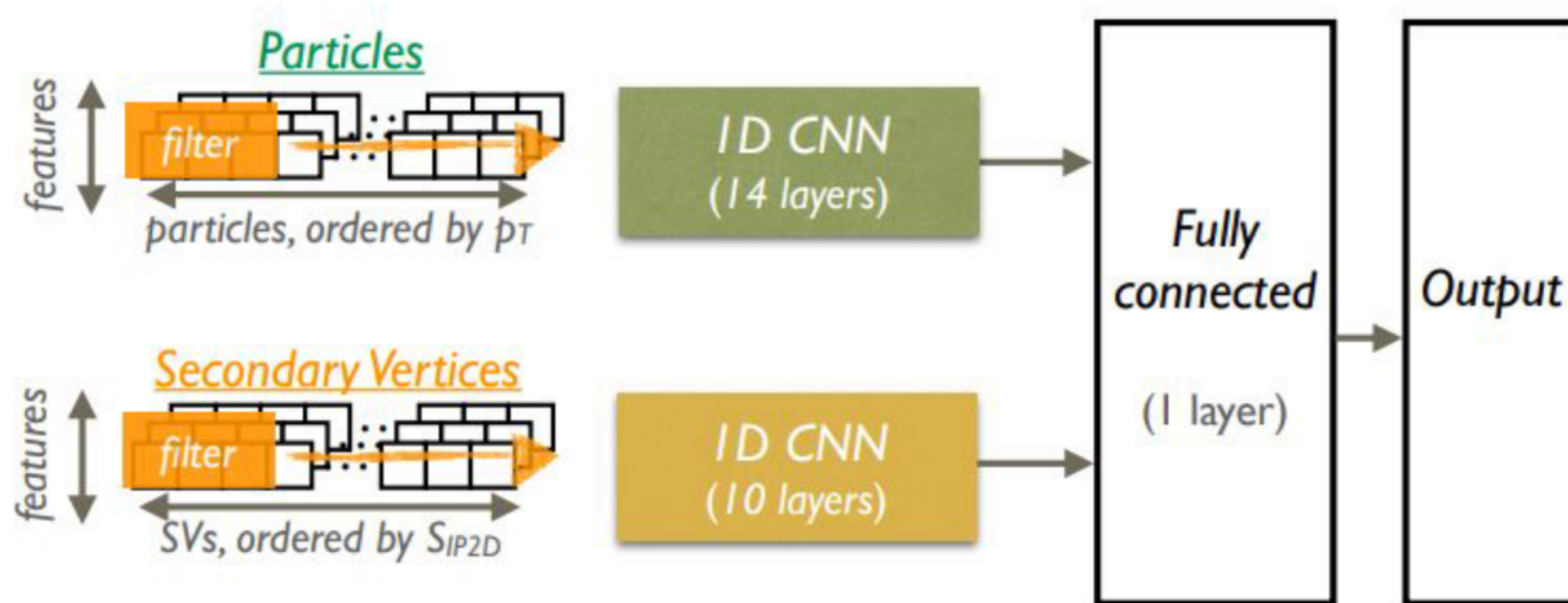




- The DeepAK8 algorithm is a multiclassifier to discriminate jets from W/Z/H/t/other, the main classes are subdivided to minor categories, e.g. Z→bb, Z→cc.
- Model with CNN layers

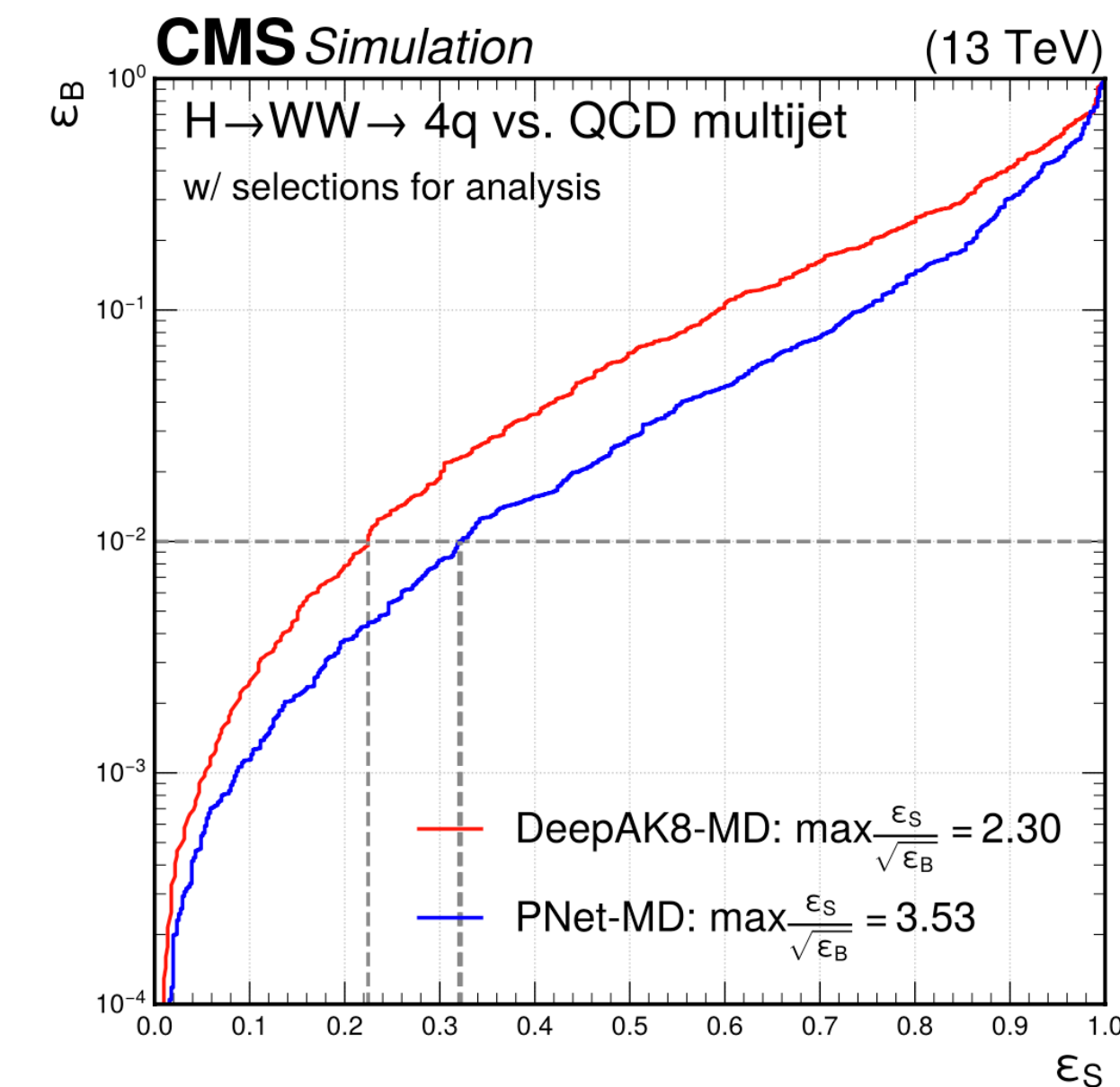
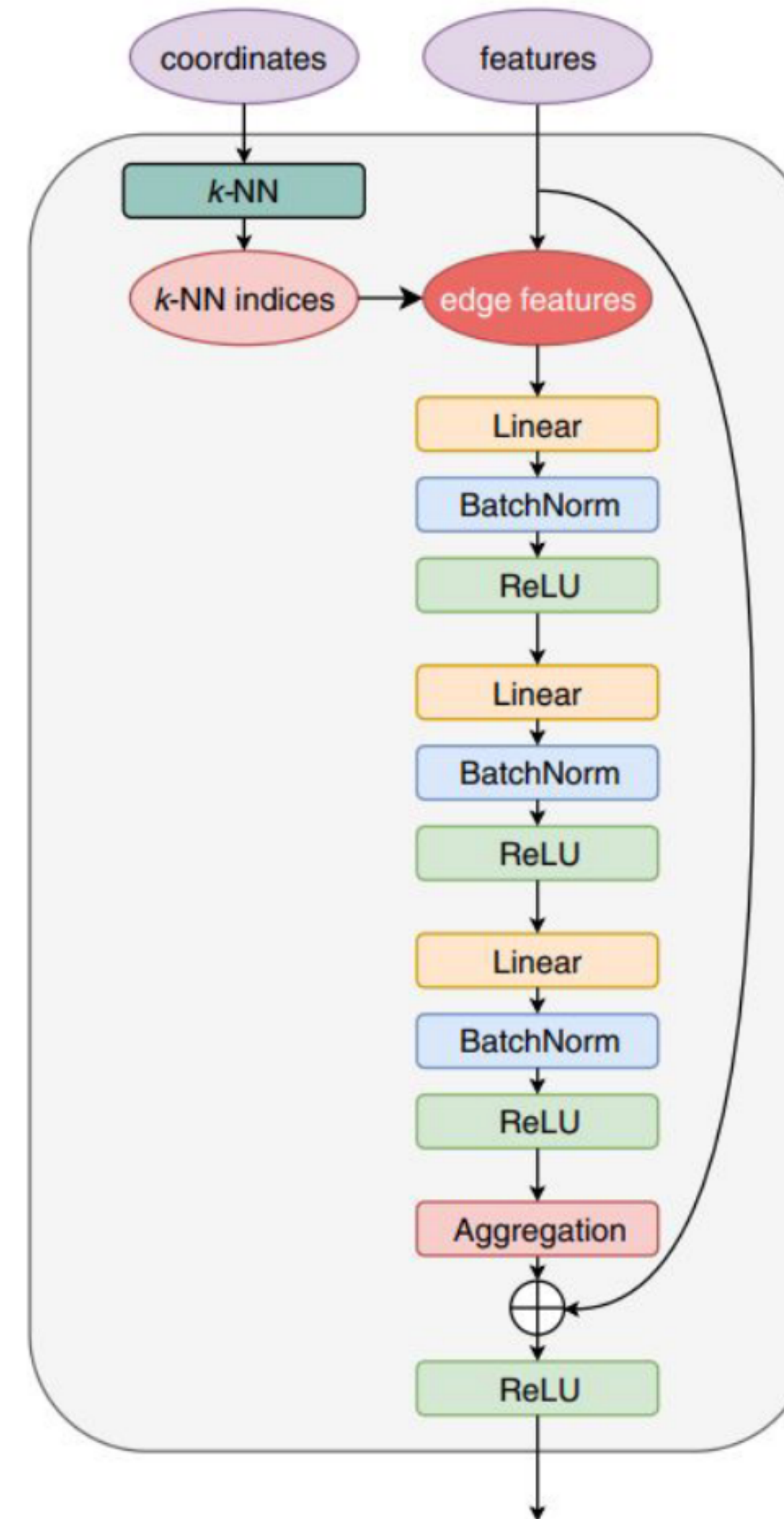
– Two list of input for each jet:

1. 100 jet constituents, order by decreasing transverse momentum, 15 features for each particle
2. Up to 7 SecondaryVertexes (SVs), ordered by 2D secondary ImpactParameter significance, 15 features for each SV



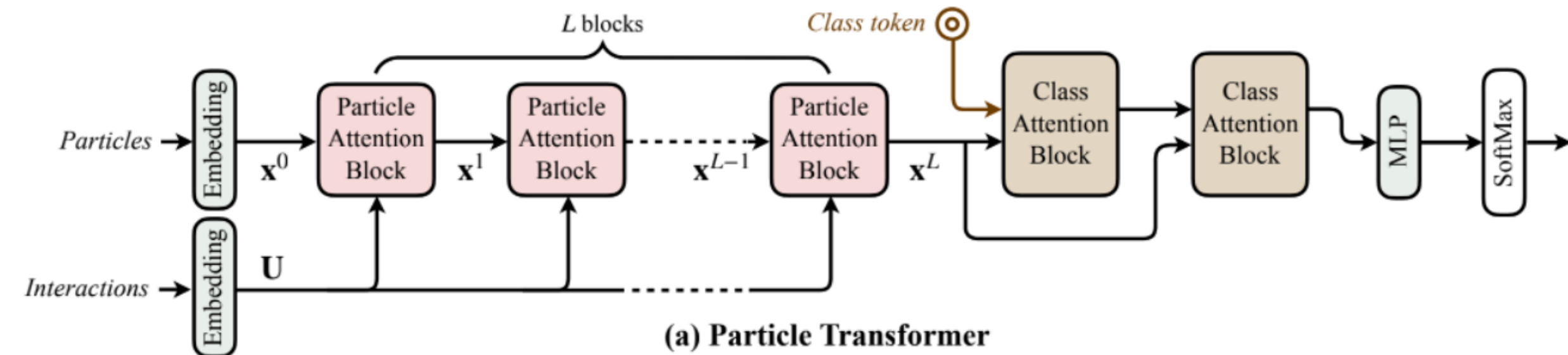


- The ParticleNet algorithm is a Dynamic Graph Convolutional Neural Network
- The jet can be seen as a ParticleCloud, unordered set of entities irregularly distributed. The elements are correlated and with a rich internal structure, taking into account non additive features.
- Imaged based to particle based:
  - no loss of information from pixelation
  - straightforward to include any kind of features for each particle
  - constituent particles of a jet are intrinsically unordered – permutation symmetry!
- Better than DeepAK8!





- The ParticleNet algorithm is an attention based Neural Network
- Input embedding: Not only inject single particle information, but also include pair-wise feature
- Better than ParticleNet!
- Updating:
  - Implementation in the CMSSW
  - GloParT3 -> transfer learning with all classes



## Global Particle Transformer 3 (GloParT 3)

Congqiao Li for the *Tagger dev working group*

**Brown U:** Loukas Gouskos,

**Caltech:** Zichun Hao,

**CERN:** Santeri Laurila, Huilin Qu,

**IHEP:** Mingshui Chen, Zhenxuan Zhang,

**INFN & UniMiB:** Raffaele Gerosa,

**PKU:** Antonis Agapitos, Dawei Fu, Qilong Guo, Congqiao Li, Qiang Li, Chengyang Pan, Sitian Qian, Yuzhe Zhao, Chen Zhou,

**UCSD:** Stephane Cooperstein, Javier Duarte, Raghav Kansal, Farouk Mokhtar, Mellisa Quinnan,

**UVA:** Cristina Mantilla Suarez,

**VUB:** Alexandre De Moor, Denise Muller

**CMS BTV Meeting**

20 September, 2024

	All classes		$H \rightarrow b\bar{b}$	$H \rightarrow c\bar{c}$	$H \rightarrow gg$	$H \rightarrow 4q$	$H \rightarrow \ell\nu qq'$	$t \rightarrow bqq'$	$t \rightarrow b\ell\nu$	$W \rightarrow qq'$	$Z \rightarrow q\bar{q}$
	Accuracy	AUC	Rej <sub>50%</sub>	Rej <sub>50%</sub>	Rej <sub>50%</sub>	Rej <sub>50%</sub>	Rej <sub>99%</sub>	Rej <sub>50%</sub>	Rej <sub>99.5%</sub>	Rej <sub>50%</sub>	Rej <sub>50%</sub>
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
<b>ParT</b>	<b>0.861</b>	<b>0.9877</b>	<b>10638</b>	<b>4149</b>	<b>123</b>	<b>1864</b>	<b>5479</b>	<b>32787</b>	<b>15873</b>	<b>543</b>	<b>402</b>
ParT (plain)	0.849	0.9859	9569	2911	112	1185	3868	17699	12987	384	311

## Model Performance discrepancy from data and MC

- Need to calibrate MC to data to for consistent performance
- SFsBDT method:
  - Use in boosted jet flavor tagging like  $X \rightarrow bb$ ,  $X \rightarrow cc$
  - Use in proxy jets from gluon splitting to a pair of bottom or charm quarks.
  - Can't use for multiple subjets cases ( $\geq 3$ )
- Lund jet plane reweighting method:
  - Use primary lund-plane regions to extract reweighting factors for each subjet
  - Works for multiple subjets cases
  - large systematic uncertainties  $\rightarrow$  no harm for search analysis

