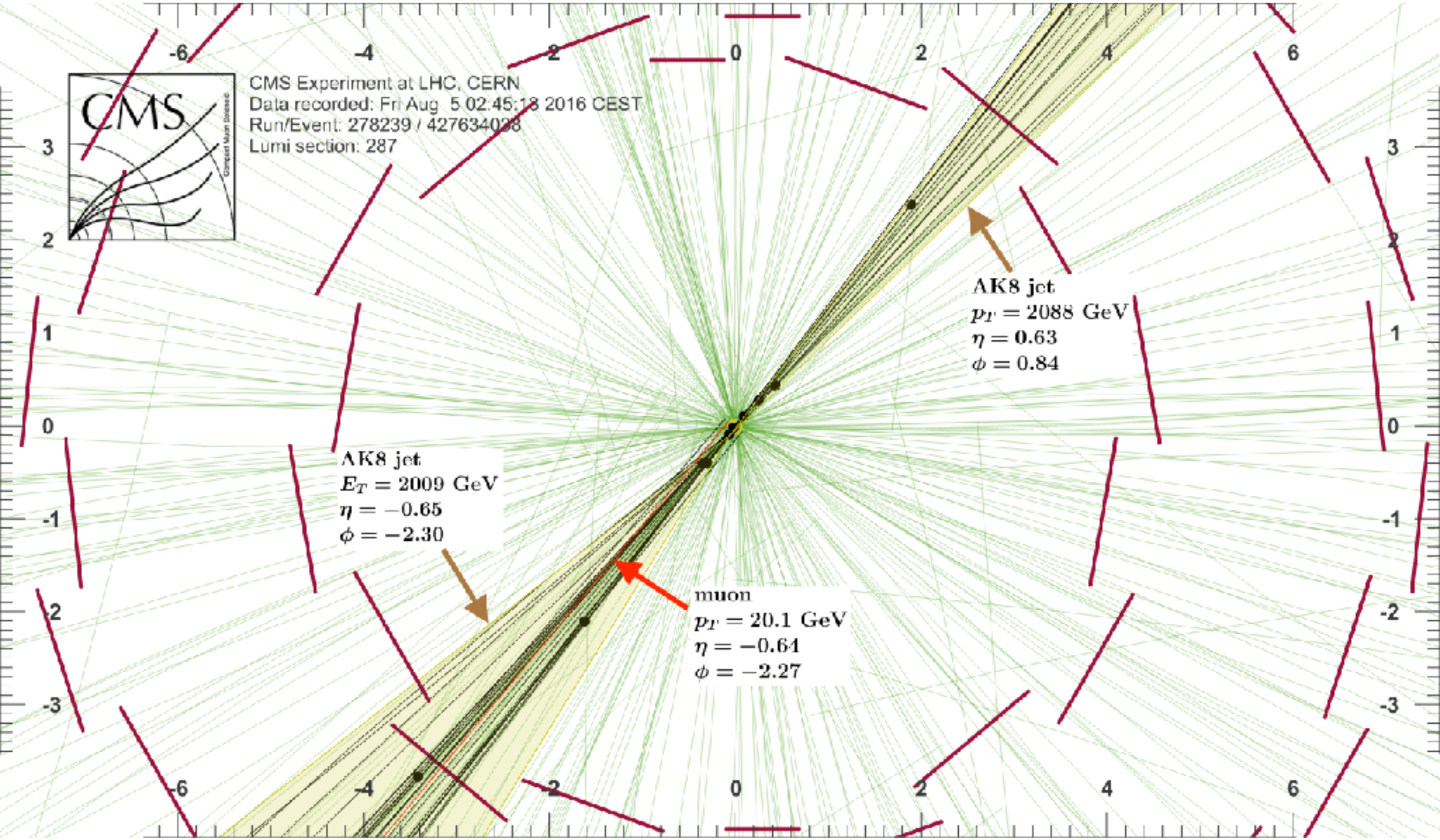
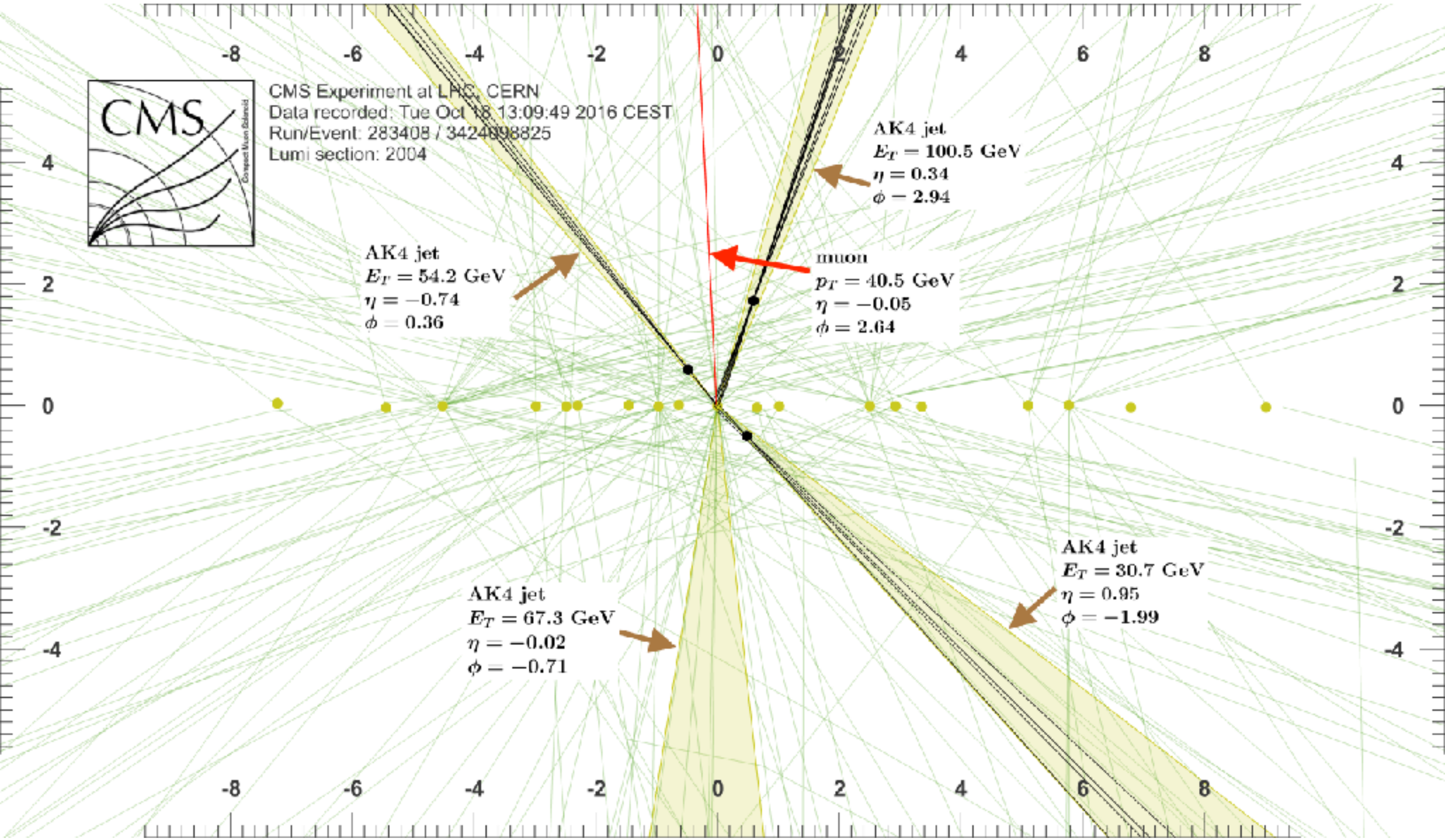
Machine learning techniques for jet flavour identification at CMS

Mauro Verzetti
on behalf of the CMS Collaboration

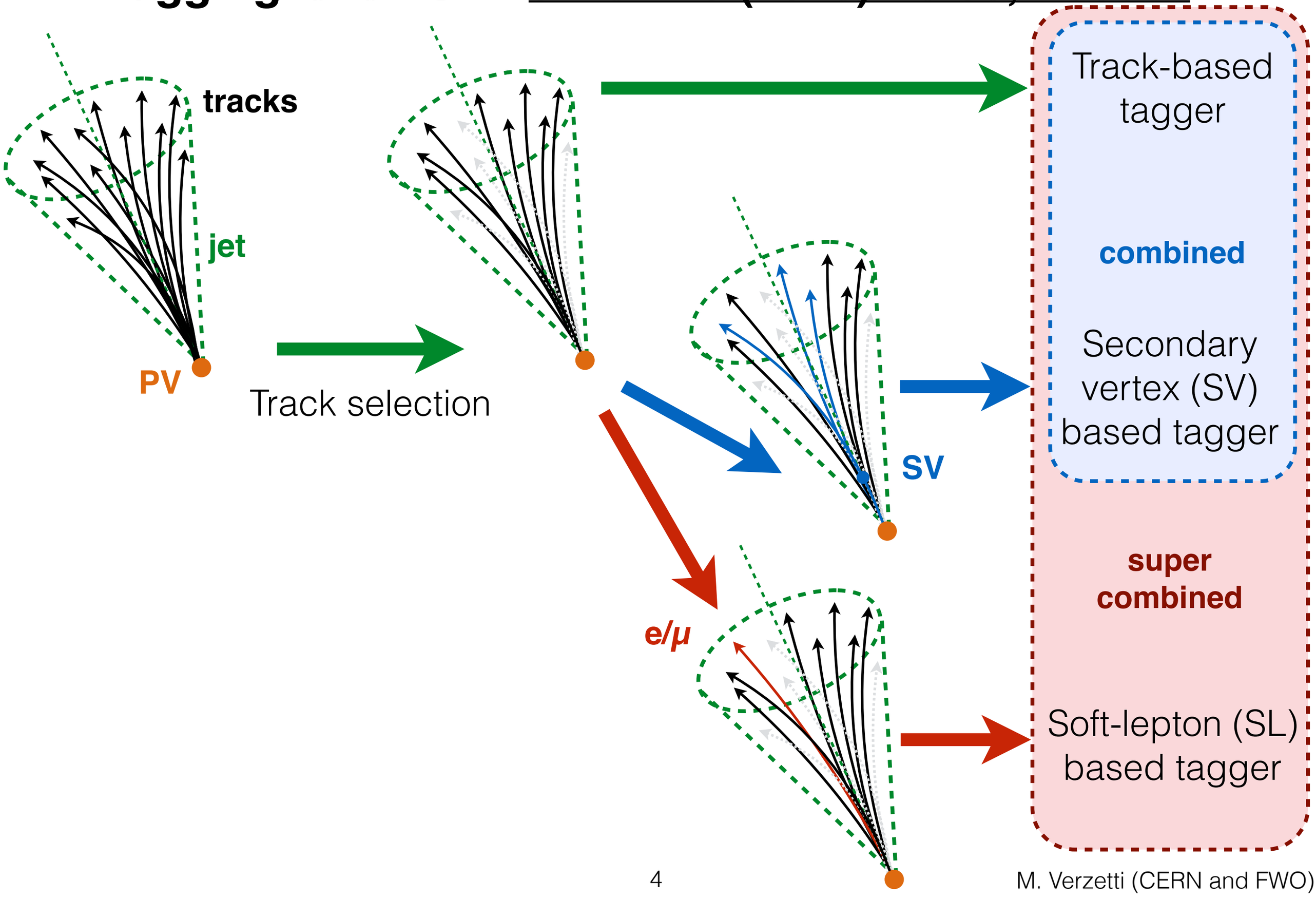
The problem


CMS
CMS Experiment at LHC, CERN
Data recorded: Fri Aug 5 02:45:13 2016 CEST
Run/Event: 278239 / 427634038
Lumi section: 287
AK8 jet
$p_T = 2088$ GeV
$\eta = 0.63$
$\phi = 0.84$
AK8 jet
$E_T = 2009$ GeV
$\eta = -0.65$
$\phi = -2.30$
muon
$p_T = 20.1$ GeV
$\eta = -0.64$
$\phi = -2.27$

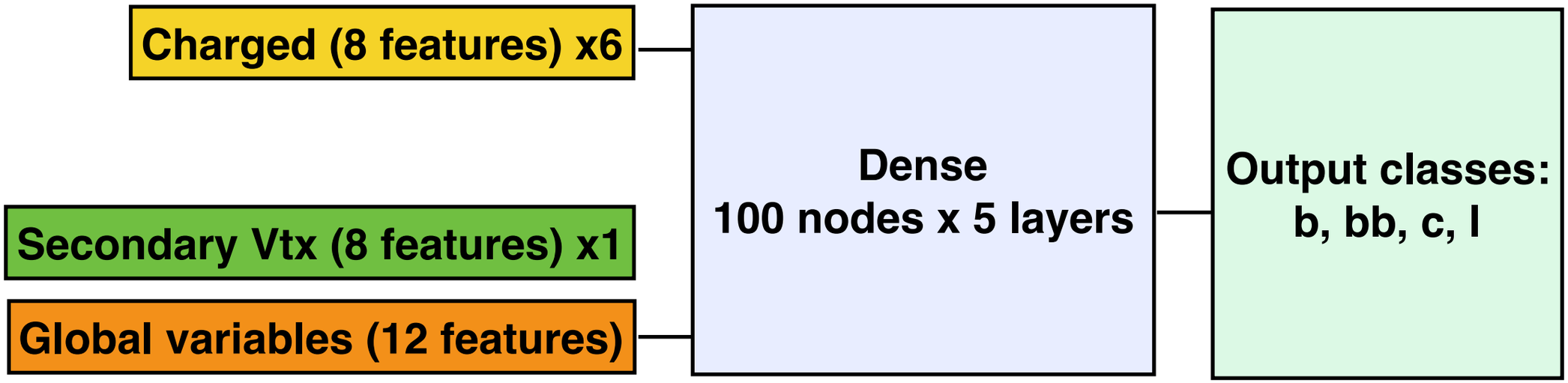
The problem


CMS
CMS Experiment at LHC, CERN
Data recorded: Tue Oct 18 13:09:49 2016 CEST
Run/Event: 283408 / 3424898825
Lumi section: 2004
AK4 jet
$E_T = 100.5$ GeV
$\eta = 0.34$
$\phi = 2.94$
AK4 jet
$E_T = 54.2$ GeV
$\eta = -0.74$
$\phi = 0.36$
muon
$p_T = 40.5$ GeV
$\eta = -0.05$
$\phi = 2.64$
AK4 jet
$E_T = 30.7$ GeV
$\eta = 0.95$
$\phi = -1.99$
AK4 jet
$E_T = 67.3$ GeV
$\eta = -0.02$
$\phi = -0.71$

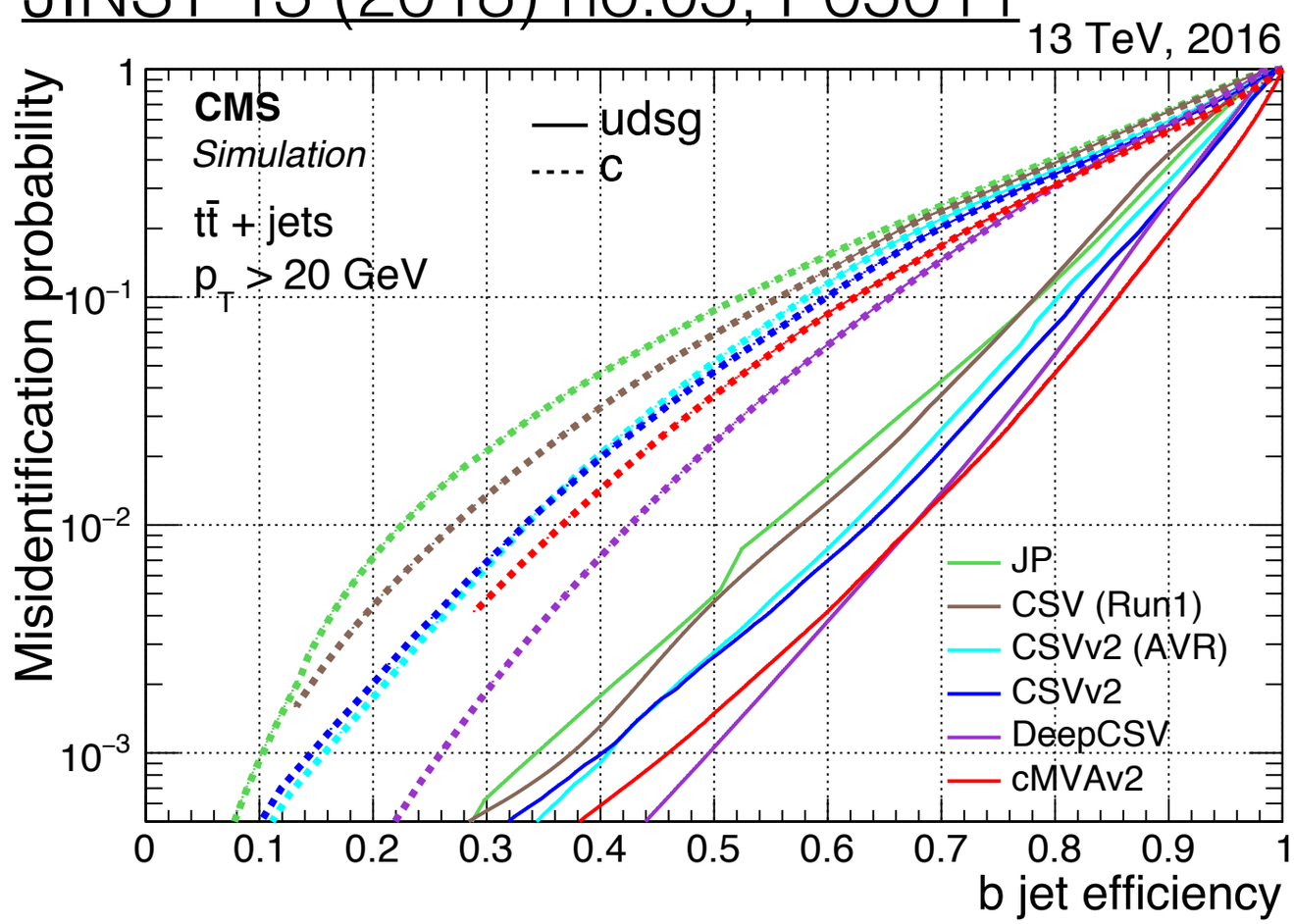
HF tagging @ CMS — JINST 13 (2018) no.05, P05011



DeepCSV

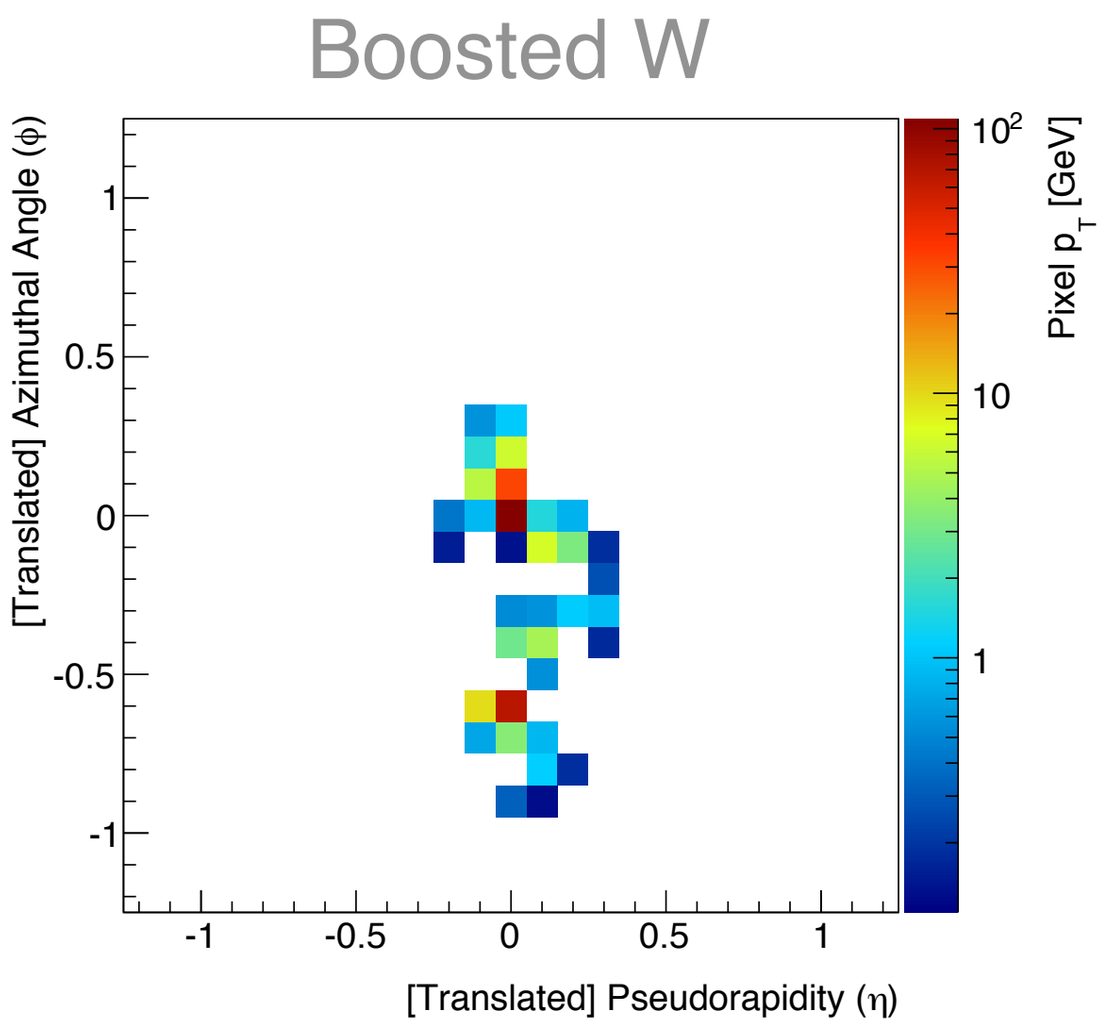


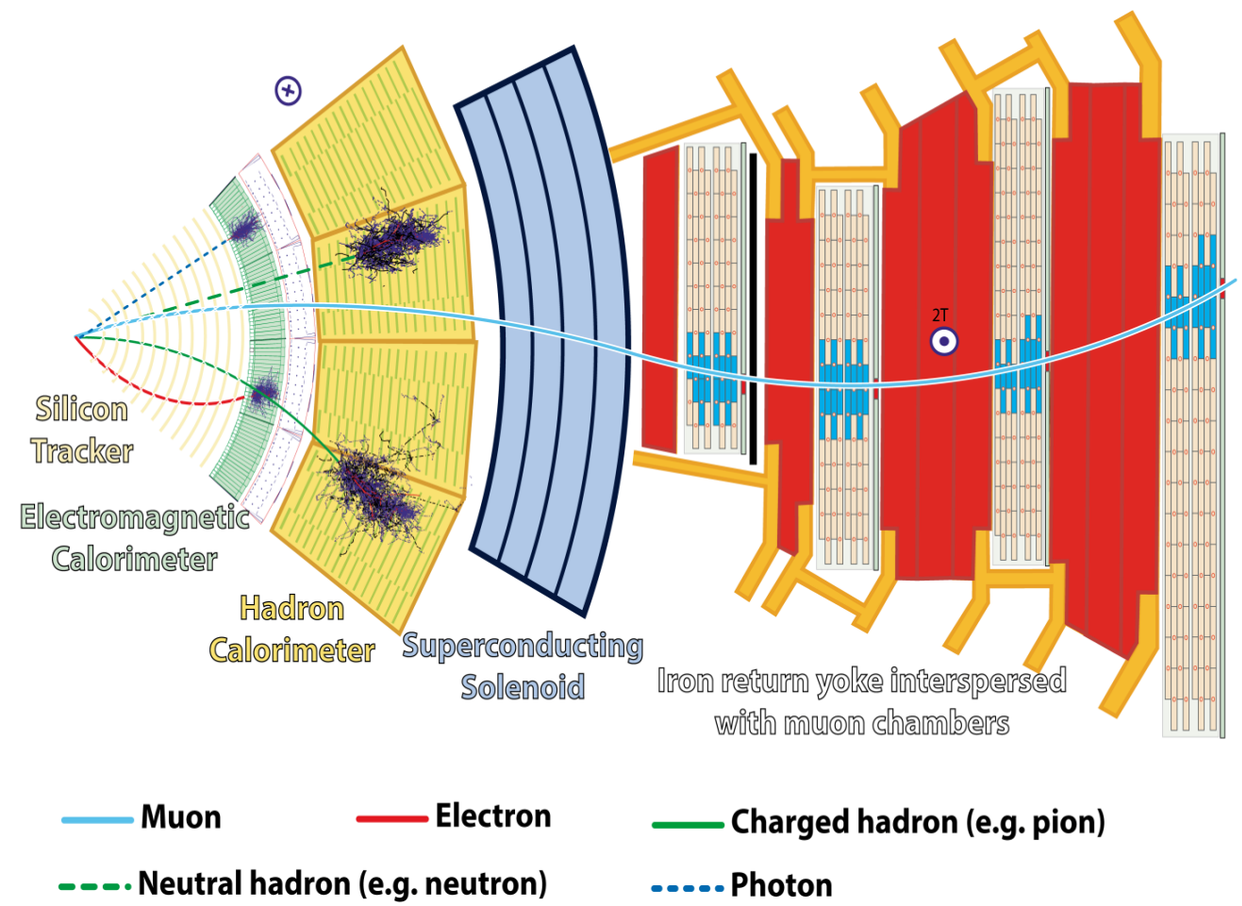
JINST 13 (2018) no.05, P05011



Trying more complex architectures

- Convolutional NN successfully applied in neutrino physics and image recognition
- Some proposals to treat jets as images

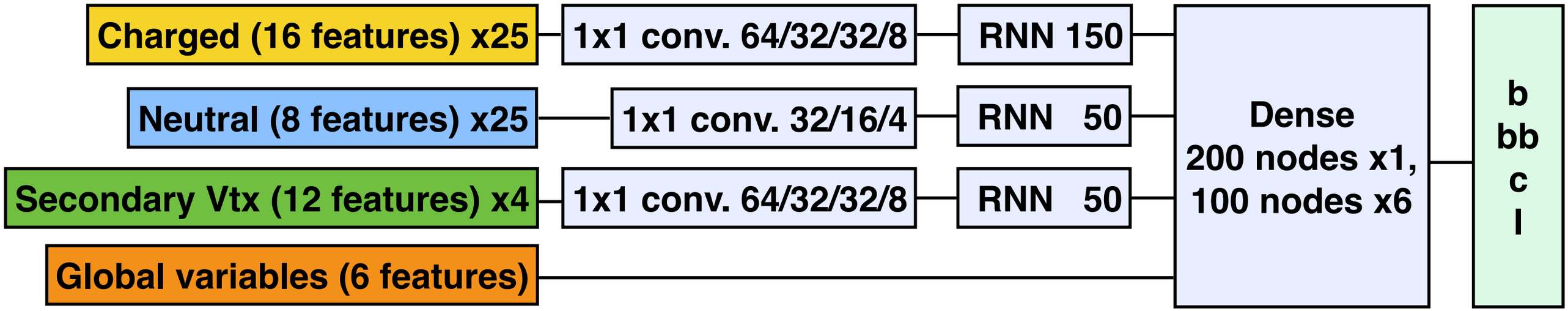




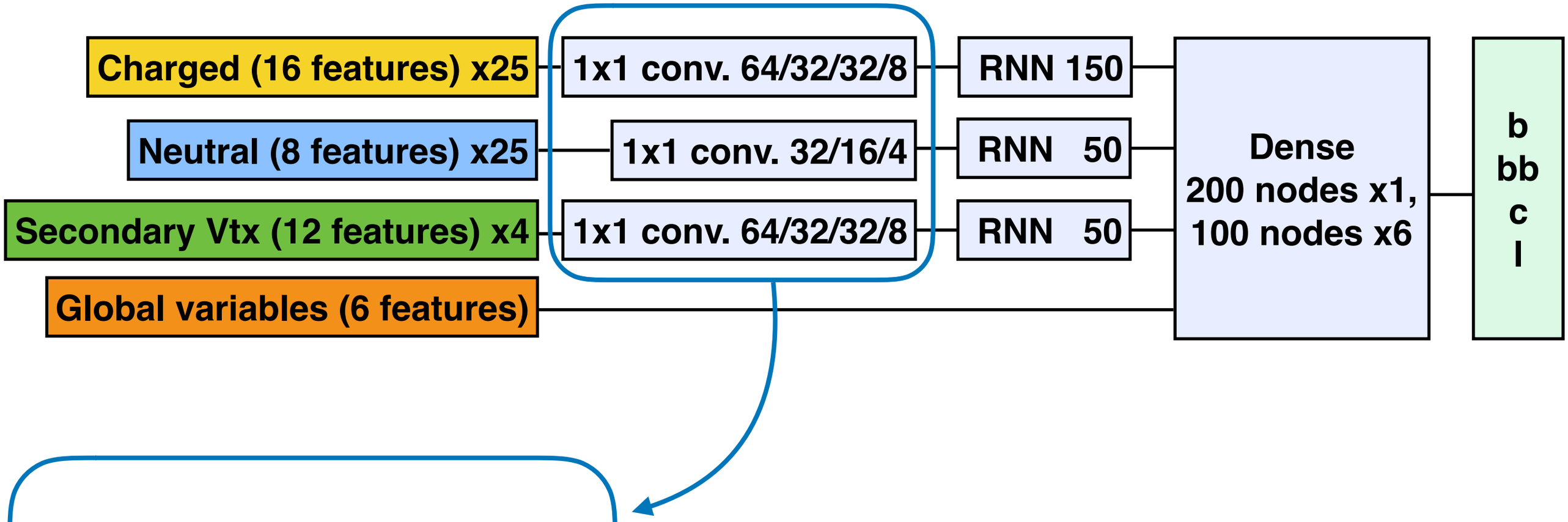
… but

- Jets do not look like normal images!
- CMS events are way more complex and bring more information than a flat image (e.g. tracking information)

Particle-based NN architecture

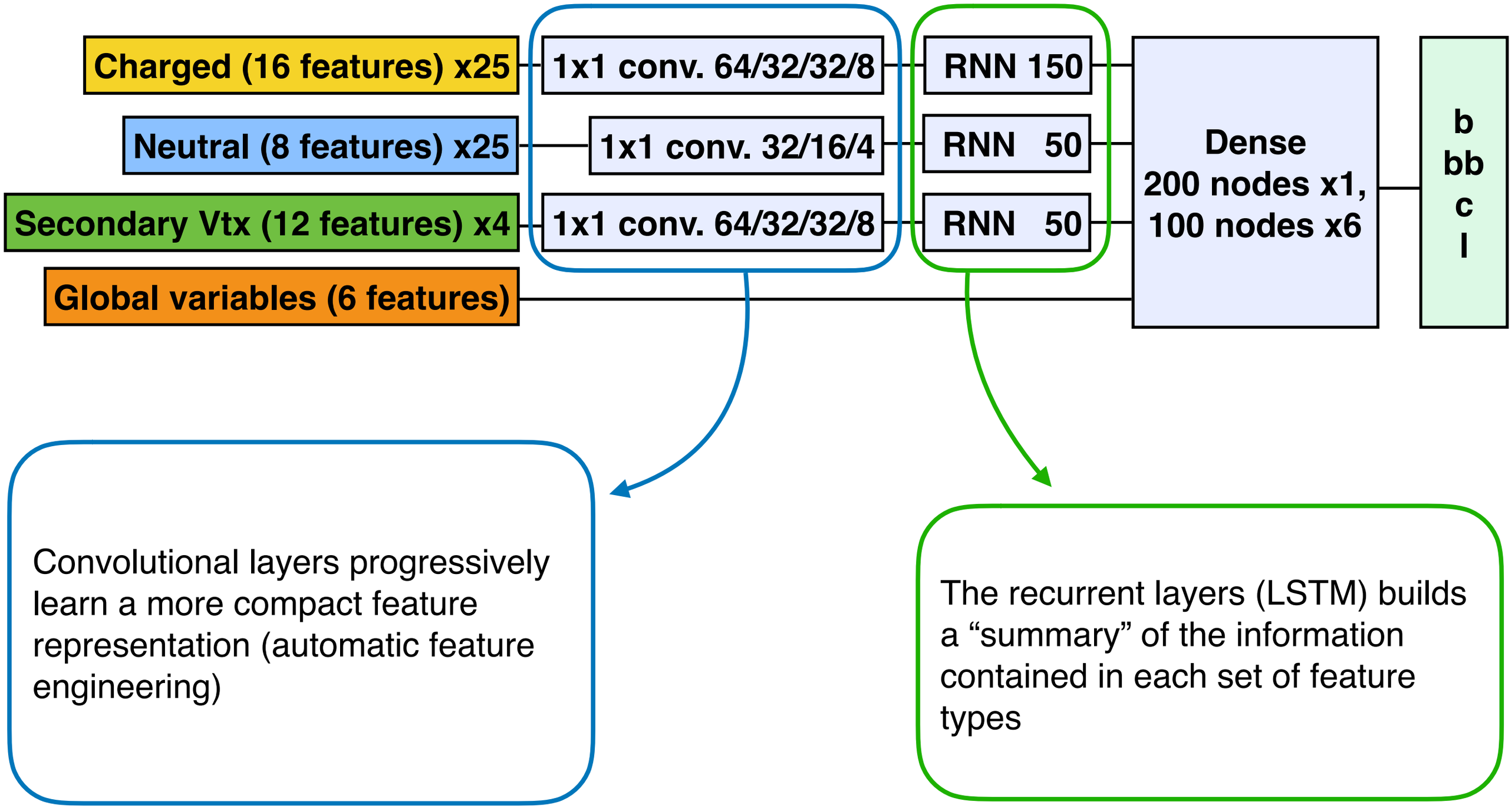


Particle-based NN architecture



Convolutional layers progressively learn a more compact feature representation (automatic feature engineering)

Particle-based NN architecture



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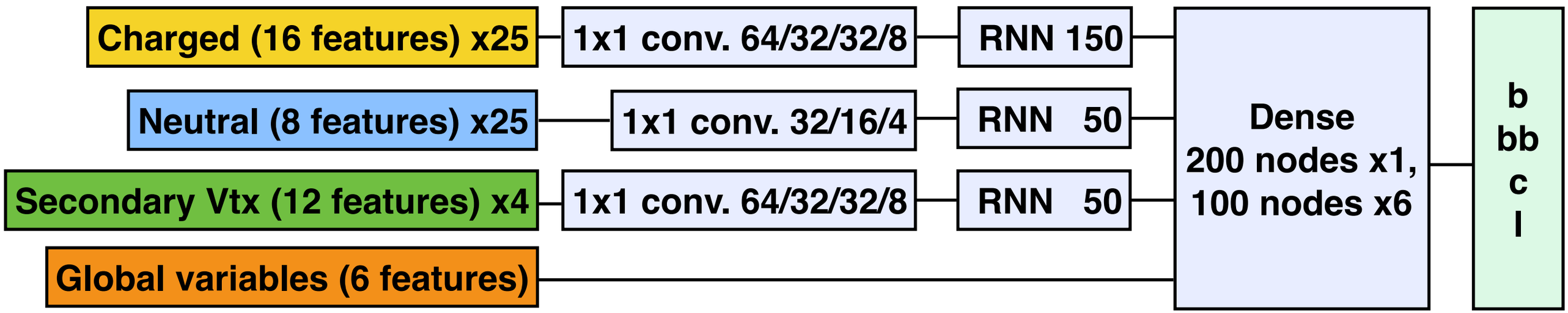
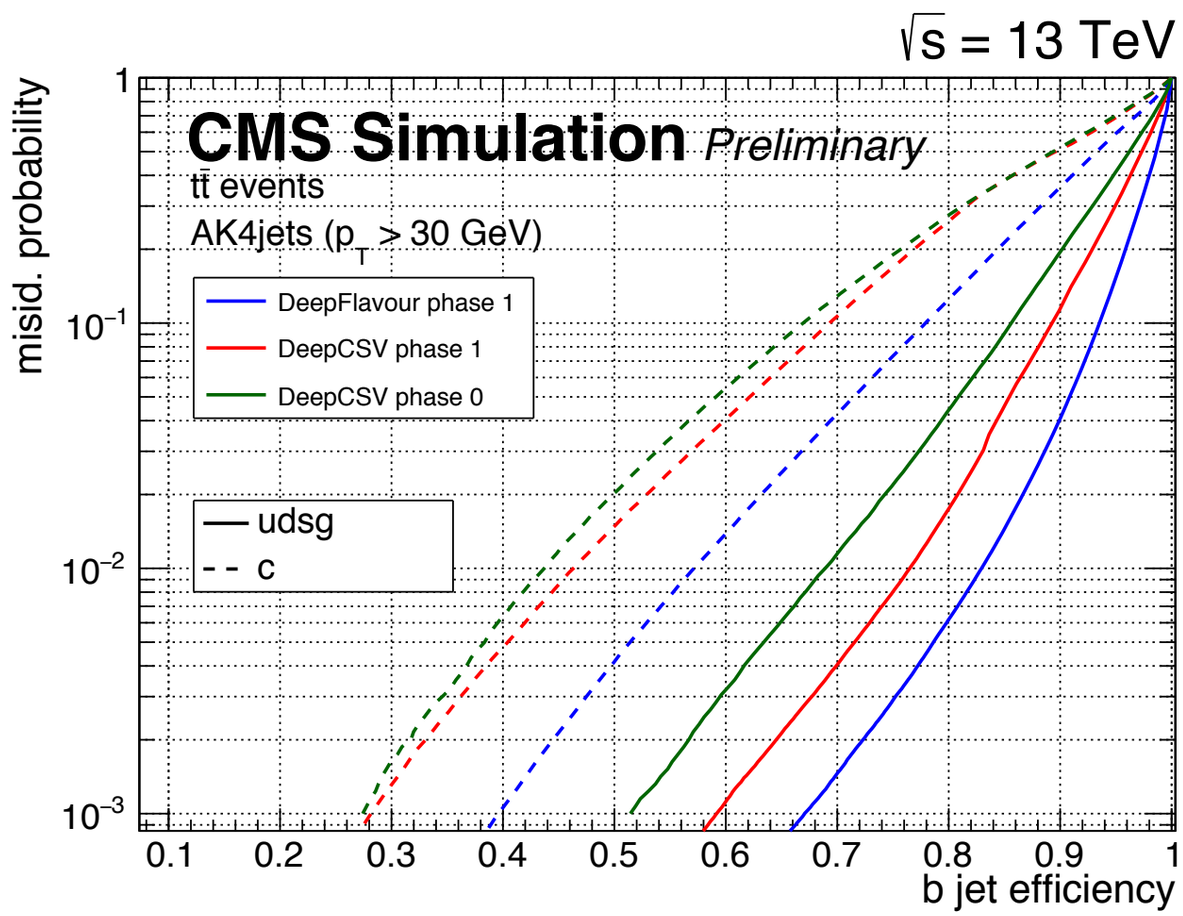
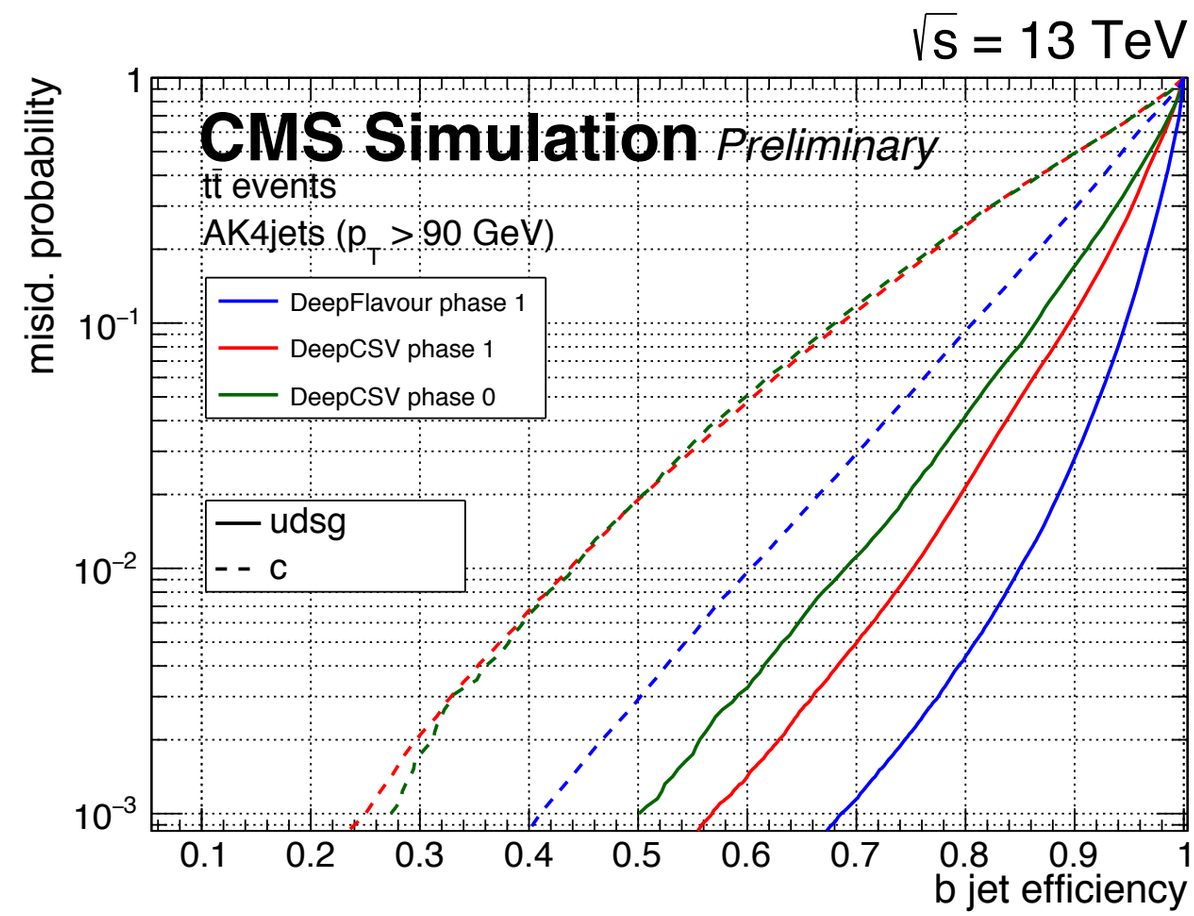
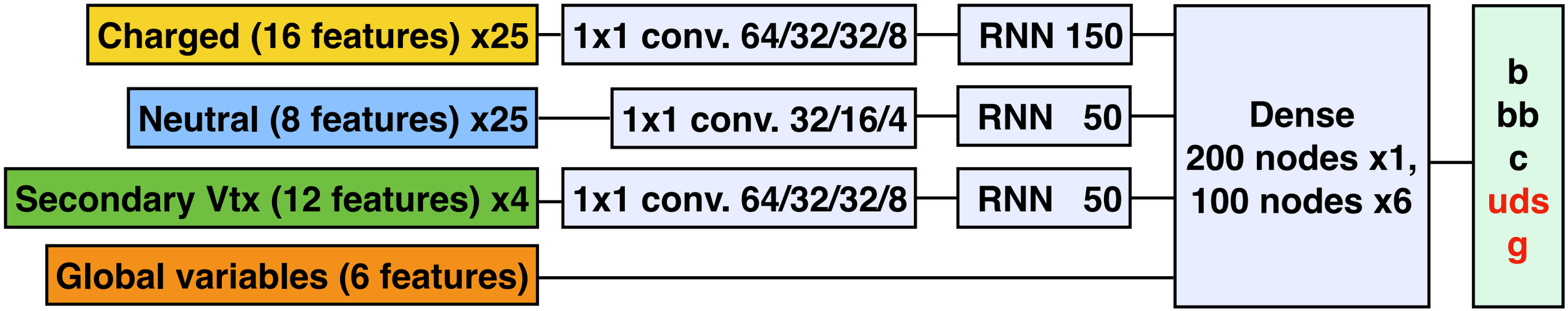






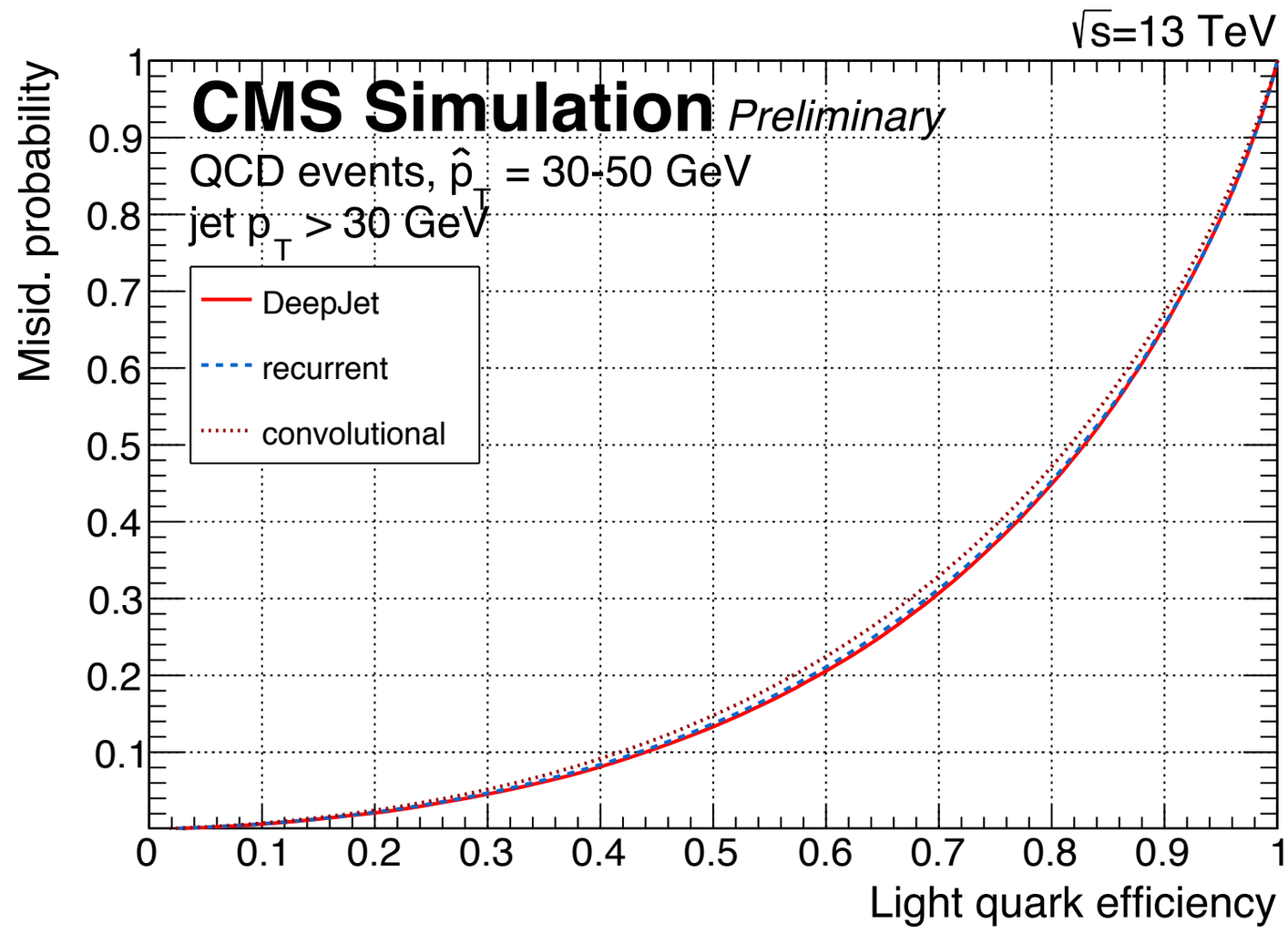
CMS DP-2018/033

Particle-based NN architecture



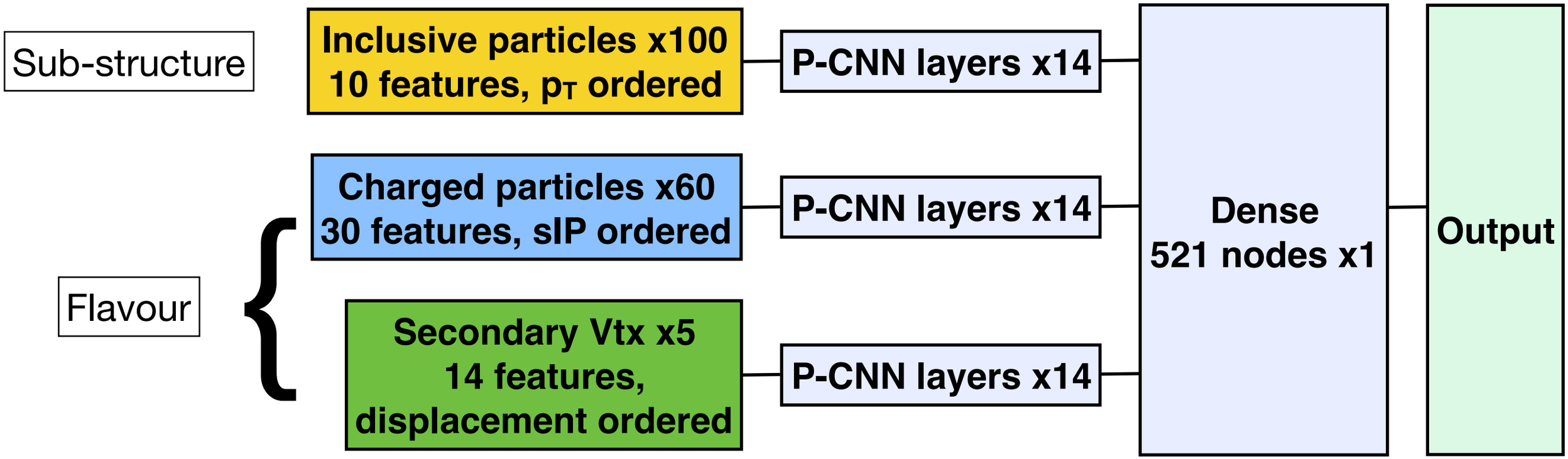
Similar performance to simpler, dedicated binary taggers, but with full multi-class power.

Significantly better performances in given regions with different quark composition



CMS-DP-2017-027

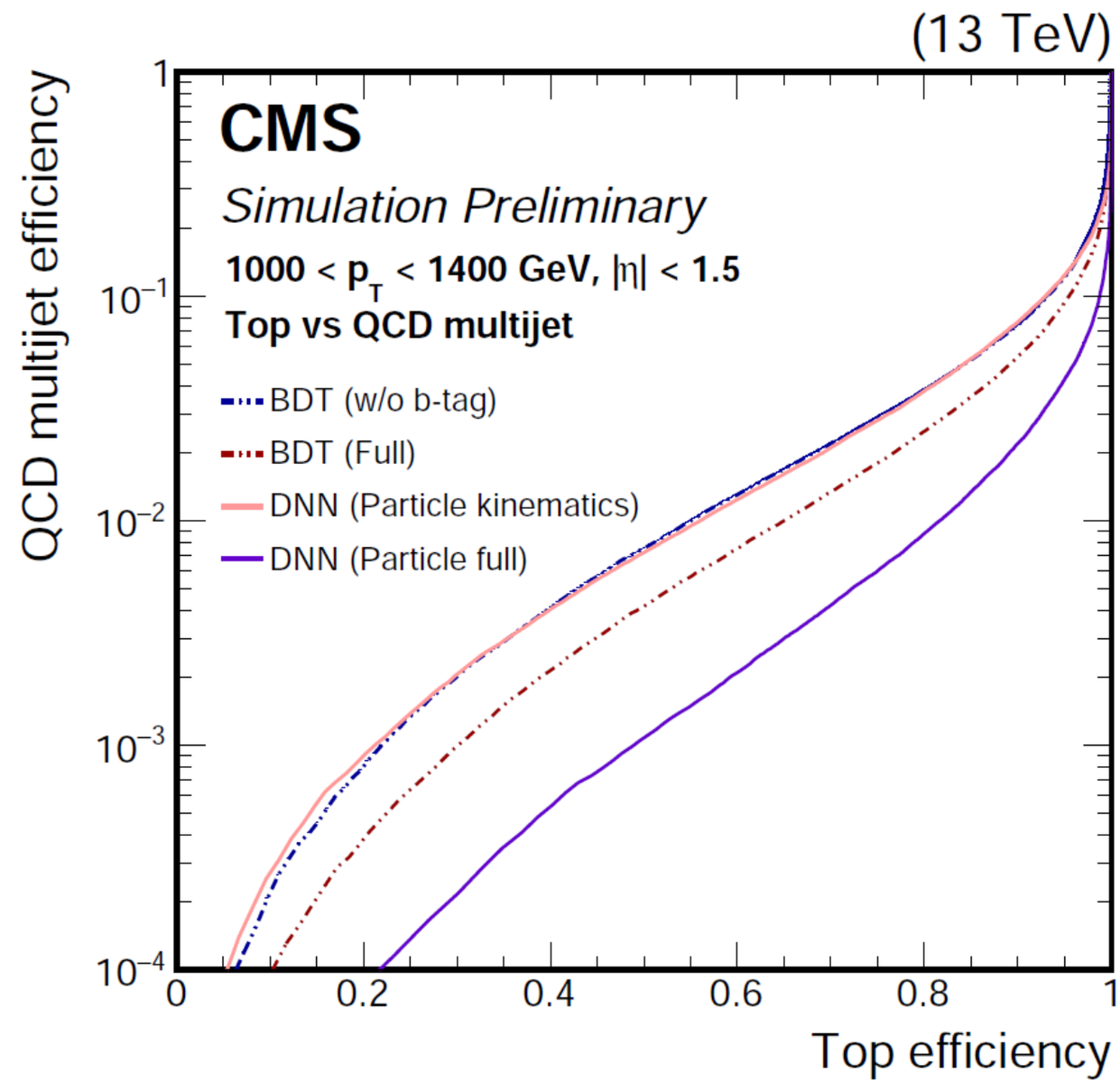
DeepJet for boosted resonances



- Significantly larger amount of candidates used to accomodate for 90% of the fat jets
- Need to learn substructure from both charged and neutral candidates
- RNNs become computationally too expensive to train
- Use particle-level convolutional layers (P-CNN) where each feature is treated as a “colour”

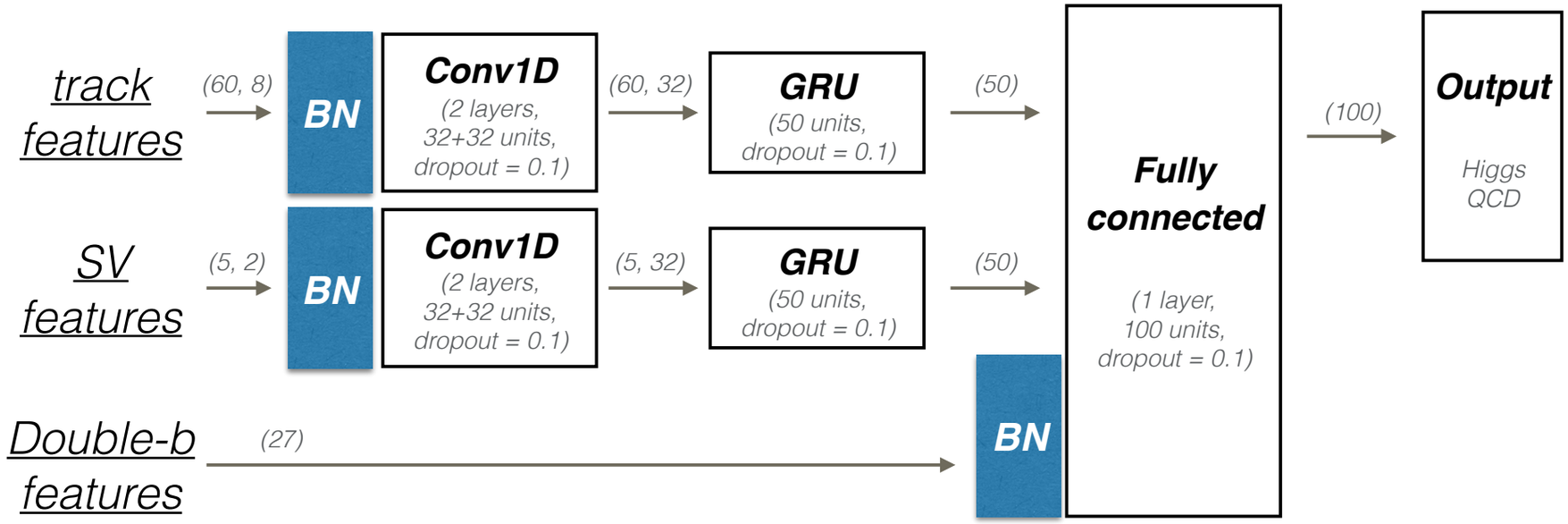
Performance

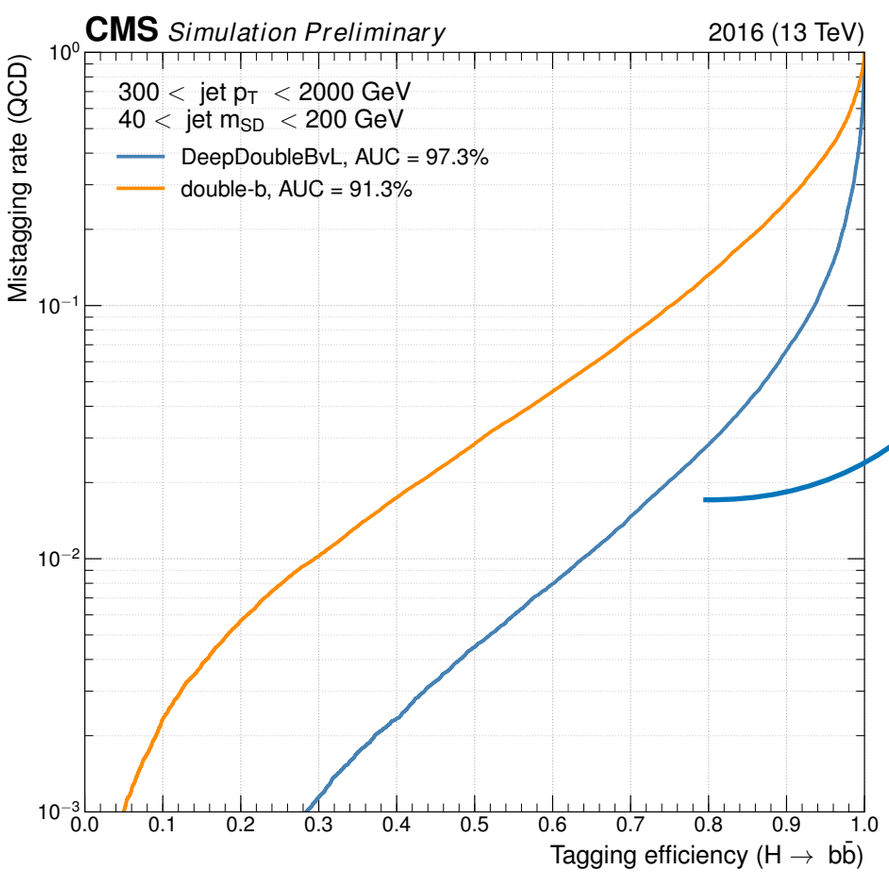
- Flavour information largely improves jet tagging
- Large improvement w.r.t to the BDT approach
- Introduces mass sculpting, not necessarily a bad thing



CMS-DP-2017-049

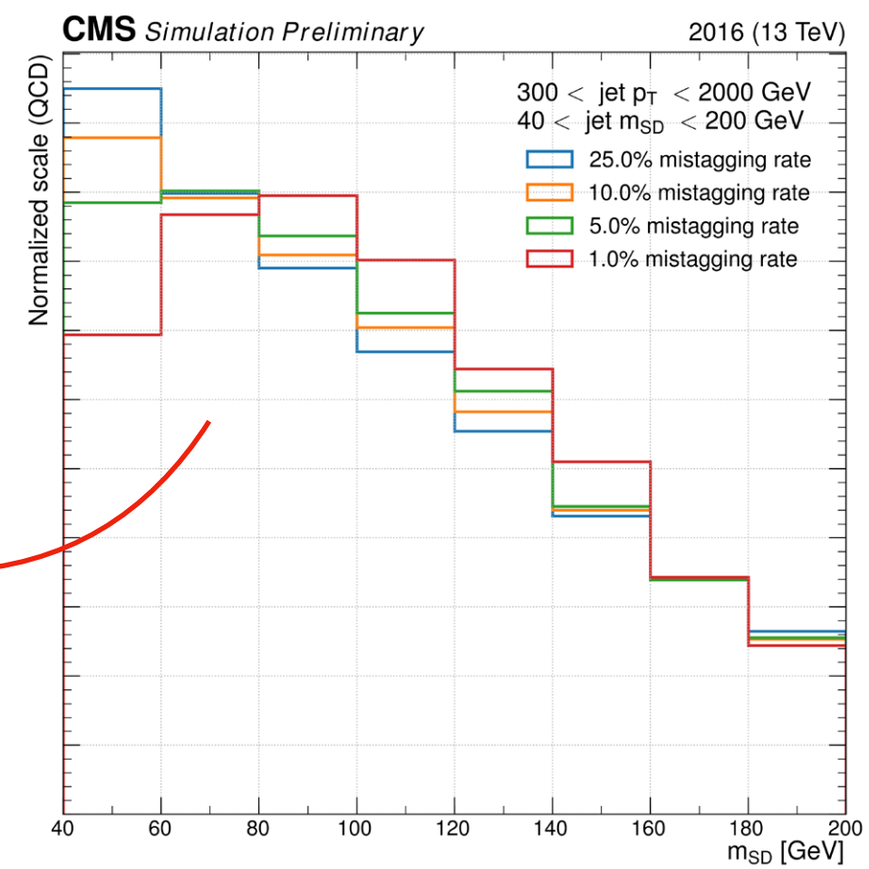
DeepDoubleB





Significantly better than current BDT approach!

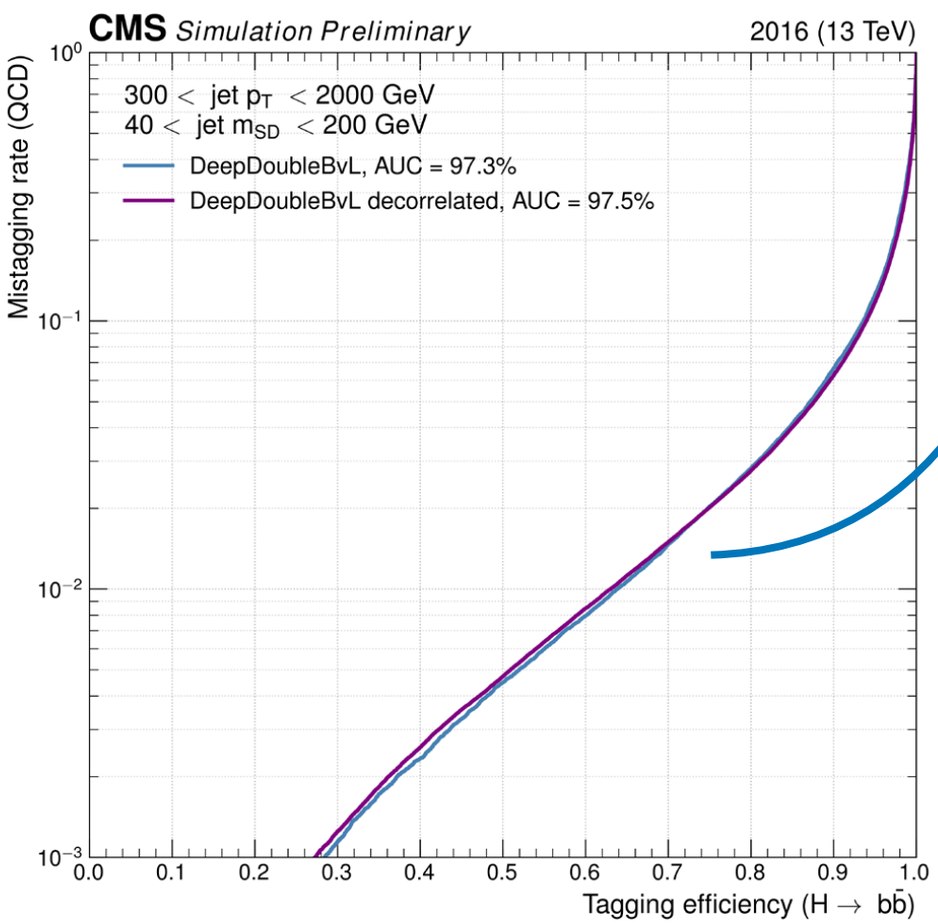
Some mass sculpting



CMS DP-2018/046

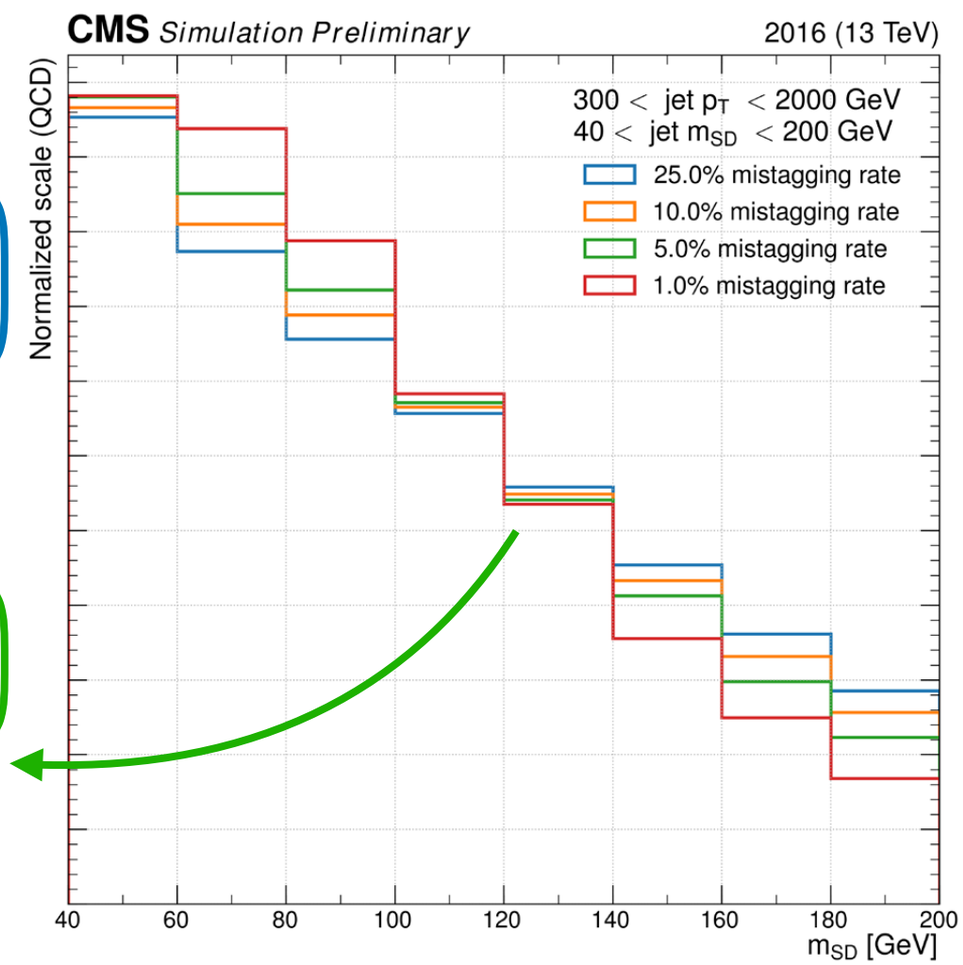
Removing mass correlation

Per-batch penalty term proportional to the Kullback-Liebler (KL) divergence



Minimal loss in performance

Mass sculpting gone



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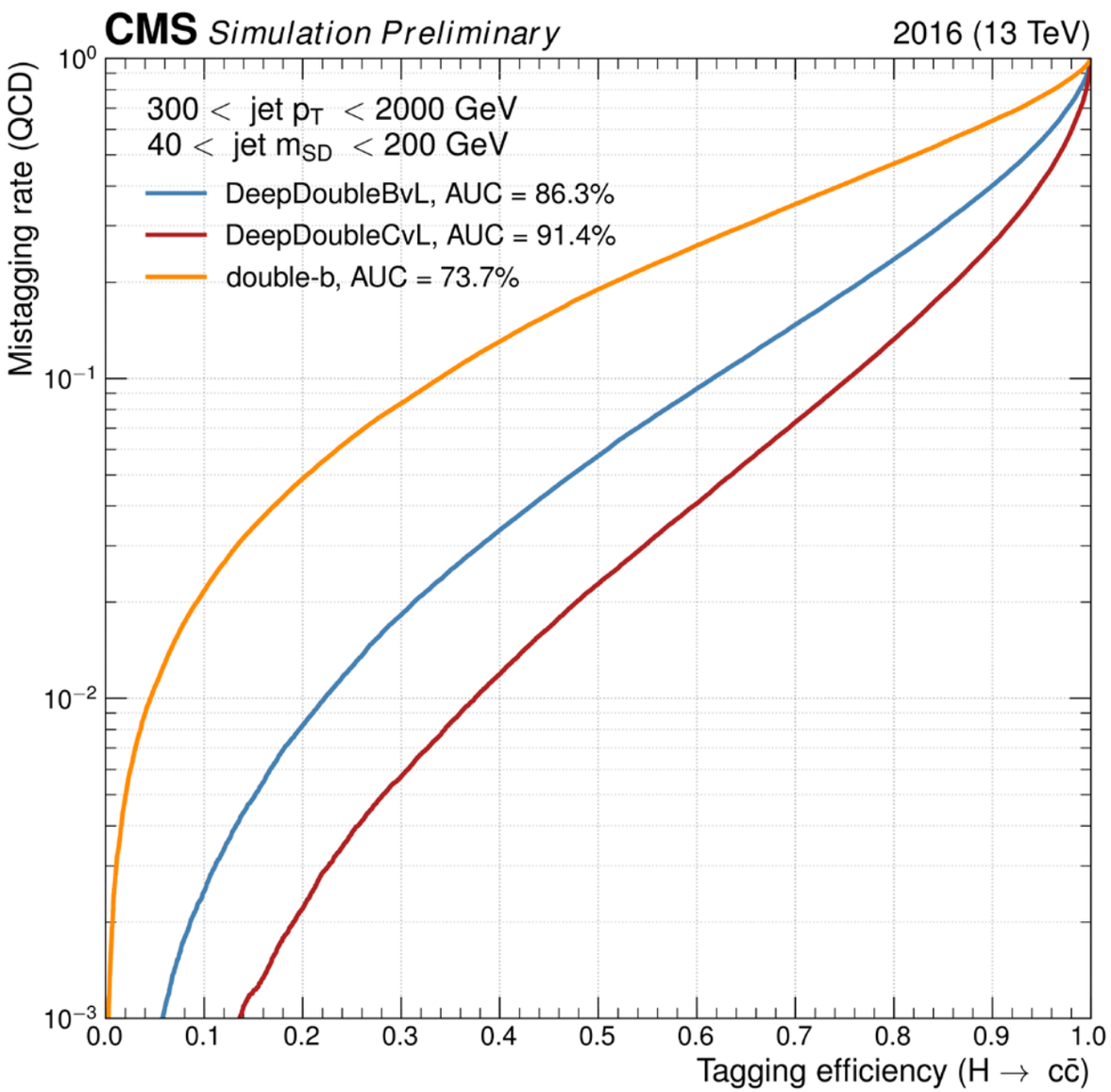
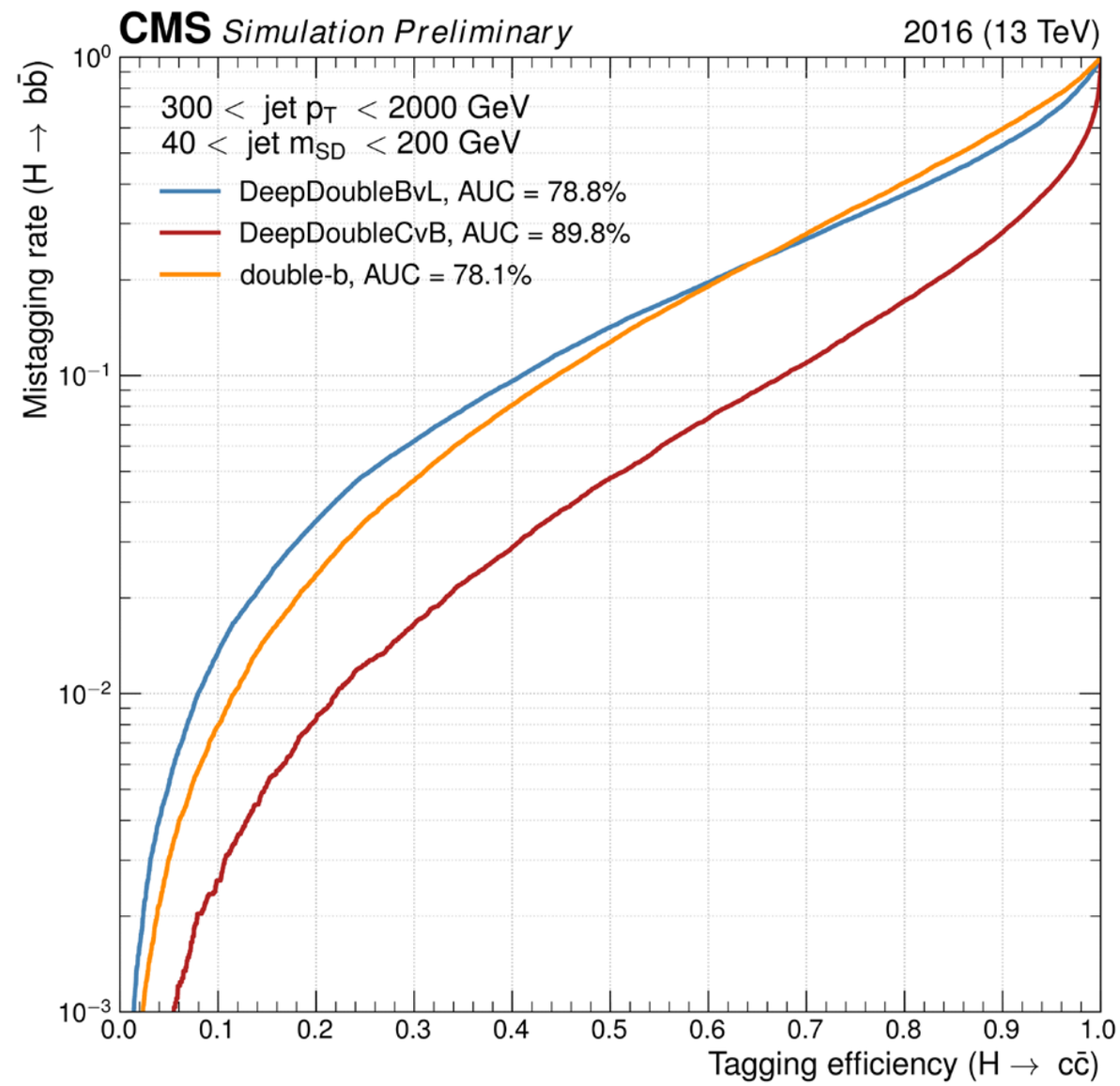
DeepDoubleC!





CMS DP-2018/046

Deploying the model — Two worlds colliding

Training / Analysis:

- Keras + TensorFlow
- Python-based
- Private productions
- Minimal interaction with ROOT
- Few processes, single threads
- Little memory constraints
- Expendable jobs

Production:

- Custom framework
- C++ based (speed!)
- Mostly ROOT-centric (at least I/O)
- Many processes, multiple threads
- Many other concurrent activities → memory constraints
- Processes cannot die (e.g. trigger)

Deployment of the model required extensive efforts to integrate in the core CMS Software, which now fully supports TensorFlow models.

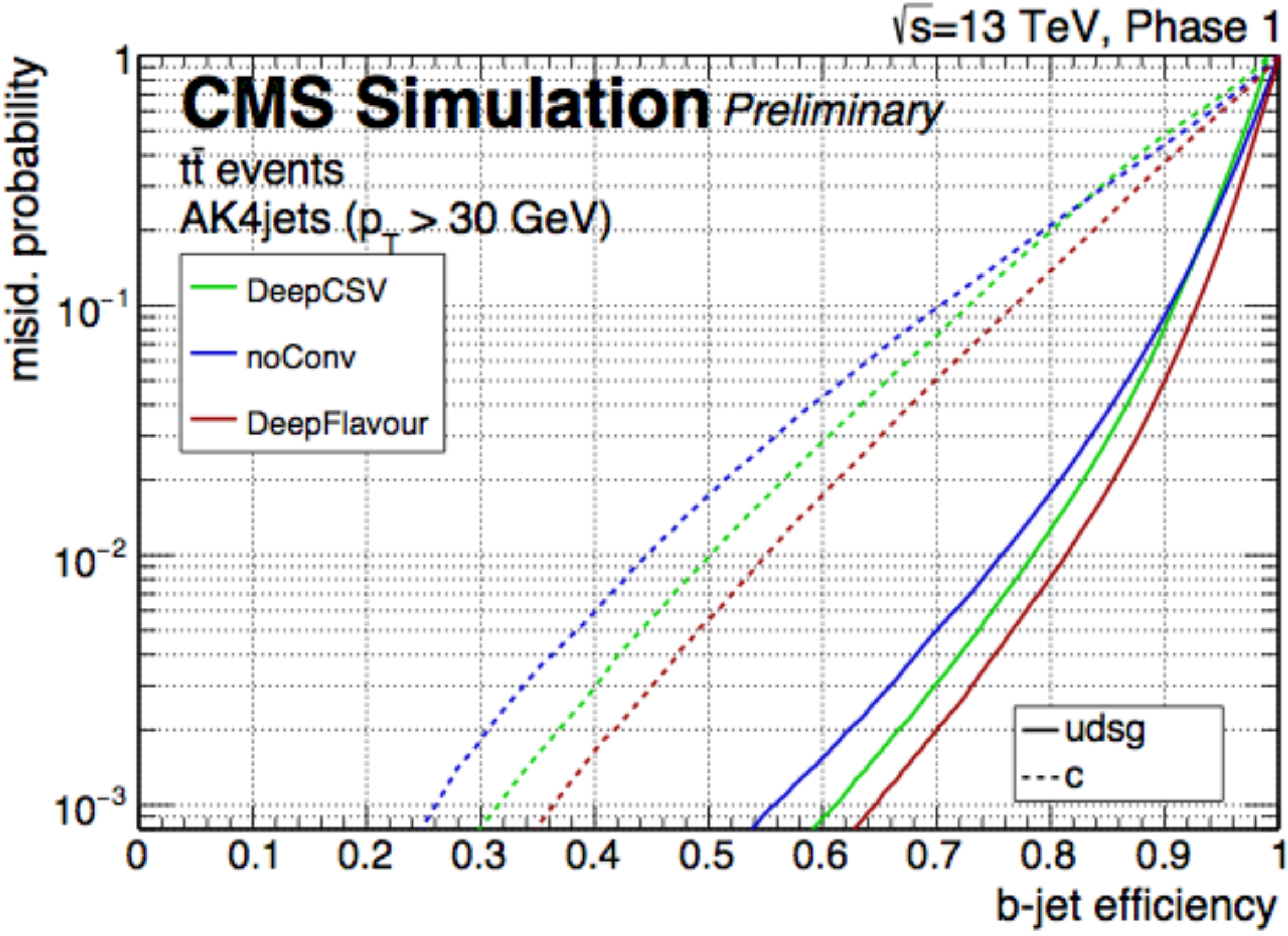
Still looking into optimising the inference performance of the models through model distilling/pruning and AOT compilation.

Summary

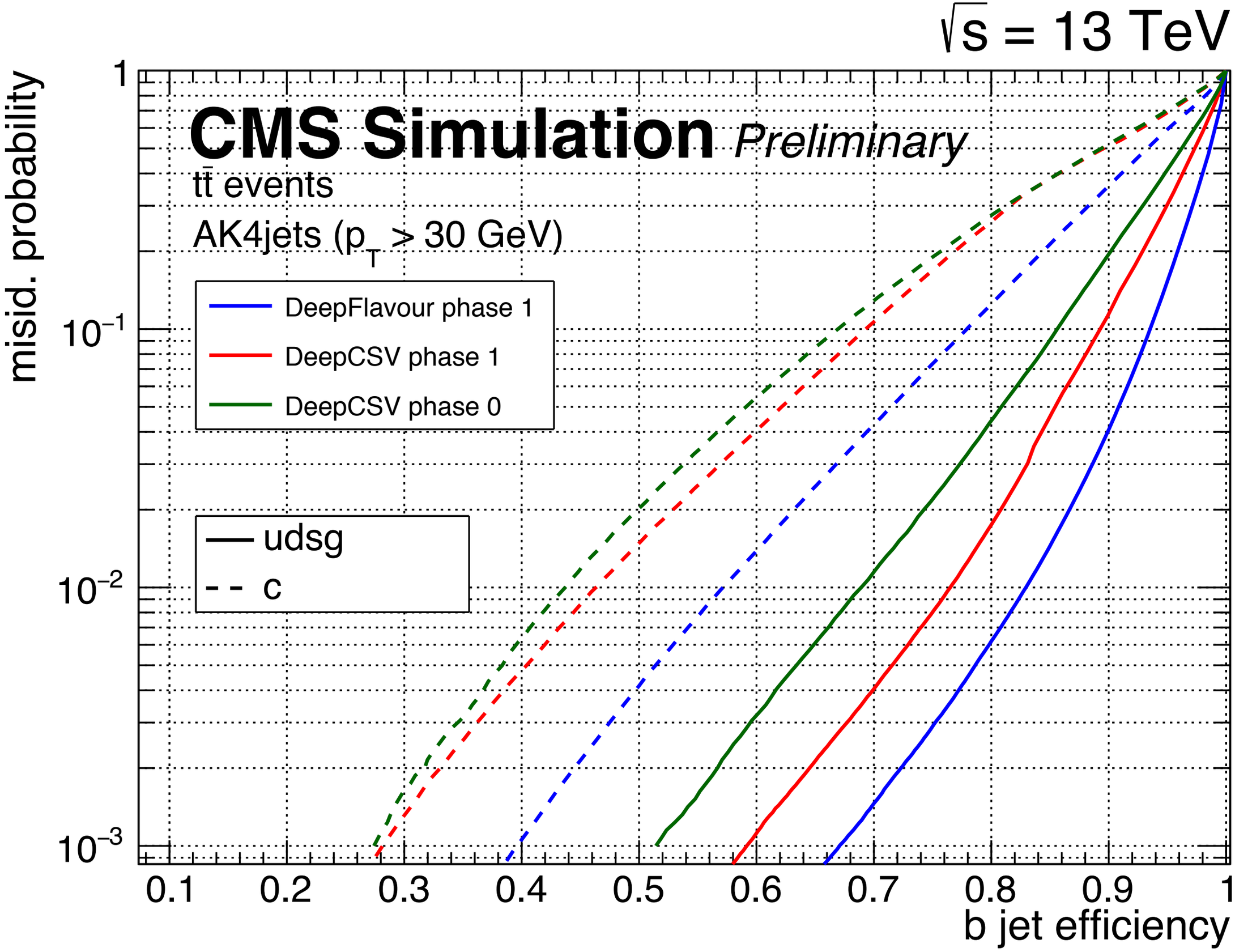
- Jet tagging is of paramount importance for the CMS Physics program
- Lots of development in the last ~1.5 years to apply modern machine learning techniques to this field
  - Large improvements in performance
  - Still some room for new developments, especially in the boosted regime
- Flavour tagging is not only fancy algorithms, but solid and performing computing infrastructures as well

Backup

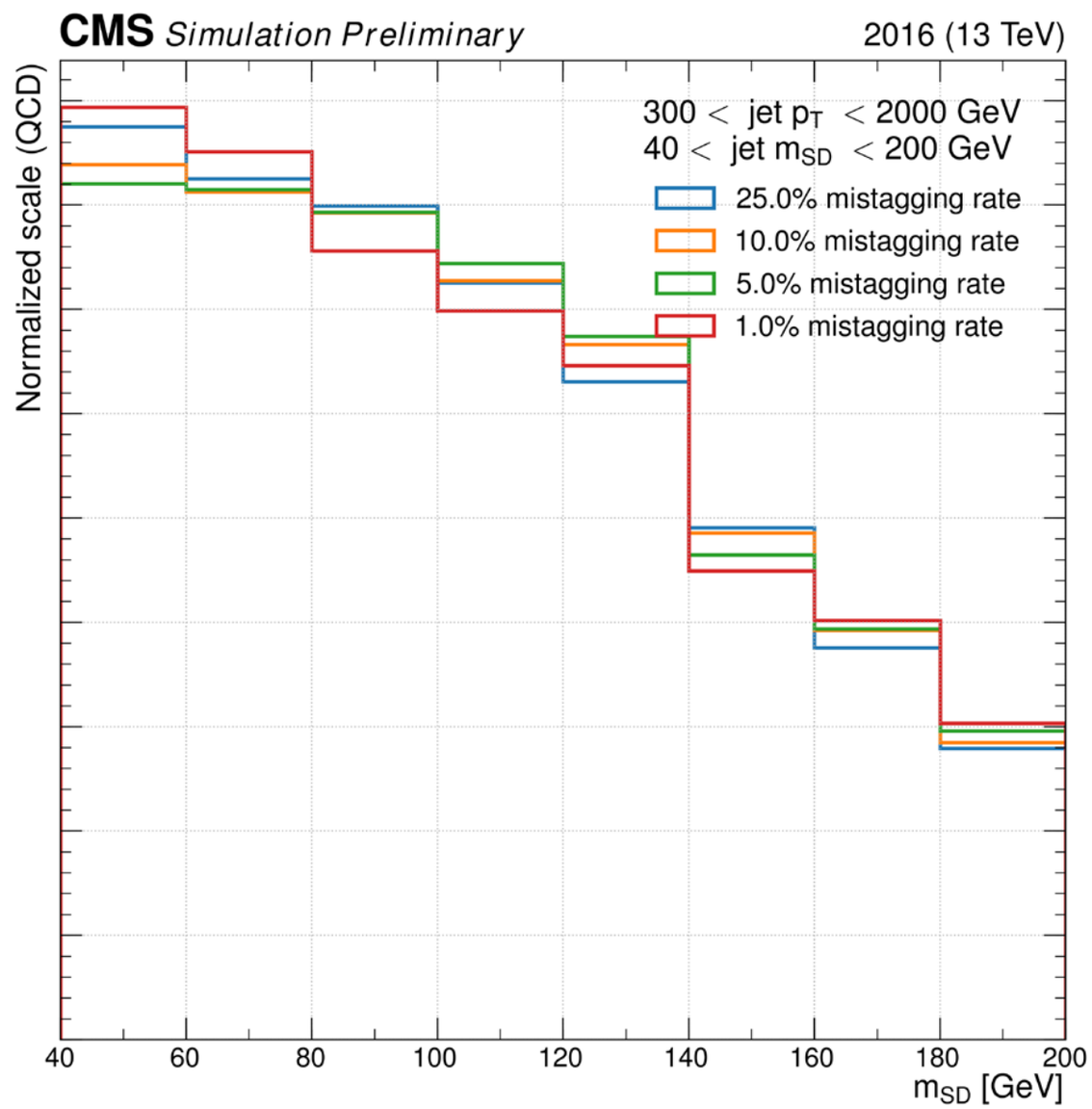
Optimistic MC simulation



Realistic MC simulation

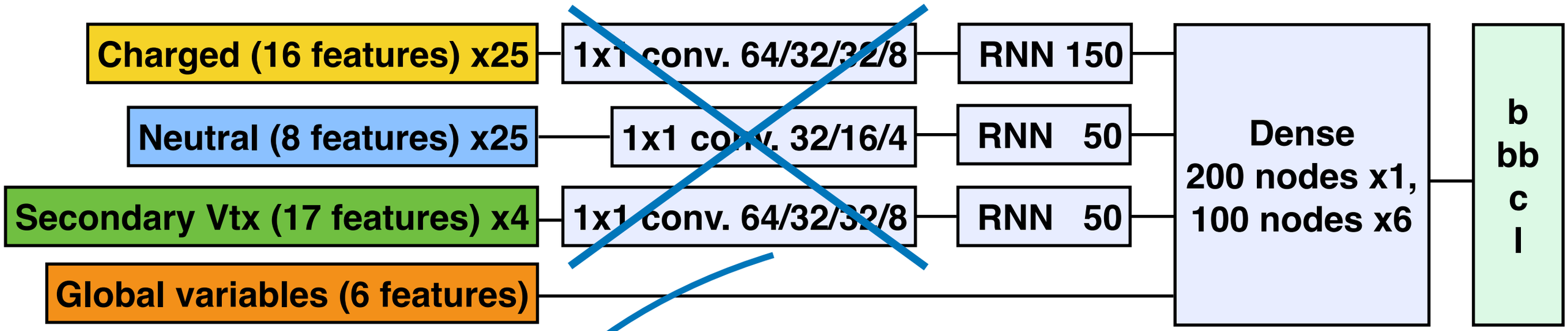


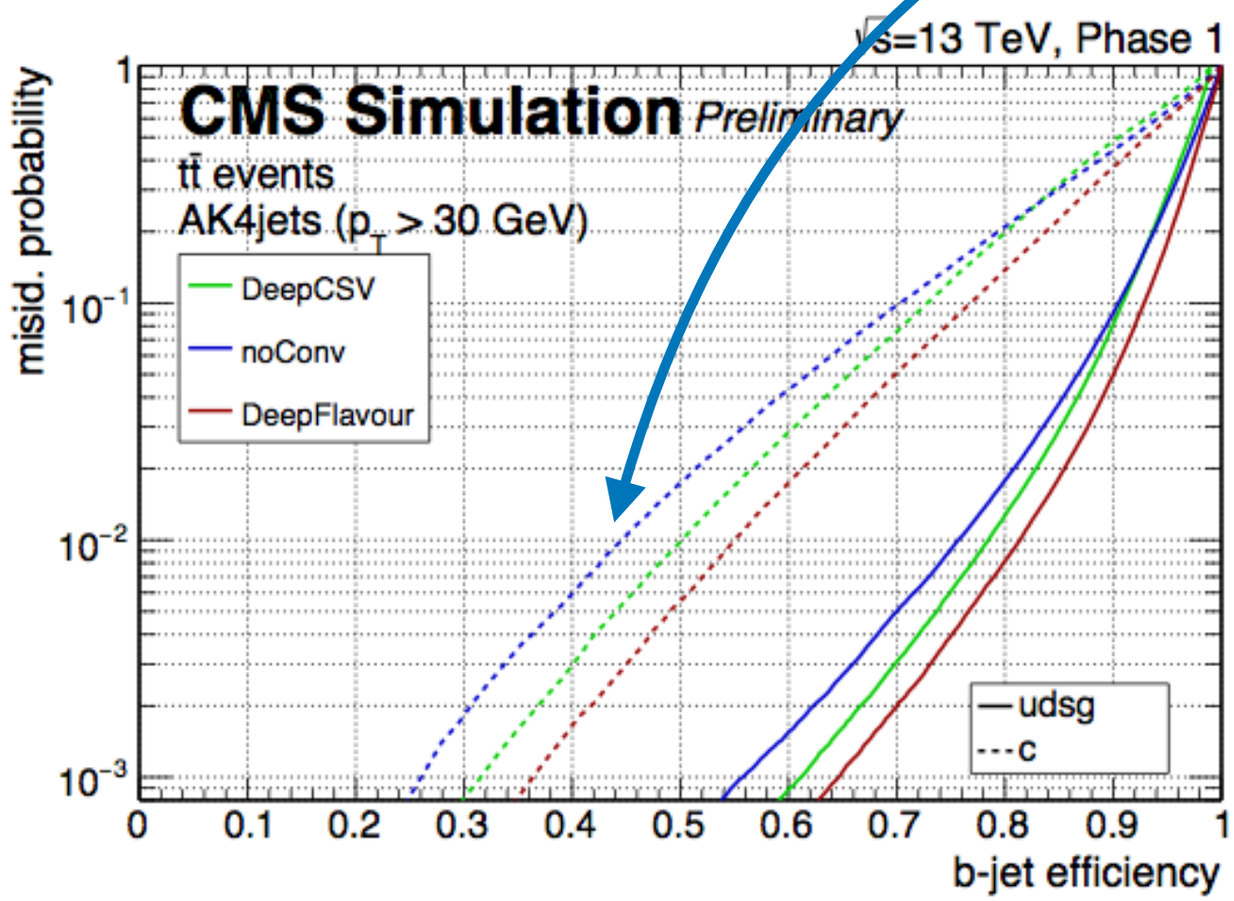
DeepDoubleC - mass sculpting

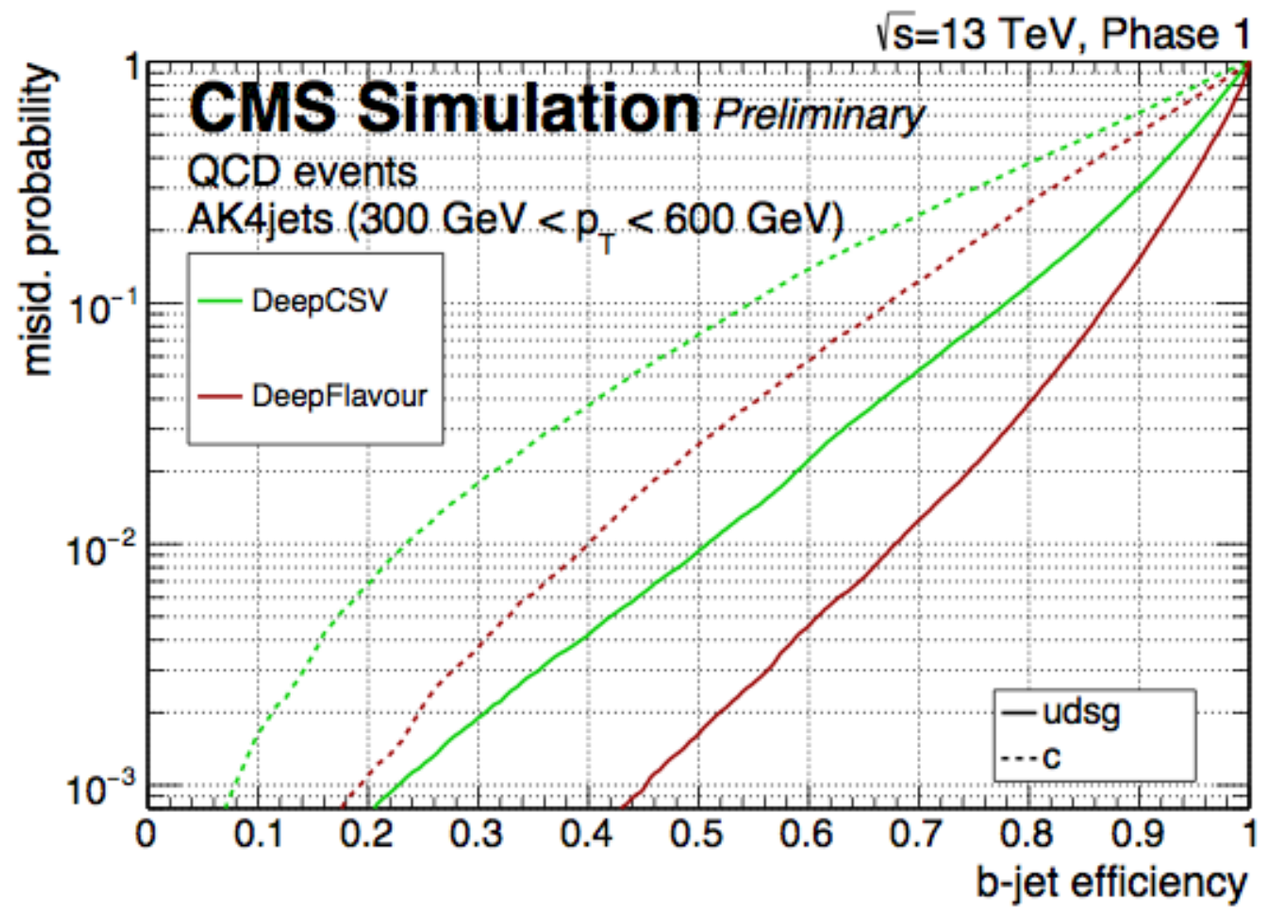


CMS-DP-2018-XXX

Particle-based NN architecture

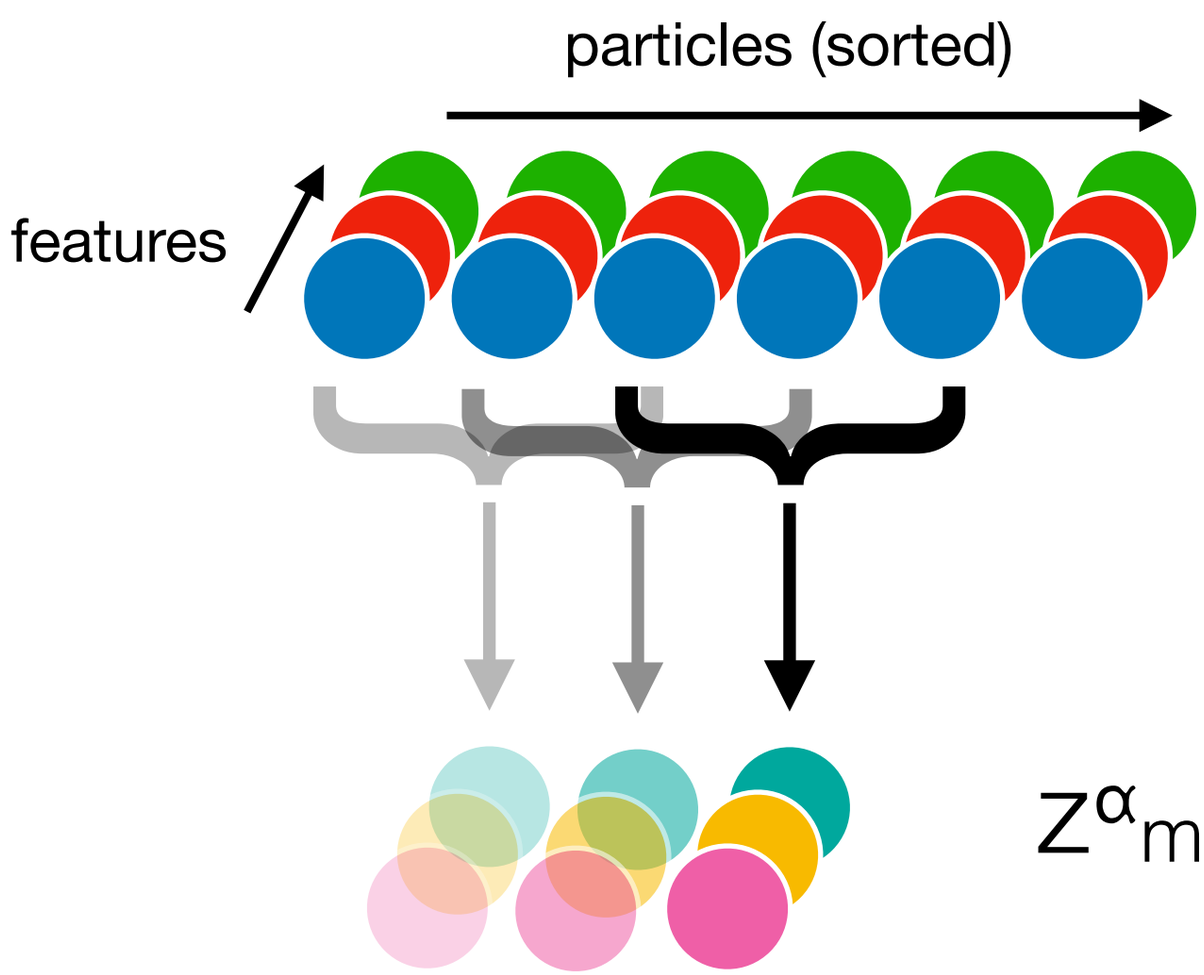






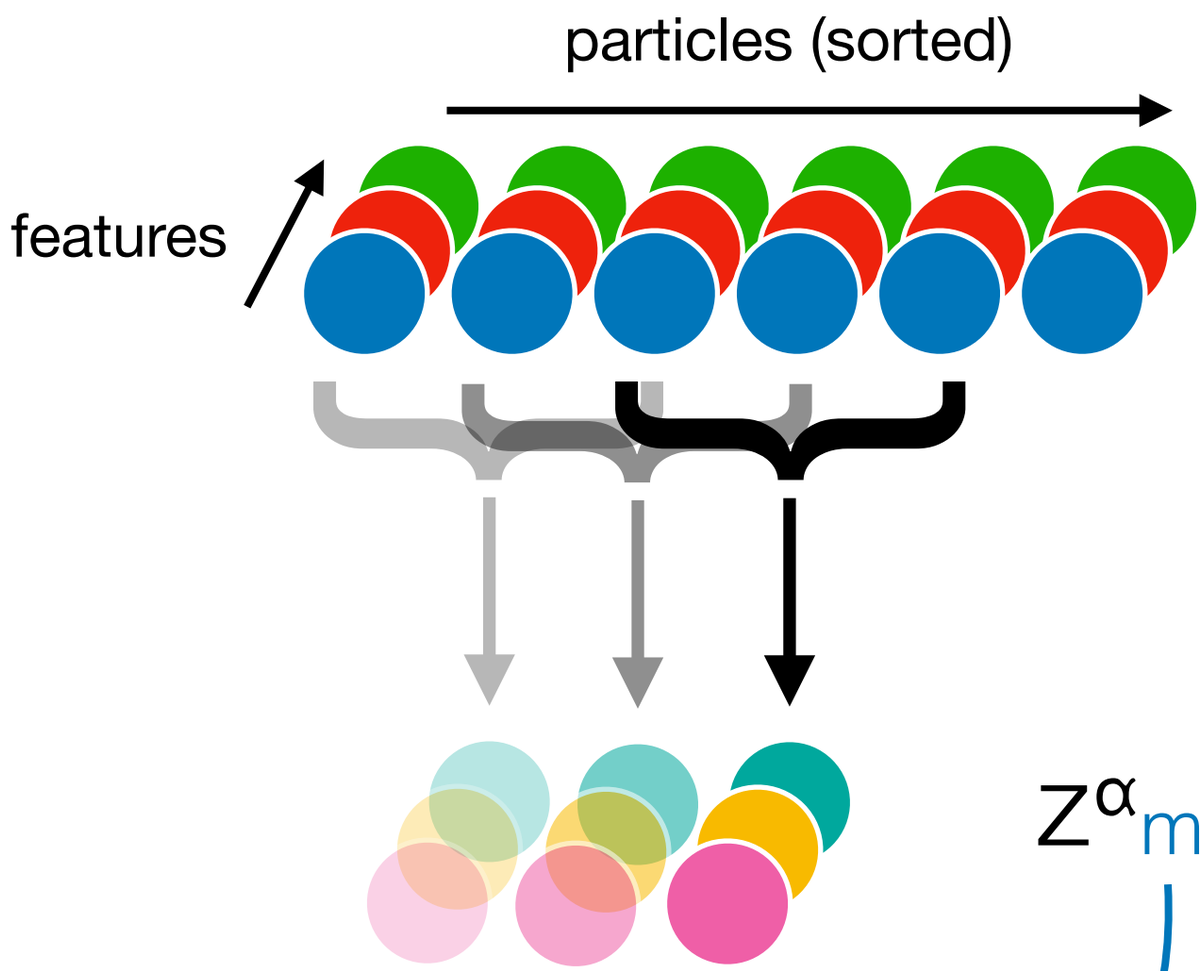
CMS-DP-2017-013

P-CNNs



$$z^{\alpha}_{m} = \sum_{a}\sum_{j} k^{\alpha}_{a,j}\, x_{a,(m+j-1)}$$

P-CNNs

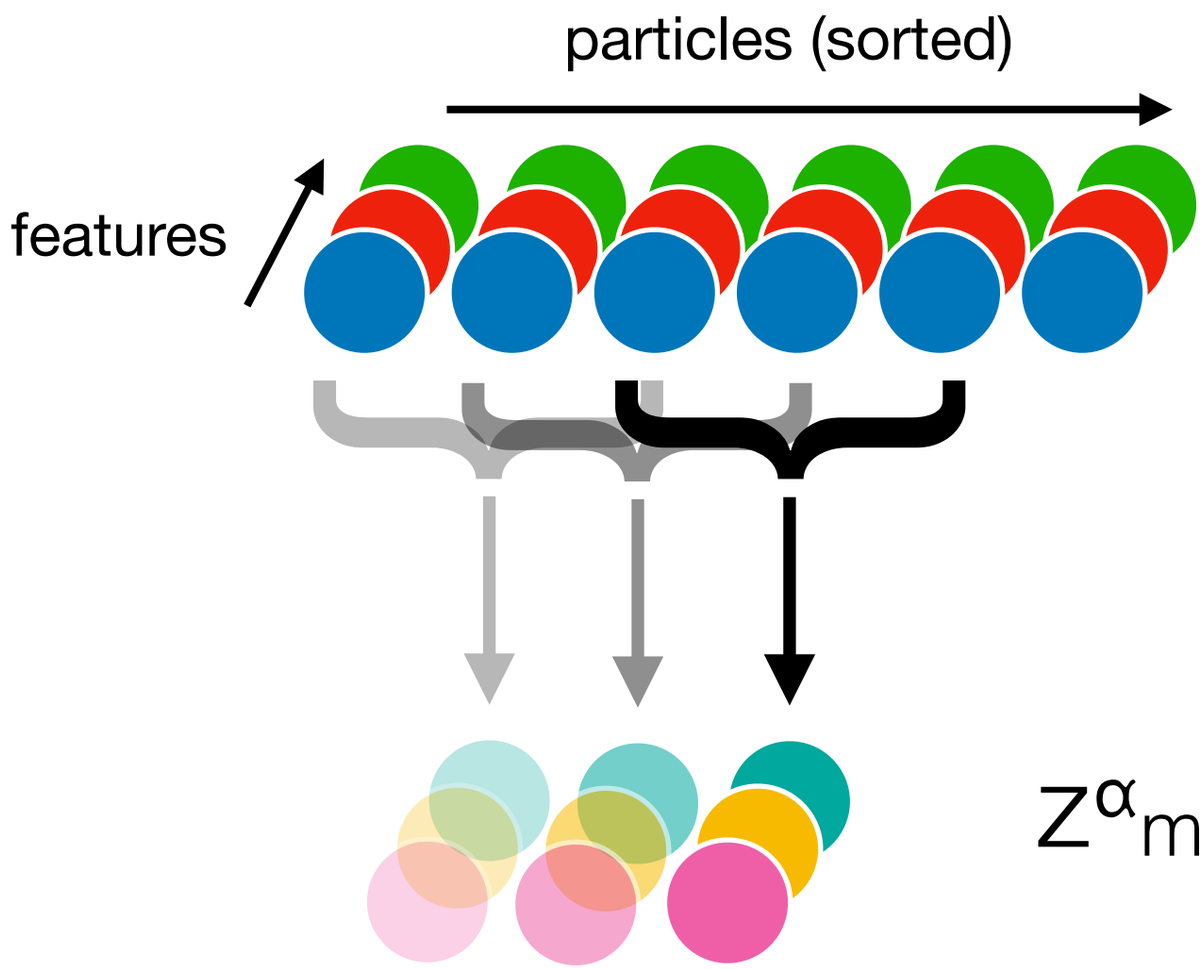


$$z^{\alpha}_{m} = \sum_{a} \sum_{j} k^{\alpha}_{a,j} \, x_{a,(m+j-1)}$$

Sweep over the elements

Loop over contiguous elements of the kernel

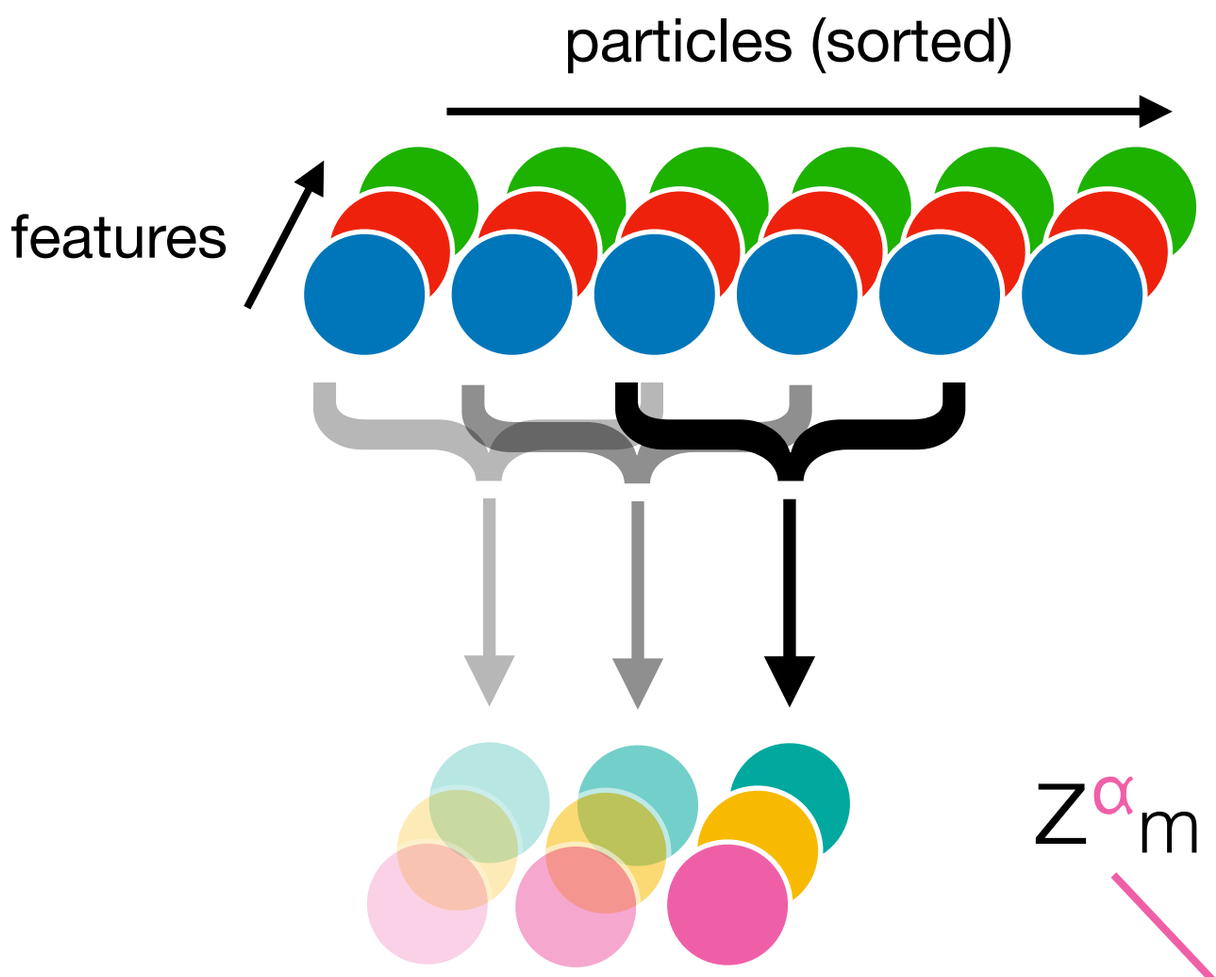
P-CNNs



$$z^{\alpha}_{m} = \sum_{a} \sum_{j} k^{\alpha}_{a,j} \, x_{a,(m+j-1)}$$

Multiple features (“colours”) are accounted computing the transformation

P-CNNs



$$z^{\alpha}_{m} = \sum_{a}\sum_{j} k^{\alpha}_{a,j}\, x_{a,(m+j-1)}$$

Different filters/kernels learn different transformations

Deploying the model

Integration of DeepJet (AK4) into CMSSW. PR #19893

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Tensorflow-based integration of new DeepFlavour tagger #19893

Merged cmsbuild merged 150 commits into `cms-sw:master` from `pablodecm:ceep_flavour_tf_rebased_20_07` on 25 Jan

Conversation 830 Commits 150 Files changed 54 +6,293 −29

pablodecm commented on 25 Jul 2017 • edited Contributor

This pull request integrates the new DeepFlavour tagger, using the library CMSSW-DNN by **@riga** (the required part is also included) and adds it to the standard sequences. You can find an overview of the reason and design behind this PR in this BTV WG presentation.

PAT vs reference training framework (latest version)

Here are some checks of compatibility of CMSSW pat-based discriminators computed using the producers develop for this PR with the output from the training framework (DeepJet) as 2D histograms

Reviewers

makortel
riga
mverzett
Dr15Jones
smuzaffar
slava77

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Backend choice

✗ Interface based on TF python API:

- Uses python C API and a pre-built TF package
- Large overhead and no handle on memory/threading

✗ Interface based on TF C API:

- Low level and not very convenient
- Lots of customisations and ad-hoc handling needed

✓ Interface based on TF C++ API:

- Access to all the needed internals for production usage with minimal need for custom code
- Shallow interface to connect TF to the CMSSW internals (e.g. logging)

For more information look here.

Remaining issues

Multithreading:

- TF **loves** threads
- Normally a good thing, has a critical impact on memory consumption in HEP frameworks, which have their own thread schemes/pools (CMSSW uses TBB)
- Solved with the implementation of two custom sessions: <u>without threading</u> and <u>sharing the threading pool</u>

Memory footprint

- DeepJet model initially very big (~150MB)
- A careful optimisation for inference only can brought O(10-100) gain in memory reduction
- Further improvements from separating graph storage (common) and graph evaluation (one each thread)
- Exploring AOT compilation as future option