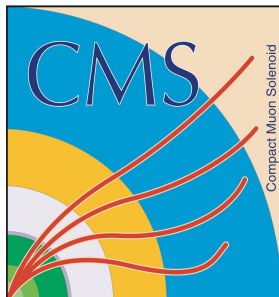


# Recent developments in heavy flavour tagging and new HH and HHH triggers for Run 3

Marina Kolosova

marina.kolosova@cern.ch

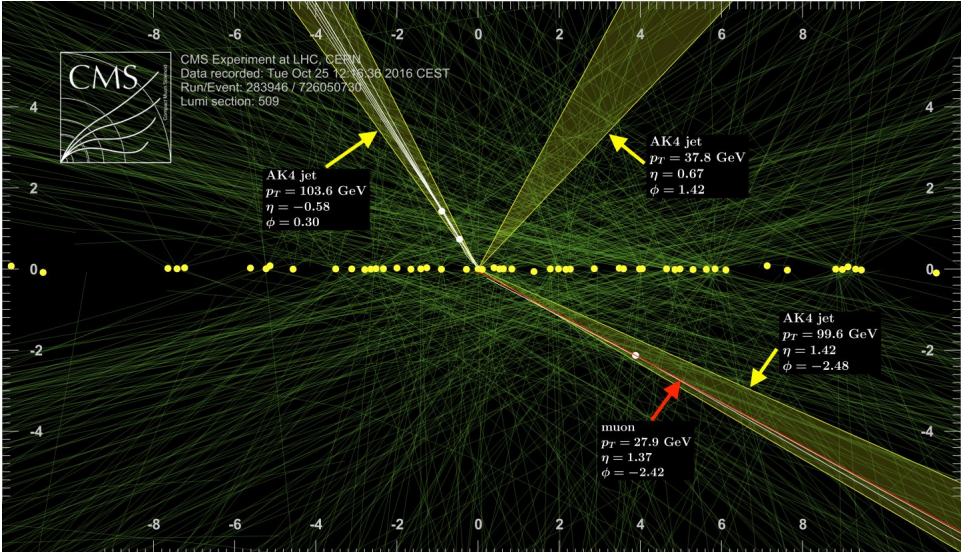
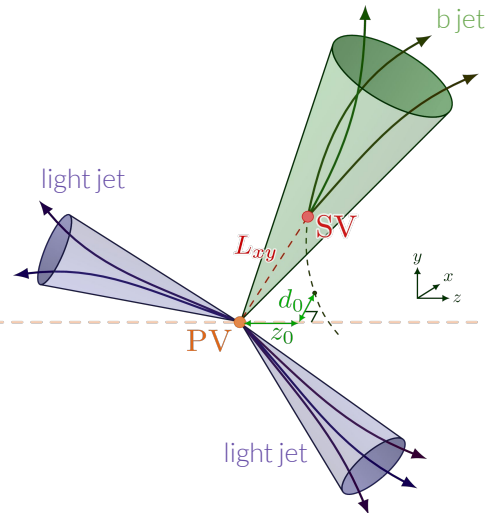
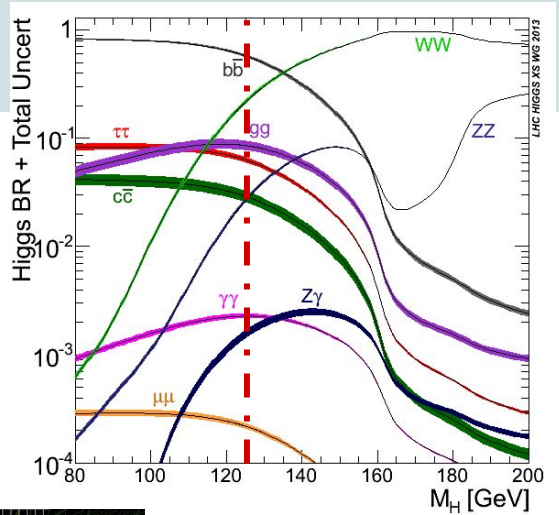


# Heavy flavour jet tagging in CMS

Heavy flavour b/c-jet tagging crucial for Higgs SM and BSM physics at the LHC

## Unique signature:

- Sizeable lifetime of b/c hadrons (ps)
  - Displaced tracks (few mm) form a secondary vertex (SV)
- Harder fragmentation and larger mass compared to light-flavour quarks/gluons
- Presence of charged leptons in 20% (10%) of b (c) hadrons decays

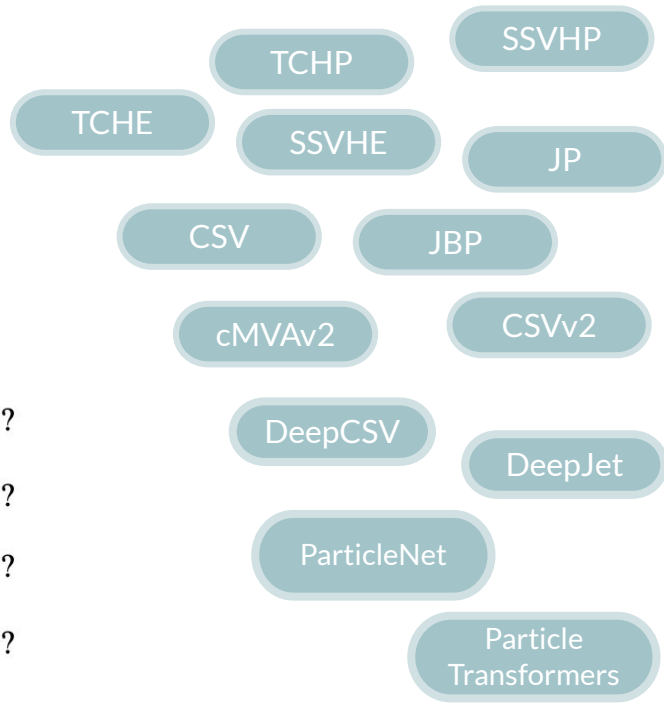
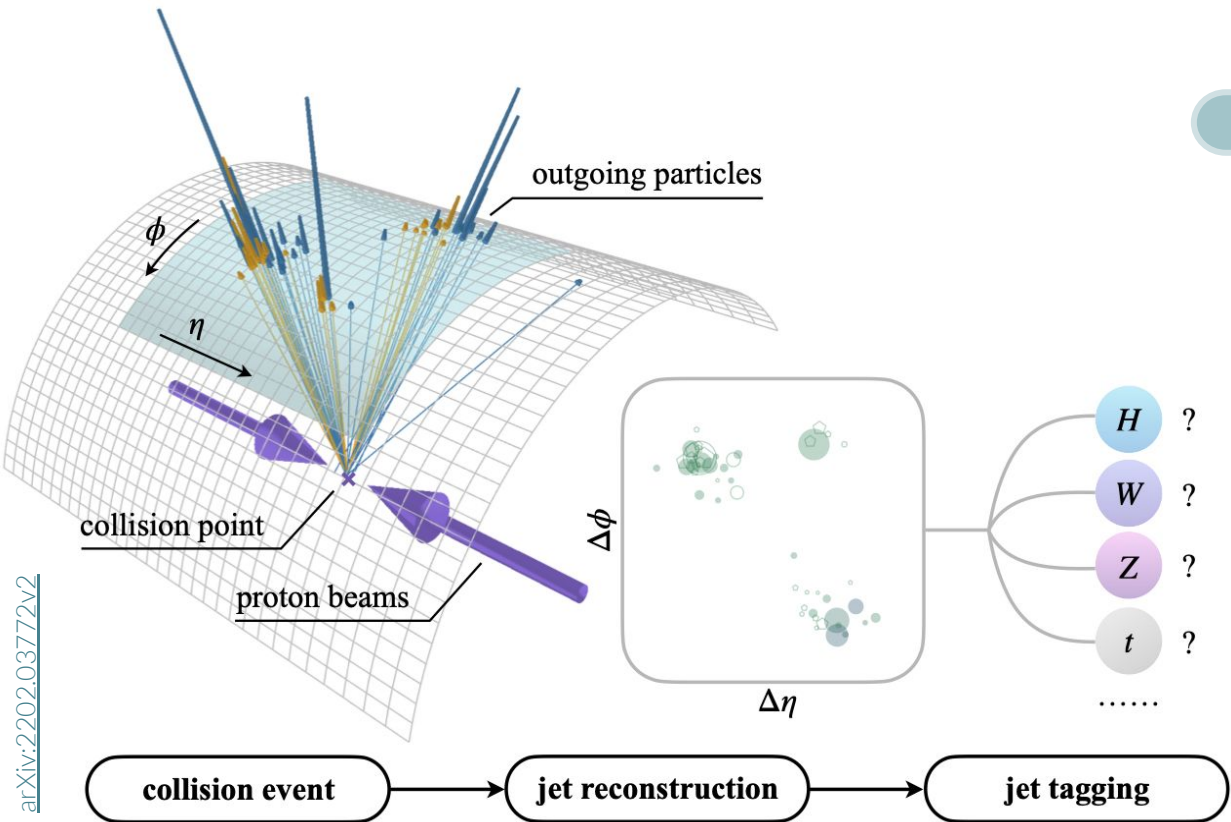


CMS collision event with 3 jets, 2 of which tagged with the CSVv2 algorithm

© 2017 CERN

# Heavy flavour jet tagging in CMS

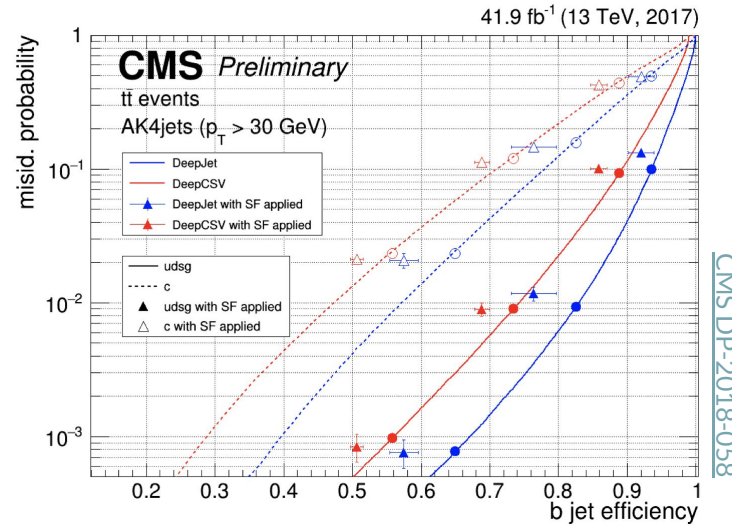
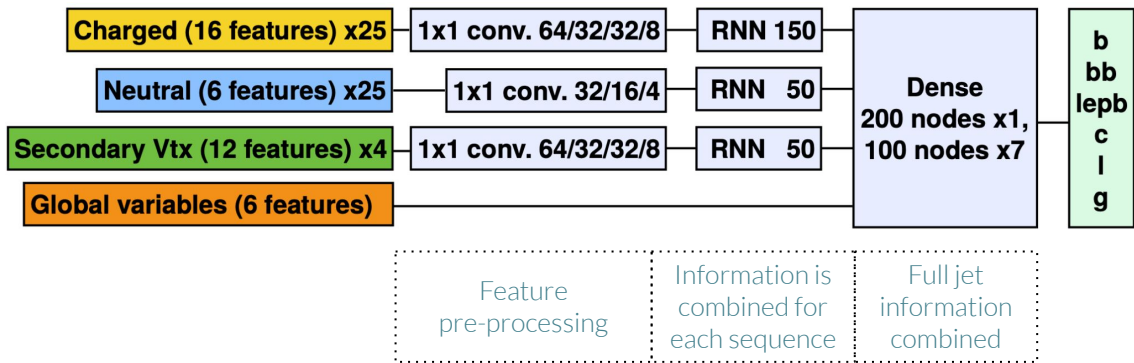
arXiv:2202.03772v2



Lots of pioneer developments since Run 1

DeepJet heavy flavour tagger has been widely used in Run 2 Legacy results

- Successor of DeepCSV and state-of-the-art in Run 2
- Uses ~650 input features:
  - Low-level: charged and neutral Particle Flow (PF) candidates and SV
  - Global-level: jet kinematics, track and SV multiplicities in jet, number of primary vertices in event
- DeepJet architecture:



Multiclass output allows for b, c-jet identification and light quark vs gluon discrimination

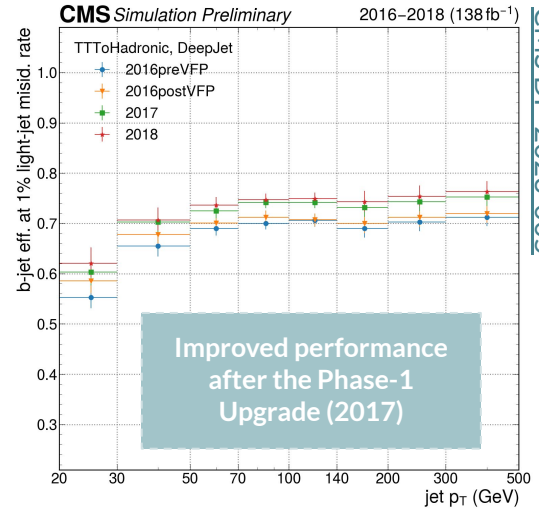
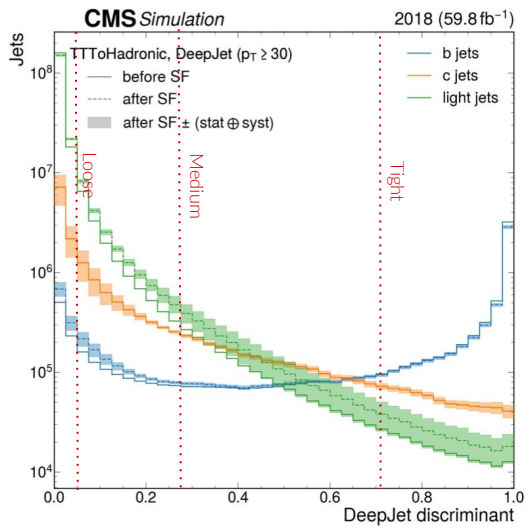


**DeepJet b discriminant:**

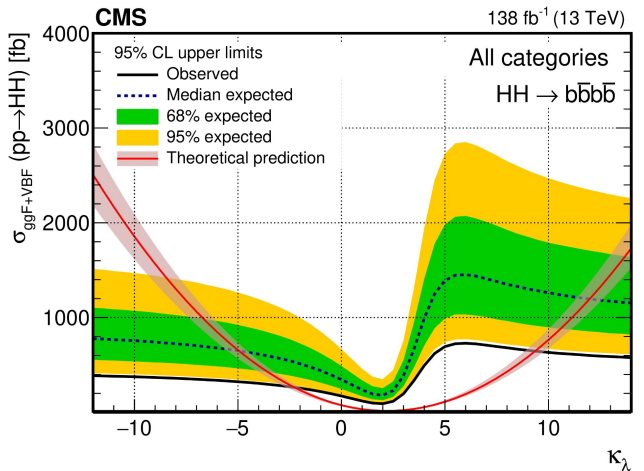
$$\frac{P(b) + P(bb) + P(b_{lep})}{P(uds) + P(g) + P(b) + P(bb) + P(b_{lep})}$$

**Usage in CMS analyses:**

- 3 working points (WPs):
  - Loose :  $\approx 91\%$  b eff, 10% mis-id rate
  - Medium :  $\approx 80\%$  b eff, 1% mis-id rate
  - Tight :  $\approx 65\%$  b eff, 0.1% mis-id rate
- Per-jet scores used as inputs to ML algorithms



CMS DP-2023-005

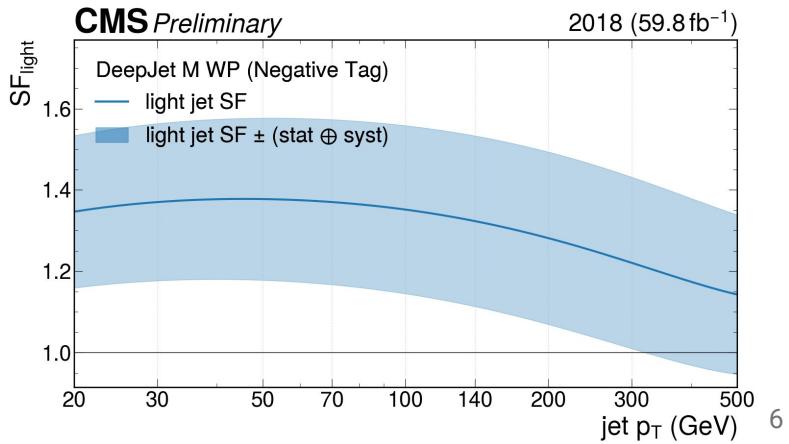
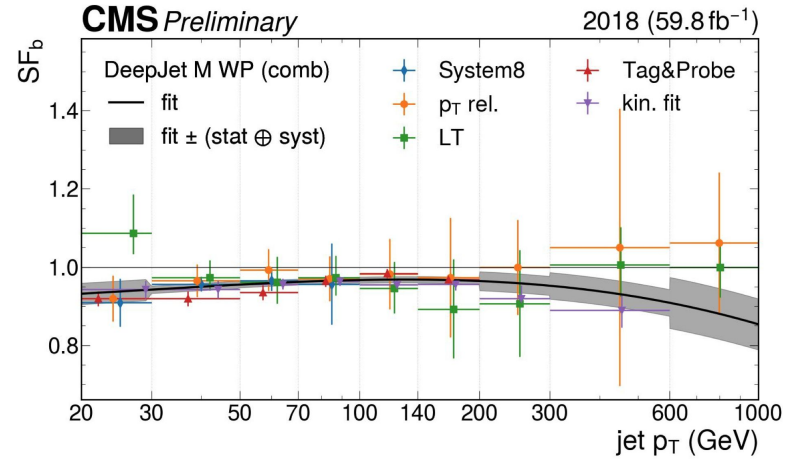


Fundamental role in  $HH \rightarrow 4b$  search:  
 Most stringent observed constraints on HH cross section!  
[Phys. Rev. Lett. 129 \(2022\) 081802](https://arxiv.org/abs/2208.08180)

Different calibration techniques used to derive scale factors (SF) to ensure same performance of heavy-flavour tagging in simulation as in data

- b-tagging efficiency measured in **multijet** and **top pair production** events
  - **System8, pT rel., Lifetime (LT)**
  - **Kin. Fit, Tag & Probe**
- The **combination** of results is used to ensure robustness of the fixed WPs SF measurement
  
- Light-jet misidentification rate measured in multijet events
  - NegativeTag

Scale factors are also available for the full discriminant shape:  
✓ Shape calibrations successfully applied in H→bb observation!  
[\[CMS Collaboration Phys. Rev. Lett. 121, 121801\]](#)

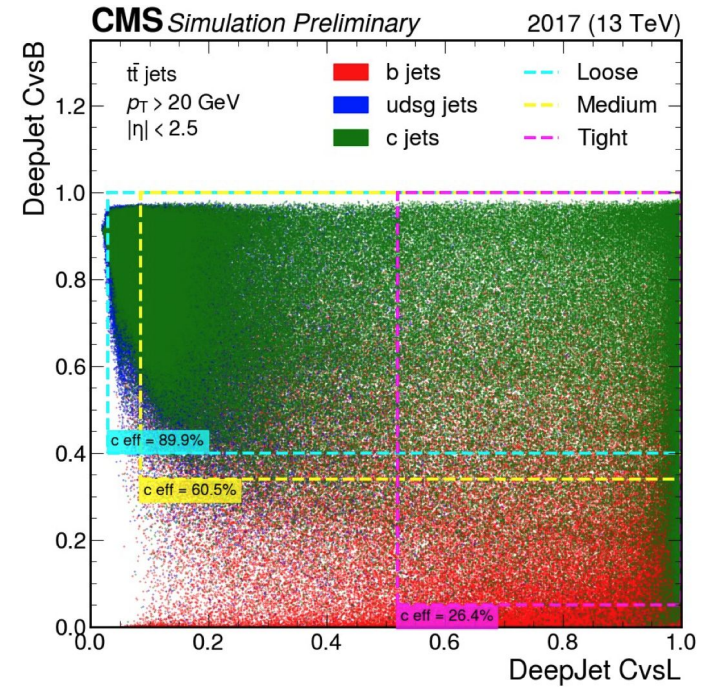
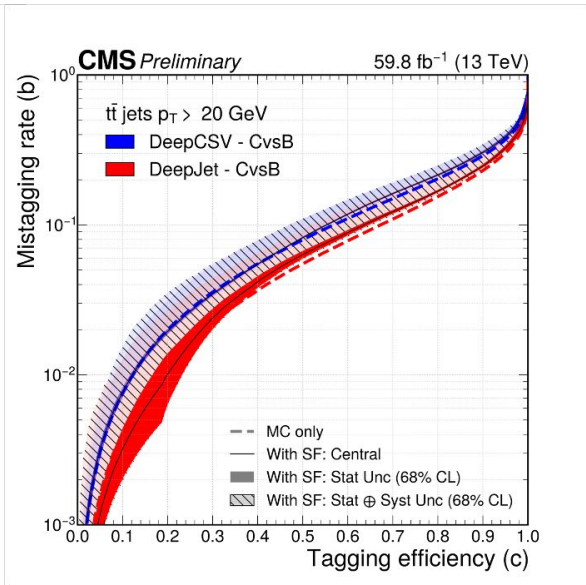
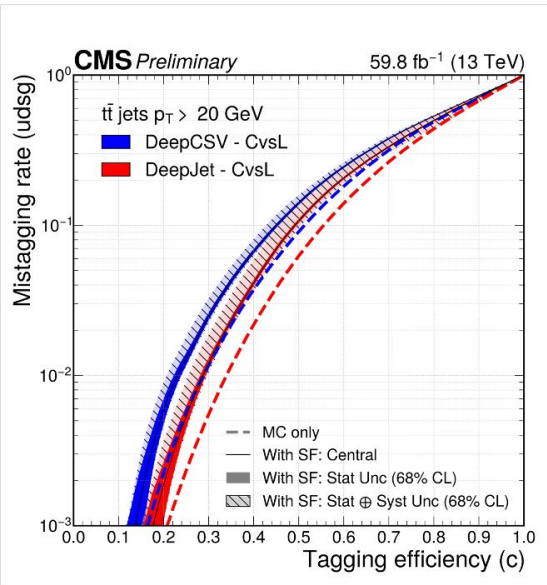


c hadrons: smaller lifetime, mass than b hadrons

- Harder to distinguish c jets from light flavour jets, or even b jets
- Two discriminating variables: CvsL, CvsB

**CvsL:** 
$$\frac{P(c)}{P(c)+P(u\bar{d}s)+P(g)}$$

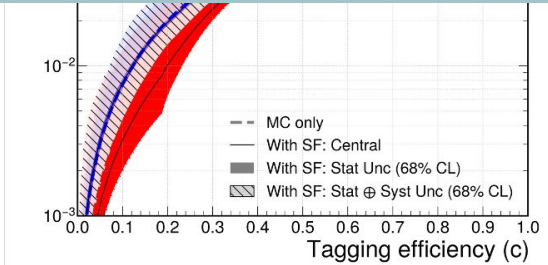
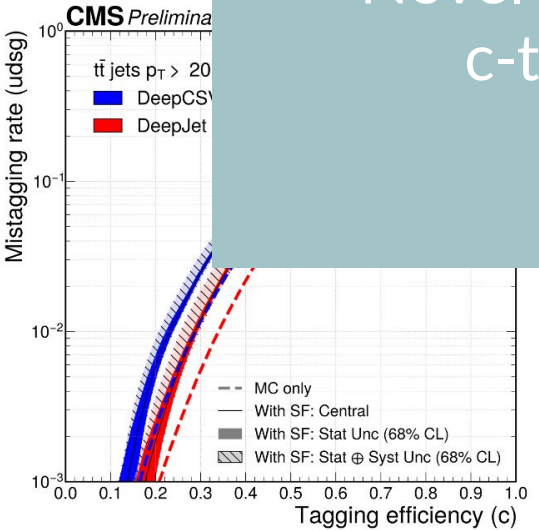
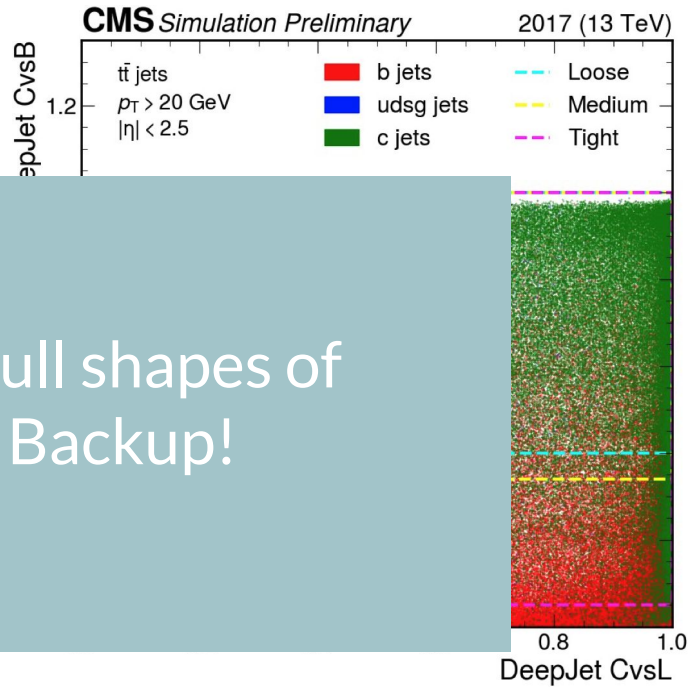
**CvsB:** 
$$\frac{P(c)}{P(c)+P(b)+P(bb)+P(b_{lep})}$$



	CvsL cut	CvsB cut	c eff.	b eff.	udsg eff.
Loose	0.030	0.400	89.9%	28.2%	93.0%
Medium	0.085	0.340	60.5%	25.7%	26.0%
Tight	0.520	0.050	26.4%	31.0%	0.60%

- c hadrons: smaller lifetime, mass than b hadrons
- Harder to distinguish c jets from light flavour jets, or even b jets
- Two discriminating variables: CvsL, CvsB

Novel technique to calibrate full shapes of c-tagging discriminants in Backup!



	CvsL cut	CvsB cut	c eff.	b eff.	udsg eff.
Loose	0.030	0.400	89.9%	28.2%	93.0%
Medium	0.085	0.340	60.5%	25.7%	26.0%
Tight	0.520	0.050	26.4%	31.0%	0.60%



# Improving robustness of DeepJet with adversarial training

Jet tagging algorithms trained in **simulation** only.

- Mismodellings can lead to non-negligible differences in performance in data

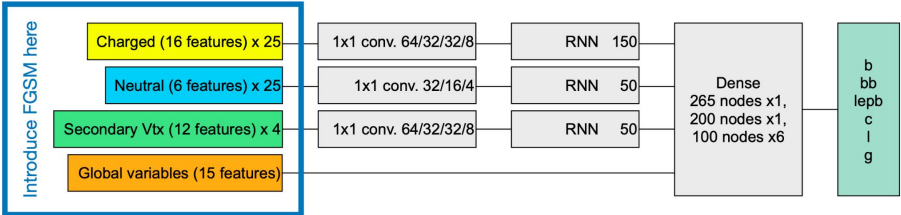
**Adversarial attack:** Adversarial inputs generated by the Fast Gradient Sign Method (FGSM):

$$x_{FGSM} = x_{raw} + \epsilon \cdot \text{sgn} \left( \nabla_{x_{raw}} J(x_{raw}, y) \right)$$

$x_{raw}$  : are the input features  
 $\epsilon$  : (small) distortion parameter  
 $J$  : loss function  
 $y$  : truth label

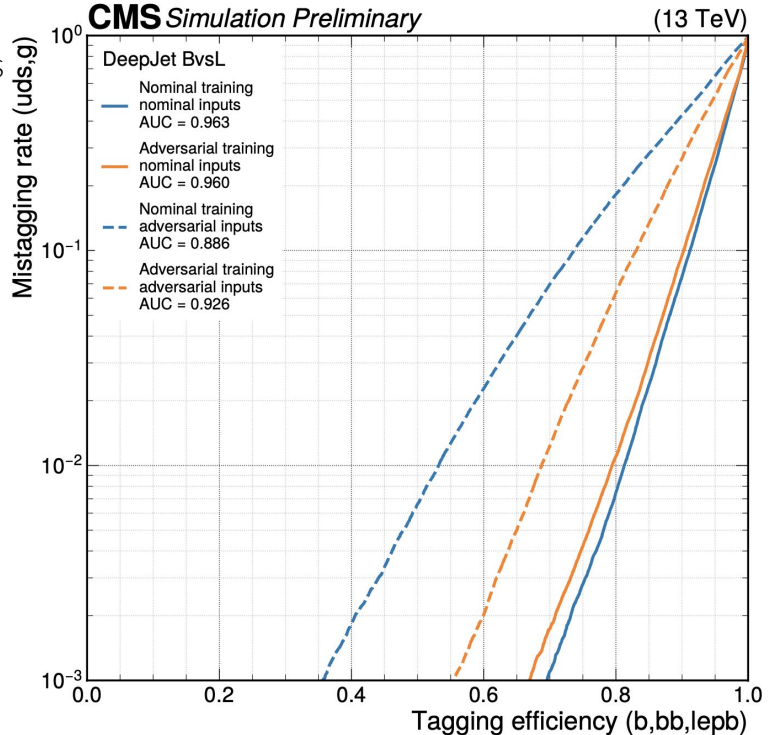
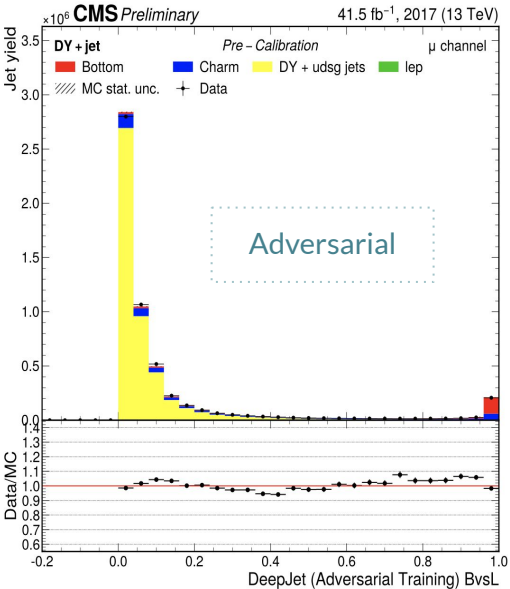
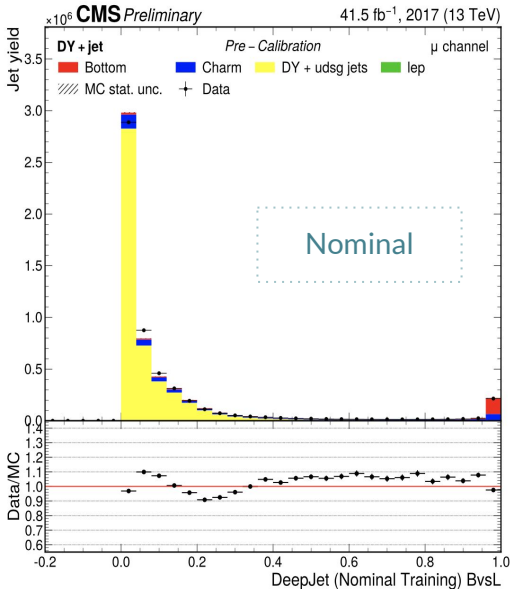
**Adversarial training:**

- Defense strategy to mitigate the impact of adversarial attacks
- Use of systematically distorted samples during training
- Apply FGSM attack in every step of the training
  - the network is less likely to learn simulation-specific properties of the training sample



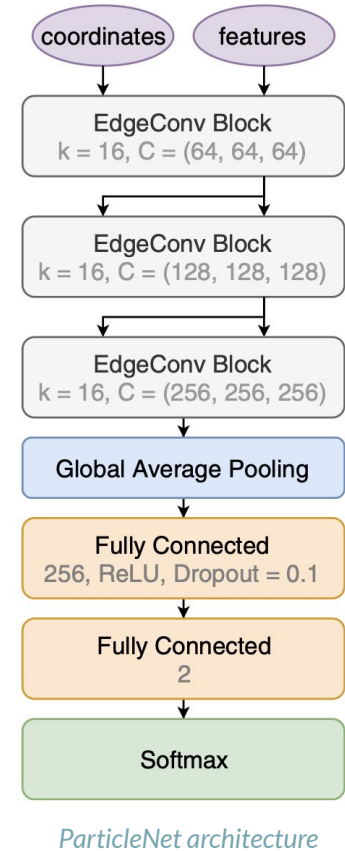
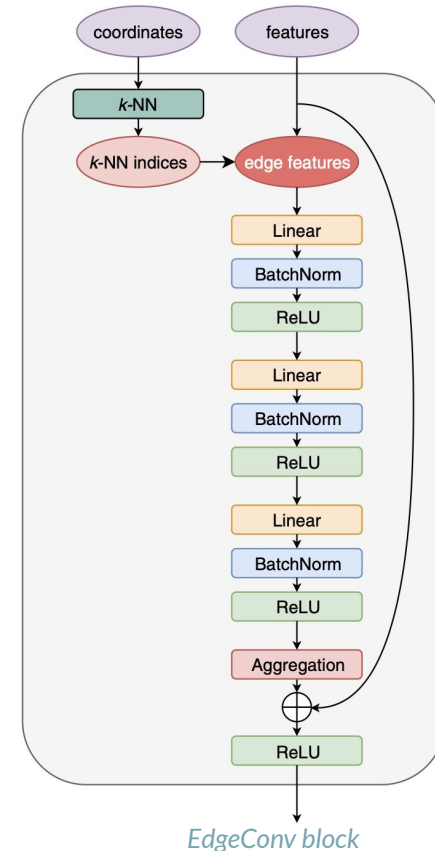
## Adversarial training:

- Two tasks: optimizing classification & withstand distortions of inputs
- Reduces data-to-simulation differences prior to any calibration



Trade-off between performance and robustness to systematic distortions

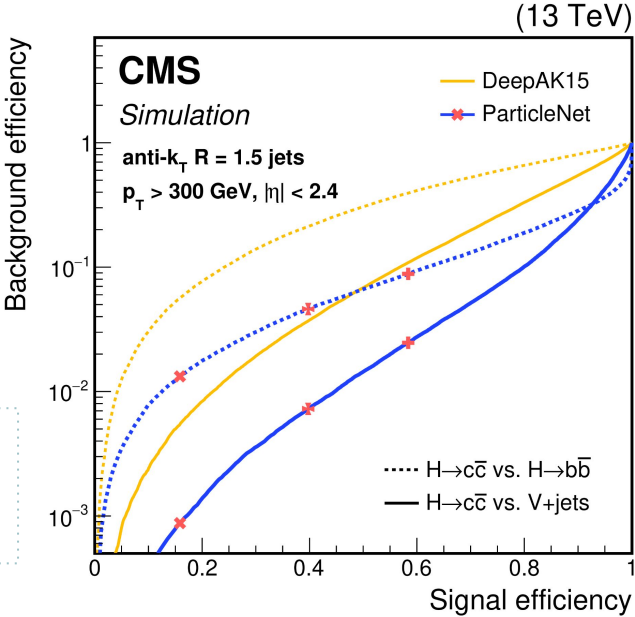
- First **graph-based** tagger at the LHC!
- Jets represented as an **unordered set of particles in space** (“*particle clouds*”)
- Uses permutation-invariant graph-neural networks: Dynamic Graph Convolutional Neural Network ([arXiv:1801.07829](https://arxiv.org/abs/1801.07829))
- Input nodes: (up to 100) PF jet constituents, SVs with set of features
- Neighboring nodes connected to learn relations
- Training performed on jets uniform in  $p_T$ /mass
- Initially used for boosted jet tagging:  
→ Multi-class approach for t/W/Z/H tagging
- More recently explored for **small-cone** jet tagging



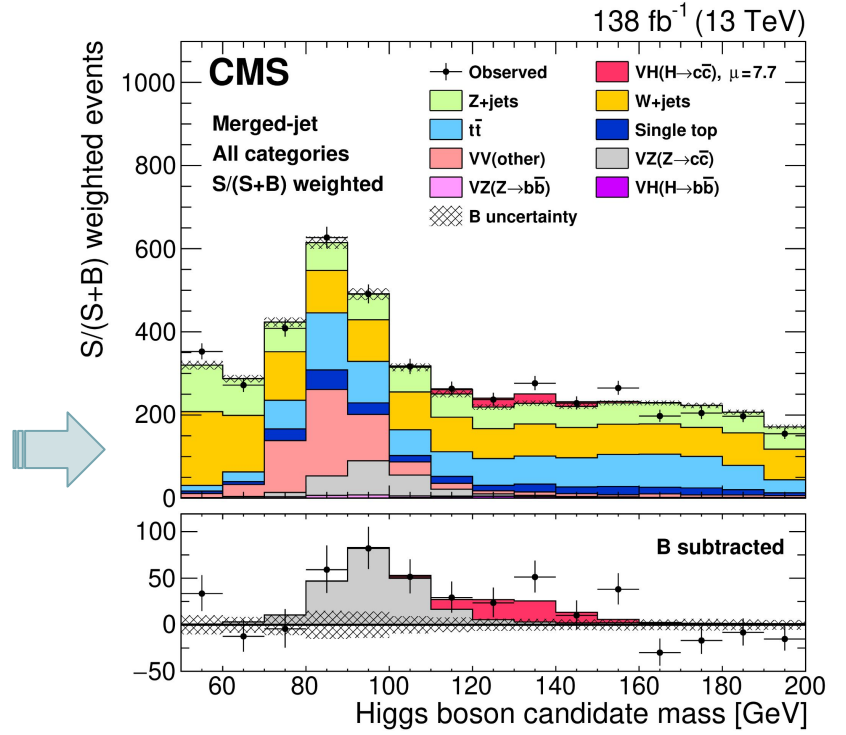
# Run 2 physics highlights with ParticleNet

- Search for  $H \rightarrow cc$  in association with a leptonically decaying W/Z boson where H is Lorentz-boosted
- Use of ParticleNet to discriminate  $H \rightarrow cc$  from  $H \rightarrow bb$  and  $V+jets$

Merged-jet  $H \rightarrow cc$  identification  
 DeepJet Vs. ParticleNet

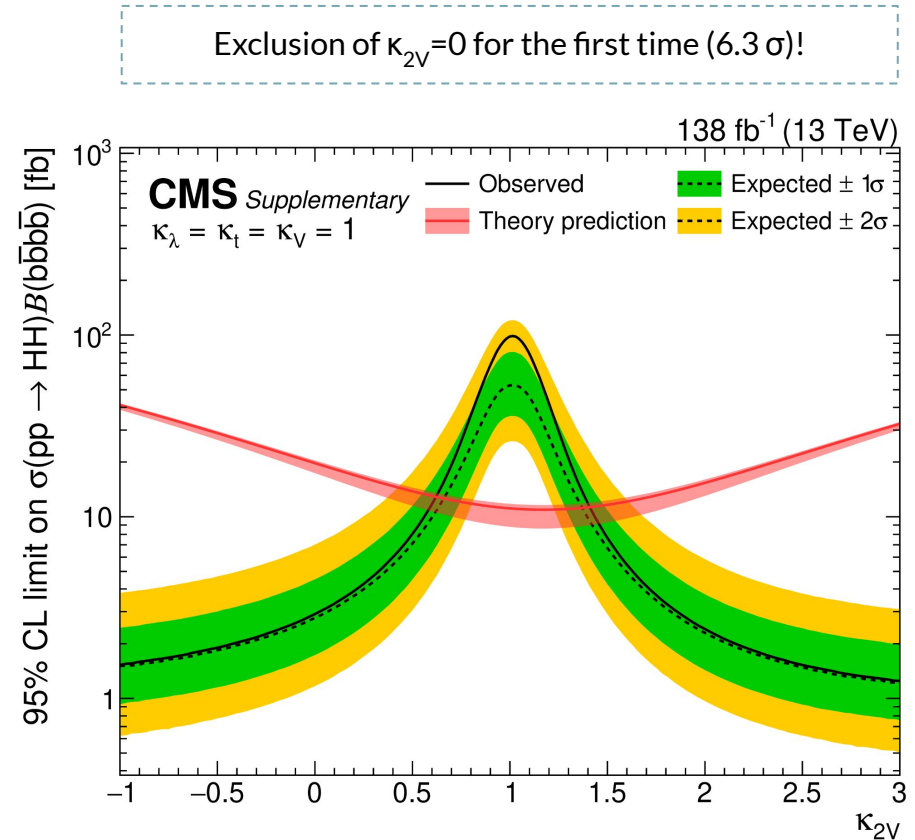


First observation of  $Z \rightarrow cc$  at hadron collider ( $5.7\sigma$ )!





- Search for non-resonant HH production via ggF and VBF in the 4b final state, with Lorentz-boosted H pairs
- Use of ParticleNet to discriminate between **H→bb** and **QCD-induced jets**
- Significant improvements in **tagging performance** and **jet mass decorrelation**
- Increased statistics (Run 2) and novel tagging techniques led to **a factor of 30 improvement** on 95% C.L. upper limits of HH production cross section wrt. previous search (2016 only)



Calibration of ParticleNet MD  $H \rightarrow bb$ ,  $H \rightarrow cc$  tagger performed for **fixed WPs** and as a function of jet  $p_T$

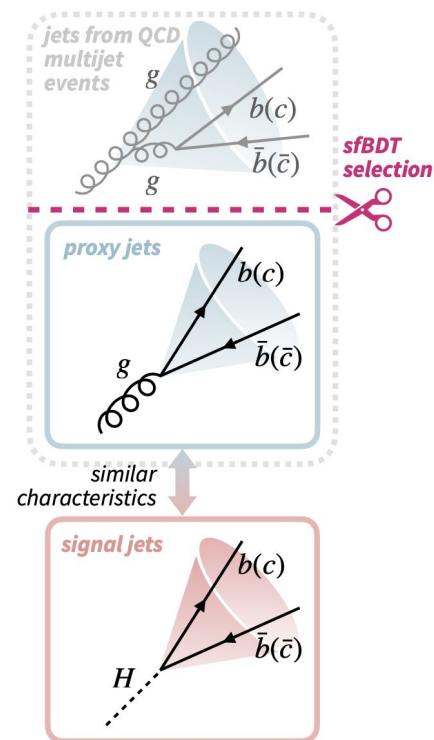
**Proxy jets:** Using  $g \rightarrow b\bar{b}/c\bar{c}$  jets obtained from QCD multijet events in data passing a BDT selection (**sfBDT**):

- **sfBDT** trained with simulated gluon-splitting  $g \rightarrow b\bar{b}/c\bar{c}$  QCD multijet events
- Separates jets with a **clean composition of quarks**, resembling more the  $H \rightarrow bb(cc)$  jets, against the ones with **large contamination of extra gluons**

- Final state gluon contamination rate  $\kappa_g$  defined as:

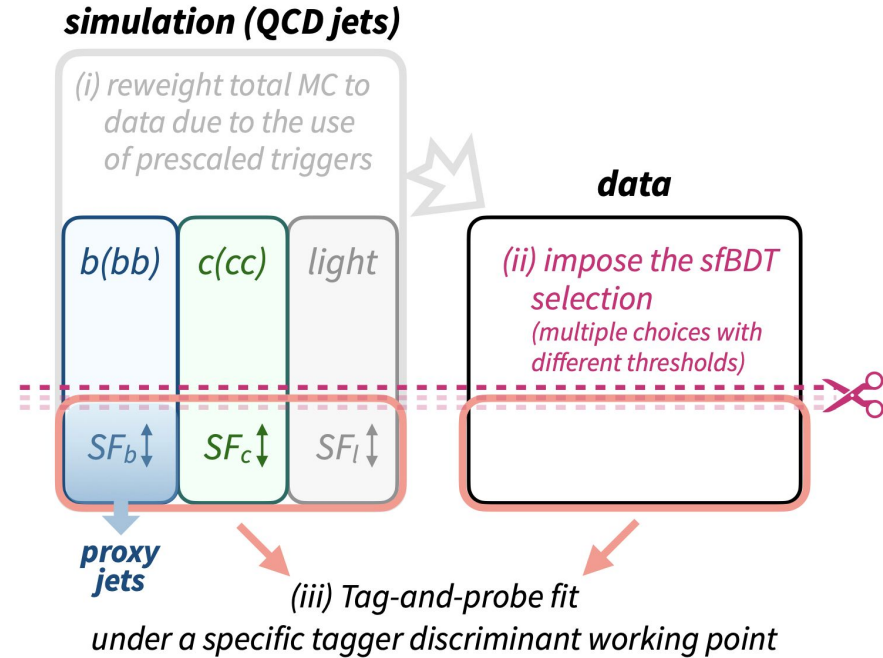
$$\kappa_g = \frac{\sum p_{T,g}}{\sum p_{T,g} + p_{T,q}}$$

- Quarks and gluons selected from parton-level truth particles associated with a jet
- Signal jets:  $\kappa_g < 0.15$ , background jets:  $\kappa_g > 0.85$
- Input variables to the sfBDT:
  - basic kinematics of the subjets
  - secondary vertices associated with the jet



## Workflow:

- All jets from the QCD multijet MC categorised into  $b(bb)$ ,  $c(cc)$ , and light based on the truth-level matching
- Proxy of  $H \rightarrow b\bar{b}$  or  $H \rightarrow c\bar{c}$  jets built from the  $b(bb)$  or  $c(cc)$  class with a **specific selection on the sfBDT**
- Proxy jets fitted to data with **tag-and-probe**, under the specific tagger WP
- 3 free-floating rate parameters  $SF_b$ ,  $SF_c$ ,  $SF_l$  assigned to the 3 classes
- Fit performed individually on multiple  $p_T$  bins
- The post-fit parameter  $SF_b$  ( $SF_c$ ) is then regarded as the SF for the  $H \rightarrow b\bar{b}$  ( $c\bar{c}$ ) signal jets



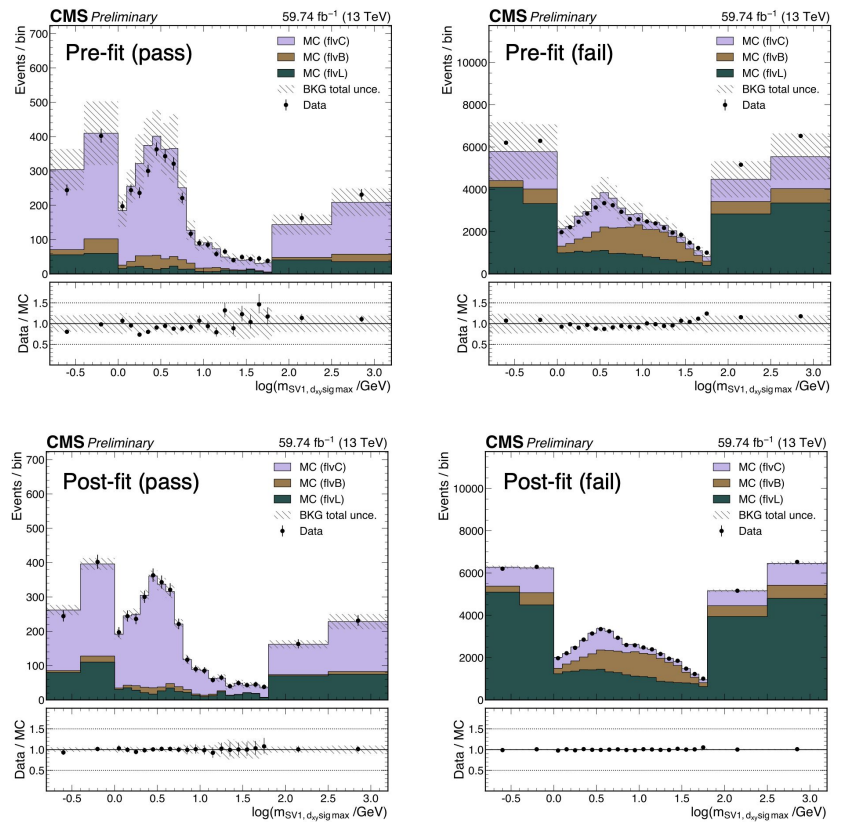
- Fit variable: **log(mSV1)** (SV1: leading SV associated with the jet with the highest impact parameter dxy significance)

Source	Uncertainties on three flavour templates		
	b(bb)	c(cc)	light
Luminosity	1.2-2.5%	1.2-2.5%	1.2-2.5%
Pileup reweighting	<0.5%	<0.6%	<1.9%
sfBDT variable data-to-MC reweighting	<0.2%	<0.2%	<0.2%
ISR parton shower uncertainty	1-3%	4-6%	3-5%
FSR parton shower uncertainty	2-6%	8-12%	17-20%
Fragmentation uncertainty on bottom quarks	14-16%	—	—
Fragmentation uncertainty on charm quarks	—	13-16%	—
Fragmentation uncertainty on light quarks	—	—	20%

Additional systematic uncertainty:

- For each calibration point:
  - 11 selections of the sfBDT → 11 proxy jet collections → 11 fits (and scale factors)
- Max distance between all 11 scale factors & central value taken as **an additional systematic uncertainty**

Pre/post-fit distributions for a single calibration point and sfBDT selection



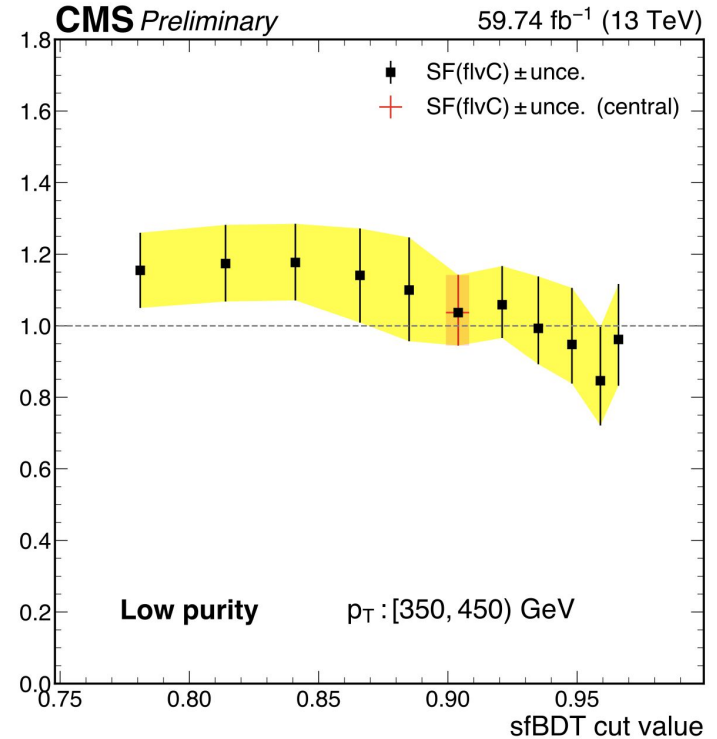


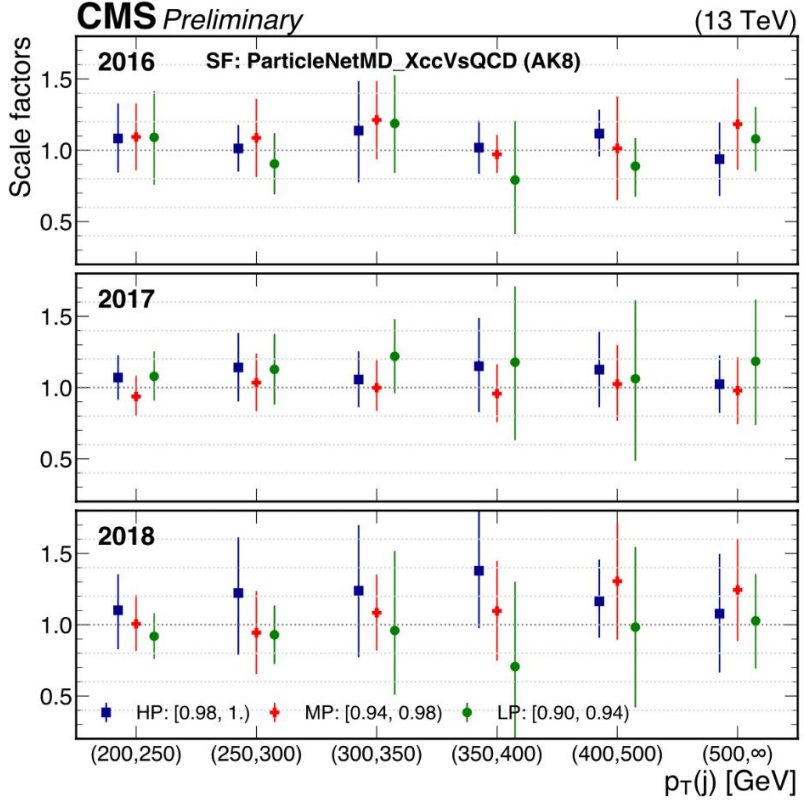
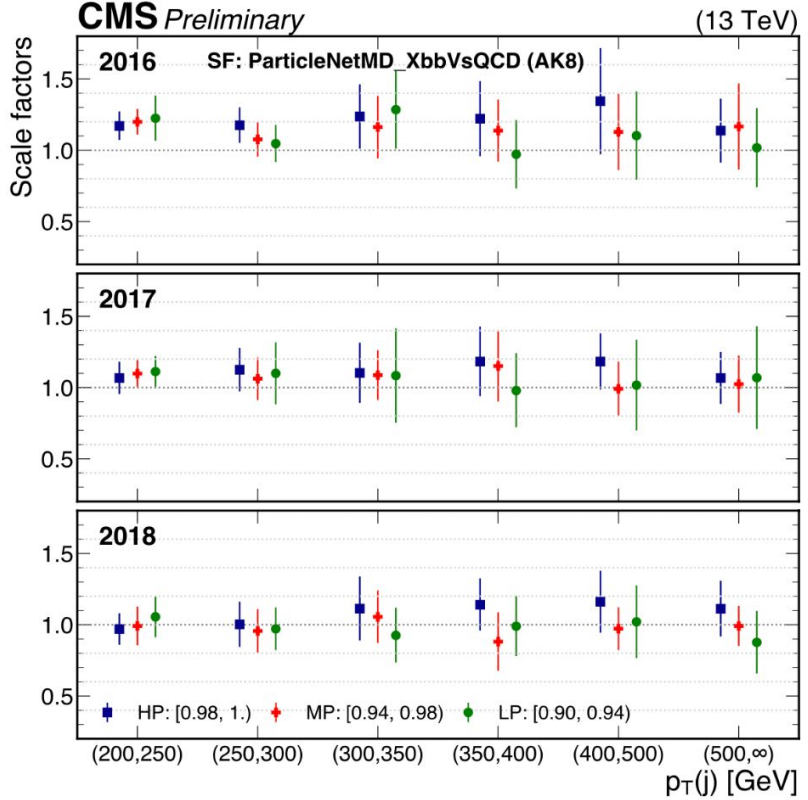
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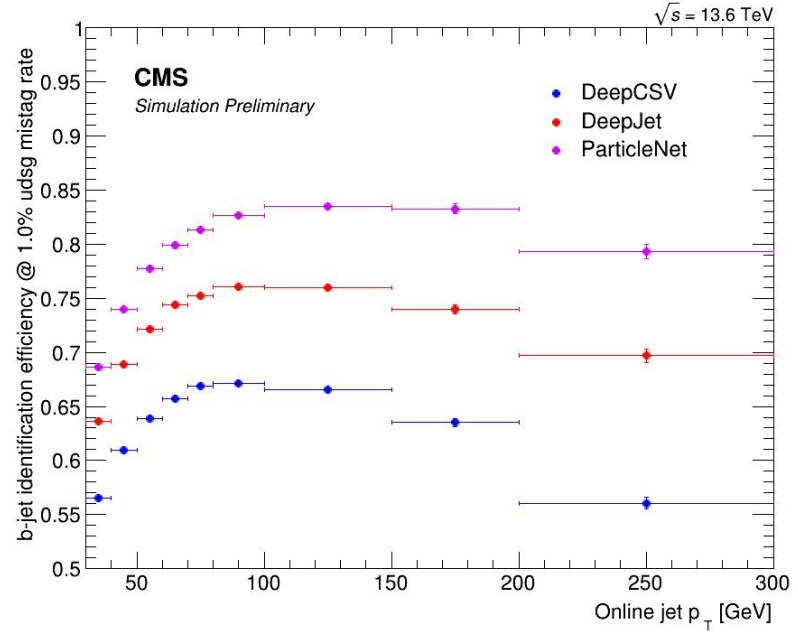
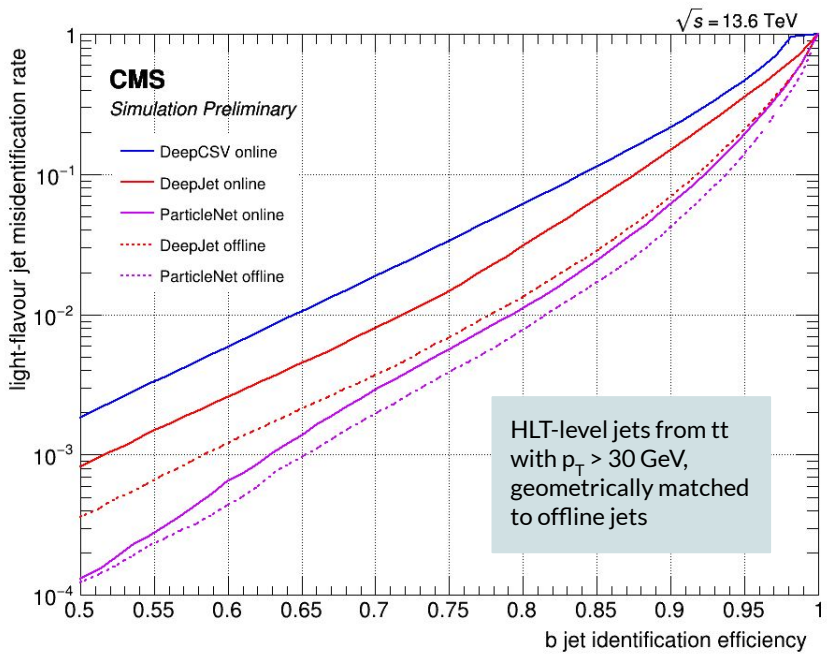
Additional systematic uncertainty:

- For each calibration point:
  - 11 selections of the sfBDT → 11 proxy jet collections → 11 fits (and scale factors)
- Max distance between all 11 scale factors & central value taken as **an additional systematic uncertainty**





Lighter version of ParticleNet deployed online since the beginning of Run 3



- ✓ Large improvements with respect to previous b taggers
- ✓ Closer online-offline performance

- ✓ 5-10% higher efficiency throughout the jet  $p_T$  range wrt. DeepJet

# Particle Transformers

- First **attention-based** tagger at the LHC!
- Inputs:
  - single particle inputs (kinematic variables, PID, trajectory displacements)
  - pairwise (physics motivated) features between particles
- Learn which neighbour particles are relevant through **attention mechanism**
- Trained on substantially larger dataset (JetClass), more inclusive in jet types

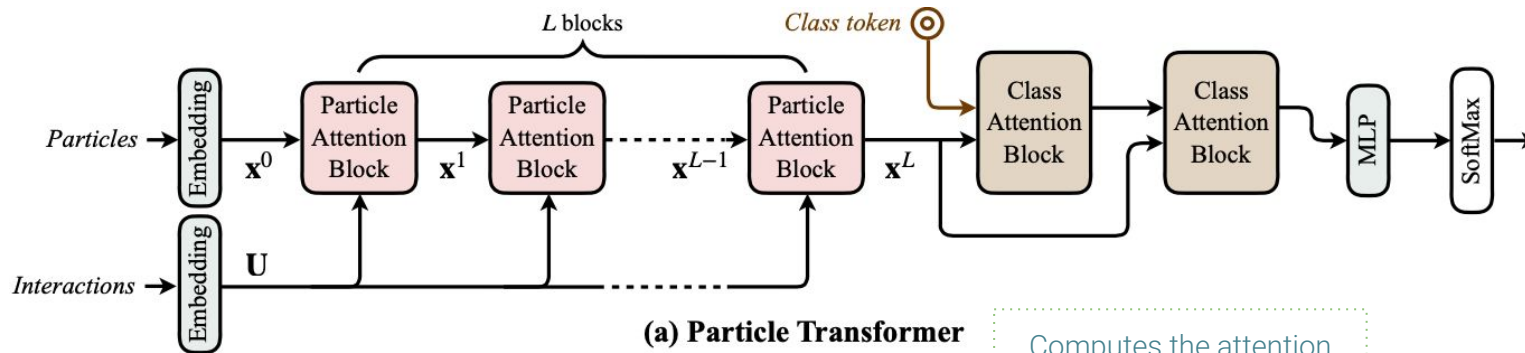
Interaction features for each pair of particles a, b:

$$\Delta = \sqrt{(y_a - y_b)^2 + (\phi_a - \phi_b)^2},$$

$$k_T = \min(p_{T,a}, p_{T,b})\Delta,$$

$$z = \min(p_{T,a}, p_{T,b}) / (p_{T,a} + p_{T,b}),$$

$$m^2 = (E_a + E_b)^2 - \|\mathbf{p}_a + \mathbf{p}_b\|^2,$$

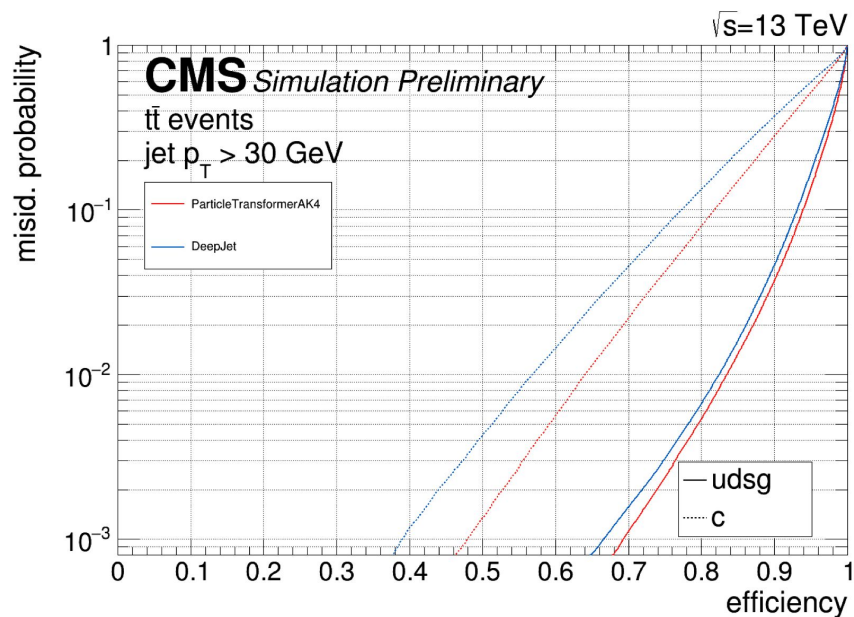


Computes self attention between particles

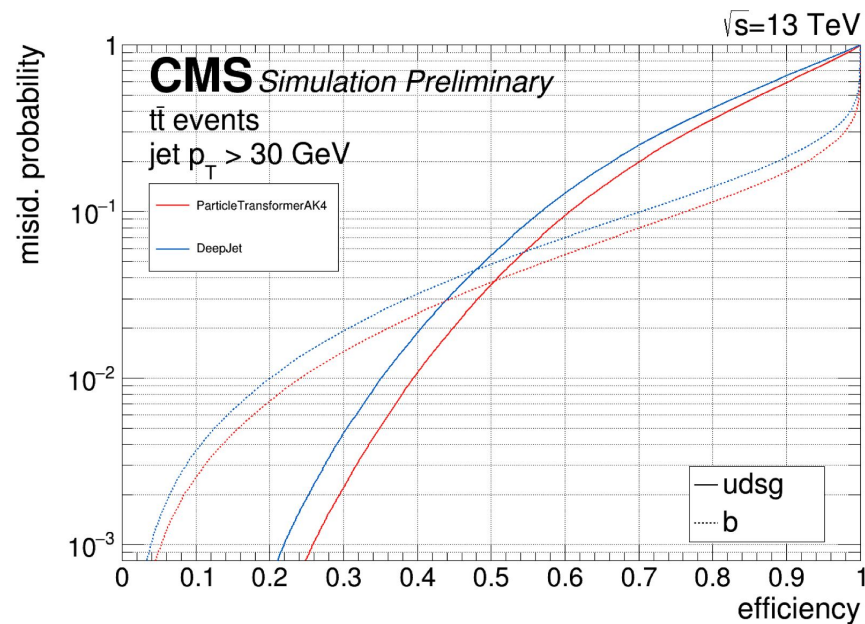
Computes the attention between a global class and all the particles



Probability of misidentifying **non-b**  $\rightarrow$  **b jets** wrt.  
efficiency of identifying b jets

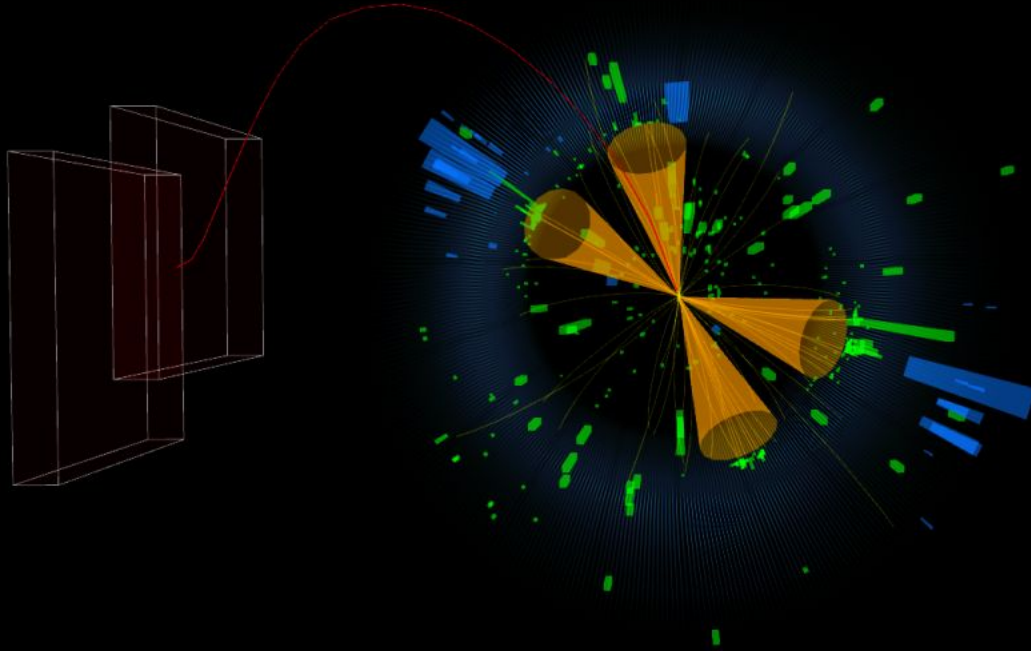


Probability of misidentifying **non-c**  $\rightarrow$  **c jets** wrt.  
efficiency of identifying c jets





# Novel trigger strategy targeting HH and HHH productions in Run 3



# Novel trigger strategy targeting $HH \rightarrow 4b$ in Run 3

**Run 2 trigger** targeting 4b final states (8 Hz @  $2E10^{34} \text{ cm}^{-2} \text{ s}^{-1}$ ):

- Scalar sum of jets  $p_T$  (PF  $H_T$ ) > 340 GeV
- $\geq 4$  jets with  $p_T > 75, 60, 45, 40$  GeV
- $\geq 3$  jets tagged with **DeepCSV** algorithm

**Run 3 2022 HH trigger** (60 Hz):

- L1  $H_T > 360$  GeV
- $\geq 4$  jets with  $p_T > 70, 50, 40, 35$  GeV
- 2 leading-in-**ParticleNet** jets have average b-disc > 0.65

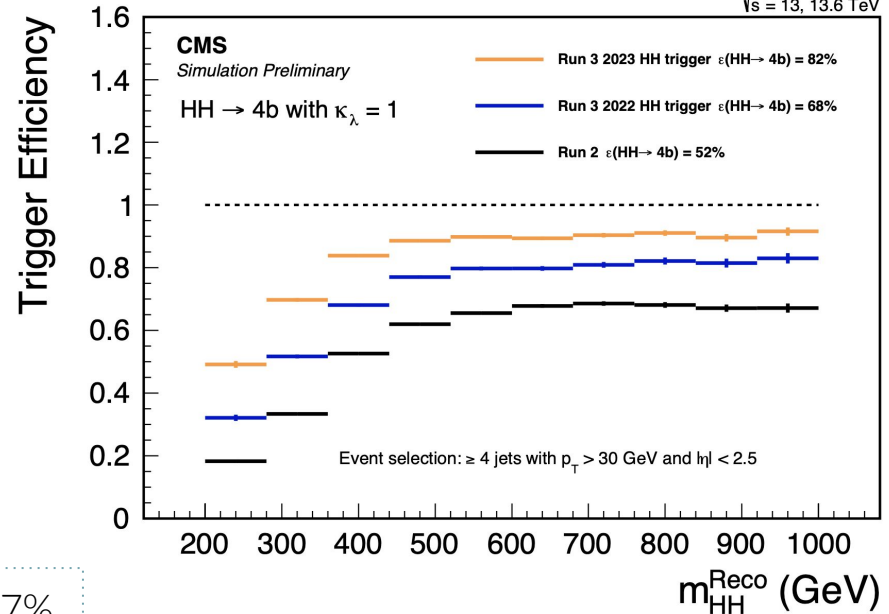
**Run 3 2023 HH trigger** (180 Hz):

- L1  $H_T > 280$  GeV
- $\geq 4$  jets with  $p_T > 30$  GeV
- 2 leading-in-**ParticleNet** jets have average b-disc > 0.55

Data Parking

✓ **Run 3 2023 HH trigger** achieves an 82% efficiency, 57% (20%) increase with respect to Run 2 (Run 3 2022) trigger!

Non-resonant  $HH \rightarrow 4b$  ( $\kappa_\lambda = 1$ )



$$\epsilon = \frac{N_{\text{events}}(\text{pass trigger and event selection})}{N_{\text{events}}(\text{pass event selection})}$$

# Novel trigger strategy targeting HH→4b in Run 3

**Run 2 trigger** targeting 4b final states (8 Hz @  $2E10^{34} \text{ cm}^{-2} \text{ s}^{-1}$ ):

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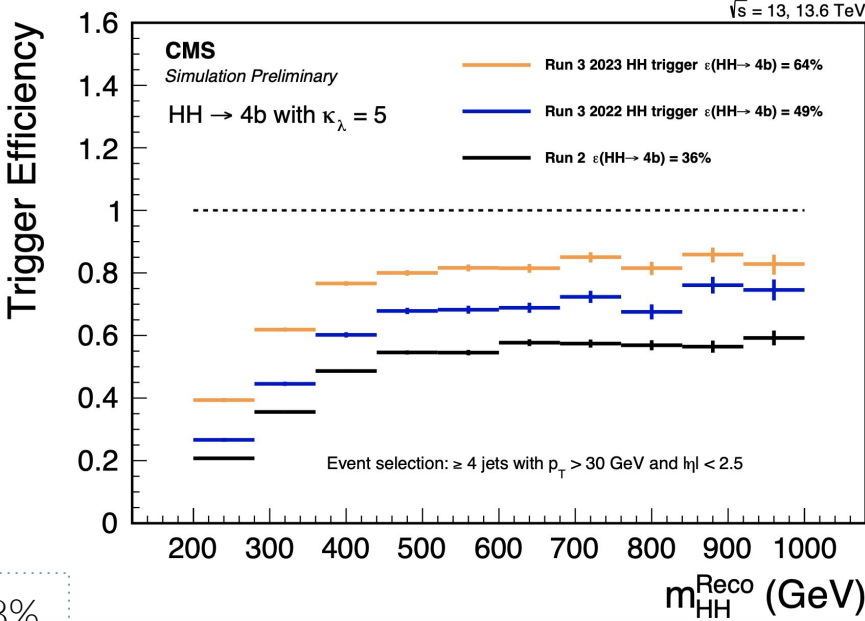
**Run 3 2023 HH trigger** (180 Hz):

- L1  $H_T > 280$  GeV
- $\geq 4$  jets with  $p_T > 30$  GeV
- 2 leading-in-**ParticleNet** jets have average b-disc > 0.55

Data Parking

✓ **Run 3 2023 HH trigger** achieves an 64% efficiency, 78% (30%) increase with respect to Run 2 (Run 3 2022) trigger!

Non-resonant HH→4b ( $\kappa_\lambda=5$ )



$$\epsilon = \frac{N_{\text{events}}(\text{pass trigger and event selection})}{N_{\text{events}}(\text{pass event selection})}$$

# Novel trigger strategy targeting $HH \rightarrow 2b2\tau_{\text{had}}$ in Run 3

Run 3  $\tau_{\text{had}}$ -triggers require: [CMS DP-2023-024]

- $\geq 2 \tau_{\text{had}}$  with  $p_T > 35 \text{ GeV}$ ,  $|\eta| < 2.1$  and tagged with DeepTau algorithm (50 Hz)
- $\geq 2 \tau_{\text{had}}$  with  $p_T > 30 \text{ GeV}$ ,  $|\eta| < 2.1$  and tagged with DeepTau algorithm + 1 jet with  $p_T > 60 \text{ GeV}$  (20 Hz)
- $\geq 1 \tau_{\text{had}}$  with  $p_T > 180 \text{ GeV}$ ,  $|\eta| < 2.1$  (17 Hz)

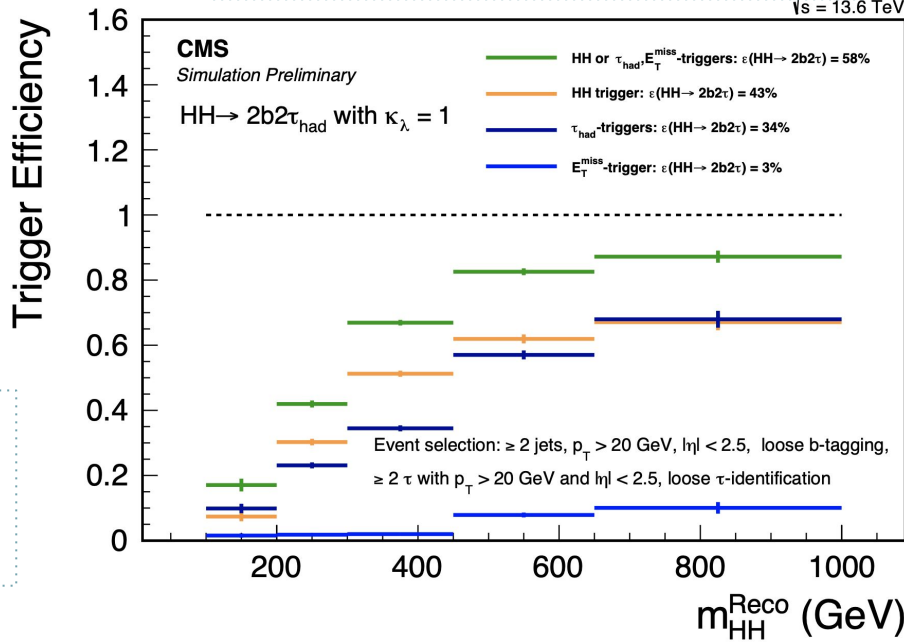
Run 3  $E_T^{\text{miss}}$ -triggers require  $E_T^{\text{miss}} > 120 \text{ GeV}$  [CMS DP-2023-016]

Run 3 2023 HH trigger (180 Hz):

- L1  $H_T > 280 \text{ GeV}$
- $\geq 4$  jets with  $p_T > 30 \text{ GeV}$
- 2 leading-in-ParticleNet jets have average b-disc  $> 0.55$

✓ Run 3 2023 HH trigger complements  $E_T^{\text{miss}}/\tau_{\text{had}}$ -triggers, reaching a combined overall efficiency of **58%**

Non-resonant  $HH \rightarrow 2b2\tau_{\text{had}}$  ( $\kappa_\lambda = 1$ )



# Novel trigger strategy targeting $HH \rightarrow 2b2\tau_{had}$ in Run 3

Run 3  $\tau_{had}$ -triggers require: [\[CMS DP-2023-024\]](#)

- $\geq 2 \tau_{had}$  with  $p_T > 35$  GeV,  $|\eta| < 2.1$  and tagged with DeepTau algorithm (50 Hz)
- $\geq 2 \tau_{had}$  with  $p_T > 30$  GeV,  $|\eta| < 2.1$  and tagged with DeepTau algorithm + 1 jet with  $p_T > 60$  GeV (20 Hz)
- $\geq 1 \tau_{had}$  with  $p_T > 180$  GeV,  $|\eta| < 2.1$  (17 Hz)

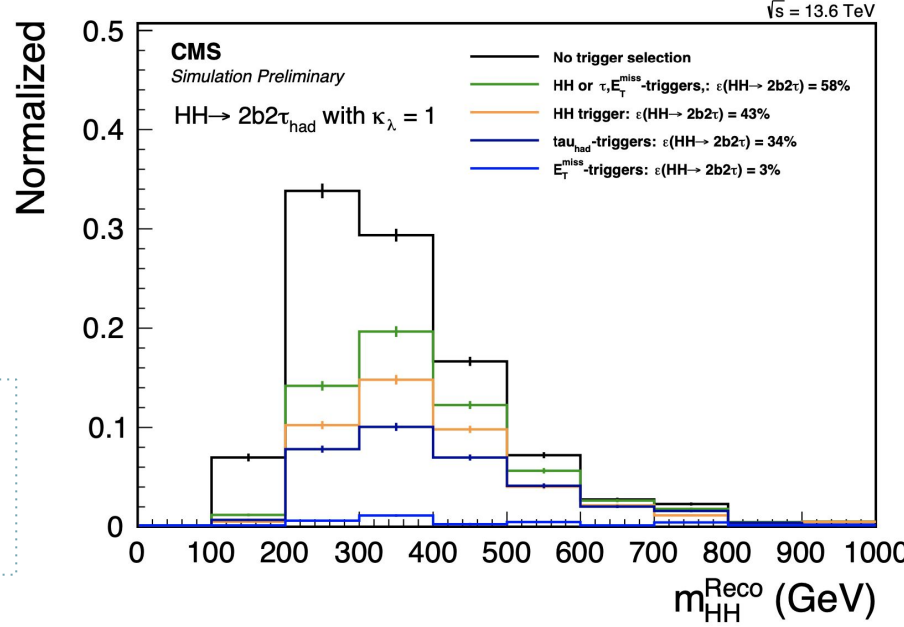
Run 3  $E_T^{miss}$ -triggers require  $E_T^{miss} > 120$  GeV [\[CMS DP-2023-016\]](#)

Run 3 2023 HH trigger (180 Hz):

- L1  $H_T > 280$  GeV
- $\geq 4$  jets with  $p_T > 30$  GeV
- 2 leading-in-ParticleNet jets have average b-disc  $> 0.55$

Non-resonant  $HH \rightarrow 2b2\tau_{had}$  ( $\kappa_\lambda = 1$ )

✓ Run 3 2023 HH trigger increases the acceptance in the intermediate  $m_{HH}$  region



# Novel trigger strategy targeting $HH \rightarrow 2b2\tau_{had}$ in Run 3

Run 3  $\tau_{had}$ -triggers require: [\[CMS DP-2023-024\]](#)

- $\geq 2 \tau_{had}$  with  $p_T > 35$  GeV,  $|\eta| < 2.1$  and tagged with DeepTau algorithm (50 Hz)
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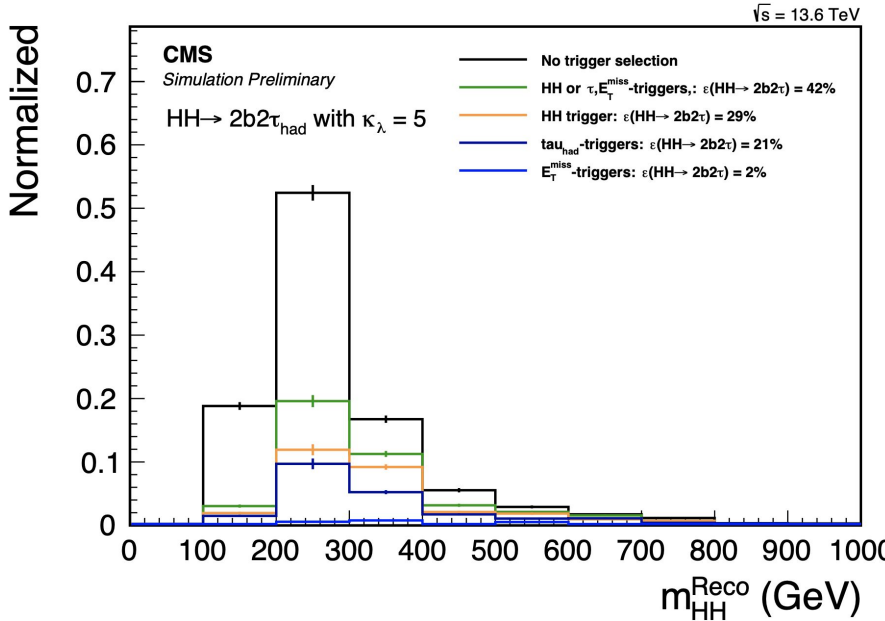
Non-resonant  $HH \rightarrow 2b2\tau_{had}$  ( $\kappa_\lambda = 5$ )

Run 3  $E_T^{miss}$ -triggers require  $E_T^{miss} > 120$  GeV [\[CMS DP-2023-016\]](#)

Run 3 2023 HH trigger (180 Hz):

- L1  $H_T > 280$  GeV
- $\geq 4$  jets with  $p_T > 30$  GeV
- 2 leading-in-ParticleNet jets have average b-disc  $> 0.55$

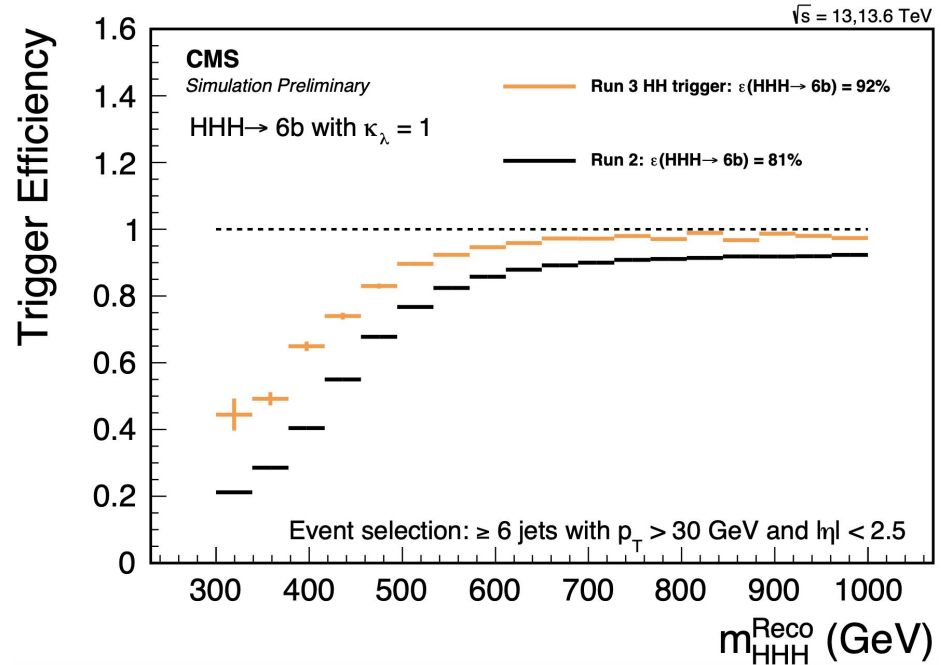
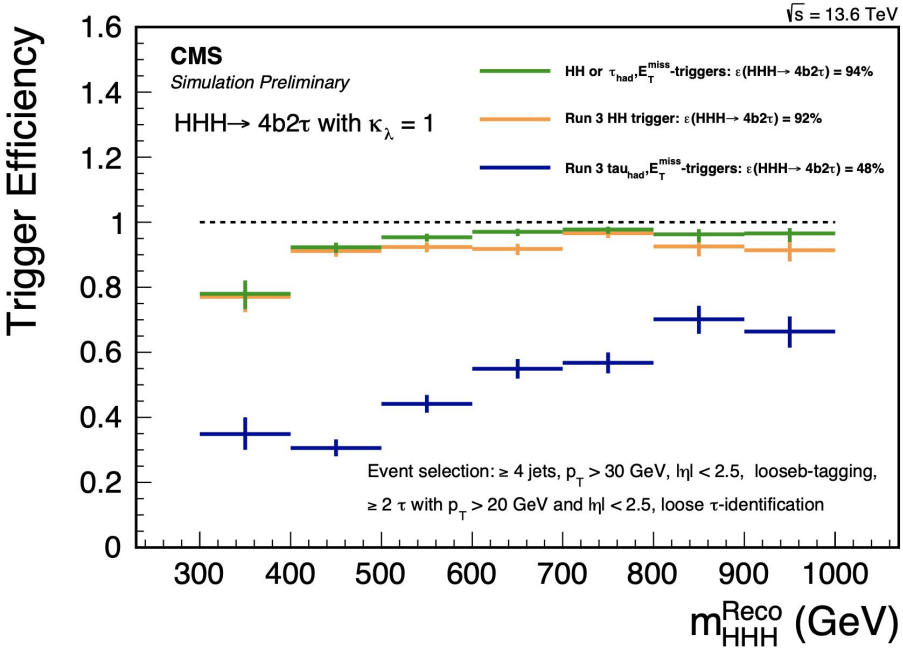
✓ Run 3 2023 HH trigger increases the acceptance in the intermediate  $m_{HH}$  region





# Novel trigger strategy targeting triple Higgs production

Same trigger(s) can be used in the search for triple Higgs production in the  $4b2\tau_{had}$  and  $6b$  final states, achieving **94%** and **92%** overall efficiency, respectively!



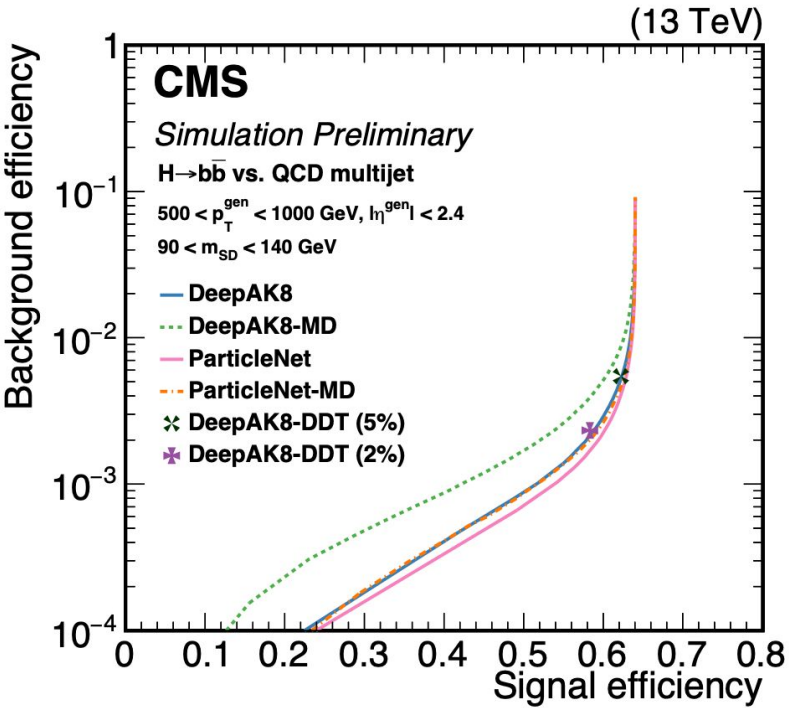
# Summary

- Modern neural networks with sophisticated architectures bring considerable performance improvements in (heavy flavour) jet tagging in Run 3
- CMS introduces a novel method to calibrate  $H \rightarrow bb/cc$  taggers
- Tagging algorithms can become more robust against simulation mismodellings with adversarial trainings
  
- ParticleNet@HLT introduced in Run 3 shows improved b-tagging performance
- New trigger targeting  $HH \rightarrow 4b$  signals now operates at 180 Hz
  - Large efficiency gain observed in  $HH \rightarrow 4b$ ,  $HHH \rightarrow 6b$ ,  $HH \rightarrow 2b2\tau_{had}$ ,  $HHH \rightarrow 4b2\tau_{had}$  final states!

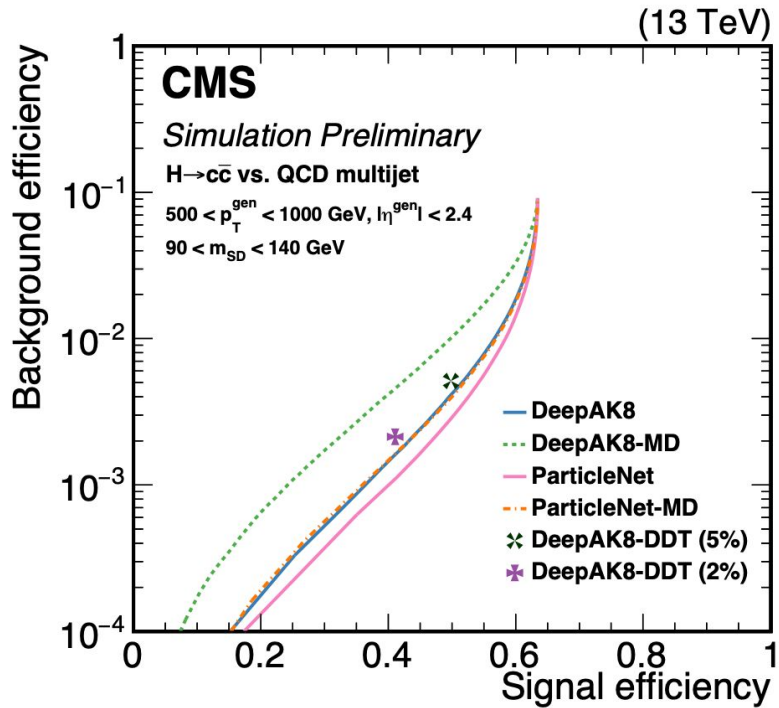
**Thank you for your attention**

Stay tuned for Run 3 physics analysis results!

# Backup



$$X \rightarrow b\bar{b} \text{ vs. QCD} = \frac{P(X \rightarrow b\bar{b})}{P(X \rightarrow b\bar{b}) + P(\text{QCD})}$$



$$X \rightarrow c\bar{c} \text{ vs. QCD} = \frac{P(X \rightarrow c\bar{c})}{P(X \rightarrow c\bar{c}) + P(\text{QCD})}$$

- ❑ **b-tagging efficiency measurements in multijet events:**
  - ❑  **$p_{T,rel}$**  – Method to measure the b-tagging efficiency in multijet events based on the transverse momenta of muons within jets with respect to the jet axis [4].
  - ❑ **System8** – Method to measure the b-tagging efficiency in multijet events with muons within jets by solving a system of 8 equations [4].
  - ❑ **Lifetime (LT)** – Method to measure the b-tagging efficiency in multijet events with muons within jets based on template fits to the distributions of the JP discriminator and secondary vertex mass [4].
  - ❑ **mu+jets** – Combination of b-tagging efficiency measurements from multijet events with jets containing muons ( $p_{T,rel}$ , System8, LT).
- ❑ **b-tagging efficiency measurements in top pair events:**
  - ❑  **$t\bar{t}$**  – Top quark antiquark pair production.
  - ❑ **Kin. fit** – Method to measure the b-tagging efficiency in  $t\bar{t}$  events with two leptons, based on a template fit to an MVA discriminator combining several kinematic observables [4].
  - ❑ **Tag&Probe** – Method to measure the b-tagging efficiency in  $t\bar{t}$  events with one lepton, based on a tag and probe method, where the medium WP is applied to one of the two b-jets expected from top pair production, while the other b jet is used as a probe [4].
  - ❑ **comb** – Combination of b-tagging efficiency measurements from  $t\bar{t}$  events (Kin. fit, Tag&Probe) and multijet events with a muon ( $p_{T,rel}$ , System8, LT).
- ❑ **Light-jet mistagging efficiency measurement in multijet events:**
  - ❑ **NegativeTag** – Method to measure the light jet mistagging efficiency in inclusive multijet events, using the tracks with negative sign of the impact parameter [4].

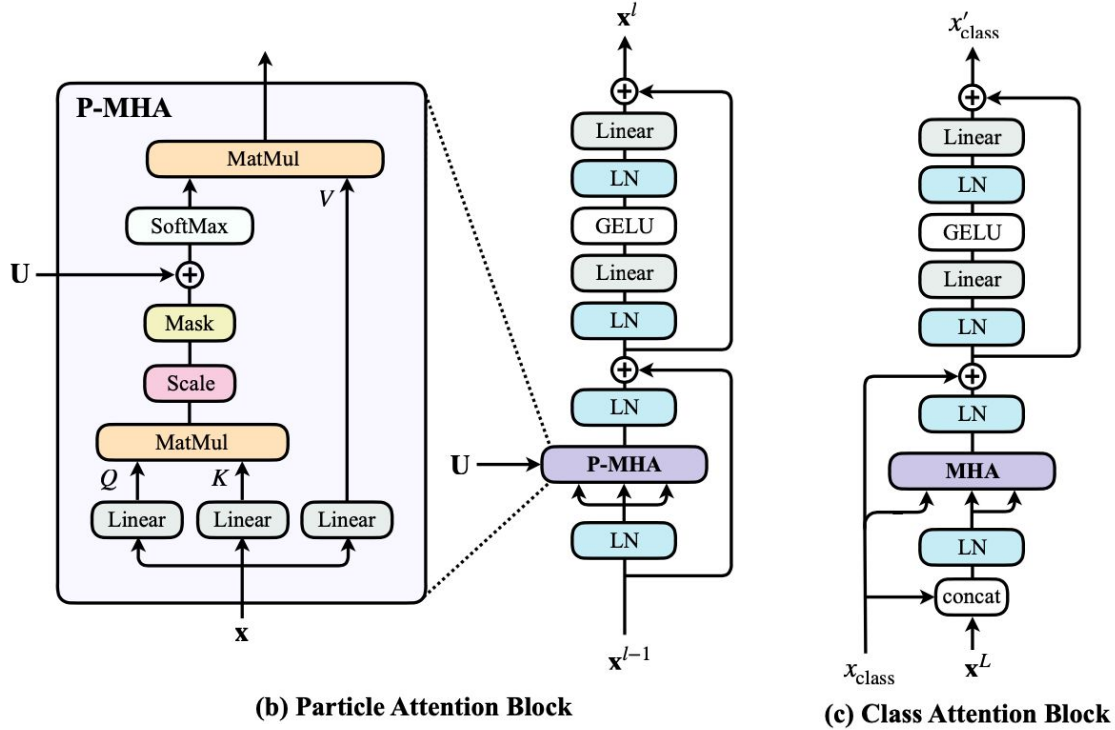
### Particle Attention block:

Computes self attention between particles:

- The multi-head attention (P-MHA) module incorporates particle interaction features and modifies the dot-product attention weights

### Class Attention block:

Computes the attention between a global class and all the particles through MHA

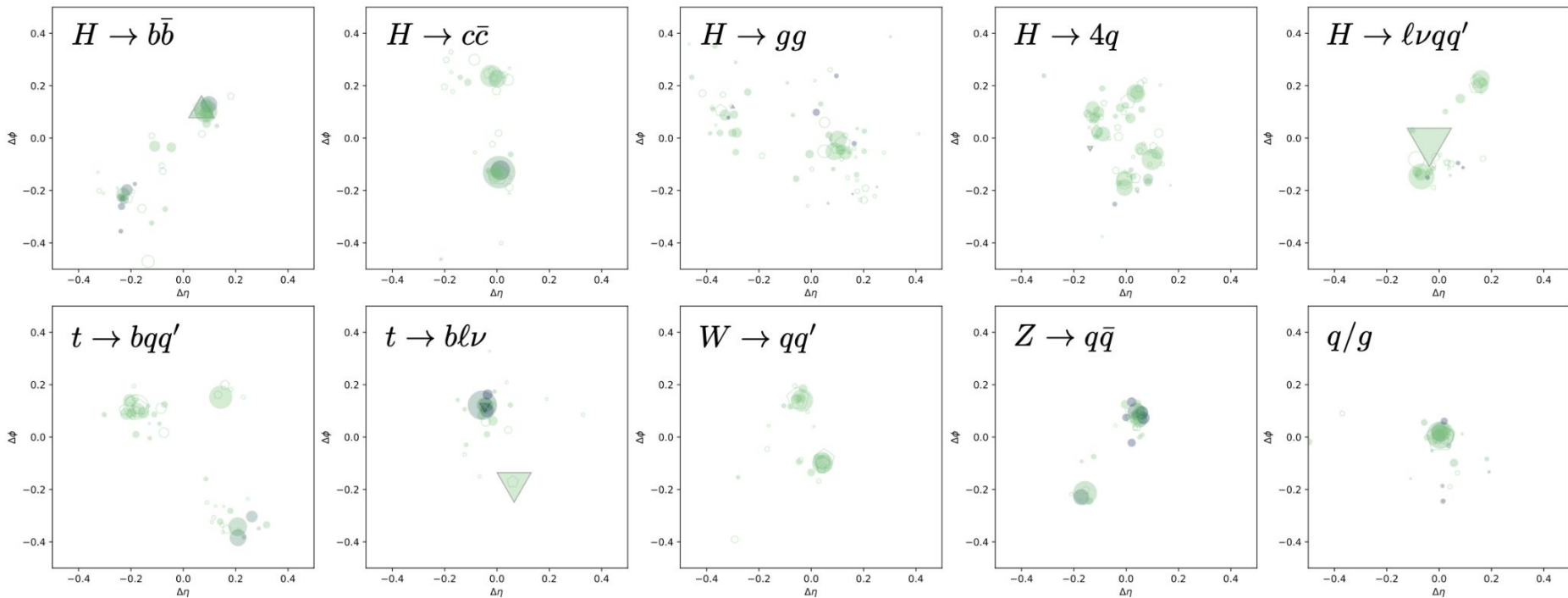


(b) Particle Attention Block

(c) Class Attention Block

Variable	Definition
$\Delta\eta$	difference in pseudorapidity between the particle and the jet axis
$\Delta\phi$	difference in azimuthal angle between the particle and the jet axis
$\log p_T$	logarithm of the particle's $p_T$
$\log E$	logarithm of the particle's energy
$\log \frac{p_T}{p_{T(\text{jet})}}$	logarithm of the particle's $p_T$ relative to the jet $p_T$
$\log \frac{E}{E(\text{jet})}$	logarithm of the particle's energy relative to the jet energy
$\Delta R$	angular separation between the particle and the jet axis ( $\sqrt{(\Delta\eta)^2 + (\Delta\phi)^2}$ )
$q$	electric charge of the particle
<code>isElectron</code>	if the particle is an electron
<code>isMuon</code>	if the particle is a muon
<code>isChargedHadron</code>	if the particle is a charged hadron
<code>isNeutralHadron</code>	if the particle is a neutral hadron
<code>isPhoton</code>	if the particle is a photon
$\tanh d_0$	hyperbolic tangent of the transverse impact parameter of the track (in units of mm)
$\tanh d_z$	hyperbolic tangent of the longitudinal impact parameter of the track (in units of mm)
$\sigma_{d_0}$	error of the transverse impact parameter
$\sigma_{d_z}$	error of the longitudinal impact parameter





Training dataset: 100 M jets!

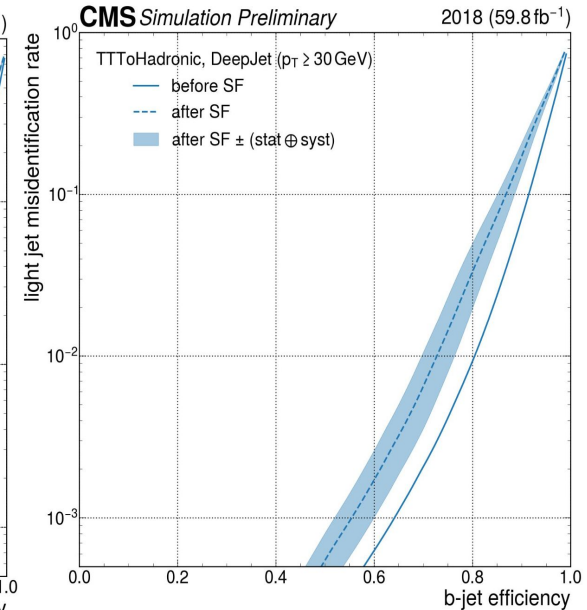
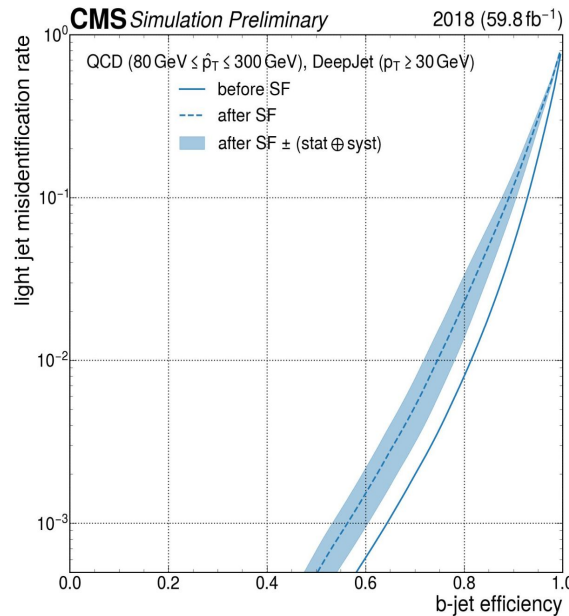
# Backup b calibration • discriminant shape calibrations

The full b discriminant shape is calibrated for b- and light-jet with an **iterative fit** method in top quark pair production events with two leptons (enriched in b jets) and Z+jet events (enriched in light-flavour jets)

- SFs are derived separately in bins of the b tagging discriminator distribution,  $p_T$  and  $\eta$

Systematic uncertainties:

- Sample purity (the fraction of heavy-flavor jets is varied by  $\pm 20\%$ )
- Jet energy scale
- Statistical uncertainty due to the limited statistics in each bin of the b discriminant
- Treatment of  $SF_c$



# Backup DeepJet c discriminant shape calibration

Calibration of c tagger done for both fixed WPs and full discriminant shapes

c discriminant shape calibrations performed in 3 samples:

## W+c (c purity ~93%):

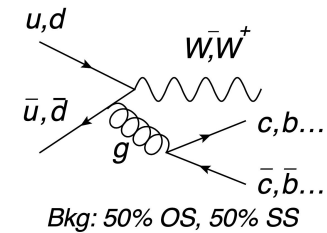
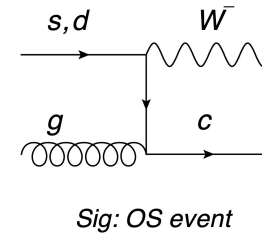
- $p_T^{\text{miss}}$ , 1 isolated lepton coming from  $W \rightarrow l\nu$  ( $l=e, \mu$ )
- At least 1 jet with a soft, non-isolated muon inside it (c jet)
- Events split into opposite-sign (OS), same-sign (OS)
- OS-SS subtraction to reduce main background

## top pair (b purity ~81%):

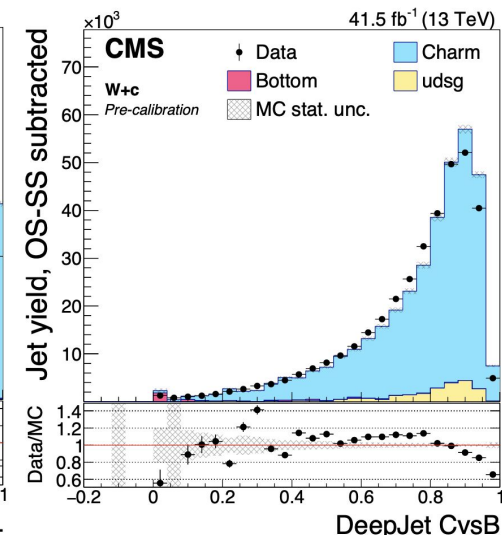
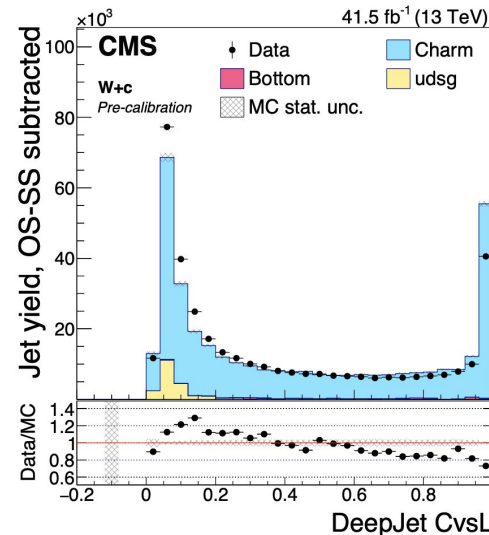
- Semileptonic: 1 leptonically decaying W boson, a jet with a soft muon from the b hadron decay + additional hadronic jets
- Dileptonic: 2 leptonically decaying W bosons, two jets with at least one containing a soft muon.

## DY+jet (udsg purity ~86%):

- $\geq 1$  jet in association with a leptonically decaying Z boson



Before calibration



# Backup DeepJet c discriminant shape calibration

An **iterative fit** is performed on these samples to derive data-to-simulation SFs in the **2D plane of CvsL and CvsB** per jet flavour

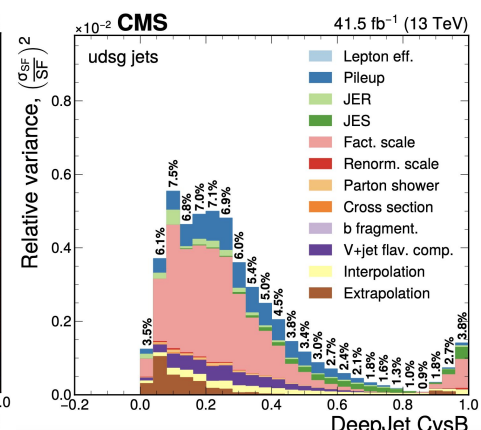
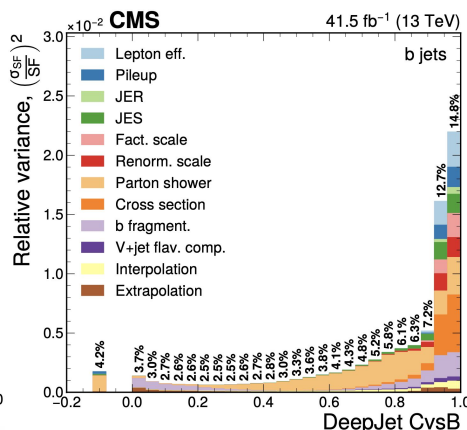
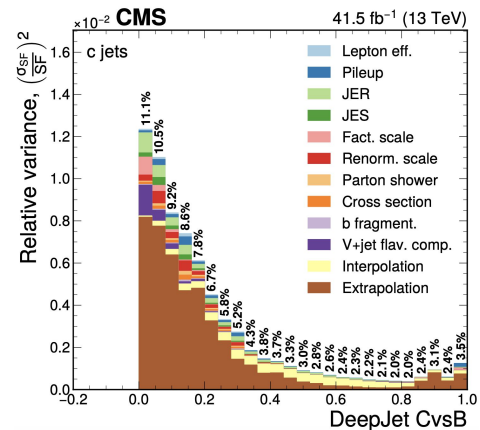
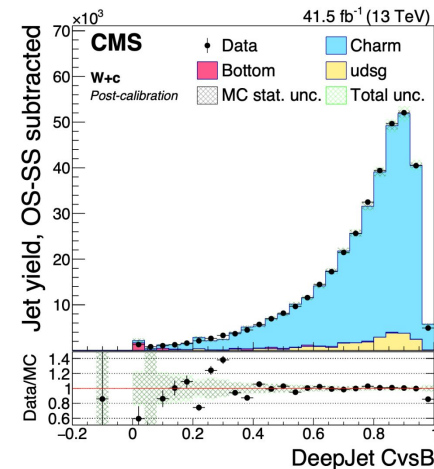
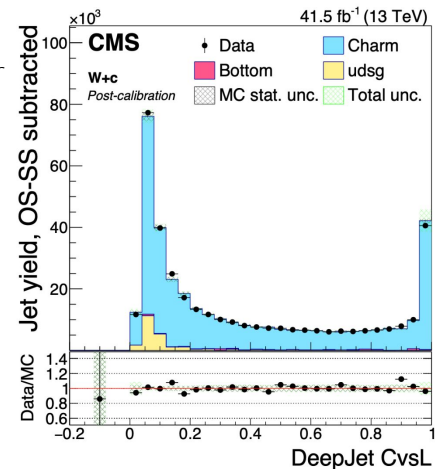
- Light/c/b components free to float until data-to-simulation differences are **minimised**
- two binning choices → a combined SF obtained through interpolation

## Main systematic uncertainties:

c-jets: interpolation & extrapolation

b-jets: factorisation scale

light-jets: ISR and FSR in the parton shower



↑  
After calibration

# Backup Run 3 triggers • Online rates

Trigger	Requirement	Rates at HLT at $2 \times 10^{34} \text{ cm}^{-2}\text{s}^{-1}$
2023 HH trigger	HT > 280 GeV, 4 jets with $p_T > 30 \text{ GeV}$ , PNet@AK4(mean 2 highest b-tag score) > 0.55	180 Hz
2022 HH trigger	4 jets $p_T > 70, 50, 40, 35 \text{ GeV}$ , PNet@AK4(mean 2 highest b-tag score) > 0.65	60 Hz
2018 triple b-tag <a href="#">[2,3]</a>	HT > 340 GeV, 4 jets $p_T > 75, 60, 45, 40 \text{ GeV}$ , 3 b-tags with DeepCSV > 0.24	8 Hz
Run 3 tau-triggers <a href="#">[4]</a>	Double medium DeepTau taus with $p_T > 35 \text{ GeV}$ $ \eta  < 2.1$ Double medium DeepTau taus with $p_T > 30 \text{ GeV}$ $ \eta  < 2.1$ , PFJet 60 GeV Single loose DeepTau on hadronic tau with $p_T > 180 \text{ GeV}$ $ \eta  < 2.1$	50 Hz 20 Hz 17 Hz
Run 3 MET-trigger <a href="#">[5]</a>	Missing transverse energy (MET) (no muon) > 120 GeV, HT (no muon) > 120 GeV	42 Hz

# Backup Run 3 triggers • trigger acceptance on HH→4b signal

