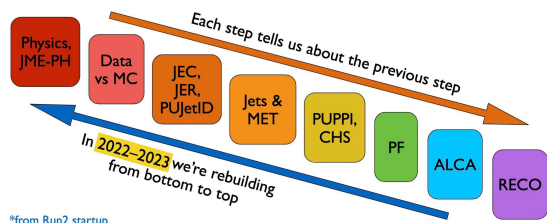
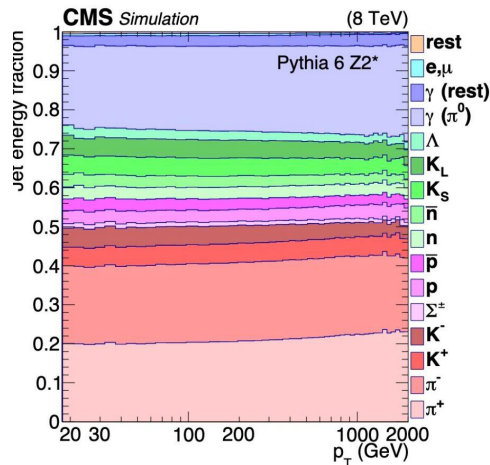


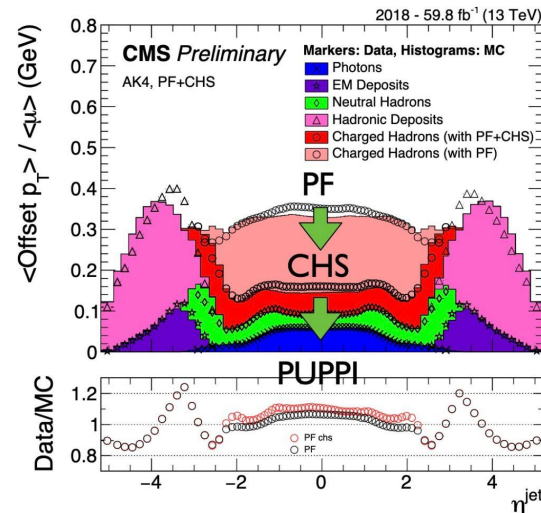
CMS



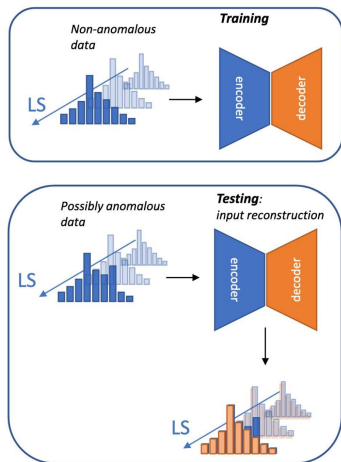
- many many particles ($\pi^0 \rightarrow \gamma\gamma$, π^+ , π^- , K^0_L , n, p etc.) from many many vertices
- Particle Flow (PF) reconstructs 3 types: charged hadrons, neutral hadrons, photons
- Charge Hadron Subtraction (CHS) and Pile Up Per Particle Id (PUPPI) remove pileup



JME-13-004

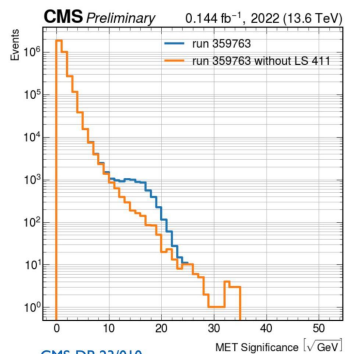


DP-2021/033

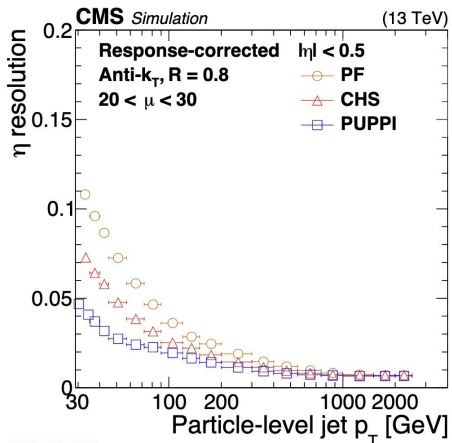


- Data quality management (DQM) with Machine Learning (ML) improves overall efficiency:

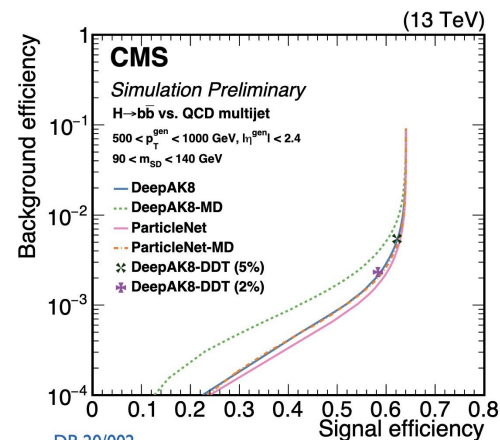
- ▶ AutoEncoder trained on good luminosity sections (LS ~ 23s) of data to learn normal behaviour
- ▶ Anomalous data flagged per LS and removed if bad



CMS-DP-23/010



JME-18-001

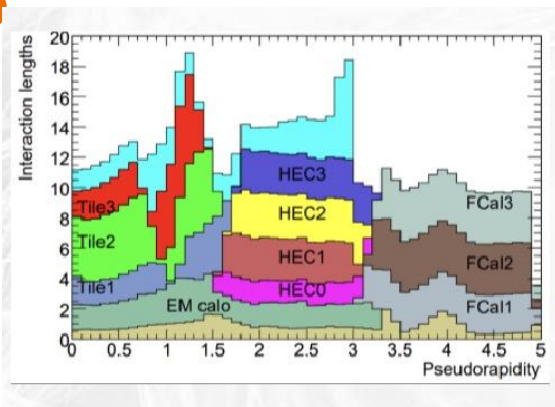


DP-20/002

A lot of novelties, long mileage covered since Run1

New ideas, that make our life easier

ATLAS



2 parts: Bias HS object energy, add PU jets to event!

PU removal at every level:

3. On jets

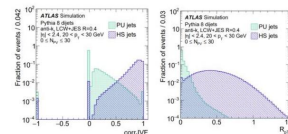
- Jet Area subtraction
- Grooming (trimming, softDrop) (backup)
- Forward Jet Vertex Tagger (fJVT)
- **Jet Vertex Tagger (JVT)**

$$R_{\text{JVT}} = \frac{\sum_k P_{T,k}^{\text{track}}(PV_0)}{P_T^{\text{jet}}}$$

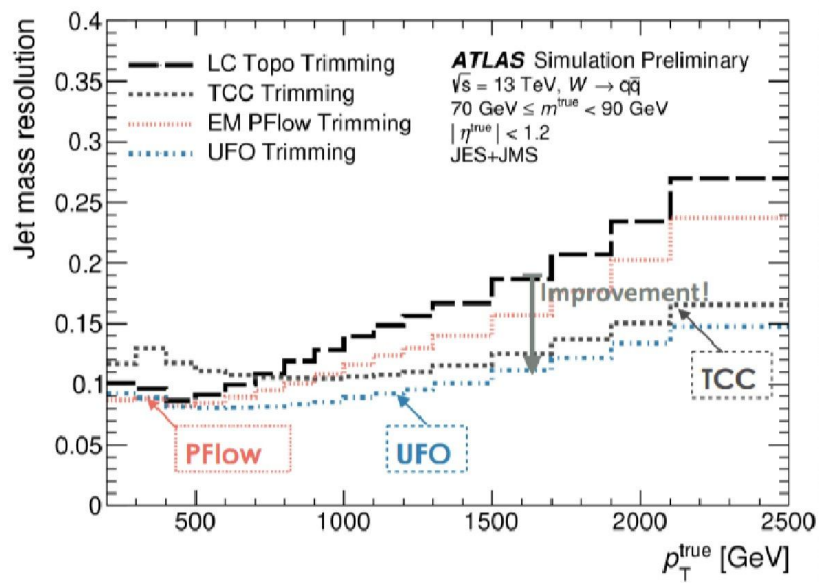
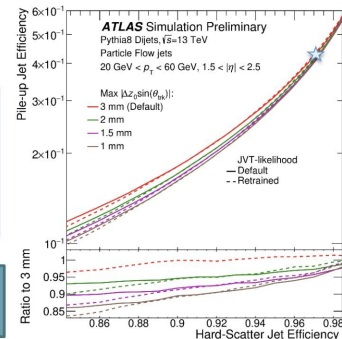
$$\text{corrJVT} = \frac{\sum_m P_{T,m}^{\text{track}}(PV_0)}{\sum_l P_{T,l}^{\text{track}}(PV_0) + \sum_{(k \neq l)} \frac{P_{T,k}^{\text{track}}(PV_0) P_{T,l}^{\text{track}}(PV_0)}{(k \neq l)_{\text{track}}}}$$

kNN Likelihood

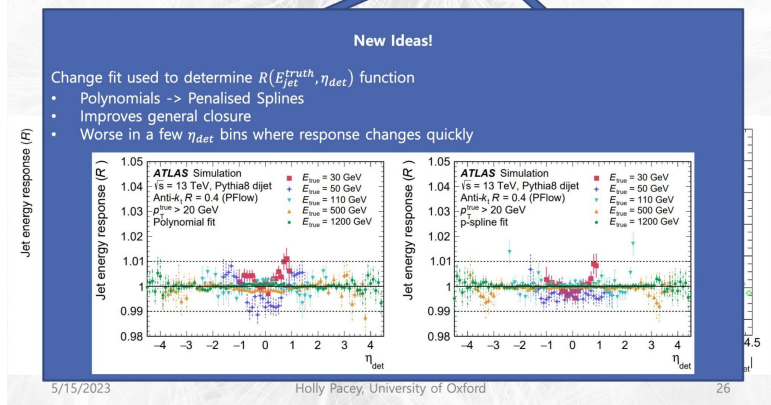
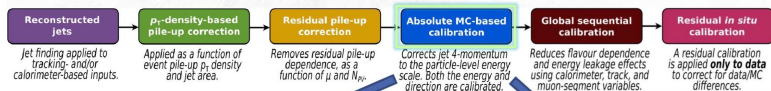
- Trained on MC dijets
- Truth-tag HS/PU jets
- JVT discriminant



Aiming to upgrade to a NN using more info



Small-R Jet Calibration



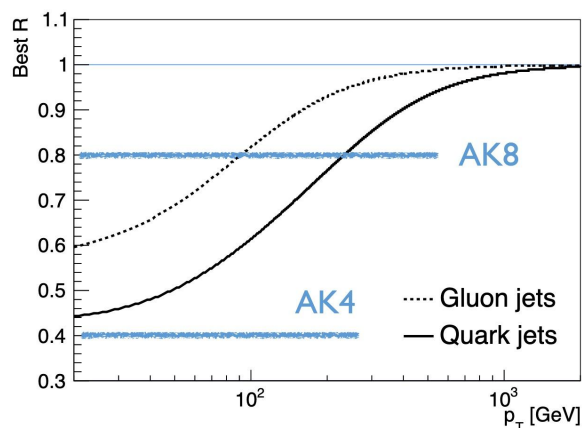
5/15/2023

Holly Pacey, University of Oxford

26

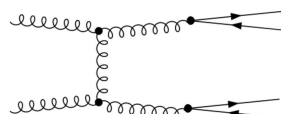
Jets clustering

Is there an optimal R?



It depends...
... on p_T and flavour

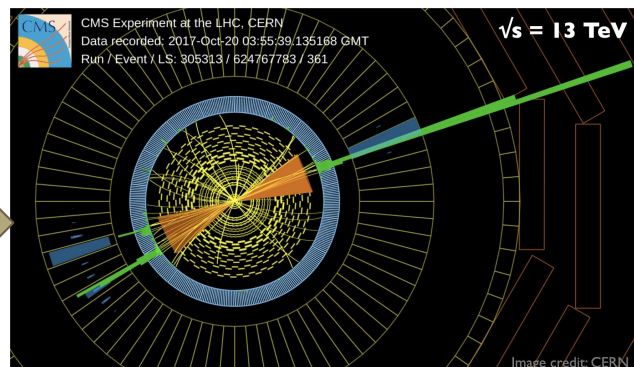
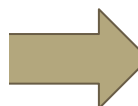
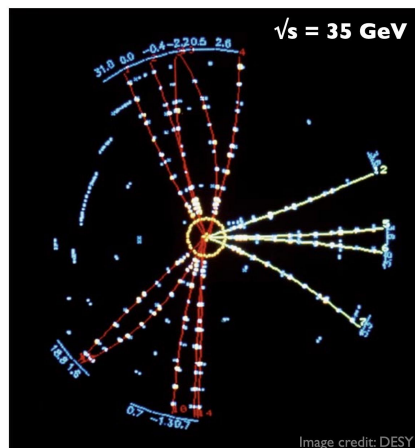
Defining Quark and Gluon Jets



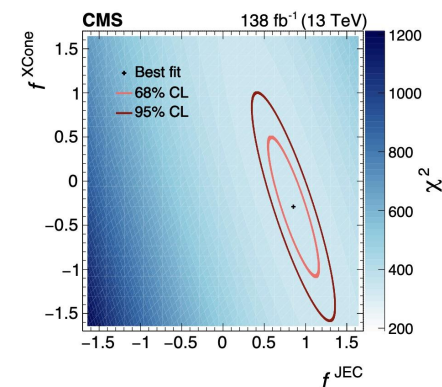
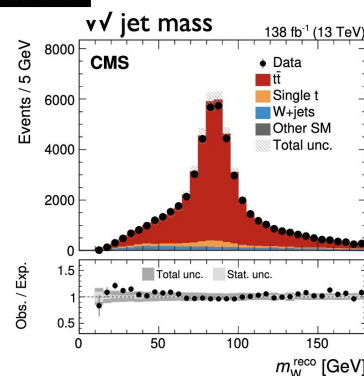
Obviously two gluon jets...
... or not!!?

- Parton flavour (from hard matrix element) is intrinsically flawed
- Physically meaningful definitions (not exhaustive)
 - N-Subjettiness [Larkoski, Metodiev, EPJC 10, 014 (2019)]
 - Possibility to unambiguously define quark jets ($\tau_N \rightarrow 0$)
 - Gluon jets always contaminated by quark jets, $(C_F/C_A)^{N_{emissions}}$
 - Flavour-kt [Banfi, Salam, Zanderighi, EPJC 47, 113 (2006)]
 - Jet topics [Komiske, Metodiev, Thaler, JHEP 11, 059 (2018)]
 - Fragmentation approach (WTA axis) [Caletti et al., JHEP 10, 158 (2022)]

TASSO at PETRA, 1979



Measuring with XConc



Heavy Object Tagger with Variable R

[Lapsien, Haller, RK, EPJC 76, 600 (2016)]

One-pass clustering with integrated subjet finding

- Jet distance measures (with variable R)

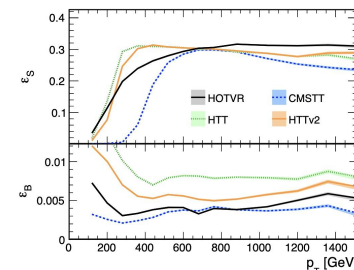
$$d_{ij} = \min[p_{T,i}^{2n}, p_{T,j}^{2n}] \Delta R_{ij}^2$$

$$d_{iB} = p_{T,i}^{2n} R_{eff}^2 \quad R_{eff} = \frac{\rho}{p_T}$$

- Clustering veto at each step
 - mass jump veto
- Store objects i and j as subjects

- Used in $t\bar{W}$ resonance search [CMS, JHEP 04, 048 (2022)]

- Works beautifully, but can be improved



[RK, STMP 284 (2021)]

Random

Clearly, a lot of new interesting ideas (ParticleNet, ML in DataCertification etc)

Common grounds for ATLAS/CM ? Room for improvement and collaboration / x-talking?

Clear intersection with theory, pheno + ML etc

Jet clustering : are we using/studying the new ideas/models in CMS/ATLAS?

- .-we certainly do in some cases, like XCone)

- .-What are we missing?