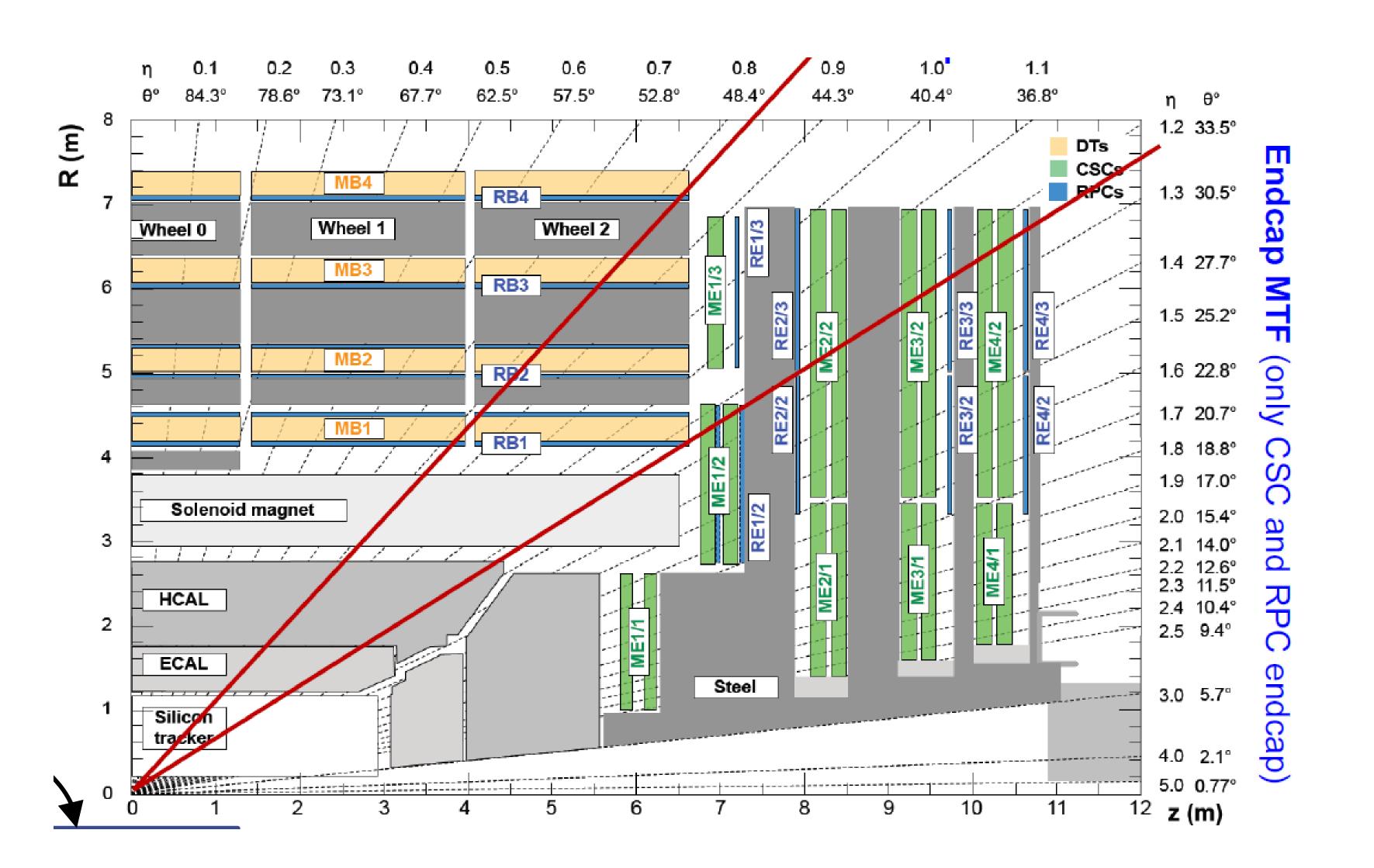


BDTs in the CMS Level 1 Muon Endcap Trigger





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CMS Level 1 trigger ("L1T") selects 100k interesting events out of 40 million collisions every second at the LHC

- Goal is ≥ 90% efficiency for events we want to keep
- Keep high transverse momentum ("pT") particles, reject low pT events

Quick trigger decision: only 3.0 µs for the entire process

Fast logic algorithms in FPGAs perform complex analysis: from raw detector inputs, reconstruct, select, and assign pT to particles

Muons leave tracks as they pass through the CMS detector

- Assign pT based on curvature in magnetic field: more bend ↔ low pT
- In L1 trigger, can only use outer muon chambers, not inner tracker

Typical "interesting" event has a single muon with pT > 25 GeV

- For every real 25 GeV muon, there are 1000 muons with pT = 5 GeV!
- Critical to reject as many low-pT muons as possible

Endcap Muon Track Finder (EMTF) creates tracks from hits in 4 forward "stations"

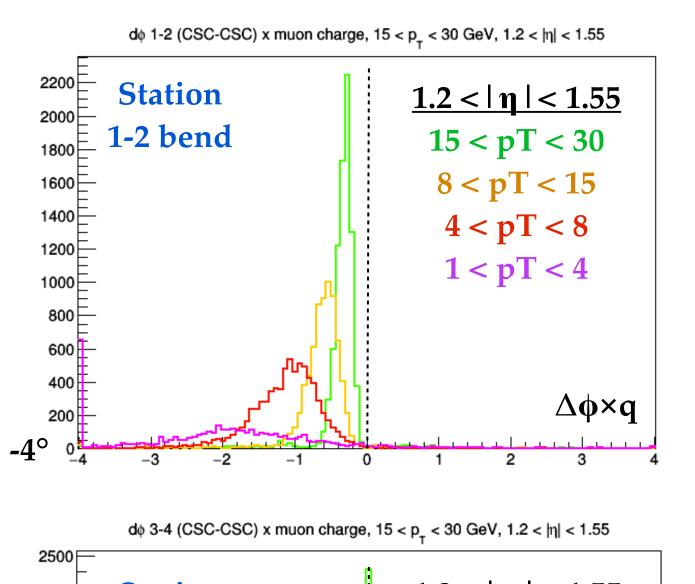
- CSC or RPC hits correlated in θ and ϕ between stations belong to the same muon
- Typically < 1° of bending in θ , up to 12° in ϕ due to magnetic field

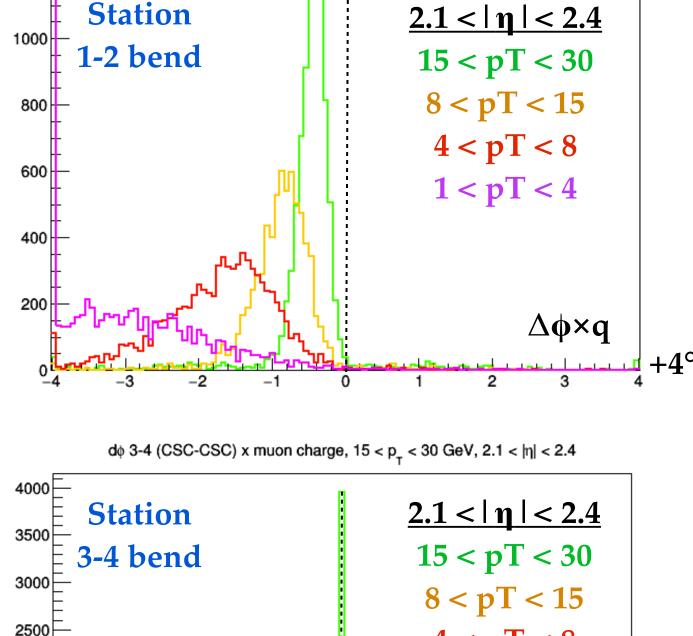
Assign pT mostly using bend in ϕ between stations vs. track θ (or η)

- Magnetic field strength varies with η, but always strongest between stations 1 and 2
- $\Delta \phi(1-2)$ is consistently "negative" (w.r.t. the muon charge), larger for low pT
- $\Delta \phi(2-3)$ and $\Delta \phi(3-4)$ much smaller, more scattering (positive or negative bend) at low pT
- Very different behavior between $|\eta| < 1.55$ (more central) and $|\eta| > 2.1$ (forward)

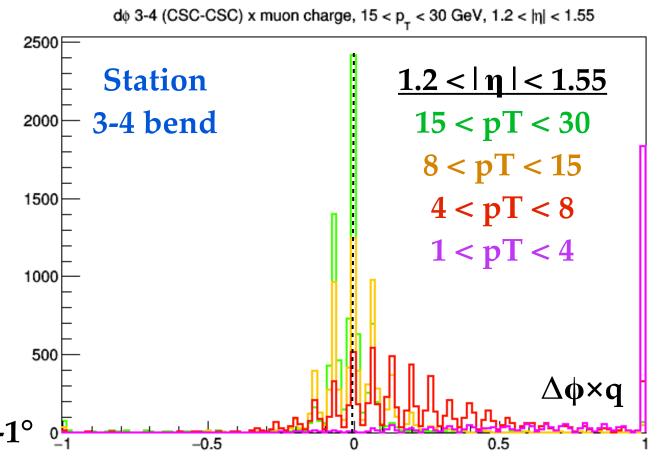
Complicated dependencies make this an ideal case for machine learning

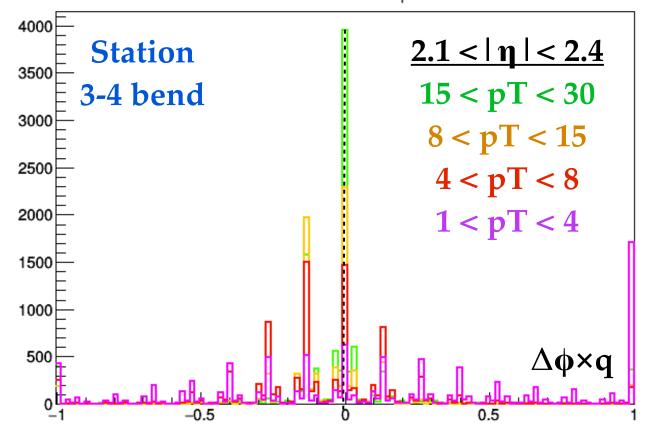
- But have only ~500 ns to run entire EMTF algorithm: track-building + pT assignment
- Instead, use Boosted Decision Trees (BDTs) offline to assign pT for 1 billion track profiles
- Write values to 1.2 GB look-up table (LUT), with 30-bit address based on input variables
- Requires some compression: $\Delta \phi(1-2)$ into 7 bits, $\Delta \phi(2-3)$ into 5 bits, etc.





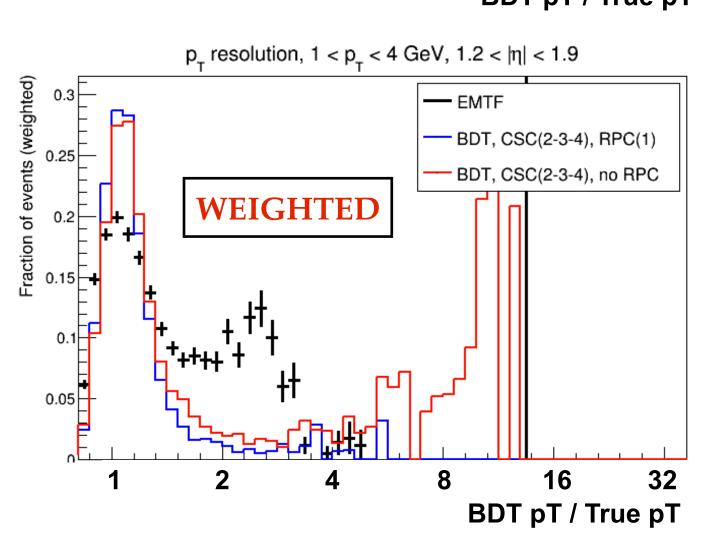
d ϕ 1-2 (CSC-CSC) x muon charge, 15 < p $_{_{\rm T}}$ < 30 GeV, 2.1 < $|\eta|$ < 2.4





$p_{_{T}}$ resolution, 1 < $p_{_{T}}$ < 4 GeV, 1.2 < $|\eta|$ < 1.9 BDT, CSC(2-3-4), RPC(1) BDT, CSC(2-3-4), no RPC **UNWEIGHTED** 0.7 BDT pT / True pT

$\boldsymbol{p}_{_{\! T}}$ resolution, 1 < $\boldsymbol{p}_{_{\! T}}$ < 4 GeV, 1.2 < $|\eta|$ < 1.9



Training Feature: Resolution

Optimization may seem straightforward

Choose the algorithm that assigns pT closest to the true pT (best "resolution")

Reality is much more complicated

- Background muon pT spectrum falls as pT⁻⁴ or pT⁻⁵, so very-low-pT muons with over-assigned pT cause the most rate
- Compare unweighted resolution (top) to resolution weighted by (BDT / true pT)³ -- suddenly see huge difference in tails

Strategies to reduce high-pT tails

- Re-weight training sample to fall as pT⁻²
- Target 1/pT in regression instead of pT -- inflates difference for low pT muons

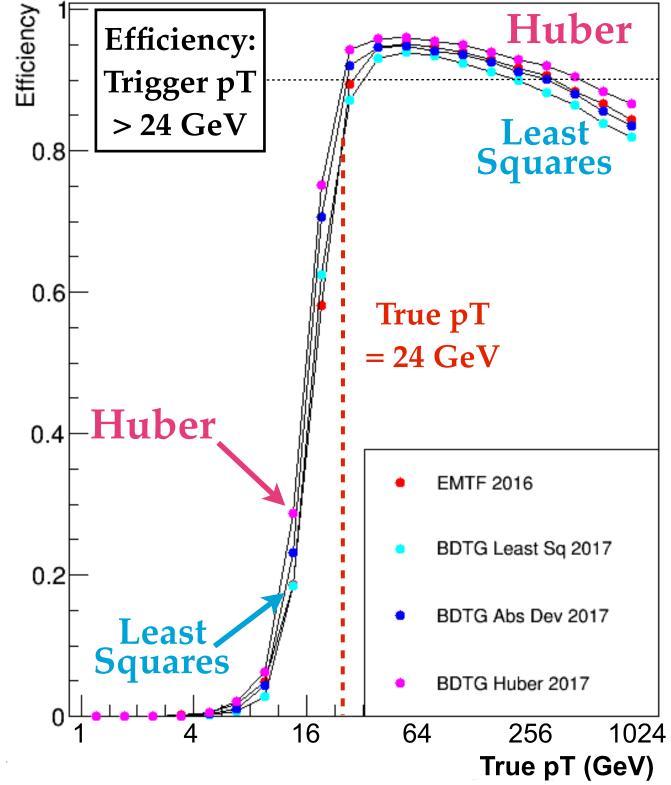
Training Feature: Loss Function

Choice of "loss function" also plays a role

- BDT minimizes Σ (loss) in training events
- loss = $(\text{true pT}^{-1} \text{BDT pT}^{-1})^2$, or loss = $|\text{true pT}^{-1} - \text{BDT pT}^{-1}|$, or "Huber": () 2 in the center, | | in the tails

Playing off rate vs. efficiency

- Functions that don't penalize tails (e.g. Huber) better in the "plateau" -- efficiency to assign pT > 24 GeV when true pT > 30
- But Least Squares has sharper "turn-on" -- fewer muons with over-assigned pT, and thus a lower background rate





In 2016, reduced background rate by a **factor of two** compared to 2015!

- Most of rate reduction comes from using BDTs to assign pT
- Small efficiency loss because RPC hits were not yet included in EMTF

In 2017, with RPC hits and new BDTs: even lower rates, higher efficiency

Plus many ideas for future improvements!

More intelligent algorithms (e.g. DNNs), custom rate vs. efficiency loss functions, training directly on high-statistics data ... and much more!

