Searching for Vector-Like Quark Pairs in the All-Hadronic Final State at Snowmass

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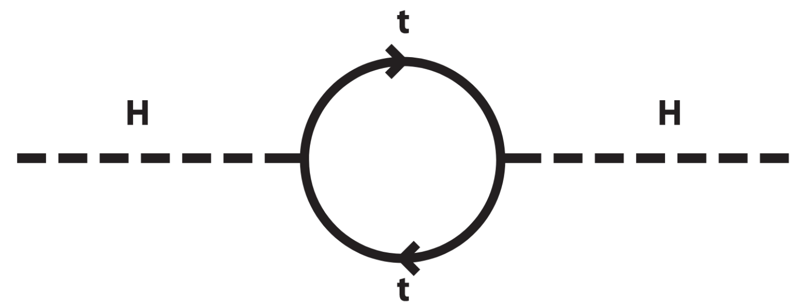
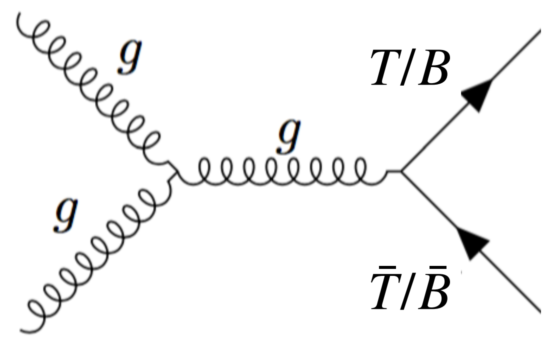
Expression of Interest…

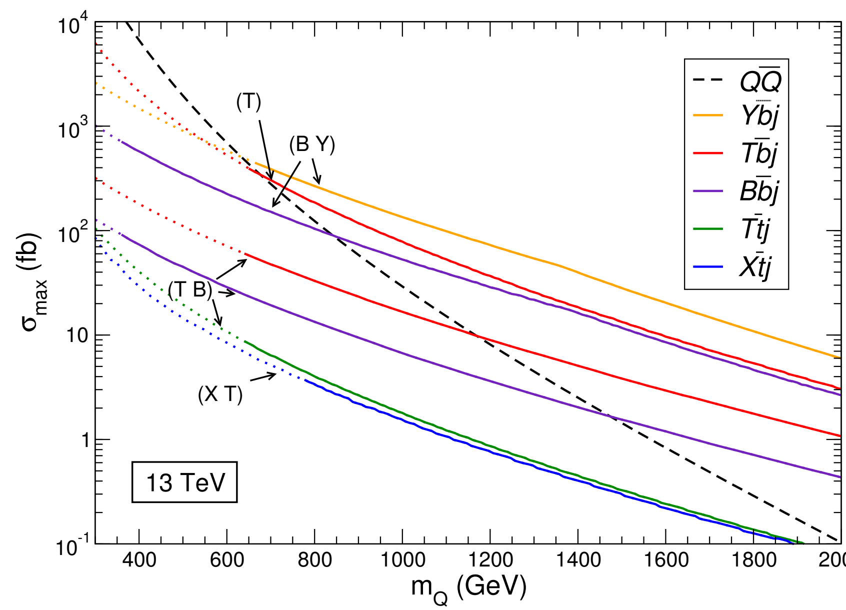
- This is meant to be an introduction, an expression of interest, and a possibility for collaborative studies
  - We have not yet done any future studies to contribute to Snowmass
  - We will introduce our most recent public work w/ CMS 2016 data
- We plan to study future reach based on Snowmass-defined benchmarks for p-p colliders (energy/intensity) and make projections.
  - We will need to request appropriate MC samples in coordination with other Snowmass studies.
  - Unsure if we will easily study also an e-e collider
- Open to collaborators or ideas/suggestions

Physics Beyond the Standard Model w/ VLQs

- The Standard Model has been a resounding success, however…
- Divergence of top quark loop -> stabilized by new physics?
  - Existing Higgs measurements exclude 4th generation chiral quarks (VLQs evade these constraints)
- Is the Higgs fundamental, or a composite particle (pNGB)?
  - If so, VLQs should be in TeV range
- Why is the top so heavy in the first place?
  - VLQs mix strongly with 3rd-gen quarks
- Always the question of dark matter







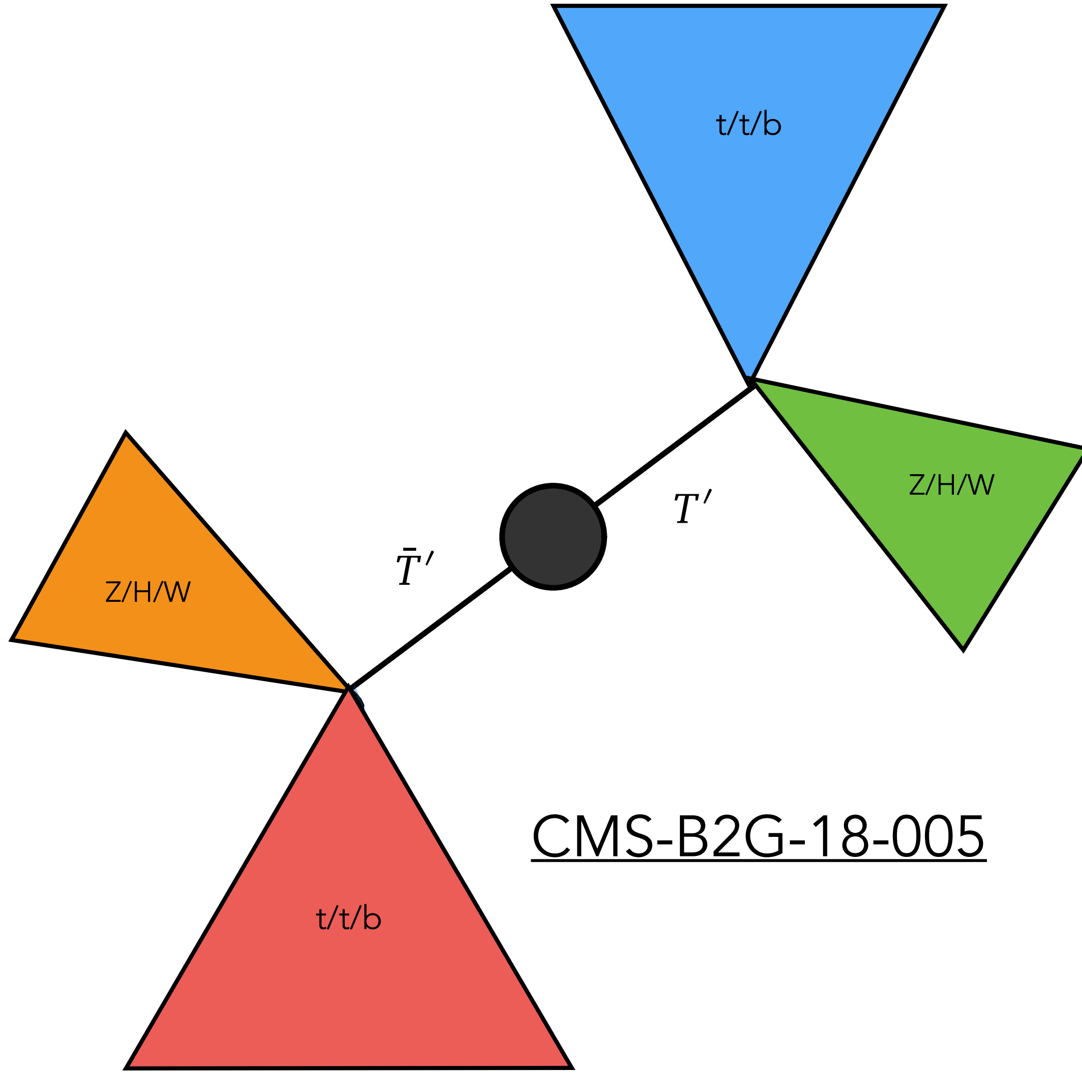
Pair-Produced VLQ Search Strategy

We performed a search with 2016 CMS data through two different jet-tagging approaches:

- One targeting the **T->bW** decay, utilizing jet substructure and soft drop mass tagging
- One targeting **all modes,** utilizing a novel neural net based tagger: "Boosted Event Shape Tagger" (**BEST**)

Currently developing analysis with full Run 2 dataset (~136 fb^{-1})

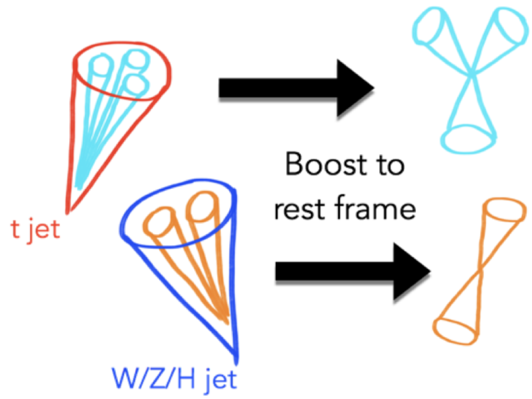
- We are focusing on improving performance of the BESTagger

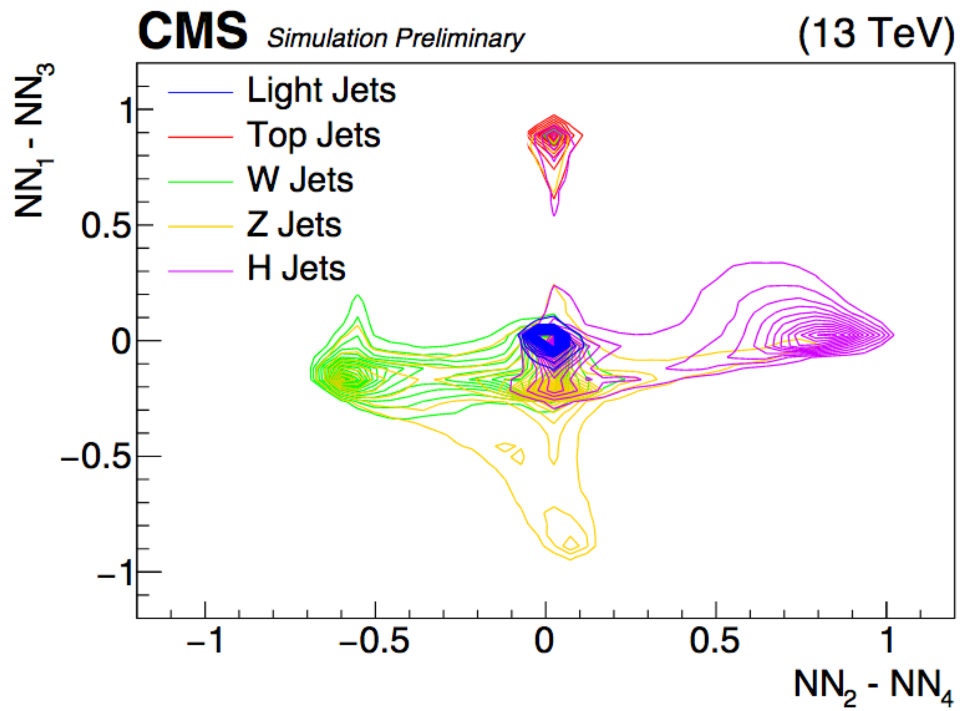


CMS-B2G-18-005

The BEST Procedure

arXiv:1606.06859
PhysRevD.94.094027

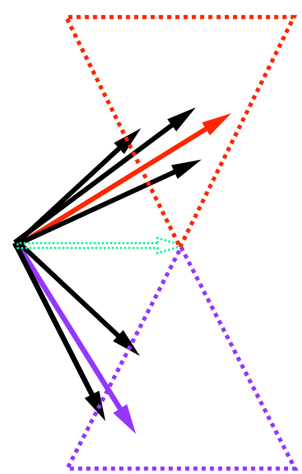




- Hypothesize different particles as origin of AK8 jet: top, H, Z, W
  - Use particle masses to apply different boosts to jet constituents

- In each reference frame, calculate event shape variables, soft drop mass, CSV, and Jet Image

- Six possible classifications: t, W, Z, H, b, light [u/d/s/c/g]



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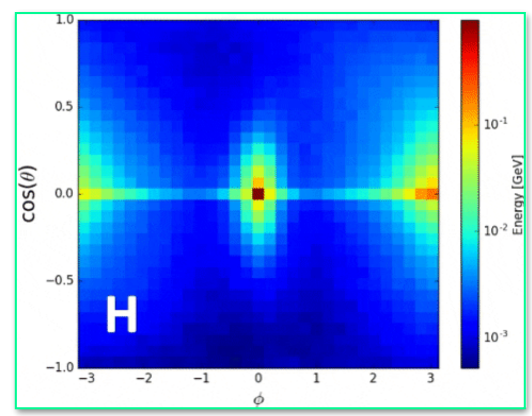
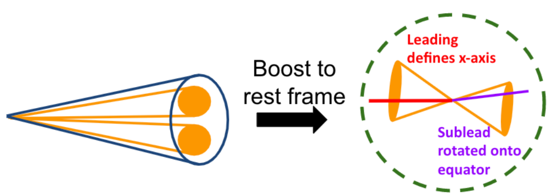
Higgs Jet in Various Frames

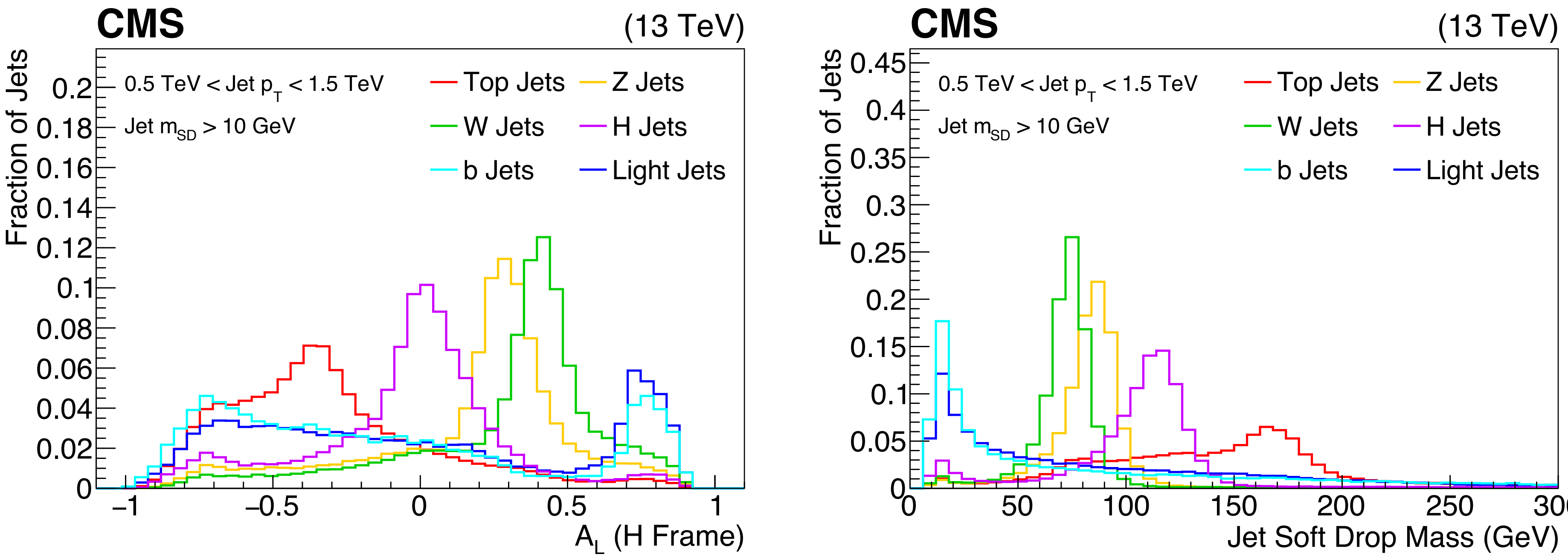




BEST Network Inputs - An Example

- **Longitudinal Asymmetry** - momentum balance along jet axis in rest frame
  - Balanced momentum (A_L = 0) more likely in correct frame
  - Calculate value in each frame

$$A_L = \frac{\sum_{jet} p_L^{jet}}{\sum_{jet} p^{jet}}$$



- **Soft Drop Mass** - Well known variable for identifying jets from heavy objects
  - Small cut on m_{SD} > 10 GeV to reduce light background

BEST Performance - 2016

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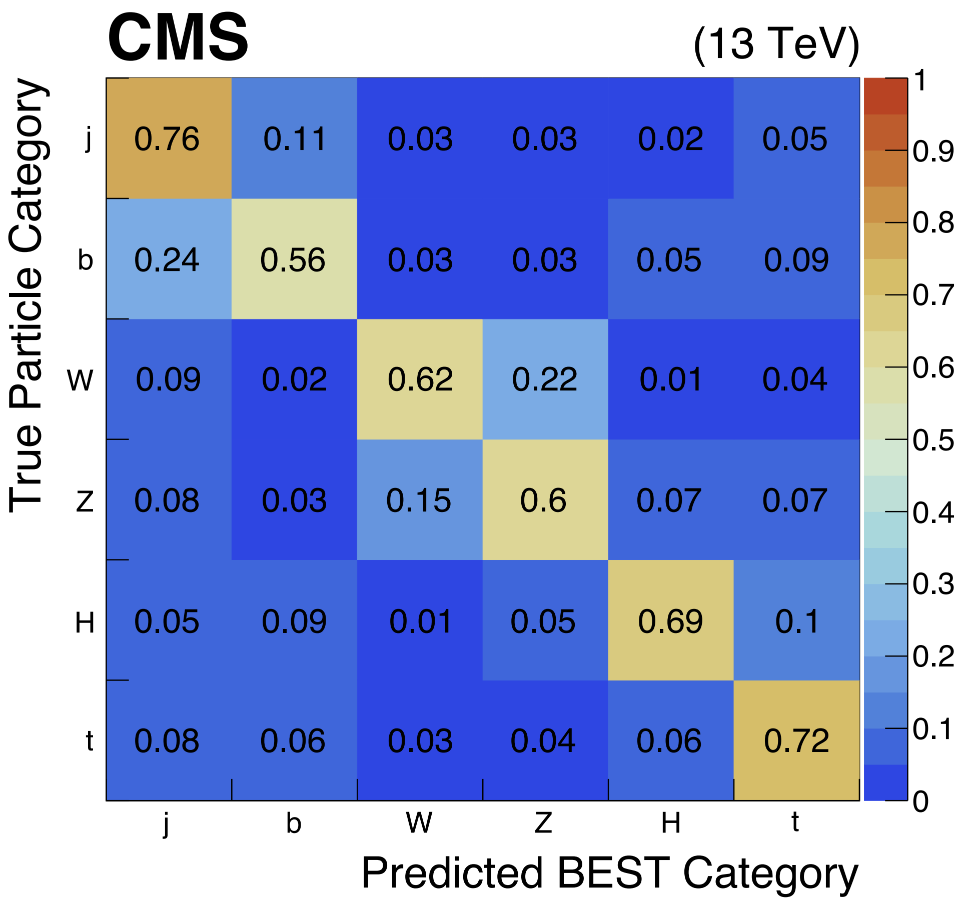
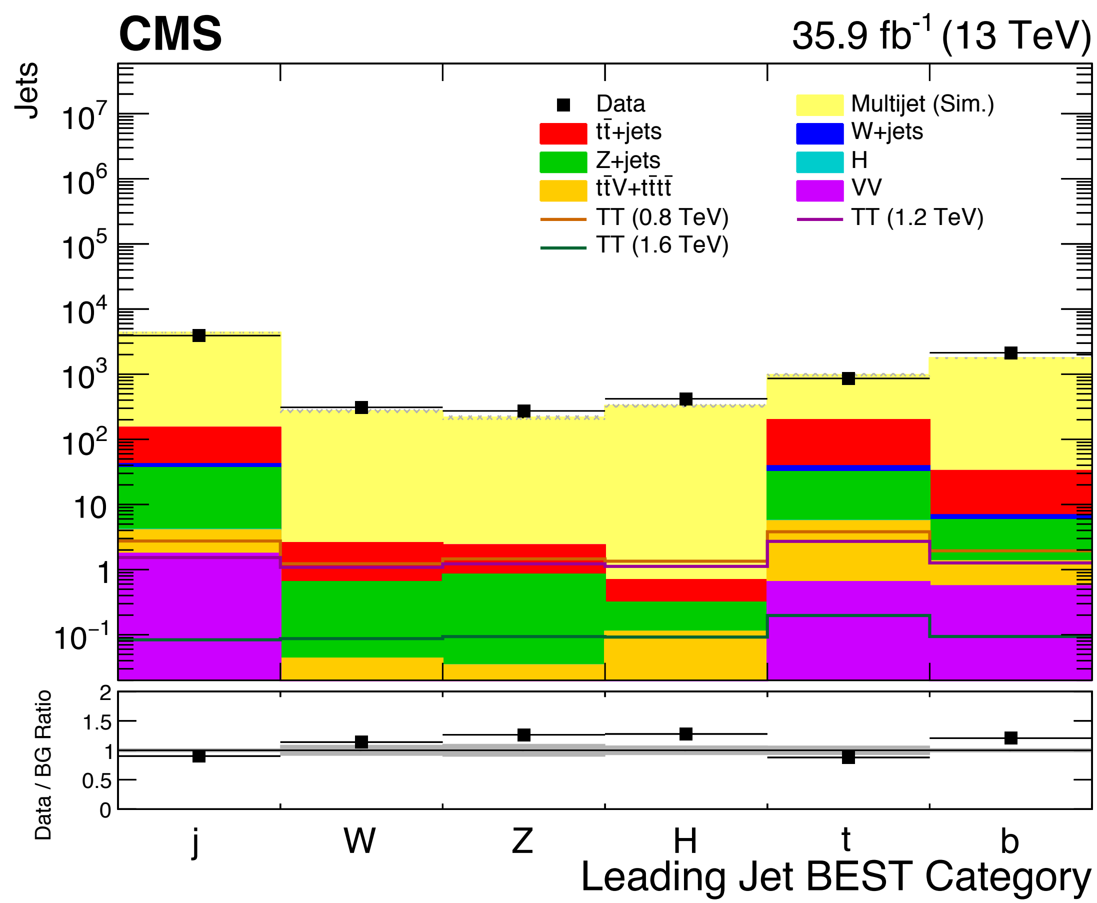


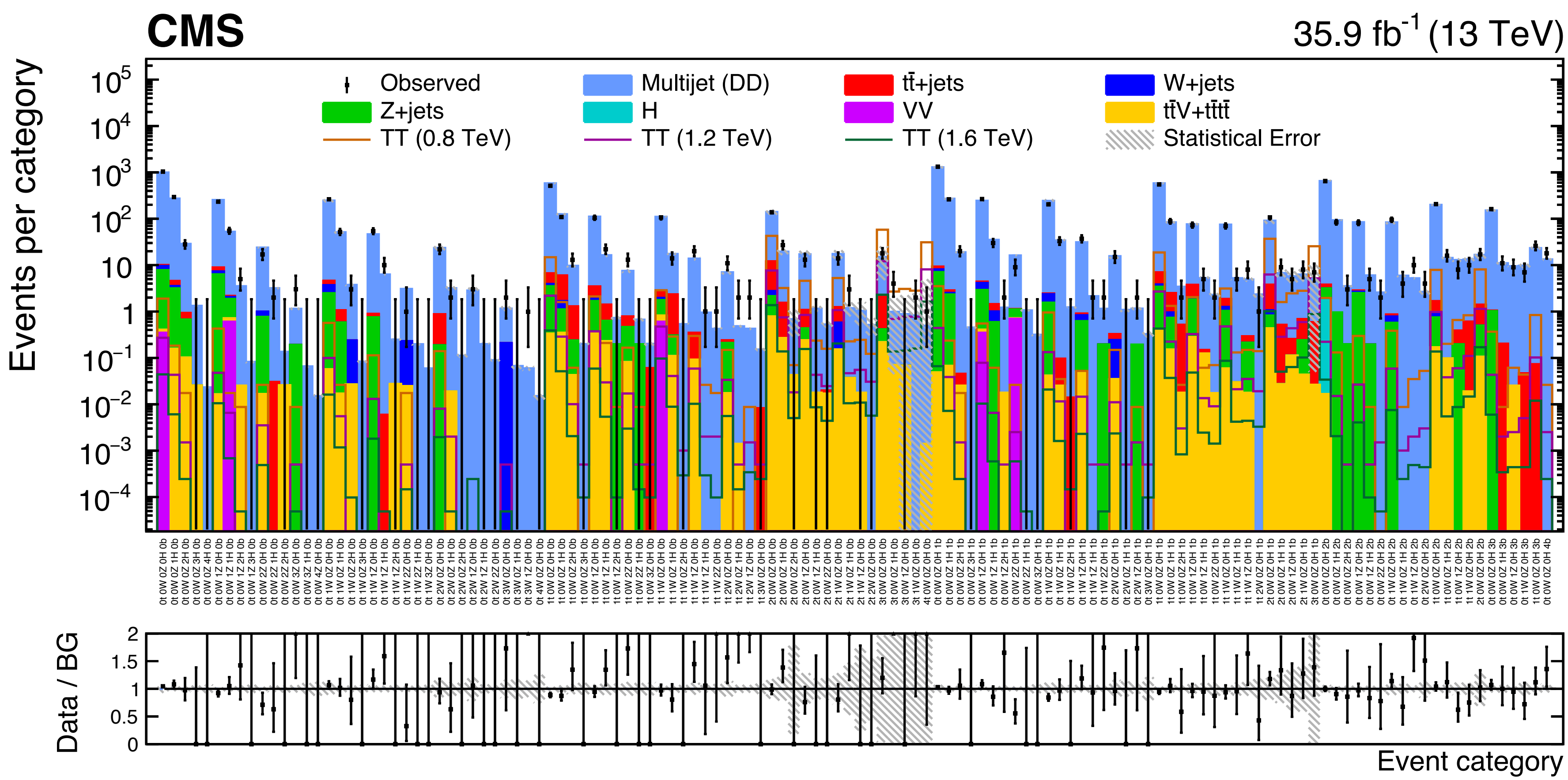


- Trained fully connected deep neural network on 500K simulated jets
  - Require jets with $p_T > 500$ GeV, to ensure decay products are fully merged
- Achieved good discrimination between particle types
- Tagging rates were found to be close to simulation

Using BEST To Search For VLQs

- **Neural Net**-based analysis signal regions include exactly 4 jets
  - Count multiplicities of objects according to BEST classification
    - Unique set of (N_t, N_H, N_W, N_Z, N_b, N_j), sum of the N_i = 4
  - **126 independent signal regions**

arXiv:1906.11903
Phys. Rev. D 100, 072001 (2019)



Exclusion Limits with BEST

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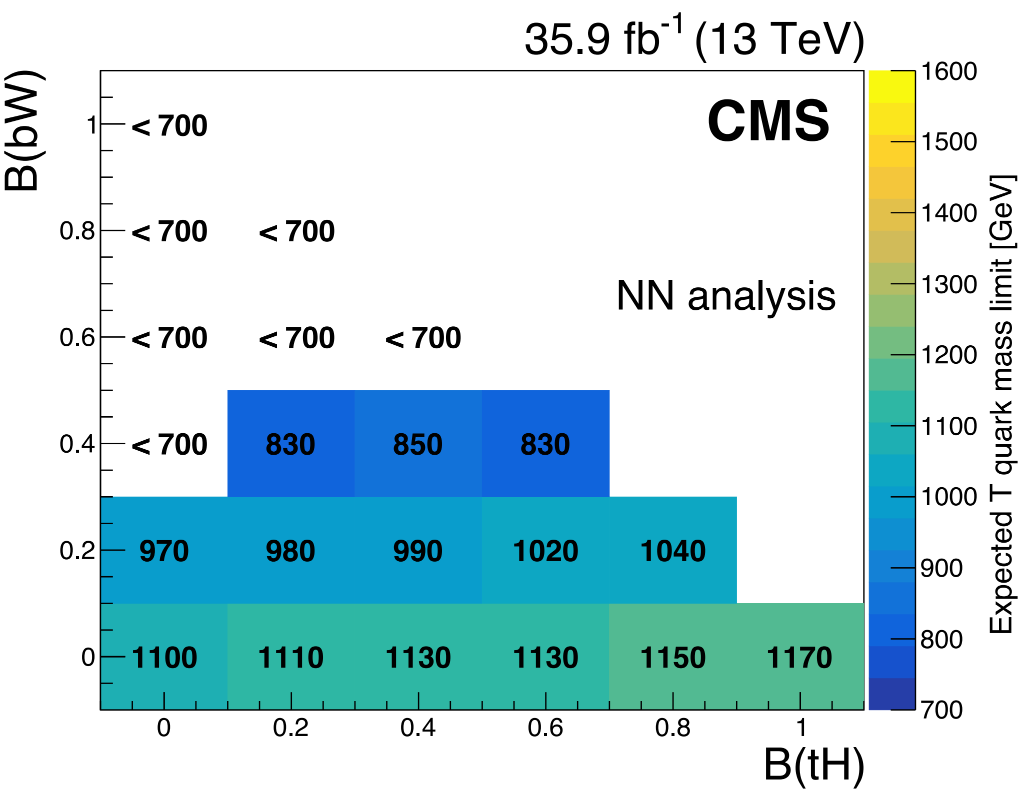
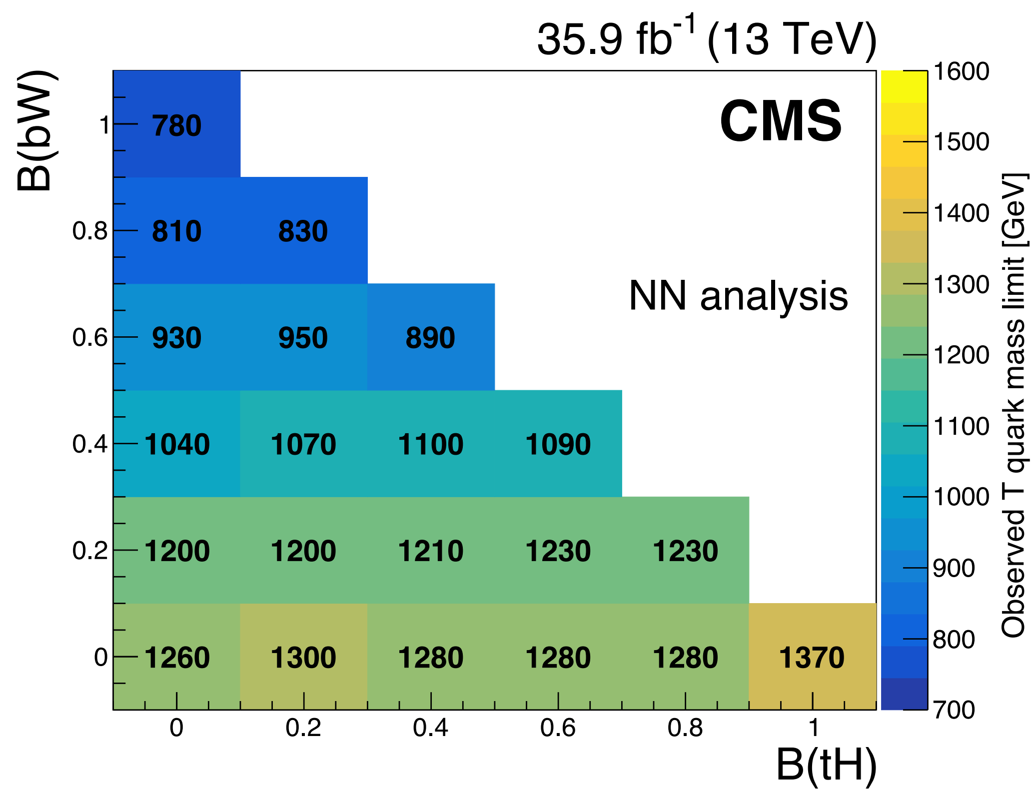
- BEST approach particularly sensitive to T->tH and T->tZ
- Not very sensitive to T->bW; the analyses complement each other
- Highest exclusion limits of any single analysis, in CMS or ATLAS

arXiv:1906.11903
Phys. Rev. D 100, 072001 (2019)



Expected



Observed

In Closing…

If new physics exists within reach of the LHC, it may couple to third generation fermions and the bosons, due to their large masses.

We must make use of new analysis techniques, and prepare our detectors to take advantage of the High Luminosity LHC.'

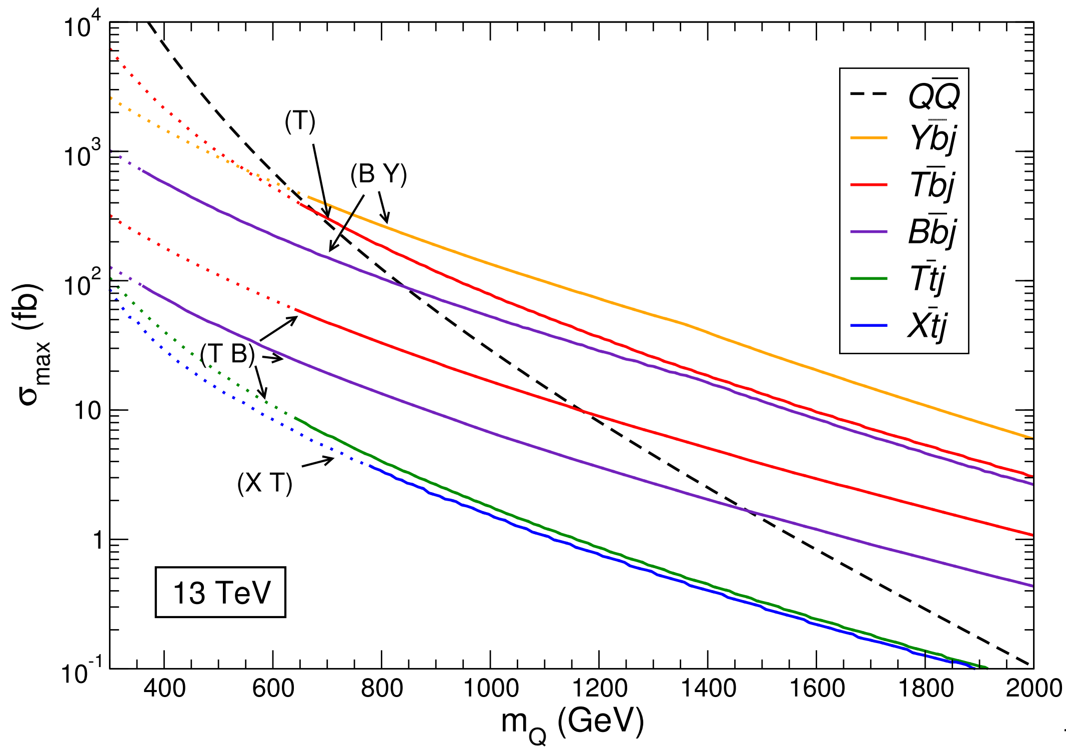
Looking further into the future, more data can get us better sensitivity. But higher energies can buys us a lot more!

Rich finals states like pair-produced T/B decays yield ample space for new, creative solutions.

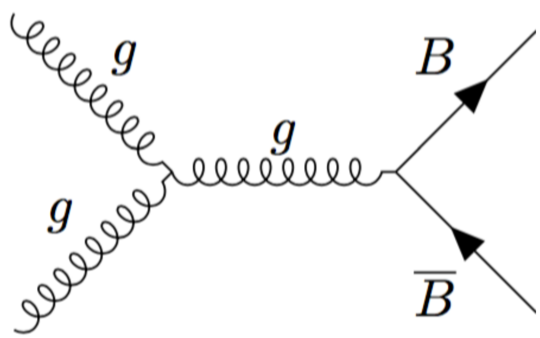
Backup Material

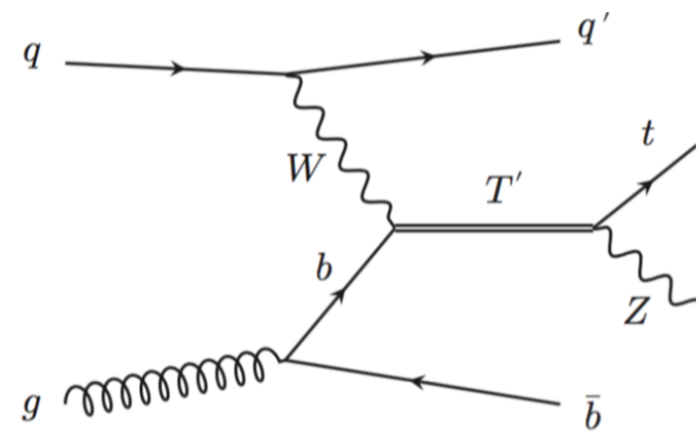
Vector-Like Quarks

- Vector-like quarks arise naturally in many theories extending SM
  - Partial compositeness
  - Higgs as a pNGB
- 4th gen of chiral quarks well excluded by existing Higgs measurements
- VLQs escape these constraints! Bare Dirac mass term allowed in Lagrangian
- Heavy Yukawa mixing with heaviest particles of up and down sectors
- Generally consider top and bottom partners, least constrained doublet



Pair vs. Single Production of VLQs





Pair production

- Production depends on strong coupling
  - Model independent! (except mass)

- Decays to at least two heavy electroweak bosons
  - Distinctive final state!
  - Can have EW-cascade decays

Single production

- Production depends on coupling of VLQ to 3rd-gen and EWK
  - Model dependent

- Cross section falls off much slower with mass
  - More sensitivity ~TeV

The BEST Procedure

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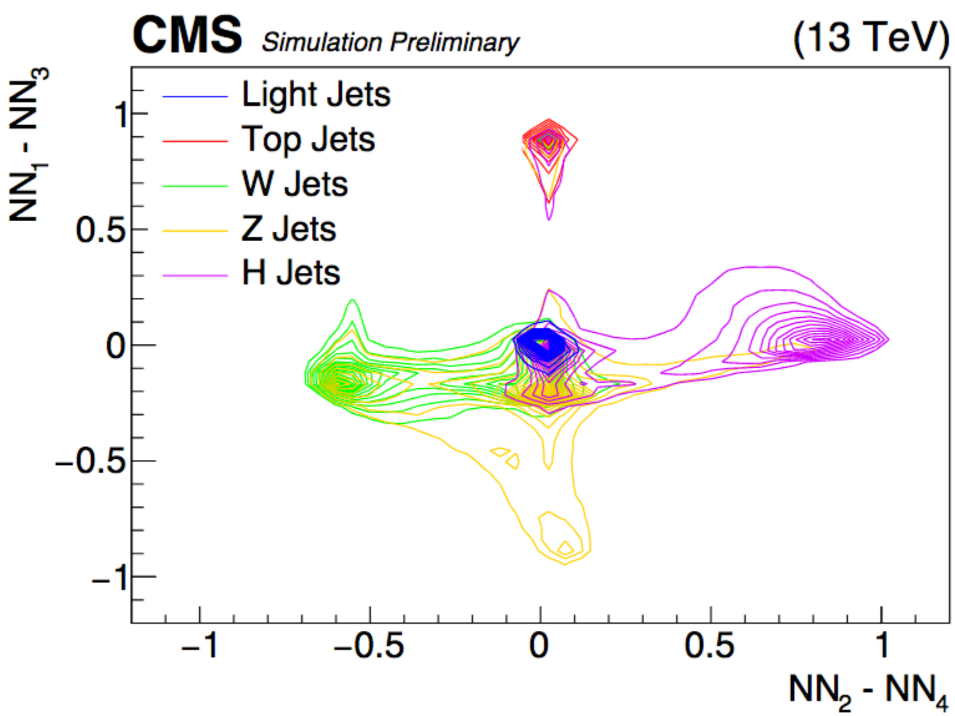
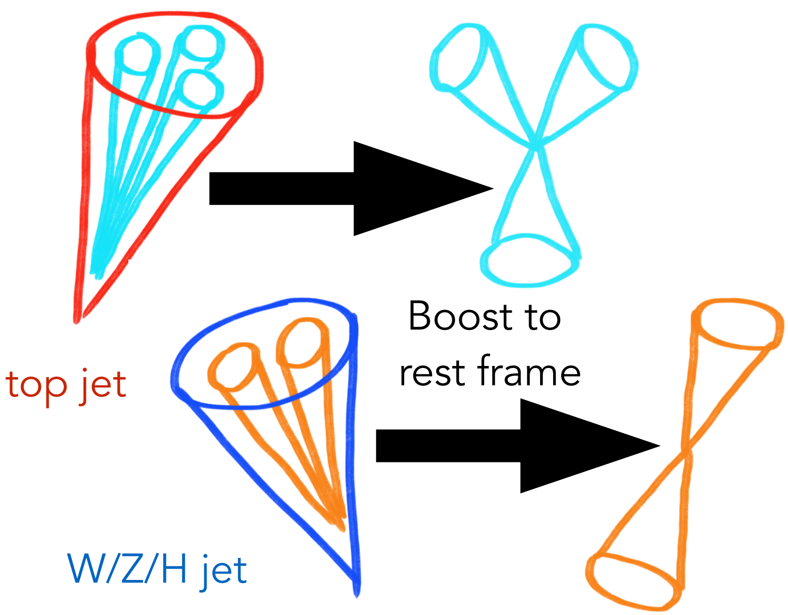
- Hypothesize different particles as origin of jet: top, H, Z, W
- Jet constituents should be isotropic in the rest frame of that particle
- Use particle masses to apply different boosts to jet constituents
- In each reference frame, calculate event shape variables

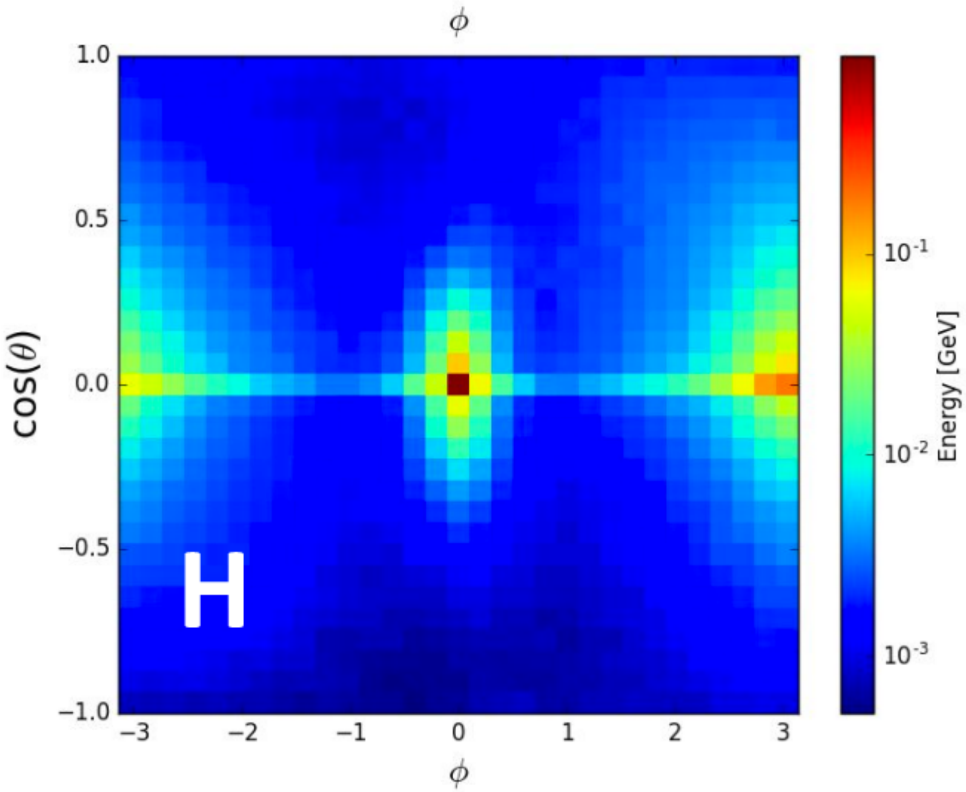


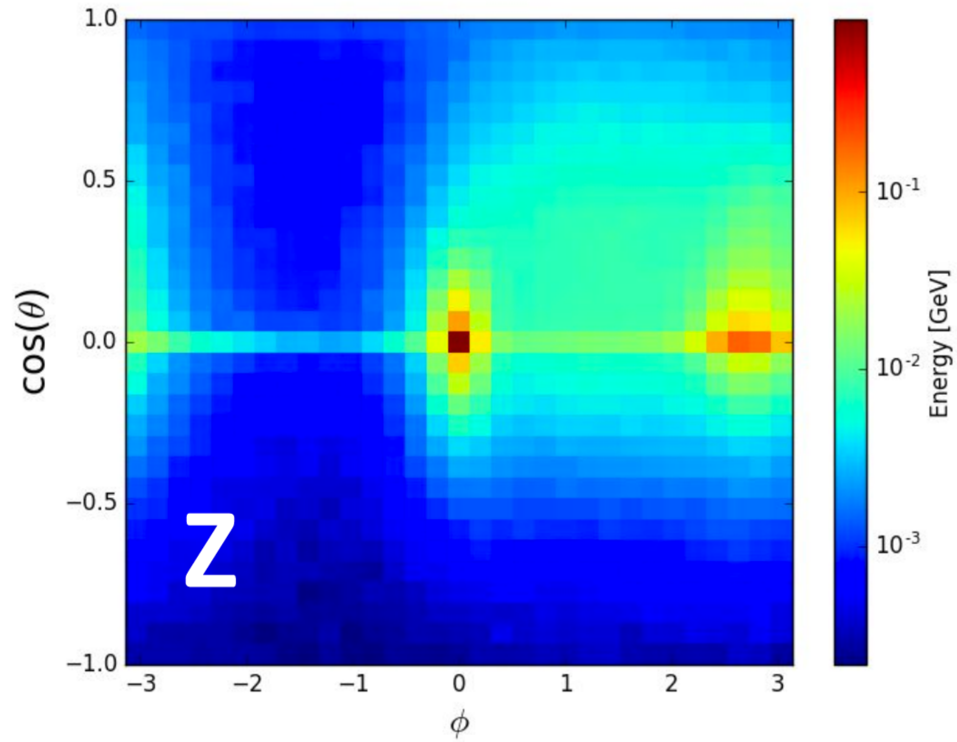


- Also use some lab frame inputs, such as soft drop mass and CSV
- Six possible classifications:
- t, W, Z, H, b, light [u/d/s/c/g]

Jet Images in BEST

- As part of our overhaul of BEST, we now utilize a convolutional neural network to identify images of jets in various boosted reference frames
- These images are binned eta/phi distributions of the jet's constituents, scaled by energy

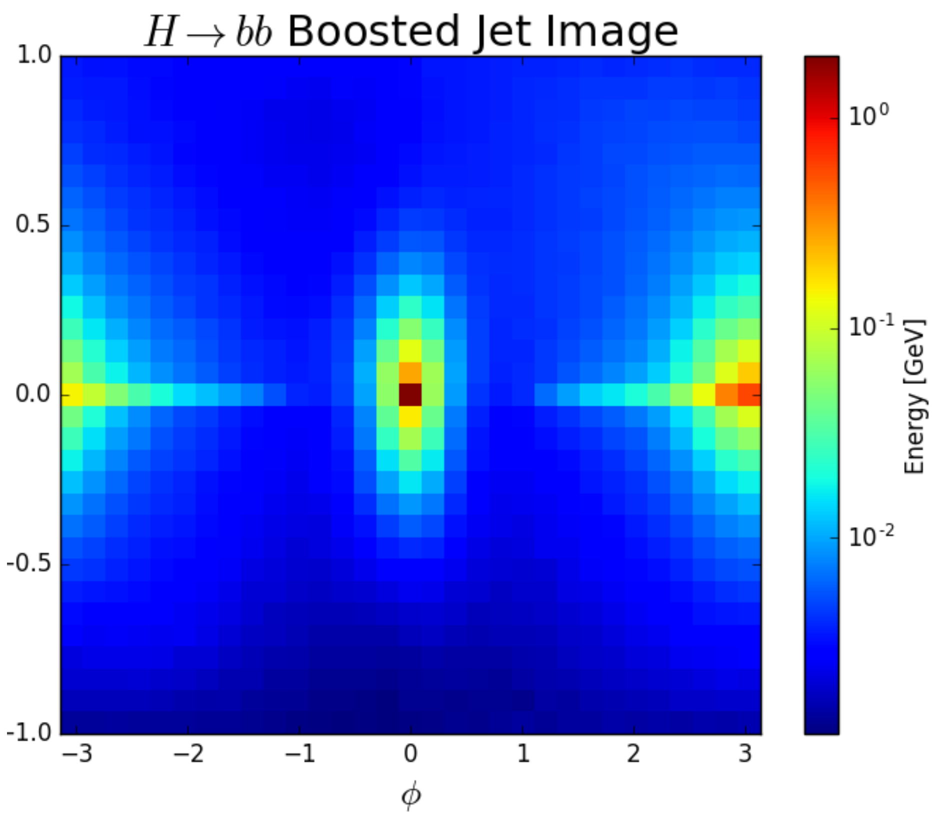


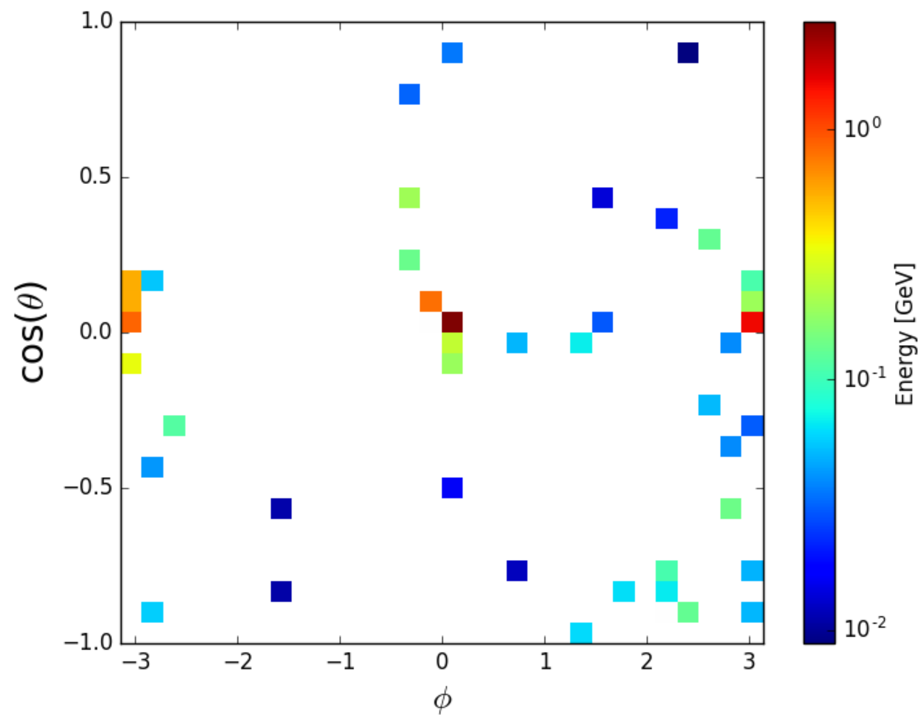


- Four images provided for each jet, one for each of the frames considered in BEST
- This integrates low-level particle information with our event shape tagger

Updating BEST - New Features

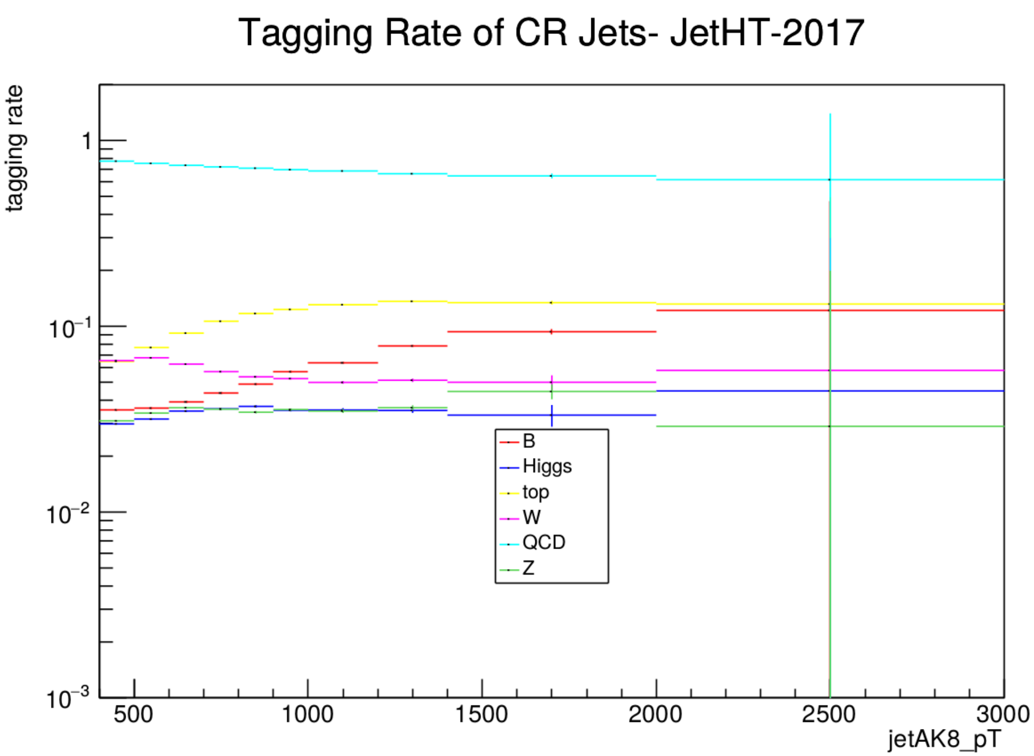
- For the next analysis with full Run-2, goal is to improve BEST's b-tagging
- Partly accomplished already by adding DeepCSV, a separate, dedicated b tagger
- Reducing training bias by flattening training set p_T spectrum
- One of our most significant changes - the addition of jet image tagging

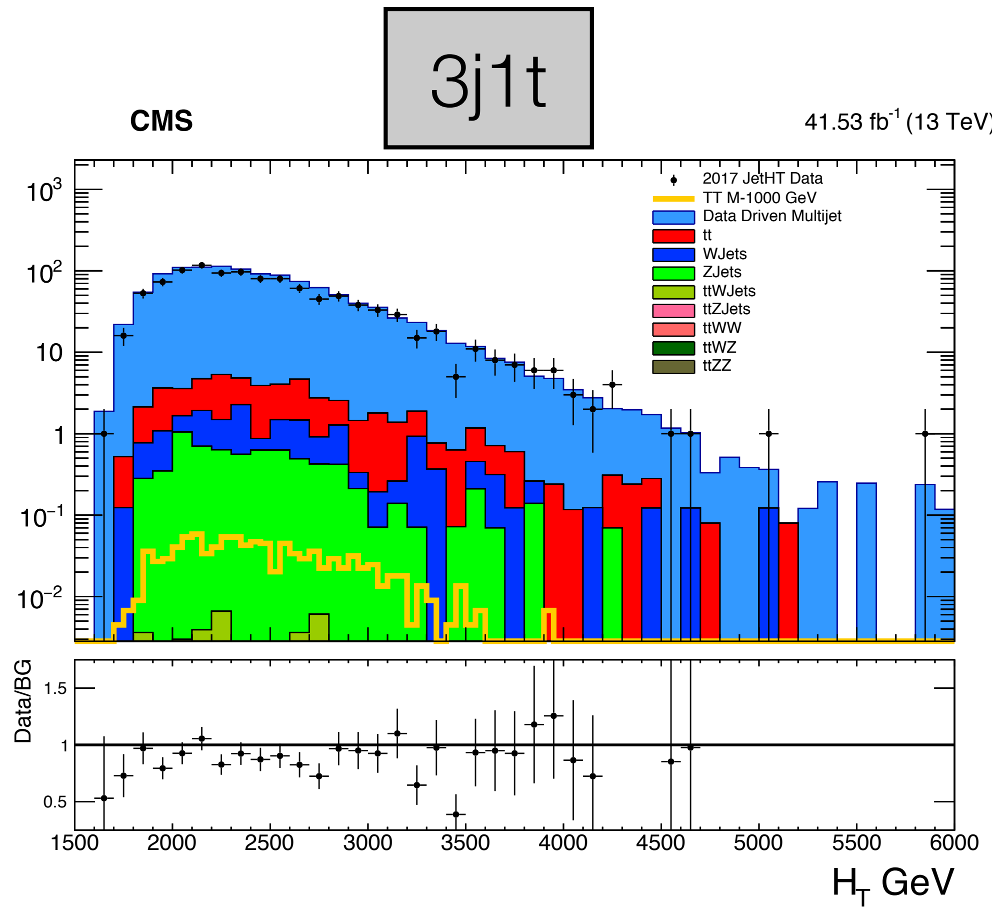




Towards a Full Run-2 Search

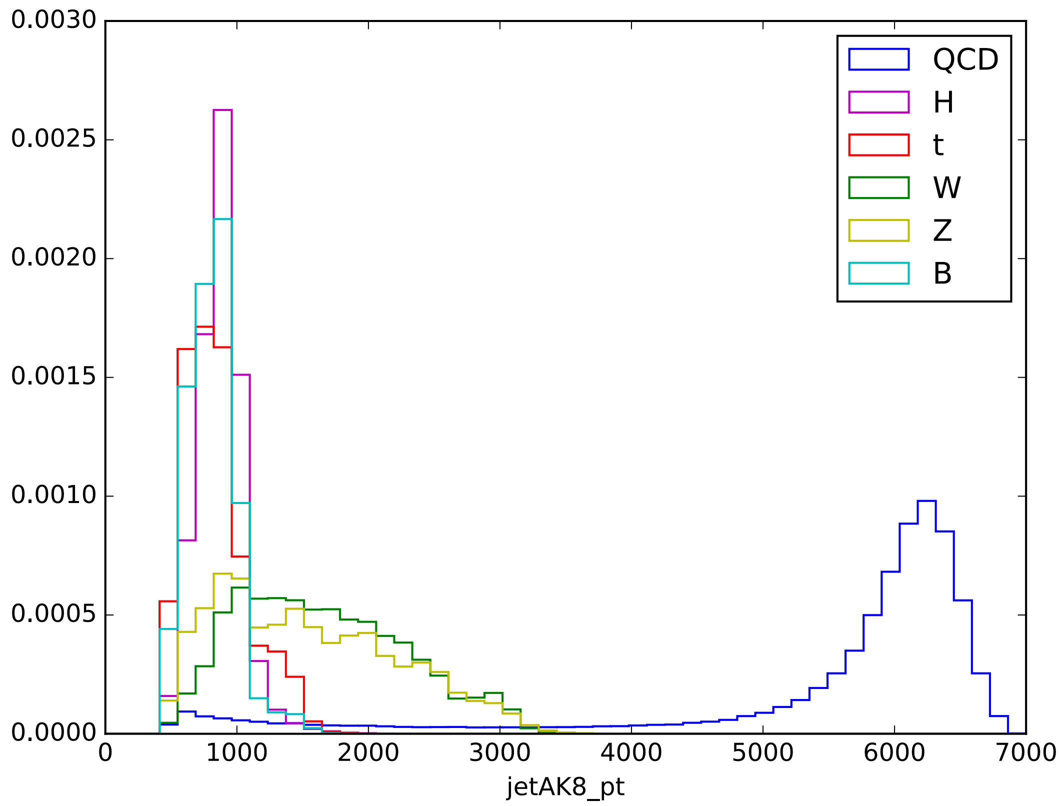
- One our most promising preliminary results is the improved b vs. QCD confusion
- This improvement can already be seen in our data-measured mistag rates
- Another major change to the analysis, validate backgrounds in low-tag regions





Training Samples - Input p_T

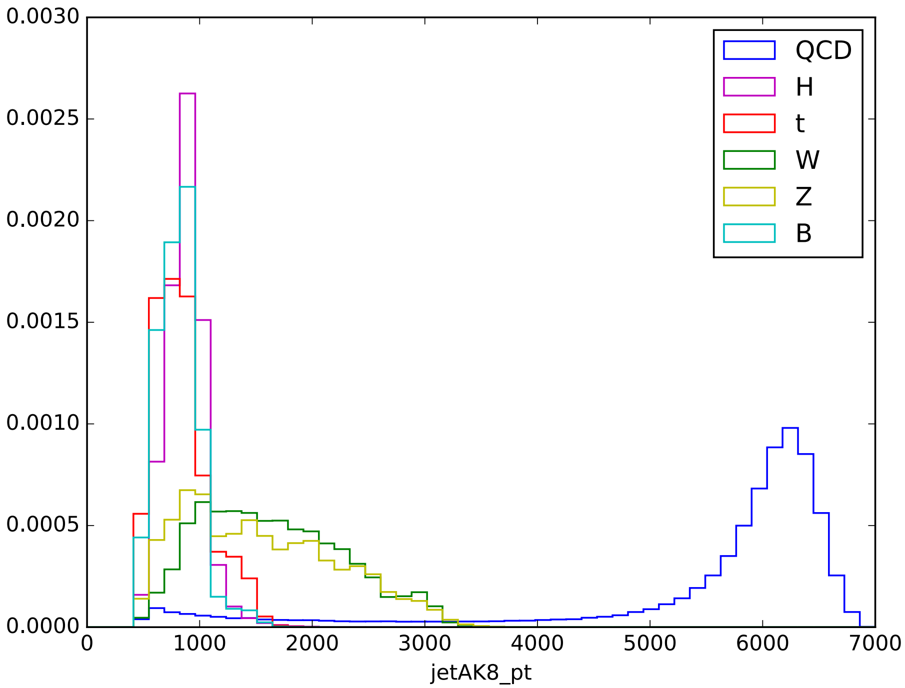
- Training samples from X->YY cover a wide range of signal masses: ~2-6 TeV
- We use many different signal samples for X, to combine statistics from other's efforts
- Unsurprisingly, p_T distribution is (unphysically) biased between classes

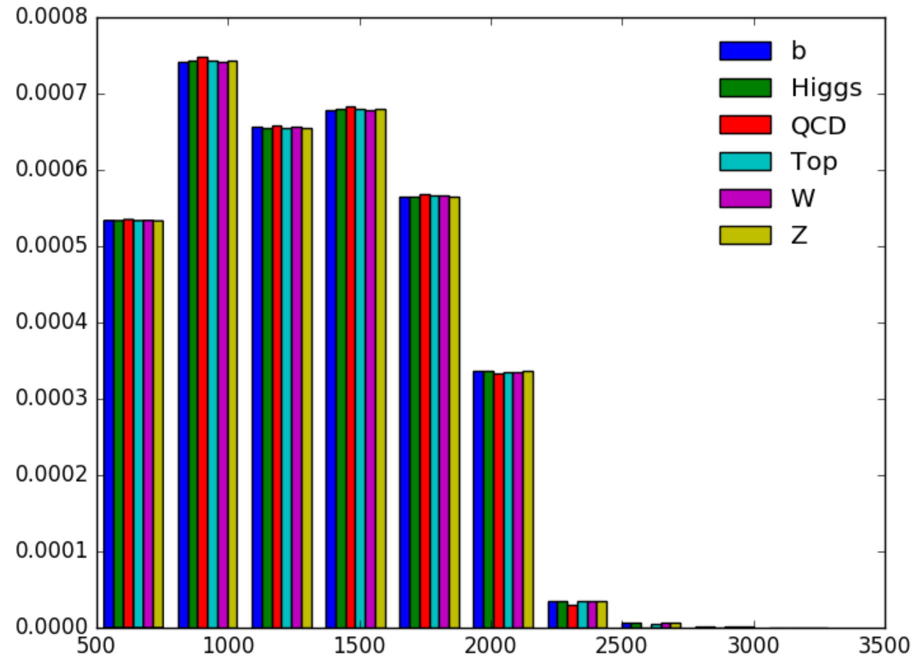


- We want to prevent the network learning this p_T directly, but learn p_T correlations
- Flatten the p_T that is shown to the network, keep it as an input variable

Flattening Input p_T

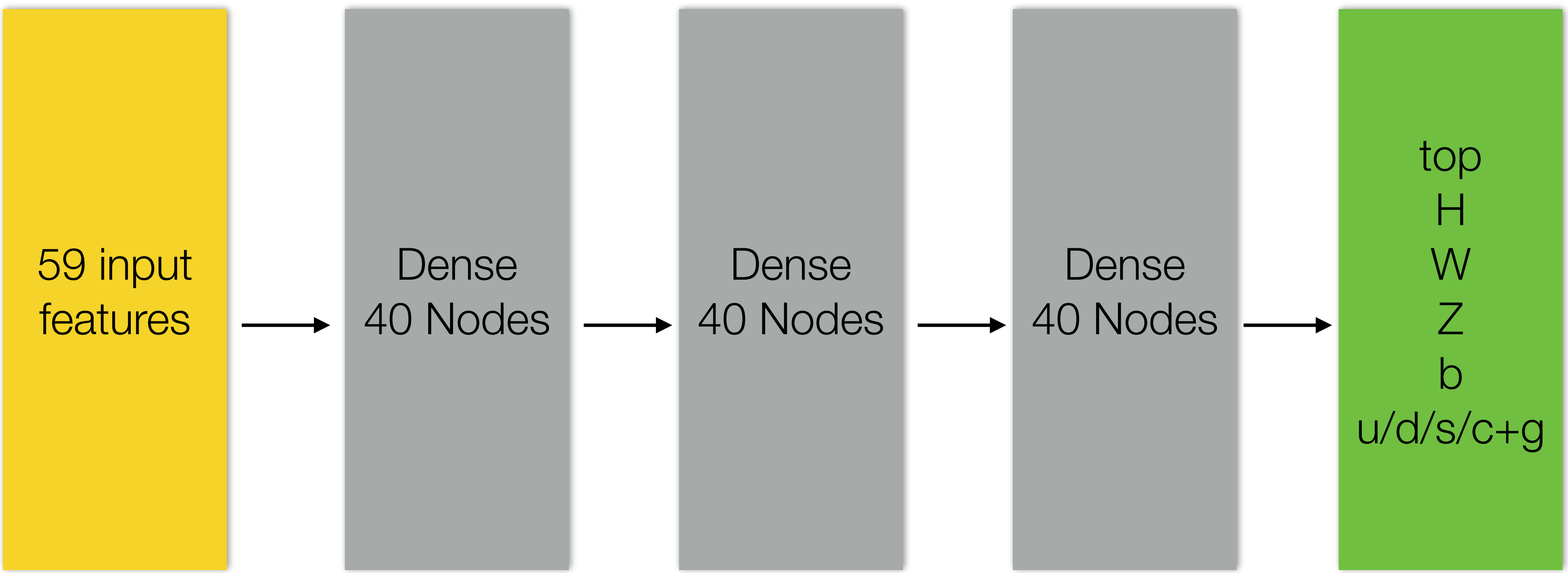
- Flattening the transverse momentum decorrelates the observable from the tagger
- Take least populated sample per bin and apply a keepProb of other samples normalized by this minimum sample.



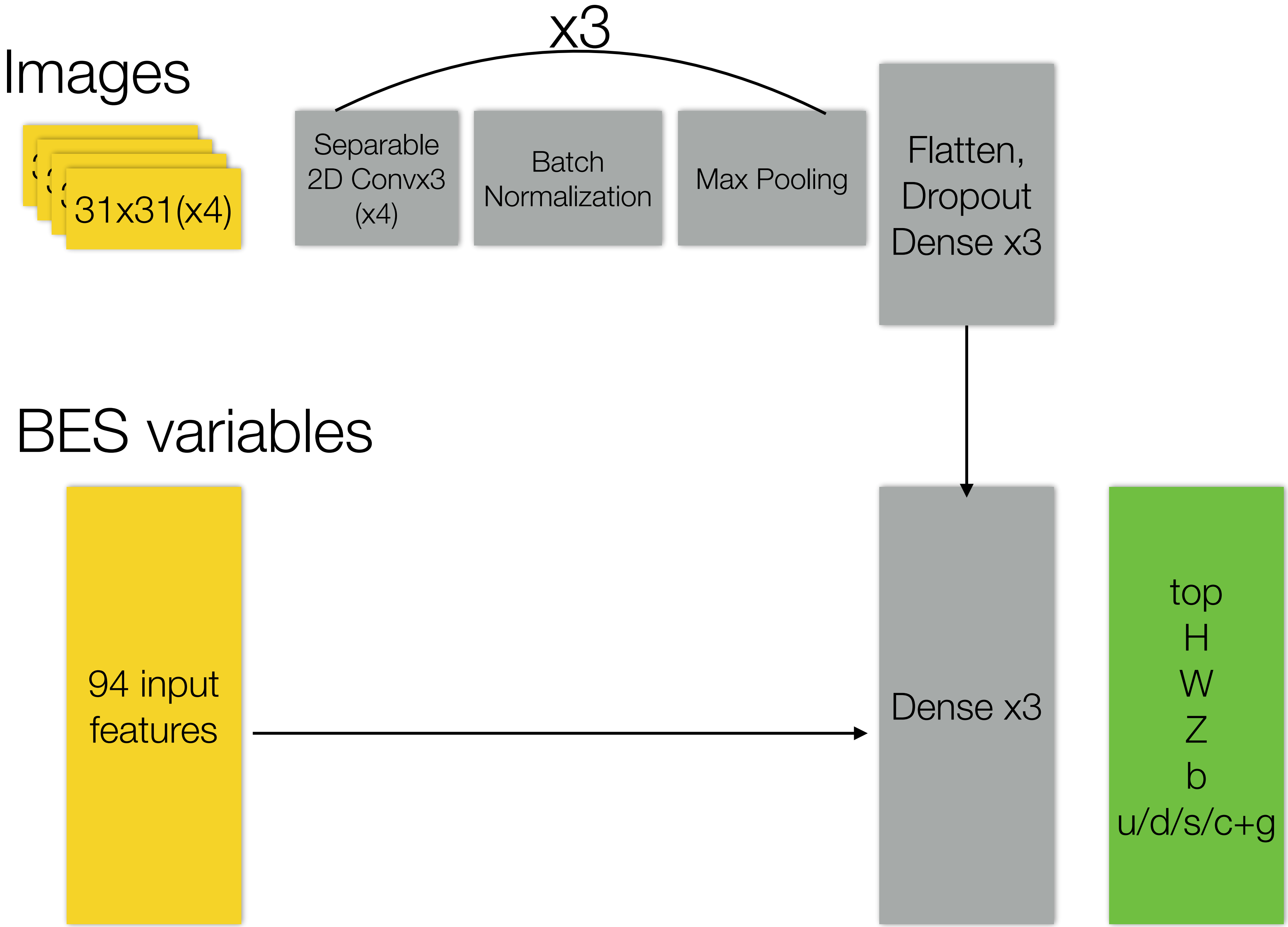


2016 BEST Architecture

- Feed-forward deep neural network with 3 hidden layers, 40 nodes each.
- Multi classification algorithm with six outputs: node with highest output determines label.
- 59 input features, 500,000 jets used to train the network.
- Use samples of high-pT boosted SM particles from high-mass resonance decays for trainin
  - Z′→tt, RSG->HH, etc.
- BEST in 2016-2018 was built as an MLP in scikit-learn, with 500k training jets
- Training was very simple, performed on CPU
- BEST now implements convolutional layers in Keras, trains on ~2 million jets
- Huge increase in network parameters demanded training on clusters with GPUs

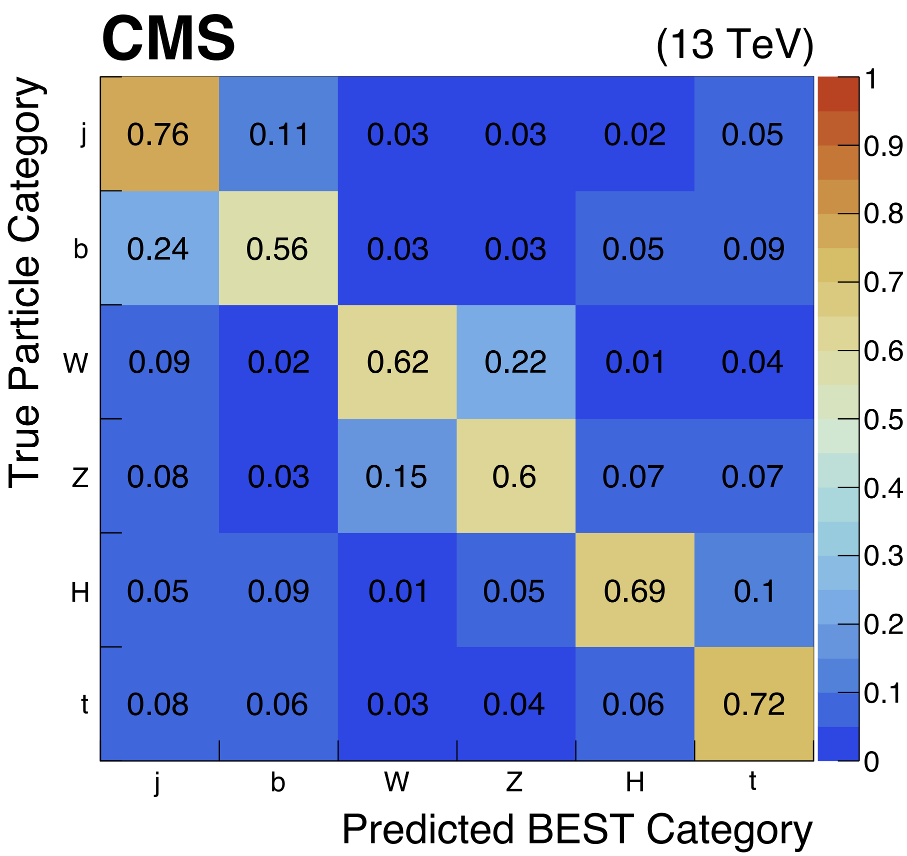


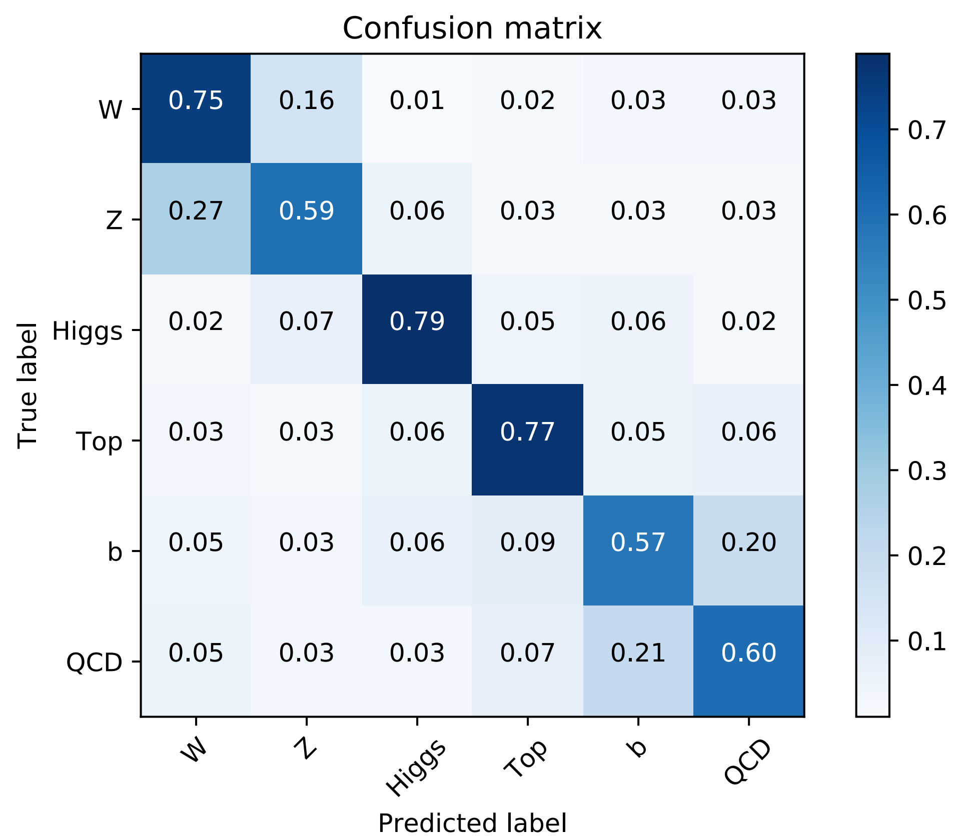
Updated BEST Architecture



Updating BEST

- We are looking to expand the BEST effort! Recently released BEST's first tag
- Initial results look quite promising! Improvement over 2016 below (not final)
- Improvements in b quark and light jet confusion quite clear
- Comparison here between 2016 and 2017 training data, some caveats





BEST - Background Estimate

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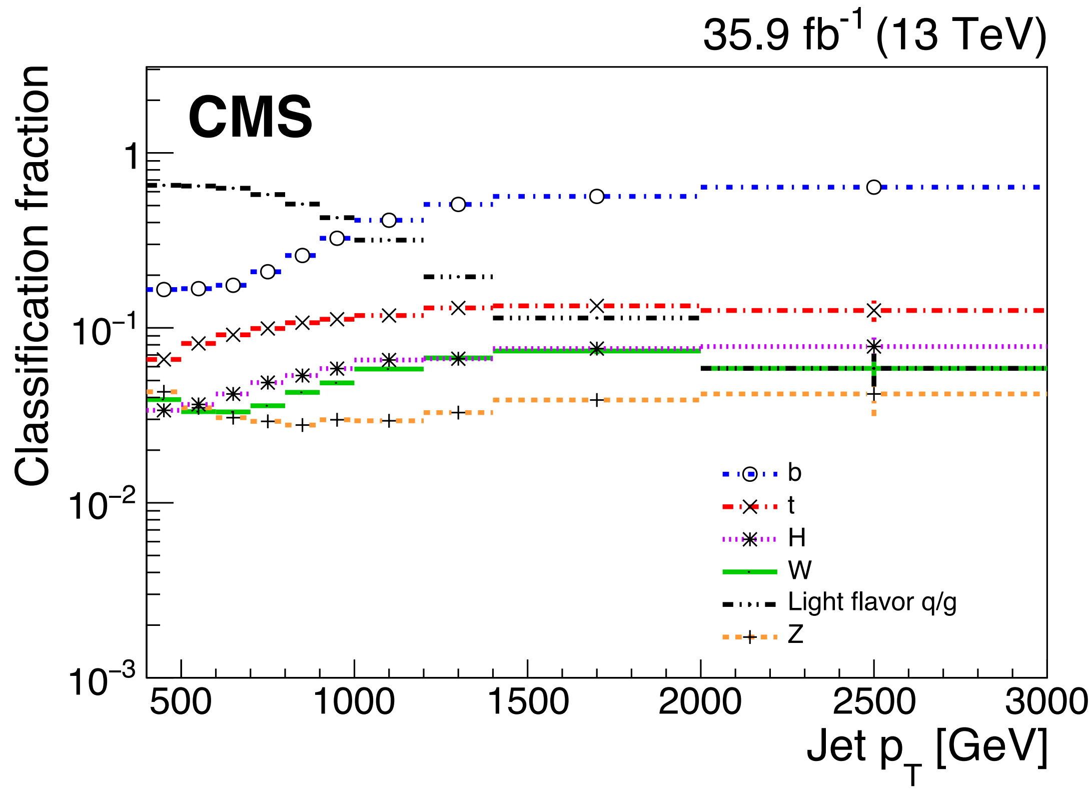
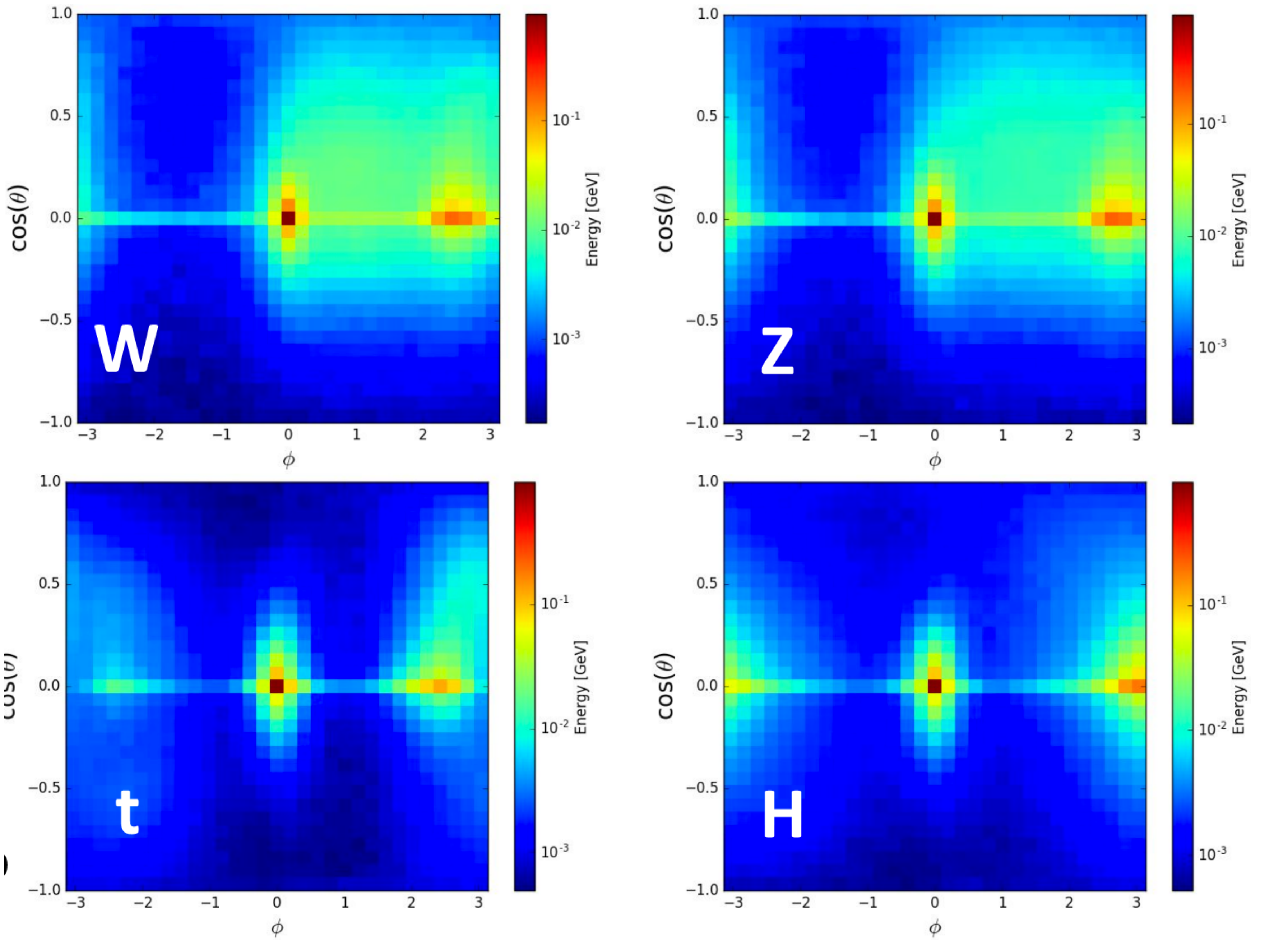
- **NN-based** analysis measures a tagging rate in independent 3 jet sample
    - As with the cut-based approach, the dominant background is QCD
    - 3-jet events overwhelmingly QCD
    - Apply rates to whole 4-jet sample to get QCD distribution per category
    - Other backgrounds taken from simulation and subtracted: W+jets, $t\bar{t}$



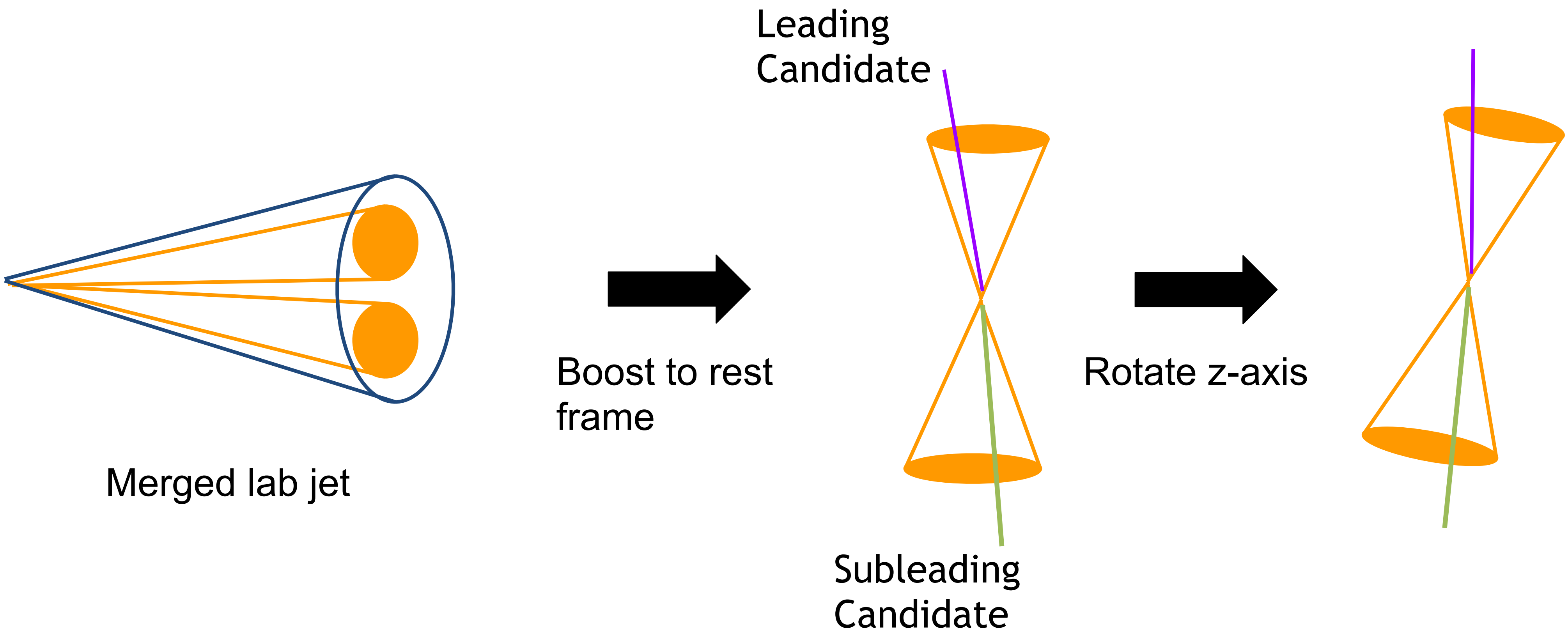
$$\epsilon_X(p_T) = \frac{\text{Number of jets with BEST class X}}{\text{Number of jets}}$$

$$R = \sum_{events} [r] = \sum_{events} [\sum_{perms} (\prod_{i=1}^{4} \epsilon_{X_i}(p_T(i)))]$$

Higgs Image In Each Frame

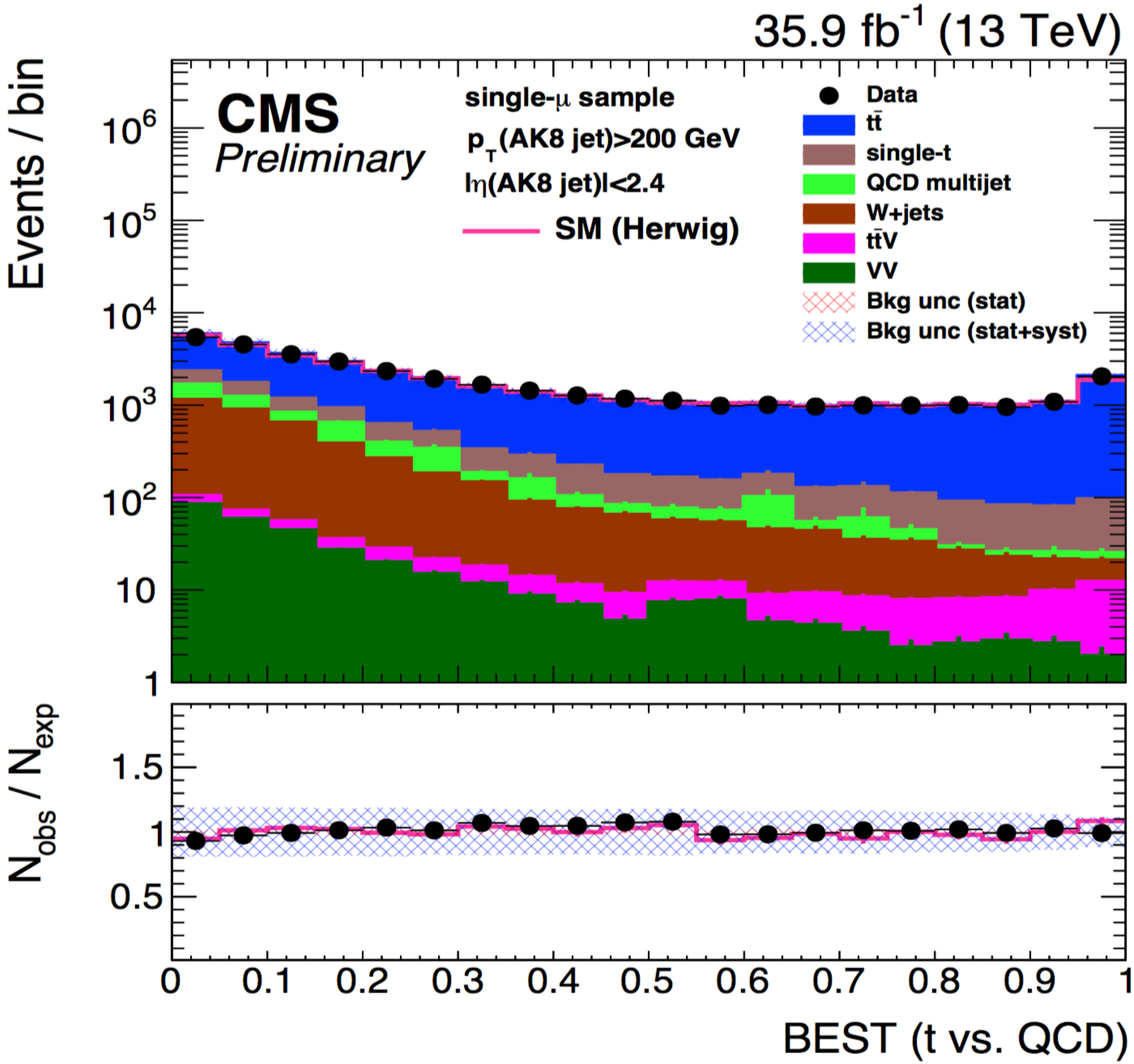


Jet Images



- New addition to BEST - Train a CNN to tag images of jets in boosted frames
- These images are binned eta/phi distributions of the jet's constituents, scaled by energy
- Four images provided for each jet, one for each of the frames considered in BEST

BEST Top Tagging Validation

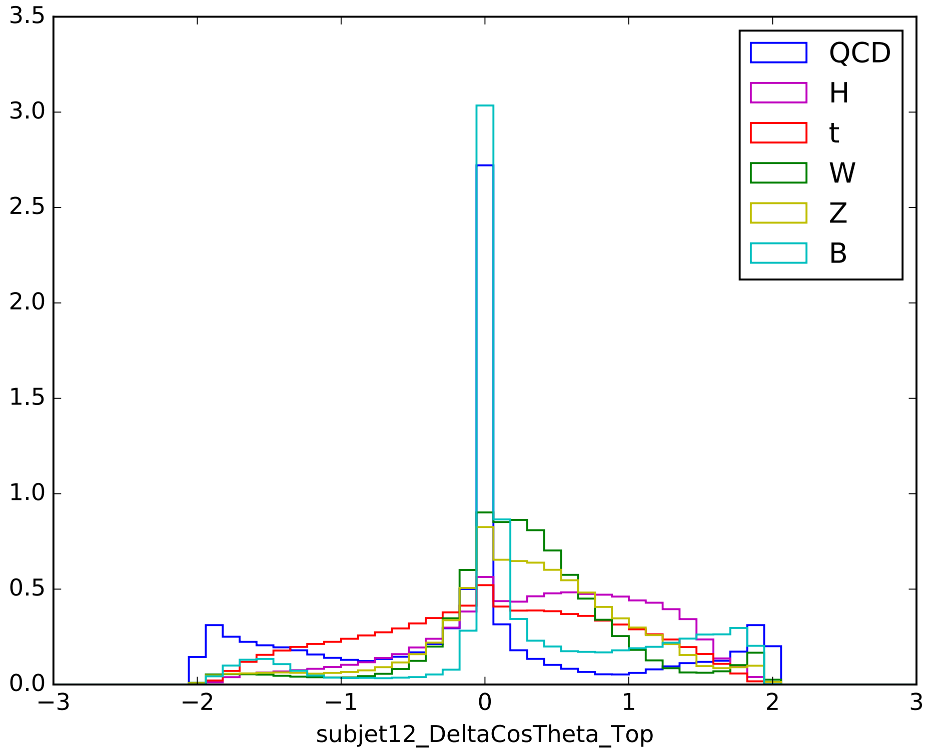


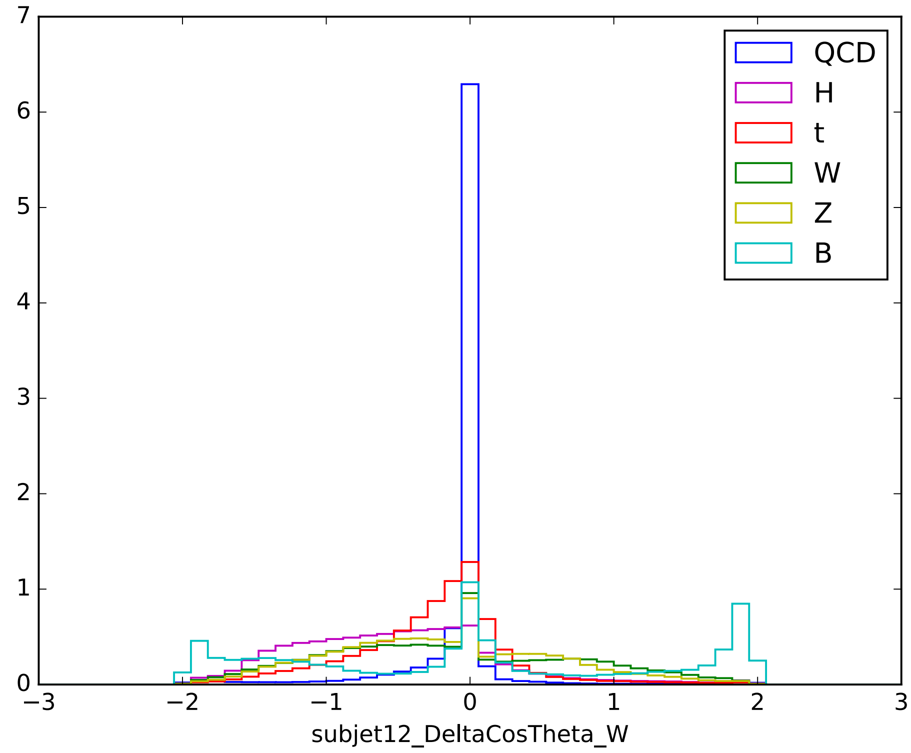
BEST Variable List (2016)

NN Input Quantities	
Sphericity (t, W, Z, H)	Jet Soft-Drop Mass
Isotropy (t, W, Z, H)	Jet η
Aplanarity (t, W, Z, H)	Jet τ_{21}
Thrust (t, W, Z, H)	Jet τ_{32}
Jet Asymmetry A_L (t, W, Z, H)	Jet Charge
Fox-Wolfram H_1/H_0 (t, W, Z, H)	Maximum Subjet CSV Value
Fox-Wolfram H_2/H_0 (t, W, Z, H)	Subjet 1 CSV Value
Fox-Wolfram H_3/H_0 (t, W, Z, H)	Subjet 2 CSV Value
Fox-Wolfram H_4/H_0 (t, W, Z, H)	m_{13} (t,W,Z,H)
m_{12} (t,W,Z,H)	m_{1234} (t,W,Z,H)
m_{23} (t,W,Z,H)	

New BEST Variables

- In addition, there have been some changes to the variables fed into the dense network
- 94 inputs in total, characterizing the momentum distribution in the boosted frame

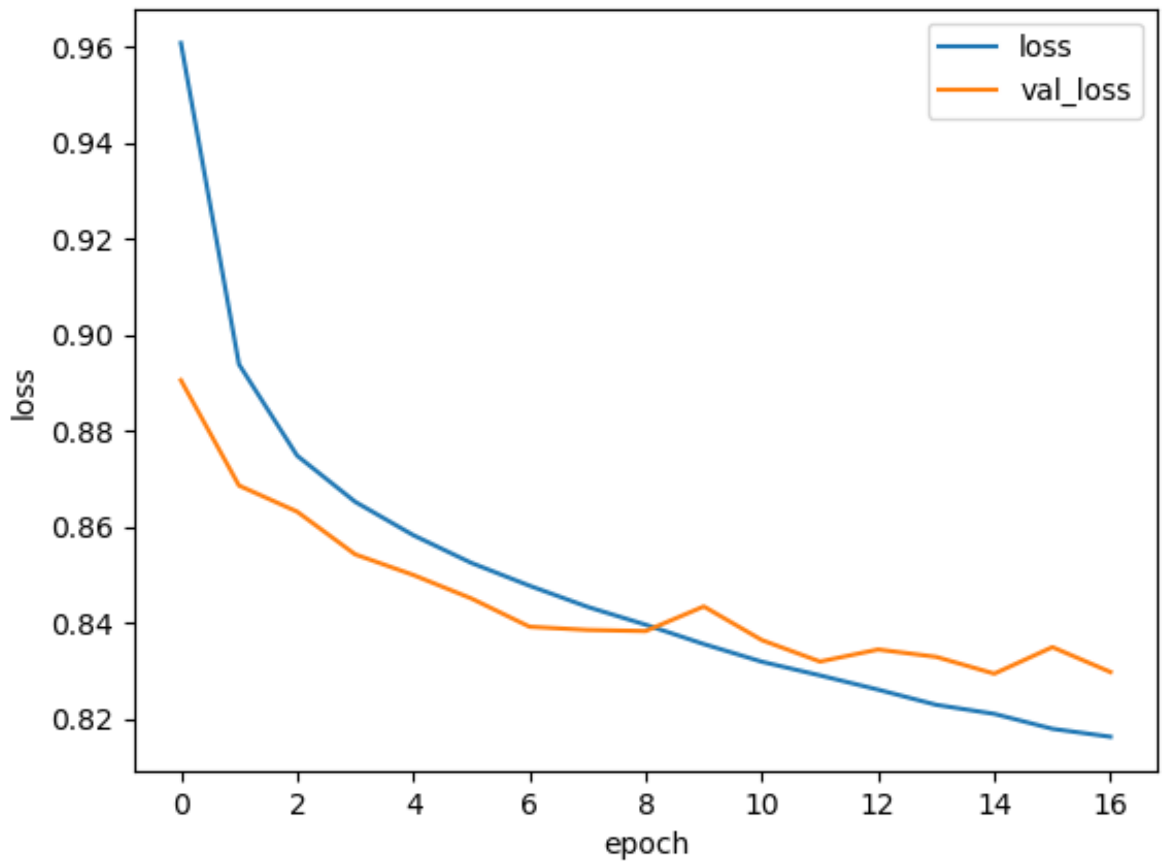




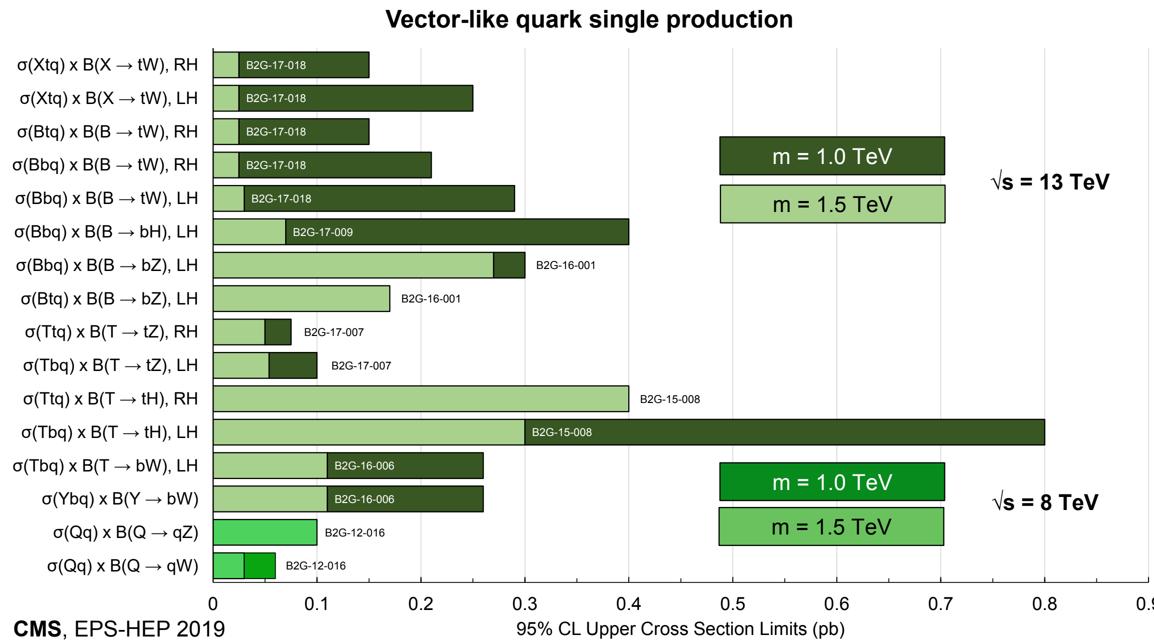
Updated BEST: Network Training

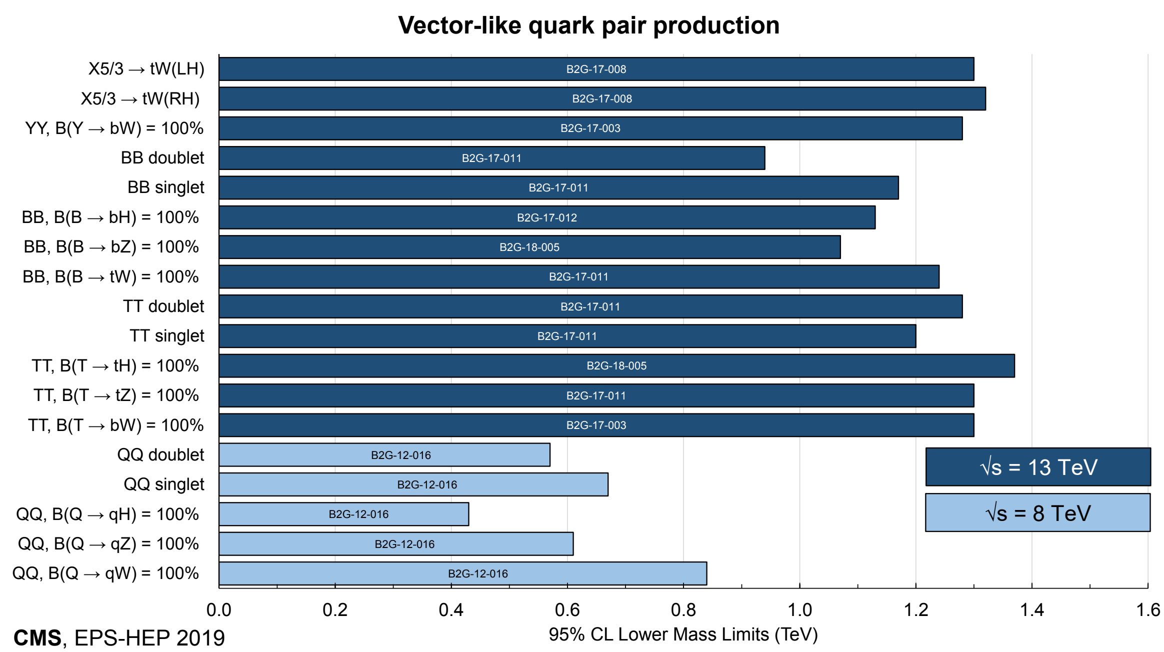
- Validation efficiency seems to plateau around ~5 epochs, training time of ~20 mins

- “Epoch” is arbitrarily defined for an infinite dataset, here means 45 batches



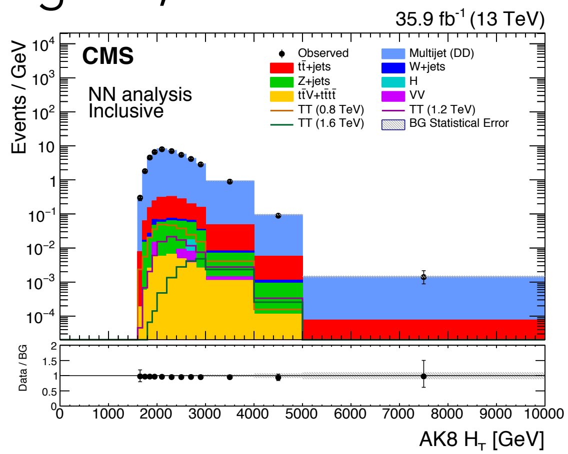
VLQ - State of Exclusion Limits

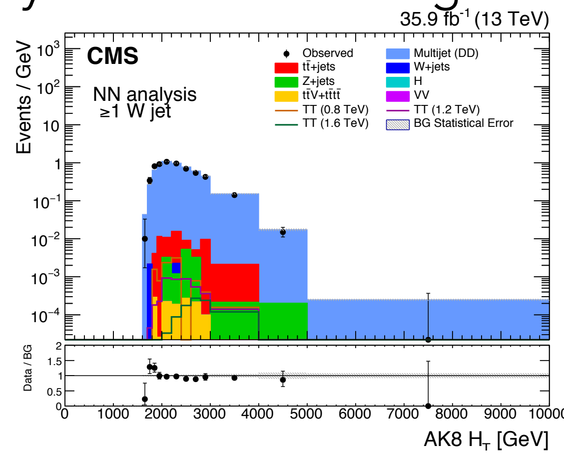


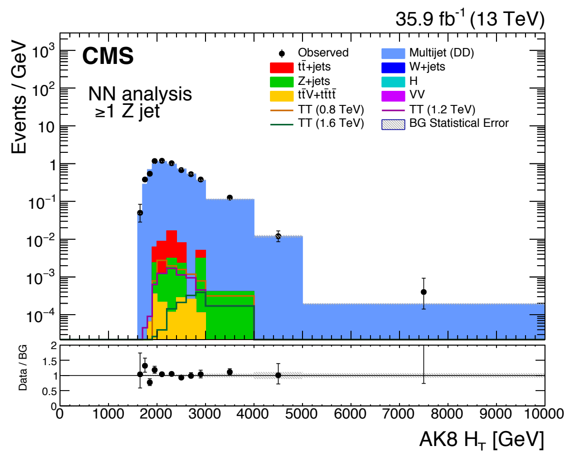


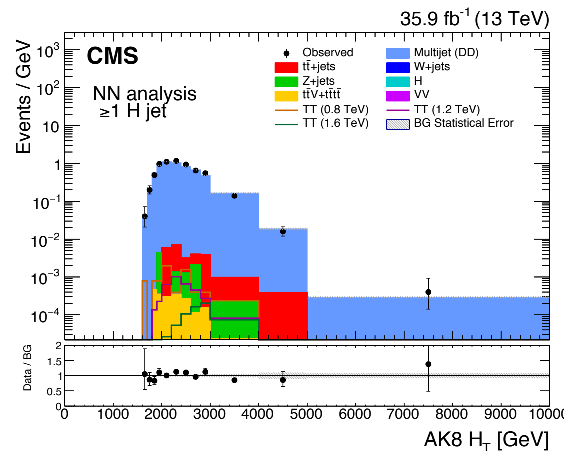
VLQ - BEST - Signal Region Summary

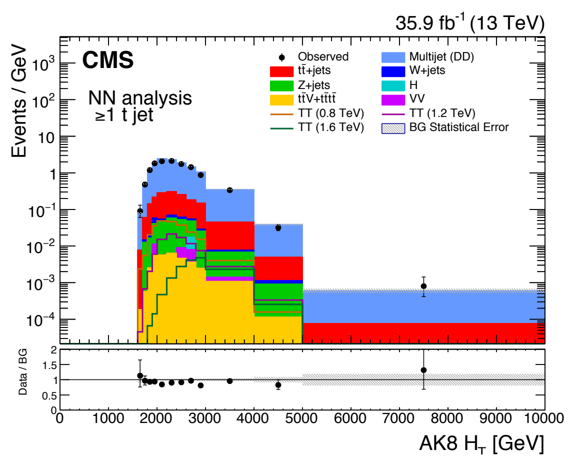
- 126 signal regions, summarized here by inclusive BEST tag categories.

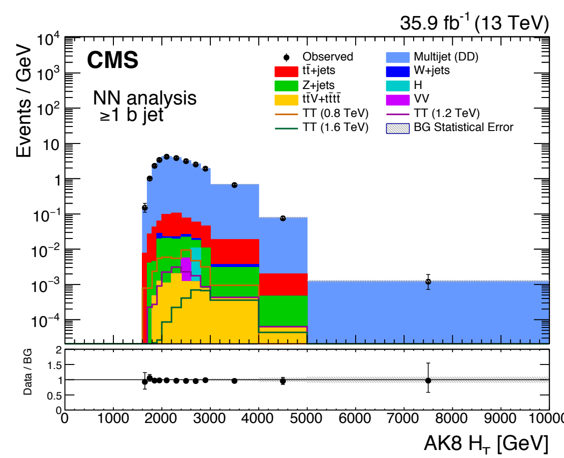












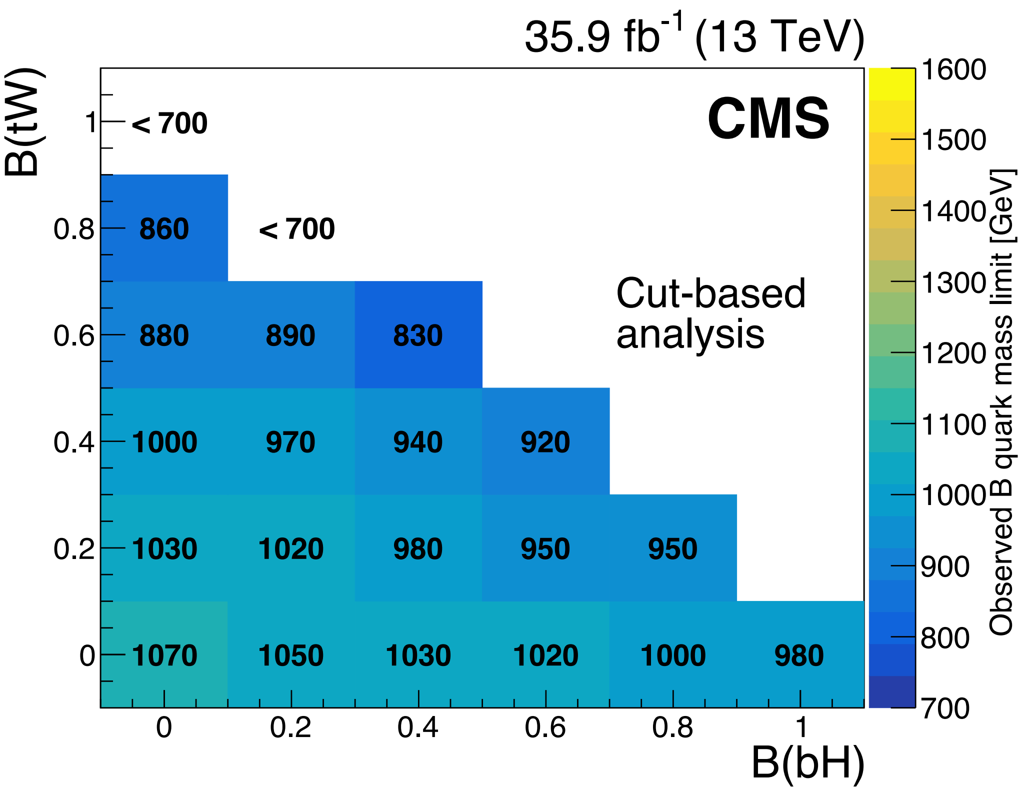
2016 Systematic Uncertainties

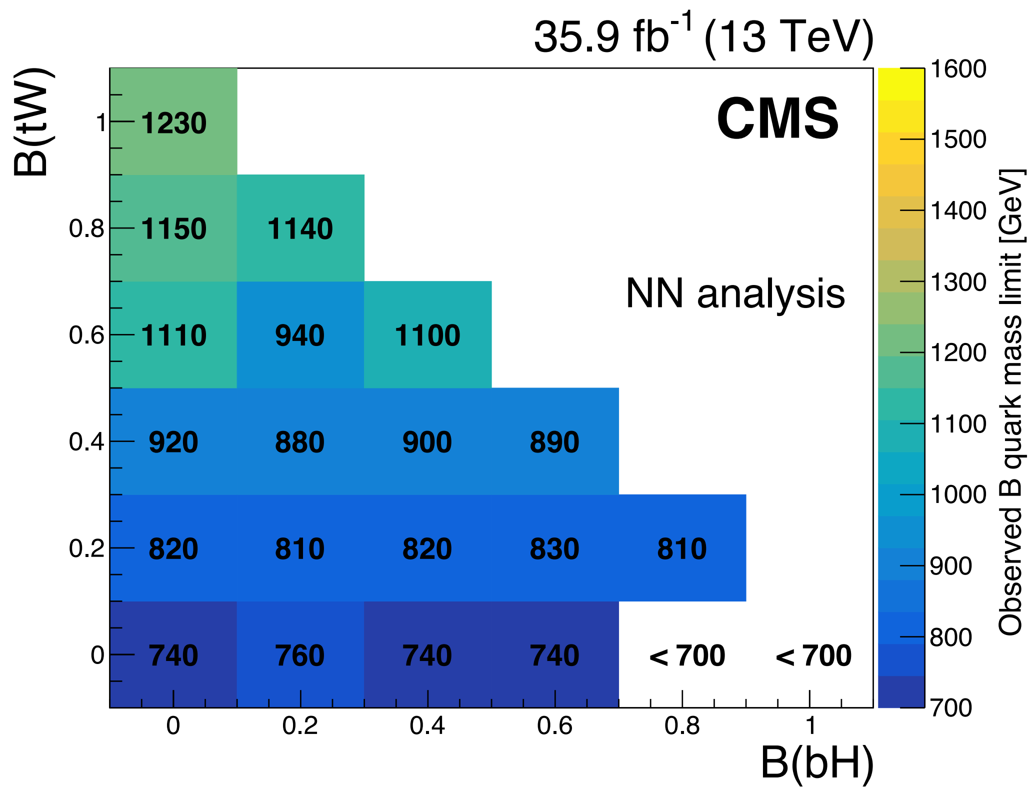
Uncertainty Source	Uncertainty	Contribution to: Cut-based	NN	Applies to samples:
Diboson cross section	50%		✓	VV only
Rare top quark process cross sections	50%		✓	$t\bar{t}V$, $t\bar{t}t\bar{t}$
Higgs boson cross section	50%		✓	H only
W+jets cross section	15%	✓	✓	W+jets only
Z+jets cross section	15%		✓	Z+jets only
Integrated luminosity measurement	2.5%	✓	✓	All simulation
Pileup reweighting	$\pm1\sigma$	✓	✓	All simulation
Jet energy scale	$\pm1\sigma(p_{\mathrm{T}},\eta)$	✓	✓	All simulation
Jet energy resolution	$\pm1\sigma(\eta)$	✓	✓	All simulation
Parton distribution functions	$\pm1\sigma$	✓	✓	$t\bar{t}$, VLQ
Renormalization and factorization scales	$\pm1\sigma$	✓	✓	$t\bar{t}$, VLQ
CSVv2 discriminant reshaping	δ(wgt., unwgt.)		✓	All simulation
BEST classification fractions	$\pm1\sigma(p_{\mathrm{T}})$		✓	QCD multijet
BEST classification scale factor	5%		✓	All simulation
BEST misclassification scale factor	5%		✓	All simulation
Trigger	2%	✓		All simulation
W tag scale factor	$\pm1\sigma$	✓		All simulation
Soft drop jet mass scale	$\pm1\sigma$	✓		All simulation
Soft drop jet mass resolution	$\pm1\sigma$	✓		All simulation
b tag scale factor	$\pm1\sigma$	✓		All simulation
Extrapolation fit	$\pm1\sigma$	✓		Background from data
Normalization of 1Wbackground prediction	1.9%	✓		Background from data
Normalization of 2Wbackground prediction	1.1%	✓		Background from data

BB Limits By Branching Fraction

B2G-18-005

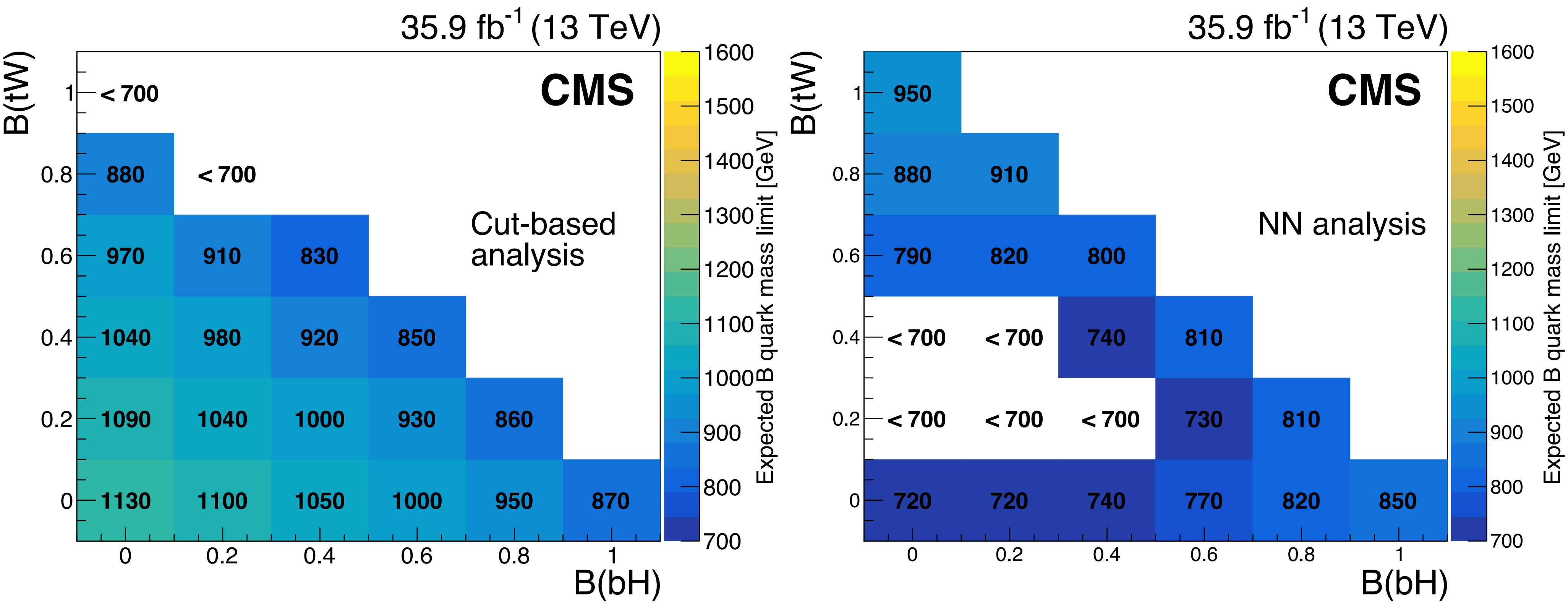
- Scan limits over the branching fractions of the VLQ
  - BEST sensitive to B->tW, B->bZ and B->bH covered by other analysis





BB Limits Expected

B2G-18-005

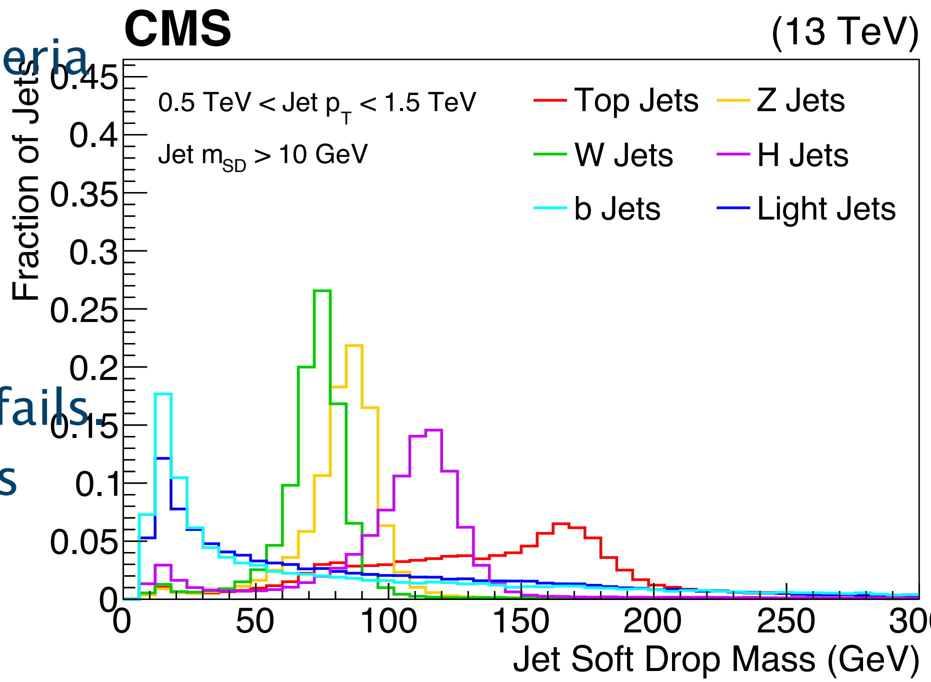


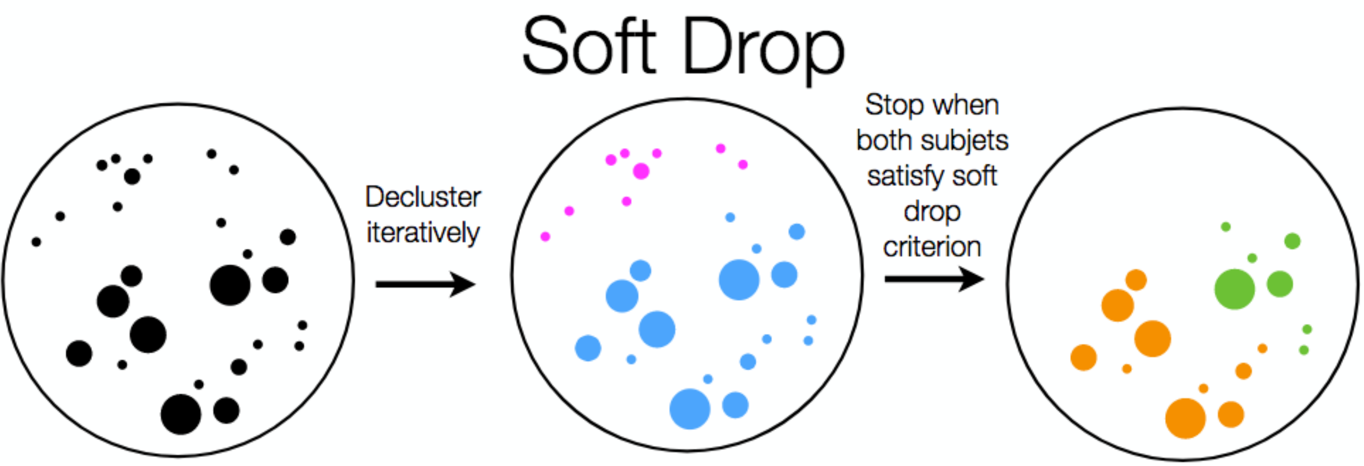
Soft Drop Mass

- Break jet into two subjets
- Remove low p_T "soft" subjets, by checking criteria

$$\frac{\min(p_{T1}, p_{T2})}{p_{T1}+p_{T2}} > z_{\text{cut}} \left(\frac{\Delta R_{12}}{R_0}\right)^{\beta}$$

- In our analysis: z = 0.1, B = 0
- Keep "harder" subjet, iterate procedure if cut fails
- Gives excellent separation of massive particles from light jets!





Mass is dependent on p_T, must be **reweighted**