Higgs Toppings Workshop - Probing Top-Higgs Interactions at the LHC – Benasque 2018

# Flavor tagging at the ILEC



Valerio Dao (CERN) Silvio Donato (UZH)





## Introduction



- Flavor tagging is one of the key ingredient of many analysis including ttH.
- **b-tagging** is one of the most discriminating variables of ttH(bb) to reject tt+lights and tt+cc.
- **c-tagger** is currently used in the search for  $H \to cc$ 
  - it might be useful to tag jets from W in ttH (BR(W $\rightarrow$ cX) ~ 50%).
- **boosted**  $X \to bb$  tagger is currently used for  $gg \to boosted H(bb)$ 
  - a natural application would be boosted ttH(bb).
- quark/gluon discriminator is currently used to reject QCD in fully hadronic ttH analysis (CMS).



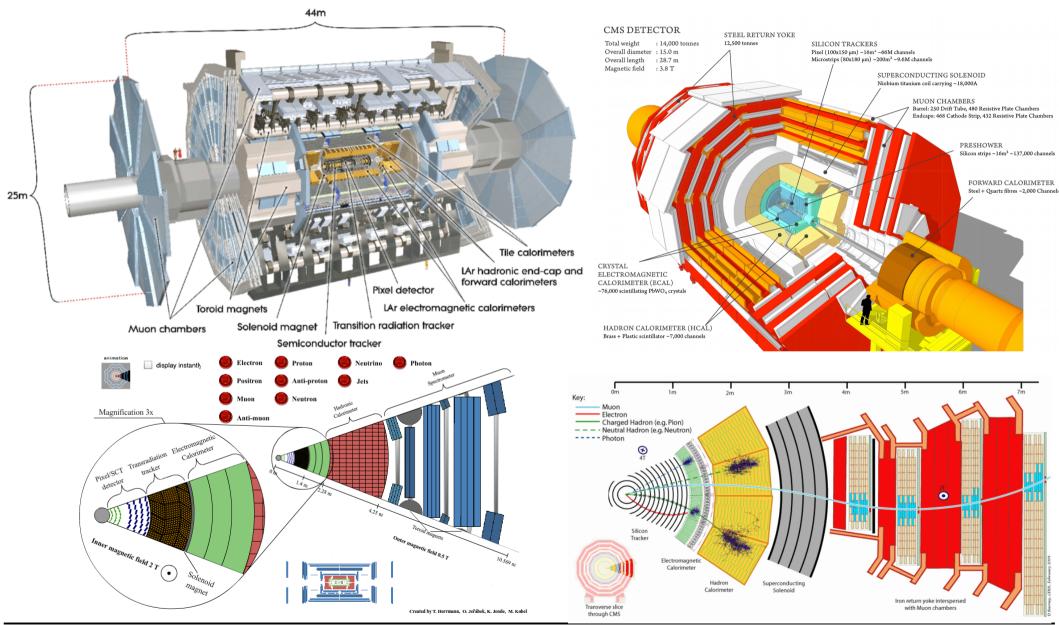
UNIVERSE

MDCCC

S XXXII

#### **ATLAS and CMS experiments**



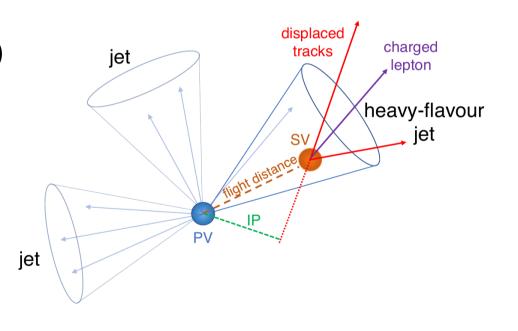




# b(c) tagging



- b(c) tagging is based on B(D) hadron decay features:
  - leptonic decay  $BR(b \rightarrow \mu \nu X) \sim 11\% + BR(b \rightarrow c \rightarrow \mu \nu X) \sim 10\%;$
  - sizable lifetime (c $\tau \sim 0.45$  mm);
  - charged multiplicity (aver.  $\sim 5.0$ ) and invariant mass ( $\sim 5$  GeV).
- Discriminating variables:
  - soft lepton  $(e,\mu)$ ;
  - track impact parameter (IP);
  - secondary vertex/vertices (SV).
- Fake: long-lived hadron decay (eg.  $K_{S^0}$  or  $\Lambda$ ), material interaction.

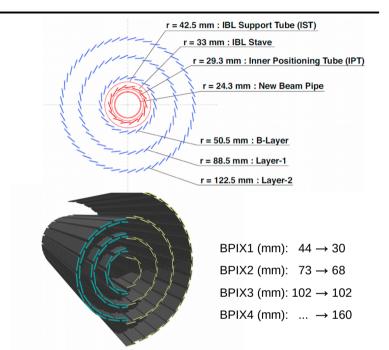




b/c tagging



- b/c tagging performance strongly depends on the **pixel detector**.
- **ATLAS** inserted a new pixel layer (Inner Barrel Layer) during LS1.
- **CMS** replaced the whole pixel detector (phase-1 upgrade) in 2016-17.



- Jet flavor definition:
  - **ATLAS**: AK4 calo jets  $p_T > 20$  GeV,  $|\eta| < 2.5$ , pile-up jet rejection(JVT) (eff. 92% fake 2%). b jet if B hadron in  $\Delta R < 0.3$ .
  - CMS: AK4 PF jets  $p_T > 20$  GeV,  $|\eta| < 2.4$ . b jet if generator B hadron is into the AK4 jet (ghost association) and  $\Delta R < 0.25$  from a gen jet  $p_T > 8$  GeV.



# Low level taggers



- Impact parameter:
  - **ATLAS**: log-likelihood ratio (LLR) based on **IP2D** and **IP3D** of jet tracks, Recurrent Neural Network Track-based tagger (**RNNIP**)  $\rightarrow$  output  $p_b, p_u, p_c$  and  $p_{\tau}$ .
  - **CMS**: JetProbability (**JP**)  $\rightarrow$  LLR of 3D IP significance. **JBP**  $\rightarrow$  only 4 tracks considered.
- Secondary vertex:
  - ATLAS: single displaced vertex (SV1) starts from two-track vertices,
     JetFitter: cascade vertex algorithm, it includes single prong vertex with jet axis.
  - CMS: Adaptive Vertex Fitter (Run-1) → Inclusive Vertex Fitter (Run-2): it doesn't use jet direction to find the secondary vertex. Originally developed for g → bb measurement.
- Soft lepton tagger:
  - ATLAS: Soft Muon Tagger. BDT discriminant (Kinematic + track quality)
  - CMS: Soft Muon and Soft Electron tagger. BDT discriminant (Kinematic + elect. ID)



# High level taggers



- ATLAS:
  - Training sample: hybrid tt + Z'.
  - BDT tagger: kinematic variables (reweighted to avoid correlation) IP2D and IP3D, sec. vertex (SV1, JetFitter) (MV2)
    - + soft muon tagger  $({\bf MV2Mu})$
    - + RNNIP (MV2MuRnn)
  - BDT **c-tagger**: as MV2 trained against b and light, optimized for ctagging (JetFitter with 1 vertex, adding track rapidities)
  - Deep Neural Network (DL1, DL1Mu, DL1MuRnn)
    - Inputs: MV2/MV2Mu/MV2MuRnn inputs + c-tagging variables soft muon tagger replaced by its inputs.
    - Output:  $p_b, p_u, p_c$ .
    - Future: Study techniques for systematic and pileup mitigation. RNNIP inputs fully integrated in DL1 training.



## High level taggers

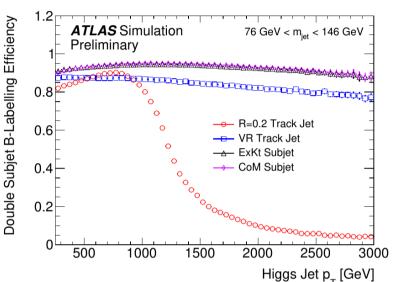


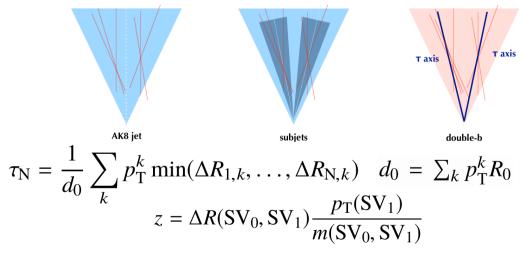
- CMS:
  - Training sample: hybrid tt + multijet.
  - Combined Secondary Vertex (CSVv2)
    - no intermediate tagger. 18 input variables used (based on kinematic and IP and SV).
  - DeepCSV
    - similar input to CSVv2, more layers, more tracks considered, 5 outputs  $(p_{bb}, p_b, p_c, p_{cc}, p_{light})$ .
  - $\mathbf{CMVAv2}$ :  $\mathbf{CSV}$  + soft muon + soft electron + JP + JPB tagger.
  - **c-tagger**: CvsL and CvsB tagger (very similar to CSV); DeepCSV c-tagger  $\rightarrow$  better performance.
  - Future: **DeepFlavour** uses properties of charged and neutral PF candidates, SV, without any specific preselection (more tracks).



# Boosted $X \rightarrow bb$ taggers

- **ATLAS**: b-tagging on track subjets ( $\Delta R=0.2$ ):
  - several possible tagging (leading subjet pT, highest/lower b-tagging, ...).
  - new subjet definition improves X->bb efficiency (Variable Radius, VR)
- CMS AK8 jet, soft drop algorithm:
  - tagging on subjects (as ATLAS);
  - new double b-tagging exploiting correlation between subjects:
    - $\tau_{N}$  algo to define parton direction;
    - track associated minimizing track  $\tau$ -axis distance;
    - use IP and SV variables, including correlation;
    - z variable to reject  $g \rightarrow bb$ .





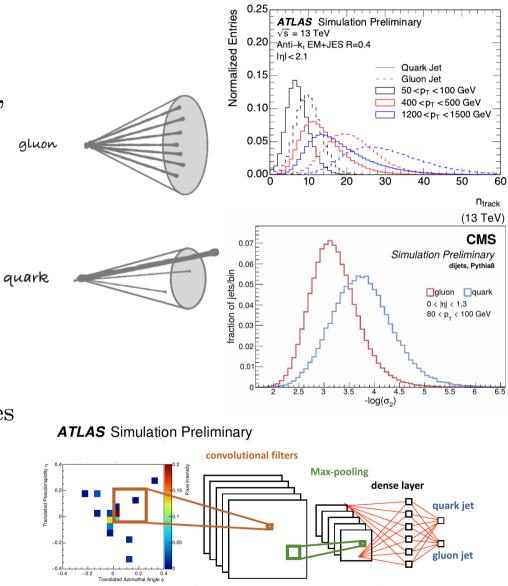




Quark/gluon tagger



- ATLAS: likelihood ratio using number of track per jet in  $(p_T,\eta)$  bins,
- **CMS**: likelihood ratio of
  - number of tracks,
  - $p_T D = \frac{\sqrt{\sum_i p_{T,i}^2}}{\sum_i p_{T,i}} ,$
  - $\sigma_2$  is the ellipse minor axis.
- Future:
  - ATLAS: ECAL towers + tracks images (Convolutional Neural Network tagger);
  - CMS: neutral and charged PF candidates as DNN inputs (DeepJet).



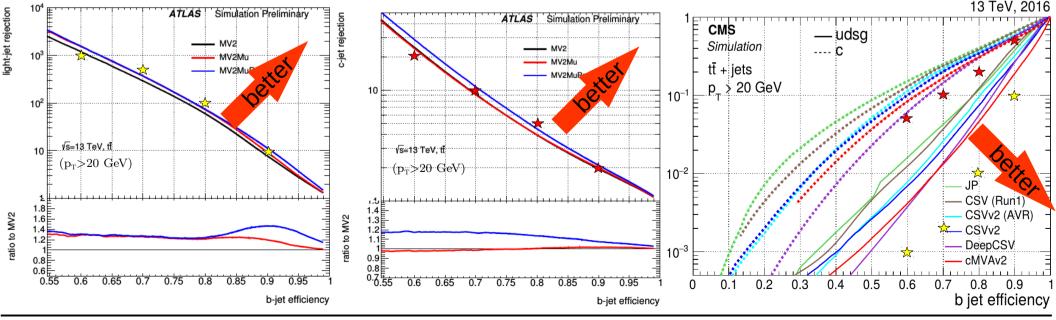
3x



## Performance b-tagger



- Plots: b-jet efficiency vs non-b jet rejection (ATLAS) or fake rate (CMS).
- Example b efficiency 80%:
  - light rejection ~ 100; c rejection ~ 5.
- In 2016, ATLAS b-tagging performance was significantly better than CMS.

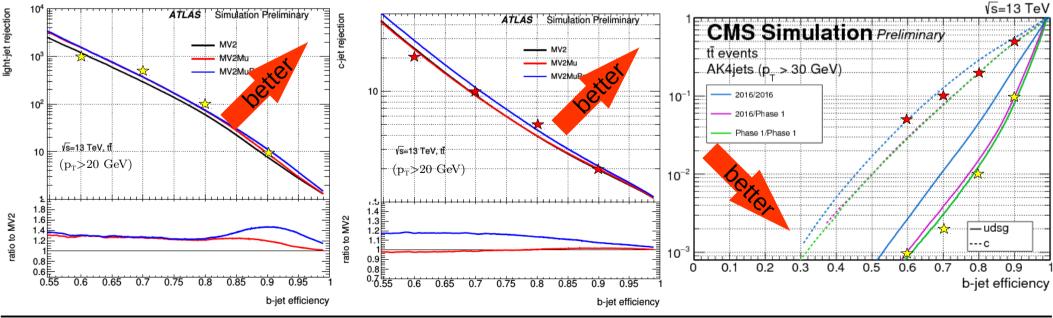




## Performance b-tagger



- Plots: b-jet efficiency vs non-b jet rejection (ATLAS) or fake rate (CMS).
- Example b efficiency 80%:
  - light rejection ~ 100; c rejection ~ 5.
- After phase-1 upgrade, the two experiments have a comparable performance similar (in simulation)  $\rightarrow$  warning: plot with different  $p_T$  range!

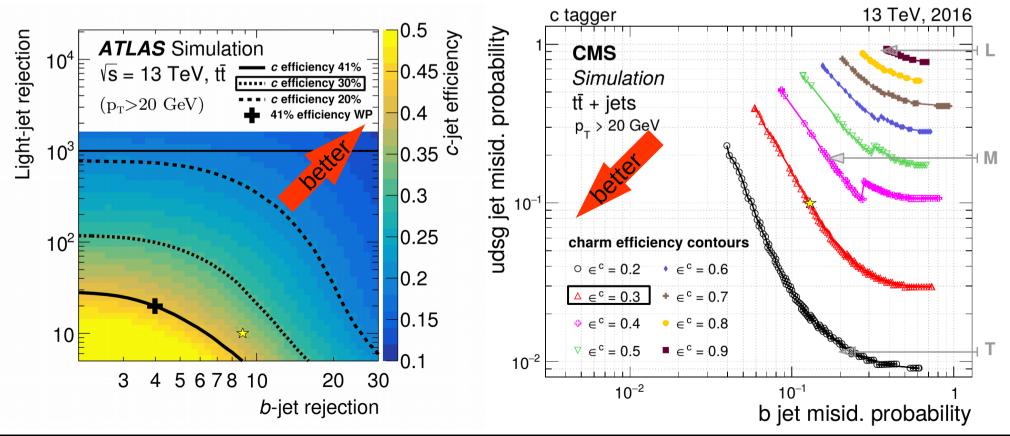








- CMS plot obtained with Phase-0 pixel detector.
- Working point used in  $H \rightarrow cc$  analysis (ATLAS)
  - c-efficiency  $\sim 41\%$ ; light rejection  $\sim 20$ ; b rejection  $\sim 4$ .

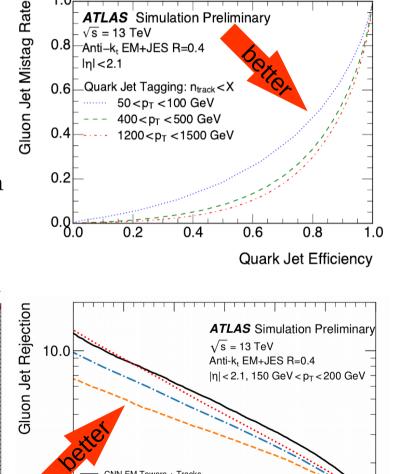




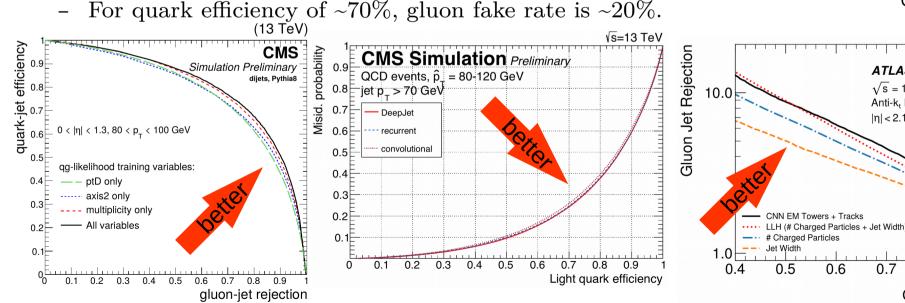
# Quark/gluon tagger



- Different jet selection  $\rightarrow$  plots cannot be compared.
- Charged multiplicity is the most discriminating variables
  - CMS q/g disciminator shows a slight improvement including other variables.
- CNN and DeepJet improvement is about  $\sim 10-20\%$  in gluon rejection.



1.0



1.0

0.8

0.9

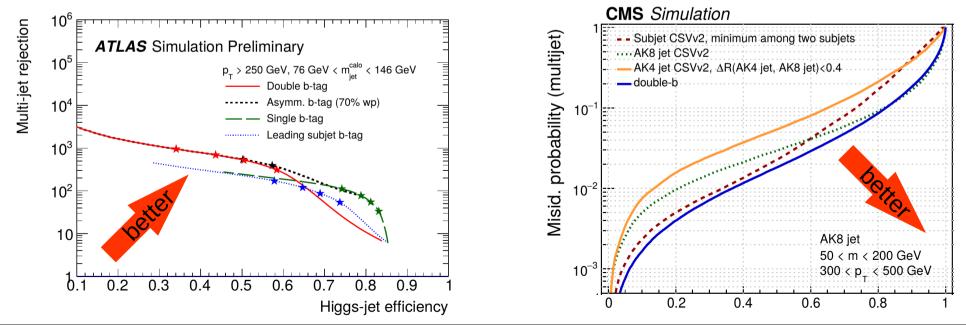
Quark Jet Efficiency



## Boosted $\mathbf{X} \to \mathbf{b}\mathbf{b}$



- Double subjet b-tag is better than single subjet b-tag in large multijet rejection region.
- As expected double-b outperforms other taggers, especially in high H → bb efficiency region.
  - multijet rejection of ~500 at H(bb) efficiency of ~50%.
- CMS plot shows only tagging efficiency (plot obtained 2016 pixels)
- Warning: different kinematic cuts  $\rightarrow$  plots cannot be compared.





## **Reference - CMS**



- "Identification of heavy-flavour jets with the CMS detector in pp collisions at 13 TeV", JINST 13 (2018) no.05, P05011
- "CMS Phase 1 heavy flavour identification performance and developments", CMS DP-2017/013
- "Heavy flavor identification at CMS with deep neural networks", CMS DP-2017/005
- "Jet algorithms performance in 13 TeV data", CMS-PAS-JME-16-003
- "New developments for Jet Substructure", CMS DP-2017/027



## **Reference - ATLAS**



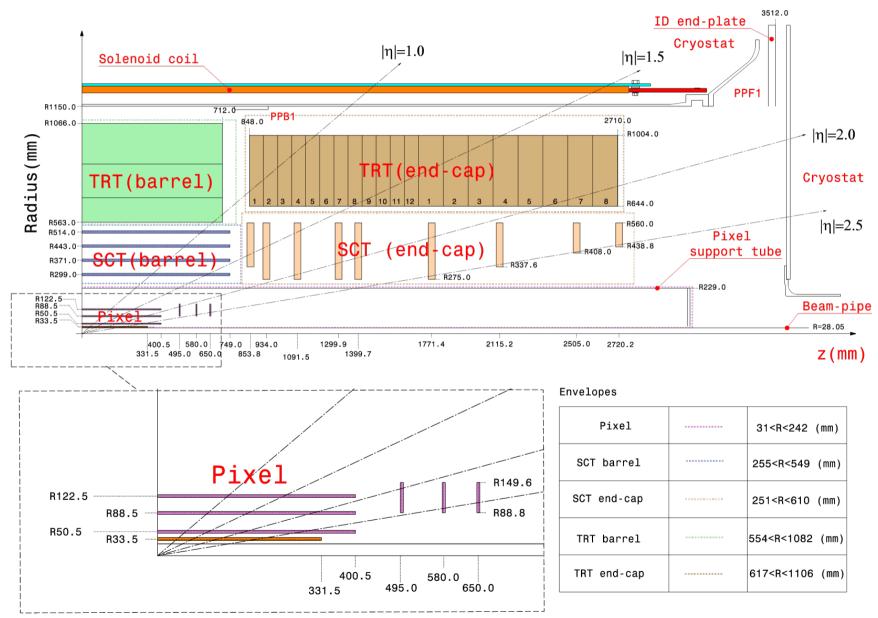
- "Optimisation and performance studies of the ATLAS b-tagging algorithms for the 2017-18 LHC run", ATL-PHYS-PUB-2017-013
- "Boosted Higgs ( $\rightarrow$  bb) Boson Identification with the ATLAS Detector at s = 13 TeV", ATLAS-CONF-2016-039
- "Variable Radius, Exclusive-kT , and Center-of-Mass Subjet Reconstruction for Higgs( $\rightarrow$  bb) Tagging in ATLAS", ATL-PHYS-PUB-2017-010
- "A new tagger for the charge identification of b-jets", ATL-PHYS-PUB-2015-040
- "Quark versus Gluon Jet Tagging Using Charged-Particle Constituent Multiplicity with the ATLAS Detector", ATL-PHYS-PUB-2017-009
- "Quark versus Gluon Jet Tagging Using Jet Images with the ATLAS Detector", ATL-PHYS-PUB-2017-017.

#### Backup



## ATLAS tracker r-z sect.



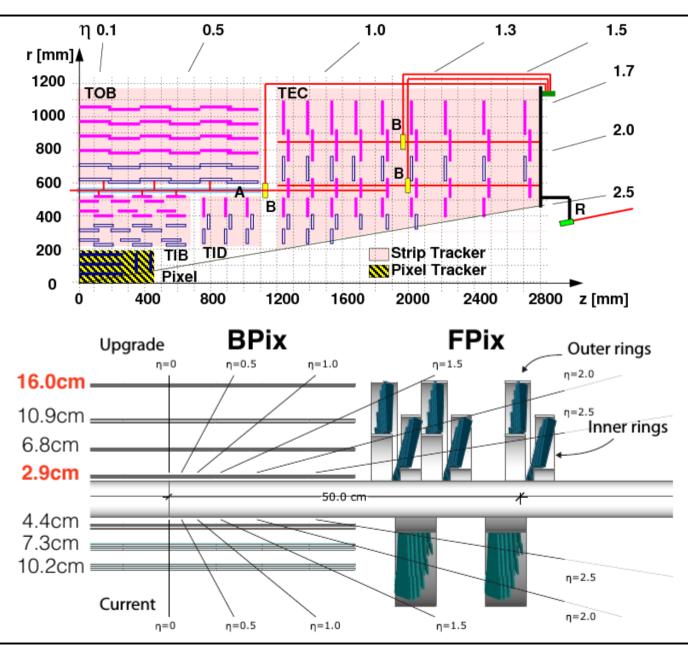


S. Donato (UZH)



## CMS tracker r-z section





S. Donato (UZH)



Working points 2016



#### ATLAS (2016)

WP	Cut value $X$	<i>b</i> -jet efficiency $(\varepsilon_b)$	<i>c</i> -jet mistag rate $(\varepsilon_c)$	LF-jet mistag rate ( $\varepsilon_{\rm LF}$ )				
85%	0.1758	85%	32%	2.9%				
77%	0.6459	77%	16%	0.77%				
70%	0.8244	70%	8.3%	0.26%				
60%	0.9349	60%	2.9~%	0.065%				
$_{50\%}$	0.9769	50%	0.94~%	0.017%				

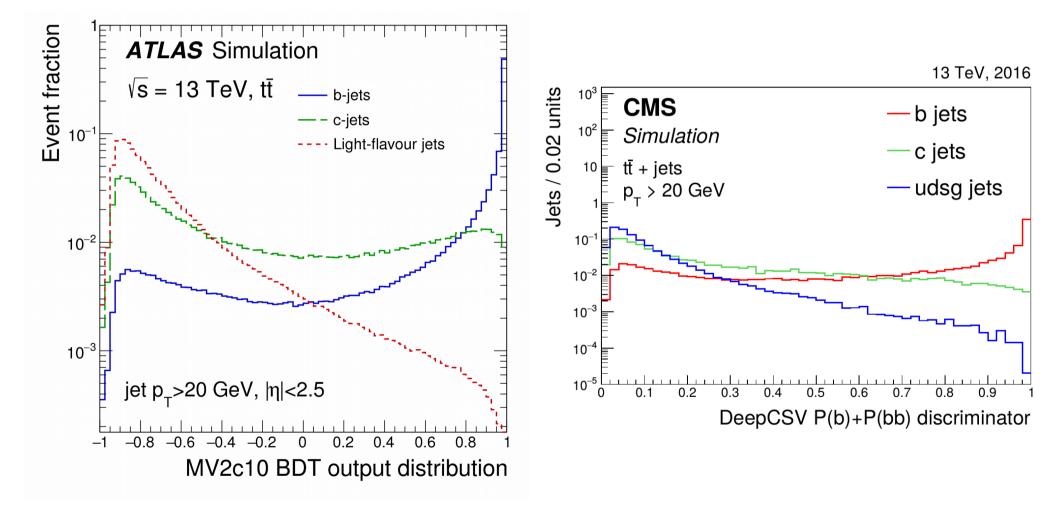
#### CMS (2016)

Tagger	Working point	$\varepsilon_{\mathrm{b}}~(\%)$	ε <sub>c</sub> (%)	$\varepsilon_{ m udsg}$ (%)
	DeepCSV L	84	41	11
Deep combined secondary vertex	DeepCSV M	68	12	1.1
(DeepCSV) $P(b) + P(bb)$	DeepCSV T	50	2.4	0.1



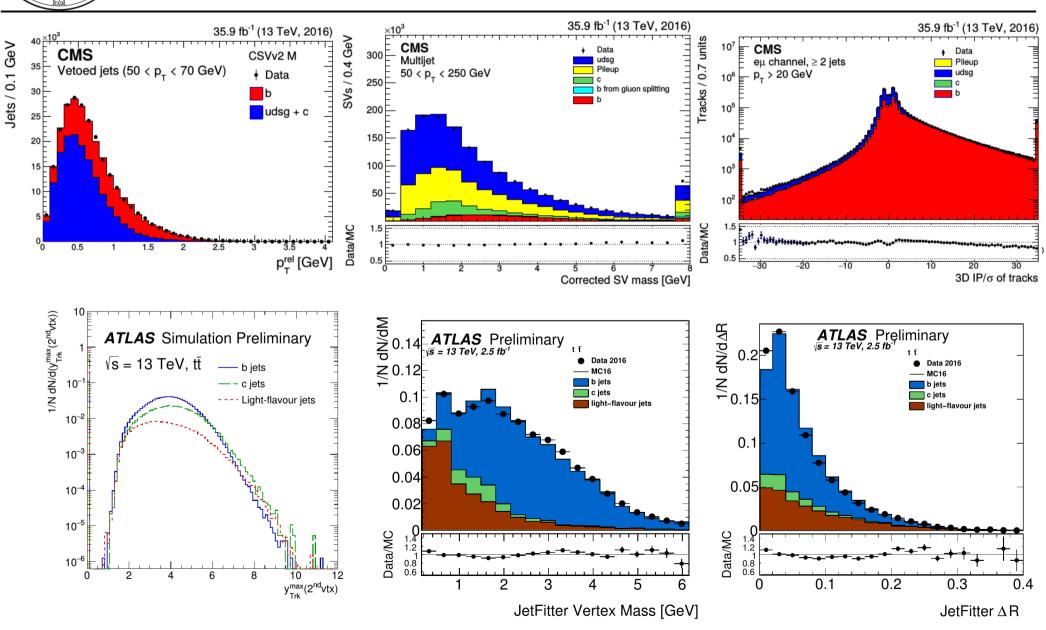
## Working points 2016





## Input variables





UNIVERSE

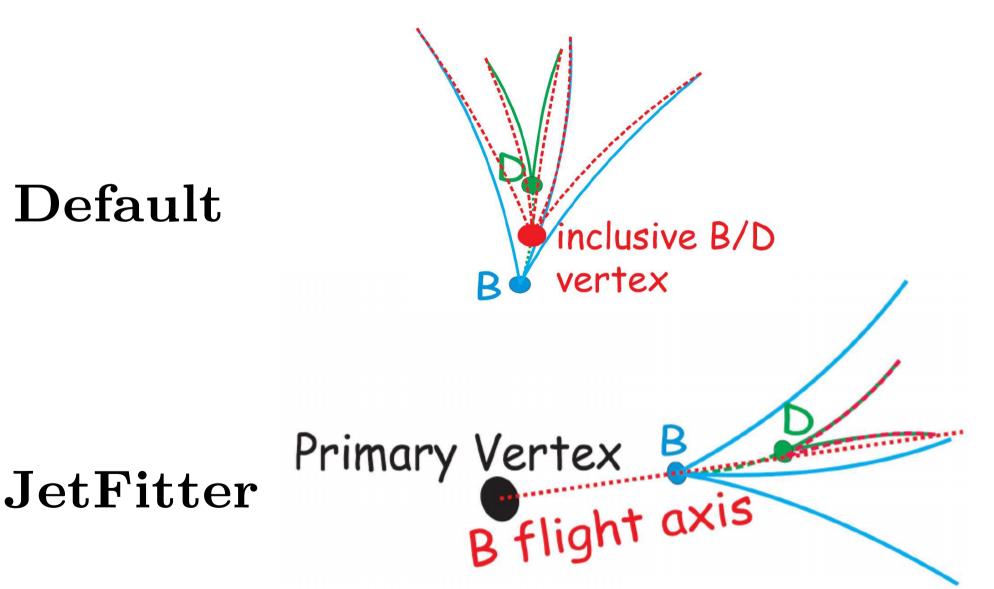
мрссс

RICENSIS



## Secondary Vertex Fitter

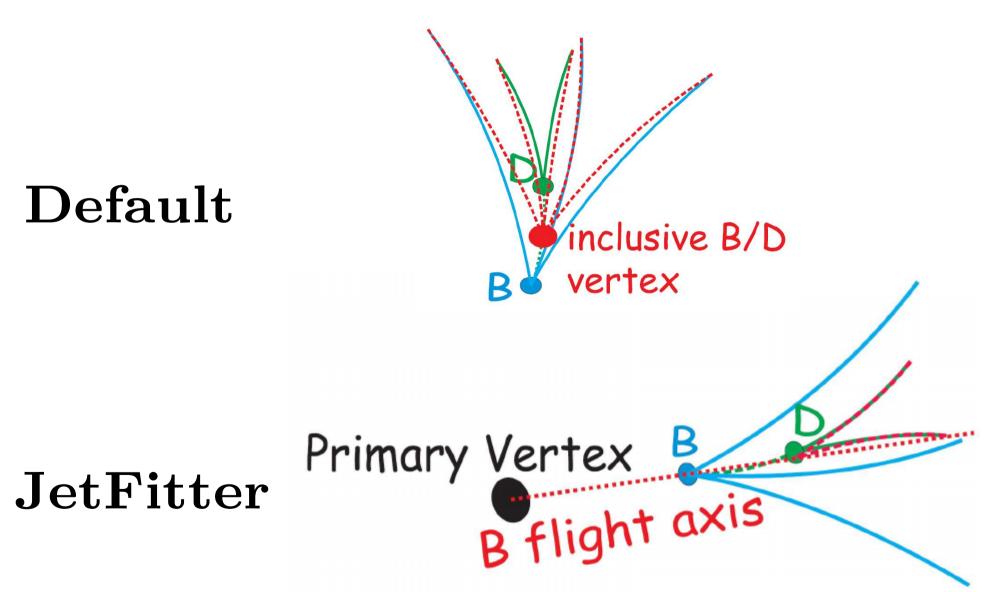






## **Inclusive Vertex Finder**

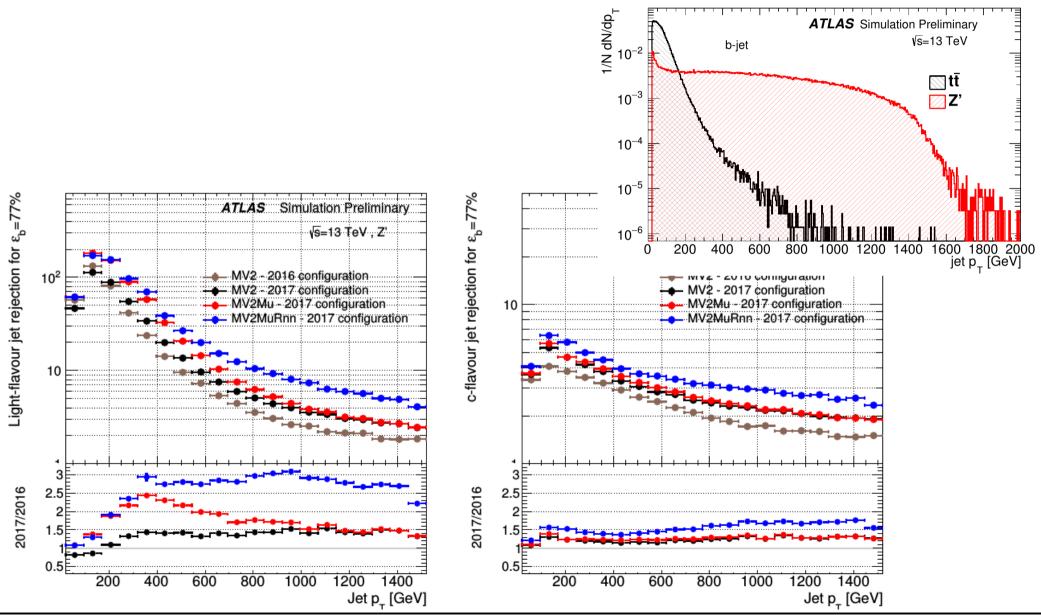






## ATLAS 2016 vs 2017

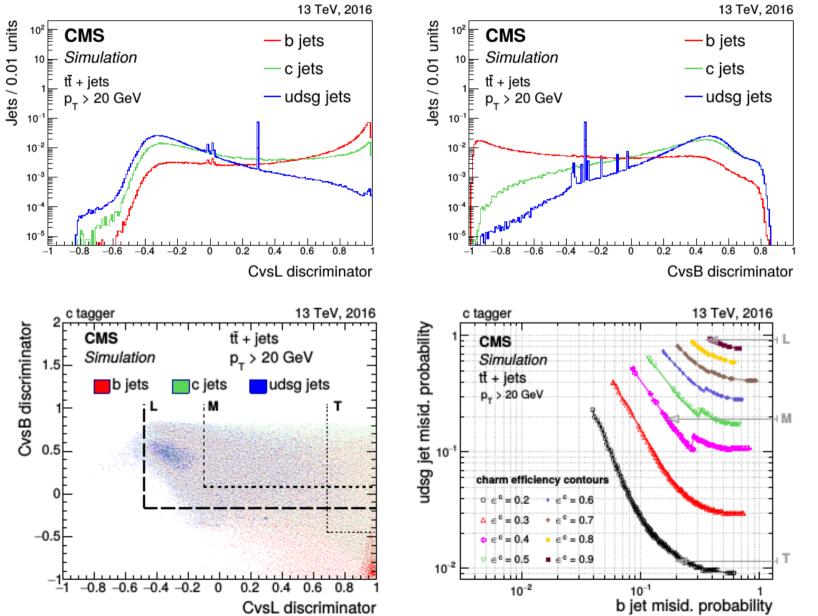










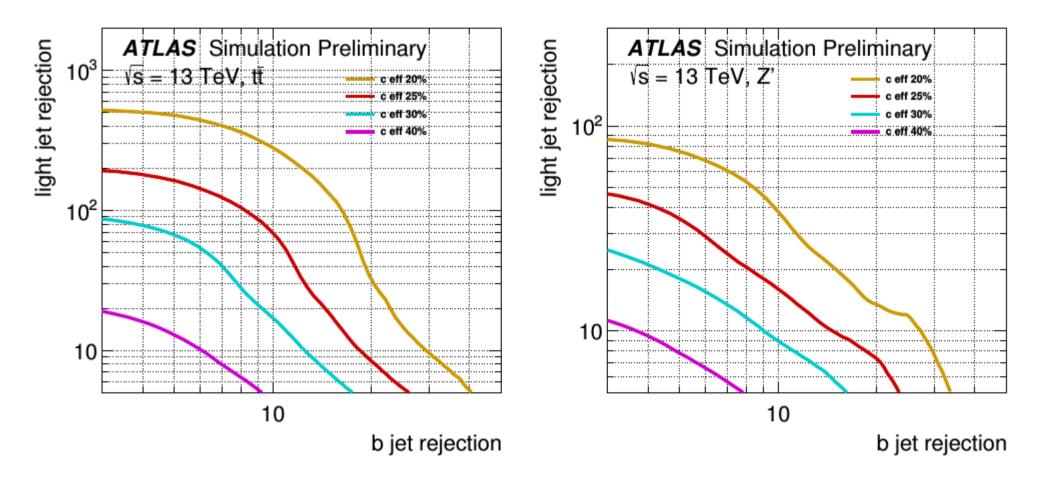


S. Donato (UZH)







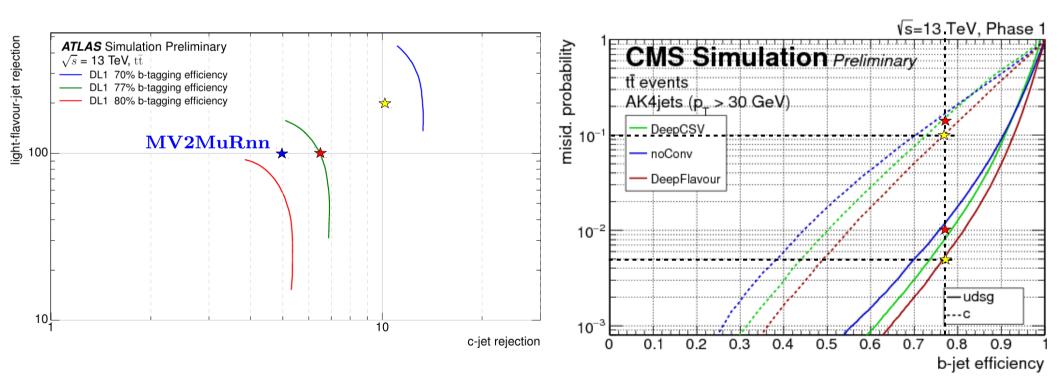




# **Deep Neural Network**



• DeepFlavour is more aggressive than DL1 (more input variables) and hence gives better performance.





#### b-tag vs PU



