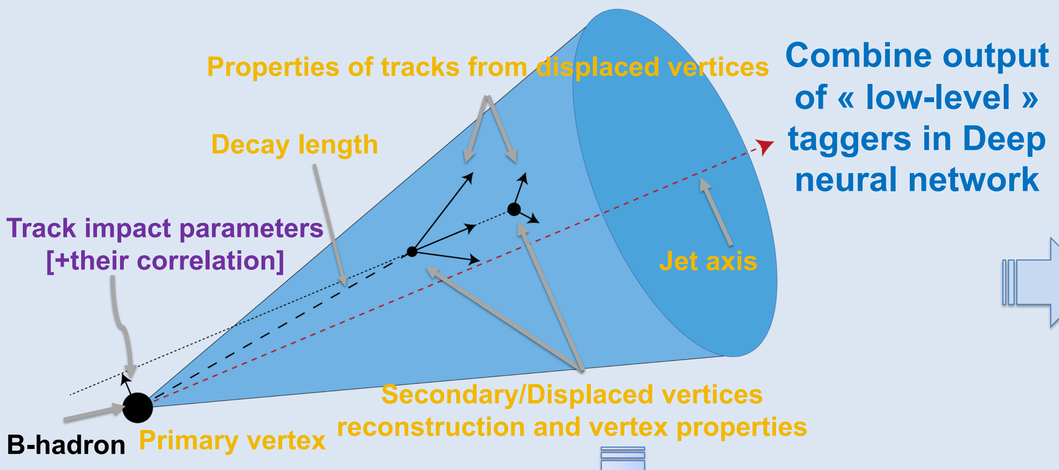
EFFICIENCY CALIBRATION FOR ATLAS B-JET IDENTIFICATION ALGORITHMS

Many analyses in ATLAS, like top quark and Higgs measurements and searches for new physics, rely on the **identification of jets containing b-hadrons (b-jets) at high efficiency** while **rejecting more than 99% of non-b-jets**. These algorithms, called b-taggers, exploit the **distinct decay properties of the b-hadrons**. Using different machine learning approaches, like Boosted Decision trees, **deep neural networks**, and recently also **Recurrent Neural Networks (RNNIP) and deep sets,** powerful discriminators are built to discriminate b-jets from c- and light jets. For the first time, the algorithms have been trained on jets reconstructed using information from the ATLAS tracker and calorimeter (“**particle flow jets**”). We measure the tagging rates in ATLAS collision data from the full Run 2 of the LHC (2015-2018) and correct the MC simulations to reflect the measured rates.

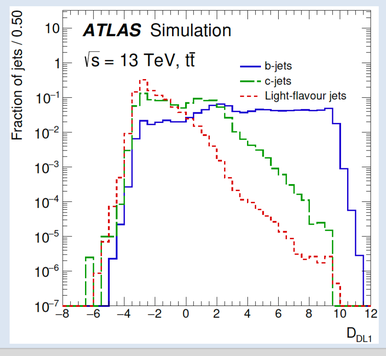
The ATLAS b-tagging algorithms

- Exploit b-hadron properties: **long lifetime**, **high mass** and high **decay multiplicity**
- Two complementary **approaches in low-level taggers**: exploit **individual properties of charged particles** or **reconstruction of displaced vertices**
- **New: RNNIP**, a recurrent neural network, exploits **correlations between track impact parameters** for tracks of b-hadron decays
  - **Improvements** in training speed and algorithm performance observed if using **deep sets (DIPS)** instead of RNNIP [ATL-PHYS-PUB-2020-014]



- Using the output of the low-level-taggers, jets are classified with an algorithm based on a **deep neural network (DNN)**
- Improvements of the **high jet pT performance** by extending the range of the jet pT spectrum of the training sample
- The DNN output probabilities (p_b, p_c and p_{light}) are combined to a **b-tagging discriminant** (f_c: effective c-jet fraction in background training sample):

$$D_{DL1(r)} = \ln\left(\frac{p_b}{f_c \cdot p_c + (1 - f_c) \cdot p_{light}}\right)$$



Improved performance of ATLAS b-tagging algorithm for Run 2 analyses with dedicated **training on particle flow jets**

- **Deep Neural network based algorithm** (“DL1”) **outperforms** the “MV2” algorithm based on boosted decision trees
- **RNNIP** improves further the performance (“DL1r”)

Larger charm & light jet rejection for the same b-tagging efficiency

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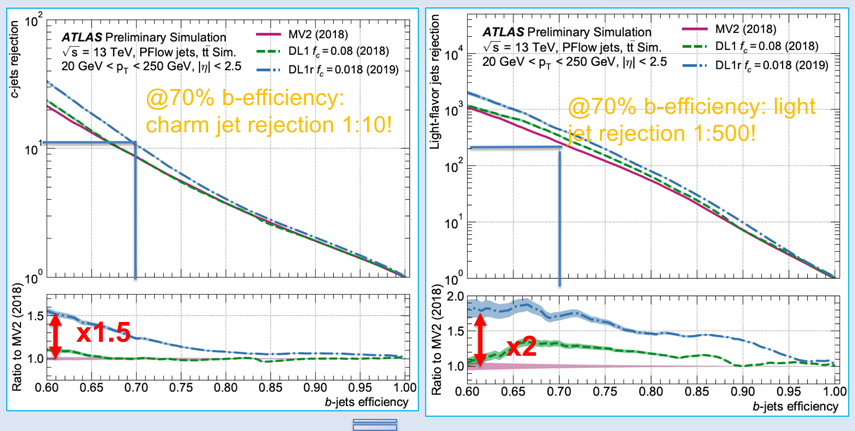

Calibration of the b-tagging algorithms

Mismodelling of training input variables causes differences in performance in MC w.r.t. data.

- **Efficiency scale factors,** defined as the ratio between data and MC performance, for b-tagging and charm and light mistag rates are necessary
- Scale factors close to 1 are desirable and show that the algorithm and its inputs are well understood in simulation

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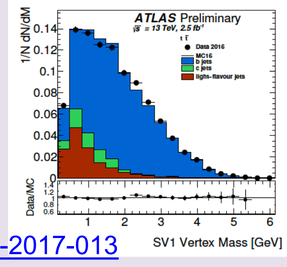
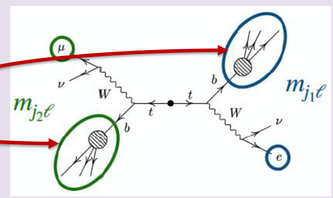


The **performance of the b-tagging algorithms is measured in data and MC** and **MC-to-data correction factors** are derived. These factors are **measured in samples enriched in either b, charm or light jets**. The efficiency measurements are provided as functions of the jet pT (transverse momentum) as the **tagger performance depends on the jet pT**. Correction factors (Scale Factors) are measured for each **single-cut operating point** defined by a cut on the discriminating variable corresponding to an average b-jet identification efficiency of 85%, 77%, 70% or 60% in simulated ttbar events. The scale factors are **smoothed as a function of the jet pT** and **differences in efficiencies between MC generators** are taken into account by adding an additional correction factor [ATL-PHYS-PUB-2020-009].

B-jet efficiency calibration: Dileptonic ttbar PDF method

Method

- Pure sample of b-jets is selected by targeting the dileptonic decay of ttbar events
- Main features of the event selection:
  - == 1 electron & == 1 muon
  - Exactly 2 jets
- Calibration is extracted using the **two jets** in the event



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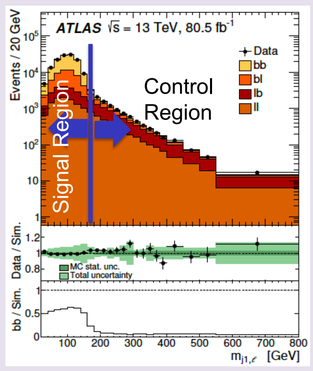

- Constrain remaining non-b-jet background using a **simultaneous template fit to data in signal and control regions**
  - **Reduces uncertainty to percent level**

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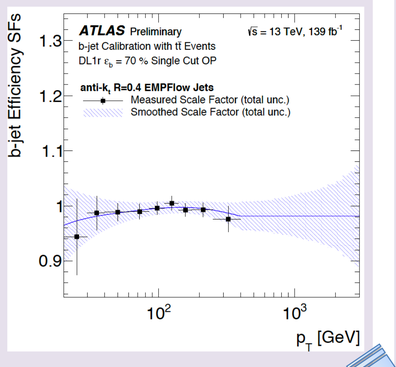
Results

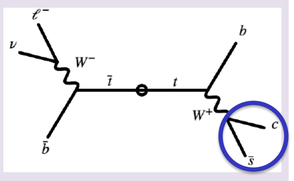
- MC-to-data correction factors consistent with 1
- **Uncertainties at percent level** (1-2%)
- Dominant uncertainties from ttbar modelling, jet energy scale and resolution



Charm jet mistag calibration: Single lepton ttbar method

Method

- Select sample of ttbar events in the lepton+jets decay
- Exploit large branching ratio of W->cX decay to create sample enriched in charm jets
- Main features of the event selection:
  - ==1 electron OR muon
  - Exactly 4 jets



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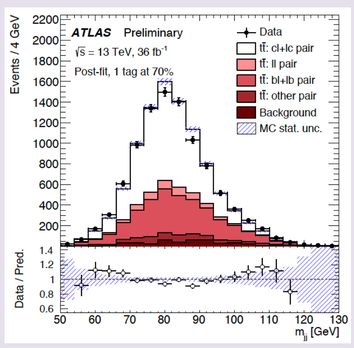

- Perform **measurement on jets assigned to the hadronically decaying W-boson**
  - Use kinematic likelihood fitter to assign jets to ttbar decay products
- Extract charm mistag efficiency in data using a **combined likelihood fit**

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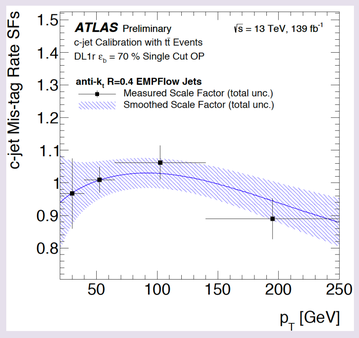
Results

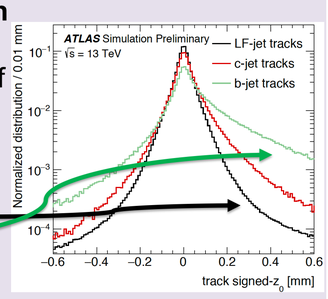
- MC-to-data correction factors largely compatible with 1
- **Uncertainties** at the level of a **few percent**
- Dominant uncertainty from ttbar modelling

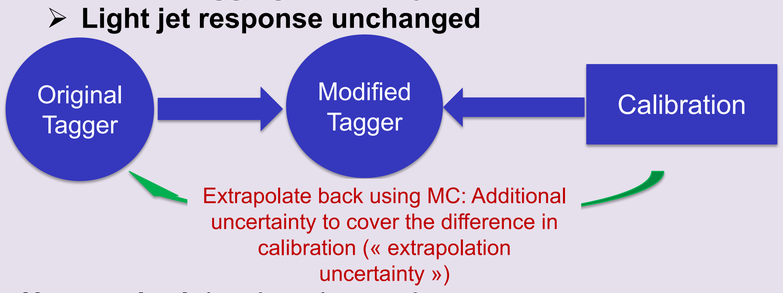


Light jet mistag calibration: Negative tag method

Method

- Difficult to create light flavor dominated sample due to **high light jet rejection of b-tagger** (1:50 – 1:1000)
- Solution: measure mistag efficiency of a **modified tagger**
  - Make use of symmetry of signed impact parameter distribution for light jets and strong asymmetry for b & charm jets
  - **Reduce tagging rate of b-jets**
  - **Light jet response unchanged**





- **New method** developed recently
  - Calibration using leading jet in Z(->ll)+jets events
  - 2D combined fit **reduces uncertainty by constraining non-light jet contribution**

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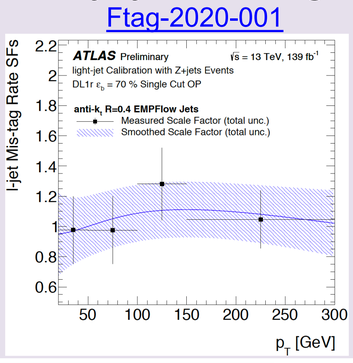
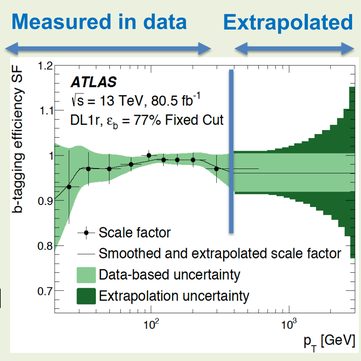
Results

- MC-to-data correction factors largely compatible with 1
- **Uncertainties** at the level of **10-20%**
- Dominant uncertainty from extrapolation, **reduced by better inner detector simulation**



High-pT extrapolation

- Data statistics insufficient for jet pT>400GeV to extract efficiency
- **Extend central value of b-efficiency for pT(jet) >400GeV**
- Derive **additional systematics using MC for pT(jet)>400 GeV**: Extrapolation uncertainties due to physics and detector modeling are added to measured uncertainties
- Improved method, simulations and use of RNNIP reduces uncertainties



Smoothing procedure

- **Smooth calibration factor** results and uncertainties with a **non-parametric regression** technique
- Remove discontinuities at bin boundaries due to statistical fluctuations
- **Improvements** due to more rigorous approach to optimize smoothing parameters

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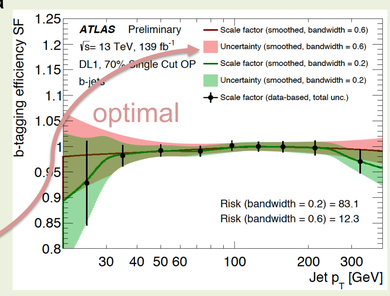

Conclusions & Outlook

- ATLAS analyses profit from taggers with **improved performance**
- **B-tag, charm and light mistag efficiencies** are measured in **data and MC**, results are mostly consistent and MC-to-data correction factors are close to 1
- Uncertainties at percent level for b-tagging efficiency and at 10-20% for light mistag rate
- Constant work on **improvements of taggers**
- **Charm-jet tagging** also possible using the b-tagging algorithms with the same training, with slight modifications to the tagging discriminant definition
- **Development of calibration methods in progress** to extend efficiency measurements to other phase space like large jet pT

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