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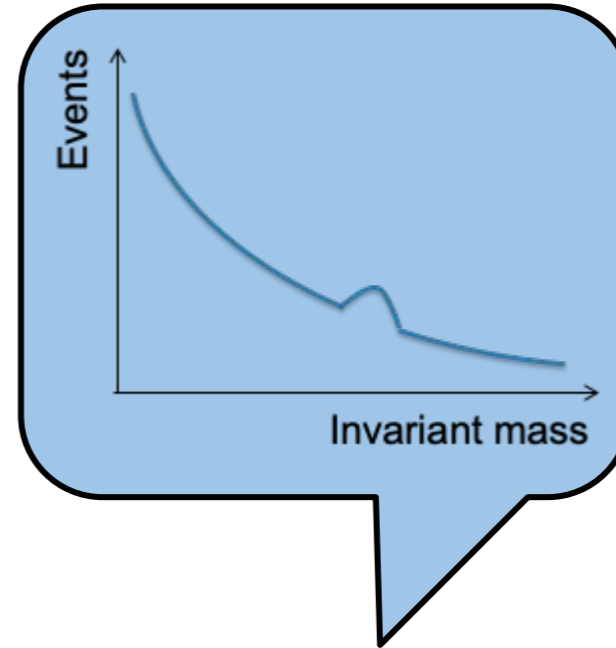
SEARCH FOR NEW RESONANCES DECAYING INTO $T\bar{T}B\bar{A}$ IN THE HADRONIC FINAL STATE WITH THE ATLAS DETECTOR

Trine Poulsen

January 3rd 2020



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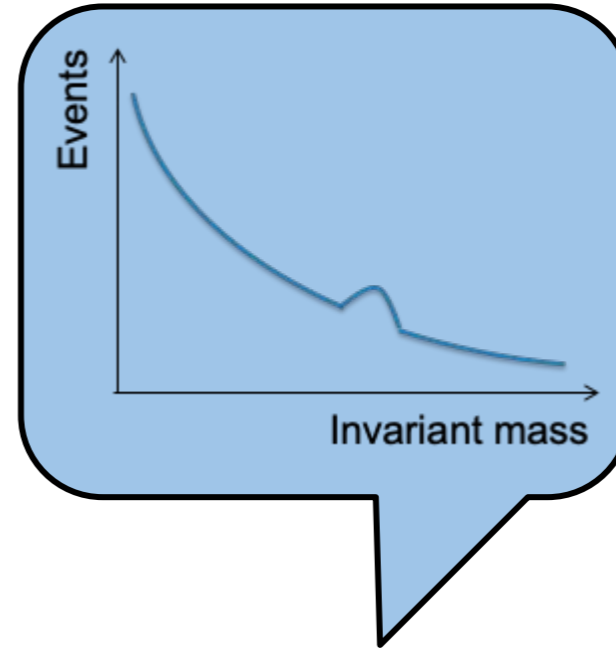
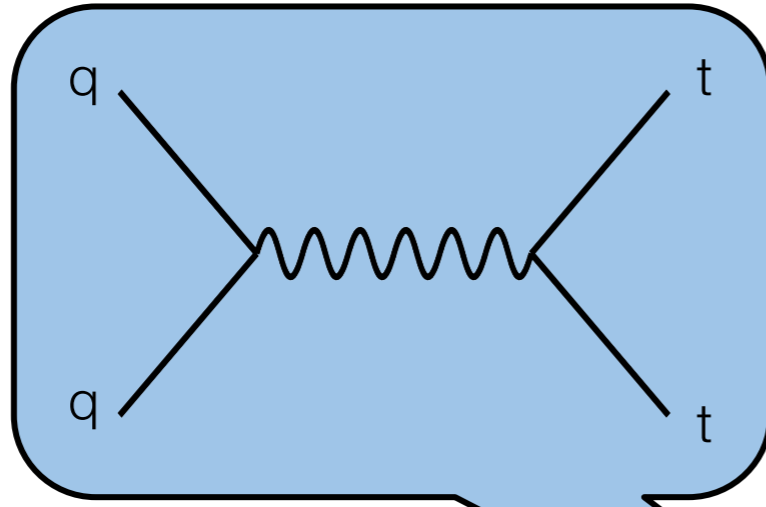
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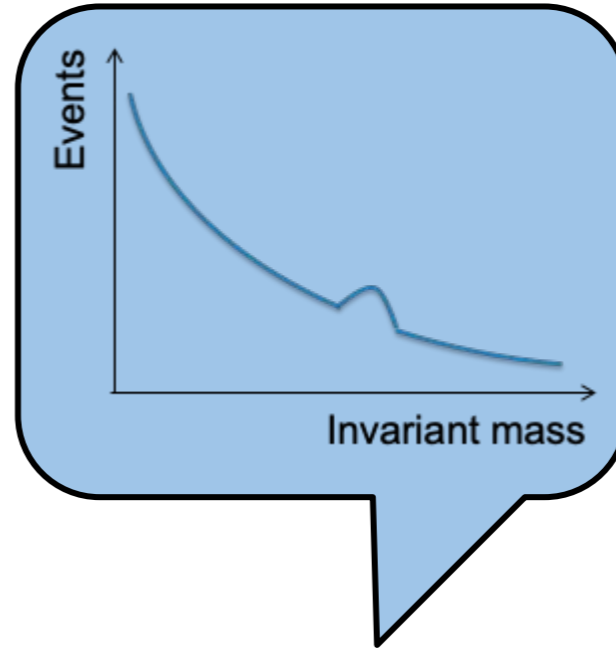
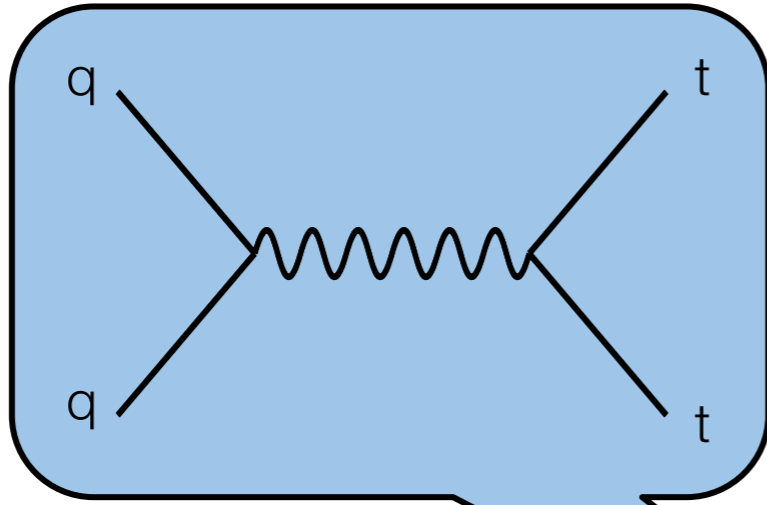
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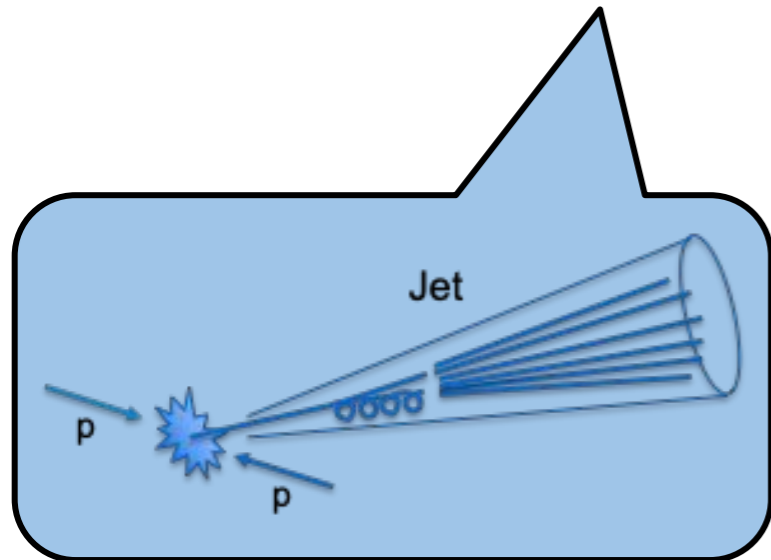
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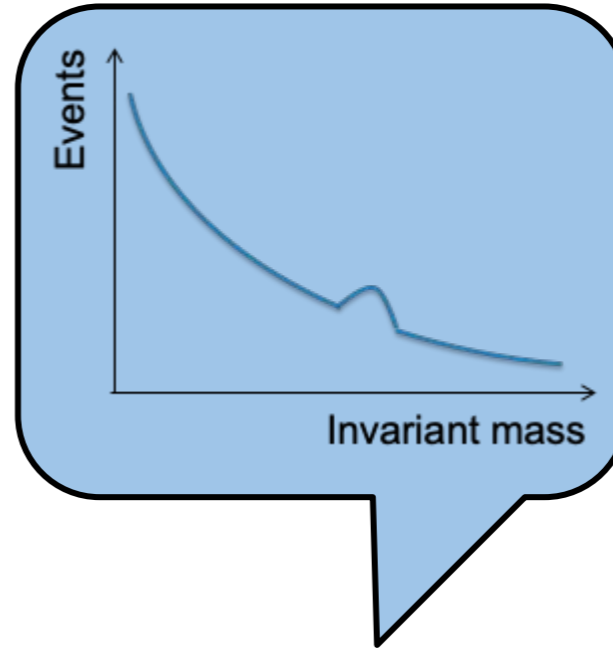
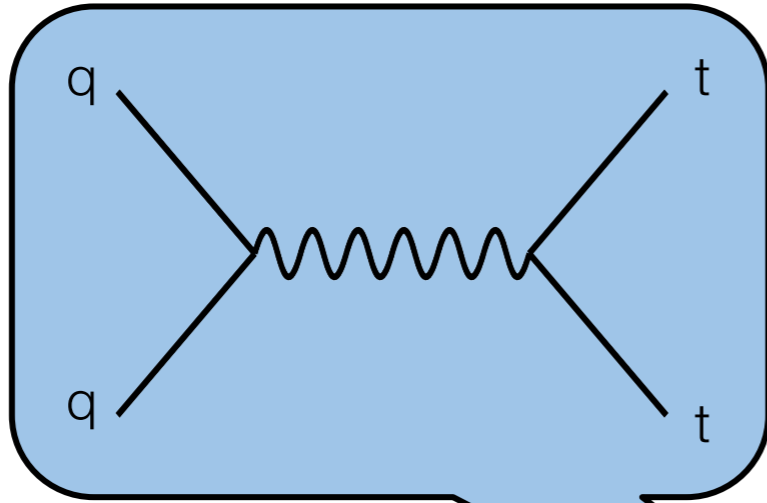
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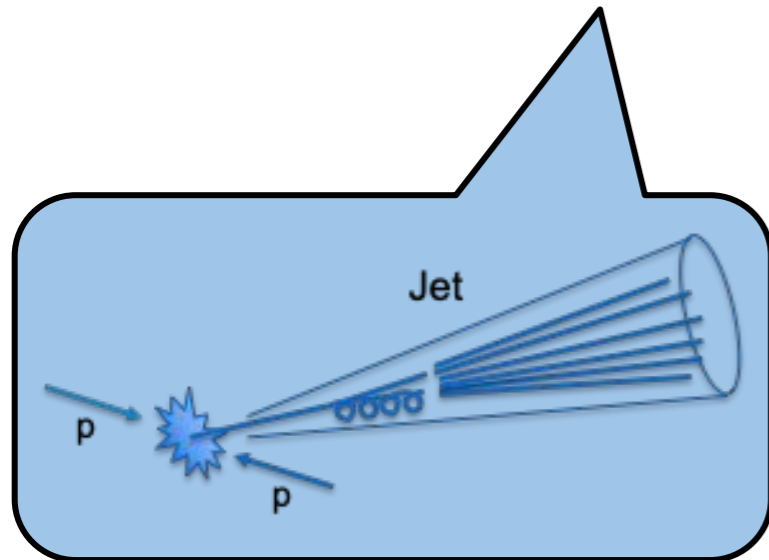
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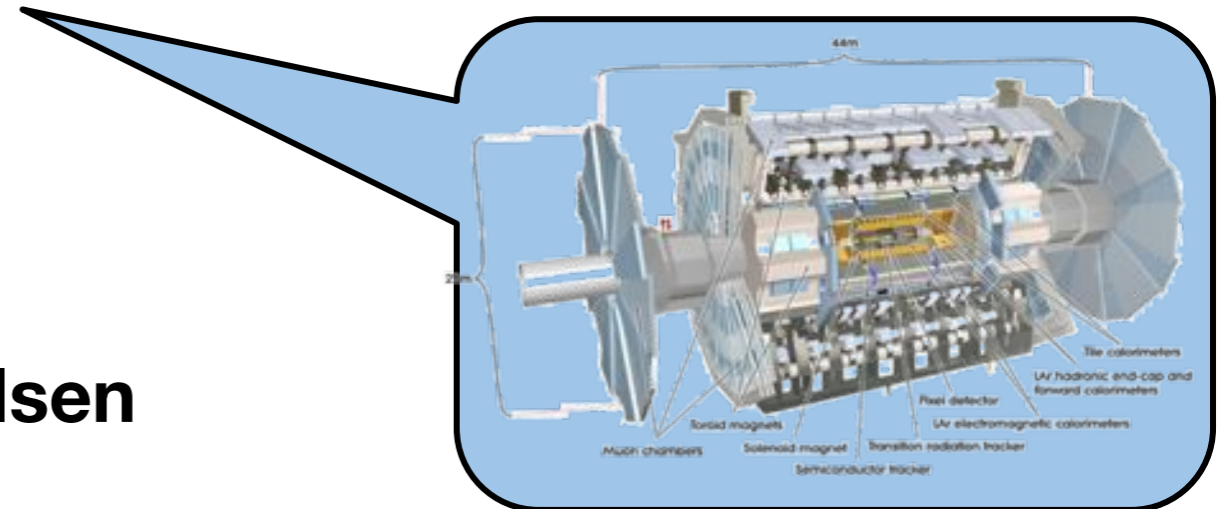
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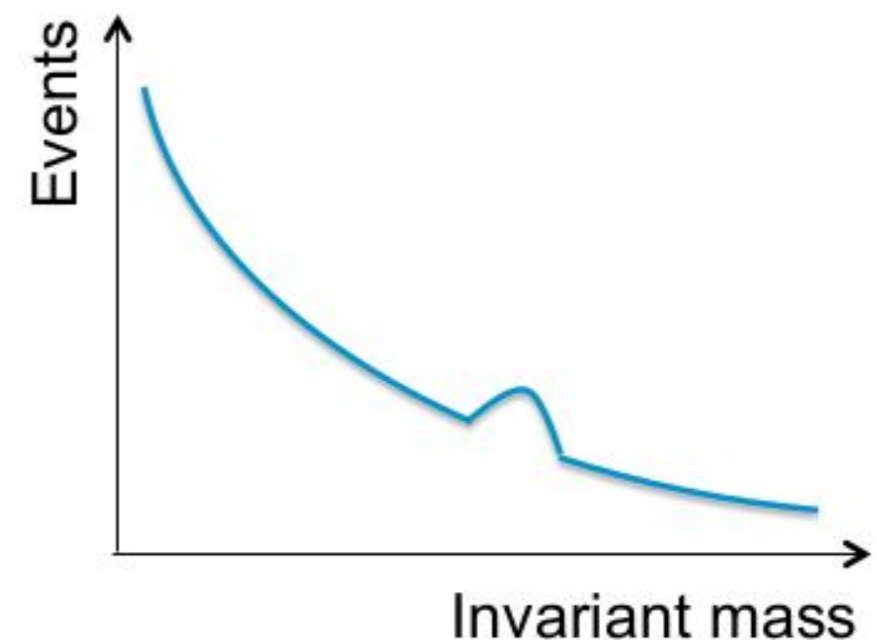
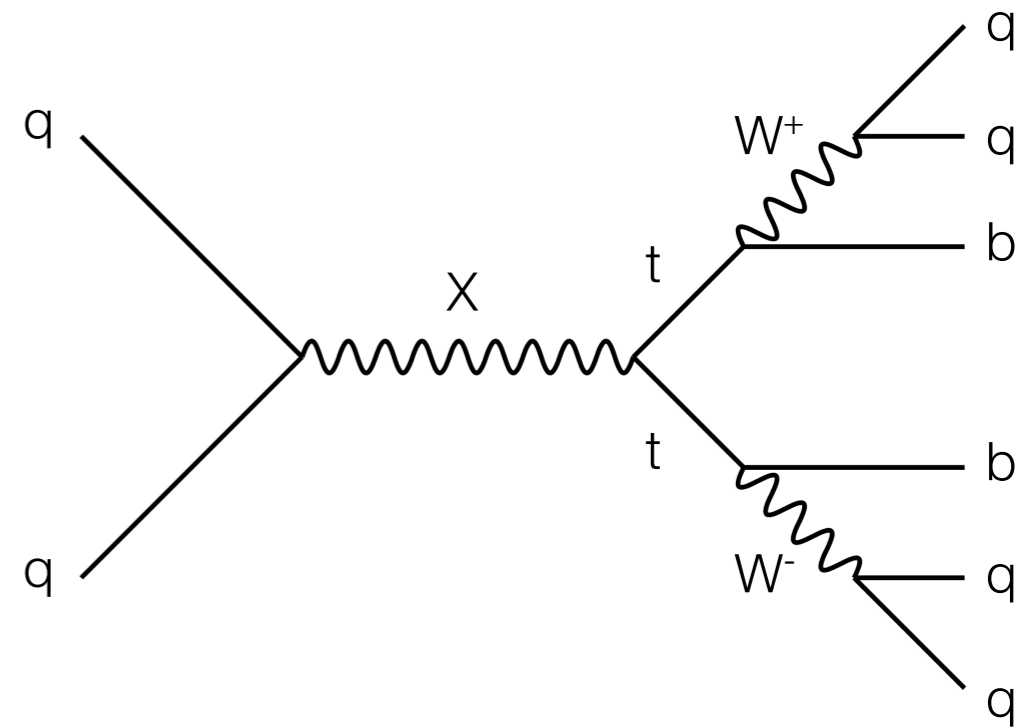


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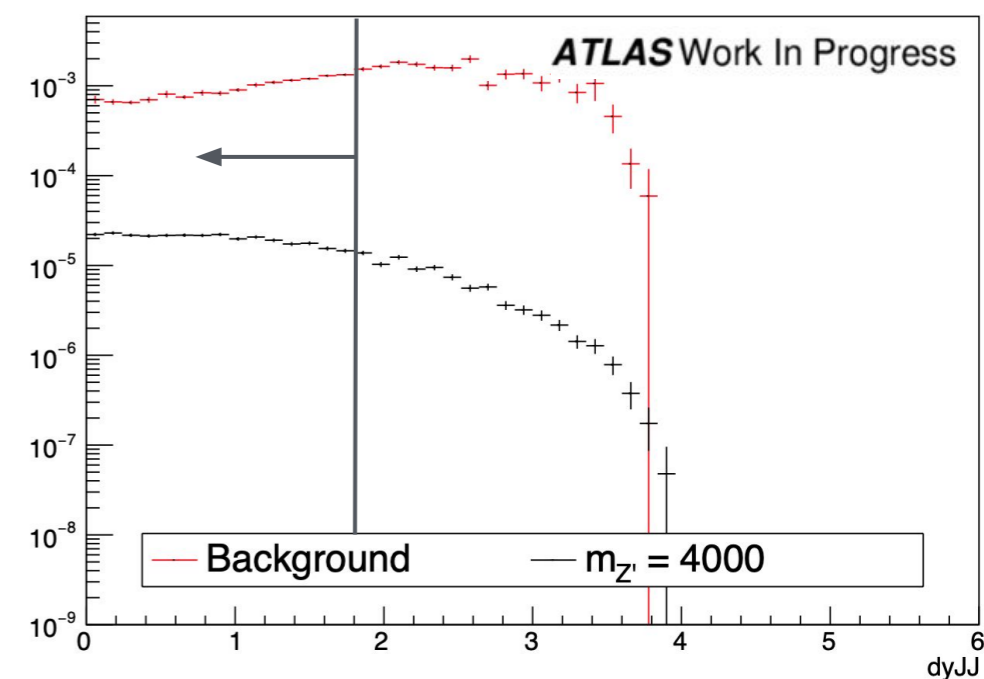
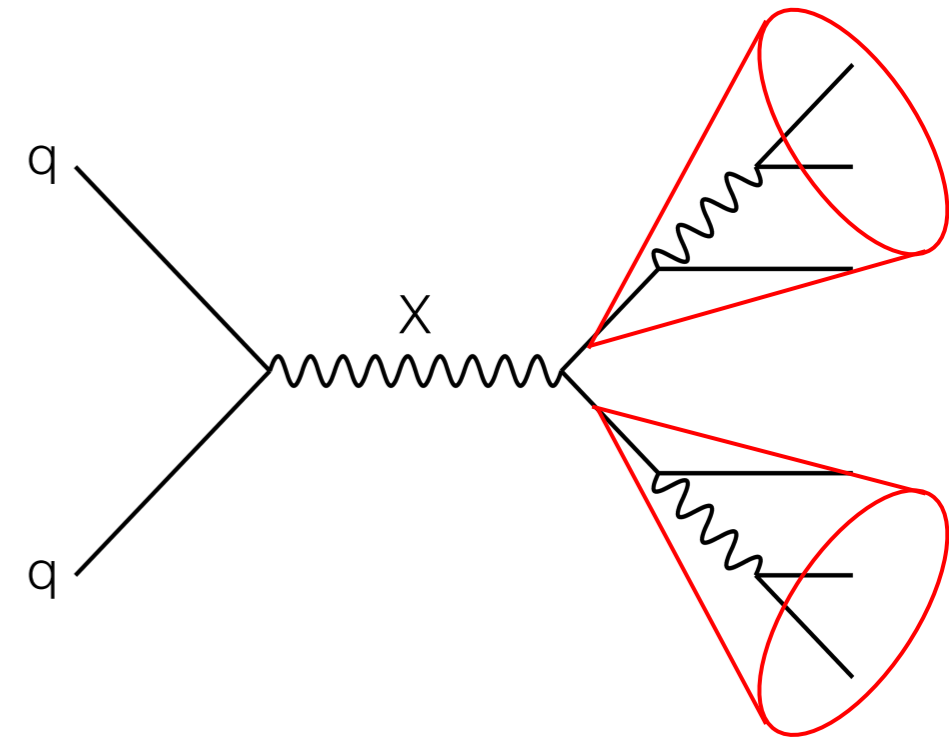
BEYOND STANDARD MODEL PHYSICS

- Looking for a particle decaying into two **top quarks** in the hadronic final state
 - $X \rightarrow tt \rightarrow bqq+bqq$
- E.g. Z' mediator
 - Arise from **extensions** of the **electroweak symmetry** in many different models
 - [Topcolor assisted technicolor](#)
- Looking for a **bump** in the invariant mass spectrum of the decay products of the two top quark candidates



OBJECT AND EVENT SELECTION

- Single jet trigger with $p_T > 460$ GeV
- Two **large radius anti-kt jets** ($R=1$) with
 - $p_{T,J1} > 500$ GeV and $p_{T,J2} > 350$ GeV
 - $d\phi(J1,J2) > 1.6$ (back-to-back)
 - $dy(J1,J2) < 1.8$ (remove SM t-channel)
- Leading and subleading large radius jets are top-tagged (**DNN top-tagger 80% WP**)
- One or both of the leading large radius jets should be matched to a b-tagged variable radius track jet (**DL1 77% WP**)
 - 1b and 2b signal region



TOP TAGGING

- Deep Neural Network (DNN) with input variables
 - Jet kinematics: m^{comb}, p_T
 - Energy corr. ratios: e_3, C_2, D_2
 - N-subjettiness: $\tau_1, \tau_2, \tau_3, \tau_{21}, \tau_{32}$
 - Splitting measures: $\sqrt{d_{12}}, \sqrt{d_{23}}$
 - Minimum pairwise invariant mass: Q_w

TOP TAGGING

- Deep Neural Network (DNN) with input variables

- Jet kinematics:

 $\mathbf{m}^{\text{comb}}, p_T$

- Energy corr. ratios:

 e_3, C_2, D_2

- N-subjettiness:

 $\tau_1, \tau_2, \tau_3, \tau_{21}, \tau_{32}$

- Splitting measures:

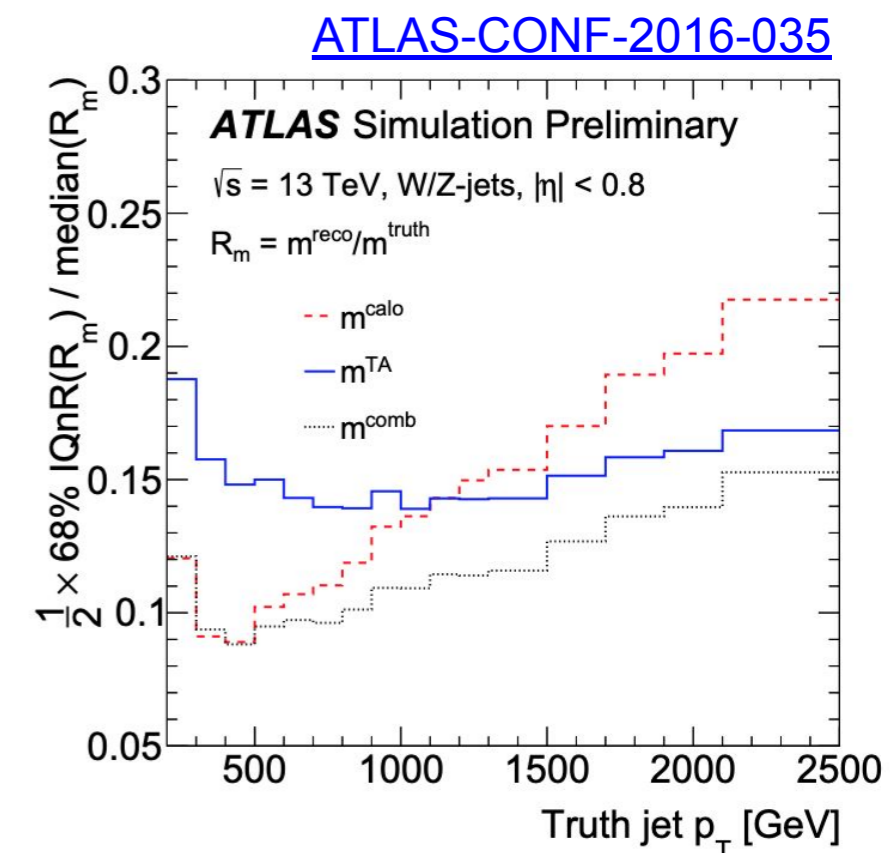
 $\sqrt{d_{12}}, \sqrt{d_{23}}$

- Minimum pairwise invariant mass:

 Q_W

- $m^{\text{comb}} = a \cdot m^{\text{calo}} + b \cdot m^{\text{TA}}$

- Combined jet mass



TOP TAGGING

- Deep Neural Network (DNN) with input variables

- Jet kinematics:

$$\mathbf{m}^{\text{comb}}, p_T$$

- Energy corr. ratios:

$$e_3, C_2, D_2$$

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$$\tau_1, \tau_2, \tau_3, \tau_{21}, \boldsymbol{\tau}_{32}$$

- Splitting measures:

$$\sqrt{d_{12}}, \sqrt{d_{23}}$$

- Minimum pairwise invariant mass:

$$Q_W$$

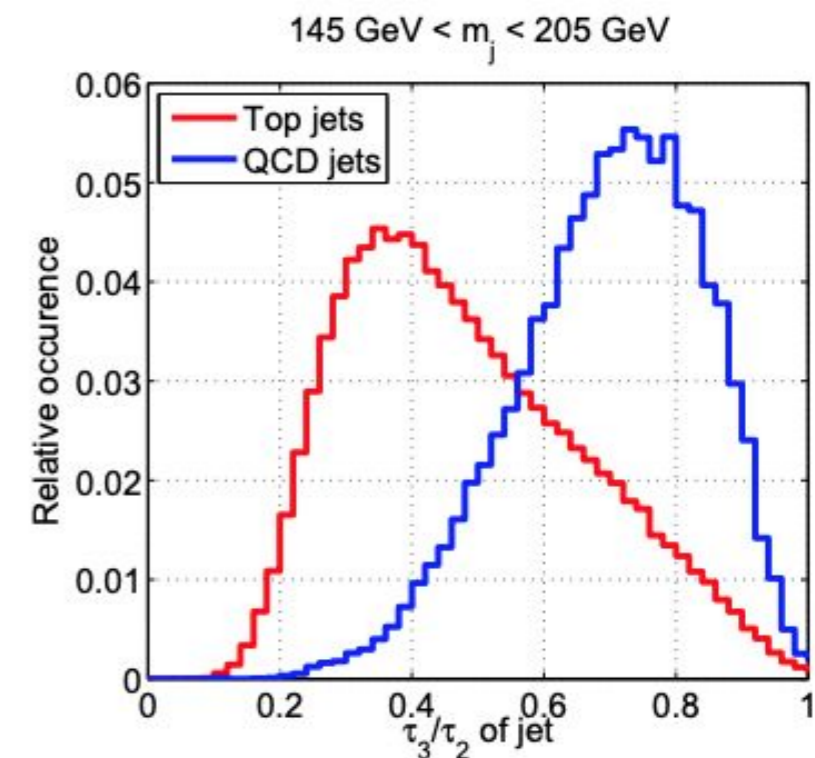
[arXiv:1011.2268v3](https://arxiv.org/abs/1011.2268v3)

- $m^{\text{comb}} = a \cdot m^{\text{calo}} + b \cdot m^{\text{TA}}$

- Combined jet mass

- $\tau_{32} = \tau_3 / \tau_2$

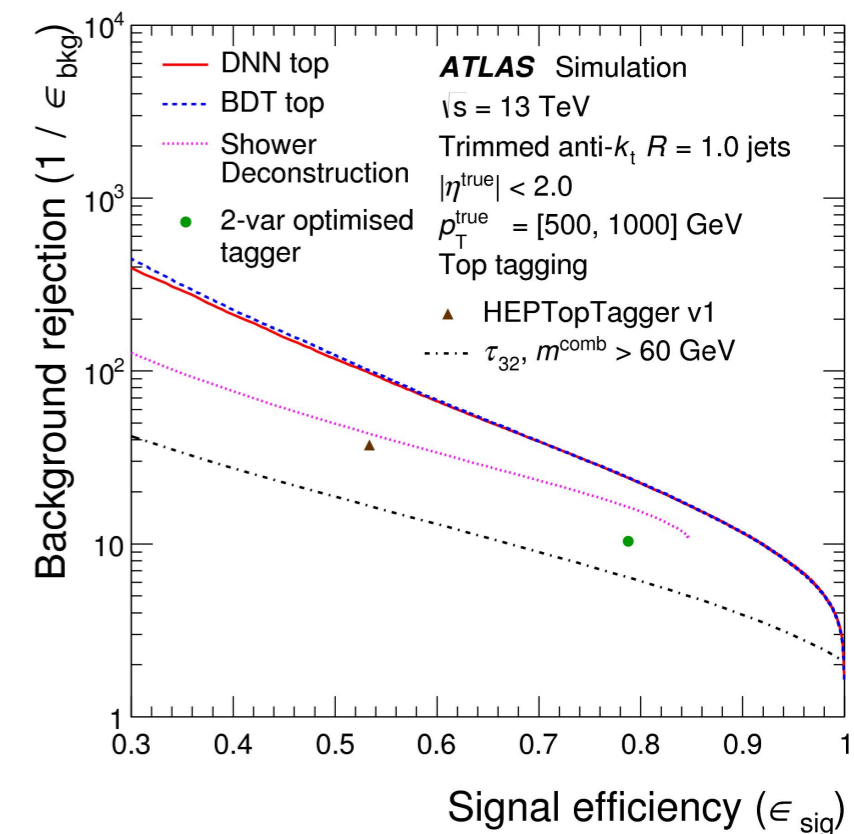
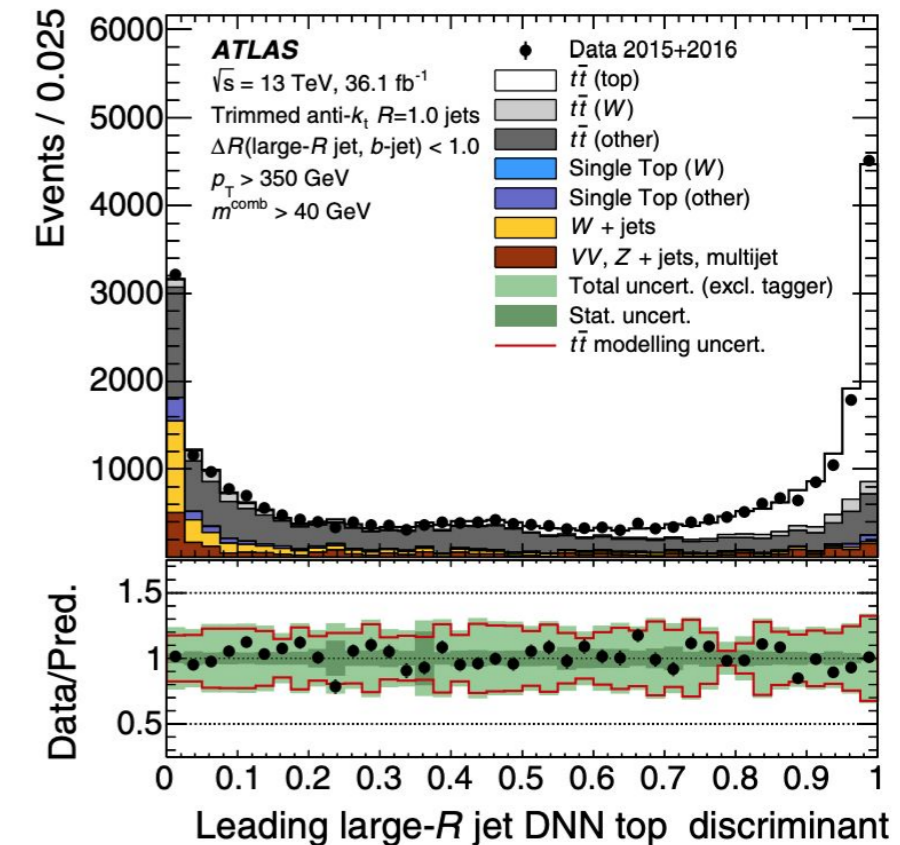
- How likely is the jet to have three prongs compared to two



TOP TAGGING

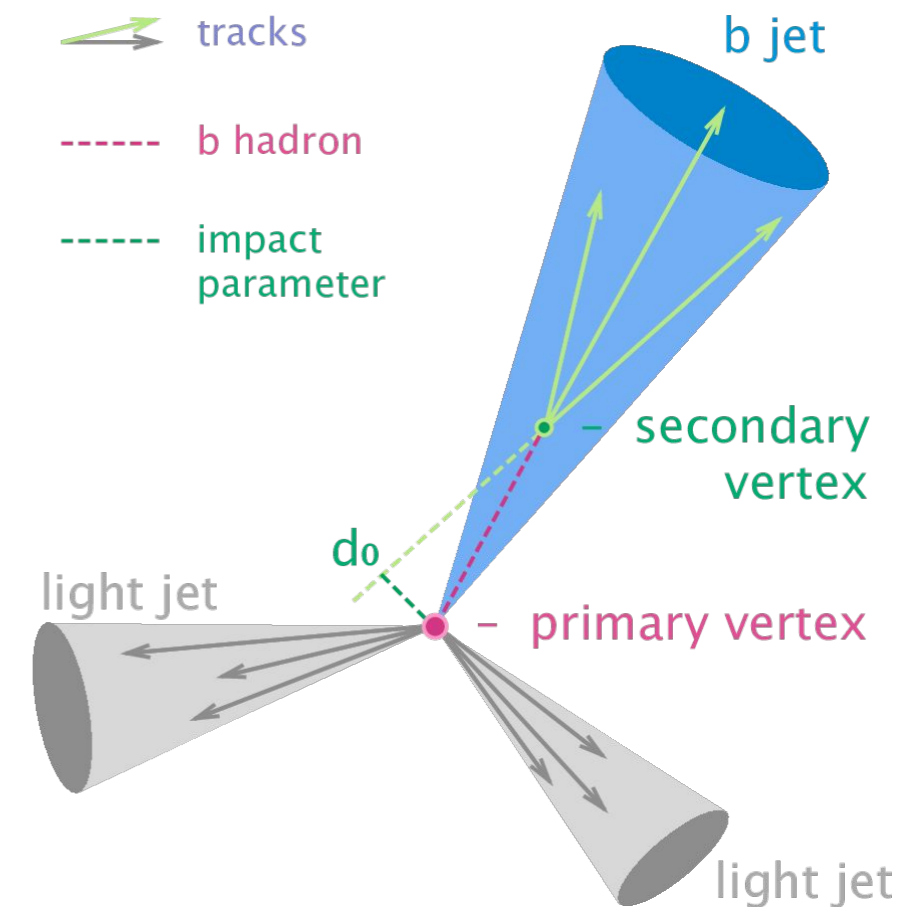
- Discriminant cut varied as a function of p_T to always have a **signal efficiency of 80%**
- The DNN tagger is **2x better** than the simple tagger based on m^{comb} and τ_{32} cuts
- BDT tagger perform similarly as expected
- This analysis is one of the **first** to use the DNN top tagger
 - Training DNN at high p_T
 - Deriving uncertainty

[Eur. Phys. J. C 79 \(2019\) 375](#)



B TAGGING

- B-hadrons have certain **characteristics** which can be used to tag a jet as coming from a b-quark
 - **Impact parameter** of tracks
 - **Displaced vertices** reconstructed in the inner detector
- DL1
 - Deep learning **neural network** based on distinctive features of b-hadrons



BACKGROUND ESTIMATION

- Fit smoothly falling m_{tt} background with **function**:

$$f(x) = p_0(1 - x)^{p_1} x^{p_2+p_3 \log x + p_4(\log x)^2 + \dots}$$

- Tests were done on **asimov dataset** and pseudo-experiments
- Method used in several Exotics searches in ATLAS
- Pros
 - Does not need huge amount of Monte Carlo simulations
 - Smaller systematic uncertainties
- Cons
 - Is the expected background completely smooth?
 - **Spurious signal test**
 - Is it affected by a potential signal?
 - **Signal injection test**
 - Not possible to discover a broad signal

ASIMOV SAMPLE

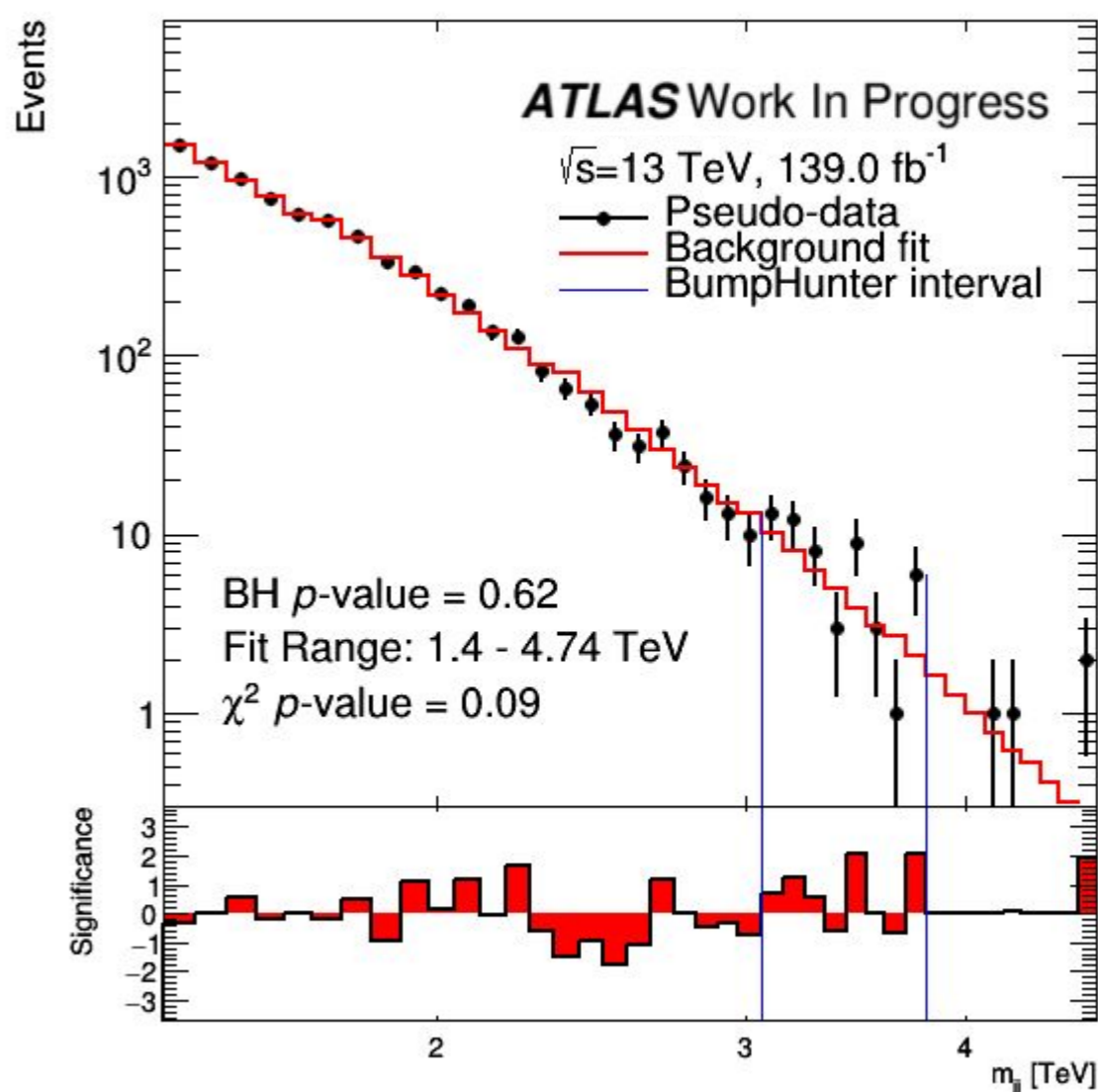
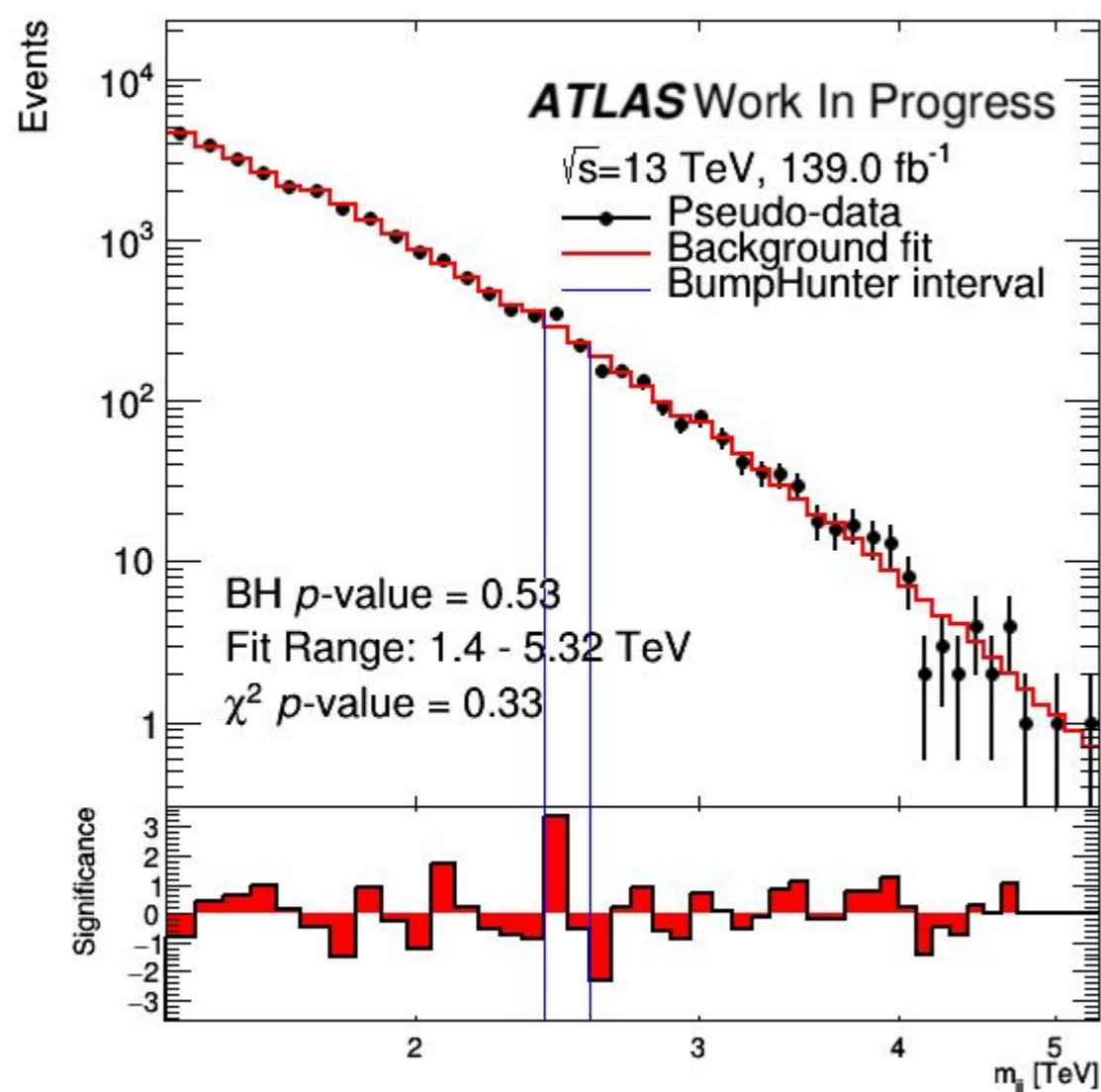
- **Dijet** samples
 - MC: Pythia8 pT-sliced samples
 - Good statistics at high m_{tt}
 - Data-driven (DD): ABCD method based on b- and top-tagging
 - Better description of dijet and good statistics at low m_{tt}
 - **Combined**: DD at low m_{tt} and corrected MC at high m_{tt}
 - Good statistics over full m_{tt} range
 - Stitch at 2410 GeV for 1bSR and 2730 GeV for 2bSR
- **Ttbar** samples
 - **MC**: All-hadronic tt and non-all-hadronic tt

FITTING PSEUDO-DATA

4 parameters

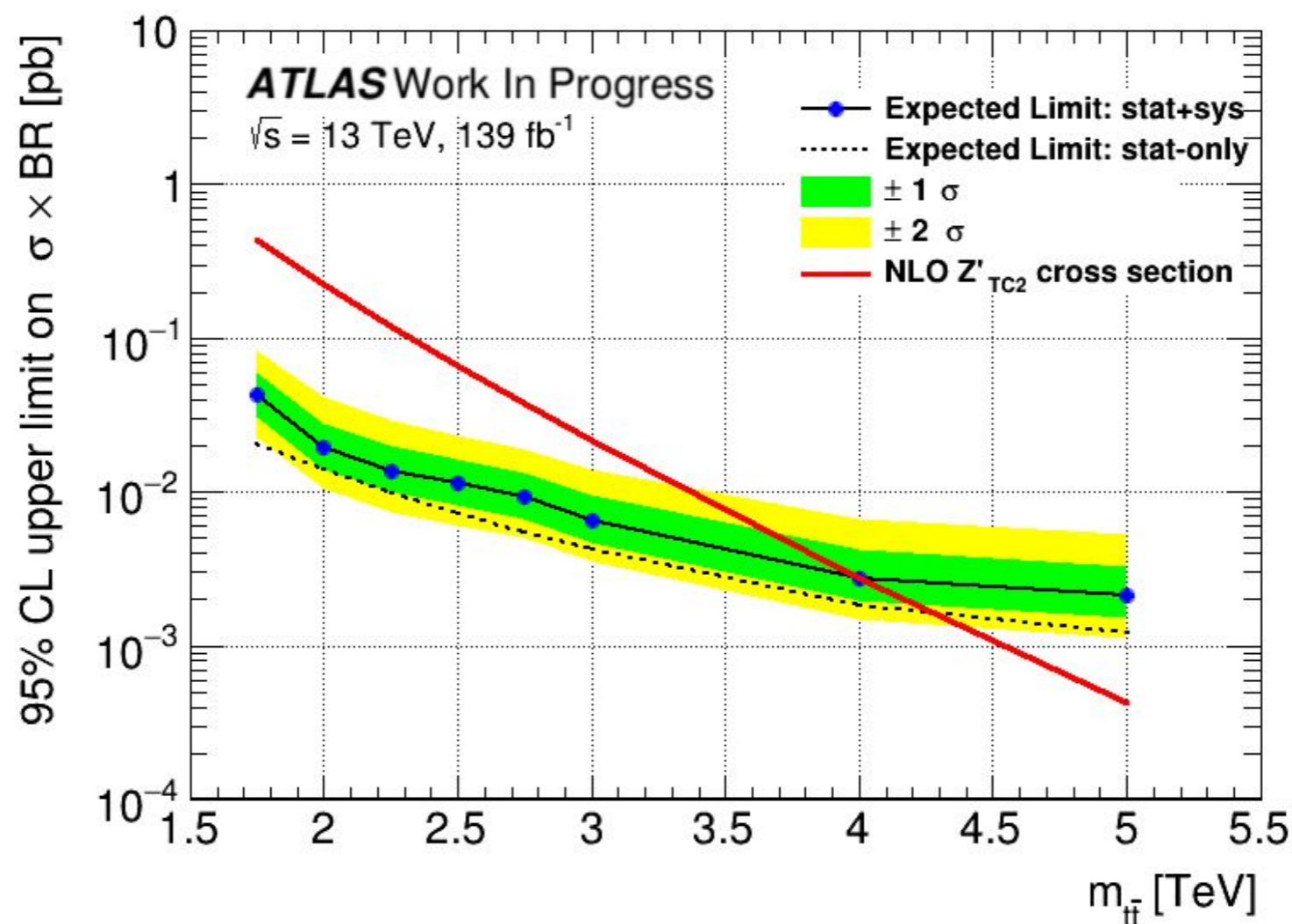
1b signal region

2b signal region



LIMIT SETTING

- Limit setting machinery in place
 - Expected limit on $Z' \rightarrow t\bar{t}$ is 4 TeV
 - Calculated with asimov sample



CONCLUSION AND OUTLOOK

- Improvements
 - **Better** top- and b-**tagging**
 - **Fit** instead of MC used for background estimation
 - Compared to previous [ttbar analysis](#) the **limit improves** from 3 TeV to 3.4 TeV when scaled to same integrated luminosity (36.1 fb^{-1})
- Plans
 - Result will be included in Heavy Resonance combination in ATLAS

BACK UP

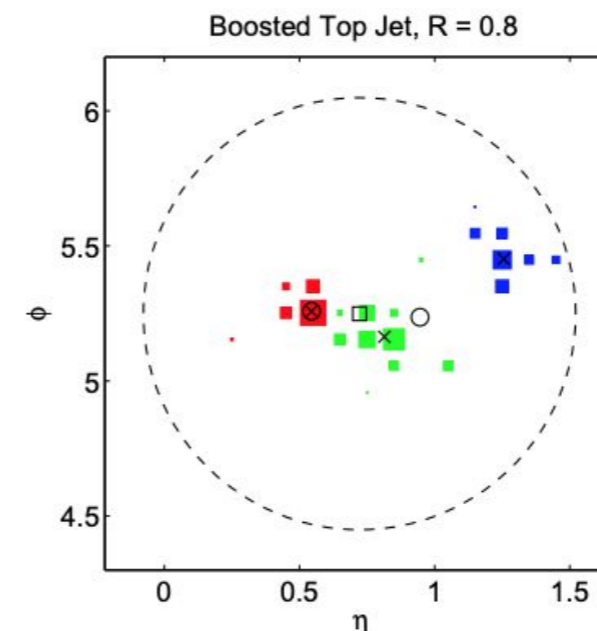
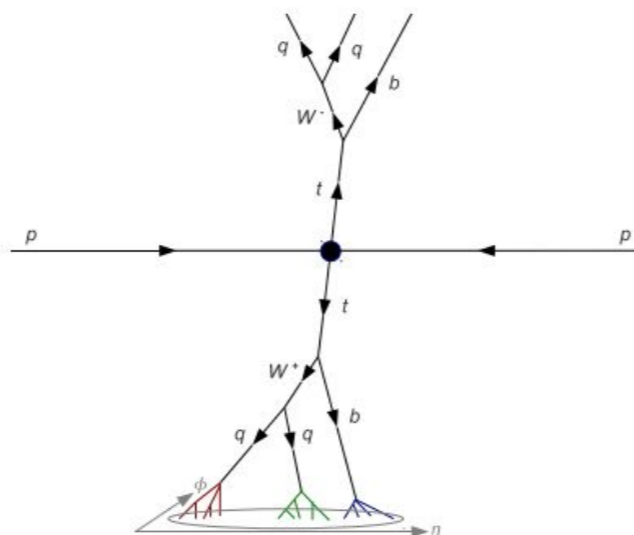
N-SUBJETTINESS

$$\tau_N = \frac{1}{d_0} \sum_k p_{T,k} \min \{ \Delta R_{1,k}, \Delta R_{2,k}, \dots, \Delta R_{N,k} \}. \quad (2.1)$$

Here, k runs over the constituent particles in a given jet, $p_{T,k}$ are their transverse momenta, and $\Delta R_{J,k} = \sqrt{(\Delta\eta)^2 + (\Delta\phi)^2}$ is the distance in the rapidity-azimuth plane between a candidate subjet J and a constituent particle k . The normalization factor d_0 is taken as

$$d_0 = \sum_k p_{T,k} R_0, \quad (2.2)$$

where R_0 is the characteristic jet radius used in the original jet clustering algorithm.



N-SUBJETTINESS

