Identifying hadronically decaying vector bosons and top quarks in ATLAS

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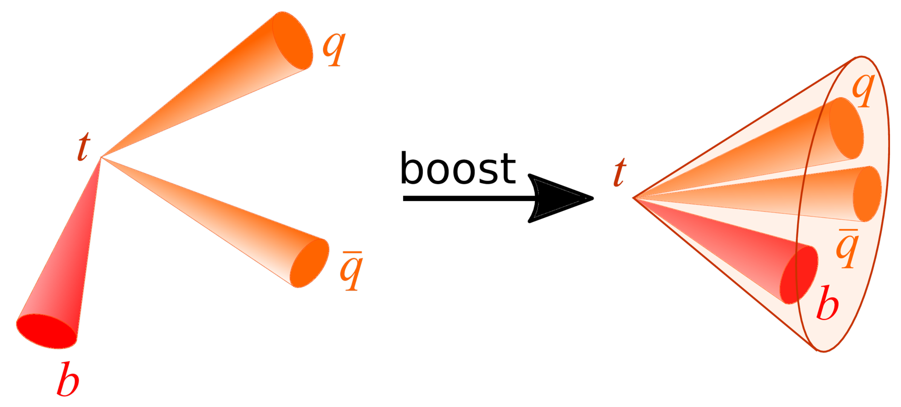
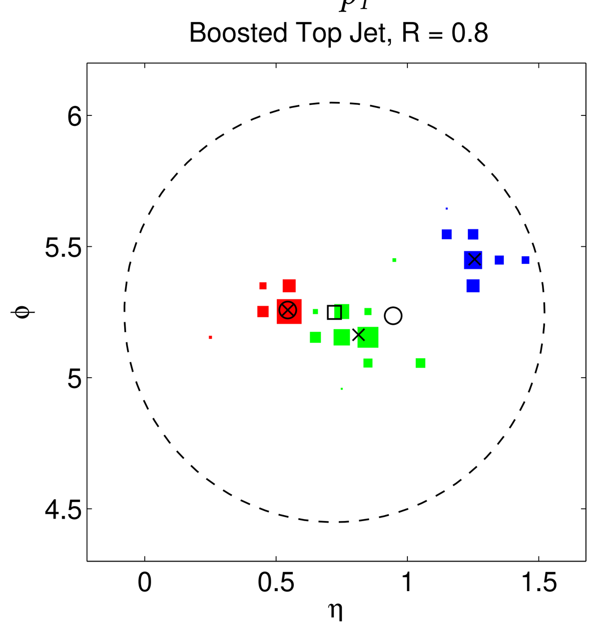
Introduction

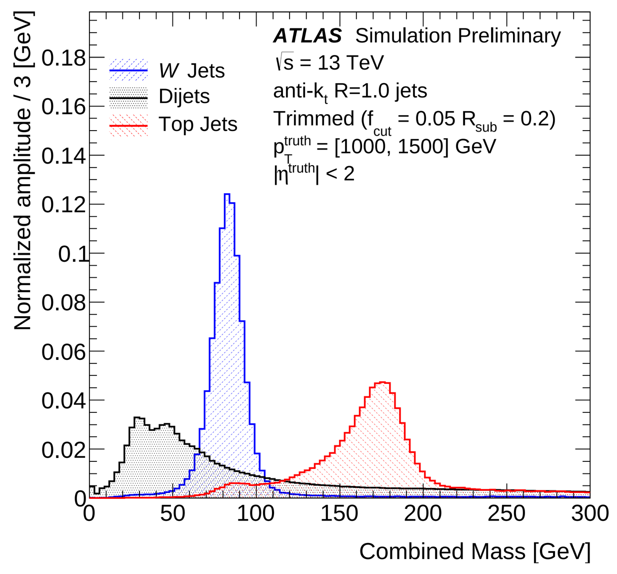
- Many measurements of the Standard Model and searches for new physics signatures involve studying top quarks and vector bosons in hadronic final states
- Quarks from the top & boson hadronic decays form **showers of particles – jets**
- Jets from decay more collimated at high energy – angular separation $\propto \frac{2M}{p_T}$
- Reconstruct **jets with large radius** (R) to capture decay products





Top jet 3-prong structure [1]

- **Boosted tagging** – use of large-R **jet substructure** to discriminate tops, W's, etc. from multijet background – light-quark/gluon jets
  - Energy patterns in the jet, multi-prong structure
  - Top(W) jets: 3(2) prongs
  - Light-quark/gluon jets: 1 prong with (typically) soft, wide-angle emissions
- Tagging algorithms optimization using Monte Carlo (MC) simulation. Check that MC describes data:
  - **Data/MC comparisons** of jet substructure observables in signal and background topologies
  - **Data/MC measurement of signal efficiency and background rejection**



Signal/background jet mass spectra [2]

Tagging algorithms investigated

- **"Simple" taggers** – selection on two substructure observables (high-level features)
- **Likelihood-based approach** – ***Shower Deconstruction*** (matrix element method) – probability of signal or background scenario based on a simplified showering model
- **Shape-based boosted decision tree & deep neural network** – extending approach of "simple" taggers, using multiple high-level features and their correlations
- **Topocluster-based deep neural network** – using fixed number of low-level features; momentum vectors of 10 highest-p_T jet constituent clusters

Boosted decision tree (BDT)

- Gradient boosting technique with bagging
- 500 trees in forest used, depth < 20
- 10(11) inputs for top(W) tagging
- Using *TMVA*

Deep neural network (DNN)

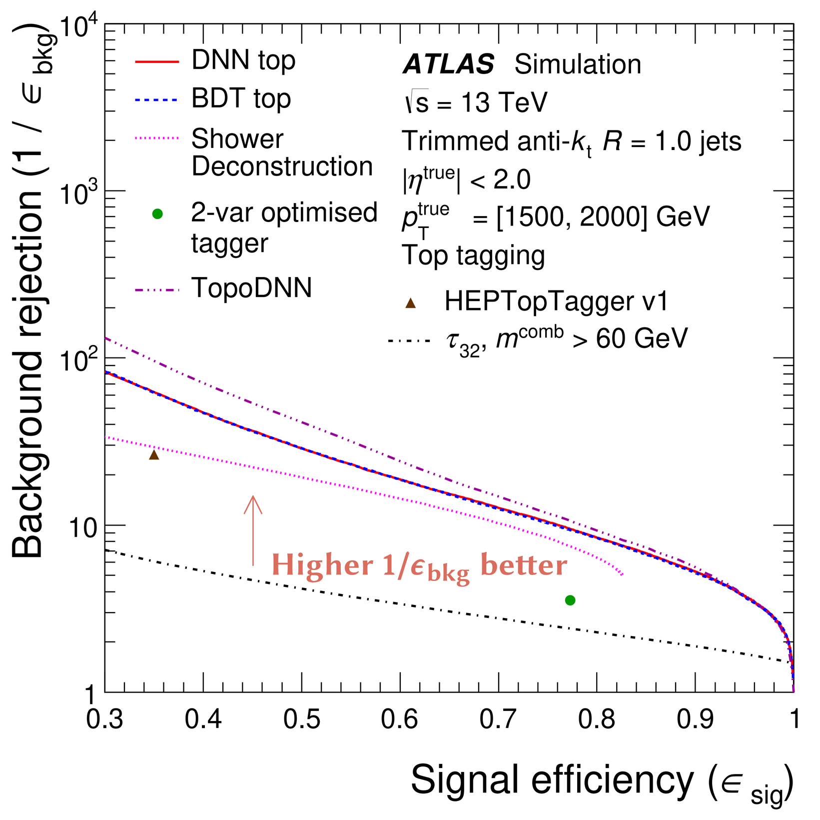
- Fully-connected feed-forward network, up to 5 hidden layers, up to 18 nodes in layer
- Adam optimizer, rectified linear unit activation function
- 13(12) inputs for top(W) tagging
- Using *Keras* with *Theano* as backend

- Training sample of jets flat in p_T for both ML techniques

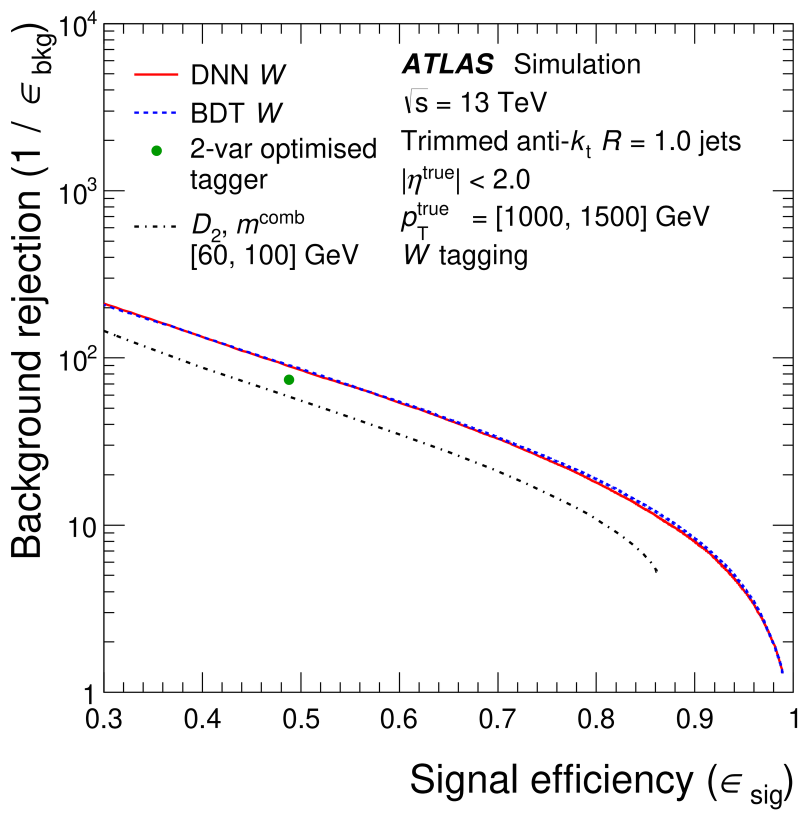
Topocluster-based deep neural network (TopoDNN)

- (p_T, η, ϕ) of 10 leading-p_T clusters, reduced dimensionality by rotating and flipping cluster vectors (rotational symmetry of the jet constituents)
- 4 hidden layers with up to 300 nodes
- Training sample jet p_T distribution signal-like (sub-sampling for light-quark/gluon jets)

Performance in MC simulation



Top tagging

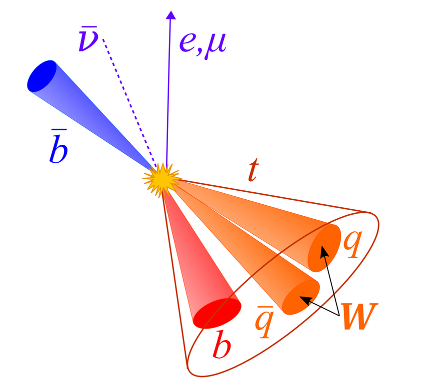


W tagging

- Machine learning (ML)-based algorithms outperform other investigated taggers
- TopoDNN at high p_T outperforms ML taggers using high-level features
- Larger performance gains by ML algorithms for top jets – more distinct decay structure

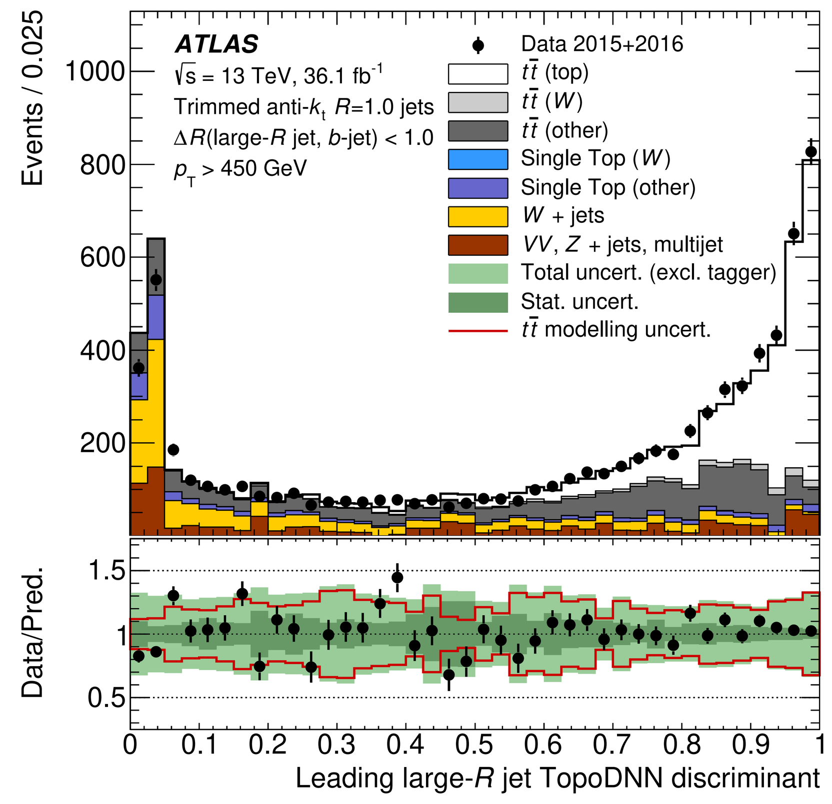
Signal efficiency measurement

- **Using boosted $t\bar{t}$ events with single lepton in final state**
- **Tag-and-probe approach**; very pure $t\bar{t}$ sample using leptonic top signature selection, probe the hadronically-decaying top
- **Top** jet (**W** jet) selection – require small-R b-jet **inside** (**outside**) large-R jet cone

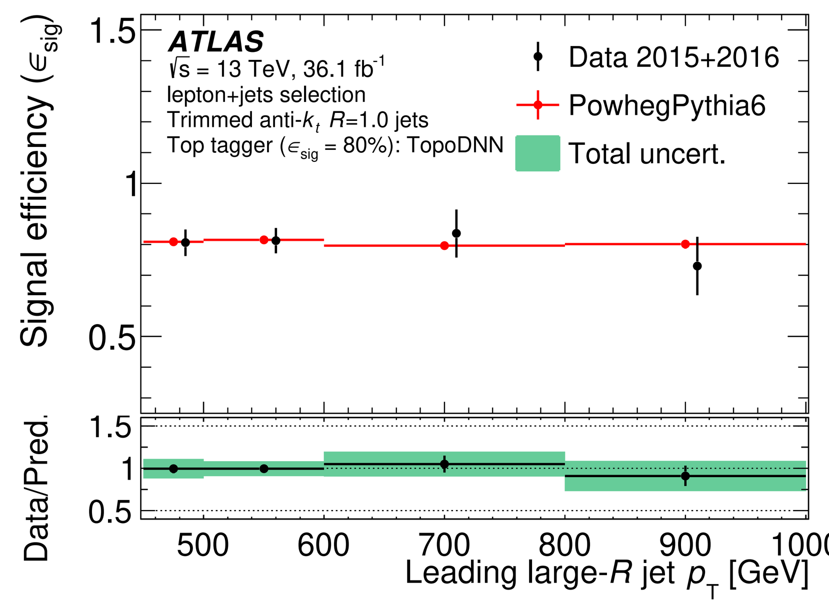


- **Signal efficiency definition in MC and data:**

$$\epsilon_{\mathrm{MC}} = \frac{N^{\mathrm{tagged}}_{\mathrm{truth\ top}/W}}{N^{\mathrm{total}}_{\mathrm{truth\ top}/W}} \qquad \epsilon_{\mathrm{data}} = \frac{N^{\mathrm{tagged}}_{\mathrm{data}} - N^{\mathrm{tagged}}_{\mathrm{truth\ non\text{-}top}/W}}{N^{\mathrm{total}}_{\mathrm{data}} - N^{\mathrm{total}}_{\mathrm{truth\ non\text{-}top}/W}}$$



TopoDNN classifier data/MC

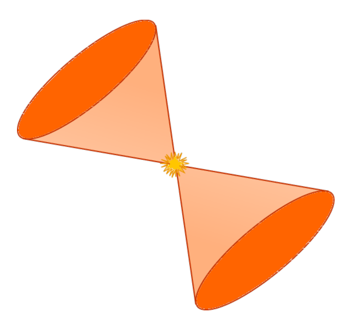


TopoDNN signal efficiency

Background rejection measurement

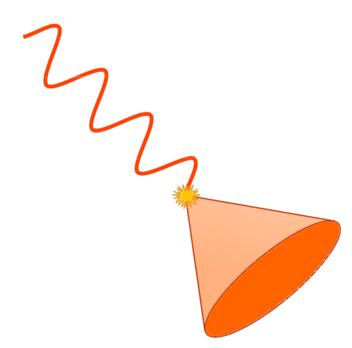
Dijet events

- Gluon-enriched mixture of jets at low p_T

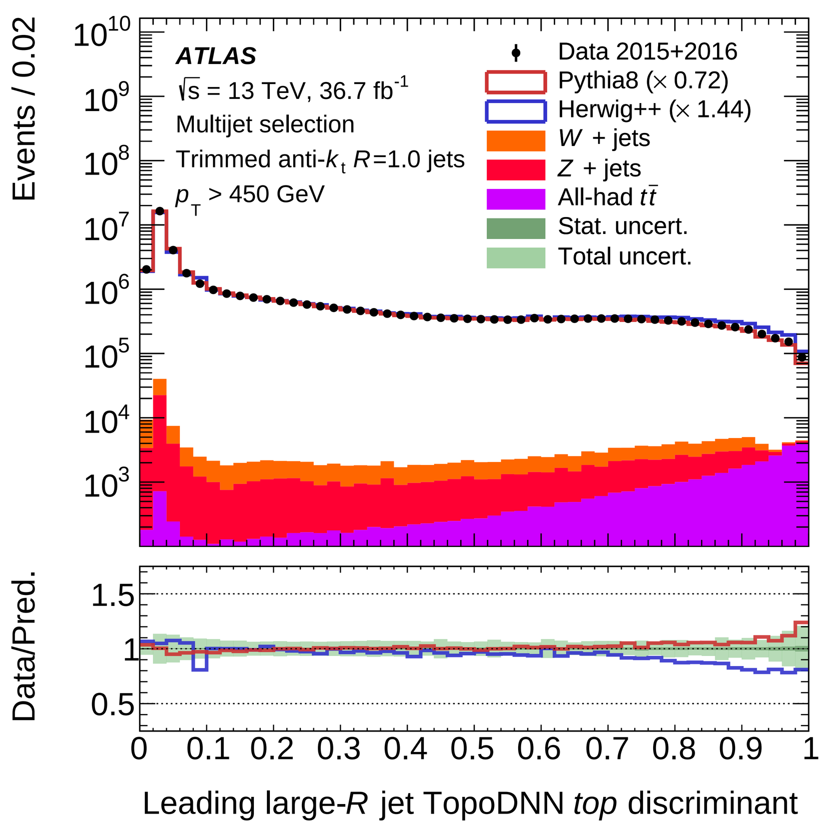


γ+jet events

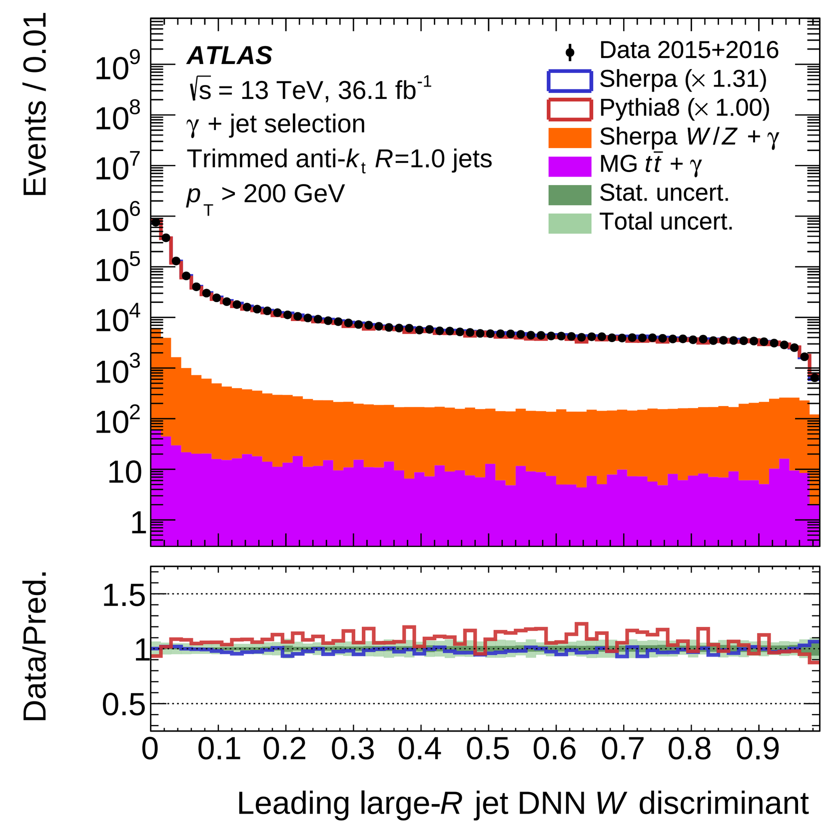
- Light-quark jets dominant contribution



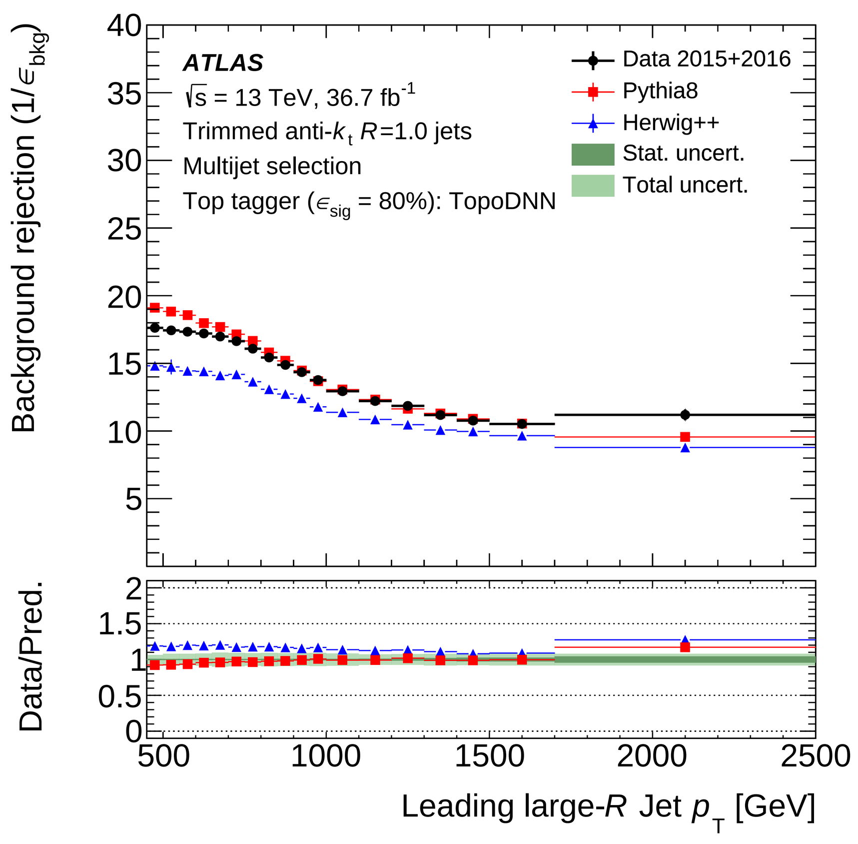
- **Background rejection in MC and data:** $\frac{1}{\epsilon_{\mathrm{bkg}}} = \frac{N^{\mathrm{total}}}{N^{\mathrm{tagged}}}$



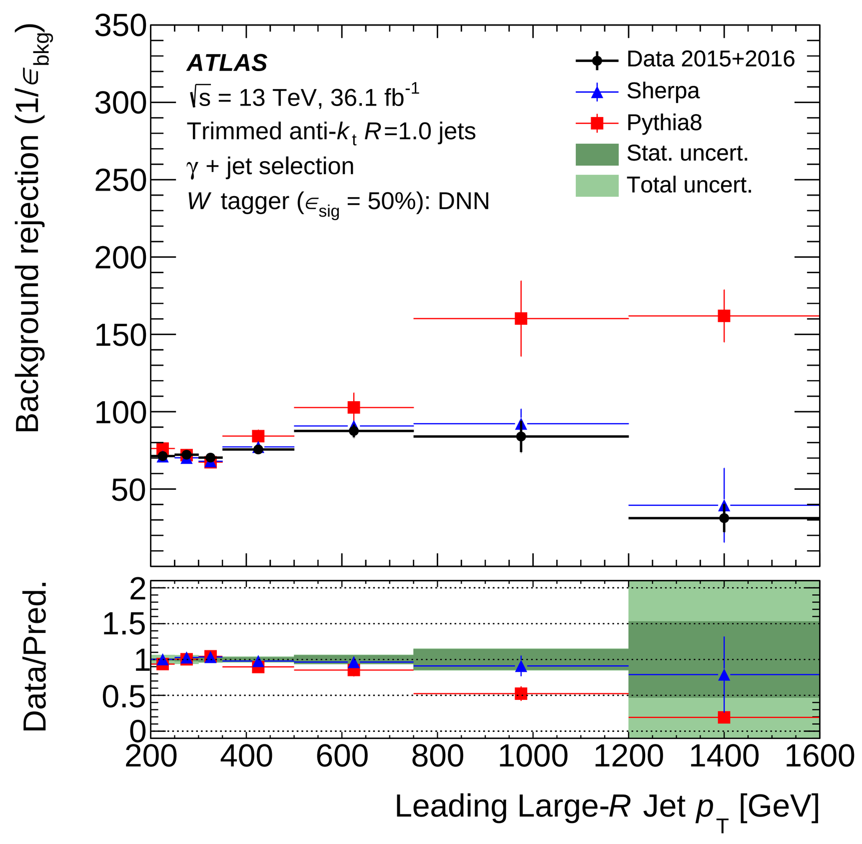
TopoDNN classifier data/MC – dijet events



DNN W classifier data/MC – γ+jet events



TopoDNN bckg. rejection – dijet events



DNN W bckg. rejection – γ+jet events

Conclusions

- First measurement of signal efficiency and background rejection for ML-based top/W tagging using Run-II data
- Signal efficiency measurements dominated by $t\bar{t}$ modelling uncertainties
- First top/W tagging background rejection measurement in γ+jet topology
  - Allows measurement of rejection rates at much lower leading jet p_T compared to dijet events
  - Probing different light-quark/gluon jet sample composition
- Some tension in dijet modelling by HERWIG++ and γ+jet by PYTHIA8

References

[1] Jesse Thaler and Ken Van Tilburg. Identifying boosted objects with N-subjettiness. *JHEP*, 03:015, 2011.
[2] ATLAS Collaboration. Performance of Top Quark and W Boson Tagging in Run 2 with ATLAS. (ATLAS-CONF-2017-064), 2017.
[3] ATLAS Collaboration. Performance of top-quark and W-boson tagging with ATLAS in Run 2 of the LHC. 2018. arXiv: 1808.07858.