MODEL AGNOSTIC SEARCHES IN FINAL STATES WITH JETS AT ATLAS

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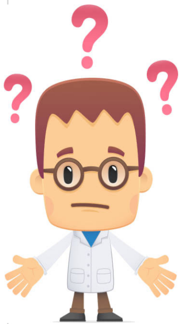
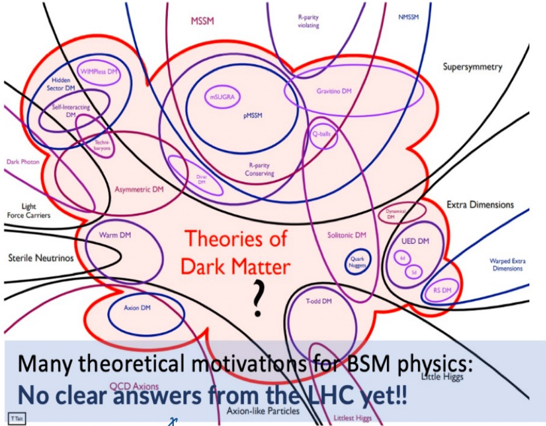
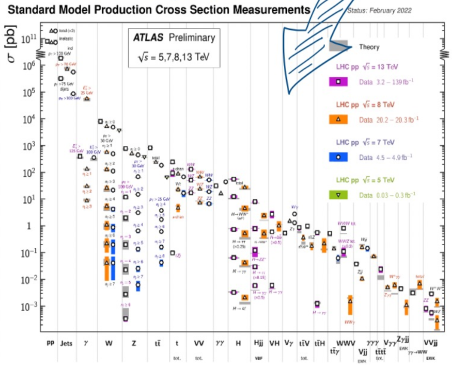
29° Symposium on Particles, String and Cosmology (PASCOS 2024), 09/07/2024, Quy Nhon

Introduction

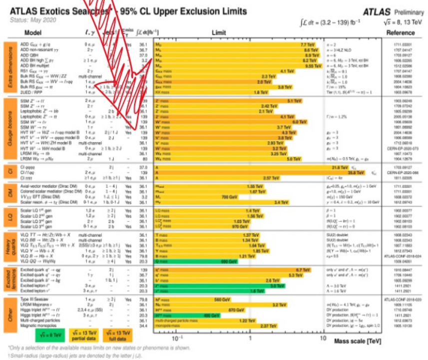




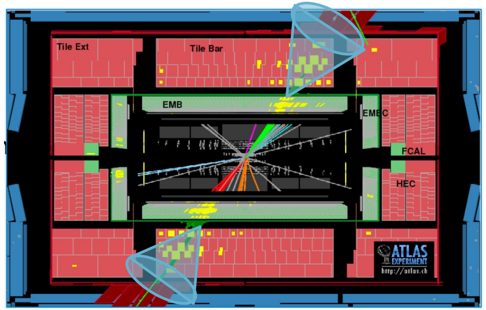
measurements



Searches

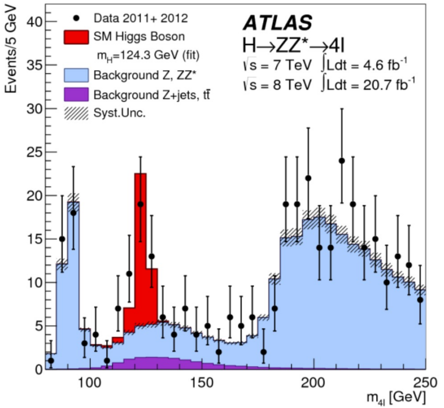


- Standard Model (SM) remarkably predictive of experimental results
  - discovery of the Higgs boson in 2012 by ATLAS and CMS
- Open questions: many Beyond Standard Model theories (Dark Matter, Gravity, Hierarchy problem ecc.)
- Search for new resonances decaying into hadronic final states jj (jets) → localized excesses (bumps) over expected background m_{jj}



Hadronization scheme of quarks/gluons

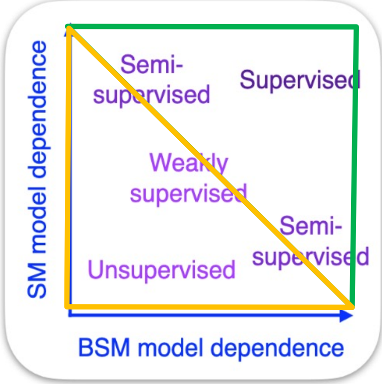
https://cds.cern.ch/record/1605823



To be or not to be model-dependent?

Model dependent approach:

- A new well motivated physics-scenario is chosen
- The search is maximized based on signal signatures (supervised machine learning methods)
- Unlikely to be sensitive to different process



Model independent approach:

- Minimal assumptions of signal properties
- Deviations from background-only hypothesis (methods often provided by Machine Learning)
- Not optimal as model-dependent, but more prone to generality

In this review

- Full Run 2 (2015-2018, 140 fb^{-1}) of LHC data (beside n. 4), pp centre of mass energy 13 TeV
- Results interpreted with 95% Confidence Levels

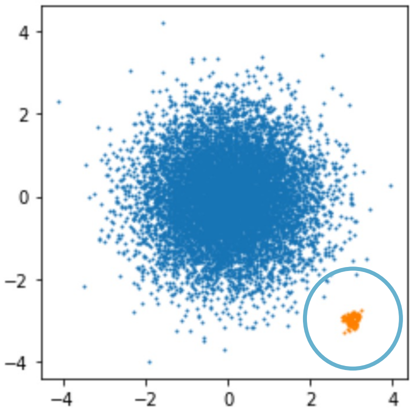
1. Search for new phenomena in dijet events using **quark tagging**
2. **Weakly-supervised anomaly detection** for resonant new physics in the dijet final state
3. **Anomaly detection** search for new resonances decaying into a Higgs boson and a generic new particle X in hadronic final states
4. Search for Low-Mass Dijet Resonances Using **Trigger Level Analysis**

Non supervised Anomaly Detection

- Anomaly Detection (AD) refers to Machine Learning (ML) techniques used to spot these outliers.

- Particle physics → Identification of features of detector data inconsistent with the expected background.

- Machine learning techniques exploited: semi-supervised (partial labels), <u>weakly-supervised</u> (noisy labels) and <u>unsupervised</u> (no labels)



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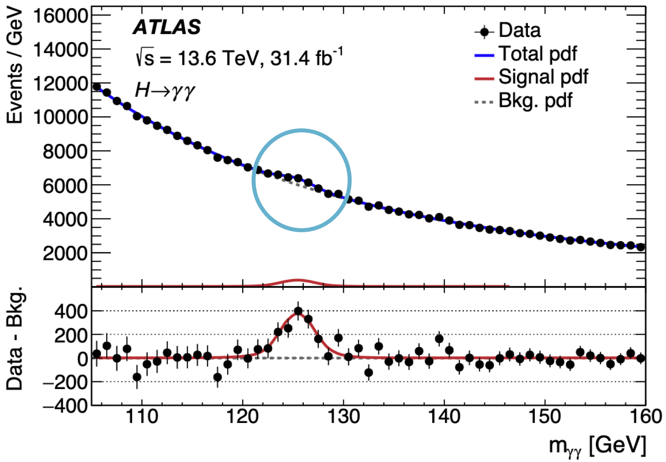
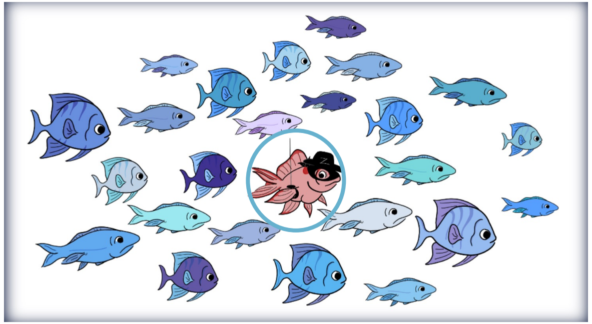


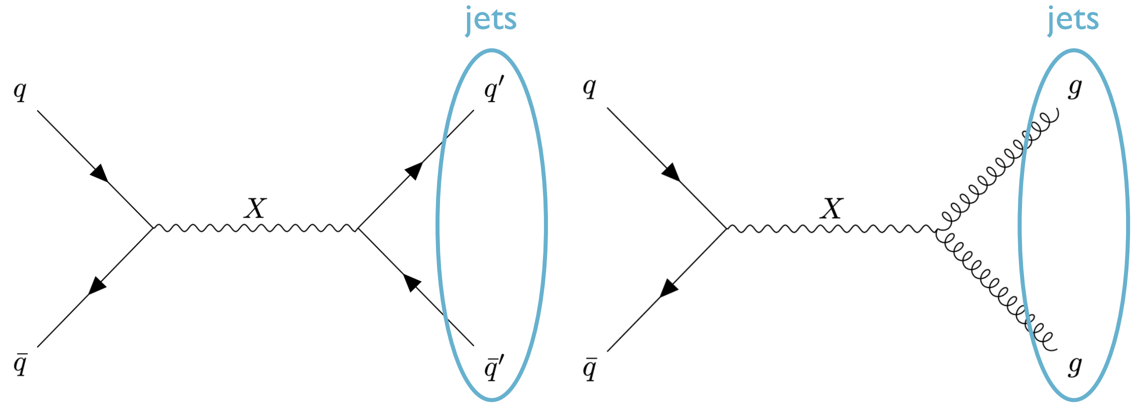


Search for new phenomena in dijet events using quark tagging

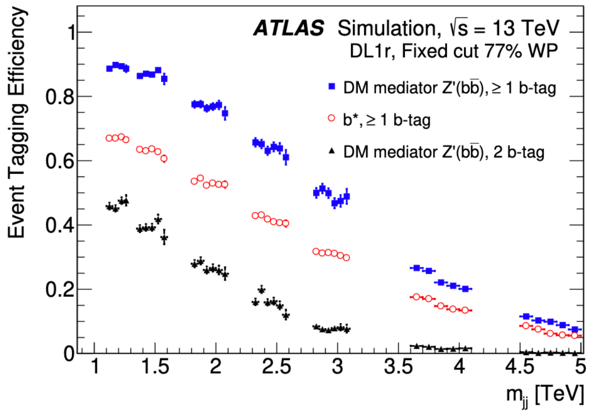
Search of new resonances in jet pairs

- Search for resonant decays of heavy BSM particles strongly coupled to quarks/gluons
  - m_{jj} spectrum ranges from 1.1 to 8 TeV
  - **3 signal regions**: Inclusive jets content and 1 or 2 b-jets required
  - Trigger efficiency cuts on jets kinematics, invariant mass and $y^* = \frac{y_1 - y_2}{2}$

- Results interpreted with many new physics scenarios, but also generic Gaussian-shaped narrow-resonance $G(m_X, \boldsymbol{\sigma}_X)$



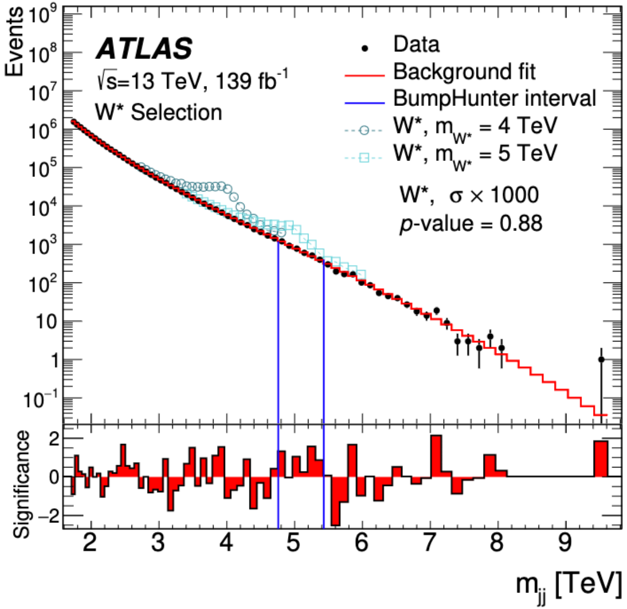
b-tagging: selection on discriminant variable from NN output

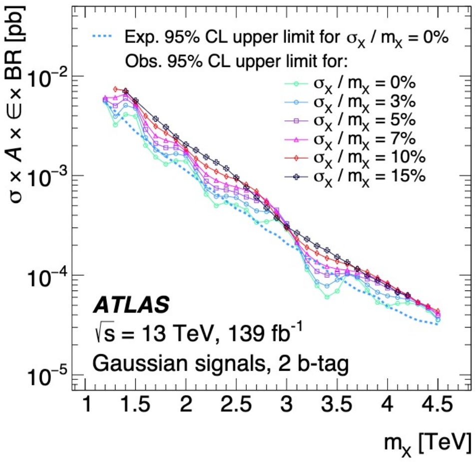


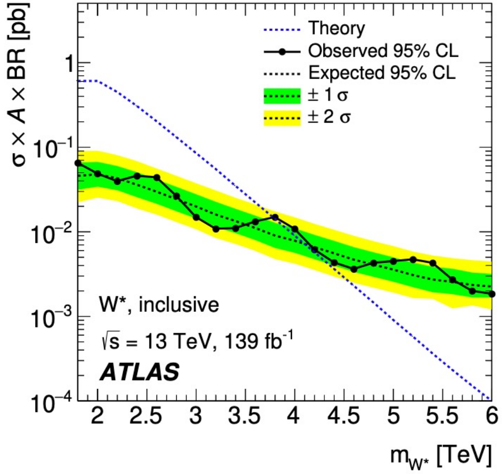
Results

JHEP03(2020)145

- Main QCD background estimated with smoothly falling fit functions on the m_{jj} distribution
- No significant deviation from background
  - Upper limits on cross sections estimated from fit considering the several signal hypothesis



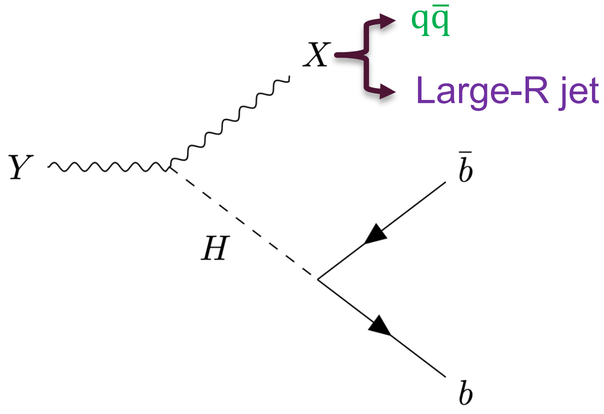


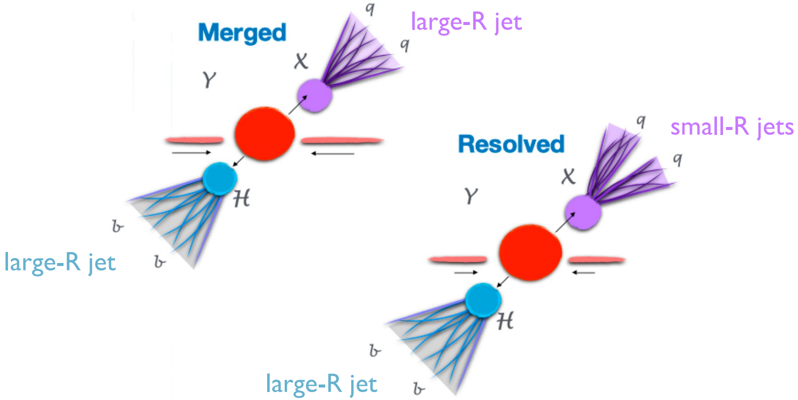


Anomaly detection search for new resonances decaying into a Higgs boson and a generic new particle X in hadronic final states

Y → XH overview

- Search for a heavy-mass resonance **Y** decaying in a Higgs boson (**H** → $b\bar{b}$) and a new particle **X** in the fully hadronic channel
- Mass range: m_Y in 1 - 6 TeV range, m_X in 65 - 3000 GeV range → boosted regime for H boson
- Signal regions:
  - Model dependent: 2-prong (X → $q\bar{q}$) boosted (m_X/m_Y < 0.3) and resolved (m_X/m_Y > 0.3)
  - Model independent: anomalous X hadronic decay in large-R jet

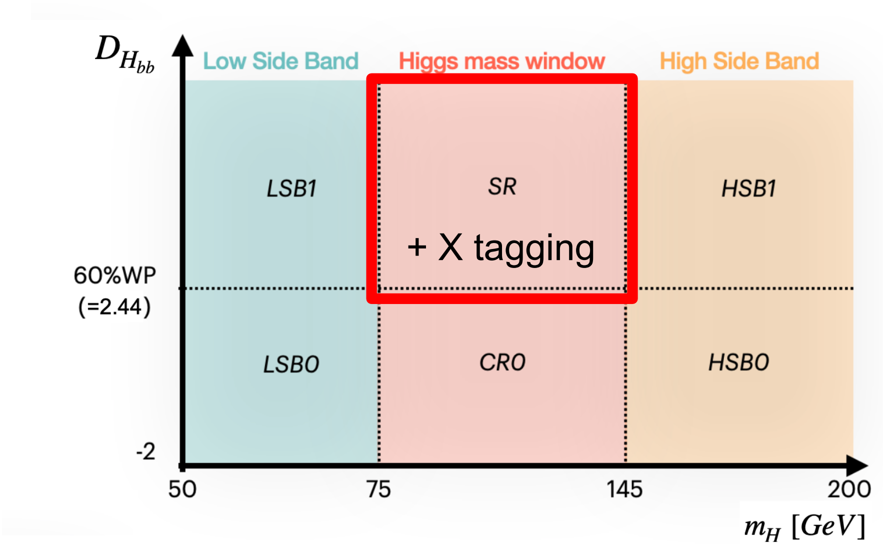


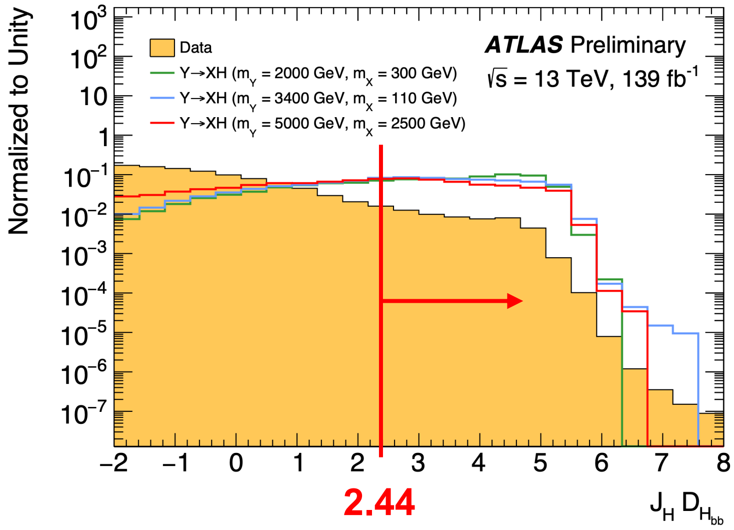


- Background is mainly composed of **QCD dijet events** (~97%), estimated fully data-driven (Machine Learning approach) → more in backup

Model independent signal region

- X and H candidate associated to pT-leading and –subleading jets, ambiguity resolved by $H \rightarrow b\bar{b}$ tagger based on Deep Neural Network
  - Discriminant $D_{H_{bb}}$ score computed from NN outputs per jet → H candidate chosen by highest score criteria
- H candidate is further tagged if $D_{H_{bb}}$ > 2.44
- X candidate tagged with discriminant from fully data-driven anomaly detection

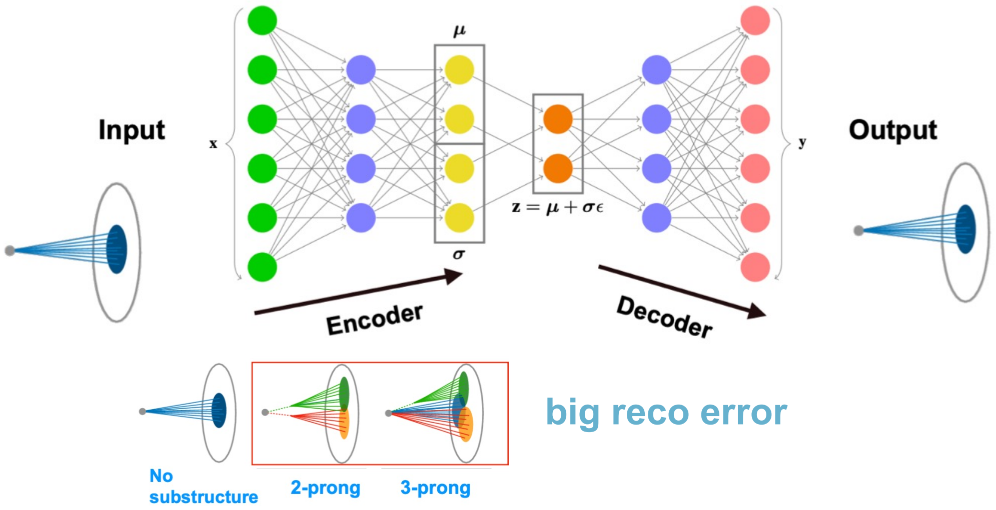


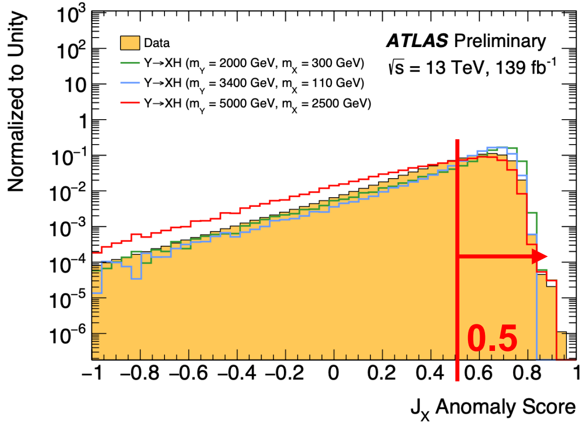


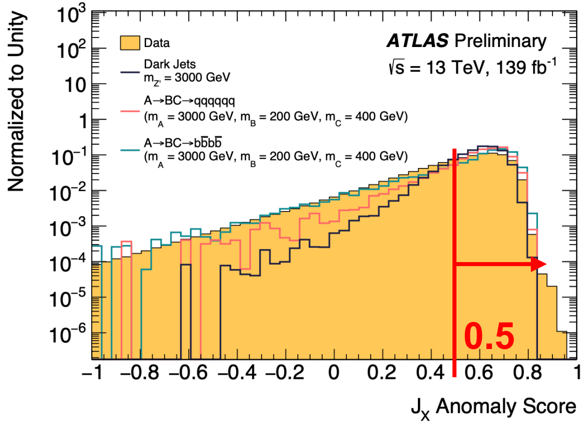
Anomaly detection X tagging

Phys.Rev.D 108 (2023) 052009

- Fully unsupervised (first in ATLAS) variational recurrent neural network (VRNN)
  - Trained over **constituents of jets** with p_T > 1.2 TeV modeled as sequence of four-vectors
- Anomaly score computed from VRNN output
  - Sensitive to alternative X decay hypothesis other than 2-prong (e.g. heavy flavor, three-prong and dark jet)



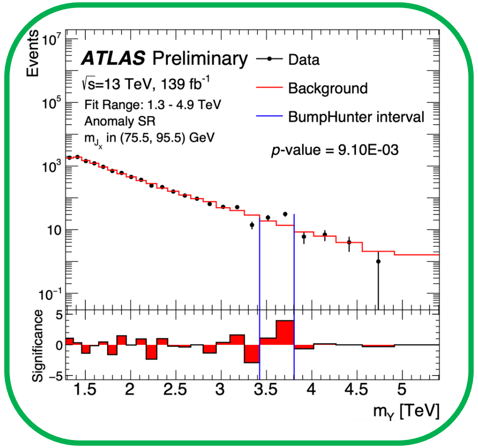


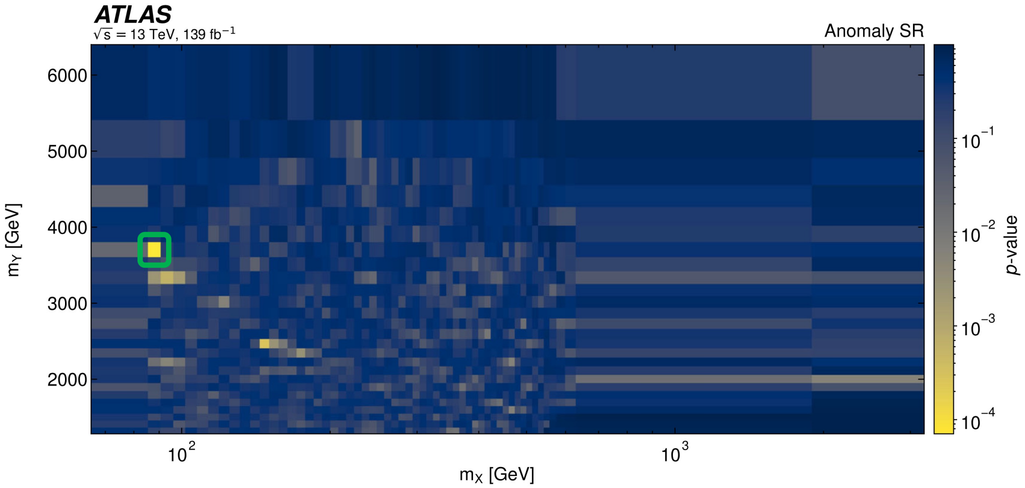


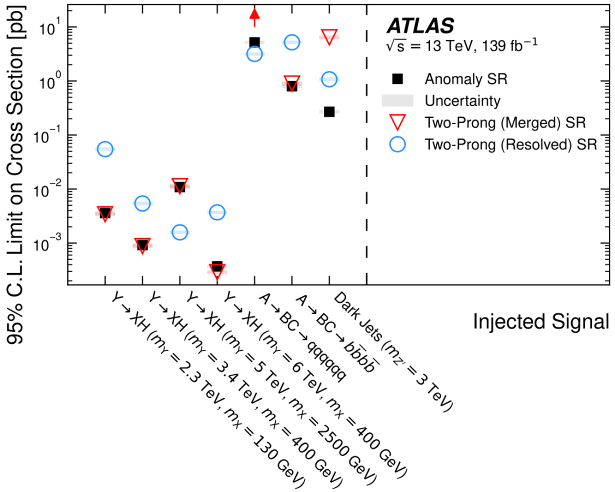
Results

Phys.Rev.D 108 (2023) 052009

- Fit performed on final state invariant mass distribution m_{jj} in SR of data, repeated several times in overlapping bins of the X candidate mass
- Calculated stat-only p-value to test compatibility with background only hypothesis
- Max deviation: 1.43σ global significance due to the several search regions defined





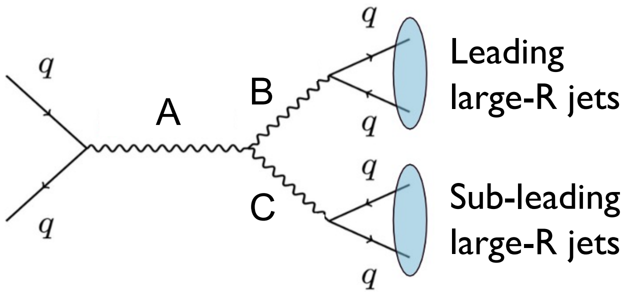


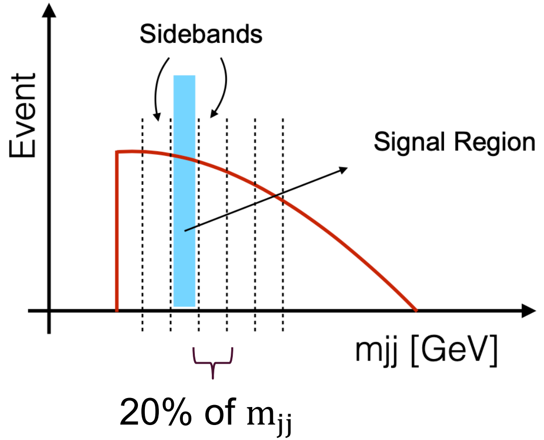
Weakly-supervised anomaly detection for resonant new physics in the dijet final state

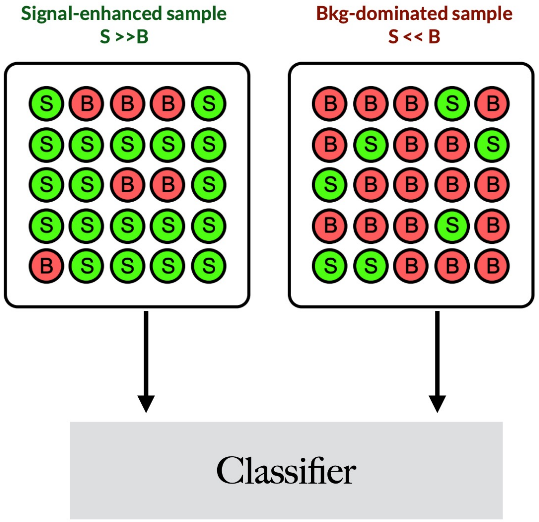
CWoLa hunting

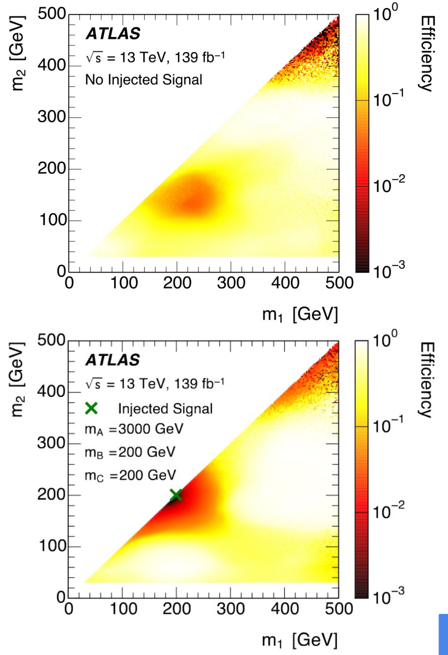
Phys. Rev. Lett. 125 (2020) 131801

- Classification Without Labels (CWoLa) method used for A → BC search
  - mass range: 1.1 - ~8 TeV
- 6 signal regions by m_{jj} splitting, jets mass > 30 and < 500 GeV, $|\Delta y| < 1.2$
- Classifier trained on two samples D1 and D2, mixtures of signal and background, to produce discriminant output
  - Input variables: m_1, m_2 (pT leading jets)





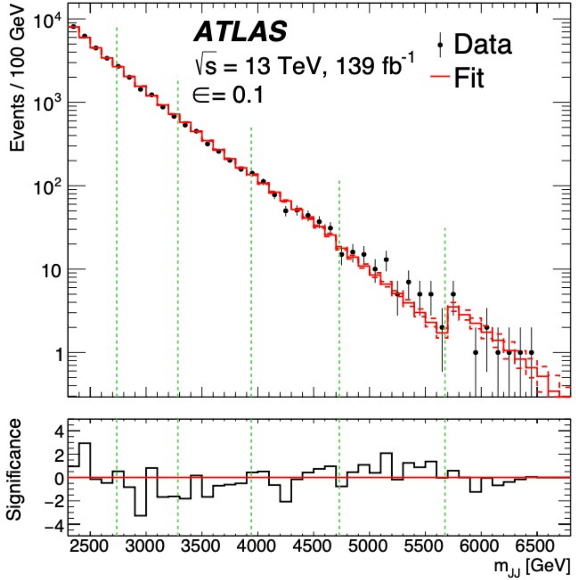




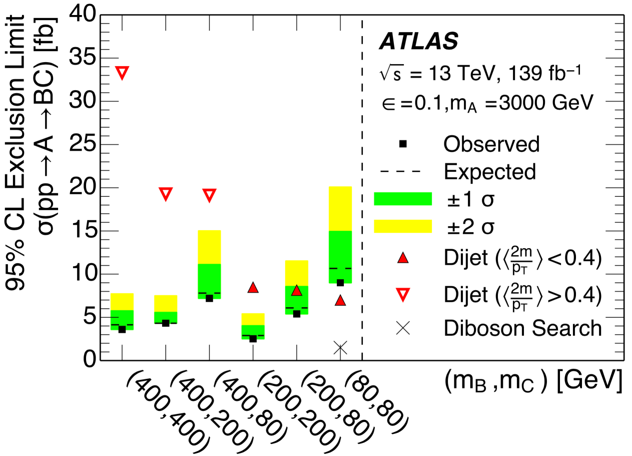
CWoLa hunting results

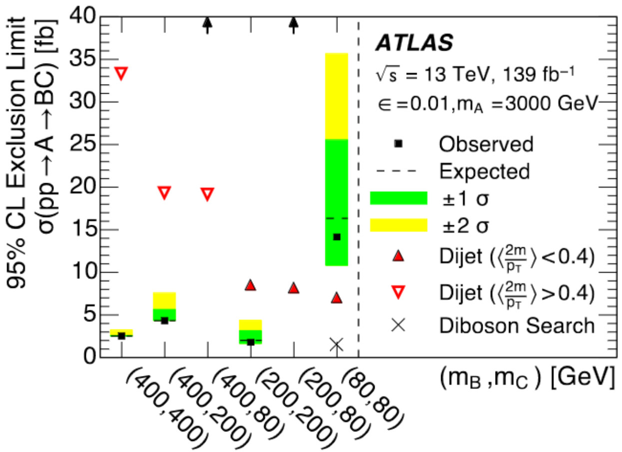
Phys. Rev. Lett. 125 (2020) 131801

- Upper limits on signal cross section, benchmark models compared with other diboson searches
  - Different values of signal selection efficiency, 0.1 and 0.01
  - QCD background estimation in SR done with functional fits
- CWoLa performs better when local signal-to-background ratio is high



Signal hypothesis: W' → WZ

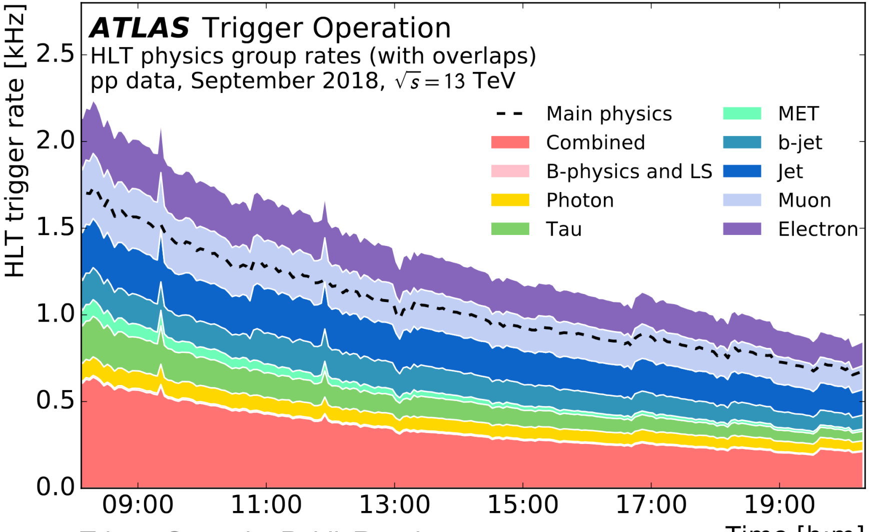




Search for Low-Mass Dijet Resonances Using Trigger Level Analysis

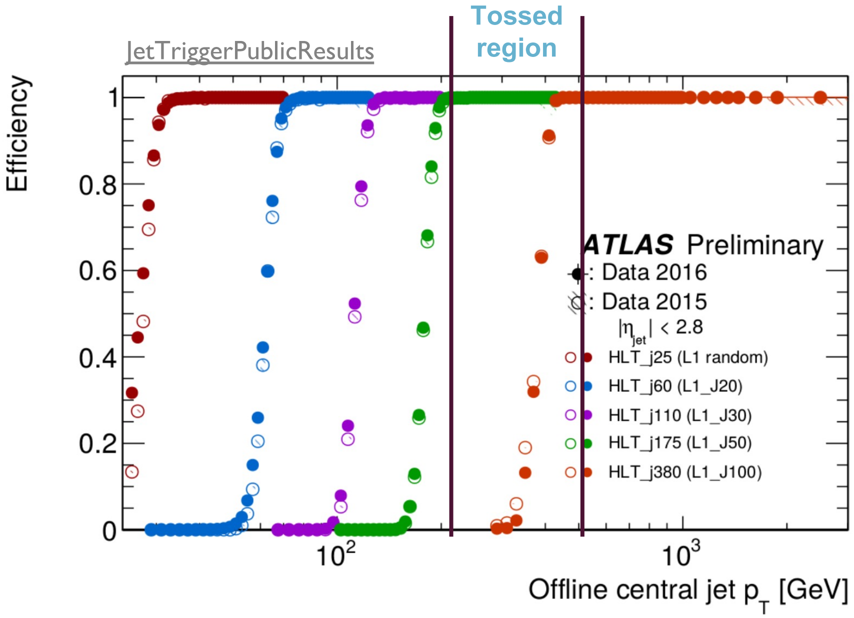
Trigger Level Analysis (TLA)

- Low pT jets physics (200 – 440 GeV) is tossed in ATLAS due to **trigger** limitations
- ATLAS normally stores the entire detector output for triggered events, limiting the rate at which events can saved
- Trigger Level Analysis chains record only the output of HLT reconstruction o(3kB/event) at extremely high rate o(3kHz)
  - Jets included (~15% of total trigger decisions)



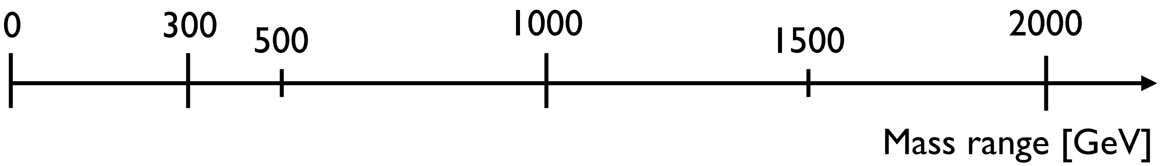
TriggerOperationPublicResults

JetTriggerPublicResults

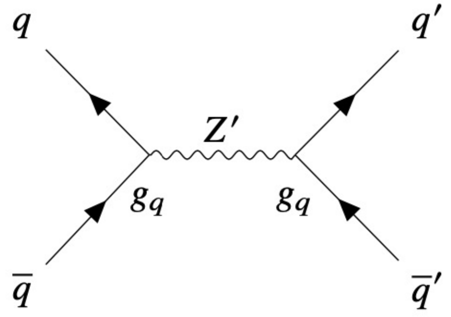


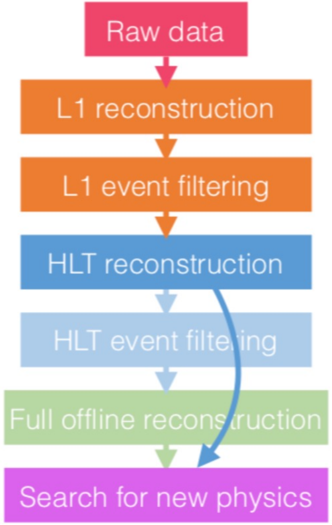
TLA search in fully hadronic final states

- Electroweak-TeV scale should be studied throughtly, as W, Z, Higgs boson and top are all found there
  - Current single jet HLT trigger (pT > 440 GeV) constraints $m_{jj} \gtrsim 1.5$ TeV
- TLA can be used to recover sensitivity at the TeV scale! → HLT reconstructed jets and event header
  - No calorimeter cells, constituents, hits or tracks are saved, no offline reconstruction
  - TLA jets calibrated to match offline reconstructed jets
- Model independent, benchmark model used to set upper limits on coupling constant g_q (29.3 fb^{-1})



Benchmark model: DM mediator

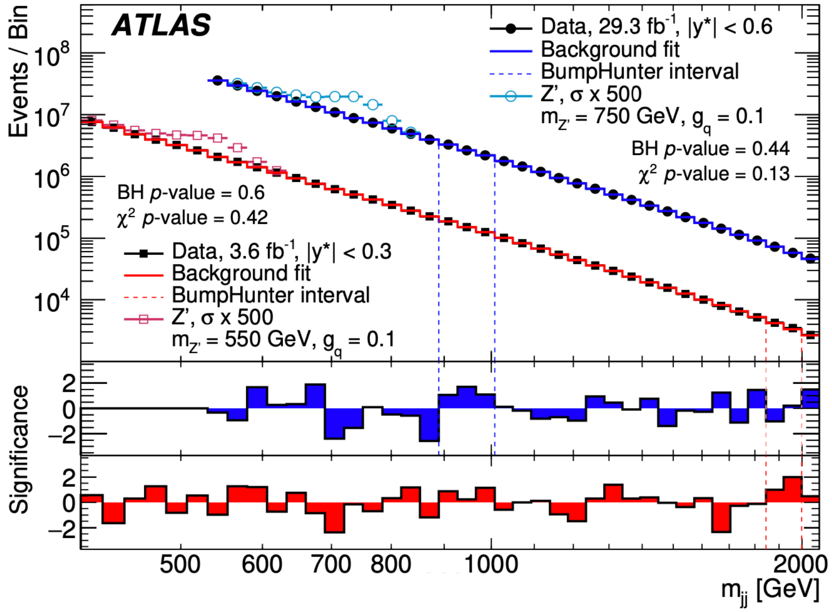




TLA search results

PRL 121 081801

- Background estimated with functional fit of subranges with sliding window
- No bump found → factor 2-5x improvement in coupling constant limits w.r.t. other searches for lower masses



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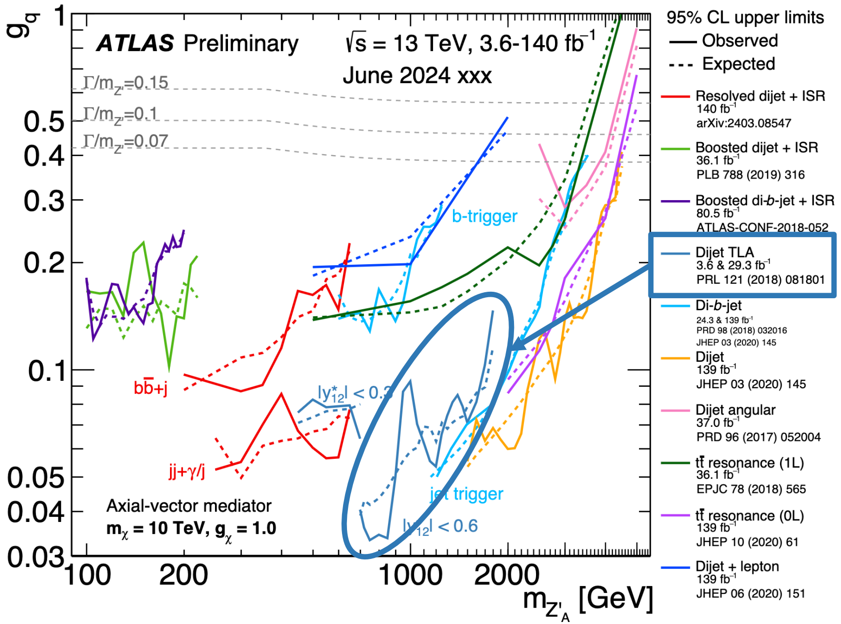

Conclusions

- No new interactions and particles since the Higgs boson's discovery $\rightarrow$ more generic searches opposed to the existing model-dependent analysis standard
- Model agnostic searches with jets in final state becoming a main topic in the ATLAS collaboration
- Exploited LHC Run 2 data collected by ATLAS, also moving on to Run 3 data
  - Run 2: TLA analysis, CWoLa, search for resonances with quark tagging, YXH
  - Run 3: Anomaly Detection with Graph Neural Networks
- Honorable mentions: Anomaly Detection search with Run 2 data (Phys. Rev. Lett. 132, 081801), search for signatures of Soft Unclustered Energy Patterns
- Take home message: **Model agnostic searches can be a powerful tool that is complementary to beyond standard model dependent searches approach**

Stay tuned and thank you for your attention!