Physics analyses with the ATLAS experiment

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Outline

Combination of searches for invisible decays of the Higgs boson

Machine Learning for Pions

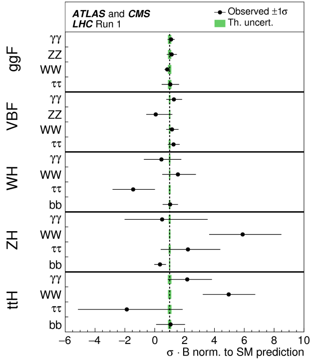
Luminosity measurement using Pixel Cluster Counting method

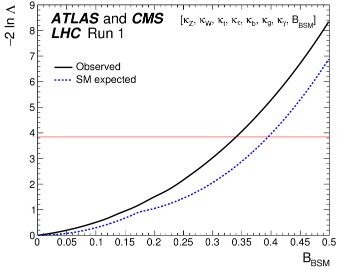
Di squark searches

(1) HIGGS BOSON

Run-1 Higgs measurements from a combined ATLAS and CMS analysis JHEP08(2016)045:

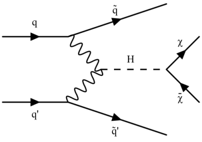
- All the measurements agrees very well with the SM so far
- $\mathscr{B}_{\text{BSM}} < 0.34\ (0.39) \implies$ Still plenty of room for BSM physics in Higgs decays



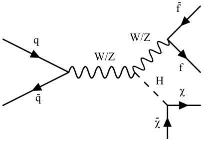


INVISIBLE HIGGS DECAYS

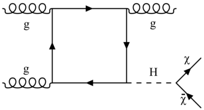
- In the SM, $\mathscr{B}_{inv}(H \rightarrow \text{invisibles}) \sim 0.1\%$ due to $H \rightarrow ZZ^{*} \rightarrow 4\nu$
- In many BSM theories, $\mathscr{B}_{inv}$ is enhanced due to Higgs decays to stable dark matter particles
- E.g. SUSY (LSP), large extra dimensions (Graviscalar)
- Tag the production of Higgs boson by VBF or associated production of W/Z or jet recoiling against it



VBF



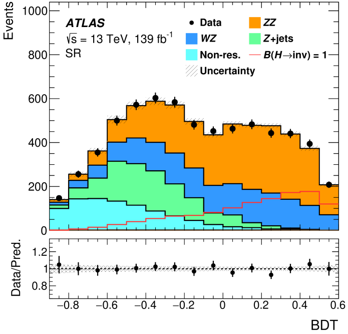
W/Z



ggF

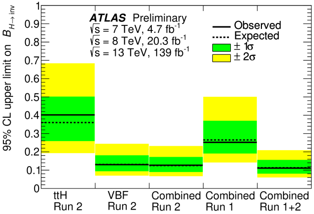
$H \to$ INVISIBLES: $E_T^{\text{MISS}} + (Z \to \ell\ell)$

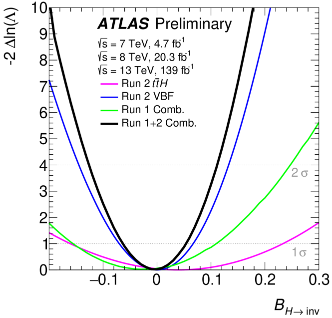
- Requires E_T^{miss} to be back-to-back with $Z \to \ell\ell$
- Major backgrounds: $(Z \to \ell\ell)(Z \to \nu\nu)$, $(Z \to \ell\ell)(W \to \ell\nu)$, and Z+jets
- A BDT is trained to separate signal from the backgrounds
- $\mathscr{B}_{inv} < 0.18$ (0.18) at 95% CL (Ref: 2111.08372)



$H \rightarrow$ Invisibles: Combination

- Preliminary combination results with All Run-1+ VBF Run-2+ ttH Run-2: $\mathscr{B}_{inv} < 0.11$ (0.11)





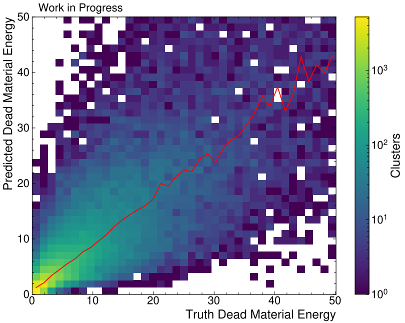
- I am currently working on the statistical combination of all $H \rightarrow$ invisibles analyses performed with full run-2 data of the ATLAS experiment

(2) Pion identification and energy calibration

- Pions are the most abundant particles in the *pp* collisions
- Separating $\pi^{\pm}$ and π^{0} and calibrating their energy response is a key element of the reconstruction in the ATLAS calorimeter
- Albert Kong is working on the pion identification using *dead material energy*
  - Energy deposited by the hadron showers which can not be measured (e.g. no active calorimeter material is present)
  - Estimated using energy in the neighbouring layers or shower topology observables

Machine Learning for Pions: Dead Material Energy

Previous work in this area[1] focussed on learning the true deposited energy with neural networks, but can we also learn the dead material energy?



- Preliminary study using a simple dense neural network gives promising results
- Investigating whether PFlow networks can improve prediction accuracy to be correct on a per-cluster basis instead of only on average

[1] http://cdsweb.cern.ch/record/2724632

(3) Luminosity measurement using Pixel Cluster Counting method (PCC)

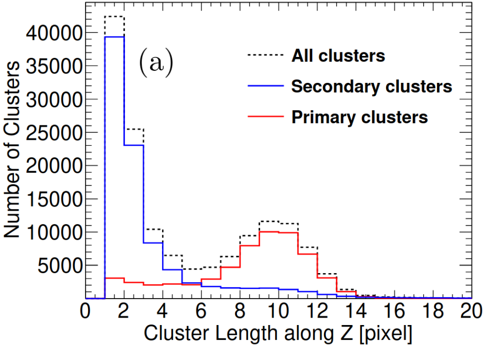
- Luminosity per bunch: $\mathcal{L}_b = \dfrac{\mu_{vis} \times f_r}{\sigma_{vis}}$

Where, μ_{vis} = Average number of visible interactions per bunch-crossing
f_r = revolution frequency
σ_{vis} = visible cross-section of inelastic pp interactions

- In ATLAS, μ_{vis} is determined using dedicated luminometers like LUCID, BCM
- It is cross-checked by track-counting analysis
- CMS uses PCC method for nominal Luminosity estimation

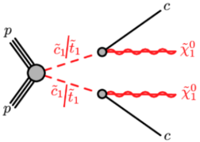
PCC method

- Charles Grant, Harish Potti and Paul Jackson recently started estimation of μ_{vis} with PCC in ATLAS
- Basic idea: $\mu_{PCC} \propto$ #clusters formed in the pixel detector
- Need to separate clusters produced by primary particles from secondary particles and noise

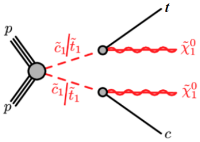


(4) Maximally mixing di-squark searches at ATLAS

- Tristan Ruggeri and Edmund Ting are searching for di-squark production in *pp* collisions
- Signal model – Strongly produced s-top or s-charm quarks
- Final state with two jets and missing energy

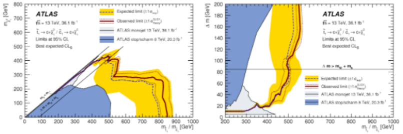


cc+MET



tc+MET

JHEP 09 (2018) 050



ANALYSIS CHALLENGES

tc+**MET**

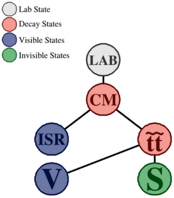
- Charm-jet tagging: No ATLAS recommended working points for charm tagging, using DL1r based tag developed by *tc*+MET group
- Signal discrimination:
  - Conventional kinematic based variables
  - Neural Net based approach
  - Recursive Jigsaw Reconstruction

cc+**MET**

- Charm-jet tagging: Tagging two charm jets with developed working points can result in statistical limitations
- Signal discrimination: Using RJR for compressed mass splitting models, later move to intermediate and boosted models.

Recursive Jigsaw Reconstruction: Di-squark searches

- Can use RJR to reconstruct particle decays with the presence of combinatoric and kinematic ambiguities, imposing specific decay topology [PhysRevD.96.112007]
- Apply mass minimisation jigsaw rules for invisible objects to split MET based on jet and parent state properties
- Allocate ISR jets in compressed models for signal discrimination variables
- Develop variables based on SM process topologies to suppress background
- RJR has been incorporated into RDataframes for increased ease of use



ISR Tree

ATLAS ANALYSES

A lot of ATLAS analyses are in the pipeline. To know more, interact with these people in the poster session:

- Machine Learning for Pions: Recent Results (Albert Kong)
- Luminosity measurement using Pixel Cluster Counting (Charles Grant)
- Overlap Removal using Global Particle Flow at the ATLAS Detector (Edmund Ting)
- How do we build a particle detector? One byte at a time (Emily Filmer)
- Searches for low-mass BSM resonances using Trigger-object Level Analysis (Max Amerl)
- Di-squark signature searches via Recursive Jigsaw reconstruction (Tristan Ruggeri)

THANK YOU