Search for new physics in final states with semi-visible jets or anomalous signatures using the ATLAS detector

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Existence of Dark Matter

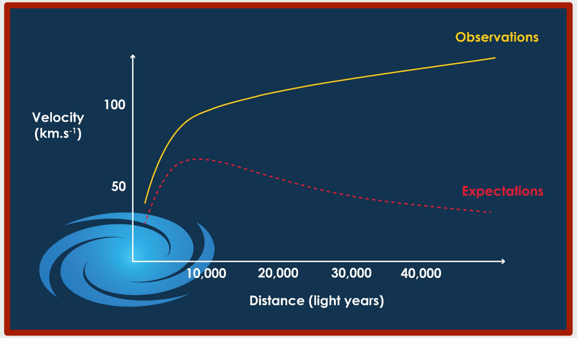
How do we know dark matter (DM) exists?

- Galaxy arms radial velocity
- Gravitational fields from the bullet cluster

Constraints on particle-based dark matter models:

- Stable or long-lived.
- Does not interact with standard model (SM).
- Abundancy must align with cosmological measurements.

No SM candidates exist,
massive array of beyond-the-standard-model (BSM) theories with DM candidates.
"QCD-like Dark Sector"!



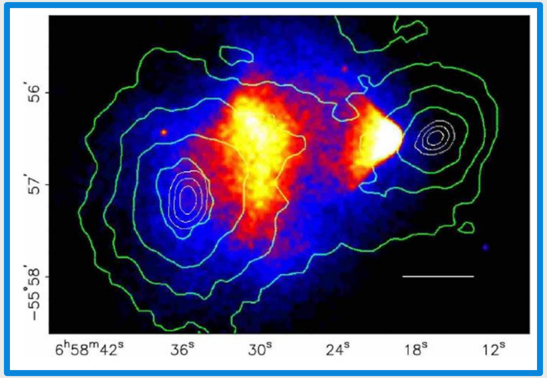
$$v(r) = \sqrt{\frac{G\,M(r)}{r}}$$

[1]

Colour: mass

Green lines: Gravitational field contours

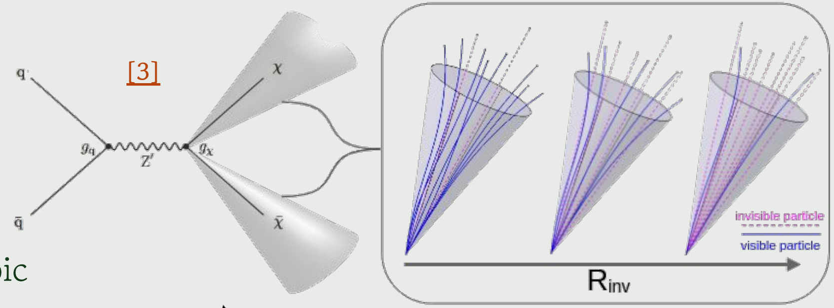
[2]



QCD-like dark sector

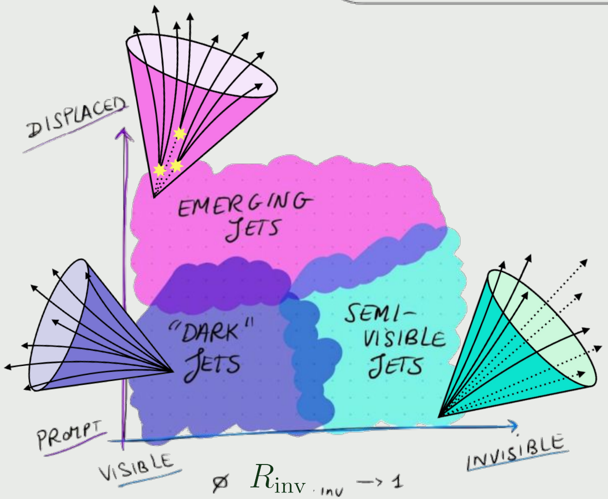
- Dark quarks can hadronise to form DM hadrons.
- Some DM hadrons are stable.
- Some decay to stable DM or SM

[3]



Interactions between SM and DM mediated by heavy leptophobic Z' boson for models considered.

Lifetime and amount of stable DM (R_{inv}) distinguish Dark Sector models into separate regimes, all with their own topologies.
ATLAS has published analysis for:



Emerging Jets: Rep. Prog. Phys. 88 (2025) 097801
Dark Jets: JHEP 02 (2024) 128
Semi-Visible Jets s-channel: Phys. Rev. D 112 (2025) 012021
Semi-Visible Jets t-channel: Phys. Lett. B 848 (2024) 138324

This talk: **Semi-Visible Jets s-channel** analysis.

SVJ Analysis Overview

Search for hadronic signatures from BSM physics in the form of SVJs, using data collected by the ATLAS detector (2015 to 2018).

SVJs are produced through the QCD-like dark sector, accessed via s-channel resonant production of the Z'.

Final state particles from Z' decay being both SM and DM cause jets to be "semi-visible".

Dual goals of the analysis:

- Limits on SVJ signal models (parameterized by Z' mass and R_{inv})
- Anomaly detection (AD)

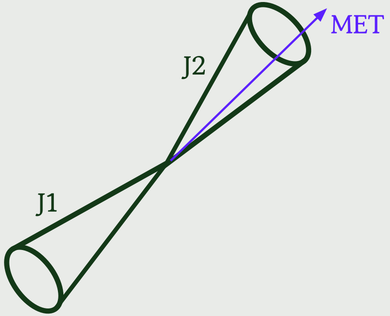
Machine learning networks used per goal to create signal-free and signal-rich regions to develop and conduct the analysis. To achieve goals, perform a resonance search by fitting functional forms to transverse mass distribution, to quantify any bumps, and set limits.

Samples and Selections

We use simulated backgrounds for ML training and strategy validation, and data to derive the final results of the analysis. After passing a single jet trigger, enforce preselection which is designed to isolate 2 back-to-back jets with missing energy (MET) aligned with the less energetic one.

After preselection:

- 76% QCD
- 12% W+jets
- 8% top and diboson
- 4% Z -> mumu



Variable	Preselection requirements
N_{jets}	≥ 2
N_{tracks} (jet)	≥ 3
N_{lep}	$= 0$
$p_T j_1(j_2)$ [GeV]	> 450 (> 150)
$\Delta\phi$ (j_1, j_2)	> 0.8
$\lvert\eta_{j_1,j_2}\rvert$	< 2.1
Δ y	< 2.8
E_T^{miss} [GeV]	> 200
m_T[GeV]	> 1500

Analysis Strategy

Transverse mass (m_T) distribution used to find any bumps caused by the resonant production of the Z' or other BSM physics as background is expected to be exponentially smoothly falling

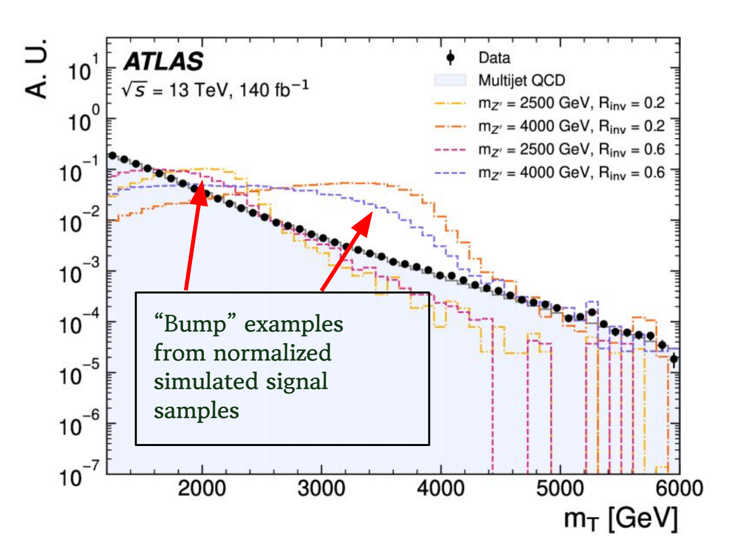
The definition of m_T includes both the dijet system kinematics and MET terms.

$$m_T{}^2 = [E_{T,JJ} + E_T^{\text{miss}}]^2 - [\vec{p}_{T,JJ} + \vec{p_T}^{\text{miss}}]^2$$

The distribution includes:

- **Data**
- Simulated QCD background
- Signals

[3]



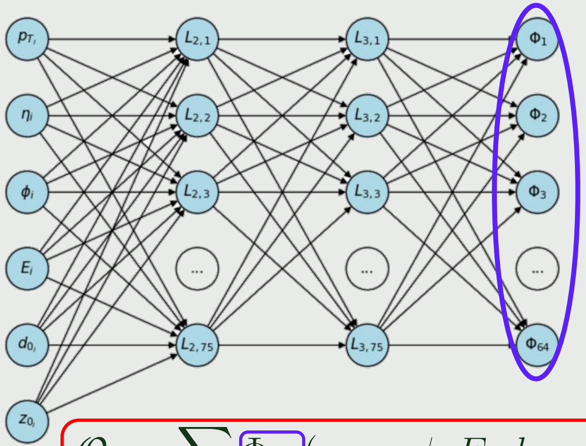
Machine Learning Model: PFN

* defined in backups.

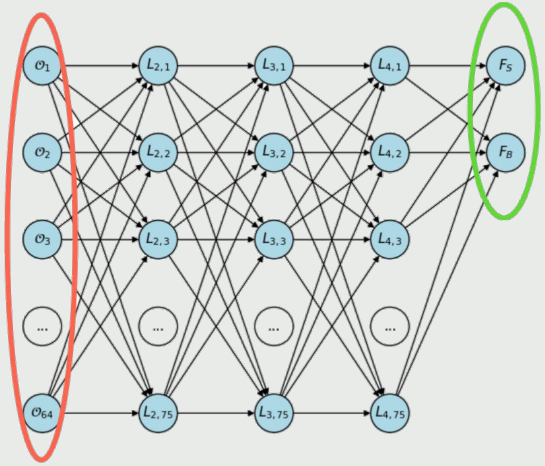
Particle Flow Network (PFN) is responsible for placing limits on the SVJ signal models.
Supervised learning approach that takes up to 160 tracks and uses track observables (p_T, η, ϕ, E, d_0, z_0*) as inputs.

Learns optimal transformations of inputs to form $\Phi_{a,i}$ per track i, such that classifying $\mathcal{O}_a = \sum_i \Phi_{a,i}$ can identify events with SVJs.
Latent features per track: *a* (64).
Main benefit of the PFN

- Permutation invariant input modelling, the transformation amd sum reduce the bias on the score from track order.



$$\mathcal{O}_a = \sum_i \boxed{\Phi_{a,i}}(p_T, \eta, \phi, E, d_0, z_0)$$

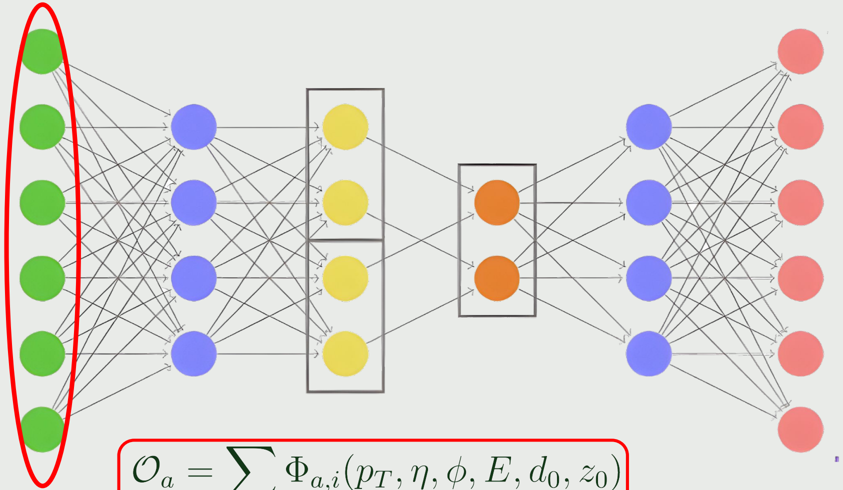


Machine Learning Model: ANTELOPE

ANTELOPE is the anomaly detection (AD) model, which uses same PFN $\mathcal{O}_a$ encoder, and a variational autoencoder to map event representations to a lower dimensionality space, than uses a reconstructor to recreate $\mathcal{O}_a$.

Uses the trained portion of the PFN to create $\mathcal{O}_a$, it only trains on (unlabelled) simulated backgrounds (MC QCD). Referred to as semi-unsupervised learning.

Upon finding a non background-like event, it will poorly reconstruct it (as only trained to accurately reconstruct background) and the event will be flagged as anomalous.



$$\boxed{\mathcal{O}_a = \sum_i \Phi_{a,i}(p_T, \eta, \phi, E, d_0, z_0)}$$

Analysis Regions

Control Region (CR) & Validation Region (VR) used to develop and test background estimation.
Signal Region (SR) used to place final limits and conduct anomaly search.

Regions defined with ML score alongside sub-leading jet width.

- Sub-leading jet: jet with 2nd highest transverse momentum

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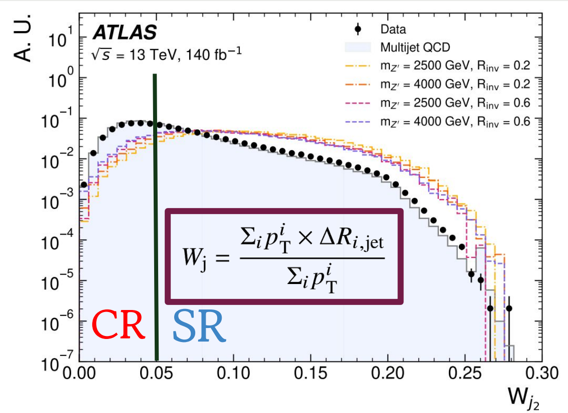
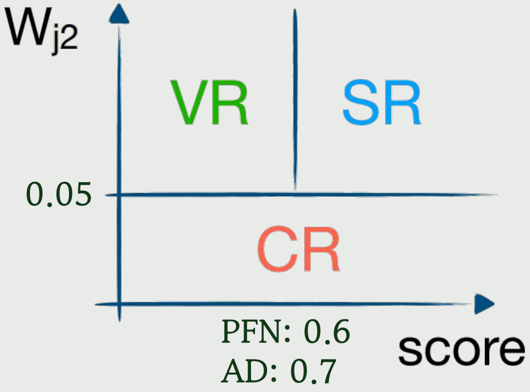
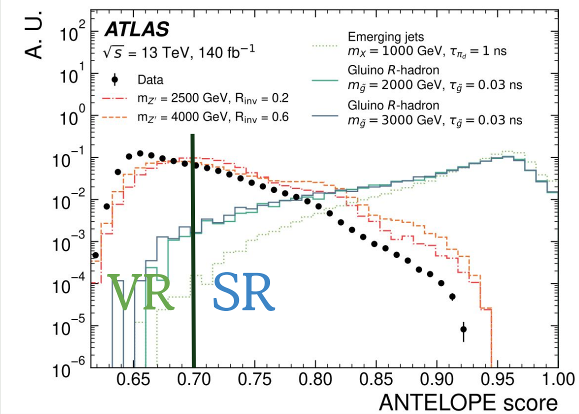
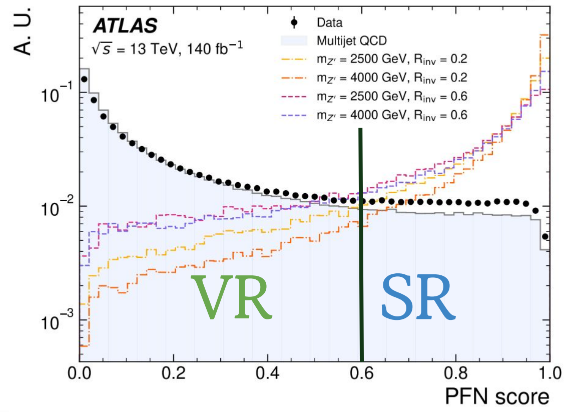








Background Fits to SRs

Fits to 90 equidistant bins using the background function:

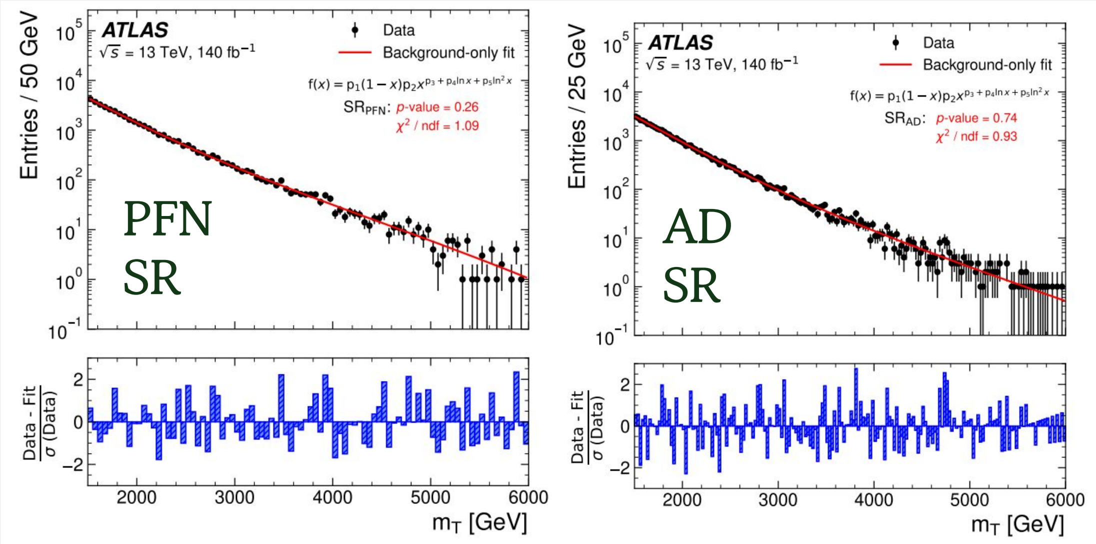
$$f(x) = (1-x)^{p_1}\, x^{p_2 + p_3 \ln(x) + p_4 \ln^2(x)}$$

$$x \equiv m_{JJ}/\sqrt{s}$$

After validating strategy in CR and VR, fit to PFN and AD SRs to check compatibility between background hypothesis (no BSM) and data.

No significant bumps observed in either PFN or AD SR.

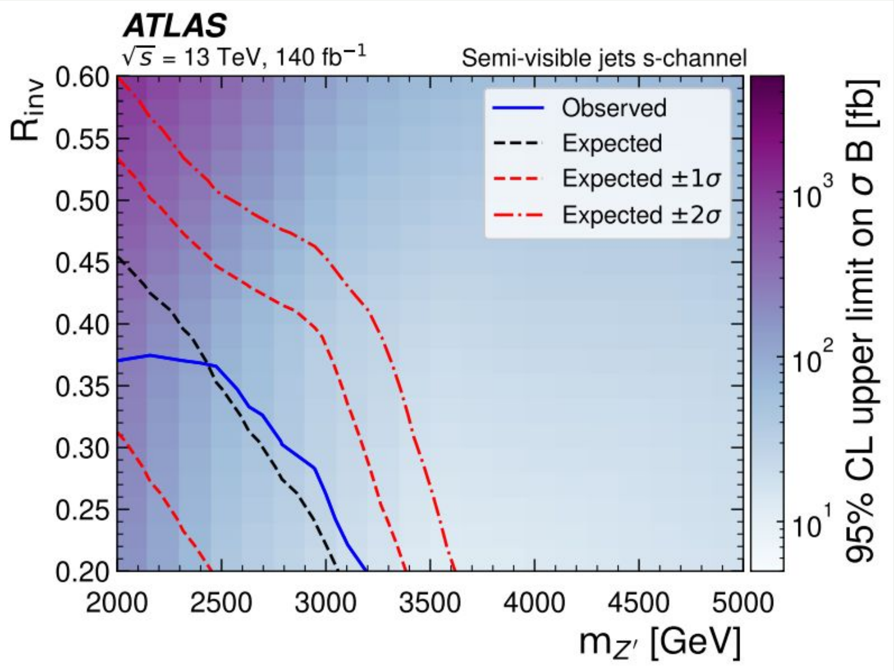
[3]



Results

[3]

Contours represent exclusion power of the analysis, Signals below contours are excluded using limits derived from **data** (observed) and their uncertainties.



<u>Conclusion</u>

AD: no significant bumps

SVJs: the analysis sensitivity reaches 0.37 in R_{inv} and 3.2 TeV in Z masses.

<u>Future work</u>

The future of "weird" dark matter searches is exciting; more DM models, more collisions, better NNs, improved analysis strategies, more promising searches!

Thank you!

Questions?

Backup

Track observable definitions:

p_T : transverse momentum (⊥ beam axis)

η : $\eta = -\ln\tan(\theta/2)$, pseudorapidity (forwardness from x-y plane)

ϕ : azimuthal angle in transverse plane

E : energy of track

d_0 : distance of closest approach from track to beamline in x–y

z_0 : distance of closest approach from track to beamline in z

Axis Z is along the beamline, Y is + vertically upward, X is horizontal & + toward mont jura.

Parameter	N_{c_D}	N_{f_D}	Λ_D [GeV]	m_{π_D} [GeV]	m_{ρ_D} [GeV]	m_χ [GeV]	g_q	g_χ
Value	3	2	10	17	31.77	10	1	0.1