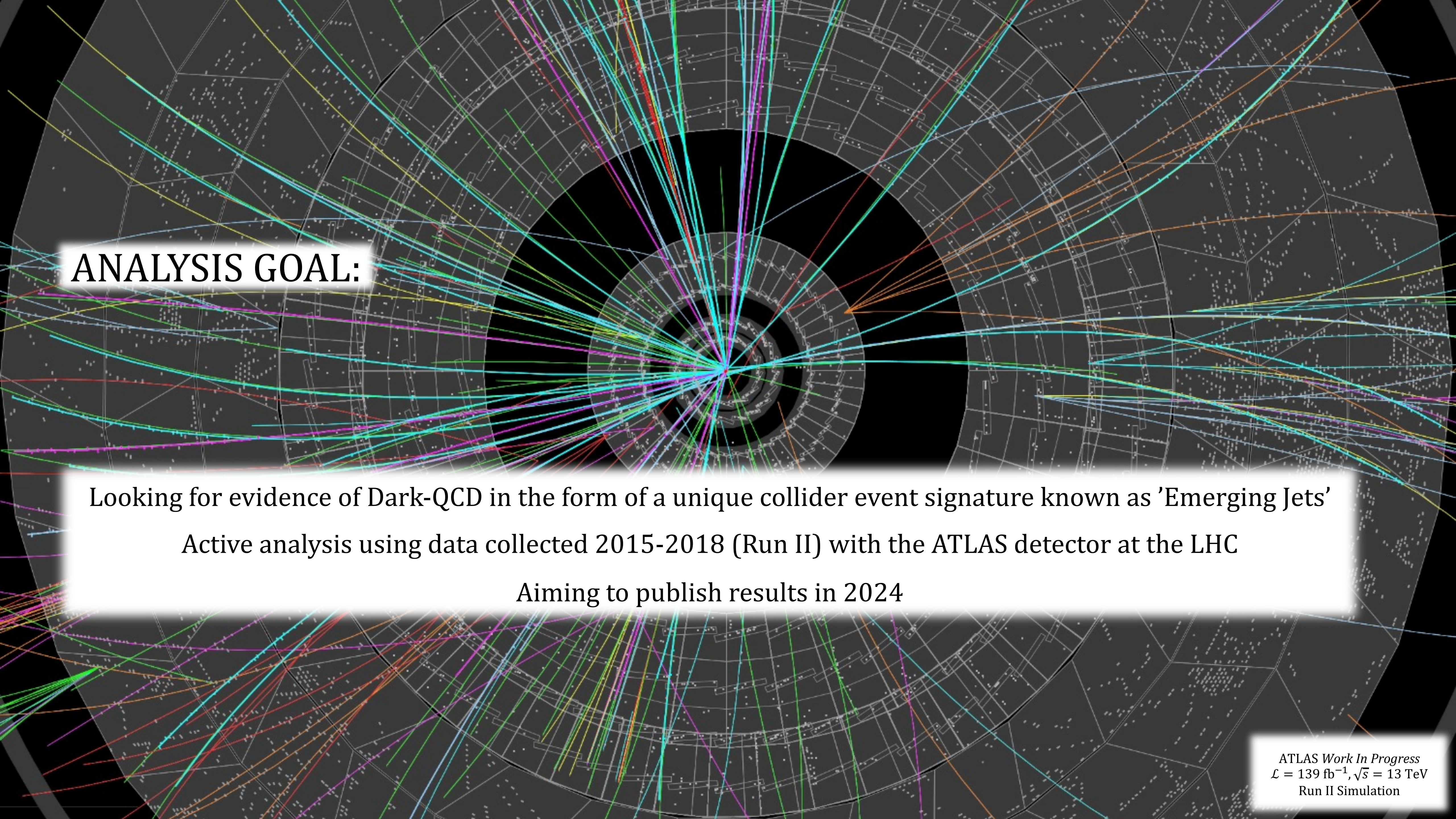
SEARCH FOR EMERGING JETS WITH THE ATLAS DETECTOR AT THE LHC

WINTER NUCLEAR & PARTICLE PHYSICS CONFERENCE

IAN RAMIREZ-BEREND

17 FEBRUARY 2024



ANALYSIS GOAL:

Looking for evidence of Dark-QCD in the form of a unique collider event signature known as ’Emerging Jets’

Active analysis using data collected 2015-2018 (Run II) with the ATLAS detector at the LHC

Aiming to publish results in 2024

THE EMERGING JET SIGNATURE

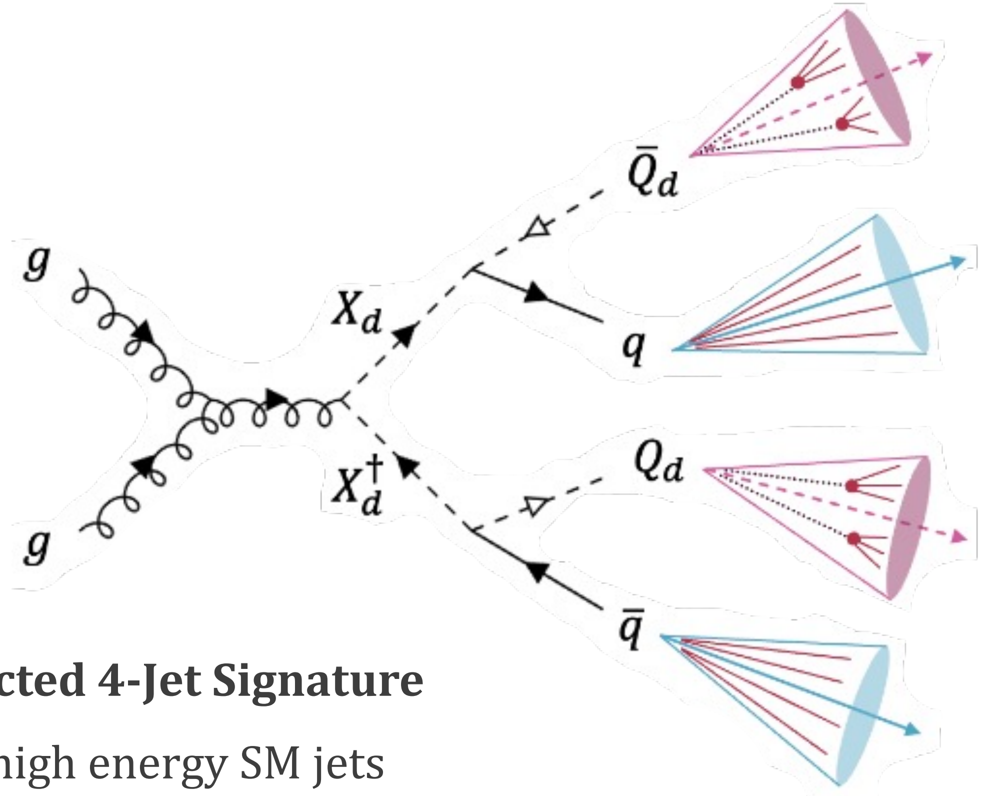
- $pp \rightarrow X_d^\dagger X_d \rightarrow 2\ q + 2\ Q_d$

  Dark Jets ($2\ Q_d$)

  SM Jets ($2\ q$)

- X_d: TeV-Scale Dark Mediator

- Q_d form GeV-Scale dark hadrons (long lived)



Expected 4-Jet Signature

- 2 high energy SM jets
- 2 ‘Emerging” jets:
  - many displaced vertices
  - Few tracks close to the collision point

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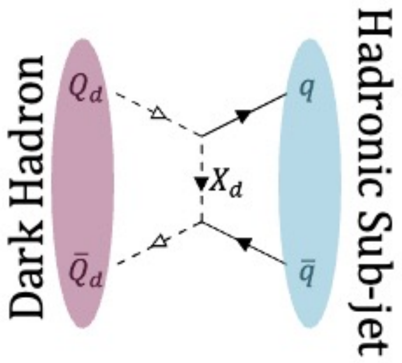
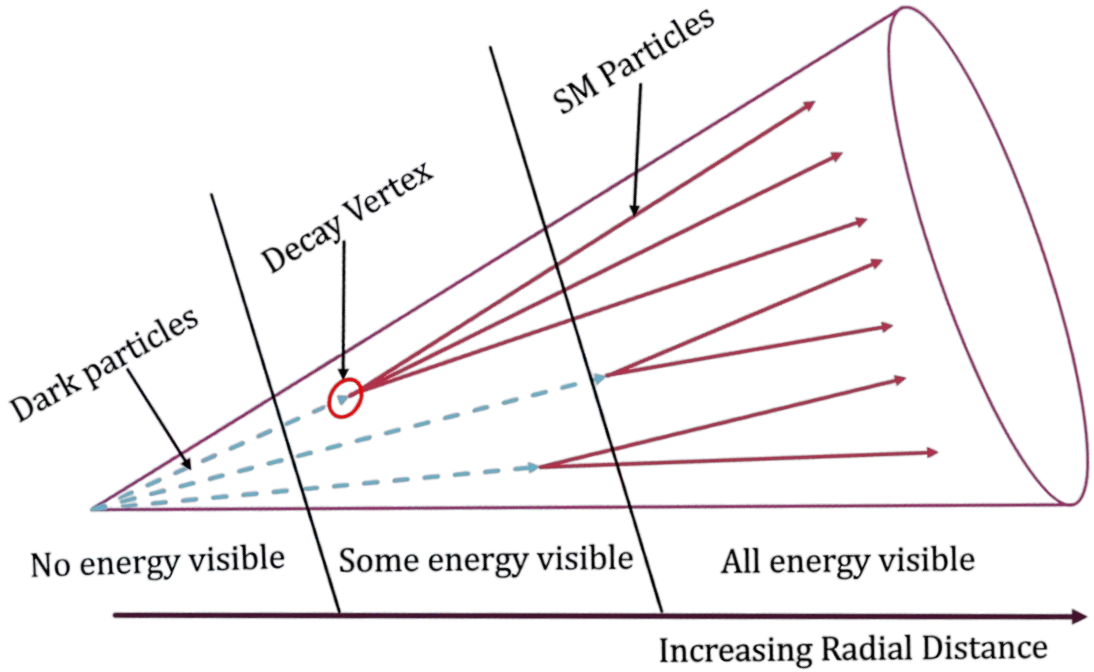
DARK JETS

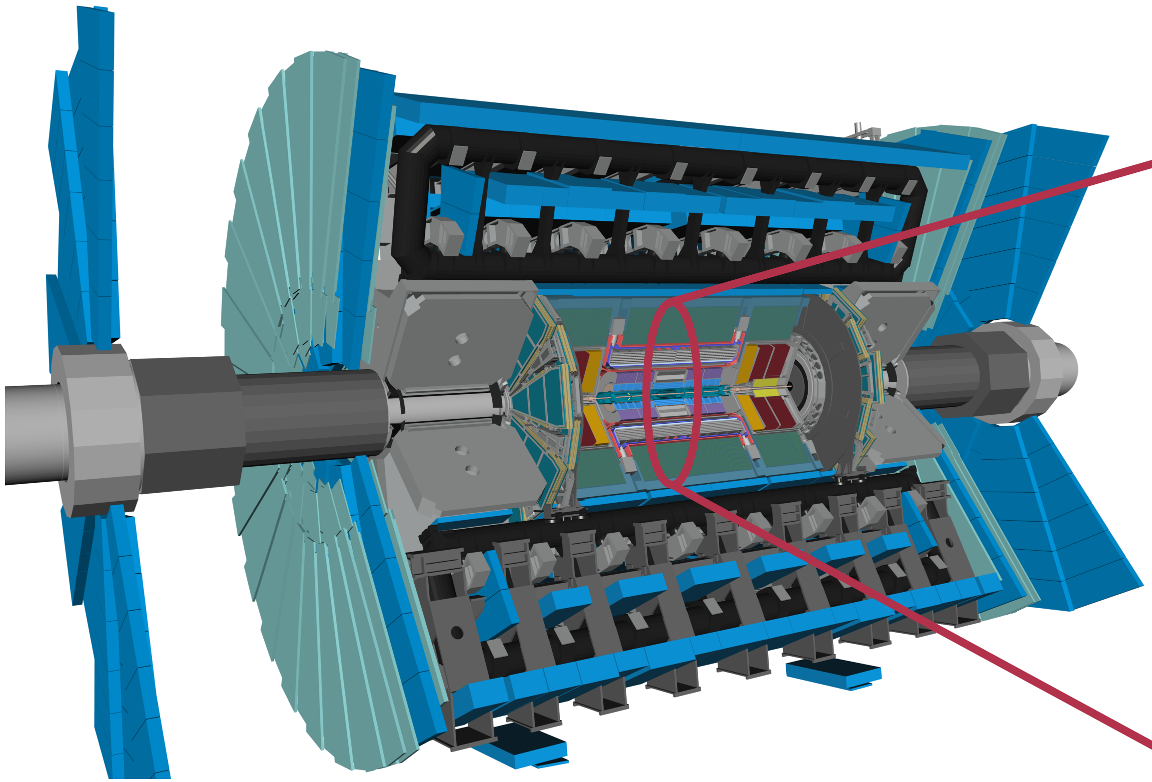


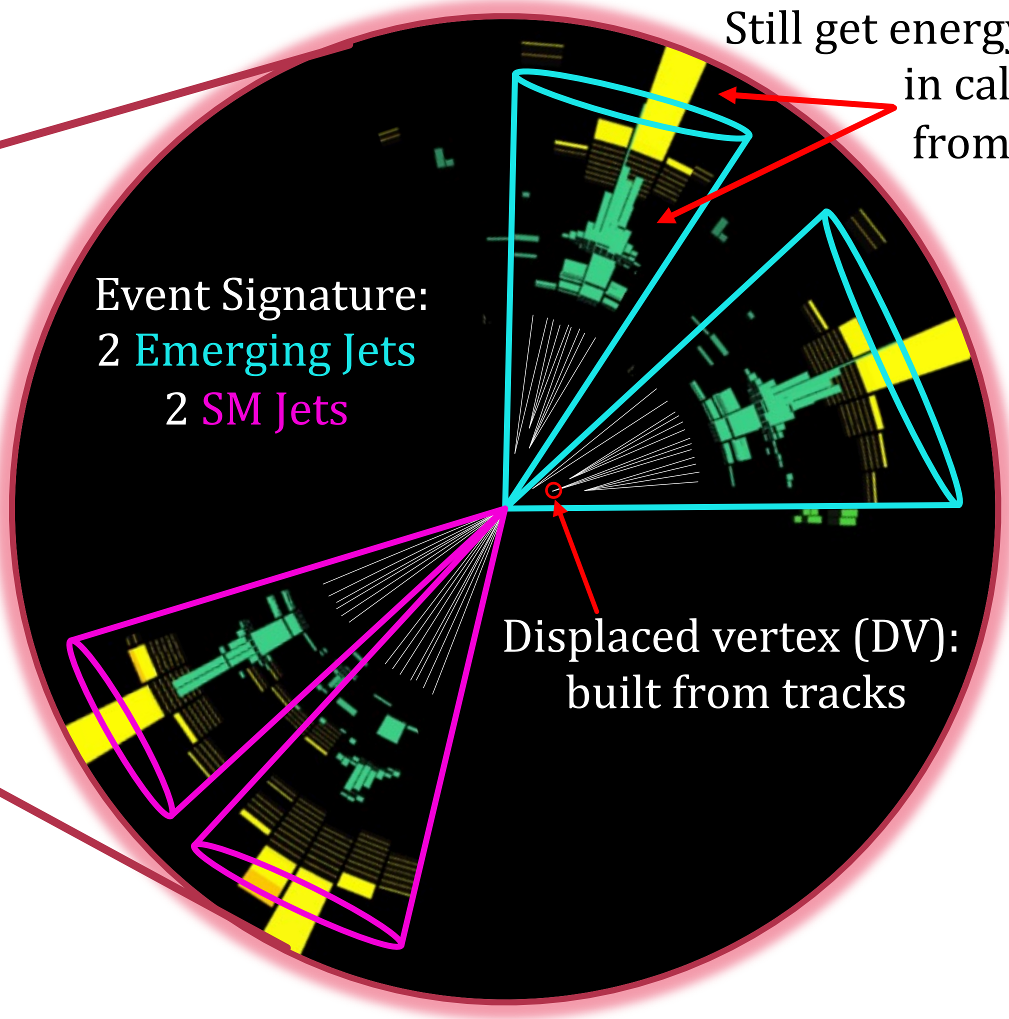
- X_d decay at interaction point
- Dark jet made of π_d (invisible)
- Each π_d decay leaves **Displaced Decay Vertex (DV)**



Emerging Jet with 3 DVs

EMERGING JETS TOPOLOGY IN ATLAS





SM background events:
4-jet events with very few DVs
(QCD multi-jet processes)

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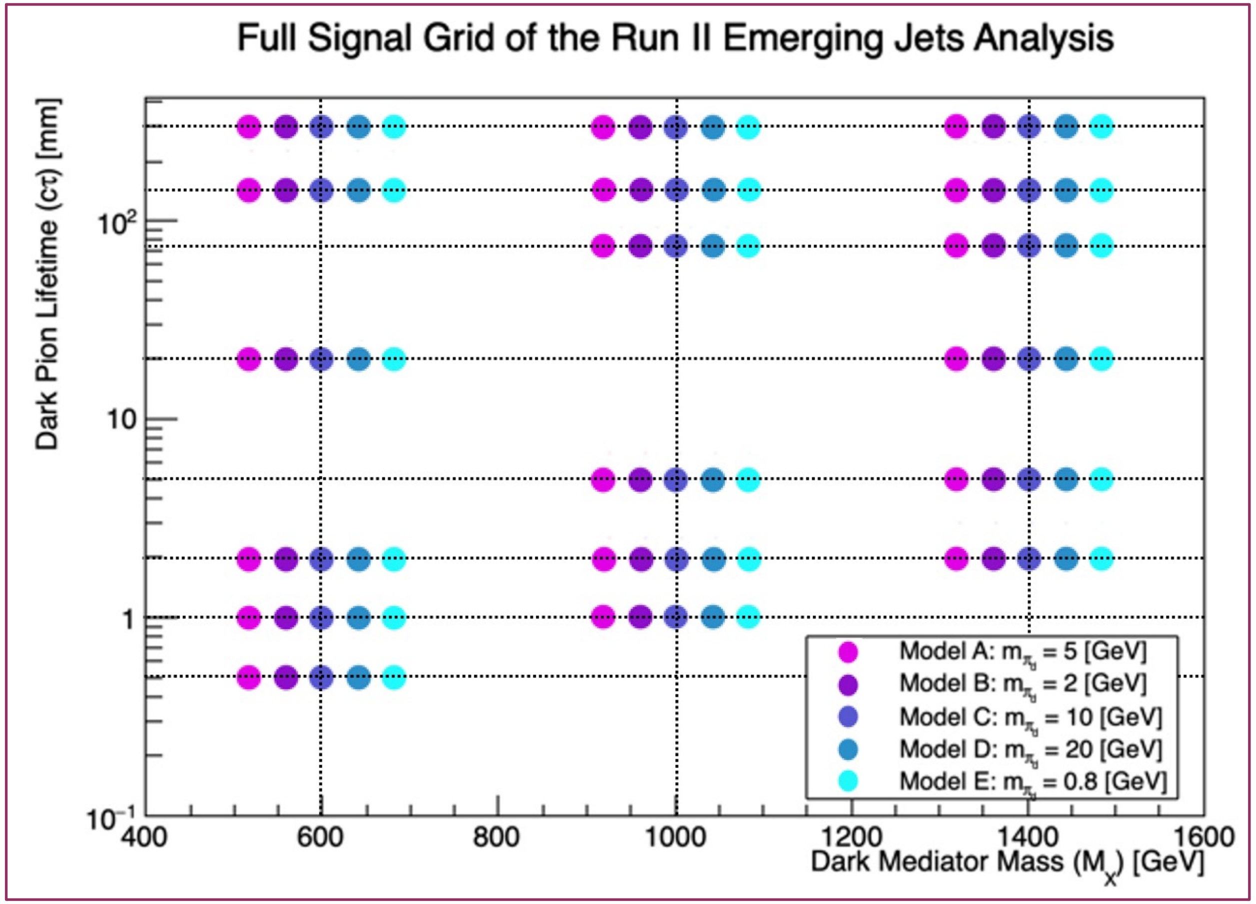
SIMULATED SIGNAL MODELS

- Three parameters of interest change the phenomenology of emerging jets:
  - Dark Mediator Mass (M_X)
  - Dark Pion Lifetime ($c\tau$)
  - Dark Pion Mass (m_{π_d})
- Define a 90 signal point grid
  - 5 GeV-scale dark pion masses: $0.8 - 20$ GeV
  - 3 TeV-scale mediator masses: $600, \; 1000, \; 1400$ GeV
  - 6 lifetimes per M_X in the range: $0.5 - 300$ mm



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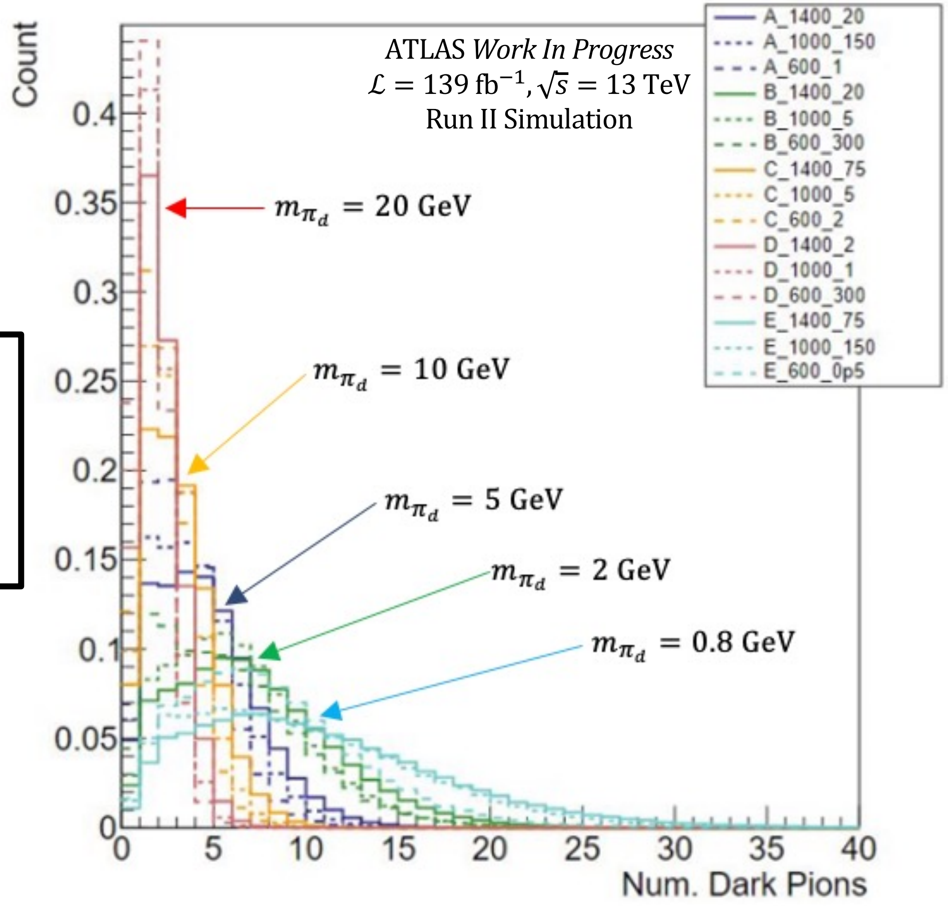
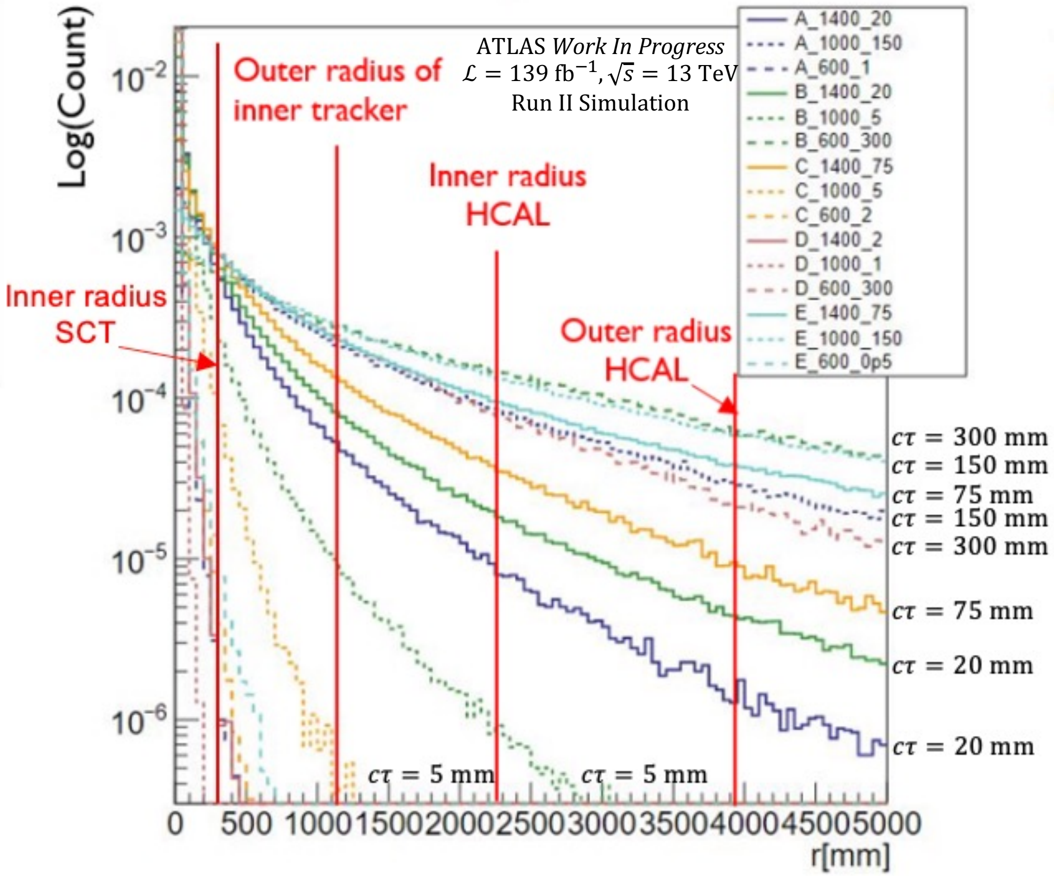
EMERGING JET KINEMATICS

$$m_{\pi d} \propto \frac{1}{N_{\pi d}} \rightarrow \frac{1}{\text{nDV}}$$

$$c\tau_{\pi d} \propto \mathrm{r}_{\pi d}^{decay} \rightarrow \mathrm{r}_{DV}$$

Signal events can look very different depending on the parameters of the model $(m_{\pi d}, M_X, c\tau_{\pi d})$





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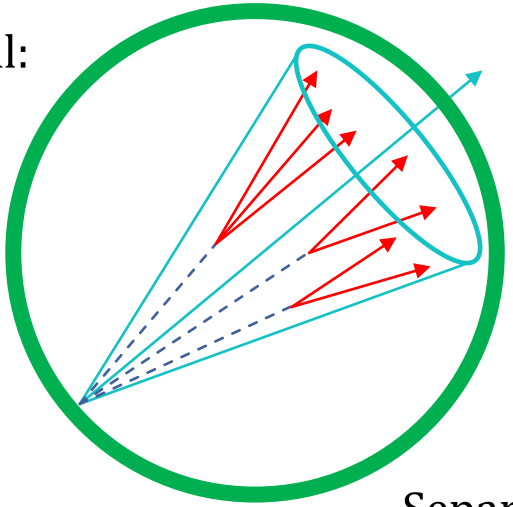
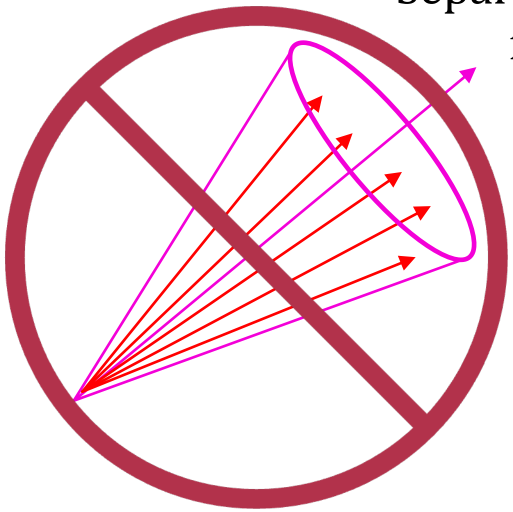
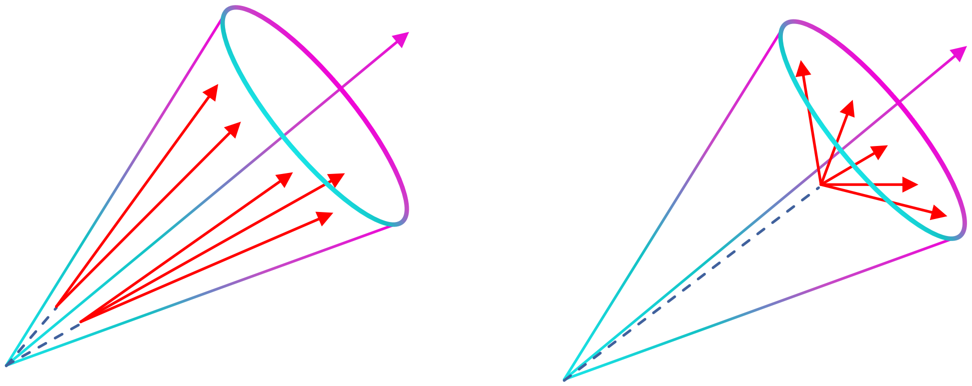
The Goal:



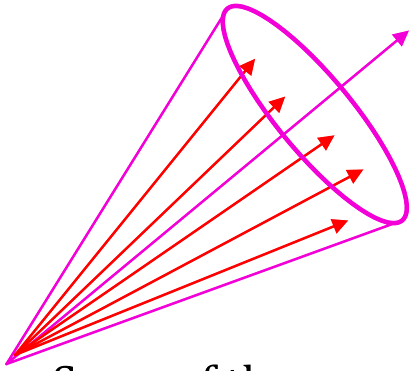


Separate Emerging Jets from SM Jets

The Problem:



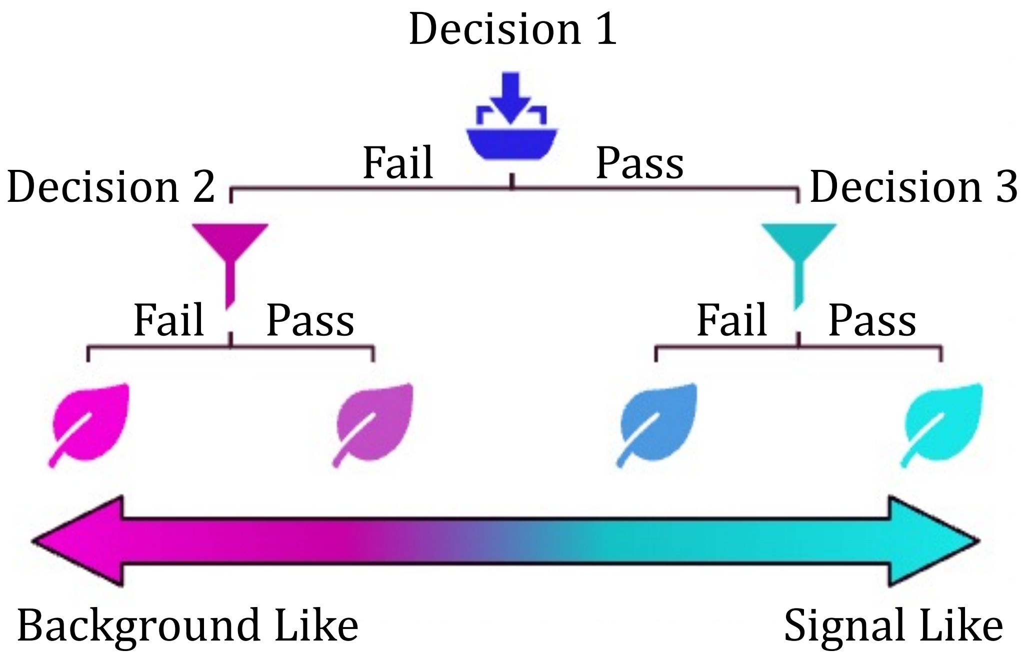
Signal Models can look very different



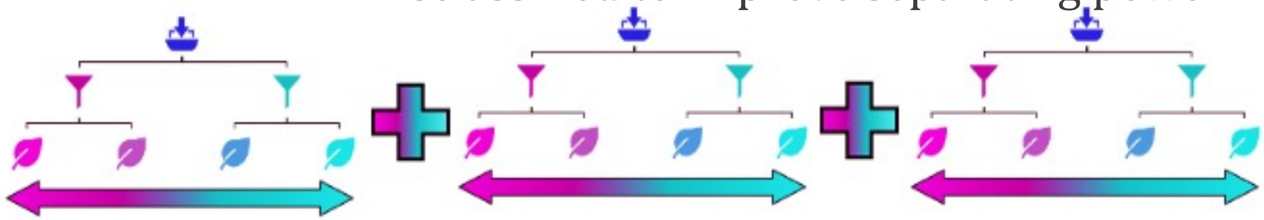
Some of them even resemble the background

The Solution: Use Machine Learning!

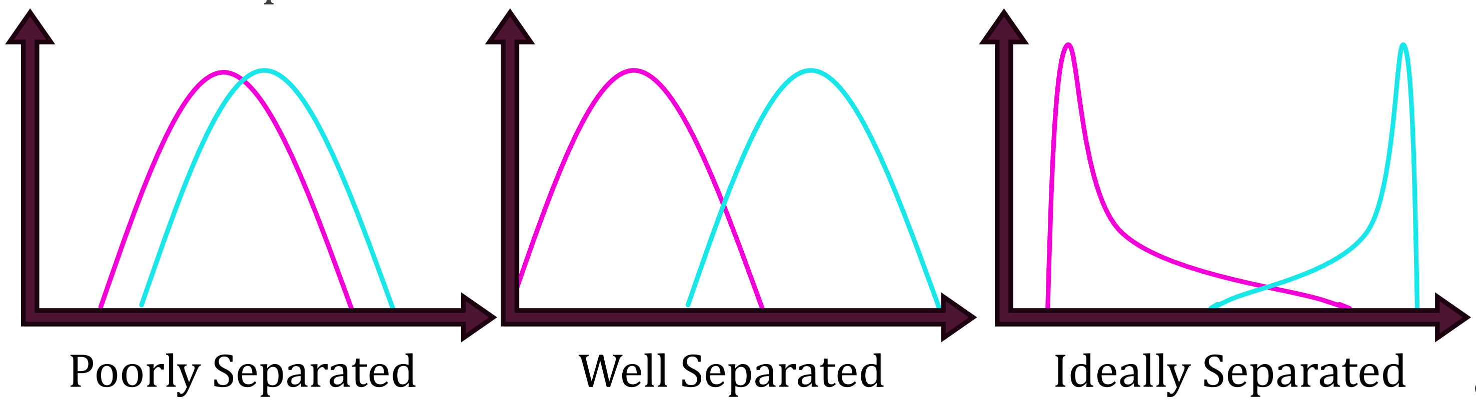
BOOSTED DECISION TREES (BDTs)



- Pass events through a series of binary decisions
- Sort events into background-like (-1) and signal-like (1)
- *Gradient Boosting*: re-train BDT several times on events which were misclassified to improve separating power



- Each event given a score from [-1, 1], aggregate of all events gives BDT Response Distribution:



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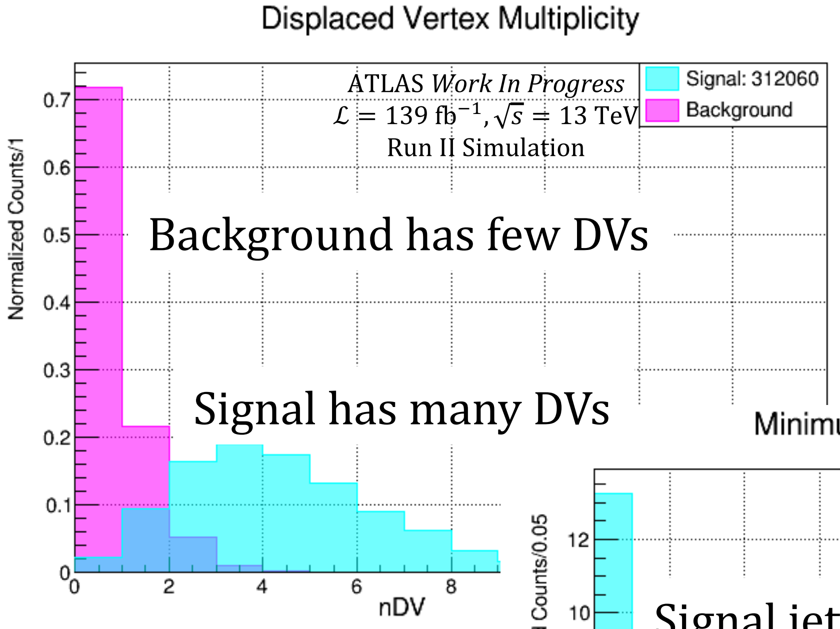
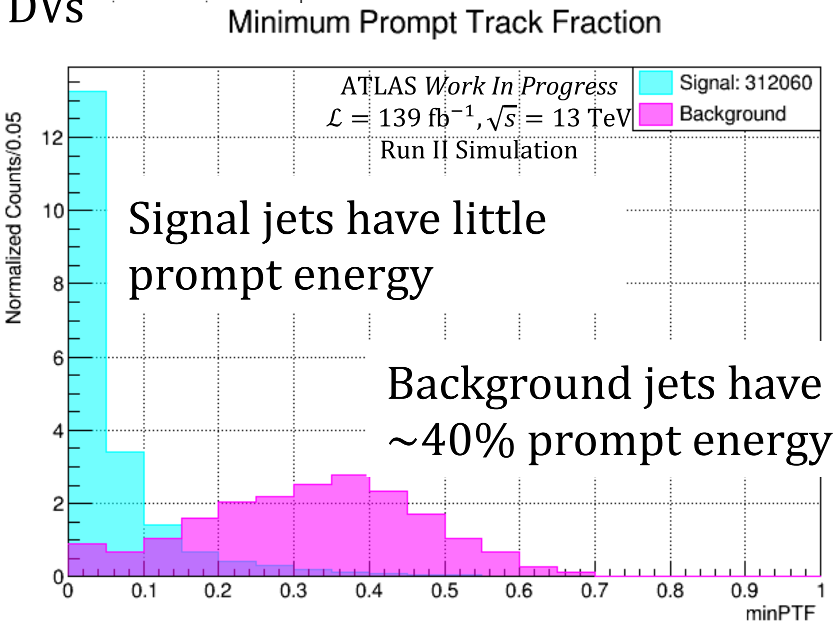
KEY ANALYSIS VARIABLES



- Baseline event signature: 4 high p_T jets
  - Require at least 4 jets per event, sum of 4-jet $p_T \geq 1000$ GeV
- Expect signal jets to have many DVs → use **jet-matched DV multiplicity**



- Expect background jets to have lots of prompt tracks, signal to have few
- **Prompt Track Fraction (PTF)**: measure of jet's energy from prompt tracks
  - Use minimum of 4 leading jets to separate signal and background

EMERGING JETS BDT STRUCTURE

- Combine all signal models together for training
- Train BDT in two steps:

1. Train on jet-level information
   - Energy, Mass, Width, η ← Calorimeter information from the visible part of jets
2. Train on event-level information
   - 4 jet BDT scores
   - minPTF, sum of jet p_T, jet multiplicity ← Variables which characterize the base event selection
   - event-shape information ← Variables which characterize the topology of multi-jet events

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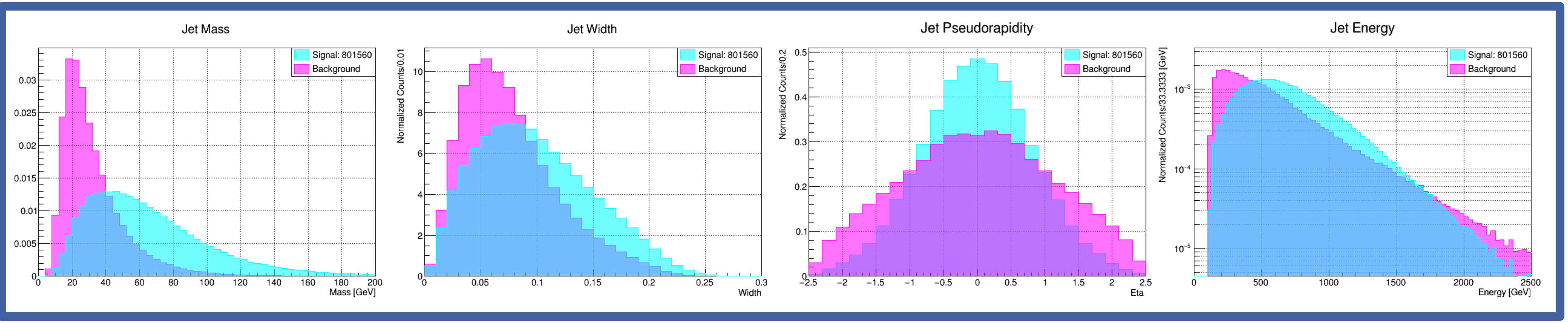
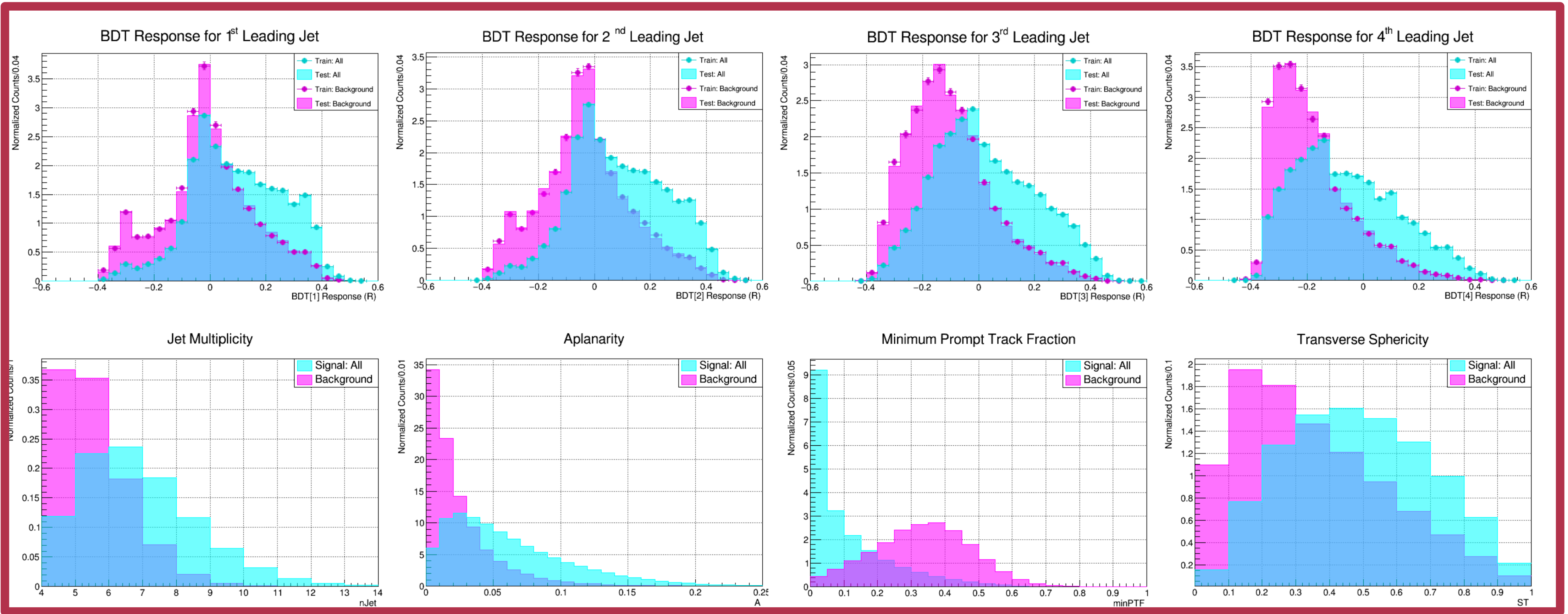


Jet-Level Variables

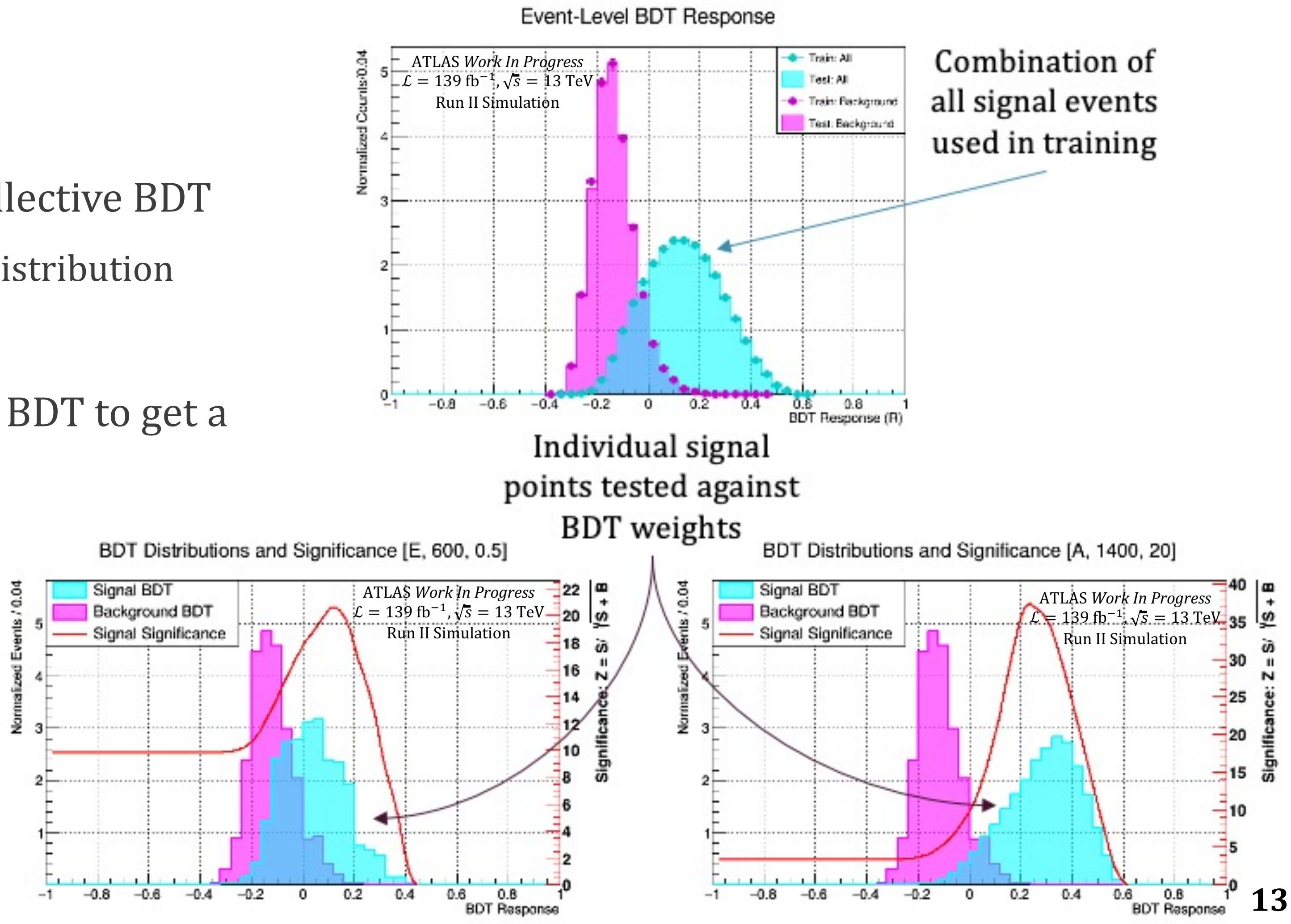


Jet-Level BDT Response

Event-Level Variables

EVENT-LEVEL BDT RESPONSE

- Test individual signal models against the collective BDT
  - Each signal model produces a different BDT distribution
  - Only one Background BDT distribution
- ATLAS Run II data is then tested against the BDT to get a data BDT distribution



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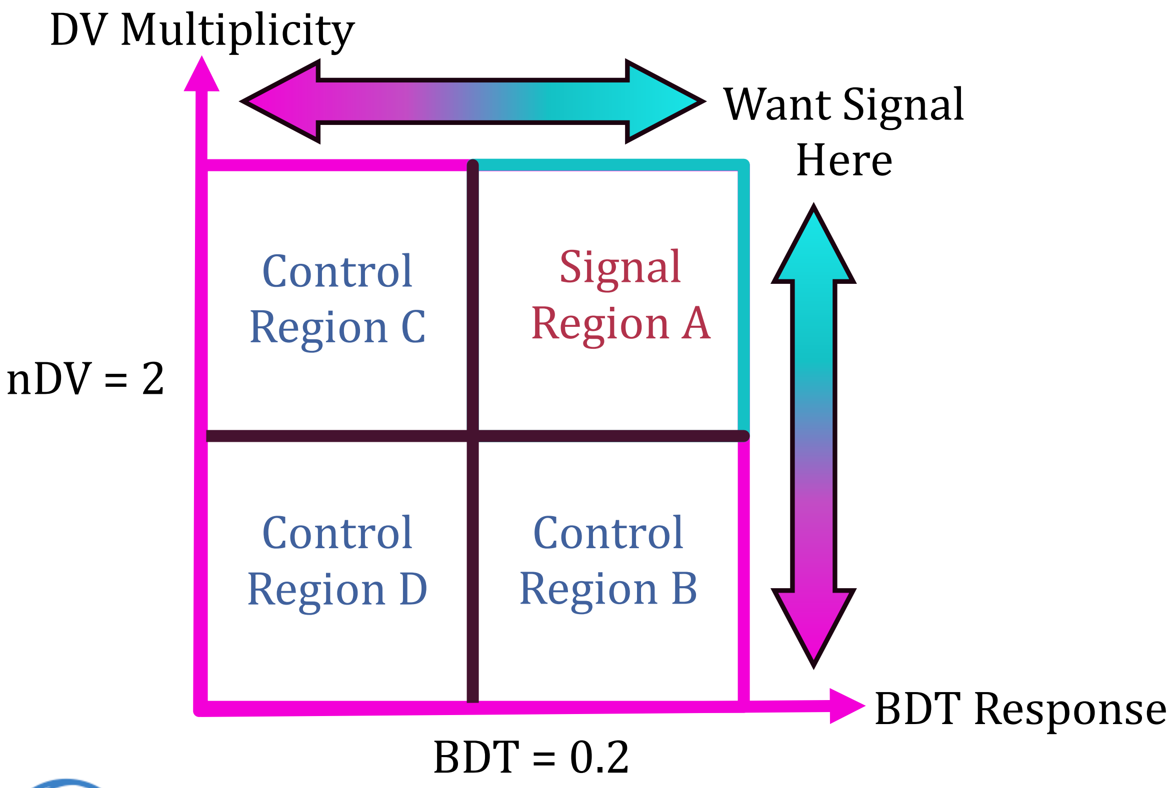
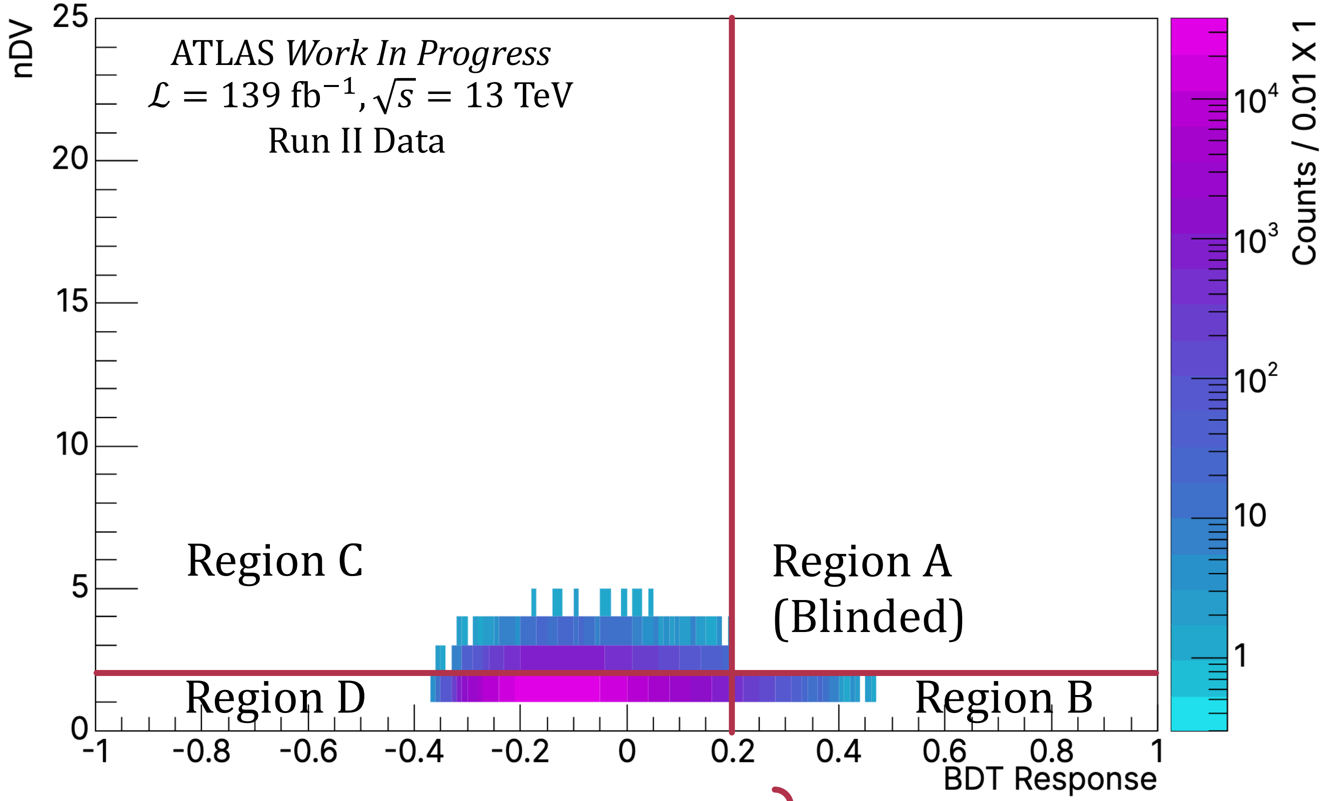
DATA-DRIVEN BACKGROUND ESTIMATION



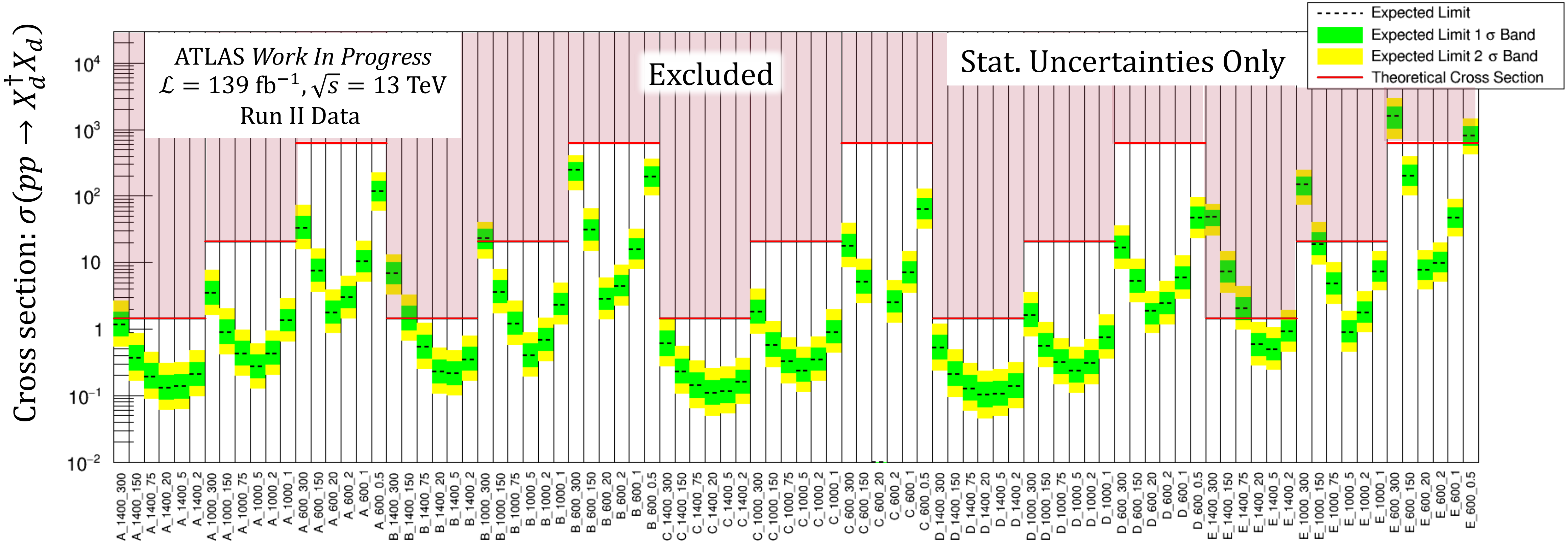


$$N_A^{est} = \frac{N_C}{N_D} \times N_B$$

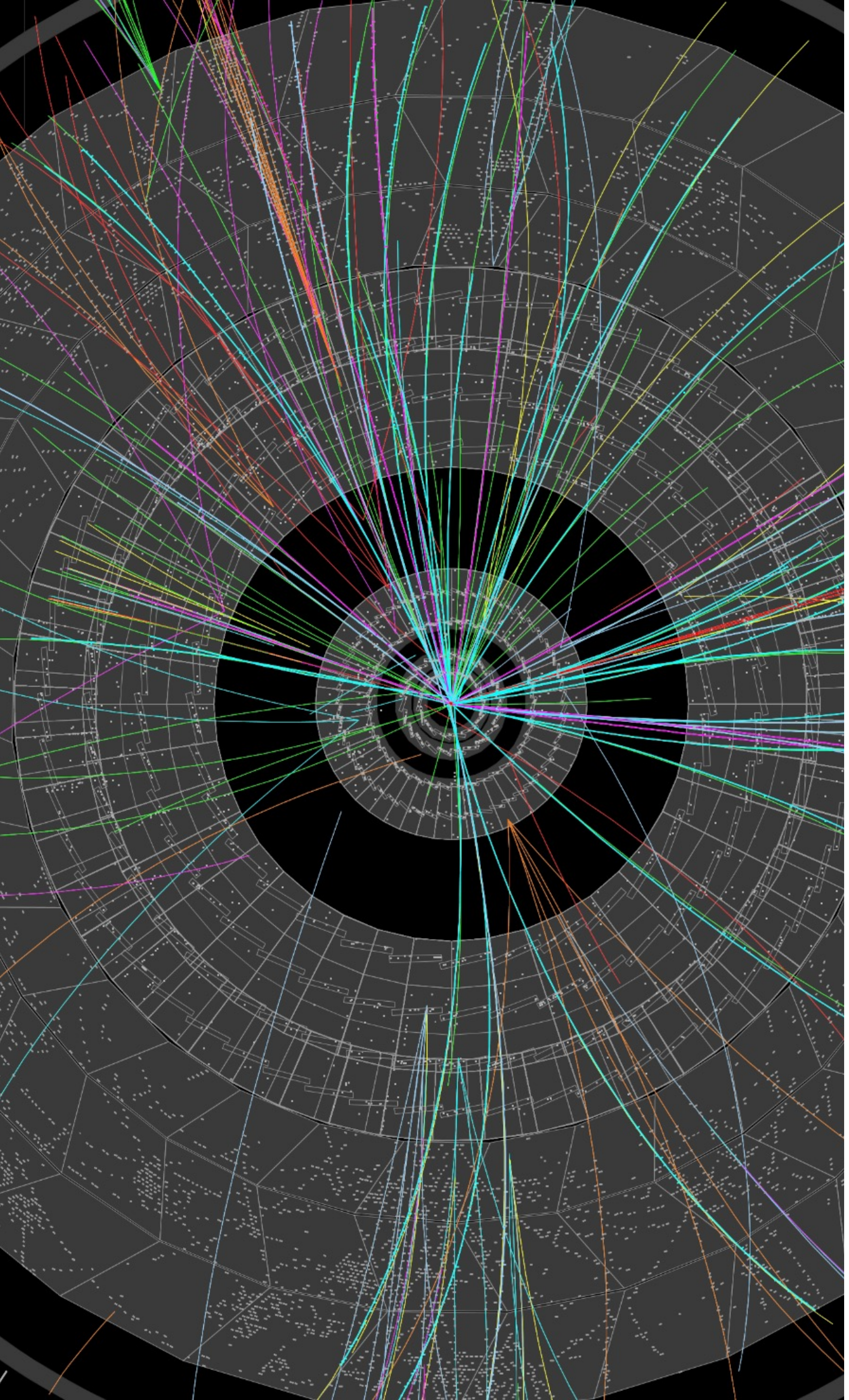
Assumption 1: Variables are Uncorrelated

Assumption 2: Signal Contained in Region A

DATA-PREDICTED RESULTS



Signal Models



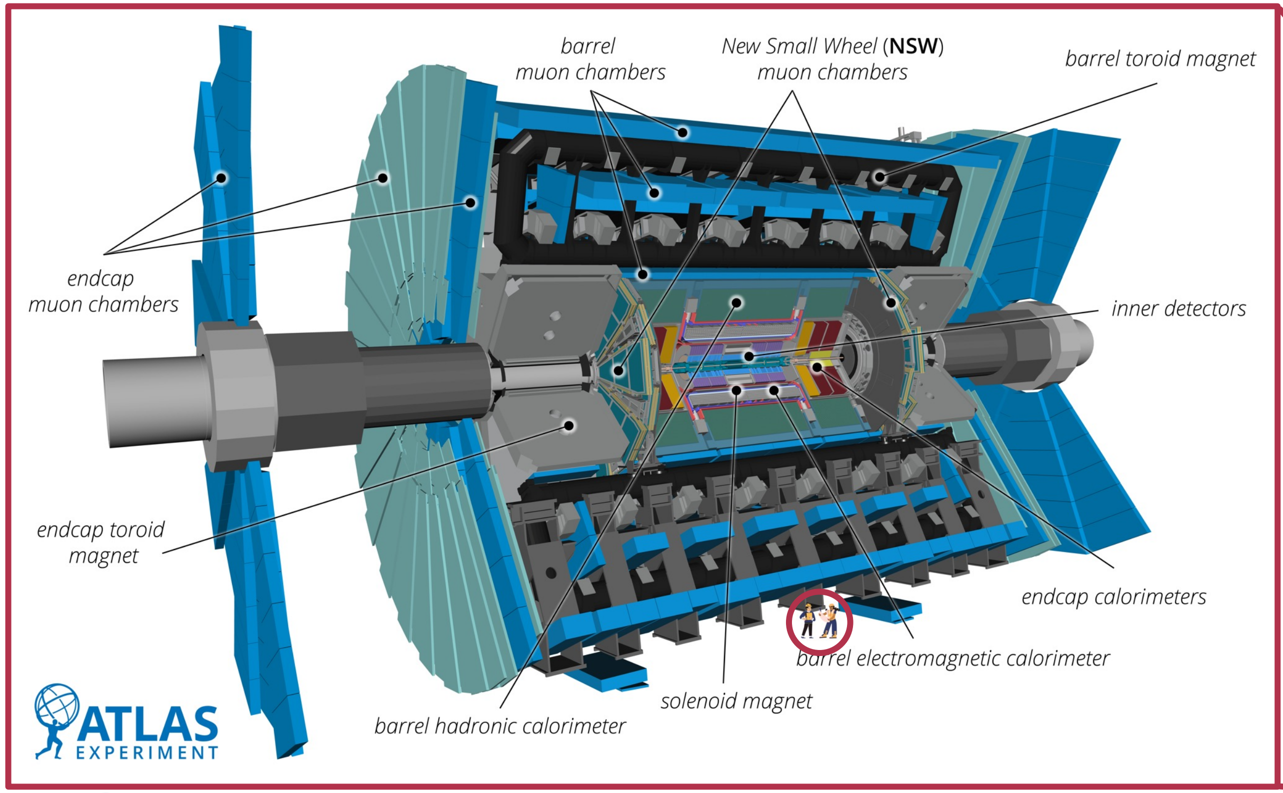
SUMMARY

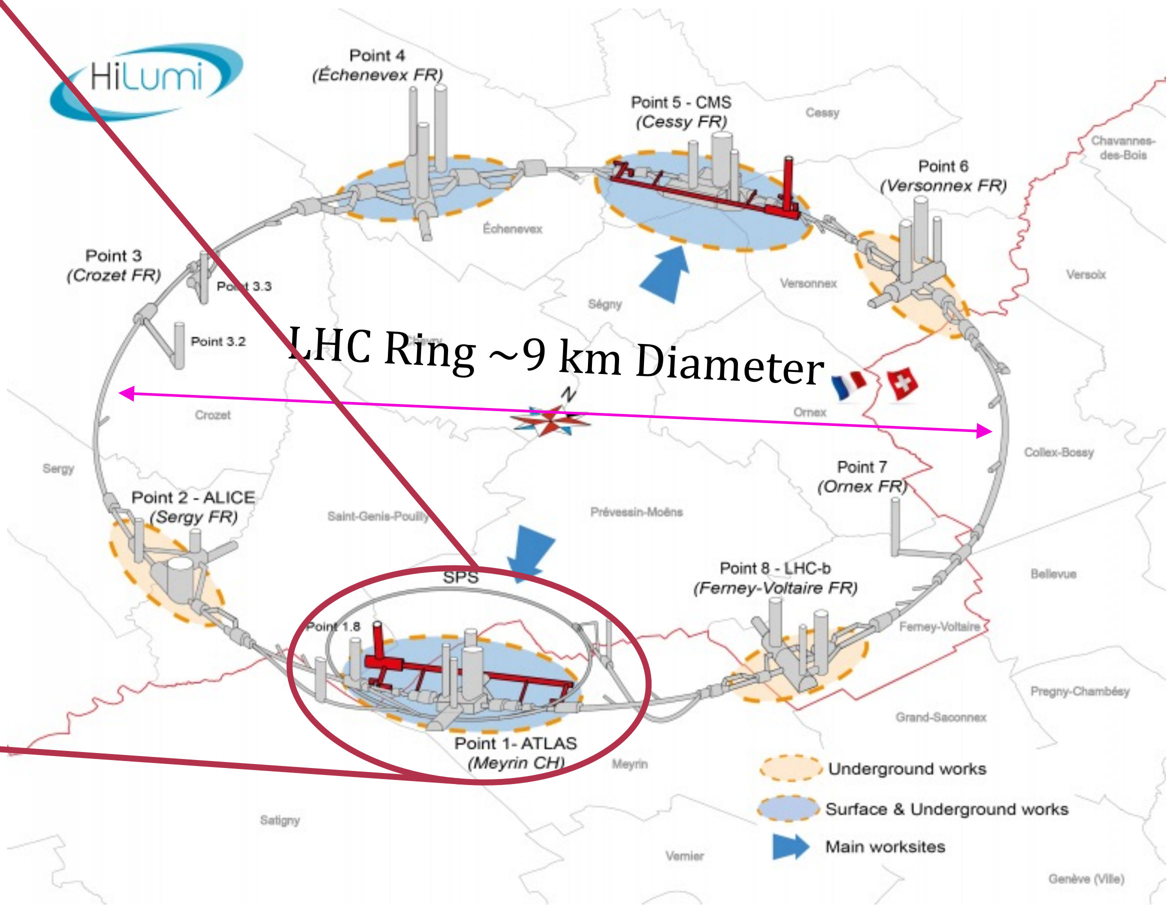
- Finalizing this ATLAS analysis, very close to publishing!
- Using Run II data, we predict sensitivity to most of our Emerging Jets models
- 1st of its kind analysis for ATLAS, expands the model space being tested for emerging-jet-like scenarios

Thank You For Listening!

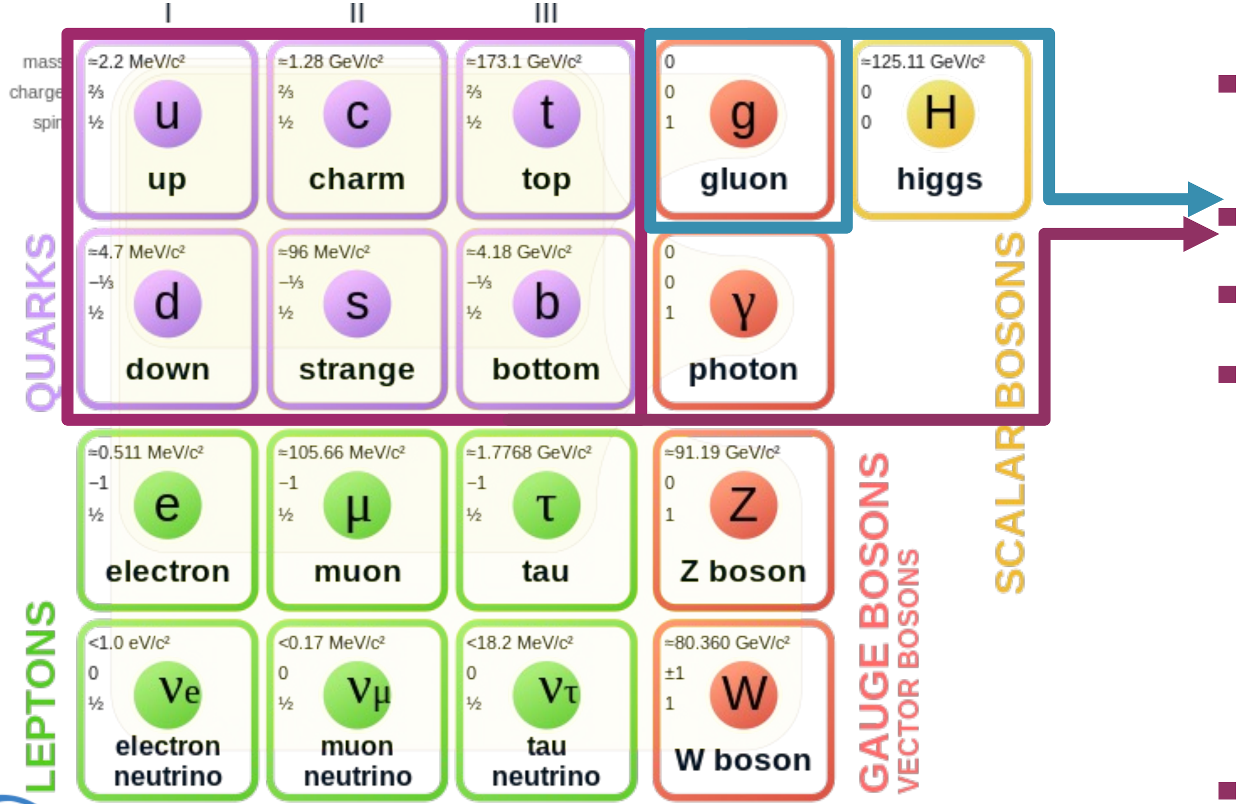
ADDITIONAL MATERIAL

ATLAS Experiment and the LHC at CERN





THE STANDARD MODEL AND QCD



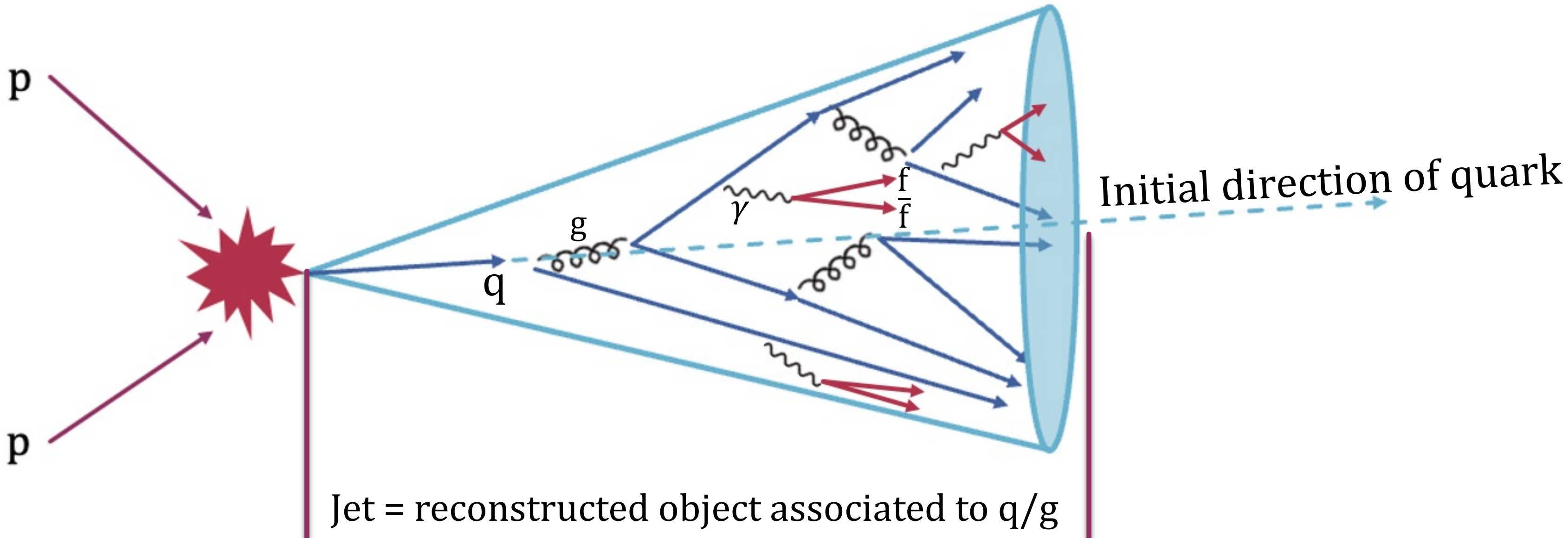
- Quantum Chromodynamics (QCD): *model* of Strong Interaction
- Describes interactions between quarks and gluons
- Introduces three colour charges (r, g, b)
- **Colour Confinement:** all physical states are colour-neutral
  - Quarks pair up into groups of 2 or 3:

$$\underbrace{g + \bar{g}}_{\text{Mesons}} \quad \text{or} \quad \underbrace{r + g + b}_{\text{Baryons}}$$

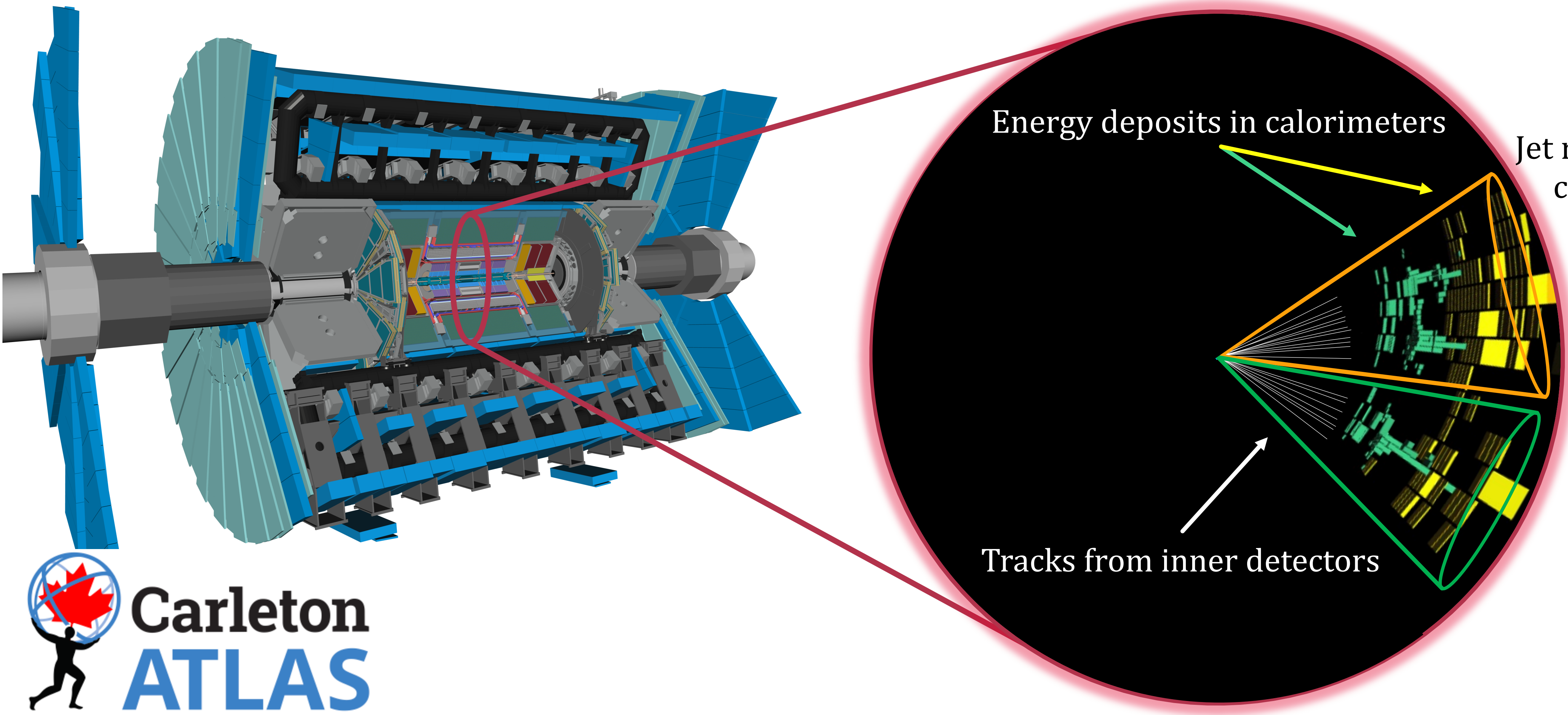
- **Asymptotic Freedom:** coupling is inversely proportional to energy transfer
  - Need high energy (collider) environments to study perturbative QCD

PARTICLE JETS

- When quarks/gluons are produced in high-energy collisions they:
  - Hadronize: quarks pull other quarks out of the vacuum to form mesons and baryons
  - Shower: hadronization creates a collimated spray of particles
- What can we measure?
  - Tracks: charged particles produced in the shower leave tracks in our detectors
  - Energy Deposits (calo clusters): particles interact (either via EM or QCD) to leave energy deposits in calorimeters



JETS IN ATLAS



Jet reconstruction clusters energy deposits into cones which point back to the initial interaction

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VARIABLE DEFINITIONS

$$H_T = \sum_{i=1}^{4} p_{T,i}^{Jet}$$

$$\mathrm{min}PTF = \frac{1}{p_T^{Jet}} \sum_i p_{T,i}^{Track} \left(d_{0,i}^{Track} < 3\,\sigma_{d_0,i}\right) \;\forall\, i = Tracks \in Jet$$

$$E_{Jet} = \sum_i E_i \;\forall\, i = CaloCells \in Jet$$

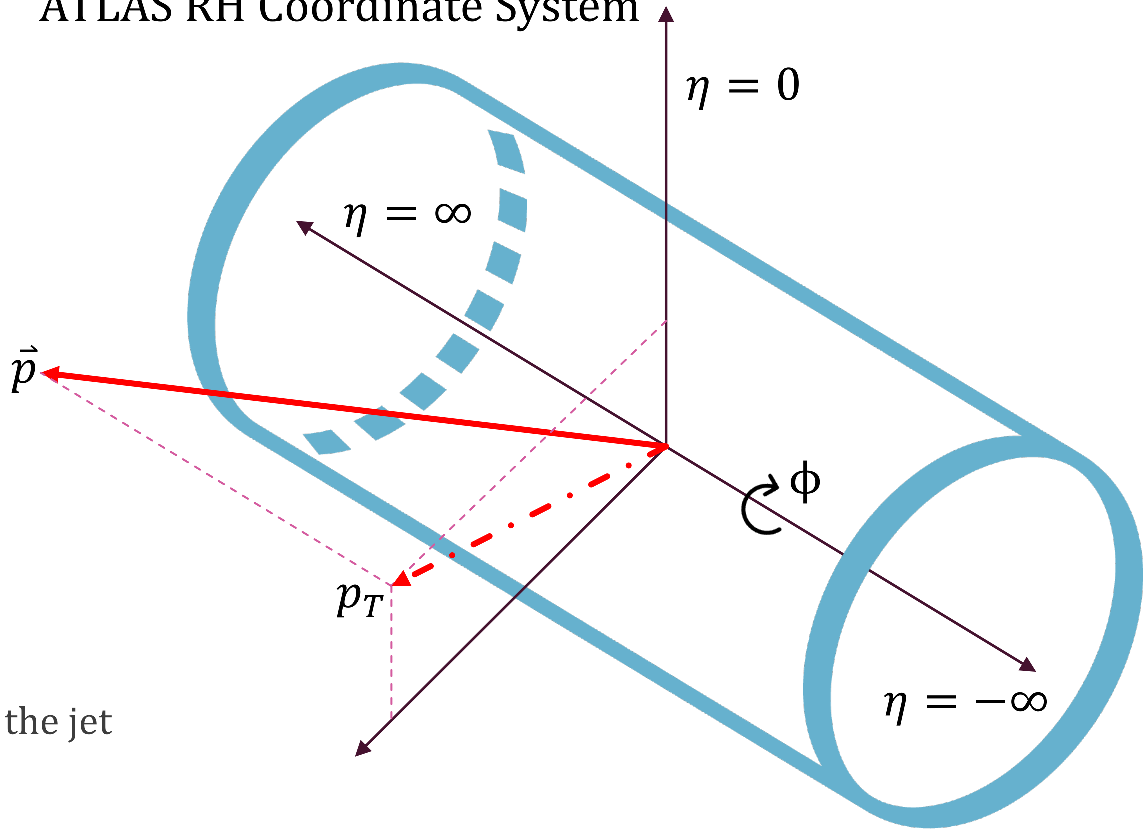
$$M_{Jet} = \sqrt{\left(\sum_i E_i\right)^2 - \left(\sum_i \vec{p_i}\right)^2} \;\forall\, i = CaloCells \in Jet$$

η_{Jet}: Measured at the central axis of the jet

$$W_{Jet} = \frac{1}{p_T^{Jet}} \sum_i p_{T,i}\,\Delta R_i \forall\, i = CaloCells \in Jet \quad \Delta R \text{ measured w.r.t. central axis of the jet}$$

$$\Delta \mathrm{R} = \sqrt{(\Delta\eta)^2 + (\Delta\phi)^2}$$

ATLAS RH Coordinate System



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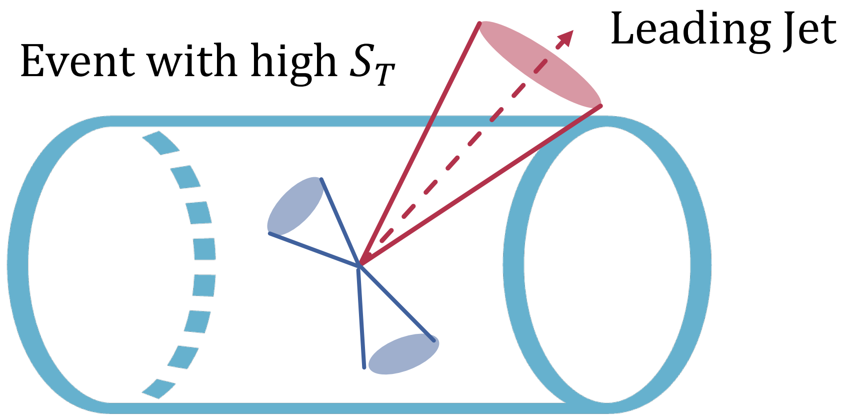
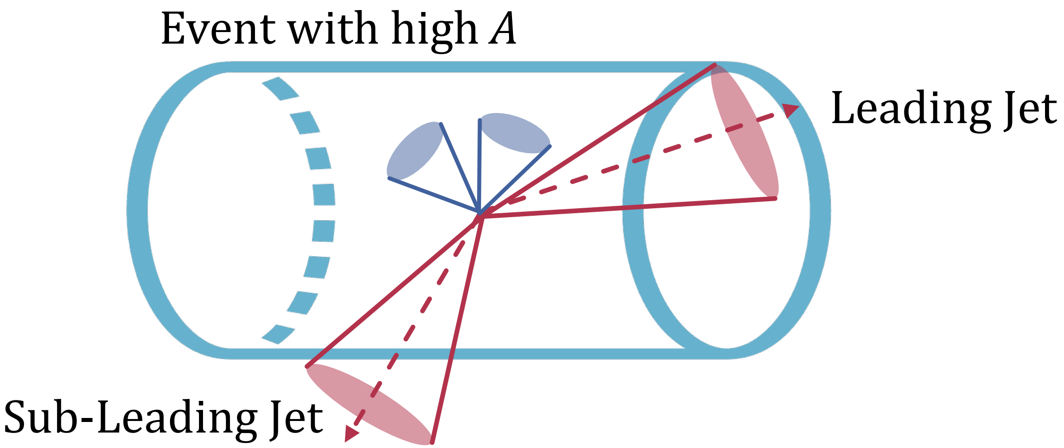
VARIABLE DEFINITIONS [CONT.]

- Event Shape Variables: try to characterize the topology of multi-jet events
- Based on Jet-Momentum Tensor:

$$\mathbb{M}_{ij} = \sum_{k=0}^{3} \frac{(p_i p_j)_k}{(p_i p^i)_k}$$

- Produces Eigenvalues $(\lambda_0, \lambda_1, \lambda_2)$ which define the variables
  - S_T: Define a plane perpendicular to the leading jet, measure of how much energy is along that plane
  - A: Define a plane through two leading jets, measure energy perpendicular to that plane





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RECONSTRUCTED ANALYSIS OBJECTS

Calorimeter Jets (r21)

- EM-topo clusters
- anti- $k_T = 0.4$
- $p_T^{jet} \geq 50$ GeV

- Event Preselection:
  - 4-jet trigger: HLT_4j90-150
  - $nJet \geq 4$
  - $p_T^{4\ leading\ jets} \geq 120$ GeV
  - $|\eta|^{4\ leading\ jets} < 2.4$

Tracks

- Combination of standard tracks and large radius tracks (LRT)
- Standard Tracks:
  - $p_T^{track} \geq 0.5$ GeV
  - $|\eta|^{tracks} < 2.7$
- LRT:
  - $p_T^{track} \geq 0.9$ GeV
  - $|\eta|^{tracks} < 5$
- Event Preselection :
  - $p_T^{track} \geq 1$ GeV

Displaced Vertices

- Built with VSI vertexing
- Tight Working Point:
  - $r\ ,\ |z| < 300$ mm
  - $|d_0| < 10$mm, $|z_0| < 100$ mm
  - $p_T^{DV} \geq 2.5$ GeV
  - $m^{DV} > 0.7$ GeV
  - Pass Material Map Veto
- Event Preselection :
  - Must be jet-matched
  - $nDV \geq 1$

VARIABLE RANKS FROM SINGLE BDT TRAINING

Jet BDT Ranks		
Variable	Importance	Separation
Mass	1	1
Energy	2	4
Width	3	2
η	4	3

Event BDT Ranks		
Variable	Importance	Separation
minPTF	1	1
nJet	4	2
A	2	3
S_T	7	7
H_T	9	9
BDT[0]	8	8
BDT[1]	6	6
BDT[2]	5	5
BDT[3]	3	4

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SIGNAL SYSTEMATICS

CP Jet Systematics:

- JES: Strong Reduction Configuration
- JER: Simple JER Configuration
- JMS: Frozen Configuration

- Up and down shifts from all NPs are symmetrized and combined in quadrature to give single values for each source
- Each jet systematic is then combined to give one overall systematic uncertainty

CP Pileup Systematic:

- Up and down pileup re-weightings are symmetrized

Tracking and Vertexting Systematic:

- Assume 2% for standard tracks, for LRT:
- Compare K-short vertices between data and MC
- Create a per-track uncertainty based on radial DV position
- Randomly remove tracks based on their per-track uncertainty
- Difference between modified and original vertex selection is taken as systematic uncertainty

PromptTrackFrac Systematic:

- Compare minPTF distributions between data and MC
- Ratios give a per-event weight used to scale the search region distribution
- Differences in signal yield gives systematic uncertainty

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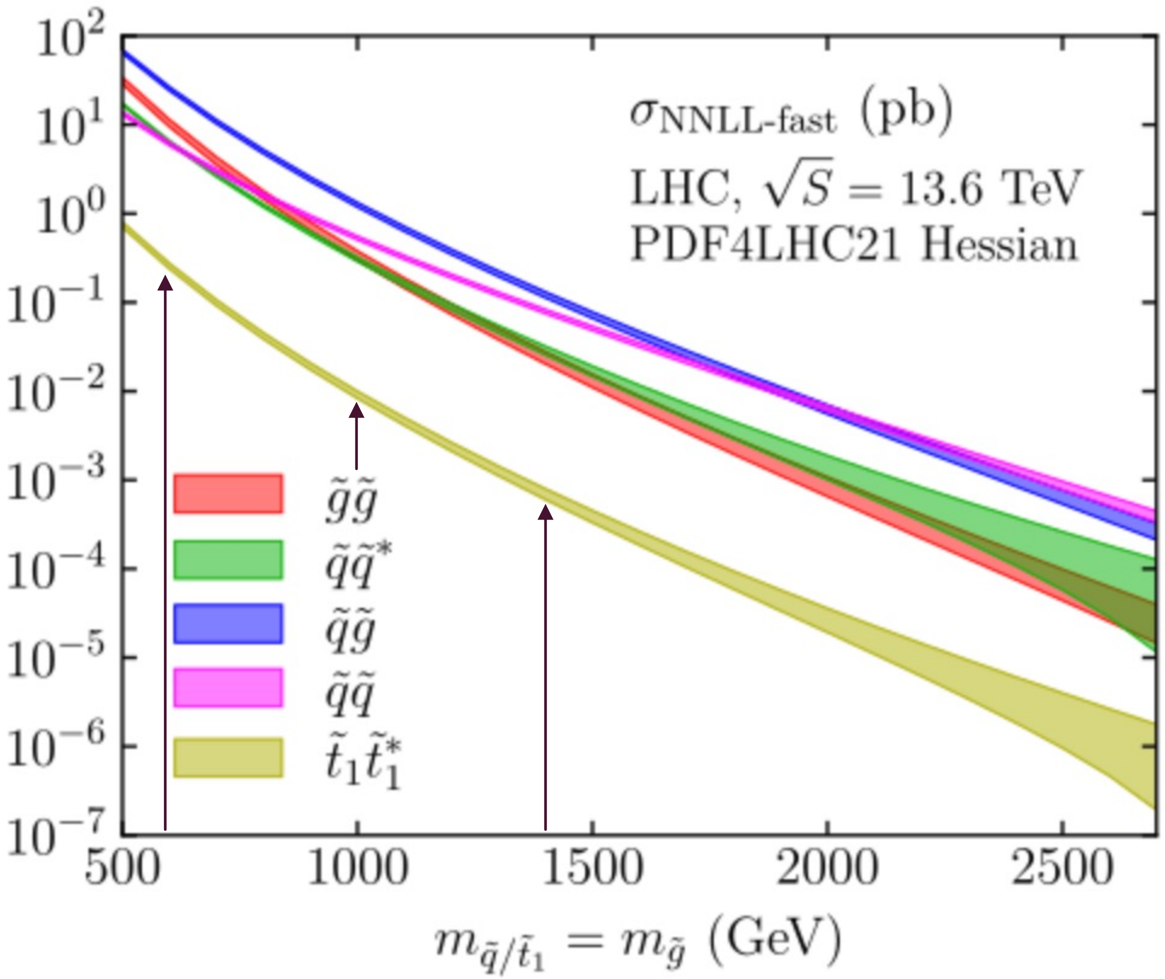
THEORETICAL CROSS-SECTION UNCERTAINTY

- Determined using stop pair production (in the limit where other squarks and gluinos have decoupled)
- Values taken from SUSY cross-section Twiki
- Since we use 3-color model, cross-sections are multiplied by a factor of 3

	M_X = 600 GeV	M_X = 1000 GeV	M_X = 1400 GeV
Old Values	430 fb	15.2 fb	1.08 fb
Updated (with uncertainty)	(650 ± 50) fb	(20.5 ± 2.3) fb	(1.42 ± 0.22) fb



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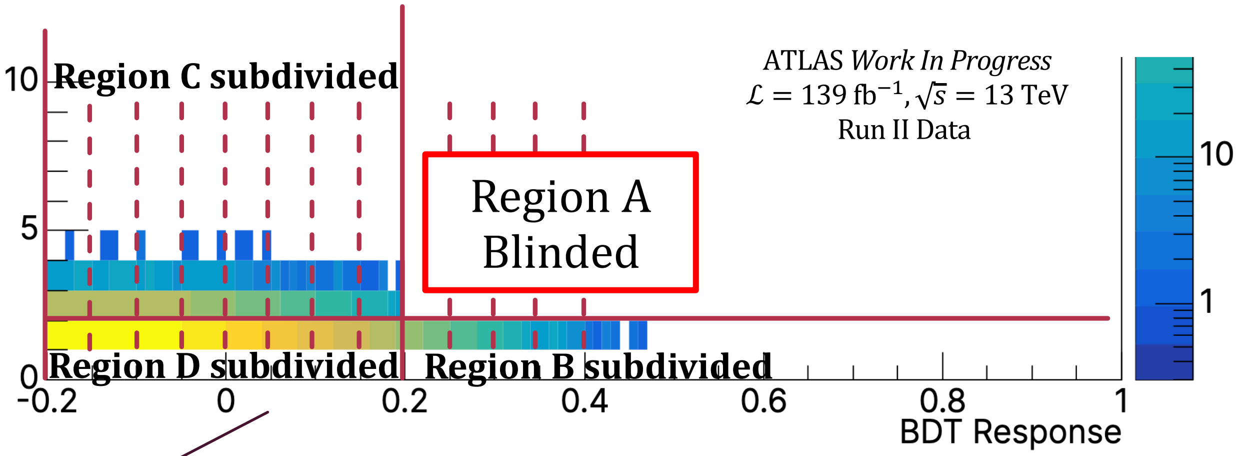
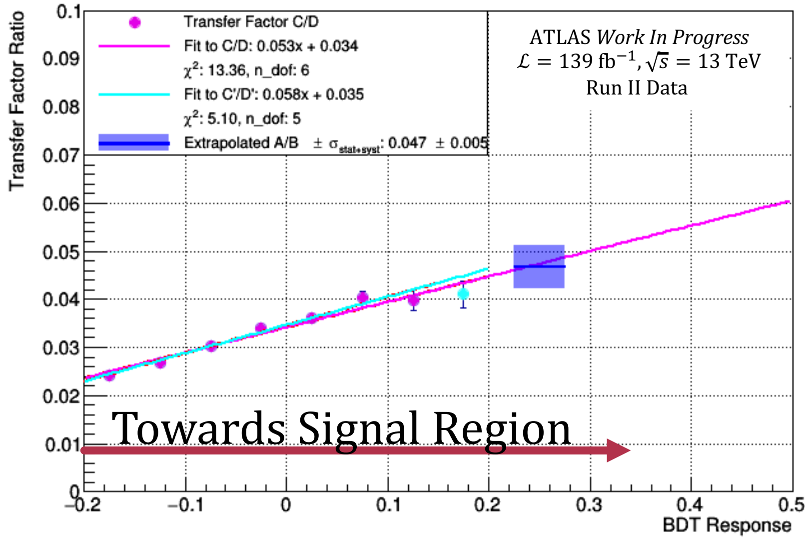
LINEAR FIT FOR ABCD METHOD



Take ratio of $\frac{N_{C,s}}{N_{D,s}}$

Fit linear function



- Instead of using just 4 regions, can break up the plane into many smaller regions
- Approximate the shape of the ratio $\frac{N_{C,s}}{N_{D,s}}$ as scanned over BDT
- Can fit a linear function to regions C and D, and extrapolate trend into A to estimate background

$$N_A^{est} = \sum_{s \in B} \underbrace{(p_1 \cdot x_s + p_0)}_{\text{Linear Function}} \cdot \underbrace{N_{B,s}}_{\text{Counts in each sub-region of B}}$$

LIKELIHOOD FIT AND CONFIDENCE LIMITS

- Simultaneous fit to entire ABCD plane, subdivided into sub-regions to fit linear function

$$\mathcal{L}(n_{i,s}|p_0, p_1, \mu, N_{i,s}) = \prod_{i=A,B,C,D} \prod_{s} \frac{e^{-N_{i,s}} N_{i,s}^{n_{i,s}}}{n_{i,s}!} \prod_{j=1}^{4} \frac{e^{-\frac{1}{2}(\frac{1-\alpha_j}{\sigma_j})^2}}{\sigma_j \sqrt{2\pi}}$$

control + signal regions

Sub-divisions

Poisson yields

Gaussian nuisance parameters

- Fit takes:
  1. Data ABCD plane
  2. Signal ABCD plane for signal subtraction
  3. 4 Gaussian nuisance parameters for systematic uncertainties

- Background prediction given by:

$$N_A^{est} = \sum_{s \in B} (p_1 \cdot x_s + p_0) \cdot N_{B,s} + \mu \cdot N_{A,s}^{Sig}$$

- Can then perform hypothesis test to find μ at 95% confidence limit
- In most cases use asymptotic formula to extract limit
  - In cases where asymptotic limits do not converge, can manually run toys to extract a limit

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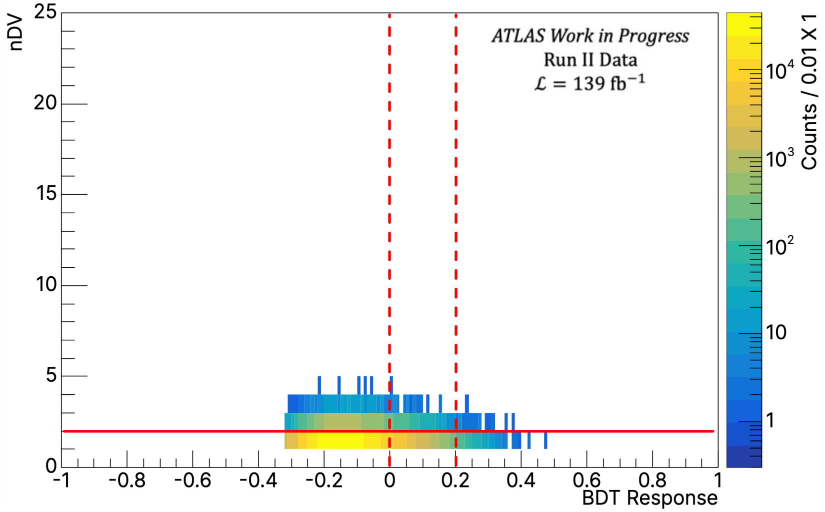
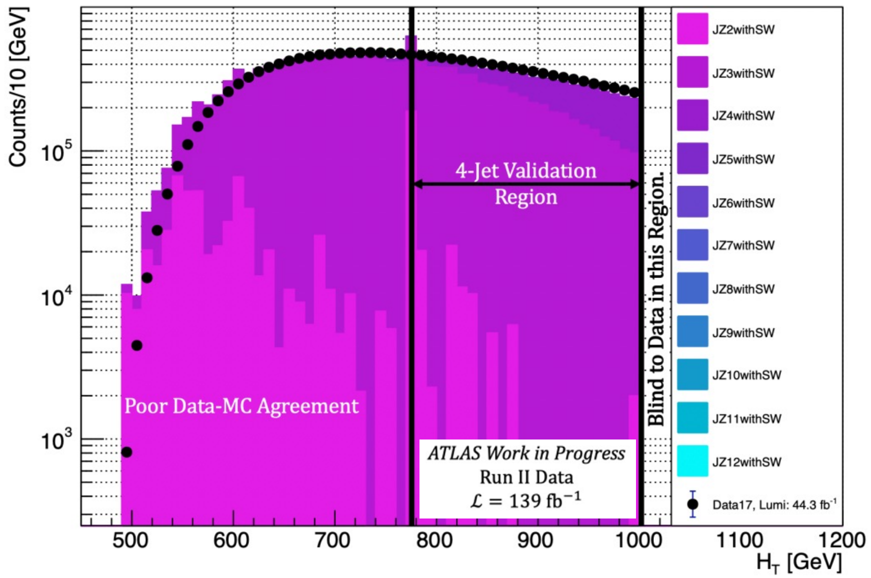
VALIDATION REGION DEFINITIONS

Use orthogonal H_T selection to define Low$-H_T$ validation region, restrict lower edge of H_T for better Data-MC agreement

$$775\ \text{GeV} \leq H_T < 1000\ \text{GeV}$$





Test two different BDT cuts in Low$-H_T$:
MC background BDT distribution runs out of stats at 0.2