A Search for Long Lived Dark Photons with the ATLAS Detector

Nevis Labs REU Program Research Project University of Wisconsin- Madison

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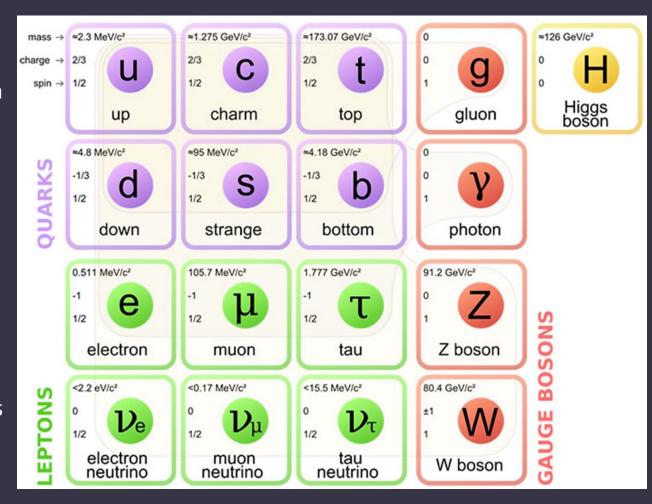


The Standard Model

Describes all known fundamental particles and their interactions

- Quarks are fermions (spin ½ particles) which interact via the strong force to make up hadrons
- Leptons are fermions that do not interact via the strong force
- Gauge bosons are mediators of the fundamental forces
 - Gluon: Mediates the strong force
 - > Photon: Mediates electromagnetic force
 - W + Z Boson: Mediate the weak force
- Have corresponding anti-particles
- The Higgs Boson is the only fundamental scalar (spin 0) particle in the standard model
 - Interactions with the Higgs field give particles mass

The standard model does not explain everything!



What is dark matter?

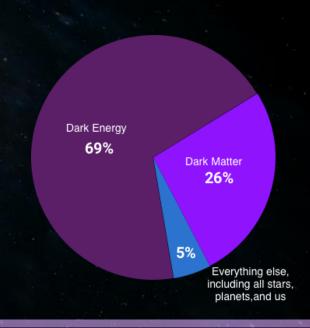
Dark matter is a form of matter that is known to exist from inconsistencies in cosmological observations that are not explained by any constituents of the standard model (SM)

What do we know about dark matter?

- ► It makes up over 80% of matter in the universe
- ► It is effectively "invisible" it does not interact electromagnetically
- It interacts with gravity and has mass
- > If it interacts with SM particles, it interacts very weakly

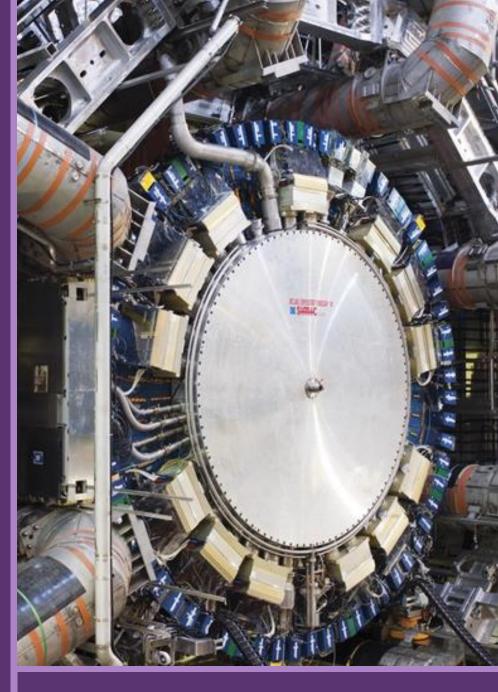
What don't we know about dark matter?

➤ Pretty much everything else

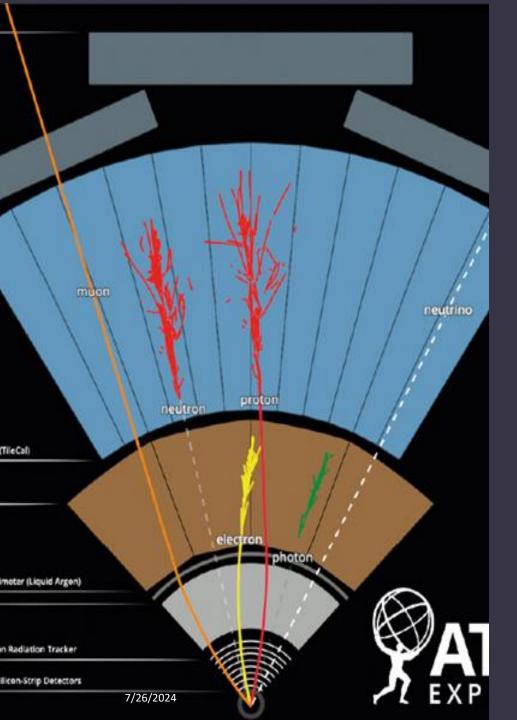


Dark Matter produced at the LHC?

- The Large Hadron Collider is the largest particle accelerator in the world
 - It accelerates protons to nearly the speed of light and collides them in 13.6 TeV collisions
- •If dark matter is a particle and interacts weakly, it may be produced during these highly energetic collisions
 - Data collected from the LHC can be used to find evidence of dark matter
- •The ATLAS detector is one of four large detectors positioned at collision points at the LHC
 - It is a multipurpose detector capable of taking high-precision measurements of resulting collisions



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ATLAS Detector

Inner detector

- Pixel Detector
- Semiconductor Tracker (SCT):
 - Extremely small strips of silicon sensors measure particle tracks with precision < ½ the width of a human hair!
- Transition Radiation Tracker (TRT):
 - Consists of 4mm diameter straws filled with gas

Magnet system

- Bends charged particles
- Particle's charge and momentum can be determined by direction and magnitude of particle curvature

Calorimeters

- Liquid Argon (LAr) Calorimeter
 - consists of layers of different kinds of metal with liquid argon between each layer of metal
- Hadronic Calorimeter
 - Layers of steel and plastic scintillating tiles

Muon Spectrometer

The Search for Long Lived Dark Photons

Motivation + Theory

The purpose of this search is to investigate a dark matter particle called a dark photon

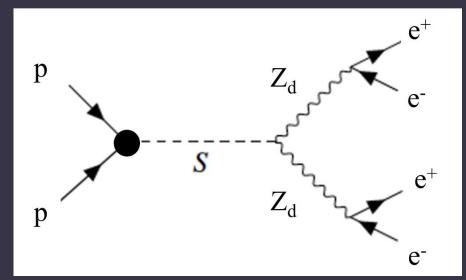
The Hidden Abelian Higgs Model (HAHM) predicts a new type of symmetry called dark gauge symmetry

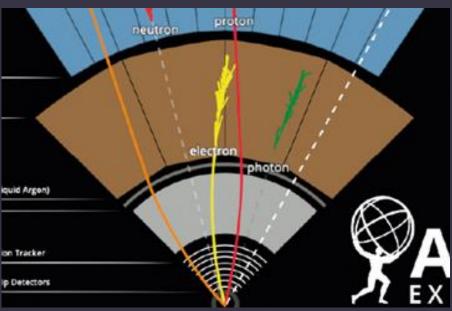
This calls for the existence of a dark gauge boson called a dark photon (Z_d) , as well as a new scalar (S)

Allows for the signal process described by the Feynman diagram

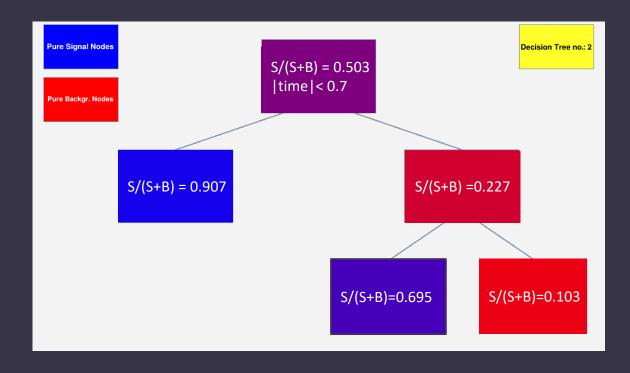
In this search, dark photons are assumed to be long lived

- > Dark photons each decay to an electron-positron pair further in the detector
- The only way ATLAS distinguishes electrons and photons is that electrons have a track and photons do not
- Since electrons produced in the edge of the TRT may not have a track, electrons produced near edge of the tracker could be reconstructed as photons





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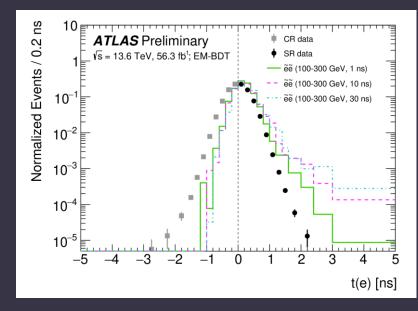
BDTs

- Boosted Decision Trees (BDTs) are a machine learning algorithm used to separate signal and background
- Decision trees take input parameters and set criteria on their values
 - Events are split based on those that meet the criteria and those that don't
 - Boosting refers to the use of information about former trees to influence new trees
 - Learns from errors on previous trees
- Splits events in half- trains BDT on one half of the events and tests on the other

8

Samples used for BDT training

- ➤ Signal: 2022 MonteCarlo (MC) events
 - > HAHM used to generate MC events of the signal process
 - Then events are passed through a simulation of the ATLAS detector to provide the information which would be given by the detector (Reconstruction)
- ➤ Control Region (CR) Background: 2022 data from the ATLAS detector
- > Preselection:
 - **>≥2** photons
 - ><2 electrons
 - ► | Photon time | < 12.5 ns
 - ➤ Due to 25 ns delay between collision at the LHC
 - ➤ Signal: Photon time > 0
 - ➤ CR Background: Photon time < 0
 - Blinds the data



Photon pair selection

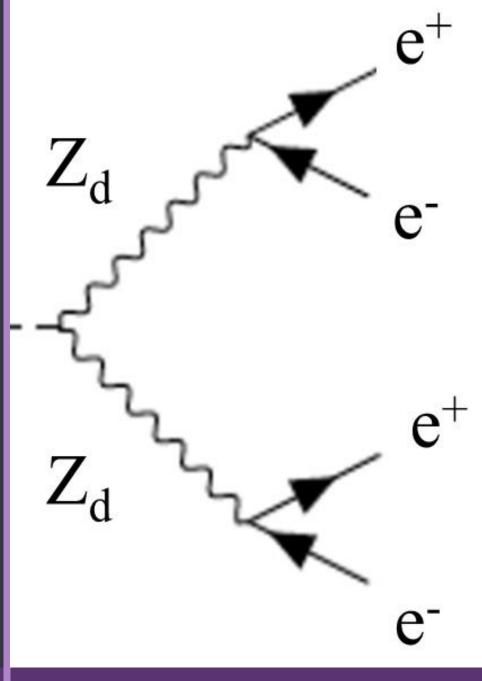
Since we input variable values for two photons into the BDT, we want to use photons which came from the same parent Z_d

Two options for photon pairing:

- Leading and subleading photons (ordered by transverse momentum)
- 2) Leading photon and photon that has lowest ΔR (angular separation) with the leading photon (minDR photon)

Can tell which photon pairs come from the same vertex by truthmatching them to the same vertex

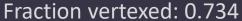
- When MC events are generated, truth information about each object is stored
- > Truth information is used to match reconstructed photons to the same vertex

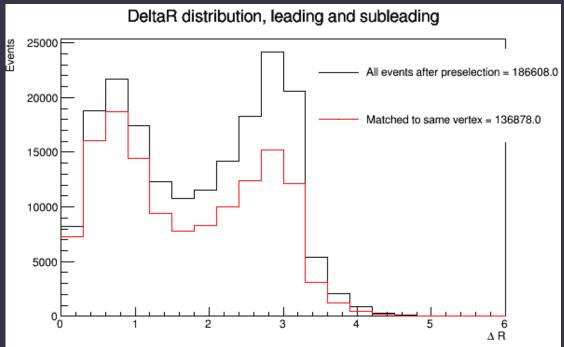


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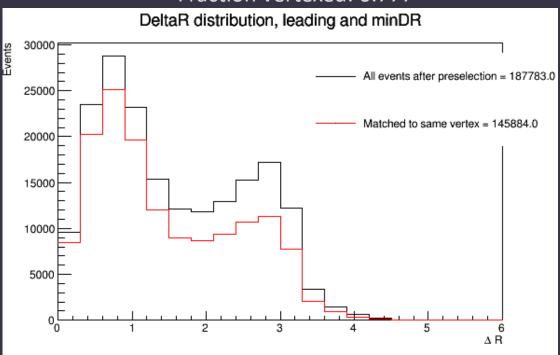
Truth Matching Results

- A larger fraction of reco leading and minDR photon pairs are truth matched to the same vertex than leading and subleading photon pairs
- Will use leading and minDR photon pairs to train the BDT





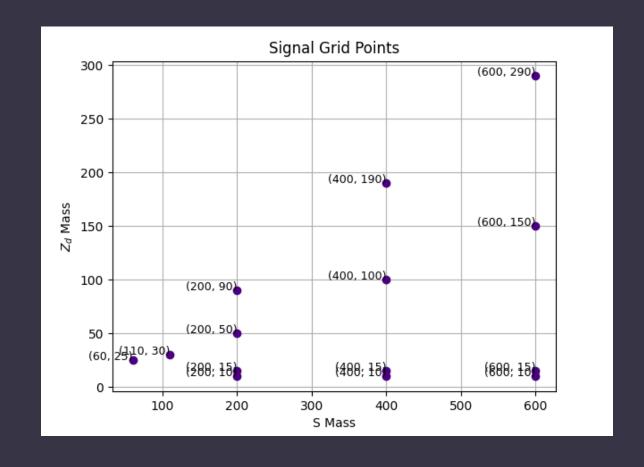
Fraction vertexed: 0.777



BDT Training over Different Signals

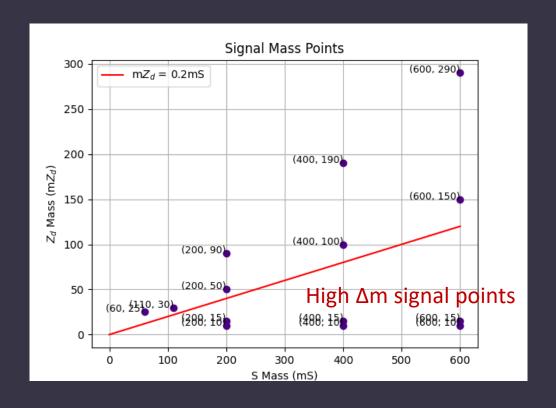
Signal Grid

- S mass, Z_d mass, and Z_d lifetime are unknown
- >Z_d lifetimes: 0.1, 0.5, 2, 10 ns
- ➤ 14 combinations of S and Z_d mass x 4 Z_d lifetimes = 56 different signal grid points
- Can one BDT be applied to all grid points?



High and Low Mass Splitting

- Mass splitting (Δm): The difference between S mass and Z_d mass
- High Δm and low Δm signals are expected to have different kinematics
- •High Δ m signals have $\frac{S}{Z_d} > 5$
- •High Δ m signals are signals with Z_d mass = 10 or 15 GeV
- Low Δm signals are all other signal points
- Will train BDT on high Δm and low Δm signal files separately, then compare to training over file containing all signal points



Top Variable Rankings

- Variables ranked by how important they were for separating signal and background
- Can look at top ranked variables to determine how different kinematics of the high and low Δm signals impacts BDT training
- ➤ This is the list of the top 7 most important variables out of 23
- Comparing the distributions for top variables gives an idea of how the kinematics of these signals are different

low ∆m

Rank	Variable	
1	t[minDR]	
2	t[0]	
3	p _t [0]	
4	In z[minDR]	
5	In z[0]	
6	f ₃ [minDR]	
7	f ₃ [0]	

high ∆m

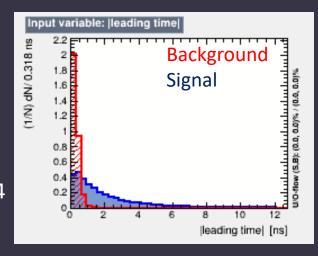
Rank	Variable
1	ΔR
2	f ₃ [minDR]
3	f ₃ [0]
4	MET
5	p _t [0]
6	ID[0]
7	f ₁ [0]

Top Variable Rankings - time

- Photon time: the time after the primary collision that the photon hits the calorimeter
- \triangleright Photon time is good for distinguishing low Δ m signals from background because Z_d is long lived, causing a delay in photon production
- \triangleright In high Δ m signals, Z_d has low mass, so it is given a lot of energy from S_d
 - > Dark photons are boosted, so the photons that are reconstructed are detected at a short time

Low Δm

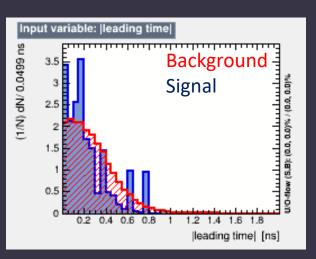
Testing sig events: 89,381 Testing bkg events: 40,264



High Δm

Testing sig events: 6,955

Testing bkg events: 40,264

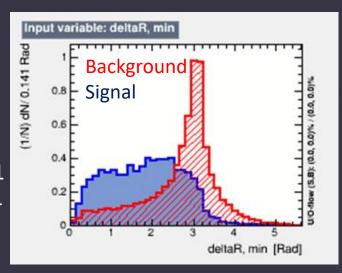


Top Variable Rankings - ΔR

- $\triangleright \Delta R$: Angular separation between the two photons
- \triangleright Δ R was ranked top in importance in high Δ m signals only
 - > This is again because the dark photons are boosted so electrons are produced very close together (collimated)
- \triangleright In the high Δ m Δ R distribution, most signal events have very small Δ R
 - \triangleright a cut on $\triangle R$ is very effective at distinguishing signal and background for high $\triangle m$ signal points

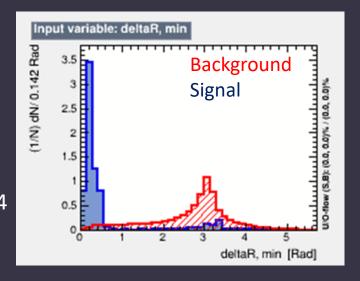
Low Δm

Testing sig events: 89,381 Testing bkg events: 40,264



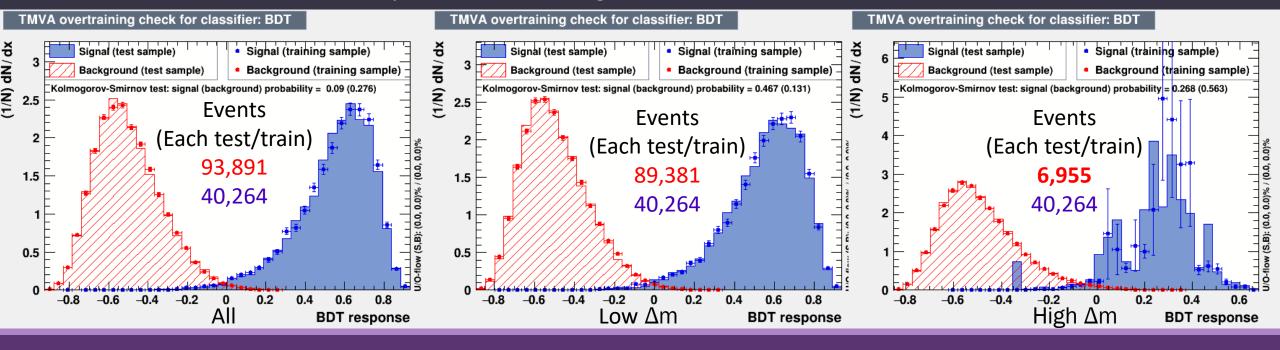
High ∆m

Testing sig events: 6,955
Testing bkg events: 40,264



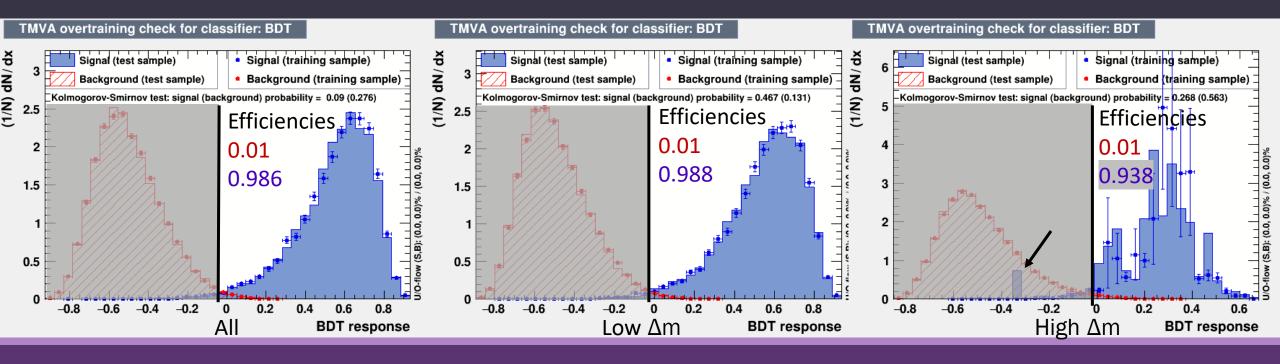
Results – BDT Score Distributions

- BDT score distribution is used to evaluate BDT performance for training over all signals and low Δm and high Δm signals
 - BDT score tells how likely an event is to be signal or background: -1 = background, 1 = signal
 - It is an average of the BDT score given to the event by each of the trees
- All and low Δm signals both show similar and good separation between signal and background
 - Because high Δm signals make up a low percentage of all the signals
- BDT score distribution indicates poor statistics for high Δm



Results — BDT Score Cuts

- Performed a cut on BDT score distribution given at BDT score corresponding to a background efficiency of 0.01
 - Tells how much signal remains (signal efficiency) when we remove 99% of the background
- Signal efficiency at 0.01 background efficiency is printed after training
- Slightly higher signal efficiency in training over low Δm signals only than for all signals together
- See much lower signal efficiency in training over higher Δm signals only
 - Low statistics for high Δm could be a cause



Conclusion + Next Steps

- \checkmark Truth matching confirmed that using photons with minimized ΔR leads to a higher fraction of photons being truth matched to the same vertex
- \checkmark Big difference in important variables used in training for low and high Δ m signals show the difference in kinematics between these signals and how that impacts BDT training
- \checkmark Poorer BDT performance in high Δm signals indicates we may want to train separate BDTs for the low and high Δm signals
- \square Redo training with improved high Δm statistics to confirm results and see if a separate BDT should be trained over high Δm signals
- □Once training is redone, we can estimate the sensitivity to our signal by computing signal/background ratios using BDT

Acknowledgements

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Thank you!

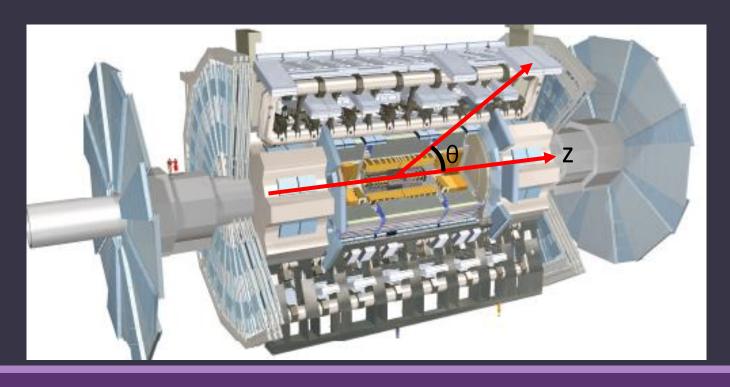
QUESTIONS?

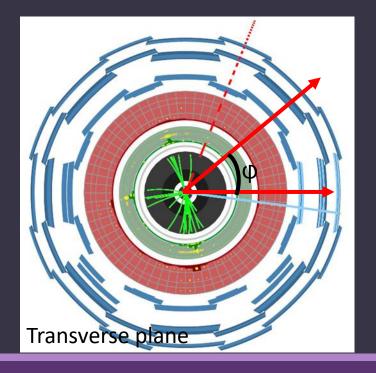
BACKUP

ATLAS Detector Geometry

Important variables:

- $\eta = -\ln[\tan(\frac{\theta}{2})]$: Angle from z-axis (beamline)
 - Lorentz invariant along z-axis necessary in proton collisions
- φ : angle in the transverse plane
- $\Delta R = \sqrt{\Delta \phi^2 + \Delta \eta^2}$: angular separation between two objects





Input variables

- >t: The time after the primary collision at which the photon is produced
- $\triangleright p_t$: Transverse momentum of the photon measured by the calorimeter
- ➤ In |z|: Pointing variable, "track" given by calorimeter
- $> f_1$: Ratio of energy deposited in 1st layer of calorimeter to the total energy of the photon
- \triangleright f_3 : Ratio of energy deposited in 3rd layer of calorimeter to the total energy of the photon
- $\geqslant |\eta|$: Magnitude of the angle from the z-axis
- ►ID: ID of the photon, roughly indicates likelihood of being a truth object
- ConversionType: Indicates whether or not a photon has been converted

The value of these variables for each of these two photons is inputted to the BDT

Input variables - continued

- $\triangleright \Delta \eta$: Difference in angle from the z-axis between the two photons
- $\triangleright \Delta \phi$: Difference in azimuthal angle between the two photons
- >In|z₁ + z₂|: Pointing variables of the two photons added
- $> \ln |z_1 + z_2|$: Difference in pointing variables of the two photons
- ➤n: Number of photons reconstructed
- $\triangleright E_T^{miss}$: Missing transverse energy
- $\triangleright \Delta R$: Angular separation between the two photons

Full Variable Rankings for each set of signals

Rank	Variable, All	Variable, Low DM	Variable, High DM
1	t[minDR]	t[minDR]	Delta R
2	t[0]	t[0]	f_3[minDR]
3	p_t[0]	p_t[0]	f_3[0]
4	ln z[minDR]	ln z[minDR]	MET
5	ln z[0]	ln z[0]	p_t[0]
6	p_t[minDR]	f_3[minDR]	ID[0]
7	f_3[minDR]	f_3[0]	f_1[0]
8	n	p_t[minDR]	eta[0]
9	f_3[0]	n	ln z_1 - z_2
10	eta[minDR]	MET	ln z[minDR]
11	MET	eta[minDR]	p_t[minDR]
12	ID[minDR}	Delta R	ln z[0]
13	ln z_1 + z_2	eta[0]	Delta phi
14	Delta phi	ln z_1 + z_2	Delta eta
15	\eta[0]	conversionType[minDR]	f_1[minDR]
16	conversionType[minDR]	Delta phi	ID[minDR]
17	Delta R	conversionType[0]	conversionType[0]
18	conversionType[0]	ID[minDR]	eta[minDR]
19	f_1[minDR]	f_1[minDR]	t[0]
20	ID[0]	ID[0]	conversionType[minDR]
21	ln z_1 - z_2	f_1[0]	ln z_1 + z_2
22	f_1[0]	ln z_1-z_2	t[minDR]
23	Delta eta	Delta eta	n

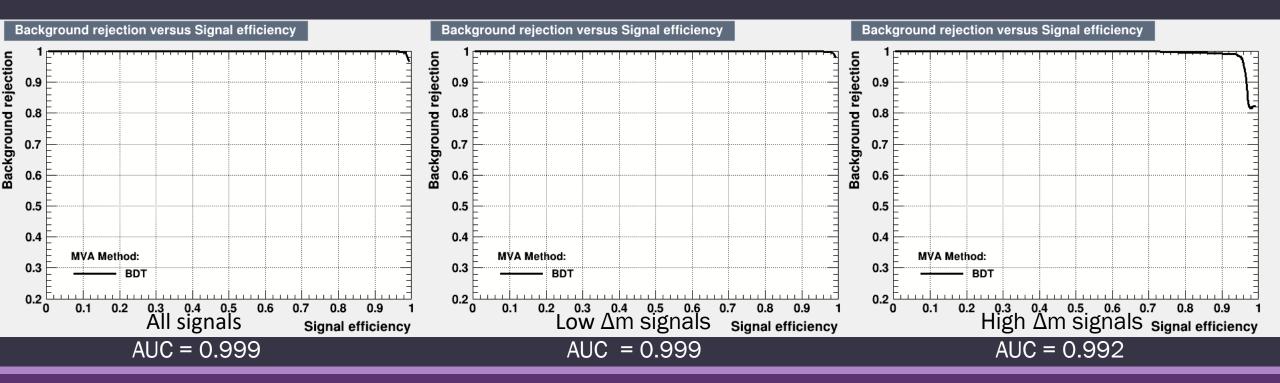
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ROC curves + AUCs

Receiving operator characteristic (ROC) curves are another way to evaluate BDT performance

- ➤ Ideal ROC is a horizontal line at bkg rej = 1: Want a signal efficiency of 1 for all values of background rejection Take the area under the ROC curve (AUC) to quantitatively compare ROC curves
- Closer to 1 = better BDT performance

Same AUC for all signals and low Δm signals provides inconclusive result of whether training separate BDTs for low and high Δm signals is beneficial



Sample Specifics

Signal- v1.0 FactoryTools ntuples for signal

- Mc23a (using 2022 ATLAS data taking conditions)
- 50k events per signal

Background, data 22

(~3 million events, LLP1 derivation trigger-skimming)

BDT Hyperparameter values

- ►NTrees=800
- ➤ MinNodeSize=7%
- ➤ MaxDepth=3
- ➤ BoostType=AdaBoost
- ► AdaBoostBeta=0.1
- ➤ UseBaggedBoost
- ➤ BaggedSampleFraction=0.6
- ➤ SeparationType=GiniIndex
- ➤nCuts=15
- Transformations = I;D;P;G,D

Link to code used to run BDT

https://gitlab.cern.ch/ewoodwar/dark-photons-bdt/-/tree/2gBDT?ref_type=heads

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