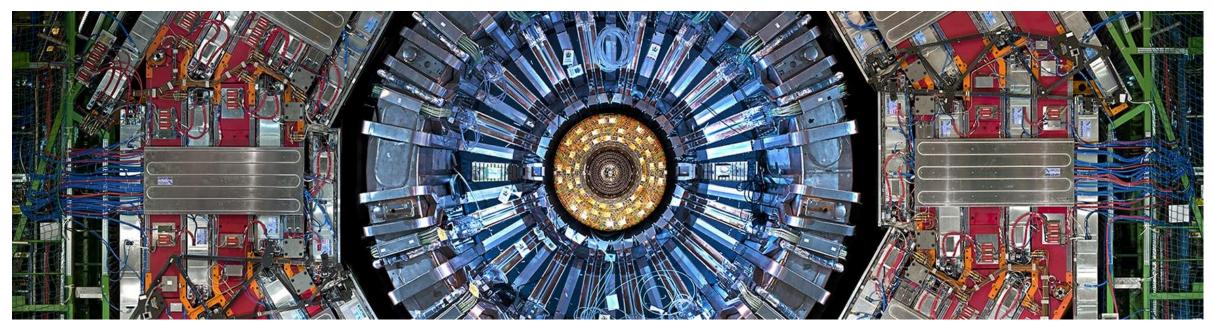




Search for Semivisible Jets at the CMS Experiment using Run 2 Scouting Data

Marcel Gaisdörfer, Markus Klute, Benedikt Maier, Brendan Regnery

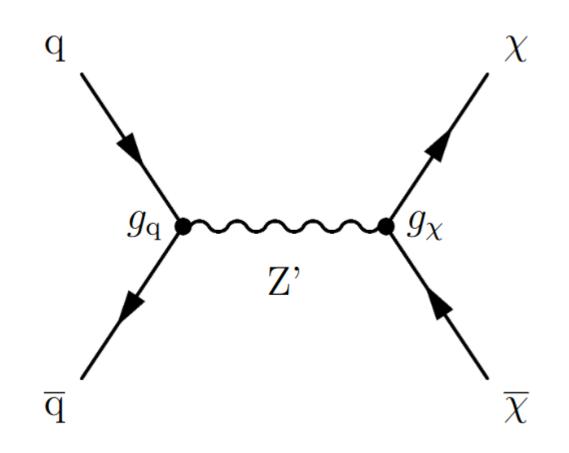


www.kit.edu

Hidden Valley Model

- Additional broken U(1) symmetry leads to massive Z' boson
- Z' acts as mediator to a QCD-like dark sector
- Coupling to the dark sector large compared to coupling to SM quarks (no coupling to leptons)

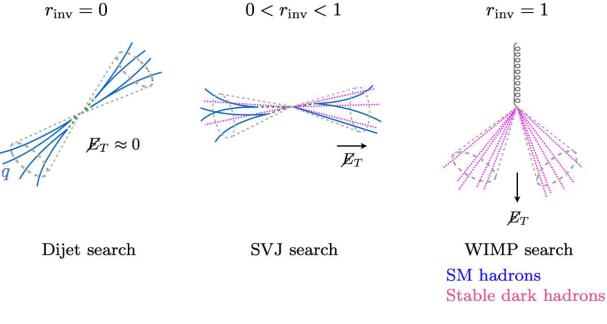




What is a Semivisible Jet?



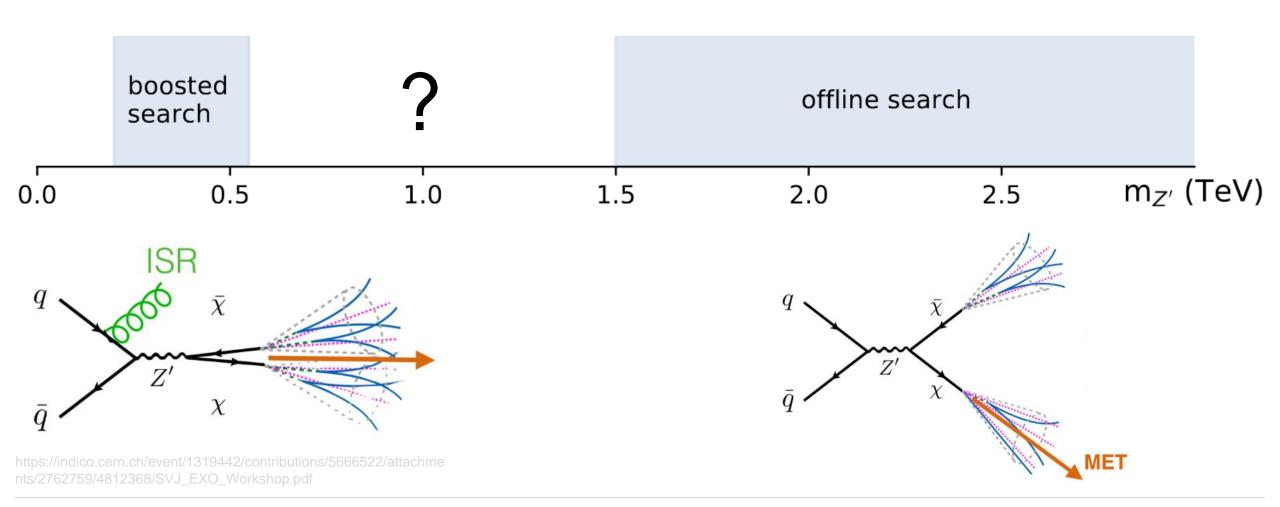
- Dark sector consists of 2 dark quarks that hadronize
- A fraction of dark quarks decay back to SM quarks
 - \rightarrow large jets with invisible particles, called semivisible jets
- Shower dynamics depend on fraction of invisible particles r_{inv}



https://indico.cern.ch/event/1319442/contributions/5666522/attachme nts/2762759/4812368/SVJ_EXO_Workshop.pdf

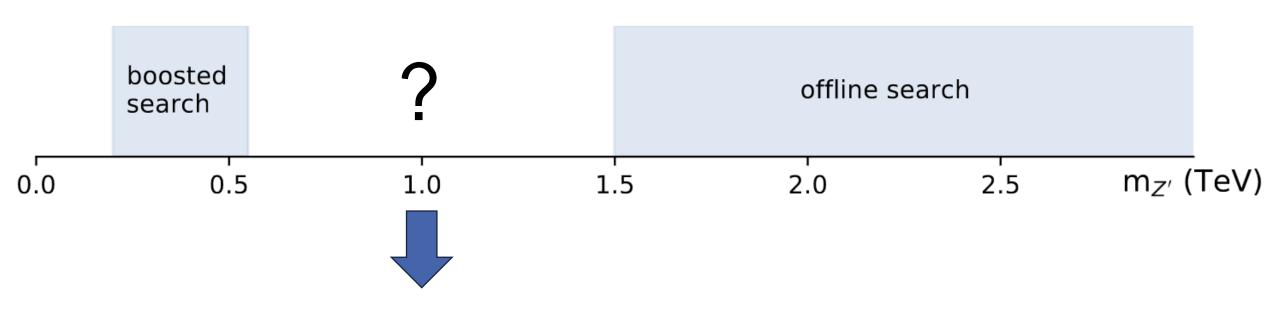


SVJ Phase Space





SVJ Phase Space

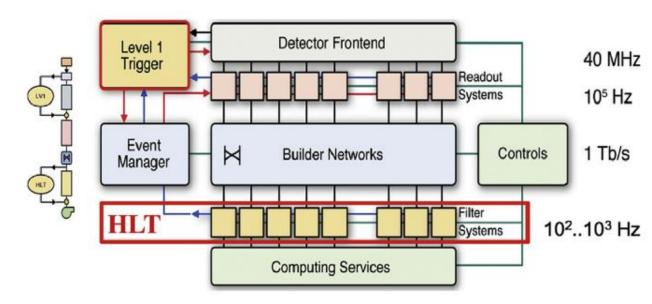


Accessible through scouting data!

Reminder: The CMS Trigger System



- Impossible to record all events produced at the LHC
- L1 Trigger: hardware-based
- HLT: software-based, uses a fast online reconstruction for decision making
- Selected events are subjected to prompt offline reconstruction



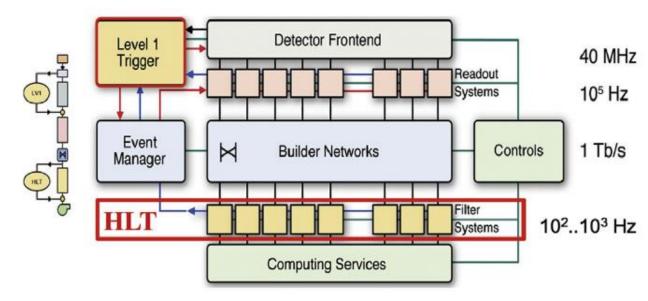
https://www.sciencedirect.com/science/article/pii/S016890021200994 ?ref=cra_js_challenge&fr=RR-1



Reminder: The CMS Trigger System

Problems:

- BSM physics could hide at low energies, below trigger thresholds
- Trigger thresholds rise with increasing luminosity (HL-LHC!)



https://www.sciencedirect.com/science/article/pii/S016890021200994 1?ref=cra_js_challenge&fr=RR-1

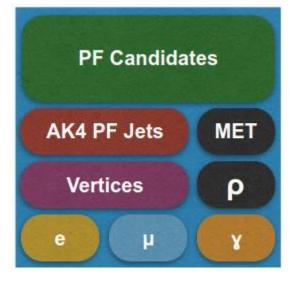
Data Scouting and Data Parking at CMS

Use online reconstruction capabilities of the HLT to only save reconstructed physics objects

Pros:

- Low file size (10-15kB/event vs 1MB/event)
 - \rightarrow can record more events at lower trigger thresholds
- Low disk space needed
- Almost no additional strain on DAQ
- HLT reconstruction not much worse than offline reconstruction





https://arxiv.org/abs/1808.00902

Data Scouting and Data Parking at CMS

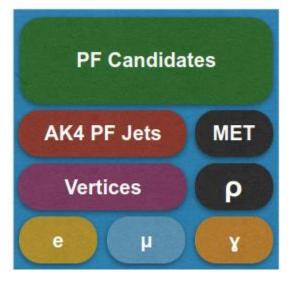
Use online reconstruction capabilities of the HLT to only save reconstructed physics objects

Cons:

- Loss of some accuracy (HLT uses slightly simplified PF)
- Loss of flexibility: custom reconstruction instead of PF impossible → data parking

Data parking: save full event information on tape without running a reconstruction (can be analyzed later if needed)

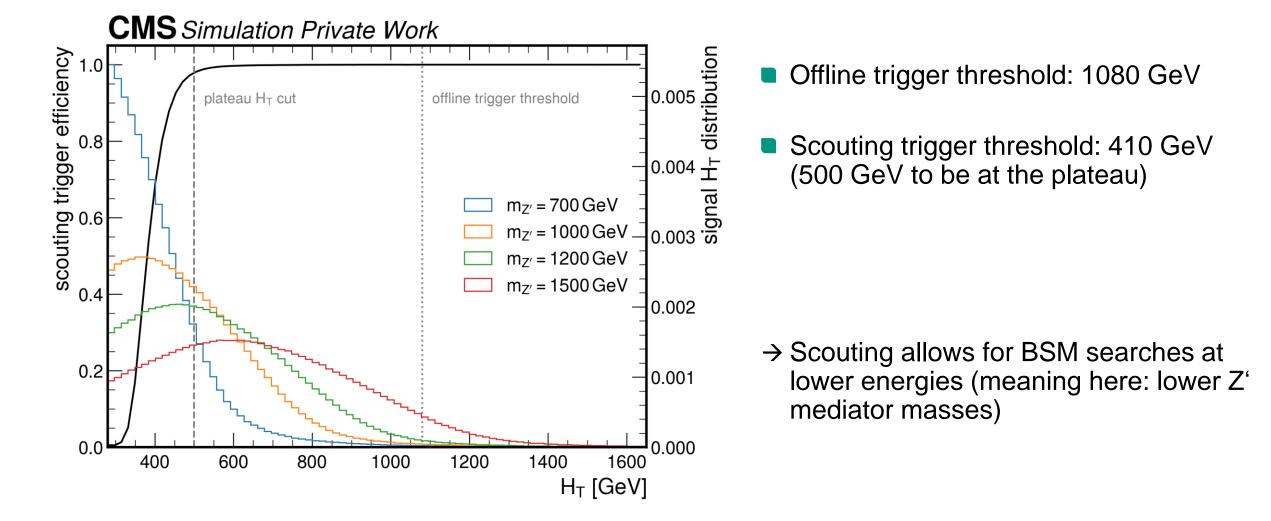




https://arxiv.org/abs/1808.00902

Data Scouting for SVJ

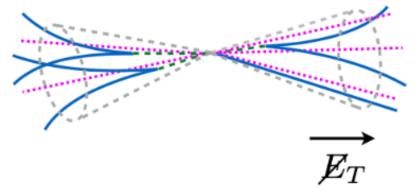




Signal-Background Discrimination

- Event signature: 2 large Jets, moderate amount of missing transverse energy aligned with one of the jets
- Main SM backgrounds: QCD multijet events, ttbar
- Two approaches: model-independent and model-dependent
 - Model-independent: cut-based event selection
 - Model-dependent: cuts + machine learning-based tagger



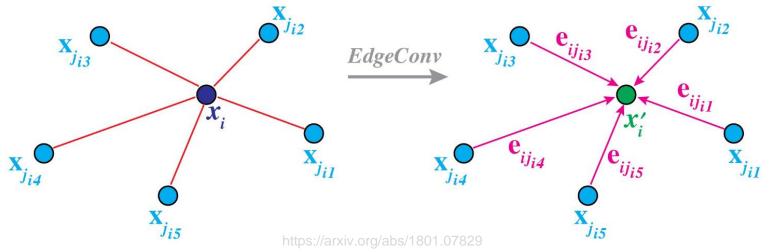


https://indico.cern.ch/event/1319442/contributions/5666522/attachments/2762759/4812368/SVJ_EXO_Workshop.pdf

GNN-based SVJ tagger



- Input: features of the constituents of the 2 leading jets (p_T, η, φ, mass, charge, pdgID), represented as a particle cloud
- Dynamic Edge Convolution used to construct local graphs from k-nearest neighbors
- Stacking of Edge Convolution builds a deep network, dynamically updating the graphs and learning jet substructure

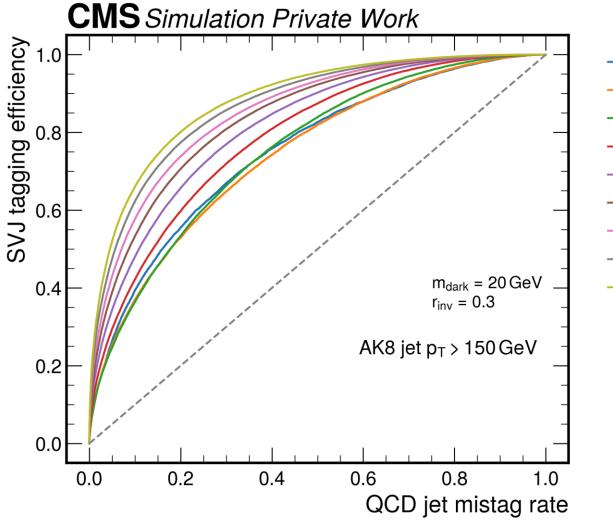


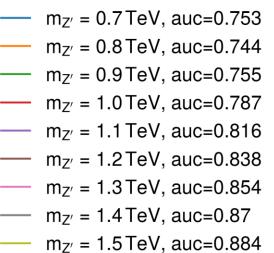


GNN-based SVJ tagger

13

April 22, 2024

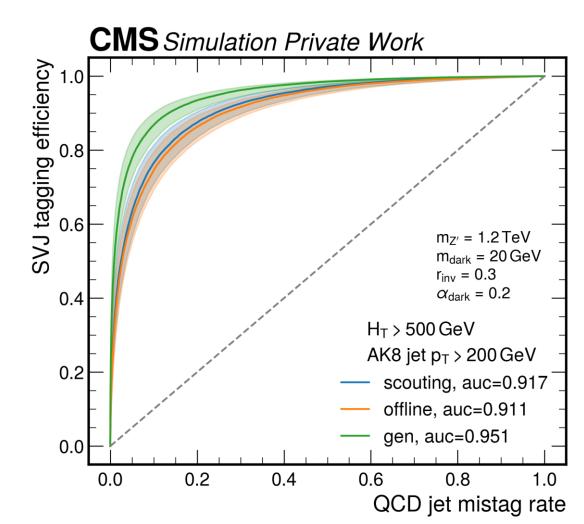




Result: SVJ tagger trained on a number of different Z' masses

Scouting Study

- Performance of the tagger evaluated on
 - Scouting data
 - Offline reconstruction
 - Genparticles
- Performance found to be similar between scouting and offline reconstruction





Sculpting

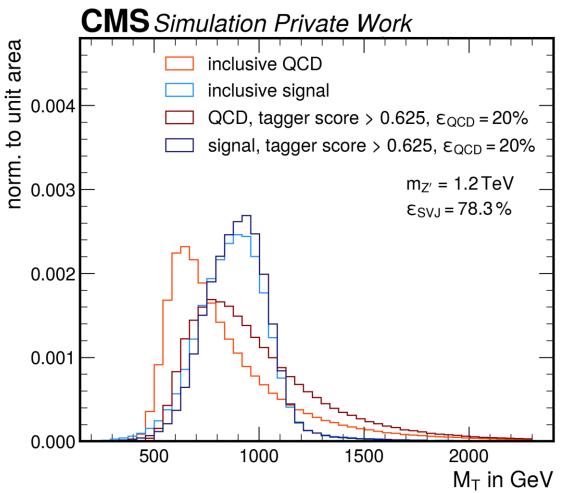
Marcel Gaisdörfer – Search for Semivisible Jets at the CMS Experiment 15 April 22, 2024 using Run 2 Scouting Data

Institute of Experimental Particle Physics (ETP)

Search strategy: typical bump hunt in M_{T} distribution

$$M_{\rm T}^2 = \left[E_{{\rm T},JJ} + E_{\rm T}^{\rm miss} \right]^2 - \left[\vec{p}_{{\rm T},JJ} + \vec{p}_{\rm T}^{\rm miss} \right]^2 = M_{JJ}^2 + 2p_{\rm T}^{\rm miss} \left(\sqrt{M_{JJ}^2 + p_{{\rm T},JJ}^2} - p_{{\rm T},JJ} \cos(\phi_{JJ,{\rm miss}}) \right)$$

Problem: applying the tagger "sculpts" the shape of the background distribution due to correlation with M_{T} \rightarrow Problems with background fit



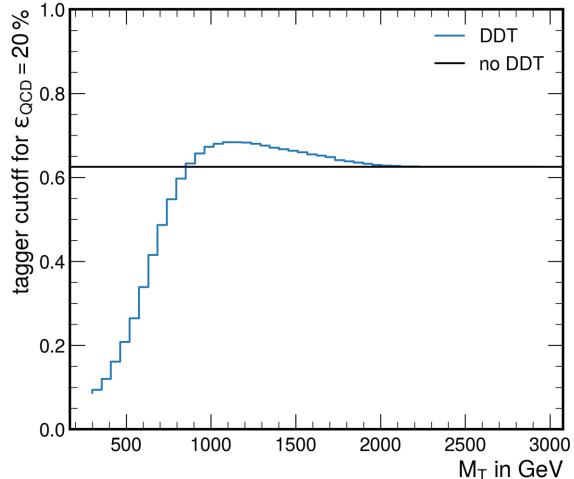


Decorrelation of the Tagger

- Separate events into M_T bins
- Calculate tagger cutoff per bin to cut off 80% of QCD events

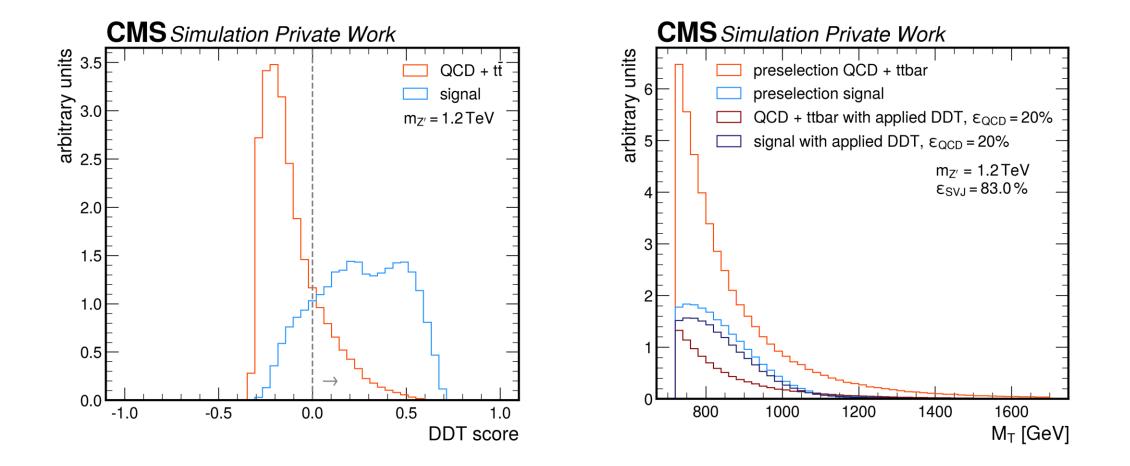
This preserves the shape of the distribution while removing most background





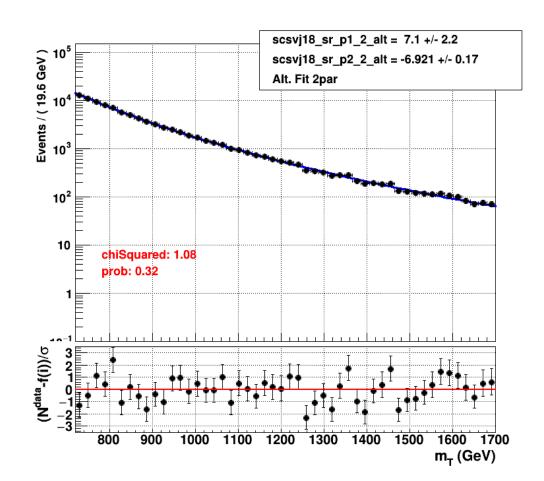
Decorrelated Distributions

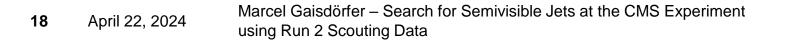




Background Estimation

- Data-driven approach: fit analytic functions to the background spectrum
- Use Fisher test to determine optimal number of parameters



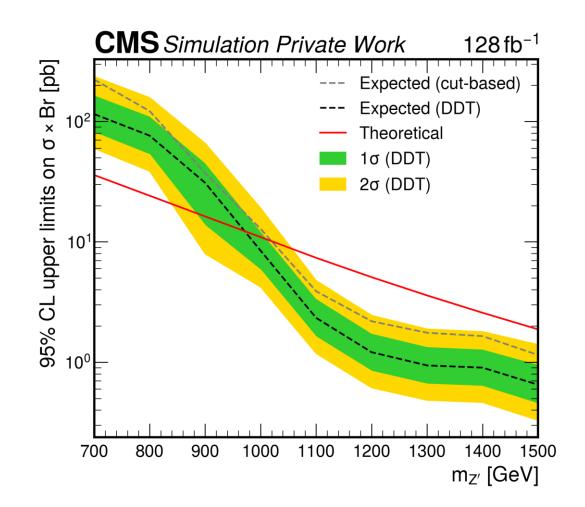




Expected Limits

- Calculated expected limits from a small mock data set (CL_s method), scaled to the entire Run 2 scouting data set
- Expected possible exclusion above 1.0 TeV (1.1 TeV without tagger)
- Limits consistent with 2022 offline analysis at m_{z'} = 1.5 TeV

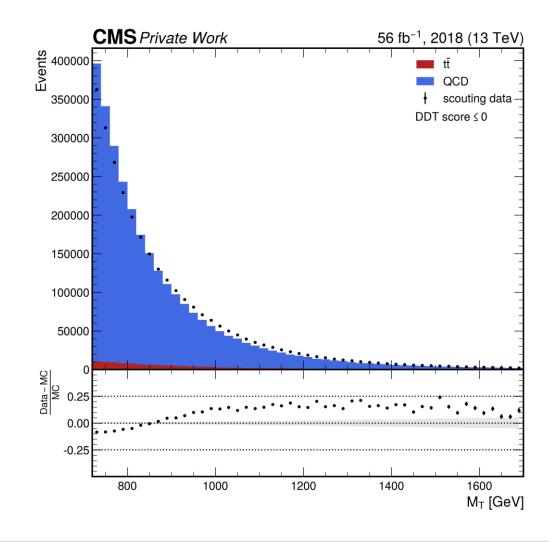




First Data Plots

- Tagger used to select backgroundlike events and blind signal
- MC normalized to data for shape comparison
- → further corrections / additional backgrounds needed





Conclusion and next Steps



- Analysis framework has been set up
- Expected exclusion 1.0 (1.1) < m_{Z'} < 1.5 TeV, limits consistent with offline analysis at shared mass point

Next steps:

- More expansive uncertainty estimation
- Could add more SM background processes
- Add further MC corrections
- Could further optimize the GNN
- **.**..
- Unblind the data to obtain final results



Backup: Selection and Cutflow



selection cuts	background efficiency	signal efficiency
2 AK8 jets with $p_{\rm T} \ge 150$ GeV and $\eta \le 2.4$	1.0000	1.0000
$H_{\rm T} > 500 { m GeV}$	1.0000	1.0000
scouting trigger	0.9985	0.9917
$M_{\rm T} > 720 { m GeV}$	0.7074	0.6509
$R_{\rm T} > 0.15$	0.0079	0.1778
$\Delta \eta_{JJ} < 1.5$	0.0064	0.1589
$\Delta \phi_{\min} < 0.8$	0.0061	0.1516

Backup: GNN Architecture



- 3-layer MLP
- 2 stacked DynamicEdgeConv operations (k=24)
- 5-layer MLP (2 10% dropout layers)
- GlobalSumPool aggregates outputs of all nodes into final prediction score

$$\begin{split} h_{\text{embed}} &= \text{MLP}_{\text{embed}}(X) \\ h_{\text{DGC1}} &= \text{DynamicEdgeConv}(h_{\text{embed}} | k = 24) \\ h_{\text{DGC2}} &= \text{DynamicEdgeConv}(h_{\text{DGC1}} | k = 24) \\ h_{\text{enc}} &= \text{MLP}_{\text{enc}}(h_{\text{DGC2}}) \\ y_{\text{pred}} &= \text{GlobalSumPool}(h_{\text{enc}}) \end{split}$$