FERMILAB-SLIDES-24-0113-CMS-CSAID-PPD

Dark QCD: the Next Frontier in Dark Matter

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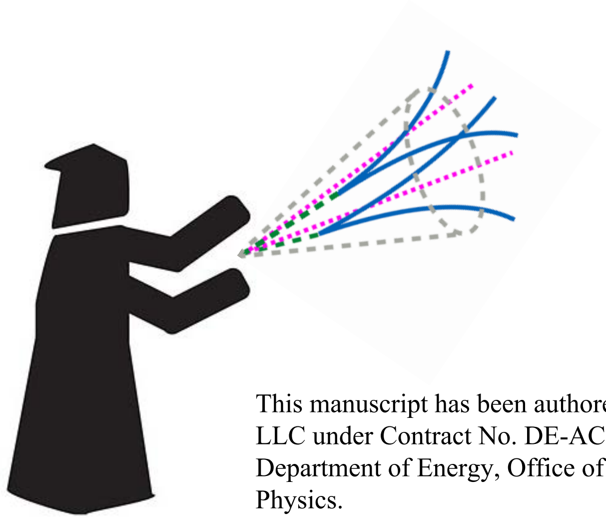
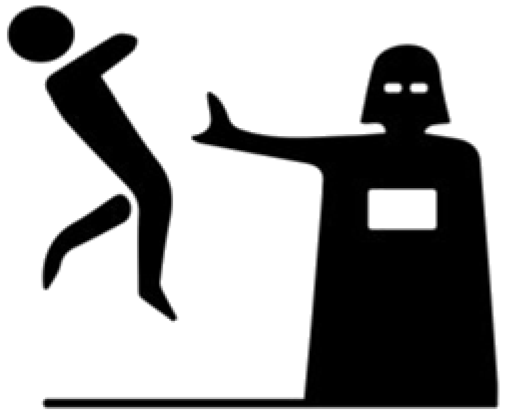
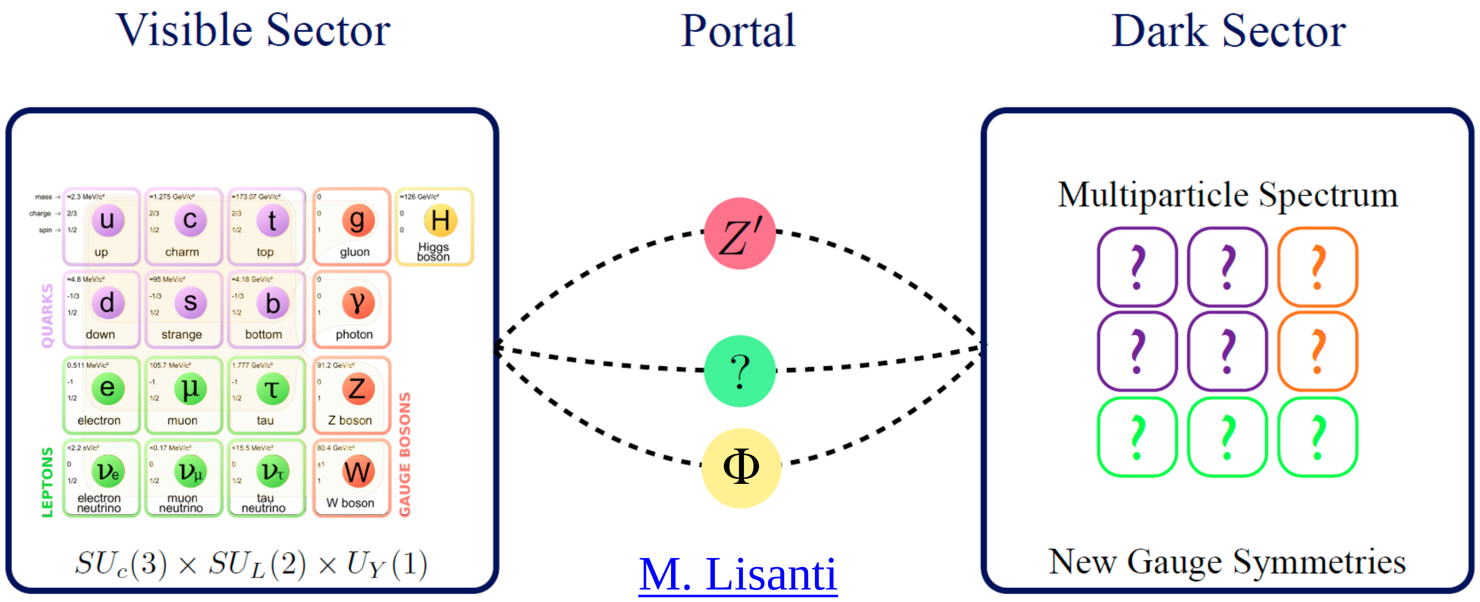
(Fermilab)
May 23, 2024



This manuscript has been authored by Fermi Research Alliance, LLC under Contract No. DE-AC02-07CH11359 with the U.S. Department of Energy, Office of Science, Office of High Energy Physics.



Strongly Coupled Dark Sectors

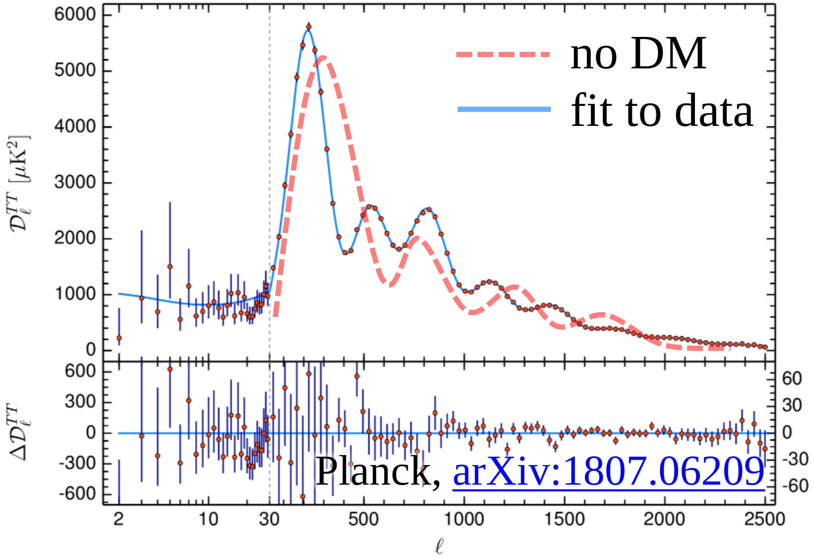


- Dark sector may consist of multiple species of particles interacting via new, dark forces
- Consider a new "dark QCD" force with corresponding dark quarks, dark hadrons, and dark gluons
  - Stable dark hadrons → dark matter candidates!
  - Unstable dark hadrons → decay back to SM

Why Dark QCD?

- We know dark matter exists and behaves differently from visible matter

Cosmic Microwave Background



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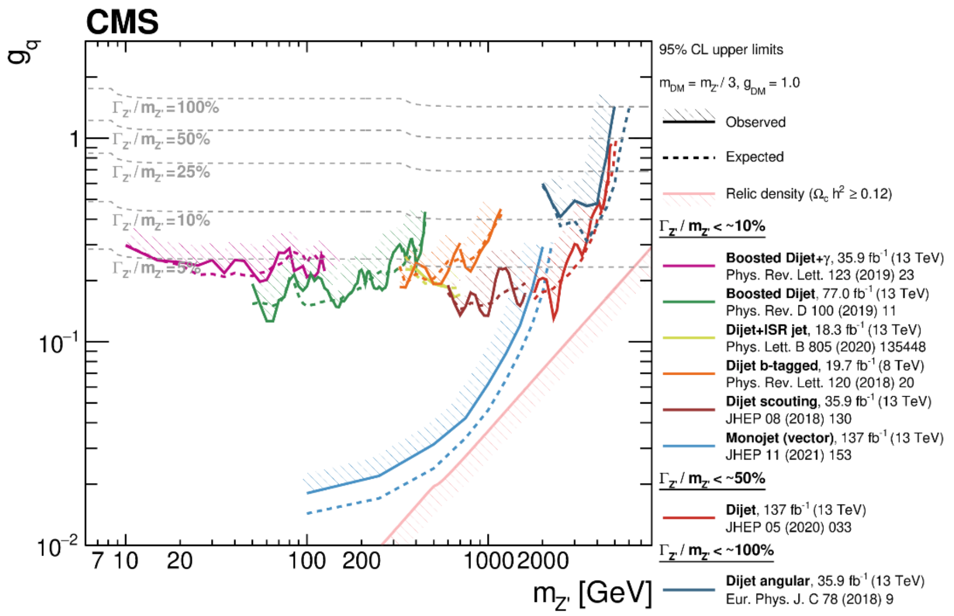
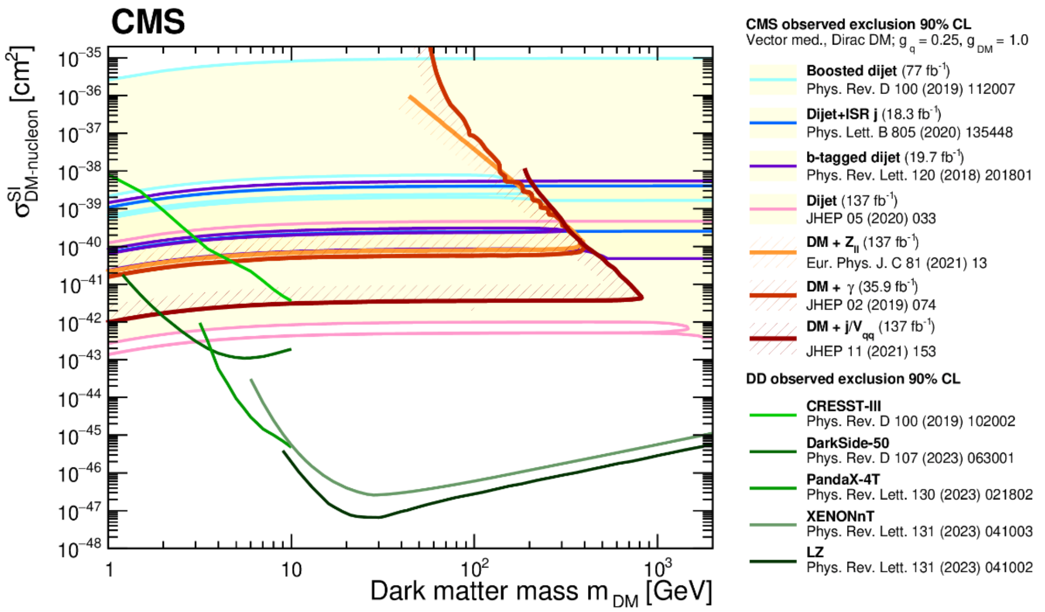
- But so far, no direct experimental evidence of its nature





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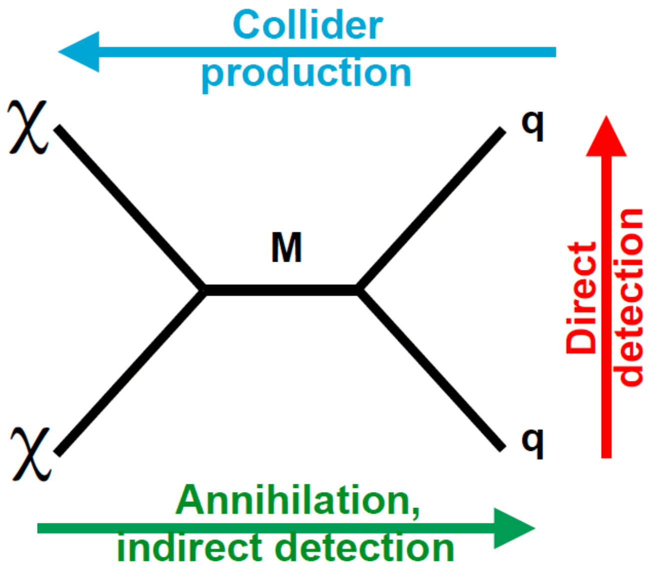

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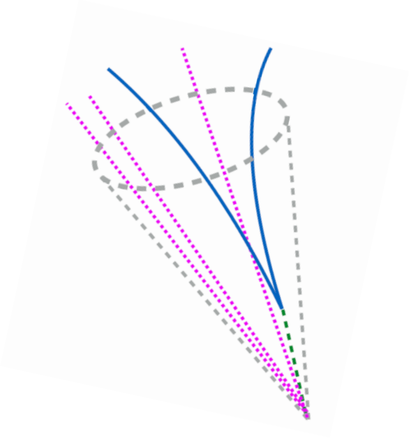
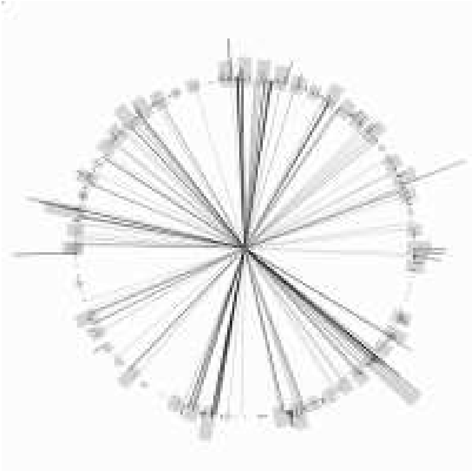
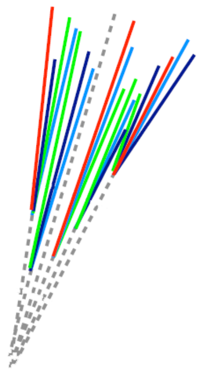
- Dark QCD signatures may *evade* current bounds:
  - Novel collider phenomenology – ignored or rejected by typical strategies that focus on large p_T^{miss}
  - Suppressed at other experiments:
    - DM abundance arises from asymmetry mechanism → no annihilation
    - DM interactions with ordinary matter highly suppressed → no direct detection







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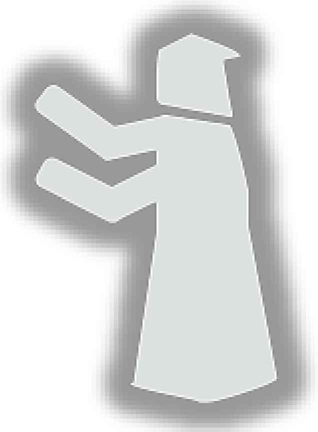
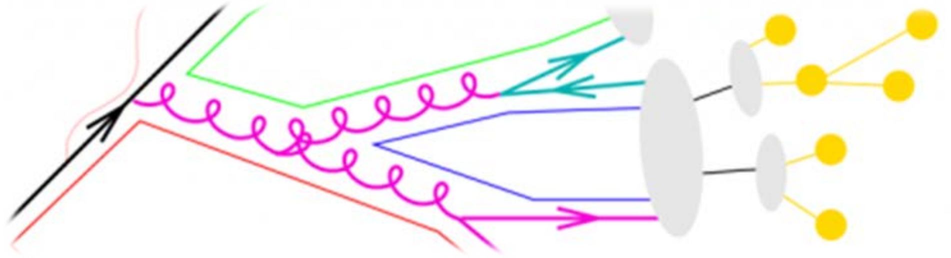
- Cosmological motivations:
  - Most visible matter is baryonic (composite); maybe DM is similar
  - DM density similar to SM density (~5× larger); $m_{DM} = 5m_{proton}$?

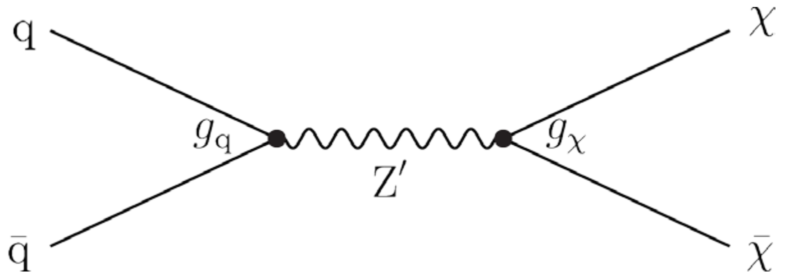
➢ Dark matter may be hiding in the existing LHC data!



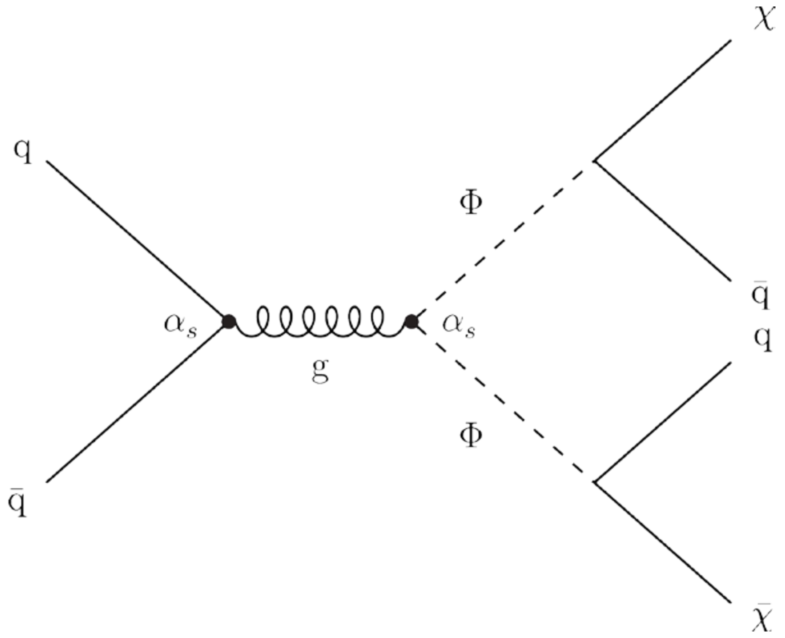
Models

- New “dark QCD” force, $SU_{\text{dark}}(N_c^{\text{dark}})$ (carried by dark gluons) with scale Λ_{dark}
- N_f^{dark} flavors of (fermionic) dark quarks χ_i (charged under $SU_{\text{dark}}(N_c^{\text{dark}})$)
- Dark quarks *hadronize* to form dark mesons and baryons → “dark showers”





- Some dark hadrons may be *stable* → DM candidates!
  - o From conserved quantities: dark baryon number, dark isospin, etc.
- Other dark hadrons decay back to SM (through virtual mediators)
  - ➢ Leads to novel phenomenology
- Hidden sector couples to SM weakly via massive mediators
  - o Z': from broken $U(1)$, vector, leptophobic, couplings g_{q}, g_χ
  - o Φ: bifundamental, scalar, charged under both $SU_{\text{dark}}(N_c^{\text{dark}})$ and $SU(3)$



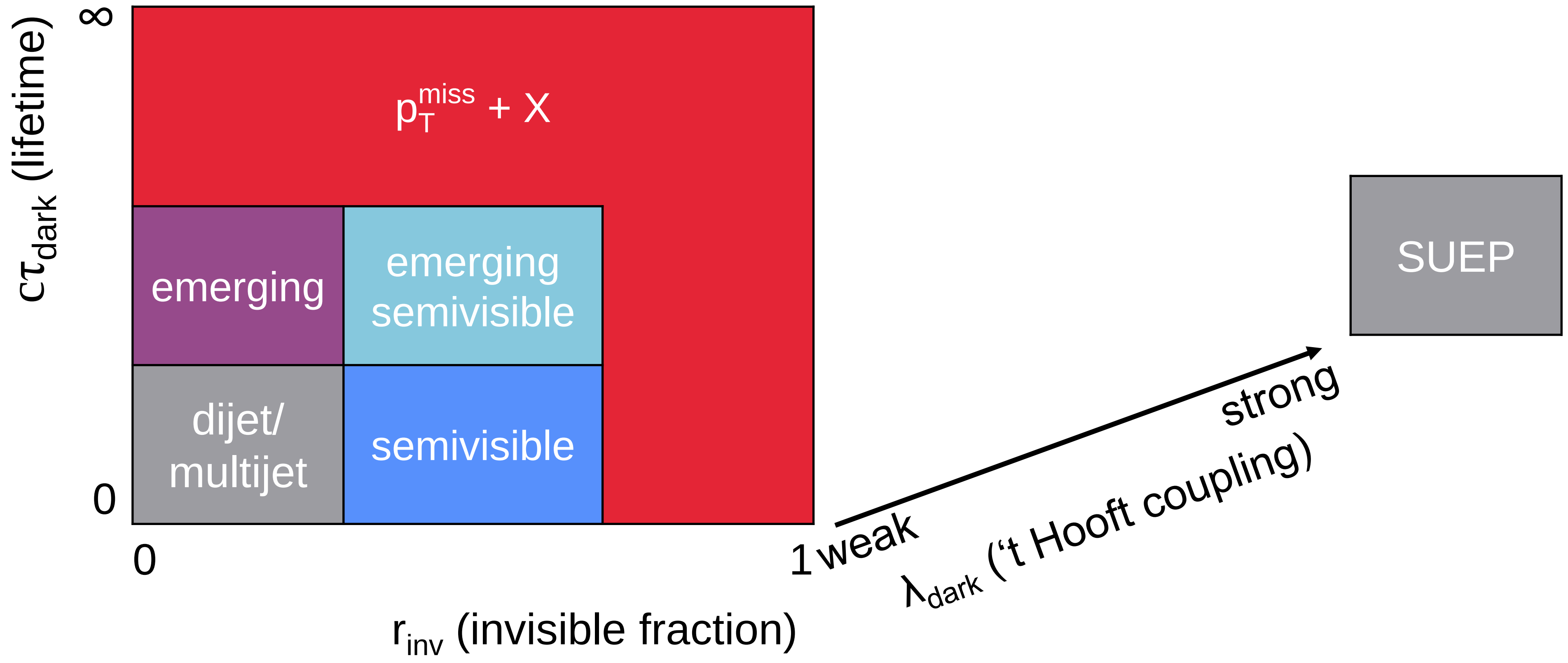
Parameter Space

- *Complete models* have *dozens of parameters*:
  - Dark QCD: scale, number of colors
  - Mediators: masses, couplings
  - Dark quarks: masses, number of flavors
  - Dark hadrons: masses, spins, lifetimes, dark quark composition, …
  - + various parameters from empirical modeling of low-energy QCD (hadronization, fragmentation)
    - SM QCD itself far from fully understood

➢ Focus on *semi-simplified models* that reproduce desired phenomenological and kinematic behavior with *effective parameters*

Effective Parameter Space

- **Semivisible jets** (SVJs): mediator mass, dark hadron mass, invisible fraction (r_{inv})
- **Emerging jets** (EMJs): mediator mass, dark hadron mass, lifetime ($c\tau_{dark}$)
- **Soft unclustered energy patterns** (SUEPs): mediator mass, dark hadron mass, temperature (T_{dark})
  - o Expanding to confining theories with large 't Hooft coupling, beyond QCD-like



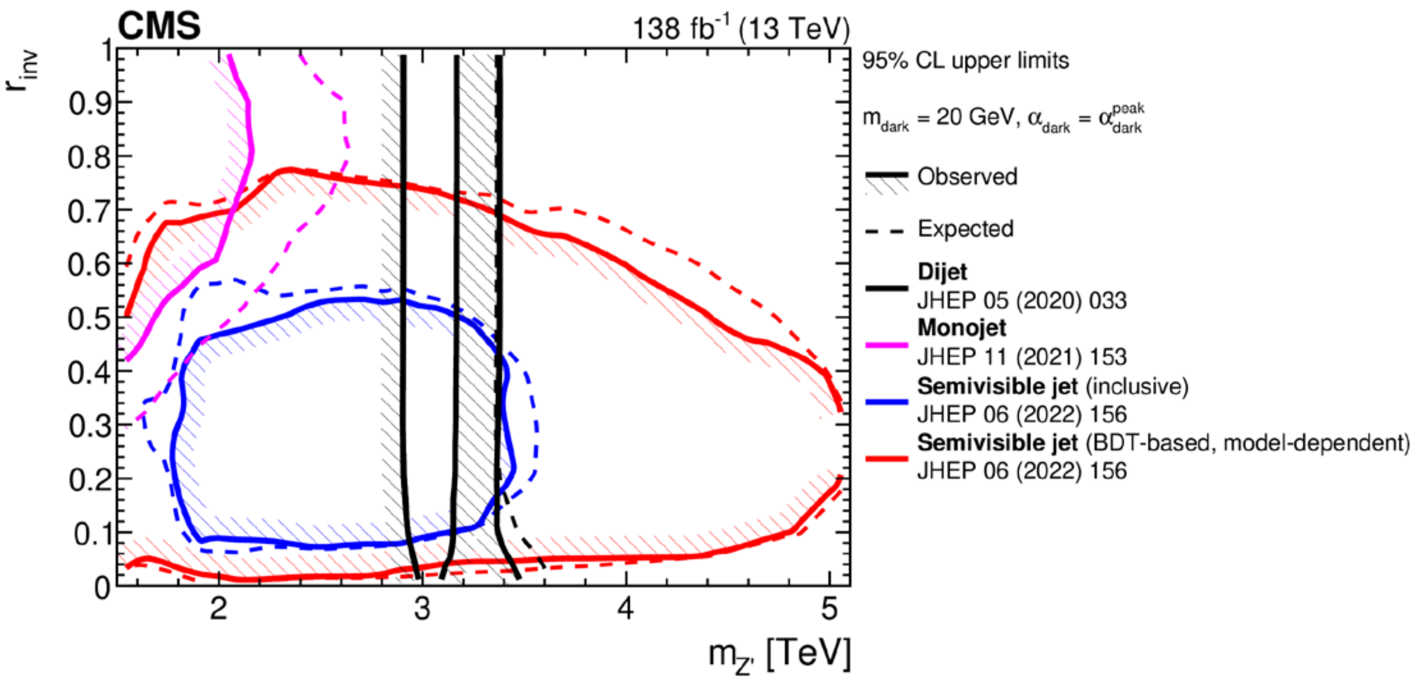
Dual Strategy

- Dark QCD theories are very complicated
  - Need to make choices about numerous parameters
    - Curse of dimensionality: dense grid in more than 2 parameters quickly leads to 1000s of models
  - Target regions of parameter space not covered by existing searches
    - Exploit complementarity with existing DM and LL search programs
- First searches for new signatures → maximize both *generality* & *sensitivity*

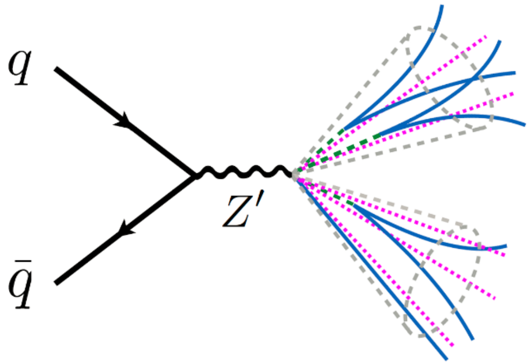
Model-independent search
- Use only simple kinematic variables (event- or jet-level)
- Results apply to any model with similar kinematic behavior

Model-dependent search
- Employ machine learning for optimized jet taggers
- Assumes chosen signal models are "correct"

Semivisible Jets



- Complementarity sensitivity between dedicated strategies and more general searches
- Many subtle details: let's walk through step by step



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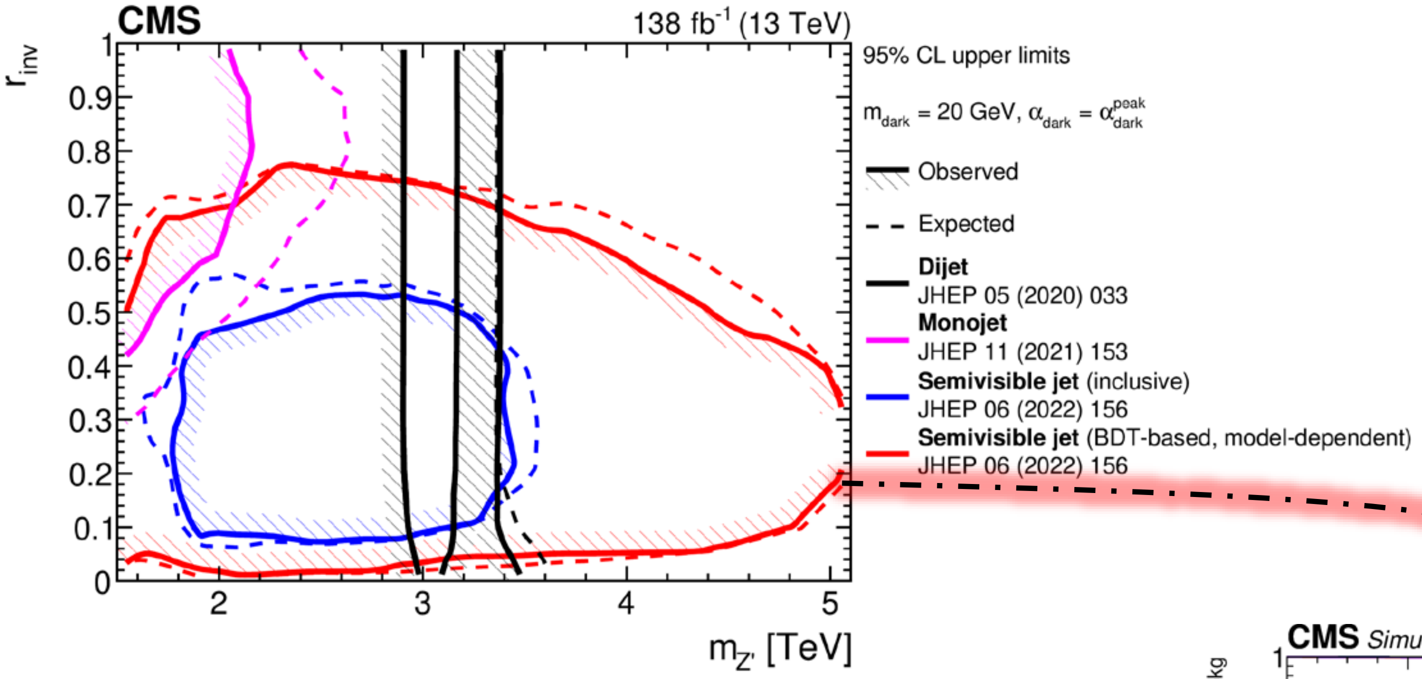
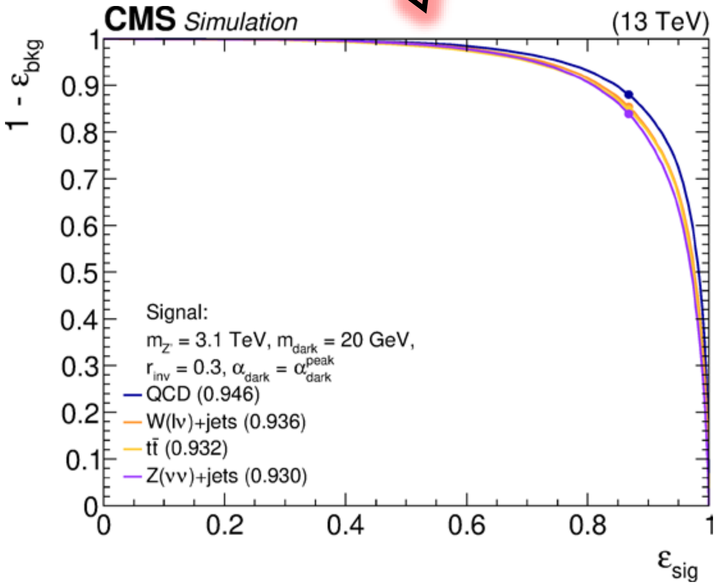
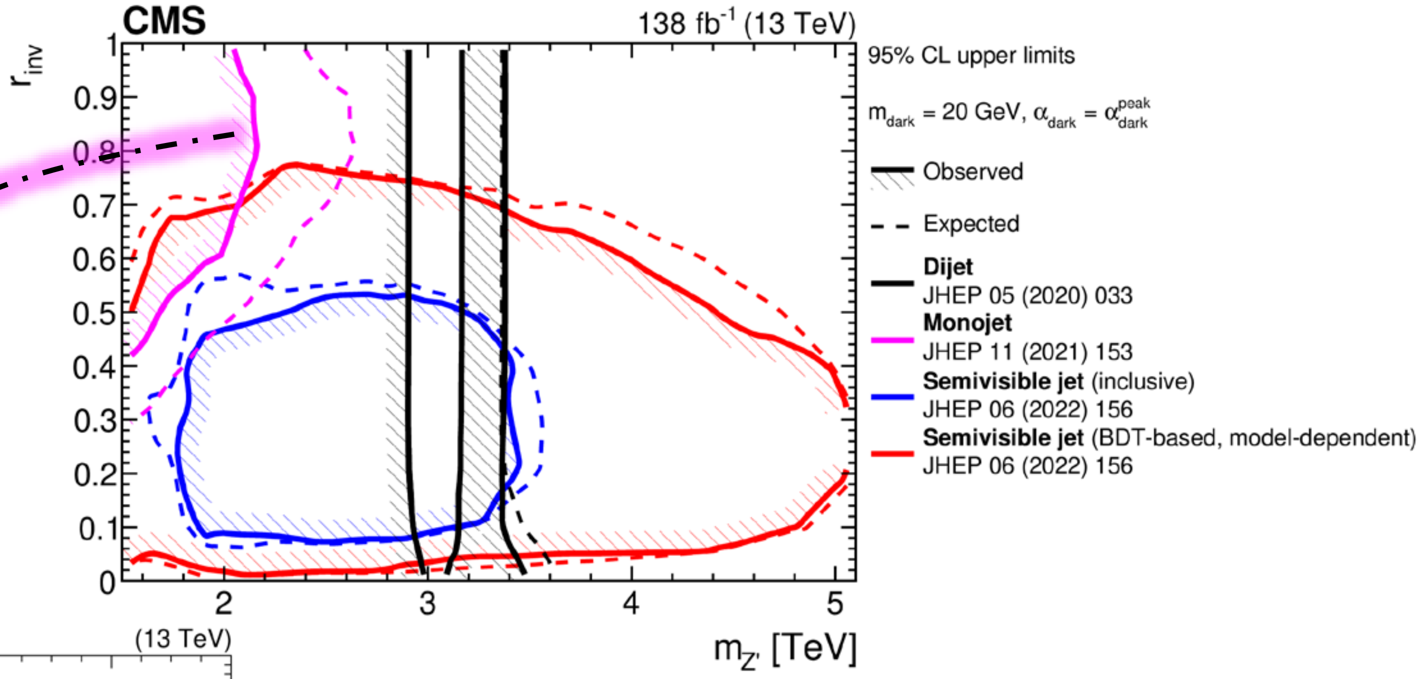
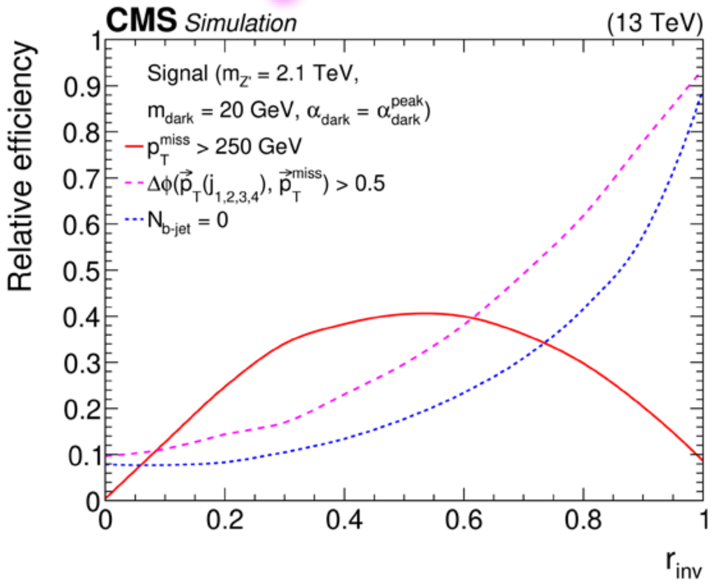




- BDT trained to tag semivisible jets using substructure variables
- Substantial improvement in limits:
  - Inclusive: $1.8 < m_{Z'} < 3.5$ TeV, $0.07 < r_{inv} < 0.53$
  - BDT-based: **$1.5 < m_{Z'} < 5.1$ TeV, $0.01 < r_{inv} < 0.77$**
- More on model dependence later…

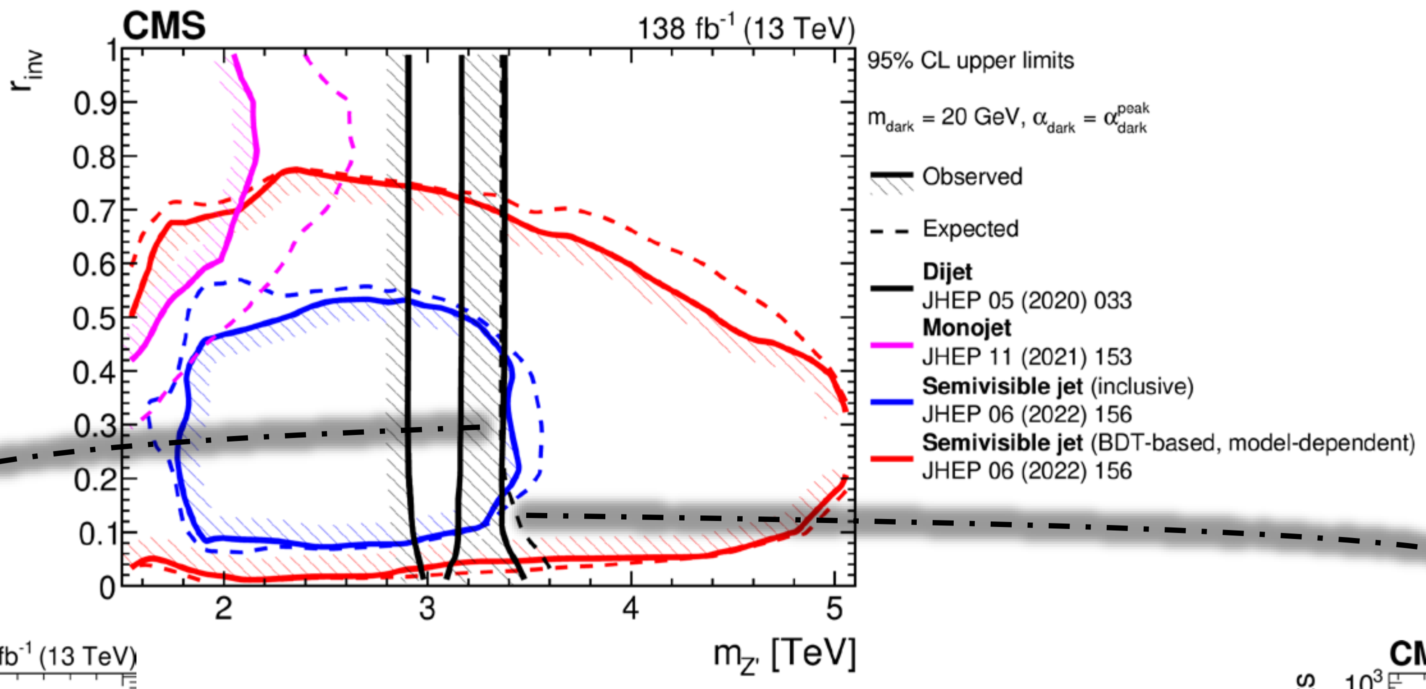
Semivisible Jets

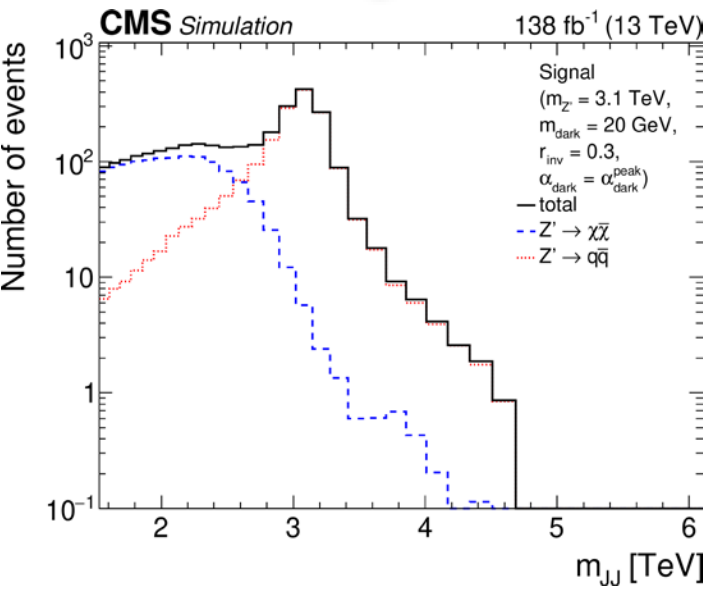




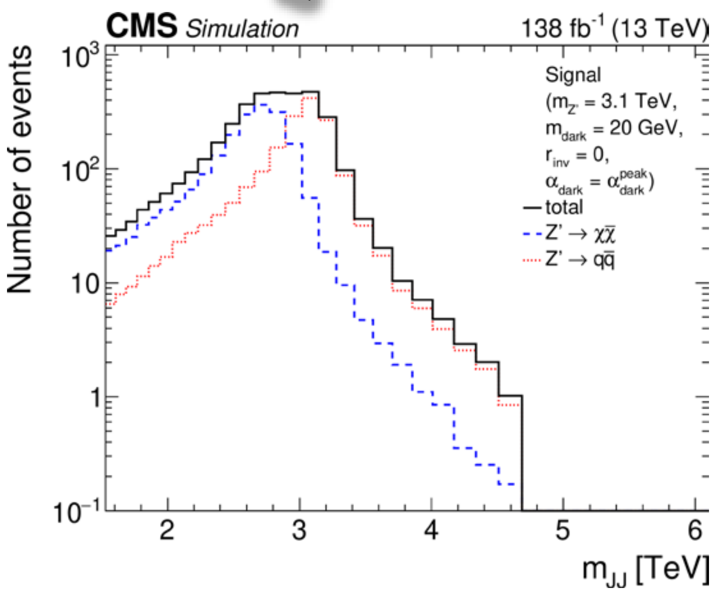
- Peak sensitivity for monojet (p_T^{miss}+X) actually at $r_{inv} \approx 0.8$
- Interplay between efficiency of p_T^{miss}, $\Delta\varphi$, and $N_{b\text{-}jet}$ selections

Semivisible Jets

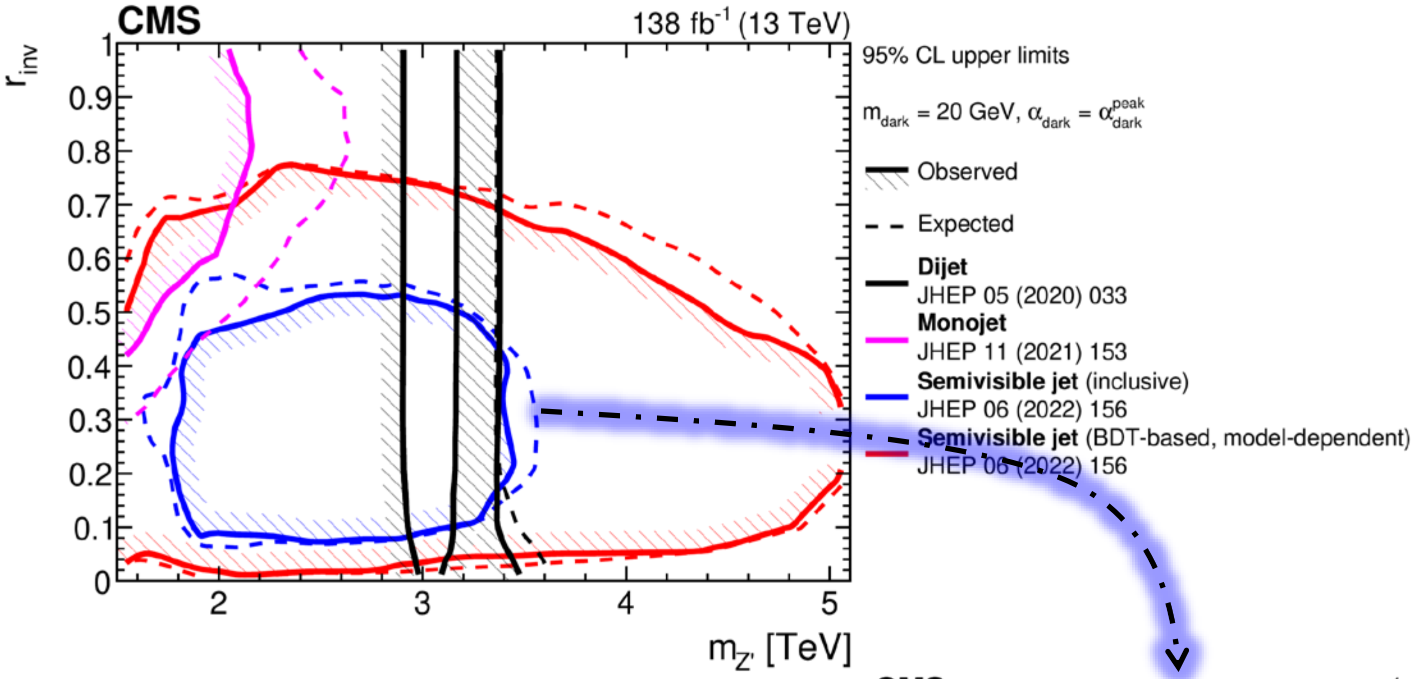


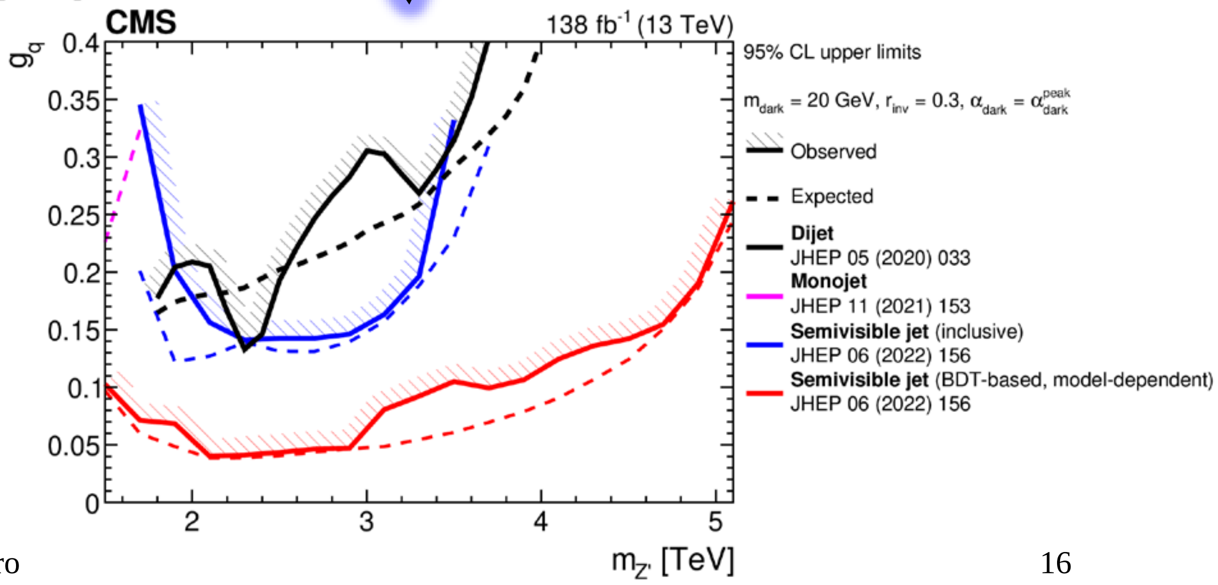


- SVJ events can enter dijet search signal region
- For $r_{inv} \gtrsim 0.1$: low m_{JJ} → high background → negligible contribution
- For $r_{inv} < 0.1$: similar mJJ → enhanced resonance peak → stronger limit



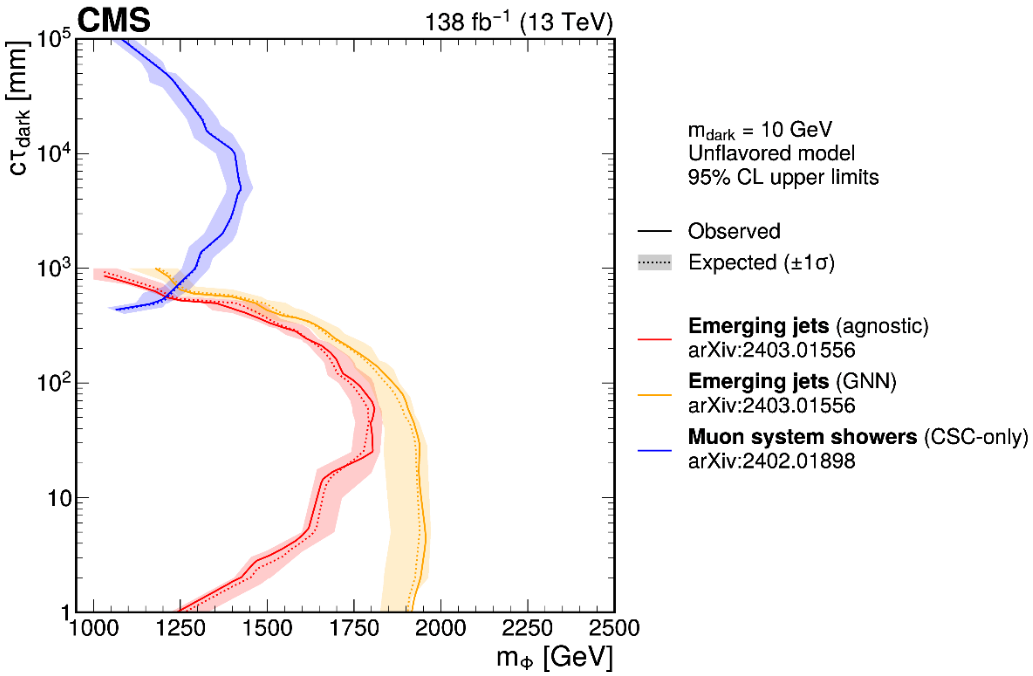
Semivisible Jets

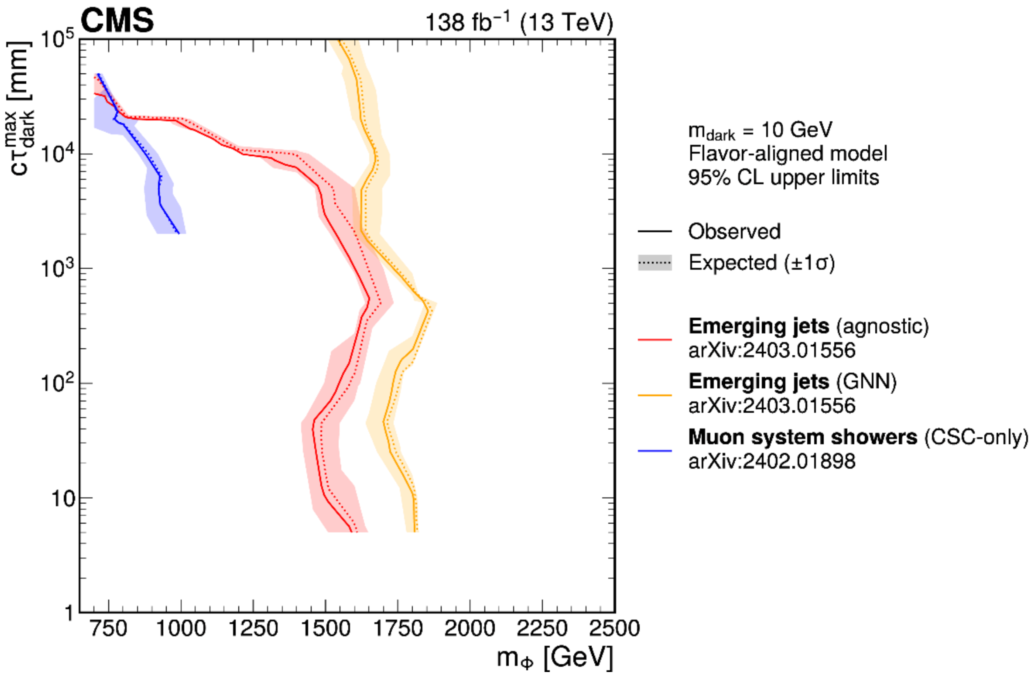




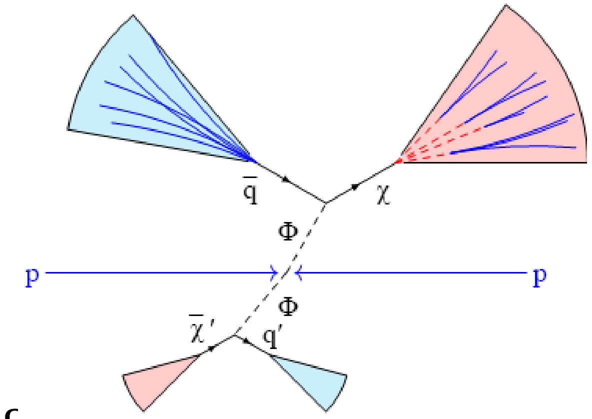
- Improvement from dedicated SVJ search vs. generic dijet search depends on both r_{inv} and *couplings*
- Default scenario: based on LHC DM WG
  - $g_q = 0.25$, $g_\chi = 1/\sqrt{(N_c^{\text{dark}} N_f^{\text{dark}})} = 0.5$, $B_{\text{dark}} = 47\%$
- Gains more apparent after converting to limit on g_q (for fixed g_χ)

Emerging Jets



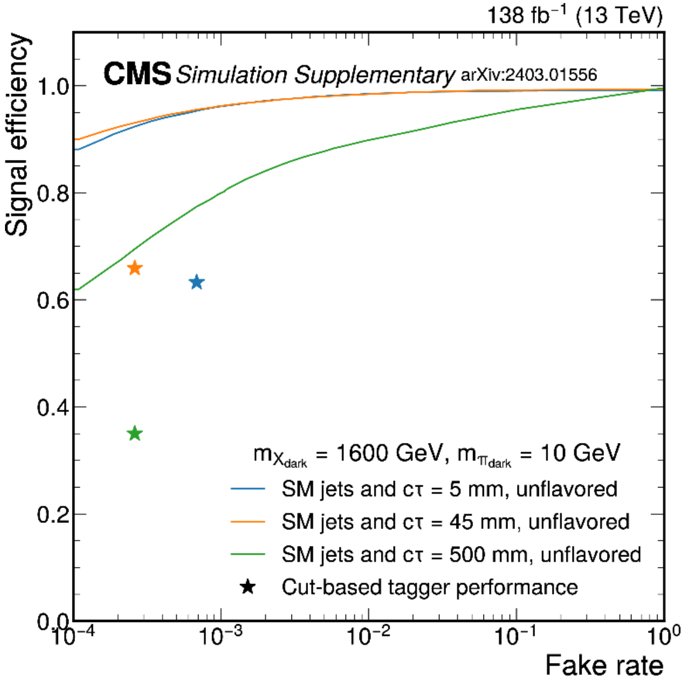


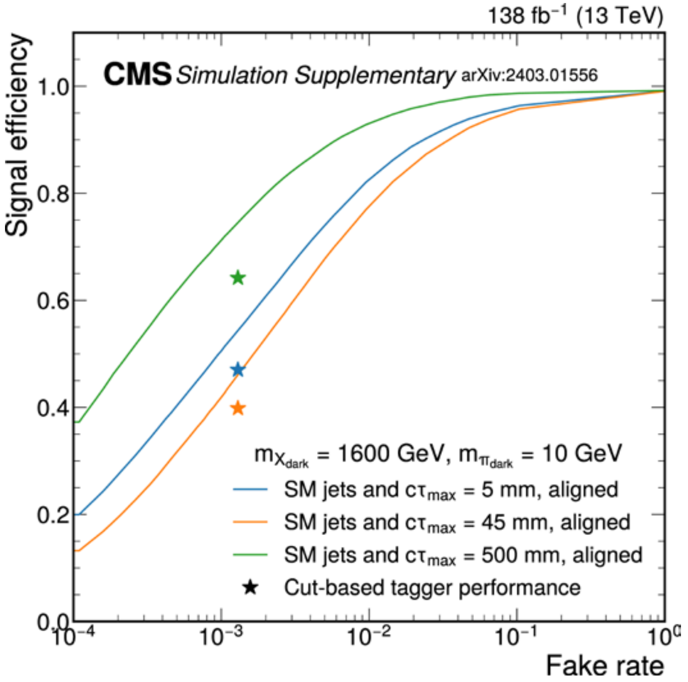
- Dedicated EMJ search focuses on track impact parameters
  - Loses sensitivity once most decays are outside tracker volume
- Muon system shower search is *complementary* at high lifetimes
  - Alternative model with flavor structure in dark sector leads to wider spread of lifetimes: weaker limits
- Other long-lived searches *not sensitive* to EMJs
  - Require few prompt tracks, displaced vertex reconstruction, or delayed timing

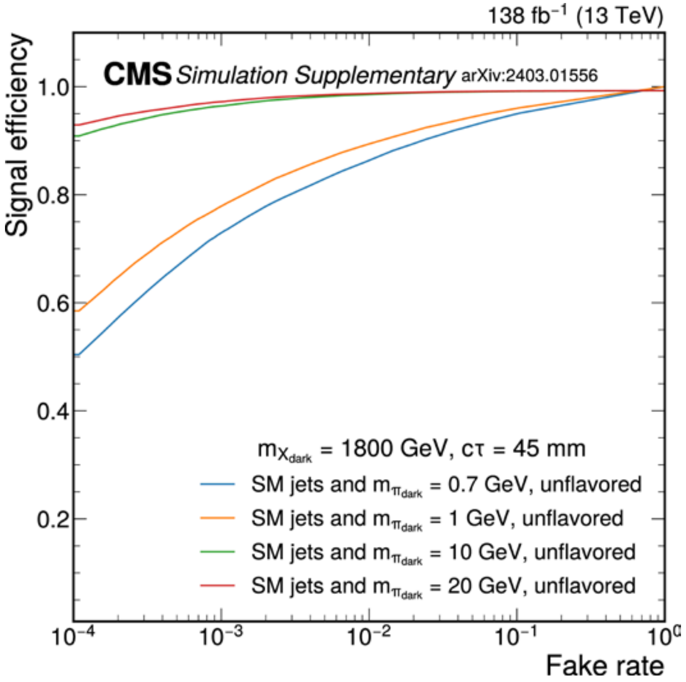


Emerging Jet Tagging

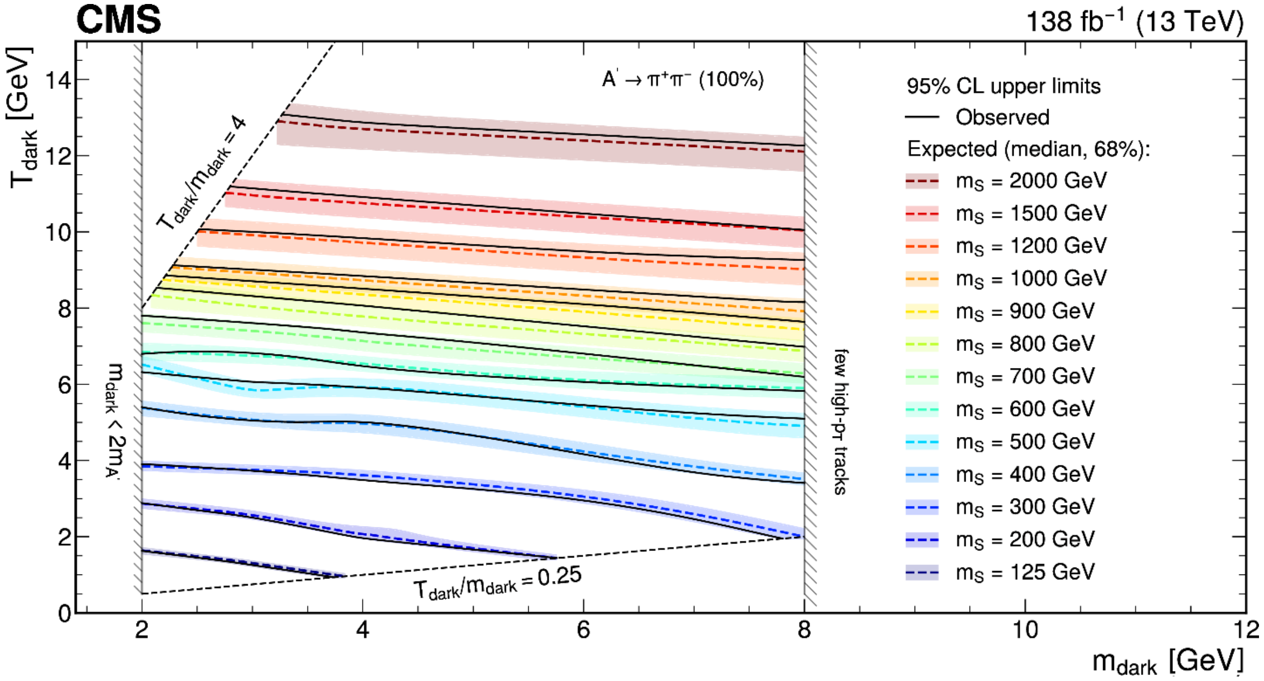
- “Model-independent” version of EMJ search uses cut-based tagger based on tracks and jet substructure
  - Working points tuned manually
- “Model-dependent” search uses GNN-based tagger (ParticleNet) based on jet constituents
  - Has to be trained separately for each signal model category (unflavored or flavor-diagonal)
  - Within a given model, actually less dependent on lifetime than simpler cut-based tagger
  - But more dependent on m_{dark}

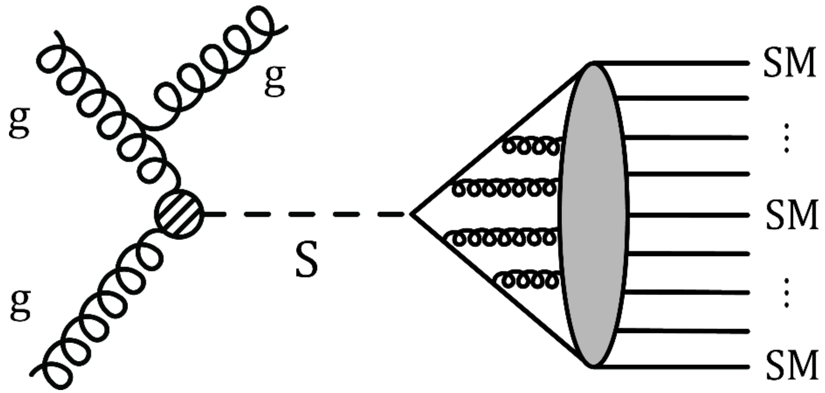






SUEPs

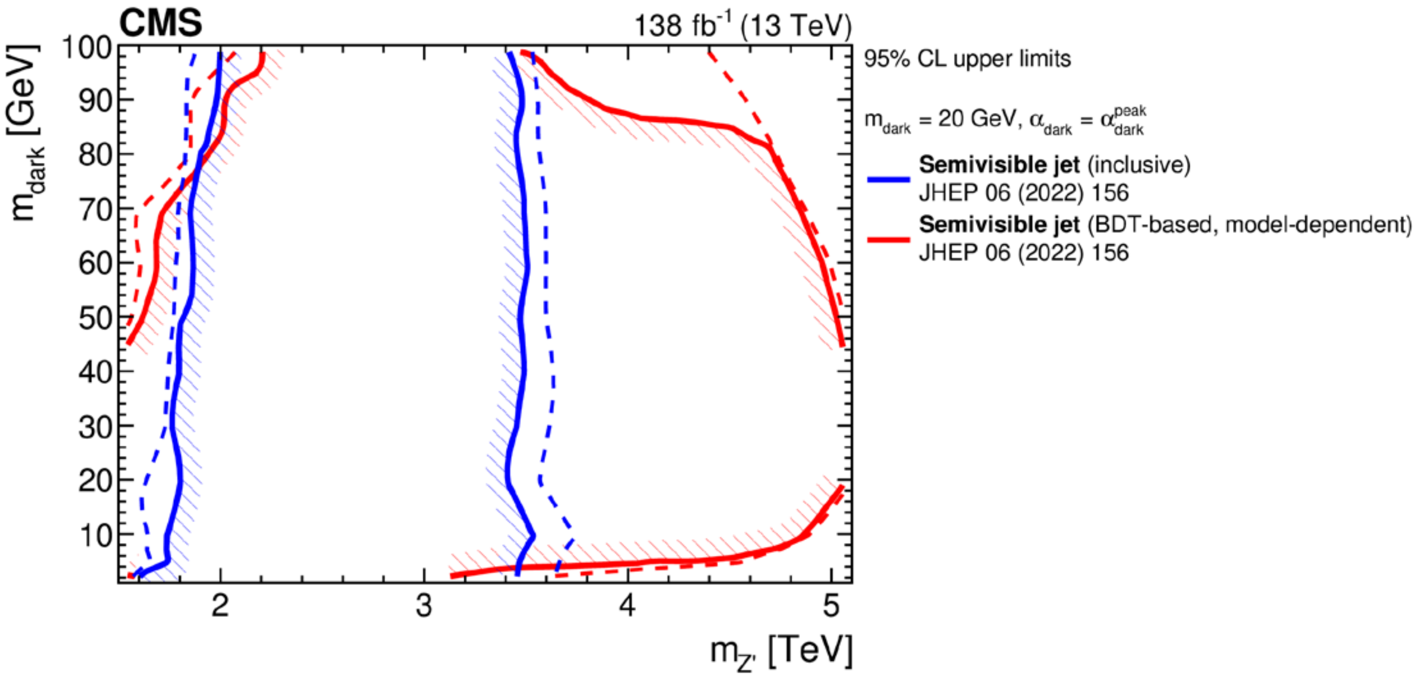




- Exclusions in model parameter space improve for higher m_S
  - Need sufficient tracks to distinguish from SM
- Model assumes dark hadrons decay to dark photons A′, which then decay to e^+e^-, $\mu^+\mu^-$, $\pi^+\pi^-$ with varying fractions
  - Results largely independent of A′ decay modes

Model Dependence

- Dark QCD models produce novel differences in jet substructure
  - Good handles to distinguish from SM… if we can use them optimally
- ML tagging approaches so far are *supervised*: depend on signal model details
  - Impossible to cover full range of complexity of dark QCD models
- BDT SVJ tagger *reduces* sensitivity for very low or very high m_{dark} values

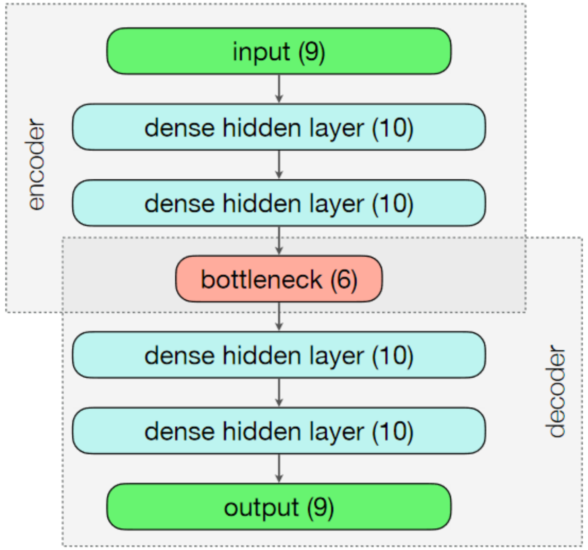


- Focus on SVJ case as generically most difficult to distinguish from SM
- EMJs and SUEPs have unusual, but distinct track signatures (typically)
- Principles apply to all cases

An Autoencoder for Semivisible Jets

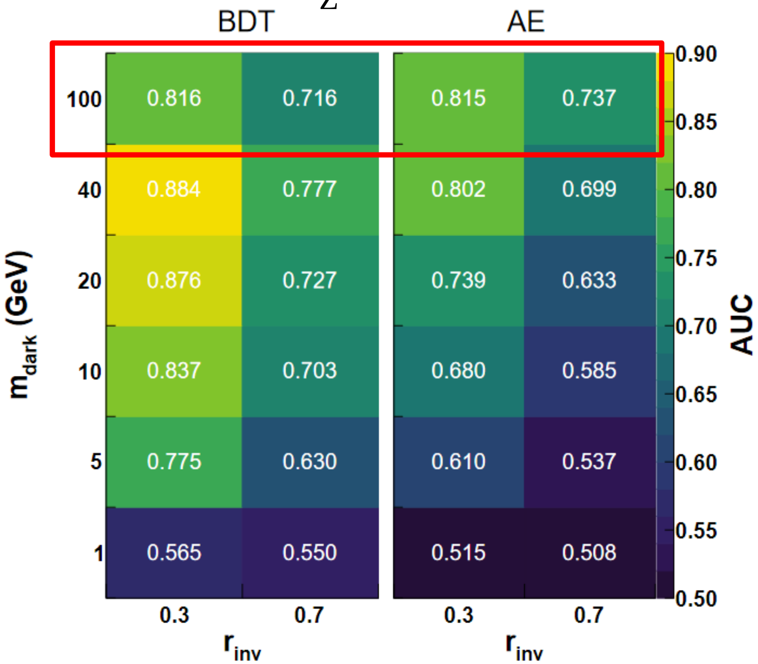
- Create a latent representation that can be used to accurately reconstruct *background*
  - Signal not used in training; identified during inference as having high *reconstruction error*
- Train autoencoder on QCD background, compare to BDT trained on signals w/ m_{dark} = 20 GeV

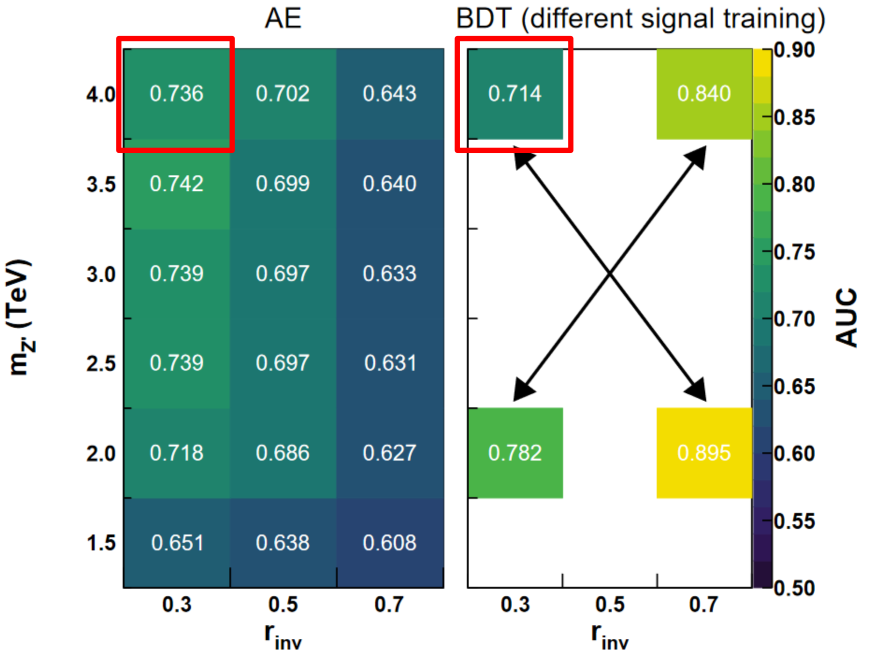
➢ Autoencoder can *outperform* BDT on signals with different m_{dark} values
  - Similar for r_{inv} (less information at high r_{inv})



[arXiv:2112.02864](https://arxiv.org/abs/2112.02864)

$m_{Z'}$ = 3 TeV

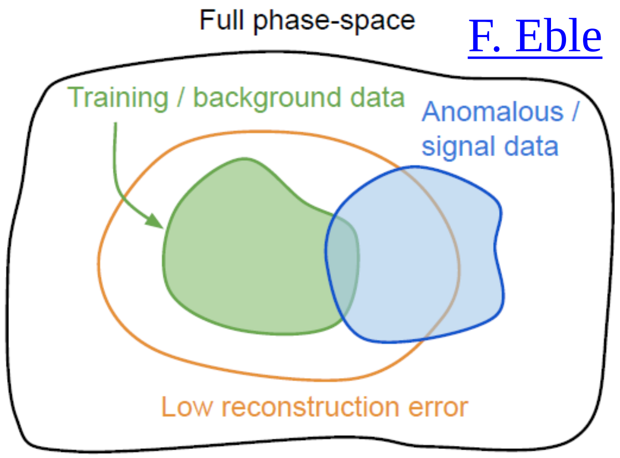




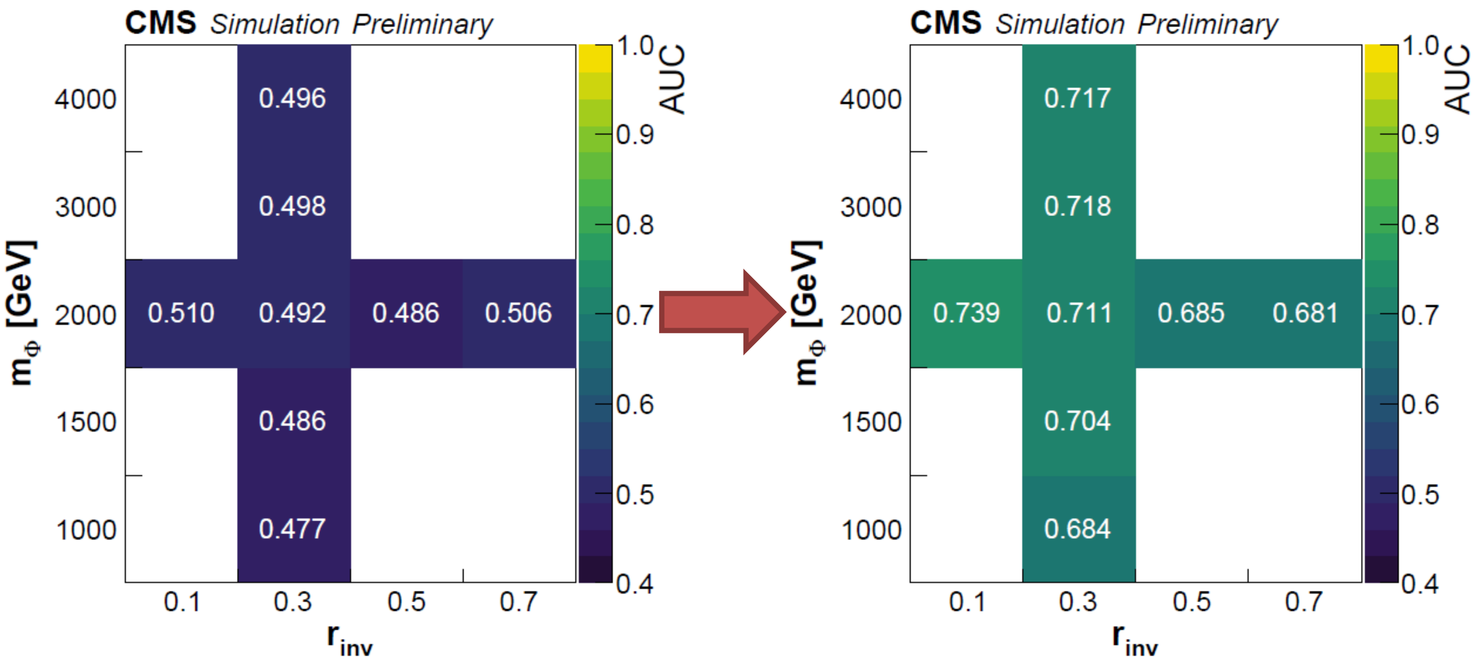
Normalized Autoencoder

- Autoencoders have *complexity bias*: may learn to reconstruct any event below some complexity level
- SVJ case: easy to discriminate against QCD (lower complexity), but not against $t\bar{t}$ (higher complexity)
  - Boosted top quark decaying to $\ell\nu b$ is closest SM analogue to SVJ with real p_T^{miss}
- Need to *sample* from low-error space during training to prevent AE from over-generalizing
  - Use Boltzmann distribution, compare "energies" between training data (E_+) & NAE output (E_-)
- Loss function $L = \log(\cosh(E_+ - E_-)) + \alpha E_+$ (additional functions/terms improve stability)
  - Differences unstable, can still mode collapse → use Energy Mover's Distance to choose best model

➢ Significantly better performance against $t\bar{t}$!



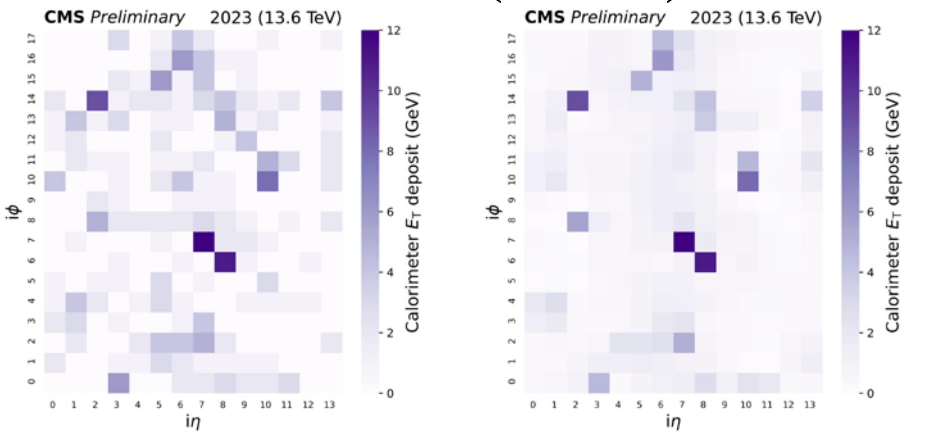
F. Eble



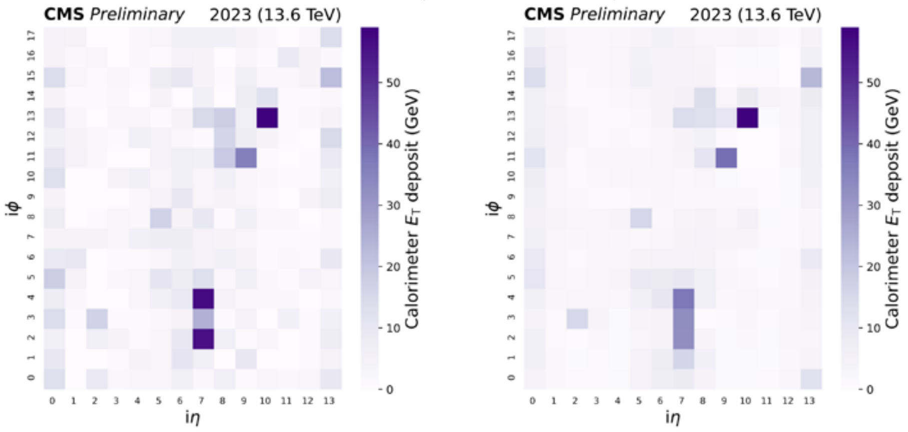
Trigger-Level Autoencoders

- Existing trigger strategies use basic kinematic quantities: jet p_T, $H_T = \sum p_T$, p_T^{miss}
  - o Can be model- or production mode-dependent: influenced by mediator mass, r_{inv}, etc.
  - o Thresholds have to be increased to handle higher event rates and pileup
- CMS has deployed two anomaly detection algorithms in L1 trigger during Run 3:
  - o AXOL1TL (Anomaly eXtraction Online Level-1 Trigger Lightweight)
    - ▪ Variational autoencoder trained on all global L1 bits
  - o CICADA (Calorimeter Image Convolutional Anomaly Detection Algorithm)
    - ▪ Convolutional autoencoder trained on calorimeter energy deposits

Zero bias (L = 0.81)

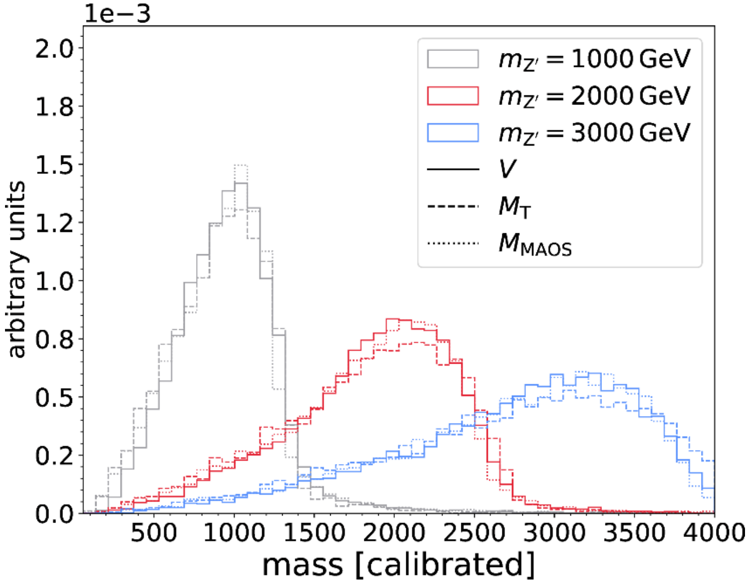


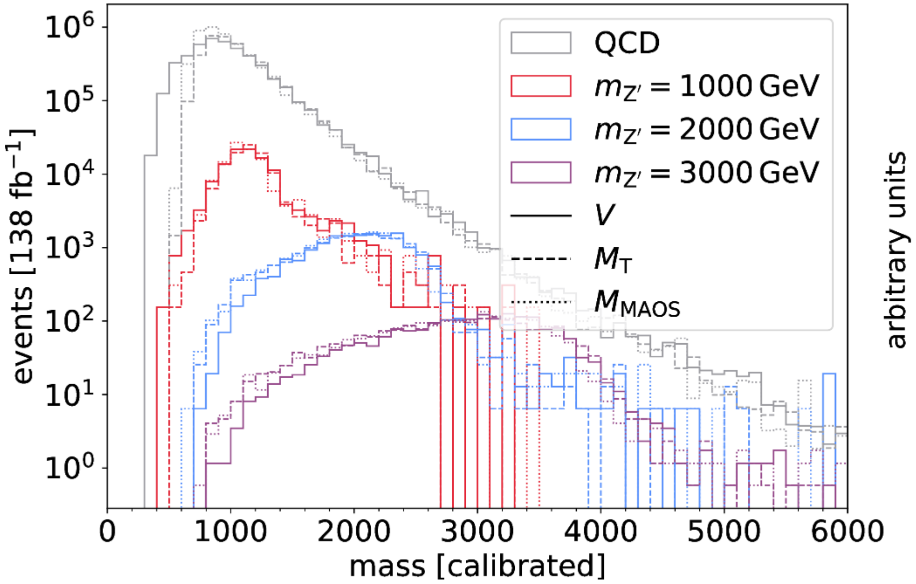
SUEP (L = 14.21)

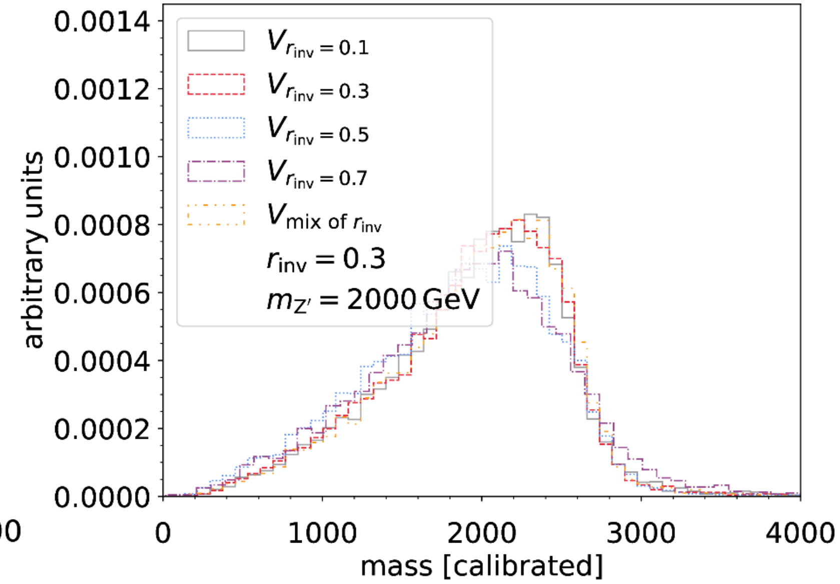


Interpretable, Semi-Supervised ML

- Rejecting background is important… but can we learn more about signal?
- Maximize mutual information between NN output and theory parameter:
  → *interpretable* output, e.g. from approximation of invariant mass *function* (not a regression!)
- Findings so far:
  - Can improve on M_T for Z' mass reconstruction (similar to [M_{T2}-assisted on shell]() algorithm)
  - Falling distribution for background, though trained only on signal
  - Generalizes well across r_{inv}



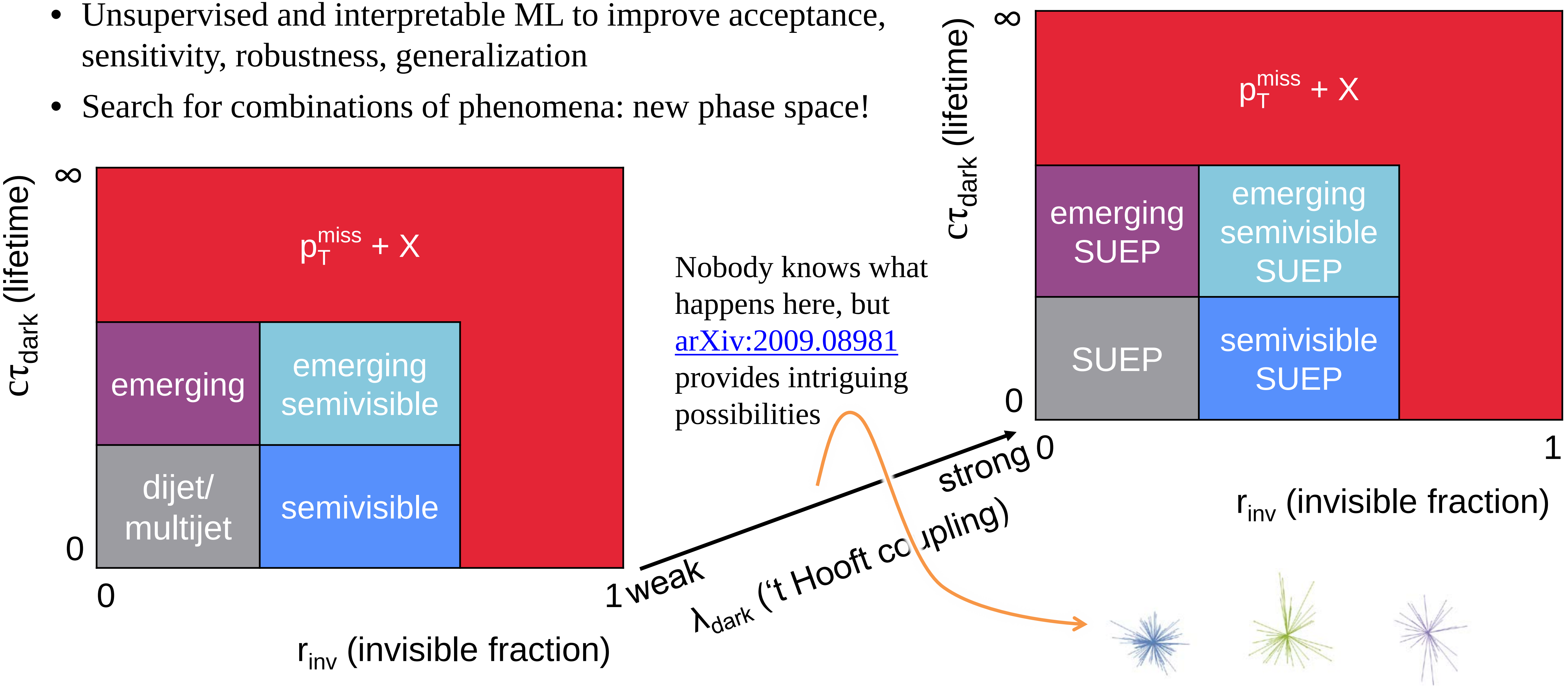




Mitchell 2024

The Future of Dark QCD Searches

- Expand to more production modes (vector, scalar, bifundamental, Higgs, …)
- Unsupervised and interpretable ML to improve acceptance, sensitivity, robustness, generalization
- Search for combinations of phenomena: new phase space!



Backup

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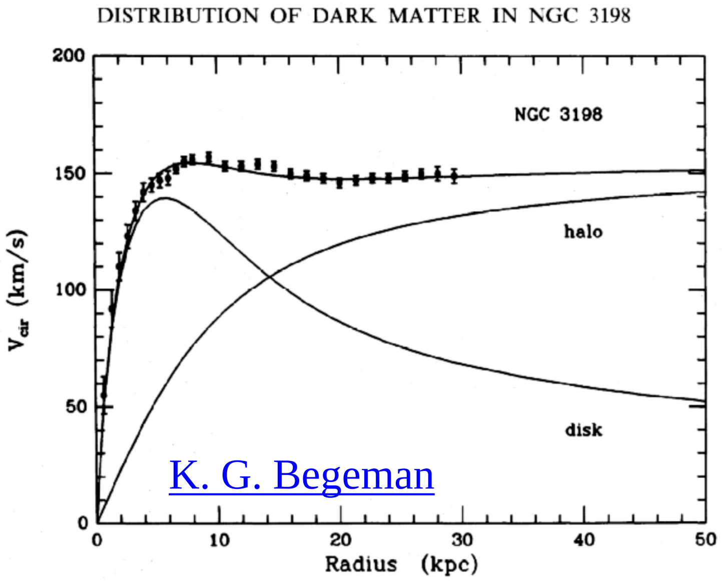
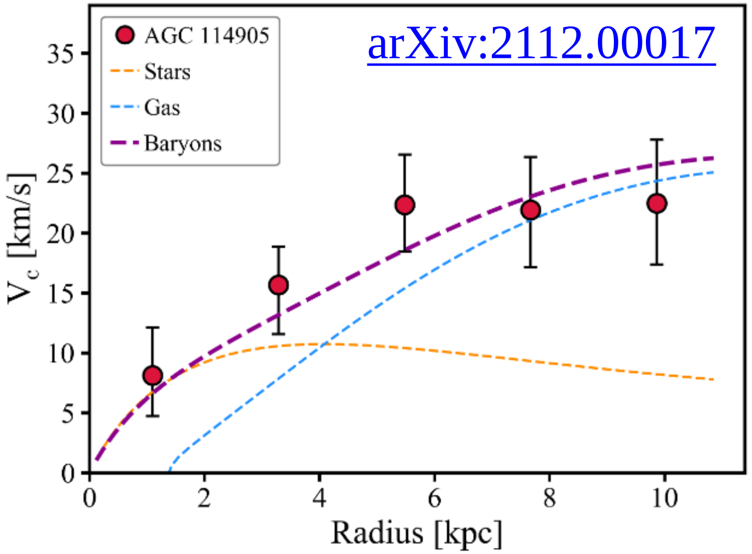
More Evidence of Dark Matter

Anomalous Galactic Rotation Curves



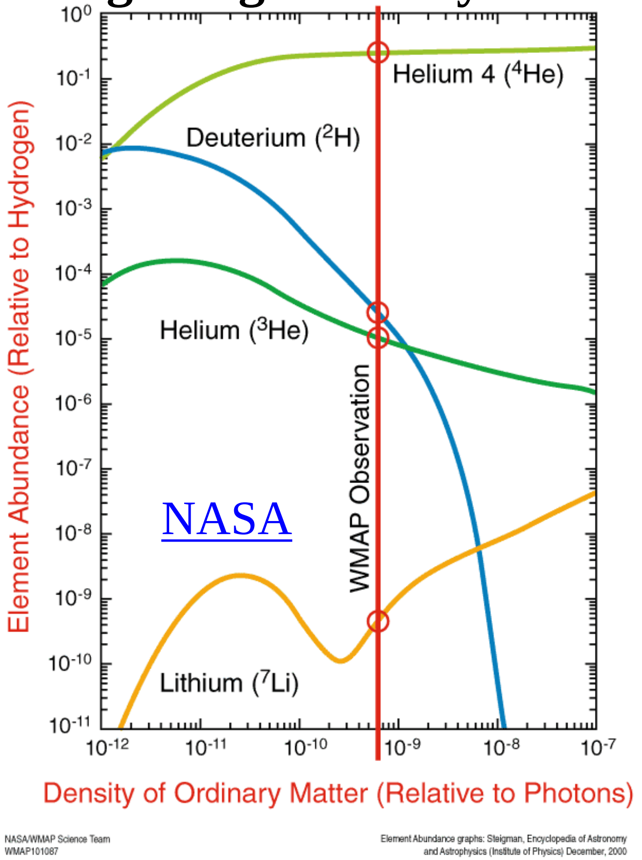
K. G. Begeman

Non-Anomalous Galactic Rotation Curves



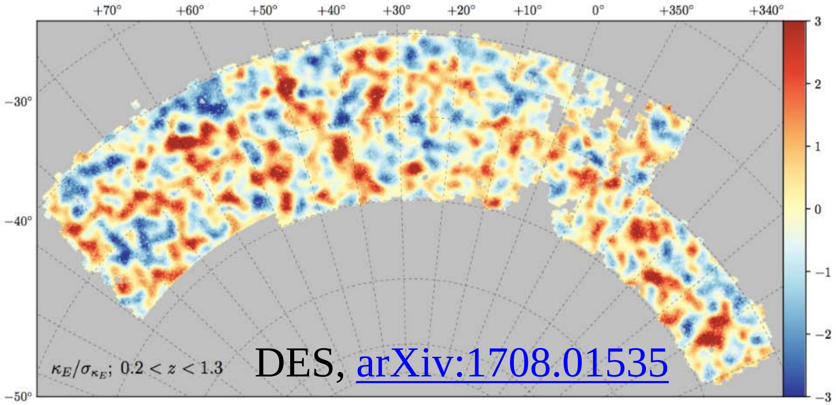
arXiv:2112.00017

Light Element Abundance in Big Bang Nucleosynthesis



NASA

(Weak) Gravitational Lensing

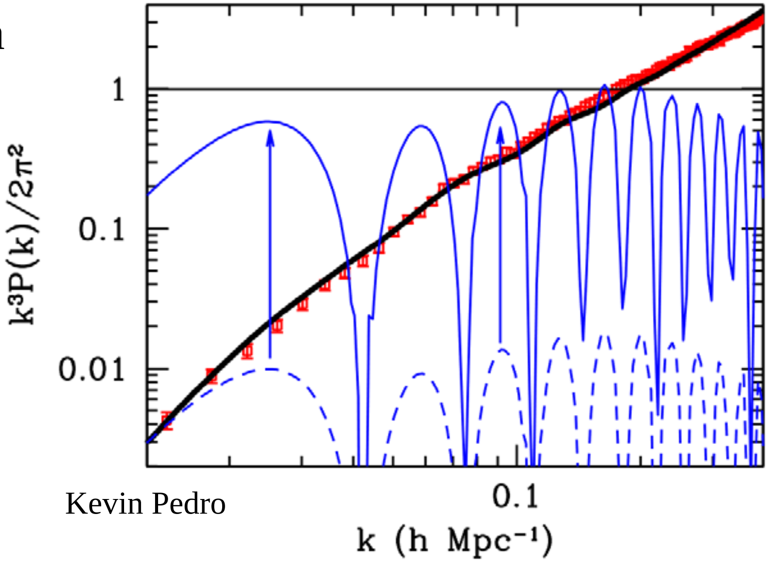


DES, arXiv:1708.01535

Matter Power Spectrum

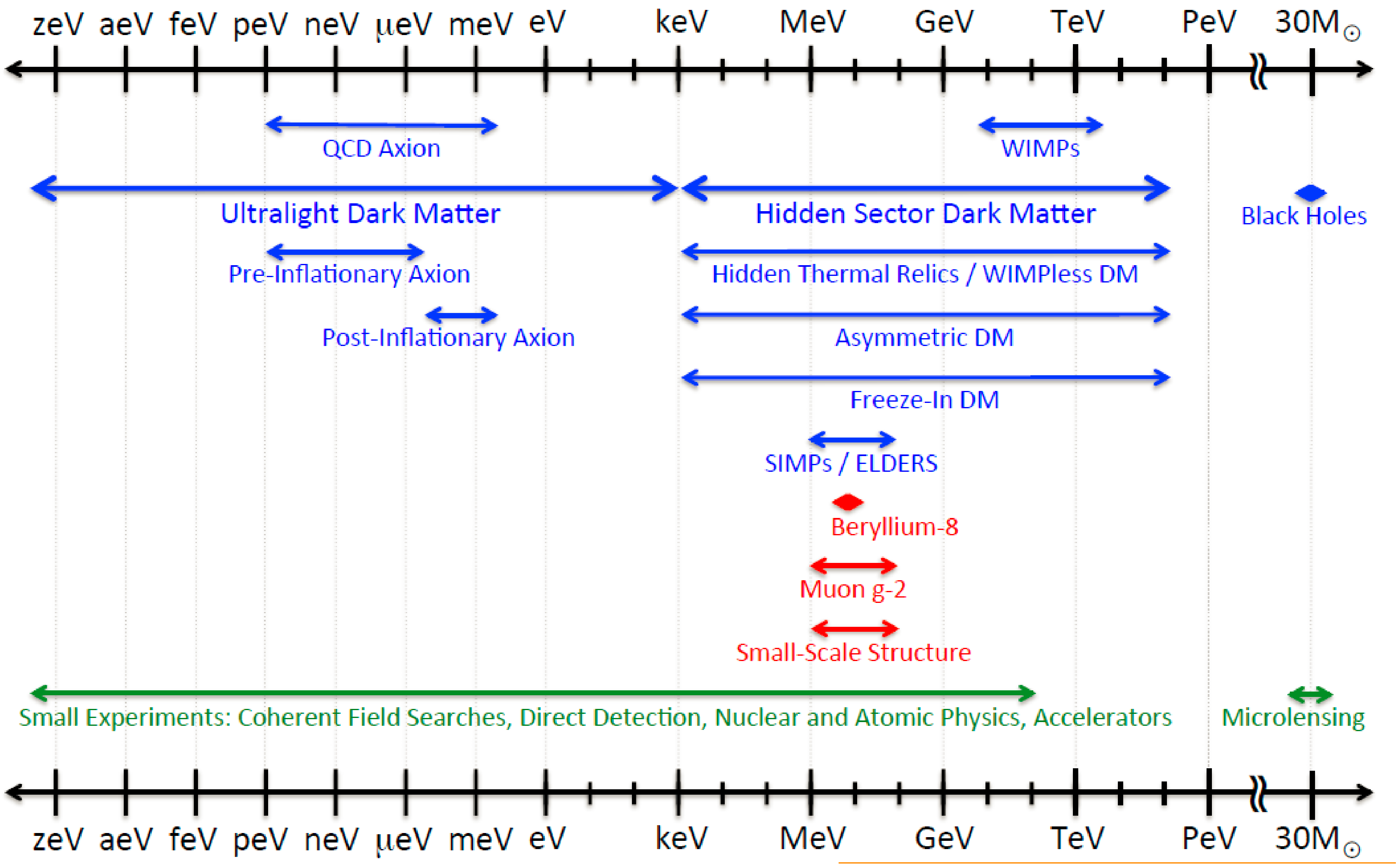
- SDSS data
- ΛCDM
- no DM
- MOND

1112.1320



Dark Matter Landscape

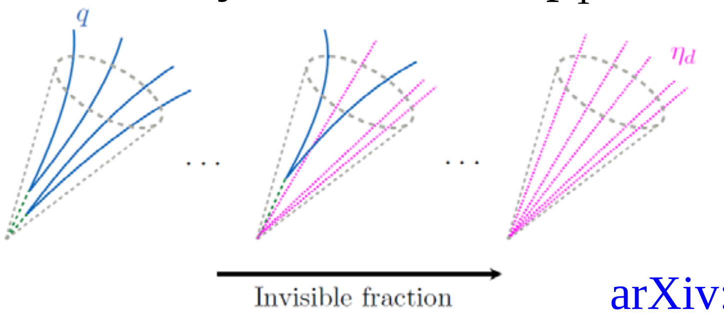
Dark Sector Candidates, Anomalies, and Search Techniques



arXiv:1707.04591, G. Landsberg

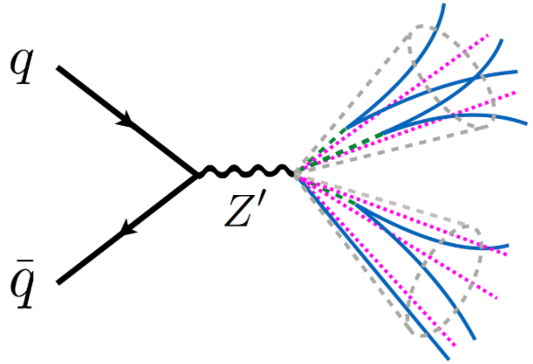
SVJ Decays

- Fraction of stable hadrons r_{inv} may vary from 0 to 1
  - Decreases w/ dark quark mass splitting, increases w/ N_f^{dark}
- ➢ Jets that contain *mix of visible and invisible particles* (prompt decays)
  - *Not covered* by existing searches for dijet resonances, p_T^{miss}+ISR



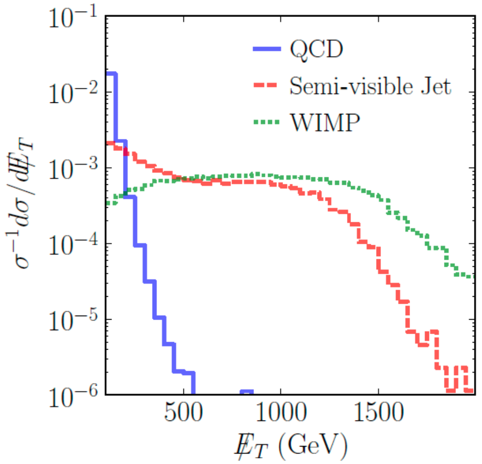
arXiv:1707.05326

- $Z' \to \chi\chi \to$ dark hadrons $\to$ SM quarks $\to$ SM hadrons
  - Decay to SM $\to$ two high-p_T, *wide* jets
  - ρ_{dark}: democratic decay
  - π_{dark}: mass insertion decay (prefer heavy flavor)
  - $N_c^{\text{dark}} = 2$, $N_f^{\text{dark}} = 2$, $m_\chi = ½m_{\text{dark}}$

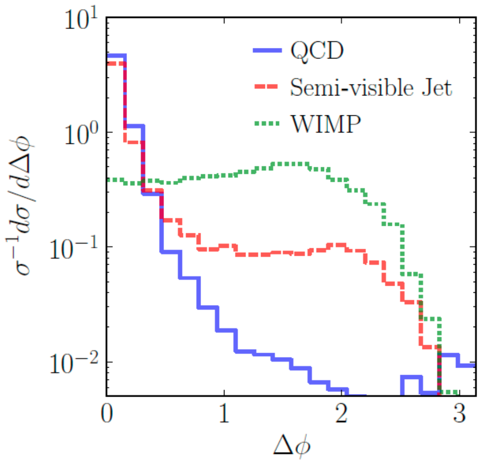


SVJ Resonant Search

- Kinematic signature: Less missing energy than WIMPs, aligned w/ jet

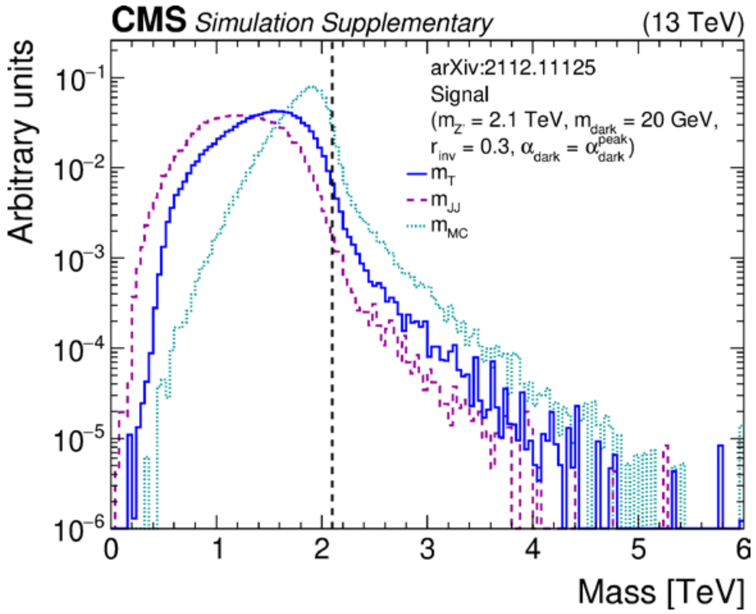


[arXiv:1503.00009](https://arxiv.org/abs/1503.00009)

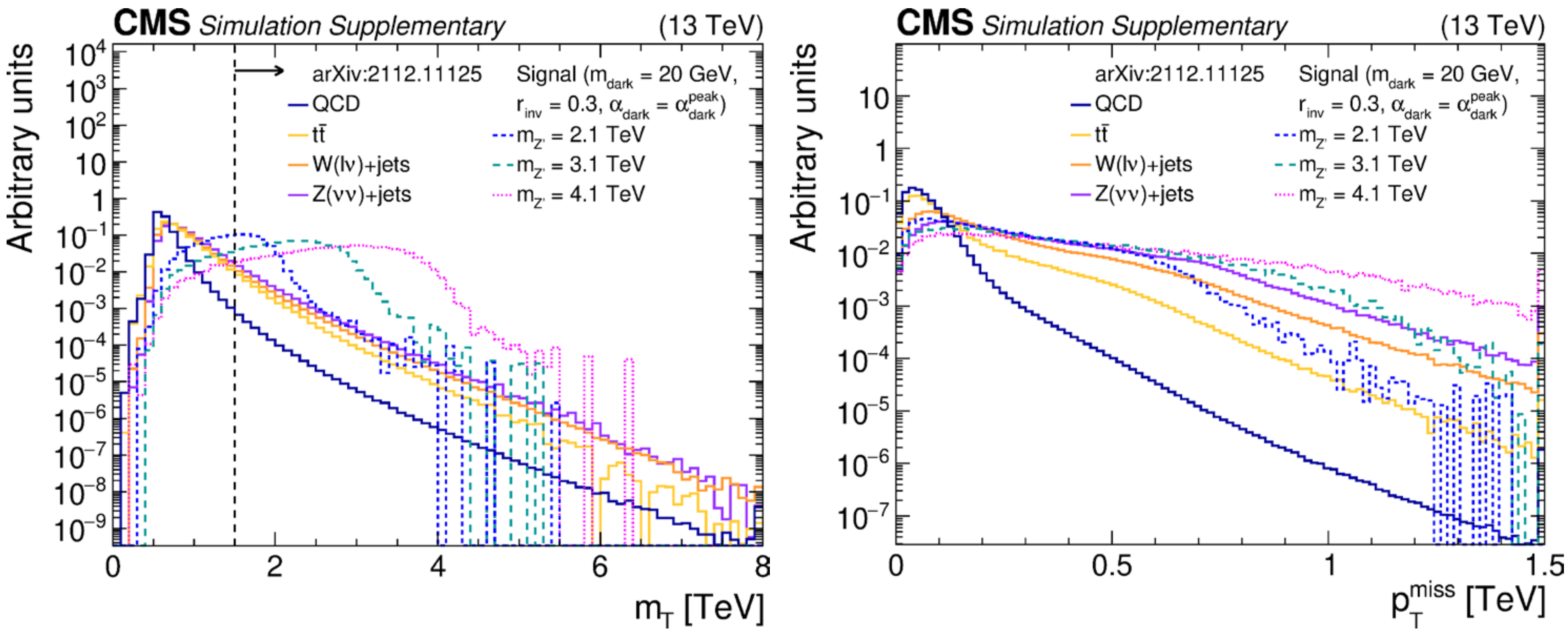


➢ Bump hunt in **$m_T(JJ, p_T^{miss})$**

- Kinematic edge at **$m_{Z'}$**
- Better resolution than **m_{JJ}**
- SM backgrounds have steeply falling distributions

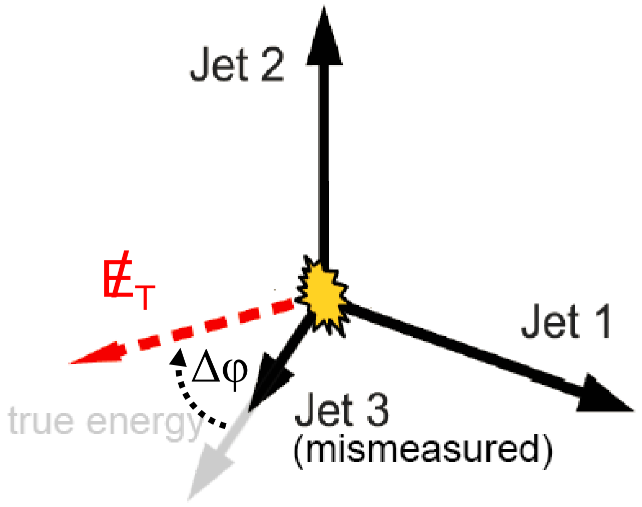


Semivisible Jet Kinematics



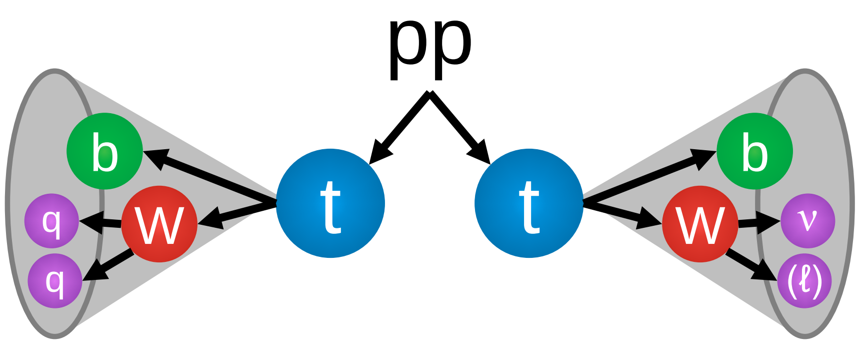
SVJ Backgrounds

QCD



- Jet mismeasurement induces $\not\!\!E_T$ aligned with jet
- Major background

$t\bar{t}$



- Wide, high-p_T jets: boosted tops
- "Lost" lepton ℓ: out of acceptance, can't veto (or hadronic τ)
- Neutrino aligned w/ wide jet: mimics semivisible jet

W(ℓν)+jets

- Lost lepton or hadronic τ
- Less likely than $t\bar{t}$ to mimic semivisible jet, but higher σ

Z(νν)+jets

- Real $\not\!\!E_T$ from νν, but least likely to align with jet

SVJ Event Selection

<u>Preselection</u>

- $N_J \geq 2$
- $p_T(J_1,J_2) > 200$ GeV, $|\eta(J_1,J_2)| < 2.4$, $J_{1,2}$ pass noise rejection
- $R_T \equiv p_T^{miss}/m_T > 0.15$
- $\Delta\eta(J_1,J_2) < 1.5$
- $m_T > 1500$ GeV
- e/μ veto ($p_T > 10$ GeV, $|\eta| < 2.4$)
- p_T^{miss} filters
- Custom dead ECAL cell filter: veto events w/ $\Delta R(j_{1,2}, c_{nonfunctional}) < 0.1$
- Inactive HCAL filter (2018 only): veto events w/ $p_T(j) > 30$ GeV, $-3.05 < \eta(j) < -1.35$, $-1.62 < \varphi(j) < -0.82$

<u>Final Selection</u>

- Gap jet filter: veto events w/ $p_T(j_1) > 1000$ GeV, $f_\gamma(j_1) > 0.7$
- $\Delta\varphi_{min}(J_{1,2},p_T^{miss}) < 0.80$

Signal topology

Data quality

Reject QCD

Trigger efficiency

Reject $t\bar{t}$, $W(\ell\nu)$

Data quality

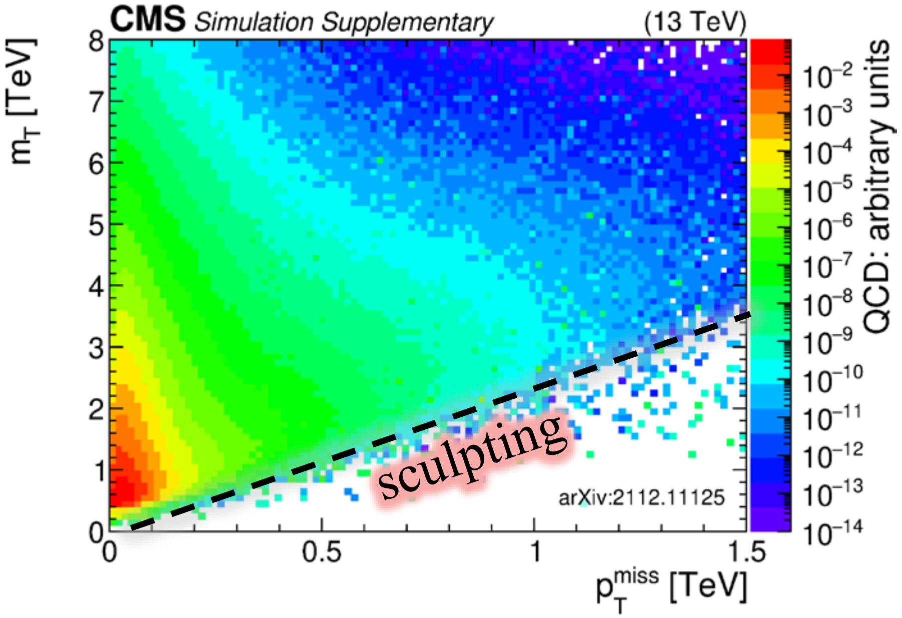
Data quality

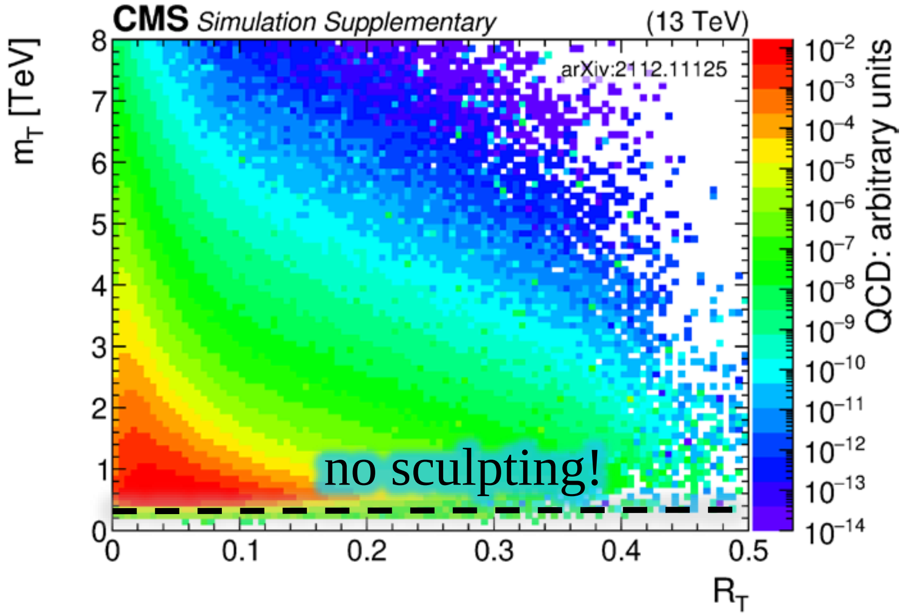
Reject $t\bar{t}$, $W(\ell\nu)$, $Z(\nu\nu)$

SVJ Cutflows

Selection	QCD	$t\bar{t}$	W+jets	Z+jets	$r_{\mathrm{inv}} = 0.3$
$p_{\mathrm{T}}(\mathrm{J}_{1,2}) > 200\,\mathrm{GeV}$, $\eta(\mathrm{J}_{1,2}) < 2.4$	1.2	6.4	2.0	1.3	83.5
$R_{\mathrm{T}} > 0.15$	1.3	12.1	18.5	34.6	39.7
$\Delta\eta(\mathrm{J}_1, \mathrm{J}_2) < 1.5$	94.9	88.0	85.1	78.8	80.0
$m_{\mathrm{T}} > 1.5\,\mathrm{TeV}$	0.20	3.1	4.0	5.6	81.8
$N_{\mu} = 0$	93.0	62.0	66.0	99.5	96.8
$N_{\mathrm{e}} = 0$	99.6	59.8	57.3	99.6	99.4
$p_{\mathrm{T}}^{\mathrm{miss}}$ filters	99.5	99.9	99.9	99.9	99.8
$\Delta R(\mathrm{j}_{1,2}, c_{\mathrm{nonfunctional}}) > 0.1$	60.6	95.1	95.2	95.6	95.2
veto $f_{\gamma}(\mathrm{j}_1) > 0.7$ & $p_{\mathrm{T}}(\mathrm{j}_1) > 1.0\,\mathrm{TeV}$	99.7	99.7	99.6	99.7	99.7
$\Delta\phi_{\mathrm{min}} < 0.8$	94.8	81.7	61.8	44.7	87.7
Efficiency [%]	1.6e-05	0.0060	0.0029	0.0085	17
high-R_{T}	9.0	29.5	38.8	39.1	45.2
low-R_{T}	91.0	70.5	61.2	60.9	54.8
high-SVJ2	0.093	0.62	0.46	0.69	34.6
low-SVJ2	1.1	1.7	0.92	0.94	42.3

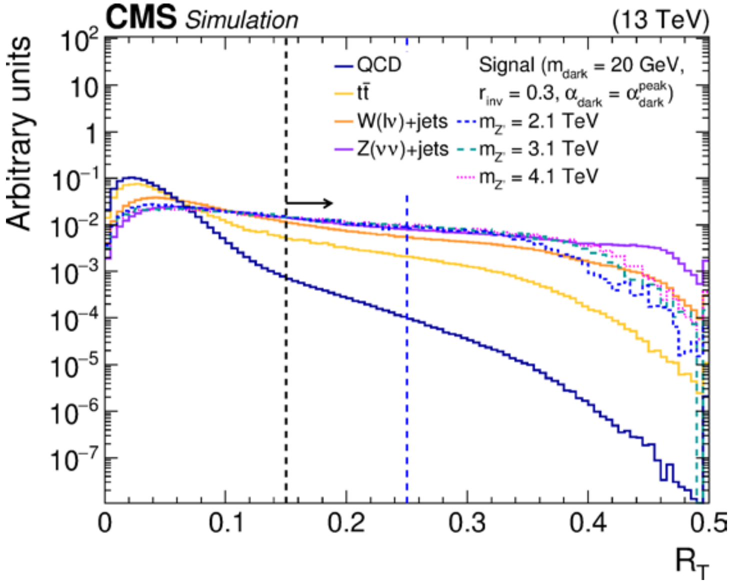
SVJ Mass Sculpting





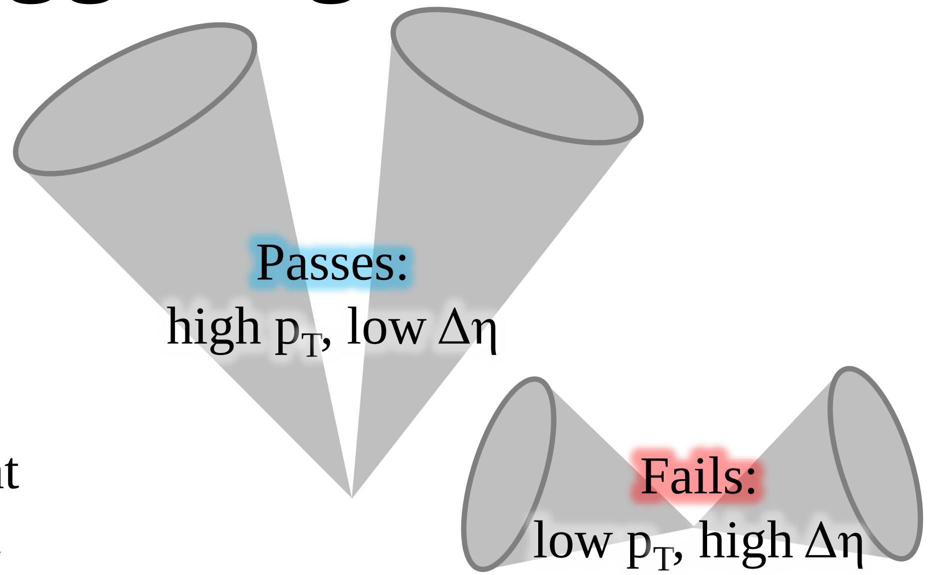
- Avoid/minimize direct cuts on m_T ingredients: p_T^{miss}, jet p_T
  - o Relative variable ("transverse ratio"): $R_T = p_T^{miss}/m_T$

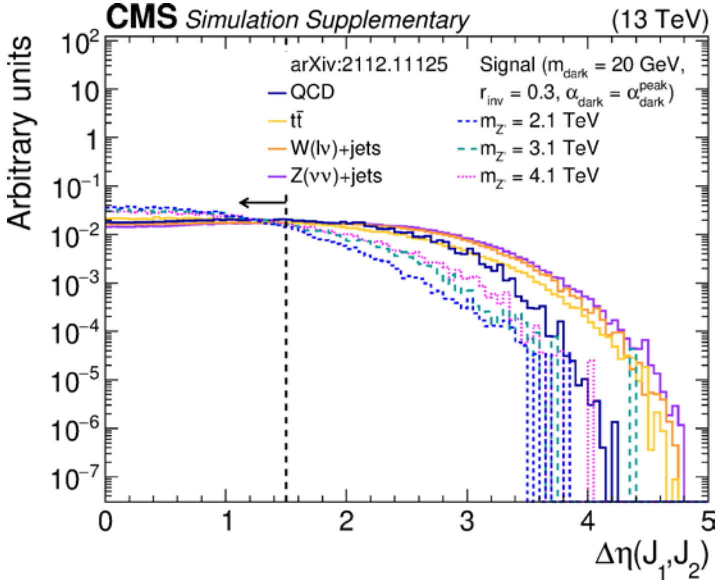
➢ Reject QCD background without shifting m_T peak

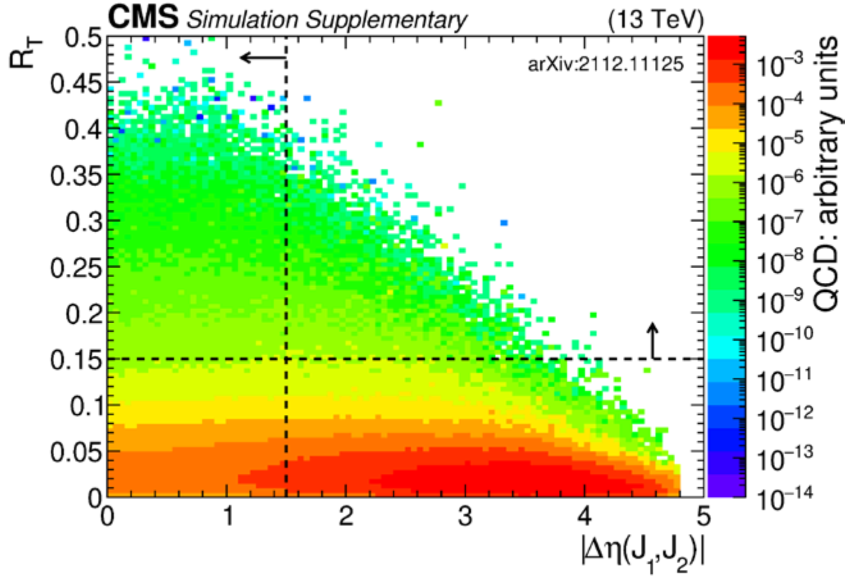


SVJ Triggering

- Trigger on jet p_T, H_T
  - ➢ Require low $\Delta\eta(J_1,J_2)$ for high efficiency
- Usually improves signal sensitivity
  - ➢ Most *t*-channel QCD events already rejected by R_T requirement
- m_T > 1500 GeV for trigger efficiency

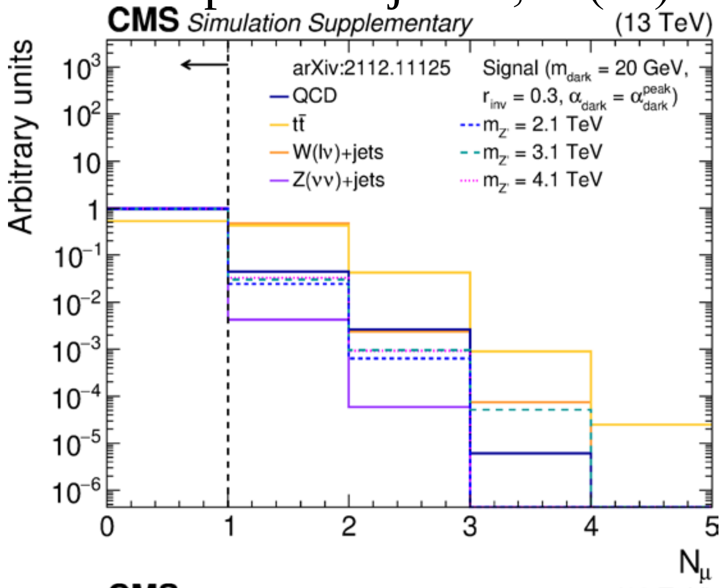


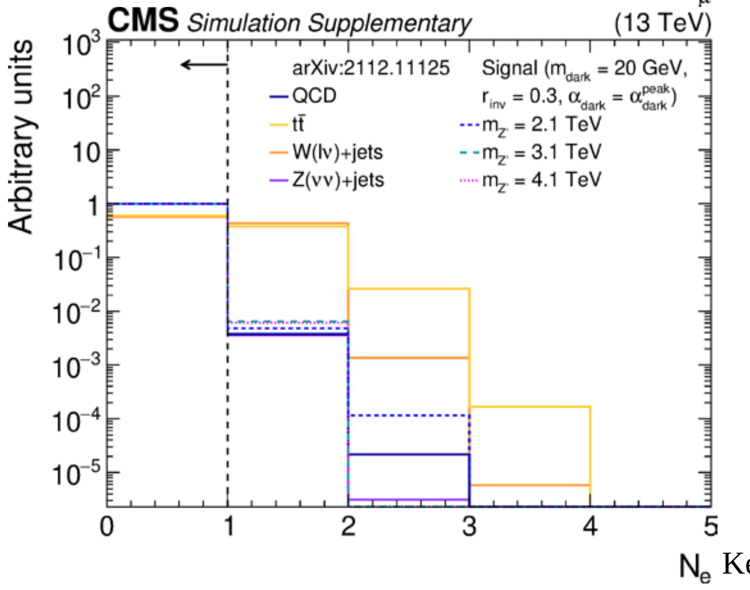




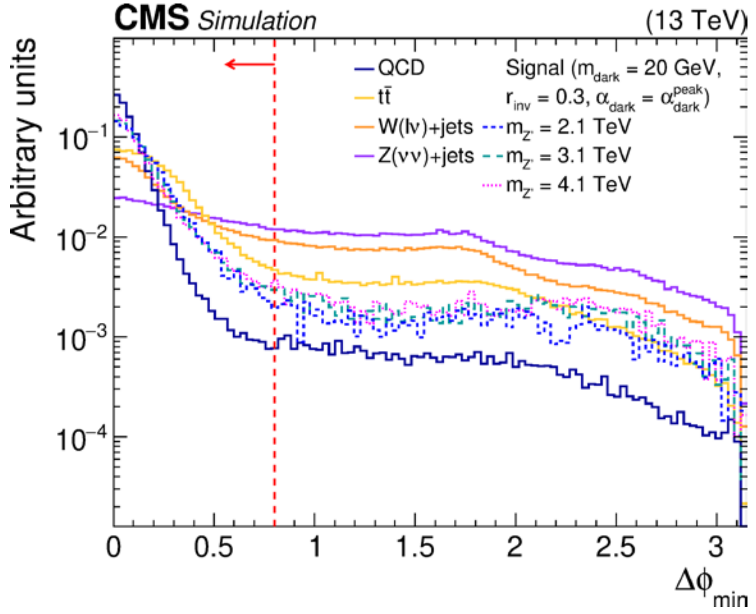
SVJ Electroweak Rejection

Veto leptons: reject $t\bar{t}$, $W(\ell\nu)$





Require low $\Delta\varphi_{min}(J_{1,2}, p_T^{miss})$:
Reject $t\bar{t}$, $W(\ell\nu)$, $Z(\nu\nu)$

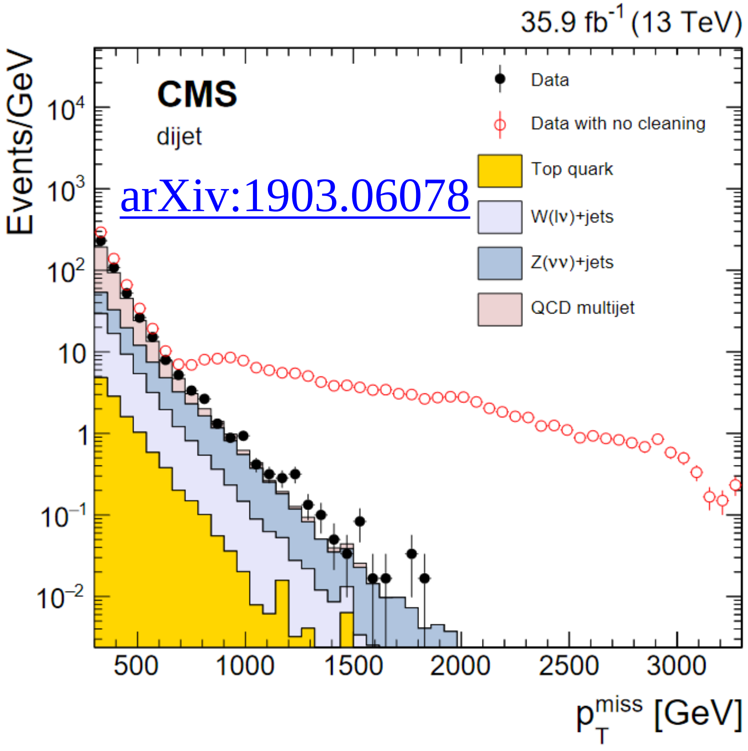


SVJ Instrumental Backgrounds

- Centrally-maintained filters reject *most* instrumental sources of artificial high-p_T^{miss} events
  - o But low-$\Delta\varphi$ region ignored by almost all analyses: filters not tuned here
- Major source of jet mismeasurement: nonfunctional ECAL readout channels ("dead" or "hot" cells)

➢ Custom filter vetoing events w/ narrow (AK4) jets w/ $\Delta R(j_{1,2}$, nonfunctional$) < 0.1$ $\rightarrow$ reject additional 40% of QCD background

  - o Signal efficiency 95%
- Misreconstructed jets near barrel-endcap gap in ECAL
  - o Appear at high p_T^{miss} and high m_T
  - o Veto events w/ $p_T(j_1) > 1000$ GeV and $f_\gamma(j_1) > 0.7$



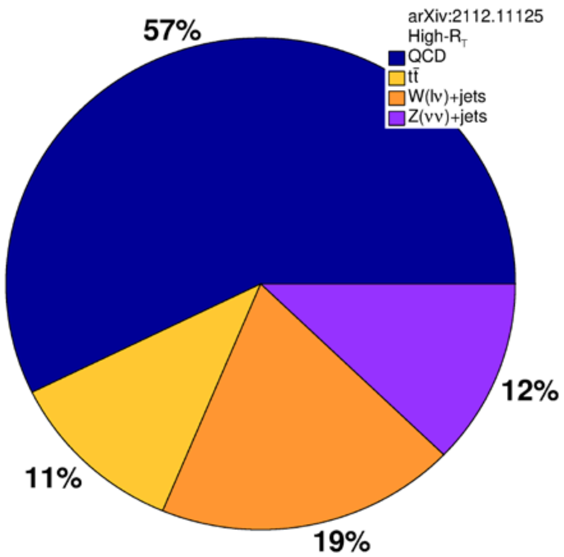
arXiv:1903.06078

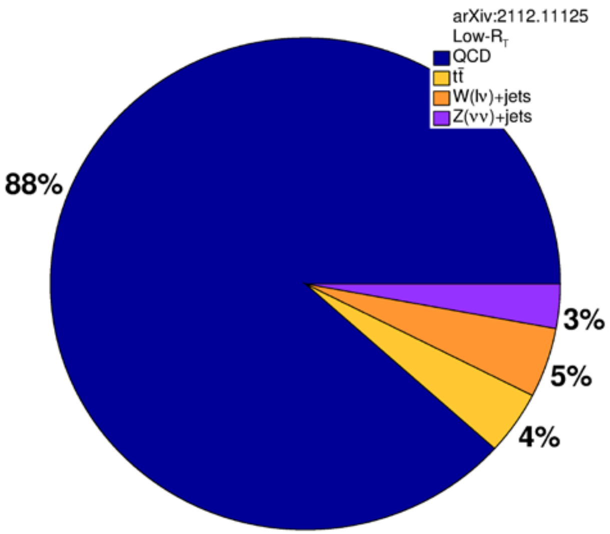
SVJ Inclusive Signal Regions

- With all inclusive selection requirements applied:

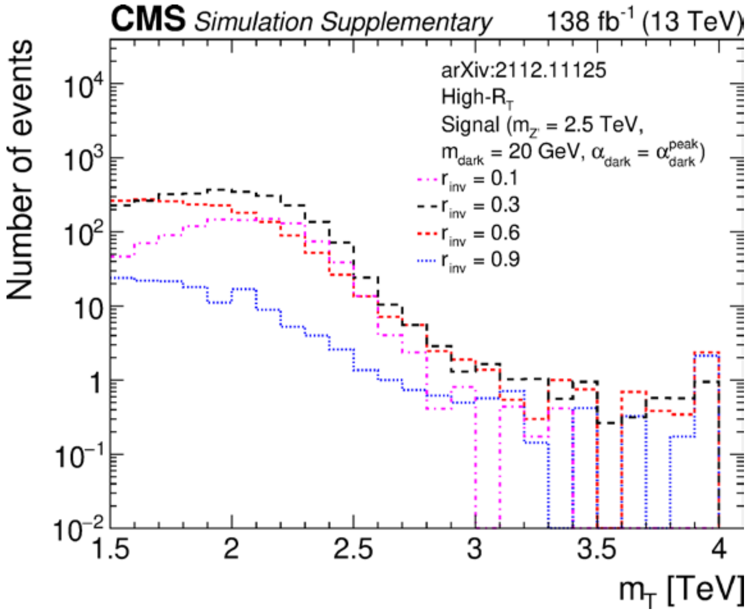
- If only one signal region were defined, high-R_T ($R_T > 0.25$) would have optimal significance
- Adding separate region low-R_T ($0.15 < R_T < 0.25$) improves expected performance

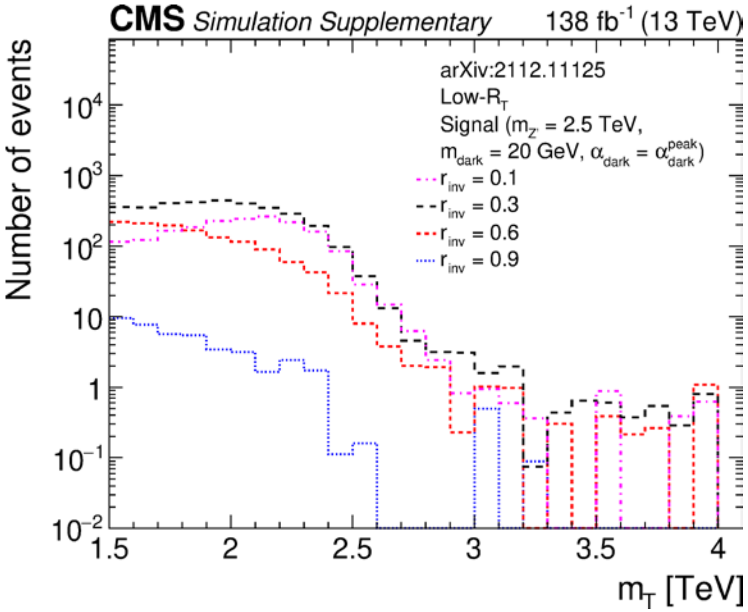
Process	Efficiency [%]
QCD	0.000016
$t\bar{t}$	0.0060
$W(\ell\nu)$+jets	0.0029
$Z(\nu\nu)$+jets	0.0085
signal	~17





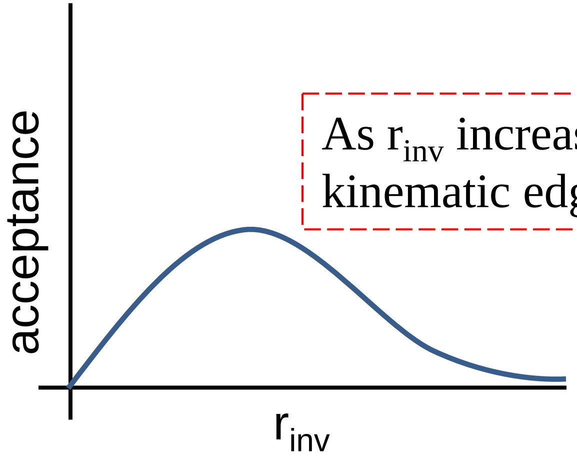
SVJ m_T Variations





- r_{inv} has largest impact on signal mass distributions
  - α_{dark} has minor impact; m_{dark} has very little impact

As r_{inv} increases, kinematic edge softens

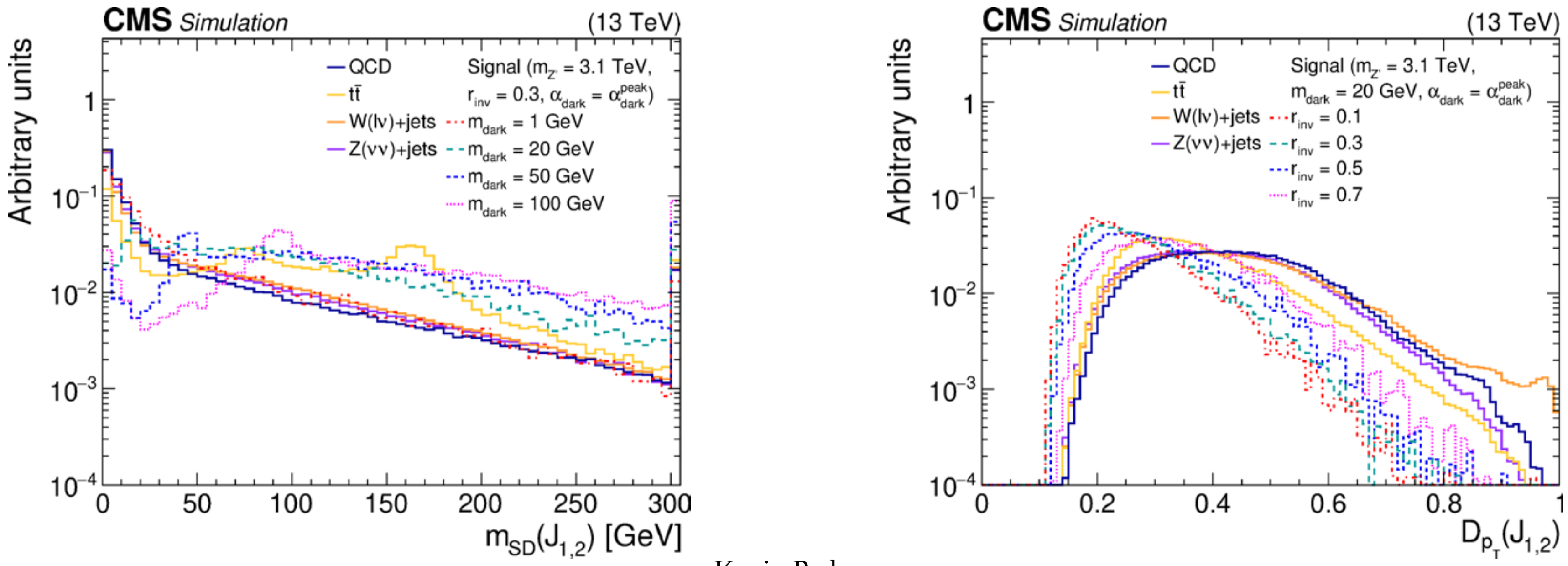


Low r_{inv} signals populate low-R_T signal region

Very high r_{inv} signals look like ISR

Tagging Semivisible Jets

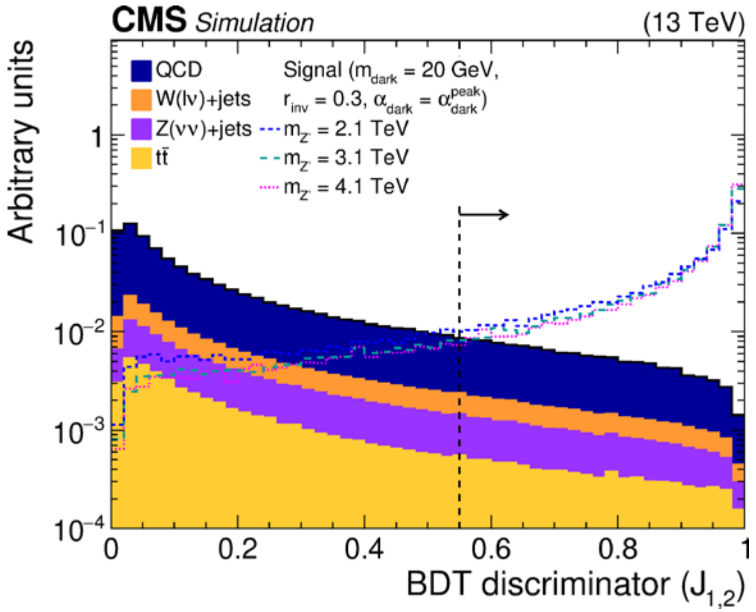
- Various jet substructure variables (& $\Delta\varphi(J, p_T^{miss})$) can weakly discriminate between semivisible jets and SM background jets
  - o Heavy object tagging: m_{SD}, τ_{21}, τ_{32}, $N_2^{(1)}$, $N_3^{(1)}$
  - o Quark-gluon discrimination: D_{p_T}, σ_{major}, σ_{minor}, girth
  - o Flavor (energy fractions): f_γ, $f_{h\pm}$, f_{h0}, f_e, f_μ
- ➢ Combine useful variables into a BDT for strong discrimination!
  - o Background: equal mix of QCD and $t\bar{t}$; signal: mix of many models
  - o Reweight background jet p_T spectrum to match signal: avoid sculpting

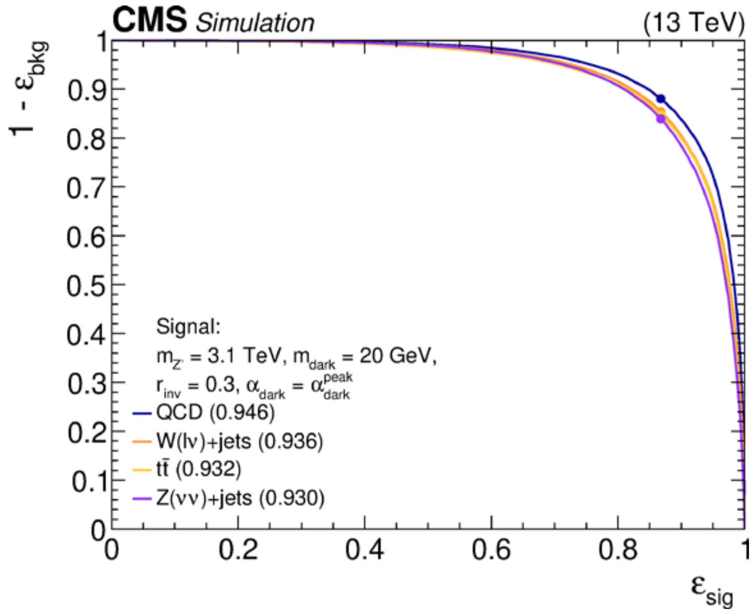


SVJ Tagger Performance

	$m_{Z'}$ = 3.1 TeV, m_{dark} = 20 GeV, r_{inv} = 0.3, $\alpha_{dark} = \alpha_{dark}^{peak}$		
	Acc (WP = 0.5)	AUC	$1/\varepsilon_B$ (ε_S = 0.3)
QCD	0.881	0.947	651.4
$t\bar{t}$	0.881	0.931	270.6
W(ℓν)+jets	0.881	0.936	441.5
Z(νν)+jets	0.881	0.930	420.7

- Strong and consistent performance
  - Training on only QCD ($t\bar{t}$) caused misclassification of $t\bar{t}$ (QCD) jets at rate of 10–20%
  - Some inefficiency for signals with high or low m_{dark}
- Working point 0.55 chosen based on background estimation

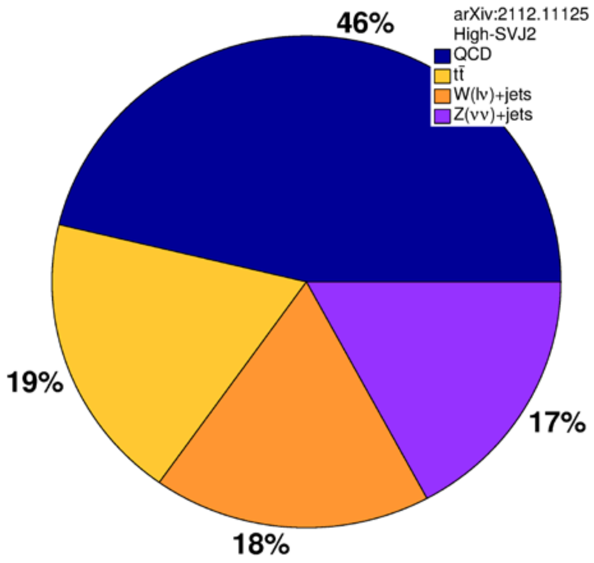


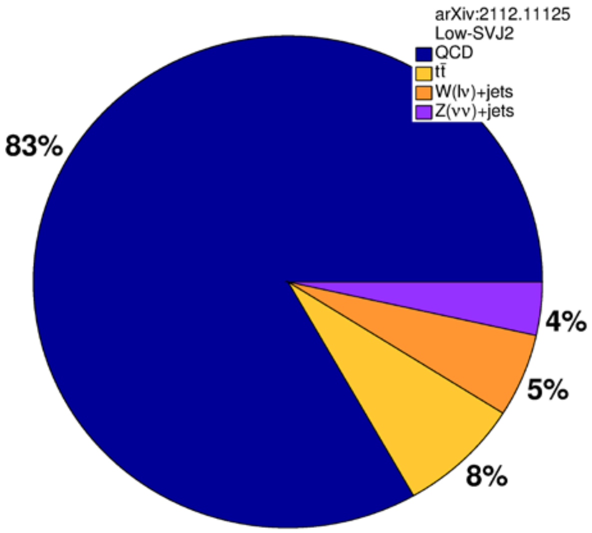


SVJ BDT-based Signal Regions

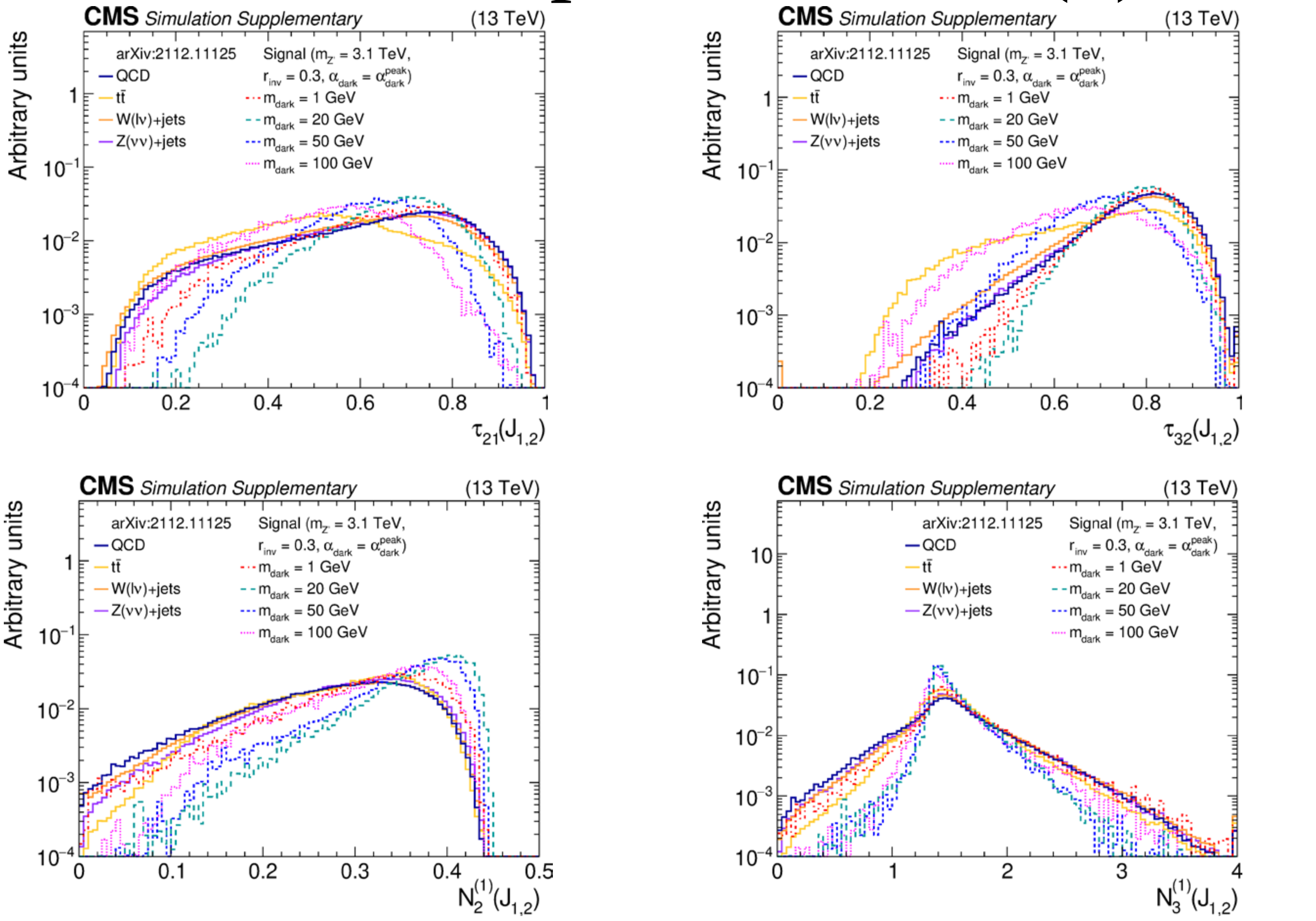
- Start from inclusive signal regions (high-R_T, low-R_T)
- Require both leading wide jets to be tagged as semivisible
  - high-SVJ2, low-SVJ2 regions: strict subsets of inclusive regions

➢ Reduce background by factor ~60 while preserving signal

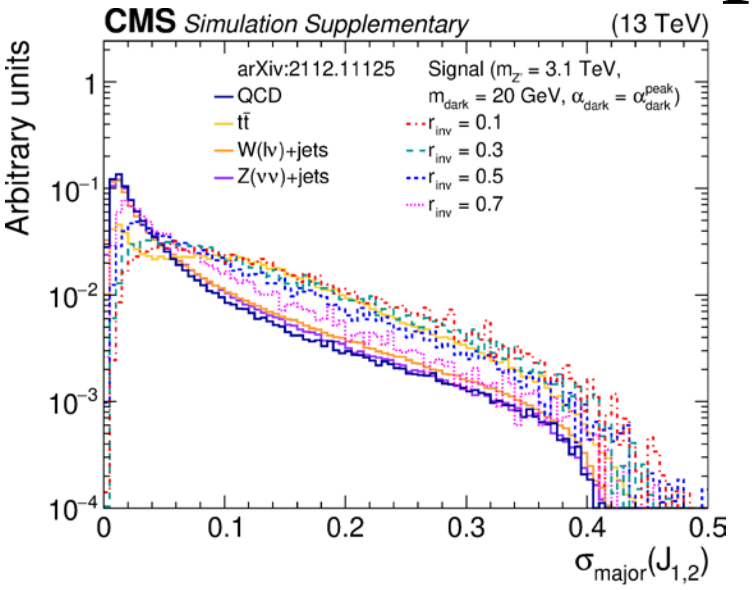


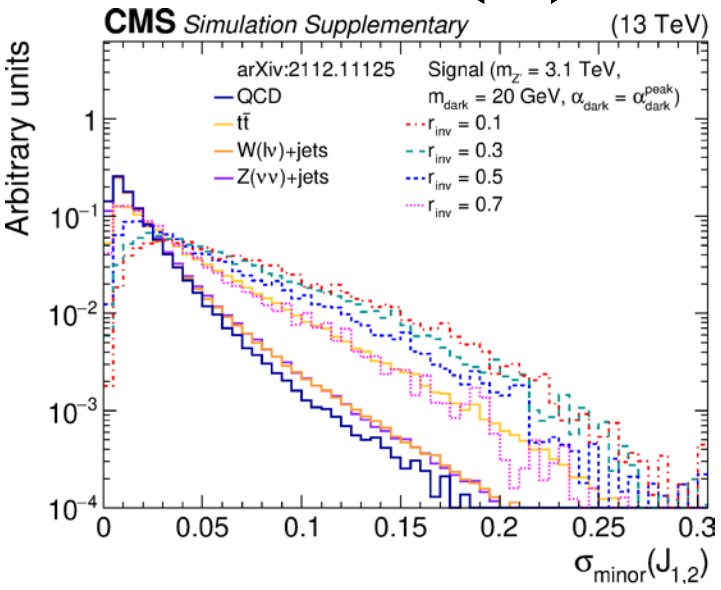


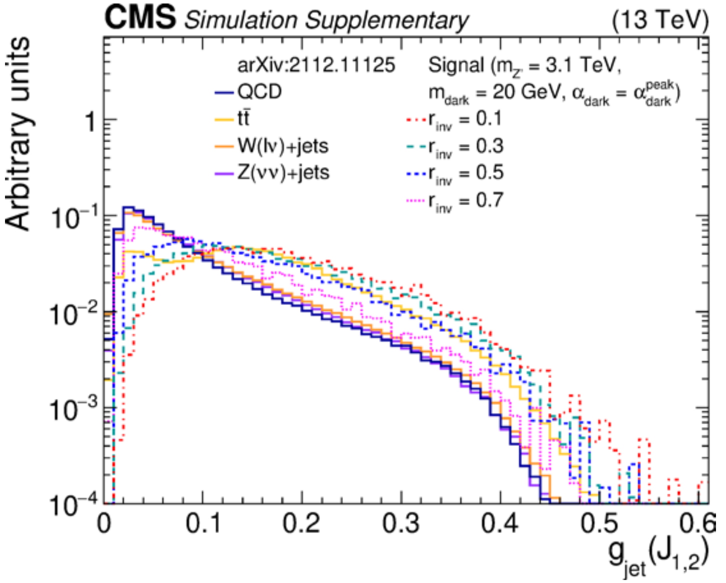
SVJ BDT Input Variables (1)

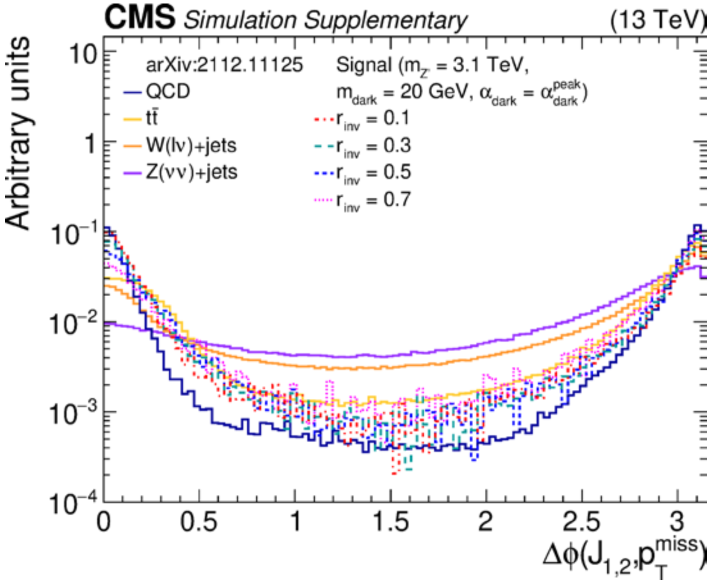


SVJ BDT Input Variables (2)

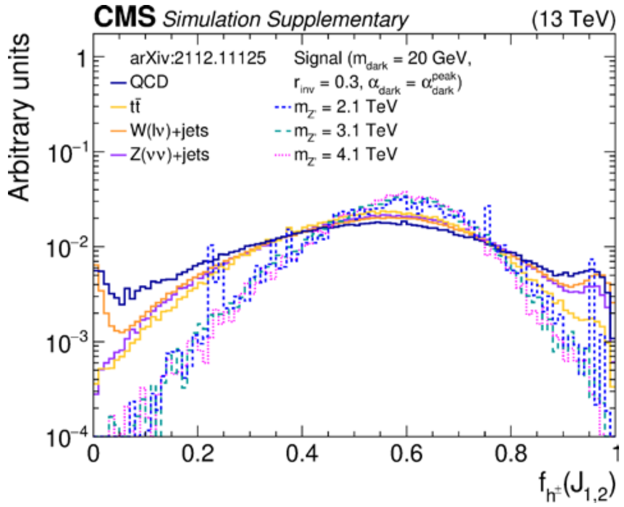


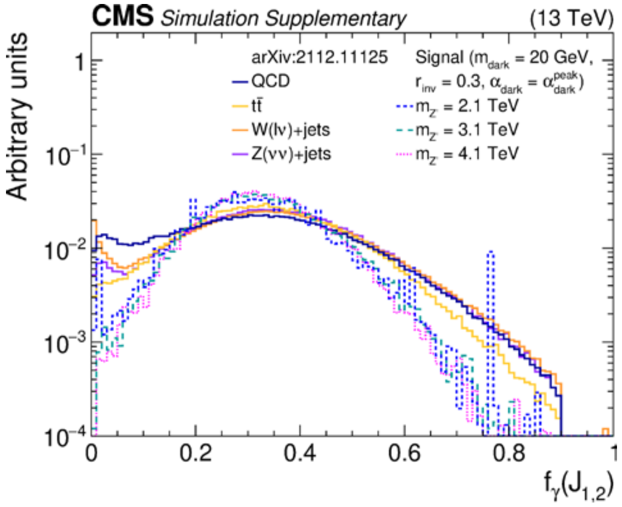


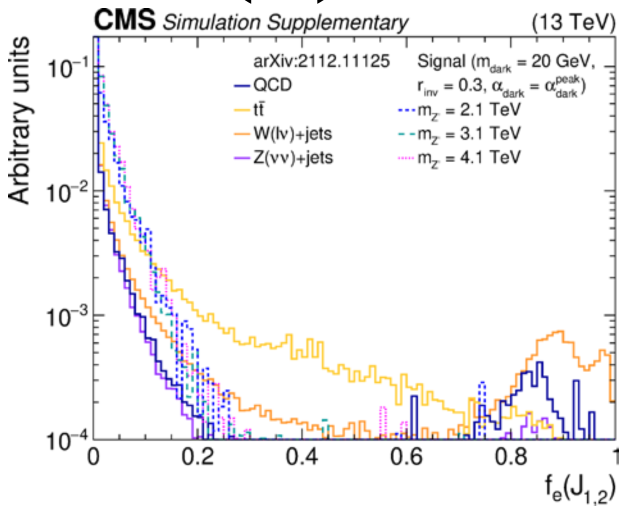


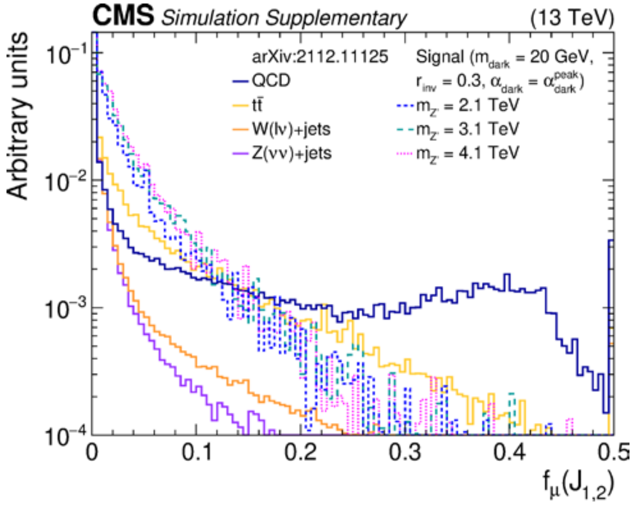


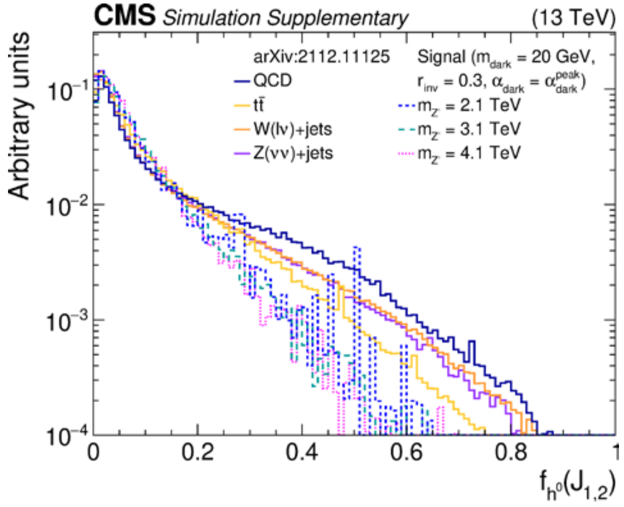
SVJ BDT Input Variables (3)



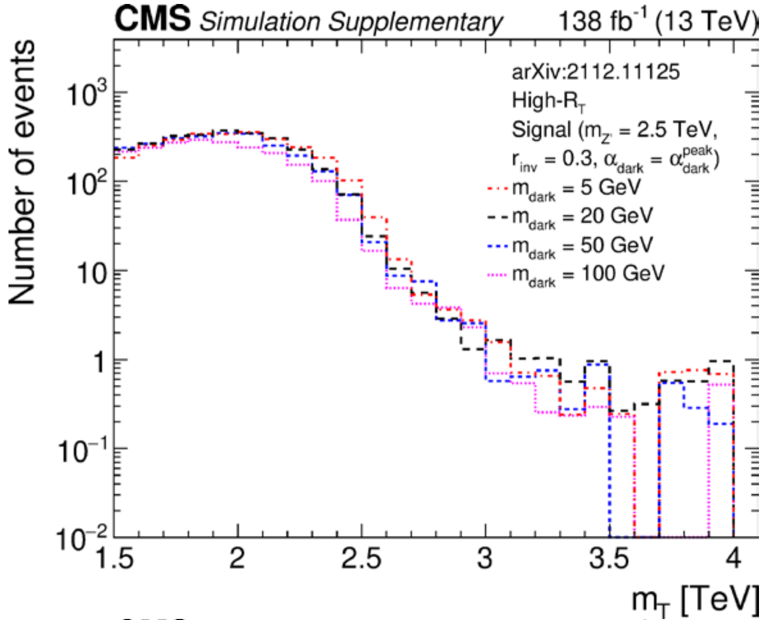




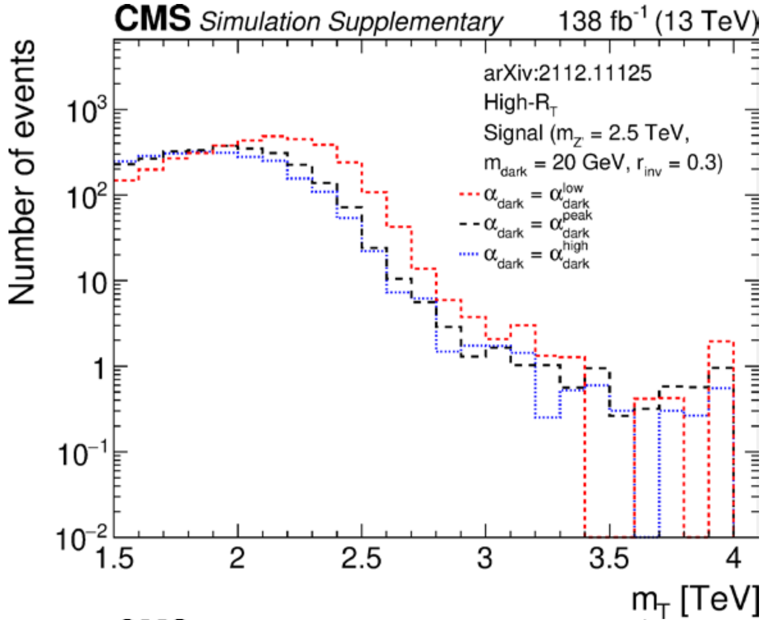


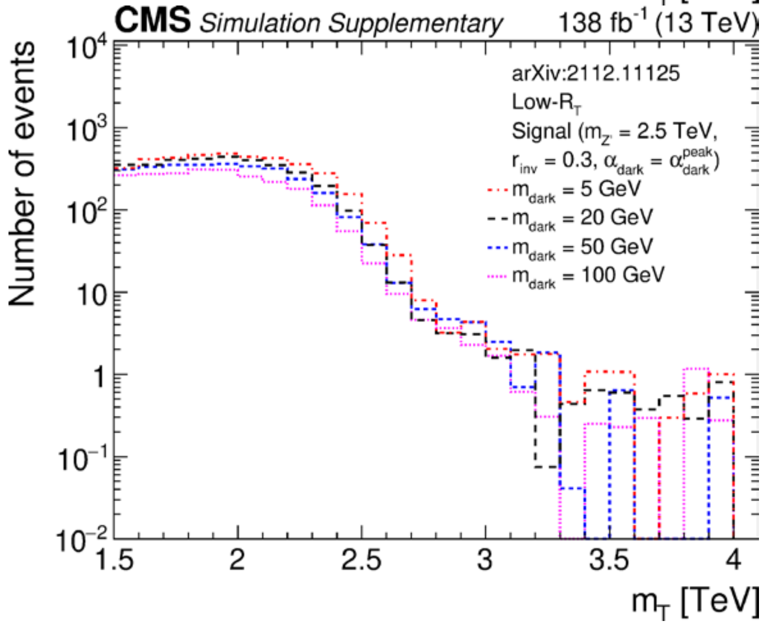


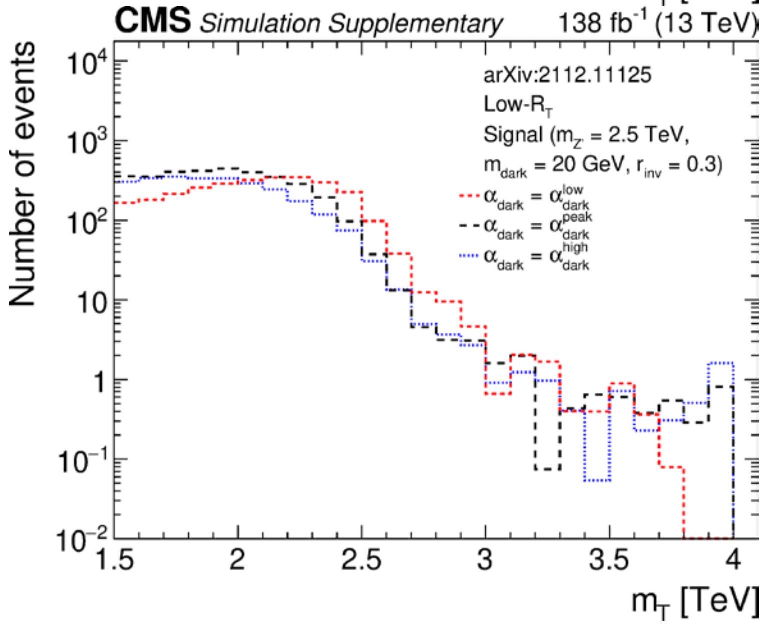
SVJ: More m_T Variations



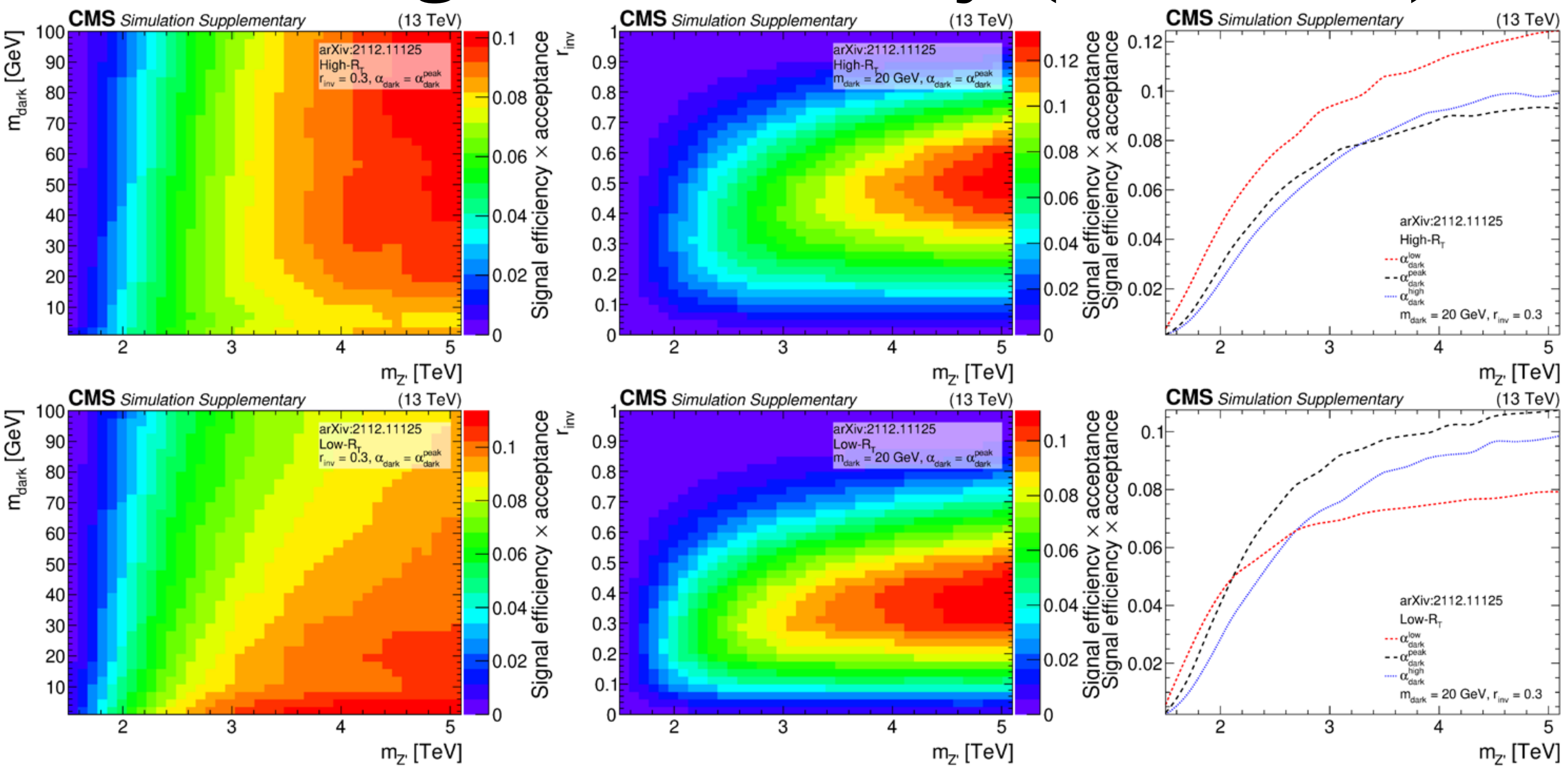
- α_{dark} has non-trivial impact
- m_{dark} has very little impact



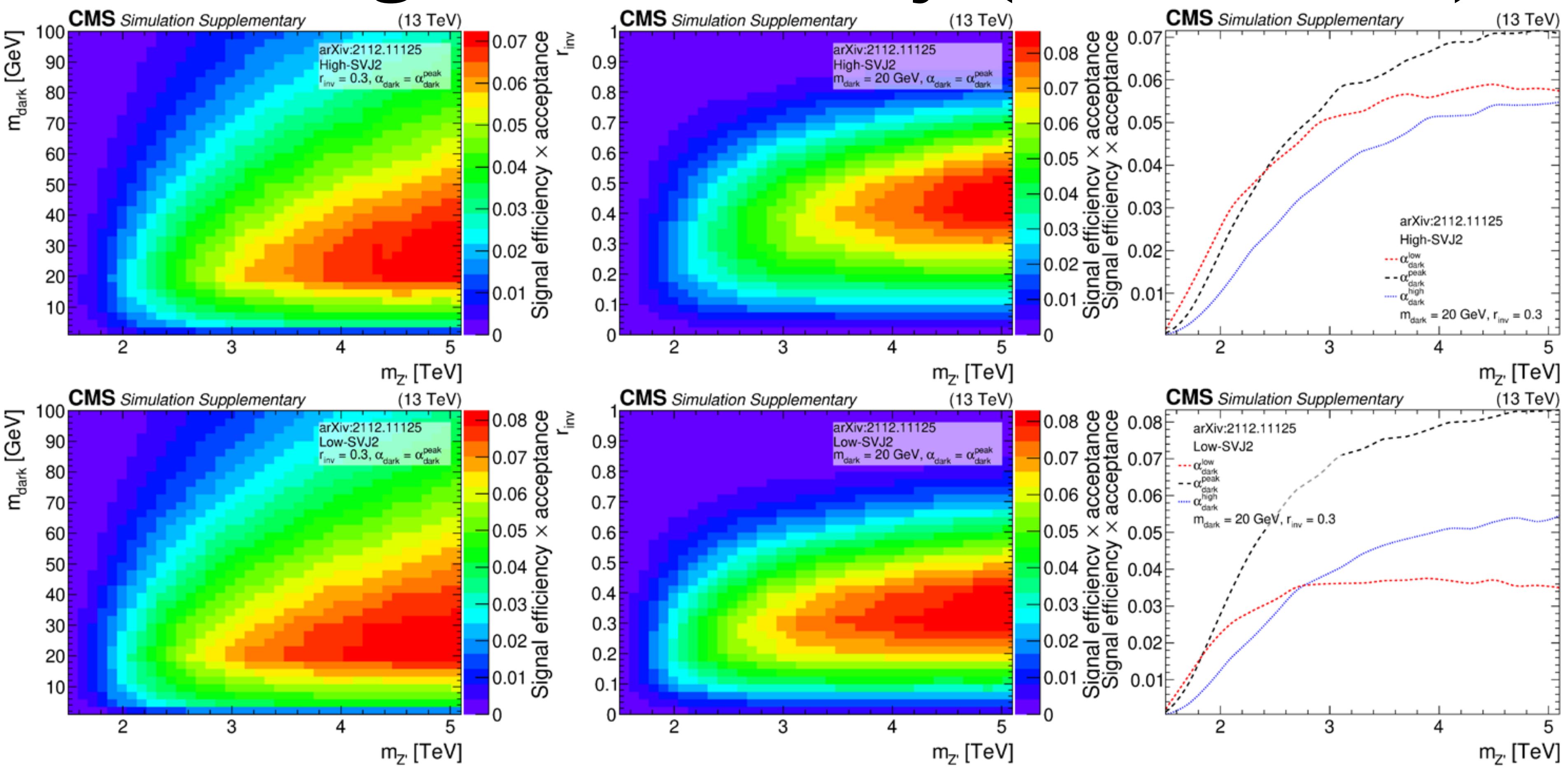




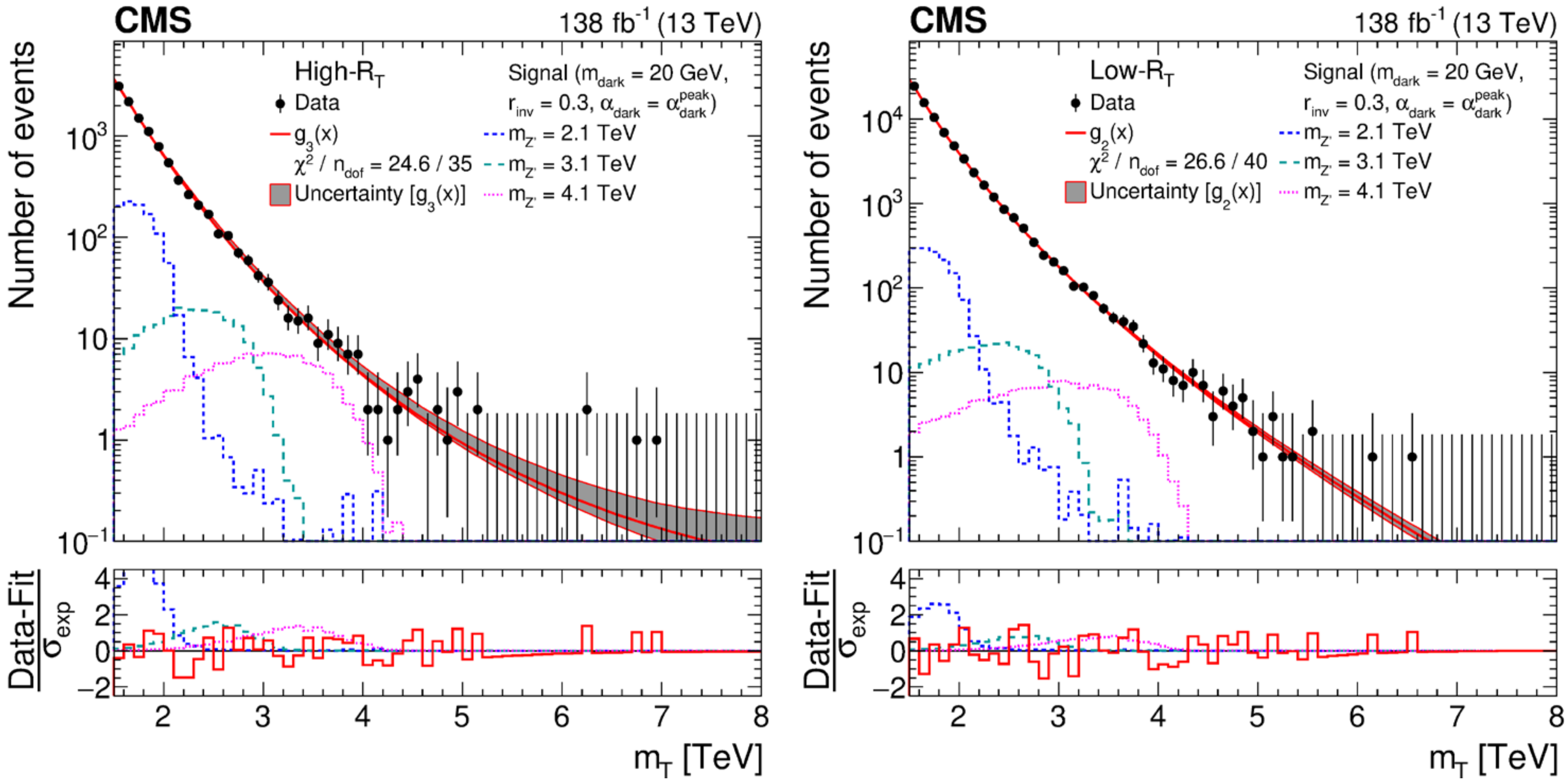
SVJ Signal Efficiency (inclusive)



SVJ Signal Efficiency (BDT-based)

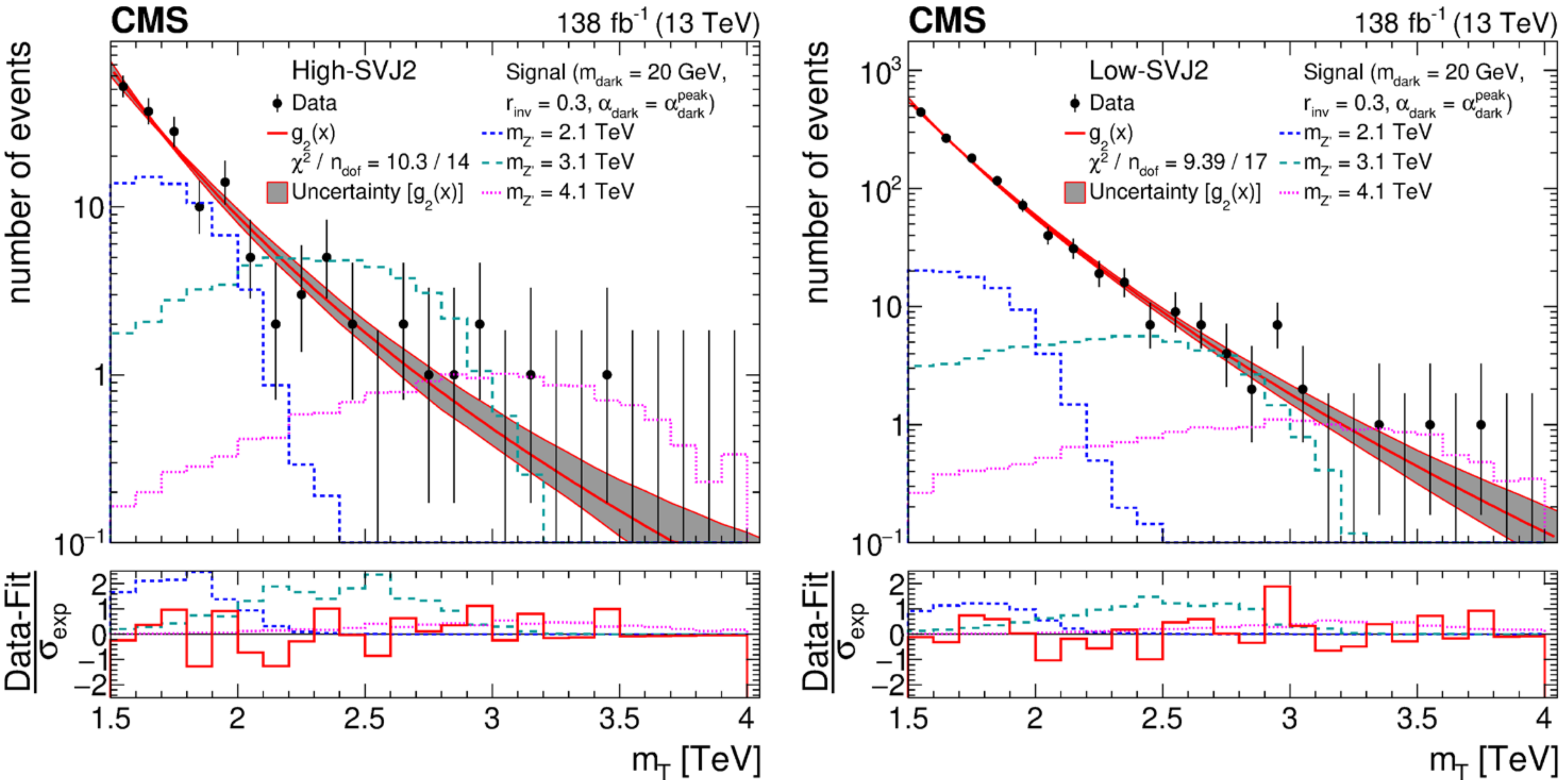


SVJ Background Fits (inclusive)



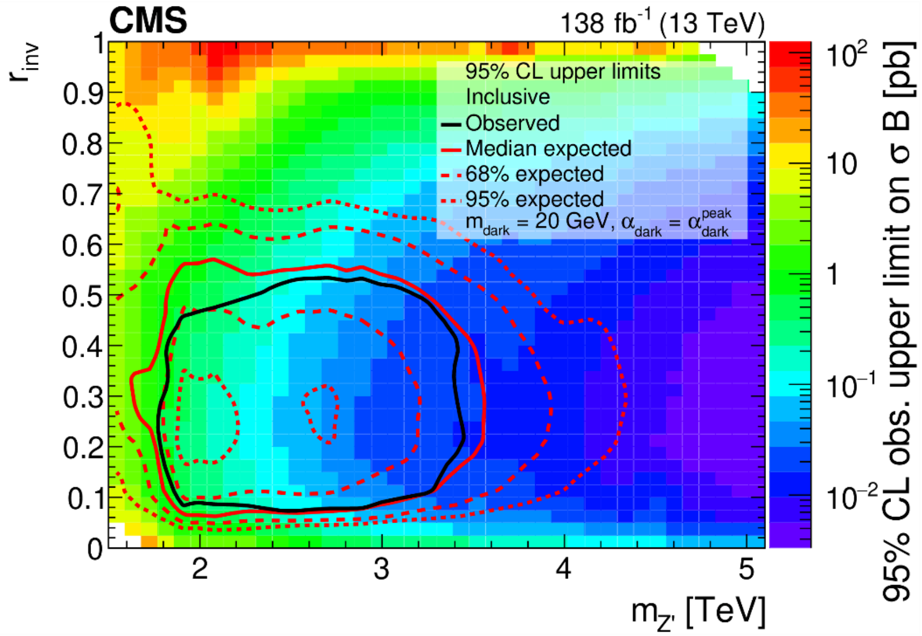
- No significant deviations from SM
  - Small pulls, few if any cases of several contiguous pulls > 0
- Signals shown w/ cross section at observed limit

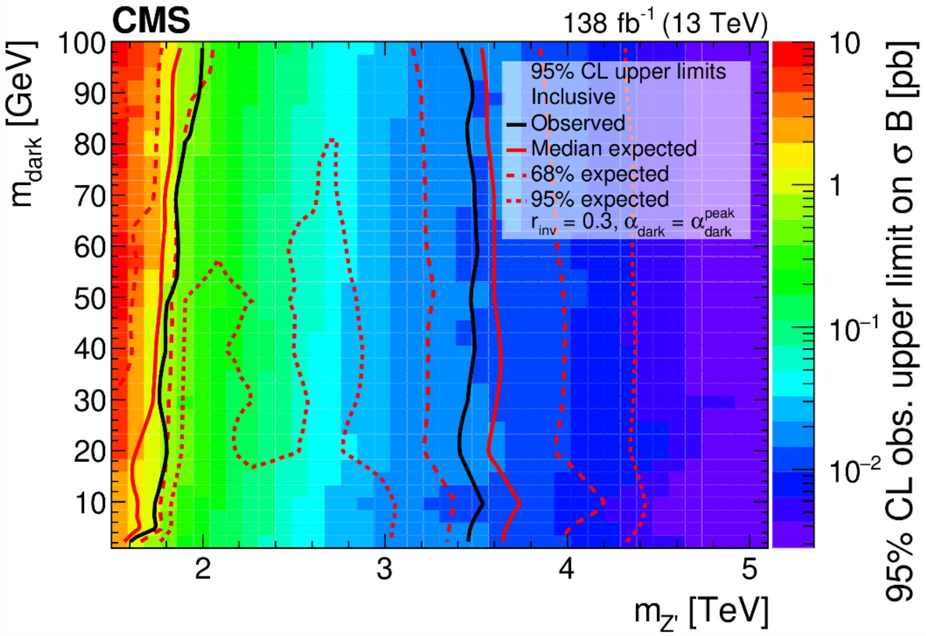
SVJ Background Fits (BDT-based)

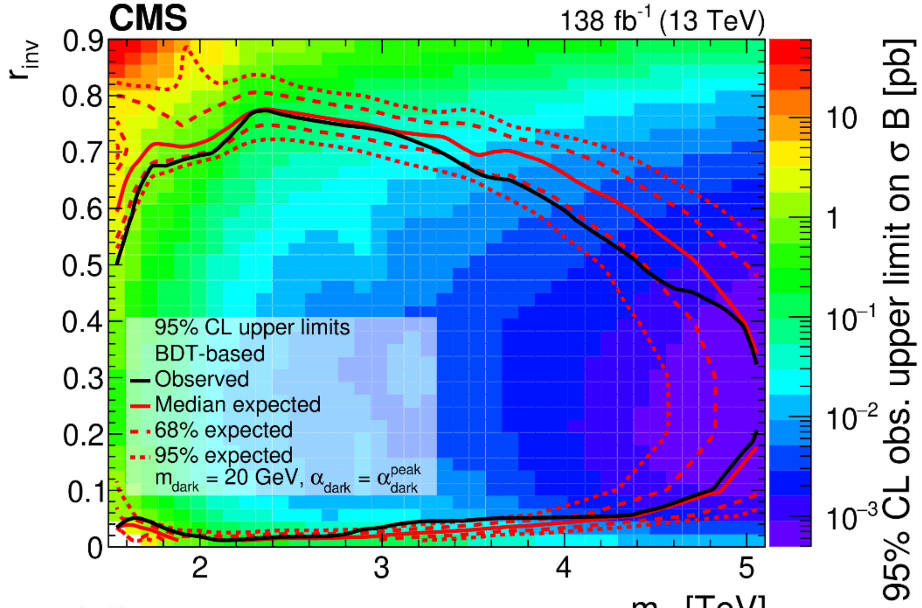


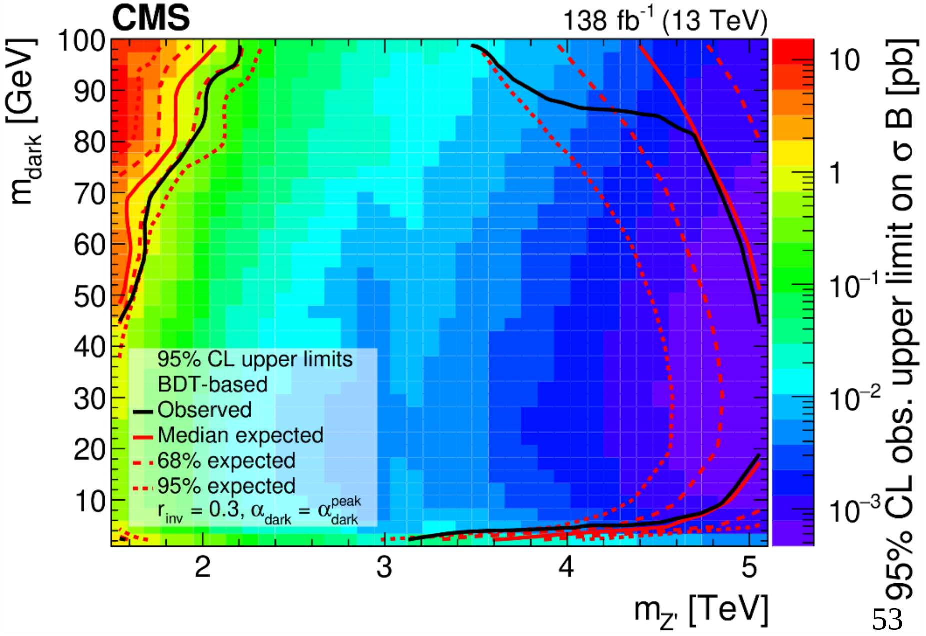
- No significant deviations from SM
  - o Small pulls, few if any cases of several contiguous pulls > 0
- Signals shown w/ cross section at observed limit

Semivisible Jet Results









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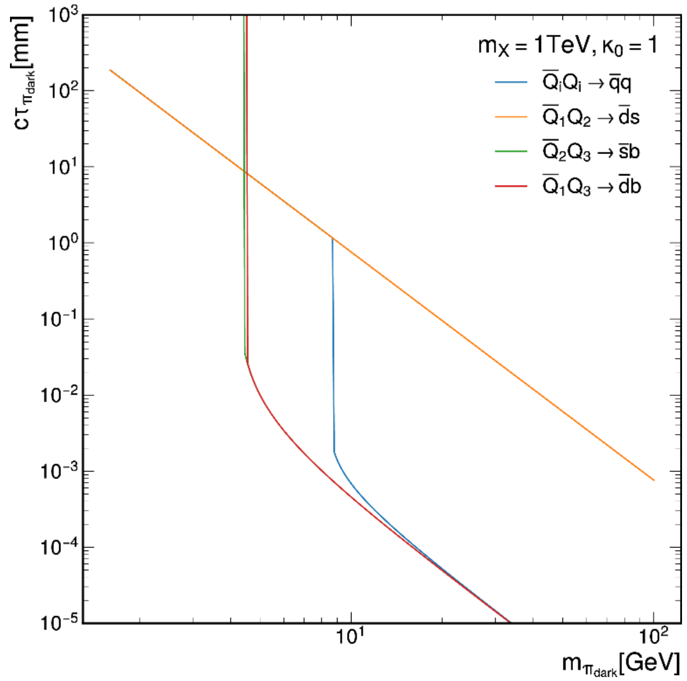
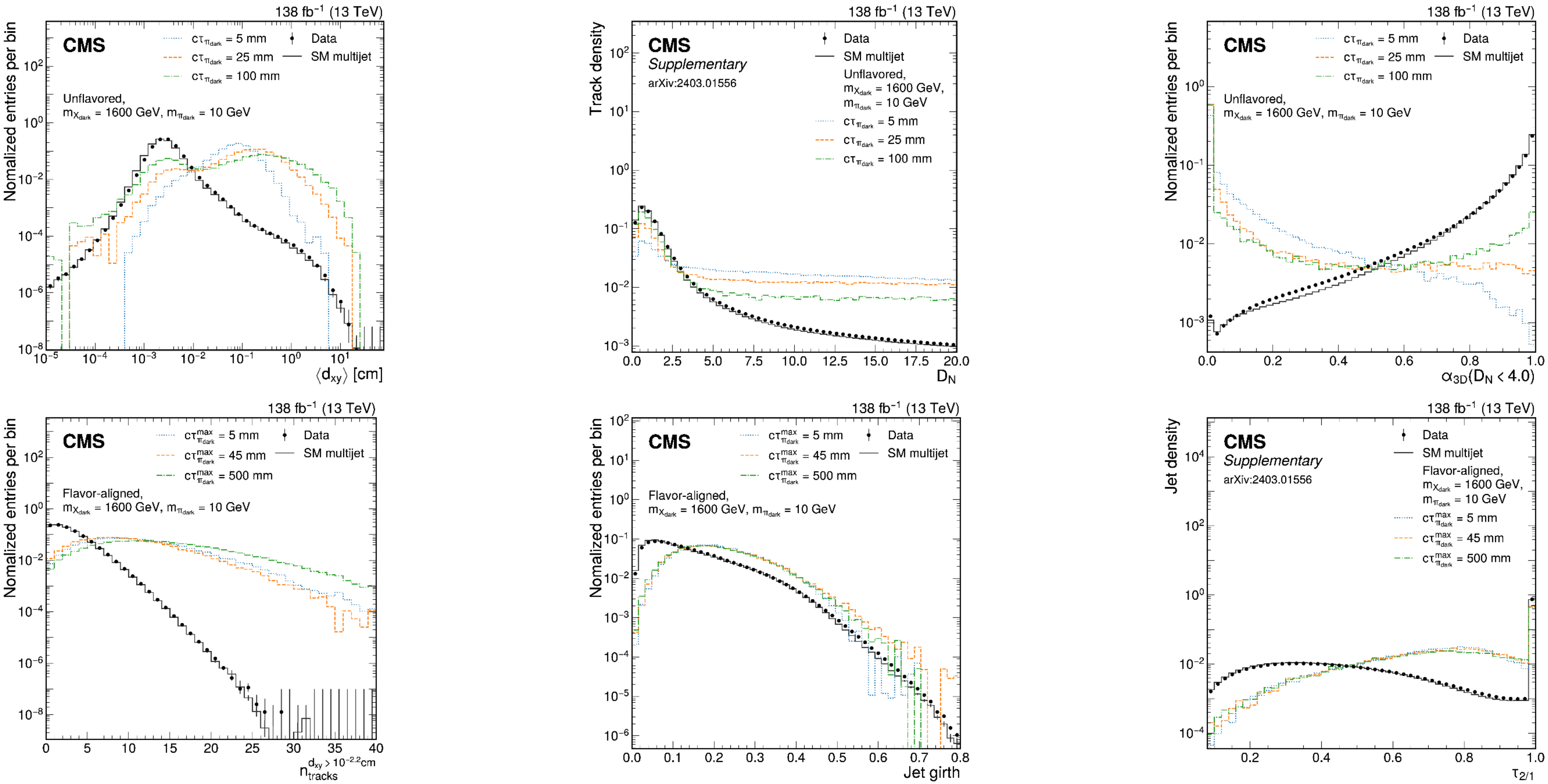
EMJ Models

- Unflavored:
  - Yukawa $\kappa_{\alpha d}$ nonzero, others zero
  - $N_c^{\text{dark}} = 3$, $N_f^{\text{dark}} = 7$
  - $m_\chi = \Lambda_{\text{dark}}$, $m_{\pi_{\text{dark}}} = \frac{1}{2} m_\chi$, $m_{\rho_{\text{dark}}} = 4 m_{\pi_{\text{dark}}}$
  - $c\tau_{\pi_{\text{dark}}} = 80\,\text{mm}\left(\frac{1}{\kappa^4}\right)\left(\frac{2\,\text{GeV}}{f_{\pi_{\text{dark}}}}\right)^2\left(\frac{100\,\text{MeV}}{m_{\text{d}}}\right)^2\left(\frac{2\,\text{GeV}}{m_{\pi_{\text{dark}}}}\right)\left(\frac{m_{X_{\text{dark}}}}{1\,\text{TeV}}\right)^4$

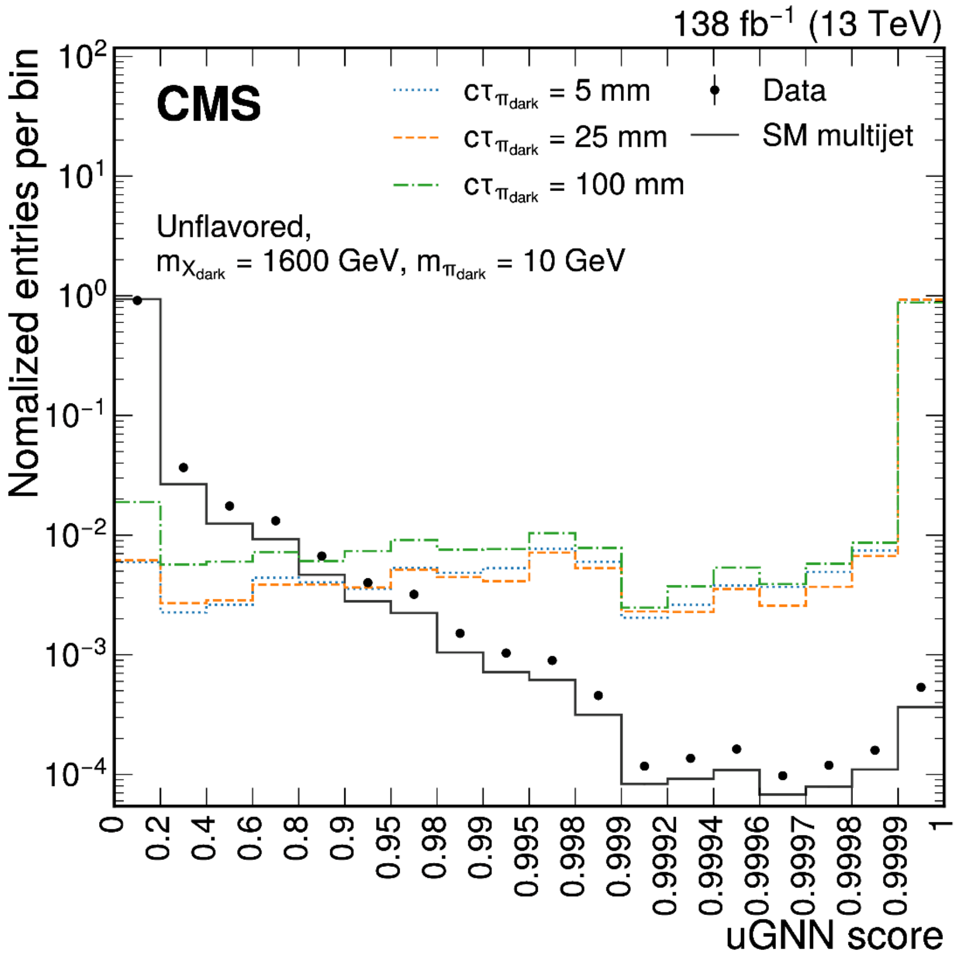
- Flavor-diagonal:
  - Yukawa κ_{1d}, κ_{2s}, κ_{3b} nonzero
  - $N_c^{\text{dark}} = 3$, $N_f^{\text{dark}} = 3$
  - $m_\chi = \Lambda_{\text{dark}}$, $m_{\pi_{\text{dark}}} = \frac{1}{2} m_\chi$, $m_{\rho_{\text{dark}}} = 4 m_{\pi_{\text{dark}}}$
  - $c\tau^{\alpha\beta}_{\pi_{\text{dark}}} = \dfrac{8\pi m^4_{X_{\text{dark}}}}{N_c m_{\pi_{\text{dark}}} f^2_{\pi_{\text{dark}}} \sum_{i,j} |\kappa_{\alpha i}\kappa^*_{\beta j}|^2 \left(m_i^2 + m_j^2\right)\sqrt{\left(1 - \frac{(m_i+m_j)^2}{m^2_{\pi_{\text{dark}}}}\right)\left(1 - \frac{(m_i-m_j)^2}{m^2_{\pi_{\text{dark}}}}\right)}}$

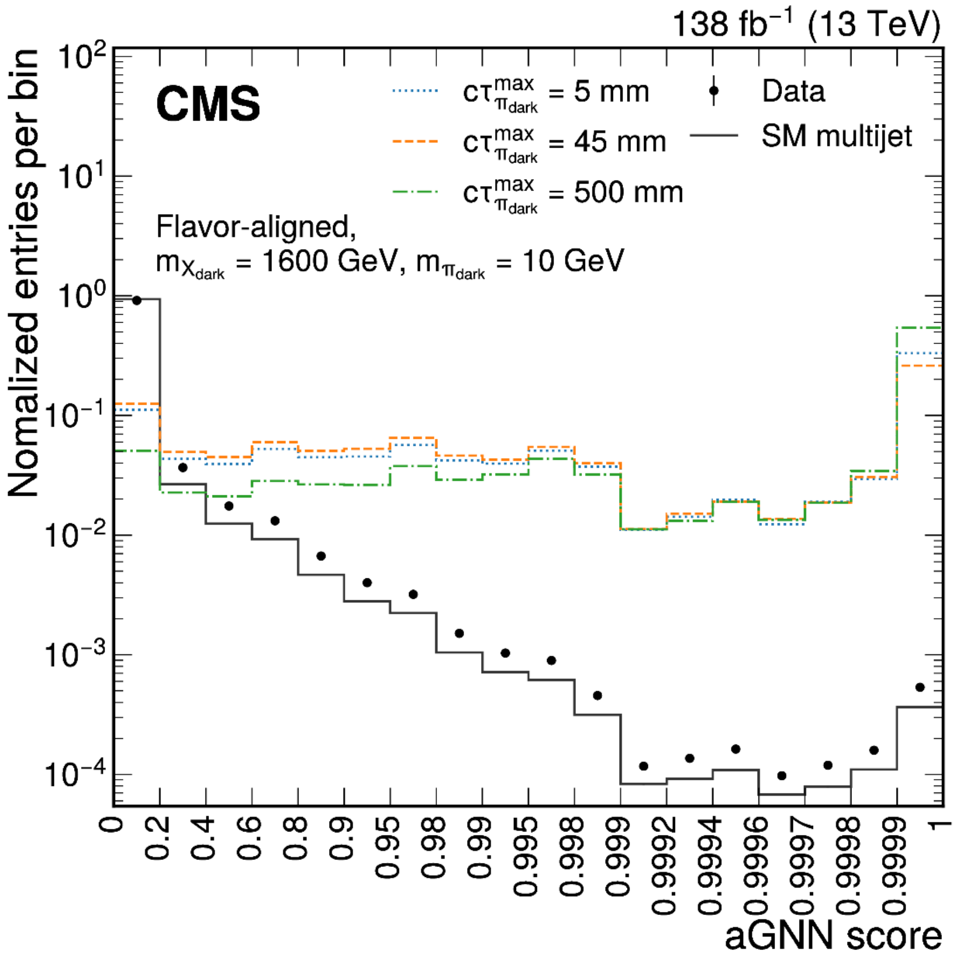


EMJ Cut-Based Tagger Inputs

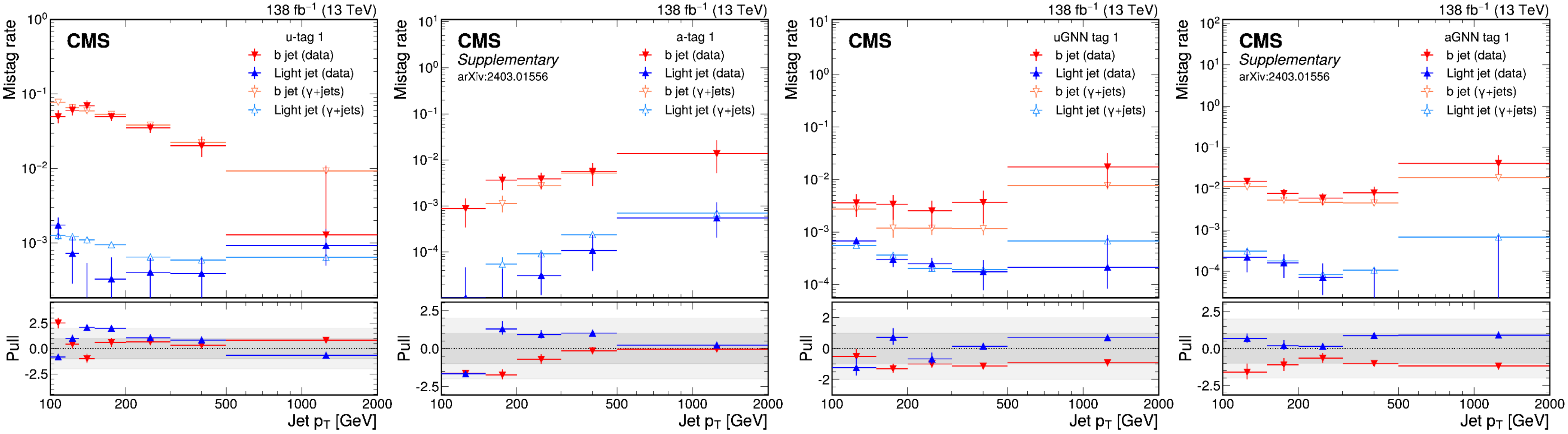


EMJ GNN Taggers





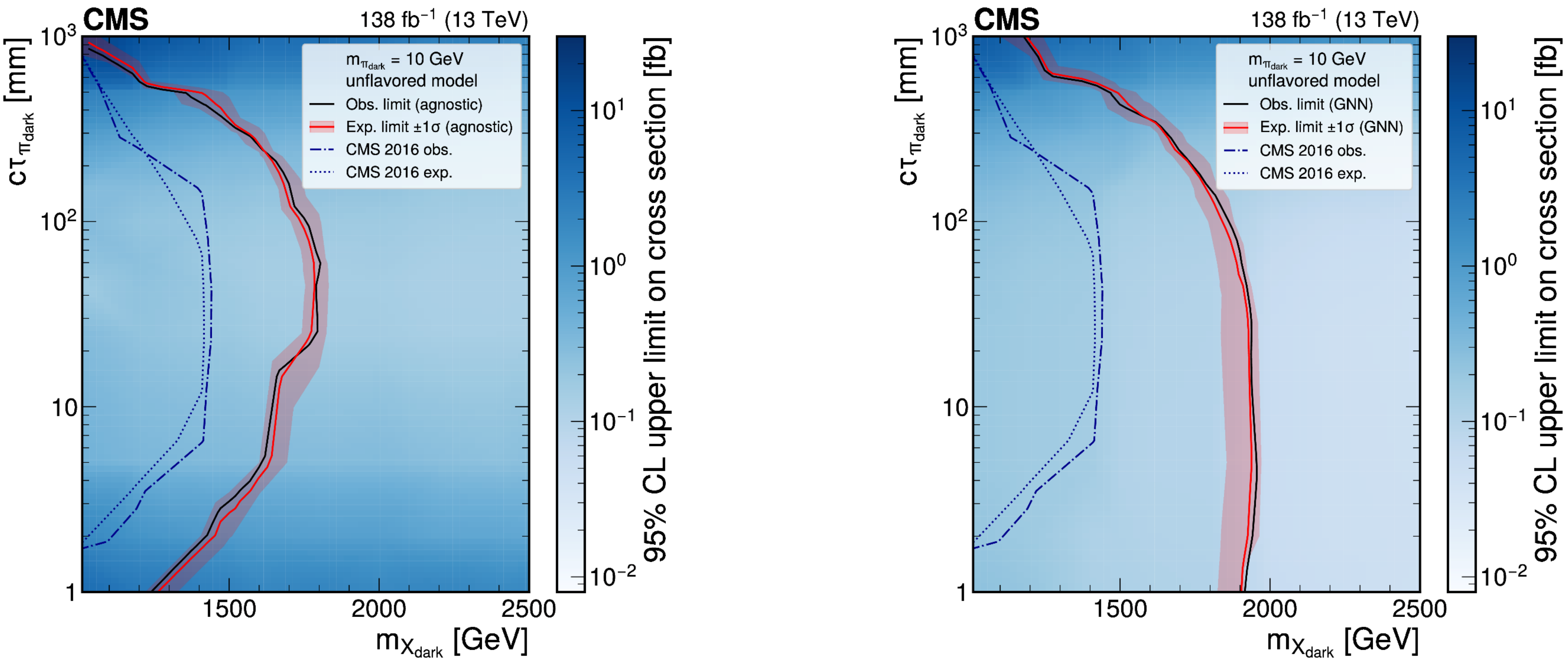
EMJ Fake Rates



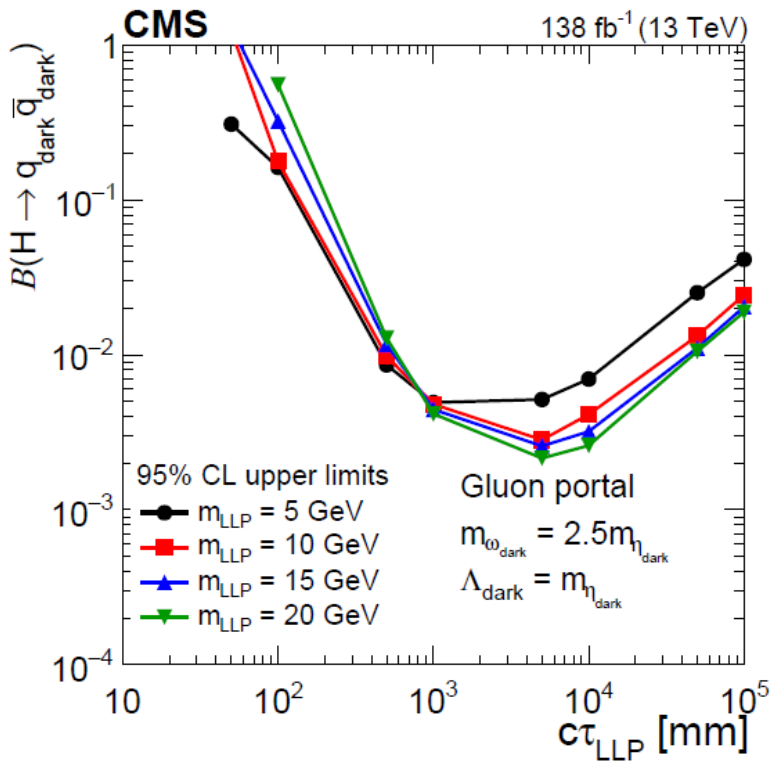
EMJ Selection Sets

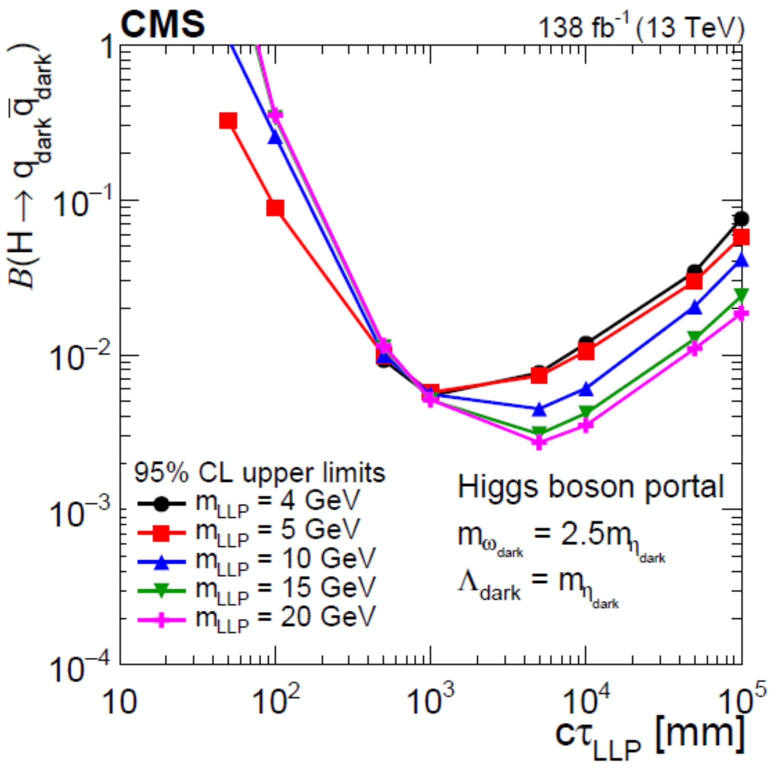
Selection set	H_T [GeV]	Jet p_T [GeV] (>)				EJ tagger
u-set 1	>1600	275	250	250	150	u-tag 1
u-set 2	>1600	200	200	150	150	u-tag 2
u-set 3	>1600	200	150	100	100	u-tag 3
u-set 4	>1500	200	150	100	100	u-tag 4
u-set 5	>1200	200	150	100	100	u-tag 5
u-set validation	1000–1200	100	100	100	100	validation u-tag
a-set 1	>1500	200	150	100	100	a-tag 1
a-set 2	>1800	250	250	200	200	a-tag 2
a-set 3	>1200	275	250	250	200	a-tag 2
a-set 4	>1500	275	250	250	100	a-tag 3
a-set 5	>1800	200	150	100	100	a-tag 4
a-set validation	1000–1200	100	100	100	100	validation a-tag
uGNN set 1	>1350	170	120	120	100	uGNN tag 1
uGNN set 2	>1750	300	260	250	250	uGNN tag 2
uGNN set 3	>1800	240	180	180	100	uGNN tag 3
uGNN validation	>1000	100	100	100	100	uGNN validation tag
aGNN set 1	>1300	200	140	120	100	aGNN tag 1
aGNN set 2	>1650	300	250	200	200	aGNN tag 2
aGNN set 3	>1400	270	220	220	120	aGNN tag 3
aGNN validation	>1000	100	100	100	100	aGNN validation tag

EMJ Results (vs. First Search)



Muon Shower Exclusions

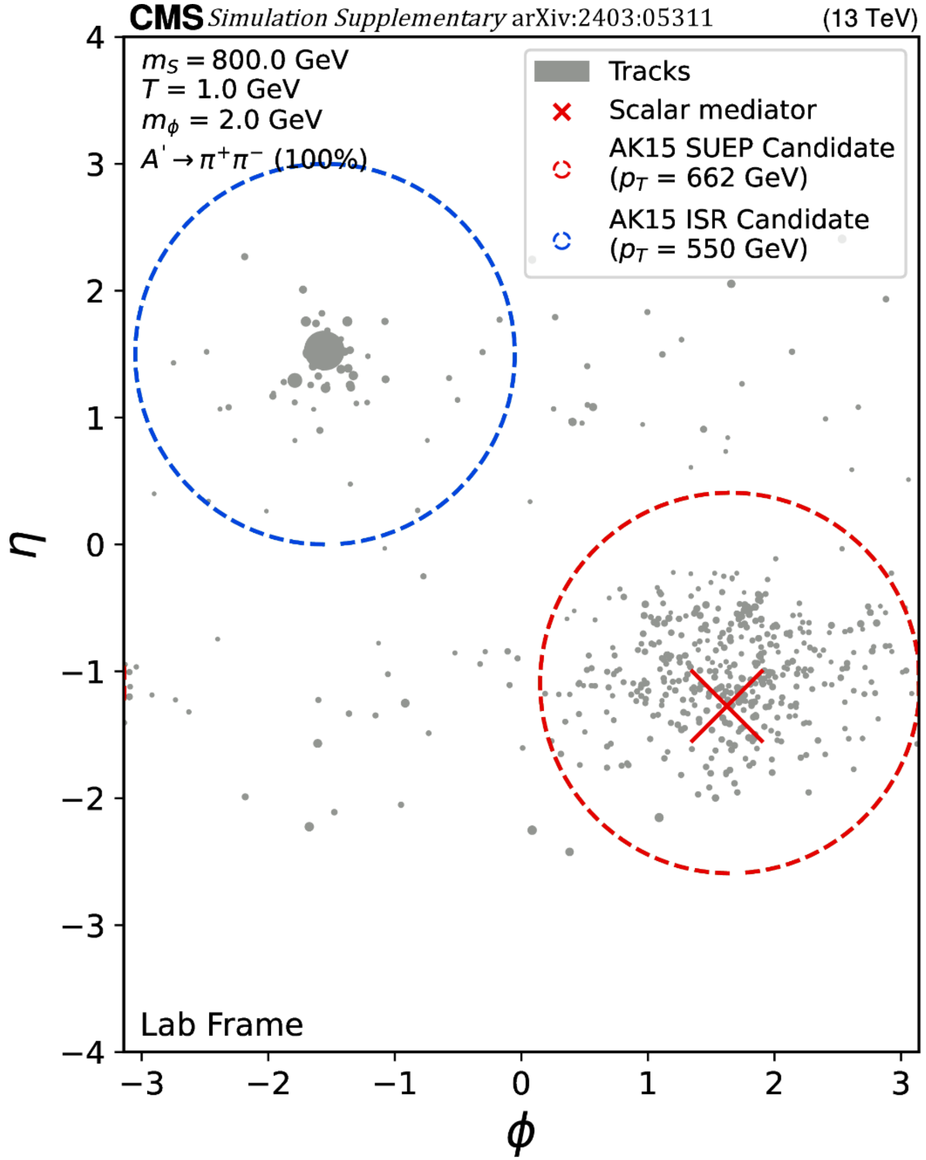


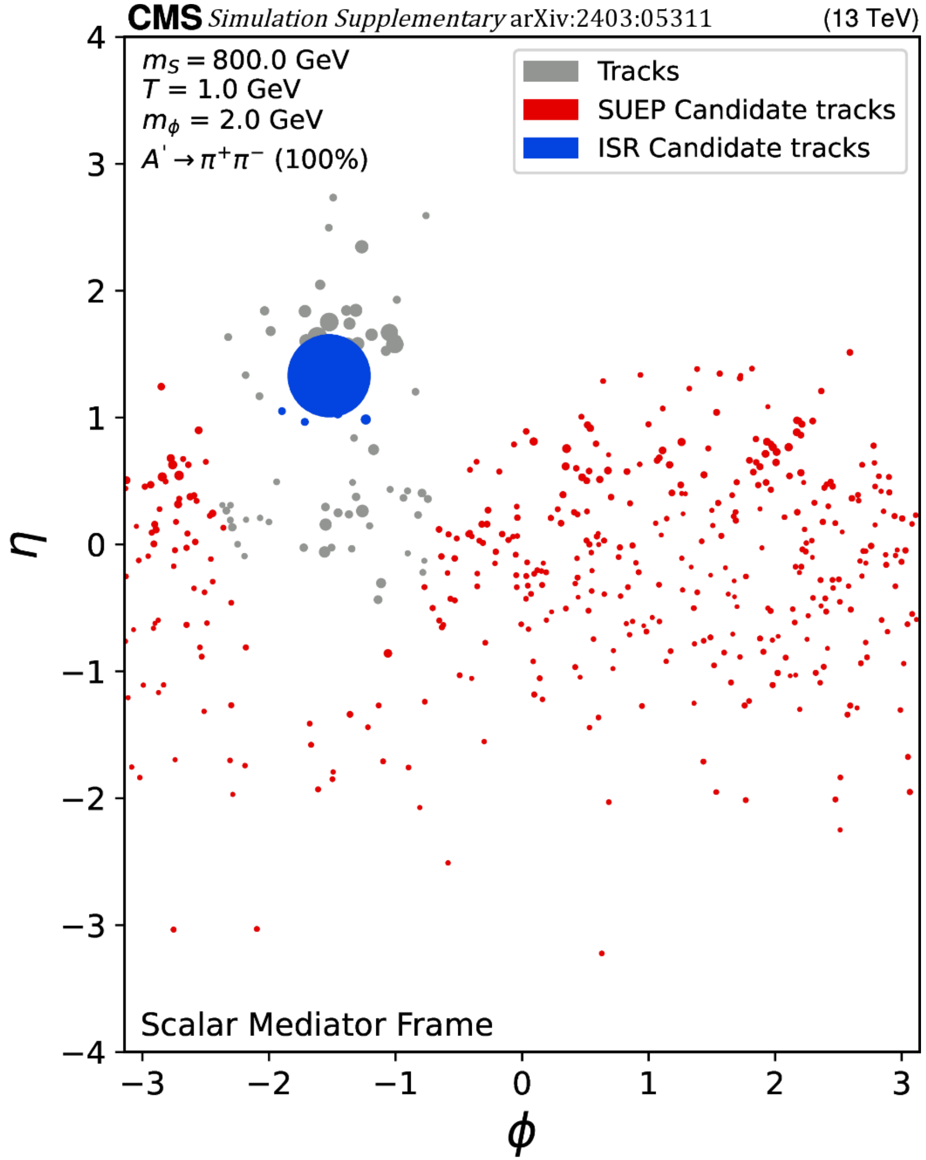


More at arXiv:2402.01898

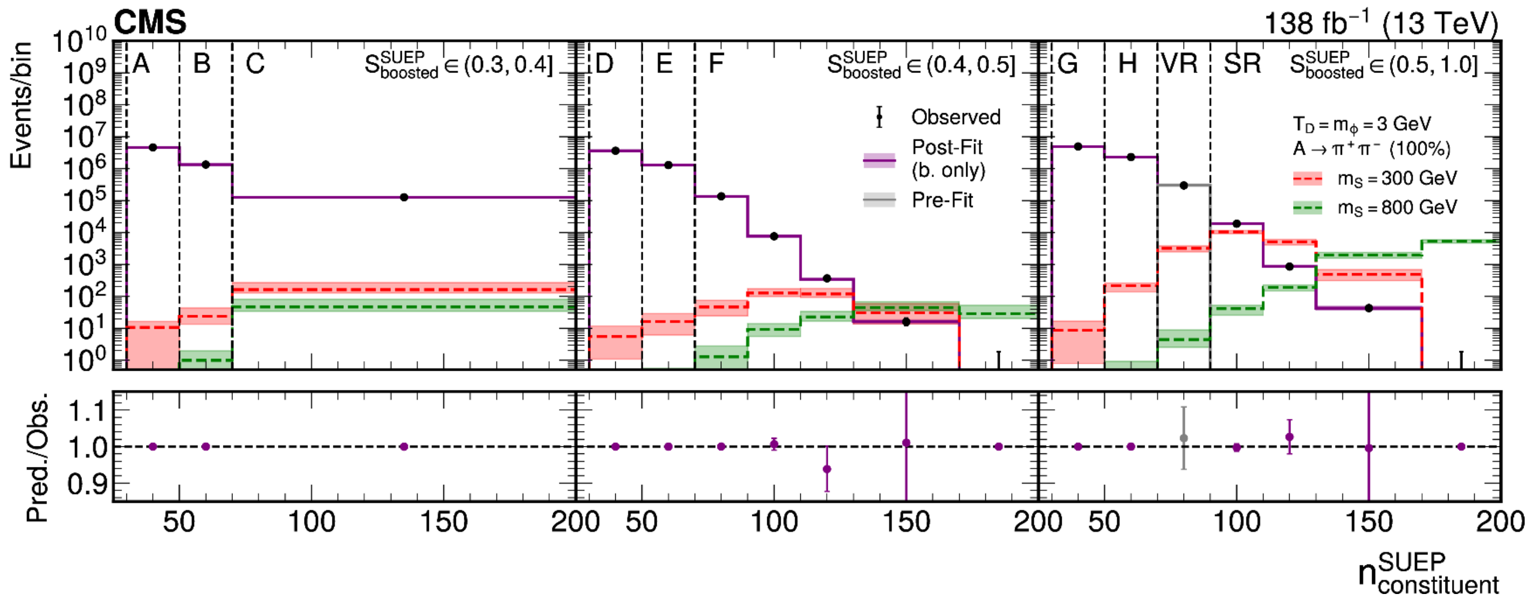
- Gluon portal: $\eta_{dark} \to gg$ (hadron-rich)
- Photon portal: $\eta_{dark} \to \gamma\gamma$ (photon-rich)
- Vector portal: $\omega_{dark} \to \ell\ell/qq$, η_{dark} stable (SVJs w/ $r_{inv} = 0.25$)
- Higgs portal: $\eta_{dark} \to bb, cc, \tau\tau$
- Dark photon portal: $\eta_{dark} \to A'A'$, $A' \to \ell\ell/qq$ (lepton-rich)

SUEP Event Display





SUEP Background Estimation

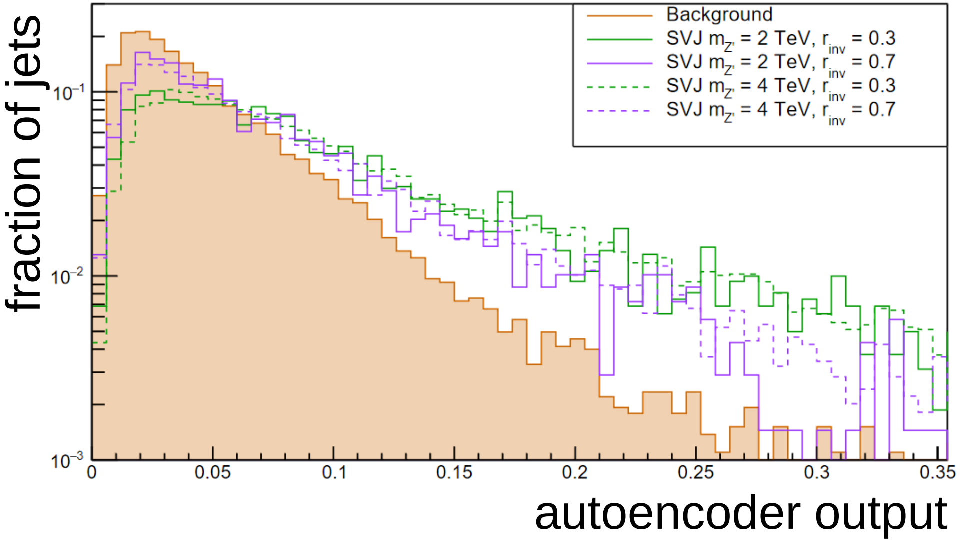


- Extended ABCD method with 9 regions:

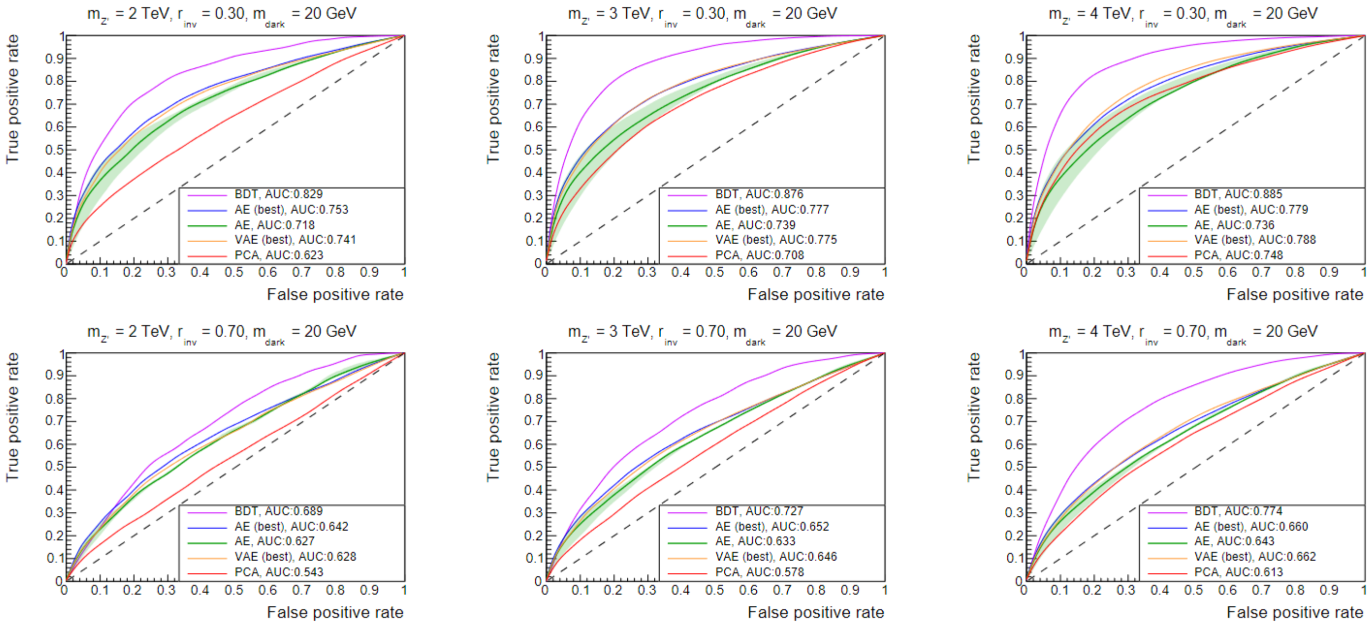
$$N^i_{SR} = N^i_F \frac{N_F N_H^2 N_D^2 N_B^2}{N_G N_C N_A N_E^4}$$

- From [arXiv:1906.10831]

SVJ AE Score



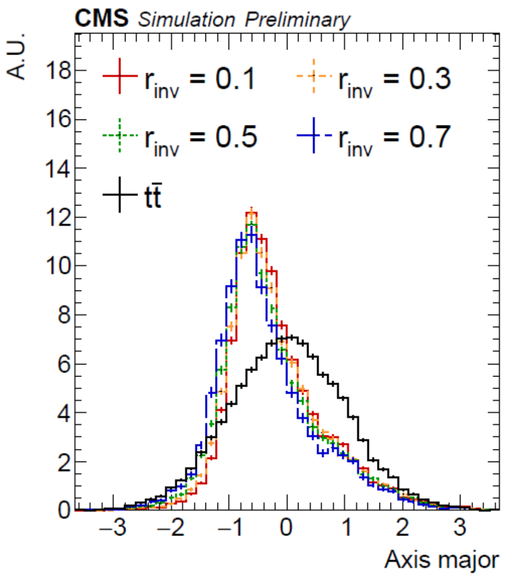
Background
SVJ $m_{Z'}$ = 2 TeV, r_{inv} = 0.3
SVJ $m_{Z'}$ = 2 TeV, r_{inv} = 0.7
SVJ $m_{Z'}$ = 4 TeV, r_{inv} = 0.3
SVJ $m_{Z'}$ = 4 TeV, r_{inv} = 0.7
fraction of jets
autoencoder output



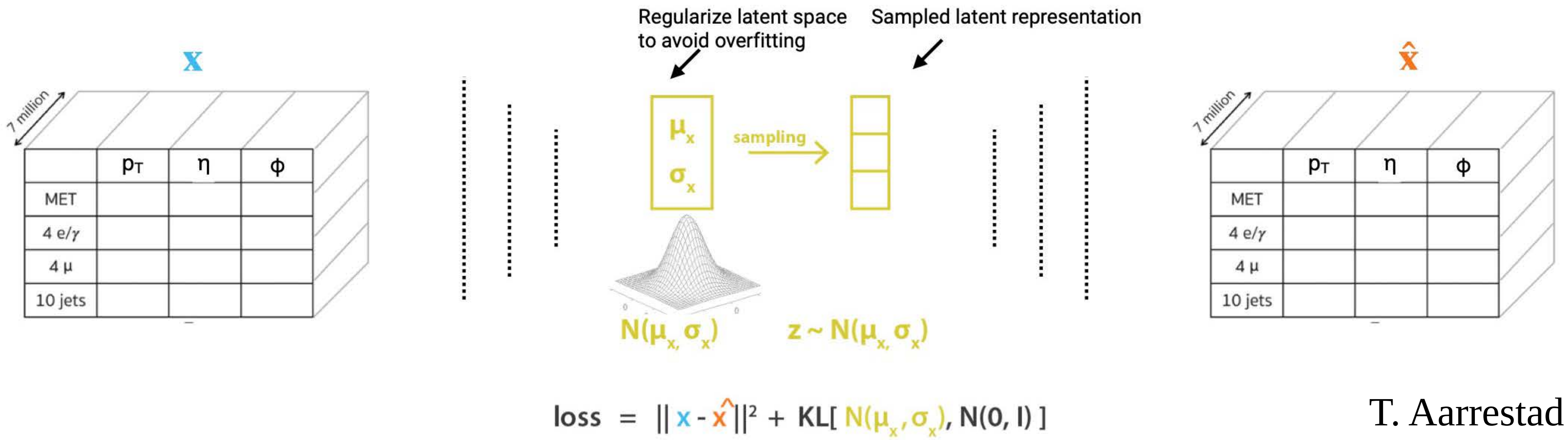
$m_{Z'}$ = 2 TeV, r_{inv} = 0.30, m_{dark} = 20 GeV
BDT, AUC:0.829
AE (best), AUC:0.753
AE, AUC:0.718
VAE (best), AUC:0.741
PCA, AUC:0.623
$m_{Z'}$ = 3 TeV, r_{inv} = 0.30, m_{dark} = 20 GeV
BDT, AUC:0.876
AE (best), AUC:0.777
AE, AUC:0.739
VAE (best), AUC:0.775
PCA, AUC:0.708
$m_{Z'}$ = 4 TeV, r_{inv} = 0.30, m_{dark} = 20 GeV
BDT, AUC:0.885
AE (best), AUC:0.779
AE, AUC:0.736
VAE (best), AUC:0.788
PCA, AUC:0.748
$m_{Z'}$ = 2 TeV, r_{inv} = 0.70, m_{dark} = 20 GeV
BDT, AUC:0.689
AE (best), AUC:0.642
AE, AUC:0.627
VAE (best), AUC:0.628
PCA, AUC:0.543
$m_{Z'}$ = 3 TeV, r_{inv} = 0.70, m_{dark} = 20 GeV
BDT, AUC:0.727
AE (best), AUC:0.652
AE, AUC:0.633
VAE (best), AUC:0.646
PCA, AUC:0.578
$m_{Z'}$ = 4 TeV, r_{inv} = 0.70, m_{dark} = 20 GeV
BDT, AUC:0.774
AE (best), AUC:0.660
AE, AUC:0.643
VAE (best), AUC:0.662
PCA, AUC:0.613
True positive rate
False positive rate

NAE Formalism

- Input features normalized to Gaussian by quantile transform
- Treat reconstruction error E_θ as "energy" for energy-based model
  - $p_\theta(x) = {}^{1}/_{\Omega_\theta} \exp(-E_\theta(x)/T)$
- Loss:
  - $\mathbb{E}_{x \sim p_{data}}[L_\theta(x)] = \mathbb{E}_{x \sim p_{data}}[E_\theta(x)] - \mathbb{E}_{x' \sim p_\theta}[E_\theta(x')] = E_+ - E_-$
- Positive energy from training dataset
- Negative energy from sampling NAE latent space and reconstructing
  - Using Markov chain Monte Carlo (MCMC)



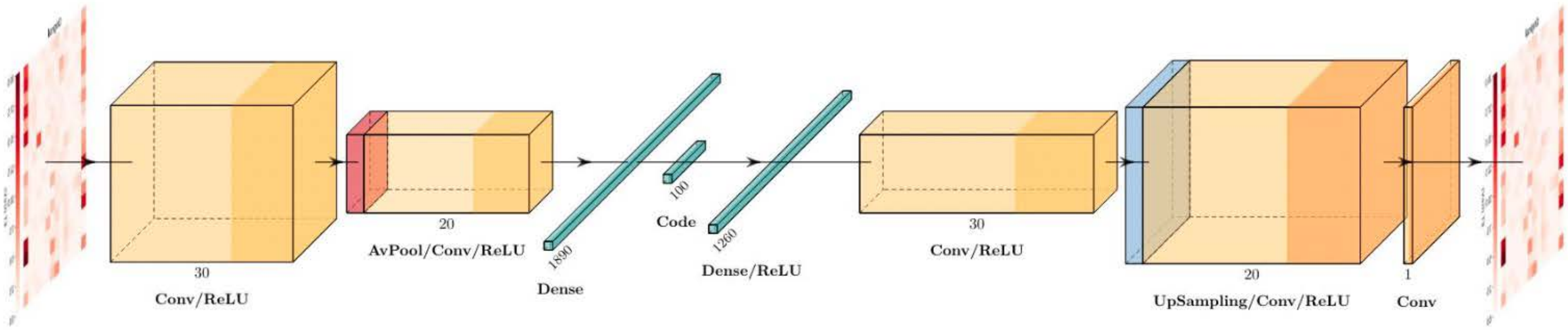
AXOL1TL

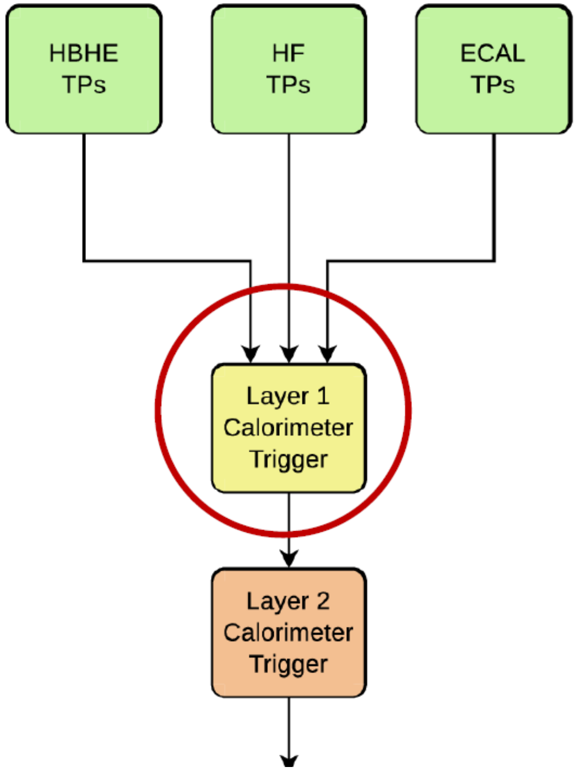


T. Aarrestad

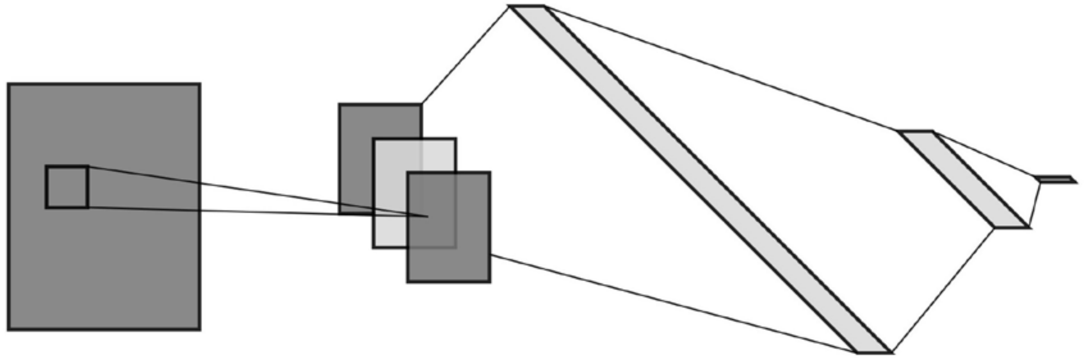
- K-L divergence expands to ~ $\mu^2 + \sigma^2 - 1 - \log(\sigma^2)$
- Dominated by just μ^2 → use this as score instead of full reconstruction error
- Drop second half of network (decoder) for inference → substantially reduces latency on FPGA (50 ns)

CICADA





- Input is 2D map of energy deposited in calorimeters (ECAL + HCAL)
- Initial model (above, "teacher"): 300K parameters
- Deployed model (below, "student"): 3K parameters
  - Trained to reproduce teacher model using knowledge distillation
  - ~100 ns latency on FPGA



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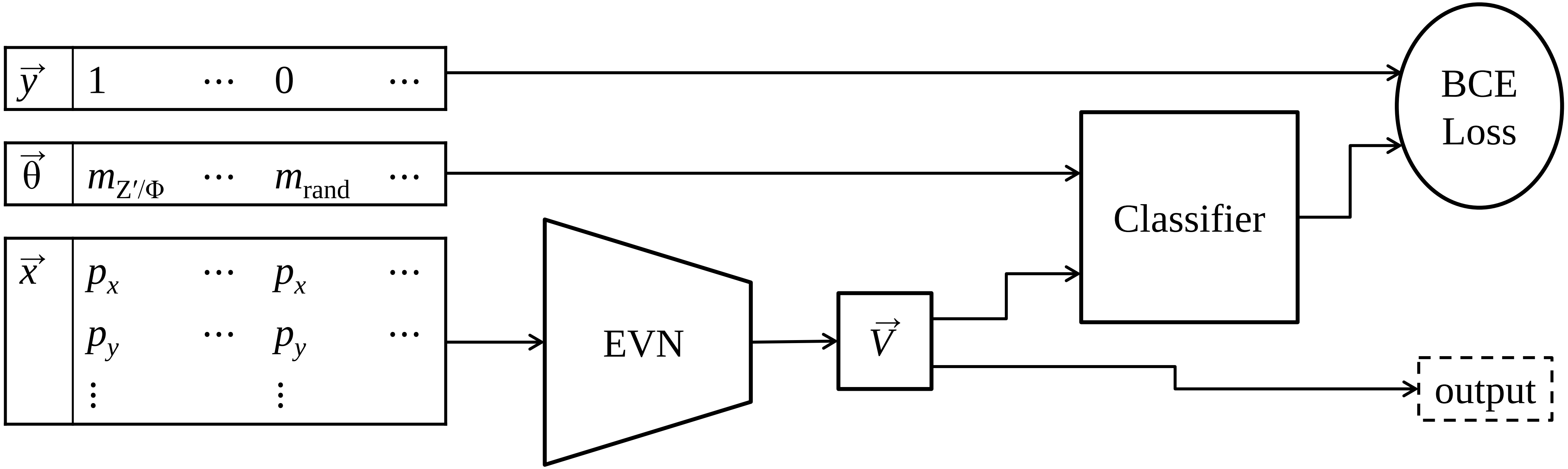
Event Variable Network



- Derive new variable(s) $\vec{V}(\vec{x})$ from inputs $\vec{x}$ to maximize *mutual information* with underlying model parameter(s) $\vec{\theta}$
  - *Not* a regression: learns an actual, generalized function of inputs
- Both components are simple fully-connected networks (few layers)
  - Classifier uses $\vec{V}$ (from EVN bottleneck) to distinguish events w/ correct $\vec{\theta}$ from events w/ wrong $\vec{\theta}$ (using binary crossentropy)
- Trains in a few minutes on a consumer GPU