Search for Emerging Jets at CMS

University of Washington EPE seminar
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2024.March.11

Outline

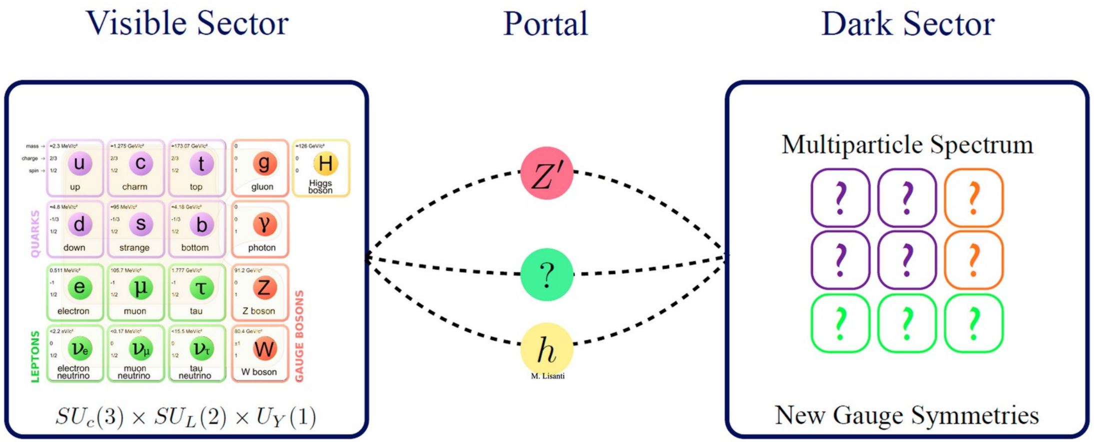
- Theoretical motivation
  - Dark-sector model for asymmetric dark matter
  - Long-lived particle signatures arising from dark-sector models
- Search for emerging jets at CMS:
  - Signature of emerging jets in detectors
  - Background estimation using data-based methods
  - Discussion about the ML-based methods
- Latest results using CMS data †
- Outlook to beyond the EMJ analysis

† Search for new physics with emerging jets in proton-proton collisions at $\sqrt{s}$ = 13 TeV (arXiv:2403.01556)

Strongly coupled hidden sectors

An alternate proposal for the particle nature of dark matter (DM) compared to the traditional "WIMP"-based approach: a dark sector (DS) of particles with a SU(N_{dark}) interaction.
Let us assume this interaction is "QCD-like" SU(N_{dark}=3):

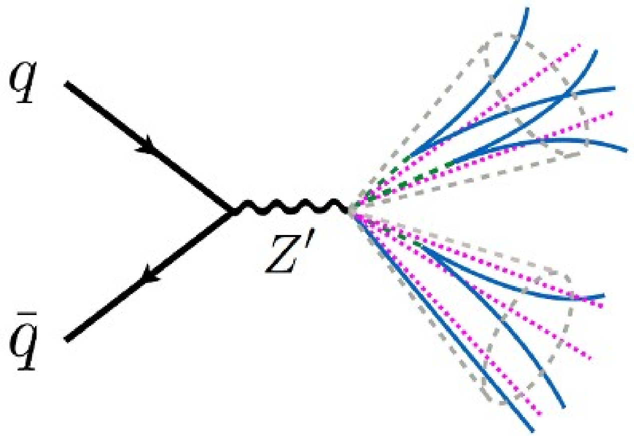
- Dark color confinement binds dark fermions into proton-like "dark hadron" states
  - Stable dark hadrons will be astronomical DM candidates
  - Confinement enforces compatibility with astronomical constraints
- "Mediator" particles couple to both SM and DS, allowing for searches at colliders
- Asymmetric Dark Matter † (ADM) also predicts DM v.s. visible matter density ($\Omega_{DM} \sim 5\Omega_B$ ‡) in cosmology through a process similar to baryogenesis



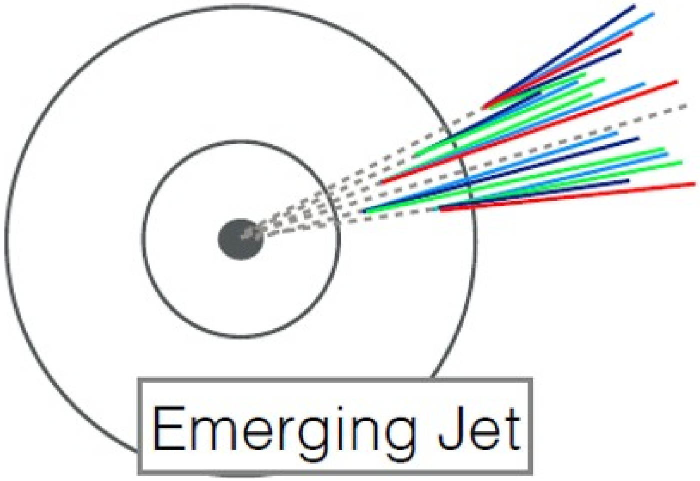
† Review of Asymmetric Dark Matter (arXiv: 1305.4939) ‡ Planck 2018 results. VI. Cosmological parameters (arXiv: 1807:06209)

Dark QCD searches

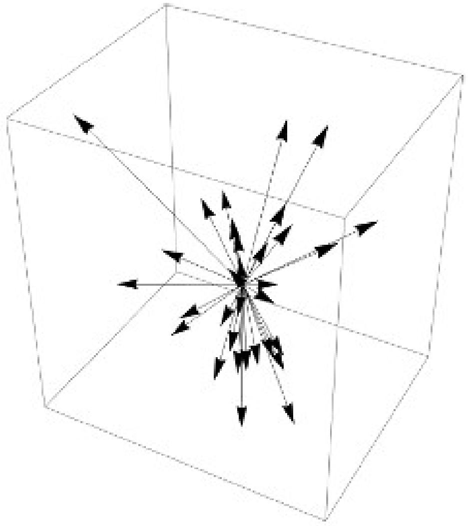
Different phenomenological signatures arise depending on the assumption of the dark sector ↔ SM interaction vs. dark sector gauge interactions



Semi-visible jets



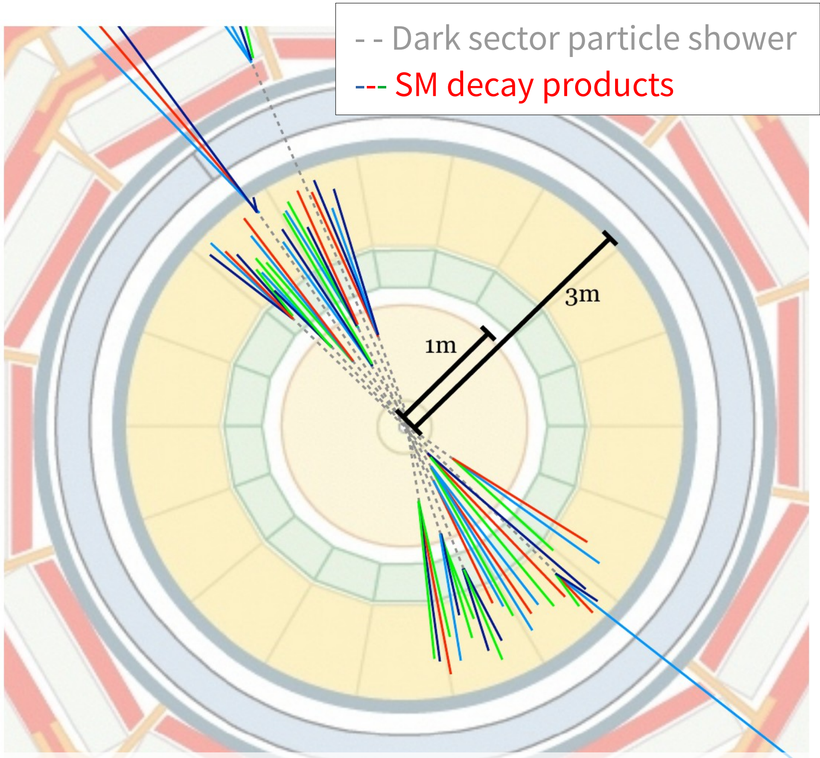
Emerging Jets



Soft unclustered energy patterns (SUEP)

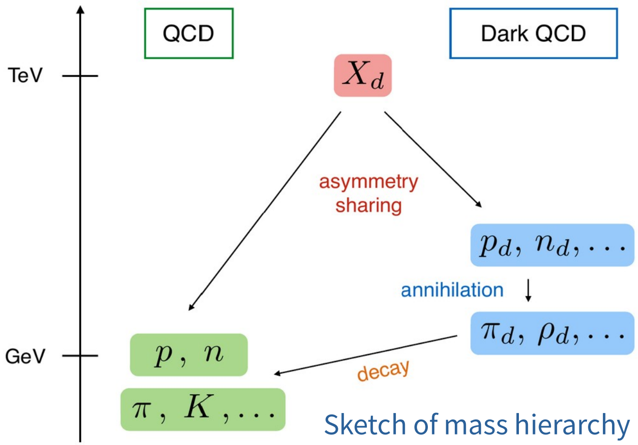
Emerging jets (EMJ) – LLP showering

- Dark sector has color confinement at low-energy scale Λ_{dark} (generates dark sector particle shower like SM hadronization)
- Dark "pions" (π_{dark}) have masses $m_{SM} < m_{\pi,dark} \lesssim \Lambda_{dark}$
- Heavy mediator (X_{dark}) couples both to SM and dark sector, allowing dark pions to decay to SM particles
- Mainly concerned with long-lived particle (LLP) shower generated from dark fermion production
  - $m_{\pi,dark} \sim O(1\text{-}10)$GeV (Shower-like dark sector "jet")
  - $c\tau_{\pi,d} \sim 10^{-3}$-1 m (Tracker geometry of LHC experiments)



Back-to-back emerging jets in detectors

Detector signature:
Energy clusters (jets) with SM particles "emerging" from vertices far from the collision point.
CMS 2016 search: 1810.10069



Sketch of mass hierarchy in proposed model

Images from "Emerging Jets" (arXiv:1502.05409)

Flavored dark sector EMJ

Existing search [‡] for EMJ was limited to an "unflavored" model:

- All DS mesons couple to the SM down quark only
- All DS mesons have the same lifetime

A more generic model [†] will have DS fermions with non-zero coupling to different SM quarks through a coupling matrix:

$$\mathcal{L} = -\kappa_{i\alpha}\bar{q}_i Q_\alpha X + h.c.$$

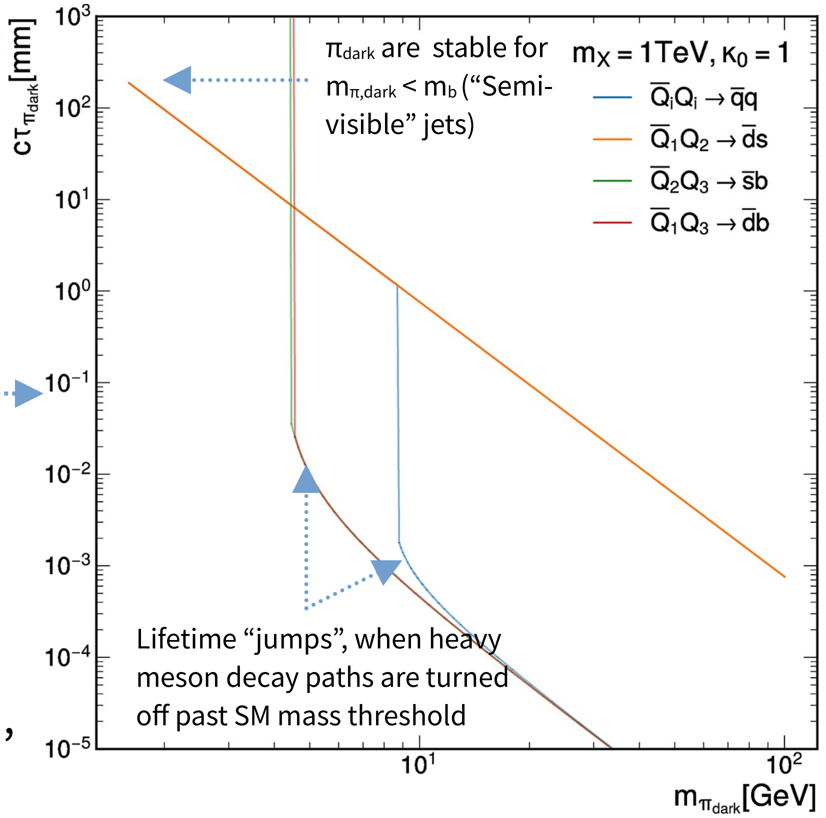
effective coupling results

SM-DS Yukawa coupling SM quarks DS quark Mediator

Even if dark mesons have roughly degenerate masses:

- DS mesons now have a lifetime spectrum driven by the SM quark mass spectrum
- Detector-level signature: a mix of LLP-displaced, b-displaced, and prompt tracks from DS particle shower

Full list of signal model parameters given in backup



Lifetime of dark pions given "diagonal" SM-DS coupling matrix (**Flavor-aligned model**)

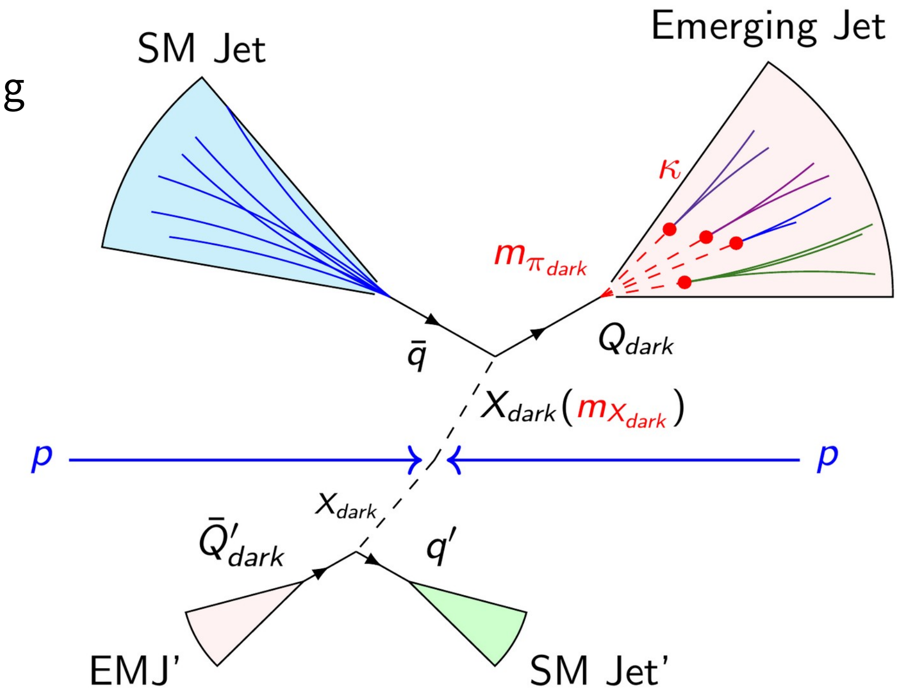
‡ "Search for new particles decaying to a jet and an emerging jet": https://arxiv.org/abs/1810.10069

† "A flavoured dark sector" arXiv:1803.08080

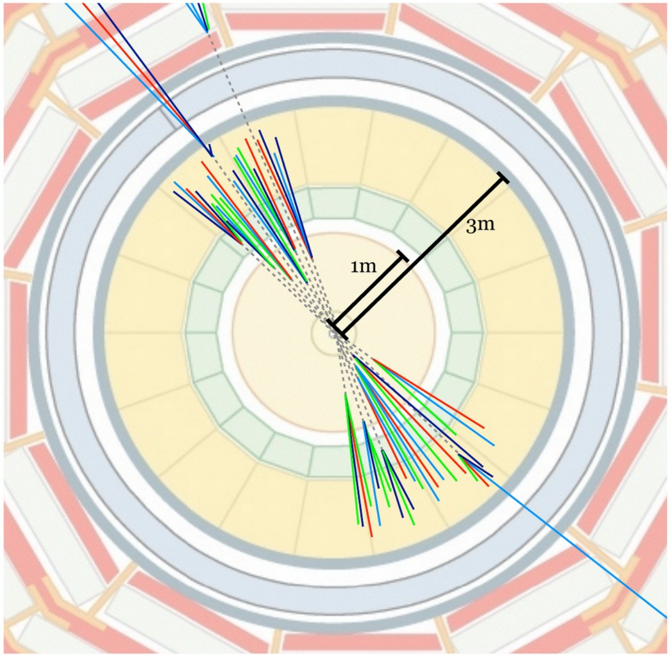
Detector signature of EMJ

Search strategy:

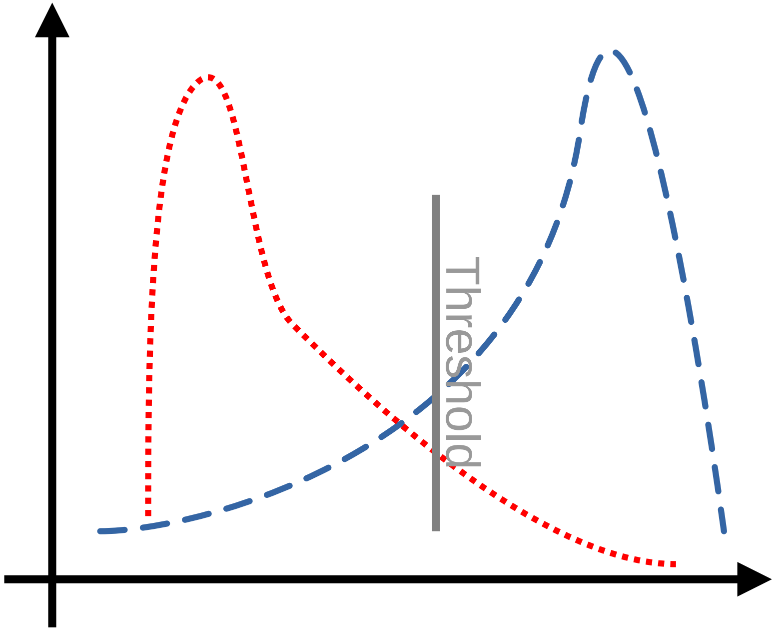
- Look for mediator pair production, with mediators decaying to SM quark (q) and DS quark (Q).
  - SM quarks ensure a reliable trigger is available
- Look for jets containing displaced tracks
  - More resilient to reconstruction deficiencies compared with secondary vertex reconstruction
  - Transverse/Longitudinal displacement: IP_{2D} / IP_z
  - SM Background: pileup jets, heavy-flavored jets
- Search space (full list given in backup)
  - Mediator mass: $m_{X,dark}$ (~1TeV-2.5TeV)
  - Dark meson mass: $m_{\pi,dark}$ (~5GeV-20GeV)
  - Dark meson lifetime:
    - Unflavored model: $c\tau_{\pi,dark}$ (1mm-10^3mm)
    - Flavored-aligned model (diagonal Yukawa): κ_0 / $c\tau_{\pi,dark,max}$



Primary event signatures:
4 energetic jets,
2 of which have displaced constituents



Some algorithm



Defining detector signatures

The CMS detector

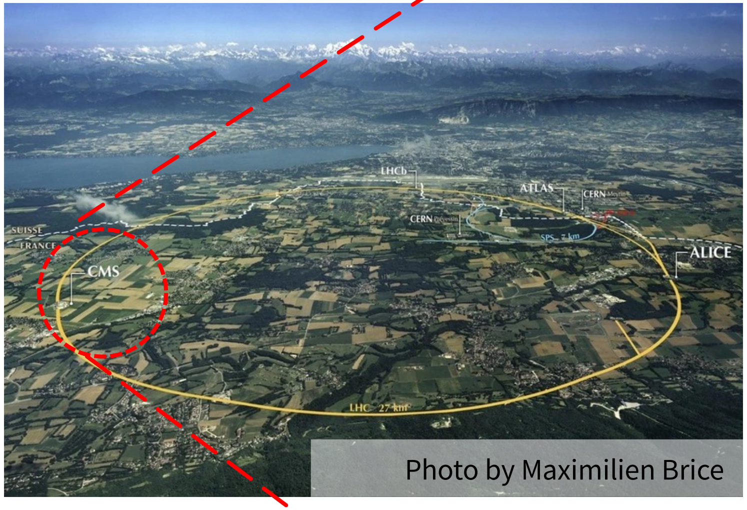
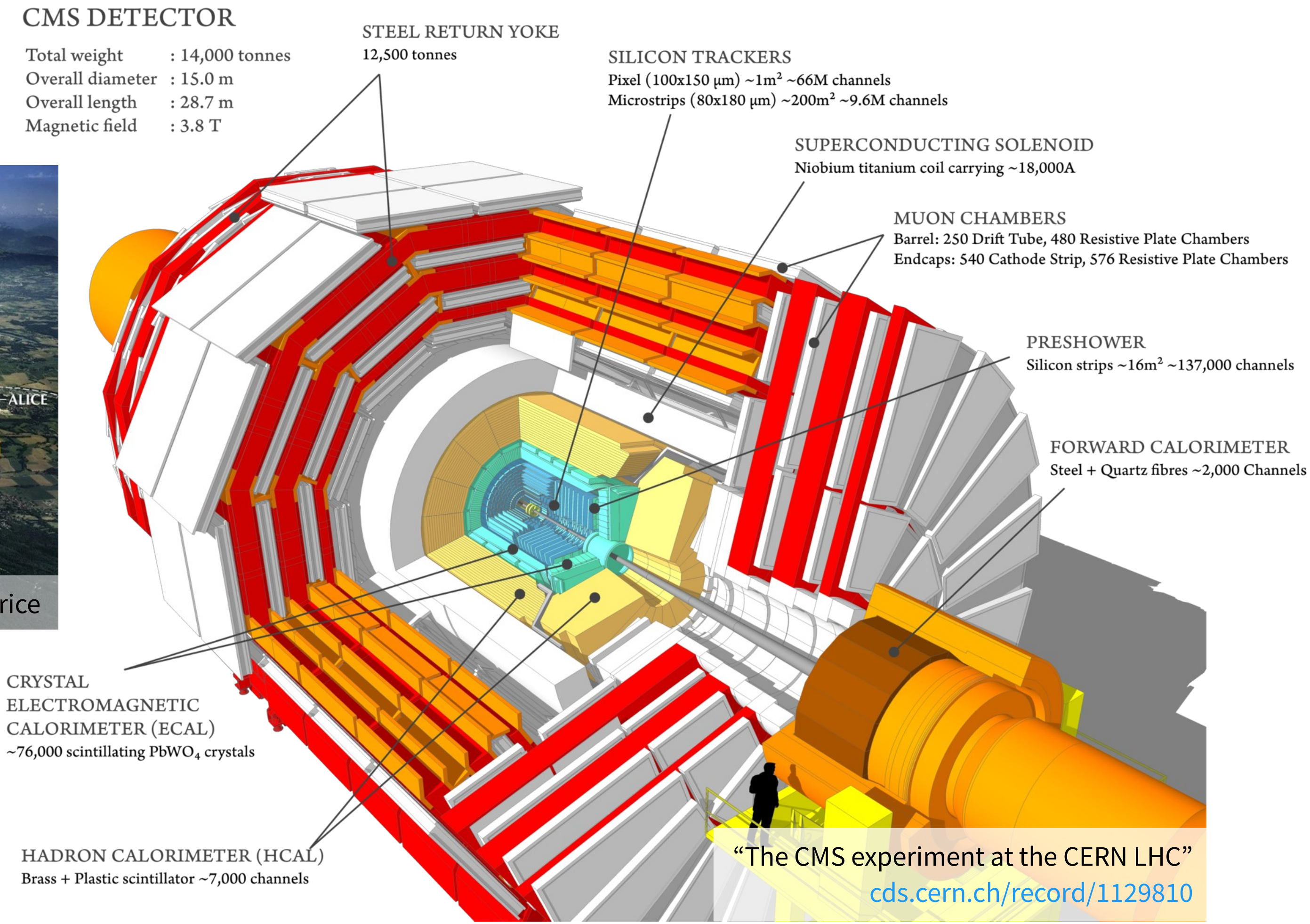


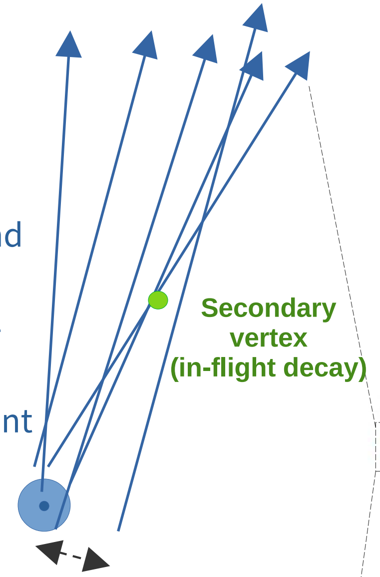
Photo by Maximilien Brice



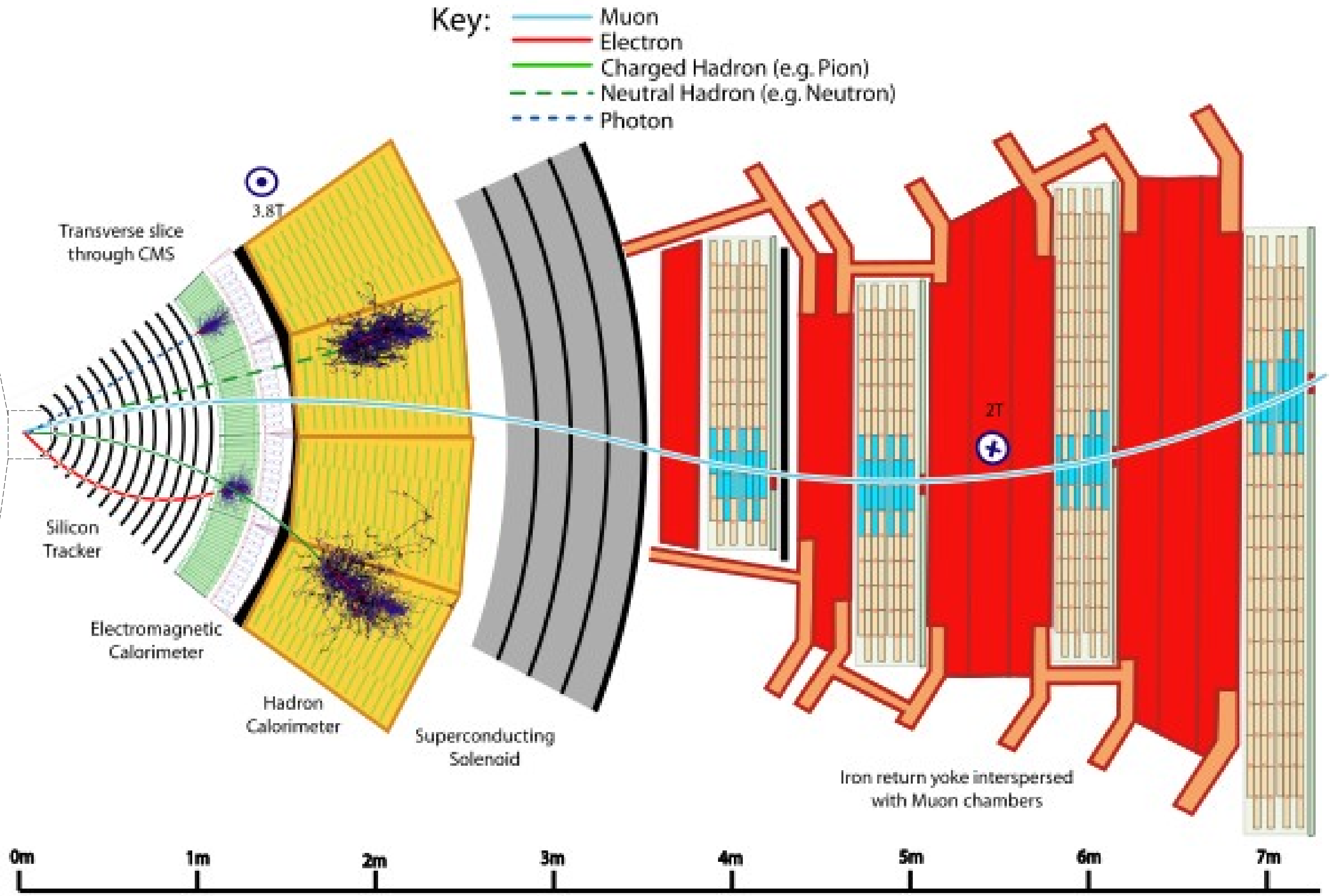
"The CMS experiment at the CERN LHC"
cds.cern.ch/record/1129810

Particle-flow reconstruction at CMS

Vertices are clustered and fitted by extrapolating tracks back to points-of-closest approach to intended interaction point



Impact parameters defined as the distance of the track trajectory to a primary vertex of interest



"Particle-flow reconstruction and global event description with the CMS detector," (arXiv: 1706.04965)

Physics object selection at reconstruction level

Work with standard CMS reconstructed objects; this ensures uncertainties are well studied with minimum surprises

Trigger

Lowest unprescaled, pure H_T trigger

- 2016: $H_T > 900$ GeV
- 2017, 2018: $H_T > 1050$ GeV

Track selection

Standard CMS fitted tracks [§]

- High-purity fitting flag must be true
- $p_T > 1.0$ GeV
- Re-associate to jets with angular matching

Primary vertex

Leading primary vertex (largest [†] Σp_T^2) is always used for track displacements calculation

Additional quality cuts:

- $|z_{PV}| < 15$ cm
- N(tracks | $d_z < 0.01$ cm) / N(tracks) > 0.1

Jets

CMS anti-k_T jet with R=0.4 jets with charge hadron subtraction [§] (standard "AK4" CMS jet)

- $p_T > 100$ GeV, $|\eta| < 2.0$ (η=-ln(θ/2), θ polar angle)
- At least 1 associated track
- Standard Jet ID selection

[†] "Primary vertices ordering in CMS". Details given in link.

[§] "Particle-flow reconstruction and global event description with the CMS detector" arXiv:1706.04965.

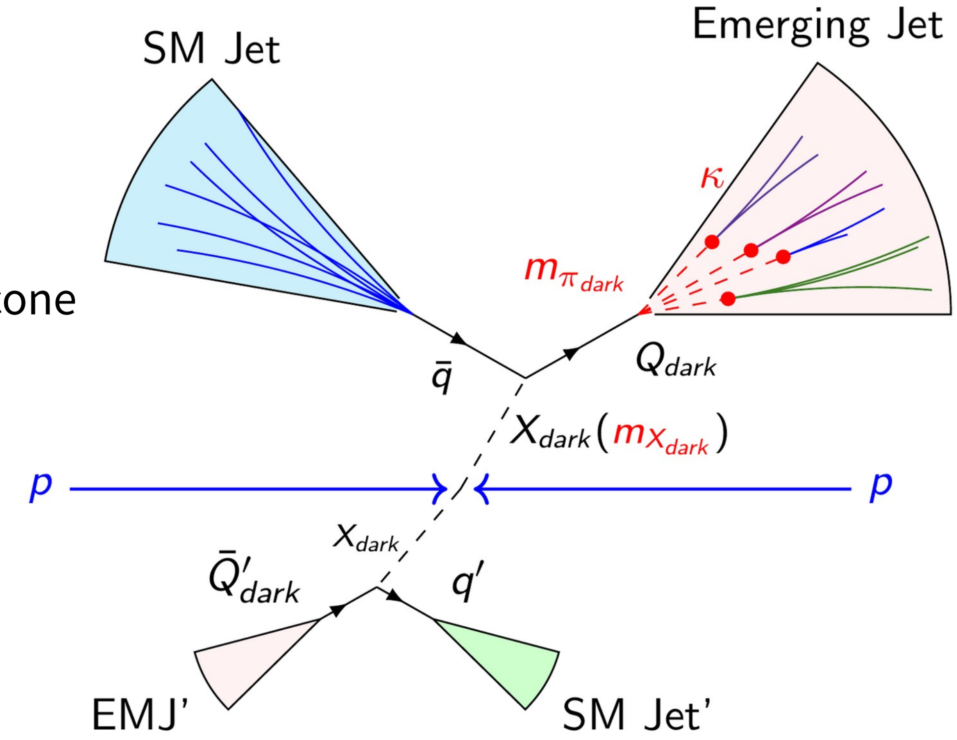
Event and object selection

Primary signal topology and energy scale:
- At least 4 jets with high p_T
- Event H_T (scalar sum of all jet p_T)
- Additional leading jet p_T selection

EMJ signature selection:
- At least 2 jets tagged as EMJ using tracks within jet cone
- To avoid displaced tracks from being dropped in standard CMS jet clustering algorithm, tracks are associated with jets angular matching with the jet energy center:

$$\Delta R = ((\Delta\phi)^2 + (\Delta\eta)^2)^{1/2} < R_{cut}$$

- <u>Key track displacement variables:</u>
  - Transverse impact parameter (IP_{2D})
  - Longitudinal impact parameter (IP_z)



EMJ tagging using standard reconstruction objects

- Tracks associated to jets via ΔR matching to energy centers
- Attempting to summarize jet-level track displacement measures of associated tracks

For Unflavored model with single $c\tau_{\pi,\text{dark}}$ lifetime, we use R_{cut}=0.4 matching

- Median of $|IP_{2D}|$ of all associated tracks
- p_T-weighted prompt track fraction α_{3D}:

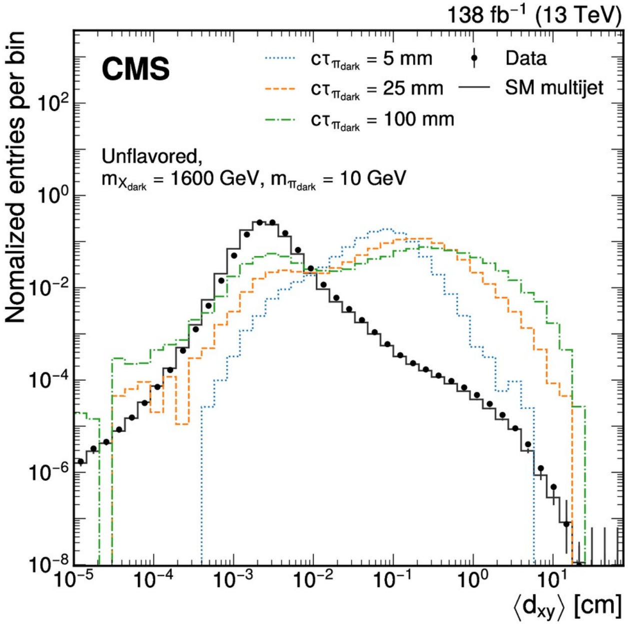
$$\alpha_{3D} = \frac{\sum_{\text{track}|D_N<D_{\text{cut}}} p_{\text{T}}}{\sum_{\text{track}} p_{\text{T}}}$$

with normalized significance

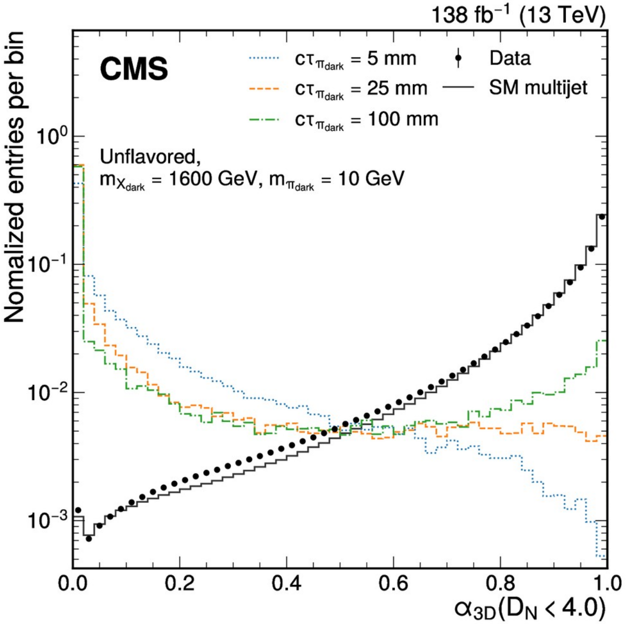
$$D_N = \sqrt{\sigma^2_{IP_{2D}} + \left(\frac{IP_z}{0.01\text{cm}}\right)^2}$$

- Maximum $|IP_z|$ requirement to reject jets from pileup interactions (PU jets)

← SM … EMJ →



← EMJ … SM→



Example of jet level variable used for unflavored model EMJ tagging
Events only require trigger and 4 jets with p_T>100GeV

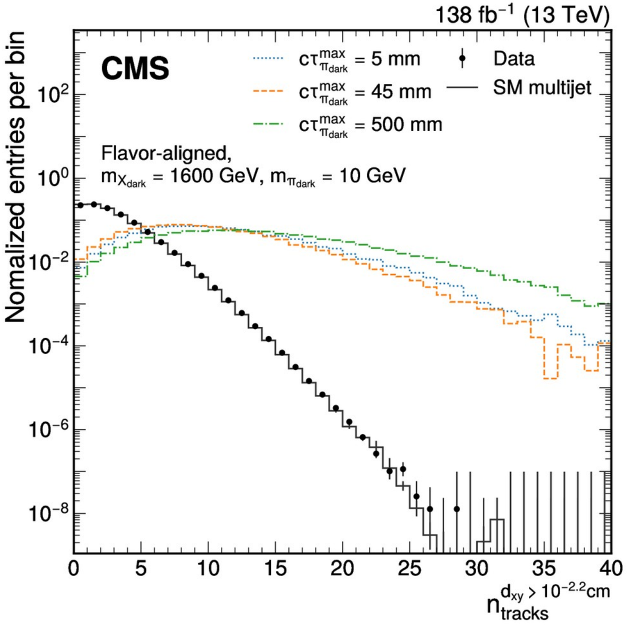
EMJ tagging using standard reconstruction objects (2)

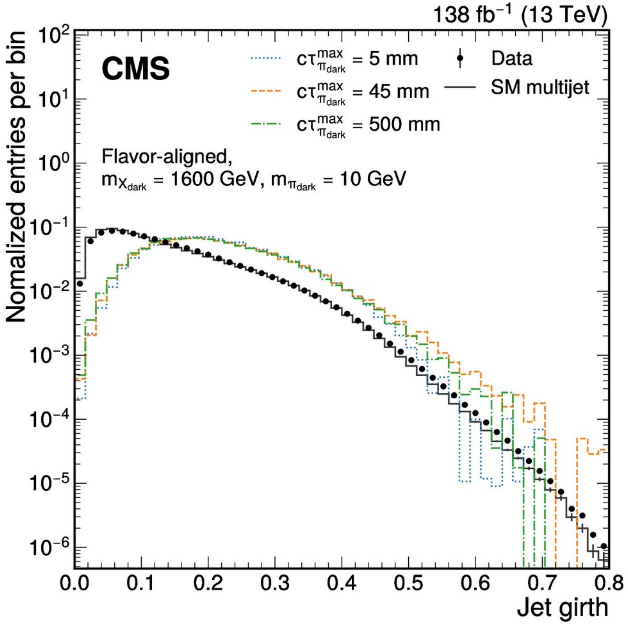
Flavored models generate mixed track displacements: this requires us to design a separate tagging method. $R_{cut} = 0.8$ used for jet track association, as model has wider particle shower from both heavier dark meson and heavier SM decay products.

← SM … EMJ →

← SM … EMJ →

- Count of displaced tracks ($IP_{2D} > IP_{2D,cut}$): mixed lifetime of particles in jet cone, but b meson are a typical product in prompt π_{dark} decay
- Track girth (p_T-weighted ΔR)
- "n-subjettiness" computed using tracks to reduce pileup contamination





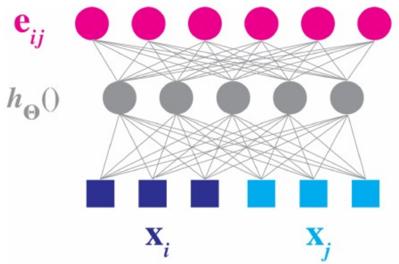
Example of jet level variable used for flavored-model EMJ tagging
Events only require trigger and 4 jets with p_T>100GeV

EMJ tagging – Machine Learning (GNN)

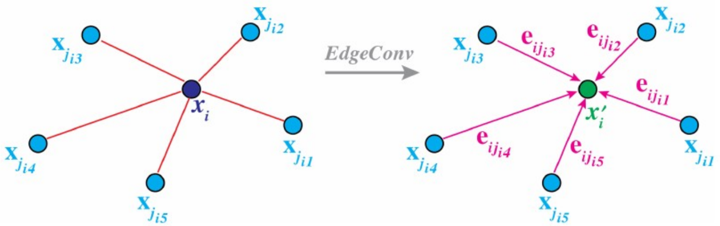
Employing **G**raph **N**eural **N**etworks (GNN) for jet tagging †: encoding discrete, unordered jet constituents information into image-like representation; train 2 GNNs for distinguishing between flavor-aligned signal model jets v.s. QCD jets (aGNN) and unflavored signal model jets v.s. QCD jets (uGNN)

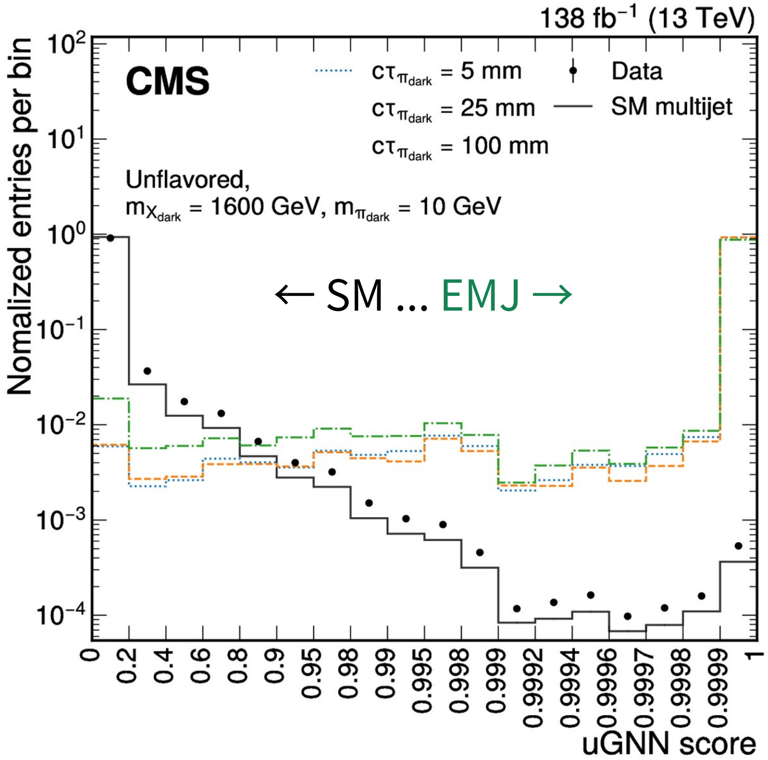
"Coordinates" features (for image-like representation)
  - $\Delta\eta$, $\Delta\phi$ relative to jet center
- Training features
  - ΔR relative to jet center
  - $\log(p_T)$, $\log(p_T / (\Sigma\, p_T))$
  - $\mathrm{sign}(IP_{xy}) \cdot \log(1 + IP_{xy} / 1\mathrm{cm})$
  - $\mathrm{sign}(IP_z) \cdot \log(1 + IP_z / 1\mathrm{cm})$

- Speeds up ML training
- Log function to compress unbound parameter values



Encoding of points to "image-like" graph representation ‡





† "ParticleNet: Jet Tagging via Particle Clouds" (arXiv:1902.08570) ‡ "Dynamic Graph CNN for Learning on Point Clouds" (arXiv:1801.07829)

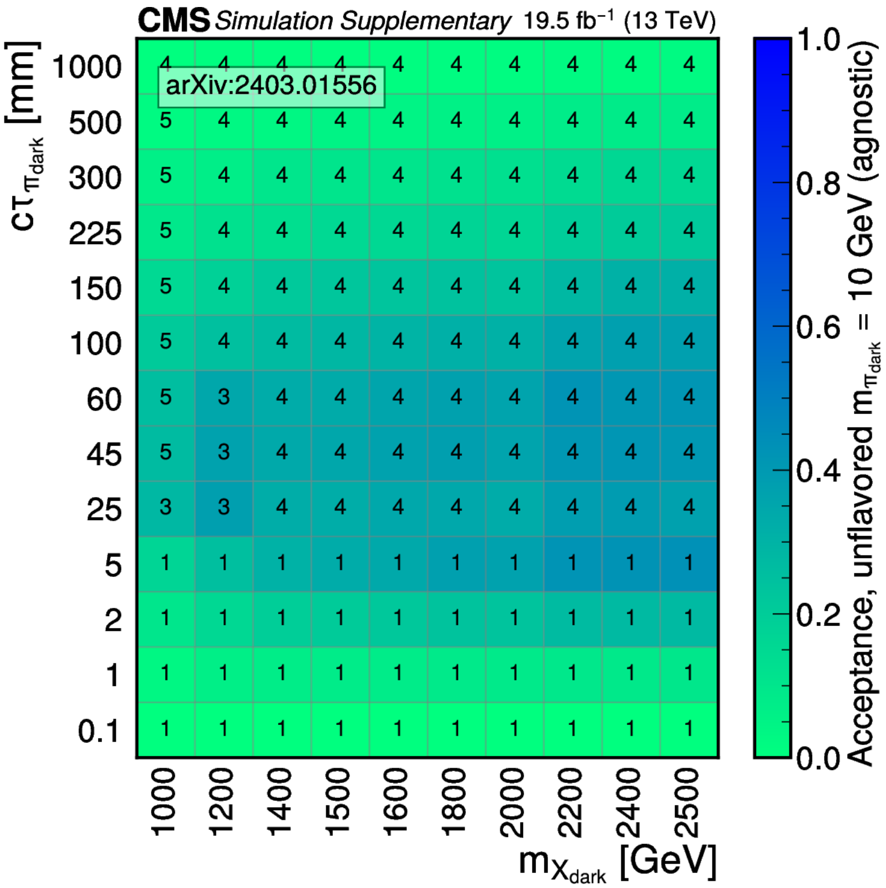
EMJ tagging – Cut point determination

Cut values for event selection and tagging determined by grid search, optimizing significance:

$$\frac{S}{\sqrt{S+B+0.1B^2}}$$

The “0.1” term is a rough estimate of the expected uncertainty that is not counting uncertainty

- Optimization is performed for all signal model surveyed
- Cut values are grouped to reduce the number of calculations required
- Full cut values can be found in following slides



Signal acceptance as a function of model parameters, numbers in the cell indicate different cut sets used

EMJ tagging – Cut point values

Example of cut values using cut-based EMJ tagging

	$H_{T\,(>)}$ [GeV]	Jet $p_{T\,(>)}$ [GeV]	R_{cut}	$\lvert d_z \rvert$ (<) [cm]	Med[$\lvert d_{xy} \rvert$] (>) [cm]	$D_{N,cut}$	α_{3D} (<)
u-set 1	1600	275, 250, 250, 150	0.4	0.5	$10^{-1.6}$	4	0.25
u-set 2	1600	200, 200, 150, 150	0.4	2.5	$10^{-1.4}$	8	0.25
u-set 3	1600	200, 150, 100, 100	0.4	5.0	$10^{-1.2}$	8	0.25
u-set 4	1500	200, 150, 100, 100	0.4	5.0	$10^{-1.2}$	12	0.15
u-set 5	1200	200, 250, 100, 100	0.4	5.0	$10^{-1.0}$	12	0.15

	$H_{T\,(>)}$ [GeV]	Jet $p_{T\,(>)}$ [GeV]	R_{cut}	$\lvert d_z \rvert$ (<) [cm]	$\lvert d_{xy} \rvert_{,cut}$ (>) [cm]	girth	$N(d_{xy}>d_{xy,cut})$
a-set 1	1500	200, 150, 100, 100	0.8	0.5	$10^{-2.2}$	0.05	12
a-set 2	1800	250, 250, 200, 200	0.8	0.5	$10^{-2.2}$	0.10	12
a-set 3	1200	275, 250, 250, 200	0.8	0.5	$10^{-2.2}$	0.10	12
a-set 4	1500	275, 250, 250, 100	0.8	0.5	$10^{-2.3}$	0.00	14
a-set 5	1800	200, 100, 100, 100	0.8	0.5	$10^{-2.4}$	0.10	14

EMJ tagging – Cut point values

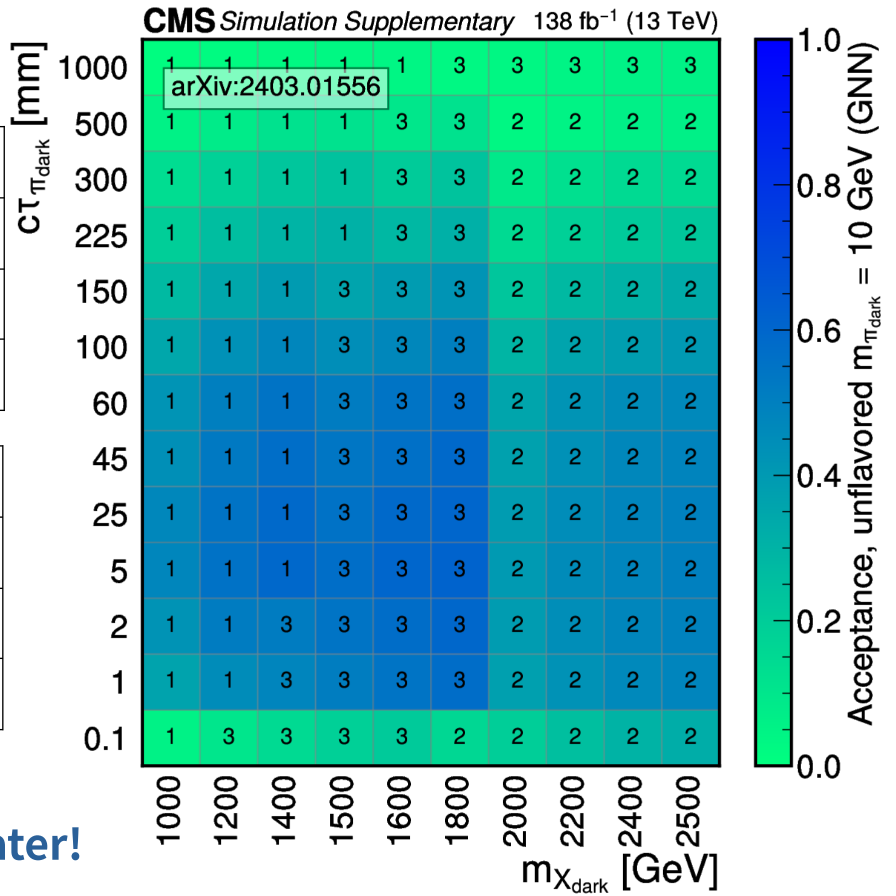
Example of cut values using GNN tagging

	$H_{T\,(>)}$ [GeV]	Jet $p_{T\,(>)}$ [GeV]	R_{cut}	u-GNN score (>)
uGNN set 1	1350	170, 120, 120, 100	0.8	0.997
uGNN set 2	1750	300, 260, 250, 250	0.8	0.998
uGNN set 3	1800	240, 180, 180, 100	0.8	0.996

	$H_{T\,(>)}$ [GeV]	Jet $p_{T\,(>)}$ [GeV]	R_{cut}	a-GNN score (>)
aGNN set 1	1300	200, 140, 120, 100	0.8	0.9953
aGNN set 2	1650	300, 250, 200, 200	0.8	0.9993
aGNN set 3	1400	270, 220, 220, 120	0.8	0.9983

In general, GNN yields higher signal acceptance.

More discussion on the implications of ML will be given later!



Data

v.s.

Simulat

More Data

Why data-based methods?

Challenges – sources of displaced tracks

Background events from SM jets being mistagged as EMJs from various displaced track sources

SM hard-scattering process:

- Heavy mesons production

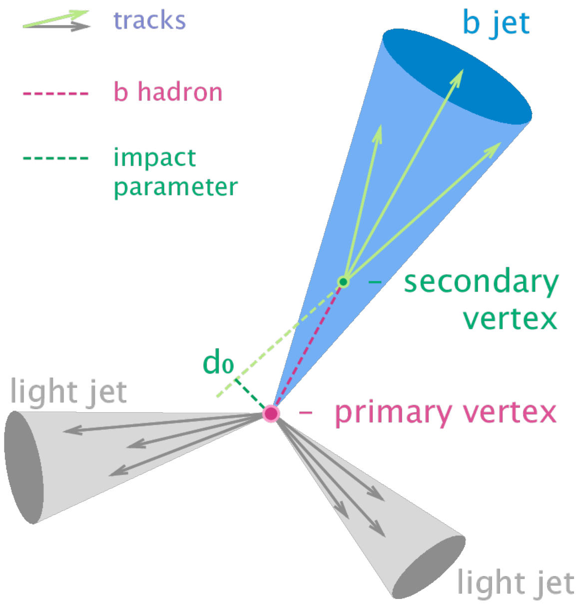
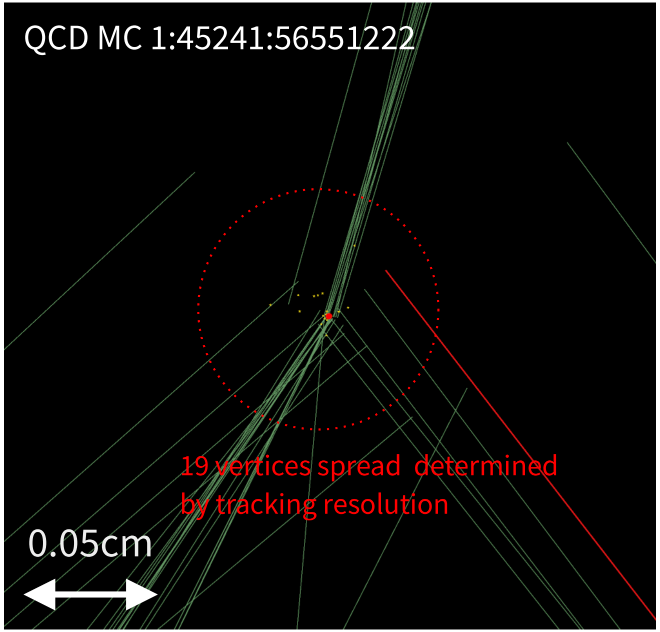


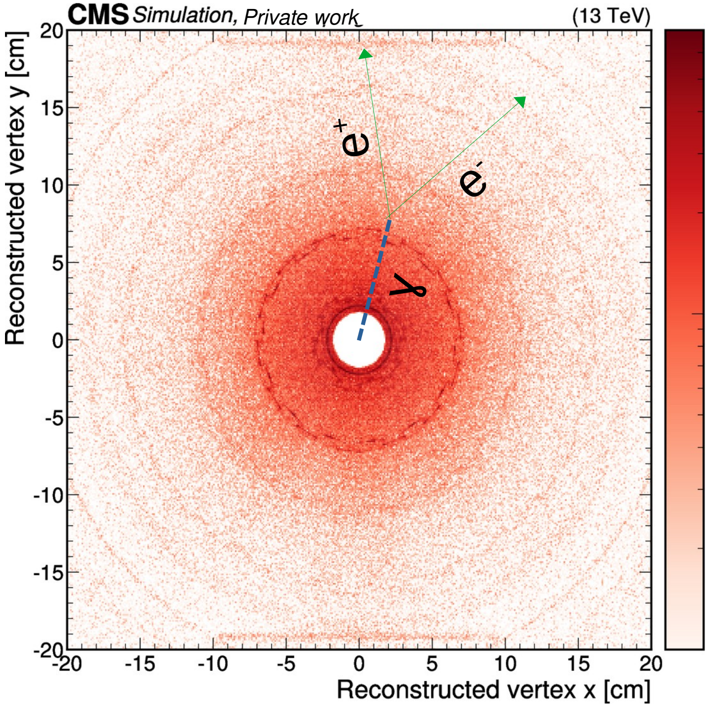
Image by Nazar Bartosik

"Random" sources

- Pile-up tracks contamination
- Detector resolution effects



- Material interaction

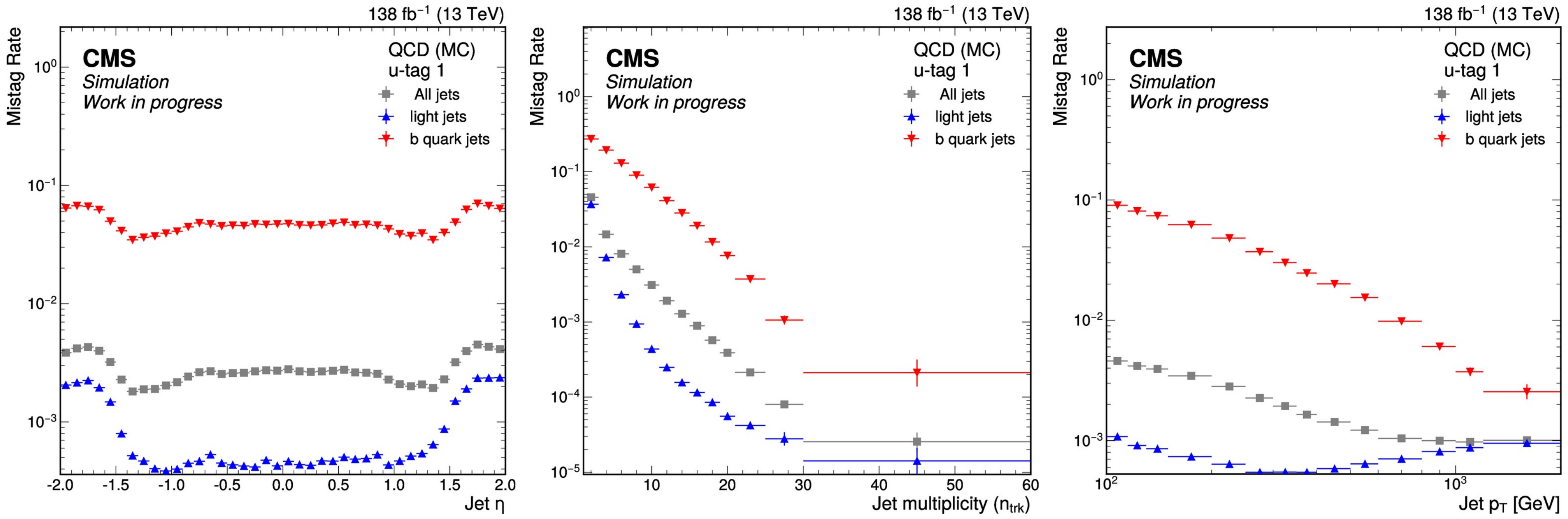


RECO-vertex position with no filter

Background estimation – mistag rate evaluation

- How much do we trust MC to get randomness right?
- How much do we trust MC to get mistag rate dependence correct?
- Can we try to evaluate EMJ mistagging in data?
  - Can we reliably extract the jet variable dependence of mistagging?

Example unflavored mistag rate using cut-based tagging



Mistag rate evaluated using QCD MC jets

Background estimation – mistag rate evaluation

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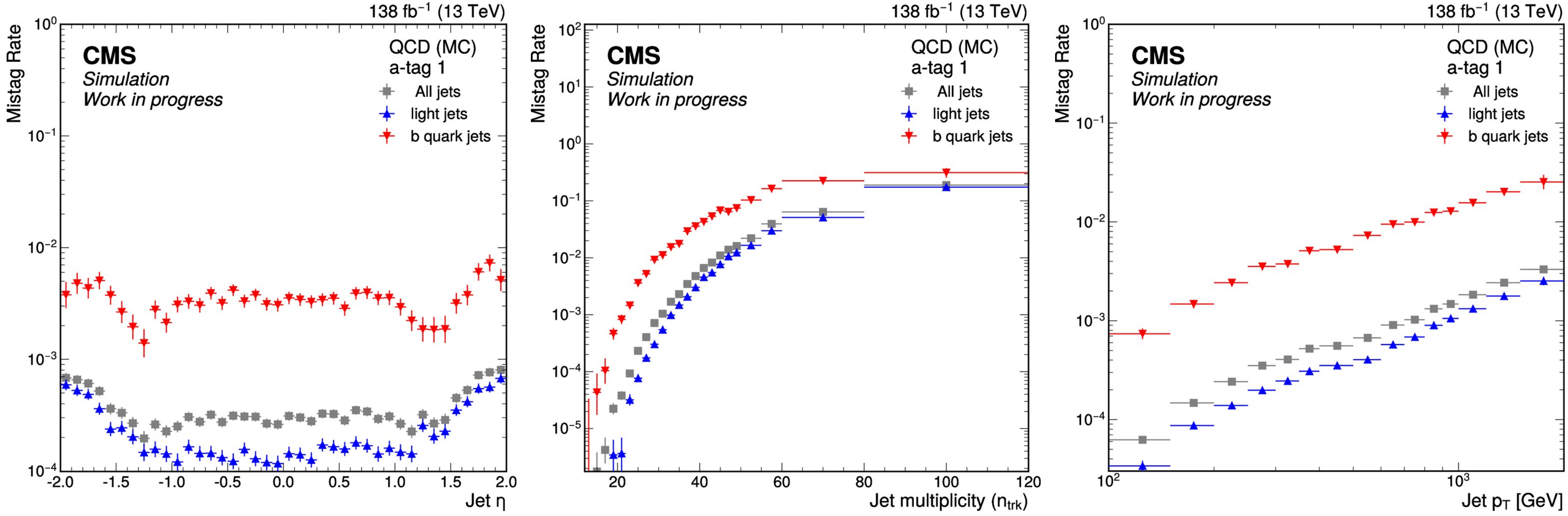
Example flavor-aligned mistag rate using cut-based tagging



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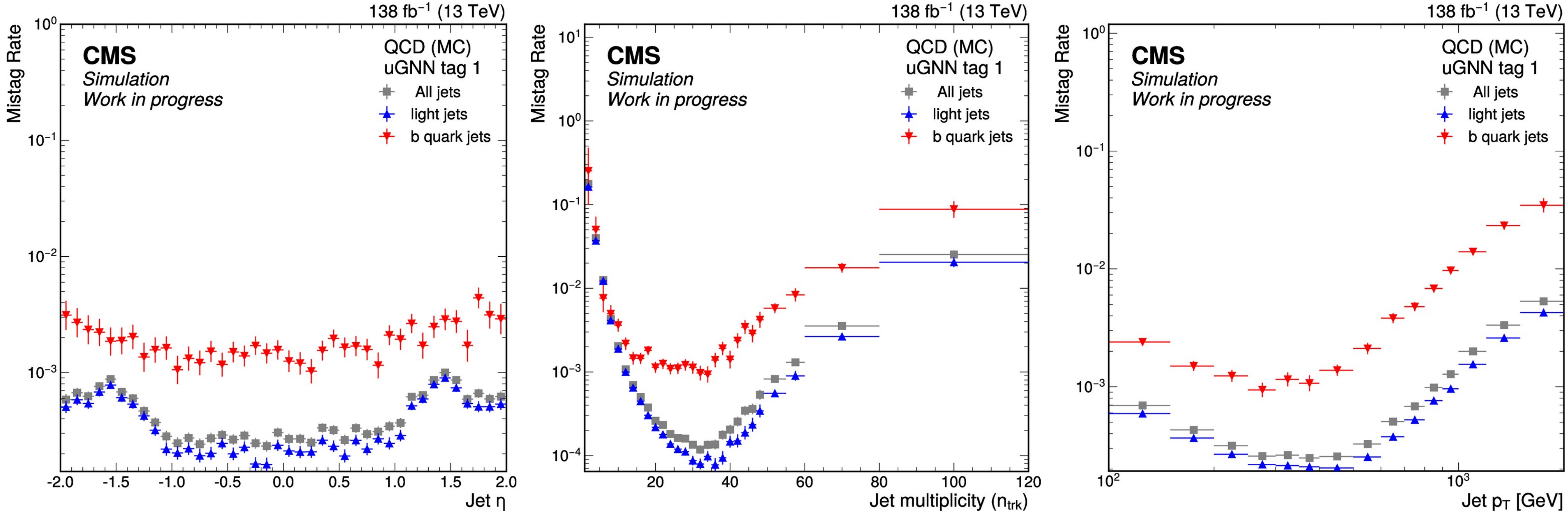
Example unflavored mistag rate using GNN tagging



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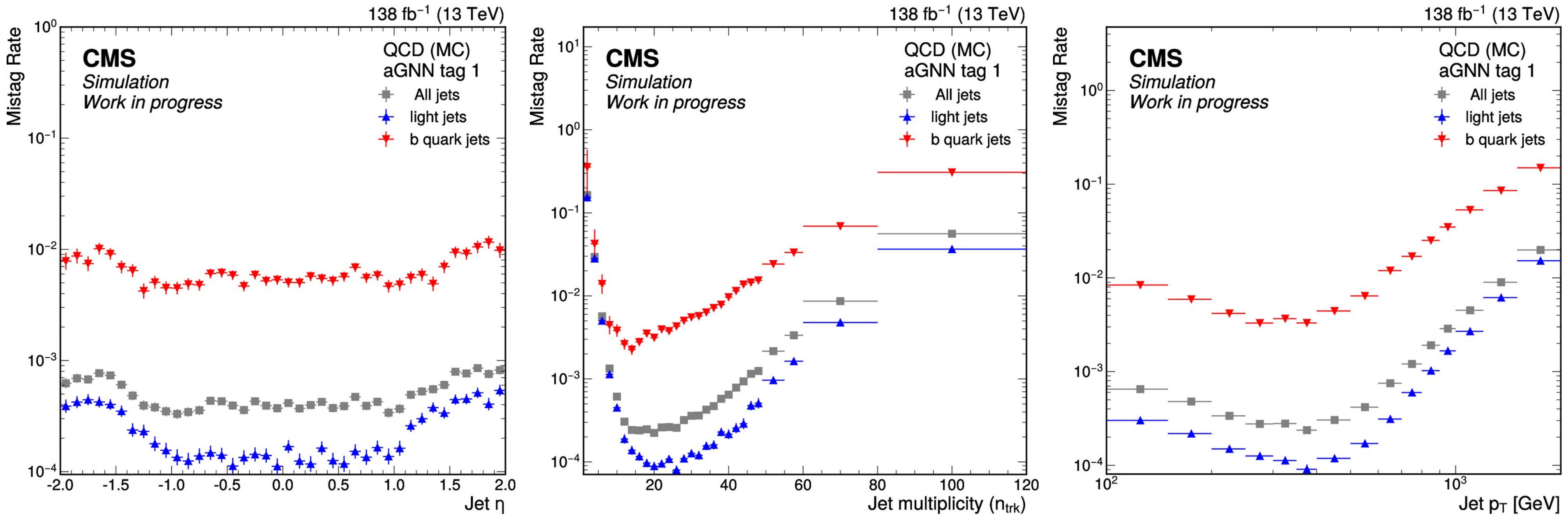
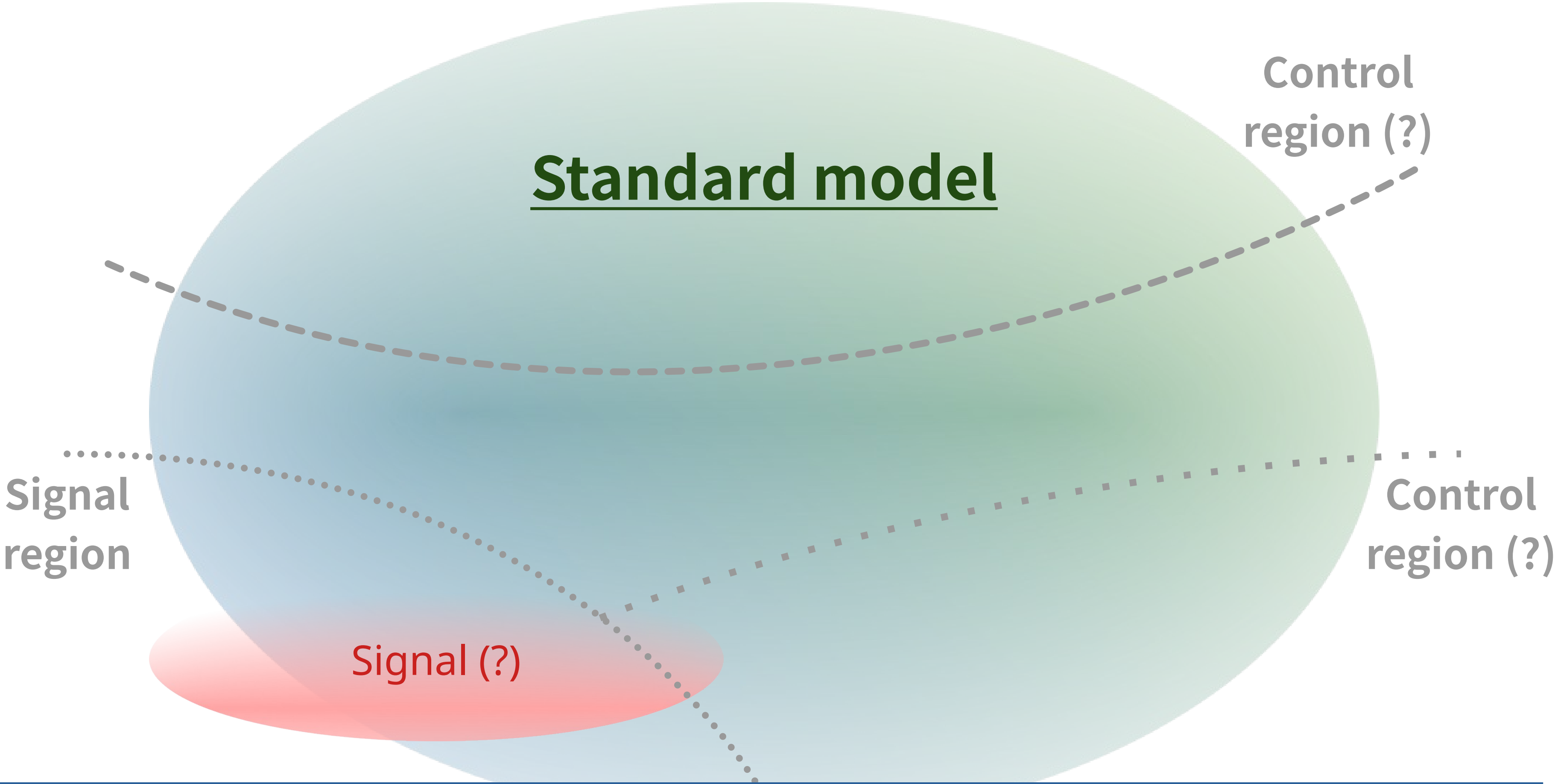
Example flavor-aligned mistag rate using GNN tagging



Mistag rate evaluated using QCD MC jets



Defining control regions

EMJ mistagging in data – Construction of FR

Signal-free region (FR) constructed using γ-triggered data stream with high-p_T photon (>200GeV)

All jets in this region are assumed to be from SM processes

- Mistag rate can be evaluated as a function of jet kinematics just by running the tagging algorithm
- For determining flavor dependence, we split the region by b-tagging results of extra jet; b jet fraction of "primary" jets is shifted without explicit kinematic cuts on primary jets
- Mistag rate of primary jets follows linear relation:

$$\begin{cases} \epsilon^E(p_\mathrm{T}) = B^E(p_\mathrm{T})\epsilon(b,p_\mathrm{T}) + (1-B^E(p_\mathrm{T}))\epsilon(l,p_\mathrm{T}) \\ \epsilon^R(p_\mathrm{T}) = B^R(p_\mathrm{T})\epsilon(b,p_\mathrm{T}) + (1-B^R(p_\mathrm{T}))\epsilon(l,p_\mathrm{T}) \end{cases}$$

Relation can be inverted to obtain flavor-dependent mistag rate!

ɣ-triggered data stream ("SinglePhoton")

Offline jet selections (p_T > 100GeV)

"Extra" jet (p_T > 50GeV)

Extra jet b-tagged

b-enhanced region

$\varepsilon^E(p_T)$, $B^E(p_T)$

Extra jet b-vetoed

b-suppressed region

$\varepsilon^R(p_T)$, $B^R(p_T)$

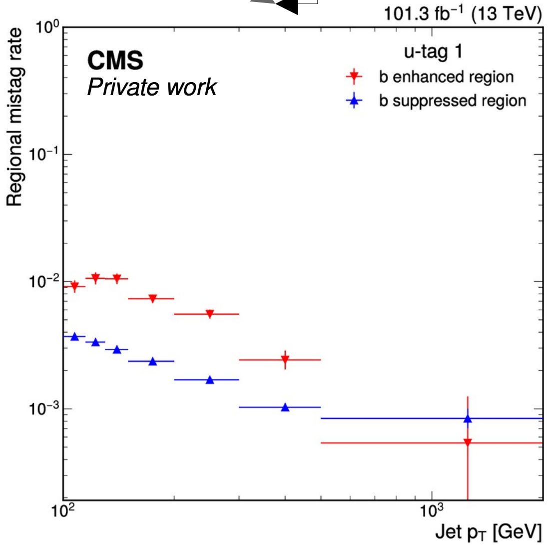
EMJ mistagging in data – Construction of FR

$$\begin{cases} \boxed{\epsilon^E(p_T)} = \boxed{B^E(p_T)}\boxed{\epsilon(b,p_T)} + (1 - \boxed{B^E(p_T)})\boxed{\epsilon(l,p_T)} \\ \boxed{\epsilon^R(p_T)} = \boxed{B^R(p_T)}\boxed{\epsilon(b,p_T)} + (1 - \boxed{B^R(p_T)})\boxed{\epsilon(l,p_T)} \end{cases}$$

- $\varepsilon^X(p_T)$: flavor-blind mistag rate evaluated in region X
- $B^X(p_T)$: estimated b-jet fraction of region X
- $\varepsilon_{inv}(f, p_T)$: flavor-dependent mistag rate from **inversion**
- $\varepsilon_{truth}(f, p_T)$:flavor-dependent mistag rate from MC **truth**

Measured in data

Calculated by inversion



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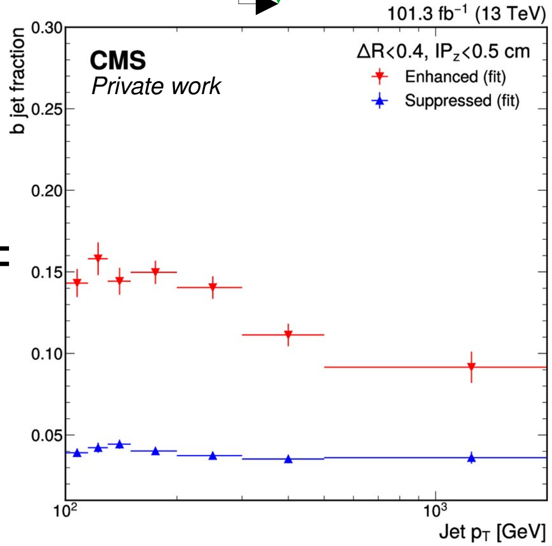

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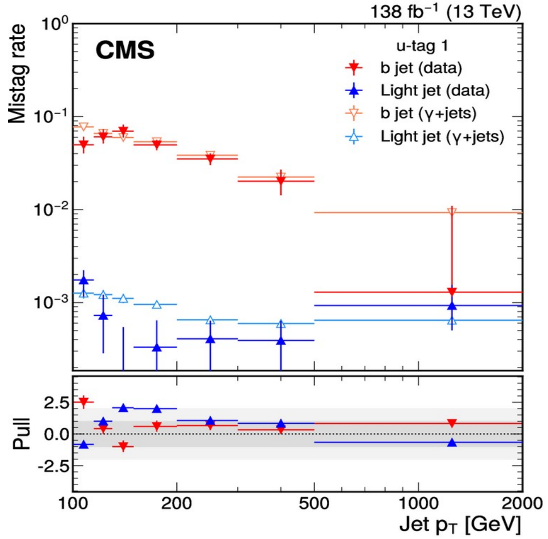


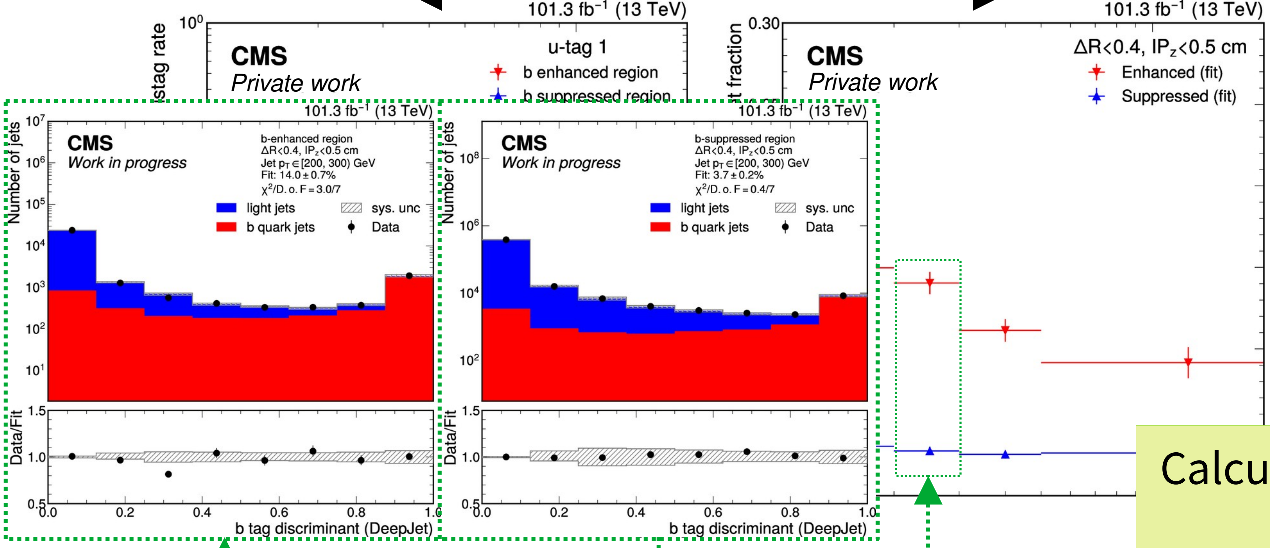
EMJ mistagging in data – Construction of FR

$$\begin{cases} \epsilon^E(p_T) = B^E(p_T)\,\epsilon(b,p_T) + (1 - B^E(p_T))\,\epsilon(l,p_T) \\ \epsilon^R(p_T) = B^R(p_T)\,\epsilon(b,p_T) + (1 - B^R(p_T))\,\epsilon(l,p_T) \end{cases}$$

- $\varepsilon^X(p_T)$: flavor-blind mistag rate evaluated in region X
- $B^X(p_T)$: estimated b-jet fraction of region X
- $\varepsilon_{inv}(f, p_T)$: flavor-dependent mistag rate from **inversion**
- $\varepsilon_{truth}(f, p_T)$:flavor-dependent mistag rate from MC **truth**

Measured in data

Calculated by inversion



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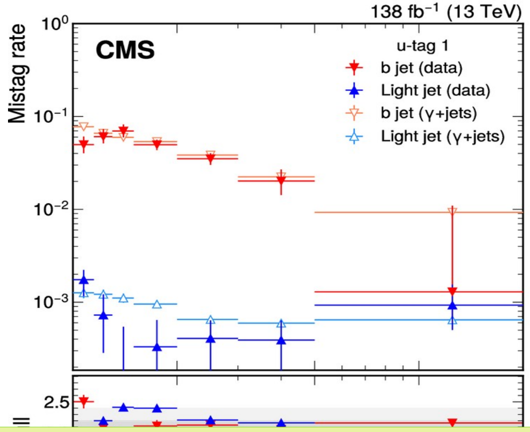


Calculating b jet fraction by fitting to CMS b discriminator distributions.

Background estimation – scale factor method

Evaluation of mistag rate can be used to map control region events (C) to signal region background (S_{SM}) by some scale factor calculated from mistag rates $SF(\{\epsilon_j\})$

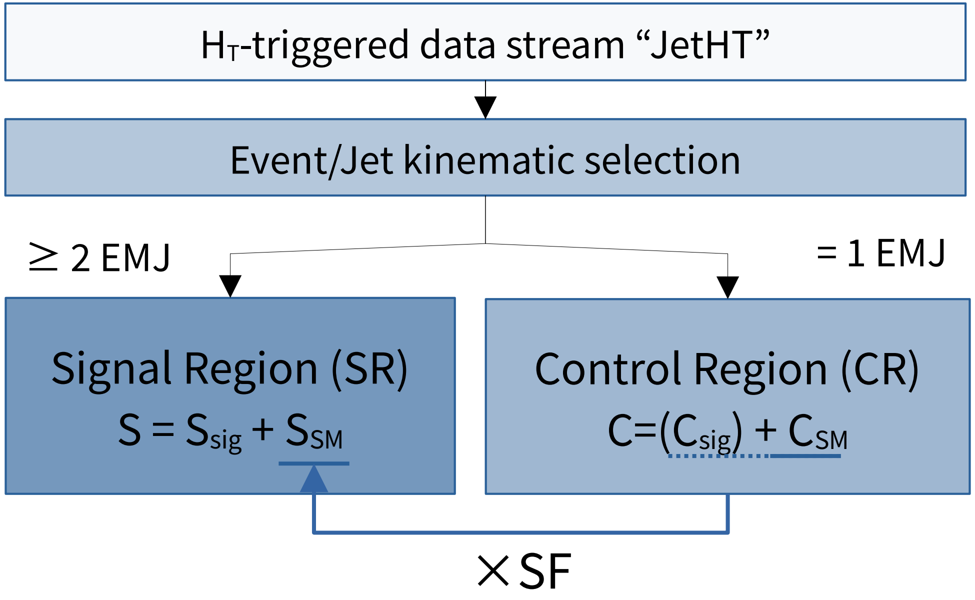
$$\mathrm{Est}_{S_{SM}} = \sum_{events \in C_{SM}} SF(\{\epsilon_j\}) \sim \sum_{events \in C} SF(\{\epsilon_j\})$$

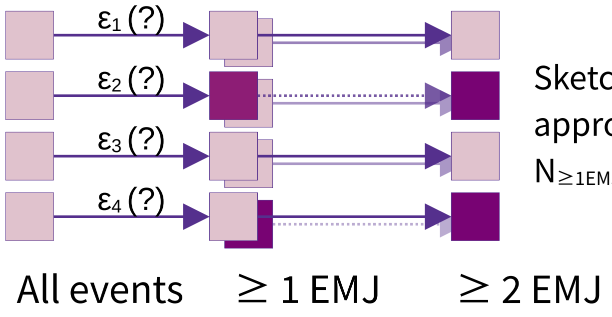
$C_{SM} \gg C_{sig}$

Assuming that SM jets in SR/CR is identical, we can work out SF to be:

$$SF(\{\epsilon_j\}) \sim \frac{1}{2} \sum_{j \notin EMJ} \epsilon_j$$

Factor of ½ comes from combinatorical factor (see right)





Sketch of ½ factor, approximation holds true if $N_{\geq 1EMJ} \gg N_{\geq 2EMJ}$ (i.e. $\varepsilon_j \ll 1$)

Full calculation will be given in backup slides

Scale factor method – flavor assignment

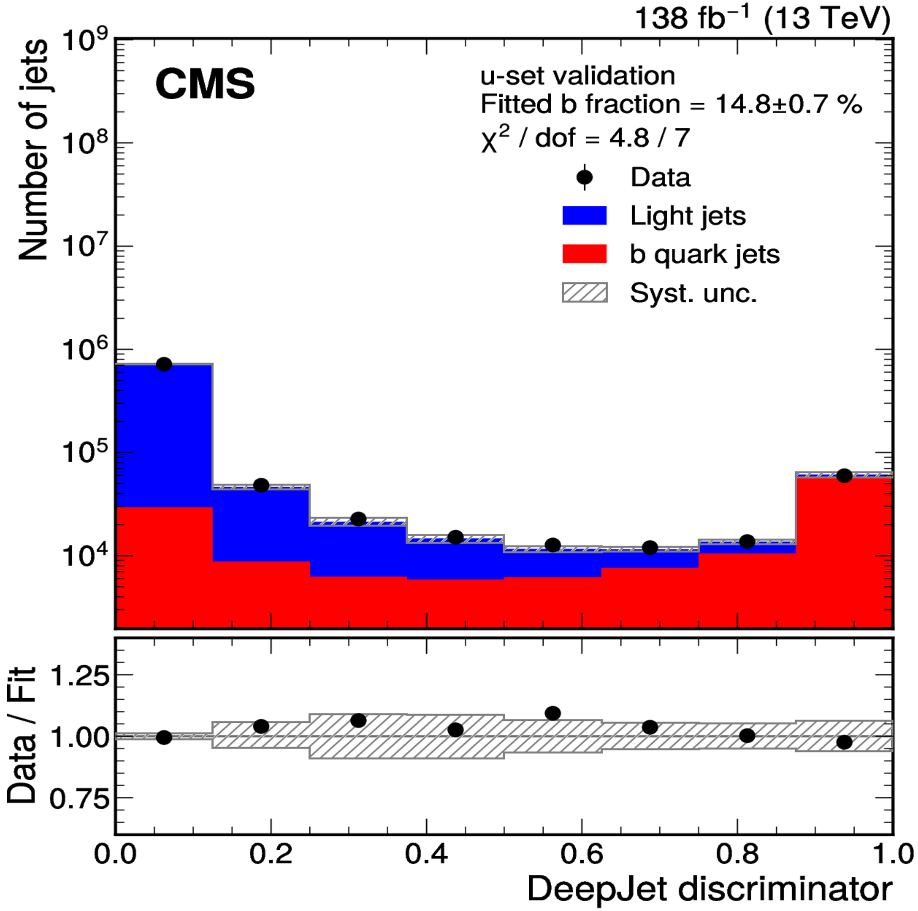
The mathematical formula for scale factor SF({ε_j}) is only true if EMJ mistagging of jets within an event is uncorrelated up to mistag rate parameterization $\varepsilon(f, p_T)$

$$SF(\{\epsilon_j\}) \sim \frac{1}{2} \sum_{j \notin EMJ} \epsilon(f_j, p_{\mathrm{T},j})$$

In practice, since it is difficult to parameterize jets in "flavor" when calculating SF, a flavor-averaged mistag rate would be employed for calculation:

$$SF_{\mathrm{avg}}(\{\epsilon_j\}) \sim \frac{1}{2} \sum_{j \notin EMJ} B^{CR} \epsilon(b, p_{\mathrm{T},j}) + (1 - B^{CR}) \epsilon(l, p_{\mathrm{T},j})$$

where B^{CR} is the estimated b jet fraction of the non-tagged jets in the CR



Background estimation – notations

Lots of moving parts to keep track of…

S: Where the SR/CR is constructed
- H_T-triggered data ("JetHT")
- QCD (MC)

F: Where the mistag rate is calculated
- Photon-triggered data "SP"
- QCD (MC)
- GJets (MC)

$$\text{CR} \times \text{SF} = \quad \mathrm{Est}^{S}_{\alpha}(\epsilon^{F}_{\beta}(p_{\mathrm{T}}))$$

α: How flavor assignment is performed in SF calculation
- MC truth
- Flavor-averaged ("avg.")

β: How flavor dependence is evaluated
- MC truth
- Linear relation inversion ("inv.")

Background estimation for fully data-based calculation: $\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{avg.}}(\epsilon^{\mathrm{SP}}_{\mathrm{inv.}}(p_{\mathrm{T}}))$

Alternate results will be used for uncertainty evaluation

Uncertainty

v.s.

Uncertainty

Limitations of data-based methods

Data-based methods – limitations

Using MC counter parts to estimate uncertainties at each stage

$$U(E_1, E_2) = \frac{2|E_1 - E_2|}{E_1 + E_2}$$

Mathematically correct

$$\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{truth}}(\epsilon^{\mathrm{JetHT|SM}}_{\mathrm{truth}}(\vec{\theta_\infty}))$$

Mistag rate jet variable dependence cannot be arbitrarily parameterized

$$\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{truth}}(\epsilon^{\mathrm{JetHT|SM}}_{\mathrm{truth}}(p_{\mathrm{T}}))$$

SM Jet cannot to isolated in signal-like region

$$\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{truth}}(\epsilon^{\mathrm{SP}}_{\mathrm{truth}}(p_{\mathrm{T}}))$$

Jet flavor is not perfectly known in data

$$\boxed{\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{avg.}}(\epsilon^{\mathrm{SP}}_{\mathrm{inv.}}(p_{\mathrm{T}}))}$$

Calculable using just data

$$\mathrm{Est}^{\mathrm{QCD}}_{\mathrm{truth}}(\epsilon^{\mathrm{QCD}}_{\mathrm{truth}}(\vec{\theta_\infty}))$$

$$\mathrm{Est}^{\mathrm{QCD}}_{\mathrm{truth}}(\epsilon^{\mathrm{QCD}}_{\mathrm{truth}}(p_{\mathrm{T,fine}}))$$

$$\mathrm{Est}^{\mathrm{QCD}}_{\mathrm{truth}}(\epsilon^{\mathrm{QCD}}_{\mathrm{truth}}(p_{\mathrm{T}}))$$

$$\mathrm{Est}^{\mathrm{QCD}}_{\mathrm{truth}}(\epsilon^{\mathrm{QCD}}_{\mathrm{truth}}(n_{\mathrm{tracks}}))$$

$$\mathrm{Est}^{\mathrm{QCD}}_{\mathrm{truth}}(\epsilon^{\mathrm{GJets}}_{\mathrm{truth}}(p_{\mathrm{T}}))$$

$$\mathrm{Est}^{\mathrm{QCD}}_{\mathrm{avg.}}(\epsilon^{\mathrm{GJets}}_{\mathrm{inv.}}(p_{\mathrm{T}}))$$

Data-based methods – limitations (2)

"A control region that eliminates exactly one physics process cannot exist"

Most mathematically correct

$$\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{truth}}\left(\epsilon^{\mathrm{JetHT|SM}}_{\mathrm{truth}}(\underline{\vec{\theta_{\infty}}})\right)$$

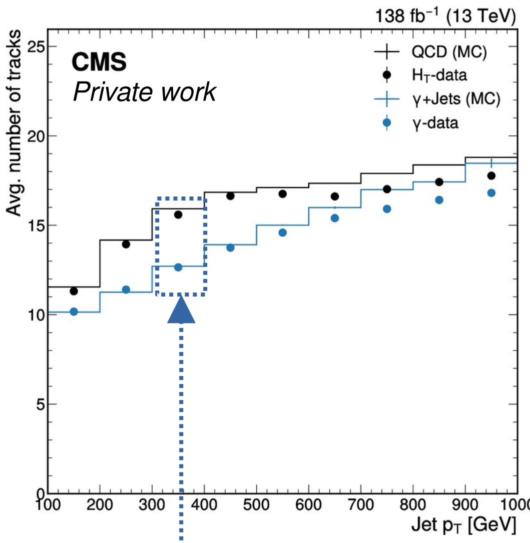
$$\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{truth}}\left(\epsilon^{\underline{\mathrm{JetHT|SM}}}_{\mathrm{truth}}(\underline{p_{\mathrm{T}}})\right)$$

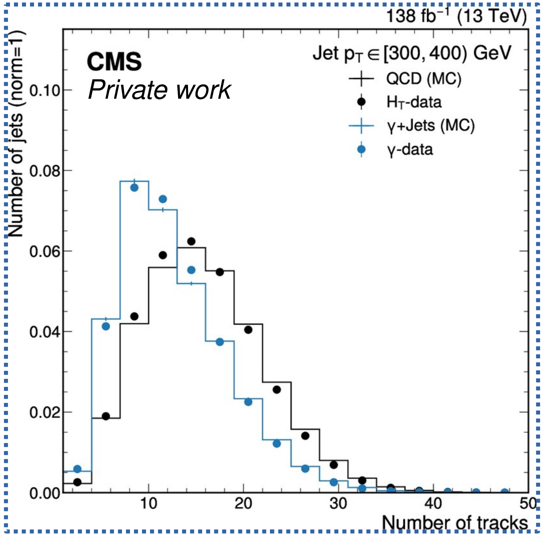
$$\underline{\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{truth}}\left(\epsilon^{\underline{\mathrm{SP}}}_{\mathrm{truth}}\right.}\left.(p_{\mathrm{T}})\right)$$

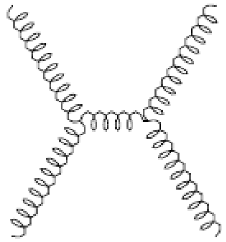
$$\underline{\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{avg.}}\left(\epsilon^{\mathrm{SP}}_{\mathrm{inv.}}\right.}\left.(p_{\mathrm{T}})\right)$$

Calculable using just data

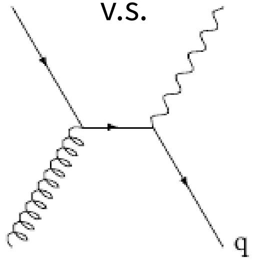
Cannot split out just SM jets in JetHT stream, so we use the SinglePhoton data stream, but jet kinematics are fundamentally different in the two data sets.







v.s.



While data and MC do not perfectly match, QCD/GJets discrepancies capture primary features of H_T/γ-triggered data set differences

MC events used to estimate impact on final estimation

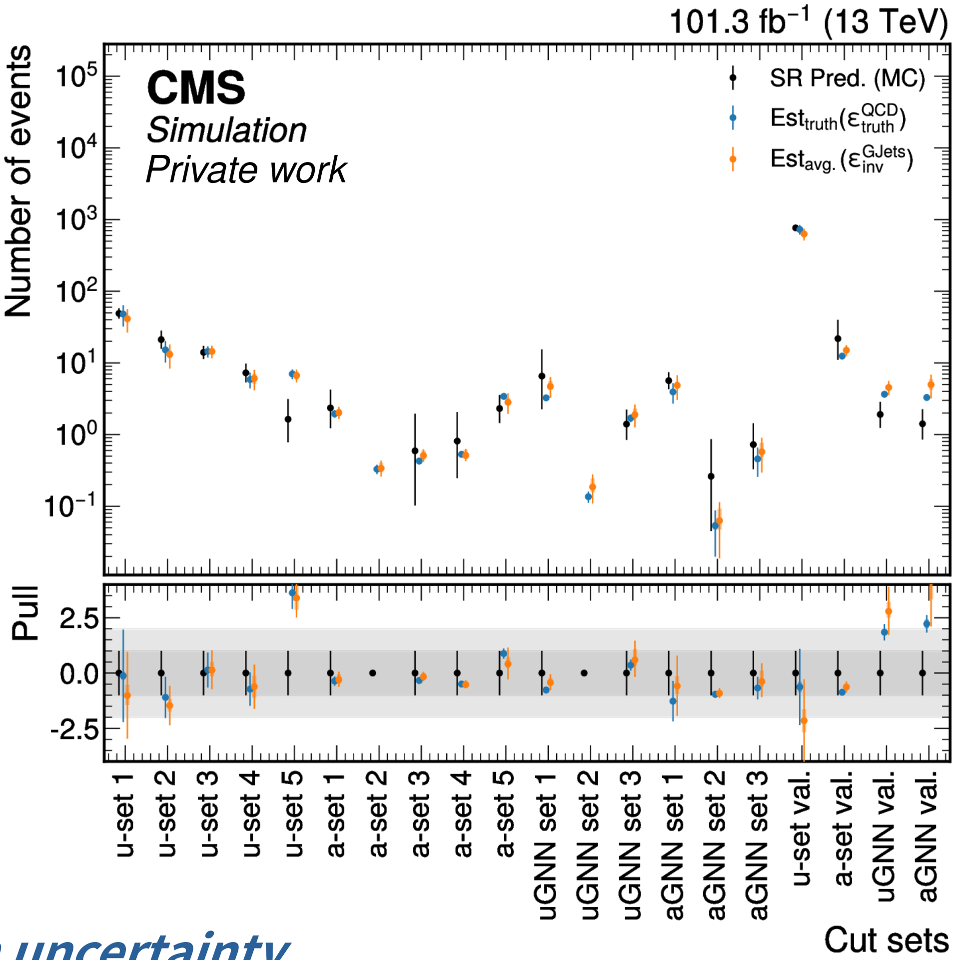
Data-based methods – validation using MC

Q: How can we be sure our background estimation calculation is correct?

A signal-free data stream should have SM events perfectly match SR = CR × SF calculation

- SM MC events as stand-in for data events:
  - H_T-triggered data → QCD MC
  - γ-triggered data → Gjets MC
- Run calculation on MC identically as what will be performed on data

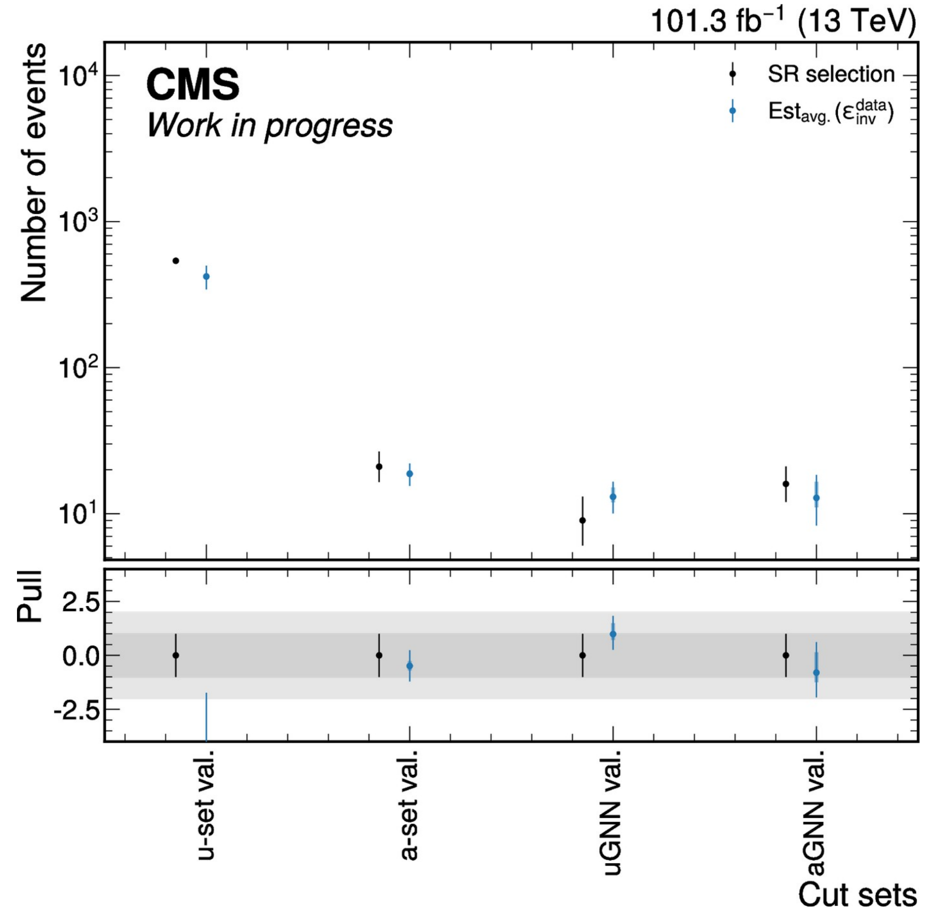
Since SM MC is by definition "signal free", we can compare SR events (black points) to CR × SF results (color points) up to uncertainties



All cutsets closes within uncertainty

Data-based method – validation using data

- **Validation** “SR/CR” pairs constructed using H_T-triggered data stream with cut values designed to be signal diluted in validation “SR”:
  - Cut-based strategy:
    - Relax EMJ tagging requirements ($S_{sig} \ll S_{SM}$)
    - Invert H_T requirements: H_T< 1200GeV (Low $m_{X,med}$ models excluded by CMS 2016 results)
  - GNN strategy:
    - Side-band GNN score value for tagging
    - Relax H_T /Jet p_T selection criteria
  - Signal contribution in these “SR” definitions is expected to be < 1% of total events
- Same calculation as what will be used for primary SR/CR calculations



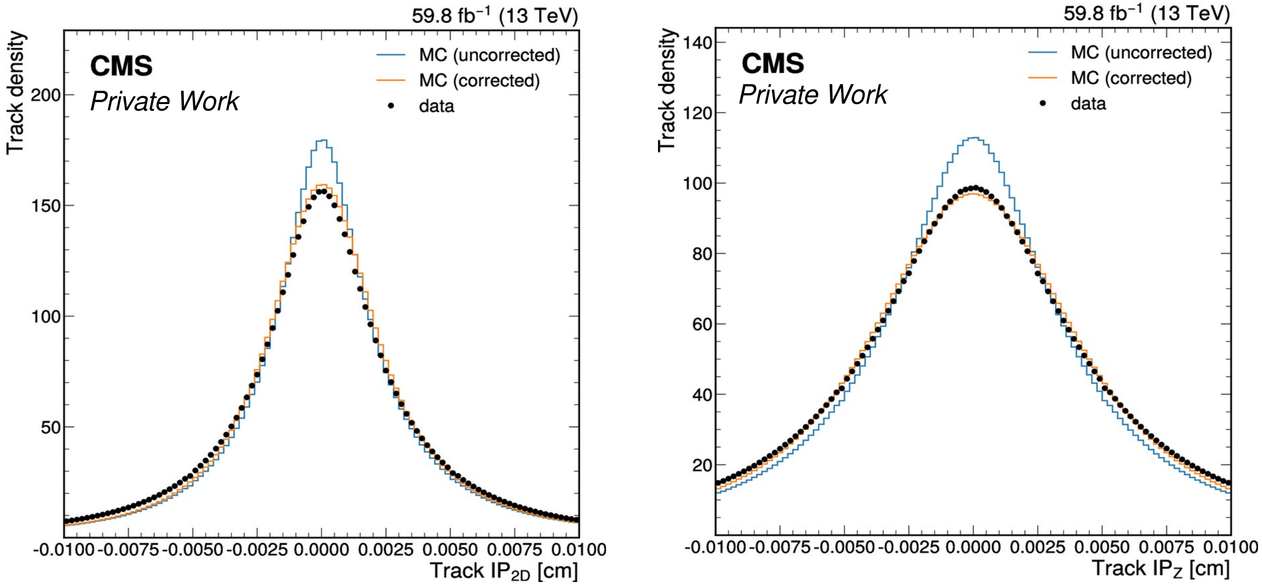
All cutsets closes within uncertainty

Signal modeling MC uncertainties

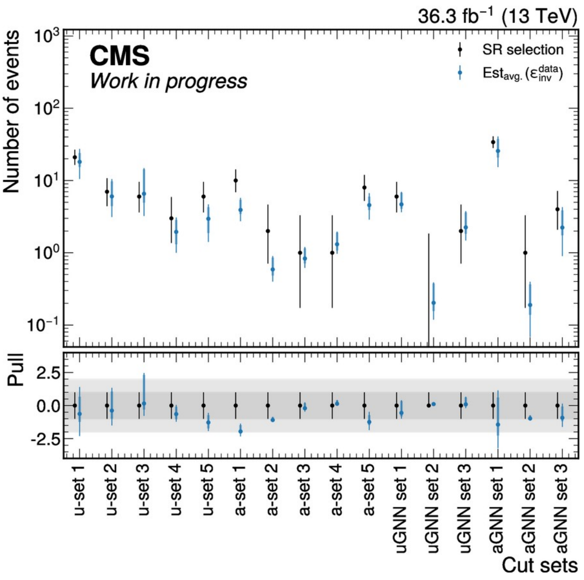
- **MC track reconstruction modeling**
- Luminosity
- Trigger efficiency
- Pileup
- Jet energy corrections and resolutions
- PDF/α_S

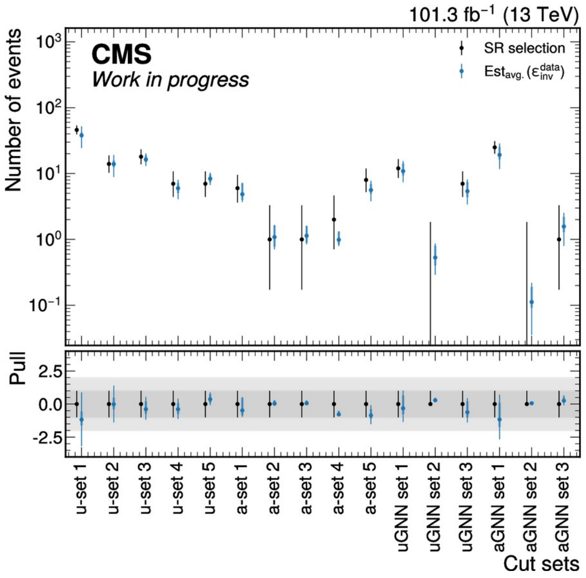
Tracks in MC typically have too good of a resolution when compared with data: remedied by injecting randomness to IP_{2D} and IP_z of MC tracks such that the final distribution matches data.

- Distribution obtained with only trigger selection, evaluated per year
- Correcting small displacement resolution effects
  - Additional discussion given in backup



Opening the box…





Results from arXiv:2403.01556

Selection set	Estimation ± stat. ± syst.	Observed yield
u-set 1	$56\ ^{+9}_{-5} \pm 20$	67
u-set 2	$20.0\ ^{+4.3}_{-2.5} \pm 7.0$	21
u-set 3	$22.9\ ^{+7.3}_{-2.1} \pm 4.9$	24
u-set 4	$7.9\ ^{+2.0}_{-1.6} \pm 2.2$	10
u-set 5	$11.3\ ^{+2.7}_{-1.9} \pm 2.0$	13
a-set 1	$8.8\ ^{+2.4}_{-1.0} \pm 2.0$	16
a-set 2	$1.67\ ^{+0.49}_{-0.23} \pm 0.38$	3
a-set 3	$1.97\ ^{+0.47}_{-0.22} \pm 0.37$	2
a-set 4	$2.30\ ^{+0.81}_{-0.30} \pm 0.39$	3
a-set 5	$10.2\ ^{+2.3}_{-1.1} \pm 3.4$	16
uGNN set 1	$15.6\ ^{+5.4}_{-1.9} \pm 3.8$	18
uGNN set 2	$0.73\ ^{+0.44}_{-0.16} \pm 0.27$	0
uGNN set 3	$7.6\ ^{+3.5}_{-1.3} \pm 2.3$	9
aGNN set 1	$45\ ^{+18}_{-8} \pm 16$	59
aGNN set 2	$0.30\ ^{+0.23}_{-0.07} \pm 0.18$	1
aGNN set 3	$3.8\ ^{+2.2}_{-0.7} \pm 2.0$	5

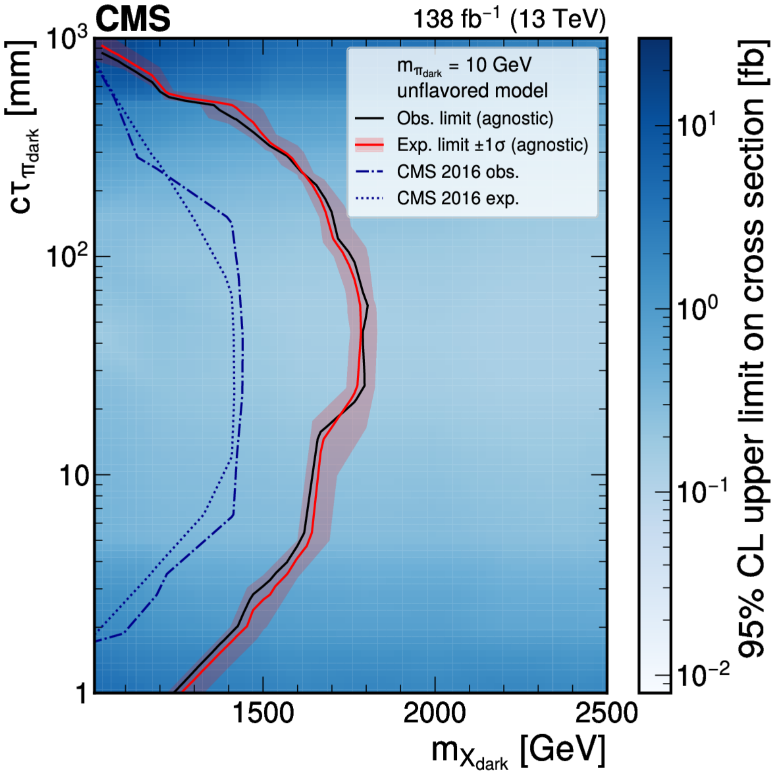
No significant excess was observed.

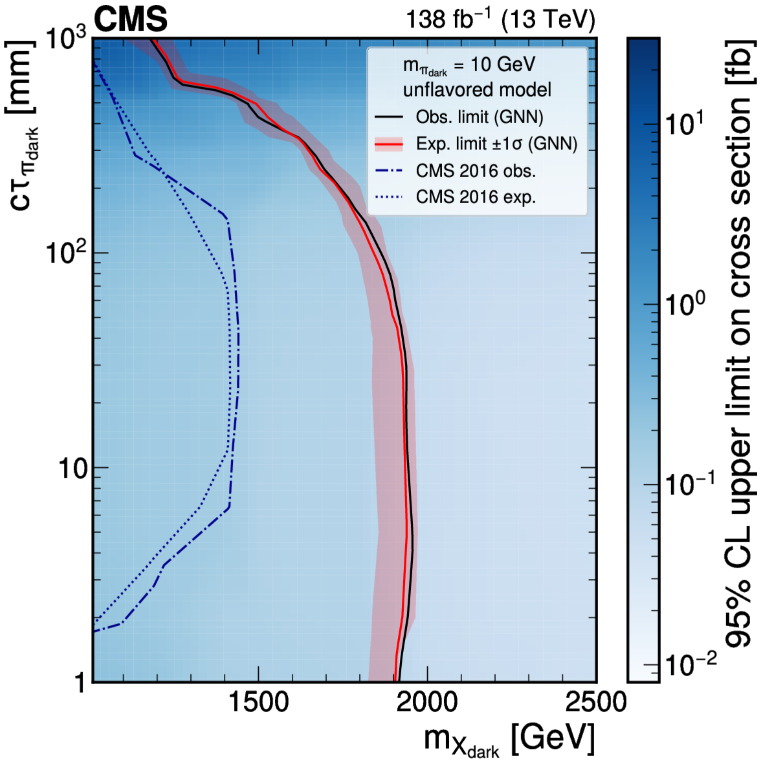
Interpreting results as setting an upper limit on dark mediator production cross section

CL_s limit – extending sensitivity using Run 2

CMS results are preparing for publication! Getting a comparison with the existing CMS results by computing CLs limit with expected background using MC samples.

- Cut-based analysis limit reach extended by ~300GeV in $m_{X,\mathrm{Dark}}$
- GNN performs better in general, particularly for low lifetime models (more discussions later!)



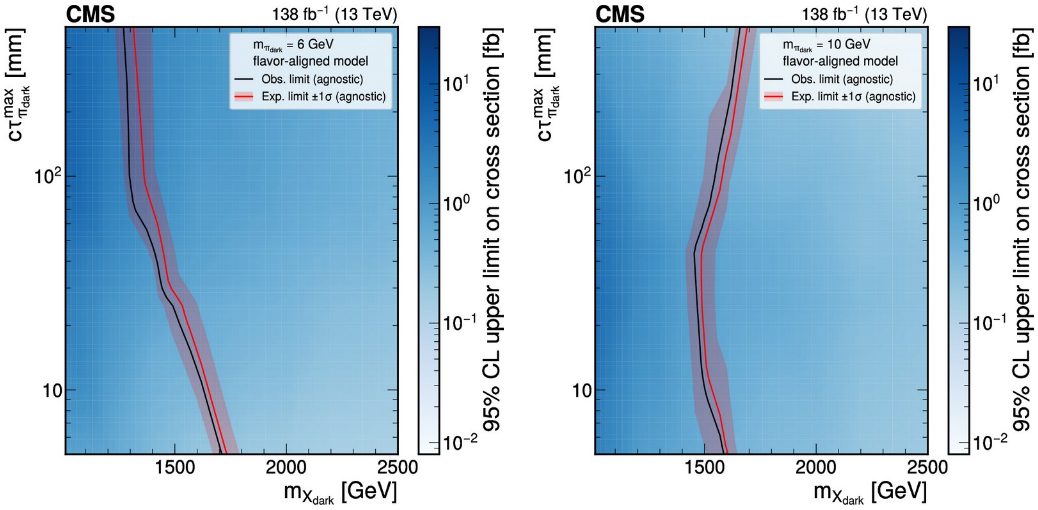


CLs limits – flavored DS models

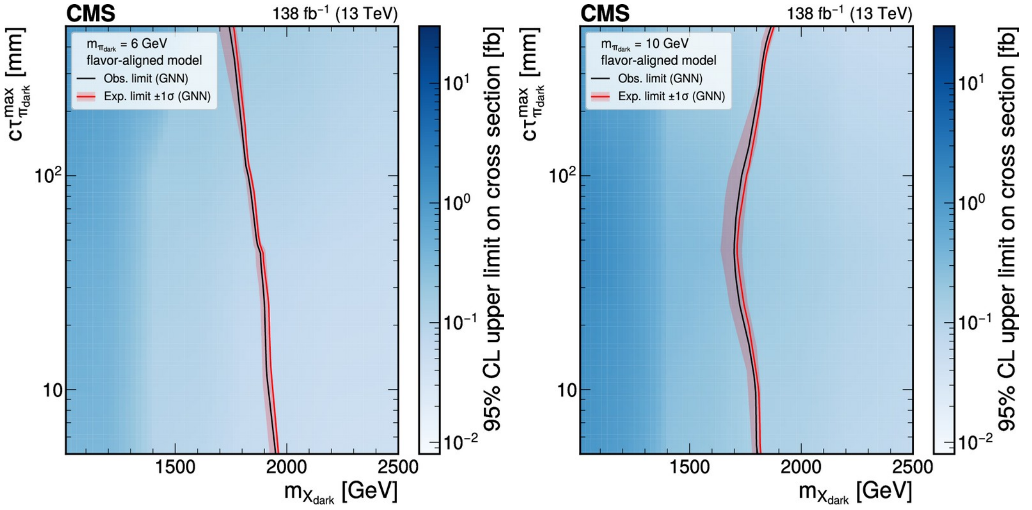
First look at the sensitivity to flavored EMJ models at CMS!

- Flatter cτ dependencies compared with unflavored, fixed-displacement signatures
  - Tension between which signature the detector is sensitive to:
    Longest lifetime particles v.s. SM heavy meson production
- GNN performs “better” than the model-generic approach

Model-generic



GNN results



Improvements since 2016

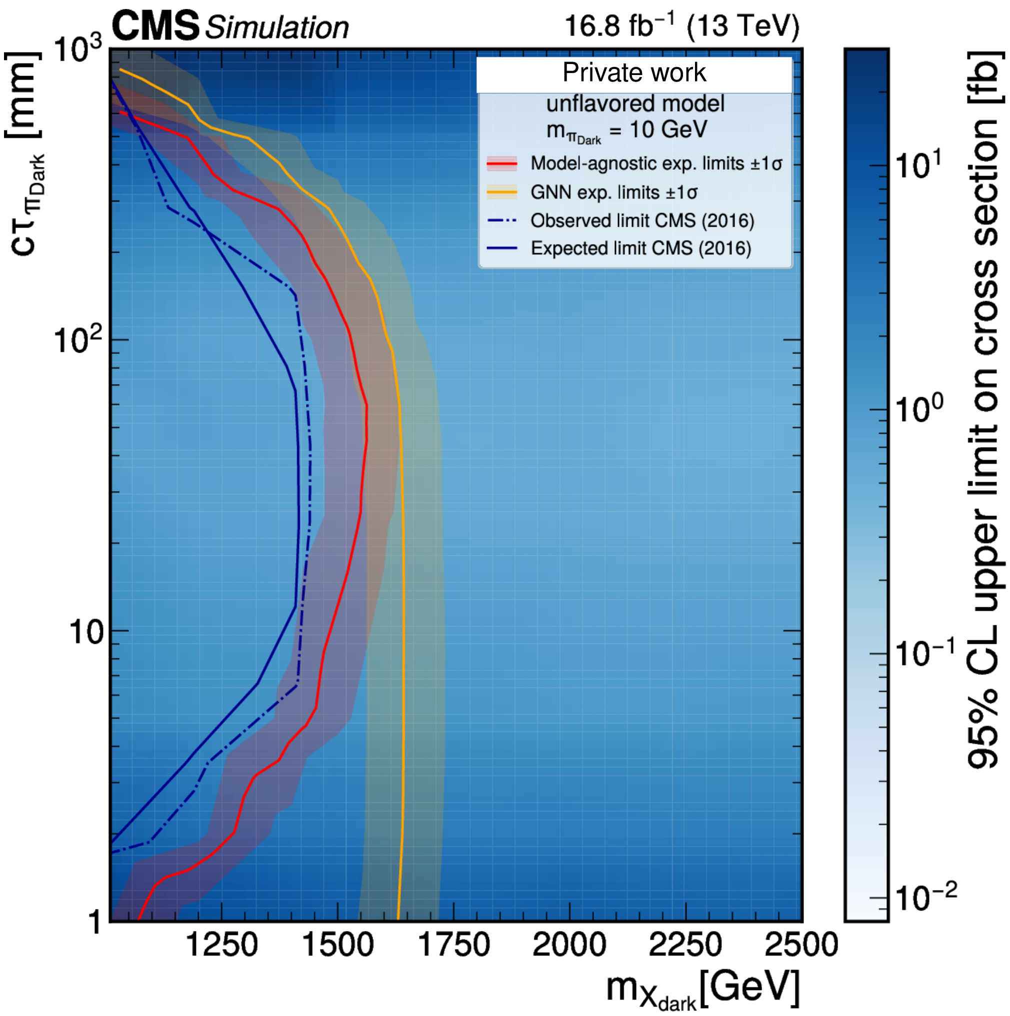
Comparison of new limits with previous CMS search ($16.8 fb^{-1}$, 2016)

- Poor limit reach at large $c\tau_{\pi,dark}$ is to be expected (no tracker-based signature)

Model-generic method: Slight boost in limit reach

- Slightly higher H_T, jet p_T selection thresholds
- More detailed uncertainty studies

GNN-based method: "*Is ML better at selecting 'signature' or better a selecting 'model'?*"

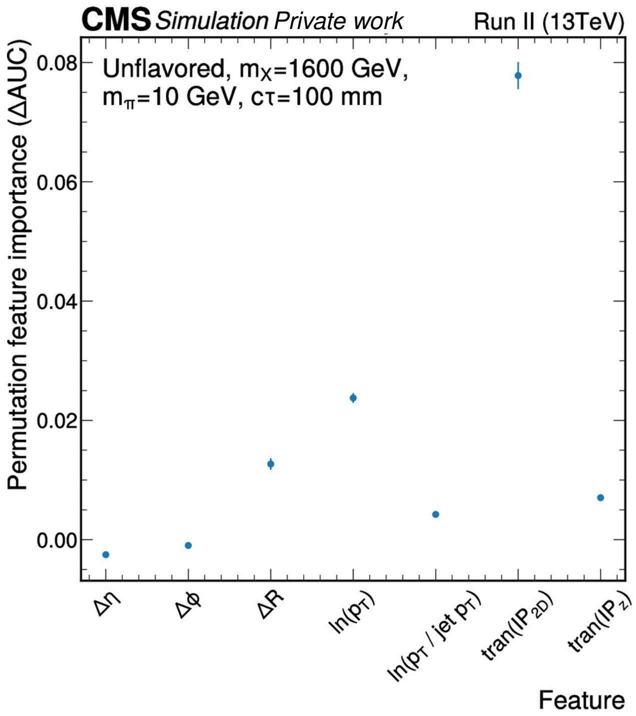


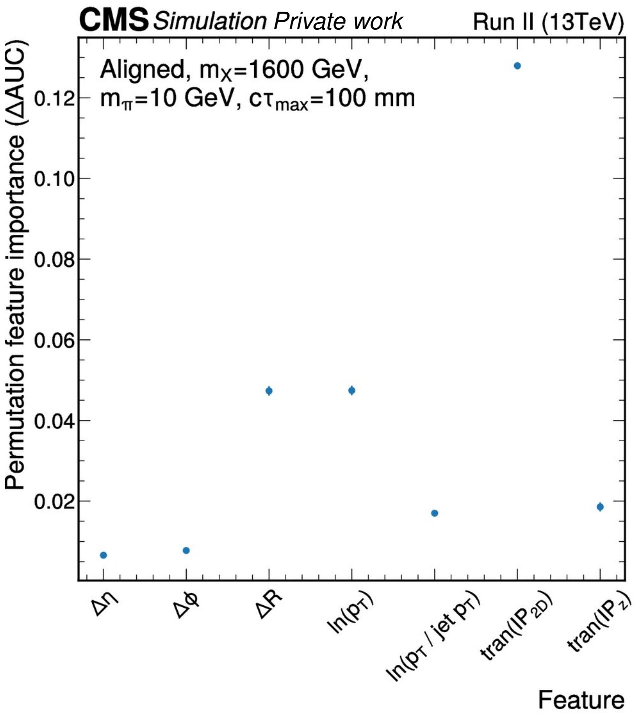
Interrogating ML results

What is an “EMJ” to the GNN?

Attempt to extract “what” the GNN is attempting to learn: reorder singular track variables in collection

- Ensures distribution of input variables are unchanged
- Decorrelate one single variable from all other inputs
- Check which variable impacts the GNN output the most (using ΔAUC measure, the change in area under ROC curve)





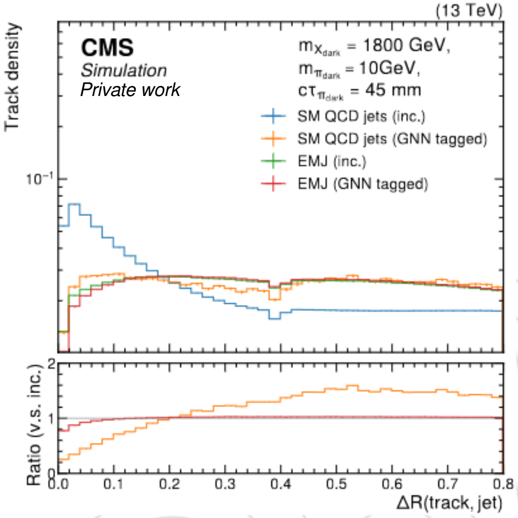
IP_{2D} is still the most important feature used in the GNN

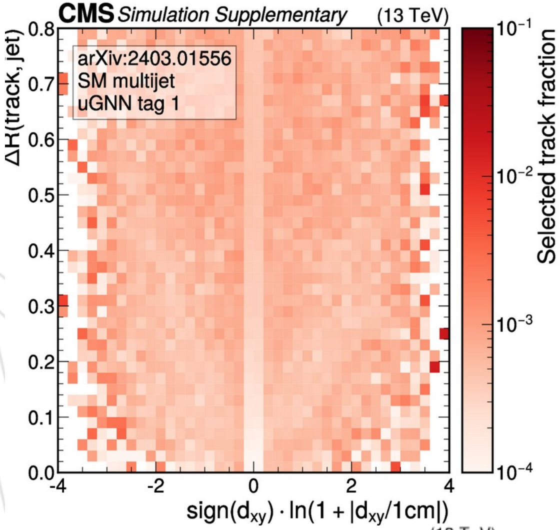
- The GNN indeed looks for displacement signatures.
- But what is it doing differently at lower mass points?

What can be mistaken to be an EMJ?

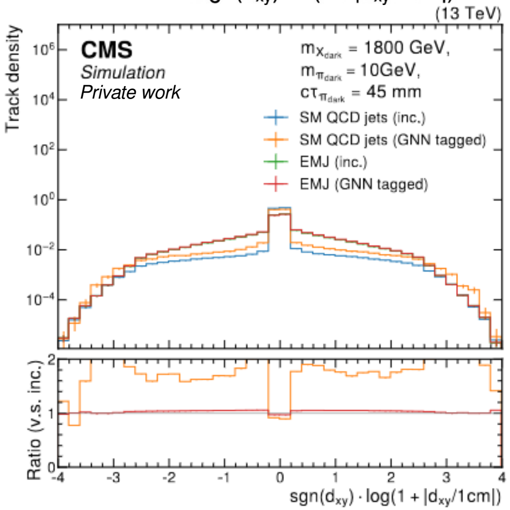
Take a look at variable shifts before and after GNN score selection.

- Signal jet distribution shifts very little (expected, since signal selection efficiency is high)
- SM background jets have significant shifts:
  - GNN-tagged jets have large displacements (target signature)
  - GNN-tagged jets have wider jet shower!
    - See the wider ΔR distribution and the smaller p_T fraction distribution
    - Double checking 2D distribution, this jet showering is primarily used for small IP_{2D} tracks
    - Consequence training GNN using heavy DS mesons masses





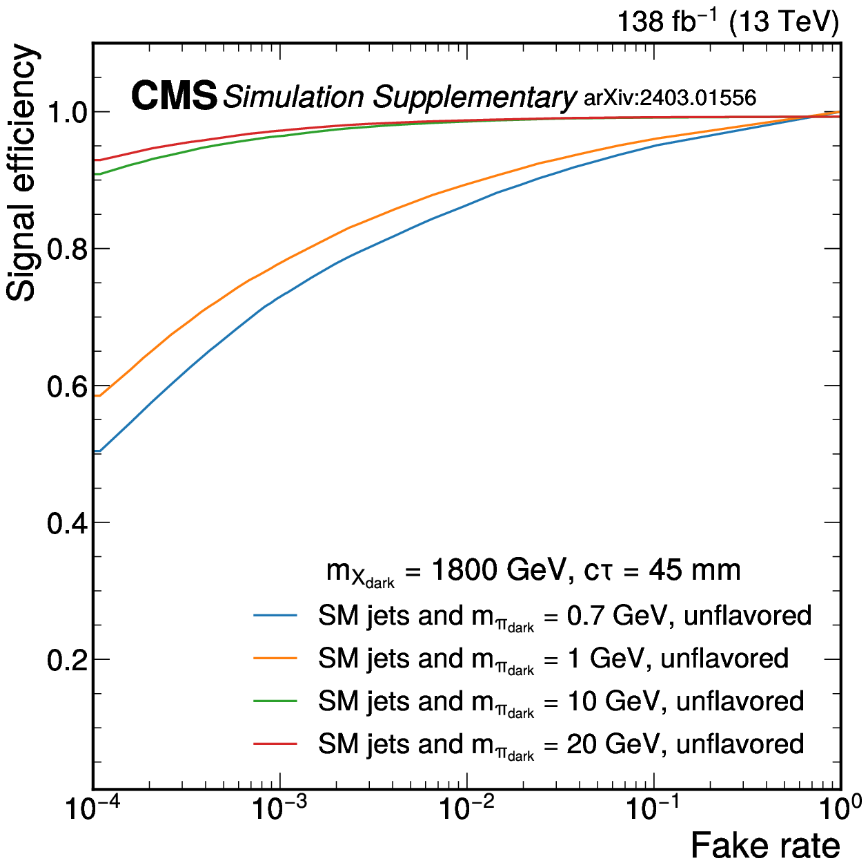
Same distribution shift projected onto different variable axes



Can the GNN be tricked?

Would there be cases where the GNN can be tricked to yield false negatives?

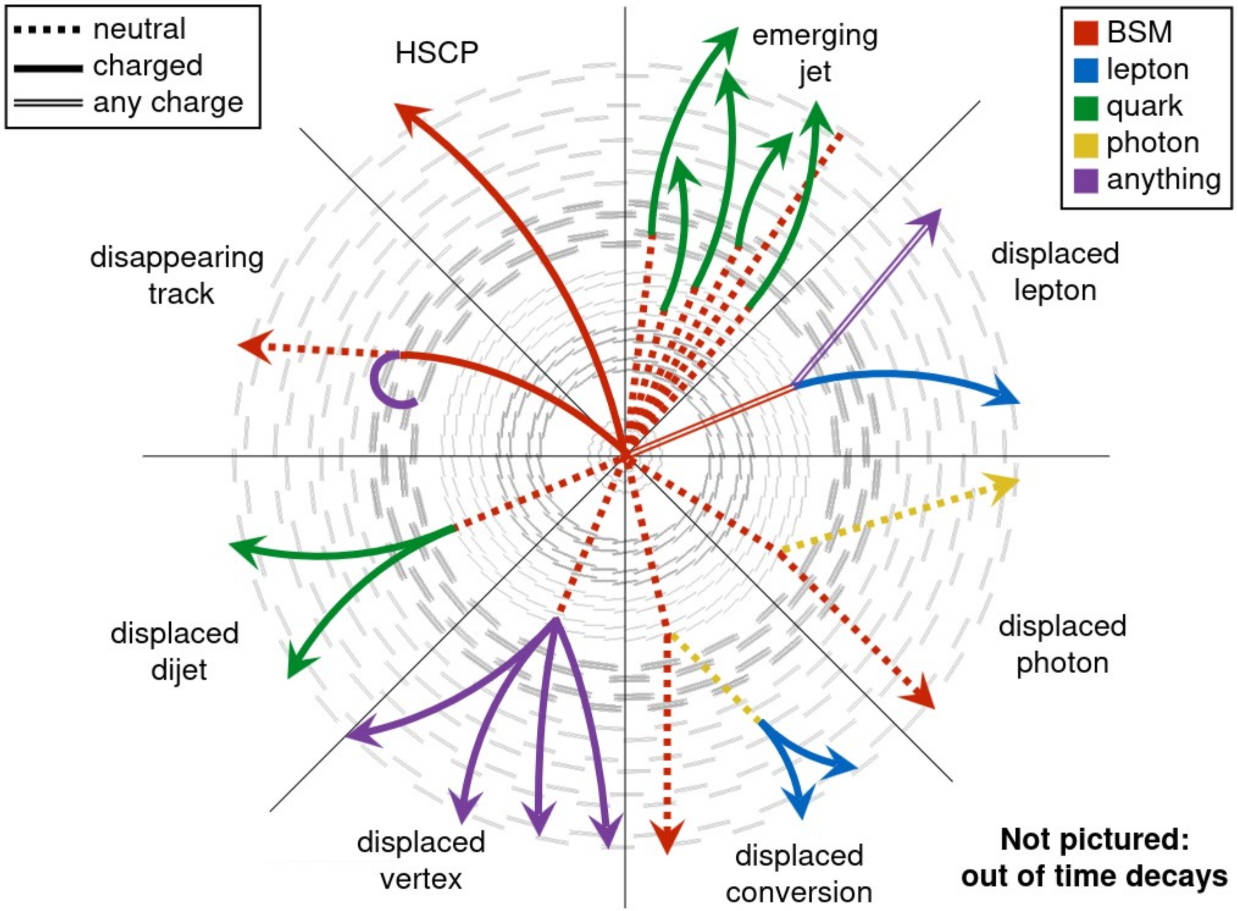
- Comparing the GNN performance on samples not used for training ($m_{\pi,dark}$ =1GeV, unflavored) shows a clear degradation in the GNN performance, even with a clear "emerging jet" signature ($c\tau_{dark}$ = 45mm).
- **Is this a feature or a bug?**
  - For flavored DS models, $m_{\pi,dark}$ models are constrained by flavor-changing neutral current observations. This class of model will likely have a larger $m_{\pi,dark}$, which should be used as a target signature.
  - For a generic BSM signatures, this is not necessarily desirable (The "alignment problem" of using ML tools)



Summary

Summary of EMJ analysis

- Presented current work for searching for the EMJ signatures in CMS
  - Defined and explored variables useful for defining jet displacement measures
  - Explored the distinguishing power of a ML-based jet tagging techniques
- Presented sensitivity using fully data-based method for estimating SM background
  - First look at flavored dark sector sensitivity using CMS data
  - Extending sensitivity of unflavored scenario by mediator mass ~300GeV (~500GeV) compared with previous CMS results
- Results are now officially public, submitted to JHEP



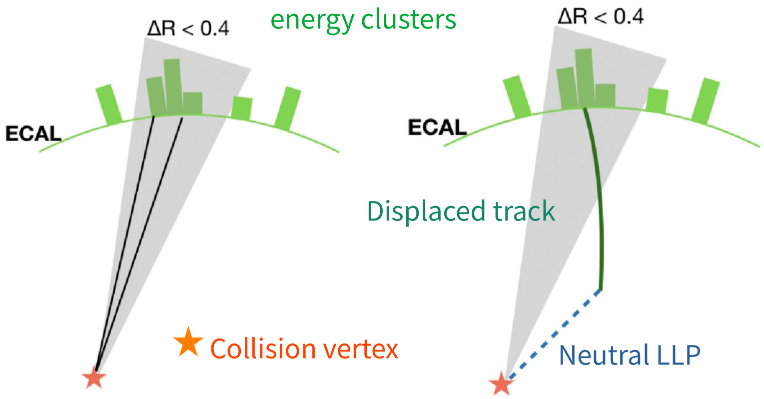
Beyond the EMJ analysis

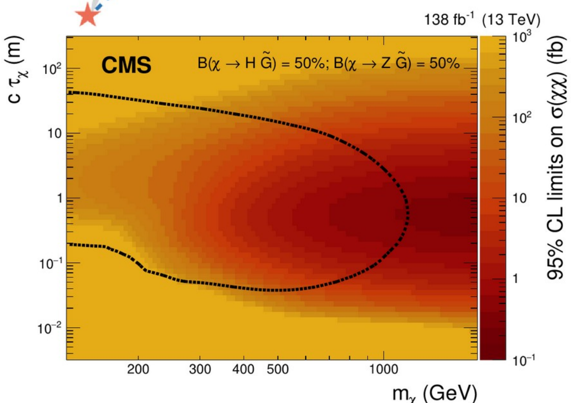
Brief summary of complementary analyses

Phenomenological complements

Trackless Jet

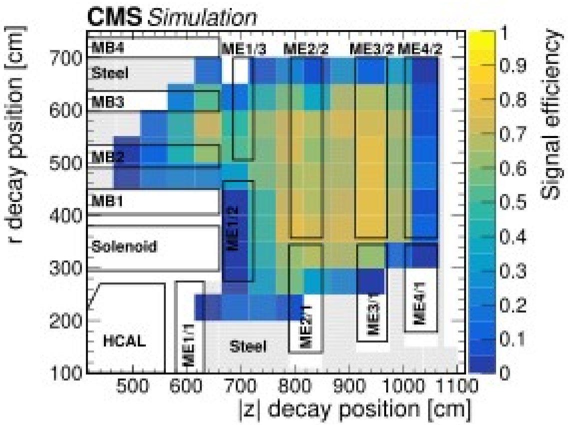
CMS analysis: EXO-21-014 (arXiv:2212.00695)

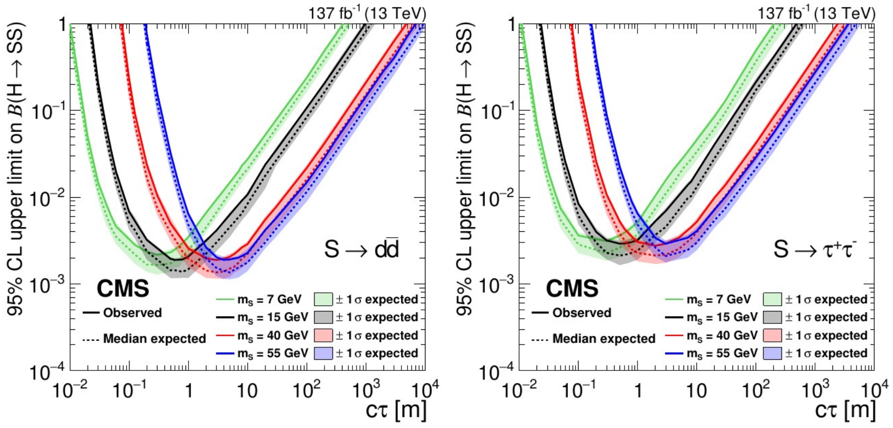




Showers in Muon chambers

CMS EXO-21-008
(arXiv: 2107.04838)



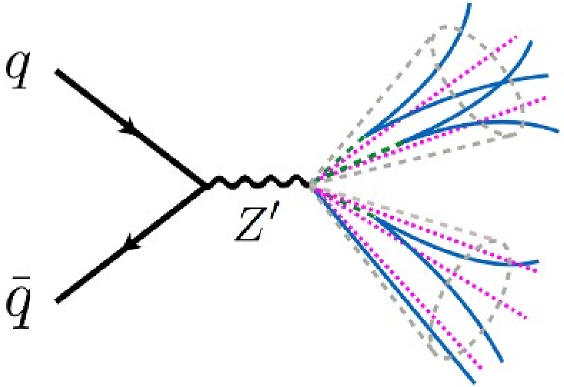


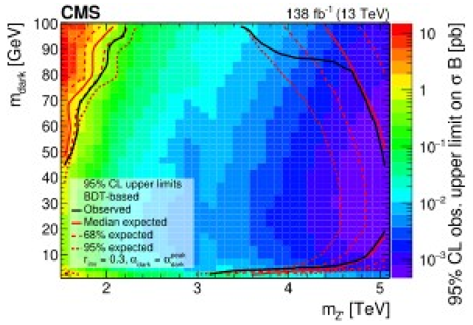
Brief summary of complementary analyses

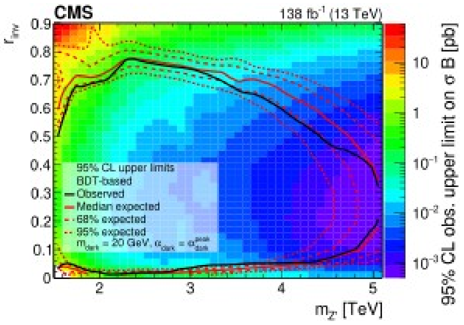
Alternate dark sector scenarios

Semi-visible jets

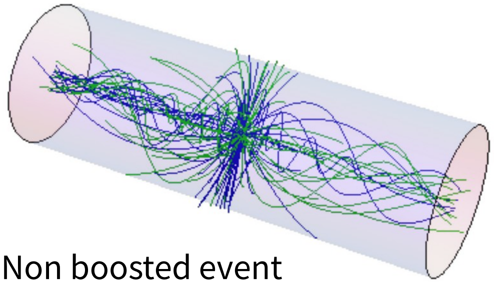
CMS analysis: EXO-19-020 (arXiv:2112.11125)
ATLAS analysis: (arXiv:2305.18037)





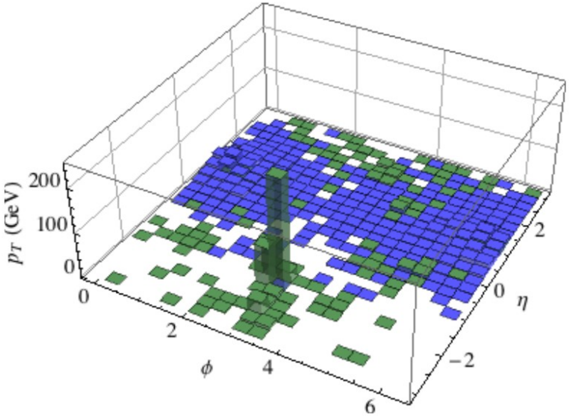


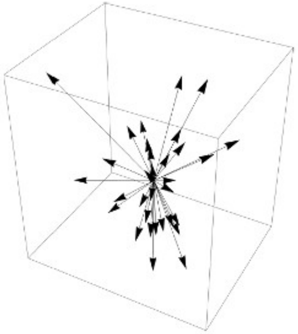
Soft unclustered energy patterns (SUEPs)



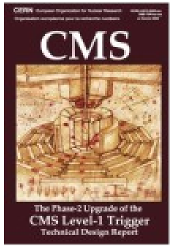
Non boosted event

Boosted event with recoil jet:

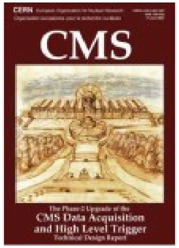




Outlook to CMS Phase-2 upgrade

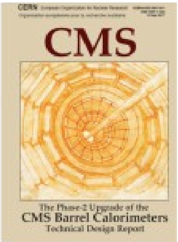


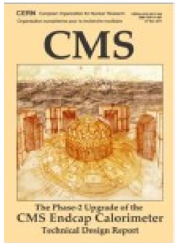
L1-Trigger
https://cds.cern.ch/record/2714892
- Tracks in L1-Trigger at 40 MHz
- Particle Flow selection
- 750 kHz L1 output
- 40 MHz data scouting



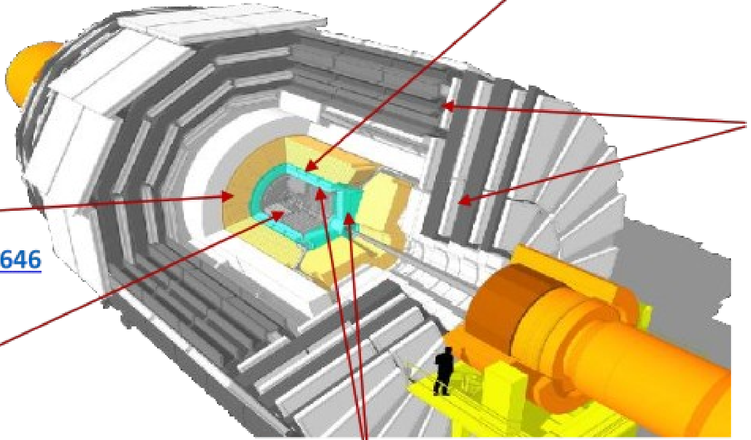
DAQ & High-Level Trigger
https://cds.cern.ch/record/2759072
- Full optical readout
- Heterogenous architecture
- 60 TB/s event network
- 7.5 kHz HLT output

Barrel Calorimeters
https://cds.cern.ch/record/2283187
- ECAL crystal granularity readout at 40 MHz with precise timing for e/γ at 30 GeV
- ECAL and HCAL new Back-End boards

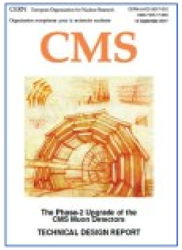


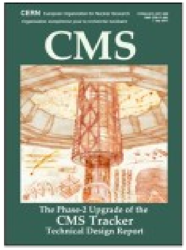


Calorimeter Endcap
https://cds.cern.ch/record/2293646
- 3D showers and precise timing
- Si, Scint+SiPM in Pb/W-SS

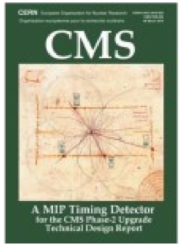


Muon systems
https://cds.cern.ch/record/2283189
- DT & CSC new FE/BE readout
- RPC back-end electronics
- New GEM/RPC $1.6 < \eta < 2.4$
- Extended coverage to $\eta \simeq 3$





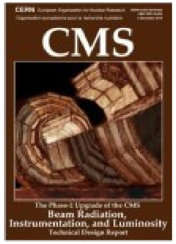
Tracker
https://cds.cern.ch/record/2272264
- Si-Strip and Pixels increased granularity
- Design for tracking in L1-Trigger
- Extended coverage to $\eta \simeq 3.8$



MIP Timing Detector
https://cds.cern.ch/record/2667167

Precision timing with:
- Barrel layer: Crystals + SiPMs
- Endcap layer: Low Gain Avalanche Diodes

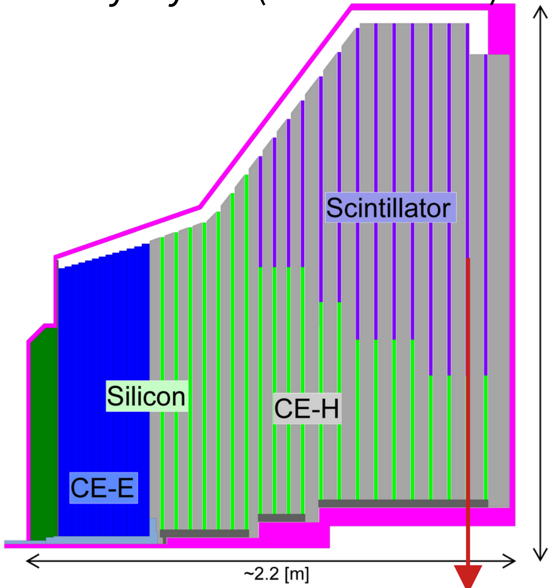
Beam Radiation Instr. and Luminosity
http://cds.cern.ch/record/2759074
- Beam abort & timing
- Beam-induced background
- Bunch-by-bunch luminosity: 1% offline, 2% online
- Neutron and mixed-field radiation monitors

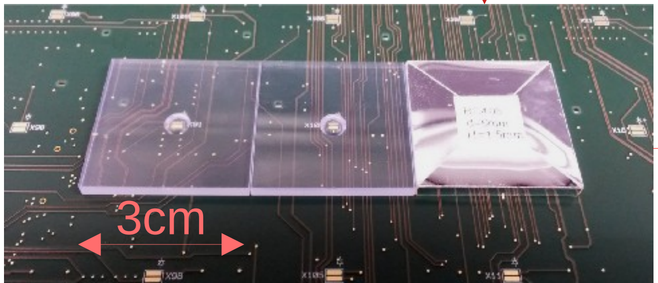


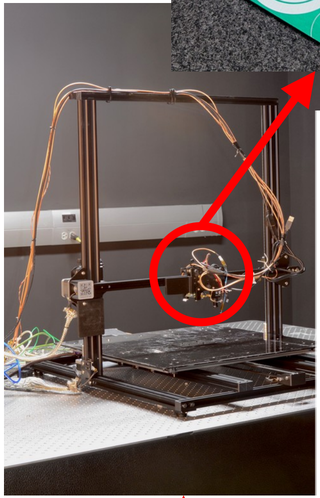
Summary presentation taken from CMS week

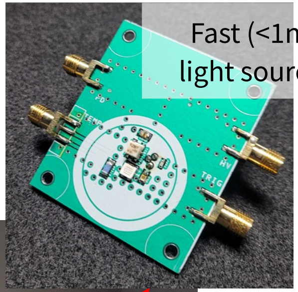
Personal works with HGCAL

HGCAL attempts to greatly boost spatial resolution in end-cap region with high-granularity layout (from CE-TDR)



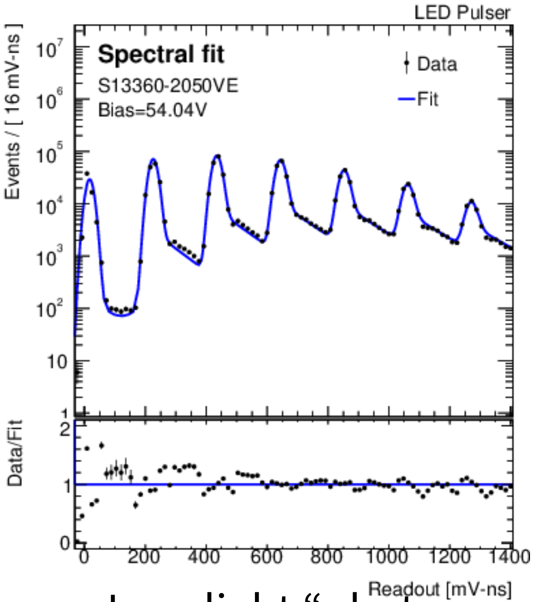




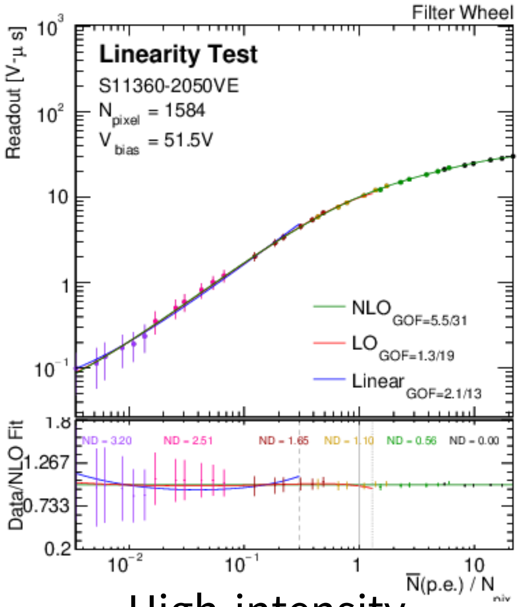


Place under fast light source

Development of automation system to calibrate SiPM across entire dynamic range of SiPM model



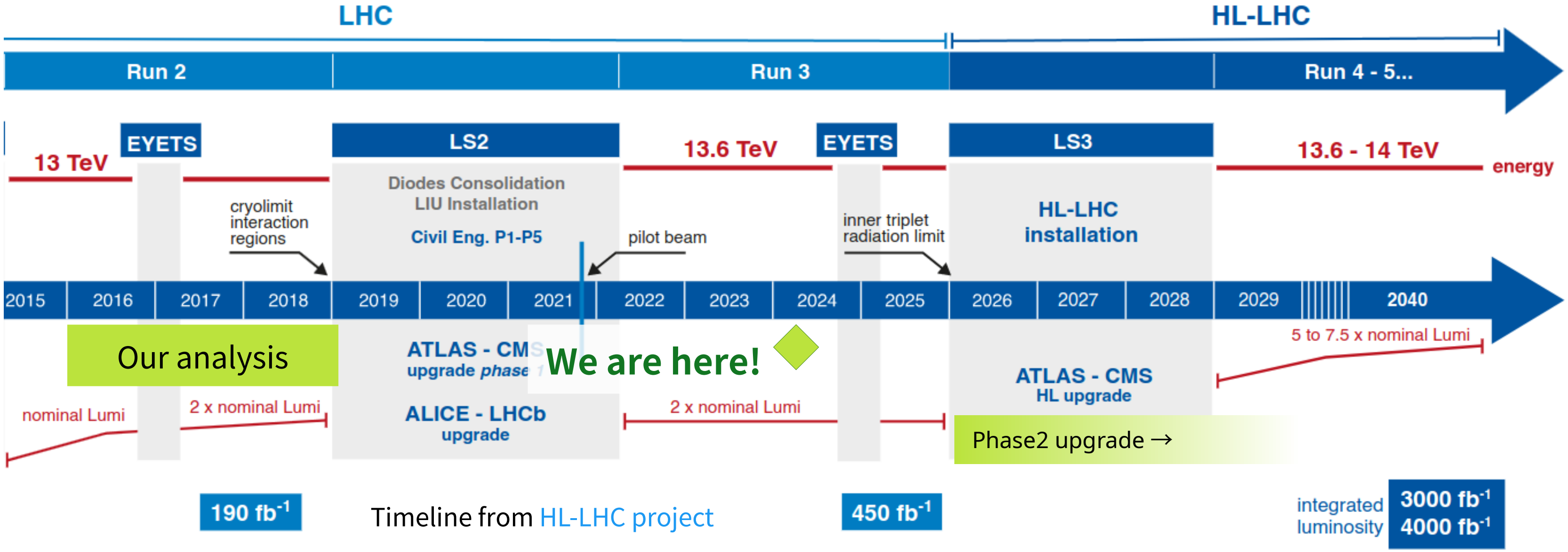
Low-light "photon-counting" mode



High-intensity nonlinear response

Outlooks to future efforts at colliders

- Long-lived particle searches continue to be of great interest!
  - Alternate beyond standard model theories with parameter space previously unconstrained
  - Predicted phenomenological signatures challenge many existing analysis paradigms
- Continued efforts from experiments to enable exotic signature searches:
  - Dedicated object trigger (Run 3 and ongoing)
  - Timing layer for additional particle in-flight information (Phase 2)
  - Higher resolution and coverage many subsystems (Phase 2)



Timeline from HL-LHC project

Thanks for you attention!

Backup slides

More details on the EMJ analysis

Full list of survey EMJ signal models

Unflavored model:

Assuming SU(N_{dark}=3) QCD-like interaction, number of dark fermions N_f=7 with degenerated mass, and couples exclusively to SM down quark. Samples a full grid on the following 3 free parameters:

- m_{dark} [GeV]: 10, 20
- $M_{X,dark}$ [GeV]: 1000, 1200, 1400, 1500, 1600, 1800, 2000, 2200, 2400, 2500
- $c\tau_{\pi,dark}$ [mm]: 1, 2, 5, 25, 45, 60, 100, 150, 225, 300, 500, 1000

Flavor-aligned model: Assuming SU(N_{dark}=3) QCD-like interaction, number of dark fermions N_f=3 with degenerate mass, and couples with SM down-type quark (d, c, b) with a diagonal Yukawa matrix with common term κ_0, the longest-lived lifetime and we can calculate this as:

$$0.761309\kappa_0^{-4}\left(\frac{1\mathrm{TeV}}{m_X}\right)^4\left(\frac{m_{\pi_{\mathrm{dark}}}}{1\mathrm{GeV}}\right)^3$$

We scan over 3 free parameters: m_{dark}, $M_{X,dark}$, κ_0, such that $c\tau_{\pi,dark,max}$ falls on the following grid values:

- m_{dark} [GeV]: 6, 10, 20
- $M_{X,dark}$ [GeV]: 1000, 1200, 1400, 1500, 1600, 1800, 2000, 2200, 2400, 2500
- $c\tau_{\pi,dark}$ [mm]: 5, 25, 45, 100, 500 (κ_0=1)

Generation for EMJ samples using pythia can be found here: https://gitlab.cern.ch/cms-emj/emj-production

CMS MINIAOD equivalent objects

- HLT trigger paths:
  - JetHT datastream@2016 HLT_PFHT900_v* | HLT_PFJet450_v*
  - JetHT datastream@2017, 2018, HLT_PFHT1050_v*
  - SinglePhoton datastream@2016 HLT_Photon165_HE10_v*
  - SinglePhoton datastream@2017, 2018 HLT_Photon200_v*
- Primary Vertex collection: "`slimmedPrimaryVertices`"
  - `IsGood && !isFake()`
- Tracks collection (extracted from "`packedPFCandidate`" collection)
- AK4 Jets "`slimmedJets`"
  - `JetID == 1`
  - `DeepFlavor` variable for b jet tagging and distribution fitting

Background estimation – Scale factor details (1)

Consider all background events with 4 jets of interest, each jet having independent probability ϵ_j of being mistagged as an EMJ. The fraction of jets with N EMJ-tagged jet P(N), can be calculated by combinatoric:

$$P(0) = \prod_j (1-\epsilon_j)$$

$$P(1) = \sum_i \left(\epsilon_i \prod_{j\neq i} (1-\epsilon_j) \right)$$

$$P(2) = \frac{1}{2!} \sum_i \epsilon_i \left(\sum_{j\neq i} \left(\epsilon_j \sum_{k\neq i,j} (1-\epsilon_k) \right) \right)$$

$$P(3) = \frac{1}{3!} \sum_i \epsilon_i \left(\sum_{j\neq i} \epsilon_j \left(\sum_{k\neq i,j} \epsilon_k \left(\prod_{l\neq i,j,k} (1-\epsilon_l) \right) \right) \right)$$

$$P(4) = \frac{1}{4!} \sum_{i\neq j\neq k\neq l\ldots} \epsilon_i \epsilon_j \epsilon_k \epsilon_l = \prod_i \epsilon_i$$

- Factors of (1/n!) appear from the use of an unordered sum ($\Sigma_{i\neq j}$ instead of something like $\Sigma_{j>i}$)
  The use of unordered sum will be important later
- If the CR/SR comparison of interest uses the N_{EMJ}=0 and $N_{EMJ}\geq 1$, then the scale factor of interest will be calculated as:

$$SF = \frac{P(1)+P(2)+P(3)+P(4)}{P(0)} \sim \sum_j \epsilon_j$$

Background estimation – Scale factor details (2)

Since our control region of interest also has 1 least 1 EMJ tagged jet, the calculation from the previous page should has take a subset of conditional combinatorics. Let us label the EMJ-tagged jet index as T, and the fraction of events with N EMJ-tagged jets as Q(N)

$$Q(0) = 0$$

$$Q(1) = \epsilon_T \left(\prod_{i \neq T} (1 - \epsilon_i) \right)$$

$$Q(2) = \frac{1}{2!} \epsilon_T \left(\sum_{i \neq T} \left(\epsilon_i \sum_{j \neq T, i} (1 - \epsilon_k) \right) \right)$$

$$Q(3) = \frac{1}{3!} \epsilon_T \left(\sum_{i \neq T} \epsilon_i \left(\sum_{j \neq i, T} \epsilon_j \left(\prod_{k \neq i, j, T} (1 - \epsilon_k) \right) \right) \right)$$

$$Q(4) = \frac{1}{4!} \epsilon_T \sum_{T \neq i \neq j \neq k \ldots} \epsilon_j \epsilon_k \epsilon_l$$

- Unordered sum allows us to quickly extract the subset of combinatorics where the T-th jet is EMJ tagged.
- Since the CR/SR comparison of interest uses the N_{EMJ}=1 and $N_{EMJ} \geq 2$, the scale factor of interest will be calculated as:

$$SF = \frac{Q(2) + Q(3) + Q(4)}{Q(1)} \sim \frac{1}{2} \sum_{j \neq T} \epsilon_j$$

Background estimation – key requirements

In the calculations of SF, we have only labeled mistag rate as ϵ_j for each jet in the event for convenience. In actuality, mistag rate is shown to be a function of the various jet variables (p_T, η, n_{tracks}… etc). The use of simple, unweighted combinatorics when calculating SF is only correct if the follow two assumptions are true:

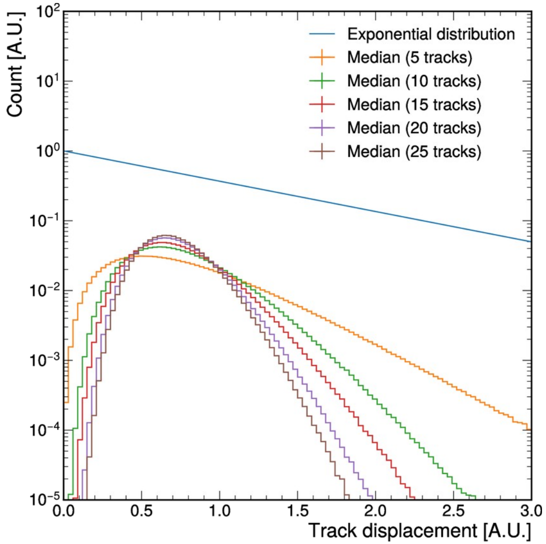
1) The Mistag rate of jets within the same event is uncorrelated up to the parameterization of the mistag rate $\varepsilon(\theta)$
2) The jets parameters used for mistag rate can be correctly assigned for each jet

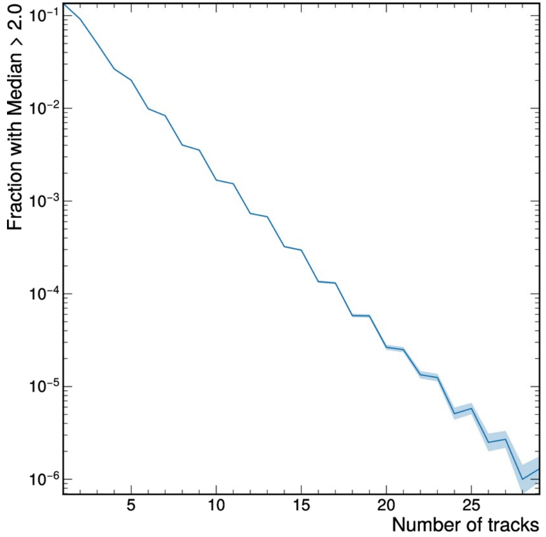
Neither of the assumptions is strictly true for what can be reasonably obtained in the the data-based calculation. We should then carefully evaluate the optimal methods of getting correct results in our calculations, and assign appropriate uncertainties.

Updating the analysis – ε parameterization

Since correlation in jet flavor is an irreducible, physics-based correlation from the hard-scatter process, we opt to always choose to parameterize mistag rate as ε(f,ν) where ν is some jet kinematic variable. The parameter ν is then chosen taking into account the following criteria:

- Which variable best encapsulates the mistag rate correlation?
- Which variable dependence is “physics driven”?
  - Has irreducible factors, flavor dependence?
  - Best encompasses the potential physics differences between the H_T data stream, and the γ-triggered data stream?



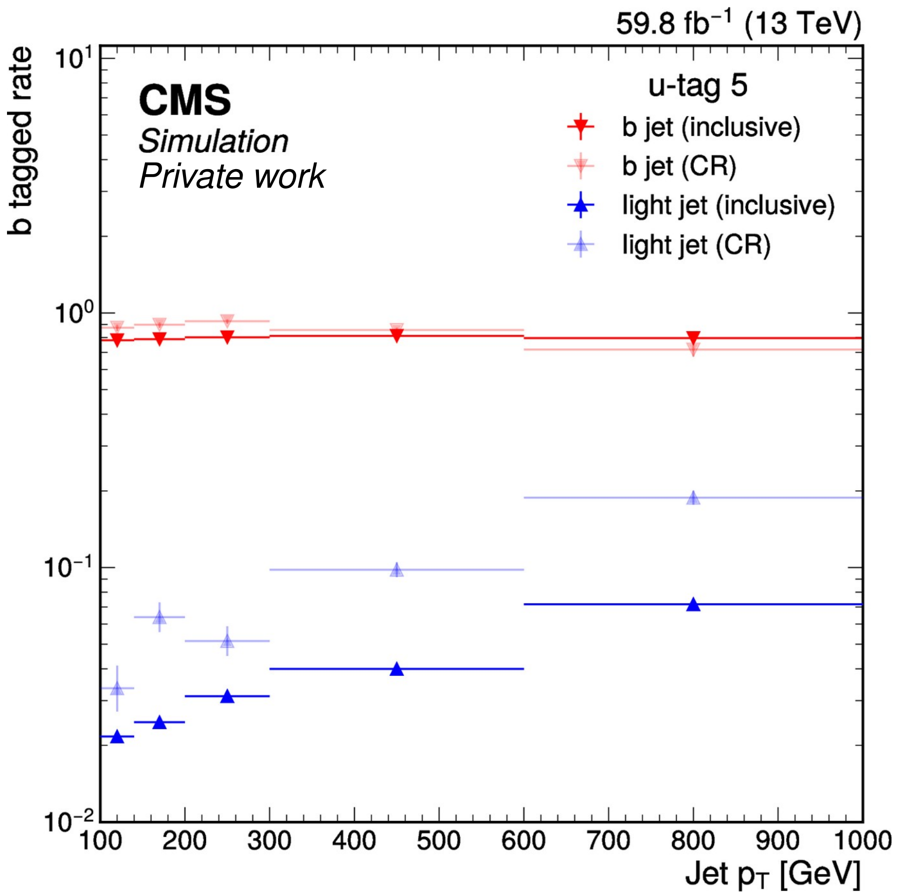


Simple numerical experiment demonstrate the steep n_{track} dependence of u-tag* taggers can be driven purely by the median algorithm (“central median theorem”)

Updating the analysis – jet flavor assignment

The flavor averaged methods only strictly works when the SR and CR has similar b jet fractions. The calculation is known to fail if we attempt a (N_{EMJ}=0) → (N_{EMJ}≥2) SF calculation (b jets typically comes in pairs from gluon splitting). In an attempt to solve this, a per-jet flavor assignment using Bayesian inference with b-tagging result was attempted.

Assuming the underlying flavor being U, and the b tagging results T, we can attempt to calculate P(U|T) from P(T|U) using Bayes theorem, and weigh the scale factor results with an assumed underlying flavor. This attempt ultimately failed, because b-tagging results will have significant shifts in distribution after imposing additional jet-level selections.

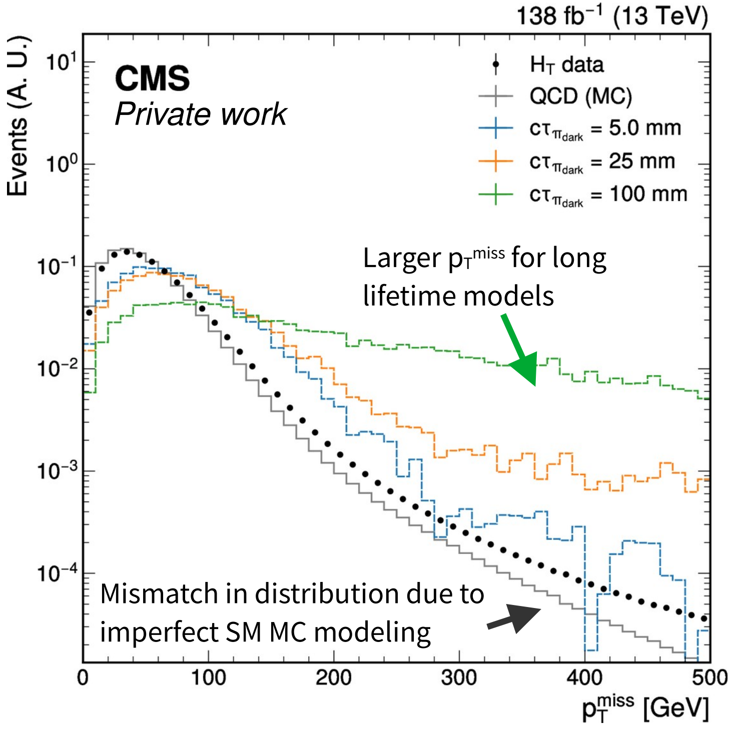


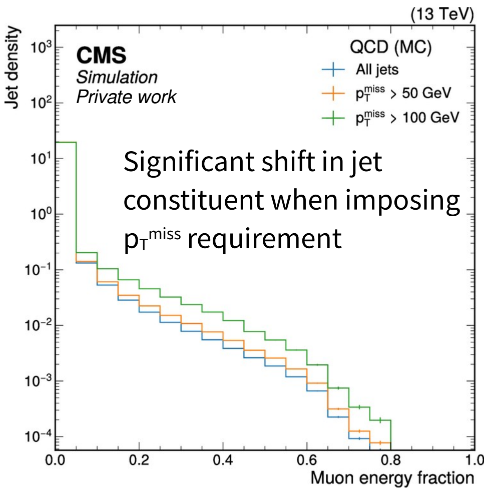
Difference of the b jet tagging rates for b jets and light jets after imposing a 1 EMJ tagging request

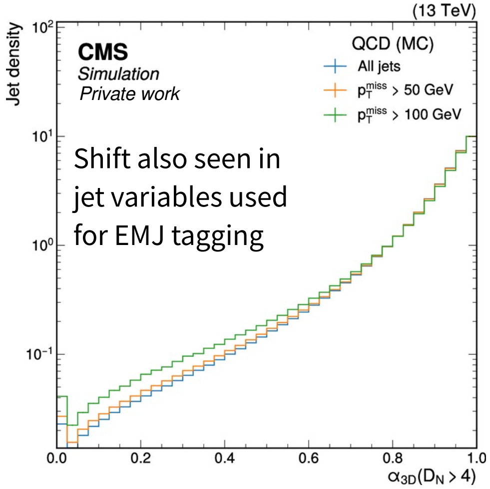
Updating the analysis – p_T^{miss} selection

In the previous analysis, we attempted to boost signal sensitivity using a minimum p_T^{miss} requirements. This was found to significantly shift the jet population, meaning that the uncertainty will be much larger when comparing mistag rates evaluated in γ-triggered data sets.

Ultimately, the limit gain was limited, so we opted to remove this event selections.







Data-based methods – variable choice uncertainty

SF calculation assumes simple combinatorics, and is only strictly correct if we can parameterize ε in arbitrary fine parameters

Most mathematically correct

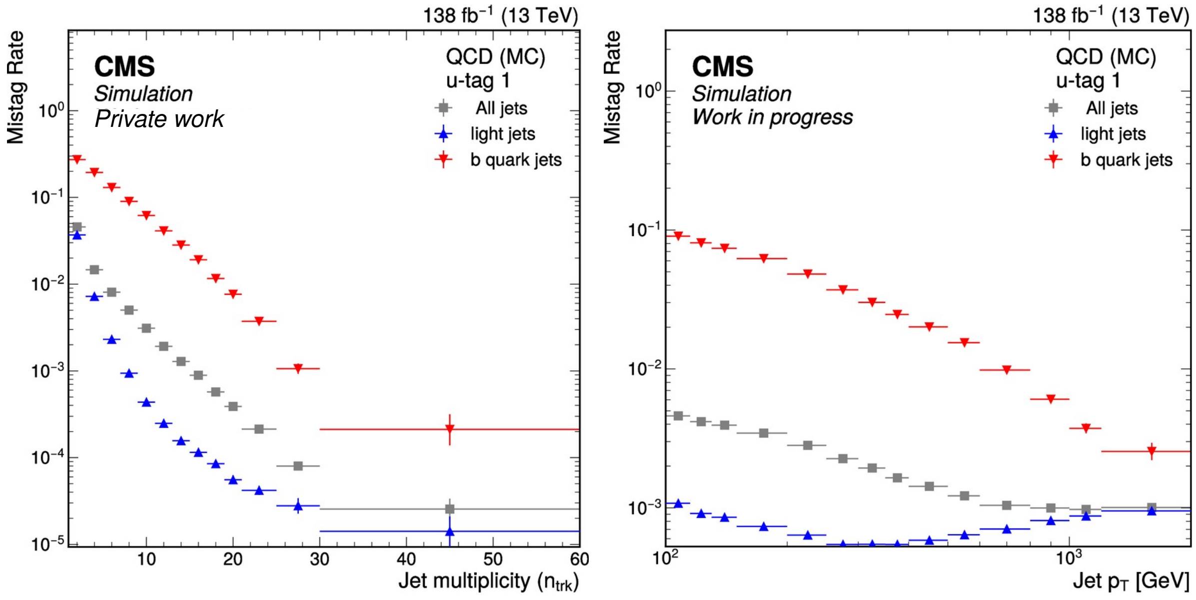
$$\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{truth}}\left(\epsilon^{\mathrm{JetHT|SM}}_{\mathrm{truth}}(\vec{\theta_\infty})\right)$$

$$\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{truth}}\left(\epsilon^{\mathrm{JetHT|SM}}_{\mathrm{truth}}(p_{\mathrm{T}})\right)$$

$$\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{truth}}\left(\epsilon^{\mathrm{SP}}_{\mathrm{truth}}(p_{\mathrm{T}})\right)$$

$$\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{avg.}}\left(\epsilon^{\mathrm{SP}}_{\mathrm{inv.}}(p_{\mathrm{T}})\right)$$

Calculable using just data



Despite the steeper apparent dependence, we choose to parameterize ε in p_T, as it better reflects tagging correlation driven by physics. An uncertainty should be associated with this choice.

Data-based methods – event-level oddities

Most mathematically correct

$$\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{truth}}\left(\epsilon^{\mathrm{JetHT|SM}}_{\mathrm{truth}}\left(\vec{\theta}_{\infty}\right)\right)$$

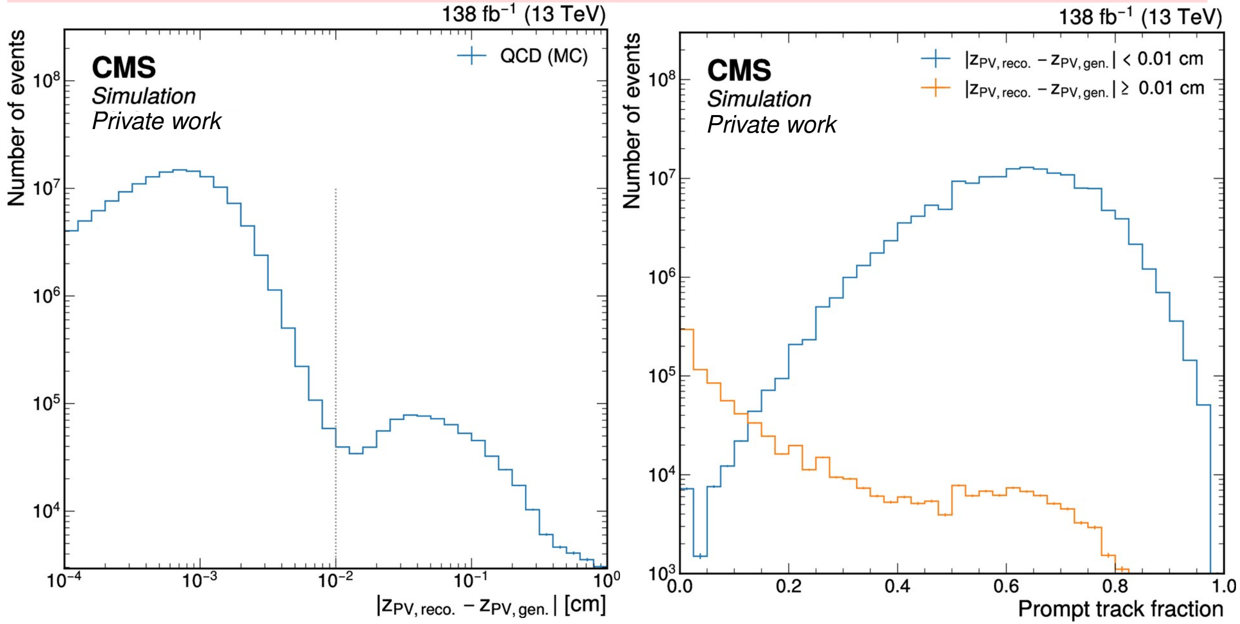
$$\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{truth}}\left(\epsilon^{\mathrm{JetHT|SM}}_{\mathrm{truth}}\left(p_{\mathrm{T}}\right)\right)$$

$$\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{truth}}\left(\epsilon^{\mathrm{SP}}_{\mathrm{truth}}\left(p_{\mathrm{T}}\right)\right)$$

$$\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{avg.}}\left(\epsilon^{\mathrm{SP}}_{\mathrm{inv.}}\left(p_{\mathrm{T}}\right)\right)$$

Calculable using just data

SF calculation assumes simple combinatorics, and is only strictly correct if we can parameterize ε in arbitrary fine parameters



Additional vertex/jet quality parameters are imposed to avoid catastrophic event reconstruction failures where all jets in an event appears “displaced”

Data-based methods – flavor correctness

Most mathematically correct

$$\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{truth}}\left(\epsilon^{\mathrm{JetHT|SM}}_{\mathrm{truth}}(\vec{\theta_{\infty}})\right)$$

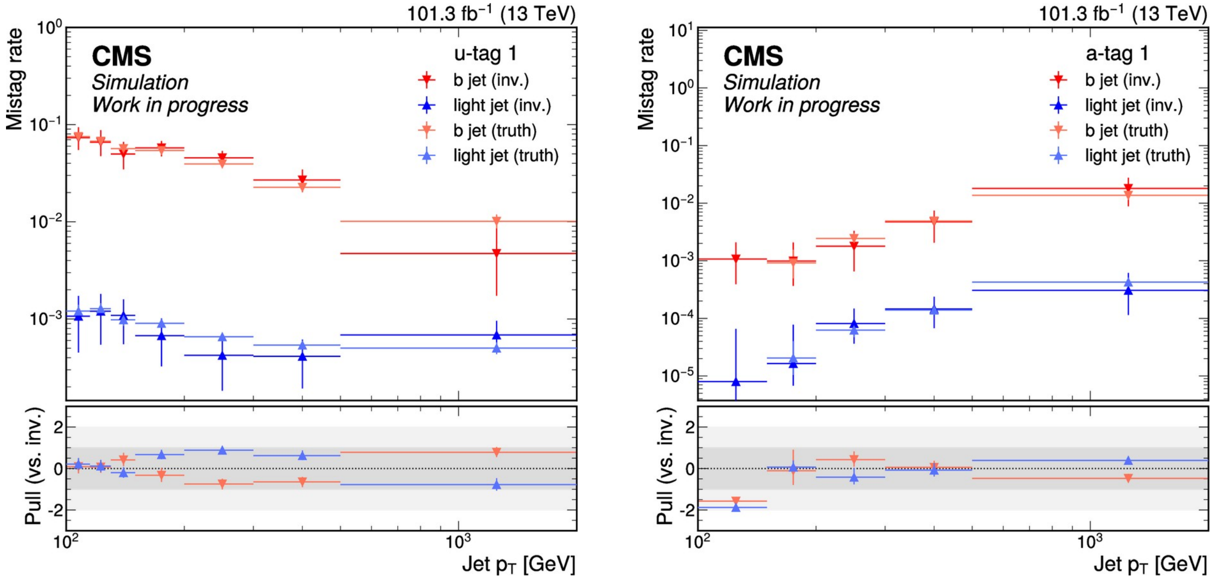
$$\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{truth}}\left(\epsilon^{\mathrm{JetHT|SM}}_{\mathrm{truth}}(p_{\mathrm{T}})\right)$$

$$\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{truth}}\left(\epsilon^{\mathrm{SP}}_{\mathrm{truth}}(p_{\mathrm{T}})\right)$$

$$\mathrm{Est}^{\mathrm{JetHT}}_{\mathrm{avg.}}\left(\epsilon^{\mathrm{SP}}_{\mathrm{inv.}}(p_{\mathrm{T}})\right)$$

Calculable using just data

Flavor information is not directly available in data: there can be errors in flavor dependence evaluation



MC events are used to estimate potential differences, where we can compare direct and indirect flavor computations.

Track modeling uncertainty

While MC is used to guide the analysis choices, the final analysis results will use a fully data-based approach. This means that discrepancies between data and MC samples are less critical for the evaluation of background contamination, but potential impacts to calculation routines should be carefully evaluated

SM background

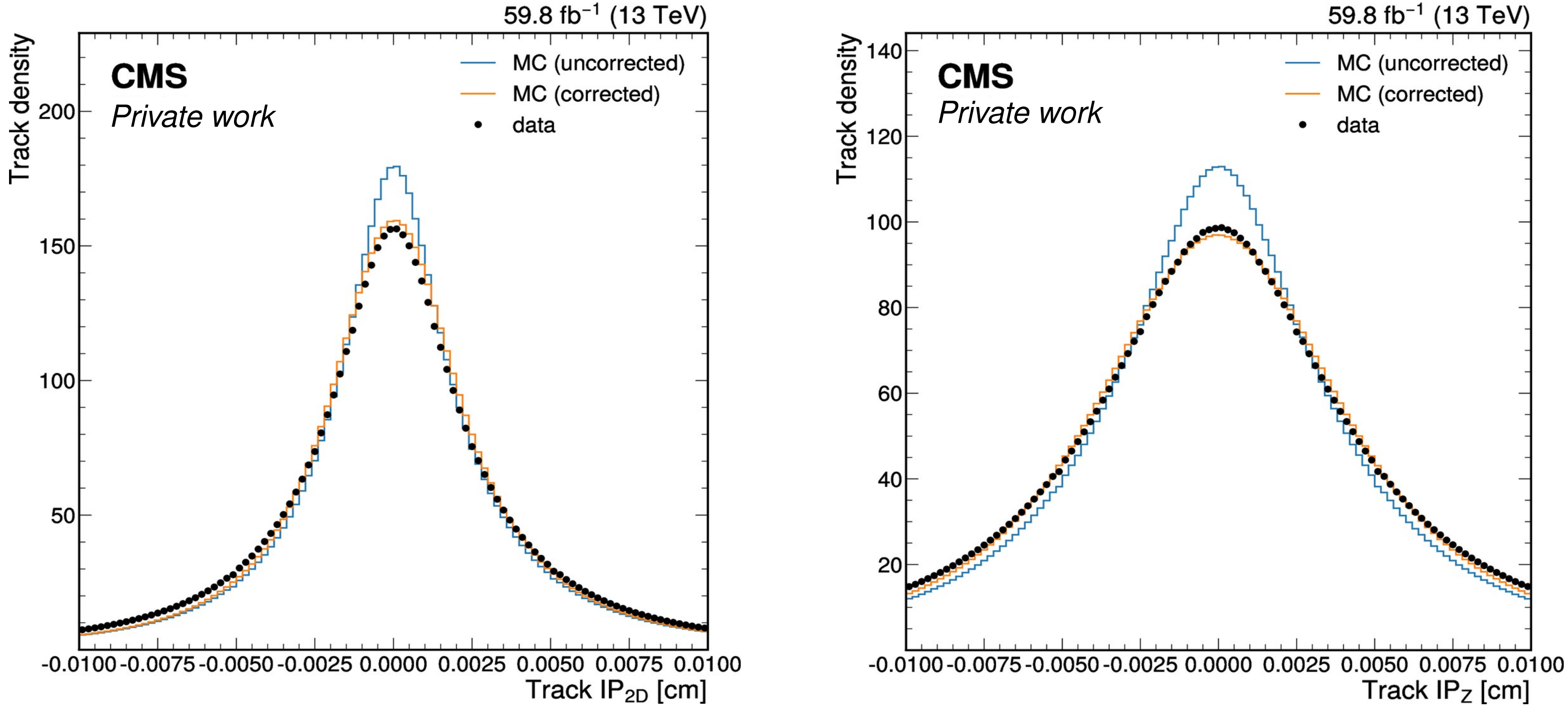
- Detector effect discrepancies (resolutions, efficiency)
  - Correctness is handled by the data-based estimate
  - Final selection cut values might be suboptimal
  - No additional actions will be done for a search analysis
- Physics-driven uncertainty (missing physics in MC set)
  - Does this introduce tagging correlations? If no, this will be largely handled by the data-based estimate
  - Non-QCD processes expected to contribute <0.1 event for all cut sets. No additional action will be taken

Signal events

- How much does it change the signal selection efficiency?
- Can we give estimate such discrepancies?
  - This is usually handled by the the CMS physics object groups
  - The only nonstandard discrepancies are the track displacements measures

Track modeling – small displacement effect

For tracks with small displacements (<10^{-1} cm), we expect that the tracking algorithm has nearly 100% reconstruction efficiency, the differences between data and MC are mainly driven by track/vertex resolution effects. This is what is used as an analysis uncertainty presented in the main presentation



Track modeling – large displacement effect

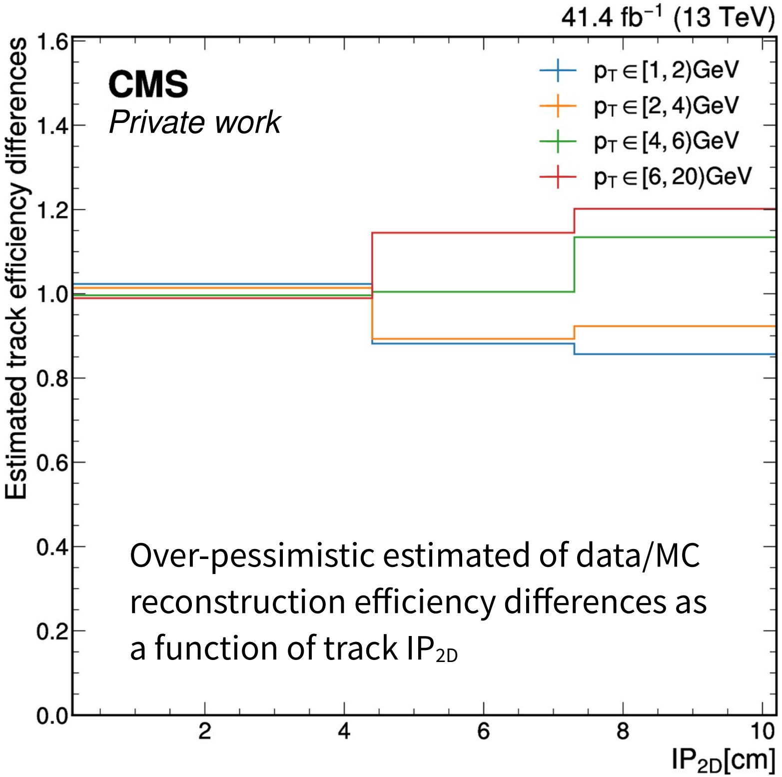
For large displacements effects, two effects may drive data/MC discrepancies:

- Missing physics processes: generation of heavy flavor mesons, or potentially signal effects
  - Data/MC needs to be evaluated in signal-free region (using photon-triggered data stream)
- *Reconstruction efficiency effects*

Reconstruction efficiency is **very** difficult to evaluate in data, we use the normalized IP_{xy} distribution in data/MC and assume:

- Reconstruction efficiency with IP_{xy} <0.1cm is 100%
- Event-level track multiplicity distribution as a function of IP_{xy} is only caused by reconstruction efficiency mismatches
- Perform a track-level reweighting when computing displacement measure
- Signal efficiency was found to **at most** be impacted by 2%, with the typical change being ~0.3%

No additional uncertainties are included in the final calculation



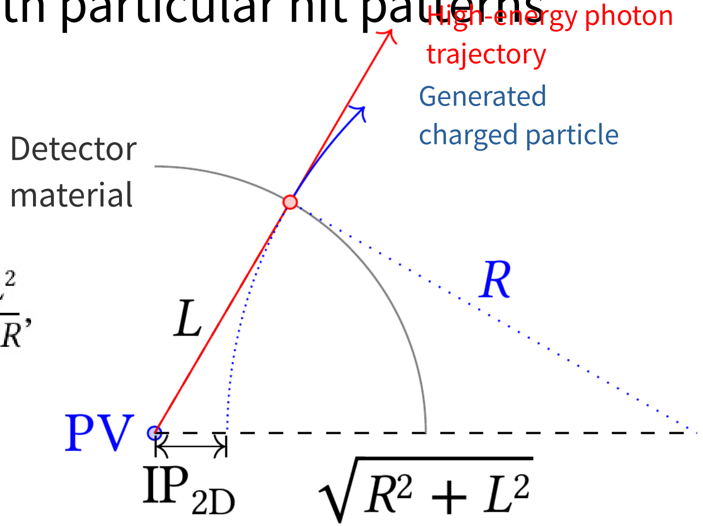
Over-pessimistic estimated of data/MC reconstruction efficiency differences as a function of track IP_{2D}

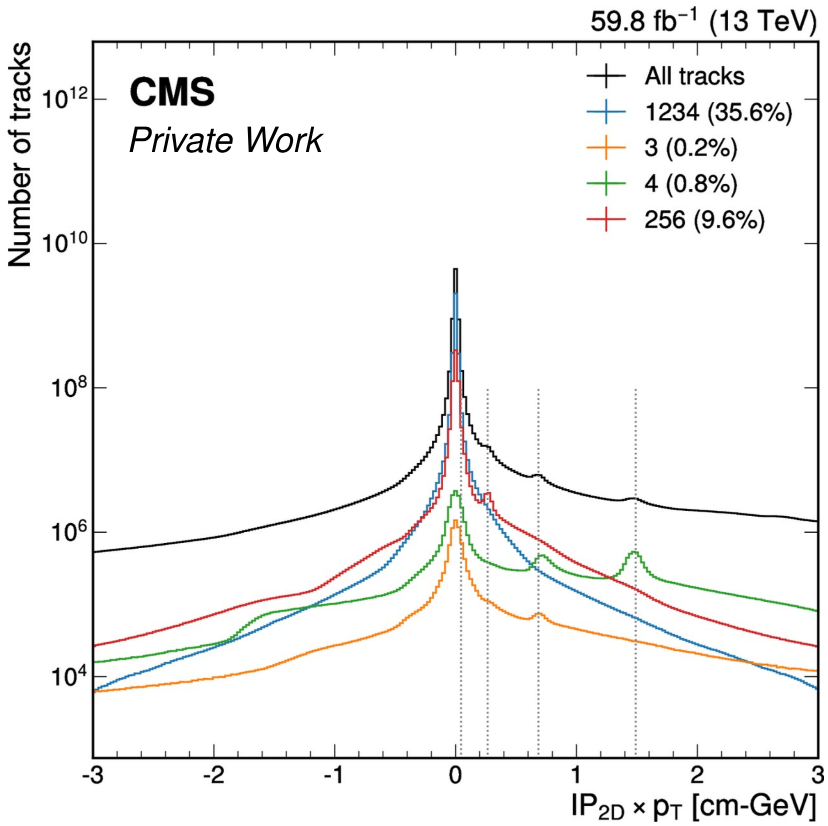
Interesting consequence of material interaction

- Material interaction generates tracks with peaking structures in the $IP_{2D} \times p_T$ spectrum (only on the positive side!)
- Purely geometrically result!
  - Argument is given in the diagram below
  - Peaking features can be isolated by limiting tracks with particular hit patterns

$$\mathrm{IP}_{2D} = \sqrt{R^2 - L^2} - R \xrightarrow{R \gg L} \frac{L^2}{2R},$$

$$\mathrm{IP}_{2D} \cdot p_T \sim \frac{L^2 qB}{2}.$$

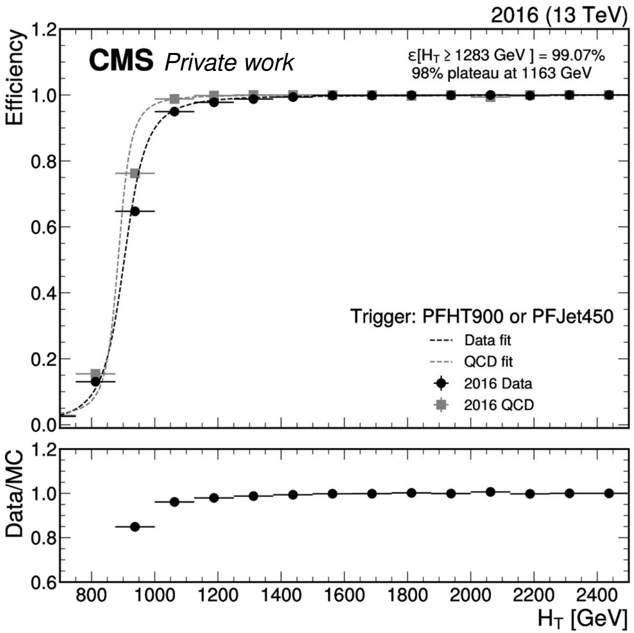


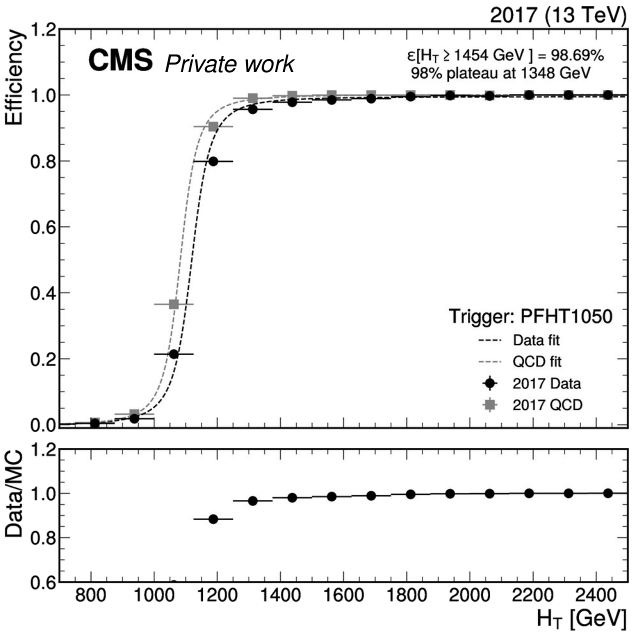


Additional signal systematics calculated

- Relative trigger efficiencies calculated compared to HLT_Mu50
- Evaluated data/QCD MC difference evaluated per-data collection era

- MC track reconstruction modeling
- Luminosity
- **Trigger efficiency**
- Pileup
- Jet energy corrections and resolutions
- PDF/α_S





Additional signal systematics calculated

- MC track reconstruction modeling
- Luminosity
- Trigger efficiency
- Pileup
- Jet energy corrections and resolutions
- PDF/α_S

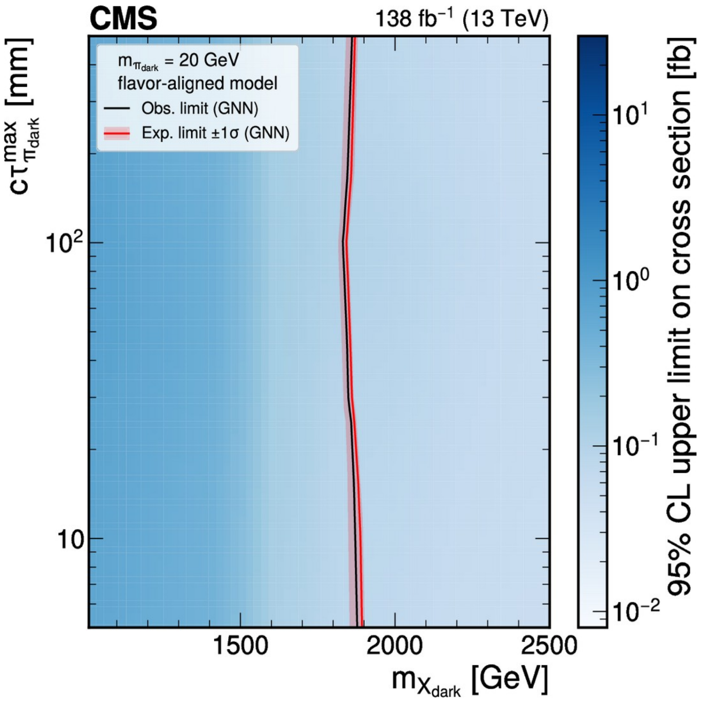
- Other effects uses POG provided correction values
- Shift kinematic/event weights by $\pm 1\sigma$, and compare the variation in final event count
- Summary of signal systematics below (units in %) model-agnostic/GNN

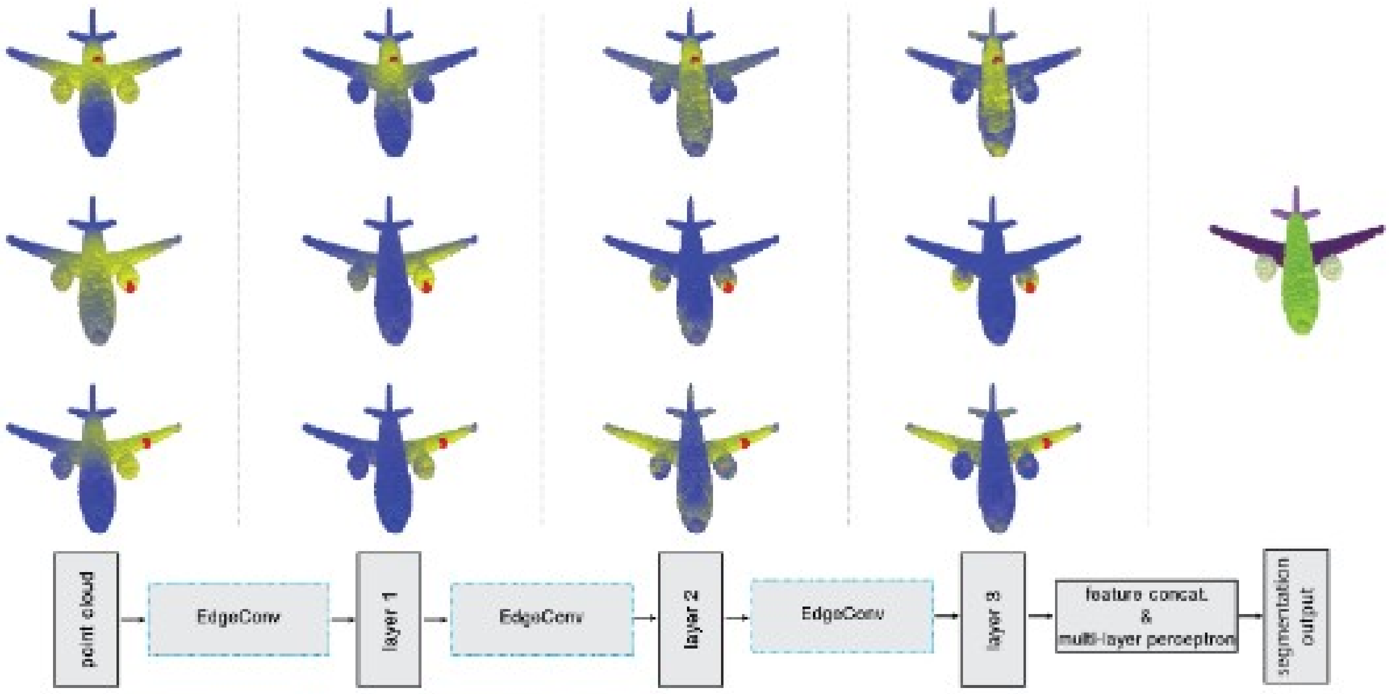
	Unflavored model		**Flavor-aligned model**	
	mean	std.	mean	std.
MC track modelling	0.2/0.3	0.3/0.8	1.4/0.5	1.8/0.6
Pileup reweighting	1.6/0.9	1.4/0.8	1.4/1.0	1.2/0.9
JEC	1.0/1.3	1.3/0.9	0.8/0.7	0.7/0.4
JER	0.3/0.2	0.4/0.3	0.3/0.2	0.3/0.1
Trigger efficiency	0.3	0.1	0.3	0.1
Luminosity	1.8	0.6	1.8	0.6
PDF variation	<0.1	<0.1	<0.1	<0.1
Matrix element scale	<0.1	<0.1	<0.1	<0.1

More discussion on sensitivity (Flavor-aligned)

Common Question: why is the sensitivity of the flavor-aligned "better" at long lifetimes and poorer at the center of the volume tracker?

- Recall that tagging feature aimed at displaced track multiplicity, with "displaced" set at around b-meson scale
- $c\tau_{max,dark}$ is parameterized by the longest lifetime dark meson, b-meson producing dark mesons have lifetime 10^{-4} compared with this:
  - There is tension between longest lifetime SM products being generated outside the tracker volume, and b-meson producing signatures generating distinguishable displaced signatures
- Similar sensitivity curve using GNN tagging indicates that the model-agnostic feature is not missing any simple features that can boost sensitivity.
- For this analysis, we have demonstrated the flatter dependence on coupling strength.
  - *Is it worth it so scan a wider region in parameter space?* That would be a good question for Run-3 analyses with newer modelling



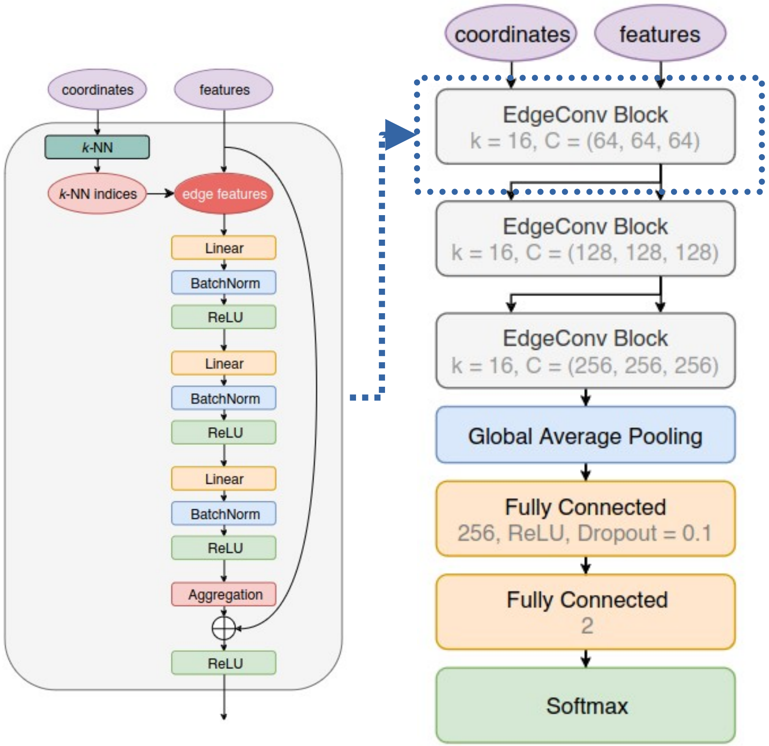


Original use-case for GNNs: 3-dimensional object classification (arXiv:1801.07829)

More details on GNNs

Detailed description of the GNN topology

- A “edge convolution” layer graph encodes spatial “point-like” information into a dense “image-like” information suitable for CNN inference†
- Suitable for jet classification, as jets are a sparse list of objects belonging the same cluster
- Now serving as the ParticleNet b jet tagger used for standard b tagging in Run 3 @ CMS

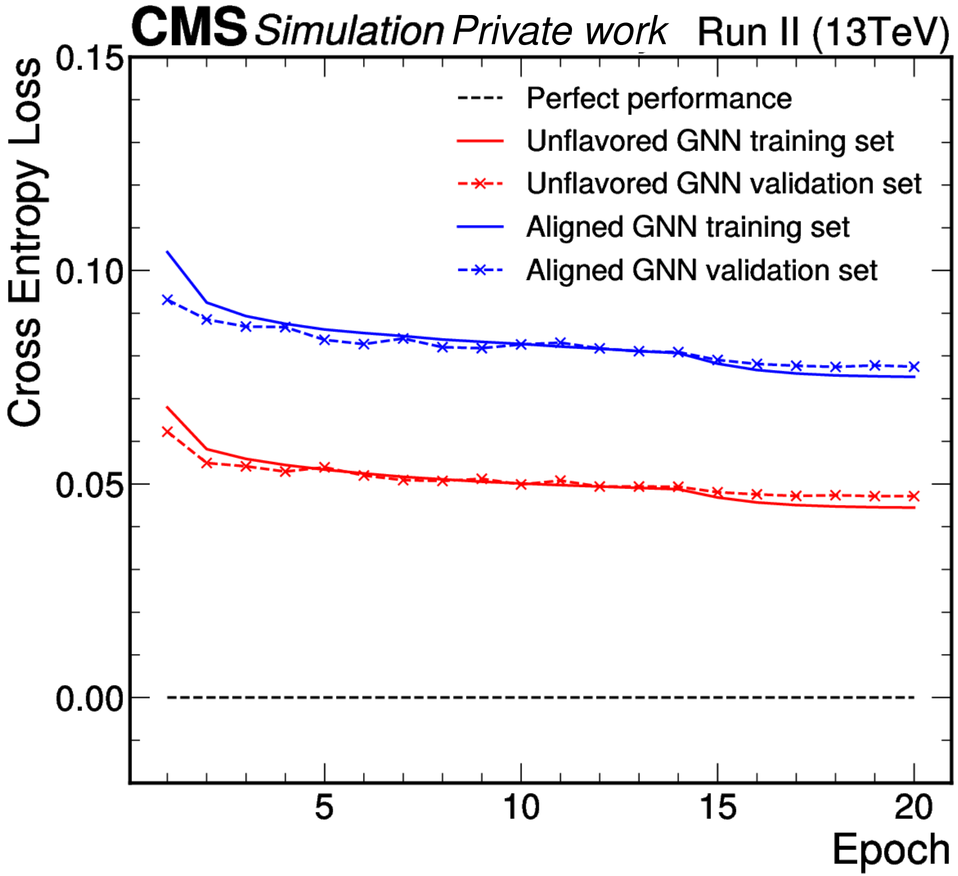


Topology of GNN network used for jet tagging. (From arXiv:1902.08570)

† “Dynamic Graph CNN for Learning on Point Clouds”, arXiv:1801.07829

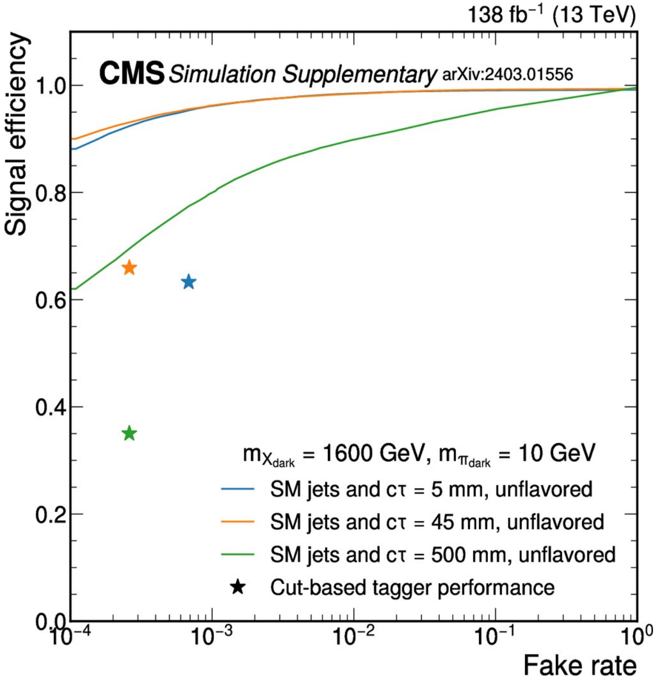
Training and validating the GNN

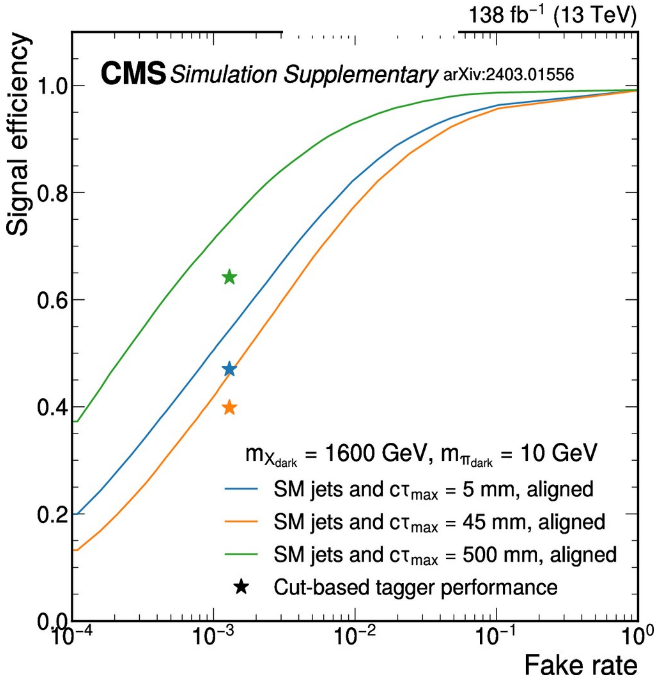
1) Jets-track clustering is ran with R_{cut}<0.8 association scheme for events passing trigger requirements in QCD and signal samples
2) Jets classified using truth information as unflavored signal/flavor-aligned signal/SM jets
   - All signal samples of the same model are grouped into the same class of jets together
3) QCD jets selected to match the number of signal jets used
4) 60% of used for training, 15% used for validation, 25% used for calculate model performance



Comparing the GNN performance

- Comparing the ROC curve, the GNN performance is better than the cut-based taggers
- Performance varies with lifetime:
  - Unflavored model: significant degrading for long lifetime (expected)
  - Flavor-aligned model: more uniform performance, "best" performance is towards longer section (see discussion regarding flavored model limit sensitivity)

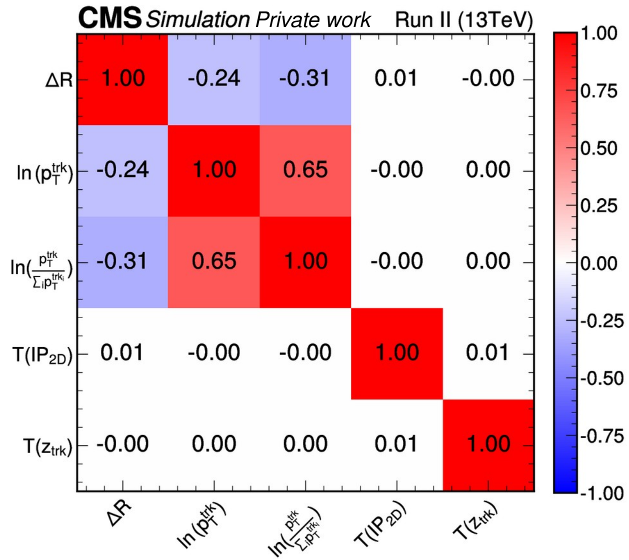




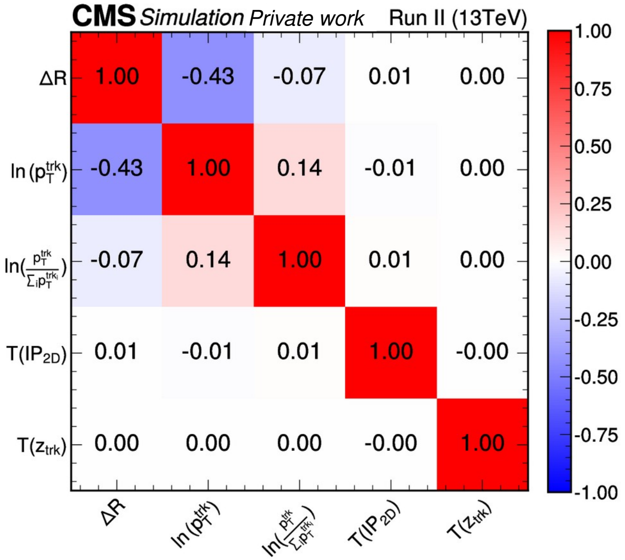
Checking GNN input

Comparison of variable correlation can also serve to distinguish what features may be important to the GNN.
Large correlation differences can be an indication that these variables can be used for distinguish jet types

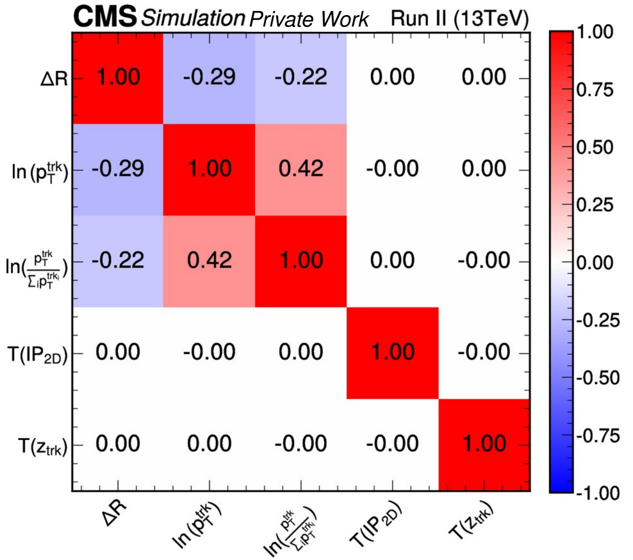
- p_T fraction and angular width driven by physics processes:
  Hadronic showing v.s. DS showering v.s. DS→SM showering



SM jets in QCD MC



Unflavored EMJ



Flavor-aligned EMJ