Casting a ParticleNet to catch dark showers

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based on **arXiv:2006.xxxxx**

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TRR 257 - Particle Physics Phenomenology after the Higgs Discovery

Strongly interacting dark sectors

- **What if the dark sector resembles QCD?**
  $\Rightarrow$ DM could be meson/baryon in confining dark sector

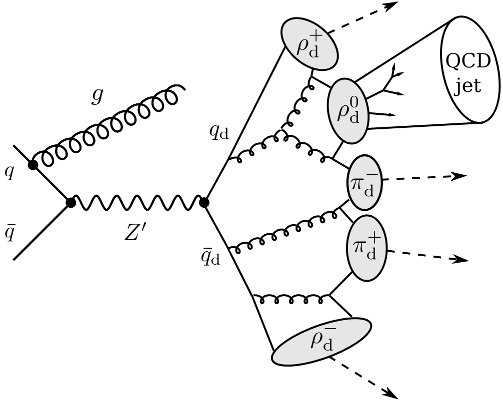
- Cosmology: relic density from interactions within dark sector
  Hochberg et al., 1411.3727
- Astrophysics: possible resolution of DM small-scale problems (SIDM)
  Hochberg et al., 1402.5143

- **Novel LHC phenomenology**:
  - dark showers
  - semi-visible jets
  - emerging jets
  - displaced vertices (Patrick's talk)

Cohen et al., 1707.05326
Schwaller et al., 1502.05409

Dark showers at the LHC

- Benchmark: dark $SU(3)$, dark pion DM, consistent cosmology
  EB et al., 1907.04346
- Production of dark quarks at the LHC via heavy vector mediator
- Shower and hadronisation in dark sector (PYTHIA HIDDEN VALLEY)

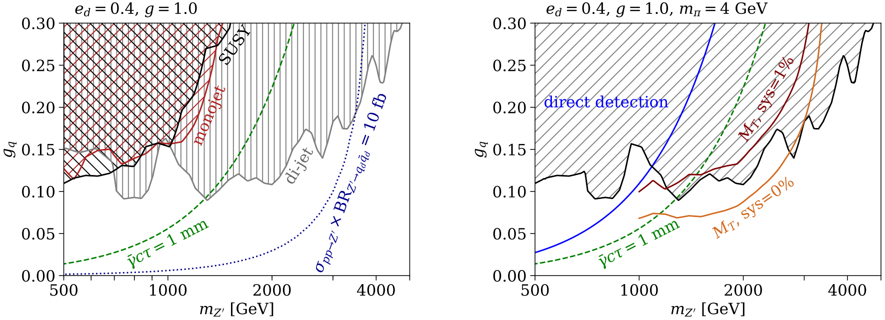


- 10 - 20 dark mesons in an event
- Most escape the detector as $\not{E}_T$
- ρ_{d}^0 decay to visible jets

⇒ **Semi-visible jets**

$m_{Z'} \sim \mathcal{O}(\mathrm{TeV})$, $m_\pi \sim m_\rho \sim \mathcal{O}(\mathrm{GeV})$

Existing and prospective LHC searches



Two classes of events:

- If one dark shower stays invisible:
  ⇒ Limits from existing monojet and SUSY searches
- If both dark showers become partly visible:
  ⇒ Prospective semi-visible jet search: bump hunt in M_T for small $\Delta\phi$

Cohen et al., 1707.05326

improves existing limits only under optimistic assumptions

Can we do better with machine learning?

- Proposed semi-visible jet search does not use jet substructure
- Semi-visible jets differ substantially from QCD

⇒ **Train a neural network classifier to distinguish dark showers from QCD**

- Wide range of supervised and unsupervised ML approaches for jet classification, most commonly benchmarked on top tagging
  Kasieczka et al., 1902.09914
  For example convolutional neural networks on jet images

- Dark showers more similar to QCD than tops: varying number of light dark mesons with varying missing energy between

Dynamic Graph CNN

- Originally from computer vision — Wang et al., 1801.07829
- Recently used as jet tagger: ParticleNet — Qu, Gouskos, 1902.08570

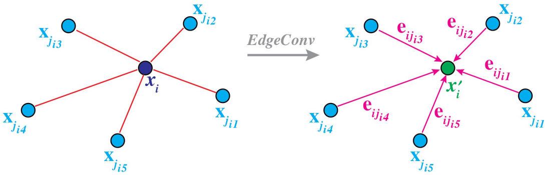
Jets as point clouds

- Every constituent is a point in a high-dimensional feature space
- No ordering

Edge convolution

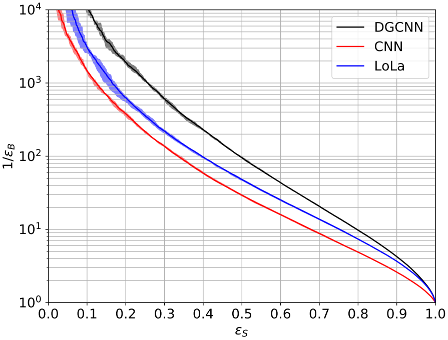
- For each point construct graph of k nearest neighbours
- Carry out convolution over edges (features of pairs of neighbours)
- $x_i' = \frac{1}{k}\sum_{j=1}^{k} h_\Theta(x_i, x_{i_j})$

  with points $x_i \in \mathbb{R}^F$ and edge function $h_\Theta : \mathbb{R}^F \times \mathbb{R}^F \to \mathbb{R}^{F'}$



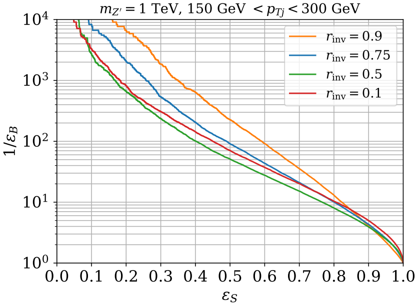
Wang et al., 1801.07829

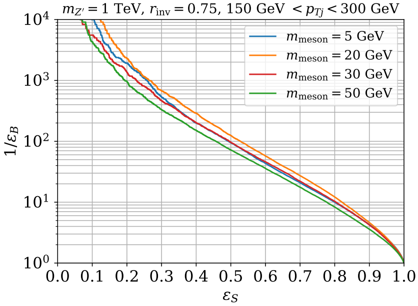
DGCNN performance in comparison to other networks



- Signal: semi-visible jets from dark showers, background: QCD jets
- DGCNN outperforms CNN operating on jet images as well as LoLa on 4-vectors
- Advantage of DGCNN is much larger than in top tagging benchmark

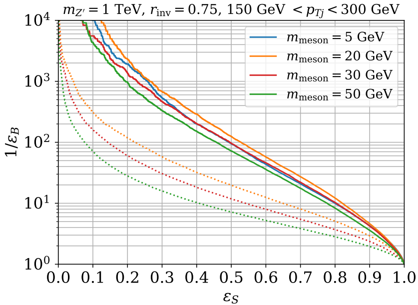
Varying dark sector parameters

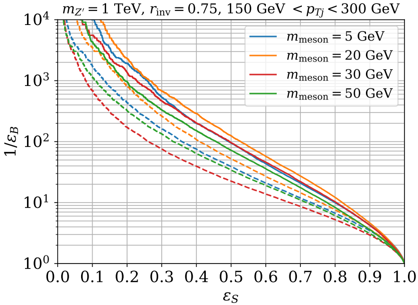




- Characteristic parameters: r_{inv} and dark meson mass m_{meson}
- Dark showers with larger r_{inv} easier to identify, except at very low r_{inv}
- Moderate effect of different dark meson masses

Mitigating model-dependence





dotted: trained on $m_{\rm meson} = 5$ GeV

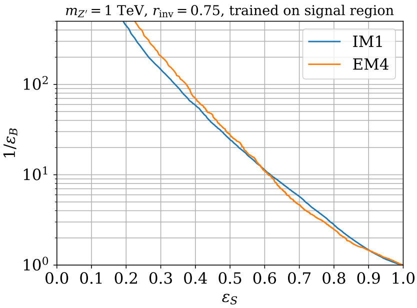
dashed: trained on mixed sample

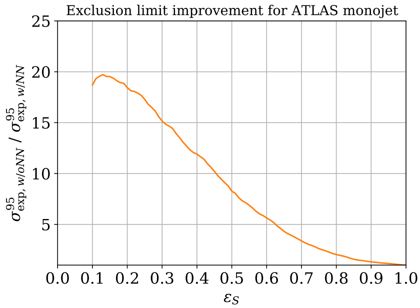
- Network learns to reconstruct the dark meson mass
- Training on a mixed sample mitigates model dependence

Applied to monojet analysis

By how much can we improve an analysis with our dark shower tagger?

⇒ Monojet search as example ATLAS-CONF-2017-060





- Train on dark showers and dominant background (Z+jets), separately for each signal region
- Require at least one jet tagged as dark shower after usual cuts

⇒ Sensitivity increased by factor ~ 20

Conclusions

- Strongly interacting dark sectors are a well motivated scenario predicting exciting new LHC signatures (including LLPs)
- Difficult to identify with conventional methods: great opportunity for machine learning
- Graph nets are particularly well suited to this task
- Model dependence can be mitigated, e.g. with mixed training
- Increases the sensitivity of searches by a lot
- Can reach into parameter space not covered by prompt or LLP searches
- Still thinking about unsupervised techniques that works for dark showers and general new physics

Backup

Consistent benchmark model

$$SU(3)_{\rm dark} \times U(1)'_{\rm mediator}$$

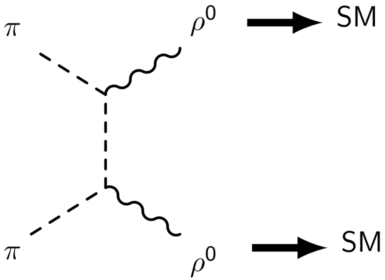
- 2 flavours of dark quarks $q_{\rm d}$
- Z' mediator $\sim \mathcal{O}(\rm TeV)$ coupling to $q_{\rm SM}$ and $q_{\rm d}$

confinement at $\Lambda_{\rm d}$

- $\pi^0_{\rm d}$, $\pi^\pm_{\rm d}$, $\rho^0_{\rm d}$, $\rho^\pm_{\rm d}$ $\sim \mathcal{O}(\rm GeV)$
- **Dark pions are DM (stable)**
- $Z'\pi^+_{\rm d}\pi^-_{\rm d}$, $Z'\rho^+_{\rm d}\rho^-_{\rm d}$ coupling
- Z'-$\rho^0_{\rm d}$ mixing $\Rightarrow$ $\rho^0_{\rm d}$ **unstable**

Freeze-out

- ρ_d in equilibrium in early Universe if $\Gamma_{\rho^0} > H$
- π_d-ρ_d decoupling sets DM relic density
- Dominant freeze-out process: $\pi_\mathrm{d}\pi_\mathrm{d} \to \rho_\mathrm{d}\rho_\mathrm{d}$ (forbidden DM, D'Agnolo et al., 1505.07107)



$$\sigma_{\pi\pi\to\rho\rho} \propto \frac{g^2}{m_\pi^2}\, e^{-2\Delta x_f}$$

$$\Delta = \frac{m_\rho - m_\pi}{m_\pi} \sim 0.2 \text{ - } 0.5$$

- Relic density can be easily produced by adjusting m_ρ/m_π.

Architectures