Casting a ParticleNet to catch dark showers

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Strongly interacting dark sectors

- **What if the dark sector resembles QCD?**
  ⇒ 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 $E_T$
- $\rho_d^0$ decay to visible jets
  $\Rightarrow$ Semi-visible jets

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

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
- Recently used as jet tagger: ParticleNet  
  Wang et al., 1801.07829
  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)

\[
    x'_i = \frac{1}{k} \sum_{j=1}^{k} h_\Theta(x_i, x_{ij})
\]

with points \( x_i \in \mathbb{R}^F \) and edge function \( h_\Theta : \mathbb{R}^F \times \mathbb{R}^F \rightarrow \mathbb{R}^{F'} \)
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: $r_{\text{inv}}$ and dark meson mass $m_{\text{meson}}$
- Dark showers with larger $r_{\text{inv}}$ easier to identify, except at very low $r_{\text{inv}}$
- Moderate effect of different dark meson masses
Mitigating model-dependence

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

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

$dashed$: trained on mixed sample

$m_{Z'} = 1 \text{ TeV}, r_{\text{inv}} = 0.75, 150 \text{ GeV} < p_{Tj} < 300 \text{ GeV}$
By how much can we improve an analysis with our dark shower tagger?

⇒ Monojet search as example

- $m_{Z'} = 1$ TeV, $r_{\text{inv}} = 0.75$, trained on signal region

- Exclusion limit improvement for ATLAS monojet

- Train on dark showers and dominant background ($Z + \text{jets}$), separately for each signal region

- Require at least one jet tagged as dark shower after usual cuts

⇒ Sensitivity increased by factor $\sim 20$
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
Consistent benchmark model

\[ SU(3)_{\text{dark}} \times U(1)_{\text{mediator}} \]

- 2 flavours of dark quarks \( q_d \)
- \( Z' \) mediator \( \sim O(\text{TeV}) \) coupling to \( q_{\text{SM}} \) and \( q_d \)
- Confinement at \( \Lambda_d \)
- \( \pi_d^0, \pi_d^\pm, \rho_d^0, \rho_d^\pm \sim O(\text{GeV}) \)
- Dark pions are DM (stable)
- \( Z'\pi_d^+\pi_d^- \), \( Z'\rho_d^+\rho_d^- \) coupling
- \( Z'\rho_d^0 \) mixing \( \Rightarrow \rho_d^0 \) unstable
Freeze-out

- $\rho_d$ in equilibrium in early Universe if $\Gamma_{\rho^0} > H$
- $\pi_d - \rho_d$ decoupling sets DM relic density
- Dominant freeze-out process: $\pi_d \pi_d \rightarrow \rho_d \rho_d$
  (forbidden DM, D’Agnolo et al., 1505.07107)

![Diagram of particle interactions]

\[
\sigma_{\pi\pi \rightarrow \rho\rho} \propto \frac{g^2}{m_\pi^2} e^{-2\Delta x_f}
\]

\[
\Delta = \frac{m_\rho - m_\pi}{m_\pi} \sim 0.2 - 0.5
\]

- Relic density can be easily produced by adjusting $m_\rho/m_\pi$. 