Casting a GraphNet to catch dark showers

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based on **arXiv:2006.xxxxx**

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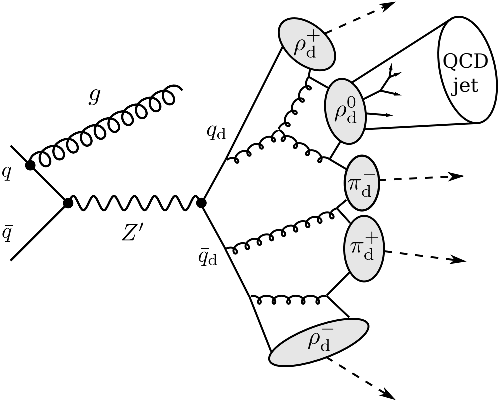
TRR 257 - Particle Physics Phenomenology
after the Higgs Discovery

Dark showers at the LHC

- Production of dark quarks leads to dark shower and hadronisation
  $\rightarrow$ Giovanni Grilli di Cortona's talk
  For benchmark model and details see EB et al., 1907.04346



- Large number of dark mesons in an event
- Most escape the detector as $\not{E}_T$
- Some decay to visible jets

$\Rightarrow$ **Semi-visible jets**

$\Rightarrow$ Exciting new signatures, but difficult to find

$\Rightarrow$ **Train a neural network to distinguish dark showers from QCD**

Dynamic Graph CNN

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

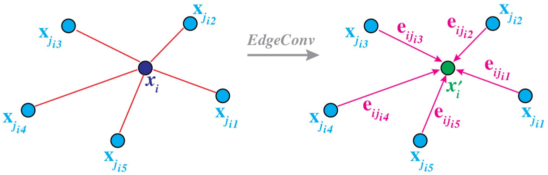
Jets as point clouds

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

Edge convolution

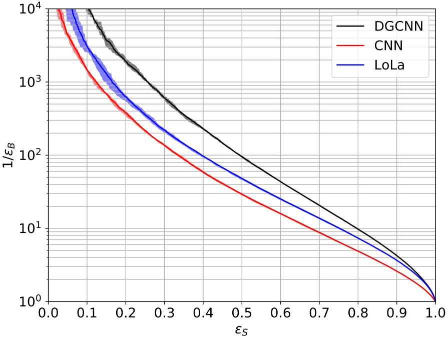
- For each point construct graph of k nearest neighbours
- Carry out convolution over edges (features of pairs of neighbours)
- $x_i' = \frac{1}{k} \sum_{j=1}^{k} h_\Theta(x_i, x_{i_j})$

  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

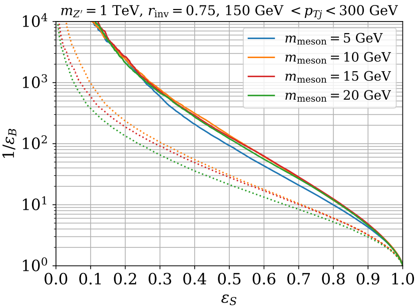
DGCNN performance in comparison to other networks



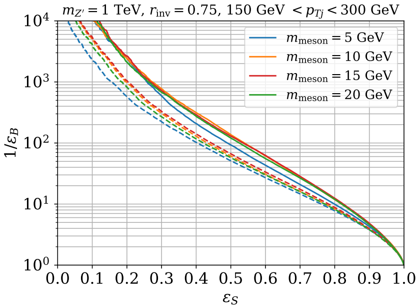
- Signal: semi-visible jets from dark showers, background: QCD jets
- DGCNN significantly outperforms more conventional architectures (e.g. CNN operating on jet images and LoLa on 4-vectors)
- DGCNN advantage is much larger than in top tagging benchmark

Varying dark sector parameters

- Moderate effect on performance from r_{inv} (average fraction of $\not{E}_T$)
- Most influential parameter: dark meson mass



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

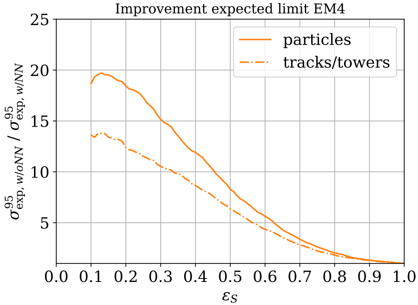
By how much can we improve an analysis with our dark shower tagger?

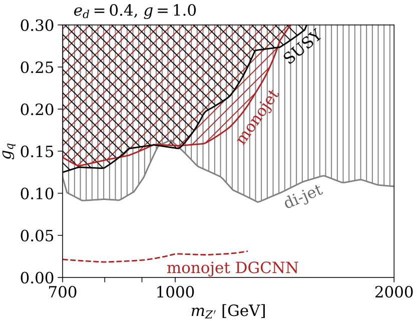
⇒ **Monojet search as example** ATLAS, 1711.03301

(sensitive to events with one visible and one invisible dark shower)

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

⇒ Sensitivity increased by factor $\sim$ 20 (assuming subdominant ttbar bg)





Model from EB et al., 1907.04346

Conclusions

- Strongly interacting dark sectors are a well motivated scenario predicting exciting new LHC signatures
- 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 even when all other cuts remain the same
- Can reach into parameter space not covered by existing prompt or LLP searches
- So far only supervised training – still thinking about unsupervised techniques that work for dark showers and general new physics